INTEGRATED VINEYARD PRECISION CONTROL SYSTEM PILOT





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Abstract

This project provides the foundational work to road-test key components of a digital vineyard guidance system that is designed to facilitate costs-of-production savings for Riverland growers. Outcomes include: (i) an audit of underpinning technologies that would support the digital guidance system; (ii) a long-range wide area network (LoRaWAN) base station at the Loxton Research Centre; (iii) a 'proof-of-concept' ground-based image retrieval system to provide visual imagery of vineyard development over time; and (iv) an open-source dashboard that can provide decision-relevant information to growers. Case studies are used to demonstrate potential grower value in terms of labour and operating cost savings.

Executive Summary

This pilot project represents a collaboration between engineers, scientists and economists from the University of Adelaide, in partnership wine grape growers in the South Australian Riverland spanning a six month period in the first half of 2019. The long-term ambition of the collaboration is to create an operational digital system that collates a variety of information that collectively can help increase information transferability, transparency and ease-of-access, support on-farm decision making, and create a return on investment both to Riverland growers through improving gross margins and profitability. This report documents the outcomes of 'stage 1' of this process, which has been designed to provide foundational proof-of-concept work to road-test all the key components of a comprehensive digital vineyard guidance system, thereby paving the way for developing operational systems in subsequent stages.

The project leverages substantial and accelerating advances both in Australia and internationally in a range of agricultural technologies, spanning sensing, connectivity, data analytics, automation and prediction. Taken as a whole, these technologies have the potential transform vineyard processes by enabling near real-time tracking and/or future prediction of vineyard decisions (e.g. irrigation, spraying, nutrition, canopy management), resource utilisation (e.g. labour, machinery, water, energy, nutrition and other chemicals) and vineyard performance (growth, yield and other measures of vine development). The vision is that by digitally linking 'actions' undertaken by growers on the vineyard with 'outcomes' (both physical outcomes such as yield and quality measures, and financial outcomes such as gross margins and profitability), it becomes possible to develop predictive analytics and advisory services to optimise vineyard decision making.

In addition to this high-level vision, the work in the pilot project responded to the following design criteria identified by Riverland growers in the early project stages:

- The need for systems to provide guidance and advice (e.g. when to irrigate or spray), rather than simply displaying data;
- The need for 'producer led' innovation models to develop operational field-tested systems that can be rapidly adopted by growers, rather than focusing on technologies that are 'stuck at the bench' or that do not move beyond proof-of-concept or pilot phase;
- The need to focus on cost-of-production issues to achieve 'fit-for-purpose' grape quality as a means of increasing gross margins and profitability, and the associated need to provide an economic lens over the technology development to ensure grower benefit;
- The need for open systems that support interoperability between different sensing systems, algorithms and visualisation solutions (e.g. dashboards), rather than multiple (often proprietary) systems that are not interoperable and can create technology 'lock-in' issues for growers; and
- The need to account for the unique characteristics of the South Australian Riverland, including being a large-area bulk growing region with very large-scale operations.

To this end, the specific outcomes of the 'stage 1' pilot project are summarised as follows:

- An assessment was conducted of the 'technology readiness level' of a range of technology solutions that can potentially be incorporated into a digital viticulture guidance system, including a review of sensor systems, connectivity solutions, algorithms and modelling solutions. The assessment found a high level of maturity *of in-situ* sensors, but less maturity in other data acquisition systems (e.g. vision data, financial data, other grower records). Commercial adoption of algorithms that 'value add' on data remains low in the viticulture industry, and integrated solutions that translate data streams to advice and decision recommendations are limited.
- A review of space-borne data acquisition streams showed a high level of technological maturity in terms of spatial, temporal and spectral resolution, yet only a small subset of potential use-cases have thus far been commercialised within a viticultural context. Potential applications of space-borne data streams in the pilot successfully demonstrated the detection of spatial anomalies in vigour using a range of satellite products with different resolutions, temporal frequency, record lengths and pricing structures.

- A proof-of-principle mobile ground-based image retrieval system was developed and demonstrated to work in-field for a range of realistic operating conditions (i.e. realistic tractor speed, vibrations and light conditions), with high potential for cost-effective 'incidental' data capture. The system is currently tractor-mounted and uses a multi-camera system to provide visual spectrum imagery (i.e. high resolution photos) and photogrammetric information that provides information on canopy size, volume and density.
- Long-range wide area network (LoRa WAN) technology was selected as the demonstration communications technology due to its low cost, long range and increasing breadth of compatible sensor options. A LoRa base station was installed and operationalised at the Loxton Research Centre, with demonstrated range up to 18 km (directionally dependent, based on line-of-sight). The technology was demonstrated using set of meteorology, soil moisture and plant sensors at the Sherwood Vineyard, located 3.5 km from the Loxton research centre.
- Computer vision technology was applied to detect bunches within a canopy, and segment key canopy elements such as bunches, canopy, trunk, and green shoots. An assessment of potential future applications of machine learning to enable monitoring of canopy indicators, flowers, berries, bunches, diseases, weeds and water shoots is provided.
- Conceptual approaches to numerically modelling physical and biological processes in the context of vineyards were identified, focusing on models that: (i) estimate and predict vine development; (ii) predict grape quality; (iii) estimate and predict yield; (iv) estimate and predict disease risk; and (v) simulate on-farm operations. The review included both machine learning and mechanistic (biophysical) modelling approaches. Pathways to develop systems that provide guidance and advice by building on existing research platforms were reviewed.
- An open-source data storage and visualisation (i.e. dashboard) system was developed that presents real-time data feeds to growers, including 'internet of things' data, satellite data, ground-based imagery from the tractor-mounted camera system, historical water pricing information and management records (e.g. spray records).
- Preliminary estimates of grower costs highlighted significant year-to-year operating cost variations across vineyards, with the largest incurred costs being hired labour, followed by contracts, interest payments, water, and repairs and maintenance. A scenario-based assessment using a small (<10 ha), medium (11-80 ha) and large farm (>80 ha) highlighted areas of pre-existing technology investment, and identified potential areas for digital technologies to save water, electricity, fuel and/or labour costs, as well as the potential to increase overall farm yield.
- Preliminary benefit-cost estimates found considerable quantitative economic benefits from digital agricultural solutions that targeted decision making, with a benefit-cost ratio conservatively estimated to be 3.38, indicating that for each dollar invested, the grower would receive a return of $3.38.

It is recommended that future project phases continue to build the open-source digital viticulture platform, with the following elements in mind:

- A visualisation platform that provides a 'one-stop-shop' for all key data streams relevant for grower decisions, with a focus on ease-of-access and display;
- A benchmarking app that enables growers to compare key on farm attributes (e.g. resource utilisation per ha, yield per ha, etc.) with anonymised 'similar' vineyards;
- A series of prediction services focusing on yield, objective quality measures and disease risk; and
- A series of advisory services, focusing on infrastructure management (e.g. adequacy of irrigation infrastructure design, and any infrastructure malfunction such as leaks and blockages), irrigation requirements, water market investments, canopy management, nutrient management and spray management.

Foreword – Riverland Wine

In June 2018, Riverland Wine (RW) invited the University of Adelaide to travel to the Riverland to participate in a 'Hack-Fest' between a team of Riverland winegrape growers and a team of senior academics from the Australian Institute of Machine Learning and the Faculty of Engineering, Computer and Mathematical Sciences (ECMS). The purpose of the exercise was to introduce the academics to the business and practical aspects of winegrape growing in the Riverland and to explore ways and means of potentially reducing production costs. Wine Australia was invited to observe the process. Over the following few months, the ***Integrated Vineyard Precision Control System Pilot Project*** emerged, and funding arrangements entered into for the foundational project. Consortium members, Riverland Wine, Wine Australia and the South Australian Government, provided pilot level funding to commence a 'foundational' project in collaboration with the University. The proposed outcome of the project was to develop a vineyard guidance system that would enable vineyard operators to utilise digital instruments, platforms and dashboards to enhance decision-making, reduce risk and enhance profitability.

In the light of the region's production dominance, its significant contribution to regional wealth and industry levy funds, the membership accepts it has responsibility to encourage collaboration and linkages between researchers, practitioners and policy-setting forums. This foundational project has underscored that position with significant cash and in-kind contributions. The region's undisputed scale, sophisticated infrastructure, track-record of innovation, production stability and its willingness and capability to co-invest, offer an outstanding platform for trialling viticultural innovation. Growers and producers are poised for the new Australian wine era, confident that the foundations are sound, ready and agile to respond quickly to the increasing demands for versatility and diversity with new and emerging technologies.

The region's growers and producers are resilient, skilled viticulturists, irrigators, wine makers and marketers. Collectively they have confronted and met the challenges presented by two decades of supressed grape and wine prices in domestic and international markets. Necessity has driven innovation and best practice. Growers aspiring to be more productive and efficient have been compromised by a lack of financial and non-financial production indicators or benchmarks. To validate cost of production savings, such systems will be crucial. The ***Integrated Vineyard Precision Control System Pilot Project*** will drive innovation in that space.

The harsh reality confronting winegrowers in the Riverland in 2019 is that inland region winegrapes are no longer competitive with other permanent, horticultural crops, including nuts, citrus and stonefruit. It is imperative that new, affordable technology solutions be developed, in consultation with practitioners in the region, to realise the potential visualised at the June 2018 Hack-Fest. RW members are ready, willing and able to play a key support role.

Chris Byrne
Executive Chair
Riverland Wine

Foreword – University of Adelaide

Agrifood and wine is not exempt from the Industry 4.0 revolution, and Agriculture 4.0 is upon us. The agrifood and wine sector understands that new technologies, robotics, artificial intelligence, big data and more sustainable systems are essential for efficiency and marketability. In this regard, food and wine producers and processors of this and the next generation need to embrace solutions that include these technologies on top of their existing knowledge and understanding of production systems.

This is the context for this project, but I knew the project was going to work as we stood there in the vineyard in mid 2018. Riverland growers described in detail the pain points for their business operations and a group of engineers and scientists, bussed into the Riverland for two days, debated the best solutions for the challenges raised. This process of consultation has produced an industry-lead viti-tech program of work with outcomes that are demanded by and by turn methods that will be taken up by the viticulture industry.

This is an exciting pilot project, but as the range of technologies that can be applied into the agriculture and viticulture sectors expand, these types of interdisciplinary projects will be in higher demand and will be required to allow production methods to keep pace with the rate of change in the sector and to develop novel solutions that improve production in a changing world.

But projects like this don't happen by accident. Behind the scenes is a dedicated and supportive group. Seth Westra and Bree Bennett and the 'Nerdy Nine' project team from the University of Adelaide have done an outstanding job of developing the program of work iteratively with the project stakeholders, delivering what was promised and keeping the work on track and partnerships together to this point – final delivery; Chris Byrne and the 'Thinking Ten' from Riverland Wine and the Riverland region opened up and welcomed the group in and were prepared to change the way things were done and present an honest account of challenges faced by the sector, which allowed the project to focus on real solutions; Paul Dalby from the Australian Institute of Machine Learning who had the vision to bring these groups together and facilitated the interactions and translations across the divide between industry and academia, as well as Liz Waters and Paul Smith from Wine Australia who supported us and came with us on the journey.

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1. Background

1.1. Project origins and philosophy

The 'integrated vineyard precision control system pilot' project is a foundational project conducted in the first half of 2019 and funded by the Riverland Wine Industry Development Council, Wine Australia and the South Australian Wine Industry Development Scheme. The initial conceptualisation of the project arose through discussions between researchers at the University of Adelaide (including staff with expertise in machine learning, mechatronics/robotics, satellite and drone-based remote sensing, water resources and environmental modelling) and growers in the Riverland in mid-2018. These discussions focused on identifying the needs and 'pain points' of grape vine growers in the region, and led to an emphasis on technology development that can reduce cost of production as a core principle of the project design.

From these initial discussions, a multi-stage collaborative vision emerged to work towards a 'digital vineyard guidance system' that will help growers optimise production processes, manage risks and drive continual improvements in vineyard profitability and sustainability. The focus on this system is on the Riverland growing context—a large-area bulk growing region with unique technology needs due to their scale of operation and market position. Ultimately, the ambition for this guidance system is to provide real-time information on current and projected future status across a vineyard, and provide guidance to growers to enable the optimisation of farm management decisions. The foundational project documented in this report represents 'stage 1' of this longer term vision, providing proof-of-concept work to test all the key components of the proposed system.

It is widely recognised that the digitisation of Australian wine grape production has the potential to bring significant economic, environmental and social benefits. There have been many technological advances over the past 20 years in sensing, connectivity, analytics, automation and prediction—the combination and integration of which are providing significant opportunities for vineyard process intensification ('more with less') and thus direct benefits on the grower bottom line. In particular, many technologies have the potential to optimise vineyard inputs (e.g. labour, water, energy, fertiliser, pesticides and herbicides) and capital expenditure for on-farm equipment, enable fit-for-purpose grape production, and thereby improve overall productivity and efficiency. Leonard et al. (2017), in the final report for the Precision to Decision Project, estimates that if digital agriculture is fully implemented in Australia, this would boost the value of agricultural production by 25% (compared to 2014-15). This is an increase of $20.3 billion to the gross value of agricultural production (GVP), translating to an estimated increase of $706M specifically for the grape and wine sector.

Although the potential estimates of benefit from digital technologies span the full grape and wine value chain, there are some applications that are unique to wine grape growers in the Riverland, due to its position as a high productivity region largely growing for the bulk-wine market that operates on very low margins. To grow (or even maintain) these margins and increase profitability, there is an ongoing need to find efficiencies in vineyard processes as input and labour costs continue to rise. An added challenge is that past research and industry experimentation has typically focused on precision viticulture and 'high end' wine production; however, there has been limited focus on solutions for the volume market (Arnó Satorra et al., 2009).

Yet despite the optimism of digital agriculture's potential for improving grower outcomes, discussions with Riverland grape growers during the project scoping phase revealed that uptake of existing technologies remains relatively low in practice. Indeed, advice from Riverland Wine suggests that most growers still monitor performance and predict yields through a combination of manual and remote measurements taken throughout the growing season that are typically taken infrequently and at sparse randomised locations. Likewise there are difficulties with existing methods of monitoring in separating out the effect of grower interventions, climate conditions and other factors on vine performance.

To combat these issues, there is a need for strategic projects that effectively translate research and development into impactful outcomes and commercially available services for growers. This includes carefully considering how to include producer views as part of the strategy to accelerate end-user adoption.

Importantly, the perception of most producers regarding technological innovations is significantly influenced by their peers; as such, peer networks have a critical role in generating conversations that propagate information and reduces perceived risks and uncertainties surround new technology. The successful facilitation of technology adoption therefore requires producer groups to be deeply involved in the assessment (and development) of new approaches or technologies.

As a result, the emphasis in this foundational project is on how to leverage research and technologies that have been developed but are not currently operationalised or adopted in the Riverland context. Consultation and collaboration with the Riverland grape growers has been embedded throughout the project by 'road-testing' various emerging technologies, and iteratively identifying the potential value of different use cases. Although stage 1 focuses on proof-of-principle work rather than technological deployment, this iterative feedback has directly influenced the project direction on multiple occasions, and will provide excellent foundations for the design and scoping of subsequent stages of the digital vineyard guidance system.

1.2. Project overview and guiding principles

The longer-term ambition for the digital vineyard guidance system is to, via close collaboration with growers, develop open-access digital systems that focus on guidance and advice (rather than simply the presentation of data streams), and has sufficient flexibility to respond to grower feedback and leverage new technologies and capabilities as they become available. A key element is the integration of multiple disparate streams (not only including physical vineyard characteristics, but also recording management actions and financial information) into a single digital 'point of truth'. When coupled with predictive tools and the capability to control a number of aspects of vine and vineyard management (e.g. canopy management, variable rate watering, etc.), this will provide the basis for optimal control of farm inputs and outputs.

The emphasis of the 'stage 1' pilot is to road test all the key components of a comprehensive vineyard guidance system, including the basic dashboard and systems architecture, on-farm IoT sensors and connectivity systems, as well as collect remotely sensed vineyard information and RGB images of vines. The project was designed with the following considerations in mind:

- **A 'producer led' approach –** where growers and researchers work collaboratively on the digital vineyard guidance system and provide iterative feedback on technology development. This iteration is made possible via feedback from growers on functionality and value of each component to ensure that the platform delivers maximum value for the growers and region.
- **An inter-disciplinary team** – comprising technologists (including experts in machine learning, machine learning, mechatronics/robotics, satellite and drone-based remote sensing, water resources and environmental modelling), economists and viticulturists, with a strong focus on knowledge exchange and collaboration between the team.
- **An open source philosophy** – to ensure that the technology can be shared and built upon by the grower and research community beyond the lifespan of the immediate project, avoiding 'lock-in' and allowing the platform to leverage a vast array of existing and available open-source technologies (communication networks, algorithms, online dashboards, crop models).
- **Stepped development of systems, technologies and processes** – whereby the development pathway is broken down into a set of achievable 'stages', with each stage providing immediate value to stakeholders, while also being an essential step towards further development.

In terms of key technologies and components, the digital vineyard guidance system can be conceptualised as comprising five essential components that contribute towards the ultimate goal of integrating new and established technology with established viticultural knowledge. These are:

- **Sensing (data acquisition)** – incorporating multiple sensing and data streams at the soil (e.g. moisture, salinity, temperature), plant (e.g. microclimate, plant water status, bud count, sugar content) and farm level (consumption of water, energy, fertilizer and pesticide rates);
- **Connectivity, Data Processing and Handling** – incorporating options for transmission and processing of the multitude of data streams in keeping with an open-system philosophy;

- **Situational Awareness and Prediction** – in the form of a dashboard platform for collating, visualising, and analysing data as well as providing predictions to enable 'what-if' scenarios to explore different intervention options;
- **Insights and Observations** – in the form of understanding current vineyard status and likely future status in terms of canopy development, nutrient status, water balance and a range of other key facets of the vineyard; and
- **Interventions and Controls** – in the form of targeted crop interventions strategies (e.g. canopy management, sprays, fertiliser, irrigation) which the grower can potentially implement at fine resolutions in space and time (e.g. variable rate application).

These five elements are represented graphically in Figure 1 as the translation of multiple data streams, via a range of connectivity options, to a 'digital twin' of the vineyard that houses the data and algorithms that reflect current and projected future vineyard state. This in turn enables visualisations that can then be translated to insights of the vineyard for the purpose influencing decisions that improve vineyard outcomes.

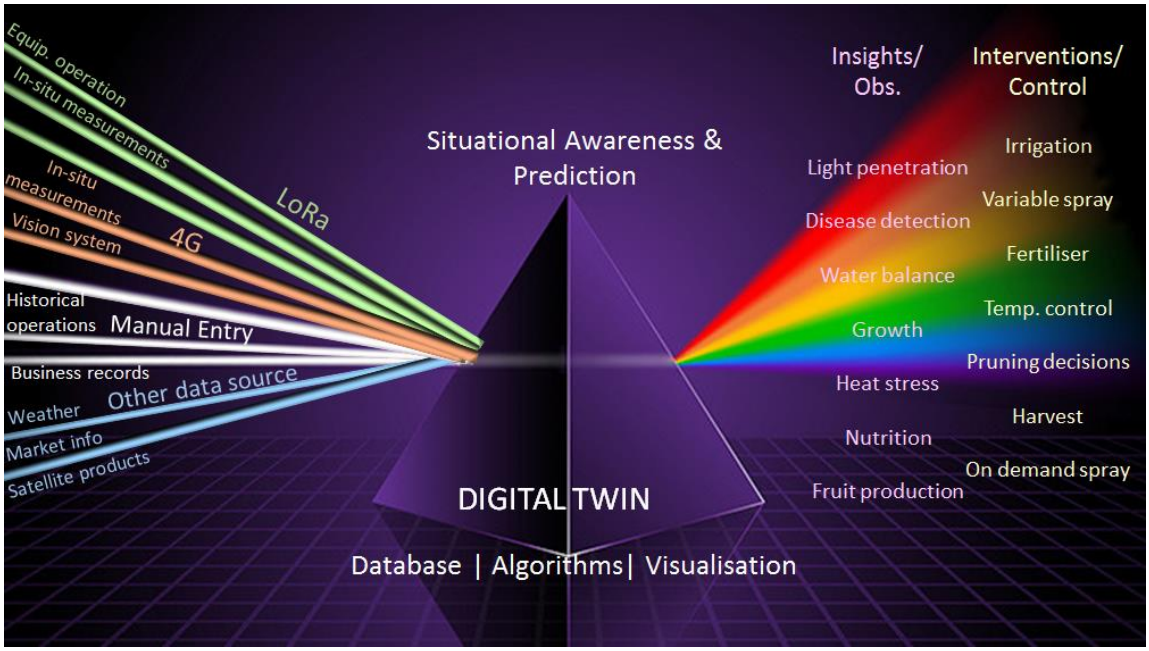


Figure 1 – Schematic of the proposed digital vineyard guidance system

The approach taken in this project represents a radical departure from many existing digital ag-tech offerings, which tend to focus either on information display (rather than guidance to enable decision making), and/or have been designed based on either a single use-case or a small number of use-cases. In particular, current ag-tech offerings often draw on either a small number of data streams, and/or focus on data visualisation rather than using this to provide guidance on operational on-farm decisions.

The philosophy taken in this project around comprehensive curation of multiple data sources into a single digital solution should not in any way diminish the value of existing platforms, of which many have been tested in the market and have demonstrated value to growers by virtue of their increasing uptake. However, it is likely that the next generation of such tools will become increasingly comprehensive in their data acquisition, and in doing so focus on cycling up the information value chain from data and information display, through to prediction, alerts and grower advice. It is indeed likely that the combinatorial power of multiple data streams (for example the combination of economics data with data on historic grower decisions such as watering and canopy management, and then with vineyard outcomes) is only gradually being exploited. *Exploration of what opportunities exist to add value to vineyard operations through carefully curating and combining multiple data streams is indeed at the heart of what the 'digital vineyard guidance system' seeks to achieve.*

Building such a system takes time and a long-term vision. Currently, it is clear that data standardisation and interoperability are major barriers for enabling the vision of digital agriculture, slowing the ingestion and 'valorisation' of data streams. These barriers do not only exist within the field of viticulture; indeed multiple agricultural sectors (e.g. broadacre horticulture) are experiencing strikingly similar challenges. Progress will no doubt be made over the coming years through building common data standards and APIs, and reducing the cost of connectivity. For example, at the time of writing, the three Riverland councils are planning on installing a long range wide area (LoRa) network throughout the Riverland that will facilitate greater adoption of 'Internet of Things' solutions. Other issues, such as privacy, data security and ownership, are also major challenges particularly when sensitive data such as financial data is integrated into these systems.

The approach taken in the pilot was first to test a wide range of components of an integrated system such as that illustrated in Figure 1, identifying available datasets and overcoming emerging challenges along the way. In parallel, economic case studies and regular end-user engagements were used to identify the priority 'use cases' in terms of grower information needs and major cost centres, to help ensure that initial efforts are directed to areas that can add the greatest and/or most immediate value. Throughout this process, the project sought to build on the vision whereby it is the combination of multiple datasets where the most unrealised (or 'latent') value can be obtained, over and above the many ag-tech solutions already commercially available to growers.

1.3. Evaluating the maturity of potential technological solutions

A key priority identified by Riverland growers is the need to translate basic and/or applied scientific research into operational products. To this end, a critical component of the 'stage 1' review is to assess the availability and 'readiness' of technology for rapid integration and adoption into useable tools that can drive down costs of production and improve operating margins. A key element is to identify the sweet spot of technology readiness: technologies that are too immature will mean that the development timelines are likely to be too long for rapid medium-term grower adoption; in contrast, technologies that are already very mature are likely to have been commercialised already, unless they are re-conceptualised as component inputs to other less mature (and likely more integrated) technologies.

A structured approach is taken in this report to enable this evaluation, including those proposed for further development in subsequent stages of this work. To this end, it is noted that the development of new and/or unproven technologies—or translation of science 'at the bench' to widely adopted operational systems—typically follows a defined lifecycle with different phases of technology maturity. The concept of 'technology readiness levels' (TRLs), originally designed by NASA but now used widely within various industrial settings, provides a measure of technological maturity and can assist in the identification of further aspects of technology development required to achieve a fully operational system, often as a commercial product[1].

In this report, the TRL concept is applied to 'critical technology elements' (CTEs) of a digital vineyard guidance system, which, for the purpose of this report, are defined as 'at risk'[2] technologies that may be critical for the successful deployment of the guidance system, but that are '*new or are being applied in novel ways or environments*' (US Department of Energy, 2011). The TRL of each CTE is represented on a nine-point scale (Table 1), which has been adapted from definitions by the US Department of Energy (2011), the CRC for Optimising Resource Extraction (2015), and the US Department of Agriculture (2016). The TRLs attached to individual CTEs of the digital vineyard guidance system are summarised in the relevant parts of Sections 2 to 5 of this report. Once the TRL of each CTE is established, technology readiness levels of various potential 'use cases' can then be ascertained by identifying the lowest-TRL sub-component of the system, which therefore represents the 'limiting technology' of the proposed system.

[1] The concept of TRLs can also be used for public good technologies that are operated by governments or through open source communities, and thus the technology development life cycle does not always need to lead to commercial outcomes.

[2] For completeness, some mature system sub-components are also reviewed in this report as part of the critical technology elements analysis, and these are given high TRL values to denote that they are no longer considered 'at risk'.

Table 1 - Description of technology readiness levels for use in assessing agricultural technologies. Adapted from US Department of Energy (2011), the CRC for Optimising Resource Extraction, and the US Department of Agriculture (2016).

Relative Level of Technology Development	Technology Readiness Level	TRL definition	Description
Preliminary Technology Solution Evaluation	TRL 1	Basic principles observed & reported	This is the lowest level of technology readiness. Scientific research begins to be translated into applied R&D. Examples include identification of industry challenges that the scientific research is capable of addressing, and the potential for the science to modify industry practice. Supporting information includes published research or other references that identify the basic principles that underlie the technology.
Experimental testing	TRL 2	Technology concept &/or application formulated	Once basic physical principles are observed, the next level involves identification or invention of practical application of those principles. This can include estimation of the value of the technology relative to existing technologies that achieve a similar purpose, or the capacity of the technology to achieve new outcomes.
	TRL 3	Analytical & experimental critical function &/or characteristic 'proof of concept'	Active research and development is initiated. This includes analytical studies and laboratory scale studies to physically validate the analytical predictions of separate elements of the technology. At TRL 3 work has moved beyond the paper phase to 'proof-of-concept' experimental work that verifies that the concept works as expected. Components of the technology are validated, but there is no attempt to integrate the components into a complete system.
Technology Development (Pre-Commercial)	TRL 4	Component and/or system validation in laboratory environment, and initial value proposition	The basic technological components are integrated to establish that the pieces will work together. This is relatively 'low fidelity' compared with the eventual system. TRL 4-6 represents the bridge from scientific research to engineering. TRL 4 is the first step in determining whether the individual components will work together as a system. The system will probably be a mix of on-hand equipment and a few special purpose components that may require customisation to get them to function.
	TRL 5	System model tested in simulated or realistic environment	The basic technology components are integrated so that the system configuration is similar to the final application in almost all respects. The major difference between TRL 4 and 5 is the increase in the fidelity of the system and environment to the actual application. The system tested is almost prototypical.
Technology Demonstration (Pre-	TRL 6	System model tested on end user site with refinement of	Engineering-scale models or prototypes are tested in an end-user site environment. Potential commercial partners will have been identified or already engaged. TRL 6 begins true engineering development of the

Commercial)		positive value proposition	technology as an operational system. The prototype should be capable of performing all the functions that will be required of the operational system.
System Commissioning	TRL 7	Full-scale system prototype, demonstrated on end-user site	This represents a major step up from TRL 6, requiring the demonstration of an actual system prototype at an end-user site. The prototype should be near or at the scale of planned operations, and have commercial partners involved.
	TRL 8	Commercially relevant system deployed on end-user site with proven value proposition	The technology has been proven to work in is final form and under expected conditions. This TRL usually represents the end of system development, and can include integration of new technology into an existing system. Outcome is often the commercial manufacture and site uptake of the technology.
Commercial Deployment	TRL 9	Actual system proven reliable through operation	The technology is in its final form and operated under the full range of operating (environmental conditions). Final bugs are fixed and the technology is routinely implemented.

1.4. Report structure

The emphasis of 'stage 1' is the provide a wide exploration of current and emerging technologies, followed about an assessment of options for system integration to address real-world cost of production issues faced by growers. This was done through a combination of:

- Audits of key technology components (or 'critical technology elements') identified in Figure 1, including in terms of technology readiness levels and potential utility for various use-cases
- 'Proof-of-principle' development of several critical technology elements, including a ground-based vision system and dashboard
- An economic assessment on likely value to growers, focusing on case studies.

This review follows conceptual organisation of elements in Figure 1. This commences with a short summary of methods given in Section 2 followed by the presentation of data acquisition technologies in Section 3, and the connectivity, data processing and handling systems in Section 4. This is followed by data analysis and visualisation (Section 5), including the presentation of the machine learning algorithms developed and the prototype vineyard dashboard.

Following on from a review and 'proof-of-principle' development of key critical technology elements, a value assessment of the technologies and case studies are presented in Section 6. Outcomes and recommendations of the project are then presented in Sections 7 to 9.

2. Method

This foundational project focuses on test and developing a diverse range of sensor technologies (e.g. on-farm IoT sensors, RGB images of vines acquired from a ground-based system and satellite imagery) as well as the development of the basic dashboard systems and architecture for inclusion in a comprehensive vineyard guidance system. An economic assessment of the likely value to growers is also provided, including case studies considering small, medium and large example farms. Table 2 summarises the methods applied in carrying out each of the project tasks. The results pertaining to these investigations are presented in Sections 3 to 6.

Table 2 - Summary of methods used.

Task	Method(s) Used
Pilot network of IoT sensors and infrastructure	Detailed review of Internet-of-Things (IoT) technologies for different grower contexts including an evaluation of range, data rates, wireless standards and the TRL of each solution to provide guidance on suitable technologies for a range of grower contexts. Deployment of a pilot IoT network for a test vineyard site in the Riverland, comprising the installation of a LoRa gateway and on-farm sensors (i.e. stem dendrometer, weather station, four multi-depth soil moisture and temperature probes and electro conductivity) as well as coverage mapping for the LoRaWAN gateway.
Evaluation of remote sensing products for viticultural applications	Detailed review of remote sensing products for different viticultural applications including an assessment of the TRLs of the products in consultation with experts in agricultural and environmental remote sensing. Collation of a range of remote sensing products that cover different spatial, temporal and spectral resolutions for the vineyard test site. Examination the utility of remotely sensed vegetation vigour for grape growers via application to the vineyard test site.
Development of a proof-of-principle vision based sensing system and processing algorithm.	Design and fabrication of a proof-of-principle mobile ground-based vision acquisition system comprising three RGB cameras as well as testing under a range of environmental (e.g. light conditions, grapevine variety, grapevine age) and operating conditions (e.g. tractor speed). Collection of RGB imagery using the developed vision system for a range of grapevine varieties (i.e. Chardonnay, Shiraz, Negroamaro and Red Fronti) at different maturities (e.g. young 1-year and 2-year grapevines as well as mature 15-year old grapevines) in the 2018-19 growing season. Development of machine-learning algorithms for the localisation and segmentation of key vine features (e.g. green shoots, canopy, berry bunches and trunk). Detailed evaluation of potential future applications of computer vision algorithms for improved vineyard monitoring and decision making.
Proof-of-principle dashboard platform	Design of potential open-source architecture for the dashboard including consideration of multiple data formats, data transfer and storage. Design of a proof-of principle dashboard to display data collected within this project (e.g. RGB imagery, remote sensing information, on-farm sensors, farm business data) and from third parties (e.g. weather forecasts and water

	market data) for a demonstration vineyard in the Riverland in consultation with Riverland growers. Interviews were conducted to collect grower feedback on the proof-of-principle dashboard. Detailed literature review of data-driven and process-based numerical models for predicting vineyard outcomes (e.g. yield, vine development, quality and disease risk) considering agricultural, environmental modelling and computer science journals.
Technology value assessment	A literature review of existing data on winegrape production in the Riverland and engagement with Riverland growers and viticulturists on typical vineyard management action and timelines for the Riverland. Scenario-based assessments for three example farm categories (small <10 ha, medium 11-80 ha and large >80 ha) to identify areas of pre-existing technology investment and potential areas that could incur savings as a result of investment in specific digital technologies. Face-to-face interviews were conducted to collect grower financial and non-financial data for these case studies. A benefit-cost analysis, conducted in accordance with the Federal (Department of Finance 1991) and South Australian (Department of the Treasury 1990) guidelines, to identify quantitative economic benefits from investment in digital agricultural solutions that target decision making.

3. Data acquisition technologies

Key findings

- A detailed audit of *in-situ* sensors highlighted the breadth of commercial or near-commercial sensor technologies available, principally for measuring weather, environmental variables, soil moisture and salinity, plant development and on-farm infrastructure. Sensors are increasingly developed with multiple connectivity options to ensure cost-effective real-time data availability, and many commercial solutions for sensor deployment exist.
- Air and space-borne sensor solutions have reached a high level of technological maturity in terms of spatial, temporal and spectral resolution, yet only a small subset of potential use-cases have been commercialised for viticultural applications, indicating significant potential for further development. Illustration of potential applications in the pilot demonstrated success in detecting spatial anomalies in vigour for a range of satellite products with different resolutions, temporal frequency, record lengths and pricing structures.
- Mobile ground-based camera sensors are only beginning to be developed and commercial solutions are not yet readily available, but these systems are likely to have the greatest potential as a 'new' data stream to provide added value on canopy indicators (e.g. growth, disease). A proof-of-principle mobile ground-based image retrieval system was developed during the pilot and demonstrated to work in-field for a range of realistic operating conditions (i.e. realistic tractor speed and light conditions), with high potential for 'incidental' data capture. The system is designed to be modular and thus can be mounted to a tractor (the application adopted in this pilot), quad bike, or (in the longer-term) autonomous vehicle to obtain regular vision capture of canopy development throughout the growing season.

