The Applications of UAV and Ground Digital Imagery Analysis for Monitoring Grapevine Canopy in Vineyard

by
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Contents

List of Tables and Figures (excluding journal articles)

Tables:

Figures:

Abstract

Canopy management is one of the key aspects of vineyard management. Understanding the canopy structure can provide valuable insights and guide canopy management to improve vineyard performance. Unmanned aerial vehicles (UAV), in combination with different sensors, can be used to capture high-resolution imagery to analyse canopy structure. To explore the potentials of UAV, innovative UAV applications, including monitoring canopy development, evaluating canopy management outcomes and detecting canopy gaps, were studied in vineyards across South Australia. Customised computer codes were developed to analyse the imagery collected and process the reconstructed three-dimensional vineyard models (digital surface model and point cloud). Ground imagery analysis and manual measurements were used as ground-truth validations. Results showed UAV can effectively estimate canopy structure. Imagery and canopy models can provide canopy structure volumetric information that are otherwise challenging to achieve in field. Future improvements should focus on creating more easily operated, open-sourced and reliable UAV systems for canopy structure measurements.

Declaration

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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Chapter 1. Introduction

In the production of grapes, a healthy and balanced grapevine canopy structure can improve yield and crop quality traits. Canopy management regulates the need of mineral nutrients and water inputs to achieve the balance between proper canopy structure and yield (Iland et al., 2011). Understanding canopy structure can help guide canopy management practices more efficiently. To estimate canopy structure, various optical sensing measurements can be used, ranging from ground-based direct leaf harvesting and ground-based proximal sensing to remote sensing through the use of manned and unmanned aerial vehicles (UAV) and satellite (Hall, 2018; Jones & Vaughan, 2010). Optical sensing has strong practical potentials in estimating the health of canopy structure and any spatial variations in the canopy structure across the vineyard (Hall, 2018).

To manage canopy structure, different training systems and applications of shoot thinning, bunch removal and leaf plucking are common approaches (Dry, 2000; Iland et al., 2011; Petrie & Clingeleffer, 2006; Wang et al., 2019). These different practices and their combinations can increase light exposure and air movement within the canopy (Smart et al., 1985). As a result, improved fruit quality and yield potential, optimal leaf area to fruit ratio and better disease control can be achieved (Reynolds & Vanden Heuvel, 2009). In contrast , poorly managed canopies can lead to unfavourable dense canopy or overly exposing canopy (Smart et al., 1985; De Bei et al., 2019). In addition, grapevine diseases and water and nutrient deficiency can also adversely influence the canopy structure (Mancha et al., 2021; Savi et al., 2018). By estimating the canopy structure properties, canopy measurements can supply critical information regarding canopy health and the detection of diseases.

Currently, the most accurate direct canopy estimation of using leaf harvesting and area measurement are labour intensive, cumbersome and destructive (Liang et al., 2012). To overcome these limitations, optical sensing applications for grapevine canopy have been studied. These applications have been used to measure different canopy structure parameters to provide specific information regarding canopy dimensions, grapevine water status and canopy health. To name a few, digital imagery analysis based plant area index (PAI) for measuring canopy cover, normalized difference vegetation index (NDVI) for estimating canopy photosynthetic activity and digital canopy model (DCM) for the three-dimensional information of the canopy structure (Njoku, 2014). Generally, the same index/parameter can be measured by a proximal ground approach as well as aerial remote sensing. For example, PAI can be measured by hemispherical canopy cover photography on the ground as well as aerial-based spectral indices, according to empirical relationships (Fournier et al., 2017; Jones & Vaughan, 2010). Three dimensional DCM can be captured by a laser scanner mounted on a ground vehicle or reconstructed from high resolution aerial imagery using photogrammetry (Siebers et al., 2018). To apply these innovative measurements in the field, research and commercialisation efforts have been focusing on providing suitable solutions for field applications.

Recent developments in optical sensing technologies have introduced new hardware and software solutions. To list a few, smartphone applications that calculate PAI using non-hemispherical canopy cover imagery can achieve similar accuracy to destructive measurements (De Bei et al., 2016; Orlando et al., 2016; Savi et al., 2018). Ground vehicles are integrated to carry multiple optical sensors for proximal canopy sensing and canopy structure modelling (Gatti et al., 2016; Grocholsky et al., 2012). UAV has been increasingly used for optical canopy sensing for the collection of high-resolution imagery (Pádua et al., 2018). Photogrammetric software can then reconstruct a canopy point cloud from the imagery which was previously only capable of using laser scanning (de Castro et al., 2018). Integrated application of remote sensing and interpolation can help identify vineyard canopy variations through the creation of maps of the targeted indices (Bramley, 2005; Di Gennaro et al., 2019; Kalua et al., 2020). With various levels of complexities collected through remote sensing, the selection of the optimal approach should be considered in conjunction with their costs and the challenges in data processing (Andújar et al., 2019; Savi et al., 2018).

This research project was sponsored by Wine Australia and the University of Adelaide through the provision of research infrastructure, funding and stipend. It is expected that the project explores the potential future applications of UAV to monitor vineyard performance more efficiently and effectively.

1.1 Objectives of the Research

The research objectives of this thesis include:

i) To investigate the feasibility of using UAV remote sensing for monitoring vineyard canopy development.
ii) To explore the potential of using UAV for various vineyard monitoring purposes that are otherwise challenging as ground/manual measurements.
iii) To develop innovative approaches in the analysis of two-dimensional imagery and three-dimensional models collected by the UAV.
iv) To recommend the suitable application scenarios for using UAV in vineyard monitoring.

1.2 Linking Statement

The research in this work is presented in chapters, including three research chapters each represents one manuscript written in the styles of peer-review journals. Two manuscripts have been accepted by peer-reviewed journals.

- **Chapter 1** is the introduction and the objective of the thesis.
- **Chapter 2** is a review of previous published literature. Starting with the physiology of a grapevine canopy and how can canopy management can change vineyard performance, followed by review of ground and aerial imagery analysis approaches and how they can be used for vineyard monitoring. Advantages and limitations of each approach are also mentioned. A summary of the literature and aims of the research are presented in the end.
- **Chapter 3** is a prepared manuscript, describing a study monitored vineyard development across two growing seasons. The study demonstrates that canopy monitoring can be performed using both ground and UAV based approaches. These approaches were also used for subsequent studies. The findings of this study showcase the feasibility of UAV remote sensing for vineyard monitoring on a regular basis during the growing season.
- **Chapter 4** is an published and peer-reviewed manuscript, describing a study that used UAV remote sensing to evaluate the outcomes of a range of canopy management practices, including leaf removal, shoot thinning and bunch thinning.

The findings show that, except for bunch removal, UAV can effectively evaluate canopy changes after the management practices.

- **Chapter 5** is also an published and peer-reviewed manuscript. It describes a study that used canopy volume, from point clouds obtained by UAV, to detect the decline in canopy development and canopy gaps in a vineyard impacted by Eutypa dieback. Point cloud analysis procedures were developed in the study to extract the low canopy volume sections along the grapevine row. The findings of this study demonstrate an innovative application of using UAV remote sensing for vineyard monitoring. Compared with tedious ground measurements, UAV can determine the length and distribution of canopy gaps in a vineyard rapidly.
- **Chapter 6** is the general discussion on the findings of this research. Three studies with different monitoring purposes are described in Chapter 3-5. Based on the findings of these studies the most suitable monitoring approach for different purposes are discussed. Various data analysis approaches for processing the data collected are compared. The limitations of both UAV and ground monitoring approaches are explained. Finally, the potential future improvements, aimed at improving the reliability and practicability of the UAV remote sensing, are described.

Chapter 2. Literature Review

2.1 Introduction

This literature review focuses on four aspects related to vineyard canopy management and monitoring based on previous research. These include the physiology of a grapevine canopy and how canopy management can alter the grape quality and yield; various approaches for measuring canopy structure using ground, aerial, and satellite platforms.

2.2 Canopy Structure Management

Light and Canopy Relationships

During canopy development and berry formation, light properties including light intensity (Photosynthetically Active Radiation (PAR) or photosynthetic Photon Flux Density (PPFD)), quality (quantum flux ratio of red to far-red light, R:FR), and photoperiod (duration of light exposure) are influential at all major growing stages (Iland et al., 2011). For example, high light intensity before bud burst has been shown to increase the number of inflorescence primordia in dormant buds, which is an important indicator of fruitfulness (Buttrose, 1969; May et al., 1976; Sánchez & Dokoozlian, 2005). The incidence of primary bud necrosis, a grapevine physiological disorder that reduces fruitfulness, has also been found to be reduced by improved light conditions (Dry & Coombe, 1994; Morgan et al., 1985; Morrison & Iodi, 1990; Perez & Kliewer, 1990). During early shoot development, leaf photosynthetic rate is limited under low light conditions, and shaded leaves have a lower net assimilation rate (Cartechini & Palliotti, 1995; Iland et al., 2011). Row orientation also influences light distribution as east-west orientated rows receive more variable light intensity than north-south oriented rows (Meyers et al., 2011; Trought et al., 2017).

Yield and quality components, such as bunch architecture and berry chemical composition, have been shown closely related to the canopy light environment, as the light condition influences these components throughout the stages of inflorescence primordia development to fully mature (Cook et al., 2015; Haselgrove et al., 2000). Various studies have shown that total soluble solids, juice pH, flavanols, and varietal thiols increased with greater light exposure, while titratable acidity generally declined (Bergqvist et al., 2001; Ristic et al., 2007; Šuklje et al., 2014). For example, Gregan et al. (2012) found total phenolics within the berry skins increased significantly with more light exposure. A recent study on flavanols, by Friedel et al. (2016), showed that the expression of flavanol synthases was absent in shaded bunches but recovered quickly under re-illumination. The anthocyanins level was also found to increase linearly with light exposure (Bergqvist et al., 2001). In addition, it is suggested that the response of anthocyanin levels is determined by the sensitivities of grapevine cultivars to the light (Haselgrove et al., 2000; Oliveira & Nieddu, 2015). In summary, having the right light environment in the canopy structure can improve the yield and fruit quality.

Direct Canopy Management Methods

To alter the canopy light microclimate by changing the canopy structure, various direct and indirect manipulation methods are used. For example, different trellis systems, leaf removal, shoot/bunch thinning practices combined with various mid-row cover crops, and irrigation practices have been extensively studied and applied. Their primary goals are to regulate yield, control excessive canopy vigour, improve canopy zone light exposure and, ultimately, improve grape quality (Dry, 2000; Wolf et al., 2003).

Training/trellis systems, used for establishing and maintaining the canopy structure, can improve the amount of light exposure and increase fruitfulness and yield per node (Dry, 2000). In many commercial vineyards, widely applied trellis systems include vertical shoot positioned (VSP), cane pruning, Scott Henry, Smart Dyson, and minimal pruning, among others. Detailed descriptions of these systems can be found in Smart & Robinson, (1991). When choosing the training system, an ideal candidate should be labour-efficient, capable of working with vineyard machinery and producing the fruit of the desired quality (Cavallo et al., 2001; Wolf et al., 2003).

Shoot thinning, bunch thinning, and leaf removal practices are destructive practices that manipulate the canopy structure by directly removing shoots, bunches or leaves from the canopy during the growing season. Research studies on these practices have shown that the timing and intensity of their applications can significantly influence their outcomes on the crop yield and quality (Table 1 and Table 2). Applications of leaf removal at early growing stages can improve the light interception in the bunch zone and improve the accumulation of sugars and anthocyanins; key colour compounds in red grapes (Cook et al., 2015; Lemut et al., 2015). Similarly, bunch thinning can also facilitate sugar content accumulation (Reynolds et al., 2005). However, excessive removal of leaves can also negatively impact the accumulation of sugar in the berry, while excessive bunch thinning can negatively impact yield without improving the overall quality (Vasconcelos & Castagnoli, 2000). Leaf removal after harvest can also reduce bud fruitfulness in the following growing seasons (Greven et al., 2016). Additionally, shoot thinning can serve as a complementary method to winter pruning to further balance fruit yield and berry composition with grapevine vigour, especially for cultivars that are susceptible to excessive crop with poor quality and high lateral shoot growth (Morris et al., 2004). In general, these destructive canopy management practices are usually used in conjunction with different training systems to provide continuous canopy regulation throughout the growing season.

Indirect Canopy Management Methods

Cover crops and deficit irrigation can help manage and modify the soil water and nutrient contents and be used as an indirect strategy to manage canopy structures. The cover crop can help to control overly vigorous grapevines (Centinari et al., 2016). Cover crops have been shown to significantly reduce canopy density, average yield, and increase fruit exposure to sunlight (Hickey et al., 2016). Another study by Vogelweith & Thiéry (2017) found that cover crops can also increase the population of beneficial insects and reduce the pest stress in the vineyard, contributing to canopy health.

Regulated deficit irrigation has been used to improve water use efficiency and alter berry composition (Cooley et al., 2017; McCarthy, 1997). In support of that, research showed that the intensity and period of deficit irrigation have a significant influence on the grape berries' composition. Niculcea et al. (2014) showed that water deficit could modify the levels of plant hormones, including indole-3-acetic acid, abscisic acid, salicylic acid, and jasmonic acid. As a result, berry size reduced, amine accumulation, and skin mass increased. Total skin anthocyanin increased with a shift from di-hydroxylated form to trihydroxilated form with deeper colour in grapevines under water stress (Cook et al., 2015; Niculcea et al., 2014). Study by

Indirect canopy management, especially deficit irrigation, offers alternative choices for canopy management. However, it is also shown the indirect canopy management used in conjunction with direct canopy management need to be monitored carefully to minimise potential adverse effects (Mancha et al., 2021). The vineyard soil type should also be taken into consideration as highly permeable soil types can significantly reduce the water holding capacity of the soil and can cause excessive vine stress under extreme heat (Savi et al., 2018). Satellite remote sensing has also shown the potentials for evaluating the economic benefits of deficit irrigation, by comparing the canopy vigour levels in NDVI imagery captured before and after the application (Bellvert et al., 2021).

2.3 Approaches for Measuring Canopy Structure

With direct and indirect canopy management approaches available and their outcomes depending on their application intensity, it is crucial to obtain accurate measurements of the canopy structure to guide canopy management decisions (Di Profio et al., 2011). Also, the time and effort required to capture canopy structure accurately need to be considered to understand its practicability for vineyard management (Preszler et al., 2010). It is impractical to directly measure every vine's condition and estimate canopy structure destructively due to the tedious and costly process. With developments in imagery analysis methods, various indirect and non-destructive canopy structure assessments developed by researchers will now be introduced.

Direct canopy structure measurements

To directly assess the canopy performance and its structure, developed methods including point quadrat analysis (PQA), vineyard scoring, and destructive defoliation have been implemented and practiced (Smart & Robinson, 1991). To perform the PQA, a thin metal rod is inserted horizontally into the canopy's fruit zone, and any contacts with leaves and bunches are recorded. The insertion of a metal rod is to mimic the light interception and contacts of the rod with the leaves and bunches are an estimate of their exposure to light (Smart & Robinson, 1991). For all insertions, the average leaf layer number (LLN) is calculated according to the number of contacts with leaves, and a LLN value between 1-1.5 is suggested to be ideal. Being a direct and easy-to-understand method, PQA only samples a limited canopy section each time, and no spatial information regarding the information is collected (Meyers &

Vanden Heuvel, 2008). Another direct assessment approach, vineyard scoring, requires the assessor to stand in front of the grapevine and assess the canopy development according to set guidelines highly subjective and based on an assessor's expertise and experience (Smart & Robinson, 1991).

To better quantify the canopy structure, leaf area index (LAI) was developed and defined by Watson (1947) as the total one-sided area of leaf tissue per unit ground surface area. Another similar parameter, plant area index (PAI) has also been widely used, which is the sum of leaf and other plant material (such as the shoots and bunches) relative to the ground area (Bréda, 2003). Studies on various crops and trees have shown LAI and PAI’s close relationships to photosynthesis net assimilation rate, spectral reflectance, absorption of photosynthetically active radiation (PAR), and evapotranspiration (Asrar et al., 1984; Bréda, 2003; Jordan, 1969; Watson, 1958). To directly measure LAI, destructive leaf defoliation and the manual area measurement for each leaf area are required. Using a digital scanning planimeter can make the leaf area measurement faster, but all leaves still need to be collected before being scanned individually (Jonckheere et al., 2004). Therefore, the overall destructive LAI measurement approach is considered slow, highly precise, and limited to scientific research. Alternatively, allometric relationships between the leaf mass and its area can be used to estimate LAI. Leaf samples are collected, dried, weighed, and multiplied by the leaf area factor (cm^2g^{-1}), which is variety specific, to obtain the total leaf area (Gower et al., 1999). LAI can then be calculated by dividing the total leaf area against the ground area (Gower et al., 1999; Grace, 1987; Sellin, 2000).

Direct measurements of LAI are time-consuming, tedious, and destructive to the canopy structure (Bréda, 2003; De Bei et al., 2016). In practice, the direct measurement's sampling volume is also limited due to its destructive nature and loss made to yield (Gower et al., 1999). Therefore, the direct methods are unfavourable for providing canopy monitoring for vineyard management purposes and mostly serve as validation methods for indirect measurements because of high accuracy (De Bei et al., 2016; Doring et al., 2014; Ollat et al., 1998).

Indirect canopy structure measurements

To overcome the limitations of direct canopy structure measurements mentioned above, optical sensing is used to monitor canopy structure indirectly. Mabrouk & Sinoquet (1998) showed the virtual simulation of the canopy, using imagery analysis software, could be used to calculate some structural and spectral indices for describing the attributes of the light microclimate. The study by Dobrowski et al. (2002) utilized spectral indices measuring single vines in the field and aerial image analysis at the vineyard scale to demonstrate that the results are similar to measurement results from woodland and forest environments.

The indirect estimation theories are based on the level of light interception and transmission by the canopy (Fournier & Hall, 2017). With the energy for photosynthesis coming from photosynthetic active radiation (PAR) (between wavelength 400-700 nm), a single, mature, and exposed grapevine leaf can absorb 87% PAR and transmit 6% PAR to the ground (Smart & Robinson, 1991). Also, the ratio of red to far-red light changes after transmission (from 1.2 to 0.18) due to stronger red light absorption by the leaf (Iland et al., 2011). Therefore, by measuring the intensity and composition of transmitted light underneath the canopy, the canopy structure can be assessed by estimating the LAI and PAI. Compared with direct measurements, indirect estimation has also been more convenient in processing large sample sets with less time taken for each sampling (Jonckheere et al., 2004).

Another parameter, the light extinction coefficient (*k*), which describes the canopies efficiency in intercepting light, also holds a key role in different indirect approaches (Campbell, 1986). A high *k* value indicates that most of the light has been intercepted by the canopy. In contrast, a low *k* value indicates high light transmission. To use the *k*, the study by Vose et al. (1995) on hardwood forest species showed that *k* needs to be calibrated specifically according to the sampling site and species. The *k* value is also linked with seasonal changes but independent of major environmental parameters, including temperature, precipitation, and LAI (Zhang et al., 2014). For grapevine, it is suggested that the *k* value of 0.7 is the most accurate for the canopies trained as a vertically shoot positioned (VSP) trellis system (De Bei et al., 2016; Sigfredo Fuentes et al., 2012). However, limited information is available about the *k* value for different grapevine cultivars, growing regions, and training systems which can have profound influences on the actual canopy structure. It requires more investigation to calibrate the *k* value in different application scenarios for more accurate results.

Non-foliage canopy structure components, aside from leaves, including the trunk, shoots, and bunches, can also absorb PAR. When calculating the canopy light absorption from transmitted light, the result includes PAR absorption by these non-foliage components (De Bei et al., 2016). Rather than obtaining LAI, the result is more likely to represent the PAI, potentially overestimating LAI (Neumann et al., 1989). For grapevine, parameters like vine age (representing trunk and cordon size) and training systems (for example, spur *vs.* cane pruning) can change the canopy structure and influence the accuracy of LAI estimation (De Bei et al., 2016). To overcome this, measurements of some non-foliage canopy components, such as trunk and cordon, during grapevine dormancy or early in the season can be used to quantify their contributions to PAI and be deducted to obtain a more accurate LAI (Sigfredo Fuentes et al., 2008). The necessity of calibration is therefore recommended to obtain the most accurate results. However, the contribution of bunches on PAI remains hard to assess as they only develop during the growing season.

Applications for vineyard monitoring

In practice, purposely designed LAI/PAI sensors have been developed to measure the transmitted PAR to estimate canopy size and vigour (e.g. SunSCAN by Delta-T). Another approach is to use a hemispherical image captured with a fisheye lens, which is then analysed to calculate the gap fraction in the image, which is analogous to light transmittance and allows for LAI determination (e.g. LI-COR sensors). These purposely designed LAI tools have been widely used in various viticulture research (Doring et al., 2014; Hall et al., 2008; López-Lozano & Casterad, 2013; Petrie et al., 2004; Walker et al., 2000). However, there is a considerable financial input to obtain and maintain the specific device, with specific training being essential to interpret the data obtained. As a result, their practicabilities for vineyard monitoring by grape growers and industry practitioners are limited.

More recently, with easier access to smartphones or tablets, these digital platforms have been used to create novel approaches for LAI estimation. For example, in a series of studies by De Bei et al. (2016), Fuentes et al. (2008), and Fuentes et al. (2014), a smartphone application (smart-app) VitiCanopy has been developed to calculate PAI based on the upward-looking digital images captured under the vine by the on-board camera. In these studies, the app is an accurate, cost-effective, and easy-to-use method to estimate the spatial and temporal LAI and canopy structure, compared to standard measurements obtained from the professional instrumentation (with a R^2 value of 0.89). Similarly, another smartphone application, PocketLAI, developed by Confalonieri et al. (2013), was applied to measure PAI and compared with the results from hemispherical photography and destructive measurements (Orlando et al., 2016). The major difference between this application and the previously mentioned VitiCanopy is that the image is obtained at the sensor angle of 57.5° off-nadir upward, compared to 90° upward VitiCanopy. This specific angle is suggested to reduce the negative effect of leaf clumping (Baret et al., 2010).

With the rapid development of imagery analysis algorithms, LAI and PAI's calculation to estimate the canopy structure has been greatly simplified. However, LAI's measurement via novel indirect methods still requires more research to reduce the inaccuracies caused by factors such as leaf clumping, variable light conditions, and different phenological developmental stages. It is also necessary to adapt, calibrate and validate these methods to different canopy manipulation practices and trellis systems (De Bei et al., 2016; Jonckheere et al., 2004; Macfarlane et al., 2007).

2.4 Platforms for Canopy Sensing

Optical sensing to obtain canopy structure parameters require remote sensing platforms that include hand-held devices, ground vehicles, manned and unmanned aircraft, and satellites. With increasing distance between the platform and the canopy, larger sensing coverage is achieved in a single capture but potentially reduced precision. Various costs and skills are also required to perform canopy sensing when using different platforms. Therefore, it is crucial to understand each platform's advantages and limitations and select the most suitable tool for vineyard monitoring according to the desired end-use.

Hand-held devices and ground vehicles

Canopy sensing using ground vehicles as the carrier platform has several advantages. First, canopy measurements are obtained with higher resolutions at a much closer sensing distance. Second, most growers have ground vehicles, such as tractors or all-terrain vehicles, meaning the deployment of field sensing activities can be more conveniently managed and responsive to immediate demands and is less constrained by the weather conditions. Third, canopy monitoring can be performed concurrently with common vineyard operations, such as spraying, shoot trimming, and slashing (Bramley et al., 2007; Gatti et al., 2016).

Historically, canopy sensing with hand-held devices evolved from Hill's fisheye lens to characterize forest light conditions (Evans & Coombe, 1959). Sensors held by hand or supported by specially designed stands are the most common forms of canopy sensing platforms using both hemispherical imagery and normal digital imagery. For instance, the professional canopy analyser and smartphone apps (VitiCanopy and PocketLAI) discussed in a previous section are based on hand-held devices (De Bei et al., 2016; Orlando et al., 2016).

