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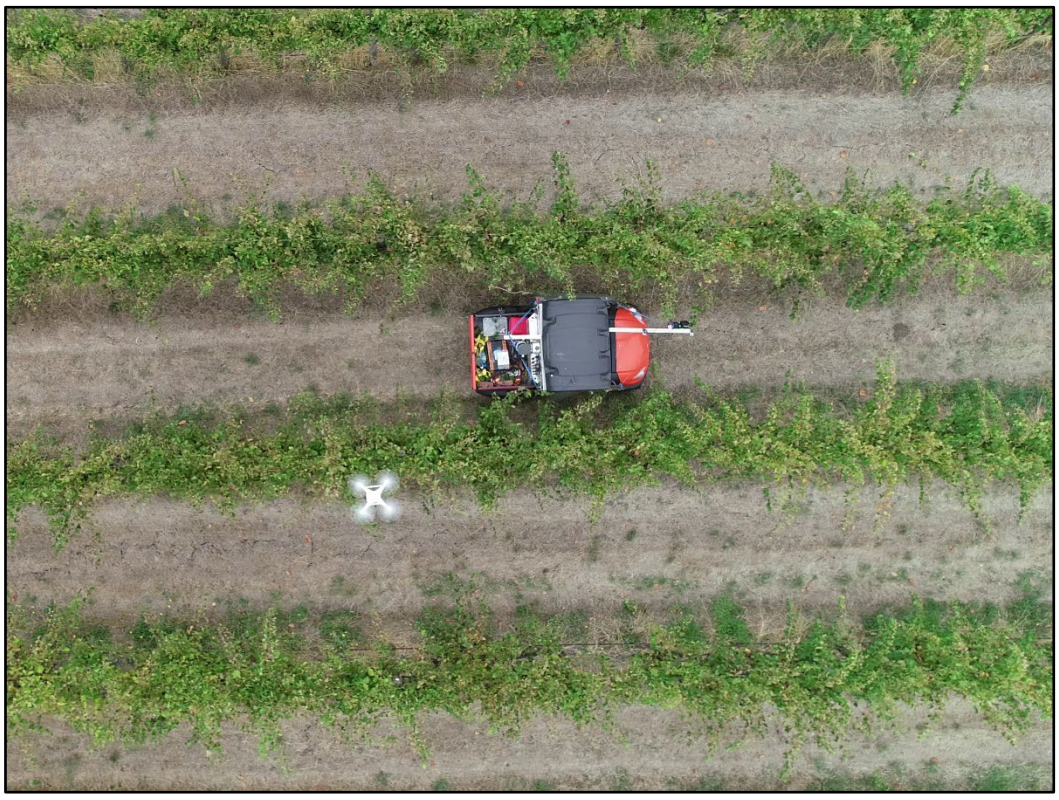
New technologies for dynamic canopy and disease management

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CSA1601

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Plain English summary

The grapevine canopy is the site of photosynthesis, the process whereby the energy the vine requires to grow, produce fruit and store to survive dormancy, is produced. Vine photosynthesis is influenced by the size and structure of the canopy, the nutritional status of the vine and other factors, such as the time of season. Further, the canopy plays a major role in determining the environment around the grape bunch, which greatly influences grape composition and, therefore, the value for winemaking. More than any other perennial crop, the commercial potential of winegrapes depends on composition, with the same variety fetching a ten-fold difference in price depending on its quality. Given these key roles of the canopy, it is not surprising that canopy management is of particular importance in viticulture. However, determining the appropriate canopy management is a decision the viticulturist has to make with very few data as there are currently only very limited tools to objectively assess a canopy size or structure.

The canopy is also the recipient of most of the agricultural sprays used in viticulture, with protection against powdery mildew the most common reason for spraying in Australian viticulture. At present a growing season spray program is typically designed with very limited knowledge of the upcoming disease pressure and is used to ensure that disease does not occur, with additional sprays added to count for specific conditions. The reason for this prophylactic approach is that by the time a disease such as powdery mildew is visible to the grower, it already has a foothold, is more difficult to control and is likely to damage the crop thereby negatively affecting the value of the fruit.

With the recent revolution in sensors and data analytics, together with a pervasive online computing infrastructure to support these, there is an opportunity to provide the grape-grower with cost effective tools to objectively assess vine structure, nutritional status, disease status and perhaps even the functional status of the vine. Furthermore, these tools can be based on whole vineyard assessments using non-destructive measurements, rather than few, small, labour intensive, destructive samples.

This project was established to test and develop technologies to provide non-contact measurements of canopy size and structure, canopy nutrition, canopy function and pre-symptomatic detection of disease. In particular, the project objectives included: assessing methods to determine the 3D structure of the canopy, data analysis methods that use this to provide growers with summary measures that aid canopy management decisions, hyperspectral imaging of the canopy to determine and map nutritional status and canopy functional status, hyperspectral tools to detect powdery mildew prior to it being visible to the human eye, and an assessment of the readiness of these technologies for commercialisation in viticulture.

LiDAR, stereo-imaging, photogrammetry (structure-from-motion) from consumer drone and photogrammetry from consumer action-cams were all used to collect 3D data on vine canopies and structure. In addition, consumer action-cams were also used to estimate canopy size from continuous video. All these devices (except the drone) were mounted on commercial vineyard vehicles and used to image commercial vineyards in collaboration with a number of wine companies (Accolade Wine, Katnook Estate, Rymill Wine). Bespoke data-processing pipelines were developed in all cases to produce grower relevant data from the sensor outputs.

Hyperspectral imaging of the same vineyards from fixed wing aircraft was undertaken by Fraunhofer IFF with Airbourne Research Australia, using a bespoke imaging system built by Fraunhofer IFF. Additionally, a lab-based hyperspectral imaging system was used to develop detailed calibrations of vine nutrition against leaf images.

The lab hyperspectral system, mounted in a glasshouse environment, was used to image grapevines with various stages of powdery mildew infection and calibrations against disease status developed. Finally, the lab-based system was used to image grapevine leaves, for which key physiological traits had been measured and preliminary calibrations produced.

The most viable sensor and data analytic packages were developed using LiDAR to determine canopy structure and consumer drone imagery with photogrammetry or consumer action-cam imagery to determine canopy size. Hyperspectral data analytics were able to reliably identify vine tissue types from spectra and then analyse those spectra for relevant traits, such as nutritional status, using calibrations developed through the project. Proof of concept calibrations against vine function and disease status were also established, although pre-symptomatic detection of disease was not clearly demonstrated.

It is recommended that each of these technology areas be assessed, with further industry input, for commercialisation potential, particularly considering the dollar value of the data to viticulturist decision making. For example, if the industry values a key canopy parameter as being cost effective at $50 per hectare, then the potential to produce that data at that cost needs to be demonstrated.

For those systems at a lower technology readiness where this assessment it not yet practical, it is recommended to continue research where there is ongoing industry support.

This project was supported by Wine Australia, through funding from the Australian Government Department of Agriculture, Water and the Environment as part of its Rural R&D for Profit program, CSIRO and the Fraunhofer Institute for Factory Operation and Automation.

Abbreviations and glossary

CCI – Chlorophyll Concentration Index

Cordon – lateral woody vine branch

DSM – digital surface map

DTM – digital terrain map

ICP-OES – Inductively coupled plasma optical emission spectroscopy

IMU – inertial measurement unit

LAI – leaf area index

LASSO - Least Absolute Shrinkage and Selection Operator

LiDAR – light detection and ranging

NDVI – Normalised difference vegetation index

NIR – near infra-red

Phenology – growth stage within a season

RF – Random Forests

RGB images – Red, Green, Blue; traditional colour digital images.

SLAM – Simultaneous localisation and mapping

SWIR – Short wave infra-red

$V_{c\,max}$ – maximum rate of carboxylation in photosynthesis

VSP – vertical shoot positioning

1 Project rationale and objectives

Minimising the cost of production and maximising the value of the fruit, whether by more consistently meeting required specifications or reaching higher specifications, will improve vineyard profitability and underpin economic sustainability. Technological developments over the last decade have greatly increased our ability to collect and collate data from vineyard enterprises. This information can be used to improve management of inputs, such as labour, water, chemicals and fertiliser, and to enhance industry capacity to achieve desired fruit composition.

New and developing technologies are providing sensors, and the software systems for monitoring and using them, that are becoming pervasive through our lives and society. From smart phones to cars to farm machinery, all contain a range of sensors that are monitored automatically with intelligent software providing us with the information we need, when we need it. This technological revolution has the potential to monitor all aspects of vineyard activity, assisting growers to make the management choices they need to achieve the outcomes they want.

A future vineyard may possess automated imaging that generates a three-dimensional model of the vine, highlighting the differences to the desired canopy structure and how to improve fruit composition through canopy management. That same imaging may provide whole of vineyard data on vine nutrition or early warning of mildew infection. Such a system could also provide a record over time and predictions of future growth and development, a 'Digital-Twin' (Moghadam et al. 2020), allowing proactive management on a rapid timescale.

Developing a digital-twin and the decision-making tools that rely on it requires a significant investment of development effort, that, critically, must be built on a solid knowledge base. The rationale of this project was to provide that base and to undertake the initial development of the hardware and algorithmic tools required.

Canopy and disease management are both major vineyard costs and this project has focussed on these aspects. Disease costs the industry $70 80 million per year for powdery mildew and $60 70 million per year for downy mildew (Scholefield Robinson Horticultural Services GWR 08/04). Ineffective canopy management can lead to greater disease in adverse seasons (e.g. high rainfall), but more importantly represents a lost opportunity to improve fruit composition. For example, the Wine Australia funded project CSP1202, suggested that choosing a different canopy structure can lead to improved compositional parameters and a more preferred wine (Edwards et al 2017).

The project objectives remained largely unchanged for the duration of the project and were:

- Test and compare two methods, LiDAR and stereo imaging, for three-dimensional measurement of vine canopy parameters, e.g. area, volume, density and porosity, and winter wood, e.g. cane mass, including additional hardware and data analysis pipelines as required.
- Utilise 3 D canopy measurements to contrast paired vineyards (same trellis type, same region) where the fruit is used for high value wine and commodity wines, to determine common differences in canopy and/or cane structure.

- Develop and test hyperspectral imaging of grapevine canopies using aerial and proximal methods. Utilise traditional (PLS/library approach) and novel (machine learning) techniques to process the data and match to point based measures of leaf composition (e.g. N, P, cations, chloride, major metabolites) and canopy density.
- Determine the potential for early detection of disease (powdery and/or downy mildew) by hyperspectral imaging, by in field imaging of diseased vines and lab-based determination of the limits of early disease detection.
- Assess the potential for 3 D canopy imaging to be developed into a commercially available system.
- Assess the potential for the hyperspectral calibrations/classifications developed to be commercialised into hardware and/or software systems for grower use.
- Prototype the integration of 3 D canopy imaging and hyperspectral indices to allow detailed information on canopy composition as a research tool.

It became clear after initial testing that whilst stereo imaging could provide 2.5 dimensional data (colour images plus depth), the limitations in this technique were likely to be overcome by using photogrammetry (structure-from-motion), which allowed 3D data to be generated from colour digital images. Consequently, photogrammetry was adopted as an additional technology and largely replaced stereo-imaging in the project.

2 Method and project locations

The major objectives of the practical work were i) to develop three-dimensional canopy imaging and associated data analysis pipelines that would provide novel indices of canopy structure, ii) develop hyperspectral calibrations against vine nutrient content; iii) assess the potential for hyperspectral imaging to be used in pre-symptomatic detection of disease; and iv) assess the potential for hyperspectral imaging to be used to estimate leaf physiological parameters. These objectives utilised a combination of cost-effective consumer products, off-the-shelf scientific grade equipment and new hardware developed by CSIRO as well as a collaboration with Fraunhofer in Germany and Airborne Research Australia in Adelaide.

2.1 Methods

The key technologies used during the project were LiDAR, RGB digital imaging and hyperspectral imaging. Laser range finding has been in use for over 50 years. The development of this for 3D imaging (LIDAR) is more recent, but has become increasingly widely used since the 1990's, from industrial monitoring systems to estimation of wood volume in forestry systems (e.g. Popescu et al. 2003). The development of the CSIRO GRover research platform was also based on the use of LiDAR to create 3-D images of vine growth (Siebers et al., 2018). A stumbling block with using LIDAR is feature recognition within the resulting point cloud. Even relatively simple statistical approaches have previously proven useful, such as for adjusting variable spray application in vineyards according to canopy density (Llorens et al. 2011), but more sophisticated approaches were developed for this project.

Hyperspectral imaging refers to the collection of a spectrum (many wavebands) for each pixel of an image. Hyperspectral sensors have been incorporated into satellites and used in aerial imaging for over 20 years. In agriculture, such systems have been investigated for disease detection, e.g. in sugarcane (Apan et al. 2004), crop growth parameters (Patel et al. 2001, Backhaus et al. 2011) and even identification of grapevine cultivars (Lacar et al. 2001). More recently, improvements in the sensitivity of sensor systems have led to use across widespread areas of research and industry alike (Mazzetto et al. 2010).

Together with the RGB digital imaging, familiar to all, these technologies were used as follows.

2.1.1 Canopy structure

Canopy management is an important tool in viticulture as it affects vine carbon acquisition and fruit quality. Due to its three-dimensional nature there are few existing tools or methods to assess canopy structure and these are impractical for grower use. The project has used and developed a variety of hardware to make 3D measurements of vineyard canopies, including static LiDAR, hand-held LiDAR, trawling LiDAR mounted on the GRover vine phenotyping platform, vehicle mounted spinning LiDAR, vehicle mounted consumer action video cameras and consumer UAV video imaging.

LiDAR: A LiDAR consists of a laser source and detector, which records the time taken for the laser pulse to be received if it is reflected by an object. The time provides the distance to the object. Typically, pulses are emitted through an arc (linescan), with the angle of each also recorded. From the time and the angle, a 3D position relative to the device can be inferred for

each returned pulse. A large number of returns is then used to build up a 3D representation of the surroundings of the LiDAR device.

A total of seven different LiDAR devices were tested during the project. Initial testing included a group of four devices at four times during a single growing season:

- Zebedee (a handheld mapping device developed by CSIRO Data 61),
- Dual Wavelength Echidna LIDAR (DWEL, a static, high resolution device developed for AusCover/CSIRO Land & Water by Boston University),
- Compact Biomass LIDAR (CBL, also developed for AusCover by UMass Boston)
- Sick LMS400, mounted on the GRover vehicle (developed for the Winegrape and Horticulture group through the Wine Australia co-funded 'Fast Phenomics' project).

While capturing data, Zebedee and GRover were mobile systems, whereas CBL and DWEL were stationary (Figure 1), but all four systems were used to monitor the same vineyard area in Langhorne Creek, where canopy and crop load were being adjusted using various methods as part of separate project. In each case a point cloud (large set of x,y,z points in 3D space) was generated from the LiDAR returns. The Zebedee and GRover had different approaches to reconstructing the point clouds, with Zebedee using SLAM to generate a trajectory and create a point cloud, whereas the trawling LiDAR on GRover assumed a straight-line direction of travel with a wheel encoder to adjust for changes in speed. GRover also had an IMU on board to allow data to be adjusted for movement in other dimensions.



Figure 1 – initial testing of LiDAR sensors at a commercial vineyard in Langhorne Creek, SA: Zebedee (top left), CBL (top right), DWEL (bottom right) and Sick LMS400 on GRover (bottom left).

The approach taken to utilise the point clouds to infer information about the scanned vines was to visualise them using the CloudCompare software package (cloudcompare.org) and to partition the 3D space into known volumes occupied by returns using an 'octree' algorithm. This splits 3D space into eight equal cubes by bisecting the space in each dimension, if returns were present the cube was retained, then a second iteration split each remaining cube into eight more cubes in the same way. This was continued in an iterative manner until comparison with ground truth data (e.g. canopy area) did not result in an improved correlation coefficient. Typically, this was around ten iterations (CSP1307 Final Report).

Subsequently, three further devices, designed and built by CSIRO Data 61, were tested. These all utilised some of the technology used with the Zebedee device and SLAM (Figure 2), but were vehicle mounted and utilised a spinning LiDAR unit, rather than manual movement required for Zebedee. These were iterations of the AgScan3D+ system, again developed by CSIRO Data 61. The first version was based on a Hokuyu UTM-30LX sensor, the second on an ASI Forecast LiDAR, whereas the third was based on a Velodyne Puck LiDAR.



Figure 2 - Hokuyo based LiDAR system mounted on the GRover vehicle (left) and ASI based system mounted on a tractor (right) being tested in Mclaren Vale.