The foundation of future digital agriculture rests on an exponential increase in our capacity to cost-effectively observe and monitor key aspects of on-farm production. The data sources are diverse, each by itself providing an incomplete picture of key physical fluxes (e.g. salinity, nutrients, water, energy), processes (e.g. canopy development, soil health), risk factors (e.g. disease risk factors, spray drift conditions), vineyard outcomes (e.g. yield, quality), and/or farm finances (e.g. costs of production and profit). Examples of key sources of data include:

1. Fixed (*in-situ*) sensors, that may monitor a range of features often continuously at single point locations. These include traditional sensors such as weather stations and soil moisture stations, as well as emerging sensors measuring a broad range of on-farm attributes;
2. Remote sensors, which may be mounted via satellite, UAV, fixed wing aircraft or via ground-based deployment such as tractor mounted, and may be collected quasi-regularly (e.g. via satellite) or on demand for most other mounting options;
3. Economic indicators related to costs of production (e.g. costs of water, energy, chemical, machinery, labour) as well as profit line items; and
4. Grower activities (e.g. spray diaries, irrigation records, canopy management and so forth).

Each of these data streams has the potential, through integration, to form the building blocks of digital solutions. Given the breadth of potential data streams to underpin digital agricultural solutions, this section provides a subset of key streams relevant to viticultural contexts—focusing on fixed and remote sensor systems that are arguably the most common data stream for existing digital solutions. Economic data streams are briefly covered in Section 6. Data on grower activities are not covered in detail in this report given this data is currently sparse and difficult to collect systematically, but constitutes a recommendation for further development in Section 9.

3.1. Continuous direct and proximal sensors

'Smart agriculture' is a concept that is based around the implementation of sensors and related technologies for monitoring of environmental, soil and plant parameters that are often used independently, but increasingly via integrated platforms for a global 'view' of the farm and crop's condition. In this section we review the range and state-of-the-art of proximal sensors for continuous monitoring of environment, soil and plant performance that can assist grape growers in improving management efficiency vis-à-vis yield, quality and resource utilisation. Following a review of individual sensor types, a tabulated summary is presented of the range of direct and proximal sensors used in agriculture and viticulture for modelling environment, soil and plant status.

3.1.1. Meteorological Sensors

Ground-based sensors to continuously measure meteorological variables such as air temperature and relative humidity have been available for several decades. These sensors typically form components of automatic weather stations and are essential to growers to observe short-term weather events as well as longer-term climate trends. Indices relevant to crop growth such as growing degree days (GDD), which is essentially thermal time, can be obtained from weather station data. In the viticulture context, GDDs closely relate to phenological stages of grapevine development, including berry development and ripening. The sensors are typically powered by portable solar panels, which are becoming more efficient and cost-effective options to using mains power that is often not available in vineyards. The solar panels are required to provide additional power to transmit the sensor (weather) data to cloud-based data servers or a nearby computer, as well as store the data locally. Data quality from these sensors is of paramount importance and therefore routine calibration is required, typically done by the manufacturer. Sensor data is either stored locally or, more typically, transmitted wirelessly using a point-to-point connection or via a wireless sensor network to a cloud-based server, which then can be accessed by end users.

Weather station-derived micro-meteorological data is widely used in vineyards to monitor patterns of grapevine growth, likelihood of diseases (e.g. downy mildew), and to enable decision making around resource applications such as water and fungicides. Weather data can be derived from regional Bureau of Meteorology (BoM) weather stations; however, differences between the micro-environments between the BoM weather station location and the vineyard means highly localised data is advantageous in situations where there is topography or large distances involved. In many cases, weather data can be integrated with other ground-based sensors such as soil moisture sensors, or plant sensors (e.g. leaf wetness) to provide indications of irrigation requirements or the potential of downy mildew infections.

Whereas precipitation and other forms of water input (e.g. from the irrigation system; see Section 3.1.5 below) are relatively easy to measure using on-farm sensors, water exports including groundwater and evapotranspiration fluxes are more challenging to estimate. Typically, evapotranspiration estimates are obtained indirectly based on evaporative potential derived from micrometeorological data (e.g. temperature, humidity, wind and solar radiation), and calculated through energy balance models such as Penman-Monteith. Additionally, crop evapotranspiration is often calculated via the use of crop coefficients and reference evapotranspiration, with crop coefficients highly variable between and within seasons for a given block (Williams and Ayars, 2005). Such approaches typically have significant simplifying assumptions particularly for heterogeneous canopies such as is the case for viticulture; however there are no commercially viable alternative solutions for characterising evaporative fluxes from vineyards. For example, weighing lysimeters have been used to measure the amount of water lost via evapotranspiration for research purposes by calculating the weight of a system (plant and soil) before and after the addition of water by precipitation or irrigation (Williams and Ayars, 2005). These are also expensive and impractical for use at scale in operational viticultural environments. Likewise, advanced meteorological sensors such as those that form flux towers for eddy covariance measurements (e.g. gas analysers, sonic anemometers), are used for scientific investigations of actual evapotranspiration because of their accuracy; however their high costs and required expertise, are not practical tools available for growers. Although a national network of

flux towers are available via the TERN OzFlux network (Beringer et al., 2016), to our knowledge there are no flux towers that have been established for viticulture applications.

3.1.2. Environmental Sensors

A number of environmental (non-meteorological) sensors including those for disease monitoring and smoke detection are becoming increasingly prevalent as these offer the ability to respond to either insect pests and fungal or bacterial diseases, biosecurity incursions into vineyards (e.g. phylloxera for grapevines), as well as, increasingly, the threat of smoke-related taints in grapes and wine due to bushfires.

Tools to detect and monitor various pests and diseases in the vineyard include phylloxera detection using DNA-based (qPCR) testing of soil samples (Pearce et al., 2018) geofencing software ('Project Boundary Rider'), which is an 'App' that tracks human movement that may result in spread of pests, diseases and weeds across SA vineyards; and spore traps to detect the level of fungal diseases of the trunk (e.g. *Eutypa lata*) and leaves (powdery and downy mildews) using loop-mediated isothermal amplification assays (Thiessen et al., 2018). Research is currently underway to detect several grapevine viruses on both symptomatic and asymptotic leaves at the University of Adelaide; this work has completed ground-based detection using visible (RGB) and hyperspectral cameras, and is migrating to their use on mobile platforms (Pagay et al., 2018).

Smoke-tainted wines result from exposure of grapes to smoke in the vineyard. Sources of smoke can be bush (forest and grass) fires and stubble burning, which can release particulate matter, volatile organic compounds and other gases into the atmosphere putting nearby vineyards at risk to exposure. The critical timing of this exposure is reported to be post-veraison (AWRI, 2018)) although earlier stages of grape berry development are also potentially at risk. Being able to detect low levels of smoke could help growers mitigate grape exposure to smoke by using strategies such as sprinklers or misters to remove particulate matter from the air before or after contact with the berries. Research is underway at the University of Adelaide with assistance from AWRI (see press release UoA, 2019). Sensors that detect smoke are based on air ionization, photoelectric detection, nephelometers, or, commonly, particulate matter (e.g. $PM_{2.5}$). These sensors can be combined with existing micrometeorological sensors (described above) to provide an integrated assessment of the risk of smoke exposure and taint to grapes/wine. For example, high temperatures combined with smoke increase the risk of both berry dehydration (shrivel) and smoke taint precursors (chemicals, particulates) attaching to the berry cuticle. Various commercial sensor options exist (e.g. Attentis Technologies (Fig. 1), Arduino-IoT, etc).



Figure 2 Attentis smoke sensor (https://attentistechnology.com/)

3.1.3. Soil Sensors

The utilisation of various sensors to monitor dynamic (i.e. time-varying) physicochemical parameters of the soil has increased over the past decade with increasing technological developments and lower deployment

costs. Some commonly measured parameters include moisture content and tension (matric potential), salinity (as electrical conductivity), and temperature. Soil moisture content measurements using microwave (dielectric) approaches have been demonstrated to provide reliable estimates (Rao and Singh, 2011) and have the convenience of being continuous and with various communication options. These sensors are already widely utilised in agriculture, vineyards included, for irrigation scheduling based on volumetric water content at specific depths as the data is relatively easy to interpret by growers (e.g. Sentek EnviroScan soil data probes). Multi-depth units provide richer information on the availability and root extraction of soil moisture in response to rain events and/or irrigation applications. Sensors based providing estimates of matric potential such as tensiometers or granular matrix sensors (e.g. gypsum block, Watermark) are lower in cost than dielectric-based sensors and have lower maintenance requirements, but have a limited lifespan usually lasting 3-5 years. They are slower to respond to changes in soil moisture compared to dielectric sensors and generally do not work well at very low soil moisture levels. Multi-purpose probes that track other soil properties simultaneously with moisture are also available (e.g. Sentek EnviroScan soil data probes can measure volumetric water content, electro-conductivity and temperature).

The choice of soil moisture sensor in a vineyard depends on soil type and irrigation strategy. In most South Australian vineyards, gypsum blocks and dielectric sensors are well-suited due to their extended range of measurement (in drier soils requiring irrigation). Coupling of these sensors to meteorological or environmental sensors is an option in commercial systems (e.g. Davis Instruments have soil moisture sensor coupled to automatic weather stations).

Soil salinity is of concern to many Australian and South Australian growers due to the high levels of salt in irrigation water and increased build-up of salts in vineyards in low rainfall years. Yield declines have been observed in grapevines when salt concentrations in the soil water exceeds 3.3 dS/m or 2.1 dS/m in some varieties (Walker et al., 2002, Walker et al., 2004) (CSIRO). Rootstocks have been bred to mitigate against this in high salinity soils; these rootstocks retain the salt within the roots system (high salt accumulators) rather than transferring the salt to leaves and fruit, leading to negatives impact on yield and quality (i.e. a salt tasting fruit) as well as vine health (e.g. leaf scorching, stunted shoot growth). Measurement of electrical conductivity (EC) in a soil solution generally provides an estimate of salinity; EC is proportional to the concentration of ions in the solution and can enable the tracking of salinity build up and well as transport within the soil. Commercial salinity sensors or EC meters can measure up to 20 dS/m and typically also provide temperature measurements. IoT versions are yet unknown although some of the existing offerings on the market (e.g. Sentek Enviroscan) are being retrofitted with LoRa radios, Bluetooth, etc. communications technologies.

Recently, a new nitrate sensor ('Field Nutrient Sensor') has been developed, which is being commercialised by Supra Sensor Technologies—a company from Oregon (US). Nitrate sensing in soils is relevant where ammonium nitrate is used as a fertiliser and is at risk of being leached out of the rhizosphere. Nitrogen leached into water bodies or streams can lead to eutrophication. However, there is a trade-off with avoiding high soil salinity levels. Continuous measurements of nitrogen in the field can enable data-guided fertigation and reduce costs associated with manual soil sampling and analysis.

3.1.4. Plant Sensors

A majority of sensors available on the market are targeted at estimations of crop water status. This focus largely stems from the interest in water savings technologies in irrigated agriculture as the price of freshwater continues to increase. Various classes of sensor for plant water status measurements exist.

Dendrometers are based on linear variable displacement transducers (LVDTs) that monitor small changes in the diameter of stems or trunks of plants (Figure 3). The difference between the diurnal variations in diameter (maximum minus minimum) provides the 'mean daily shrinkage' (MDS), which is related to the water stress of the plant. Some models are enabled with wireless connectivity, e.g. LoRa. Use of these sensors is currently being investigated in other South Australian viticultural regions (i.e. Coonawarra) in terms of how this information can be used to improve irrigation decisions thereby increase water use efficiency, for improved grape and wine quality and increase profitability.



Figure 3 - Dendrometer (http://phyto-sensor.com)

Measures of cell turgor (or hydrostatic pressure) are useful to know the water status of single or multiple cells. Single cell measurements of turgor are possible using a cell pressure probe, which is primarily a research tool. Turgor measurements on entire leaves are now possible using the ZIM-probe (Figure 4), a pair of magnetic sensors that clamp on to the leaf to measure small changes in leaf thickness (influenced by cell turgor). These sensors also have wireless connectivity and can be used in the field although the measurements of single leaves makes extrapolation to the plant or vineyard very error prone. Hence, these are not practical tools for vineyard operational decision making.



Figure 4 - Yara ZIM leaf probe

Routine measurements of water potential—the energetic status of water—in leaves and stems are often done using a leaf pressure chamber, a robust and portable instrument that has been used to monitor crop water status since the 1970s. These measurements correlate well with water flux (transpiration) measurements from a leaf, and also to soil moisture, hence to date is one of the more reliable measures of crop water status, together with porometry, which measures stomatal conductance. The drawback of both instruments is that they are single-leaf measurements that are not automatable. Recently, continuous measurements of stem water potential have been made possible with a novel 'microtensiometer', a stem-embedded sensor that is being commercialised through FloraPulse, a US-based startup (Figure 5). The advantage of continuous measurements include the ability to automate the control of irrigation pumps and larger data volumes over multiple timepoints.

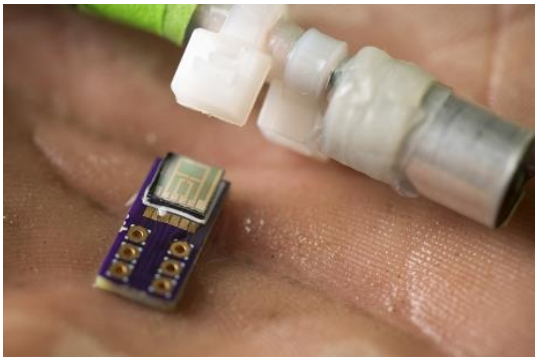


Figure 5 - FloraPulse microtensiometer (http://www.florapulse.com/)

Interest in continuous sensing of crop water stress has also recently led to the development of temperature-based crop water stress sensors such as the Athena thermography (infrared, IR) tower. These sensors work on the principle that water stressed plants have reduced transpiration and thereby higher leaf temperatures compared to well-watered plants. The technology is undergoing commercialisation and has LoRa-based communication capability.

Although commercial sensors exist for the measurement of xylem cavitation, which occurs under high water stress conditions, this option is not convenient or cost-effective for growers, and a degree of interpretation is required to enable decisions making on irrigation. They are therefore primarily a research tool.

3.1.5. Irrigation Monitoring Sensors

Irrigation monitoring can be based on changes in pressure or flow rates in addition to knowing the valve status. For example, pulse flow meters are available commercially to track deliveries of water through irrigation systems. These systems can be connected wirelessly via remote terminal units (RTUs), integration boxes that read pulsed outputs from the meter and transmit data via LoRa radio or telemetry. This technology could be valuable in identifying specific vineyard locations where there may be either blocked or leaking lines and drippers.

Historically these irrigation faults would have been only detected manually through visual inspection by an operator and potentially following a significant delay between the fault occurring and fault detection. This has the potential to lead to the loss of vines and the creation of vine water stress. For example, blocked lines may result in high vine water stress that can lead to potential reductions in yield and quality. In contrast, leaking lines result in the loss of water and again decrease water use efficiency and potentially lead to a reduction in grape quality. Monitoring irrigation efficiency at high spatial resolutions will allow growers to track and respond to these types of irrigation system failure in real-time.

3.1.6. Summary of continuous direct and proximal sensors

Table 3 presents a sample of direct and proximal sensors used in agriculture and viticulture for monitoring environment, soil, and plant performance. The sensors listed are at different ‘technological readiness levels’ (TRLs), which characterises their ability to be easily deployed and used by growers. The sensors can be divided into non-continuous and continuous categories, the former usually involving destructive sampling whereas the latter involving non-destructive sampling. The advantage of non-destructive sampling is that continuous measurements can be made and data can be integrated into control systems for feedback control of the operation; for example for irrigation pumps and other on-farm equipment. These continuous sensors can be coupled to wireless communication technologies for rapid data acquisition, and for this reason are the focus of the review.

In reviewing the technology readiness level of individual sensors within an agricultural context, it should be noted that the greatest challenge with field-deployed continuous sensors is their ability to function reliably under harsh and often extreme conditions, including heat, direct sunlight, animal damage, rain, and/or physical damage from vineyard machinery. These features can also be considered when it comes to

deploying sensor systems that are capable of providing information for grower decisions. For example, the ability to build redundancy into the network by having multiple sensors per location is one strategy to minimise the risk of sensor failure. A similar approach can be taken for communications technologies; having more than one pathway to the database or server would minimise the risk that data access or transmission from the nodes (sensors) would be or delayed or fail. Lastly, sensor system design—including sensor placement—should account for factors such as placement (e.g. in sheltered environments away from direct exposure to spray chemicals, vineyard machinery, or extreme weather) and maintenance (including scheduling, cleaning, checking battery life, and general maintenance of the unit). The highest TRL ratings are therefore reserved for sensor systems that been commercially deployed taking each of these factors into account.

Table 3 – TRLs for continuous direct and proximal sensors

Data source	TRL	Comments	Ease of application for decision making	Examples of commercial options
Meteorological sensors				
Weather station: air temperature, relative humidity, wind speed and direction, solar radiation, rainfall, barometric pressure	9	Multiple commercial solutions exist for farm-level meteorological sensing, and sensor development was not considered in pilot. Connectivity options such as LoRaWAN emerging.	Easy	MEA, Davis, HOBO, Atmos, Campbell Scientific, Bosch (IoT)
UV sensor	9	Can be integrated into existing data loggers with several options for connectivity.	Easy	Apogee Instruments, Vishay (IoT)
Flux towers: gas analysers for water and carbon fluxes	9	Primarily a research tool for actual evapotranspiration measurement; impractical for growers.	Difficult	LI-COR, Campbell Scientific, Tule Tech.
Actual evaporation - Class A Pan	9	Relatively expensive	Easy	MEA, HyQuest, Campbell Scientific
Environmental sensors				
<u>Smoke</u>: **Sensors based on ionization, photoelectric, nephelometer, particulate matter (e.g. $PM_{2.5}$)**	8	Although commercial options exist, sensitivity to diluted smoke drift from distance may be an issue.	Moderate	Attentis, Honeywell, Sensirion (IoT), Bosch
<u>Disease monitoring</u>: **Leaf wetness sensor**	9	Can be integrated into existing data loggers with several options for connectivity.	Easy	Campbell Scientific, METER, Davis, ADCON

Molecular (DNA-based) e.g. LAMP	7	Not yet automatable; primarily for research	Moderate	TBD
Hyperspectral cameras	5	Ground-based validation successful for virus detection; not continuous	Difficult	Not commercialised
Soil sensors				
<u>Moisture content:</u> **Neutron probe**	9	Phased out due to radiation risks	Moderate	ICT Intl. (Hydroprobe)
Gamma ray attenuation	9	Phased out due to radiation risks; relatively high cost.	Moderate	
Dielectric techniques: - **time domain reflectometry**	8	Not compatible with most data loggers; options for connectivity are limited.	Moderate	Campbell Scientific
- **frequency domain reflectometry**	9	Capacitance probes are widely used in agriculture; can be integrated into existing data loggers with several options for connectivity.	Easy	Sentek, Decagon (Meter), Whitebox Labs (IoT)
<u>Water potential (tension):</u> **Tensiometers**	9	Used in agriculture but limited use in vineyards	Easy	METER, Irrometer
Thermal conductivity	8	Data logger options available	Easy	PlantCare (IoT)
Electrical resistance	9	Data logger options available	Easy	Campbell Scientific, Irrometer (IoT)
Psychrometer	7	Not practical for growers to use	Difficult	ICT Intl., Wescor
<u>Salinity</u>: **Electrical conductivity**	9	Can be integrated into existing data loggers with several options for connectivity.	Easy	METER, Sentek, Spectrum Tech., Hanna

Temperature: **Soil temperature probe**	9	Can be integrated into existing data loggers with several options for connectivity.	Easy	Campbell Scientific
Nitrates	7-8	Being commercialised; wireless connectivity option	TBD	Supra Sensor Technologies
Plant sensors				
Dendrometry	8	Commercial options exist with data logging	Moderate	ICT Intl., Phytek
Leaf turgor pressure: - **Cell pressure probe**	5	Primarily research tool	Difficult	TBD
- **Magnetic pressure clamp (Zim Probe)**	6	Primarily research tool; wireless capability	Moderate	Yara ZIM
Water potential (tension): - **Leaf pressure chamber**	9	Not automatable; robust; widely used	Easy	PMS Instruments, Soil Moisture Equipment
- **Microtensiometer**	6	Data logging options exist; can offer wireless in the future	Moderate	FloraPulse
Acoustic emissions	6	Not automatable; primarily a research tool	Moderate	Physical Acoustics
Water flux: - **Porometry**		Not automatable; some use by vineyard consultants	Easy	METER, Delta-T, LI-COR
- **Sap flow**	8	Some use in commercial farms; data logging and connectivity options	Moderate	Dynamax, ICT Intl.,

<u>Leaf/canopy temperature:</u> - **Thermography tower**	7	Advanced testing in commercial vineyards; data logging and connectivity options	Easy	Athena Irrigation Technologies
Irrigation monitoring sensors				
Pulsed flow meters	9	Commercial options exist	Easy	Netafim, Toro, Hunter, Bermad

3.2. Air and space-borne remote sensing

Remote sensing by satellite, aircraft or unmanned aerial vehicles (UAV) comprises to a suite of technologies whereby biophysical properties are measured remotely, usually through the distinctive interaction of some form of radiation (e.g., visible light, infrared or thermal radiation, or microwaves as in RADAR) with a specific physical or biological phenomena. These technologies have been adopted in numerous fields including agriculture (Shanmugapriya et al., 2019), oceanography (Devi et al., 2015, Rajeesh and Dwarakish, 2015), hydrology (Rango, 1994, Xie et al., 2016, Tang et al., 2009), geology (van der Meer et al., 2012), and for various vegetation measures including vegetation mapping (Xie et al., 2008), evapotranspiration (Liou and Kar, 2014, Zhang et al., 2016), leaf area index and fractional cover (Carlson and Ripley, 1997). These latter vegetation applications illustrate the ability of remote sensing to measure biophysical variables of direct relevance to vineyard management.

Within vineyards, remote sensing has been demonstrated to be capable of measuring (or being used to map) the following quantities:

- water stress (Baluja et al., 2012, Zovko et al., 2019);
- evapotranspiration (William P. Kustas et al., 2018);
- chlorophyll$_{ab}$ content (at both leaf and vineyard scale; (Zarco-Tejada et al., 2005);
- leaf area (Johnson et al., 2003);
- fractional green vegetation cover (Tondriaux et al., 2018);
- canopy extent (Pádua et al., 2018);
- grape phenolics (Lamb et al., 2004);
- phenological metrics (e.g., start of season, end of season; (de Castro et al., 2018);
- grapevine variety (Gutiérrez et al., 2018b);
- discrimination between diseased and healthy vines;
- discrimination of one vine disease from another (i.e. *Flavescence dorée* (FD) from grapevine trunk disease (GTD) (Albetis et al., 2018); and
- vine vigour zones and within-vineyard variability (Tondriaux et al., 2018).

These derived data streams have the potential to be used for a wide range of applications, ranging from improving water efficiency, variable fertilizer and spray application, and yield and quality prediction. However, in common with some other areas of agricultural technology reviewed in this report, there has been relatively little adoption of remote sensing methods by the grape and wine industry. One of the barriers to adoption may be the highly technical nature of remote sensing; all aspects of remote sensing, from imagery acquisition, through essential pre-processing (to ensure quality), to analysis and mapping require specialised skills. However, the capacity to automate workflows regarding remote sensing applications continues to increase due to a range of technological advances, and there is now a significant body of relevant past research that can provide the basis for integration into application-ready tools.

3.2.1. Tailoring remote sensing technologies to sensing goals

Table 4 presents a range of remote sensing goals that are potentially relevant for the viticulture industry, including a review on appropriate 'technology readiness levels' of individual applications, as well as guidance on the appropriate:

- spectral resolution, which ranged from simple three-band red-green-blue (RGB) cameras (Pádua et al., 2018), multi-band multispectral sensors (Khaliq et al., 2019, de Castro et al., 2018) through to hyperspectral sensors with hundreds of spectral bands (Zarco-Tejada et al., 2005, Zovko et al., 2019, Gutiérrez et al., 2018b);
- spatial resolution, which ranged from much smaller than a vine-row (e.g., 5 cm, as in (Matese et al., 2015)) to much coarser (e.g., 250 m, as in (de Castro et al., 2018)); and
- temporal resolutions ranged from single date (Baluja et al., 2012) through to acquisitions every 5 to 16 days over a growing season (Khaliq et al., 2019, William P. Kustas et al., 2018) to daily acquisitions over years (de Castro et al., 2018).

In interpreting the table, it is important to consider a number of important caveats. In particular, the appropriateness of a given resolution (spatial, spectral or temporal) is heavily dependent on the phenomenon being measured, and is not necessarily intuitive. For instance, if the goal was to map vine water status, the obvious method would be thermal imaging: vines with ample access to water will respire freely and the state-change of water will cause their temperature to be low; while water-stressed vines will respire less, and consequently have a higher temperature. Indeed, Baluja et al. (2012) demonstrated a strong relationship between vine leaf stomatal conductance (LSC) and stem water potential (SWP) and remotely sensed temperature (R^2 = 0.68 and 0.50 respectively). However, Baluja et al. (2012) also found that vegetation vigour indices were arguably better measures of plant water status (R^2 = 0.84 for the best measure). This was likely due to the factors affecting vine water status being longstanding (e.g., soil properties), and therefore having influenced vine growth substantially over a period of weeks. However, if the goal had been to detect plant water stress caused by an irrigation failure, the effectiveness of the two methods would likely have been reversed. Thermal imaging would likely be effective in just one or a few days in hot weather (as soon as vines became water stressed and reduce respiration their temperature would increase), while the v*e*getation vigour indices would likely take a little longer (leaf cell structure is a major driver of vegetation vigour indices, so as leaf cells lose turgor and wilt these indices will produce lower and lower values).

Thus, selection of an appropriate spectral measure is not trivial. In the above example, method-appropriateness is influenced by both the proximal goal (measure plant water status) and the ultimate goal (e.g., either mapping the influence of soil on plant water status, or detecting irrigation failure). Other application areas are similarly nuanced. With these caveats in mind, the following is provided as a non-exhaustive guide to the technical requirements for different monitoring goals. The absence of an item from the guide does not mean it is not amenable to remote sensing. Design of remote sensing solutions should be done by—or in consultation with—an experienced imagery analyst.

A final comment is that higher-resolution is not ‘always better’. Increasing resolution significantly increases data storage and processing requirements, and can counterintuitively reduce result quality significantly. Lower resolutions (with pixel sizes coarser than leaves) allow measurement of the ‘whole-of-plant’, and complexities such as leaf geometry, shadow and leaf reflection are all compensated for in the integrated signal. Higher resolutions (with pixel sizes finer than leaves) capture this within canopy variation, and may require substantial additional work to compensate for these effects. However the value of this additional workflow would need to be assessed on a case-by-case basis, relative to the intended application for which the imagery is to be used.

Table 4 – Technology readiness levels (TRLs) and spectral, spatial and temporal resolutions for a range of remote sensing goals.

Sensing goal	TRL	Spectral	Spatial resolution (indicative)	Temporal resolution (indicative)	Notes
Canopy extent of each vine	9	RGB or better	Ultra-high (<10 cm)	Single acquisition	Requires UAS imagery, and generation of high-density point cloud
Single-row irrigation failure**,** tiny: **affecting only one vine (e.g., approx. 1.5 m along one row)**	1	Thermal or Multispectral	Very-high (~ 30 – 50 cm)	Very high	Temporal resolution depends on maximum acceptable delay between irrigation failure inducing water-stress, and detection of that water-stress.
Single-row irrigation failure**,** small – large: **affecting several vines in one row (e.g., approx. 6 m or longer along one row)**	1	Thermal or Multispectral	Very-high (<70 cm)	Very high	Temporal resolution depends on maximum acceptable delay between irrigation failure inducing water-stress, and detection of that water-stress.
Multi-row irrigation failure**,** medium: **many vines along 2 or more rows**	2	Thermal or Multispectral	High (3 m)	Very high	Temporal resolution depends on maximum acceptable delay between irrigation failure inducing water-stress, and detection of that water-stress.
Multi-row irrigation failure, large: **many vines along more than approx. 15 rows**	2	Thermal or Multispectral	Medium-high (10 m)	Very high	Temporal resolution depends on maximum acceptable delay between irrigation failure inducing water-stress, and detection of that water-stress.
Discriminating diseased from healthy vines**, and** one disease from another**: individual vines**	2	Multispectral or hyperspectral	Ultra-high (~ 10 cm) to very-high (~50 cm)	Single acquisition	Some success has been demonstrated discriminating discriminating vines infected with *Flavescence dorée* (FD) and grapevine trunk disease (GTD) from healthy vines, and discriminating FD from GTD vines.
Mapping grapevine variety **with** field spectroscopy	2	Hyperspectral	Imaging sensor mounted on all-terrain-vehicle	Single acquisition	
Mapping grapevine	1	Hyperspectral	High (2 m)	Single acquisition	

variety **with** airborne hyperspectral imagery					
Evaporation**,** transpiration **and total** evapotranspiration**,**	5	Multispectral	UAS and manned aircraft: Ultra-high (~ 15 cm) Landsat satellite: medium to low (30 m – 100 m) MODIS satellite: low to very-low (250 m – 1000 m)	Flux tower: ultra-high (every few seconds) UAS: at least one per growing season during model development Manned aircraft: one acquisition Landsat satellite: Moderate (1 per 16 days MODIS satellite: Very high (daily)	Very hard to do, but already demonstrated on a moderate scale in research in California; lead by United States Department of Agriculture Research Service. Relies on data-fusion of data from field flux tower, ultra-high spatial resolution UAS and manned aircraft imagery, and moderate to low resolution satellite imagery (Landsat = 30 m - 100 m, MODIS = 250 m - 1000 m).
Mapping of major soil units**, prior to vineyard establishment**	2	Multispectral or hyperspectral	High to medium-high (2 – 10 m)	Single acquisition	Imagery must be acquired while soil is bare, and preferably disturbed (e.g. recently tilled), prior to vineyard establishment.
Phenology metrics **(start of season, end of season, etc.)**	1	Multispectral	Low (250 m)	Very high	Requires daily imagery processed into 16-day cloud-free composites; currently only available from MODIS imagery at 250 m resolution, so only viable for quite large vineyards.
Mapping and prediction of end-of-season berry constituents **(colour and total phenolics)**	2	Multispectral	High (3 m)	Single acquisition	In Cabernet Savingon, some berry constituents (at harvest) are moderately predictable (r^2 ~ 0.35) from NDVI imagery collected at veraison.
Leaf area	3	Multispectral	High (3 – 4 m)	Single acquisition	TRL for this is 9 for broadacre crops. The lower TRL for viticultural application reflects the lack of application in this area, and the complexities of dealing with inter-row spaces. Measures of leaf area could inform plant growth models, or support management decisions regarding canopy management or irrigation.

Vegetation vigour **(index of total leaf area and per-leaf chlorophyll content) at single point in time**	9	Multispectral	High (3 m) to Medium (30 m)	Single acquisition	Could inform areas either of undesirably low or high vegetation growth, and support related management decisions.
Vegetation vigour **in a** seasonal context	1	Multispectral	High (3 m) to Medium (30 m)	Very high	Expected vegetation vigour temporal profiles (a graph of vegetation vigour over a growing season) could be derived for each vineyard or each pixel. Then in each new growing season, on each image date the measured vigour could be compared to the expected, and unexpected areas flagged (e.g. areas either substantially higher- or lower-than the expected vigour for that period of the season).
Vegetation vigour **in a local** spatial context	2	Multispectral	High (3 m) to Medium (30 m)	Single acquisition to Very high, as desired	For each vineyard mean vegetation vigour would be derived, and then areas of unexpected vigour flagged (e.g., areas significantly higher- or lower-vigour than the mean-vigour for that vineyard). Measure could be produced once, at a critical time of year (e.g. veraison), or as frequently as imagery allowed. It is expected that this would flag areas that were unexpectedly deviating from the management expectation for that vineyard.

3.2.2. Overview of remote sensing products

As discussed in the previous section, selection of appropriate spatial, spectral and temporal resolution requires expert weighing of the project needs, and careful balancing of trade-offs. For instance, higher spatial resolution usually requires a trade-off of reduced temporal or spectral resolution. With this caveat in mind, we have collated a list of satellite-based sensing options that cover the range of resolutions (

Table 5). The table below is not exhaustive, but is provided to illustrate the range of options. Aircraft- or UAV-mounted products are generally of higher resolution and can be adapted in terms of spectral bands, temporal resolution and spatial coverage, but tend also to be significantly more expensive than satellite-based alternatives.