Hand-held devices with sensors have the advantages that (i) provide real-time information on current canopy performance and (ii) serve as a ground-truthing method for remote sensing-based systems, algorithms, or instruments (e.g., used for the UAV platform accuracy assessments). However, hand-held sensors' limitations include the discrete data points, limited capacity to build 3D canopy architecture models, and the time-consuming nature of data collection in the field. Nonetheless, with the convenience and accessibility of having a smartphone capable of acquiring, storing, and processing high-resolution images, hand-held devices' potential should not be underestimated.

Canopy sensing using ground vehicles to measure grapevine vegetative parameters generally uses similar indices as aerial remote sensing. Different studies have designed various novel systems. Stamatiadis et al. (2006) investigated the relationship between NDVI and several grapevine properties, including pruning weight and berry sugar content. Additionally, with multispectral sensors mounted on a tractor, images can be obtained at nadir and side view angles. Results showed that the images from nadir view (R^2=0.64) were more correlated with biomass than from side view (R^2=0.41). A high correlation was also found between NDVI and the biomass (R^2=0.80).

In more recent studies, Grocholsky et al. (2012) and Nuske et al. (2014) described a tractor-mounted laser scanning system to: (i) measure the canopy shape and volume and (ii) estimate yield based on berry texture, colour, and shape; where both approaches were within 10% error. Similarly, Gatti et al. (2016) introduced the multi-sensor MECS-VINE® system, which measures Canopy Index (CI) using two sideway RGB sensors. CI is a novel index for describing canopy wall biomass that takes the canopy size and canopy wall thickness into account. The results showed the system was suited to small-sized vineyards, especially for those less than two ha. It also suggested that the 3D canopy point cloud can be converted into a 3D occupancy grid to reduce the large dataset generated. For applications beyond the growing seasons, Kicherer et al. (2017) designed a dormant cane analysis system that used depth map calculation and image segmentation to estimate pruning weight. The system claims to serve as an objective method to select healthy canes for propagation phenotypically.

In addition to new systems, commercially available methods also attract critical evaluation to examine their application capacity in different growing environments. Bramley et al. (2007) tested the feasibility of measuring canopy porosity using the tractor-based system, Grapesense developed by Lincoln Venture (Lincoln, New Zealand) for Australian vineyards. However, the system was shown to have difficulties in controlling the distance between leaves and the camera during driving, and the problem became more significant as the canopy vigour level increased during the growing season. Suggested improvements include hardware and software design changes for late-season measurements and relocation of the camera from the rear to the front so that the 3-point linkage at the back of the tractor can be reserved for fieldwork machinery. Similar to studies mentioned before, sensors with a mounting height of 0.7m on a tractor were shown to be most suitable and accurate for these measurements.

Satellite and airborne platforms

As widely used remote sensing platforms, satellite and manned aircraft have been used to monitor vineyard performance for scientific research and commercial production purposes. Satellites carrying multispectral or hyperspectral sensors can generally capture metre level resolution imagery, such as Landsat (30m resolution) and Sentinel (10m resolution) series satellites, with some more recent high-resolution candidates capable of achieving sub-meter level resolutions, such as WorldView series satellites (Di Gennaro et al., 2019; Jones et al., 2020; Sun et al., 2017). Manned aircraft can achieve higher resolutions at sub-metre or centimetre levels, depended on the flight height (Bellvert et al., 2016). Unmanned aerial vehicle (UAV or more commonly known as 'drone') can further acquire sub-centimetre resolution imagery with the advantage of low flight height but at the cost of much smaller coverage, compared with satellite and manned aircraft (Hall, 2018). For both satellites and aircrafts, a wide range of sensors can be carried, such as Red-Blue-Green (RGB), multispectral, hyperspectral, thermal, and laser sensors (Colomina & Molina, 2014; Hall et al., 2018)

Different imagery resolutions captured by satellite and manned aircraft can be used for various monitoring purposes. Metre level resolution imagery can be used to show the spatial canopy variability in the vineyard and divide the whole vineyard or block into zones with different canopy structures using classification algorithms (Bramley, 2005; Sun et al., 2017). However, it is challenging for metre level resolution imagery to distinguish canopy and the background soil in the imagery when a single pixel is wider than the canopy width. Because each pixel, being the basic component of the imagery and cannot be further divided, can contain the combined reflectance from the canopy and the ground (Njoku, 2014). When the inter-row background soil is included in the imagery, it reduces the canopy structure estimation accuracy (Ouyang et al., 2020). Ground interference can be introduced if ground vegetation is present in the vineyard. Similarly, the segmentation and analysis of an individual vine will also be difficult with limited resolution since each pixel can potentially contain reflectance from different vines (Chanussot et al., 2005, Jones et al., 2020).

Improved resolution from metre to even centimetre levels allows identifying the row pattern of the established grapevine canopy in the vineyard (Bellvert et al., 2016). It also enables the segmentation of the canopy from the background soil and offers much stronger capabilities to identify the vineyard's spatial variabilities. The interference from the ground vegetation can also be filtered out by either extracting canopy-related pixels according to spectral indices thresholds or according to the polygon masks defining individual rows' boundaries. Identifying individual vines in the imagery can also be achieved with higher resolution, which offers great value to precision vineyard management. The improvement in imagery resolution by using better sensors or captured at a closer distance also quantifies the spatiotemporal uncertainties in the data and improve the overall data quality (Kalua et al., 2020).

UAV, defined by the International Civil Aviation Organization, is “a pilotless aircraft which is flown without a pilot-in-command on-board and fully controlled from another place”. The rapid development in the UAV design and manufacturing has further enabled this platform to carry a wide range of optical sensors, similar to those carried by manned aircraft and satellite. Compared with aircraft or satellite sensing, UAV sensing demonstrates advantages in its flexibility, high image resolution, precision and the ability to capture individual grapevine vigour discontinuity (Gatti et al., 2017; Matese et al., 2015). Therefore, the gaps in continuous canopy or missing vines common in commercial vineyards can be detected (de Castro et al., 2018).

Various studies using the UAV platform for estimating canopy structure correlated with ground measurement or other remote sensing approaches (Table 3). For example, studies presented by Mathews and Jensen (2013) and Poblete-Echeverría et al. (2017) demonstrate that the LAI predicted from point clouds, reconstructed from overlapped RGB imagery captured by UAV, has moderate to good correlations with ground based measurements. Additionally, canopy models can be used to identify canopy, canopy shadow, and the background soil according to height differences (Weiss & Baret, 2017). The canopy structure's dimensions calculated from the 3D models, such as canopy height and canopy volume, also align with ground-based canopy dimension measurements (de Castro et al., 2018; Pádua et al., 2018). The 3D models created by UAV-based imagery enable the creation of large-scale vineyard models without expensive laser scanning techniques. They can deliver more practical measurements for vineyard management (Njoku, 2014). Despite the advantages mentioned above, various studies also outline UAV limitations, such as limited coverage from a single flight and the requirement for regular battery changes, due to the limited power in each battery (Table 3).

Similarly, carrying multiple sensors for capturing multiple types of data also substantially reduces the coverage in a single flight, due to an increase in payload and a potential increase in power requirement if there is a need to power additional sensor(s). For vineyard monitoring, UAV operations for the vineyard area above 50 ha have been less cost-effective than air-plane and satellite (Andújar et al., 2019; Matese et al., 2015). The operating costs of satellite and aircraft to capture imagery over a large growing area generally involve marginal increases (Matese et al., 2015). In comparison, UAV operating in the same scenario will require a substantially higher payload to carry a larger battery or change batteries considerably more frequently, both of which can increase the operational costs (Andújar et al., 2019; Matese et al., 2015).

Some other limitations when using UAV include complicated and customized image analysis algorithms, software, and systems involved in analysing the UAV imagery (Jones & Grant, 2015; Matese et al., 2015). This may create difficulties in transforming research outcomes into practical systems for vineyard monitoring. In future studies, creating UAV-based canopy sensing systems that are light in weight, open-source in algorithms, and reliability tested under various environments can significantly improve the system's practicability and reliability.

2.5 Data Analysis for Canopy Optical Sensing

Data analysis approaches

Depending on the platform and the onboard sensor, various types of data can be collected during the optical sensing of canopy structure; examples include imagery, video, and point cloud (by LiDAR scanning, (Siebers et al., 2018)). Currently, imagery is the main data type collected, with a wide range of imagery sensors available and a rich range of computer vision algorithms. Depending on the spectral band collected, panchromatic, RGB, multispectral, and hyperspectral imagery can be collected. For satellite remote sensing, panchromatic imagery, which represents the sum of all spectral bands sensed, is also collected and can be used to improve the resolution of RGB and multispectral imagery, using the process called pan-sharpening (Njoku, 2014). As mentioned previously, with photogrammetry development, digital models of the vineyard, including the digital surface model (DSM) and point cloud, can be reconstructed from digital imagery. This allows for the creation of 3D canopy models without laser scanning techniques (LiDAR) and allows more information to be extracted from the aerial imagery analysis (Mathews & Jensen, 2013).

Data collected using sensors in handheld devices is generally as discrete points created as the assessor walks along the rows, such as PAI measurements reported in De Bei et al., (2016), Wang et al. (2019), and Orlando et al. (2016). This approach is useful as a random sampling approach for understanding canopy size and development. The data volume and complexities in the data processing are also substantially reduced with the discrete sampling points. As such, measurement results are available promptly in the field, avoiding complicated data processing for continuously collected data, such as sensors mounted on the tractor (Nuske et al., 2014; Siebers et al., 2018). Compared with purposely designed measurement equipment (such as LI-COR and GreenSeeker sensors), the sampling locations' geographic coordinates can be collected by the smartphone app during the sampling process, using the internal GPS receiver (Orlando et al., 2016). However, it cannot achieve a continuous measurement of the canopy structure, leading to an undetected canopy between data points. For example, missing grapevine and canopy gaps may not be captured during the process if not sampled intensively in the area of interest.

For processing large volumes of data generated from continuous canopy sensing, the rich range of machine learning (ML) algorithms available for computer vision applications has also been used by researchers (de Castro et al., 2018; Jones et al., 2020; Poblete-Echeverría et al., 2017). Using ML algorithms, the precision in canopy detection can be improved, and the time required for data processing can be reduced. To apply ML, the majority of the data is used to train the classification model. In contrast, a small set of data is used to validate the training results, and the training repeats itself multiple times until a satisfactory detection accuracy is achieved. The model in the training stage will constantly adjust itself to improve the detection accuracy. A confusion matrix is often used to quantify detection accuracy by comparing the manual classification and the ML classification algorithms' output (de Castro et al., 2018; Poblete-Echeverría et al., 2017). During multispectral image analysis, the combinations of different wavelengths allow various vegetative indices to be generated. To determine the most suitable indices for canopy monitoring, they can also be fed into different training models to select the one that has the strongest correlation to the validation data or the ground measurement (Albetis et al., 2017; Poblete-Echeverría et al., 2017). In the study by Poblete-Echeverría et al. (2017), four classification methods K-means, artificial neural networks (ANN), random forest (RForest), and spectral indices (SI) were applied to detect canopy related pixels in the UAV imagery. Results showed that the ANN and the SI method complemented with the Otsu method for thresholding presented the best performance in canopy classification. In Jones et al. (2020), a convolutional neural network was automatically used to detect and segment vineyards across Australia using satellite imagery.

Mapping vineyard spatial variation

Spatial variation of canopy development in vineyards is widely observed and causes variability in yield and crop quality in different zones within the same vineyard (Bramley et al., 2017; Ledderhof et al., 2017). In light of that, various studies have focused on using canopy sensing to characterize vineyard performance and identify the causes of spatial canopy variation. Identifying the spatial variability also allows for zonal management to be applied to mitigate and reduce variability. The precise locations of the underperforming canopy determined by canopy sensing can greatly benefit growers when planning and executing vineyard management practices.

Using remote sensing imagery in different spectral bands, Romero et al. (2018) and Bellvert et al. (2016) used UAV-based multispectral imagery and airborne thermal imagery, respectively, to estimate the water status in vineyards treated with different irrigation treatments. Results demonstrate the strong potential of these imagery types to be used as a trigger for irrigation application to maximize the efficiency of irrigation water usage. High-resolution imagery can also demonstrate the difference in water stress on a plant-by-plant basis, which can be an important indicator for plant health. Using satellite imagery-based canopy sensing, which has a lower resolution than imagery obtained using UAV and aircraft, vineyards can be divided into different zones, representing various canopy development stages, yield, and even crop quality. Sun et al. (2017) used Landsat multispectral imagery derived NDVI and LAI indices to identify zones with different canopy development in the vineyard. The yield prediction generated by satellite remote sensing recorded less than 20% error, compared with the yield at harvest. Similarly, the study by Carrillo et al. (2016) showed that canopy sensing could assist yield prediction and improve the prediction accuracy by 5-7%. However, yield predictions for the next growing season using satellite imagery did not show comparable results compared with bud dissection results (Cunha et al., 2010).

With a combination of remote sensing and data collection in the field, a series of studies by Bramley and Hamilton (2004), Bramley (2005), Bramley et al. (2011), Scarlett et al. (2014), and Bramley et al. (2017) demonstrate the process of identification and mapping of spatial variability in vineyard. These studies focused on identifying the spatial variability of yield and distribution of the rotundone compound, contributing to ‘pepper’ flavours in the grape. A combination of remote and proximal canopy sensing, high-resolution electromagnetic induction EM38 soil surveys, geographic information collection in field and berry component chemical analysis was performed to achieve these targets. Results show that differences in soil types, water availability and topographic formations of the vineyard were found to be the important drivers for within-vineyard variation.

To deliver a more uniform quality crop at harvest, zonal management in the vineyard is suggested to be the key approach for mitigating and reducing spatial variability. In Bellvert et al. (2021), Bellvert et al. (2016) and Savi et al. (2018), different irrigation sectors were set up according to remotely sensed canopy vegetation indices and the economic returns of the crop were improved, as a result. In Di Gennaro et al. (2019) and Sun et al. (2017), zones set up according to vegetation indices correlates well with the crop yield at harvest and provide potential solutions for selective harvest. Apart from these previous studies, zonal management can also be used for vineyard management applications such as variable mulching rates and canopy manipulation intensities.

Various ground and aerial remote sensing-based approaches have effectively mapped spatial canopy variability in vineyards. However, further improvements and research are needed for system design, software-hardware integration testing, open-source development, and system robustness. As previous studies have proven the feasibility of using image analysis approaches for canopy monitoring and setting up zonal management, future studies can focus on developing practical applications and case studies for specific vineyard management purposes. These monitoring systems can be explored, assessed, and improved. By addressing these aspects, the reliability of innovative canopy monitoring approaches can be enhanced and, therefore, improve the wine industry's productivity.

2.6 Conclusion

Canopy structure directly affects yield and fruit quality and is influenced by multiple environmental factors, especially light conditions. Canopy structure can be manipulated by various canopy management practices to balance vegetative growth and fruit development. Applying management practices at different input levels and during different canopy developmental stages can influence the canopy structure. To measure and quantify the canopy structure, the indirect measurements of canopy vigour using aerial or ground imagery analysis are superior to direct measurements as they are more cost-effective and convenient. Among various optical sensing parameters, LAI calculated from RGB imagery has a strong correlation with destructive measurements. Multispectral imagery can provide additional information on the canopy performance. Point cloud can offer precise three-dimensional measurements to the canopy structure. Various ground and airborne vehicles can be employed as the sensor carrier platforms for canopy structure measurement with multiple advantages and limitations. Future studies should focus on creating tools/systems tailored for practical purposes such as canopy development monitoring, canopy manipulation evaluation, and grapevine decline detection with the limited adoption of imagery analysis in vineyard monitoring.

Chapter 3. Prepared Manuscript: Monitoring Grapevine Canopy Development Using Aerial and Ground-based Imagery Analysis

Prepared manuscript for peer-review journal: Computers and Electronics in Agriculture

Statement of Authorship

Title of Paper	Monitoring Grapevine Canopy Development Using UAV and Ground-based Imagery through Point Cloud Analysis.
Publication Status	☐ Published ☐ Accepted for Publication ☐ Submitted for Publication ☑ Unpublished and Unsubmitted work written in manuscript style
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Principal Author

Name of Principal Author (Candidate)	JING YUN OUYANG		
Contribution to the Paper	Collecting ground data Conducting UAV Flights Data Analysis & Manuscript writing		
Overall percentage (%)	60%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	24/09/2020

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Roberta De Bei (10%)		
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Contribution to the Paper	Manuscript review & Comments • Manuscript writing • Data interpretation and analysis • Experimental design		
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Name of Co-Author	Sigfredo Fuentes (10%)		
Contribution to the Paper	Manuscript Review & Comments • Manuscript writing • Experimental design • Data interpretation and analysis		
Signature		Date	22/11/2020

Name of Co-Author	Cassandra Collins (10%)		
Contribution to the Paper	Manuscript Review & Comments. • Manuscript writing • Experimental design • Data interpretation and analysis		
Signature		Date	23/11/2020

Monitoring Grapevine Canopy Development Using Aerial and Ground-based Imagery Analysis

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Keywords: remote sensing, unmanned aerial vehicle, point cloud, plant area index, grapevine canopy

Highlights

- Canopy volume calculated from UAV based point cloud offers accurate measurements of canopy structure for the whole vineyard.
- Ground-based PAI from imaging can be used as a rapid and convenient parameter related to canopy structure in the field.

- Other capabilities and limitations of ground and UAV optical grapevine canopy sensing were summarized.
- The selection of UAV or ground measurements should be determined by the purpose of the monitoring.

Abstract

Monitoring grapevine canopy development is an important practice for vineyard management. However, measuring canopy architecture is a complex task. Aerial remote sensing using unmanned aerial vehicles (UAV) can capture high-resolution images and create three-dimensional point cloud data. This study aimed to compare UAV-based remote sensing with ground measurements to monitor canopy architecture and its development. UAV flights were conducted over a vineyard in South Australia, and RGB and multispectral imagery were collected. Vegetative indices from UAV imagery, including normalized difference vegetation index (NDVI), plant area index (PAI), and canopy volume calculated from point cloud data were compared to PAI calculated from ground canopy cover imagery. Results showed that both UAV-derived and ground measurements detected peak canopy size around veraison. Canopy volume correlated well with ground-based PAI ($R^2>0.6$, $p<0.05$). However, at early developmental stages, the accuracies of spectral indices were impacted by inter-row ground vegetation. For the latter case, point cloud data analysis by height variation can effectively filter out ground vegetation and only extract the canopy structure for monitoring canopy development. At the peak of canopy size, PAI calculated from aerial imagery was overestimated compared with ground measurement due to lower canopy porosity captured in the UAV imagery than ground imagery. This study showed that UAV remote sensing could be an alternative approach to ground measurements for vineyard monitoring. Still, UAV remote sensing in viticulture faces the challenges of integrating sensors, running customized image analysis procedures and fulfilling specific weather conditions. As a general guide, the selection of ground and/or UAV approaches for canopy development monitoring should be based upon the targeted levels of detail and precision required for management purposes.

Introduction

Maximizing grape quality traits and yield can be achieved by manipulating grapevine canopy architecture (Jackson and Lombard, 1993). More open canopies, with high porosity that allow more light to reach the fruit zone have been reported to improve the accumulation of colour and flavour in berries. In contrast, dense canopies can reduce them (Dokoozlian and Kliewer, 1995). Moreover, grapevine diseases, such as trunk disease, can adversely impact canopy development (Sosnowski et al., 2008; Valtaud et al., 2011). Therefore, canopy architecture is a key factor of vineyard performance as it is closely related to the yield and quality of grapes (Dry, 2000; Smart and Robinson, 1991).

To assess canopy architecture, leaf area index (LAI), defined as the total one-sided area of leaf tissue per unit ground surface area, has been widely used (Vasconcelos and Castagnoli, 2000; Wang et al., 2019; Watson, 1947). To accurately calculate LAI, labor-intensive destructive measurements are usually required (Gower et al., 1999; Jonckheere et al., 2004). Similar procedures are also needed for plant area index (PAI), which is defined as the sum of LAI and woody structures or non-leaf material (Bréda, 2003). To overcome this disadvantage, indirect measurements of LAI and PAI performed by capturing canopy cover images have been developed (Fuentes et al., 2014) and were shown to achieve very close correlation with the destructive measurements ($R^2 = 0.9$; De Bei et al., 2016; Orlando et al., 2016).

Remote sensing is used to monitor grapevine canopy development. Aircraft and satellite-based remote sensing have been used to detect spatial and temporal variation in canopy development using spectral vegetative indices such as normalized difference vegetation index (NDVI) and plant cell density (PCD) (Hall, 2018). Recently, unmanned aerial vehicles (UAV) have gained increasing research interest in capturing high-resolution vineyard images (Matese et al., 2015). These images can be used to create high-resolution vineyard orthomosaic images and point clouds containing the three-dimensional (3D) structural information (Blaschke et al., 2014; Njoku, 2014). Recent studies have applied UAV remote sensing to monitor canopy health, disease incidence, and grapevine water status (Albetis et al., 2017; de Castro et al., 2018; Romero et al., 2018; Su et al., 2016). The potential to monitor spatial-temporal changes in grapevine canopy structure (e.g., canopy height, area, and volume) has also been investigated (Pádua et al., 2018).

Point cloud analysis created from UAV imagery offers great potential for canopy monitoring (Mathews and Jensen, 2013). Point cloud analysis has been commercially used to quantify forest canopy volume (Lisein et al., 2013; Njoku, 2014; Tanhuanpaa et al., 2016). However, its applications to monitor grapevine canopy development are still relatively limited to scientific research. Unlike forest models, vineyard-focused models trained with continuous canopy systems contain a repetitive row-space pattern at a high density. The latter normalizes the background inter-row terrain in vineyards more technically challenging, with the terrain partially covered by the canopy (Ballesteros et al., 2015; de Castro et al., 2018). Therefore, the vineyard point cloud requires the precise detection and extraction of canopy points before being used to monitor canopy structure.

When implementing UAV-based remote sensing for vineyard management, it is critical to compare ground and UAV based monitoring outcomes and how their accuracy changes during the growing season. Summaries of the advantages and limitations of UAV applications will also help guide similar work in the future. With this in mind, this research aims to explore and compare practices of monitoring spatial-temporal vineyard canopy development using ground and UAV-based measurements, including imagery and point cloud analysis.

Materials and methods

Site description, vineyard management

The vineyard used for this study was located at the Waite Campus, University of Adelaide (South Australia, Australia; Lat 34°58'3.0"S, Lon 138°38'0.6"E). Grapevines were trained to a bilateral spur-pruned cordon with vertical shoot positioning (VSP) at a cordon height of 0.8m. A Shiraz block (11 rows) and a Semillon block (9 rows) with 14 panels per row were monitored in this study (Figure 1). At the same panel length of 5.4m, there are two vines per panel with 2.7m spacing in the Shiraz block. In the Semillon block, there are three vines per panel at the 1.8m spacing. The total vineyard area monitored was 0.5 ha (683 plants). Rows are set up in a north-south orientation with a spacing of 3m. Standard canopy management practices were applied across the two growing seasons (Table 1).

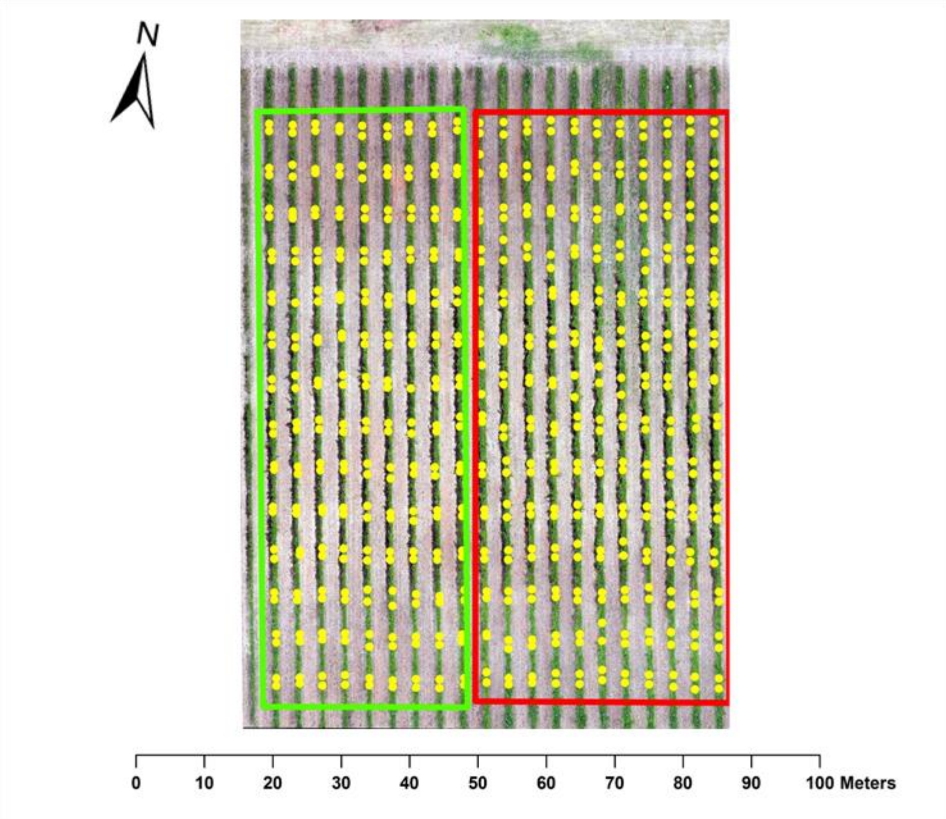

Figure 1. The monitored vineyard in South Australia, containing a Shiraz block (□) and a Semillon (□) block. Dots denote the locations of ground imaging.