The Hokuyu based sensor was tested at the Accolade site in Mclaren Vale at the end of the 16/17 growing season, whereas the ASI Forecast based system was used for the majority of the work reported here (2016/17 – 2019/20 growing seasons), primarily mounted on a Kubota RTV 500 farm vehicle. The final, Velodyne based, iteration was tested together with the ASI based iteration at the Accolade vineyards towards the end of the project (February 2020).

The spinning LiDAR systems could not be mounted on a vehicle without parts of the vehicle being within the view of the system. These areas of view had to be filtered from the resulting data and varied depending on mount point. For practical reasons the ASI based instrument had

to be mounted behind the cab of the Kubota, meaning that grapevine canes that were moved by the vehicle also had to be filtered from the view. The instrument was additionally tested forward facing on a tractor kindly provided by Accolade.

A different approach was taken with the AgScan3D+ data than with the earlier LiDAR tests. Although a point cloud could be built in the same way, the 'ray-cloud' was used instead, thus the result of every laser pulse was used, rather than just the returned pulses, with aboveground non-returned pulses assumed to have reached beyond the range of the sensor. The 3D space was again split into cubes (voxels), but this time of a fixed volume (0.12 x 0.12 x 0.12 m) and as the angle of each laser pulse that entered that volume was known, as well as whether it was returned or not, a mathematical model of leaf area could be built. The leaf area per volume data was then able to be utilised in a variety of ways (see Section 3.1.1).

Consumer action-cams: In contrast to the bespoke instrument development required for LIDAR use, our second approach was to use commercially available 'action cams' to record video and then a range of computational analyses to infer canopy information from the videos. Standard Go-Pro cameras (various models, Hero5 – Hero 7; JB Hi-Fi, VIC, Australia) were mounted either looking almost directly up through the canopy (Figure 3 left) or at various angles facing the canopy (Figure 3 right). Imaging was undertaken at all sites and at various times during the 2017/18 to 2019/20 growing seasons.



Figure 3 - consumer action-cams mounted on farm vehicle. Upward facing view for gap fraction estimation (left), arc of six cameras for full canopy photogrammetry and side-view (right).

The upward facing camera was used to estimate leaf area index (LAI), using a similar approach to the VitiCanopy smartphone app (De Bei et al. 2016, Macfarlane et al. 2007). The pipeline segments each frame in the video to retain the feature of interest (canopy) and discard areas of camera distortion, trunks, posts, etc. and then uses a gap fraction analysis to estimate LAI. Figure

4 provides a schematic of this pipeline and serves as an example more broadly for data processing pipelines developed as part of this project.

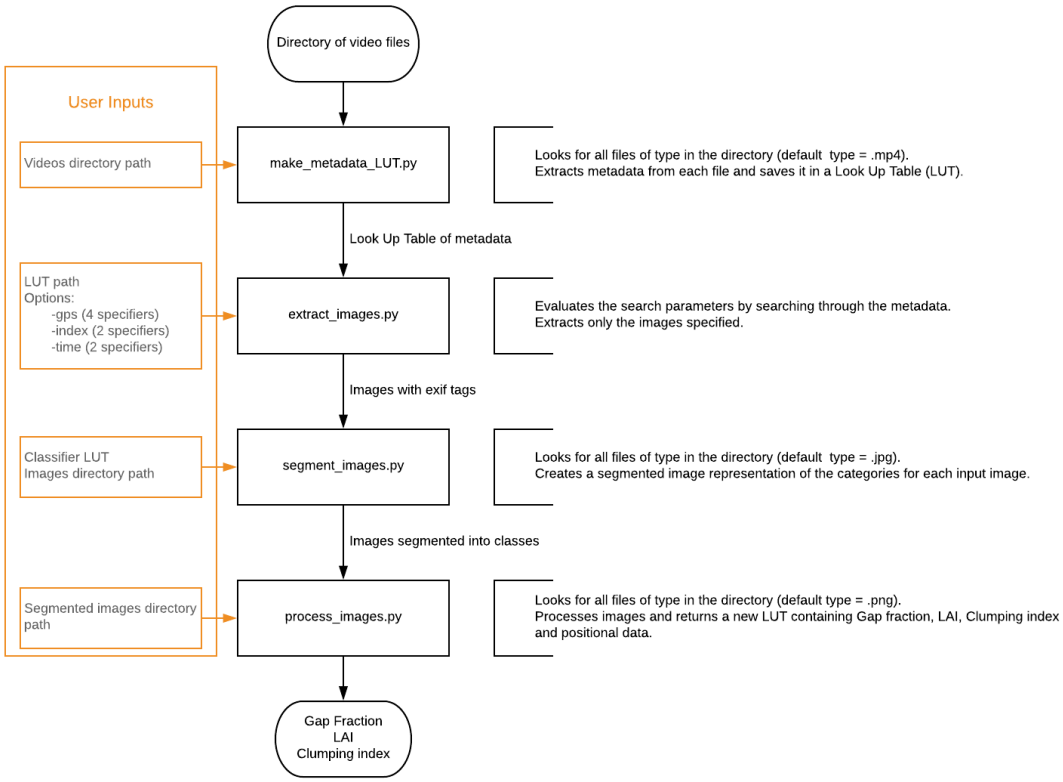


Figure 4 – schematic of data processing pipeline for LAI estimation from gap fraction.

Videos taken from other angles were primarily used in the sister project CSA1602 for imaging fruit, but were also trialled with photogrammetry to generate a point-cloud. This was similar to those created with LiDAR, but with the addition of colour information for each point and unable to penetrate into the canopy. Photogrammetry is a computationally intensive process which takes many images taken at slightly different angles (e.g. video frames from a moving vehicle) to generate a 3D position, relative to the trajectory of the camera, for features in those images. The video derived point clouds do not allow a ray cloud approach, but do allow voxelisation and other techniques to infer information about the canopy.

Consumer UAV: The third method used to look at vine canopy size and structure was with a drone. Typically, the pixel size of satellite imagery is too large to accurately separate vine canopy from mid-row and is also dependant on clear skies, but drones provide a much higher resolution image. We used a consumer drone (Phantom 4+, DJI, Shenzhen, China) with its in-built video camera (see front cover) at various times during the 2017/18 to 2019/20 growing seasons.

Drone video data is commonly used to create an orthomosiac image of the site of interest, but as with the Go-Pro videos, the drone videos can be used with photogrammetry and this offers the potential to use height information to assist with segmenting canopy from midrow, particularly

important where both are green. Photogrammetry was used with bespoke analysis pipeline to generate maps of canopy cover (see Section 3.1.1).

2.1.2 Vine nutrient content

Analysis of leaf spectral reflectance was considered the only realistic non-destructive, non-contact method to determine key elements of leaf composition. Specifically, hyperspectral imaging in the near infra-red (NIR) was used with various statistical and machine learning tools to build calibrations against key nutritional elements. Utilising imaging also allowed careful selection of 'pixels' to ensure only vines or vine leaves were included in any data analysis pipeline.

Two approaches were used. Firstly, a lab-based system was purchased to build calibrations of leaves collected from the field and greenhouse under controlled lighting conditions. This consisted of a Headwall Micro eVNIR line-scan camera with a Headwall halogen light source (Portable Analytical Solutions, NSW, Australia) and Zaber linear stage (Edmund Optics, Singapore) to move the sample past the camera. The specifications of the camera also allowed it to be trialled in the field.

This system was used to collect hyperspectral images, with 100 wavebands over a spectral range of 550-1650 nm, of a variety of tissue samples and a large number of individual grapevine leaves collected from local sites. The images were corrected using white and dark references spectra, segmented to separate the leaves from the background by using the 'red-edge' of chlorophyll, i.e. the ratio of the 650 and 900 nm bands and then normalised to account for small differences in illumination due to the leaf surface not being completely flat. A range of statistical and machine learning methods were tested and used to generate calibrations against leaf compositional data. These included: Chlorophyll Concentration Index, obtained using an Apogee MC100 Chlorophyll Meter (ICT Instruments, NSW, Australia); wet lab determined chlorophyll content according to Parry et al (2014); nitrogen content, determined using mass spectrometry; and content of various cations, determined using ICP-OES.

The second approach was to use aerial imaging from fixed-winged aircraft through the collaboration with Fraunhofer IFF (Figure 5). Hyperspectral data acquisition was undertaken in February 2018 and February/early March 2019. The flight missions were conducted by engineers from Fraunhofer IFF (Germany) and Airborne Research Australia (Flinders University). The measurement setup consisted of Norsk Elektro Optikk VNIR 1600 and SWIR 320m-e hyperspectral cameras, a Novatel IMU (SPAN CPT), and a data acquisition unit all mounted in a wingpod of an ECO Dimona airplane. The two cameras jointly covered the wavelength range between 400 nm and 2,500 nm with 416 spectral bands.

The sensor systems were operated at an altitude of 850 m above ground. This altitude results in a ground sampling distance of 16 cm per pixel for the VNIR 1600 data and 65 cm for the SWIR 320m-e data. In postprocessing the imaging data was resampled to a resolution of 0.4 m per pixel for both, VNIR and SWIR hyperspectral cameras.

The hyperspectral measurements were accompanied by ground-based samples, which provided reference data for statistical modelling. For the 2018 flight, CCI, N and ICP data were determined for the samples from Accolade, Mclaren Vale. For the 2019 flight, CCI data were not collected, but ICP-OES and N data were collected for all three sites.



Figure 5 - Hyperspectral remote sensing with data acquisition from an ECO Dimona airplane. Mounting equipment in a wingpod (left), ECO Dimona passing the Accolade vineyard (center), inflight sensor operator station (right).

Two sampling methodologies were examined, high sampling density with small samples (2018) and low-density with large samples (2019). The high-density sampling took a two-leaf sample per vine panel (approx. 150 per vineyard block), whereas the low-density sampling took approximately 50 twenty-leaf samples per block. The choice of sampling position in the vineyard for the low-density sampling was based on flight data from 2018 (see Section 3.1.3).

The compositional data were used as reference data for the generation of prediction models as well as for validation of the obtained models.

2.1.3 Early disease detection

Again, the only realistic method to detect pre-symptomatic disease on leaves using an on-the-go non-contact method was with hyperspectral imaging. Powdery mildew was targeted as the most prevalent fungal disease affecting vine canopies in Australian viticulture. To build a library of spectra from pre-symptomatic leaves required inoculating leaves with fungal spores and then regularly scanning them to find leaves and/or areas of leaf which succumbed to the disease.

Initially, this was done using individual leaves isolated in Petri dishes with wet tissue behind them to ensure humidity remained at or close to 100% (Figure 6 left). Later a double Petri dish system with the petiole of the leaf cut under water in the lower dish was used (Figure 6 right), to ensure an even background was present behind the leaf in the NIR scan and maximise the life of the cut leaf. The leaves were scanned *in-situ*, with the dish lids removed, on a daily basis using the lab based hyperspectral camera system described above.

The single leaf assay was subsequently replaced with whole vines in a glasshouse environment. This was due to the concern that data analysis may be unable to differentiate the accelerated senescence of the infected leaf from senescence of a non-infected leaf and thus that results would only be applicable where a known inoculation had occurred. Two groups of vines were prepared in the same glasshouse compartment and kept separate. One group was sprayed on the surface of individual leaves, which were tagged, whereas the second group was sprayed only with water.

To scan the vines the Headwall hyperspectral camera was built into a larger field instrument with halogen lighting and mounted on a 2 m linear stage (Figure 7). The vines were then each scanned from three angles, 90° apart. As with the leaf composition work, a variety of statistical

and machine learning approaches were assessed for their ability to indicate the sites of infection. The results of this work will be analysed and continued as part of Wine Australia project CSA1701-3.1.

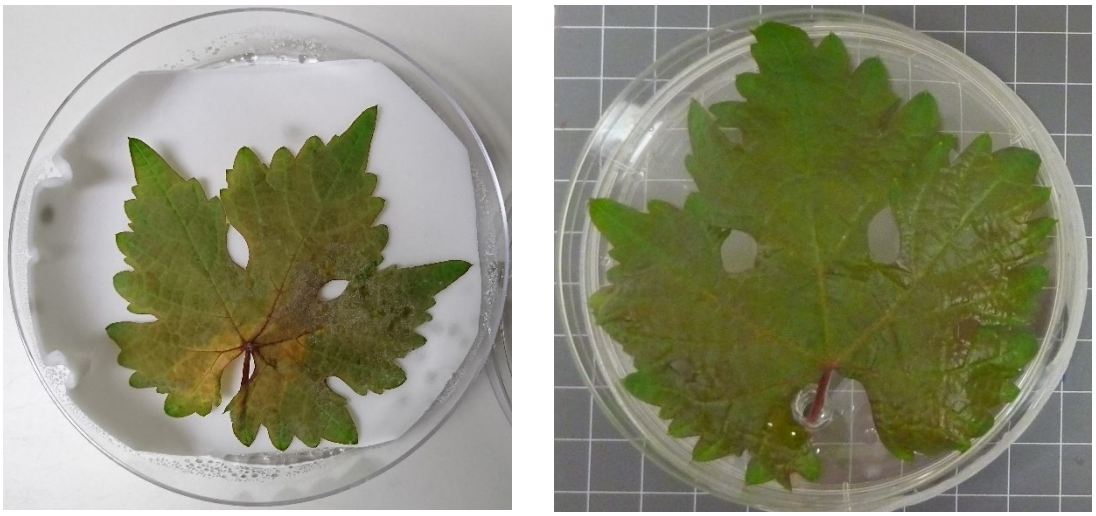


Figure 6 - isolated leaves infected with powdery mildew. Maintained on damp filter paper (left) or in a double Pteri dish with water (right).



Figure 7 - hyperspectral instrument set up in glasshouse with halogen lighting off (left) and on (right).

2.1.4 Measuring vine physiology

The potential to use hyperspectral data for estimating canopy physiology was tested by undertaking gas exchange measurements on a range of vines, field, glasshouse and shadehouse grown, encompassing a range of varieties, using a LiCOR 6400XT Portable Photosynthesis Analyser (LiCOR, Nebraska, USA), followed by imaging with the Headwall Micro camera. Thirty-eight individual plants were identified, and a CO_2 response curve measured under saturating light and the area illuminated within the LiCOR 6400 chamber marked. Following this the leaf was removed from the vine, with petiole intact, placed on ice in a flattened plastic ziplock bag and scanned within a few minutes of leaf removal using the hyperspectral imaging system described above.

The area used for the gas exchange measurement was manually selected from the hyperspectral data and the individual spectra corrected using dark and white reference data before being scaled as previously. The median spectrum per leaf measurement area was then used for the calibration. A LASSO model using the full data set (leaves and wavebands) was calculated and used to determine a small number of key wavebands for each recorded gas exchange parameter. These were then used to retrain the model and the model fit determined.

In addition, the leaves were dried, ground and analysed for N and cation content to be incorporated into the lab-based leaf composition calibration described above. This will be completed subsequent to this report.

2.2 Locations

Development of sensor equipment, laboratory and desktop analysis work was carried out at a number of CSIRO locations:

- CSIRO Pullenvale, QLD - LiDAR hardware and novel canopy indices development.
- CSIRO Waite Campus, SA – consumer action cam system development, lab based hyperspectral and matching wet lab leaf analysis, testing of disease detection, development of consumer UAV video data analysis.
- CSIRO Marsfield, NSW – stereo camera development and data analysis, hyperspectral data analysis.

In addition, Fraunhofer undertook their own hyperspectral sensor development and data analysis at their Magdeburg site in Germany and sensor testing and application was undertaken with Airborne Research Australia at Parafield Airport, SA.

Testing of equipment, methods and tools was undertaken across a range of vineyards, intended to be representative of the majority of Australian viticulture. At the Accolade, Rymill and Katnook sites, multiple contrasting blocks were utilised.

Commercial vineyards:

- Adelaide Hills – SA
    - Woodside – private vineyard
- Langhorne Creek – SA
    - Cleggett's – private vineyard
- Mclaren Vale – SA
    - Accolade
    - Madgett's Block
- Coonawarra – SA
    - Rymill Wine
    - Katnook Estate

Research stations/farms:

- Adelaide – SA
    - University of Adelaide Waite Campus
- Murray Valley – VIC
    - CSIRO Irymple/Koorlong experimental farm

The major structural differences between vineyards across Australia are trellis type, vine and row spacing, pruning strategy and vine vigour. The technologies developed and assessed were all intended to provide information on the vine canopy and thus were intended to be agnostic towards vineyard differences, indeed it is exactly some of those differences that the technologies assessed. The majority of Australian vineyards are spur-pruned with a single or double bilateral cordon and then trained with some degree of vertical shoot positioning (VSP) or allowed to 'sprawl'. All of the sites used, bar a small section of the Woodside site, were spur-pruned vines and thus the research undertaken is most likely to be representative of this section of the industry. However, although testing in cane-pruned, bush vines or more esoteric, non-vertical, trellis systems was not undertaken, it is expected that all of the technologies included in this report would be applicable to these vineyards also.