Table 5 – Satellite-based remote sensing product options

Sensor	Resolution Spectral	Spatial	Temporal (revisit time)	Positional accuracy	Indicative cost
Planetscope	Multispectral (4 band; blue, green, red, near-infrared (NIR))	3 m	Daily, always acquiring (single observation, subject to cloud)	3 – 5 m	\$3.65 / km^2 / year for for new imagery \$5.60 / km^2 for dl access for a year for new imagery \$3-4 / $km^2$for viewing access \$1-2 / km^2 for dl of archival
Rapideye	Multispectral (5 band; blue, green, red, red edge, NIR)	5 m	Daily (tasked)	10 m	\$1.28 / km^2
Skysat	Multispectral (4 band; blue, green, red, NIR)	1 m	Daily (tasked, up to 2 times per day)	0.72 m	\$10 / km^2 (minimum of 25 km^2)
	Panchromatic	0.8 m			
Worldview 2	Multispectral (8 band; coastal, blue, green, yellow, red, red edge, NIR 1, NIR 2)	2 m	1 – 4 days (tasked)[3]	3.5 m CE90[4]	\$36 / km^2
	Panchromatic	0.5 m			
Geoeye 1	Multispectral (4 band; blue, green, red, NIR)	1.84 m	1 – 8 days (tasked)[5]	5 m CE90	\$36 / km^2
	Panchromatic	0.46 m			

[3] Maximum tasking frequency depends on the location of the subject area in relation to the current satellite orbit.
[4] A minimum of 90 % of measured points have a horizontal error less than the stated CE90 value.
[5] Maximum tasking frequency depends on the location of the subject area in relation to the current satellite orbit.

Sentinel 2	Multispectral (4 band; blue, green, red, NIR)	10 m	5 days	7 – 8 m CE90	Free
	Multispectral (6 band; red edge 1, red edge 2, red edge 3, narrow NIR, shortwave infrared (SWIR) 1, SWIR 2)	20 m			
	Multispectral (3 band; coastal aerosol, water vapour, SWIR cirrus)	60 m			
Landsat 8	Multispectral (8 band; ultra blue, blue, green, red, NIR, SWIR 1, SWIR 2, cirrus)	30 m	16 days	11.4 m CE90	Free
	Panchromatic	15 m			
	Thermal (2 band; thermal infrared (TIRS) 1, TIRS 2)	100 m			

3.2.3. Illustration of satellite-derived products in the Riverland

In this section, the range of spatial and temporal scales at which satellite remote sensing works is illustrated in the context of vineyards in the South Australian Riverland, and ways in which each of these scales might inform vineyard management are suggested. The following examples use the normalised difference vegetation index (NDVI)—a measure of vegetation vigour—where vigour in this context is a composite of per-leaf photosynthetic activity and the number of leaves per unit area (pixel). The NDVI is based on the contrast between red and near infra-red reflectance, and the differential reflectance in these two regions of green vegetation versus other land cover types. The index is formulated so that strongly growing vegetation produces high NDVI values, up to an index value of 0.8, whereas dead vegetation or exposed soil produce low NDVI values of approximately 0.2, and open water can result in NDVI values of 0 or lower.

The following sub-sections provide examples of the ways in which three specific space-time domains of remotely sensed imagery might inform vineyard management:

- Fine scale, high temporal frequency – PlanetScope;
- Moderate scale, moderate temporal frequency – Sentinel 2A and 2B; and
- Very broad scale, very high temporal frequency – MODIS.

This sub-section provides a simple visual illustration of the spatial resolution of these three imagery sources over a vineyard at 515 Anderson Road, Loxton North.

Aerial photography (Figure 6 A, approximately 0.5 m resolution) allows identification of row ends and accurate delineation of vineyard boundaries. PlanetScope imagery *(*Figure 6 B, 3 m resolution)

allows detection of within-vineyard variation in vegetation vigour, and quite accurate delineation of vineyard boundaries. Sentinel 2A and 2B imagery (Figure 6 C, 10 m resolution) still allows detection of within-vineyard variation in vegetation vigour for larger vineyards, and general delineation of vineyard boundaries. Finally, MODIS imagery (Figure 6 D, 250 m resolution) does not allow for mapping within-vineyard variation, and large vineyards may be covered by only one or two pixels. However, the signal recorded by each MODIS pixel is the area-weighted-mean vegetation vigour, meaning that if a pixel is mostly or wholly over one vineyard, it is recording the mean vigour of that area. This may be useful for establishing expected mean vine performance for a given vineyard at a given time of year. This expected performance could potentially be compared to measures of actual vigour derived from higher spatial resolution imagery to detect areas of either unusually high or low vigour. These methods are not likely to be appropriate for smaller vineyards.

Potential applications for different the imagery is now presented for each of the three scales.

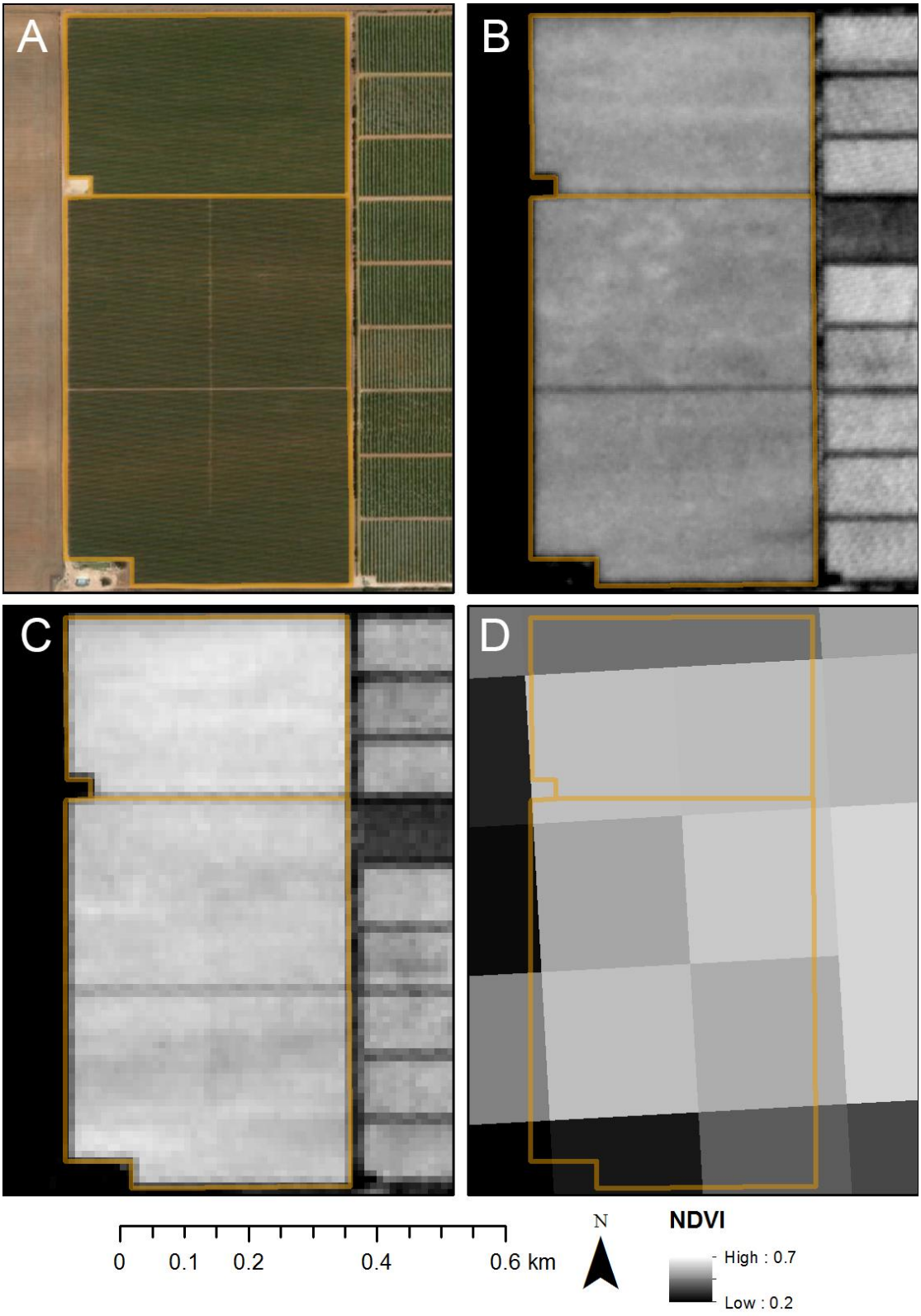


Figure 6 - Illustration of four different spatial resolutions of remotely sensed imagery, A) aerial photography true colour imagery, approximately 0.5 m resolution; B) PlanetScope NDVI imagery (24 Dec 2018), 3 m resolution; C) Sentinel 2A and 2B imagery (18 Dec 2018), 10 m resolution; and D) MODIS imagery (1 Jan 2019), 250 m resolution. NDVI values in these images range from 0.2 (bare soil / dead vegetation) to 0.7 (very strongly growing vegetation with a dense canopy). Aerial photography source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community.

Fine scale, high temporal frequency – PlanetScope

Fine scale imagery, with high temporal frequency (e.g., PlanetScope), enables examination of within-vineyard variation in vegetation vigour, and the way that vigour changes over time. PlanetScope has a spatial resolution of 3 m, and is acquired every day, though is limited by cloud cover.

Here we provide an example where a selection of four cloud free PlanetScope images acquired over two months in 2018 (13 Oct, 10 Nov, 1 Dec, and 24 Dec) has been processed to NDVI to map vegetation vigour in the vineyards at 515 Anderson Road, Loxton North (Figure 7, left column). This allows for evaluation of absolute changes in vegetation vigour from day to day, showing significant increases in overall vigour at the start of this period, and then significant overall decreases at the end.

However, in a correctly functioning vineyard all vegetation should follow a similar growth trajectory, greening and senescing at approximately the same rate and same times. Viewing absolute vegetation vigour does not enable detection of any areas that are deviating from this expected growth trajectory. We can attempt to detect these areas by calculating the change in vegetation vigour between each image date (Figure 7, right column), and determine that there are three areas where vine-vigour has decreased more than in surrounding areas between 10 November and 1 December (areas in blue boxes in Figure 7, right column).

These methods can be used to detect unusual increases or decreases in vine vigour, but not to determine their cause. These kinds of changes might result from irrigation failures or soil properties limiting growth, but field investigation would be necessary to determine the specific cause.

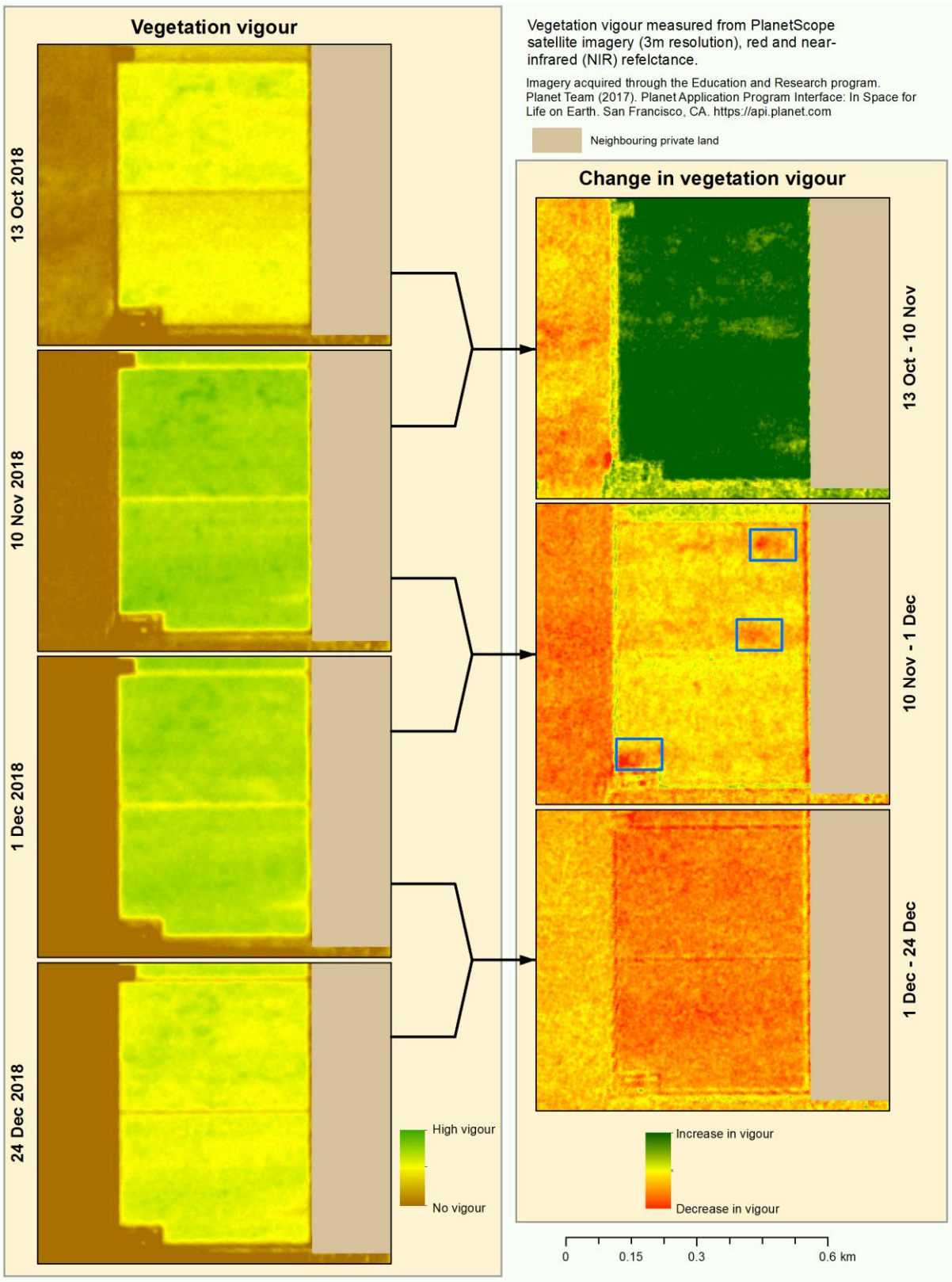


Figure 7 - Detection of unusual decreases in vine vigour (515 Anderson Road, Loxton North). Left: PlanetScope imagery (3 m resolution, available every day (subject to cloud)) mapping fine scale vegetation vigour (NDVI) on four dates over two months. Right: Change in vegetation vigour between each image date. Blue boxes (right column) highlight areas of unexpectedly large decrease in vine-vigour.

Moderate scale, moderate temporal frequency – Sentinel 2A and 2B

Moderate scale imagery with moderate temporal frequency (e.g. Sentinel 2), allows study of the way vineyard vigour changes over time. Sentinel 2A and 2B have a spatial resolution of 10 m and is acquired every 5 days, though is limited by cloud cover.

The example provided here focuses on the property at 1469c Bookpurnong Road, Loxton, and is constructed from the 53 cloud free Sentinel 2 images from 1-Jan-2017 to 21-Feb-2019 (Figure 8). On the left, 3 (of the 53) imagery dates are shown as examples (13-Dec-2017, 16-Jun-2018, and 18-Nov-2018), and two vineyards are highlighted; 19.CHA (P26) is outlined in blue, and 62.SHZ is outlined in green. On the right, time traces of vegetation vigour extracted from all 53 cloud free images are shown for the two highlighted vineyards: 19.CHA (P26) with a blue line, and 62.SHZ with green.

In combination, this figure shows 19.CHA (P26) going through a normal seasonal cycle of high vigour in summer 2017, low vigour in winter 2018, then high vigour again in summer 2018. In contrast, 62.SHZ has high vigour in summer 2017, very low vigour in winter 2018 (appearing to have been cleared), and still very low vigour in summer 2018. While only 2.5 years of Sentinel 2 data exist now, the archive will continue to grow rapidly, enabling more temporal analyses. It will be possible to extract average or expected seasonal growth profiles, and track vigour within a growing season to the expected vigour. Alternatively, it may be better to derive these expected seasonal vigour profiles form the broader scale MODIS imagery, due to its longer archive (2001 to present) and the essentially cloud-free nature of that imagery (see next section for more detail).

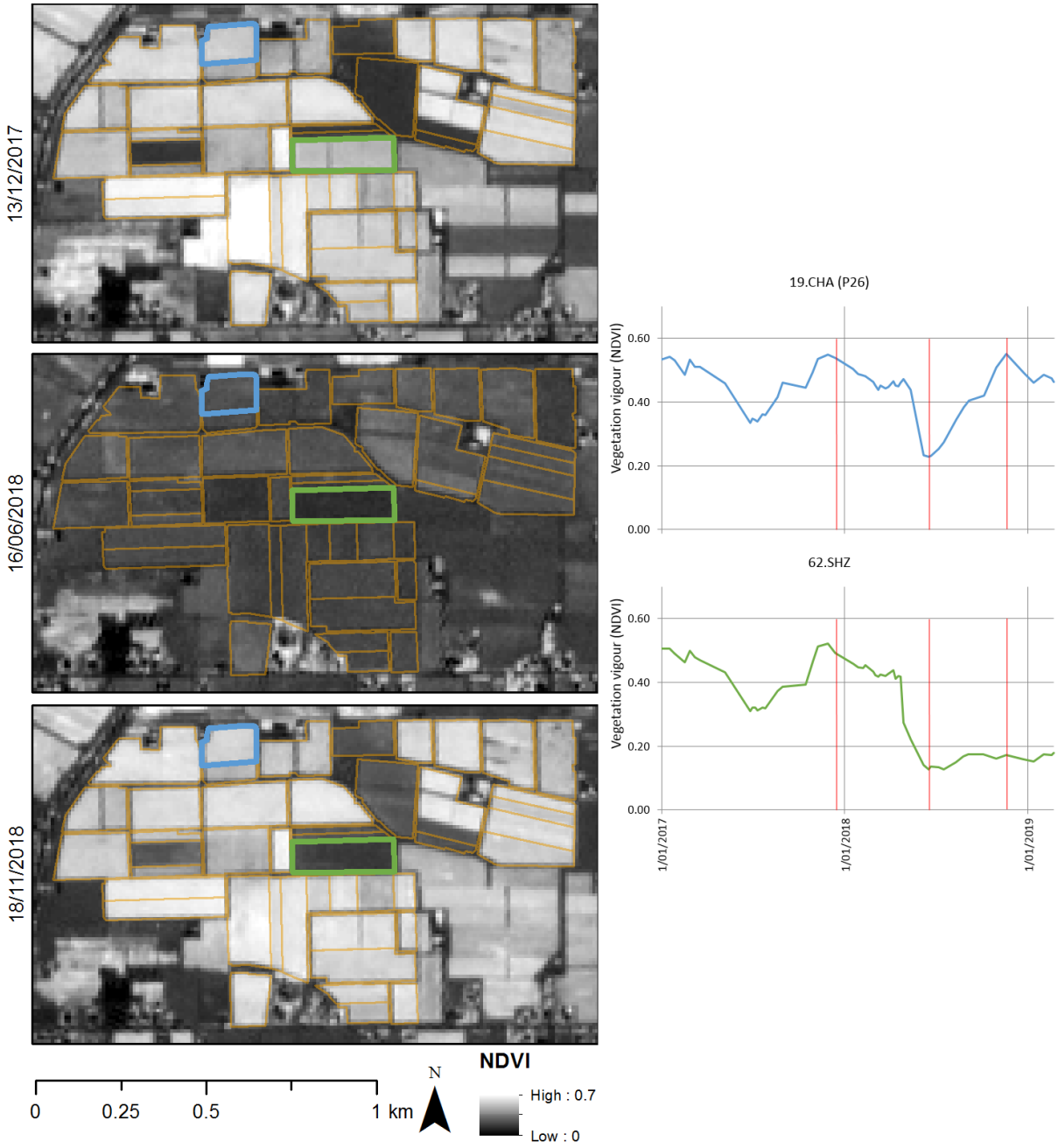


Figure 8 - Tracking whole-of-vineyard change in vegetation vigour over time (1469c Bookpurnong Road, Loxton). Left: Three dates of Sentinel 2 imagery (10 m resolution, available every 5 days (subject to cloud)) mapping moderate scale vegetation vigour (NDVI) for all vineyards in the Bookpurnong property. Two vineyards are highlighted, 19.CHA (P26) is outlined in blue, and 62.SHZ is outlined in green. Right: For the two highlighted vineyards, time trace of vegetation vigour extracted from all 53 cloud free Sentinel 2 images from 1-Jan-2017 to 21-Feb-2019 (right); red lines overlain indicate the three example imagery dates. In combination, this figure shows 19.CHA (P26) going through a normal seasonal cycle of high vigour in summer 2017, low vigour in winter 2018, then high vigour again in summer 2018. In contrast, 62.SHZ is seen to have high vigour in summer 2017, very low vigour in winter 2018 (appearing to have been cleared), and still very low vigour in summer 2018.

Very broad scale, very high temporal frequency – MODIS

MODIS imagery (250 m resolution) is very high temporal frequency (1 acquisition per day) and provides a continuous, cloud-free record of variation in vegetation vigour for almost two decades (Feb-2000 to present). This data allows for characterisation of average seasonal growth pattern, and detection of long-term trends of either increase or decrease in vegetation vigour.

The MODIS NDVI product is a cloud-free composite product available every 16 days, and is created from the highest quality cloud-free pixels in all MODIS images collected in a given 16 day period (1-2 images per day). The result is an archive of cloud-free images with complete coverage of the world every 16 days from the start of the MODIS archive (early 2001). The continuous and cloud free nature of this product enables examination of the temporal behaviour of vegetation.

Here we provide two examples, one for the vineyard 61.SHZ (P21) (henceforth referred to as 61.SHZ), 1469c Bookpurnong Road, Loxton (Figure 9), and one for the vineyard 51.CHA, 515 Anderson Road, Loxton North (Figure 10). Mean vegetation vigour (MODIS NDVI) was extracted for both vineyards for all imagery dates, and then analysing these temporal profiles with the Breaks For Additive Seasonal and Trend (BFAST) algorithm (Verbesselt et al., 2010). This algorithm detects and characterises repeating seasonal patterns, and any long term trends and breaks from those trends.

The outputs of the BFAST algorithm are the raw temporal vegetation vigour (Yt), average seasonal vigour profile (St), trends and breaks between trends (Tt), and residual variation in vegetation vigour not explained by average season (et).

Looking at the temporal vigour profile (Yt) in both examples, we see that the 61.SHZ appears to show a distinct seasonality, with periods of higher vigour from 2000 to 2002, and from 2010 to 2013 (Figure 9). Conversely, 51.CHA shows less pronounced seasonality, high maximum vigour from 2000 to 2002, then very low vigour increasing steadily from 2002 to approximately 2015 (Figure 10). Looking at the average seasonal component (St), we see that the algorithm has identified two periods of vegetation growth within each year for both vineyards. In both the main growth pulse appears to occur over summer, and is reflective of the vine canopy growth and then senescence, and this is followed by a lesser period of vegetation vigour over winter.

Finally, the trend and breaks component (Tt) has identified different long term patterns for the two vineyards. For 61.SHZ the major trends appear to show strong climatic influences, clearly showing a period of higher vigour from 2000 to 2002, then a long period of reduced and declining vigour resulting from the millennium drought (2002 – 2010), followed by three shorter term cycles started by a very high vigour year followed by small decreases in vigour in the following two years. On the other hand, the major trends for the 51.CHA vineyard show little climatic influence; a period of decline in vigour from 2000 to 2002 is followed by long steady increase in vigour from 2002 to present, starting from a very low base. It's also worth noting that the growth between 2000 and 2002 appears typical of cereal cropping (winter-spring growth followed by summer senescence). This suggests a new vineyard was established on an area of former cereal cropping land in 2002, and adequate irrigation enabled steady establishment and prevented the millennium drought from causing reduced vigour.

While MODIS data is only suitable for large vineyards, due to the 250 m resolution, these kinds of analyses may provide valuable information directly to managers (e.g., by enabling comparison of vineyards performance across space and time), or indirectly to finer scale image based analyses (by providing evidence of average seasonal vigour, to support analyses based on imagery with shorter archives).

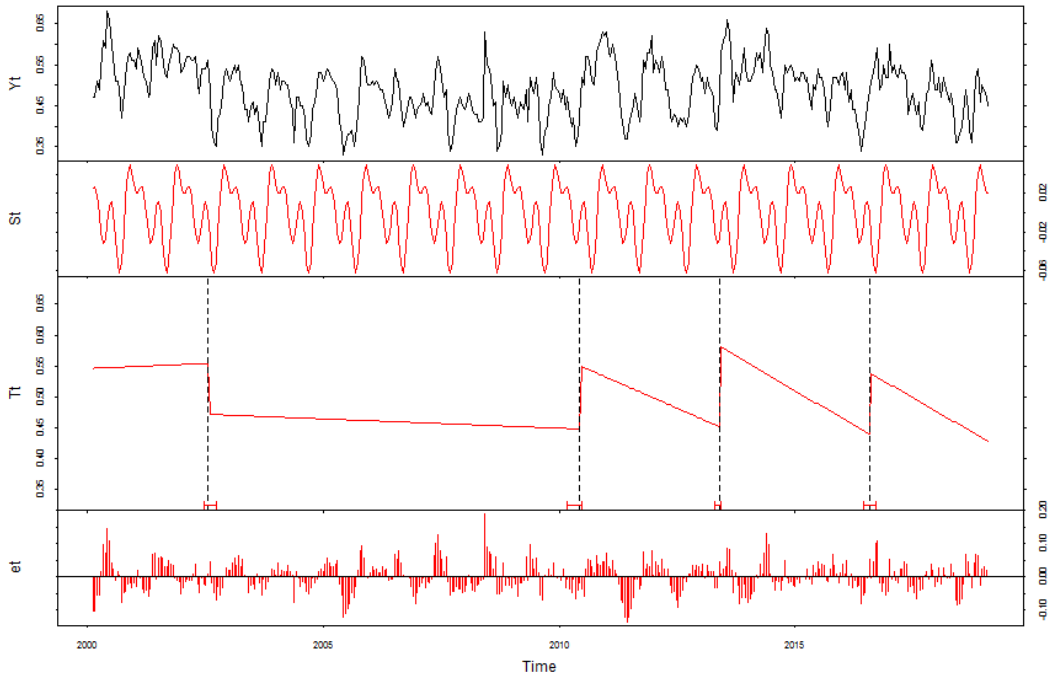


Figure 9 - Temporal vegetation vigour (Yt), average seasonal vigour profile (St), trends and breaks between trends (Tt), and residual variation in vegetation vigour not explained by average season (et), derived from MODIS vegetation vigour (NDVI), for vineyard 61.SHZ (P21), 1469c Bookpurnong Road, Loxton.

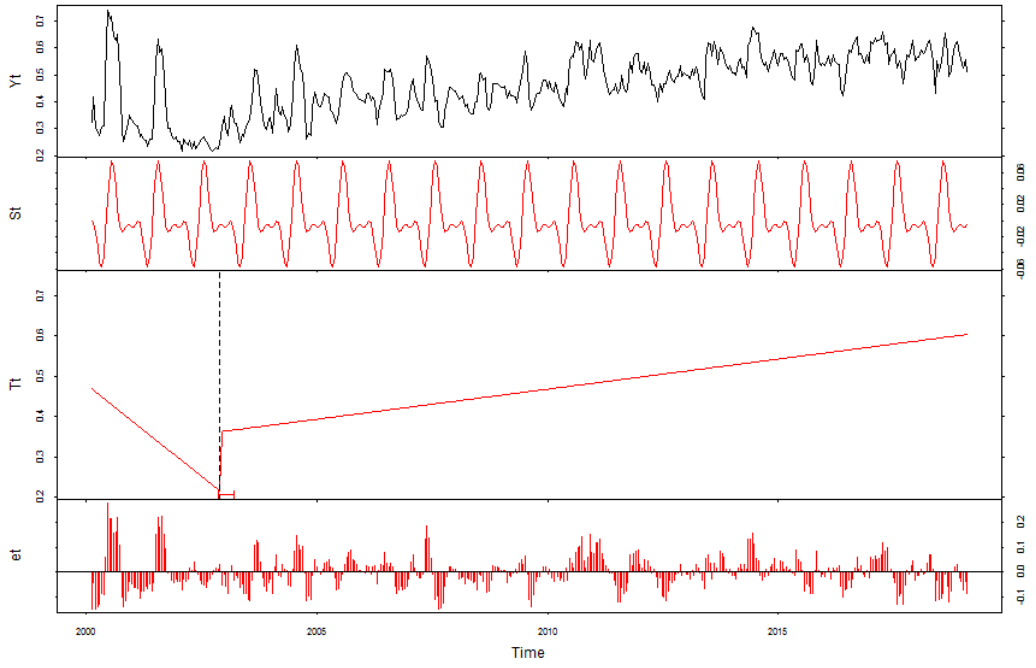


Figure 10 - Temporal vegetation vigour (Yt), average seasonal vigour profile (St), trends and breaks between trends (Tt), and residual variation in vegetation vigour not explained by average season (et), derived from MODIS vegetation vigour (NDVI), for vineyard 51.CHA, 515 Anderson Road, Loxton North.

3.3. Mobile Ground Image Retrieval System

Following discussions with the growers, some of the key concerns identified were related to the ability to effectively monitor vine canopies for size, shape, onset of disease and berry characteristics as a primary need to make decisions on rates of irrigation, fertilisation, fungicide application.

Minimising the rates of application would result in savings on costs on diesel, water and chemicals, and reduce workload.

The concept of the Mobile Ground Image Retrieval System (MGIRS) was developed to explore how an array of red, green, blue (RGB) cameras mounted on a tractor during routine operation could be used to address many of these key concerns. Key design features of MGIRS are provided in the table below.

Table 6 - MGIRS feature set

Feature	Comments
Capacity to retrofit into an operational tractor	This feature is designed to significantly lower adoption cost by: - Focusing on 'incidental capture' (i.e. image capture during normal tractor operations), thereby not expanding to grower time commitments; and - Eliminating the need to develop a dedicated platform
Be automated to require minimal input from user	Similar to the first feature, the system should operate with minimal additional intervention and/or technical expertise required by the grower.
Simple and low-cost design, with minimal research and development of hardware and software, using established methods and components	Reduce development costs and accelerate development time
Be adequately flexible to integrate a range of sensor options as the concept develops over time	Current design focuses on RGB imagery; however by building in flexibility into the design, other camera systems (e.g. multi- or hyper-spectral, thermal, etc) could be incorporated into the same platform to provide additional sensing options in the future.
Be flexible to integrate with a range of platforms	Although the current design focuses on tractor retrofit, future adaptations could include mounting on a quad bike, or on an autonomous platform. This latter solution would ensure that image acquisition will not be linked to timing of tractor passes, but will require further development.

The MGIRS is an array of multiple RGB cameras mounted on a mast that is retrofitted onto a tractor. The multiple camera array is designed to deliver a photogrammetric solution for the measurement of canopy characteristics such as shape and volume and high resolution images for further analysis with computer vision technologies.

Close range photogrammetry has been established in agricultural research to be useful for measuring canopy characteristics (Deery et al., 2014) with examples in forestry (e.g. Mikita et al., 2016), wheat (e.g. Walter et al., 2018), and tomatoes (Aguilar et al., 2008), to name a few. Photogrammetry is the technique of making measurements from images. Although possible with single images, multiple images captured appropriately allows for the generation of three-dimensional models of the surface and allows for the measurement of canopy size, height and depth

(Westoby et al., 2012). An additional benefit of the use of multiple images is that if appropriately configured, the scale of the object can be inferred directly from the images themselves, whereas single images require either a constant distance to the subject or a reference scale in the image.

The MGIRS consists of four main components: the MGIRS mast, the camera array, the control unit, and the data analysis system comprising of the photogrammetric analysis software and the computer vision system (discussed in Sections 3.3.2 and 5.1). The camera array consists of three 20 megapixel Sony RX100 iii (Table 7) low cost cameras mounted on a mast designed to be retrofit onto the front mounting plate of a John Deere 5090R tractor. The control unit consists of hardware and software for the operation of the cameras. The data retrieval system is comprised of the hardware and software on the control unit and a laptop to transfer the data to the laptop.

Table 7 - Sony RX100 iii specs (abridged to relevant specs).

Price	
MSRP	USD$799
Body type	
Body type	Compact
Body material	Aluminium
Sensor	
Max resolution	5472 x 3648 (20MP)
Sensor size	1" (13.2 mm x 8.8 mm)
Angle of view	73.7 x 53.1 degrees
Field of view @ 1m	1.5 x 1 m
Image	
ISO	Auto, 125-12800
Image stabilization	Optical
Optics & Focus	
Focal length (equiv.)	24

Photography features	
Maximum shutter speed	1/2000 sec
Single shot cycle time	~ 0.6 sec*
Storage	
Storage types	SD/ SDHC/SDXC
Connectivity	
USB	USB 2.0 (480 Mbit/sec)
HDMI	Yes (micro-HDMI)
Remote control	Yes (wired remote)
Physical	
Environmentally sealed	No
Battery	Battery Pack
Weight (inc. batteries)	290 g
Dimensions	102 x 58 x 41 mm
Other features	
GPS	None

The mast is constructed of welded 3 mm steel tubing and 7 mm steel mounting plate, selected for rigidity and durability to decrease the effects of tractor motor vibration on the quality of the images (Figure 11).