Table 1. Canopy management practices applied to the monitored vineyard (DAB: Day after budburst; PS: phenological stage, defined by E-L stages) (Coombe, 1995).

DAB	PS	Canopy management practices
68	20	Foliage wire lifting
77	31	Leaf removal in the bunch zone
79	31	Second foliage wire lifting and shoot trimming
114	36	Overhead netting for bird control applied (no further UAV flights)

Ground PAI measurements

Upward-looking digital cover images were acquired in the vineyard using the method described in De Bei et al. (2016) and the VitiCanopy smartphone app. Two images were taken from each panel using the front camera of an iPhone 7 (Apple Inc., Cupertino, CA, USA) with a resolution of 7.2 megapixels, for a total of 28 images per row. The images were taken at ground level (0.8m below the cordon) every three to four weeks from budburst (E-L stage 4) to harvest (E-L stage 38, Table 2, (Coombe, 1995). During each measurement time point, 560 images were acquired from the Shiraz (n=308) and Semillon (n=252) blocks. More than 7000 images were collected across the two growing seasons.

Table 2. Ground image acquisition dates and the corresponding days after budburst (DAB) across the two growing seasons (2017-18 and 2018-19).

2017-18	DAB	2018-19	DAB
20/9/17	4	3/10/18	13
15/10/17	27	18/10/18	28
20/11/17	63	31/10/18	41
6/12/17	79	15/11/18	56
21/12/17	94	28/11/18	69
16/1/18	120	11/12/18	82
		4/1/19	106

Ground-based PAI (PAI_g) and foliage projective cover (FC_g), which has been defined as the "proportion of ground area covered by the vertical projection of foliage and branches," were calculated from the imagery (De Bei et al., 2016; Macfarlane et al., 2007). The same position was used for image acquisition in all measurements across the two growing seasons (Figure 2). A length measurement was carried out to collect the imaging position (considered to be more precise than those recorded by the smartphone's GPS on the fly (±5m)). The distance (l) between every image and the posts at the row end was recorded in the length measurement. The posts' geographic coordinates at the row end (x, y) and the row angle (β) were recorded from the geo-referenced orthomosaic imagery. The geographic coordinates (x_i, y_i) of all locations of imaging were calculated as follows:

$$\begin{aligned} x_i &= x + l/\sin\beta \\ y_i &= y + l/\cos\beta \end{aligned} \tag{1}$$

x_i and y_i (dots in Figure 1) were also used as the coordinates for extracting remote sensing measurements to compare with ground-based measurements.

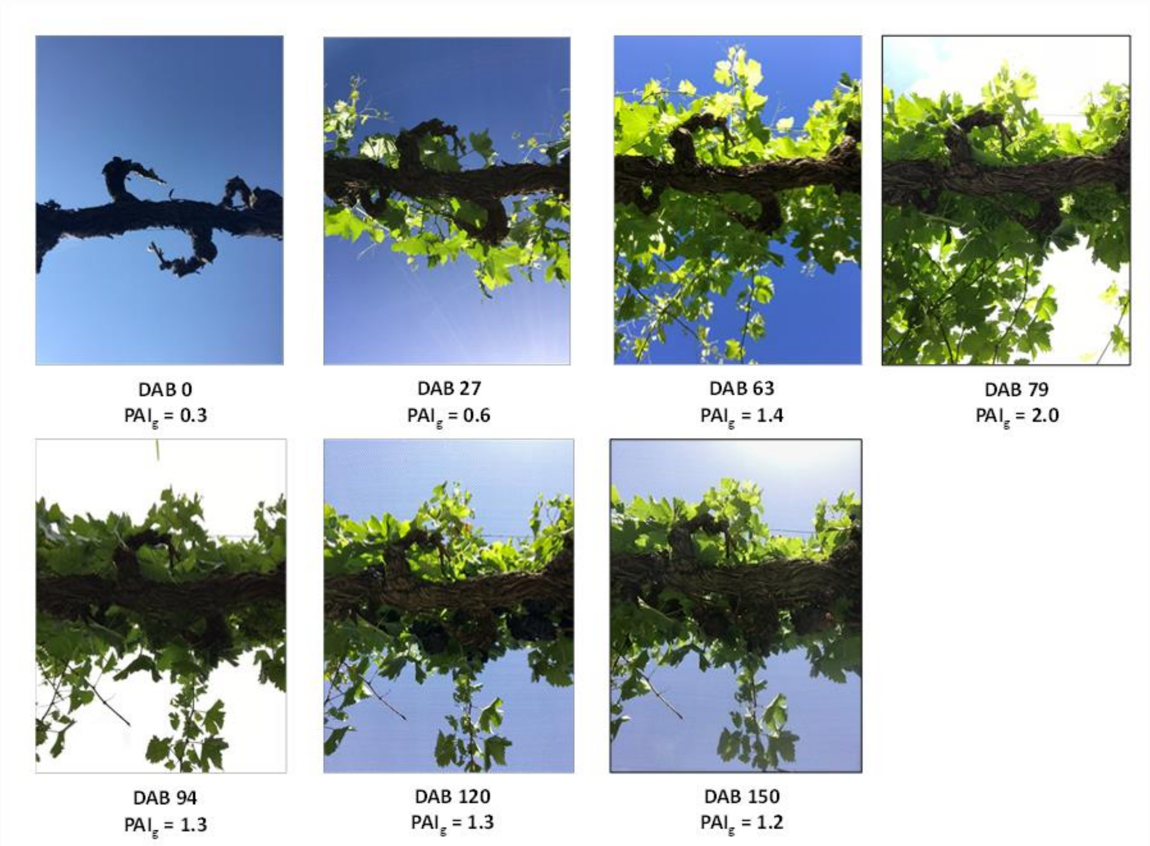

Figure 2. Example of images captured during the development of the same Shiraz canopy section in the 2017-18 growing season, days after budburst (DAB), and ground-based PAI values (PAI$_g$) calculated by the VitiCanopy app are shown below each image.

UAV-based aerial measurements

UAV flights were performed at the same stage as ground measurements. Seven flights were carried out in both growing seasons. Flights were conducted around solar noon (between 1200 and 1400 hr, solar time) to minimize the shadow effect and enhance the color segmentation between vegetation and ground (Poblete-Echeverría et al., 2017).

UAV flight plans were set and controlled by a remote controller with flight routes set through the flight control software Pix4Dcapture (Pix4D, 2018a). Flights were maintained at an altitude of 30m and a speed of 2m/s. Nadir imagery acquisition was triggered automatically at the 85% overlap ratio between two nearby images. The geographic coordinates of all images were recorded during the flight.

Both RGB and multispectral imagery were collected during the flight using the same UAV. RGB images were captured by the integrated Phantom 4 Pro quadcopter camera with 20 megapixels resolution (DJI, Shenzhen, China). Multispectral images were acquired with a Sequoia multispectral camera (Parrot SA, Paris, France) with 1.2 megapixels resolution, recording reflectance at green (550nm, bandwidth 40nm), red (660nm, bandwidth 40nm), red edge (735nm, bandwidth 10nm), and near-infrared (NIR, 790nm, bandwidth 40nm) bands. The multispectral images were radiometrically calibrated by a downwelling sunlight sensor and a calibrated reflectance panel (MicaSense, Seattle, USA). The average ground sampling distance for the RGB and multispectral images were 0.9cm and 3.6cm, respectively. In the 2017-18 growing season, a single grid flight route was used while a double grid route was applied in 2018-19 to test the potential of improving reconstructed point cloud quality.

Point cloud analysis for calculating canopy volume and area

From aerial RGB and multispectral images, vineyard orthomosaic image and point cloud were reconstructed using the commercial structure-from-motion images processing software Pix4Dmapper (Pix4D, 2018b). After reconstruction, orthomosaic imagery was geographically referenced to ground control points. Point clouds were stored in a polygon file format containing about 11-15 million points for the 0.5 ha vineyard.

For the point cloud analysis, a customised point cloud analysis procedure was developed in Matlab ver.2018b (Matlab®, 2018; Figure 3). The method includes canopy feature selection, grapevine row extraction for the canopy volume, and area (surface and projected) calculations. In the procedure, the point cloud was first displayed at a perspective view, and canopy point cloud centres at the first and last rows were then manually selected. Intermediate row centre 1coordinates were calculated from the row spacing distance and the first and last row coordinates (step 1). When using row coordinates, the vineyard point cloud was separated into individual row point clouds (step 2). A single-row point cloud was further divided into individual panel point clouds (step 3). In each panel point cloud, the ground points (purple) and canopy points (green) were identified by the MLESAC method (Torr and Zisserman, 2000) using limited angular distance among neighbouring points (step 4). Generally, in a single panel point cloud, less than half of the total points were canopy points with other points corresponding to ground, floor vegetation, trunk, and overhanging shoots (Figure 4). An alpha shape was created from the canopy points using the set alpha radius (α=0.2m, step 5) (Edelsbrunner et al., 1983). With an increasing α, the alpha shape expands to a convex hull, potentially overestimating the actual canopy structure (Milella et al., 2019). The volume and area (surface and projected) of the alpha shape were calculated as the canopy volume (V, m^3/m) and area (A_s and A_p, m^2/m).

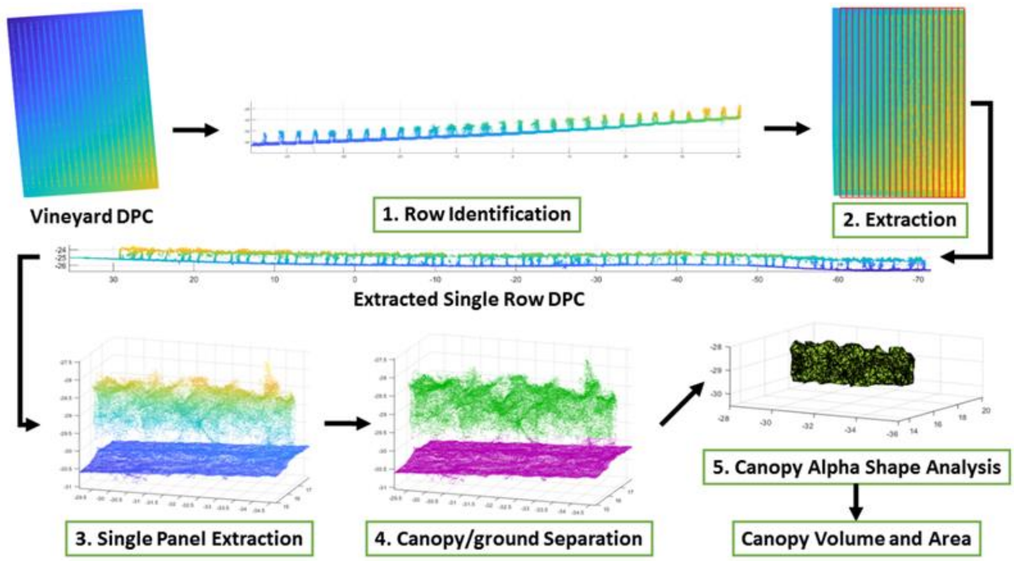

Figure 3. Flowchart for the point cloud analysis program for canopy volume and area (projected and surface) calculations for an individual panel using a vineyard point cloud.

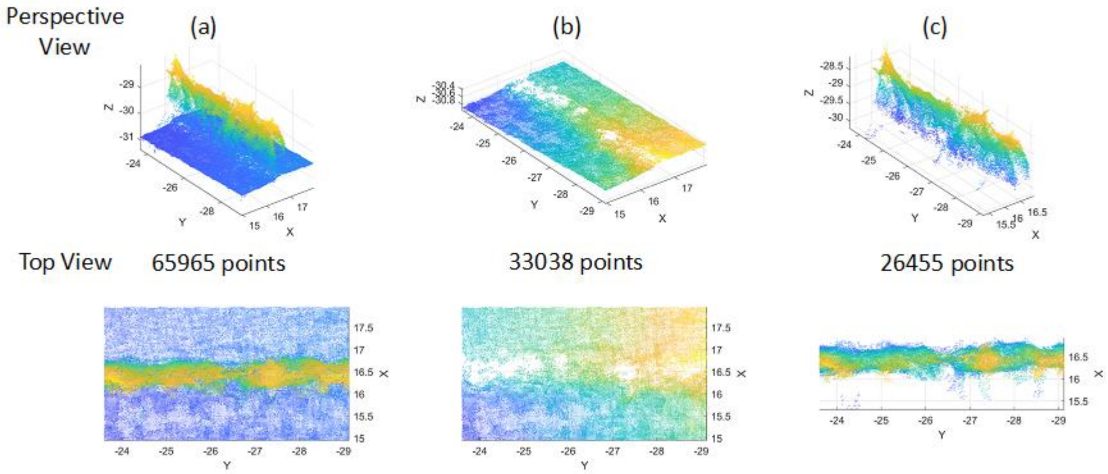

Figure 4. From left to right: (a) Single panel point cloud; (b) ground point cloud; (c) extracted from the original point cloud using the MLESAC method; (d) canopy point cloud after the exclusion of ground points and points below the cordon height.

Multispectral and RGB orthomosaic calculations

Spectral indices NDVI and PCD, were calculated from individual red (660nm) and near-infrared (NIR, 790nm) band images with the following equations:

$$\mathbf{NDVI} = \frac{\mathbf{NIR - Red}}{\mathbf{NIR + Red}} \tag{2}$$

$$\mathbf{PCD} = \frac{\mathbf{NIR}}{\mathbf{Red}} \tag{3}$$

The canopy pixel layer was extracted from the vineyard raster using unsupervised classification. With fixed vine and row spacing, a single vine raster was extracted from the canopy pixel layer, and the mean spectral index value per vine was calculated.

RGB orthomosaic image was processed using a Lab colour space profile threshold to extract green canopy pixels, resulting in another canopy pixel layer. The canopy pixel layer was then converted into a binary raster, and UAV-based PAI and FC (PAI_u and FC_u) were calculated from the binary raster based on Beer's Law (De Bei et al., 2016; Fuentes et al., 2019; Macfarlane et al., 2007).

Statistical analysis

The development of ground and UAV based measurements during the growing seasons were plotted using GraphPad Prism (ver. 8.0). Correlation matrices were also created to calculate the coefficient of determination (R^2) values, based on linear relationship assumption, using the curve fitting toolbox in Matlab (MathWorks Inc, 2018). It should be noted that the NDVI, PCD, $PAI_{u,}$ and FC_u data collected before DAB 30-40 contained a high level of background interference from ground vegetation. This data was excluded from the correlation calculation to improve the overall accuracy (see discussion below). It also allowed the assessment of performance measurements for these measurements during the critical growth stage of grapevine flowering and veraison.

Results and discussion

Canopy development monitoring by ground and UAV-based measurements

Similar canopy development patterns were observed for the two varieties over two growing seasons in both ground and aerial-based point cloud measurements (Figure 5). Point cloud-derived canopy volume and area (V, A_s, and A_p) and ground-based PAI and FC (PAI_g and FC_g) increased from budburst (DAB 0) and peaked at around veraison (DAB 100) (Figure 5 and Figure 6). PAI_g increased rapidly from values of 0.2-0.3 to 1.8-2.0, reflecting a rapid increase in shoot length, leaf number, and leaf size during spring. After the peak in PAI_g, canopy management practices were applied to regulate canopy development. Around one month before veraison (DAB 90), V and Ap also peaked at the same stage, similar to Pádua et al. (2018). After the peak at veraison, values remained stable until the last measurement (at DAB 110).

In comparison, spectral indices (PCD and NDVI) and UAV-based PAI measurements (PAI_u and FC_u) demonstrated a clear overestimation at early development stages (Figure 5 and Figure 6), likely caused by the interference of vineyard floor vegetation in the vineyard during winter and spring (discussed later). The measured values declined after DAB 30-40 with the reduction in floor vegetation and then increased and peaked again at around DAB 100 due to canopy growth.

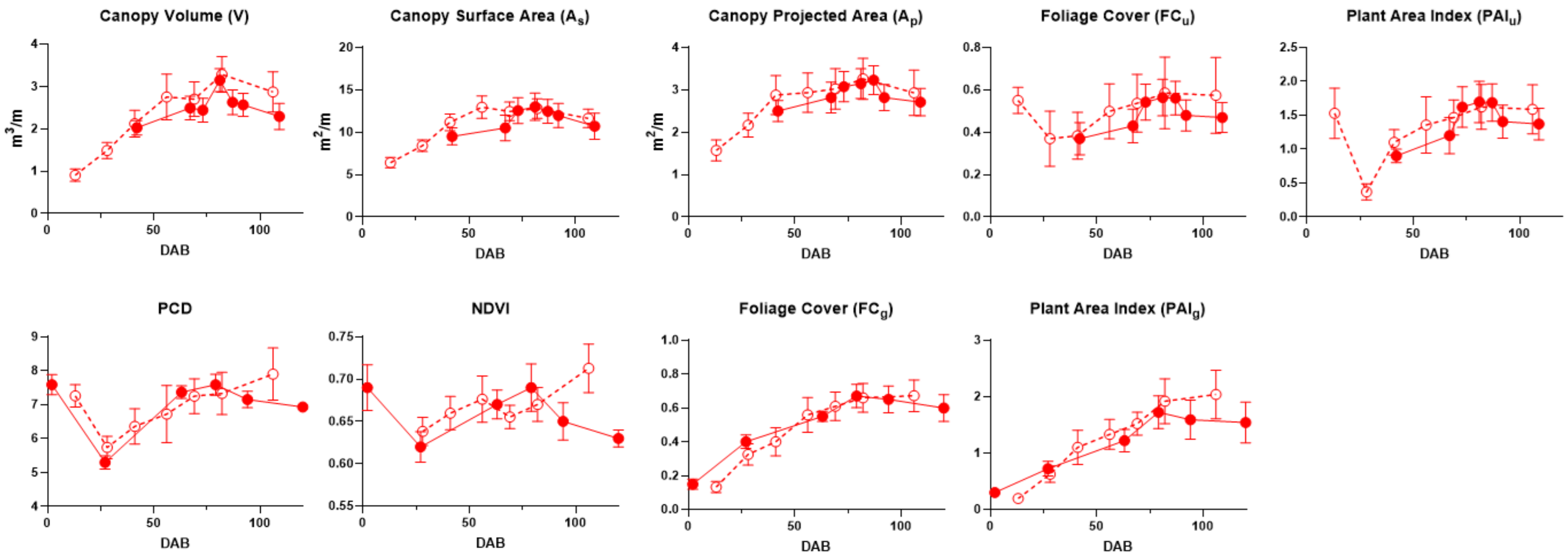

Figure 5. Canopy structure parameters monitored in a Shiraz block, South Australia, during 2017-18 (●) and 2018-19 (○) growing seasons. Measurements dates were recorded as days after budburst (DAB). Parameters shown are: canopy volume per meter canopy length (V, m^3/m); canopy surface area per meter canopy length (A_s, m^2/m); canopy projective area per meter cordon length (A_p, m^2/m); foliage cover calculated from UAV imagery (FC_u); plant area index calculated from UAV imagery (PAI_u); plant cell density (PCD); normalized difference vegetation index (NDVI); foliage cover calculated from ground imagery (FC_g) ; plant area index calculated from ground imagery (PAI_g). Except for point cloud-derived parameters (V, A_s, and A_p), all other measurements are unitless. Error bars show the standard error of the mean of each measurement.

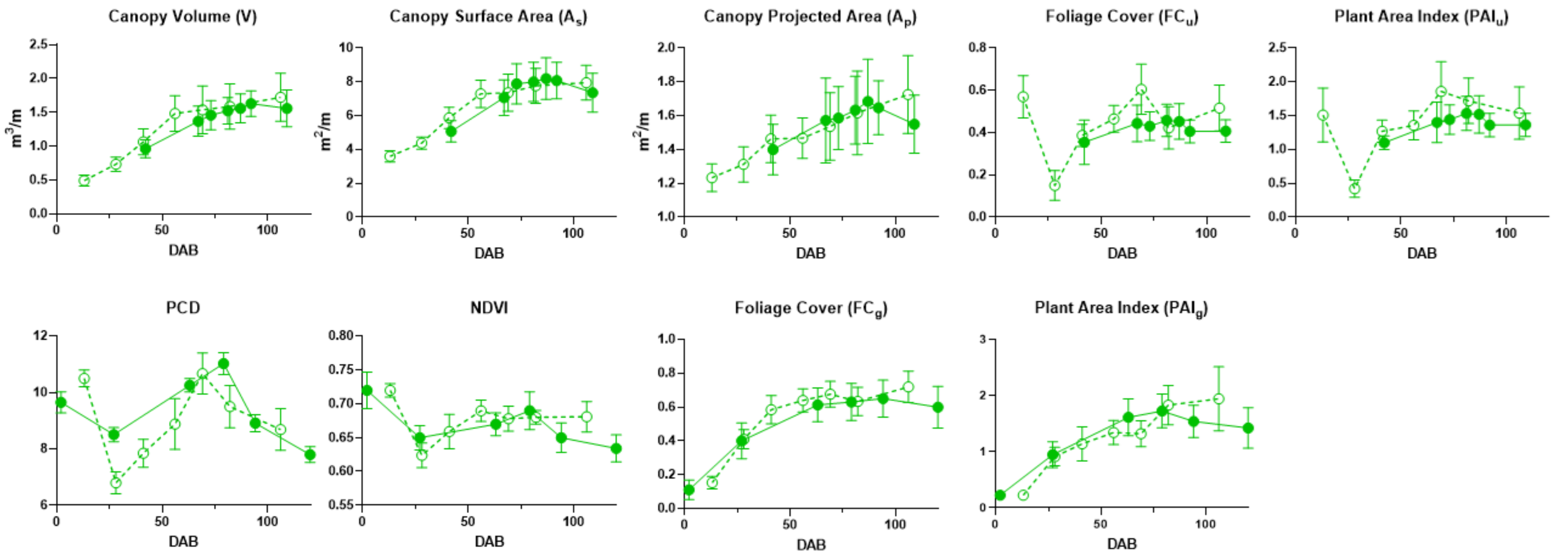

Figure 6. Canopy structure parameters monitored in a Semillon block, South Australia, during 2017-18 (●) and 2018-19 (○) growing seasons. Measurements dates were recorded as days after budburst (DAB). Parameters shown are: canopy volume per meter canopy length (V, m^3/m); canopy surface area per meter canopy length (A_s, m^2/m); canopy projective area per meter cordon length (A_p, m^2/m); foliage cover calculated from UAV imagery (FC_u); plant area index calculated from UAV imagery (PAI_u); plant cell density (PCD); normalized difference vegetation index (NDVI); foliage cover calculated from ground imagery (FC_g) ; plant area index calculated from ground imagery (PAI_g). Except for point cloud-derived parameters (V, A_s, and A_p), all other measurements are unitless. Error bars show the standard error of mean of each measurement.

In the correlation matrix for Shiraz (Table 3(a)), canopy volume (V) showed a high correlation with most of the other measurements (R^2 ranging between 0.72 and 0.88), except for NDVI (R^2=0.58 in both seasons). The latter results demonstrate the potential of using canopy volume as a representative parameter for measuring the canopy structure.