3 Project Outcomes

3.1 Project level achievements

This project has encompassed a significant amount of work by a large, geographically dispersed, team across a broad range of technologies and industry targets for digital viticulture. The reporting of project achievements below is necessarily a brief summary of that work and the learning associated with it. The project has achieved its objectives of developing and testing technologies for 3D imaging of vineyard canopy structure, of developing and testing hyperspectral imaging methods for assessing vine nutrient status, and of testing hyperspectral methods for pre-symptomatic disease detection. The project utilised three sets of paired vineyards with different fruit qualities (as assessed by the wine style targeted by the grower) in order to assess the potential for altering canopy management to improve fruit value, although that potential outcome is not directly addressed in this report. With the exception of pre-symptomatic disease detection, the work presented here has demonstrated the viability of each of the approaches tested and we suggest that this is followed up by further assessment of the potential of these technologies for commercialisation in partnership with the wine industry.

3.1.1 Technologies to assess and contrast canopy structure

LiDAR: the initial LiDAR work built on the Wine Australia funded project CSA1307, which developed the GRover vehicle for grapevine phenotyping, including a trawling LiDAR instrument that was used to estimate canopy size. The GRover instrument was intended to produce high-resolution information on a relatively small number of vines, whereas the current project aimed to produce maps of canopy size and structure on a whole block scale. CSIRO Data61 possessed significant experience using LiDAR with Simultaneous Localisation and Mapping (SLAM) algorithms, including the commercialisation of the Zebedee and Hovermap products. SLAM self-assembles 3D data at scale and seemed an ideal technology for working with whole block LiDAR data.

A handheld Zebedee device was tested in a commercial vineyard at four phenological timepoints during the 2016/17 growing season together with the GRover vehicle and two static LiDAR devices, the relatively low cost CBL and the, unique in Australia, DWEL. All these devices exhibited some limitations. The Zebedee SLAM implementation didn't cope with the long grapevine rows without errors (see doubling in Figure 8), the data pipeline for GRover only scans a single side of a row and the LiDAR used suffers from noise in bright sunlight, the CBL was low resolution and static, the DWEL was also static and being bespoke has a very high cost. The DWEL instrument did demonstrate the potential value of a dual wavelength LiDAR, should they become cost effective, with ratios of the intensity of return from the two lasers able to differentiate fruit and canopy (Figure 9). As might be expected, the GRover system was the most successful of the three in terms of detecting vine structure at scale (Figure 10), but still somewhat impractical for largescale measurements.

Late in the 2016/17 season a new device was tested. Whilst based on the sensor (Hokuyu) and principal of the Zebedee, it utilised a spinning LiDAR, rather than being moved by hand, and could be mounted on any vehicle. In fact, it was mounted on GRover and run together with the trawling LiDAR already installed. Together with the SLAM implementation, the device was successfully able to assemble a point cloud for an entire row (both sides), by driving around it

completely (Figure 11). However, this device was still not practical for full vineyard scans due to a limited field of view, meaning that the SLAM reconstruction often failed due to a lack of data at the end of a row. Furthermore, the point density was lower than most other devices utilised to date.

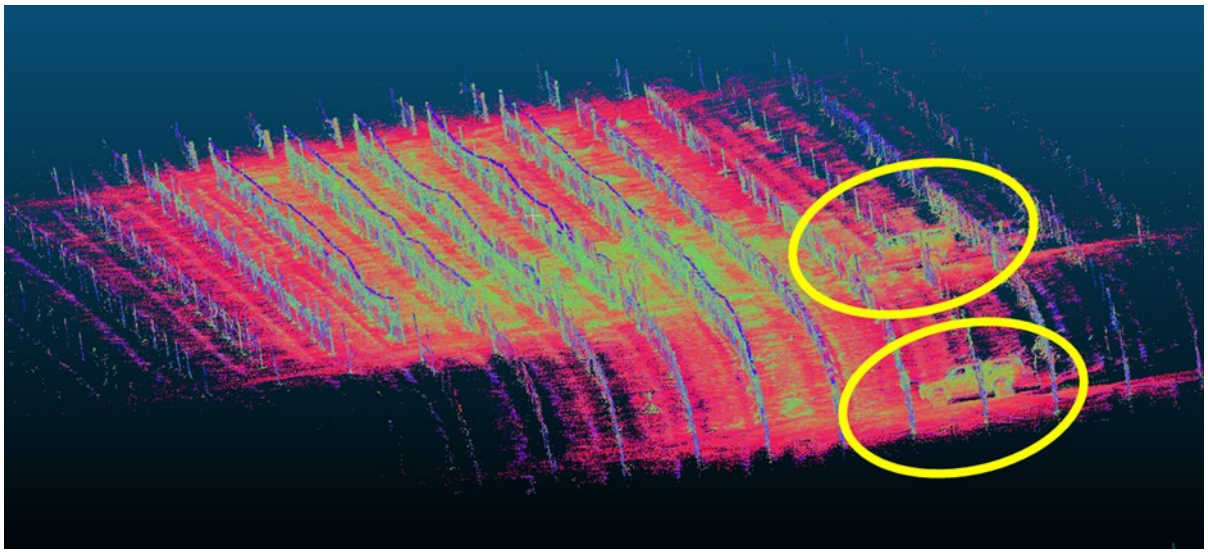


Figure 8 - Zebedee scan of the SARDI research site in Nuriootpa, SA. Replicated parts of the point cloud are highlighted. Although the vehicle was not moved during the measurements the vehicle appears to be present in two separate parts of the point cloud.

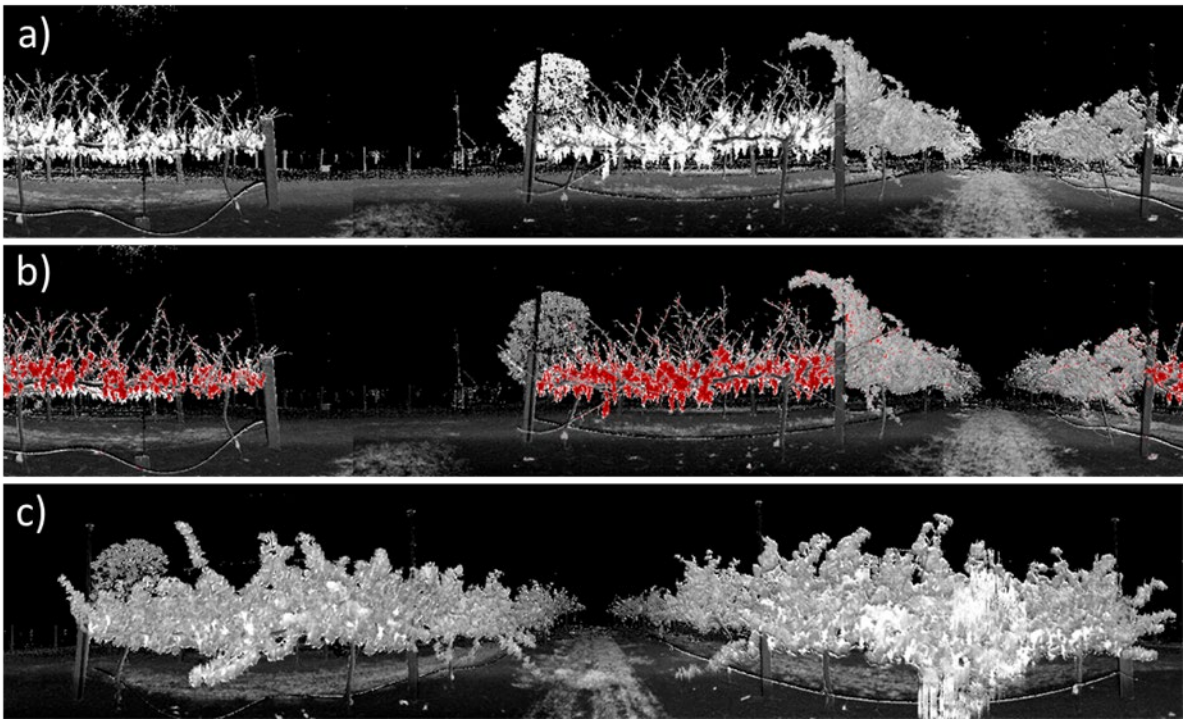


Figure 9 - Greyscale renders of DWEL data, a) vines with leaves stripped away to expose fruits, b) highlighted using a ratio of the two DWEL wavelengths, and c) vines with leaves in place.

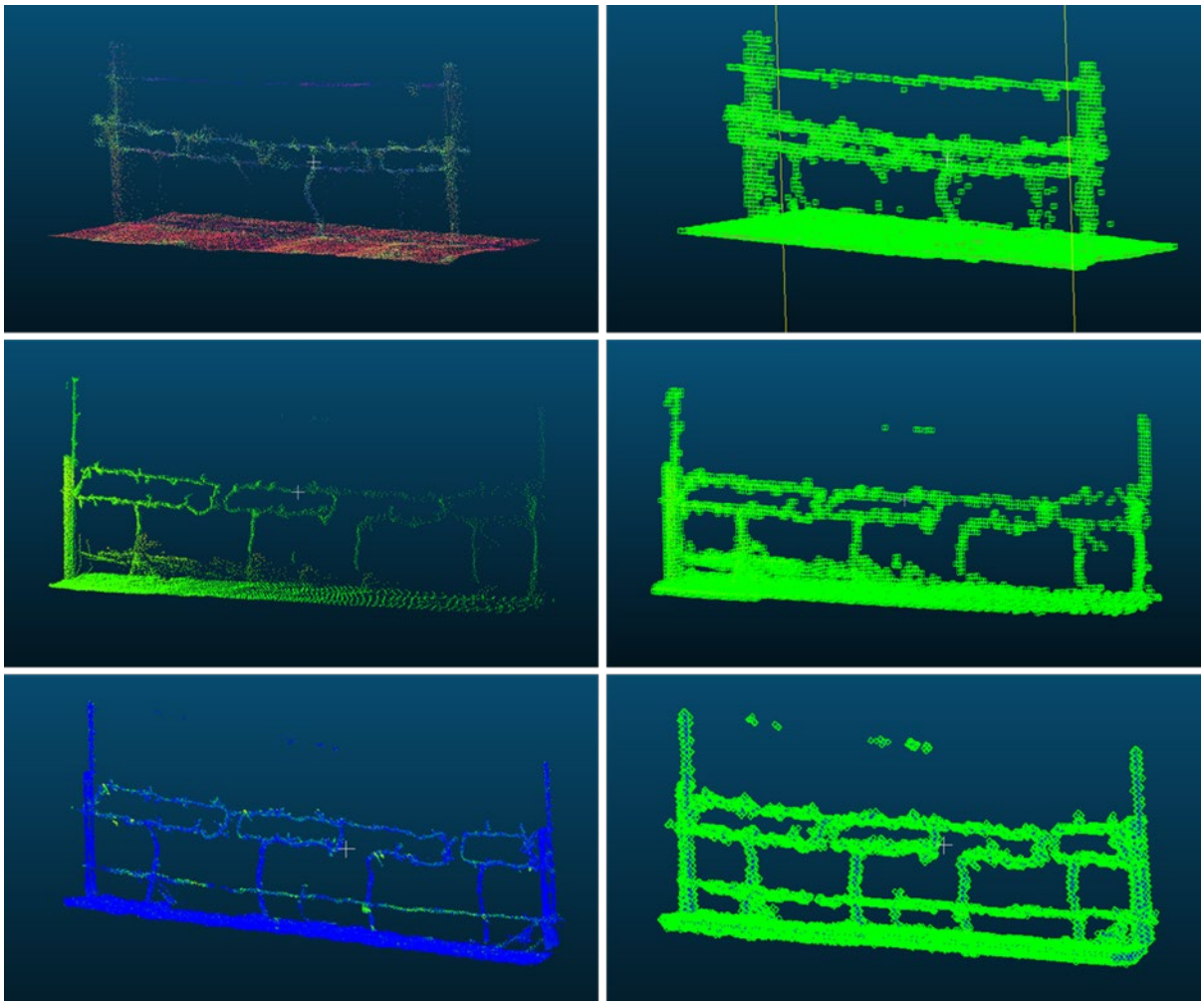


Figure 10 - voxelisation of LIDAR scans for data analysis, left column is original point cloud, right column is octree output, for Zebedee (top pair), CBL (middle pair) and GRover (bottom pair).

A second spinning LiDAR device, the AgScan3D+, was used for the remainder of the project. The AgScan3D+ was vehicle mounted and easily able to scan a small vineyard block in around 30 minutes (Figure 12). As with the Zebedee device the SLAM algorithm often resulted in non-straight rows and other artefacts. To prevent this the AgScan3D+ included a low-cost USB GPS receiver, with a small portion of the GPS signal used to constrain the SLAM. This allowed datasets at the vineyard block scale to be consistently processed.

The GRover LiDAR was used to generate a point cloud, which was then 'voxelised' to estimate an object volume, which could be used directly or equated to another parameter, such as leaf area. The same approach could be used with the AgScan3D+, and was tested together with GRover (data not shown), but together with the lack of extraneous noise in the data (due to using an IR rather than red laser) the method used to collect the LiDAR data allowed more sophisticated analysis tools to be developed. In particular, an approach based on a 'ray-cloud' rather than point-cloud was used. This meant that the path of every laser pulse with a return was known and thus it could be determined whether a laser pulse had passed through any particular volume of space. In addition, it could be assumed that non-returned pulses had reached the end of the range (30 m) and, therefore, also passed through that path unimpeded. Finally, a key difference

between the spinning and trawling LiDAR devices is that, as it moves through the vineyard, the latter results in laser pulses into and through the canopy at almost any angle. The result of this is far more data from the inside of the canopy and thus it is better able to be used to determine canopy structure rather than just volume.

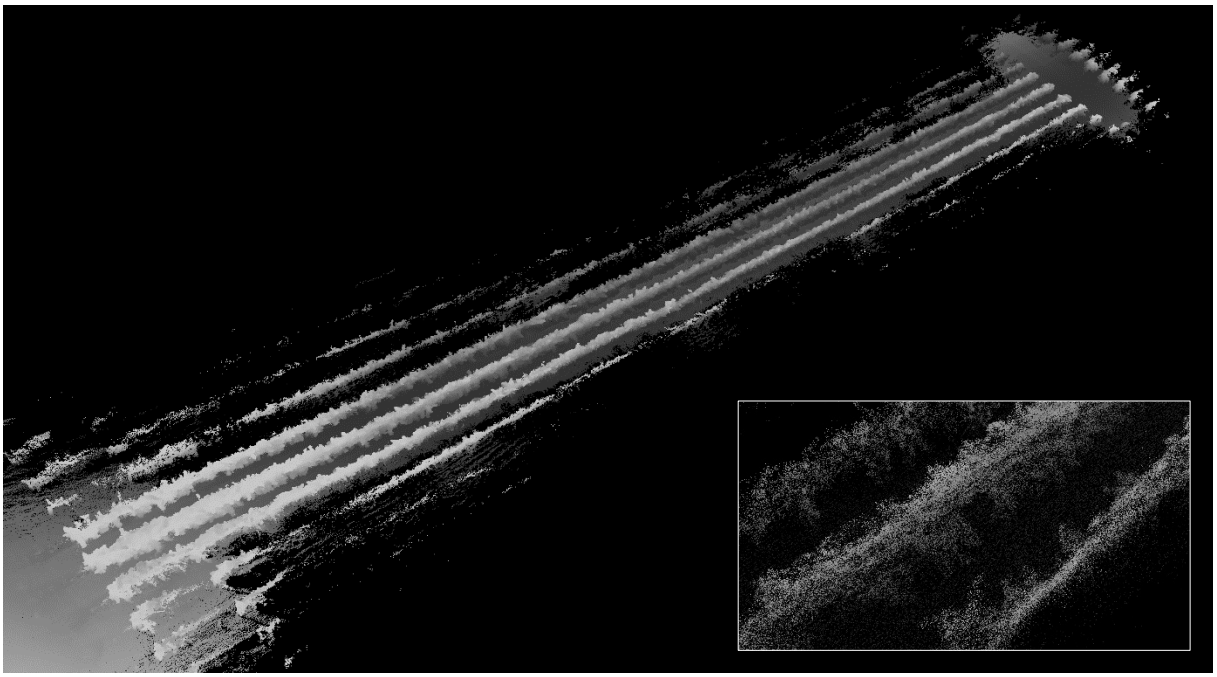


Figure 11 – Render of single row scan using the Hokuyu based spinning LiDAR mounted on GRover. Close-up of points inset.