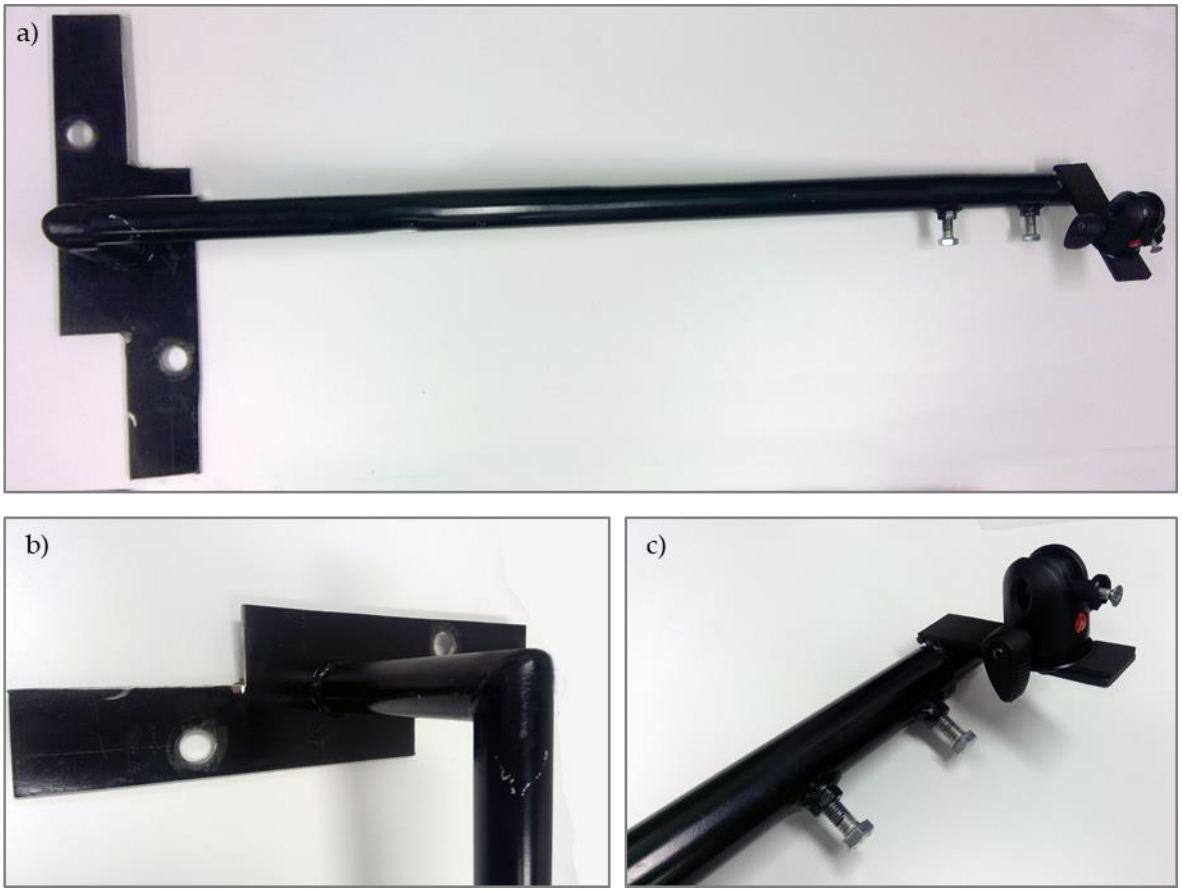


Figure 11 – (a) The overall unextended mast, (b) the mounting plate, and (c) the ball joint for attaching the camera array bracket

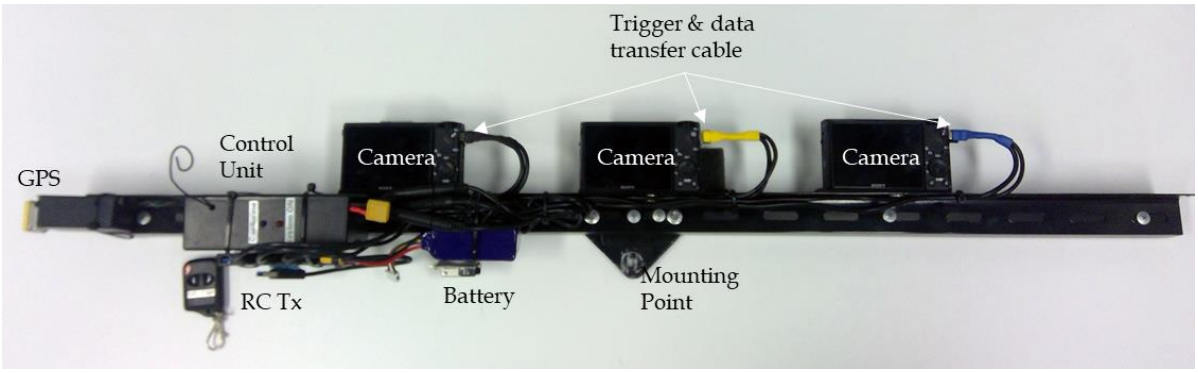


Figure 12 - Camera array bracket

The MGIRS consists of four main modules, as illustrated in Figure 13:

1. Mast
    a. Mounting plate
    b. Mast
    c. Camera array bracket mounted with a ball joint for adequate rotation about all axes
2. 3x Sony RX100 iii cameras
3. Control unit
    a. Power supply unit and battery
    b. Remote control (RC) transmitter and receiver
    c. Arduino microcontroller

    3x customised cables for camera triggering and data transfer

d. USB hub

4. Data processing workflow
    a. Data transfer software
    b. Data transfer to machine learning vision analysis
    c. Array image set processing (generation of point clouds)
    d. Information extraction methods

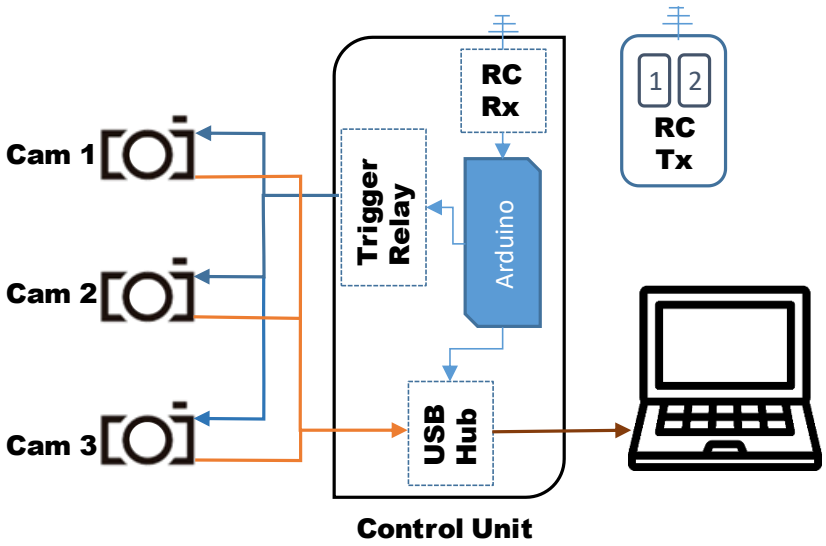


Figure 13 - MGIRS schematic

3.3.1. Field operation of the MGIRS

Operation of the MGIRS system is designed with simplicity in mind, and thus the current design requires the following steps:

1. Initialisation
    a. Turn cameras on
    b. Press RC button 1 to initialise the control unit
2. Capture
    a. Press RC button 2 to begin image capture
    b. Normal operation of tractor commences at a fixed speed
    c. User press RC button 2 to cease capture
3. Data transfer
    a. Plug USB hub into laptop with attached USB cable
    b. Press button 1 to begin transfer of data to laptop
    c. Initialise data transfer program on laptop
    d. Wait for the data transfer to complete
    e. Unplug USB cable
    f. Power down the control unit (cameras power down automatically)

The MGIRS control unit triggers the three cameras simultaneously at programmed intervals measured in seconds, with a maximum capture rate of 1 frame per second. The images are stored locally on each camera SD card. Once triggering is ceased, the control unit is plugged in to a laptop, where custom software (MGIRS Data Copier.exe, Zygmunt Szpak) is used to transfer the images to the laptop before the program automatically clears data from the SD cards. The image from the middle camera (Cam 2) is transferred to the machine learning algorithm for further processing.

Although currently data transfer occurs via USB cable, future designs could explore additional process automation, potentially with greater on-board processing to manage data volumes.

3.3.2. Imaging with the Camera Array

The three cameras are arranged in portrait orientation 0.5 m apart (Figure 14). When the array is 1 m from the canopy, the effective footprint of each camera is 1.5 m vertically and 1 m horizontally, with spatial resolution of 0.33 mm per pixel (Table 8). The distance between the cameras ensure that at the minimum distance to the canopy, 67% overlap exists between at least two of the images. A minimum of 60% overlap is necessary to ensure that each point of interest in the subject (the canopy), is imaged with adequate information to generate a 3-dimensional point cloud. If the distance from the camera array to the canopy decreases to 0.8 m, there is inadequate overlap to generate 3-dimensional information (Table 8). The footprint of the images and overlap increases as the distance to the canopy increases. Greater distance equates with greater overlap, allowing for the generation of denser and more reliable point clouds, but at the cost of image resolution (Table 8). Typically, the inter-row distance will not allow for the 1 m minimum distance between the array and the canopy; however the effective distance to canopy can be increased by angling the array forwards.

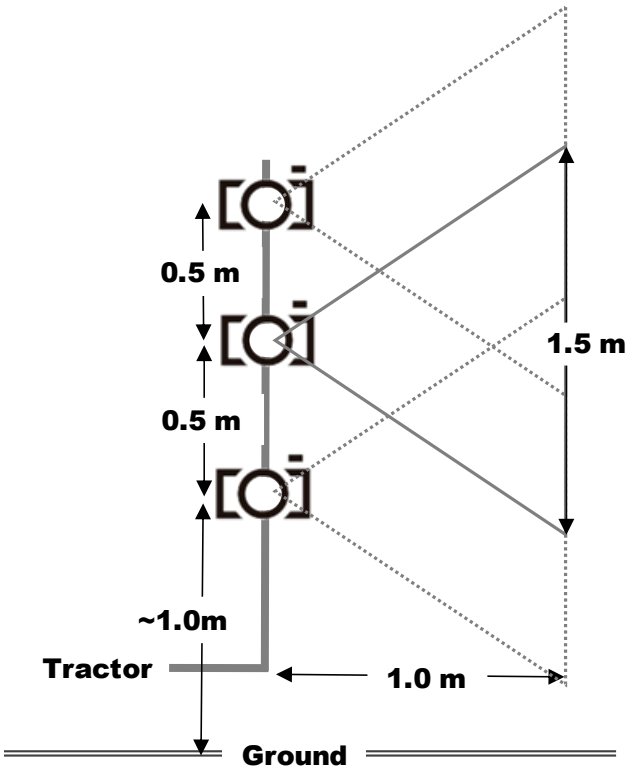


Figure 14 - Arrangement of the camera array with each camera's footprint and overlap at the minimum distance of 1 m



Figure 15 - MGIRS mounted on a John Deere 5090R for field trials

Table 8 - Camera footprint and array overlap as distance to canopy increases

	Distance to canopy (m)					
	0.8	**1**	**1.5**	**2**	**2.5**	**3**
Vertical camera footprint (m)	1.2	1.5	2.25	3	3.75	4.5
Vertical overlap (%)	58	67	78	83	87	89
Image resolution (mm)	0.33	0.41	0.62	0.82	1.03	1.23

Each time the camera array triggers, three images are captured simultaneously to form an image set (e.g. Figure 16). The images are arranged appropriately to be processed as sets with the Agisoft Metashape photogrammetry software. The processing involves camera alignment followed by the building of dense point clouds using the parameters in Table 9, the result of which is exemplified by Figure 17.

Ultimately, the point cloud will be an intermediate data product. The point cloud may be used to quantify structural characteristics of the canopy such as (Hosoi et al., 2011, Hosoi and Omasa, 2007, Mathews and Jensen, 2013):

- Leaf Area Index,
- Leaf Area Density; and
- Leaf inclination angle

The canopy profile is also expected to provide valuable information on canopy surface area and shape (Figure 18). Though many of the methods developed have been applied to LiDAR data, the data format and content are extremely similar.



Figure 16 - A set of array images from Cam 1, Cam 2 and Cam 3. Taken from Chardonnay Patch 19, Row 7

Table 9 - Agisoft Metashape point cloud generation parameters for image sets

Parameter Group	Parameter Name	Value
Camera alignment	Accuracy	Medium
	Generic Preselection	Yes
	Key point limit	40,000
	Tie point limit	4,000
	Adaptive Camera model fitting	No
Build Dense Cloud	Quality	Medium
	Depth filtering	Aggressive
	Calculate point colours	Yes
	Number of Points	**Data vol.**
Result	1 - 1.5 million	12 MB



Figure 17 - Example point cloud from MGIRS array from two angles

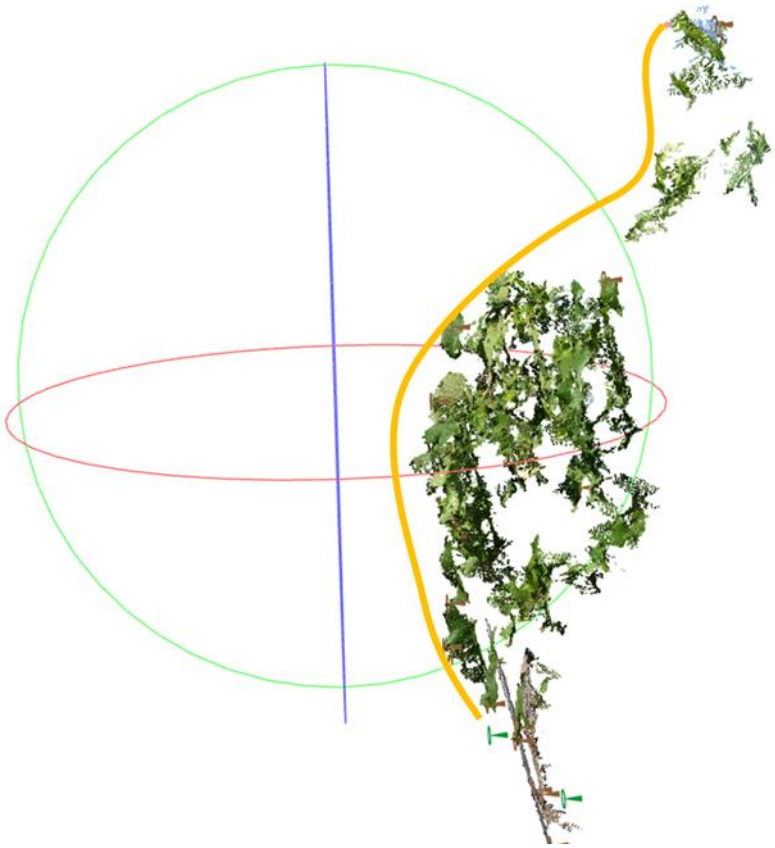


Figure 18 - Maximum surface profile of a canopy estimated from the point cloud

The Sony RX100 array is capable of capturing images free of blur provided there is adequate sunlight or if the platform speed is limited (Table 10). At speeds above 8 km/h, the shutter speed required requires relatively bright conditions (EV > 12). However, at speeds of 5 km/hr, operation can continue until dusk (EV > 10) without an external light source. Given generally favourable light conditions in the Riverland, during likely times of the year where the system is to be operated, this demonstrates operational viability of the technology. However, the system may benefit from further developments for low-light operations, given tractor speeds typically range from 7-10 km/h.

Table 10 - Minimum shutter speeds required on the Sony RX100 iii and equivalent cameras to eliminate motion blur for platform speeds under different lighting conditions. Canopy distance is held at 1.5 m, with F/5.6 held constant for adequate depth of field characteristics, and ISO held at 800 to image under the lowest light conditions without introducing excessive noise.

	Light (EV)				
	Sunset	Deep shade	Cloudy	Partly Cloudy	Full Sunlight
Speed (km/h)	11	12	13	14	15
5	1/800				
6		1/1000			
7		1/1250			
8		1/1250			
9			1/1600		
10			1/1600		
11			1/2000	*Adequate light*	
12			1/2000		
13			1/2000		
14	*Underexposed/Blurry*		1/2500		
15			1/2500		
16			1/2500		
17				1/3200	
18				1/3200	
19				1/3200	
20				1/3200	
ISO 800	F/5.6	Distance = 1.5m			

3.3.3. Field Trials

The MGIRS was initially trialled at the Coombe Vineyard (Waite Campus, University of Adelaide) on various dates in April 2019 to test components and design. The final trials were performed at Sherwood Estates on the 15th and 16th May, 2019—after harvest has taken place. The MGIRS mast was mounted on the John Deere 5090R tractor on site, with some minor modifications made to the mounting plate to accommodate two bolts that could not be removed.

Six trials were run across two sections of the vineyard under varying lighting conditions, ranging from bright sun, bright overcast, and moderately low overcast sunlight. The tractor was held at a constant speed of 8 km/h. The majority of the trials were conducted in a similar manner to collect data on different canopies (e.g. mature and dense, young and sparse) with an image capture interval of 1 second. The final trial was performed to test the array with a slower interval to test the system for greater coverage with similar data volumes.

Examples of imagery obtained through the field trials are given in Figure 16 and Section 5.1.

Table 11 - Sherwood Estate field data capture summary

Trial No.	Patch No.	Rows captured	Length sampled (m)	Interval		Num. Image Sets	Data Vol. (GB)	Lighting	Comments
				Time (s)	Dist (m)				
1	19. CHA (P26)	2	300	1	2.2	119	1.3	Bright overcast	First test
2	19. CHA (P26)	2	300	1	2.2	122	1.3	Bright overcast	Refined capture parameters
3	17. NEA	2	500	1	2.2	205	2.1	Bright overcast	2 year old vines, sparser canopies
4	62. SHZ	2	580	1	2.2	190	2.0	Overcast	Very young vines, fine canopies
5	67. SHZ (P22)	2	250	1	2.2	101	1.1	Moderately low light, overcast	Mature canopy, moderately low light, overcast
6	19. CHA & 14. FRR	15	2,200	5	10.8	201	2.4	Bright, sunny, distinct shadow	Lower capture rate to test operation over two patches

3.3.4. Current status and opportunities for future development

The aim of this component was to build and test an imaging system that could be retrofit onto existing operational platforms. The overall MGIRS consists of four main components.

1. Mast
2. Sensor array
3. Control unit

(1–3: Image retrieval system)

4. Data processing workflow

Each component has been developed to a stage that demonstrates the functional capabilities of the system as a whole, with opportunities to explore its further development. The image retrieval system is comprised of the mast, camera array and control unit. The processing software and derived information represent a separate element of development that remains in a nascent stage of development.

3.3.5. Image retrieval system

The image retrieval system is currently estimated to be performing at TRL 3. The components have been successfully integrated to demonstrate the function of the system. However, substantial improvements to the system are necessary to operationalise it in realistic environments.

Mast design and construction

The mast was designed and constructed from widely available materials that could:

- be fabricated quickly and simply
- endure sustained field operation
- dampen vibration from the tractor
- provide adequate flexibility to alter the configuration and combination of sensors

The current build satisfies these criteria for the testing phase at one vineyard. However advancing the MGIRS would benefit from industrial design considerations that:

- Minimise cost of materials and fabrication
- Constrain the flexibility to the necessary ranges
- Is simple to mount, detach and maintain
- Does not hamper other functions of the platform
- Is mountable on alternative tractor types

Sensor array

The model of camera used in the MGIRS array was selected for its image quality and operational functions. However, the cameras are consumer-grade either with inadequate functions or are surplus to need. Consumer grade cameras are comprised of the numerous components and features that are unnecessary for commercial operation and hinder customisation, including camera control buttons and dials, internal batteries, microphones and LCD screens. Such cameras typically lack features that allow for low level control of their operation, including external power management and control of image capture parameters such as shutter speed and aperture.

Industrial cameras typically comprise a sensor, lens, and microcomputer with software development kits (SDKs) that offer low level control of multiple cameras from a central control unit that can synchronise camera parameters in response to greater ranges of environmental conditions. Additionally, industrial cameras are typically capable of higher image capture rates (e.g. 15 frames per second vs 1 frame per second) under lower light conditions, allowing for their operation at higher speeds under greater ranges of lighting conditions.

The development of an industrial camera solution would require additional development of software and hardware such as the control unit and light metering. Although additional

development would be necessary, the opportunities for complete automation of image capture with little to no input from the grower is attainable. External power supply can be simply delivered via the control connections with options such as USB3 and Power Over Ethernet (PoE) GigE connections. Industrial cameras with improved performance over consumer grade cameras are readily available with established performance characteristics and SDKs, e.g. the Lumenera Lt945R and the Adimec S-25A80.

The camera array consists of three RGB cameras to simultaneously capture high resolution imagery and generate 3-dimensional information on canopy structure. The configuration was chosen to demonstrate these features at the lowest cost, to demonstrate potential commercial viability of the approach. Alternative configurations should also be considered to capture useful data.

It should be noted that two cameras can be sufficient to collect similar data, but requires greater software development and is more sensitive to the minimal distances between the array and the canopy. Other sensors that could provide similar or additional information include LiDAR sensors and spectral imagers (such as multispectral and thermal). These sensor types have attained a level of maturity currently available in form factors suitable for integration onto a system similar to the MGIRS mast for commercial and research applications. Each sensor type presents costs and benefits that need to be considered. Costs include price, integration effort, data volume storage, transport and processing requirements, customisability and sensitivity to environmental conditions. Benefits to be considered include the ability to sense canopy characteristics of interest including canopy structure such as LAI, canopy volume and area, canopy chemical composition and transpiration rates.

Control unit

An automated sensor system requires a central control unit to minimise grower interaction with its operation in order to reduce impediments to grower workflows and the requirement for instruction on its operation. The control unit at present requires minimal input from the tractor operation. Currently the system requires the operator to initialise the cameras, power on and start the control unit, stop the unit and connect cables to a laptop to transfer the data and power down the unit. However, the cameras do require some manual camera parameter setting to capture high quality imagery and batteries require maintenance.

With appropriate development time, each step of interaction can be eliminated from the operation workflow with commercially available hardware and software.

It is envisaged that the power supply to the control unit and cameras can be sourced from the tractor battery / alternator to eliminate the need for a battery which requires replacement / recharging. This is trivial for industrial cameras as they are typically powered over the trigger / control cabling (USB 3 or PoE GigE) and can be simultaneously be used to power the cameras on and off via the control unit. Consumer camera batteries such as the Sony RX100iii can be modified to allow for an external power source; however this would still require manually powering the cameras on.

Widely available microcomputers, such as the Arduino or Raspberry Pi, are necessary to perform numerous tasks. These include receiving inputs from light sensors, GPS, user inputs from the remote control. It can also be programmed to manage outputs such as trigger events, receive data from the sensors and transfer data from the unit following capture. Onboard software can be developed to interpret information from the light sensor to set industrial camera capture parameters using manufacturer SDKs.

Positional information from a GPS receiver can be used to geotag the images with positional accuracy dependent on the GPS technology employed, ranging from 5 cm with the standard L1C GPS signal, to 2 cm precision with Realtime Kinematic (RTK) or Post Processed Kinematic (PPK) positioning systems. Data throughput from local storage can be managed via physical connections

such USB, SD card Ethernet. Alternatively, the data could be managed via WiFi which would require an external router to transfer the data to a standalone computer for processing, or to transfer the data over the internet to a server side processor.

3.3.6. Data volume

The MGIRS is currently configured to generate significant data volumes, posing important constraints on how the data can be managed and processed. Each capture event generates three images resulting in approximately 30 MB to image approximately 1 metre of one canopy side. Complete coverage of a kilometre of canopy would generate 30 GB of data. At 8 km/h, the system can generate up to 15 GB of data per hour.

Although these data volumes appear very significant, it should be noted that the system was designed to demonstrate the utility of the imagery at full resolution for machine learning and point cloud generation for structural measurement. These data volumes can be considerably reduced once the limits of detectability of the features of interest are determined. Factors to be considered include:

- The necessary resolution for detecting visible features (e.g. grape bunch size, canopy disease).
- Assessing the necessity for two vs three camera arrays to generate adequate 3-dimensional information to capture and characterise canopy structure.
- Identify the minimum capture rate necessary to attain adequate statistical power in the sampling of canopy characteristics such as disease onset, berry counts to estimate yield or canopy structural variation to estimate resource use efficiency.

Furthermore, on-board processing could be used to reduce data volumes significantly prior to data transfer. The identified resolution and sampling rate will drive the data transfer and processing method. Data transfer pipeline considerations are discussed in Section 4.2.

3.3.7. Summary

A mobile ground image retrieval system (MGIRS) was developed to explore the possible practical applications of an image collection system mounted on a tractor in a working vineyard. The MGIRS is a relatively autonomous image capture system that demonstrates how image capture can be integrated into the grower's workflow to generate data for characterising canopy structural characteristics and high resolution imagery for machine learning applications.

The MGIRS can be further developed with mature imaging technologies that can be integrated with some development. Key considerations that have to be accounted for in advancing the development of the MGIRS include selecting both the appropriate sensor technologies and image processing methods to adequately characterise grapevine canopies for improved decision making.

4. Connectivity, data processing and handling

Key findings

- A review of low data-volume connectivity solutions reviewed a range of communications technologies each with different specifications in terms of range, data rates, wireless standard and other properties.
- Long-range wide area network (LoRa WAN) technology was selected as the demonstration communications technology due to its low cost, long range and increasing breadth of compatible sensor options. A LoRa base station was installed and operationalised as part of the pilot at the Loxton Research Centre with demonstrated range up to 18 km (directionally dependent, based on line-of-sight).
- A weather station, five soil moisture sensors (four multi-depth), a salinity sensor and a dendrometer were deployed on a vineyard approximately 3.3km from the Loxton Research Centre, providing real-time visibility of key on-farm variables through an open-source dashboard.
- Given the significant data requirements associated with the mobile ground-based image retrieval system, specification of a data management system is provided to enable potential future deployment of the technology.

Connectivity, data processing and handling solutions can be described simply as the 'glue' that joins the data streams such as reviewed in Section 2, to the algorithms and visualisation approaches that drive the value of the data to growers in Section 4. Although the purpose of this technology is straight forward, up until recently, digital agriculture in Australia has to a large extent been hampered by poor connectivity solutions. To this extent, solutions such as those described below are one of the prime enablers of 'cloud-based' digital agriculture, driving down costs and increasing accessibility.

Costs are the primary driver to ensuing successful value propositions of digital agriculture. To this extent, there is significant interest in low data-volume connectivity solutions, given their suitability not only to *in-situ* sensors (Section 2.1), but also the acquisition of key indices from ground-based vision systems (Section 3.3) and other third-party data services. A review of options for low-cost connectivity, together with the deployment of a preferred option as part of the pilot, is covered in Section 3.1. This is followed by the specification of a potential data management system in Section 4.2 to be used for data-intensive applications such as the ground-based image retrieval system as well as the integration of other data streams.

4.1. Low-volume connectivity solutions

'Smart farming' exploits the range of modern sensing technologies and communication protocols to deliver data to growers to aid in decision making. As described in Section 3.1 continuous sensors provide near real-time data of variables including those weather-related, soil and crop water status, soil salinity, and irrigation volumes. With the development of wireless communication technologies, sensor data can be accessed rapidly and at relatively low cost, saving growers potentially significant time and money. Recently, the concept of 'Internet of Things' (IoT) has emerged, which refers to the interconnected network of sensors that relay data to the user via the cloud (Figure 19).

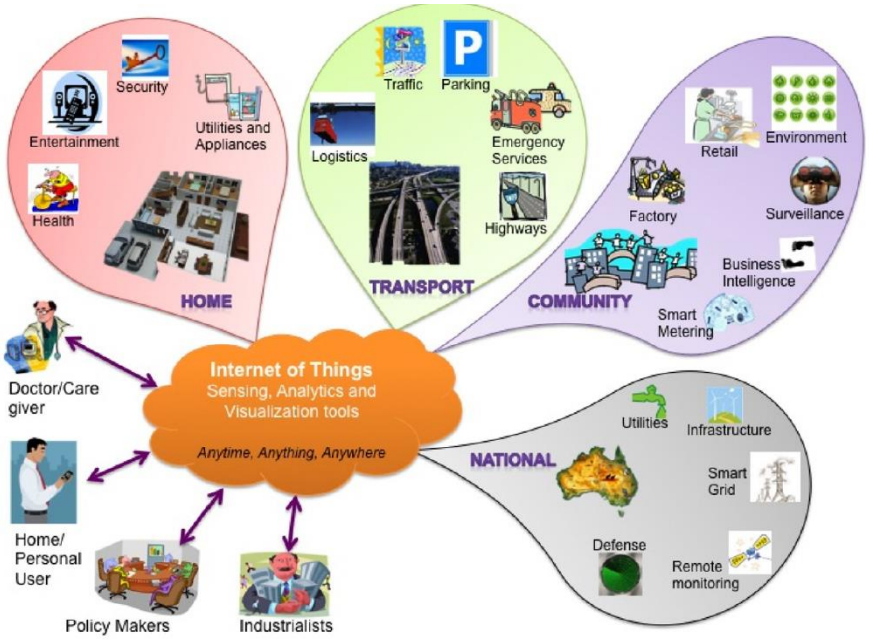


Figure 19 Internet of Things (IoT) schematic (Gubbi et al. 2013)

The datasets are hosted on cloud computers that provide additional infrastructure including computational power, data storage, and permanent availability ("always on") such that data access is rapid and available on demand. Existing wireless telecommunication networks such as 3G, 4G (LTE) and, more recently, 5G networks allows high volume data to be transmitted between mobile devices. Applications that require high data rates include streaming media, large file transfers, and in the future, tracking of autonomous vehicles and other similar applications. In the context of agricultural applications, this would likely include vision-based technologies (e.g. RBG images). In contrast, IoT devices generally require low bandwidth due to the small data packet sizes transmitted. These low bandwidth networks can utilise low power wide area network (LPWAN) wireless communication technologies such as WiFi, ZigBee, LoRaWAN, Sigfox, and others. IoT enables connectivity of a multitude of on-farm sensors to provide an integrated view of soil and crop status, and other farm activities. The ability to access multiple datasets from sensors and integrate these would allow growers to make decisions to optimise their production practices. We review some of the connectivity options for on-farm sensors and discuss their relative performance.

Advances in technologies over the past decade, particularly in the areas of wireless communications using low power integrated circuits (ICs) and miniaturisation, allows these technologies to be used in small proximal and direct sensors. These sensor "nodes" form what is known as a wireless sensor network (WSN) that enable the measurement of a multitude of signals (environmental, soil, plant), and data collection, storage, processing and analysis. Extending from the WSN framework is the manipulation of the data through analytical methods and data transformations to reveal insights for crop management, marketing, and future planning.

WSN architecture typically consists of four elements or modules:

(i) sensors or nodes
(ii) communications hardware and protocols
(iii) power module; and,
(iv) data storage/processing/computation.

Sensors (nodes) were discussed in Section 3.1. We now review options for communications technologies available for IoT network architectures. Table 12 provides a summary of the various options available for wireless connectivity of IoT sensors for data transmission.

Several low volume wireless connectivity options are available some of which are being using in commercial agricultural and environmental sensing (e.g. soil, plant and weather monitoring). For example, Sentek EnviroScan soil moisture probes (capacitance probes) have recently been enabled with Bluetooth capability. Amongst the various low volume connectivity options LoRa has been gaining increased visibility in the wireless sensor network generally for several reasons including its low cost, long range and the increasing number of sensor options available for this connectivity solutions. Importantly, a LoRa network can support hundreds to thousands of sensor nodes. For these reasons the current project has adopted LoRa as the preferred wireless communication protocol, the details of which are outlined in Section 4.1.1.

Table 12 - Summary of common wireless communications technologies available for IoT WSNs (adapted from Tzounis et al. 2017, Aqueel-ur-Rehman et al. 2014).

Communication technology	Wireless standard	Network type	Operating frequency	Range	Data rate	Power consumption	Australian availability
Bluetooth	Bluetooth/IEEE 802.15.1	WPAN[1]	2.4-2.4835 GHz	100 m	1-3 Mbps	1 W	Y
Bluetooth Low Energy (BLE)	IoT interconnect	WPAN	2.4-2.4835 GHz	100 m	1 Mbps	10-500 mW	Y
GPRS (2G)	3GPP[2]	GERAN[3]	850, 1900 MHz	25 km/10 km	171 Kbps	2 W/1 W	N
LoRaWAN	LoRaWAN	WPAN	EU: 863-870 MHz US/Can: 902-928 MHz AUS: 915-928 MHz	2-15 km	0.3-50 kbps	Low	Y
LTE (4G)	3GPP	GERAN/UTRAN[4]	0.7-2.6 GHz	28 km/10 km	0.1-1 Gbps	5 W/1 W	Y
RFID	Multiple	P2P[5]	13.56 MHz	1 m	423 Kbps	1 mW	Y
Sigfox	Sigfox	WPAN	908.42 MHz	30-50 km	10-1000 bps	Low	Y
WiFi	IEEE 802.11a,b,g,n,ac,ad	WLAN[6]	2.4, 3.6, 5 GHz	100 m	6-780 Mbps	1 W	Y
Zigbee	IEEE 802.15.4	Mesh	2.4-2.4835 GHz	10-1600 m	250 Kbps	1 mW	Y

[1] Wireless Personal Area Network
[2] 3rd Generation Partnership Project involving seven telecom standards development organisations
[3] GSM (Global System for Mobile Communications) EDGE (Enhanced Data rates for GSM Evolution) Radio Access Network
[4] UMTS Terrestrial Radio Access Network
[5] Point to Point
[6] Wide area Local Area Network

4.1.1. LoRa network overview

LoRa, which stands for Long Range, is a low power and low data rate wireless communications network originally developed by Semtech that is being increasingly used for Internet of Things (IoT) applications. Technically, it is a radio modulation scheme using a chirped format. The electronics are capable of sending and receiving data packets over significant distances and low signal strength making this technology attractive for environmental and other sensing applications. LoRa Alliance is the industry body established in 2015 that provides the open standard for IoT connectivity based on LoRa. The technology is particularly attractive to IoT sensing as it uses low power (i.e. has a long battery life), can support thousands to millions of nodes (sensors), and has long range of data transmission (15-20 km typical with line of sight).