Table 3. Correlation matrix, showing the coefficient of determination (R^2) values, for all canopy parameters monitored in the (a) Shiraz and (b) Semillon block, during 2017-19 growing seasons. R^2 values shown are colour-coded: green for strong correlation (> 0.8), yellow for moderate correlation (0.5-0.8) and red for poor correlation (< 0.5). Parameters compared are: canopy volume per meter canopy length (V, m^3/m); canopy surface area per meter canopy length (A_s, m^2/m); canopy projective area per meter cordon length (A_p, m^2/m); foliage cover calculated from UAV imagery (FC_u); plant area index calculated from UAV imagery (PAI_u); plant cell density (PCD); normalized difference vegetation index (NDVI); foliage cover calculated from ground imagery (FC_g); plant area index calculated from ground imagery (PAI_g).

(a) Shiraz

		2017-18								
		V	A_s	A_p	FC_u	PAI_u	PCD	NDVI	FC_g	PAI_g
	V		0.66	0.66	0.73	0.55	0.72	0.58	0.74	0.65
	A_s	0.88		0.52	0.47	0.47	0.54	0.63	0.51	0.69
	A_p	0.77	0.55		0.87	0.82	0.23	0.38	0.52	0.62
	FC_u	0.83	0.72	0.66		1	0.71	0.7	0.8	0.67
2018-19	PAI_u	0.86	0.69	0.72	0.99		0.68	0.64	0.70	0.52
	PCD	0.72	0.53	0.50	0.74	0.75		0.89	0.70	0.66
	NDVI	0.58	0.43	0.60	0.58	0.52	0.85		0.72	0.64
	FC_g	0.83	0.72	0.61	0.85	0.75	0.69	0.61		0.81
	PAI_g	0.77	0.56	0.65	0.72	0.74	0.70	0.73	0.84	

(b) Semillon

		2017-18								
		V	A_s	A_p	FC_u	PAI_u	PCD	NDVI	FC_g	PAI_g
	V		0.72	0.68	0.71	0.64	0.52	0.64	0.69	0.62
	A_s	0.96		0.72	0.58	0.42	0.47	0.51	0.79	0.52
	A_p	0.68	0.56		0.87	0.83	0.53	0.61	0.69	0.54
	FC_u	0.75	0.71	0.61		1	0.59	0.60	0.72	0.53
2018-19	PAI_u	0.70	0.53	0.59	0.99		0.50	0.44	0.62	0.65
	PCD	0.76	0.71	0.38	0.53	0.53		0.82	0.77	0.64
	NDVI	0.67	0.71	0.37	0.35	0.43	0.82		0.66	0.63
	FC_g	0.75	0.70	0.49	0.78	0.60	0.77	0.73		0.87
	PAI_g	0.71	0.58	0.61	0.54	0.66	0.62	0.64	0.93	

The correlation between V and PAI_g, in the 2018-19 Shiraz dataset, with an R^2 of 0.77, was higher than the R^2 between the similar PAI measurements of PAI_g and PAI_u ($R^2 = 0.86$) in the same block. This can potentially be explained by removing the early-developmental stage PAI_u data that reduced the value range of the data points in the DAB scale and lowered the R^2 value. The R^2 values (0.54-0.66) of the canopy surface and projected area (A_s and A_p), compared against PAI_g, were also found to be lower than V. Potential reasons reduced the accuracy of the area measurements from UAV imagery will be discussed in the following section. Comparisons between measurements derived from the same data are also shown to have higher R^2 values, as can be found in pairs such as PAI_g vs FC_g, PAI_u vs FC_u and NDVI vs PCD.

For measurements impacted by ground vegetation interference, after removing data points collected in the early stages in both varieties and years, PCD and NDVI demonstrated moderate to strong relationships with PAI_g ($R^2 = 0.62$-0.73, Table 3). The current R^2 values were also in line with previous studies using satellite images of VSP trained vineyards where the correlation between LAI and NDVI showed values R^2 between 0.5 and 0.8 (Döring et al., 2014; Johnson et al., 2003; Sun et al., 2017).

Comparisons between some parameters, such as those between spectral indices and point cloud-based canopy area measurements (A_s and A_p) showed poor correlations. Although various canopy management strategies changed canopy structure substantially, canopy greenness, measured by spectral indices, remained relatively stable. Therefore, it suggests that spectral indices might not be reliable measurements to assess the impact of canopy management practices. However, it remained unclear why some other canopy measurements, such as V and PAI_g, had better correlations with spectral indices. Potential explanations can be canopy area measurements (A_s and A_p) can contain higher levels of error when the canopy management changed the canopy structure, caused by the incomplete reconstruction of the canopy (discussed below).

Canopy monitoring at early developmental stages

Point cloud analysis demonstrated its potential to monitor canopy development at early developmental stages (before DAB 40). During this period, the growth of cover crops and weeds in the mid-row and under-vine area are stimulated by rainfall during winter and early spring. By extracting canopy points based on height variations, points cloud analysis effectively filtered out the ground and floor vegetation, regardless of their colour or spectral properties. Figure 7 shows extracted canopy point cloud at DAB 13 demonstrated clear row patterns of the established vine rows as only canopy-related points were extracted. Volume and areas of the canopy (V, A_s, and A_p) were shown to be low at early developmental stages as they measured the dormant cordons and early shoot development (Figures 5 and 6).

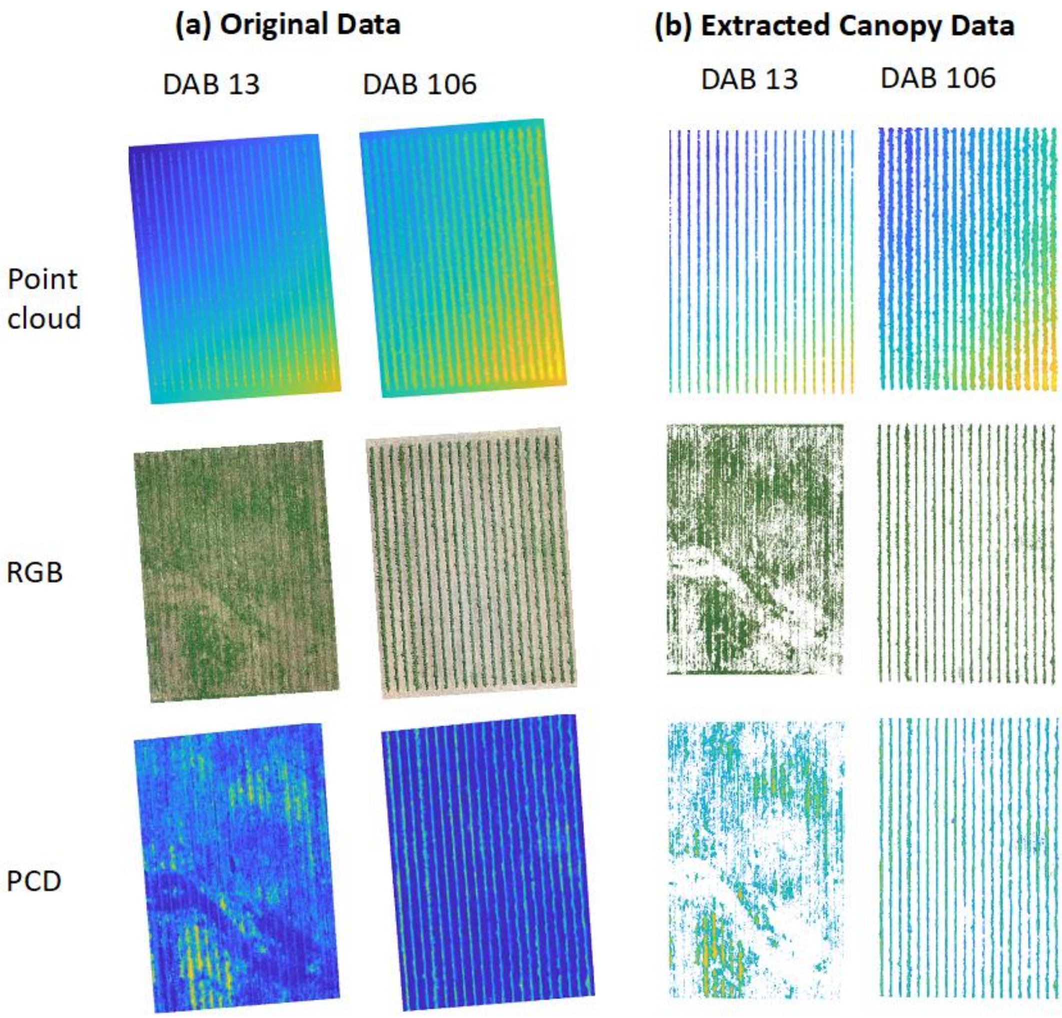

Figure 7. Comparisons between original UAV remote sensing data (point cloud, RGB, and PCD orthomosaic imagery) and processed canopy data after filtering out ground pixels/points. Data was collected at DAB 13 and DAB 106 during the 2018-19 growing season to demonstrate canopy growth at early and middle developmental stages in the growing season. RGB: red, green, and blue imagery; PCD: plant cell density imagery.

The average PAI from ground images for both cultivars was around 0.2-0.3 at early developmental stages (Figures 5 and 6), similar to the results generated from point cloud analysis. These values corresponded to the bare cordon contribution, which was similar to values observed by De Bei et al. (2016) and Fuentes et al. (2014). The upward-looking images used for the ground measurements effectively excluded floor vegetation (Figure 2). No differences in canopy development were found between varieties.

During the same period, in contrast to point cloud and ground measurements, RGB and multispectral remote sensing accuracy were negatively impacted by floor vegetation in the vineyard (Figures 5 and 6). In both growing seasons, PAI_u, PCD, and NDVI values are high at the early developmental stages (1.4-1.5, 8-10, and 0.65-0.75, respectively). However, the actual canopy only consisted of young shoots with small leaves and low leaf numbers at early developmental stages. This can be proved by the lower PAI_g measurement results where ground vegetation was not captured in the imagery. Therefore, it is inferred that the high vegetative indices captured were due to the vineyard floor vegetation interference.

Since the similarities in reflectance properties and colour profiles of the canopy and the floor vegetation caused unsatisfactory extraction of the canopy pixels, substantial inter-row vegetation area cannot be effectively removed in the extracted RGB and PCD raster (Figure 7). Similar to the overestimation of spectral indices, the low porosity within the extract RGB raster due to dense floor vegetation also led to the overestimation of foliage coverage (FC_u) and the plant area index (PAI_u) from aerial imagery. The current study supports that, without the effective control of vineyard floor vegetation, it remains difficult to monitor early canopy development using either RGB or multispectral orthomosaic imagery from UAV.

Canopy monitoring of established canopy

Flowering and veraison are the two critical phenological stages of canopy monitoring for management purposes. These are the stages when the canopy structure is an important indicator of the potential yield and fruit quality at harvest (Jones and Grant, 2015). Therefore, it is important to investigate the performance of different canopy structure measurements at these stages. When reaching full canopy size at DAB 100, Shiraz had a larger canopy volume and area than Semillon. Shiraz's maximum canopy volume ranged between 3.5-4m^3 compared with 1.5-2m^3 in Semillon (Figures 5 and 6). Compared to Semillon, Shiraz is known to have longer mature shoots due to longer internodes resulting in a larger canopy volume (Champagnol, 1984; Louarn et al., 2007). de Castro et al. (2018) also found varietal differences in canopy volume, when estimated by UAV remote sensing: Merlot, Albariño, and Chardonnay vineyards grown under similar conditions had different canopy volumes, ranging between 1.5 and 3 m^3 per vine. Despite various studies showing the potential of point cloud and RGB orthomosaic imagery for vineyard monitoring, as introduced previously, in the current study, it was found that there are still several aspects that require extra attention during their application, especially when measuring dense canopies.

An incomplete reconstruction of the point cloud was observed in large and dense canopies, especially in the Shiraz block. Figure 8a shows that trimmed Shiraz canopies allowed creating a fully-enclosed point cloud without any obvious gaps (Figure 8b). For untrimmed canopy (Figure 8c), the reconstructed point cloud can contain incomplete sections due to missing points under the sprawling canopy (Figure 8d). When generating the alpha shape, the point cloud contained incomplete sections resulting in a lower volume calculation as the alpha shape dented inward. In extreme cases, the whole alpha shape could fail to enclose and created a hollow alpha shape. These hollow alpha shapes can result in low volume values while the canopy surface area is exaggerated as both internal and external surfaces were calculated. The possible reason for incomplete sections to occur was due to sprawling shoots (Figure 8c). With low light penetration and shadow covering, these shoots can create shadowed areas during point cloud reconstruction, resulting in incomplete point clouds.

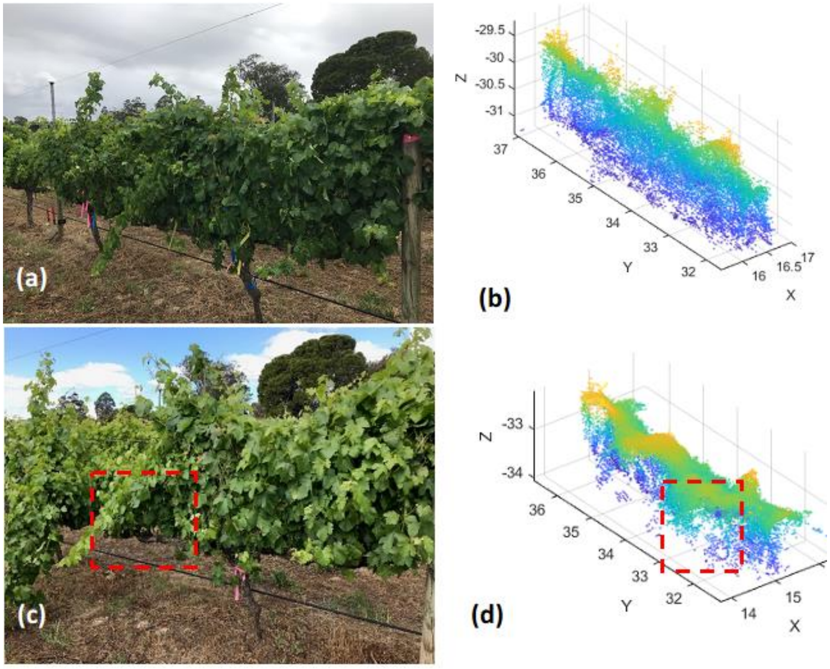

Figure 8. Trimmed Shiraz canopy (subplot a) and the corresponding fully enclosed canopy point cloud (subplot b). In comparison, untrimmed Shiraz canopy (subplot c; sprawling shoots highlighted) and the corresponding point cloud with incomplete sections (subplot d; the point cloud hole highlighted).

It was also found that UAV flight routes with more overlap, from the single grid in 2017-18 to double grids in 2018-19, did not improve the quality of the point cloud and the canopy alpha shape derived from the point cloud. Although the R^2 values related to the canopy volume in the 2018-19 season are higher than those in the 2017-18 season, it can also be caused by the one extra flight conducted in 2018-19. Future improvements in UAV photogrammetry should focus on eliminating these incomplete point cloud reconstructions. Modifications to fill defective areas by creating points from averaging nearest points coordinates can overcome the issue but at the cost of creating potentially redundant points and artifacts. It is suggested that the point cloud reconstruction quality should always be monitored, and the presence of incomplete reconstruction be checked when using UAV remote sensing in vineyards with dense canopies.

Another factor to consider for point cloud applications is selecting an appropriate alpha value (α) for creating a canopy alpha shape. Canopy digital simulations showed that VSP trained grapevines had lower canopy volume than other non-VSP trained canopies at the same LAI (Louarn et al., 2008a, 2008b). It was found in this study that an α value can significantly influence the canopy volume. For example, by increasing the α value from 0.2m to 0.4m, the canopy volume can increase substantially (up 60% and 54% for point cloud at DAB 28 and 82, respectively). Therefore, it is suggested that the α value should be variable according to the different training systems and canopy manipulation practices, even though the canopy may have the same PAI_g value. Future studies to improve canopy alpha shape creation can temporally calibrate the most suitable α values for different training and canopy manipulation practices by using more precise ground laser scanning (LiDAR), depth camera scanning, or direct allometric/destructive modeling (Iandolino et al., 2013; Milella et al., 2019; Siebers et al., 2018).

The canopy size can also influence the calculation accuracy of PAI_u and FC_u from the RGB orthomosaic imagery using Beer's law. It can potentially generate overestimation when applied on a dense canopy. In the parallel comparison between ground-based and aerial imagery of the same canopy section, the PAI and PAI_u of a sparse canopy showed similar results (1.12 *vs* 1.08, Figure 9). However, in an established dense canopy, the overestimation of PAI_u in the orthomosaic imagery was observed (3.45 vs 4.85). The overestimation was suggested to be caused by the higher foliage cover (FC_u) in the orthomosaic imagery. With lower resolution in the aerial imagery and the different image capturing approach (downward-looking in aerial imagery *vs* upward-looking in-ground imagery), it is found that canopy orthomosaic imagery tended to contain fewer canopy pores than the ground imagery, especially around the canopy edges, and resulted in higher foliage cover. Therefore, it is suggested that the calculation of PAI_u for dense canopies should be checked in conjunction with ground imagery samples to prevent potential overestimations.

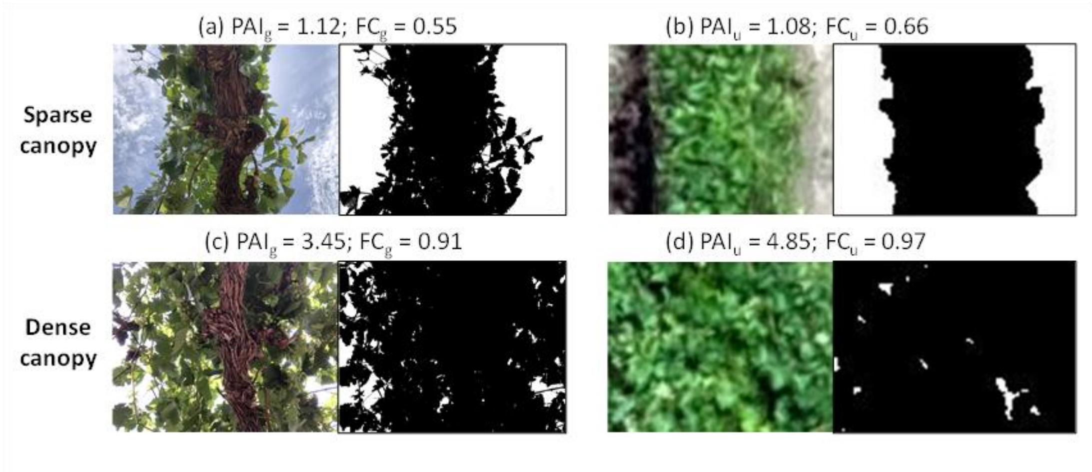

Figure 9. Comparisons between the ground canopy cover imagery (a and c) and UAV based orthomosaic imagery (b and d) of the same canopy sections, at two different canopy structures (sparse and dense). Samples were selected from the same Shiraz block, captured on the same date (DAB 106) during the 2018-19 growing season. The original imagery and its binary imagery are shown in each sample with the plant area index (PAI) and foliage cover (FC).

Selecting the ideal UAV or ground-based measurement

UAV remote sensing, as so far discussed, can be used to quantify canopy development by calculating a range of canopy architecture estimations using point cloud and spectral indices. Vineyard point cloud, containing tens of millions of points with 3D coordinates, also offers a wide range of possibilities for understanding and mapping canopy structure (de Castro et al., 2018; Mathews and Jensen, 2013; Pádua et al., 2018; Weiss and Baret, 2017). In this study, it showed advantages, compared to other methods, when monitoring the vineyard at early developmental stages. However, with the scarcity of commercially available point cloud analysis programs tailored for vineyards, point cloud analysis requires a high level of expertise. It often relies on the creation of customized programs or codes. Incomplete reconstructions, as mentioned above, can also increase the difficulty of analysing the point cloud. Point cloud processing also requires higher computational and storage capacity than 2D RGB and multispectral rasters. During the same UAV data collection, the current one-hectare vineyard point cloud required 400-500MB of storage space with more than 10 million points, while around 200MB is needed for RGB orthomosaic less than 100MB for PCD and NDVI rasters. If the point cloud also requires RGB colour matrices, the file size will increase substantially.

Inexpensive UAVs usually include an RGB sensor that is readily available for capturing RGB images that can be used to create RGB orthomosaic imagery and point cloud. For UAV-based multispectral remote sensing, a specialized UAV or custom integration between sensors and UAVs is generally required, as in the current study and previous studies (Albetis et al., 2017; Romero et al., 2018; Vanegas et al., 2018). Also, extra sensors implemented on the UAV require additional calibrations due to interference between the sensor and the aircraft, such as the inertial measurement unit (IMU) and compass calibration. The sensors themselves as radiometric and compass calibration. A range of factors, such as the flight route's overlapping ratio and the flight height, can influence image quality during a flight. High overlap ratios and/or low flight heights can help reduce GSD (higher resolution) and improve point cloud details and increase point count. However, a longer flying time requires more batteries to cover a given area. The feasibility of applying multirotor UAV remote sensing on a large growing area is dependent on regular battery replacements. Many recent studies where a multirotor UAV was used as the sensor carrier platform used vineyard areas equal to or lower than one hectare (de Castro et al., 2018; Pádua et al., 2018; Poblete et al., 2017; Weiss and Baret, 2017).

Geo-tagged ground-based canopy cover imagery can be used to map spatial canopy variability. The sampling distance, or the imaging frequency, needs to be carefully planned to achieve the best mapping outcomes. More frequent image acquisition will improve map resolution and enhance spatial variability detection, but it can also increase the time required. Ground imaging helps growers record canopy development and measure canopy structure variances between cultivars from a few images. Apps for ground measurement, such as VitiCanopy used in this study, can supply on-the-go assessment and return measurement results immediately in the field. This is advantageous to UAV remote sensing, which involves complicated image processing, sometimes across several programs/software. UAV remote sensing can provide imagery with high spatial resolution, and the point cloud reconstructed to provide detailed and continuous canopy structure information. It was also more cost-effective than integrated mobile ground systems (Andújar et al., 2019).

Based on the previous discussions, Table 4 summarises UAV and ground-based image analysis approaches' advantages and limitations. UAV aerial remote sensing can provide 2D, 3D, and spectral measurements to the canopy structure, while ground measurements can supply more detailed measurements on the canopy architecture. UAV can monitor a large growing area with more complicated processing than the ground approach. However, with a higher cost and more strict operational conditions, UAV remote sensing may be more suited to high-resolution vineyard mapping during critical growing stages.

Table 4. Comparisons between the ground and UAV-based image analysis applied in this study for vineyard canopy development monitoring.

	Ground	UAV - RGB & Multispectral
Measurements	PAI_g and FC_g	V, PAI_u, PCD, etc.
Major advantage	Detailed canopy architectural information	High resolution, vineyard scale measurement
Image acquisition procedures	Planned and acquired by the assessor	Planned by the operator and automatically triggered
Image type	Upward looking	Downward looking (nadir)
Image quality requirements	Avoid direct sunlight exposure	Avoid canopy projected shadow and ground vegetation, except for point cloud
Image processing	Simple and on-the-go	Complicated processing
Geographic coordinate precision	Meter level inaccuracy	Centimetre level inaccuracy
Map resolution	Medium	High
Maximum measurement time	Several hours per battery charge	Around 30 minutes per battery charge
Cost	Low	Medium to high
Weather requirements	Avoid rain	Avoid rain and strong winds
Other requirements	-	Operating license(s)*, sensor integration and calibration, etc.

*Dependent on the jurisdiction.

Conclusion

Point cloud-derived canopy volume was closely related to the ground-based PAI throughout the whole season (R^2>0.6). Point cloud was also able to achieve more representative results at early developmental stages when the vigorous floor vegetation influenced RGB orthomosaic imagery and spectral indices analysis. At peak canopy size, incomplete point cloud reconstruction can reduce point cloud analysis accuracy, and PAI calculation from RGB orthomosaic imagery can generate overestimation due to the lack of canopy porosity. UAV remote sensing and ground measurements were shown to have their strengths and limitations. It is concluded that the most suitable approach should be selected with clearly identified monitoring purposes.