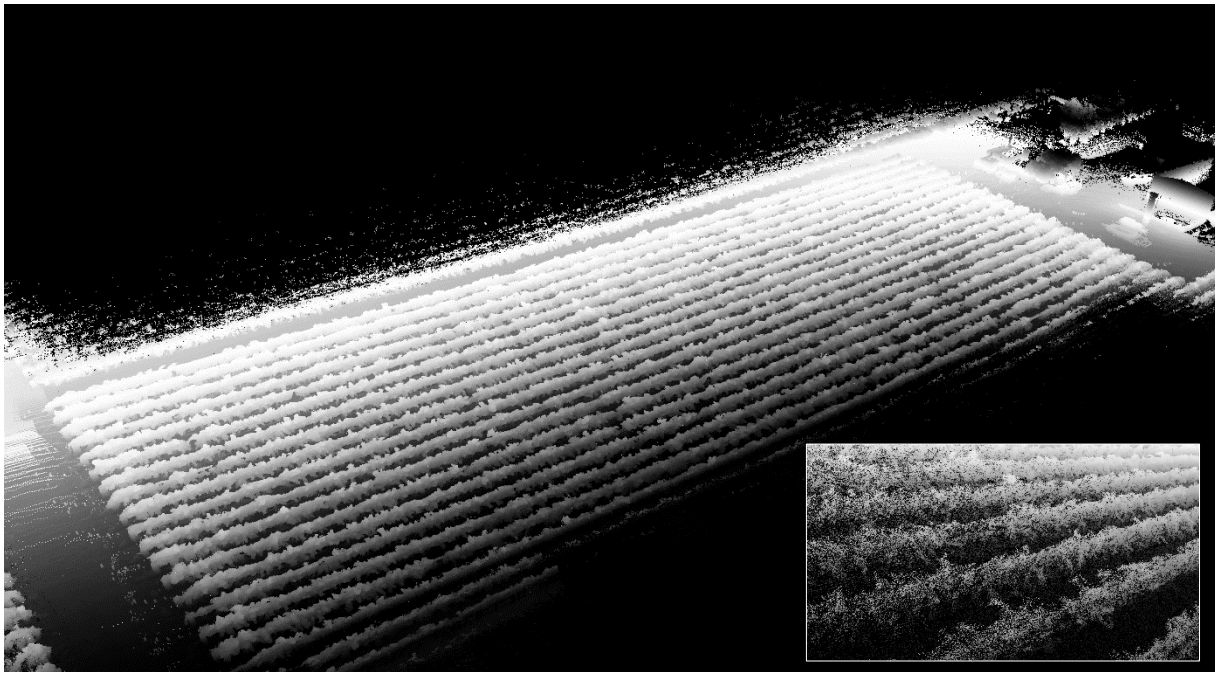


Figure 12 – render of whole block scan using the AgScan3D+ spinning LiDAR device. Close-up of points inset.

Then light absorbing area of the canopy is the major determinant of vine production and water use for a given environment and thus it was decided that single-sided leaf area per volume of 3D space would be the most flexible parameter to determine from the AgScan3D+ data, as it could be used for canopy density and area (or LAI) determinations. A mathematically determined relationship was developed between leaf area in 3D space and proportion of laser returns to rays passed through and tested with simulated data (refereed publication in preparation). The end result of this was a 3D dataset, with an estimate of leaf area per volume of 3D space ($m^2\ m^{-3}$). Using the field collected AgScan3D+ data the optimal volume of space, balancing robustness of determination and resolution of result, was a cube with 12 cm sides (1,728 cm^3, 0.0017 m^3). The data could be represented by a point-cloud with one point per 12 cm cube and the point value being the leaf area density (Figure 13).

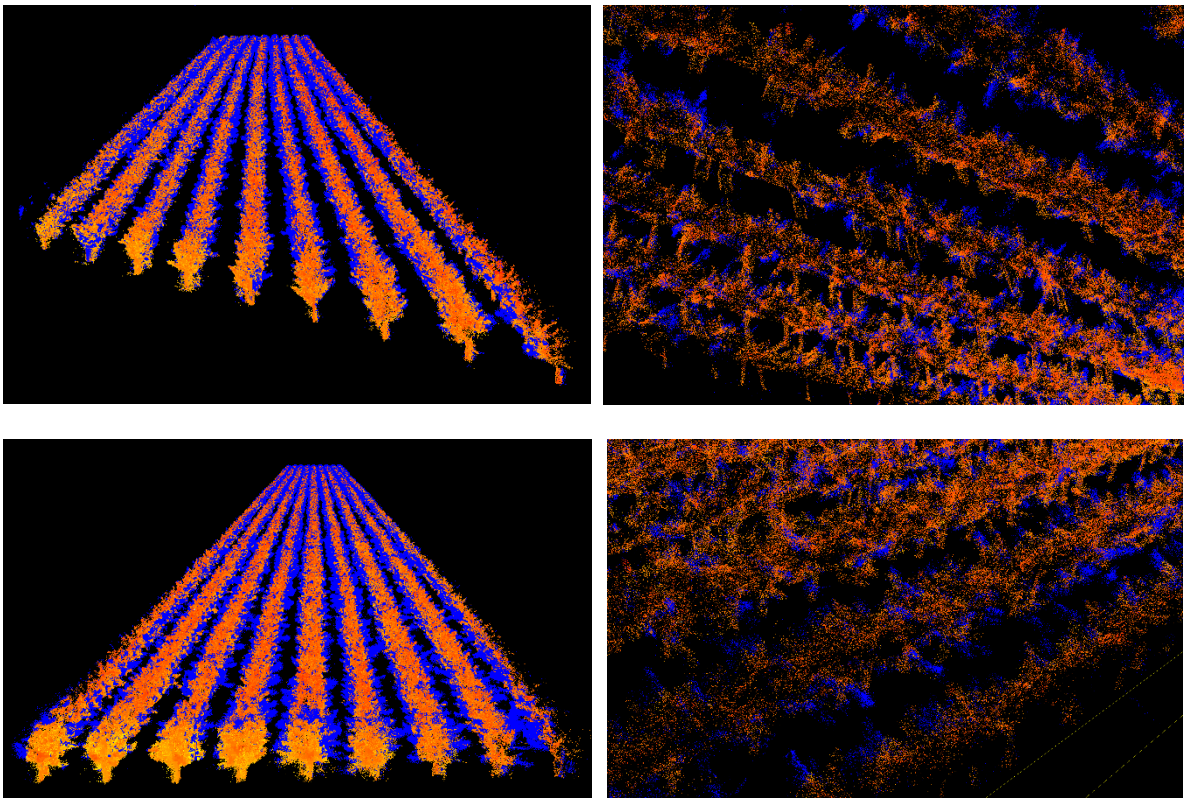


Figure 13 - representation of canopy density as a coloured point-cloud with colour (from blue to red) representing density. Several rows of vineyard block (left two panels), view from underneath the vineyard with ground removed (top right) and view from above (bottom right).

The 3D representation of canopy density can then be collapsed in any combination of dimensions and/or summed to provide an estimate of total canopy area. For example, Figure 14 top shows three sample rows from each of three different vineyards integrated vertically, to provide a representation of canopy area per unit ground area (equivalent to very high-resolution LAI) with intra- and inter-row variability clearly visible. Figure 14 bottom shows a single row from the same vineyards integrated along the row, to generate a vertical cross-section that represents the entire row. The difference between loose VSP (left) and tight VSP (right) can clearly be seen and the comparison with a larger 'sprawl' canopy (centre) shows low leaf density in the middle of the canopy compared with the VSP sites.

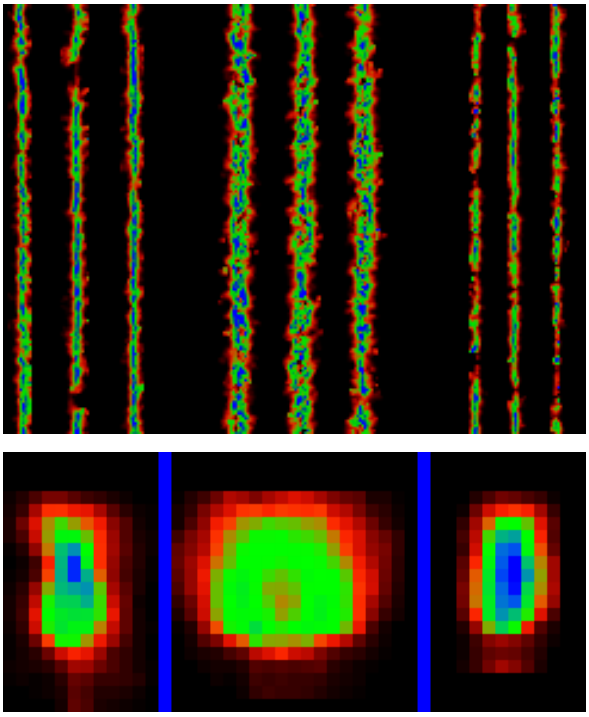


Figure 14 - 2D representations of canopy density data. Vertically integrated (top) and integrated along the row (bottom). Vines are loose VSP (left), sprawl (centre) and tight VSP (right).

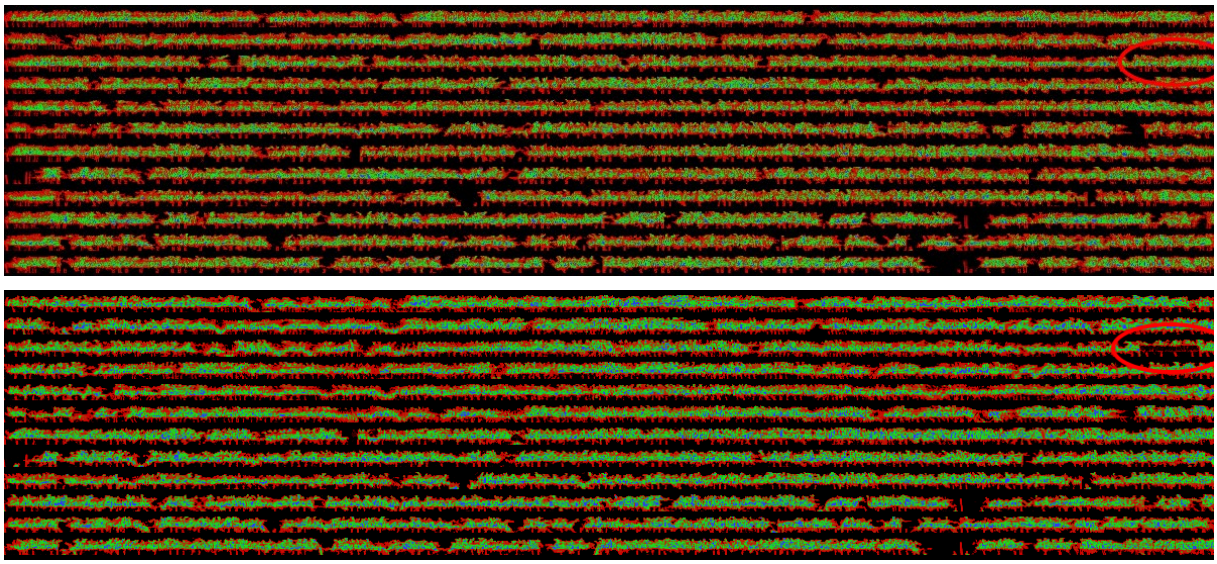


Figure 15 - 2D representation of a vineyard block, integrated horizontally through the row, at different phenological stages, pre-veraison (top) and pre-harvest (bottom). The circled area marks a panel of vines where the canopy over the bunch zone was removed.

The data can also be integrated horizontally through a row, providing a vertical distribution of canopy (Figure 15). Finally, the data can be integrated through two dimensions to provide information on a per length of row basis (not shown).

Consumer action-cams: a second method to determine canopy size and generate some information on canopy structure was based on determining gap fraction and, therefore, LAI from RGB imagery. This used the approach previously employed with SmartPhone images in the VitiCanopy app, but based on continuous video from a Go-Pro camera mounted on a vineyard vehicle such that it faced upwards from below the canopy.

The pipeline developed extracts metadata and corresponding video frames. Each frame is cropped to exclude neighbouring vine rows and colour classifier is used to categorise pixels as sky/leaf/post/wood/grapes. The gap fraction of the resulting image can then be estimated by excluding non-leaf elements. At present, open sky is also excluded producing an LAI of the canopy only, effectively a density estimate. However, the image could be sectioned in other ways, e.g. to estimate LAI of the entire view or of specific sections of the canopy. Figure 16 shows the gaps detected with the open sky excluded and a 1D estimate of LAI down the row assembled from sequential video frames.

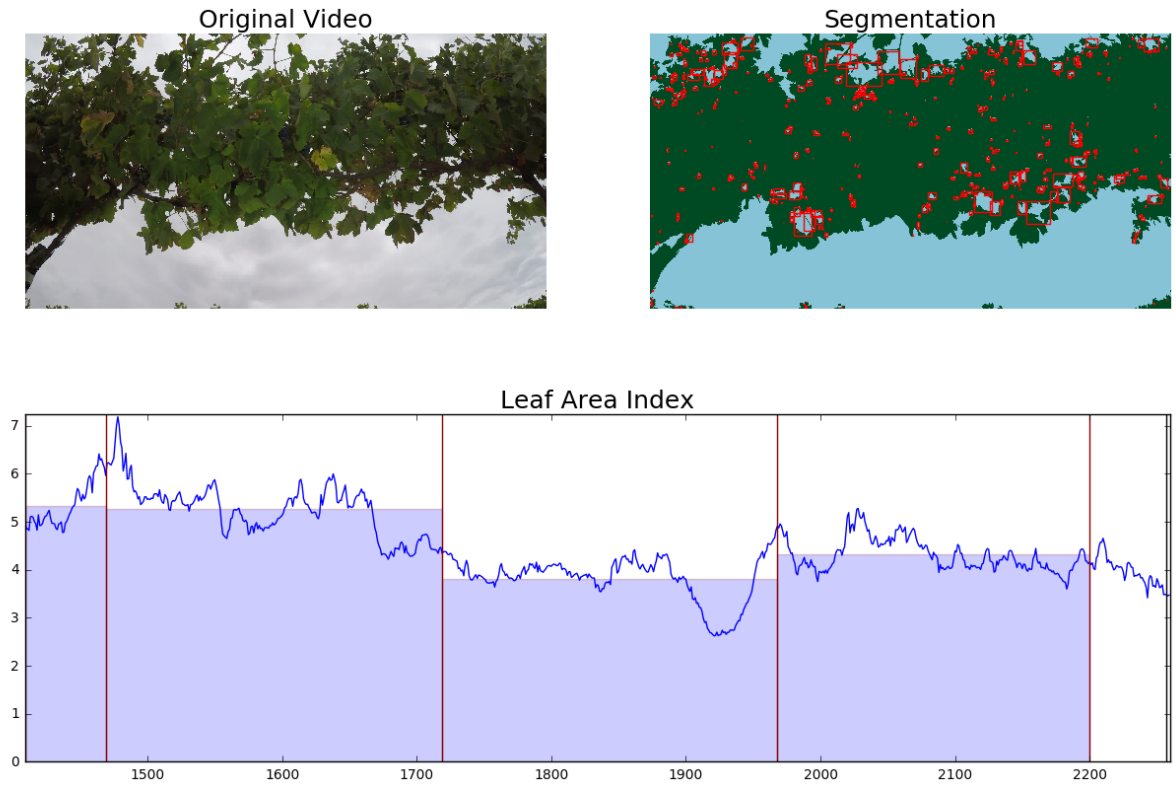


Figure 16 - video still, colour segmented image and trace of LAI estimation from gap fraction.

Drone: a major advantage to using a drone over other techniques for looking at canopy size is the ability to rapidly get data on a large scale, e.g. a 4 ha vineyard block can be flown in under 20 minutes from an altitude of 30 m (Figure 17). Disadvantages include the short flight time due to battery limitations with most drones and regulatory compliance. To maximise the potential uptake of a drone-based technique to assess the canopy, we utilised a standard consumer drone and its built in RGB camera system. Even with this equipment, the pixel size was more than small enough to produce accurate canopy measures, being <1 cm. The video imagery, or sequence of stills, is commonly assembled to form an ortho-mosaic, a top-down view of an entire

area. Whilst this can be used to estimate canopy cover, the task can become quite difficult when there isn't a good contrast between canopy and ground, such as when a live cover crop is in place. Further, it is also difficult to extract other information about the canopy from this imagery.



Figure 17 – reduced resolution orthomosaic of 'sprawl' vineyard block at Accolade, Mclaren Vale, used throughout the project, imaged from 30 m by drone.