LoRa technology consists of a number of hardware and software components, which comprise the network topology shown below. The essential elements of these components include:

(i) a physical (hardware) layer or RF interface, which enable the communication between IoT nodes (with LoRa radios) and other elements of the network;
(ii) the software layer comprising the LoRa open source protocol stack (as defined by the LoRa Alliance); and
(iii) LoRa wide area network (LoRaWAN), which is the overall network that is built on top of LoRa (technically, the media access (MAC) layer) that supports wireless nodes, mostly wired, and typically used for public wide area networks. LoRaWAN consists of gateways, networks, applications, and devices (Figure 20).

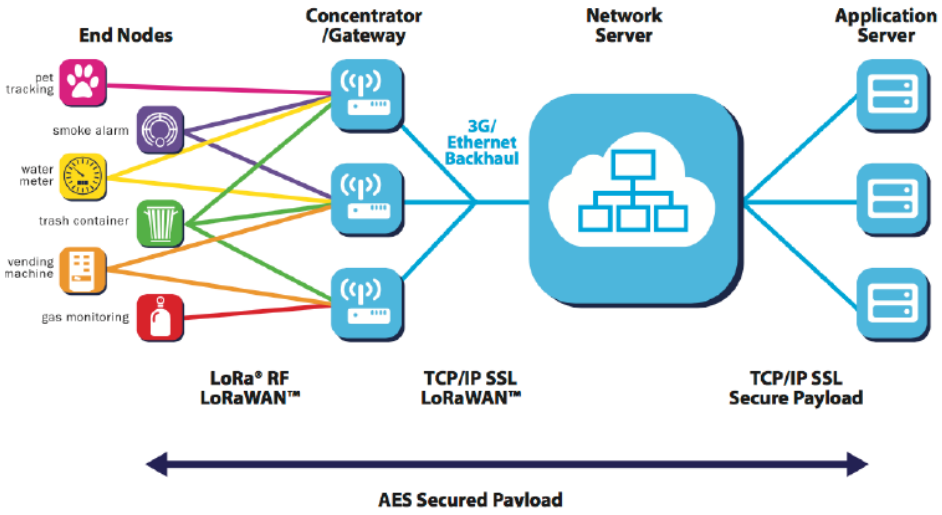


Figure 20 - LoRa WAN articulture (From Cheong et al, 2017)

Some typical performance parameters for a LoRa system are provided in Table 13.

Table 13 - LoRa radio parameters and typical performance figures (Sources: LoRa Alliance; www.electronics-notes.com)

Parameter	Performance
Signal format	CSS[1]
Spreading factor (SF)[2]	7-12
Data rate	0.3 – 50 kbps
Bandwidth	125-500 kHz

[1] Chirp spread spectrum: fixed amplitude frequency modulation (FM)
[2] Chirp duration: higher SF numbers indicate lower data transmission rates but longer range.

4.1.2. LoRaWAN gateway and sensor node deployment

The LoRaWAN gateway consisted of one LORIX unit operating at 915 Mhz coupled to an 4.15 dBi antenna that was mounted on mast on the roof of the Loxton Research Centre (LRC) building, approx. 3.3 km (transect) from the furthest vineyard location (SM1) with the sensor nodes. The mast was approximately 12 m above ground level. The gateway was connected via Ethernet coaxial cable to the internet provided by SARDI/Riverland Wine at the LRC. The gateway is powered over Ethernet using a Power over Ethernet (PoE) injector unit.

As part of the LoRa IoT network, the backhaul (data transmission to the Internet) is enabled by a LoRaWAN gateway, an electronic communication board with a RF transmitter/receiver that sends/receives IoT data packets from sensors to the Cloud through which users communicate with the individual sensors. The gateway was located at the Loxton Research Centre (LRC), Loxton SA (Figure 21) where power and Internet access was available to enable data communication with the Cloud.

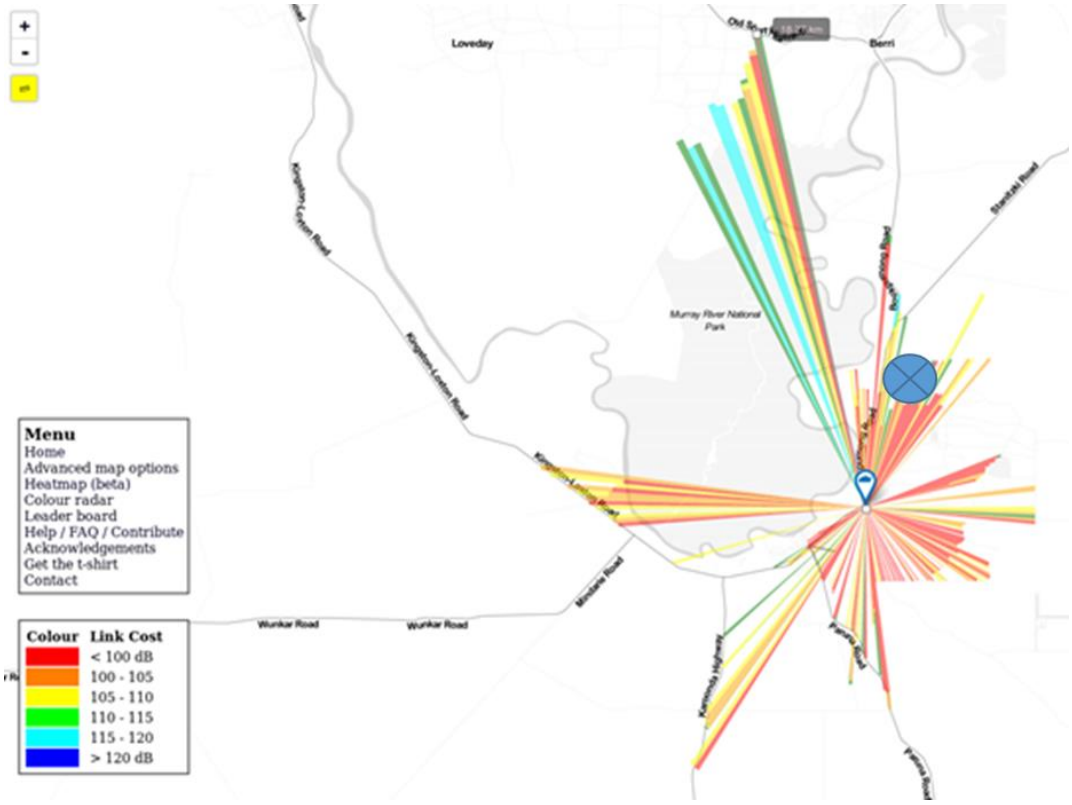


Figure 21 - LoRaWAN gateway coverage map showing the transmitter signal strength (in dB) at various locations around the Loxton Research Centre. The approx. location of the Sherwood Estates vineyard with IoT sensors is shown as the blue dot with cross.

The location of the deployed IoT sensors is approx. 3.3 km from the LRC but not line of sight, therefore the signal strength was moderate to low based on the coverage map shown above. The LRC location was chosen for the gateway since it was central to other vineyards that are likely to be connected with IoT sensors in the future. LoRaWAN signals were capable of being received as far away as Berri, approx. 18 km from the LRC provided line of sight was available. The key to long transmission distances is the height of the gateway to minimise interference from buildings, trees, etc. on the ground.

A 1.6 ha Chardonnay block was chosen for the installation of LoRa-enabled ground-based environmental, soil, and plant water stress sensors; the approx. locations of these sensors is shown in the map below (Figure 22).

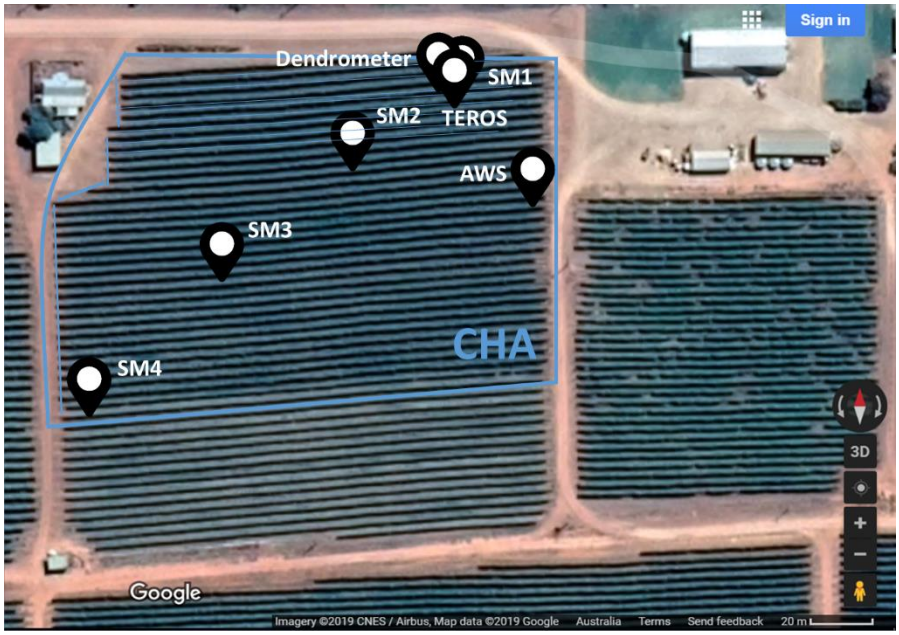


Figure 22 - Approx. sensor locations in the Chardonnay block at Sherwood Estates, Loxton, SA. SM = multi-depth capacitance probe for soil moisture measurement; WS = automatic weather station; Dendrometer = Linear Variable Differential Transformer (plant water stress sensor); TEROS = soil electrical conductivity, soil volumetric water content, soil temperature.

Exact sensor locations and sensor product information are provided in Table 14. The sensors were installed on May 3, 2019 and data collection commenced soon thereafter. Photos from the sensor installation are shown in Figure 23.

Table 14 - Sensor details and locations in the Chardonnay block at Sherwood Estates.

Sensor	Row #	Vine #	Product Information
SM1 (EnviroPro EP100GL-08)	3	5	https://enviroprosoilprobes.com/Pages/About/
SM2 (EnviroPro EP100GL-08)	12	22	https://enviroprosoilprobes.com/Pages/About/
SM3 (EnviroPro EP100GL-08)	23	45	https://enviroprosoilprobes.com/Pages/About/
SM4 (EnviroPro EP100GL-08)	33	65	https://enviroprosoilprobes.com/Pages/About/
TEROS-12 (METER)	3	5	https://enviroprosoilprobes.com/Pages/About/
Dendrometer (ICT Intl. DPS 40)	3	5	http://ictinternational.com/products/dps40/dps40-pivot-stem-dendrometer/
AWS (ATMOS 41)	12	1	https://www.metergroup.com/environment/products/atmos-41-weather-station/



(a)



(b)



(c)



(d)

Figure 23 - (a) EnviroPro EP100GL-08 multi-depth capacitance probe for soil moisture (volumetric water content, %VWC) and temperature measurements every 10 cm down to 80 cm depth; (b) METER TEROS-12 soil electrical conductivity, soil volumetric water content, soil temperature probe installed at 10 cm depth; (c) ICT Intl. DPS40 dendrometer measuring trunk diameter; (d) ATMOS-41 micro-environment automatic weather station measuring air temperature, relative humidity, barometric pressure, wind speed and direction, precipitation, vapour pressure, and a solar panel.

Exampled the time series traces of the various deployed IoT sensors are shown in Figure 24 to Figure 26. The first (below) shows environmental variables from the ATMOS-41 automatic weather station (AWS) being reported in near real-time.

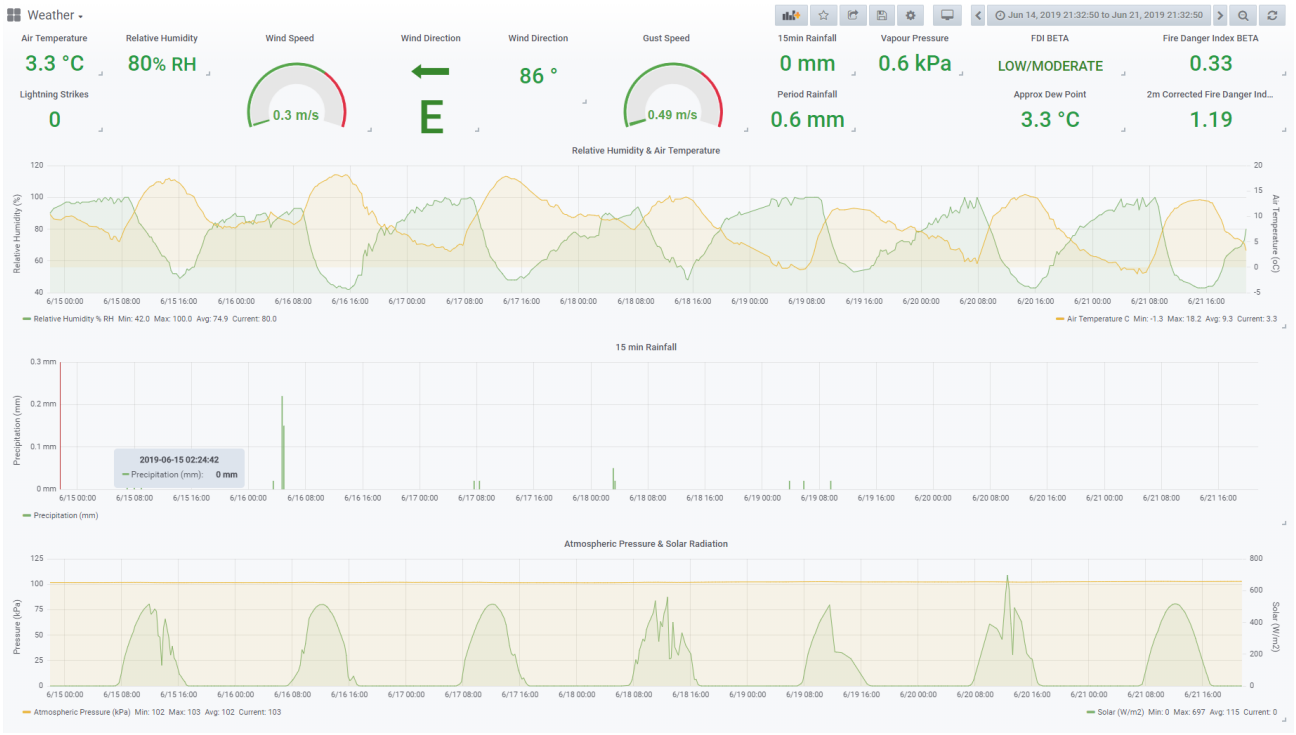


Figure 24 – Illustration of data collected via AWS in near real-time.

The traces below show the EnviroPro soil moisture and temperature sensors' outputs (Figure 25). The top graphs shows the volumetric water content of eight sensors located 10 cm apart down to 80 cm. The bottom graphs shows the same depths for soil temperature.

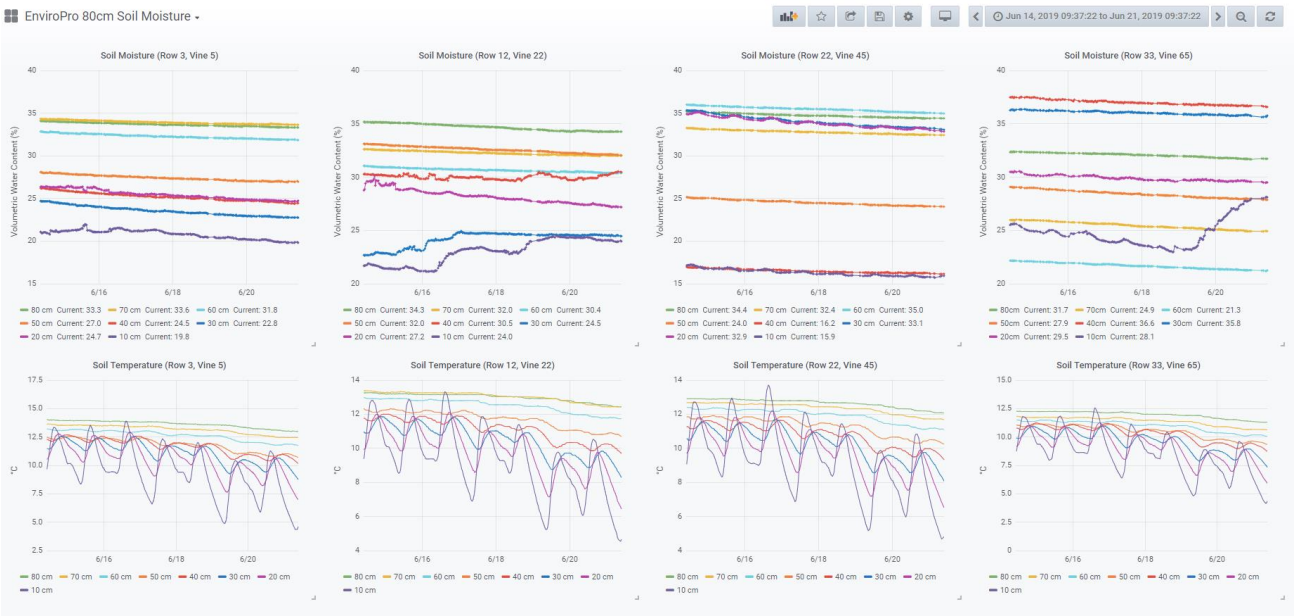


Figure 25 - Illustration of data collected via EnviroPro soil sensor probes in near real-time including, %Volumetric water content (top) and temperature (bottom) at multiple depths. Greatest variations in soil temperature are observed in the upper horizon sensors as they are more influenced by air temperature.

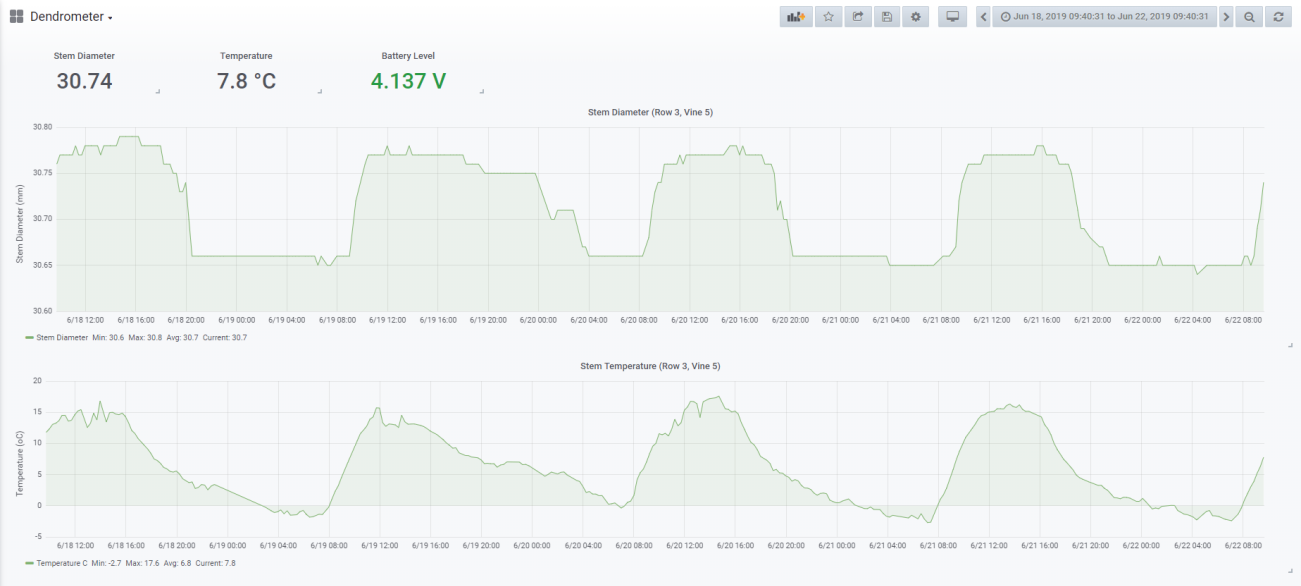


Figure 26 - Illustration of data collected via dendrometer including stem diameter (top) and temperature (bottom).

The use of low-cost IoT sensors in agriculture and viticulture have slowly but surely made their mark in farms and vineyards and are being embraced by even traditional growers. The motivation stems from the ability to realise efficiencies in the production chain, enable precision farming that optimises resource inputs (e.g. labour, chemicals, water) thereby maximising grower profit. Increases in yield are sometimes realised but in premium viticulture, this is not a key target but rather grape quality that requires an increased awareness of the state of the vineyard and vine. This awareness is where IoT sensors, coupled with communication and data analytics technologies, have the potential to make their greatest impact. The availability of rich data suites allows growers to be more resilient to extreme weather events and pest incursions to remain profitable and farm sustainably well into the future. Data-enabled decision making will underpin this resilience.

4.2. Data management system

Due to the collection of a large volume of in-field data from multiple sensors and sensor types in multiple locations as well as the collection of data from external providers (e.g. satellite products), a data management system is required. The purpose of this system is to enable the collection, processing and storage of the amassed data. This systematic management of acquired data is particularly important for enabling the presentation and visualisation of the data (e.g. via a dashboard) or management of the data as an input to models such as computer vision algorithms for detecting grapevine features like berry bunches or green shoots.

Additionally, the development of a modular and scalable data management system allows for the management of larger datasets that may cover multiple vineyards or vineyard regions. With the capacity to effectively manage these larger datasets comes further modelling and prediction opportunities (i.e. machine learning) that are infeasible with smaller siloed datasets; for example, using data mining and machine learning techniques applied to an industry-wide scale system. It is indeed likely that the careful collation, curation and management of data onto a common platform—rather than maintaining smaller datasets across multiple platforms with poor interoperability or cross-visibility—enables the next iteration of value creation in digital agriculture.

To achieve the objectives of the digital vineyard guidance system, a data management system design is proposed that will manage the data pipeline in a way that is scalable and flexible such that it enables the integration of a diverse range of datasets. It is recommended that the data management system is broken down into two components:

1. **Vineyard data system** – which provides connectivity to multiple sensors and computing nodes (Figure 27 (left)) and enables the transfer of the collected data via a data messaging protocol(s). This, in turn, enables handling of the network environment conditions and data requirements.
2. **Centralized data system –** which collects data from multiple remote vineyard networks and other data sources to provide access to the data though multiple platforms (Figure 27 (right)). To create an industry-wide data collective this will be a centralized internet-connected server.

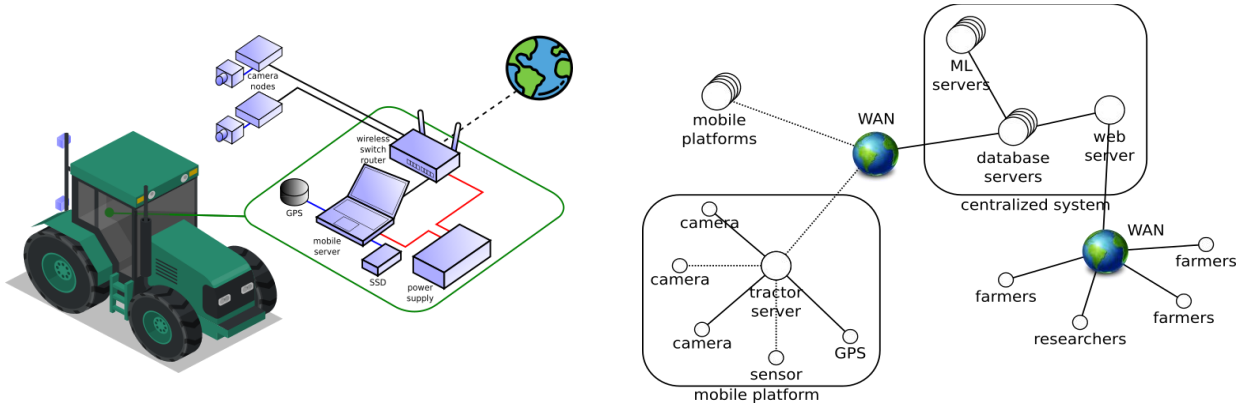


Figure 27 - Illustration of potential components for a vineyard (left) and centralised (right) data system.

To ensure the development of a flexible and scalable data management system the potential data sources that may be input to a fully developed system have been reviewed. Table 15 summarises these potential data sources.

Table 15 - Summary of potential system data sources

Data Source	Examples
Video and images	Visible, infrared, ultra-violet, multi-spectral, hyper-spectral, thermal, LiDAR. These may be collected on-farm or be procured from third parties (e.g. satellite products).
***In-situ* weather and environmental data**	Temperature, precipitation, humidity, soil moisture, wind speed, electro conductivity, smoke, disease monitors.
Farm operations data	Spray diary, irrigation scheduling, fertiliser program, canopy management program, harvest timing, yield.
Business data	Expenses on inputs (fertiliser, water, fuel, machinery), production quantities, wastage and rejection quantities, pricing, yield.
Metadata	High-resolution timestamps (from precision real-time clocks, networked clock protocol and GPS), geospatial location (i.e. from GPS), orientation and accompanying motion (e.g. accelerometer), identification numbers (farm, location, operator, user, etc).
Textual data	Farmer and workers' annotations and journal notes.
Audio data (microphones)	Wildlife/pest such as birds and insect, machinery, weather, vibrations, etc.
Forecast information	Weather forecast information (potentially from third parties).

The data sources above can be classified into the following four overarching categories:

- Time-series data,
- Geo-spatial and temporal information,
- Video and images, and
- Heterogeneous and unstructured data such as metadata and documents.

This data review indicated the need for a system that can handle unstructured, heterogeneous and asynchronous data, and will need to scale as traffic volume increases when the system user base grows. These considerations are central to the design of a central database system.

A number of attributes and requirements have been collated to guide the system's ongoing development, considering the system's needs in terms of the variety of data types, data sources, and the need to provide an interface to the data for users. The identified system development requirements are a system that is scalable, stable, secure and maintainable. Each of these factors briefly discussed in Table 16.

Table 16 - Data management system development principles

Development principle	Description
Scalability	For the longevity of a system that will accumulate data and data sources as it matures, it is important that all developed system components are scalable. Therefore a modular development process is required.
Stability	The system needs to deliver data in a timely and continuous manner. This requires low latency, high throughput and enough compute power to both receive and deliver data as the system user-base grows. Downtime for the system must also be kept to a minimum.
Security	Due to the sensitive nature of some data (i.e. business and financial) the security of the system is also a paramount consideration. Without clear security protections the adoption of the system will likely be inhibited due to end-user concerns. Additionally, as the dataset grows its value increases for the user base and third parties. This also indicates the need for a secure system. Privacy considerations (including the extent to which information can be shared between grower groups, potentially anonymised across grower groups) will need to be carefully considered as part of the design of a secure, trusted system.
Maintainability	In addition to stability, the system must be maintainable as it grows. To do this in an open-source environment, platforms and processes with active open-source communities will be leveraged.

The careful design and development of a system such as that described above will be critical to shift from 'research grade' (relatively low TRL) applications to commercial applications that are capable of widespread deployment. Although the system developed as part of the 'stage 1' pilot project has not been taken to the level, the pilot project has assisted to clearly identify key considerations that will need to be taken into account as part of future stages.

5. Data analysis and visualisation

Key findings

- Computer vision technology was applied to detect bunches within a canopy, and segment key canopy elements such as bunches, canopy, trunk, and green shoots. An assessment of potential further applications of machine learning to enable monitoring of canopy indicators, flowers, berries, bunches, diseases, weeds and water shoots is provided.
- Conceptual approaches to numerically modelling physical and biological processes in the context of vineyards were identified, focusing on models that (i) estimate and predict vine development; (ii) predict grape quality; (iii) estimate and predict yield; (iv) estimate and predict disease risk; and (v) simulate on-farm operations. The review included both machine learning and mechanistic modelling approaches. Pathways to develop systems that provide guidance and advice by building on existing research platforms were reviewed.
- An open-source data storage and visualisation (i.e. dashboard) system was developed to present real-time data feeds to growers, including:
    - 'internet of things' data (soil moisture sensors, weather station data, plant status);
    - satellite data;
    - ground-based imagery from the tractor-mounted camera system;
    - historical water pricing information; and
    - management records (e.g. spray records).

  Although the pilot focuses on data visualisation, the system will ultimately be developed to include 'apps' that provide advice and operational decision support to growers as part of the longer-term development plan.

Data analysis and visualisation provide the 'value' associated with digital agricultural solutions, through the use of computational models and algorithms to translate data to information, which then can be provided to growers to make actionable decisions.

Most commercially available digital agricultural solutions have invested heavily in data acquisition and display/visualisation, and the number of such solutions has increased exponentially in recent years. For example, a digital tool may provide a measure of vineyard state at one or several points throughout the growth season, but it is then left to the grower to determine what if any decisions need to be made, based on some reference ideal vineyard state combined with a suite of management tools that might be available to the grower at that point in the growth cycle (e.g. watering, feritigation, canopy management, and so forth).

It is the thesis of this report that the next wave of digital agriculture will move beyond data display, and seek to provide guidance and advice to growers to help facilitate decision making. This 'higher-order' information has the potential to add significant value the collected data; however many obstacles remain to achieve this more ambitious goal. From a technological point of view, two main obstacles include:

- Most grower decisions are made based on a multitude of information sources, yet most commercialised digital viticulture systems are based on a small number of information streams that are often aggregated and capture only a subset of key information (whether it be in terms of spatial comprehensiveness, temporal resolution, granularity of data and diversity of data streams)
- In order to translate information to advice, a digital system needs to have visibility over both the potential management options, and the likely outcomes of those management options given the

range of local factors relevant to a particular vineyard. These data streams are not readily available at present.

This report does not provide a full solution to the above challenge; rather, we identify the components and a pathway to enable such a vision to be realised. In this section, we first cover a suite of tools collectively known as 'computer vision' that—when combined with vision systems such as the mobile ground-based image retrieval system—will facilitate a step-change in the granularity and nuance of critical data streams available to growers to support decisions (Section 4.1). This is followed in Section 4.2 by a review of current and emerging modelling approaches (including machine learning techniques and bio-physical modelling approaches) that connect data streams to specified outcomes (e.g. yield, quality indicators, disease risk and so forth), often making assumptions on, or allowing modifications to, key management options that influence those outcomes (e.g. irrigation, fertigation, canopy management). This latter feature provides the opportunity ultimately to shift the technology from data display to advice and guidance; in particular, though inverting biophysical and/or machine learning models, it becomes possible to specify the management actions that would lead to desired outcomes, given the current vineyard state. Lastly, key elements of a proof-of-principle dashboard platform are illustrated, including documentation of grower feedback (Section 4.3).

5.1. Computer vision and machine learning for vineyard monitoring

Growers periodically take measurements and make observations of their vineyard throughout the growing season. These measurements are typically taken infrequently and at sparse, randomised locations. More generally, growers regularly observe the development of their vineyards, and experienced growers have extensive memories of vineyard outcomes across different seasons, sometimes spanning multiple generations; however sharing this information between growers and with advisors can be difficult and at times unreliable. As such, there is the opportunity to automate and streamline the collection of these observations to improve their spatial and temporal resolution using computer vision.

Computer vision based algorithms leverage the power of machine learning algorithms to extract high-level information from images. At its essence, machine learning is enabling computers to learn without being explicitly programmed. Here the computer vision algorithms are trained to detect grapevine features that humans—in this case growers or viticulturists—observe visually; for example, the appearance of berry bunches or green shoots. These features are associated with not just the grapevine feature itself but also the phenological stage, and hence can be used to provide grapevine status information. The immediate value of the developed computer vision algorithms will be through the reduction in labour through the automation of data collection and the identification of 'trouble areas' that need further inspection and potentially intervention, thereby improving vineyard uniformity.

Computer vision algorithms are trained using a set of images that have been manually (or semi-automatically) annotated to provide 'ground-truth' labels. These annotations may include information such as the vine phenological growth stage or the location of buds, flowers and grapes within the image. For more nuanced grapevine features the specification of the computer vision algorithm and annotation should be guided by growers and viticulturists in consultation with machine learning specialists. The performance of computer vision algorithms is largely dependent on the collection of a large dataset that contains the grapevine features that are of interest and the quality annotation of a sufficient subset of images.

For this pilot project, images were collected via the Mobile Ground Image Retrieval System (see Section 3.3) at both Sherwood Estates (Loxton North) and the Coombe Vineyard (Waite Campus, University of Adelaide). These images were then used to develop computer vision algorithms to detect and segment vine features. The dataset of over three thousand collected images covered a range of grapevine varieties (i.e. Chardonnay, Shiraz, Negroamaro and Red Fronti) as well as grapevine age (e.g. young 1-year and 2-year grapevines as well as mature 15-year old grapevines). By spatially referencing each image, the grapevine features extracted from each image can be plotted on a map providing actionable information to the grower. Algorithms were developed that detected and segmented a selection of vine features that were visible

during the data collection period (i.e. berries, canopy, trunk and green shoots). These demonstrations of the developed algorithms are presented in Section 5.1.1.

Due to the timing and short duration of the project (commencement in January 2019) relative to the growing season, annotation of grapevine features for computer vision algorithm training and development algorithms to detect and segment early season grapevine features (such as bud count, shoot count and leaf appearance) was not possible. Nevertheless, the application of computer vision algorithms to the images that were collected provided valuable learnings that can be incorporated in future collection campaigns.