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Chapter 4. Published Article: UAV-Based Imagery Analysis Detects Canopy Structure Changes after Canopy Management Applications

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Name of Principal Author (Candidate)	YANG YUN OUYANG		
Contribution to the Paper	Collecting ground sampling. Conducting UAV flights Data Analysis & Manuscript Writing		
Overall percentage (%)	~~60%~~ 70%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
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Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Name of Co-Author	Cassandra Collins (10%)		
Contribution to the Paper	Manuscript Review & Comments. • Data interpretation and analysis • Experimental design • Manuscript writing		
Signature		Date	25/9/2020

UAV and Ground-Based Imagery Analysis Detects Canopy Structure Changes after Canopy Management Applications

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ABSTRACT

Aim: To analyse unmanned aerial vehicle (UAV)-based imagery to assess canopy structural changes after the application of different canopy management practices in the vineyard.

Methods and results: Four different canopy management practices: i–ii) leaf removal within the bunch zone (eastern side/both eastern and western sides), iii) bunch thinning and iv) shoot trimming were applied to grapevines at veraison, in a commercial Cabernet-Sauvignon vineyard in McLaren Vale, South Australia. UAV-based imagery captures were taken: i) before the canopy treatments, ii) after the treatments and iii) at harvest to assess the treatment outcomes. Canopy volume, projected canopy area and normalized difference vegetation index (NDVI) were derived from the analysis of RGB and multispectral imagery collected using the UAV. Plant area index (PAI) was calculated using the smartphone app VitiCanopy as a ground-based measurement for comparison with UAV-derived measurements. Results showed that all three types of UAV-based measurements detected changes in the canopy structure after the application of canopy management practices, except for the bunch thinning treatment. As expected, ground-based PAI was the only technique to effectively detect internal canopy structure changes caused by bunch thinning. Canopy volume and PAI were found to better detect variations in canopy structure compared to NDVI and projected canopy area. The latter were negatively affected by the interference of the trimmed shoots left on the ground.

Conclusions: UAV-based tools can provide accurate assessments to some canopy management outcomes at the vineyard scale. Among different UAV-based measurements, canopy volume was more sensitive to changes in canopy structure, compared to NDVI and projected canopy area, and demonstrated a greater potential to assess the outcomes of a range of canopy management practices.

Significance and impact of the study: Canopy management practices are widely applied to regulate canopy growth, improve grape quality and reduce disease pressure in the bunch zone. Being able to detect major changes in canopy structure, with some limitations when the practice affects the internal structure (i.e., bunch thinning), UAV-based imagery analysis can be used to measure the outcome of common canopy management practices and it can improve the efficiency of vineyard management.

INTRODUCTION

Among the vineyard management practices, canopy management is widely applied to regulate canopy growth, reduce disease pressure, improve bud fertility and improve berry quality (Dry, 2008; Mirás-Avalos et al., 2017; Trought et al., 2017; Wolf et al., 2003). Commonly applied canopy management practices such as leaf removal, shoot trimming and bunch thinning aim to modify the source–sink relationship by reducing leaf density and/or crop load (Smart & Robinson, 1991). By selecting different practices and their levels/intensity of application, canopy treatments can have various outcomes. Low levels of input often have a limited impact on the canopy structure and are inefficient. In contrast, excessive application can negatively impact yield and quality including increasing the risk of exposing the crop to extreme weather conditions, such as heat waves (Caravia et al., 2016; Reynolds et al., 2005; Vasconcelos & Castagnoli, 2000).

To effectively apply canopy management practices, it is crucial to have convenient and accurate assessments of their outcomes. One approach could be to directly compare the differences in canopy structure before and after the application of canopy management practices, through the assessment of parameters such as plant area index (PAI: total leaf and cordon area per unit ground area) (Bréda, 2003; De Bei et al., 2016) and canopy volume. However, the most accurate estimations for these parameters involve destructive and labour-intensive sampling practices in the field (Gower et al., 1999; Jonckheere et al., 2004). To overcome these disadvantages, there have been recent developments in smartphone apps that analyse upward-looking canopy cover imagery and offer an objective and accurate solution to the measurement of PAI (De Bei et al., 2016; Fuentes et al., 2014; Poblete-Echeverria et al., 2015). These tools, that estimate PAI, have been effectively applied to assess changes in canopy structure during the growing season (De Bei et al., 2019; Wang et al., 2019).

Alternatively, optical remote sensing using unmanned aerial vehicles (UAV), aircraft and satellite platforms can be applied to estimate canopy structure (Hall, 2018). Amongst these platforms, recent advancements in UAV related research have led to a wide range of UAV applications for monitoring vineyard performance such as the rate of canopy development, canopy structure spatial variability, disease incidence and canopy water status (Albetis et al., 2018; de Castro et al., 2018; Mathews & Jensen, 2013; Pádua et al., 2018; Romero et al., 2018; Su et al., 2016). Through the collection of high-resolution red/green/blue (RGB), multispectral or hyperspectral imagery, UAV-mounted sensors are capable of providing data to create high-resolution RGB and spectral indices maps at the vineyard scale, e.g., normalized difference vegetation index (NDVI) and plant cell density (PCD) maps (Xue & Su, 2017). In addition, three-dimensional digital models, including vineyard point cloud and digital canopy model (DCM), can be created from overlapping images captured by the UAV (Comba et al., 2018). From vineyard digital models, parameters such as canopy height, projected area and volume can be calculated and provide detailed information regarding the canopy structure (Matese & Di Gennaro, 2018; Weiss & Baret, 2017). Compared with manned aircraft and satellite-based remote sensing, UAV also offers convenience in simple flight preparation, flexible operation options (Khaliq et al., 2019) and is more cost-effective for small and medium-size vineyards (Andújar et al., 2019; Matese et al., 2015). These advantages can help obtain a prompt evaluation of canopy management outcomes during critical developmental stages. Despite the demonstrated potential of these techniques, applying UAV remote sensing for measuring canopy management outcomes is currently limited.

This study aimed to assess whether UAV remote sensing can detect canopy structure changes after the application of different canopy management practices. These assessments were compared to ground-based PAI measured at the same time as the UAV flights. The advantages and limitations of using UAV as a monitoring platform in evaluating canopy structure changes are discussed.

MATERIALS AND METHODS

Study vineyard and experimental design

A commercial Cabernet-Sauvignon vineyard in the wine region McLaren Vale, South Australia (Lat—35.218, Long—138.542) was used for the study during the 2017–18 growing season. The climate of the region is classified as Mediterranean with low summer rainfall and the soil type is red/brown loamy sand (Wine Australia, 2020). In the study vineyard, vine and row spacings were 2 m and 3 m, respectively, and row orientation was north to south. Vines were trained with spur pruning and develops a sprawling canopy at the approximate width of 1.3 m and the cordon height of 1.1 m. The commercial vineyard was managed with standardised management practices, drip irrigated and no cover crop was grown in the mid-row or under-vine.

At veraison (E-L stage 35), four canopy management treatments were applied: i) leaf removal on the eastern side of the canopy, ii) leaf removal on both sides of the canopy, iii) bunch thinning and iv) shoot trimming on the eastern side of the canopy (Table 1). Removing leaves and/or shoot trimming on the eastern side only is often performed to reduce canopy density while protecting the bunches on the western side from the intense afternoon sunlight (Reynolds & Vanden Heuvel, 2009). A randomised replicate design was used to apply the treatments in the vineyard. As shown in Figure 1, each replicate consisted of six vines (two panels) and the different coloured sections in the figure correspond to different treatments. Each treatment was replicated six times; 180 grapevines in total were monitored and measured in the study.

Table 1. Treatment code, description and purpose of the different canopy management practices applied at veraison (E-L stage 35) in the study vineyard, during the 2017-18 growing season.

Code	Treatment description	Purpose of treatment
C	Control	No canopy management applied
LR-E	Leaf removal at bunch zone on east side only	Reduce canopy density and increase light penetration in the bunch zone on the east side
LR-B	Leaf removal at bunch zone on both sides (east and west)	Increase light into bunch zone on both sides
BT	Bunch thinning	Reduce bunch number by 50%
ST-E	Shoot trimming east side only	Reduce shoot length/canopy size by 50%

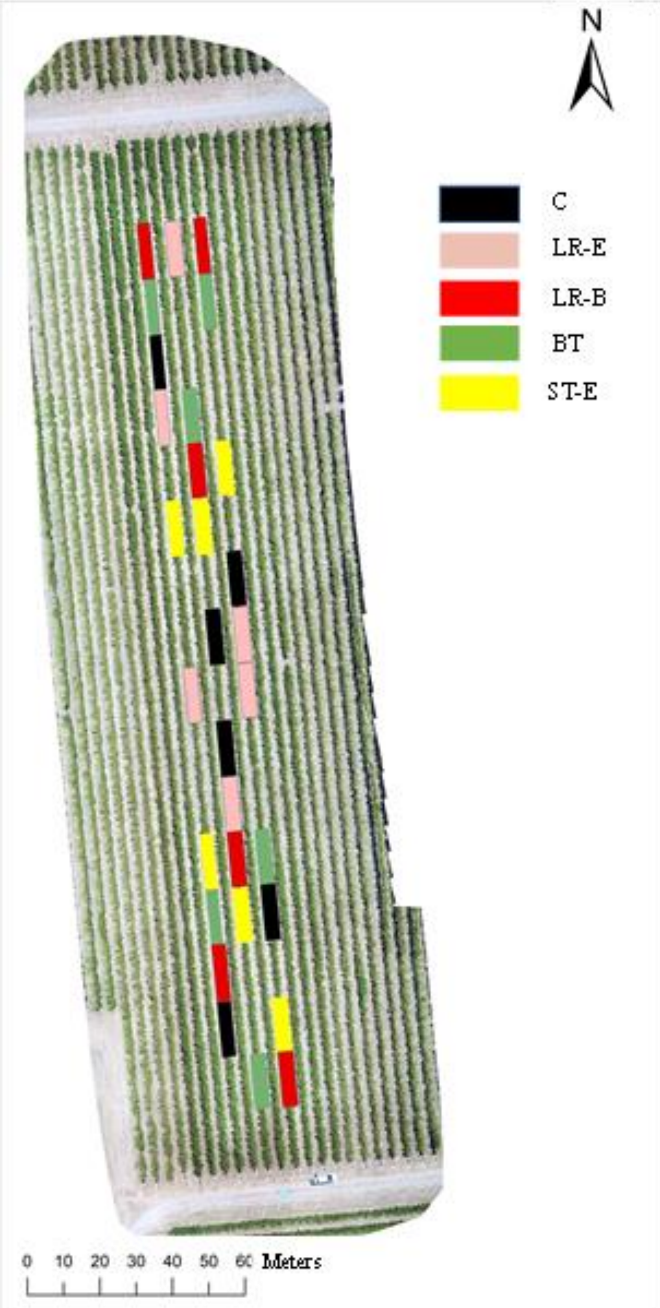

Figure 1. Cabernet-Sauvignon experimental trial vineyard in McLaren Vale, South Australia. Four different canopy management practices were applied: i) leaf removal on the eastern side of the canopy (LR-E), ii) leaf removal on both sides of the canopy (eastern and western, LR-B), iii) bunch thinning (BT) and iv) shoot trimming on the eastern side of the canopy (ST-E) (colour-coded according to the treatments received). Each treatment was applied to six replicates. The background RGB orthomosaic image was captured at veraison (E-L stage 35).

2.2 Ground and UAV-based Imagery Acquisition and Analysis

To measure the impact of treatments on canopy structure, a combination of ground and aerial imagery analysis was used. Measurements were taken: i) before treatment application (E-L stage 35), ii) one week after treatment application and iii) at harvest (E-L stage 38). For the ground measurement, two images were acquired from the middle vine in each panel, one on the left and one on the right side of the trunk. A total of 24 images were acquired per treatment at each measurement. From these images, PAI was calculated using the smartphone app VitiCanopy (University of Adelaide, South Australia, Australia). The ground imagery was captured by the frontal RGB camera of an Apple iPhone 7 at a resolution of 7.2 megapixels (Apple Inc., Cupertino, CA, USA), detailed procedures for image capture and PAI calculation can be found in De Bei et al. (2016). The PAI was also calibrated against real LAI, measured by destructive leave removal measurements in the same study site, and their correlations can be found in the supplementary information.

UAV flights were performed to acquire RGB and multispectral imagery of the study vineyard. RGB imagery was captured by the RGB sensor of a Phantom 4 Pro quadcopter (DJI, Shenzhen, China) at a resolution of 20 megapixels. Multispectral imagery was acquired by the Parrot Sequoia multispectral sensor (Parrot SA, Paris, France) recording spectral bands at green (550 nm), red (660 nm), red edge (735 nm) and near-infrared (790 nm) bands, at a resolution of 1.2 megapixels. The Sequoia camera was integrated into a Phantom 3 Adv (DJI, Shenzhen, China) quadcopter using a customized integration package (MicaSense, v1.3, Seattle, USA). The multispectral images were radiometrically calibrated by the onboard downwelling sunlight sensor during the flight and a calibrated reflectance panel on the ground (MicaSense, Seattle, USA). On a clear day, the flights were conducted at solar noon to minimise any shadow effect. The single-grid routes covering all replicate panels at an overlap ratio of 80 % were set. The aircraft was maintained at a height of 30 m above ground and a constant speed of 2 m/s during the flight. The geographic coordinates of images captured were recorded by the onboard Global Positioning System (GPS) receiver.

The commercial photogrammetry software PIX4Dmapper (v.4.4.12; Pix4D SA, Lausanne, Switzerland) was used for UAV imagery reconstruction, the RGB orthomosaic images and the digital surface model (DSM) rasters of the vineyard were reconstructed from RGB images (Figure 2). Using multispectral images, single-band orthomosaic images were created from images of each spectral band. The average ground sampling distances (GSD) of the RGB and single-band orthomosaic images were 0.8 cm and 3.2 cm, respectively. Using a customized processing procedure in ArcGIS (v.10.5.1; ESRI, Redlands, CA, USA), the DSM was normalized to generate the digital canopy model (DCM) rasters. Using the image processing toolbox in Matlab (v.2019b, Natick, Massachusetts, United States), green canopy pixels in the RGB orthomosaic imagery were extracted according to the Lab colour space profile to create the canopy layer for projected canopy area calculation.

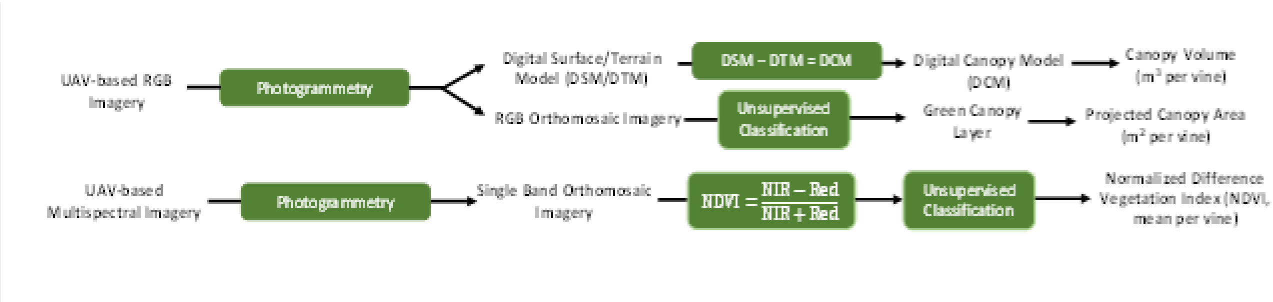

Figure 2. Flow chart of the unmanned aerial vehicle (UAV)-based RGB/multispectral imagery processing procedures for generating canopy volume, projected canopy area and normalized difference vegetation index (NDVI) in the current study.

To create the normalized difference vegetation index (NDVI) raster for the study vineyard, a calculation was performed using single band orthomosaic images as follows:

$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \qquad \text{(Rouse et al., 1974)}$$

Where:

NIR = Near infrared band orthomosaic image;

Red = Red band orthomosaic image.

With the NDVI raster for the whole vineyard, unsupervised classification was performed to extract the canopy-related pixels using the Iso Cluster Unsupervised Classification function in ArcGIS. As a result, the raster was classified into two classes: background and grapevine canopy. The canopy class was extracted as the classified NDVI raster for the calculation of mean NDVI per vine.

Vineyard rasters of DCM, RGB imagery of green canopy layer and classified NDVI containing only canopy-related pixels were stored in the tagged image file format (.tiff) image files. Rasters were geo-referenced using ground control points and experimental replicates were marked using the high-resolution RGB imagery by identifying posts separating individual panels. Polygon vectors for replicates were then created and used as masks to extract replicate rasters. According to the fixed planting distance, single grapevine rasters were further separated from the individual replicate rasters. Using the single vine rasters, canopy volume per vine (m3) were calculated from the DCM using volume above the cordon height plane (1.1 m above ground). Projected canopy area per vine (m2) was calculated using the sum of the single canopy pixel area in the RGB green pixel layer. The mean NDVI per vine was calculated from the mean NDVI values of all extracted canopy class pixels.

2.3 Statistical Analysis

Analysis of variance (ANOVA) was performed to determine if canopy treatments led to significantly different canopy structures ($p < 0.05$). Statistics were performed in the statistics and machine learning toolbox of Matlab and GraphPad Prism (v.8; GraphPad Software, San Diego, USA). Mean values, standard errors of the mean and statistical significance of measurements have been reported.

RESULTS AND DISCUSSION

With the application of canopy treatments, changes in the canopy structure were observed (Figure 3). Significant reductions in the mean canopy volume per vine were observed after leaf removal (LR-E and LR-B) and shoot trimming (ST-E). Leaf removal and shoot trimming applied to one side of the canopy (LR-E and ST-E) had also lowered canopy volume (from 1.29 m3 to 1.06 m3 and from 1.37 m3 to 1.12 m3, respectively). Double-sided leaf removal reduced canopy volume (from 1.42 m3 to 0.82 m3) more than the single-sided application. No difference in canopy volume was found when bunch thinning was applied and compared to the control group. This was expected as bunch thinning only removed bunches at the bunch zone inside the canopy which was covered by leaves and shoots, meaning the overall dimensions of the canopy were not altered. At harvest, the canopy volume of all treatment groups declined to significantly lower levels than after treatment application. The general decline in the canopy volume can be explained by the seasonal reduction in canopy development due to leaf senescence leading to leaf fall and the reduction in irrigation application (Pádua et al., 2018).

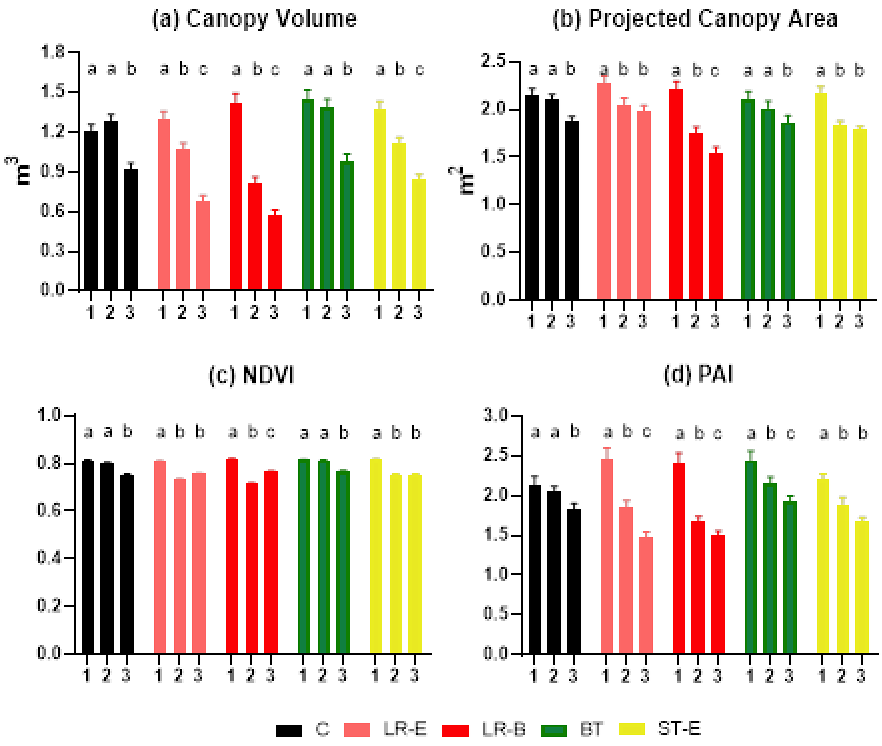

Figure 3. Canopy structure measurements from UAV-captured imagery. (a) canopy volume (m3) per vine, (b) projected canopy (m2) area per vine, (c) normalized difference vegetation index (NDVI) and (d) ground-based plant area index (PAI). Four different treatments applied were: leaf removal on the eastern side of the canopy (LR-E), leaf removal on both sides of the canopy (LR-B), bunch thinning (BT) and shoot trimming on the eastern side of the canopy (ST-E). Canopy treatments were applied at veraison (E-L stage 35). Measurements were performed at three timepoints: 1) before the treatment, 2) one week after the treatment and 3) at harvest (E-L stage 38) to track changes in canopy structure. In each graph, bars are grouped by treatment and within each group, measurements at different timepoints are shown. Significant differences ($p < 0.05$) between measurements in the same group are annotated by different letters and bars show the standard errors of the mean value.

Similar to canopy volume, projected canopy area and NDVI values in the treatment groups where leaf removal and shoot trimming were applied (LR-E, LR-B and ST-E) were reduced while the control and bunch thinning groups (C and BT) remained relatively unchanged. Ground-based PAI measurements recorded significant differences in all treatment groups, including the bunch thinning treatment which was not detected by the UAV based remote sensing approaches. PAI was calculated from upward-looking canopy cover imagery (De Bei et al., 2016), and was shown to be capable of detecting the changes of internal canopy structure under foliage cover, such as the removal of bunches (Figure 4). In addition, canopy porosity, which is an important indicator of the light conditions inside the canopy and closely related to PAI, can also be generated from the canopy cover imagery (De Bei et al., 2016). Thus, PAI was found to be more advantageous in detecting variations in both internal and external dimensions in the canopy structure than remote sensing approaches which only detected external dimension and spectral value variations.

(a) Control (C) (b) Bunch thinning (BT)

Figure 4. Examples of ground-based canopy cover images for (a) control and (b) bunch thinning. Note the decrease in the bunch number in the bunch thinning group, compared with the control group.

Comparing different measurements for the same treatment group, canopy volume and PAI were found to detect greater differences in canopy structure after canopy management practices were applied. When comparing measurements taken before and after treatment application (Figure 5), canopy volume and PAI demonstrate the largest percentage changes for leaf removal and shoot trimming treatments. In contrast, very little change was observed in NDVI values with the largest decline of 13 % when double-sided leaf removal was applied. The same treatment recorded reductions of 43 % and 30 % in canopy volume and PAI measures, respectively. At harvest (Figure 5), canopy volume recorded the biggest percentage change across all measurements, followed by PAI. This may have been accentuated by leaf fall. Canopy volume and PAI measures detected greater differences in canopy structure and may be more useful measures for making informed decisions and determining the effectiveness of canopy management practices.

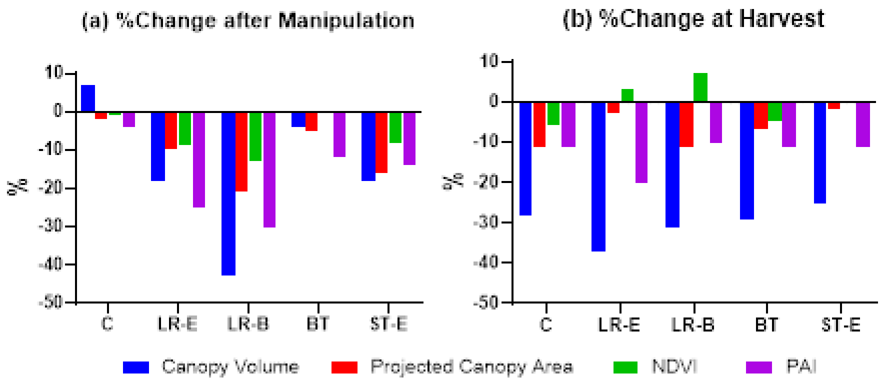

Figure 5. Percentages of change in the measured parameters for the same treatment group between stages. (a) between pre and post canopy treatments at veraison (both at E-L stage 35); (b): between post-treatment (E-L stage 35) and harvest (E-L stage 38). The data were grouped by four different treatments and within each group, the mean percentage change of four measured parameters are shown (canopy volume (m3), projected canopy area (m2), NDVI and PAI). Treatments applied were leaf removal on the eastern side of the canopy (LR-E), leaf removal on both sides of the canopy (LR-B), bunch thinning (BT) and shoot trimming on the eastern side of the canopy (ST-E).