A range of tools now exist to use photogrammetry with drone imagery. This is a computational tool that makes use of the overlap between adjacent or still images, meaning that any area of ground is imaged multiple times from slightly different angles. The parallax allows the distance to that area to be estimated and a portion of the pixels in any one image to be assigned a depth from camera value. The result is a 3D point-cloud, with RGB colour information applied to each point. Having 3D positional information allowed methods to remove the ground from the collected data to be developed, even where live cover crops were in place, and offered the potential to look at aspects of canopy shape.

We used this methodology to develop a pipeline to generate a spatial map of canopy cover from drone imagery. The RGB point-cloud could be produced using commercially available software, but we opted to use the freely available open-source 'OpenDroneMap' tool, to maximise the potential for a comprehensive package to be developed without being encumbered.

The first step was to create a digital terrain map (DTM), this a map of the landscape surface underlying the vineyard structure, which forms a digital surface map (DSM). Adjusting the point cloud for the DSM allows the landscape shape to be removed and the point-cloud flattened to make further processing simpler. A statistical approach was then used to select the points that represented the ground and remove them from the point cloud, leaving the points that represented the vines or other vineyard structure. The row structure was then determined mathematically, without any need for *a priori* knowledge of the vineyard. Finally, a mask was applied, covering the area from mid-row to mid-row and a nominated distance along the row (e.g. per m) and the ground cover fraction by the canopy determined. A map of ground cover was then produced. Figure 18 illustrates this overlaid on a Google Earth image. The advantage of this approach to colour segmentation, or even using NDVI (which would require a more expensive set-up), are that it does not rely on contrast between ground and canopy, so can be flown at any time of the season. Also, the pipeline produces data that can be mapped as the user prefers, be adapted to other purposes, such as estimating 'wire-fill', and offers the potential to use the point-cloud to look at some aspects of canopy structure.

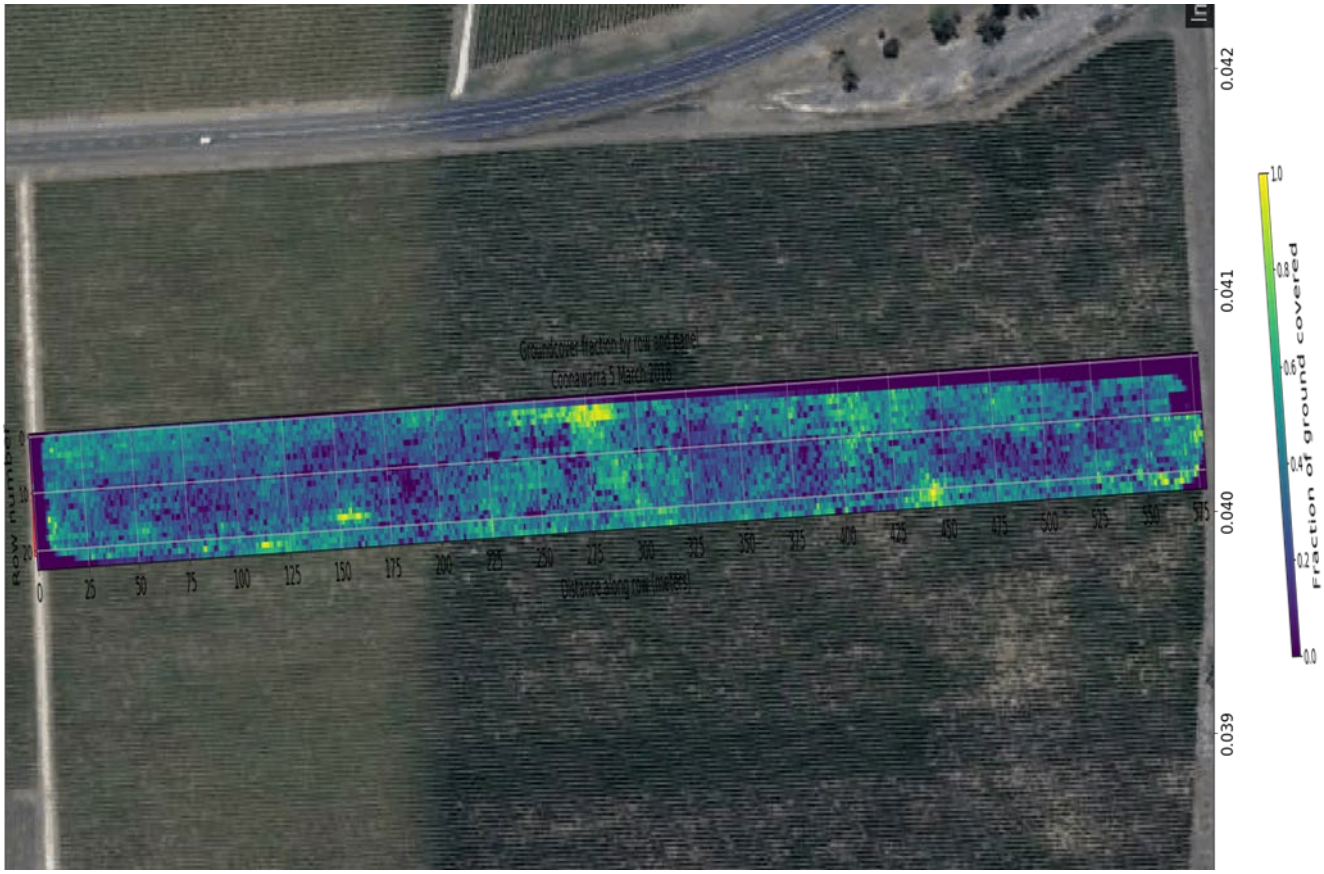


Figure 18 - ground cover data estimated from photogrammetry of drone imagery

Conclusions: all of the methods and technologies described above, whether based on bespoke hardware or readily available consumer hardware, were designed to provide information on canopy size and structure not readily available to the grower at present and for that information to be able to be collected at a time of the growers choosing. Whilst the presentation of the data to the grower was beyond the scope of this project, the data produced from these methods can readily be adapted or adjusted to area mapping, distance down a row or other format as required. The outputs offer the potential to zone canopy management within a vineyard or to adjust canopy management on-the-fly, by turning a leaf plucker on and off as you move down a row for example.

3.1.2 Vine tissue classification using hyperspectral imaging

In-field hyperspectral imaging is necessarily going to view a mix of tissue types and background objects. The wider the view the more likely that this will occur. Automatic object identification in RGB images is a significant process that requires significant development (see final report for sister project CSA1602 for examples). With hyperspectral imaging, not only is shape data available, but also spectral information for each pixel. The development of a robust classification library was a desirable outcome that would assist in many aspects of hyperspectral image analysis for both this project and CSA1602.

Five tissue types were defined: green canes, inflorescence, leaf, tendril and shoot tip. A large number of each were scanned with the laboratory hyperspectral camera system (see Table 1

totals) and the spectra corrected as previously described. A Random Forest classification was trained using the median spectra for 150 objects of each tissue type to ensure a balanced input data set. When applied to the entire dataset (Table 1), accuracy was 98%. Figure 19 provides per pixel classification for sample objects. In addition, the relative importance of each waveband was determined and a second model trained with the number of wavebands reduced from 150 to just 16. This model was still able to achieve an accuracy of 97% (data not shown).

This classification model was used for a wide range of purposes within this project, CSA1601, and its sister project, CSA1602, primarily to isolate specific tissues from background data (e.g. Figure 24 in section 3.1.4 below).

Table 1 – Identification of tissue sample spectra from a Random Forests classification model and number of spectra available.

Tissue type	Predicted tissue type					Total No.
	Green cane	Inflorescence	Leaf	Shoot tip	Tendril	
Green cane	268	0	0	0	2	420
Inflorescence	21	2203	0	17	8	2399
Leaf	0	1	432	11	2	596
Shoot tip	0	0	0	92	0	242
Tendril	3	10	7	4	962	1136

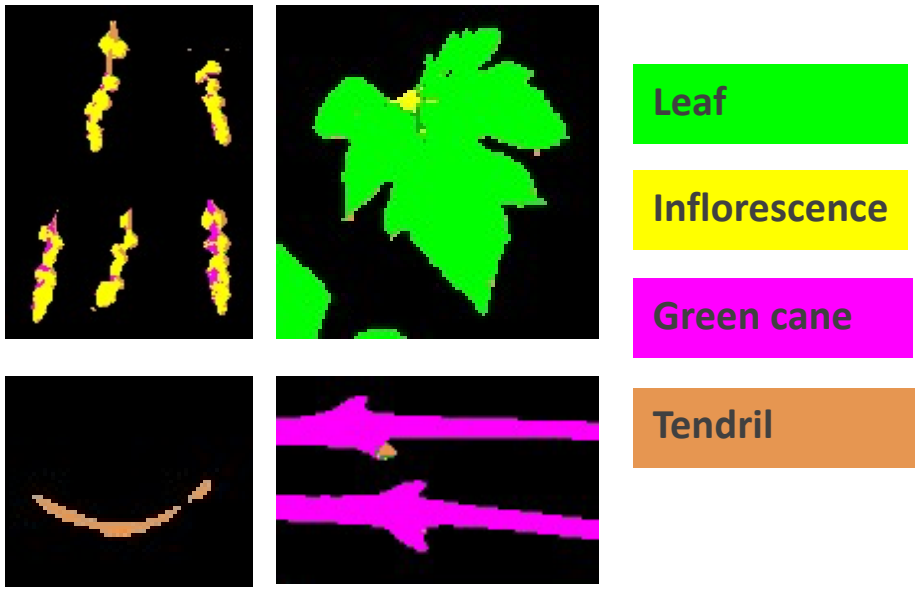


Figure 19 - hyperspectral scans of four tissue types with per pixel predicted classification.

3.1.3 Assessing vine nutrition with hyperspectral imaging

The project took two approaches to assessing vine composition/nutrient status. Firstly, a ground-based approach with the aim of using proximal hyperspectral imaging in the field and, secondly, aerial hyperspectral imaging with a fixed wing manned aircraft. The ground-based approach was to use controlled laboratory conditions to build detailed calibrations against key nutrients and then to move this to the field. At the time of writing, this approach had

concentrated on building the laboratory calibrations, with only a proof of concept field test (described in the final report for CSA1602).

Ground/Lab based: scans were taken as previously described and corrected to reflectance using a white reference and a dark reference per scan. Corrected leaf spectra were then isolated from the background using the red edge (see below) or tissue classifier (see above) and a median spectra per leaf calculated, which was used for training of various multi-variate regression models. Based on previous results, LASSO and Random Forest (RF) techniques were assessed for this task.

For the two chlorophyll measurements (CCI and DMSO extraction) the two techniques gave similar results (Table 2), but for estimating leaf nitrogen content, LASSO outperformed RF (r^2 = 0.91 vs 0.77). Chlorophyll and nitrogen are typically well correlated in leaves due to the large proportion of leaf protein that is associated with photosynthesis. Consequently, there was a risk that leaf N predictions were driven by leaf greenness and not leaf N content *per se*. In this dataset, the correlation between chlorophyll and N was significant, but only had an adj r^2 of 0.17. Examination of the wavebands contributing to the outputs confirmed that this was not the case (data not shown) and a comparison of the relationship between predicted leaf N and predicted leaf chlorophyll demonstrated that this successfully matched that of the lab-based measurements (Figure 20).

Table 2 – ability of LASSO and RF modelling to predict leaf compositional traits for a set of 200 leaves against median spectra per leaf (Med spec) and average of per pixel prediction (Mean pix), as adj r^2 and RMSE. Mean and range of ground-truth results also provided.

	CCI		**Chlorophyll**		**Leaf %N**	
mean (sd)	14.45 (6.95)		0.316 (0.105)		2.54 (0.79)	
min – max	2.7 – 57.27		0.001 – .702		0.48 – 5.20	
Algorithm	**LASSO**	**RF**	**LASSO**	**RF**	**LASSO**	**RF**
Med spec	0.91 (3.09)	0.97 (1.60)	0.94 (0.03)	0.93 (0.04)	0.82 (0.45)	0.73 (0.55)
Mean pix	0.90 (3.17)	0.92 (3.04)	0.94 (0.04)	0.94 (0.04)	0.91 (0.35)	0.77 (0.55)

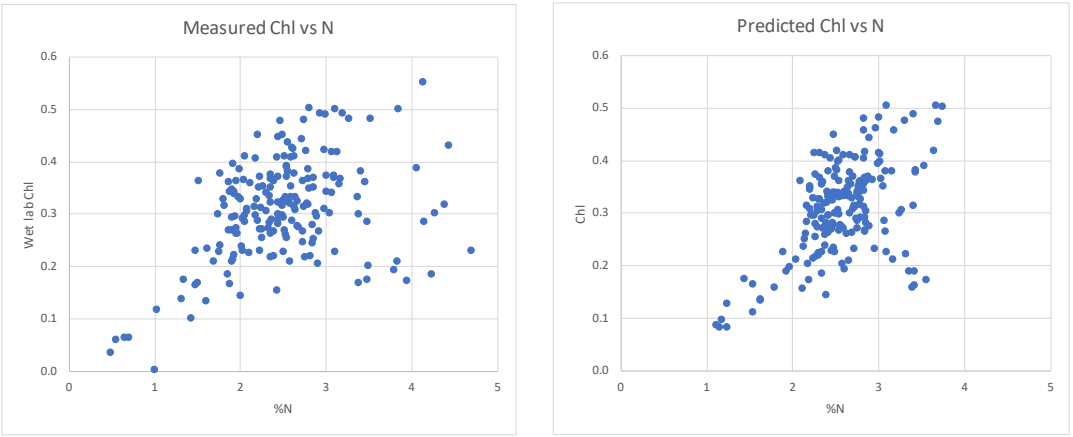


Figure 20 - relationships between lab based (left) and predicted (right) chlorophyll and nitrogen measurements.

The same leaf scans and samples were used to build calibrations for the other key nutrients, P & K, and other cations (Table 3). None of these were able to be predicted as well as N for this dataset. In both data sets, the LASSO results were unstable, that is, where per pixel predictions were made, although the mean value per leaf was reasonable, the individual pixel values varied wildly (data not shown). Consequently, it may be that some over-learning of the dataset was occurring due to the sample number being less than double the waveband number, and the RF results were potentially more reliable. Further data (hyperspectral scan+leaf composition) is already available, but has not yet been able to be incorporated and future work will expand upon this dataset.

Table 3 - ability of LASSO and RF modelling to predict leaf compositional traits for a set of 200 leaves against median spectra per leaf. Mean, standard deviation and range of ground-truth results also provided.

	Ground truth data		**LASSO Prediction**	**RF Prediction**
	Mean (SD)	**Range**	**adj r^2 (RMSE)**	**adj r^2 (RMSE)**
Al	79.2 (68.6)	5 - 411	0.61 (42.9)	0.34 (58.2)
B	53.2 (24.7)	10 - 138	0.35 (19.8)	0.39 (20.4)
Ca	1.92 (0.9)	0.36 – 4.53	0.76 (0.46)	0.42 (0.72)
Cu	163.7 (178.6)	1.19 - 682	0.28 (160.0)	0.41 (144.4)
Fe	135.2 (67.9)	49 - 701	0.27 (57.7)	0.37 (60.3)
K	0.88 (0.32)	0.23 – 1.93	0.51 (0.22)	0.54 (0.24)
Mg	0.31 (0.11)	0.14 – 0.76	0.63 (0.06)	0.51 (0.08)
Mn	115.9 (90.13)	13.1 - 651	0.41 (77.9)	0.43 (73.1)
Na	208.9 (207.5)	13.8 - 1265	0.36 (200.5)	0.37 (174.4)
P	0.21 (0.15)	0.06 – 0.96	0.36 (0.12)	0.49 (0.11)
S	0.20 (0.06)	0.05 – 0.49	0.42 (0.05)	0.38 (0.05)
Zn	17.84 (7.2)	5.3 – 40.9	0.51 (5.15)	0.56 (5.4)

Hyperspectral imaging in the NIR and SWIR are unlikely to directly measure the content of these elements in the way that atomic absorption spectroscopy might as typically, these elements do not have absorption bands in the NIR/SWIR range. Further, the very small concentrations compared with other elements in the surrounding tissue would make any bands that were present in this range unlikely to be detectable. However, many nutrients affect the plant tissues depending on their availability and NIR/SWIR cover a spectral range where many organic compounds are expected to have a signal. Thus, the expectation in using hyperspectral imaging is that these are the signals being used in any calibration for nutrient content.

The adj r^2 of the predictions vs ground truth were moderate, but given the sample size (see above) and the low concentration of some elements (for example, there was no known aluminium toxicity and any of the leaf collection sites), it is possible the lower correlations were effectively spurious. Based on the RF results in table 3, K, Mg, P and Zn may be the best targets for the spectral range of the instrument used. Interestingly three of these are key nutrients.