Further capabilities for computer vision and their potential uses are then discussed in Section 5.1.2. For example, the longer-term collection of data that occurs throughout the annual growing cycle of a grapevine will allow for the detection of new shoots and the tracking of vine development throughout the season according to phenological stage.

5.1.1. Detection and segmentation of grapevine features

Object detection is an approach of computer vision and image processing that deals with detecting instances of objects in digital images and videos. It predicts where the object is located in the image by drawing a bounding box around it.

In this project the state-of-the-art deep learning object detection approach, Faster RCNN (Ren et al., 2015), has been extended used to detect bunches of berries within full grapevine canopies. The Faster RCNN algorithm uses convolution layers to extract information from input images to generate bounding boxes. Boxes with sufficient confidence levels are reported as detected objects. This approach also has the ability to detect many other objects in a vineyard in addition to berry bunches, for example, weeds. Figure 28 shows an example of the modified Faster RCNN algorithm developed for detecting bunches. The red bounding boxes indicate the detection and localisation of the bunches. The overlayed percentages indicate the confidence level in the bunch detection by the algorithm.

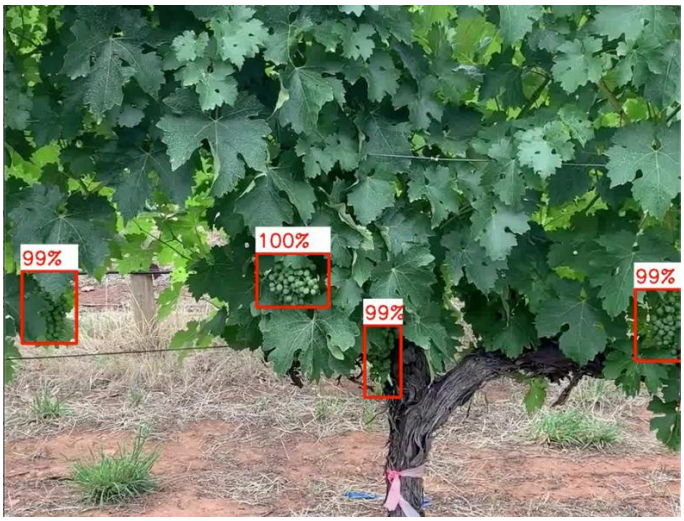


Figure 28 - Illustration of bunch detection algorithm

In addition to object detection, computer vision algorithms can be used to determine the boundary (i.e. the outline) and segmentation of objects within images. For example, to obtain measurements of the change in a grapevine's growth throughout a season it is necessary to identify the boundaries of the trunk, leaf and bunches in addition to detecting these features.

Here the Mask RCNN (He et al., 2017) algorithm was used to segment berry bunches within a fully developed grapevine canopy (Figure 29). The algorithm was deemed effective at segmenting the berry bunches and was subsequently extended to also segment additional grapevine features including trunk, canopy and green shoots (Figure 30 and Figure 31). Additional grapevine features can be incorporated with the collection and annotation of images that show the features of interest. The potential for computer vision algorithms to

segment a range of grapevine features and potential uses of the detection and segmentation of these features is discussed in in Section 5.1.2.



Figure 29 - Segmentation of berry bunches (rendered as green).



Figure 30 - Segmentation of the bunches (rendered as red), trunk (blue), and canopy (green)

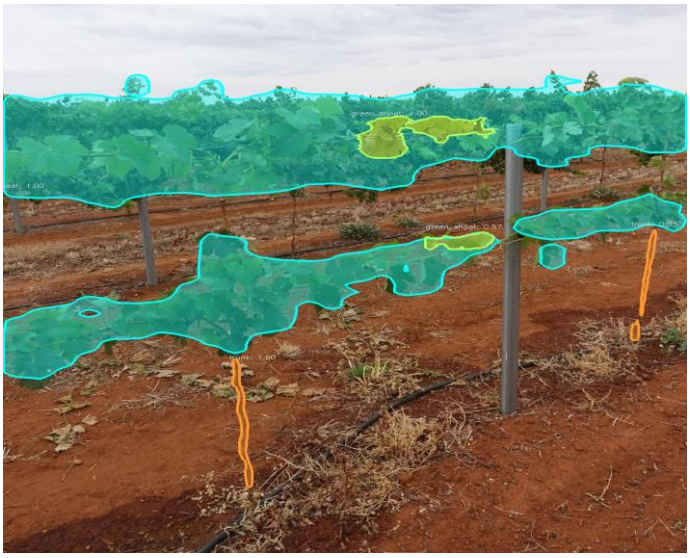


Figure 31 - Segmentation of the green shoots (rendered as light green), trunk (orange), and canopy (cyan).

5.1.2. Development of a library of computer vision vineyard monitoring algorithms

Section 5.1.1 demonstrated the utility of computer vision applied for grapevine feature detection and segmentation. Further extension of the approach to detect and segment additional grapevine and vineyard features through the course of a growing season has the capacity to enable growers to make actionable decisions. For example, the detection of new shoots throughout a season can provide a grower with information about the grapevine's growth stage as well as the nutrition and water status of the grapevine. This information can then be used to 'tune' the inputs (i.e. water and fertiliser) applied to the vineyard.

Table 17 summarises a number of potential applications of object detection and segmentation that were identified for a range of vineyard concerns including, canopy monitoring, flower berry and bunch monitoring, disease monitoring and weed and 'water shoot' monitoring. For each case the detected vineyard or grapevine feature is discussed alongside the potential uses as well as operational difficulty. The operational decisions that can be supported by the extracted information (e.g. canopy, irrigation and nutrition management decisions) as well as the potential modelling applications of the extracted information (e.g. yield prediction, modelling vine growth) are also presented.

Table 17 - Potential uses of machine learning when applied to vineyard imagery

Vineyard feature	Description	Sensors required	Potential uses (e.g. what can this measure tell us? why is this likely to be of value to growers?)	Operational Difficulty (H/M/L)
Canopy monitoring				
Visual image of canopy	Provide growers with a 'Google maps' type library of vineyard state on each pass of the vision system (e.g. every 10 days).	RGB	Helps provide a living record of vineyard growth over time (ultimately over many growing seasons), and facilitate communication of issues between growers, and with advisors (e.g. agronomists). This will potentially reduce time for identifying issues for further investigation, shorten the delay between issue identification and action, and consolidate learnings rather than relying on grower memory and manual documentation. This could also facilitate continual learning through identification of variability in performance across the vineyard and enables year-to-year vine performance comparison. *Information to support decisions related to: canopy management, nutrition, irrigation scheduling.*	L
Canopy height & volume	Measurement of canopy volume and height throughout vineyard.	RGB	Enables tracking of growth/vigour of vineyard over time which may be used in canopy management decision making, irrigation decision making and decisions surrounding canopy spraying. May lead to dynamic spray concentration adjustment thereby enabling a reduction in the total spray volume required. May also be used to reduce irrigation rates. *Information to support decisions related to: canopy management, nutrition, irrigation scheduling, and application of sprays (i.e. fungicide).* *Input for model(s) of: vine and canopy growth.*	M
Canopy colour	Measurement of canopy colour to enable estimation of vine nutrition status and growth stage. System trained initially to mimic grower assessment.	RGB Multispectral	Enables estimation and tracking of vine growth stage and nutrition status throughout the vineyard. This may enable the spatially variable application of nutrition and water throughout the vineyard to improve vineyard uniformity. Further gains may be possible with multispectral cameras. *Information to support decisions related to: canopy management,*	M

			nutrition, irrigation scheduling. *Input for model(s) of: vine and canopy growth.*	
Canopy light penetration	Measurement of the ability of light to penetrate canopy.	RGB (under canopy camera)	Enables decision making related to irrigation rates for the purpose of optimising canopy density (i.e. reduction of disease risk and spray application). *Information to support decisions related to: canopy management, nutrition, irrigation scheduling.* *Input for model(s) of: vine and canopy growth.*	M
One-year old cane length and length of stems	Measurement of one-year old wood to as an indication of pruning weight and vine vigour in next season.	RGB LiDAR Stereoscopic cameras	Provides information on vine vigour, related to irrigation and fertilisation that can be optimised. This measurement also provides an indication of vine vigour in the next season. *Information to support decisions related to: canopy management, nutrition, irrigation scheduling.* *Input for model(s) of: vine and canopy growth.*	M
Leaf blade/petiole angle	Measurement of leaf blade/petiole angle. System trained initially to mimic grower assessment regarding growth stage and water status.	RGB	Enables tracking of growth stage and monitoring of water and heat stress in the vineyard. This tracking of water stress could allow for the on demand application of irrigation. *Information to support decisions related to: canopy management, nutrition, irrigation scheduling.* *Input for model(s) of: vine and canopy growth.*	M
New shoot count & length	Detection, measurement and count of new shoots as an indication of vine growth stage, water stress and nutrition status (i.e. visibility indicates highly vigorous canopies related to excess nitrogen or water).	RGB Multispectral imagery	Enables the estimation and tracking of growth stage, vine water stress and nutrition status. This allows for the modification and potential optimisation of inputs (e.g. nitrogen, water, etc.). These measurements are also indictors of potential yield and fruit quality. *Information to support decisions related to: canopy management, nutrition, irrigation scheduling.* *Input for model(s) of: vine and canopy growth, yield prediction, yield quality.*	M

Flower, Berry and Bunch Monitoring				
Bud count	Measurement of the number of buds as an indicator of future shoot density and yield.	RGB	Measurements provide an indication of future shoot density and yield. Potential input to predictive model of for yield and vine growth. *Information to support decisions related to: nutrition, irrigation scheduling.* *Input for model(s) of: vine and canopy growth, yield prediction.*	L
Fraction buds burst	Measurement of the fraction of buds burst.	RGB	Measurements provide an indication of future shoot density and yield. Potential input to predictive model of for yield and vine growth. *Information to support decisions related to: nutrition, irrigation scheduling.* *Input for model(s) of: vine and canopy growth, yield prediction.*	L
Number of flowers	prediction of potential yield	RGB	Measurements provide an indication of future yield. Potential input to predictive model of for yield. *Information to support decisions related to: nutrition, irrigation scheduling.* *Input for model(s) of: vine and canopy growth, yield prediction.*	M-H* *Requires canopy manipulation*
Number flowers that have set fruit	potential yield estimate, estimate of crop thinning required	RGB	Measurements provide an indication of future yield and any crop thinning required. Potential input to predictive model for yield. *Information to support decisions related to: nutrition, irrigation scheduling.* *Input for model(s) of: vine and canopy growth, yield prediction.*	M-H* *Requires canopy manipulation* manipulat
Bunch count	Detection and count of berry bunches.	RGB	Measurements provide an indication of future yield. Potential input to predictive model for yield. *Information to support decisions related to: nutrition, irrigation scheduling.* *Input for model(s) of: vine and canopy growth, yield prediction.*	M-H (requires canopy manipulation)

Berry count per bunch	Detection and count of berries in a bunch.	RGB	Measurements provide an indication of future yield. Potential input to predictive model for yield. *Information to support decisions related to: nutrition, irrigation scheduling.* *Input for model(s) of: vine and canopy growth, yield prediction.*	M-H (requires canopy manipulation)
Berry size	Measurement of berry size throughout fruit development.	RGB	Measurements provide an indication of future yield. Potential input to predictive model for yield. *Information to support decisions related to: nutrition, irrigation scheduling.* *Input for model(s) of: vine and canopy growth, yield prediction, quality.*	M-H (requires canopy manipulation)
Disease Monitoring				
Powdery mildew	Detection and monitoring of downy mildew infections. System initially trained to mimic grower assessment.	RGB	Enables earlier disease detection, and in turn enable on-demand spraying rather than calendar spraying. *Information to support decisions related to: application of sprays (i.e. fungicide).* *Input for model(s) of: disease.*	M-H (requires canopy manipulation)
Oil spots	Detection and monitoring of downy mildew infections via detection and counting of oil spots	RGB	Enables earlier disease detection, and in turn enable on-demand spraying rather than calendar spraying. *Information to support decisions related to: application of sprays (i.e. fungicide).* *Input for model(s) of: disease.*	M-H (requires canopy manipulation)
Trunk Colour	Measurement of trunk colour as an indication of disease status.	RGB	Enables automated disease identification. *Information to support decisions related to: application of sprays (i.e. fungicide), nutrient management.* *Input for model(s) of: disease.*	M-H (requires canopy manipulation)

Weed & 'Water shoot' Monitoring				
'Water shoots'	Selective ground/trunk spraying	RGB *side /bottom mounted camera*	Enables the identification of 'water shoots' for selective spraying. *Information to support decisions related to: application of sprays (i.e. herbicide).*	M-H
Weed detection	Imaging of vineyard floor	RGB *side /bottom mounted camera*	Enables the identification of weeds for selective spraying. *Information to support decisions related to: application of sprays (i.e. herbicide).*	M-H

5.2. Integration of physical and biological process considerations

Numerical modelling of the biophysical processes in the vineyard refers to a suite of tools (broadly classified as either data driven or process driven) that can be used to simulate and predict vineyard features (e.g. vine development, yield, soil-water balance, disease and farm operations), and which are often designed to inform operational vineyard decision making. However, in line with other technologies reviewed in this report, these models largely have not transitioned from research environments to an operational environment. Interesting, this appears to lie in strong contrast to other agricultural domains, some of which rely heavily on predictive models for 'on-farm' decision making. For example, a number of tools have been developed for wheat growers that rely on dynamic soil-crop models (e.g. GrainCast (CSIRO, 2019); yield prophet (Birchip Cropping Group, 2017)), while apple growers rely on predictive modelling to make decisions around the application of chemicals for thinning fruit (Lehnert, 2014).

In order to assess the capacity of existing modelling approaches to support vineyard decision making, the following sections review and summarise a range of models for simulating vine development (Section 5.2.3), yield (Section 5.2.4), grape quality (Section 5.2.5), vineyard disease risk (Section 5.2.6) and farm management (Section 5.2.7), beginning with a brief overview of conceptual modelling approaches and the key management strategies of interest for the Riverland (Sections 5.2.1 and 5.2.2). The different approaches are then summarised in terms of their ability to model the impact of different management actions on outcomes of interest (i.e. yield, quality, disease) in Section 5.2.8. Future opportunities for supporting operational decision making via numerical modelling is provided in Section 5.2.9.

This review is confined to decision making for an operational vineyard and does not extend to decisions around vineyard planning or managing longer terms impacts (e.g. climate change).

5.2.1. Conceptual approaches to vineyard modelling

This review considers both the estimation and prediction of vineyard features as relevant to vineyard operational decision making. For the purpose of this review, 'estimation' of vineyard features encompasses using measurements of the vineyard to estimate status at the same time (e.g. the collection bunch weights at a given point in time to estimate yield at the same time). Although estimation methods can be used to assess vineyard status at any historical timeframe, the value of these methods can be particularly useful when applied in near-real-time contexts, providing situational awareness of various critical attributes of vineyard status. In contrast, 'prediction' uses current vineyard measurements to predict future status (e.g. the use of current weather conditions to predict future yield). Predictions can be 'deterministic' (i.e. a single prediction) or 'probabilistic' (describing the probability of various plausible vineyard outcomes), and/or can be made conditional on a particular set of assumptions (e.g. management actions) occurring.

There are a range of approaches for classifying environmental models in general, and viticultural models in particular. One useful approach is to classify models as either empirical/statistical or process-based models. It should be noted that in many cases the distinction between the two classes of model is not absolute, with many process-based models often having been developed based on the identification of empirical relationship between key biophysical processes but subsequently generalised or adjusted based on underpinning biophysical laws or principles.

Empirical models rely on historical (measured) relationships between environmental parameters (e.g. climate data, remotely sensed indices) and plant characteristics of interest—in many cases including growth stages, disease or insect risk (Terribile et al., 2017). Empirical models can range from relatively simple statistical relationships between variables, through to more complex machine learning approaches that identify key relationships and sometimes adapt with data availability. However, most empirical models reviewed within the viticulture context are often intuitive (Terribile et al., 2017) and well-accepted by practitioners. Empirical models are attractive in that they typically have smaller numbers of parameters that can be estimated relatively easily based on observed data (Dai et al., 2010). However, drawbacks include the level of calibration required to adapt the model to new environments, and an inability to account for non-linear relationships between the plant and environment (i.e. water resource management, crop-soil water

balance and yield) (Terribile et al., 2017, Dai et al., 2010, Moriondo et al., 2015) or account for interactions of feedbacks between variables (Araujo 2014). This is likely to make empirical models difficult to apply under new or adaptive vineyard management scenarios.

Process-based crop models attempt to enable greater generalisation and applicability by modelling the physical and biological processes (Terribile et al., 2017) to simulate crop development. These are often developed to run on a daily basis, with key vineyard features (e.g. soil moisture state, plant water stress, etc.) and outcomes (e.g. yield and quality measures) resulting from the accumulation of processes (e.g. water deficits and heat stress) over a period of time. Generally these process-based models are modular and enable the consideration of site specific characteristics (e.g. soil, climate, hydrology and vine characteristics) (Keating et al., 2003, Brown et al., 2014a, Brisson et al., 2003, Nogueira Júnior et al., 2018, Terribile et al., 2017). However, these models typically require the estimation of many parameters, which may be difficult to estimate based on physical measurements (Dai et al., 2010).

In addition, hybrid modelling approaches (a combination of process-based and empirical) elements have also been developed to predict factors like grape quality (Bonfante et al., 2017, de Cortázar-Atauri et al., 2009). or disease impacts (Leroy et al., 2013). These hybrid models leverage the strengths of the two modelling types as some outcomes are easier to simulate using empirical data-driven approaches (e.g. quality) whilst other benefit from process-based modelling (e.g. where the impact of changes in vineyard management strategies are investigated).

5.2.2. Consideration of vineyard management strategies

To inform vineyard decision making there is a need to consider the modelling of vineyard outcomes in the context of the management actions applied throughout a growing season. The following four key vineyard management strategies have been identified as relevant for the Riverland and are considered throughout the subsequent sections in terms of modelling capabilities:

- **Irrigation strategies** – For vines grown in areas where there is limited water, like the Riverland, the need to consider irrigation and the impacts of changes in irrigation is likely to be critical. Riverland vineyards are irrigated and the application of water represents a major cost centre for growers in this region. Hence, the ability to consider the impact of irrigation on vineyard outcomes (e.g yield) and to ensure that irrigation is used wisely indicates that this modelling capability may be useful for supporting irrigation decisions.
- **Canopy management** – It is common practice in the Riverland to trim ('tip') canopies throughout the growing season in addition to winter pruning which suggests a need to model this management action in the context of vine development and impacts on other vineyard outcomes (e.g. yield).
- **Nutrition management** - Riverland growers typically rely on fertigation to apply nutrients to large areas via their drip irrigation system for both pre- and post-harvest nutrition. Therefore there may be use for considering the nutrition needs of the specific cultivar and production targets through modelling.
- **Intercropping** – Although cover crops are not typically planted deliberately as common practice in the Riverland, many growers manage a 'weed-based' cover crop that grows in the mid-row and is slashed throughout the growing season. These weeds are not irrigated (and weeds under vines are sprayed with herbicide), so they will die into the season and hence are a lower priority for modelling.

5.2.3. Vine development prediction and estimation

In the context of this review, vine development considers a range of vine features including phenological stage, canopy development (e.g. leaf area), biomass accumulation and water status of a vine. There are a number of available models, both empirical and process-based, that simulate the development of a vine over multiple seasons or within a single season. These models typically focus on relating environmental conditions (i.e. temperature and rainfall) to specific vine features of interest (e.g. leaf area development, accumulation of biomass, water stress).

Empirical models typically rely on specific environmental inputs translated in to a single output related to vine development (see Dai et al., 2010). For example, Schultz (1992) developed an empirical model that uses thermal time to simulate leaf area appearance for a given canopy structure. Machine learning approaches (which are inherently empirical, drawing on the supplied data to develop relationships between the observed inputs and predictors of interest) have also been used to predict elements of vine development. For example, Brillante et al. (2016) used a machine learning approach to predict vine water stress as a function of climate and soil characteristics. Machine learning approaches have also been used for the 'on-the-go' estimation of vine water status based on thermal images of vineyards (Gutiérrez et al., 2018a).

A limitation of empirical models such as those descried above is that they typically do not provide information regarding the contribution of underlying processes to vine development or status. In contrast, process-based growth models are typically modular, breaking down the simulation of vine development in to sub-components that consider processes like soil-water interactions, biomass accumulation and canopy development. Many of these process-based models are generic modular crop models that have been adapted for grapevines (Nogueira Júnior et al., 2018, Araujo et al., 2016, Brisson et al., 2003). Process-based crop models have also been developed for a range of specialised applications surrounding vine development including water availability (Celette et al., 2010, Lebon et al., 2003), carbon balance (Lakso and Poni, 2005, Lakso et al., 2008), timing of vine phenology (Walker et al., 2006), expected yield and grape quality (Terribile et al., 2017).

Vine growth models are also commonly used to evaluate the impacts of climate change on vine feature like the timing of phenology (Fraga et al., 2016) (Webb et al., 2006, Webb, 2006) as well as the impacts on vineyard management strategies (e.g. irrigation needs (Fraga et al., 2018)). For a review of vine growth models used in climate change impact assessment see Moriondo et al. (2015).

In addition to developing predictions of various features of vine development or long-term climatic changes, process-based models have been used to evaluate the impact of a range of vineyard management strategies on vine development. These include:

- **Irrigation strategies** – A number of models enable the examination of changes in irrigation strategy on vine development including STICS (Brisson et al., 2003), APSIM (Araujo et al., 2016), vineLOGIC (Walker et al., 2006, Godwin et al., 2002) and VitiSim (Mirás-Avalos et al., 2018, Lakso and Poni, 2005). For example, STICS has been utilised to evaluate different water management strategies for vineyards on grapevine phenology, biomass production and soil water content (Valdés-Gómez et al., 2009, Celette et al., 2006) and also to evaluate water needs under climate change (Fraga et al., 2018). In contrast, a number of models in development either do not consider irrigation or do not enable the consideration of changes in irrigation in their current form (Nogueira Júnior et al., 2018, Leolini et al., 2018). Some models enable the consideration of irrigation water salinity on vine growth, for example, vineLOGIC (Walker et al., 2005) and SWAP (Ben-Asher et al., 2006). For vines grown in areas where there is limited water, like the Riverland, the need to consider irrigation and the impacts of changes in irrigation is likely to be critical.
- **Canopy management** – Vitisim, a model focused on the carbon balance (Lakso and Poni, 2005, Lakso et al., 2008, Poni et al., 2006), was used to evaluate and compare a minimally and conventionally pruned concord vines. The model also allows for the consideration of vine trimming throughout the season (Poni et al., 2006). Likewise, the MoDeM_IVM Decision Support System (Cola et al., 2014) was developed to predict grapevine growth and production and has the capacity to account for some aspects of canopy management (i.e. trimming) by influencing the leaf development module based on the date and severity (according to number of leaves left on main shoots after trimming) of trimming. In contrast, some models only allow the consideration of the initial pruning to a number of buds at the start of a season (Walker et al., 2006), and ignore the influence of canopy management during the growing season.

- **Nutrition management** – A few models enable the consideration of fertiliser application on vine development including, STICS (Brisson et al., 2003) and APSIM (Araujo et al., 2016). Nendel and Kersebaum (2004) developed a model, NVINE, that simulates vineyard soil nitrogen dynamics and simple plant development module that also predicts yield (approximate by fruit dry matter). Although the model can be used to diagnose nitrogen deficiencies it does not explicitly provide an input for fertiliser application. Riverland growers typically rely on fertigation to apply nutrients to large areas via their drip irrigation system for both pre- and post-harvest nutrition. Therefore there may be use for considering the nutrition needs of the specific cultivar and production targets through modelling.
- **Intercropping** – Water baLance for Intercropped Systems (WaLIS) (Celette et al., 2010) was developed to simulate the soil-water balance for an intercropped vineyard and used to evaluate the water stress for both the grapevine and intercrop over multiple years. VineLOGIC also enables the modeller to consider the impact of a cover crop (Walker et al., 2006). Although cover crops are not typically planted deliberately as common practice in the Riverland, many growers manage a 'weed-based' cover crop that grows in the mid-row and is slashed throughout the growing season. These are not irrigated (and under the vine is sprayed with herbicide) – so they will die into the season – hence lower priority for modelling.

A summary of the above models in terms of their inputs, outputs and vineyard management strategies is provided in Table 18 and Table 19.

5.2.4. Yield Estimation and Prediction

The estimation and prediction of yield informs a range of vineyard decisions surrounding timing and expected vineyard labour, as well as creating flow on implications for the wineries supplied (Daniel and Monga, 2019). Industry standard methods for yield quantity estimation are timing consuming and labour intensive (Liu et al., 2013, Daniel and Monga, 2019, Dunn and Martin, 2004), typically relying on the manual and destructive sampling of grape bunches throughout the vineyards. Issues have also been raised surrounding the accuracy of these approaches due to the sampling approaches (Clingeleffer et al., 2001), and weights biased towards healthier vines.

One approach currently being explored in the literature is the automation of bunch counting methodologies using computer vision for yield estimation (Dunn and Martin, 2004, Liu et al., 2013, Daniel and Monga, 2019). Liu et al. (2013) as well as Dunn and Martin (2004) used image based techniques to relate the number of fruit pixels to fruit weight with good predictive performance. However, these tests were completed under ideal conditions (e.g. good lighting and white background well exposed bunches, vertical shoot positions) and not under real-world conditions like those experience in the Riverland (i.e. large canopies with concealed bunches).This is a commonly observed limitation of vision based yield estimation approaches (Nuske et al., 2014). Similarly, Daniel and Monga (2019) evaluated the use of a convolution neutral network to predict yield from images collected via a smartphone. Again, the images were collected under conditions unlike the Riverland. Nuske et al. (2014) developed a yield estimation approach that used images from a camera side mounted on a utility vehicle driven at 5 km/h under a range of light conditions with good predictive performance. In contrast, Aquino et al. (2018) developed a system that used segmentation of night-time acquired images from an all-terrain vehicle for yield estimation. However, canopies used in these studies appear smaller and less sprawling than those in the Riverland, which may lead to issues with fruit detection due to the concealment of berries and bunches. Another explored approach was the estimation of grapevine yield derived from early season counting of grapevine shoots derived from video imagery (Liu et al., 2017) which may avoid some of the issues associate with bunch counting given the likely occlusion of bunches.

These bunch and shoot counting based techniques are particularly attractive as they can potential be expanded to produce spatial maps of estimated yield once operationalised. There have also been models

developed that relate remotely sensed vegetation vigour (i.e. normalised difference vegetation index) and crop yield to produce estimates of crop yield that consider spatial variability (e.g. for wheat Gaso et al., 2019). Empirical yield estimation based on the monitoring of trellis tension have also been explored (Blom and Tarara, 2009).

The above approaches focused on estimating yield from bunches or earlier season indications of fruit load (herein termed yield estimation). Approaches also are available for the longer-term prediction of yield (herein termed yield prediction) based on environmental factors. For example, standard yield prediction methods use historical weather records considering factors like rainfall, temperature and sunshine hours coupled with historical yield records to predict yield (Liu et al., 2013). Multiple studies have developed regression models that related yield and weather variables (typically temperature and precipitation) (Santos et al., 2011, Lobell et al., 2007, Lobell et al., 2006). Although, Quiroga and Iglesias (2009) developed an empirical model for predicting yield that looked at a number of agricultural management factors (i.e. irrigated area, fertiliser applied and mechanisation) in conjunction with climate data (i.e. temperature and precipitation) to predict yield. This is one of the few empirical studies that has attempted to consider vineyard management practices as part of an empirical approach to yield prediction.

Process-based models have also been used to investigate the impact of a range of vineyard management strategies on yield. In particular:

- **Irrigation strategies** – A range of mechanistic models have the capacity to consider irrigation strategies for the purpose of exploring impacts on yield, including vineLOGIC (Walker et al., 2006, Godwin et al., 2002), STICS (Brisson et al., 2003) and APSIM (Araujo et al., 2016) (approximated by live berry weight). VitiSim (Mirás-Avalos et al., 2018, Lakso and Poni, 2005) also enables the consideration of irrigation inputs, although the model's approximation of yield using dry fruit weight requires improvement.
- **Canopy management** –Some process-based models that are used for yield prediction consider canopy management interventions. For example, the MoDeM_IVM Decision Support System, presented in (Cola et al., 2014), has the capacity to account for some aspects of canopy management (i.e. trimming) by influencing the leaf development module based on the date and severity (according to number of leaves left on main shoots after trimming) of trimming. Similarly, Vitisim allows for the consideration of vine trimming throughout the season (Poni et al., 2006) as well as start of season pruning, and has been used to compare a minimally and conventionally pruned concord vines (Lakso and Poni, 2005, Lakso et al., 2008, Poni et al., 2006). However, the model's approximation of yield using dry fruit weight requires improvement. Genecrop-P (Nogueira Júnior et al., 2018) also enables the consideration of canopy management throughout the season by considering the relative rate of pruning on the specific pruning dates when simulating yield. A drawback to Genecrop-P is the lack of consideration of soil water or nutrient processes at this stage, including the lack of an ability to consider irrigation. In contrast, some models only account for the initial pruning to a number of buds at the start of a season (Walker et al., 2006), and to do not allow the simulation of canopy management interventions during the growing season.
- **Nutrition management** – A few models enable the consideration of fertiliser application. For example, STICS (Brisson et al., 2003) and APSIM (Araujo et al., 2016). Nendel and Kersebaum (2004) developed a model, NVINE, that simulates vineyard soil nitrogen dynamics which includes a simple plant development module that also predicts yield (approximate by fruit dry matter). The model was developed with the goal of being a practical tool for viticultural fertiliser management. Although the model can be used to diagnose nitrogen deficiencies Nendel and Kersebaum (2004) do not explicitly provide an input for fertiliser application.
- **Intercropping** – Very few models have the capacity to examine the impact of intercropping on yield (e.g. vineLOGIC; Walker et al., 2006, Godwin et al., 2002).

A number of studies have also used a simple growth model for climate change impact assessments looking at yield (Bindi et al., 1997b, Bindi et al., 1997a, Ferrise et al., 2016). Likewise, APSIM has been used (with modification) to investigate the impact of drought on yield in South African vineyards (Araujo et al., 2016).

A summary of the above models in terms of their inputs, outputs and vineyard management strategies is provided later in Table 18 and Table 19.

5.2.5. Grape Quality Prediction

Ensuring grape quality is a key factor in the management of many vineyards. Although many growers in the Riverland are not paid based on quality attributes for their grapes, it is worthwhile considering how quality measures could be modelled for vineyards within the region.

Climate has a strong influence on berry composition and the year-to-year variability of the grape harvest (Barnuud et al., 2014, Grifoni et al., 2006) Webb et al. (2008) and at all scales (Jones et al., 2012). As a result there are many investigations in the literature into establishing empirical relationships between meteorological conditions and wine quality. For example, in their review of investigations into ambient temperature and berry composition Bonada and Sadras (2015) comment that the number of papers linking temperature and grapevines in growing exponentially. In particular there is a focus in the literature on predicting and evaluating impacts and challenges for wine quality as a result of climate change (for example, a change in berry ripening) (Jones and Alves, 2012, Webb et al., 2008). Most of these studies have been undertaken at the regional scale.

Overall, studies have largely taken an empirical approach (Barnuud et al., 2014, Grifoni et al., 2006) to modelling these relationships. Grape quality has been considered in terms of the following factors in these empirical studies:

- **Anthocyanin levels –** Barnuud et al. (2014) developed a generic empirical model that used meteorological conditions (rainfall in the growing season, growing season length, number of hours air temperature above 25^{o}C) to anthocyanin levels. Additional variants of the model were also produced for two varieties that considered additional temperature indicators and the solar radiation over the ripening period. vineLOGIC (Godwin et al., 2002, Walker et al., 2006), a largely mechanistic model, relies on an empirical relationship to predict anthocyanin levels based on December to January light conditions.
- **Juice pH –** Barnuud et al. (2014) developed a generic empirical model that used meteorological conditions (growing season degree days and October mean daily vapour pressure) to juice pH.
- **Titratable acidity –** Barnuud et al. (2014) developed a generic empirical model that used a temperature indicator throughout the growing season (e.g. growing season degree days, minimum temperature, etc.) to titratable acidity.
- **Vintage score / rating** – Jones et al. (2005) investigated the relationship between vintage score (a surrogate for wine quality) and optimum growing season temperatures to develop a regression model that was used to evaluate climate change impacts on quality. Grifoni et al. (2006) also examined the relationship between vintage rating and large scale meteorological conditions (i.e. air temperature, precipitation, 500 hPa geopotential height, southern oscillation index, sea surface temperatures, etc.) as a precursor to developing a wine quality forecast model.
- **Wine grape price** – Webb et al. (2008) used wine grape price as an indication of quality following the finding that wine grape price correlated with wine grape colour and Glycosyl-glycose levels. The relationship between wine grape price and ten weather variables for 14 varieties was investigated, concluding that 64% of the variation in price could be explained by variation in mean January temperature. This lead to the development of a function relating mean January temperature and wine grape price for the 14 varieties.