The treatments used in this study showed the limitations of NDVI and canopy area measurements in detecting changes in canopy structure. As discussed previously, bunch thinning cannot be detected by remote sensing approaches due to foliage cover. In addition, it was also found, in the shoot trimming group (ST-E), that the leaves and portion of shoots that were trimmed and left on the ground were detected by the NDVI and canopy area measurements using unsupervised classification (Figure 6a and b). The portion of the canopy that was removed at trimming likely had similar spectral properties to the canopy that remained on the vine. When unsupervised classification was applied, both pixels on the grapevine and on the ground (residual pixels) were extracted and these residual pixels reduced the accuracies of NDVI and canopy area. For the canopy area, residual pixels increased the total canopy pixel number for the measured grapevine and, as a result, increased the canopy area. By setting higher thresholds in the Lab colour space profile when extracting canopy pixels, some residual pixels in the RGB orthomosaic were filtered out (Figure 6c). Nonetheless, strict thresholds also filtered out part of the canopy pixels and resulted in the underestimation of the projected canopy area. With these measurements already taken one week after the shoots were trimmed, they are unlikely to be capable of providing accurate real-time assessments of the canopy structure immediately after shoot trimming. Therefore, it is suggested that NDVI and canopy area measurements using UAV-based two-dimensional rasters (e.g., spectral indices and RGB rasters) for the assessment of shoot trimming should be avoided to minimise any potential errors.

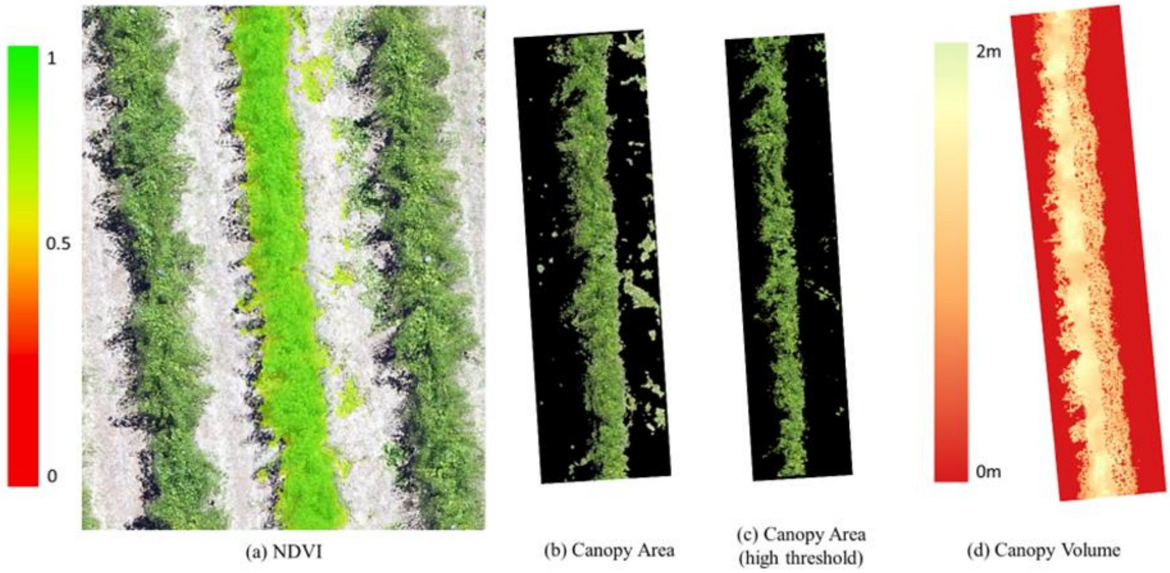

Figure 6. A comparison of different remote sensing approaches for extracting the grapevine canopy. Rasters of the canopy that received shoot trimming, captured one week after the application at veraison (E-L stage 35), are shown: (a) NDVI raster (overlaying RGB orthomosaic image), (b) canopy pixel raster for calculating projected canopy area, (c) canopy pixel raster with the higher extraction threshold for green pixels and (d) digital canopy model (DCM) for calculating canopy volume. Note the trimmed shoots and leaves left on the ground (residual pixels) were captured by NDVI (a) and canopy area measurements (b). Canopy pixel extraction with the higher threshold (c) filtered out most ground residual pixels but also reduced the actual projected canopy area in the canopy zone. In comparison, DCM (d) can effectively filter out ground interference.

In Figure 6d, DCM was shown to contain only the grapevine canopy after filtering out shoots left on the ground during DSM normalization. Without the interference from ground residual pixels, the canopy volume calculated from the DCM reflected more accurately the volume measurements of the grapevine canopy. Canopy volume measurements can also be obtained immediately after canopy management practices are applied without the interference of the trimmed shoots or leaves on the ground, unlike NDVI and projected canopy volume measures. In addition, although no ground vegetation (weed or cover crop) grew in the study vineyard, it has been found that DCM can also filter out the interference from ground vegetation as only the partial volume of the DCM that was above the cordon height was included (Vanegas et al., 2018; Weiss & Baret, 2017). With these advantages, canopy volume calculated from DCM displayed potential as a suitable tool for monitoring canopy management outcomes.

Compared with UAV, the ground-based PAI measurement has a simpler process and offers the convenience of collecting and analysing the data quickly. It can assess the outcomes of the canopy management practice and report the results in the field which allows growers to promptly adjust their management practices. Nonetheless, as the canopy cover imagery for the PAI calculation was collected discretely between vines, the sampling distances between images should be considered in conjunction with target map resolution when using this method for mapping the spatial variability. By integrating the ground imagery acquisition system with vineyard vehicles can potentially enable the on-the-go canopy structure assessment, as explored in previous studies (Bramley et al., 2007; Liu et al., 2017; Rose et al., 2016). However, these systems often require regular calibrations during the operation for capturing suitable imagery under the dynamic light conditions in the field and more research is required to improve the robustness of the integrated system.

Between UAV-based remote sensing approaches, the processes for data collection and primary analysis were similar, both in terms of the UAV flight and the vineyard raster reconstruction. For canopy volume, DSM needs to be normalized to create the DCM which was more complicated than the canopy pixel classification and extraction for the NDVI and projected canopy area calculation. However, the collection of multispectral imagery for NDVI calculation required integrating extra multispectral sensors while the DCM was created from the RGB imagery captured by the originally on-board RGB sensor. Therefore, the cost and labour required for the acquisition and integration of multispectral sensors can be avoided by using DCM. In addition, DCM can also be used to provide the surface area of the canopy and knowing the volume and surface area of the canopy can potentially be useful for guiding other canopy management operations. For example, it can be used to advise the chemical spray volume required and the spray application rate can be adjusted during the operation according to the canopy size (Llorens et al., 2010; Llorens et al., 2011). The latter authors proposed the use of ultrasonic and LIDAR sensors for the proximal sensing of canopies in vineyards and concluded that these sensors could provide valuable information on canopy volume and leaf are index. However, they also concluded that the post-processing of LIDAR-acquired information can be a limiting factor to its usability. Similarly, the work from Siebers et al. (2018) has demonstrated that proximal sensing in viticulture could provide useful information on canopy architecture; the authors developed a proximal sensing platform, the Grover, equipped with LiDAR but with the capability to host and test multiple sensors. Diago et al. (2019) proposed the use of an on-the-go system to collect RGB images for the assessment of grapevine canopy parameters with successful results. Similar to our findings an on-the-go system can be used as a tool to assess the efficiency of canopy management operations.

UAV-based remote sensing can be used to provide assessments of the whole area before or after the application of canopy management practices to advise the optimal input level and assess outcomes. Various flight control software also helps maintain the course and speed of the aircraft automatically during the flight which greatly reduces the difficulties and complexities in capturing overlapped imagery suitable for the reconstruction of orthomosaic imagery using photogrammetry. The operational flexibility of UAV also allows the timely assessment of the canopy management outcomes, compared with manned aircraft and satellite remote sensing.

CONCLUSION

The UAV-based canopy volume assessment was able to account for differences obtained through canopy management, specifically the canopy structure. Canopy volume is more sensitive to changes in the canopy structure compared to NDVI and projected canopy area. It is also a more cost-effective measure than the multispectral index NDVI, where a multispectral sensor is required, increasing costs of hardware and analysis and interpretation requirements. The accuracies of NDVI and projected canopy area measurements were negatively impacted when practices such as shoot trimming, which leave plant material on the ground were applied. Due to the cover of foliage, UAV-based measurements cannot be used to measure the impact of bunch thinning on canopy structure. However, UAV-based approaches can be used to provide vineyard scale measurements that cover all the grapevines in the vineyard and have the potential to be integrated with other vineyard management practices, such as targeted chemical spraying. PAI calculated from ground-based canopy cover imagery can be used to measure all three types of canopy management practices (leaf removal, shoot trimming and bunch thinning) assessed in this study and was a convenient approach for in-field assessments.

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Chapter 5. Published Article: Assessment of canopy size using UAV-based point cloud analysis to detect the severity and spatial distribution of canopy decline

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Principal Author

Name of Principal Author (Candidate)	JINGYUN OUYANG		
Contribution to the Paper	Collecting ground-truth samples. Conducting UAV flights Data Analysis & Manuscript writing		
Overall percentage (%)	80%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	24/09/2020

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Contribution to the Paper	Manuscript Review & Comments • Manuscript writing • Experimental design • Data interpretation and analysis		
Signature		Date	25/09/2020

Please cut and paste additional co-author panels here as required.

Assessment of canopy size using UAV-based point cloud analysis to detect the severity and spatial distribution of canopy decline

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ABSTRACT

Aim: This study aimed to validate the use of UAV-based point cloud analysis to detect canopy decline severity and its spatial distribution in vineyards.

A new approach of assessing canopy decline, caused by Eutypa dieback-like symptoms, using unmanned aerial vehicle (UAV) remote sensing was compared with ground visual assessment in the vineyard.

Methods and results: Canopy point cloud captured by UAV-based imagery during the growing season was analysed by a customized program to determine canopy decline severity and spatial distribution in a symptomatic Shiraz vineyard in Eden Valley, South Australia. Experienced assessors performed a ground visual assessment in the vineyard at E-L stage 15. *k*-means clustering was used to detect reduced canopy volume due to Eutypa dieback-like symptoms. Results from point cloud analysis showed that 12.5 % of the total canopy length in the vineyard had Eutypa dieback symptoms while the ground visual assessment detected 11.4 %. Confusion matrix results show an accuracy of 87.4 % and a kappa coefficient of 0.43 compared with ground visual assessments. Additionally, automatic analysis of the point cloud was quicker than the ground visual assessment and generated precise geographic coordinates of the symptomatic canopy sections.

Conclusions: Point cloud analysis can detect Eutypa dieback severity and its spatial distribution with 87.4 % accuracy, compared with the ground assessment. Similar to ground visual assessment, E-L stage 15 appears to be a suitable stage to apply point cloud analysis to make Eutypa dieback-like symptom assessments.

Significance and impact of the study: Grapevine canopy decline, caused by various factors such as Eutypa dieback and inadequate management, can cause grapevine canopy decline, yield reduction and

threaten vineyard longevity. Compared with tedious ground visual assessments, point cloud analysis can accelerate the assessment of canopy decline in vineyards and help with the planning of remedial practices using precise geographic coordinates of the affected sections.

INTRODUCTION

In the vineyard, canopy decline can lead to yield losses and quality reductions (Magarey et al., 2000). Canopy decline can be caused by factors such as grapevine trunk diseases, virus and inappropriate canopy management practices (Bowman, 2018). Grapevine trunk diseases as an example, which include diseases such as Eutypa dieback and Botryosphaeria dieback, contribute to grapevine decline and threaten the longevity of vineyards globally (Sipiora and Cuellar, 2015). In Australia, Eutypa dieback is widespread with all major grapevine varieties grown being susceptible (Wine Australia, 2019). It has also been found that, if trunk disease is detected early and preventive practices are applied, the lifespan of an infected vineyard can be extended by between 26 %–47 % (Kaplan et al., 2016).

As a major cause for canopy decline, Eutypa dieback infection can occur when fungal spores enter through pruning wounds on the grapevine (Gramaje et al., 2018). As the infection develops along the cordon, the foliar symptoms of dieback will appear on shoots and gradually grow towards the trunk at the speed of around 50 mm per year (Sosnowski et al., 2008). Due to its slow development, the canopy structure between infected and healthy vines and even between cordons of the same infected grapevine can be highly variable. Remedial surgery on infected cordons has been shown to improve productivity (Sosnowski et al., 2011). Remedial surgery practices include cordon removal, retraining and replanting and the application of each differs depending on the severity of Eutypa dieback (Creaser and Wicks, 2004; Sosnowski et al., 2011). Therefore, mapping of the severity and spatial distribution of canopy decline in a vineyard is crucial to plan preventative and remedial activities. Knowing the proportion of canopy decline relative to total canopy length can also indicate the reduction in potential yield (Munkvold et al., 1994).

To assess canopy decline symptoms such as Eutypa dieback, visual assessments of foliar symptoms in the field are commonly carried out in spring, when shoot length is around 30–70 cm, between E-L stages 12–17 (Bertsch et al., 2013). During these developmental stages, Eutypa dieback incidence, severity and spatial distribution can be estimated. Currently, this practice is performed by experienced viticulturists and can be tedious and costly for large vineyards. Another potential option to assess canopy decline is the use of digital applications on portable devices. Recently, several smartphone applications such as VitiCanopy have been developed to calculate plant area index (PAI) from canopy cover imagery (De Bei et al., 2016; Fuentes et al., 2014; Poblete-Echeverria et al., 2015). PAI is a measurement of the canopy structure and corresponds to the total area of leaf and cordon per unit ground area (Bréda, 2003). The use of PAI to quantify canopy size and structure may also be useful in assessing the canopy decline.

Remote sensing has been applied to measure the severity and distribution of grapevine canopy decline in the vineyard with the advantages of lowering labour requirements and costs (Andújar et al., 2019; Delenne et al., 2010; Hall, 2018). Red-green-blue (RGB) and multispectral imagery captured by aircraft and satellites have been used to detect missing grapevines and spectral reflectance changes in the canopy due to disease infection (Albetis et al., 2018; Chanussot et al., 2005; MacDonald et al., 2016). However, for Eutypa dieback-derived canopy decline assessment, analysis of aerial imagery captured in spring can be challenging due to interference from ground vegetation (Matese et al., 2015; Poblete-Echeverría et al., 2017). The inclusion of ground vegetation in imagery analysis has been found to reduce the accuracy of detecting missing grapevines and can potentially reduce the accuracy of canopy decline detection and decline severity assessments (Delenne et al., 2010). Therefore, it remains unclear whether the canopy development stages (E-L 12–17), suitable for ground visual assessment, still apply to UAV remote sensing.

Alternatively, point clouds reconstructed from high-resolution RGB imagery captured by an unmanned aerial vehicle (UAV) can potentially be used. Point cloud data contains three-dimensional canopy information that can be analysed to calculate canopy height, surface area and volume values (de Castro et al., 2018; Pádua et al., 2018). As a result, severity and distribution of canopy decline may be detected from low volume canopy sections, potentially representing stunted shoots and bare cordons with no canopy growth. The analysis of point cloud can also effectively filter out floor vegetation, by only extracting points above the cordon height, to reduce the interference of ground vegetation in two-dimensional imagery (Weiss and Baret, 2017). Therefore, point cloud analysis may have greater potential for measuring canopy decline in spring when the symptoms are most obvious and ground vegetation is more likely to be present.

This study aims to investigate the potential of point cloud analysis in the estimation of canopy decline severity and spatial distribution. To achieve this, UAV flights were performed and compared with ground visual assessments that are typically used to assess canopy decline, in a vineyard infected by Eutypa dieback. Subsequent UAV flights were also performed through the whole growing season (spring to autumn) to compare the performance of point cloud analysis at different developmental growth stages.

MATERIALS AND METHODS

1. Experimental site details

A 1.2 hectare Shiraz vineyard block in Eden Valley, South Australia, Australia (Lat 34°37'57.0"S, Lon 139°06'56.8"E, elevation 386.8 m) was selected for this study during the 2018-19 growing season. In the vineyard, grapevines displayed canopy decline, likely caused by the symptoms of Eutypa dieback (Figure 1). However, the distribution and severity of canopy decline were unclear. The block contained 20 rows of grapevines at a row spacing of 3.2 m and rows orientated east-west. Each row consisted of panels of three vines, planted at a spacing of 2 m. The grapevines were trained to a vertical shoot position (VSP) trellis system and the cordon height was 1.3 m above ground. Standard commercial vineyard management and irrigation practices were applied in the vineyard during the study period.

Figure 1. Examples of a (a) healthy grapevine canopy, (b) canopy with stunted shoots and uneven development and (c) canopy section with no growth. Images were taken at E-L stage 15 (Coombe 1995) in a Shiraz block used for this study in Eden Valley, South Australia.

2. UAV imagery collection and process

From budburst to harvest, UAV flights were performed approximately every two weeks, with a total of 11 flights performed. Among the data collected, the focus of analysis in this paper was concentrated on the second flight at E-L stage 15, considered the optimal stage for ground assessments (Bertsch et al., 2013). Using a Phantom 4 Pro UAV (DJI, Shenzhen, China), the on-board RGB sensor was used to capture nadir imagery at 20 megapixels resolution. The UAV flight plan was set and controlled by a remote controller connected to a smartphone installed with the flight planning software Pix4DCapture (v.4.2; Pix4D SA, Lausanne, Switzerland). A double-grid flight route covering the whole block and an imagery overlap ratio of 85 % were set for every flight and the aircraft was maintained at a constant travel speed of 2 m/s and height of 30 m above ground. Each flight took around 1hr to capture the entire block. During each UAV flight, around 1000 images were collected and the geographic coordinates of the imagery were recorded by the onboard Global Positioning System (GPS) receiver.

Using the commercial photogrammetry software PIX4Dmapper (v.4.4.12; Pix4D SA, Lausanne, Switzerland), the orthomosaic images and the point clouds of the vineyard block were reconstructed from the RGB images and stored as .ply files. The orthomosaic images had an average ground sampling distance (GSD) of 0.69 cm and point clouds covering the study block contained around 40 million points on average. Using the MATLAB computer vision toolbox and statistics and machine learning toolbox (v.2019b; Natick, Massachusetts, United States), a customized process was developed to analyse the vineyard point cloud and extract canopy points.

In the process, the vineyard densified point cloud (DPC) was first rotated to horizontal view. In this view, the coordinates of the first and last row centroids were manually selected, and middle row centroid coordinates were calculated automatically using the fixed row spacing (Figure 2, step 1). With row coordinates determined, region of interest (ROI) polygons (2 m wide), wider than the canopy width but narrower than row spacing, were created and vineyard point cloud was separated into individual row point clouds (Figure 2, step 2). According to the panel length, the single row point cloud was then further divided into separate panel point clouds (Figure 2, step 3). The ground points in each panel point cloud were identified using the MLESAC method (Torr and Zisserman, 2000). This was achieved by setting the maximum absolute angular distance among neighbouring points and maximum Euclidean distance of points from the plane. With the ground plane determined, all points were categorized as either canopy points (green) or non-canopy points (purple, Figure 2, step 4). After categorization, canopy points were appended into a separate canopy point cloud which included around 6–10 million, depending on the canopy size at different growing stages. An alpha shape (polyhedra) was created from the canopy point cloud (Figure 2, step 5) (Edelsbrunner et al., 1983; Milella et al., 2019). The volume (m^3) of the alpha shape was calculated as the corresponding grapevine canopy volume.

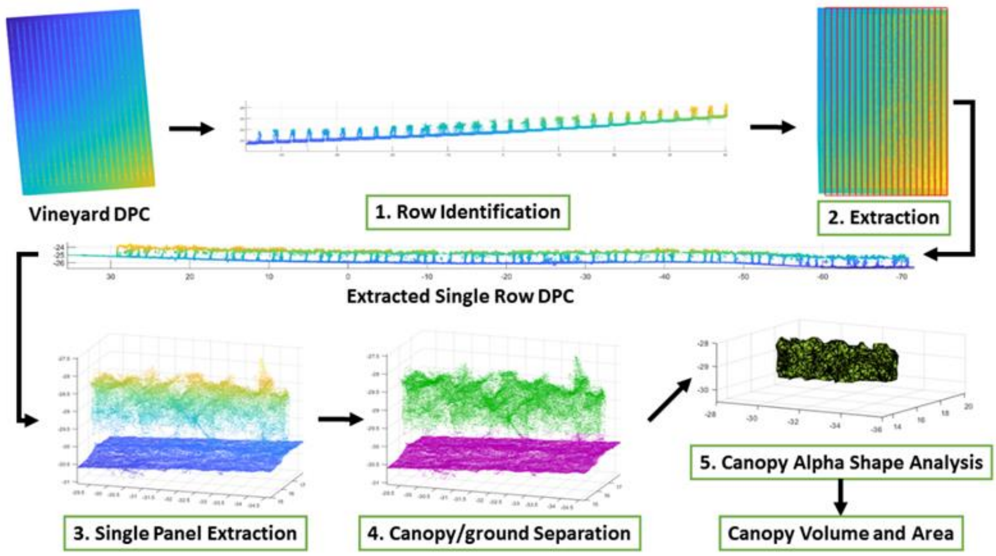

Figure 2. Point cloud analysis procedure for canopy volume calculation.

To detect canopy-decline-induced canopy volume reduction, canopy point clouds were divided into subsections (0.05 m wide) along the row orientation (Figure 3). The volume of all the subsections followed a normal distribution. Any stunted or no growth canopy subsections were detected when their volume was below the set thresholds. Fixed thresholds for defining low canopy volume were unsuitable for the rapidly expanding canopy in the spring. To create thresholds for detecting low canopy volume between different growing stages, the *k*-means clustering was used to categorize the subsection volume values at each stage into five classes. The number of classes was adopted from the classification approach described in Sosnowski et al. (2016). Subsections with volume above the first (smallest) class threshold were labelled as “healthy”. Sections with volume below that threshold were labelled as either "stunted" or "no growth". The first class was then further divided into another five classes with the first two smallest classes labelled as 'no growth' and the larger three classes as "stunted". The threshold between "no growth" and "stunted" category within the class was determined empirically according to their ratio in the ground assessment. With all sub-sections labelled, consecutive subsections labelled as "stunted" or "no growth" longer than 0.2 m (four subsections) were recorded. The length threshold of 0.2 m was used to filter out gaps from the natural spacing between shoots and could be variable for different vineyards according to the shoot density.

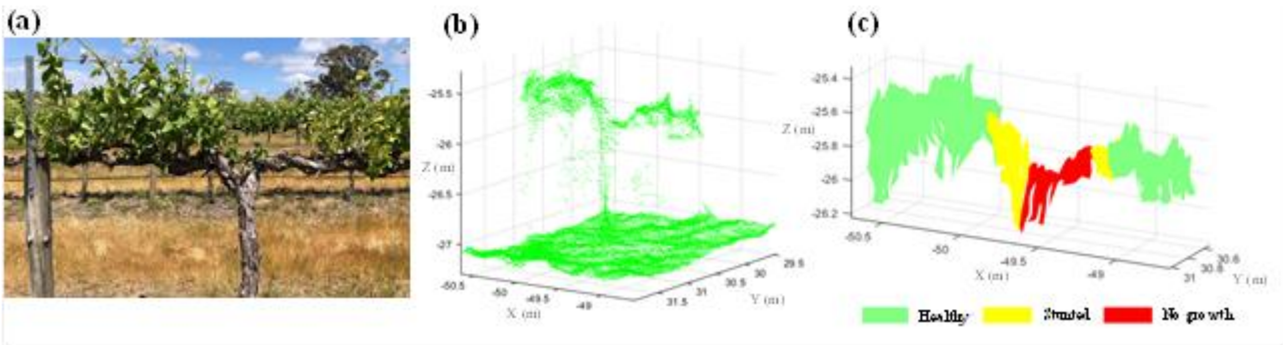

Figure 3. Example of the point cloud analysis process for detecting canopy decline: (a) the grapevine cordons were found to contain both healthy canopy, stunted growth and no growth sections; (b) corresponding single grapevine point cloud selected from the vineyard point cloud; (c) canopy points selected from the vine point cloud and divided into sections (0.05 m in length). For all canopy sections, *k*-means clustering was used to generate labels of "healthy", "stunted" and "no growth" (colour coded). In this study, any stunted canopy or no growth sections longer than 0.2 m on a target grapevine were recorded. Point coordinates are for illustration only, not the actual geographic coordinates.