Aerial imaging: Two sets of flights were undertaken as part of the collaboration with Fraunhofer, one in the 2017/18 growing season and one in 2018/19. Fixed wing aircraft offer a compromise

between satellite images, which are typically of too low a resolution to image a row crop effectively, particularly in non-visible light wavebands, and drones, which have a very limited carrying capacity and short flight time. The Fraunhofer hyperspectral imaging system produced resolutions of about 40 cm per pixel, enough to separate canopy from cover crop, and 400 wavebands from visible to SWIR. The latter was significantly more, and covered a broader range, than even the lab system used. However, precisely because the aerial imagery was easily able to cover multiple hectare vineyard blocks, this generated a difficulty with sampling for ground truth data to build a calibration. To examine this problem two sampling regimes were used, high-density small samples in 2017/18 and low-density large samples in 2018/19. In addition, in-field leaf chlorophyll measurements were made in 2017/18 using a non-destructive chlorophyll meter, which sampled a far smaller area than the two-leaf samples taken in that season.

Model predictions of chlorophyll content were built using the hyperspectral data and the ground truth results. Even with 40 cm pixels there was a two-fold range in the per pixel data (Figure 21, top). An assessment of the model was only possible by aggregating the data to the scale of the sampling i.e. per panel per row (Figure 21, bottom). Including all panels resulted in a coefficient of determination (r^2) of only 0.3. Excluding panels where there was little correspondence between the two ground-truth chlorophyll measures improved this to 0.5, but a third method where the model was developed using spectra from only areas of high NDVI (i.e. areas of heavier canopy) and where there was consensus between the ground truth measurements improved this further to an r^2 of 0.8.

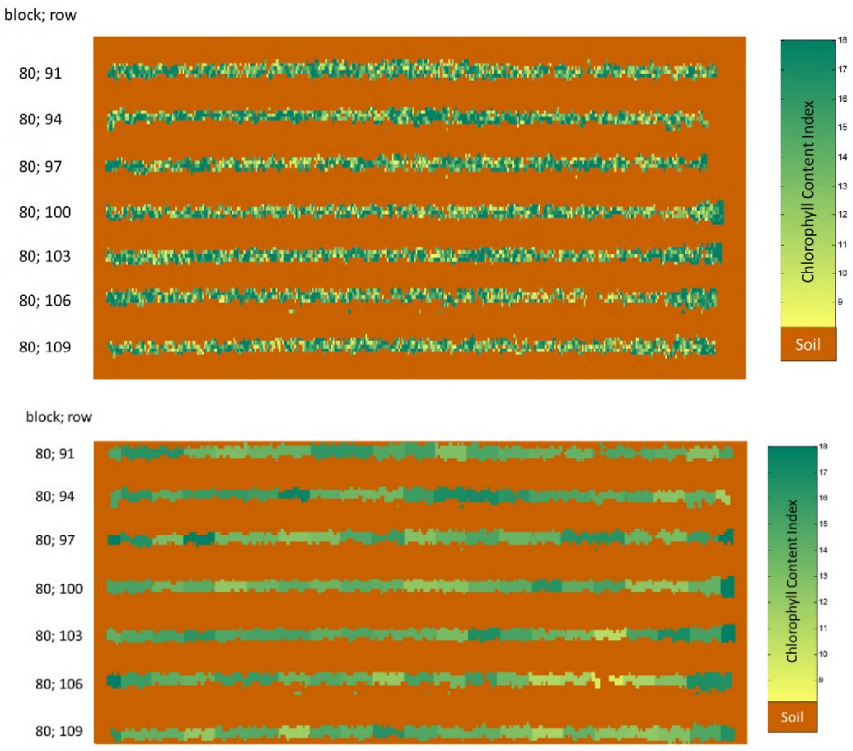


Figure 21 - Map of chlorophyll content based on statistical models on a per pixel basis (top) and per panel basis (bottom) for the Accolade Mclaren Vale VSP vineyard.

Estimating chlorophyll was not a key aim and used primarily as a test of the methodology, so wasn't repeated using the sample methodology of 2018/19, but demonstrates some of the complexities of building calibrations with aerial data that must be overcome to make best use of this technology.

The decision to use fewer, larger samples in 2018/19 increased the risk of randomly chosen sample positions not representing the variation in the field. To reduce the risk of this IFF Fraunhofer used a clustering approach based on the 'Growing Neural Gas' algorithm (Martinetz & Schulten, 1991) to choose sites that best represented the block, based on the 2017/18 flight data for each vineyard. The effectiveness of this is demonstrated in Figure 22.

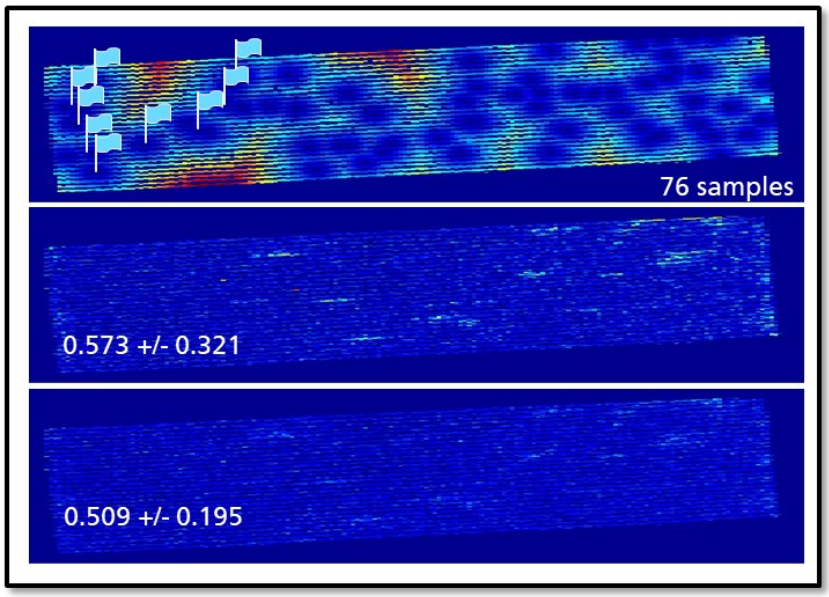


Figure 22 – Validation of the automated selection of sampling locations for 2018/19 season. Distance of pixel of nearest ground truth sample (top; red = far, dark blue = close; flags mark a subset of chosen positions), Euclidian distance to next representative of the spectral domain (lower is better) for random choice (middle) and automated selection (bottom).

A comparison of model performance for predicting tissue nutrient content at the Mclaren Vale Accolade site demonstrated that the new sampling methodology was beneficial, increasing the Pearson's correlation coefficient (r) for all nutrients measured (Figure 23).

This part of the project has demonstrated the potential to use aerial hyperspectral imaging for assessment of vine nutrient status at scale, a prior proof-of-concept collaboration between CSIRO and Fraunhofer also demonstrated that the same data may provide information on other aspects of the canopy, such as canopy density (unpublished data). We have also highlighted the difficulty in collecting appropriate ground-truth data to build such calibrations and significant further sampling would be required prior to a commercial rollout of a service based on this type of instrument. However, once calibrations across a broader range of vineyards have been generated our results would suggest that service providers using fixed winged aircraft should be able to use NIR/SWIR instrumentation to provide spatial data on vine nutrient status, thereby assisting growers in optimal fertiliser application.

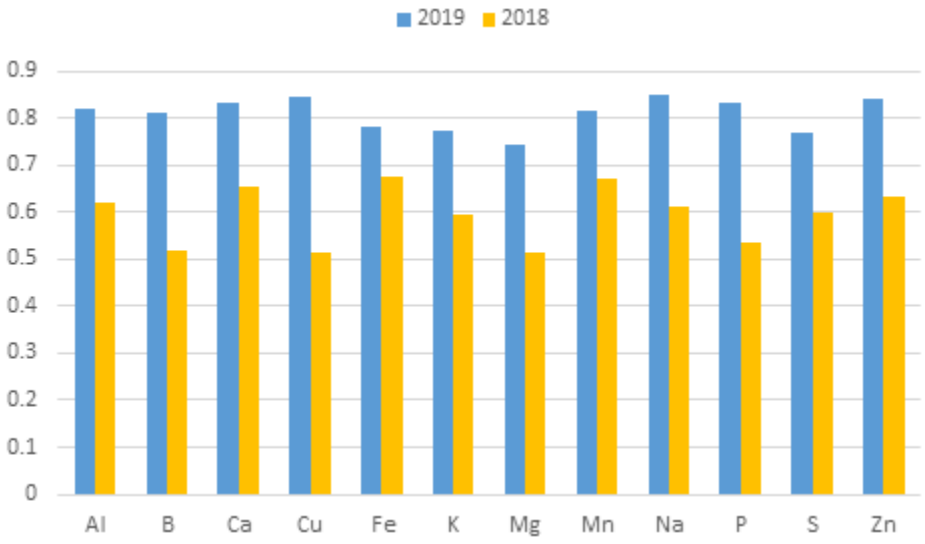


Figure 23 - Improved Pearson correlation between predicted and reference values in 2019 due to changes in ground-based sampling for calibration of the models.

Figure 24 provides a low resolution whole vineyard block views of predicted canopy elemental content for the elements examined. A single scale is used across all vineyards making between vineyard differences clearer than within vineyard data, but an interactive data provision would allow more flexibility than a single figure does for grower use.

Comparison of lab and aerial calibrations: although the laboratory equipment had a more limited range than the aerial equipment and natural lighting conditions preclude the use of some wavebands for the aerial data, an attempt was made to assess the potential to use lab calibrations to inform aerial calibrations, thereby solving some of the ground-truth data problems for aerial deployment.

To achieve this the spectral range of the aerial data was limited to that of the lab data (i.e. reduced to 550-1650 nm from 400-2500 nm) and the data was all rescaled. Despite this there were significant differences in spectral shape between the lab (full range halogen illuminated) and aerial (sunlight illuminated) data. For our initial testing reported here this was ignored, but a more careful selection of wavebands less impacted by the restoration process used to cope with atmospheric absorption (see section 2) may improve the results below further.

For the combined dataset (approx. 500 samples) new LASSO and RF models were trained and predictions correlated with ground truth data made for N. The adj r^2 (and RMSE) values were 0.58(0.38) and 0.55(0.39) respectively. In terms of spectral shape, the most extreme deviations were seen in the Rymill data, so additional models were trained excluding this data. The RF result was marginally improved to 0.60(0.32). Whilst performance of these models were below that of those trained on the individual datasets (e.g. Table 2) the results are promising considering the limited data processing used so far. Figure 25 provides a visual representation of the difference between the two RF models.

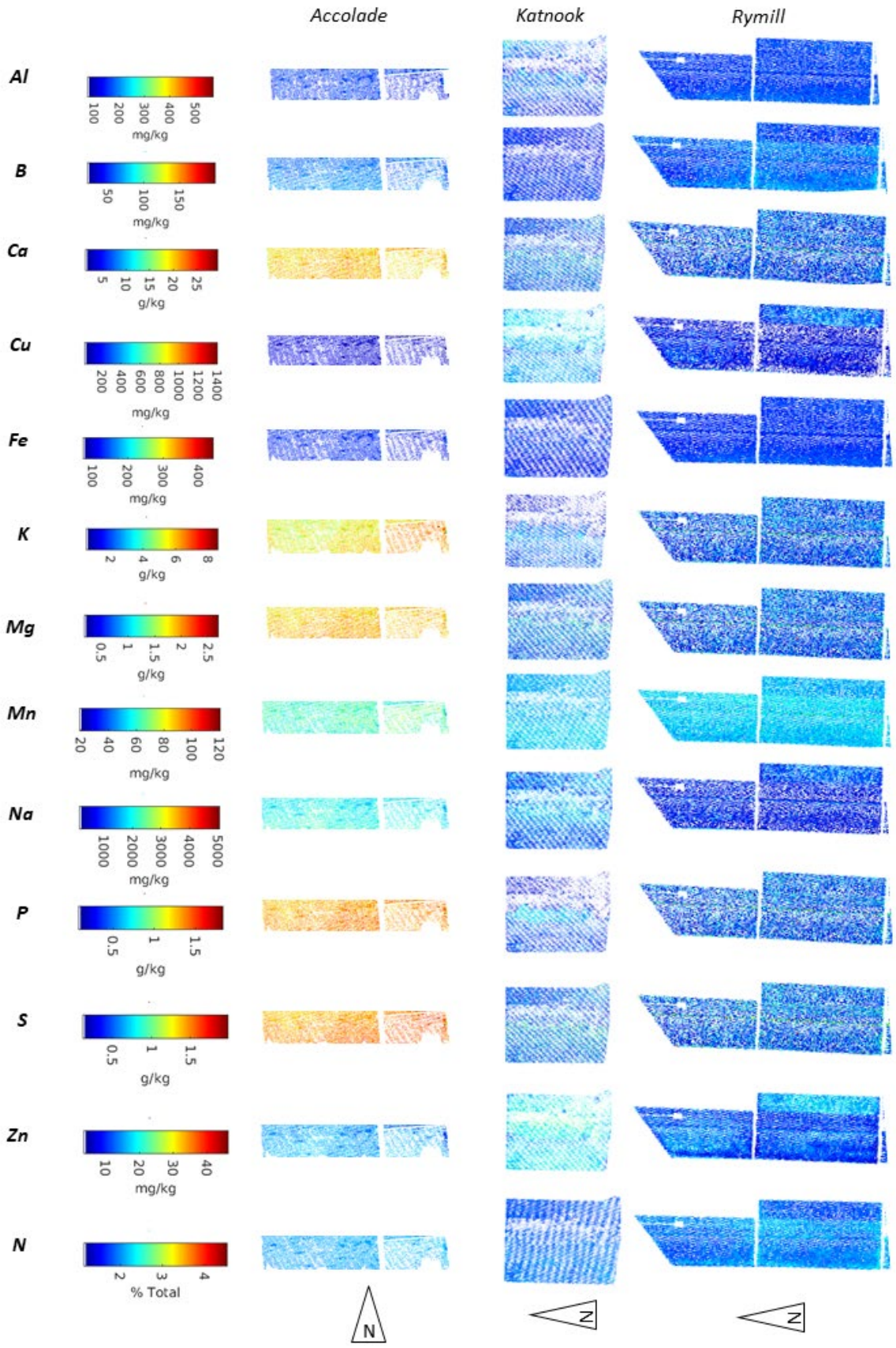


Figure 24 - visualisation of whole block vine nutrition data for all tested nutrients for paired Accolade Mclaren Vale blocks (left), Katnook Estate, Coonawarra (centre) and paired Rymill, Coonawarra blocks (right).

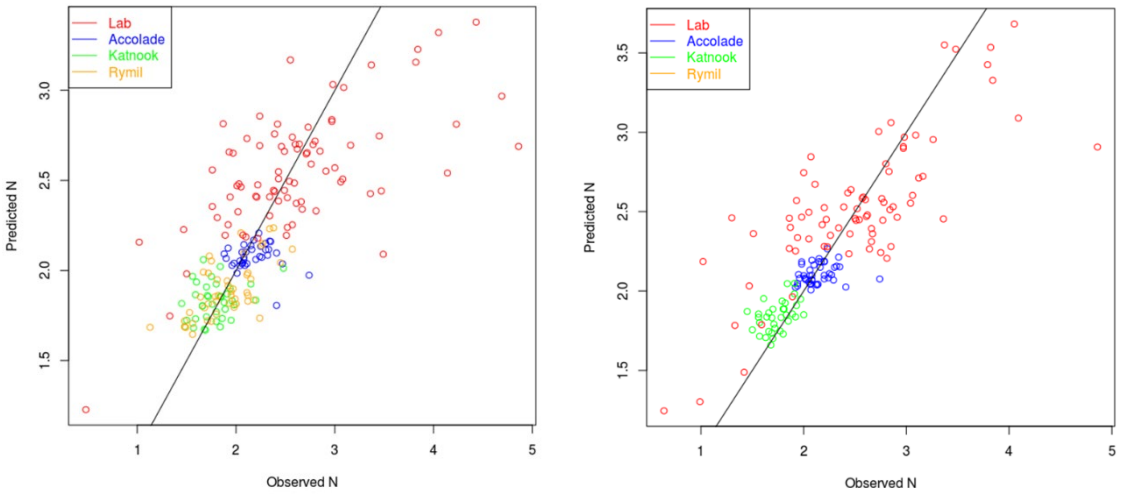


Figure 25 - output of RF model for leaf N built with all aerial and lab data (left) and excluding Rymill (right).