A limitation of these empirical models is that typically vineyard management practices and differences across sites are not taken into account, although they can contribute to differences in berry composition (Barnuud et al., 2014). Although process-based models that capture plant physiology could potentially address this deficiency, currently no process-based models are available to investigate these impacts (Barnuud et al., 2014). However, some studies have adopted a hybrid approach (Bonfante et al., 2017), in which the development of the grapevine is modelled using a process-based model and quality is related to dynamic model outputs using empirical relationships. For example, Bonfante et al. (2017) predicted grape grade as a function of water stress using a dynamic model, SWAP (Ben-Asher et al., 2006), and then applying a definition of grape grade based on water stress threshold. Similarly, STICS relies on empirical approximation of quality based on the simulated berry water content (de Cortázar-Atauri et al., 2009).

At this stage there are very few models that enable investigations into the effects of vineyard management strategies on yield and models that enable investigations into management actions are typically of low technological maturity and thus have not been adopted for operational decision making.

5.2.6. Disease Risk Estimation and Prediction

There are many models of disease applicable to vineyards the main disease risks faced by the Riverland (due to its hot dry climate) are that of powdery and downy mildew. Therefore this review focuses on the estimation of risk and prediction of these particular diseases and does not consider the evaluation of infection severity (e.g. Birchmore et al., 2015). Typical disease management for the Riverland involves applying a spray for powdery mildew every 10 to 14 days throughout the growing season which poses a considerable cost in terms of time, labour and chemicals. Through the use of models of disease risk or disease prediction there may be opportunities to reduce chemical useage.

Commonly used tools for modelling disease include disease progress curves, simulation models, statistical tools and visual evalutation approaches (see review by Contreras-Medina et al., 2009). An overview of modelling plant diseases for decision making is provided in Rossi et al. (2010) and a review of several empirical models and mechanistic models is provided in Caffi et al. (2007).

There are readily available empirical models for assessing the risk of powdery and downy mildew based on weather conditions (e.g. temperature and rainfall). These models typically take the form of providing an indication where conditions pose a risk of infection. For example, for downy mildew there is a risk of primary infection where there has been 10 mm of rainfall and it has been at least 10^{o}C for at least 24 hours (Magarey, 2010). This relatively simple rule can easily be applied to weather and weather forecast information. Likewise, for powdery mildew (the main target of chemical spraying in the Riverland) UC Davis have developed a powdery mildew disease risk index that is based on the temperatures throughout the growing season (Gubler et al., 2006, Gubler et al., 1999). The index provides a guide for appropriate spraying intervals depending on risk severity and can provide for a reduction of at least two to three fungicide applications a year (Gubler et al., 1999). The index has also been revised in recent years to account for higher temperatures (Peduto et al., 2013). This disease risk index has been provided via websites drawing on local weather station information and can be calculated from on-farm weather station data.

Disease early warning systems have been developed for both powdery (Caffi et al., 2012) and downy mildew (Madden et al., 2000, Caffi et al., 2010) with the objective of reducing the number of chemical sprays applied throughout a season. For example, over a seven year trial in Ohio, Madden et al. (2000) was able to demonstrate that the number of sprays for downy mildew could be reduced by using a warning system that told growers to spray when weather conditions were conducive to primary downy mildew infections rather than according to a calendar spraying program with no increase in disease incidence. Caffi et al. (2010) also demonstrated a reduction in downy mildew spraying by up to two-thirds via the use of an early warning system that dispatched a text message alert based on short-term weather forecast information. Similarly, Caffi et al. (2012) was able to demonstrate a reduction in spray applications of between 36 and 75% using a similar warning system for powdery mildew which represented savings of between 56 €/ha/year and 161 €/ha/year for an Italian grower. Again, equivalent disease control was achieved compared with the calendar spraying program with reduced fungicide application and associated costs.

There are important tradeoffs between the application of chemicals in a vineyard and the mitigation of yield losses. However, there are few crop growth models account for yield losses due to pests or disease (Leroy et al., 2013). Such a model would need to both simulate the effects of the disease (given weather and vine management), simulate the vine growth over the year including yield, and integrate the impact of disease on to the vine production. For example, the generic crop models STICS and APSIM do not include components to incorporate disease impacts (Leroy et al., 2013). Some progress has been made in using a hybrid approach which uses a mechanistic grapevine growth model, STICS, and then using the developmental stage predicted by the model in conjunction with weather data to simulate disease development and then damage and loss to yield (Leroy et al., 2013).

5.2.7. Farm operation models

A few models have been developed that are focused on the 'realistic' modelling of the scheduling of vineyard activities and vine management practices. For example, Dhivine (Martin-Clouaire et al., 2016) models the dynamic scheduling of work activities and the allocation of farm resources (i.e. machinery and labour) to these tasks, relying on a simple plant life-cycle model to enable the alignment of activities with vine growth stages. Dhivine considers a range of vineyard management activities (trimming, pruning, chemical weeding, spreading of fertiliser, trellising, pesticide spraying) at plot scale. Complementary activities can be scheduled at the same time. This enables the consideration of different management strategies (i.e. the prioritisation of different activities) throughout the vineyard. This type of farm management model may be useful as a basis for exploring the economic impacts of different vineyard intervention strategies in conjunction with an economic model. At this stage, to the authors' knowledge, there is no readily available model that incorporates this economic modelling with dynamic farm management modelling.

Tools have also been developed to support viticultural planning and management for region wide grower associations and decision makers that focus on modelling the system at the landscape scale (e.g. GeoVit Terribile et al., 2017). These are beyond the scope of this review which focuses on models to assist the vineyard scale operations.

5.2.8. Modelling summary

Following a review of empirical, process-based and hybrid modelling approaches the different approaches are summarised in terms of their ability to model the impact of different management actions on outcomes of interest (i.e. yield, quality, disease).

Table 18 presents a summary of the reviewed empirical models in terms of the following:

- **Input variables** - which are generally regarded as the primary variables that will determine vineyard output;
- **Vineyard features** - which are defined as attributes of the vineyard that are relatively static;
- **Management actions** - which represent the aspects of vineyard operation that can be controlled by growers during the season; and
- **Output variables** - which are the variables of interest.

An attractive feature of these models is the small number of input parameters for the quick calculation of predictions of interest (i.e. yield and quality). However, these models do not typically consider the influence of different management strategies on the predictions which limits their ability to evaluate the impact of changes in vineyard management on key outputs for the Riverland like yield.

Table 18 – Summary of empirical prediction models

Model	Inputs	Vineyard Features	Management Actions	Output
Santos et al. (2011)	**Climate data:** Temperature Precipitation			Yield
Lobell et al. (2007) **and** **Lobell et al. (2006)**	**Climate data:** Temperature Precipitation			Yield
Quiroga and Iglesias (2009)	**Climate data:** Temperature Precipitation		Irrigated area Fertiliser consumption Mechanisation	Yield
Barnuud et al. (2014)	**Climate data:** Temperature Precipitation Growing season length	Variety		Quality
Webb et al. (2008)	**Climate data:** Temperature			Quality
Jones et al. (2005)	**Climate data:** Temperature			Quality
Grifoni et al. (2006)	**Climate data:** Temperature Precipitation Southern Oscillation Index Sea Surface Temperatures	Variety		Quality
Brillante et al. (2016)	**Climate data:** Temperature Precipitation	Soil characteristics		Vine water stress
Powdery mildew disease risk index (Gubler et al., 2006, Gubler et al., 1999).	**Climate data:** Temperature			Disease risk

Table 19 summarises the mechanistic models in terms of their predictive capabilities, required inputs, parameterised components, decision variables (i.e. management actions that can be modelled throughout the vine's growth). The licensing associated with the models is also presented, with some models forming part of a larger modelling framework with licensing restrictions for commercial uses (e.g. APSIM, STICS, UNIFI.GrapeML and vineLOGIC) and others existing as research code with no readily available licensing information (e.g. WaLIS). Some of the mechanistic models do not currently contain functionality to investigate management strategies of interest for the Riverland (Leolini et al., 2018, Bindi et al., 1997b, Bindi et al., 1997a, Nendel and Kersebaum, 2004).

Table 19 – Summary of process-based model inputs, parameters and capabilities

Model	Inputs	Parametrised component	Decision Variables (management strategies)	Outputs	Licensing
vineLOGIC (Walker et al., 2006)	**Climate data:** Precipitation Temperature Radiation	**Vineyard characteristics:** Soil Vineyard parameters (e.g. row, trellising) Drainage (e.g. tile drain) Depth to ground water table **Plant characteristics:** Winter pruning Variety (inc. root stock)	Irrigation, Intercropping	Salinity Vine growth (phenological stages) Leaf Area Index Yield Quality (anthocyanin level)	Restricted license. User interface and Fortran.
Vitisim (Lakso and Poni, 2005, Lakso et al., 2008, Mirás-Avalos et al., 2018, Poni et al., 2006)	**Climate data:** Temperature (max & min) Precipitation Relative Humidity Wind Speed Solar Radiation (calculated vapour pressure deficit and Potential Evapotranspiration).	**Vineyard characteristics:** Row & vine spacing **Plant characteristics:** Initial inputs of number of shoots Clusters per shoot Berries per cluster	Trimming Irrigation (Mirás-Avalos et al., 2018)	Leaf Area Dry Matter Accumulation Yield (approximated by dry fruit weight)	Research code (no readily available licensing information)

MoDeM_IVM DSS (Cola et al., 2014)	**Climate Data:** Temperature Precipitation Relative Humidity Global solar radiation Wind Speed Precipitation	**Vineyard characteristics:** Vine spacing Row spacing Trellis features Soil **Plant characteristics:** Canopy size ranges (height, width, density) Number of shoots	Canopy management (trimming)	Vine growth (phenological stages) Leaf Area Index Yield	Incorporated into the Italian decision support software for vineyard Vine.net (Rossi et al., 2014)
STICS (Brisson et al., 2003) adapted for vineyards by de Cortazar-Atauri (2006) and applied in (Valdés-Gómez et al., 2009, Fraga et al., 2015)	**Climate Data:** Temperature (mix & max) Solar Radiation Precipitation Potential evapotranspiration (optional)	**Vineyard characteristics:** Soil characteristics Cropping system	Irrigation Fertilisation	Leaf Area Index Biomass Yield Crop water status Soil water status Quality*	Not for commercial use. Available for education and research use.

APSIM (Keating et al., 2003) using the PLANT2 framework (Brown et al., 2014b) using the prototype VINE module (Araujo, 2014, Araujo et al., 2016)	**Climate Data:** Temperature (mix & max) Solar Radiation Precipitation	**Vineyard characteristics:** Soil characteristics Planting characteristics (row spacing, planting density) Winter pruning (bud number)	Irrigation, Fertilisation	Leaf Area Index, Biomass Vine growth (phenological stages) Yield (approximated by berry Live weight)	Free for non-commercial use. Commercial use by agreement. Development or modifications may be submitted for incorporation by review.
UNIFI.GrapeML (Leolini et al., 2018) part of the BioMA frmawork	**Climate Data:** Temperature (max, min), Global Solar Radiation, Precipitation, CO_2 Atmospheric Concentration	**Vineyard characteristics:** Soil Characteristics Initial water stress Variety (e.g. chilling requirement, flowering requirement) Number of shoots Planting density	NA	Vine growth (phenological stages) Yield (fruit biomass) Soil water content	Not for commercial use. All derivatives must be non-commercial in nature.
Genecrop-P (Nogueira Júnior et al., 2018)	**Climate Data:** Temperature (max, min) Global Solar Radiation	**Vineyard characteristics:** row spacing plant spacing winter pruning	Pruning (relative rate of pruning)	Vine growth (phenological stages) Leaf Area Leaf Area Index Biomass accumulation Yield (fruit biomass)	Research Code (no readily available licensing information). Based on the genecrop framework.

'Simple mechanistic model' (Bindi et al., 1996, Ferrise et al., 2016)	**Climate Data:** Temperature Solar Radiation CO_2 concentration	**Vineyard characteristics:** Planting density Variety (limited options)	NA	Leaf Area, Biomass accumulation, Yield	Research Code (no readily available licensing information).
WaLIS (Celette et al., 2010)	**Climate Data:** Temperature Precipitation Relative Humidity Global Solar Radiation Wind Speed	**Vineyard characteristics:** Soil Characteristics **Plant characteristics:** Canopy size	Intercropping	Water stress of grapevine Water stress of intercrop	Research Code (no readily available licensing information).
SWAP (Ben-Asher et al., 2006)	**Climate Data:** Temperature Precipitation Global Solar Radiation	**Plant characteristics:** Initial dry crop weight	Irrigation	Leaf Area Index Salinity Transpiration Soil Water Content Dry Matter Accumulation	Research Code (no readily available licensing information).
NVINE (Nendel and Kersebaum, 2004)	**Climate Data:** Temperature Precipitation Global Solar Radiation	**Vineyard characteristics:** Soil characteristics	NA	Soil Water Content Soil Nitrogen Content	Research Code (no readily available licensing information).
IVINE (Andreoli et al., 2019)	**Climate Data:** Temperature (air and soil) Precipitation Global Solar Radiation Wind Speed Wind Direction Atmospheric Pressure	**Vineyard characteristics:** Soil characteristics Geography **Plant characteristics:** Variety Plant Density Mean Number of Clusters Mean Number of Berries per cluster	Trimming Thinning	Vine growth (phenological stages) Leaf Area Index Yield (berry weight) Berry sugar concentration	Research Code (no readily available licensing information).

A summary of the process-based models categorised by simulated output and management action is provided in Table 20. Across the four identified management strategies no single model appears against all management strategies for the prediction of canopy development, yield, quality, disease or profit margin. This indicates a need to develop additional modelling capabilities.

Table 20 – Model summary in terms of predicted outcomes and management strategies considered.

		Outcome				
		Water balance/Salinity	**Canopy development**	**Yield**	**Quality**	**Disease**	**Profit Margin**
Management strategy	**Canopy management (during season)**		VitiSim Genecrop-P MoDeM_IVM	VitiSim Genecrop-P MoDeM_IVM			
	Irrigation	vineLOGIC SWAP	vineLOGIC STICS APSIM	vineLOGIC STICS APSIM VitiSim	vineLOGIC* STICS**		
	Intercropping	WaLIS	vineLOGIC	vineLOGIC	vineLOGIC*		
	Fertiliser application		STICS APSIM	STICS APSIM			

** In vineLOGIC anthocyanin levels are provided as a quality indicator.*
*** STICS uses an empirical relationship of berry water content to sugar content as a measure of quality.*

Lastly, to evaluate the maturity of these models for application to Riverland vineyards, Table 21 evaluates the different modelling techniques in terms on their TRL and easy of application for decision making.

Table 21 – TRLs for existing models of yield, quality and disease for application in Riverland vineyards.

Model type	TRL	Comments	Ease of application for decision making	Examples of models
Empirical yield estimation **(manual bunch sampling)**	9	Current industry standard approach. Issues surround the time and labour in manual bunch sampling as well as accuracy of this approach.	Easy	Current industry practice.
Empirical yield prediction **(computer vision based)**	2	This approach is currently in development in the literature. Progress has been made in terms of image acquisition, shoot and berry identification as well as operating speeds. However, the dense and large Riverland canopies remain a challenge for these non-invasive	Easy	Daniel and Monga (2019) Aquino et al. (2018) (Liu et al., 2017) Nuske et al. (2014) Liu et al. (2013)

		techniques.		
Empirical yield prediction **(weather information based)**	2	These approaches have a long history in the area of climate change impact assessment but have not been adapted for operational vineyard decision making. Typically the impact of management actions is ignored in these approaches.	Hard	(Santos et al., 2011) (Quiroga and Iglesias, 2009) (Lobell et al., 2007, Lobell et al., 2006)
Mechanistic yield prediction	2	This models are commonly used in research but not operationalised for decision making in vineyards.* These models typically driven by input weather data and allow the consideration of some management actions on yield and state variables of interest (e.g. leaf area index).	Hard	UNIFI.GrapeML (Leolini et al., 2018) STICS (Brisson et al., 2003) APSIM (Keating et al., 2003) vineLOGIC (Walker et al., 2006)
Empirical quality prediction **(weather information based)**	2	These approaches have a long history in the area of climate change impact assessment but have not been adapted for operational vineyard decision making. Typically the impact of management actions is ignored in these approaches. Some machine learning approaches have been trialled in this area.	Hard	Brillante et al. (2016) (Barnuud et al., 2014) Webb et al. (2008) Grifoni et al. (2006) Jones et al. (2005)
Hybrid model quality prediction	2	Models that use both empirical and mechanistic modelling to predict grape quality are in development in the literature. They have not been operationalised for vineyard decision making. They do enable the consideration of some management actions on quality.	Hard	(Bonfante et al., 2017) (de Cortázar-Atauri et al., 2009).
Empirical disease risk	5	These models have been trialled in vineyards around the world to demonstrate a reduction in spray application. Tests to validate these models for Riverland conditions may be required.	Medium	(Gubler et al., 2006, Gubler et al., 1999)
Mechanistic disease models	5	Caffi et al. (2011) and Rossi et al. (2008) have been incorporated into the Italian online decision support software for vineyard Vite.net (Rossi et al., 2014).	Medium	Rossi et al. (2008) Caffi et al. (2011) Vite.net (Rossi et al.,

	Tests to validate these models for Riverland conditions may be required.	2014)

**This type of model is at a higher TRL for decision making in other crops e.g. (apple thinning decisions, wheat).*

Although the majority of the above models currently have low TRLs and require development to make them easy to apply in Riverland vineyards, there are opportunities based on hybrid modelling approaches, machine learning and data assimilation for developing crop models that are suitable for the development of modelling tools to support vineyard management decisions.

5.2.9. Future modelling opportunities

Empirical models can also enable investigations into changes in management practices on key outputs (e.g. yield or quality) when coupled with mechanistic models as part of a hybrid approach. For example, Bonfante et al. (2017) predicted grape grade as a function of water stress predicted using a dynamic model. The development of more models of this hybrid type could leverage the strengths of the two modelling approaches to enable the rapid development of models for exploring changes in management practices on key outputs. This approach is may be particularly powerful where data-driven machine learning type empirical models and coupled with existing mechanistic models. Machine learning approaches are typically data intensive and the use of the hybrid approach could enable the strategic collection of data in relation to key vineyard features. This way the collection of data for machine learning applications could be strategically planned so that data relating key features could be captured.

A further opportunity is available through the use of mechanistic models via data assimilation in which observations of the state of the vineyard (e.g. leaf area index, soil moisture) are used to adjust the state variable within the model for the purposes of improving predictions of interest. Data assimilation approaches using remotely sensed data applied to crop models have typically focused on the adjustment of the leaf area index state variable for the purpose of improving yield prediction of broad-acre crops like wheat, sugar beet, maize, rice and sugarcane (see review by Jin et al., 2018). A number of mechanistic models have been used for this purpose including, STICS (Brisson et al., 2003), SWAP (Ben-Asher et al., 2006) and APSIM (Keating et al., 2003). For example, remotely sensed observations of corn, wheat and soybean have been used to correct the modelled leaf area index and other variables like sowing date, start of senescence for the purposes of improving yield and biomass prediction in wheat using the STICS crop model (Jégo et al., 2012, Prévot et al., 2003). Similarly, satellite observations of canopy reflectance via a radiative transfer model have been used to improve the simulation of biomass accumulation in maize using APSIM and to produce spatially distributed biomass predictions (Machwitz et al., 2014). There is also the potential for data assimilation to be applied using computer vision derived observations (e.g. segmentation of canopy, trunk, leaf area development, etc.). To the authors' knowledge this technique is not currently being used for grapevines.

5.3. Vineyard dashboard platform

The dashboard developed as part of this project is designed to display and visualise a range of data streams (from spatial information on plant vigour to average water price to local soil moisture readings) to a grower to provide assistance for on farm decision making. The need for an application that could provide a range of information and data in a single location was identified in consultation with Riverland growers as part of the specification of the pilot project. This need was identified due to the number of unconnected commercial (e.g. local in-situ sensor dashboard, plant vigour map dashboard, spray diaries) and public applications/information sources (e.g. weather services, water trading information) that growers used. The need to engage with each of these sources individually without a central location that enabled easy comparison or synthesis of information was deemed a bottleneck for growers in terms of on-farm decision making. The lack of specific guidance provided by current services was also identified as a limitation of current systems.

This dashboard is a proof-of-principle implementation to enable the display of data collected throughout this project as well as providing a means for engaging with Riverland growers around the utility of different data streams and the need for guidance or advice as part of a digital vineyard advisor. This proof-of-principle version of the dashboard was developed over a 7 week sprint. Longer-term development of the dashboard will extend its capabilities beyond the visualisation of key data streams to the provision of supporting guidance and advice.

Here the dashboard features and underlying system architecture are presented in Sections 5.3.1 and 5.3.2 followed by a summary of grower feedback on current dashboard functionality with accompanying suggestions for extension of the dashboard (Section 5.3.3).

5.3.1. Overview of proof-of-principle dashboard features

The proof-of-principle dashboard (currently accessible at http://13.55.239.255) has been designed to display a range of data from different sources for on-farm decision making. To do this the dashboard draws on different data streams and services as part of the development towards a single location for all on-farm relevant information and guidance.

The dashboard displays the following general types of data and information:

- **Vineyard records (Farm and Business)** – this includes the display of weather forecast information, historical patch yield records, growth stage and spray diary information as well as water trading information that is live updated from the Bureau of Meteorology. Each of these charts are interactive and allow the selection of different time windows for displaying the data as well as 'hover over' text.
- **Spatial vine vigour information (NDVI Map)** – this is presented as a NDVI map of the region that can be 'zoomed in' to the farm or patch level with the capacity to interrogate different dates so that changes throughout a season and between years can be displayed.
- **Farm patch information (Patch Map)** – displays a spatial information summary of a vineyards different patches with hover over text to display the variety. The patch average NDVI is also displayed for patch comparison purposes with the option to choose different dates.
- **Patch specific observations (Sensor Map)** – this displays the location of multiple in-situ sensors (red pin icons) as well as an example of the imagery locations (blue dot icons) collected by the ground-based camera system (Section 3.3). Clicking on the icons brings up the relevant sensor details page. These detail pages show the real-time readings of the in-situ sensors (i.e. weather observations, dendrometer, soil moisture, electro conductivity) and for the ground-based imagery the details page shows that vine's image with some accompanying example vine information (note - these are illustrative vine statistics) and the time series of NDVI for the patch.

Examples of the spatial vine vigour information display through the dashboard are shown in Figure 32, the farm patch information in Figure 33, the farm and business data dashboard pages in Figure 34, and the interactive sensor map in Figure 35. Detail pages for the specific sensors are shown in Figure 36 to Figure 39 as well as the vine statistics page showing the collected ground-based imagery in Figure 40.



Figure 32 - Dashboard 'NDVI Map' page.

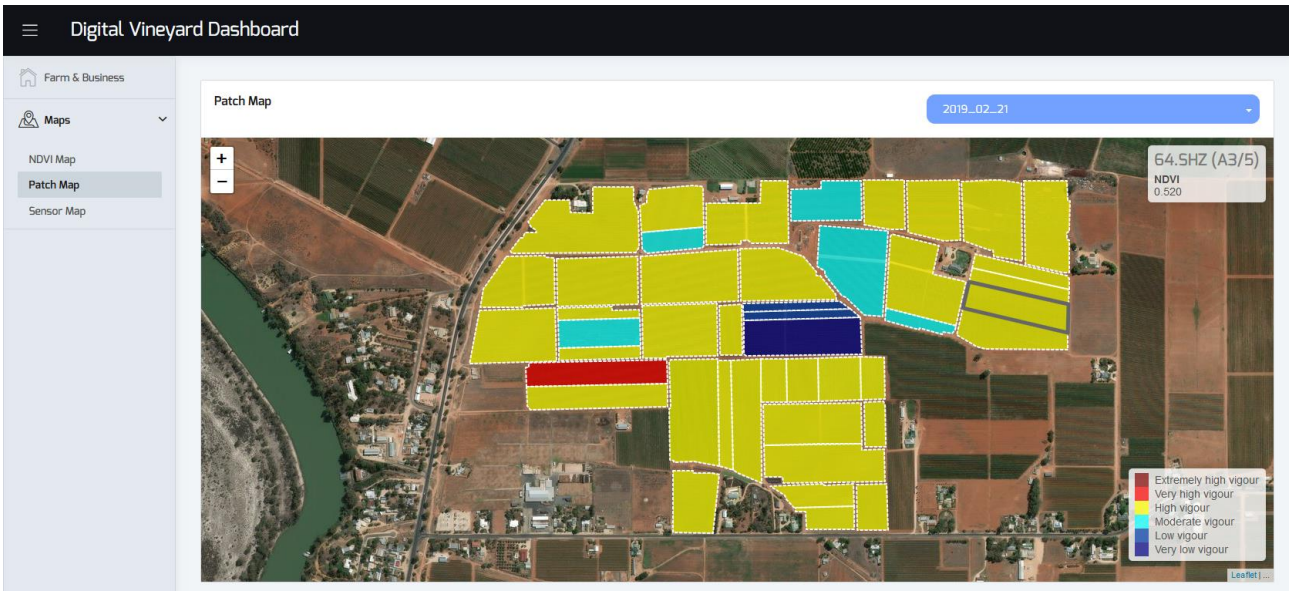


Figure 33 – Dashboard 'Patch Map' page.

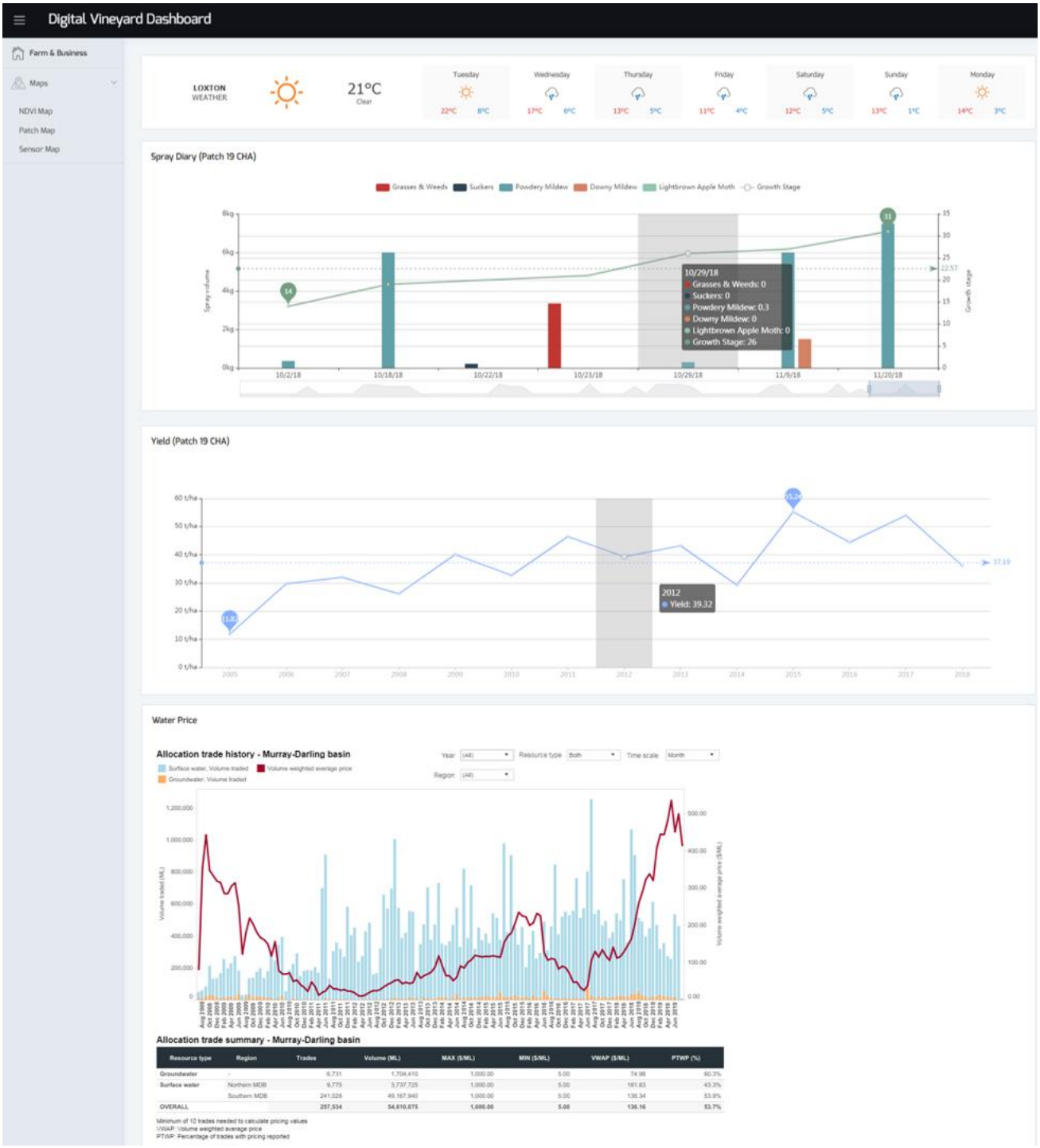


Figure 34 - Dashboard 'Farm and Business' page.

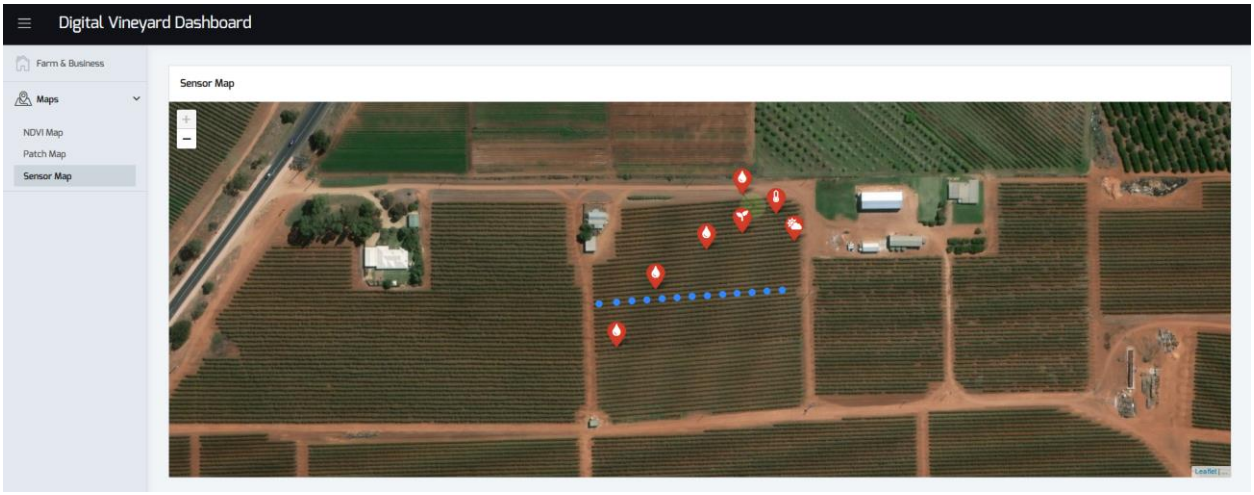


Figure 35 - Dashboard 'Sensor Map' page.