3. Ground assessments of the canopy decline

To provide the ground truth measurements, the grapevines in the study block were assessed by a combination of visual assessment, canopy cover imagery analysis and canopy development measurements. The visual ground assessment was performed at E-L stage 15 in spring to better capture stunted canopy sections and no growth sections before they were filled or covered by rapidly developing healthy shoots. During the assessment, experienced assessors walked through all rows in the block and visually evaluated canopy health and searched for foliar symptoms on every vine. Plants displaying canopy decline had (1) the severity (%) estimated; (2) the recorded section location as either left cordon, trunk or right cordon of the vine recorded (Figure 4) and (3) length of the sections measured. The smartphone app, VitiCanopy was used to capture canopy cover imagery and calculate PAI, in parallel with ground visual assessments. PAI measurement was used to measure the difference in canopy structure. Briefly, one image was collected for each of the two cordons per vine (sampling distance = 1 m; n = 2160) and detailed procedures can be found in De Bei et al. (2016). The severity of the canopy decline was also assessed by counting the total shoot number and measuring mean shoot length from three randomly selected shoots. Sections found without any shoot development were labelled as no growth. For comparison with the canopy structure of declined canopy, the shoot number and shoot length of 20 randomly selected grapevines with healthy canopy were also recorded.

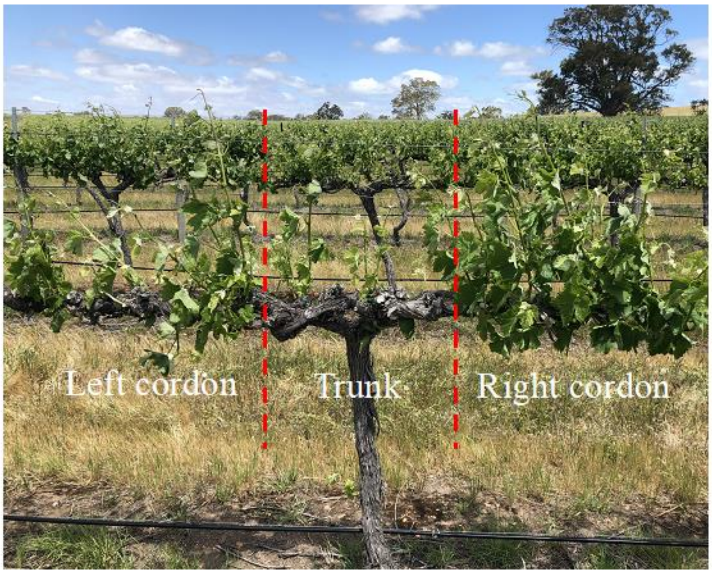

Figure 4. Location of grapevine canopy decline during visual assessments was classified as either left cordon, trunk or right cordon.

4. Canopy decline mapping and accuracy analysis

To enable the mapping of the multiple measurements taken, the geographic coordinates of individual grapevines are necessary. Theoretically, with fixed plant spacing, the geographic coordinates of all grapevines in any given vineyard can be calculated from the point cloud. The precision (centimetre level) of the coordinates calculated from the point cloud was also considered to be higher than what portable Global Navigation Satellite System (GNSS) terminal can achieve (2–3 metres) unless more complicated and expensive professional systems are used (e.g. differential GNSS or real-time kinematic). However, due to variable plant spacing in row-end panels in the vineyard, additional in-field measurements were taken to obtain the vine number and spacing in the end panels. With the vine coordinates, the spatial distribution of Eutypa dieback-like symptoms and PAI can be interpolated from field measurement points using kriging in QGIS (v.3.12.0, QGIS Project) with the spherical model used for the empirical semivariogram.

To map the distribution of canopy decline, centroid coordinates of low canopy volume sections detected by point cloud were calculated. For ground measurements, the centroid coordinates were calculated from the combination of relative positions of sections on the vine and vine coordinates. Using the length and centroid coordinates of the stunted canopy section and no growth sections, polygon vector geometries were created and stored as shapefiles (.shp) to represent sections displaying canopy decline. To determine the accuracy of the point cloud analysis, compared with ground visual assessments, a confusion matrix was constructed using QGIS and the kappa coefficient was calculated (Landis and Koch, 1977).

To assess the variance in shoot length, shoot number and canopy volume measurements, mean value and standard error of mean were calculated using MATLAB statistics and the machine learning toolbox (v.2019b; Natick, Massachusetts, United States).

RESULTS AND DISCUSSION

Eutypa dieback-like symptom detection: ground vs. point cloud

The severity of the Eutypa dieback infection, representing the level of canopy decline, measured by visual assessment, can be visualised in Figure 5. The severity of Eutypa dieback (Figure 5a), was found to be higher in the northern part of the block and lower towards the south which clearly demonstrated the progression of the Eutypa dieback-induced canopy decline. In comparison, the PAI map Figure 5b) shows variable patches in the vineyard with lower canopy growth, which do not fully align with Eutypa dieback-like symptom distribution. As will be discussed later, this can be explained by the spatial variability in canopy development caused by a range of factors, such as soil profile, water availability, management variability, etc. It is important to note that since canopy variability can be influenced by multiple factors and weak canopy growth without obvious foliage symptoms can still be healthy. Furthermore, PAI at this development stage is relatively low and demonstrates the challenges with assessment at early developmental stages and vineyard variation when using imagery.

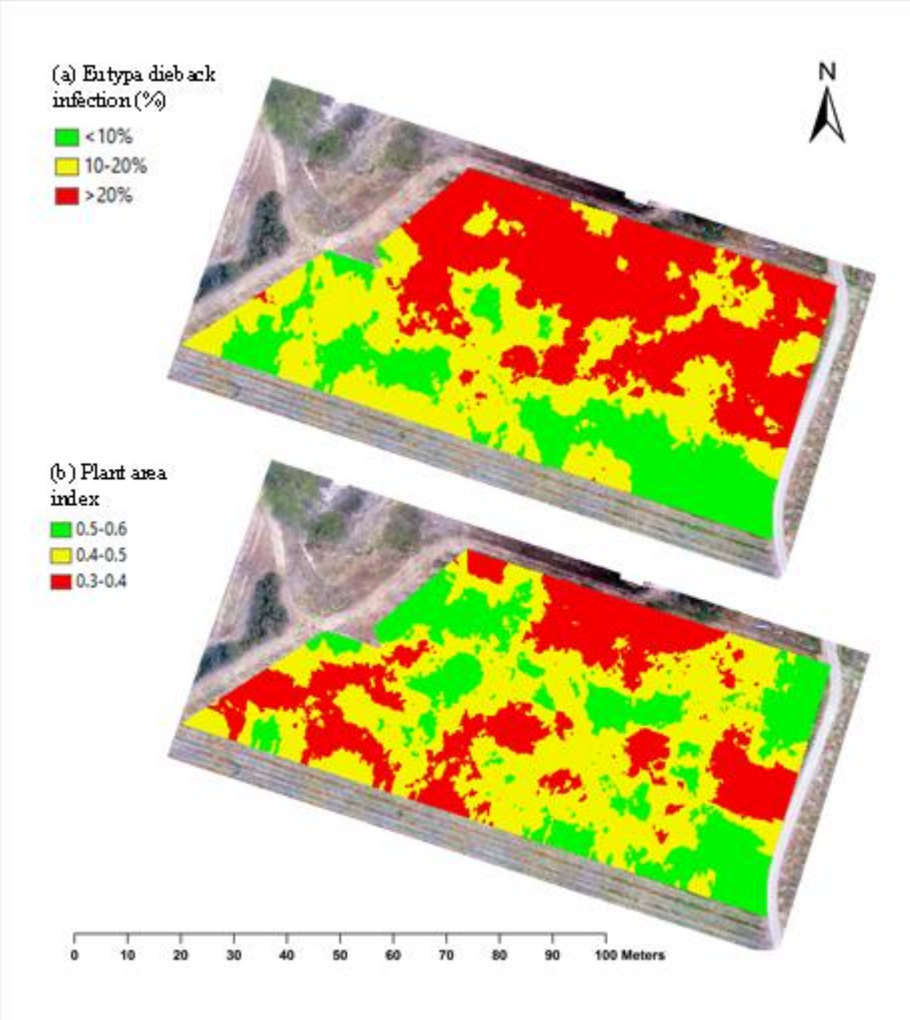

Figure 5. Field measurement results; (a) Eutypa dieback infection level per vine (%) and (b) Plant area index (PAI) of the study block at E-L stage 15. Eutypa dieback infection level was assessed according to foliar symptoms of the Eutypa dieback. PAI was calculated from canopy cover imagery using VitiCanopy.

Average shoot number, shoot length and canopy volume, were also found to be significantly impacted by Eutypa dieback (Table 1). At E-L stage 15, the mean shoot number in stunted canopy sections was significantly less than healthy sections and stunted shoots were less than half of the length of healthy shoots. For no growth sections, no shoots were present and the mean shoot length was zero. Mean canopy volume, derived from point cloud analysis, of the stunted canopy and no growth sections were significantly smaller than healthy canopy sections. Although cordons with no growth contained no shoots, the canopy volume of the canopy gaps was greater than 0. The residual canopy volume reflects the volume of the bare cordons, as shown in Figure 3. Only in the case of cordon removal, was a canopy volume of zero recorded. Using the no growth section volume, point cloud analysis also provides the potential to distinguish between dead cordons and missing cordon/grapevines which can be otherwise challenging for two-dimensional imagery analysis of RGB and multispectral imagery (Delenne et al., 2010; Poblete-Echeverría et al., 2017; Puletti et al., 2014).

Table 1. Canopy growth parameters of healthy, stunted and no growth sections at E-L stage 15. Average shoot number per metre and shoot length (cm) were measured during ground visual assessments. Canopy volume per metre (m^3/m) was calculated using point cloud analysis. For each measurement, the standard error of mean is also shown.

Canopy types	Average shoot number per metre	Average shoot length (cm)	Canopy volume (m^3/m)
Healthy canopy	13.7 (0.48)	47.2 (1.22)	1.2 (0.13)
Stunted canopy	4.4 (0.33)	20.0 (0.64)	0.3 (0.07)
No growth	0.0 (0.00)	0.0 (0.00)	0.2 (0.03)

From point cloud analysis, the study block's total canopy length was 2398.1 m (Table 2). Ground visual assessment found 181.1 m stunted canopy (7.6 % of total length) and 91.8 m no growth cordon (3.8 %). With the *k*-means clustering categorizing the canopy volume, point cloud analysis detected 207.8 m stunted canopy (8.7 %) and 91.7 m canopy gaps (3.8 %). The total length of the stunted canopy and no growth cordon was found to be 272.9 m (11.4 %) and 299.5 (12.5 %), as measured by ground assessment and point cloud analysis, respectively.

Table 2. Summary of ground visual assessment and point cloud analysis results for Eutypa dieback-like symptom detection in the study block, measured at E-L stage 15. The grapevine canopy was categorized into three types: healthy, stunted and no growth. The total length of each reported in metres and percentages of each relative to the total canopy length are also shown.

Total canopy length in the block: 2398.1 m (20 rows)

Type	Ground visual assessment	Point cloud analysis
Healthy canopy (m)	2125.2	2098.6
Stunted canopy (m)	181.1	207.8
No growth (m)	91.8	91.7
Stunted + no growth (m)	**272.9**	**299.5**
Healthy canopy (%)	88.6%	87.5%
Stunted canopy (%)	7.6%	8.7%
No growth (%)	3.8%	3.8%
Stunted + no growth (%)	**11.4%**	**12.5%**

Ground visual assessment revealed that both stunted canopy and no growth sections were present in every single row (Figure 6). Point cloud analysis also identified widespread stunted and no growth canopy sections. Both approaches detected large sections of canopy decline in the first three rows in the north of the block, indicating the severity of the Eutypa dieback problem. However, as can be observed in Figure 6, the ground visual assessment identified more short canopy sections with dieback symptoms than the point cloud analysis. This can be explained by the multiple factors used to grade the Eutypa dieback-induced canopy decline in ground assessment, including foliage symptoms and the overall canopy growth. As a result, ground measurement provided a more detailed but subjective assessment of the canopy decline.

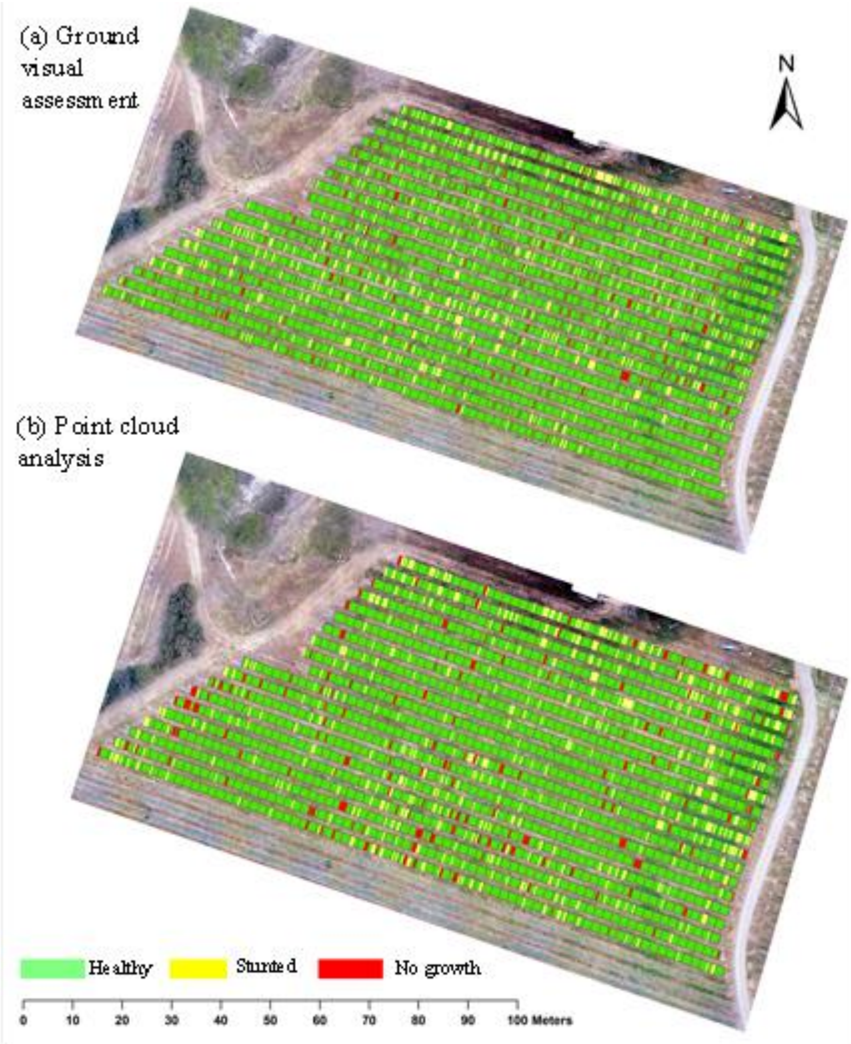

Figure 6. A comparison of the stunted and no growth canopy section detection using (a) ground visual assessment and (b) point cloud analysis at E-L stage 15. Green = healthy canopy, yellow = stunted canopy, red = no growth. The length of the rectangles was determined by the length of canopy sections impacted by Eutypa dieback-like symptoms. The boundaries of individual grapevine canopy are marked with black rectangles.

Using the confusion matrix of the classification accuracy, the performance of the point cloud analysis for canopy decline detection was quantified (Tables 3 and 4). When thresholds were set for point cloud analysis to detect the similar total length of symptomatic sections with ground assessments, 87.4 % (cells in green) of the categorization by point cloud analysis matched with sections detected by ground measurement (Table 4). However, the chances of false positives (healthy canopy classified as stunted or no growth in point cloud analysis) and false negatives (stunted or no growth canopy detected as healthy in point cloud analysis) were 4.3 % (cells in red of the first column) and 5.1 % (cells in red of the first row), respectively (Table 3). In addition, 3.3 % (cells in yellow) of the detection were misclassified between stunted or no growth classes (Table 3). The kappa coefficient of 0.43 also showed moderate agreement between the point cloud analysis and ground visual assessment (Table 4). The percentage agreement observed is also higher than the percentage agreement expected by chance. The analysis of point cloud demonstrates interesting and promising results that with further development may become a method for canopy decline assessment in vineyards.

Table 3. Confusion matrix of the canopy decline detection accuracy of UAV-based point cloud analysis, compared against ground visual assessment. Detection accuracies are colour-coded to show the correct and incorrect classifications. Green stands for the correct classifications between point cloud analysis and ground visual assessment. Red stands for incorrect classifications of the healthy canopy as declined categories (stunted or no growth) and vice versa. Orange stands for incorrect classifications between the declined categories.

		Ground Visual Assessment		
		Healthy	Stunted	No Growth
Point Cloud Analysis	Healthy	82.5 %	2.8 %	2.3 %
	Stunted	3.3 %	3.7 %	1.7 %
	No Growth	1.0 %	1.6 %	1.2 %

Table 4. Summary of the %observed agreements, %agreements expected by chance, kappa coefficient (kappa), weighted kappa and standard error (SE) of kappa for canopy decline detection accuracy of UAV-based point cloud analysis, compared against ground visual assessment.

Parameter	Result
%observed agreements	87.4 %
%agreements expected by chance	77.9 %
Kappa	0.43
Weighted kappa	0.46
SE of kappa	0.02

Several potential reasons for Eutypa dieback-like symptom detection variations between ground and point cloud analysis approaches have been found and summarised:

Potential reasons leading to the **location variations** include:

1. The locations of the ground measurements were less precise than results from point cloud analysis. The ground measurement only recorded relative locations (left cordon, trunk or right cordon) of the infected sections on the grapevine. In comparison, point cloud analysis provided more precise geographic coordinates of the infected sections with sub-centimetre level precision (0.69 cm Ground Sample Distance (GSD)).

2. Real grapevine cordon length could be variable. This was caused by the existing remedial surgery practices that cut back some severely infected or dead cordons and extended healthy cordon from another grapevine to fill in the canopy gap (Sosnowski et al., 2011). It can also be caused by the differences that occurred during the initial vineyard set up. Therefore, the actual grapevine boundary could be different to the boundary from point cloud analysis, calculated according to fixed grapevine spacing. The boundary detection in continuous canopy point cloud remains difficult and the accuracy of Eutypa dieback-like symptoms detection at the grapevine level can be reduced as a result.

Potential reasons leading to the **classification variations** include:

1. Inaccuracies from the point cloud analysis program. As the infected canopy has a smaller size and fewer points in the point cloud than a healthy canopy point cloud, the canopy alpha shape created from a reduced number of points can be less accurate (Park et al., 2005) and the accuracy of the canopy volume may be influenced, as a result. Points representing posts between panels can also be counted as canopy points due to similar height. Although these points have a different colour profile to the canopy points, colour thresholds for more precisely selecting canopy points were not applied in the current study. Increasing the point density during point cloud reconstruction and the additional analysis of point colour may help improve classification accuracy but potentially at the cost of longer processing time and larger point cloud file size.
2. Human error from ground visual assessment as it depends on the experience and judgement of the assessor.
3. Canopy sections with low volume detected by point cloud analysis may also be influenced by other environmental factors (Iland et al., 2011; White, 2015). Ground assessors identified canopy sections with Eutypa dieback-like symptoms according to foliar symptoms and asymptomatic grapevines, even with relatively smaller canopies but healthy, were not recorded. For point cloud analysis, the detection of the infected canopy was solely dependent on the canopy volume and its accuracy can be reduced when canopy growth variations are large across the vineyard. This is considered to be a limiting factor for the current photogrammetry for point cloud reconstruction. Unless the RGB imagery resolution is much higher to be able to reveal the foliage symptom of the Eutypa dieback-induced canopy decline, it remains challenging for point cloud to distinguish between weak growth canopy and Eutypa dieback-induced canopy decline. This range of error for point cloud analysis will also increase with the canopy structure variability in the vineyard.

Implications of mapping Eutypa dieback-like symptoms for vineyard management

Areas with high levels of Eutypa dieback-like symptoms may require remedial surgery to control the further spread of Eutypa dieback and the application of pruning wound protection in nearby rows may become necessary (Sosnowski and Mundy, 2019). The mitigation of Eutypa dieback using remedial surgery practices (e.g., top work to re-establish the cordon or replanting) can be expensive and result in a loss in productivity for several years (Sosnowski et al., 2011). Preventive measures on early symptoms can improve the economics and effectiveness of application (Kaplan et al., 2016). Using point cloud analysis to combine the spatial distribution of Eutypa dieback-like infected canopy, infection severity and their percentages of the total productive canopy may provide important information when making decisions on preventative measures, reworking and whether or not to replant the vineyard when considering overall vineyard performance (Baumgartner et al., 2019; Munkvold et al., 1994).

For the 1.2 ha study block, the ground visual assessment took four experienced assessors eight hours, equivalent to 32 man-hours, and the capture of canopy cover imagery for LAI calculation took three man-hours. In comparison, the UAV flight and the data preparation took around four man-hours and the automatic analysis workflow can complete the analysis of vineyard point cloud in around two hours. However, it is important to note that the development and implementation of the codes needed for the point cloud analysis program took a considerable amount of time to complete and test.

The Eutypa dieback-like symptom detection provided by point cloud analysis offers a convenient and labour-saving alternative to visual assessment. It also suggests that point cloud analysis may be especially useful when assessing large vineyards where performing ground visual assessment can be very costly and not practically feasible. The automatic point cloud analysis process also limits potential human errors when using ground assessments which are related to the experience and judgement of the assessor (Kaplan et al., 2016). The highly precise geographic coordinates of the infected canopy extracted from the point cloud also offer other integration potentials, e.g., variable chemical spray rates for healthy and stunted canopy and the option to stop spraying where the cordon is bare (Wandkar et al., 2018).

Eutypa dieback-like symptom detection through the growing season using point cloud analysis

Across the whole growing season, 11 UAV flights were performed and the percentages of stunted and no growth canopy sections at each flight were calculated from point clouds (Figure 7). The highest levels of stunted and no growth canopy sections were detected at E-L stage 11 in the first flight. This was considered to reflect the natural shoot spacing and variation in shoot development at early development stages (before E-L stage 10) more than Eutypa dieback infection. After the first measurement, the percentages of stunted canopy and no growth sections declined substantially with canopy development. At E-L stage 15, when the ground visual assessment was performed, an infection level of 12.5 % was found and it dropped to around 8 % at E-L stage 17 and 25. The estimated infection levels reduced further to around 5 % at E-L stage 27 and remained stable until harvest (E-L stage 38).