3.1.4 Viability of early disease detection with hyperspectral imaging

Powdery mildew and downy mildew are generally considered the most important leaf diseases in Australian vineyards and a significant proportion of vineyard sprays are preventative sprays aimed at controlling powdery mildew in particular. Consequently, powdery mildew was chosen as the disease where an early detection system could have the most industry impact.

The principal of future application would be regular passes in the vineyard with a hyperspectral device that would image the entire vineyard, or a large proportion of it, and detect the initial stages of disease early enough that spraying or other management could be enacted prior significant disease establishment. For this to occur, the disease needs to be detected as early as possible and prior to any clear visual symptoms.

The need to determine disease status prior to it being observable to the human eye creates a difficulty for the generation of ground-truth data that can be used to produce a spectral calibration, as it requires knowledge of where the disease will and will not develop. Effectively, this requires vine tissue to be inoculated, or not, with mildew spores and that tissue tracked until symptoms are present, with regular hyperspectral imaging. The data can then be followed back to compare areas with and without disease.

The CSIRO Agriculture & Food laboratories at the Waite Campus already had an established system for generating powdery mildew infection on isolated leaves and this was used to generate tissue that could be known to have disease and be compared with tissue that could be known not to have disease.

A trial with twelve leaves, six infected and six control, was conducted with leaves imaged up to nine days after inoculation. Two analysis methods were used, one based on an endmember approach to determine spectral classes for diseased and non-diseases tissue, the second using manually defined areas of leaf to determine classifications of spectra. Figure 26 shows a

diseased leaf, manually selected areas of high disease and then colour coded automated classification of spectra into diseased or healthy tissue and petiole.

The endmember approach only 'detected' diseased tissue at day nine of the experiment, long after symptoms were apparent visually (data not shown), whereas the manual classification, based on visual assessment of RGB images, produced differences in the proportion of pixels classified as diseased or healthy between inoculated and non-inoculated leaves just 24 hours after inoculation (Table 4). However, although the proportion of diseased pixels was high nine days after inoculation, after six days it was still low and similar to the first day results, despite clear visual differences.



Figure 26 - RGB image of diseased leaf nine days after innoculation (left), selection of spectra for disease classification (center) and colour coded by pixel as idsease (pink), healthy (green) or petiole (dark red).

Table 4 – Proportion of leaf pixels classified as infected ($Prop_d$) over all six leaves for control and infected 'True Class' 0, 1, 6 and 9 days after inoculation. Range $Prop_d$ shows the range of $Prop_d$ across the six individual inoculated leaves.

True Class	Day	$Prop_d$	Range $Prop_d$
Control	0	0.003	0.001-0.008
Inoculated	0	0.011	0.002-0.044
Control	1	0.011	0.006-0.039
Inoculated	1	0.072	0.006-0.201
Control	6	0.004	0.001-0.021
Inoculated	6	0.093	0.015-0.246
Control	9	0.025	0.016-0.037
Inoculated	9	0.676	0.450-0.999

The initial experiment was supplemented with five further experiments, bringing the total number of leaves to nearly 70 inoculated leaves and the same number non-inoculated leaves. Utilising the same approach did not improve the results, despite the more than ten-fold increase in replicates. Utilising other approaches, such as a semi-supervised clustering with limited number of classes, showed some ability to differentiate between tissue types and diseased/non-diseased areas of leaf (Figure 27), but was not adequately robust or reliable leading to

significant false detections in control leaves and missed detections of disease in areas where disease was obvious visually. . Ultimately, hyperspectral imaging requires significant changes in the chemistry or structure of the leaf to detect temporal changes and in the isolated leaf system the control leaves were undergoing a senescence process, due to their having been removed from the vine, with the diseased leaves undergoing a similar process at an accelerated rate. Even with a sensitive assay for this rate it would be unlikely to be able to be successfully applied to a commercial, field situation. Consequently, despite the relative ease of working with isolated leaves, the use of intact vines was required.

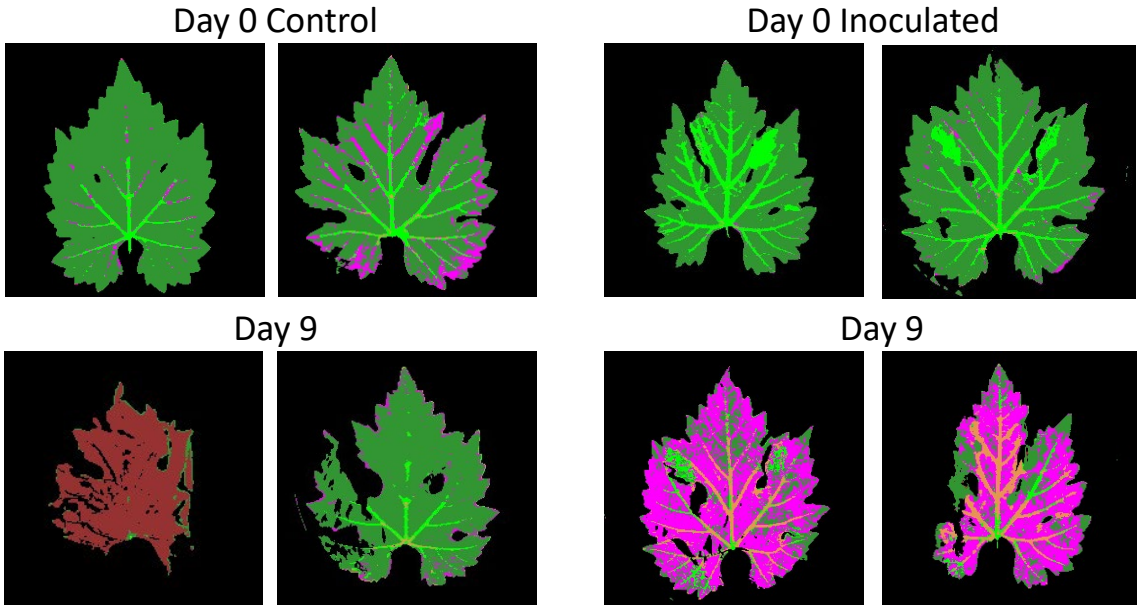


Figure 27 – classification of hyperspectral image pixels as leaf (dark green), vein (light green), senesced tissue (brown) or infected tissue (pink). Leaves were non-inoculated (left) or inoculated (right) and the same leaf was imaged immediately after inoculation (top) or nine days after (bottom).

To undertake work outside of the lab an instrument was built with the same hyperspectral line scanner, paired with an RGB camera and an external light source. Initially this was a high-output xenon flash, with the flash and line scans synchronised (Figure 28). The camera and flash system were then moved past the vine of interest on a linear stage. Testing was undertaken using two vines in a shadehouse, one without powdery mildew symptoms, the other heavily infected (Figure 29, top).

The leaves were separated from the background in the hyperspectral data using the tissue classifier described above, with only pixels that classified as leaves included. A semi-supervised clustering approach was again used, with the diseased and healthy leaves easily distinguished (Figure 27, bottom).

Following this successful trial, a continuous lighting rig was built and the camera plus lighting system mounted on a 2 m long heavy duty (60 kg capacity) linear stage in a glasshouse (Figure 7).

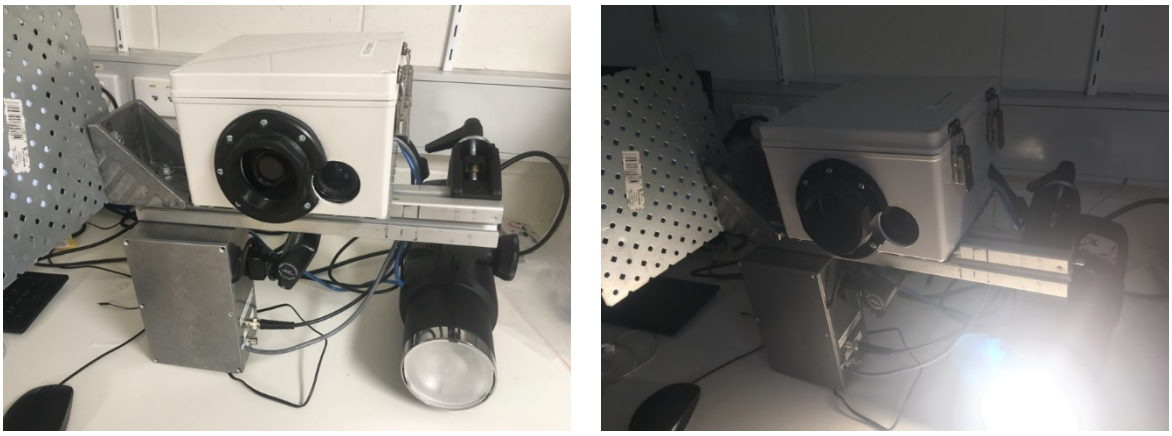


Figure 28 - hyperspectral camera with RGB and flash.

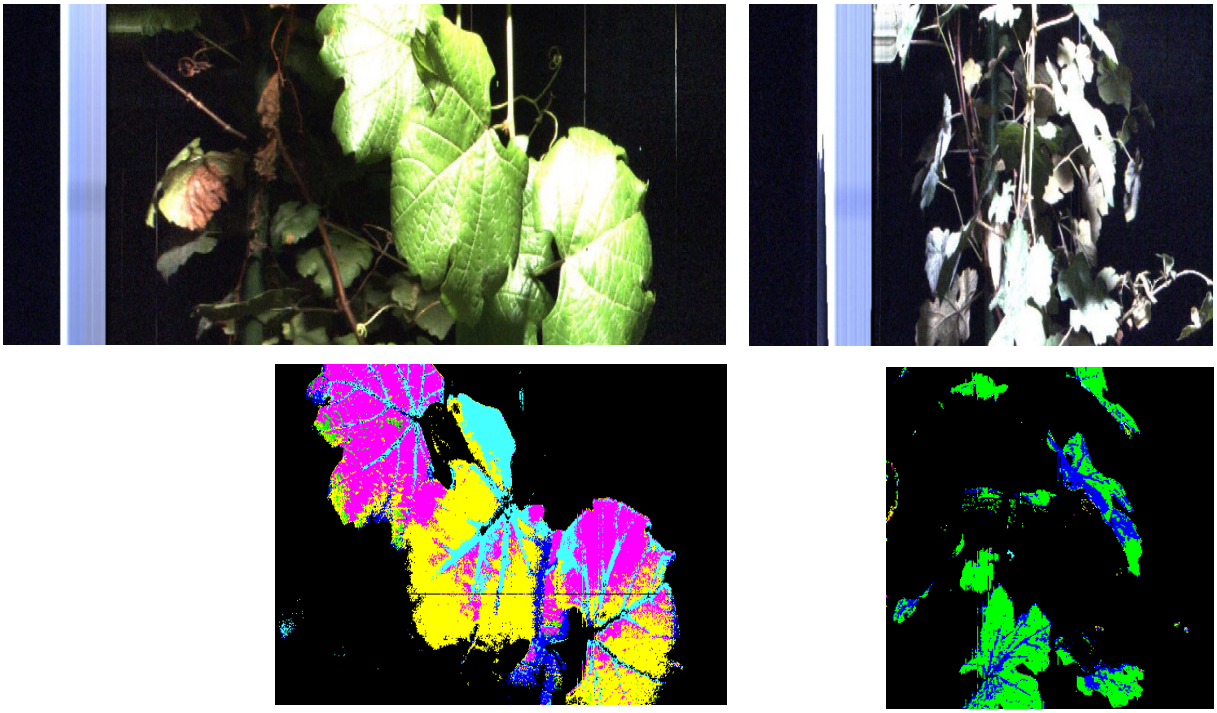


Figure 29 - RGB image (top) and cluister classes (bottom) of healthy (left) and diseased (right) vines.

3.1.5 Viability of assessing vine physiological parameters with hyperspectral imaging

Assessing vine function, rapidly, non-destructively and at scale in the field would allow a wide range of vineyard management decisions from irrigation scheduling to canopy management to crop thinning to be made with a high degree of confidence and desired fruit quality outcomes to be met with unprecedented accuracy. This is conceptually possible using in-field hyperspectral imaging in the NIR-SWIR range or other more complex technologies, but impractical at present.

The first step towards such an outcome is an assessment of which aspects of vine physiology are most amenable to such an approach and a test of the approach under controlled conditions. To simplify the practical aspects of the relevant data collection a physiological parameter that is not highly variable temporally (i.e. doesn't change over minutes to hours), but still viticulturally

relevant was desirable. The photosynthetic capacity of the canopy is ideal in this respect, it drives carbon uptake by the vine and therefore growth and fruit filling, typically varies on a scale not less than hours, more often days to weeks and can be assessed at the leaf level by determining the maximum carboxylation rate (i.e. RuBISCO activity; $V_{c\,max}$), a standard measurement that can be performed *in-situ* under almost a wide range of conditions.

$V_{c\,max}$, is measured using gas exchange, a process that also provides measurements on a number of other leaf physiology parameters potentially useful in viticulture and thus these were included in the analysis, despite being likely to vary within the time between measurement and hyperspectral imaging. Although the time to measure a single leaf (approximately 30 minutes) limited the number samples in this trial to 38 a wide range of ($V_{c\,max}$), values, required for an effective calibration, was achieved through careful selection of plant material, ranging from 14-93 µmol m^{-2} s^{-1}.

A preliminary calibration was based on $V_{c\,max}$ adjusted to a temperature of 25°C and calculated from instantaneous values of assimilation according to Harrison et al (2009). The correlation between predicted and observed estimates of $V_{c\,max}$ in the LASSO model using the full range of wavebands was high and seven bands were identified as providing the predictive power of the model (Figure 30).

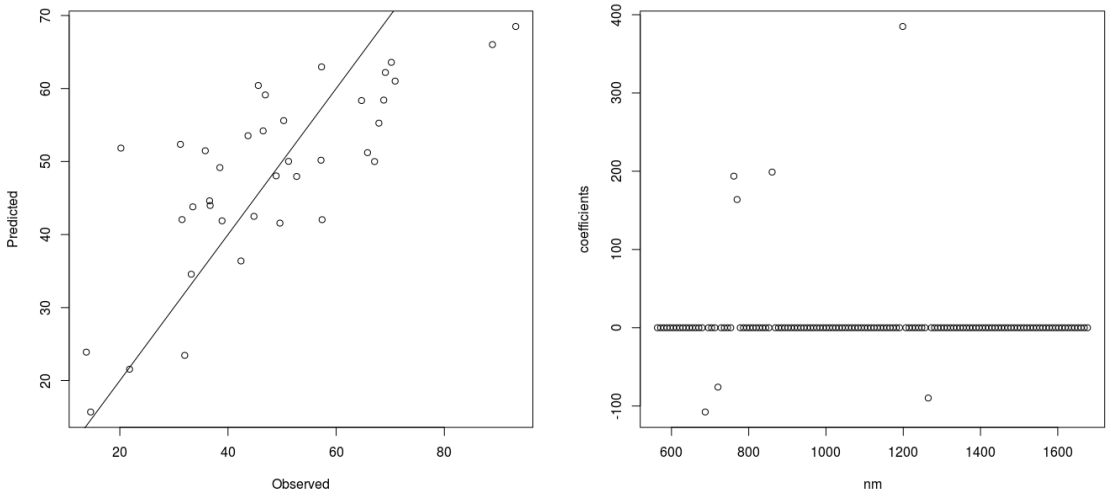


Figure 30 - Predicted vs observed $V_{c\,max}$ from LASSO model using all imaged wavebands (left) and the key wavebands that drove the model (right).

As the model was likely to overfit the dataset, due to the number of wavebands (150) being much higher than the number of samples (38), the model was retrained using six of the identified key wavebands, providing a similar result (Figure 31). The adjusted r^2 of the correlation between predicted and observed values 0.62 (Table 5). Given the limitations of the dataset and the preliminary analysis, this suggests that $V_{c\,max}$ is likely to be amenable to being quantified by a hyperspectral imaging approach, but further sampling needs to be undertaken to confirm this prior to any attempt to move the system into the field.

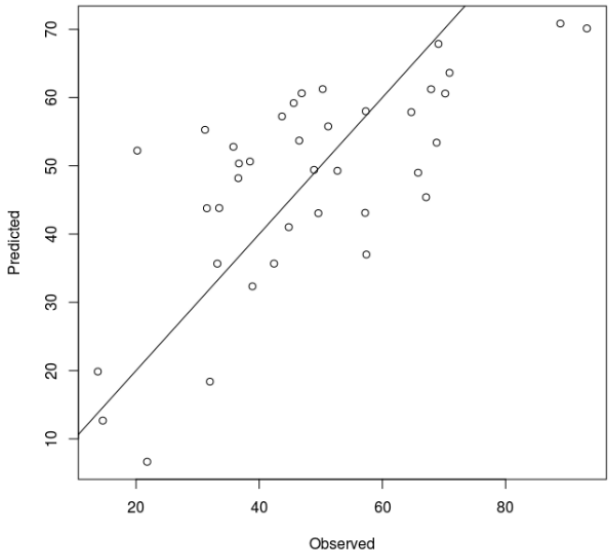


Figure 31 - predicted vs observed $V_{c\,max}$ from LASSO model using six wavebands.

The process was repeated for the other parameters assessed during the gas exchange measurements, assimilation under saturating light (A_{sat}), stomatal conductance (g_s), transpiration (E), intrinsic water use efficiency (A/g) and instantaneous water use efficiency (WUE). The most successful of these was E, possibly due to a relationship with leaf water content (not measured), which is easily picked up in the hyperspectral data due to multiple water absorbance bands in the wavelength range used. In addition, two further gas exchange parameters that were known to be different at the time of measurement to the time of imaging, intercellular CO_2 concentration (C_i) and leaf temperature (T_{leaf}), were assessed (Table 2).

Table 5 – correlation between measured gas exchange values and those predicted with a LASSO model based on hyperspectral data using the range of wavebands available or a reduced set.

Measured parameter	Adj R^2 (RMSE) all wavebands	Adj R^2 (RMSE) reduced wavebands	No. of reduced wavebands	Parameter mean
$V_{c\,max}$	0.62 (11.5)	0.50 (11.8)	6	48.4
A_{sat}	0.42 (4.56)	0.29 (4.49)	3	13.2
g_s	0.74 (0.12)	0.59 (0.15)	9	0.317
E	0.90 (0.87)	0.67 (1.52)	13	5.56
A/g	0.38 (27.3)	0.30 (29.6)	2	63.5
WUE	0.70 (0.29)	0.58 (0.33)	6	2.50
C_i	0.46 (37.6)	0.31 (42.6)	3	273
T_{leaf}	0.45 (1.53)	0.32 (1.70)	4	33

The adj r^2 for the correlations between observed and predicted for these parameters was approximately 0.3 and they also used fewer wavebands (selected through the initial LASSO results) than the better predicted parameters. A_{sat} and A/g had similar adj R^2 values and also

used fewer wavebands, suggesting that the prediction results for these two parameters were spurious and unlikely to be repeatable. Previous reports have demonstrated significant correlations between spectral reflection data and A_{sat}, at least within a single dataset, but in these cases the spectral data has been taken at the time of ground truth measurement and typically with a contact instrument (Serbin et al. 2012).

3.2 Contribution to program objectives

The program objectives of program RnD4Profit-15-02-018, Digital Technologies for dynamic management of disease, stress and yield, were:

a) generating knowledge, technologies, products or processes that benefit primary producers;
b) strengthening pathways to extend the results of rural R&D, including understanding the barriers to adoption; and
c) establishing and fostering industry and research collaborations that form the basis for ongoing innovation and growth of Australian agriculture.

The project has focussed on developing, prototyping and assessing technologies and data analytic pipelines that will benefit the winegrape growers of Australia. Specifically, the project has:

- examined a range of LiDAR based sensors for applicability at commercial scale;
- developed a LiDAR based sensor that can be used to map grapevine canopy structure in three dimensions;
- developed a LiDAR processing pipeline and new method of assessing canopy structure with the flexibility to be applied in vineyards, irrespective of commercial production targets and current canopy management techniques employed;
- developed a range of RGB digital imagery techniques using consumer equipment to map aspects of grapevine canopy cover and structure at a commercial scale;
- examined proximal (primarily lab-based) and aerial (fixed-winged manned aircraft) methods for non-destructively assessing vine nutritional status at scale;
- developed a machine learning based tissue classification tool for grapevines using NIR spectra;
- developed a vine nutrient status tool for VIS-NIR-SWIR spectra;
- assessed the practicality of using currently available NIR hyperspectral imaging for early disease assessment (powdery mildew) in grapevines.

Whilst the tools and technologies utilised through this project are at various technology readiness levels, the project team has maintained a dialogue with it's industry partners (Accolade Wine, Rymill Wine, Katnook Estate), it's industry reference committee (including members from a number of wine industry companies) and has presented work at key industry events, such as the Australian Wine Industry Technical Conference and Exhibition. The team are also in active discussions with Wine Australia about ways of ensuring commercialisation of the most suitable technologies occurs.

Finally, the project collaborated with a number of industry partners (see above) as well as developing an international research partnership with the Fraunhofer Institute in Germany and undertaken informal discussions with the TeleVitis team at the University of Rioja, who are

developing related technologies for the Spanish wine industry, about future interaction, particularly in the area of hyperspectral imaging of vineyards. These collaborations are aimed at supplementing Australian skills and know-how with relevant overseas experience to provide additional resources and thereby improve the efficiency of developing tools for Australian growers.

4 Collaboration

This project included a contracted collaboration with the Fraunhofer Institute for Factory Operation and Automation (IFF) in Magdeburg, Germany, which ran over two years. The original collaboration was built on to a small extent with discussions over how to bring together ground-based hyperspectral calibrations and aerial-based measurements. This led to the preliminary test of the idea described in section 3.1.3. CSIRO Agriculture and Food and Fraunhofer IFF have agreed to look for future opportunities to build on the collaboration, including joint publications. Fraunhofer IFF undertook their flights in collaboration with Airborne Research Australia and Everard Edwards was directly involved in those collaborative discussions. It is likely that if scientific fixed-wing aircraft flights are required in the future by CSIRO Agriculture and Food at the Waite Campus, we would look to build on that contact.

Although not formally listed in the original funding application, a discussion with Accolade Wine (Alex Sas, Warren Birchmore) to undertake work described in this report at their Mclaren Vale vineyards pre-dated the project. Further collaboration with commercial Wine Companies and grape growers was critical for field testing of equipment and methodologies in a commercial setting. In addition to the collaboration with Accolade, the project leads arranged to work with Wingara Wine Group (Chris Brodie) and Rymill Wine (Shannon Sutherland, Josh Clementson) in the Coonawarra, both of whom offered access to paired vineyards in close proximity with different fruit quality outcomes. Later in the project imaging of the vineyard owned by Oli Madgett was undertaken and an ongoing discussion about access his Platfarm platform for display and sharing of data from the project. Finally, the Woodside vineyard managed by Adam Loveys provided access to some highly managed vines of alternative varieties, but was unfortunately lost in the 2019/20 season bushfires.

It is worth mentioning that the project has also aided collaboration within CSIRO, with three different groups based in three different states coming together to generate novel hardware and data processing pipelines that would have been difficult to undertake within CSIRO Agriculture and Food alone.

The collaboration with Accolade will continue through the CSIRO-Wine Australia project CSA1702-3.1, which will undertake further development of the technologies described in this report and commercialisation suitability assessment. It is anticipated that the collaborations with Wingara Wine Group (through their Katnook Estate winery) and Rymill Wine will also continue.

5 Extension and adoption activities

This project was intended to develop commercially applicable sensors and data analytics for future commercialisation. As such extension activities to growers has not been practical for much of the project. That said, all of the development work has been carried out in collaboration with commercial growers (see section 4, above). However, information has been provided to the industry through:

- A workshop provided as part of the 17th AWITC workshop program
- A plenary presentation at the 17th AWITC, with a video of the presentation and a conference paper available to attendees.
- A YouTube video of a presentation on the project to the Televitis group at the University of Rioja is available at: https://youtu.be/PsKBD46py_s

In addition, conversations with potential commercial partners have been undertaken in conjunction with Wine Australia.

6 Lessons learnt

As is often the case, contracting was slow, which delayed the start-up of the project and meant that much of the first growing season was missed. The project lead arranged for some related CSIRO internally funded work to make data accessible to the project, which helped to minimise this.

This project brought together previously disparate groups within CSIRO, staff from Fraunhofer IFF in Magdeburg, Germany and a number of wine companies with sites across South Australia. Whilst we consider this to have been a highly successful endeavour, the time required to ensure that all parties had a common understanding was more than expected and a greater allowance in the project planning for this may have eased the project start-up.

Whilst CSIRO is uniquely placed, in Australia, to bring together diverse teams from different research areas, it was still necessary to bring mechatronics and coding expertise into the domain knowledge team at Agriculture & Food as part of the technical support. This was only partially anticipated and probably delayed the optimal team structure being established.

7 Appendix - additional project information

7.1 Project, media and communications material and intellectual property

Peer reviewed papers:

No research papers for publication in peer reviewed journals have been published at the time of writing.

Canopy Density Estimation in Perennial Horticulture Crops Using 3D Spinning LiDAR SLAM. Lowe, T, Moghadam, P. Edwards, E.J. & Williams, J. has been submitted to the *Journal of Field Robotics* and is under review.

Conference presentations:

Phenotyping vineyards by means of airborne hyperspectral imaging. U. Knauer, E.J. Edwards, A. McGrath, U. Seiffert (2018) Poster presentation at the 5th International Plant Phenotyping Symposium, Adelaide.

Estimation of plant vitality in Australian vineyards by analysis of airborne hyperspectral images. U. Knauer, A. McGrath, E. Edwards, U. Seiffert (2019) Poster presentation at the Annual Meeting of the DGPF, Vienna.

Digitising the vineyard: developing new technologies for viticulture in Australia. E.J. Edwards, M.R. Thomas, S. Gensemer, P. Moghadam, T. Lowe, D. Wang, R. Lagerstrom, C. Hargrave, J. Ralston. (2019) Poster presentation at the 21st GiESCO meeting, Thessaloniki.

Digital opportunities: from the vineyard to the winery door. E.J. Edwards, M.R. Thomas, S. Gensemer, P. Moghadam, T. Lowe, D. Wang, R. Lagerstrom, C. Hargrave, J. Ralston. (2019) Oral presentation and conference paper at the 17th Australian Wine Industry Technical Conference. Adelaide.

Intelligent systems for commercial application in perennial horticulture. Edwards, E. J. and Moghadam, P. (2020). Oral presentation at TropAg 2019, Brisbane. Abstract published in: *Multidisciplinary Digital Publishing Institute Proceedings*, **36**(1):59.

Digital twin for the future of orchard production systems. Moghadam, P., Lowe, T., and Edwards, E. J. (2020). Poster presentation at TropAg 2019, Brisbane. Abstract published in *Multidisciplinary Digital Publishing Institute Proceedings*, **36**(1):92.

Intellectual Property

IP produced by this project included:

1. New knowledge on objective measurements of canopy structure, condition, physiology and nutrition.

2. New data processing pipelines for measuring canopy structure, condition and nutrition.
3. Hyperspectral calibrations and datasets (hyperspectral images with matching ground-truth data) for disease detection, canopy nutrition and physiology.

7.2 Equipment and assets

Headweall eVNIR Micro hyperspectral camera

7.3 References

Apan A, Held A, Phinn S and Markley J 2004. Detecting sugarcane'orange rust'disease using EO-1 Hyperion hyperspectral imagery. International Journal ofRemote Sensing 25, 489–498

A. Backhaus, F. Bollenbeck and U. Seiffert, "Robust classification of the nutrition state in crop plants by hyperspectral imaging and artificial neural networks," 2011 3rd Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS), Lisbon, 2011, pp. 1-4, doi: 10.1109/WHISPERS.2011.6080898.

De Bei, R., Fuentes, S., Gilliham, M., Tyerman, S., Edwards, E., Bianchini, N., … Collins, C. (2016). VitiCanopy: A Free Computer App to Estimate Canopy Vigor and Porosity for Grapevine. Sensors, 16(5), 585. https://doi.org/10.3390/s16040585

Edwards, E. J., Smith, J., Walker, A., Barril, C., Boettcher, A., & Foster, D. (2017). Targeted manipulation of vine balance : does vine balance directly affect fruit composition? In K. Beames, E. Robinson, P. Dry, & D. Johnson (Eds.), Proceedings - Sixteenth Australian Wine Industry Technical Conference (pp. 96–100). Retrieved from https://awitc.com.au/proceedings/16AWITC.pdf

Harrison, M. T., Edwards, E. J., Farquhar, G. D., Nicotra, A. B., & Evans, J. R. (2009). Nitrogen in cell walls of sclerophyllous leaves accounts for little of the variation in photosynthetic nitrogen-use efficiency. Plant, Cell & Environment, 32(3), 259–270. https://doi.org/10.1111/j.1365-3040.2008.01918.x

Lacar, F. M., Lewis, M. M., & Grierson, I. T. (2001). Use of hyperspectral imagery for mapping grape varieties in the Barossa Valley, South Australia. IGARSS 2001. Scanning the Present and Resolving the Future. Proceedings. IEEE 2001 International Geoscience and Remote Sensing Symposium (Cat. No.01CH37217), 6(C), 2875–2877. https://doi.org/10.1109/IGARSS.2001.978191

Llorens, J., Gil, E., Llop, J., & Escolà, A. (2011). Ultrasonic and LIDAR Sensors for Electronic Canopy Characterization in Vineyards: Advances to Improve Pesticide Application Methods. Sensors, 11(12), 2177–2194. https://doi.org/10.3390/s110202177

Macfarlane, C.; Hoffman, M.; Eamus, D.; Kerp, N.; Higginson, S.; McMurtrie, R.; Adams, M. Estimation of leaf area index in eucalypt forest using digital photography. Agric. Forest Meteorol. 2007, 143, 176–188.

Martinetz, T., Schulten, K.: A “Neural-Gas” Network Learns Topologies. In: Kohonen, T., Mäkisara, K., Simula, O. (eds.) Artificial Neural Networks, vol. 1, pp. 397–402 (1991)

Mazzetto, F.; Calcante, A.; Mena, A.; Vercesi, A. Integration of optical and analogue sensors for monitoring canopy health and vigour in precision viticulture. Precis. Agric. 2010, 11, 636–649.

Moghadam, Lowe, & Edwards. (2020). Digital Twin for the Future of Orchard Production Systems. Proceedings, 36(1), 92. https://doi.org/10.3390/proceedings2019036092

Parry, C., Blonquist, J. M., & Bugbee, B. (2014). In situ measurement of leaf chlorophyll concentration: Analysis of the optical/absolute relationship. Plant, Cell and Environment, 37(11), 2508–2520. https://doi.org/10.1111/pce.12324

Patel, N. K., C. Patnaik, S. Dutta, A. M. Shekh, and A. J. Dave. 2001. “Study of Crop Growth Parameters Using Airborne Imaging Spectrometer Data.” International Journal of Remote Sensing 22 (12): 2401–2411. doi:10.1080/01431160117383.

Popescu, S.C., Wynne, R.H. & Nelson, R.F. (2003), Measuring individual tree crown diameter with LIDAR and assessing its influence on estimating forest volume and biomass, Canadian Journal of Remote Sensing. Vol. 29(5): 564 – 577.

Serbin, S. P., Dillaway, D. N., Kruger, E. L., & Townsend, P. a. (2012). Leaf optical properties reflect variation in photosynthetic metabolism and its sensitivity to temperature. Journal of Experimental Botany, 63(1), 489–502. https://doi.org/10.1093/jxb/err294

Siebers, M., Edwards, E., Jimenez-Berni, J., Thomas, M., Salim, M., & Walker, R. (2018). Fast Phenomics in Vineyards: Development of GRover, the Grapevine Rover, and LiDAR for Assessing Grapevine Traits in the Field. Sensors, 18(9), 2924. https://doi.org/10.3390/s18092924

7.4 Staff

Ordered by role, research organisation and home site

Research scientists

Everard Edwards
Mark Thomas
Stephen Gensemer
Giacomo Betti
Matthew Siebers
Mick Schaefer
Peyman Moghadam
Tom Lowe
Ross Dungavell
Emili Hernandez
Ryan Lagerstrom
Dadong Wang
Udo Seiffert
Uwe Knauer

Technical staff

Don MacKenzie
Adam Smith
Najid Periera-Ishak
Paul Adkins
Wytse Gensemer
Tarita Shiraishi Furlan
David Haddon
Stephen Brosnan

7.5 Monitoring and evaluation

Project management was as planned at the start of the program, with six-monthly written reports to Wine Australia and steering committee meetings with Wine Australia, the industry reference group and the leaders of the other projects within the RRD4P program led by Wine Australia every six to twelve months. These were normally hosted by CSIRO Agriculture and Food and included detailed presentations on work since the previous steering group meeting. The meetings were useful to get some industry feedback on the project and this was used to help focus the direction of the work.

The project has successfully demonstrated a range of technology applications as detailed above and this has helped the program achieve its objectives of generating new knowledge and technologies to benefit primary producers and to build collaborative linkages between research and industry.

7.6 Budget

A budget reconciliation will be provided separately.