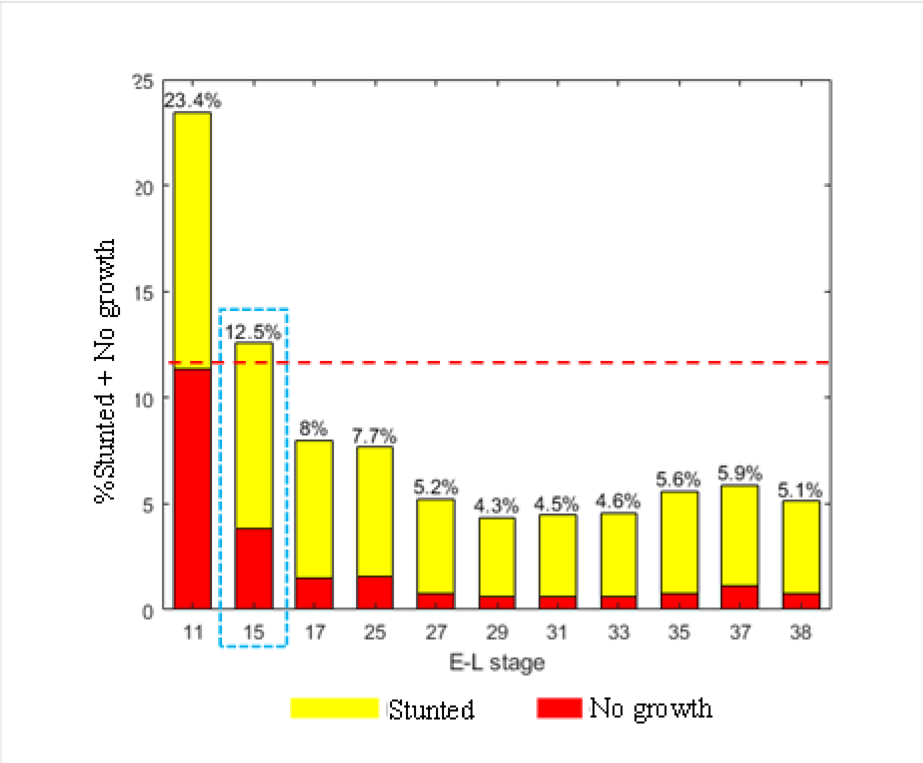

Figure 7. The percentages of total canopy length in the study block detected with stunted canopy (yellow) and no growth (red) sections during the 2018–19 growing season, calculated by point cloud analysis. At E-L stage 15 (highlighted), both the UAV flight and the ground visual assessment were performed. Percentage of symptomatic canopy length (11.4 %) determined by ground visual assessment were shown as the horizontal red dash line (---).

The ideal stage for performing ground visual assessments for Eutypa dieback has been suggested to be between E-L stages 12-17 when the symptoms are most obvious (Bertsch et al., 2013). The point cloud analysis at stage 15 in this study generated similar results to ground measurements. In Figure 7, the percentage of the stunted canopy and no growth sections found after this stage were lower suggest a limitation to the application of point cloud analysis. Therefore, these findings support previous studies, which indicated that a suitable time to apply point cloud analysis is around E-L stage 15.

Conclusion

The analysis of the vineyard point cloud at E-L stage 15 can be used to assess Eutypa dieback-induced canopy decline in a vineyard. Canopy health classifications by the point cloud were accurate during this stage when compared with ground visual assessment (87.4 %). Point cloud analysis also supplied the precise geographic coordinates of the infected canopy to map the spatial distribution of Eutypa dieback-like symptoms and facilitate the application of remedial practices. The automatic analysis of the point cloud is more convenient and less labour-intensive than ground visual assessment. However, factors including existing canopy remedial surgery, limited point density and the vineyard environmental conditions can influence the accuracy of point cloud analysis. Results from this study suggest that E-L stage 15 is suitable for Eutypa dieback detection using point cloud analysis as it aligns well with visual assessments. The number of infected canopy sections this method can detect declines later in the season as the canopy develops.

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Chapter 6. General Discussion

As demonstrated in the previous three chapters, vineyard monitoring was performed using UAV-based aerial remote sensing across three consecutive growing seasons in vineyards across South Australia. The performance of UAV-based systems in multiple aspects was assessed and compared with ground-based measurements. In the first study, canopy development was measured from budburst to veraison by regular UAV flights during the same period. The second study explored the potential use of UAV to evaluate the changes in the canopy structure after applying a range of common canopy management practices. The third study investigated the feasibility of using UAV to detect canopy decline potentially caused by grapevine trunk diseases. With the knowledge gaps identified in the literature review, these three studies were designed to explore tools/systems/approaches suitable for practical purposes in the vineyard. These studies showed the feasibility and potential use of UAV as an approach to monitor canopy development during the growing season, especially at critical developmental stages.

Based on research findings, ground-based canopy imagery analysis is also a suitable approach to monitor canopy development. Being a more convenient and straightforward approach requires a simpler skillset than the requirements to conduct UAV flights and the analysis afterwards. With a lower input cost, the ground measurements may also be more effective and convenient than UAV-based remote sensing, depended on the monitoring purposes. However, ground-based measurements can require more time and labour to complete if high-resolution maps or complicated measurements are required. In summary, a clear definition of the vineyard monitoring purposes will largely determine the most suitable monitoring approach, either from the air or on the ground.

6.1 Monitoring Purpose(s)

To understand and improve vineyard performance, vineyard monitoring purposes can be diverse, ranging from calculating planting area, estimating canopy dimensions, measuring plant water status, to disease incidence and severity detection. Depending on the purpose, the systems used to conduct measurement can differ significantly. For example, thermal sensors are used to measure vine water status, while RGB or LiDAR sensors are used to measure canopy dimensions.

In this work, UAV imagery's potential to monitor canopy development, evaluate canopy manipulation outcomes, and detect canopy decline were studied. The sensors used to capture imagery were either RGB and/or multispectral sensors for monitoring canopy development. RGB and vegetation indices rasters representing the whole growing area can be reconstructed from individual imagery using photogrammetry. By comparing rasters, canopy development at different phenological developmental stages within and between seasons can be visualized. The general trends in canopy development across the vineyard can also be better understood. The potential management decisions made from spatial variability monitoring can help set up the vineyard's zonal management, such as zones with different canopy management practices, irrigation regimes, fertilization application rates, mulch application rates, etc.

Imagery resolution is an important factor for planning UAV flight and is determined by the amount of details required to make a management decision. The suitable imagery resolution should be determined by the monitoring purpose(s) and examples of different imagery resolutions are shown in Figure 1. In examples A to D, the GSDs of NDVI rasters provided for vineyard monitoring, from high to low resolution, range from 10m (A, metre level, representing low-resolution satellite imagery), 3m (B, metre level, representing medium resolution pan-sharpened/unsharpened satellite imagery), 0.5m (C, sub-metre level, representing low-resolution UAV imagery captured at high flight height, manned aircraft imagery or high-resolution pan-sharpened satellite imagery) to 0.04m (D, centimetre level, representing high-resolution UAV imagery captured at low flight height).

It is clear that 10m resolution can only provide very limited information and is too coarse for defining zones within the vineyard. Higher resolution (3m) imagery offers more details regarding spatial variability, but individual vines and mid-row crop identification are still challenging. Fine resolution (0.04m and 0.5m) imagery offers more detailed information regarding the development of individual vines and mid-row crops. It should also be noted that

0.04m resolution imagery only provided limited additional information than the 0.5m resolution imagery. For more specific monitoring purposes such as detecting canopy gaps, having the 0.04m resolution may help the accurate measurement of the gap length. Therefore, considering the effort required to acquire higher resolution imagery rasters and the large dataset needed to be analysed, it is crucial to select the most suitable and efficient imagery resolution. From the studies conducted in this study, it is recommended that a submeter resolution or higher (examples C and D in Figure 1) will generate the optimal outcomes.

Image stitching may be one of the main limitations of UAV compared to other remote sensing platforms, namely, manned-aircraft and satellite. Imagery stitching for UAV imagery to form a vineyard raster or imagery reconstruction, is a time-consuming step because the coverage of individual UAV imagery can be quite small, especially at the low flight height when trying to obtain high resolution imagery. To form a vineyard raster, it can take hundreds of images per hectare and several hours of highly intense computation to perform the stitching, as described in the first study. Examples of commercially available imagery stitching software include Pix4D (Pix4D S.A., Prilly, Switzerland) and Agisoft (Agisoft LLC, St. Petersburg, Russia). In comparison, manned aircraft can acquire imagery with much larger coverage and thus reduce the reconstruction effort and satellite imagery generally does not require reconstruction as a single imagery can cover hundreds of square kilometres in a single capture. The resolutions of these approaches are also increasing gradually with better sensors. Since timing is critical for vineyard management, this is especially important that UAV imagery can be analysed in a timely way, even if at the cost of imagery resolution.

The purposes of vineyard monitoring can be diverse, ranging from the basic calculation of planting area to estimating canopy dimensions, measuring plant water status, disease detection, etc. Depended on the actual purpose, the systems used to conduct measurement can also differ significantly. In this work, evaluating canopy manipulation outcomes and detecting unproductive canopy were studied. Results showed that these two targets require high-resolution RGB imagery to precisely measure the external dimensions of the canopy structure. The dataset generated for the UAV vineyard monitoring can also vary significantly from the RGB imagery, such as DSM in the second study and the point cloud in the third study. Understanding the information provided by different data types and choosing the most appropriate and efficient way to analyse data was the key to ensuring a successful outcome of vineyard monitoring.

6.2 Data Analysis Approaches

Different types of data are generated during the UAV flight. Datasets need to be analysed with various programs to extract the most useful and relevant information. Photogrammetry and GIS platforms are usually the essential tools for imagery stitching, spatial analysis, raster visualization, and data mapping, etc. Some other customized programs may also be required for specific steps, such as point cloud generation and analysis, multi-sources data fusion, and customized geometry calculation and analysis, depended on the complexity. It is worth mentioning that with limited commercialised tools currently available for vineyard monitoring purposes, all three studies conducted in this work involved creating customized programs in Matlab, which increased the technical complexity, impacting the use for practitioners. In the future, having customised commercial programs for vineyard monitoring would improve the adoption of UAV based vineyard remote sensing.

Depended on the purpose, the UAV flights can be conducted flexibly at a weekly or monthly basis. The data collected should be simple to reduce the complexities and time required in data analysis so that results can be generated promptly. In the first study, multispectral imagery consisting of multiple visible and invisible bands and RGB imagery were collected. Without the requirement to use a complicated classification or machine learning approach, simple unsupervised classification was shown to be effective and efficient enough to separate the established canopy from the background soil and floor vegetation.

However, it should be noted that if a large portion of the vineyard floor is covered by vegetation, either be vineyard weeds or cover crops, the accuracy of the unsupervised classification might be reduced significantly due to the highly similar spectral properties between the canopy and the floor vegetation. This is demonstrated by the unsatisfactory classification results in the first study during early developmental stages where canopy measures were not accurate. One potential mitigation to that challenge can be using geometric definition to reduce the inclusion of non-canopy-related pixels by only selecting pixels from the vine row and within the canopy width. In the future, either classification methods, unsupervised, supervised or machine learning, used in combination with the vine row's geometric definition should be explored to improve the accuracy of canopy monitoring. This can be achieved by creating vine row polygons at the canopy width as masks to extract pixels inside the polygons. As a result, the floor vegetation in the row spacing can be filtered out.

The three-dimensional (3D) models of the vineyard, including DSM and point cloud, were more sensitive to the change in canopy structure than two-dimensional RGB and spectral indices rasters due to an additional dimension of canopy height. Canopy manipulation and the detection of canopy decline by trunk diseases are the two examples where 3D models were used in this work. Compared with rasters, 3D models can also measure the canopy structure at early developmental stages by filtering out ground vegetation using height differences. This advantage is particularly useful for assessing canopy decline during early developmental stages where the symptoms are the most obvious and the canopy gaps are not covered by canopy development of healthy vines.

The steps to create 3D vineyard models are more complicated as the canopy structure needs to be extracted from the background. DSM needs to be normalized to create a digital canopy model (DCM) and ground points and points below the canopy height removed before calculating the canopy volume and area parameters. A few different approaches to achieve canopy extraction and analysis are proposed and detailed in this work and demonstrate that the canopy structure can be accurately extracted. With the extra steps required, which involves additional programming, software, and setting up various input parameters, such as canopy height threshold and the alpha value, the processing time is generally longer. A deeper understanding of the 3D canopy model is also required for the user.

6.3 Limitations and Future Improvements

The limitations of using UAV captured imagery include the complex skills required, limited system reliability under various environments, and costs associated with hardware and analysis software. Having a better understanding of these limitations and their causes can also help users to choose the most fit-for-purpose monitoring approach (Table 4).

As a useful measurement, point cloud's potential to improve vineyard management has not been fully utilized in a way that allows for easy adoption. Research conducted using point cloud generally involves complicated hardware and software systems (Andújar et al. 2019; Siebers et al. 2018). The algorithms used to process the data can also be complicated and difficult to customise (Siebers et al. 2018; Weiss & Baret 2017). If UAV operations are offered as a commercial service, complications in integrating the sensor and platform, conducting the flight operation, and data processing need to be resolved as these challenges will increase the operation and maintenance costs substantially.

Ground monitoring using either manual or canopy cover imagery analysis can generate data at megabyte level per hectare (MB/ha). In comparison, UAV-based aerial remote sensing can generate much larger datasets at gigabyte level per hectare (GB/ha), such as high-density point clouds and high-resolution rasters. However, large datasets can pose challenges for the storage, analysis, and spatial-temporal data comparisons. Future research should determine the optimal point density and GSD for point cloud and raster, respectively, to reduce data size and retain critical information, such as canopy dimensions and canopy pixels. More scientific and commercialization efforts will be required to overcome these limitations and make the UAV-based systems more reliable and economical to their end-users.

Based on the findings in this work, the canopy structure measurements using UAV systems can provide valuable information for understanding the spatial variability of the vineyard. It can also assist with vineyard management in achieving specific targets, such as evaluating canopy management outcomes and measuring the severity and location of canopy decline. Depending on the monitoring purposes, the most suitable ground and aerial-based approaches should be selected in combination with different sensor and data analysis choices.

Point cloud analysis has demonstrated a strong potential to measure canopy structure with accuracy and robustness, especially during early development stages. Future research in vineyard canopy sensing could focus more on creating more easily operated, open-sourced, and reliable systems to improve practicability, reliability, and accuracy.

Table 1. Summary of impacts of leaf removal on grapevine and wine properties, with additional notable findings from individual studies. Studies are categorized by the growing stage when manipulation was applied (modified E-L stage, Coombe, 1995).

	General findings	Application stage	Other findings
Leaf removal	• Reduced leaf layer numbers and improve canopy light environment. • Increase soluble solids accumulation in berries at harvest. • Yield reduction at around 20 to 30%. • Improve fruit and wine quality (e.g. higher total phenolics and total anthocyanins). • Reduced lateral shoot development.	Early (0-14)	• Improved control on microbial population, bud fruitfulness and reduced bunch rot risk (Gatti et al., 2015; Komm & Moyer, 2015; Lemut et al., 2015). • Lower leaf-area-to-yield ratio (Bubola et al., 2017). • The total skin anthocyanins can be further improved when applied with regulated deficit irrigation (Cook et al., 2015). • The relative developments of berry properties are affected independently from absolute berry mass (Tardaguila et al., 2010).
		Flowering-veraison (15-35)	• Reduced bunch compactness, fruitfulness and yield when applied in cold climate (Acimovic et al., 2016). • Reduction in potassium accumulation, malic to tartaric acid ratio and wine pH (Coniberti et al., 2012). • Soluble solids decreased when excessive leaves removed (Vasconcelos & Castagnoli, 2000).
		Harvest (36-38)	• Applied at around 16-17 °Brix was reported to be most effective in delaying sugar accumulation in Sangiovese berries (Palliotti et al., 2013).
		Post-harvest (39-43)	• Reduced carbohydrate and nitrogen reserve in permanent structure and reduced bud fruitfulness over several consecutive seasons (Greven et al., 2016).

Table 2. Summary of impacts of leaf removal and bunch thinning on grapevine and wine properties, with additional notable findings from individual studies. Studies are categorized by the growing stage when manipulation was applied (modified E-L stage, Coombe, 1995).

	General findings	Application stage	Other findings
Shoot/ bunch thinning	• Reduced average bunch number per vine. • Increase average shoot weight and length with higher average leaf area. • Significantly higher soluble solids, total phenolics and anthocyanins accumulation in the berry. • Elevated pH level.	Early (prior to stage 14, inclusive)	• The influence on titratable acidity accumulation depended on the cultivar (Reynolds et al., 2005). • Cluster thinning was found affecting only red cultivars (Morris et al., 2004).
		Fruitset (stage 15-34)	• Lower leaf layer numbers and better leaf and cluster exposures compared with early shoot thinning (Reynolds et al., 2005). • Improved resveratrol level in wine with in better antioxidant capacity (Prajitna et al., 2007).

Table 3. Summary of recent UAV based optical remote sensing studies conducted in vineyards.

Authors	**Target parameter(s)**	**Data type**	**Accuracy assessments**	**Sampled vineyard(s) (area)**	**Study duration**	**Remarks**	**Limitations**
Mathews and Jensen (2013)	Leaf Area Index (LAI)	RGB images	Ground LAI measurement (R^2=0.567)	One (1.9 ha)	Single flight	Potential to estimate LAI using slow from motion (SfM) point cloud and 3D modelling.	Limited data obtained from single flight.
Ballesteros et al. (2015)	LAI, green canopy cover (GCC) and canopy volume (V)	RGB images	Ground LAI analyser (0.84<R^2<0.93)	Two (2.5 ha)	Three growing seasons	Exponential polynomial and second-order polynomial models fit for estimating LAI from GCC.	The relationship between LAI, GCC and V need to be calibrated for trellis systems, irrigation systems and plant canopy types.
Kalisperakis et al. (2015)	LAI	Hyperspectral and RGB images	Ground leaf counting and reflectance measurements (R^2>0.73)	One (area not available)	Single flight	Hyperspectral and 3D canopy model achieved higher correlation than RGB orthomosaic images.	LAI subject to overestimation with sparse, weak or unhealthy canopy.
Sepúlveda-Reyes et al. (2016)	Crop water stress index (CWSI)	Thermal images	Ground thermal images (R^2=0.8)	One (area not available)	Single growing season	CWSI has stronger correlation with plant-based variable when under water stress.	Low values of R^2 were obtained in the beginning and the end of growing season.

(Table 3 continue)

Poblete-Echeverría et al. (2017)	Canopy detection	RGB images	A confusion matrix is used to test the classification accuracy of machine learning (Accuracy: 80%-100%)	One (Area not available)	Single growing season	Machine learning methods can improve the accuracy of vineyard canopy segmentation.	Limited flight number over the season (6 flights); human interventions required for calibrating the models with training data.
Weiss and Baret (2017)	Vineyard 3D macro-structure	RGB images	Ground measurements (root mean square error = 9.8, 8.7 and 7 cm for row height, width and spacing, respectively)	Twenty $100m^2$ plots (0.2 ha)	Single growing season	Sufficient images need to be taken to ensure point cloud quality.	Insufficient RGB images reduced the quality of DPC; DPC density is lower at row edges.
Albetis et al. (2017)	Grapevines canopy disease *Flavescence dorée* identification	Multispectral images	Discrimination of infected vine and severity in field (%identification: red cultivar >87%; white cultivars <80%)	Four (3.1 ha)	Single flight	Infected vines from red cultivars were more easily identified while white cultivars identification was unfavourable.	A systemic overestimation of %infection at parcel scale existed.
Romboli et al. (2017)	Normalised difference vegetation index (NDVI)	Multispectral images	Indirectly validated by juice and wine sample chemical analysis	One (0.38 ha)	Single growing season	Temperature at fruiting zone and bunch level is strongly influenced by vine vigour.	Ground measurements on grapevine vigour level should be made to compared with NDVI.

Table 4. Comparisons of capabilities and limitations of UAV and ground measurement approaches for vineyard monitoring.

	UAV	**Ground**
Major capabilities	High resolution imagery, vineyard scale measurement and canopy gap detection	Canopy architectural measurements
Image analysis	Complicated and customised	Simple and on-the-go
Geographic coordinate precision	Centimetre level inaccuracy	Meter level inaccuracy
Map resolution	High	Medium
Cost	Medium to high	Low
Weather limitations	Rain and strong winds	Rain
Other requirements	Operating license(s)*, sensor integration and calibration, etc.	-

*Dependent on the jurisdiction.

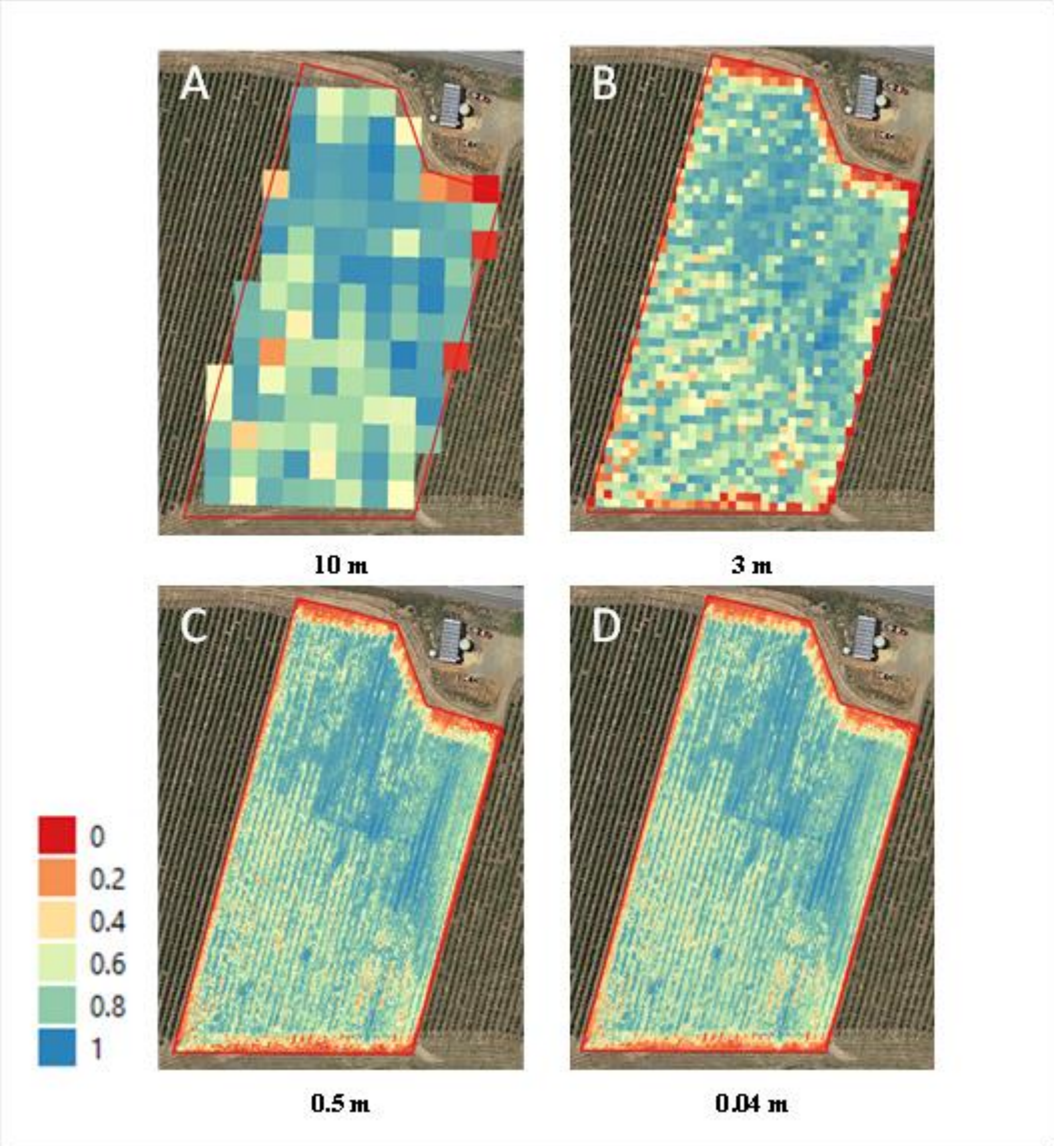

Figure 1. The NDVI rasters of the same Chardonnay block with high spatial variability, captured by UAV flights during the 2020 growing seasons in the Adelaide Hills region, Australia. Rasters with four different ground sample distances (GSD) are shown: (A) 10m (meter level), (B) 3m (meter level), (C) 0.5m (sub-meter level) and (D) 0.04m (centimetre level), representing different levels of details and information within the imagery. Rasters A-C are for indication only and representing simulated results from the recalculation of the original raster D.

Chapter 7. Literature Cited (Literature Review and General Discussion)

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