Figure 36 - Example of a multi-depth soil moisture and temperature details page



Figure 37 - Example of the 10 cm depth volumetric water content, electro conductivity and temperature details page



Figure 38 - Example of the stem dendrometer details page

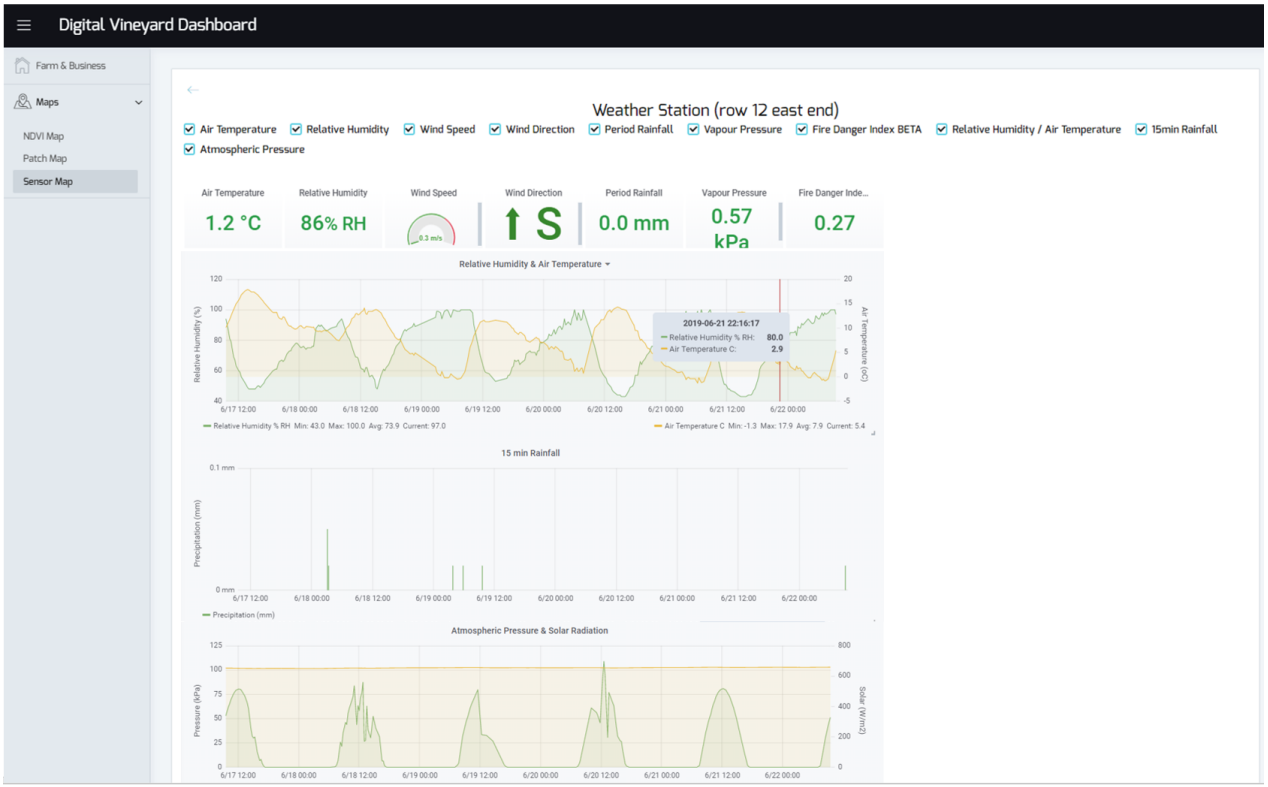


Figure 39 - Example of the weather station details page

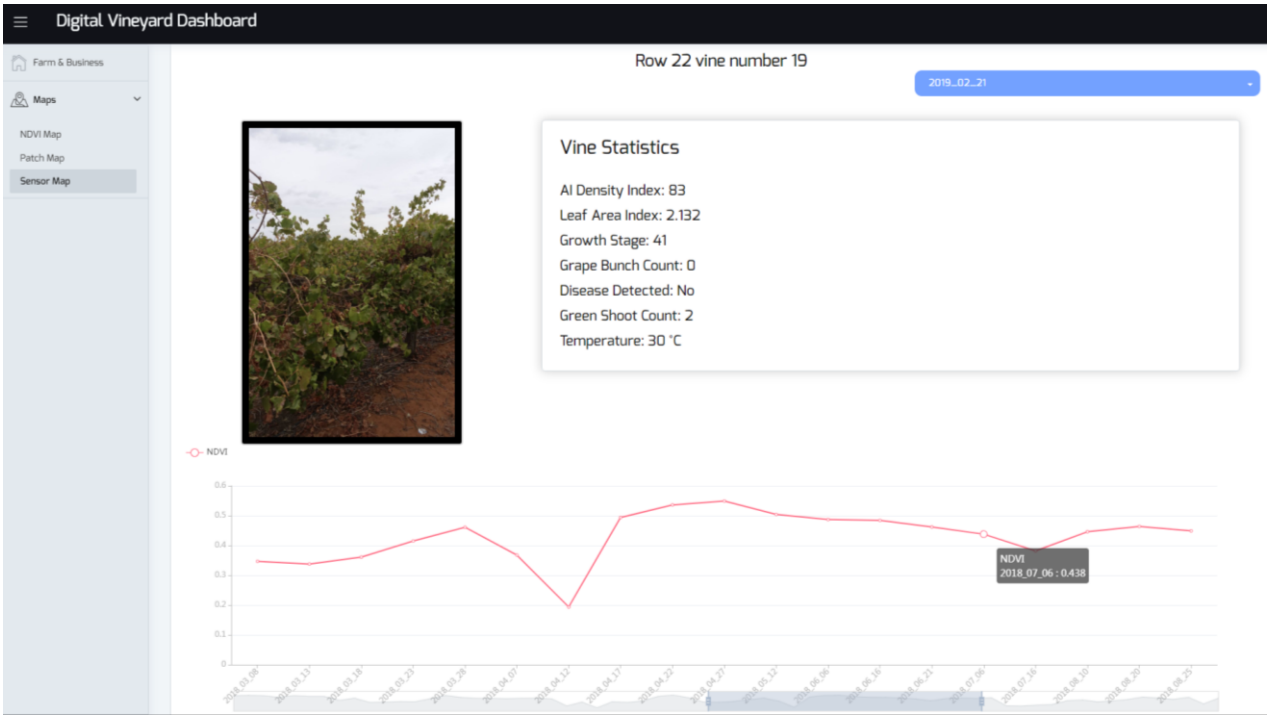


Figure 40 - Example of the vine statistics details page showing the collected ground-based imagery and NDVI time series for the Chardonnay patch. Note vine statistics provided are illustrative.

5.3.2. Proof-of-principle dashboard architecture

The dashboard has been designed as a web application that can be viewed via a web browser on desktop computer or smart phone using the Angular framework. This enables access to the dashboard as and when required by the grower for actionable on-farm decision making.

The dashboard has been developed as an open-system drawing on open-source resources (i.e. the Angular platform and framework as well as the Nebula components library). A range of attributes of these open-source systems were critical to the development of the proof-of-principle dashboard and provide a good foundation for its extension including the ability to integrate a range of data formats, modular framework design which facilitates rapid prototyping, layout that adapt to the viewing platform. This range of attributes is summarised in Table 22.

Table 22 – Summary of required attributes for current and ongoing dashboard development

Attribute	Description
Open-source	The use of open-source frameworks enables the dashboard to benefit from a vast array of open-source technologies (communications networks, algorithms, dashboards, crop models) that have already been developed. It also ensures that intellectual property can be shared amongst growers. Moreover, this is more likely to create a supportive environment that would encourage researchers in Australia and internationally to connect and contribute, and thus act as a vehicle to create scale that might otherwise be difficult to achieve.
Modular and extendable framework	Use of a logical and modular framework makes it easy for developer to understand existing projects like this dashboard and to build on them in the future. The provision of a range of component templates as well as the ability to extend and customise the components is also key for the development of a fit-for-purpose dashboard solution.
Capacity for rapid prototyping	The ability to add and duplicate dashboard components (e.g. windows of charts) easily. This enables the prototyping of dashboard features as part of the iterative software development process.
Integration of a range of data formats and embed information from other sources	Capacity to handle a range of data sources and formats as well as the displaying data from third party sources is key in the development of an integrated dashboard that growers can rely on as a 'single port of call'.
A single framework for multiple platform targets (e.g. web, desktop, etc.)	Responsive layouts across a range for different platforms (e.g. web, mobile web, native mobile and native dashboard). This allows growers to interact with the dashboard when the need it on their desired platform.

Figure 41 illustrates the current dashboard system architecture. The currently the dashboard and dashboard database is hosted by Amazon Web Services.

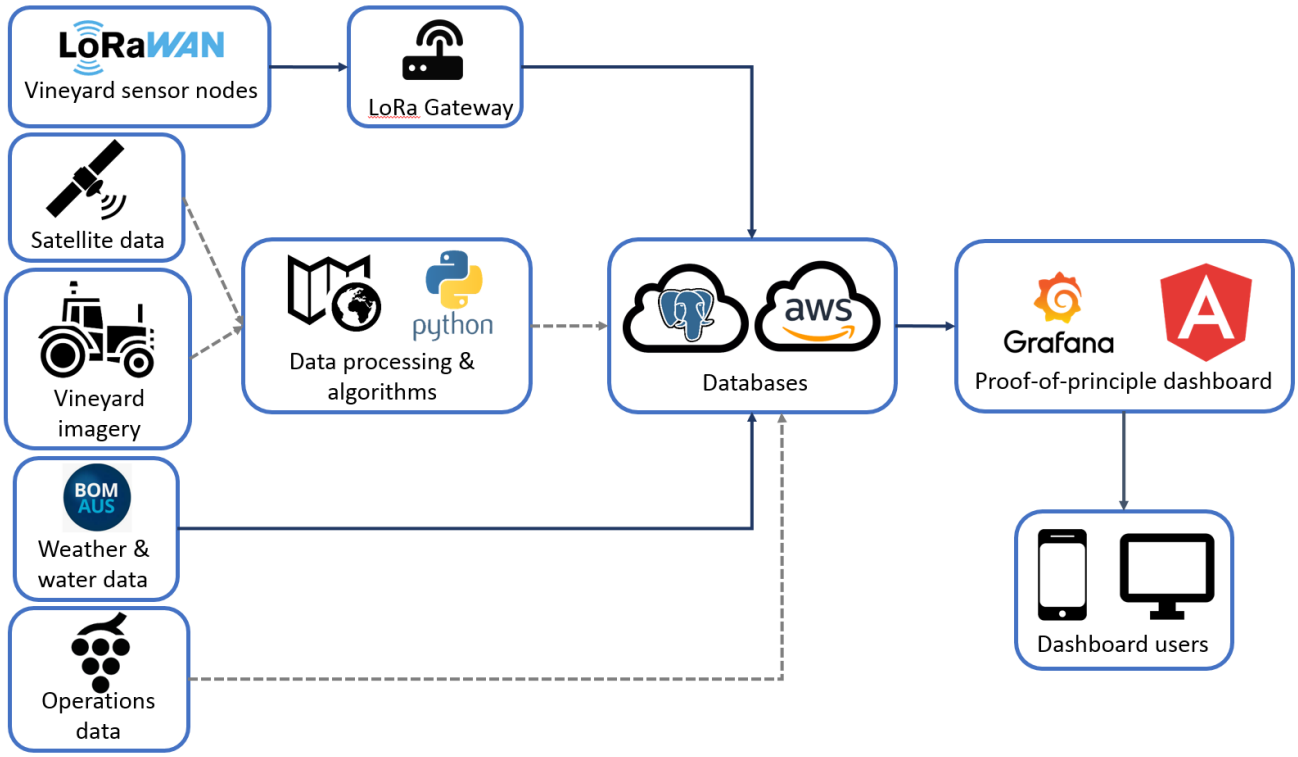


Figure 41 – System architecture. Grey dashed arrows indicate transfer processes that are not fully automated as part of the proof-of-principle system.

5.3.3. Grower feedback on dashboard functionality and layout

Following the development of a prototype vineyard dashboard, feedback was sought from Riverland grape growers on the layout and functionality of the dashboard. These comments have been tabulated according to the dashboard component (e.g. web page) they concern (see Table 23). Suggestions to augment dashboard functionality as well as observations around missing or awkward functionality are also presented.

Table 23 – Summary of grower proof-of-principle dashboard feedback

Component	Sub-component	Current functionality	Suggested extension
Farm & Business			
	General comments	Good to help centralise records that would be useful if the property was sold. Creates a property history.	
	Weather forecast	Good to have this information in one spot. Would regularly check this page to check the forecast conditions.	Predicted rainfall amounts and percent chance of rainfall should be added to make it comparable to other weather services.
	Spray diary and growth stages	Good to be able to do a year to year comparison as an interactive chart. Can be used to discuss the development of a spray program as part of operations planning.	Would be useful to overlay rainfall data to enable a year to year comparison (e.g. was it a wet year?). Need to add in a report on disease outbreak for that spray program (including scouting reports). This would enable a comparison of the conditions and the effectiveness of the spray program. For example, could have a short note regarding the season: '*Powdery mildew found in patch X, eliminated in X sprays. High wind conditions*.' Add in record of chemical type so that growers can ensure chemical rotation.
	Yield chart	Good to see progression year to year.	Suggest to couple chart with rainfall and irrigation applied each quarter to gauge annual conditions.
	Water pricing and transactions	Ability to interact with the graph using live Bureau of Meteorology data is a good feature (e.g. change to resolution to season, month, etc.). Would regularly check this page to check the water price.	Would be good to remove 'zero dollar' trades to get a better picture of current market activity.
	Water usage and flow rate	Missing from current version.	Would like to see water usage and flow through irrigation valves for irrigation monitoring purposes.
	Farm maintenance actions	Missing from current version.	Addition of ability to log jobs done or to do would allow for delegation of tasks easily to workers, especially if jobs could be tagged with a location.

NDVI Map			
		A regular NDVI map is very useful for detecting spatial anomalies (e.g. blown irrigation lines, re-developed patches, change in variety within patch)	Alerts for unexpected deviation with option to accept anomaly if cause known (e.g. canopy 'tipping').
		Can see the value in the ability to review NDVI changes over time.	Needs the addition of an overlay of roads and landmarks (e.g. patches) to assist with user orientation.
Patch Map			
		The patch map is awesome including the incorporation of NDVI to allow patch to patch comparison.	Incorporation of higher resolution NDVI into patch map would be useful.
			Addition of more informative hover over text, in addition to the NDVI, would be useful for farm operations (e.g. clone, variety)
Sensor Map			
	Landing page	Growers enjoyed this feature and the ability to interrogate data collected by the spatially referenced sensors.	Direct access to the in-situ sensor information (i.e. not via the map) Addition of a slider to zoom in and out and scroll back in time is needed.
	Electro conductivity	Good feature. Has been used by grower to enable tracking of fertiliser applied through soil profile so it can been kept in the root zone.	
	Multi-depth soil moisture	Multi-depth soil moisture used to confirm and check the impact of rainfall and irrigation.	Advice on plant water status or demand displayed alongside the soil moisture level would be useful, especially if tied to vine growth stage.
	Weather station	Provision of weather station data is useful for making on farm decisions (e.g. wind and humidity was used to assess if suitable for spraying conditions).	Needs to also display the time the reading was logged (e.g. updated at 6.00 am).
	Tractor collected canopy imagery (blue icons)	Gives a good impression of the canopy without having to walk or drive the rows. Some page view problems with low speed internet.	

General comments		
	Features work on both desktop computer and via phone browser. Useful creation of property history.	The black top border takes up too much of the screen when viewed on a phone and should be re-designed as users will want to interact via their smart phones. Need alerts to make fast operational decisions. Ability to locate your own position (e.g. standing in which patch) would be useful.

6. Technology value assessment

Key findings

- Preliminary estimates of grower costs highlighted significant year-to-year operating cost variations across vineyards, with the largest incurred costs being hired labour, followed by contracts, interest payments, water, and repairs and maintenance.
- Scenario-based assessments using a small (<10 ha), medium (11-80 ha) and large farm (>80 ha) highlighted areas of pre-existing technology investment, and identified potential areas for digital technologies to save water, electricity, fuel and/or labour costs, as well as the potential to increase overall farm yield.
- Preliminary benefit-cost estimates found considerable quantitative economic benefits from digital agricultural solutions that targeted decision making, with a benefit-cost ratio conservatively estimated to be 3.38, indicating that for each dollar invested, the grower would receive a return of $3.38.

A clear articulation of the benefits and costs of digital technologies to inform grower decision-making is a critical component to help frame the grower value proposition, develop solutions that are suitable for commercialisation, and encourage adoption of suitable technologies. This analysis can assist in identifying key grower costs and/or opportunities for increased profit that could potentially be optimised through digital agricultural solutions.

The objectives of this study are threefold: 1) collect secondary data wherever possible to provide an overview of economics of grape production in the Riverland (as compared to the Australian situation); 2) undertake a series of three case studies for a small, medium and large viticultural farm on the benefits and costs that they perceive with the new potential technology; and 3) provide a broad estimate of the economics of the potential technology using standard benefit cost analysis. This analysis provides a conservative preliminary estimate of benefits and costs.

6.1. Review of existing data

Ongoing engagement with Riverland growers enabled the development of an operational action and decision timeline. This timeline demonstrated the diverse range of operational activities required each growing year each with their own associated costs.

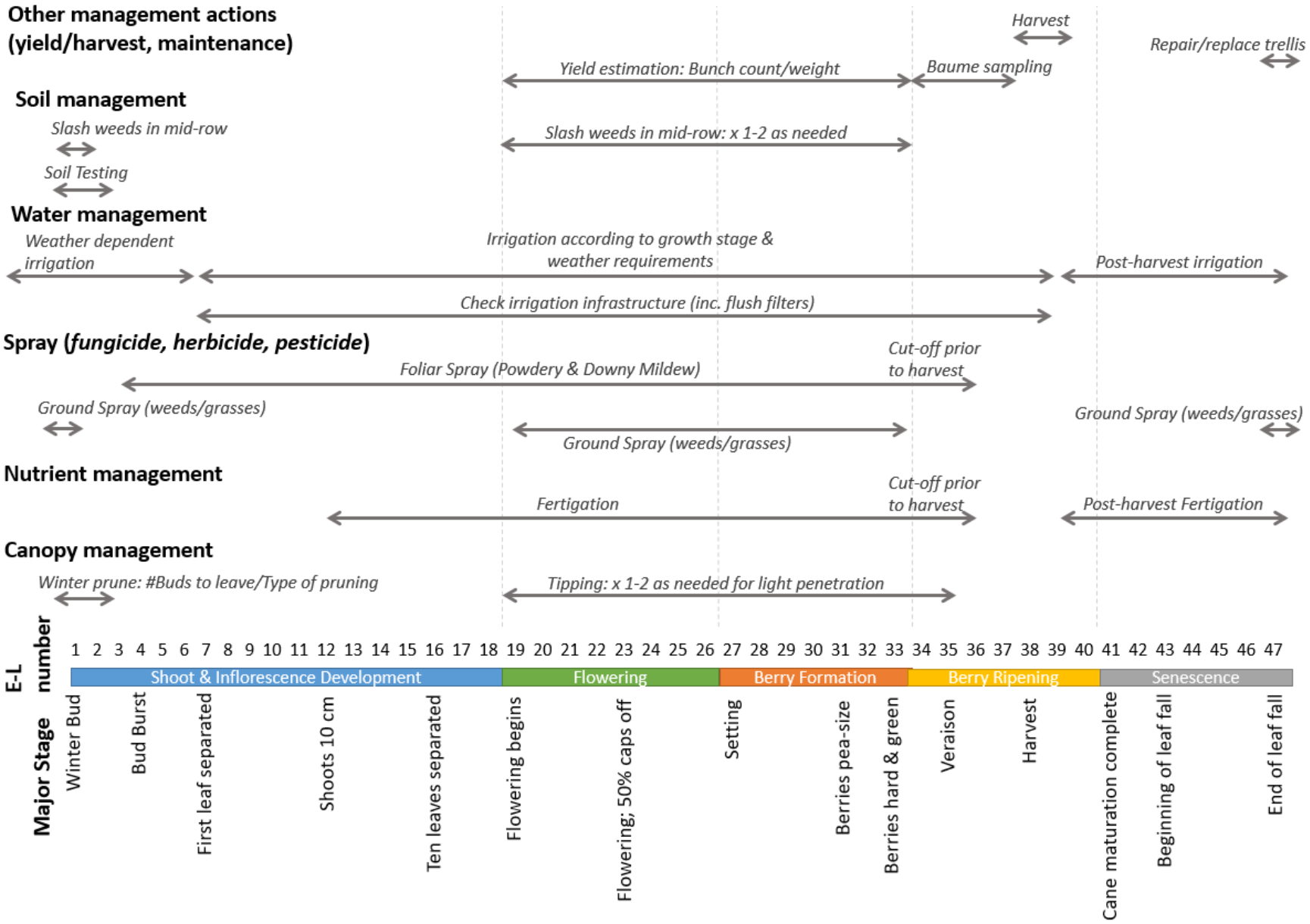


Figure 42 - Timeline overview of Riverland grower actions and decisions

A review of the existing literature in this space revealed that there is a lack of consistent, up-to-date information on the economics of grape production in the Riverland. Some important high level information that is available from sources such as ABARES (2017), AWRI (2019), various consulting reports and ABS agricultural census (specialised requested information) include:

- Yield (tonnes/ha) for 2015 and 2016 by region in Australia and tonnes produced for Australia from 1988-89 to 2015-16;
- Grape price (red/white/total) ($/tonne) for 2016 by region, and prices for Australia from 1988-89 to 2015-16;
- Vineyard operating costs ($/ha) for some inland wine regions for 2006/07; 2008/09; 2010/11), and for Riverland from 2002/03 to 2006/07;
- Farm cash income/rate of return/capital investment/adoption of irrigation infrastructure (%) of Murray-Darling Basin viticulture for 2006/07 to 2015-16 and proportion of total cash costs (average for time period).

Figure 43 illustrates the changing nature of grape production and prices in Australia.

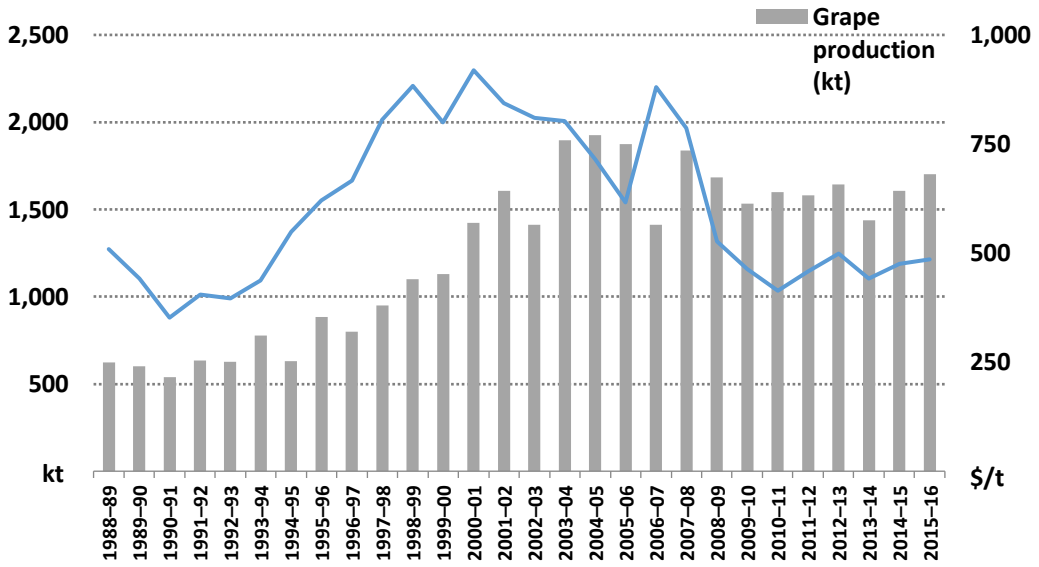


Figure 43 **- Australian grape production and prices from 1988-89 to 2015-16. Source: Created from data within ABARES (2017)**

Table 24 illustrates specific yields and prices of regions in 2015 and 2016. For the Riverland in particular, it achieved 57% higher yields in 2016 (89% higher yields in 2015) (tonnes/hectare) than the weighted Australian average overall, but it received 42% lower prices than the average weighted Australian price in 2016 (highlighted in Table).

Table 24 - Grape production yields and prices in 2015 and 2016 by region

	Yield (t/ha)		Grape price per tonne in 2016 ($)		
Regions	*Total 2016 survey yield*	*Total ABS 2015 yield*	*Red grapes*	*White grapes*	*All grapes*
Adelaide Hills	10.1	8.7	1506.6	1281.9	1348.0
Barossa Valley	6.5	5.2	2015.4	753.3	1810.6
Beechworth	5.8	5.9	N/A	N/A	N/A
Clare Valley	7.2	5.4	1281.9	978.0	1149.8
Coonawarra	7.0	5.8	1486.8	588.1	1440.5
Eden Valley	5.3	5.8	2160.8	1308.4	1718.1
Geelong	2.1	3.5	1922.9	1784.1	1837.0
Granite Belt	4.0	2.3	1500.0	938.3	1467.0
Great Southern	5.8	3.4	1467.0	1083.7	1288.6
Heathcote	7.5	6.4	1149.8	892.1	1136.6
Hilltops	6.8	7.1	885.5	627.8	786.3
Hunter	5.4	3.3	1467.0	1130.0	1182.8
Langhorne Creek	13.6	7.9	806.2	581.5	766.5
Macedon Ranges	5.7	4.0	2207.1	2293.0	2233.5
Margaret River	6.7	5.3	1519.8	1196.0	1308.4
McLaren Vale	8.8	6.0	1698.2	806.2	1599.1
Mornington Peninsula	4.9	4.2	2781.9	2431.7	2570.5
Mudgee	7.4	4.5	740.1	1400.9	740.1
Murray Darling	24.5	23.6	323.8	297.4	310.6
Orange	8.6	6.7	978.0	997.8	984.6
Riverina	15.7	15.4	363.4	284.1	317.2
Riverland	**21.0**	**23.0**	**343.6**	**277.5**	**304.0**
Rutherglen	6.1	5.4	1090.3	1433.9	1176.2
Tasmania	9.1	5.8	2907.5	2583.7	2709.3
Wrattonbully	9.5	7.1	1050.7	674.0	964.8
Yarra Valley	8.5	6.4	1744.5	1506.6	1612.3
Cool/temperate (weighted)	7.9	6.6	1315.0	958.2	1196.0
Warm inland (weighted)	21.1	20.5	343.6	284.1	317.2
Australia (weighted)	13.3	12.1	647.6	403.1	522.0

Source: Created from data within AWRI (2019: pp 159 and 164); based on ABS yield survey and census data, and Wine Australia grape price data.

Figure 44 and Figure 45 illustrate the total cash costs and the breakdown of costs of Murray-Darling Basin vineyards in the past decade, using ABARES data. Within the wine areas of the warm irrigation regions of the Murray-Darling Basin, Scholefield Robinson Horticultural Services Pty Ltd (2008) illustrated that the nominal vineyard operating costs were highest for Sunraysia, then the Riverland and then Riverina. Median operating costs (in 2006-07 dollars) were estimated at around $6000 per hectare in the Riverland (Scholefield Robinson Horticultural Services Pty Ltd (2008) (or $7,477 in 2015 dollars). Although it is difficult to directly compare the definitions of operating cash costs across various reports given a lack of information provided, there is some evidence to suggest that the total cash costs in Figure 44 may reasonably represent Riverland viticulture, but further investigation is needed.

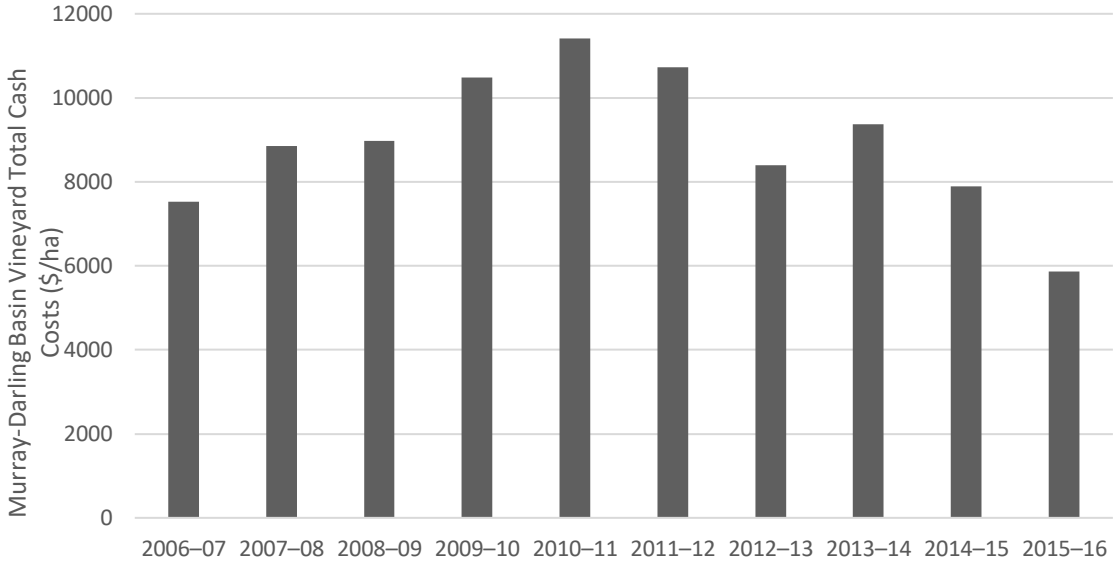


Figure 44 - Murray-Darling Basin Vineyard Total Cash Costs ($/ha) from 2006/07 to 2015/16. Source: created from data in ABARES (2017), estimates are based on average farm sizes and average total cash costs (in 2015-16 dollars).

Figure 45 illustrates the percentage of total cash costs incurred by Murray-Darling Basin vineyards (averaged over the time-period of 2006/07-2015/16). Hired labour costs made up the biggest cost on average, representing 14% of total cash costs, followed by contracts, interest payments, water and repairs and maintenance.

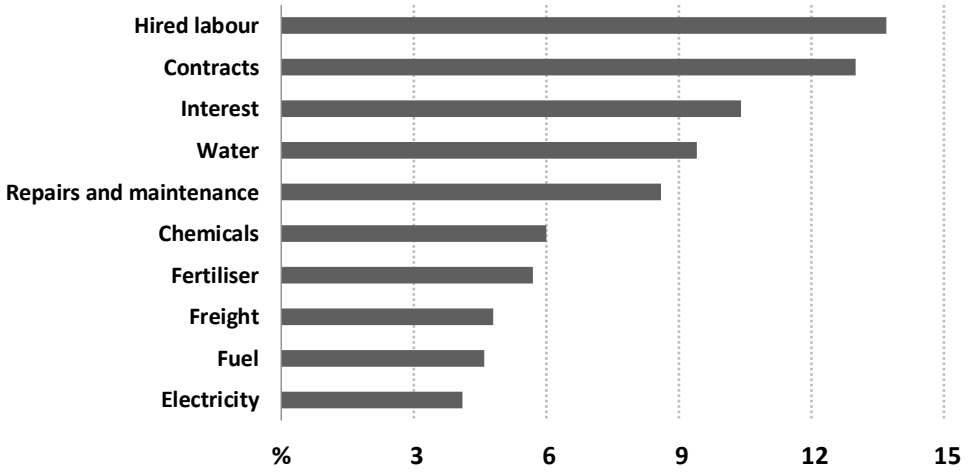


Figure 45 - Murray-Darling Basin Vineyard Proportion of Total Cash Costs by Major Expense (%) average from 2006/07 to 2015/16. Source: ABARES (2017; Figure 6).

For the detail available on benchmarking data on the Riverland, it can be seen that operating costs have been variable, while overhead costs have fallen over time, and debt servicing has increased over time.

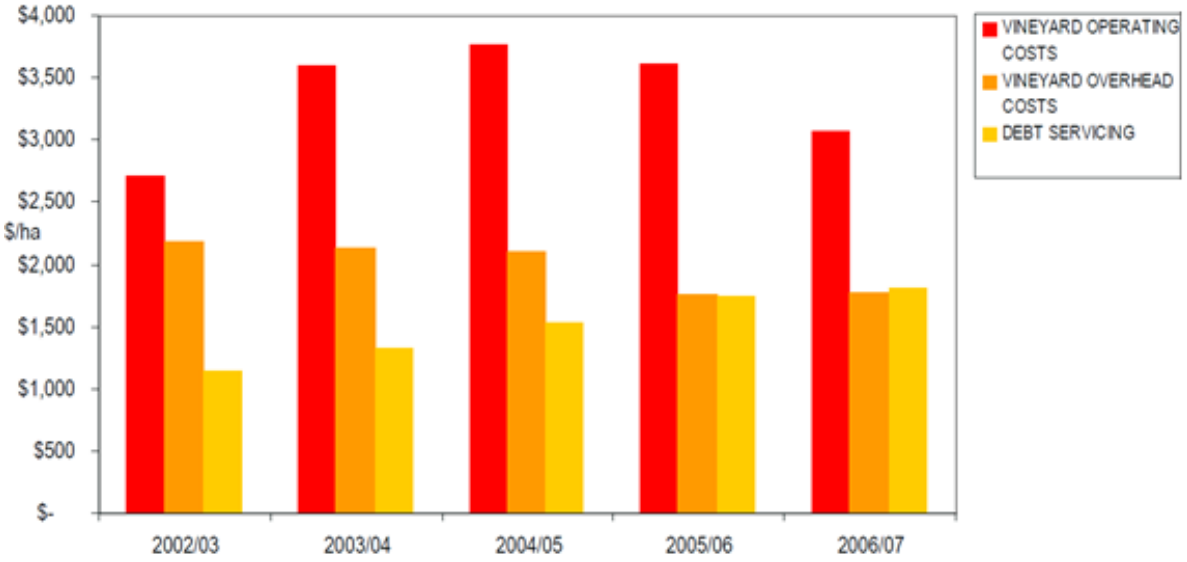


Figure 46 - Riverland Vineyard Average Total Costs ($/ha) from 2002/03 to 2006/07 (in 2006/07 prices). Source: Scholefield Robinson Horticultural Services Pty Ltd (2008; 19).

In the 2015-16 census, it was estimated that there were 786 businesses in the South Australian Murray-Darling Basin region growing grapes, with 23,784 hectares of grapevines (and 21,925 hectares watered with 144,119 ML for an application rate of 6.6 ML/ha). Yield was estimated at 21 tonnes/hectare.

Figure 47 illustrates that over the time-period from 2006/07 to 2014/15, around half the number of farms in the ABARES survey did not engage in any water allocation market trade, while slightly more (27%) were a net seller compared to being a net buyer (22%). Farms were much more likely to be net sellers in high rainfall years, and net buyers in drought years. These results highlight that on average, a static gross margin analysis should not include water leasing, however, sensitivity analysis should be conducted for wet and dry years. Figure 48 highlights the adoption of irrigation infrastructure technology, with drip irrigation increasing from 50 to 90% over this time-period and other forms of irrigation reducing in importance.

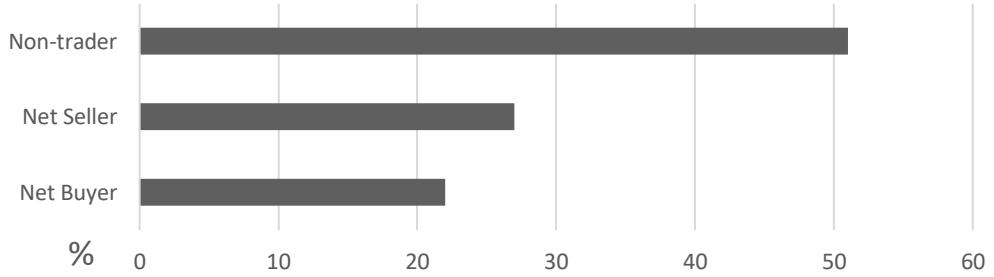


Figure 47 - Murray-Darling Basin Viticultural farms engagement (%) in water allocation trade – average from 2006/07 to 2014/15. Source: adapted from data in ABARES (2017).

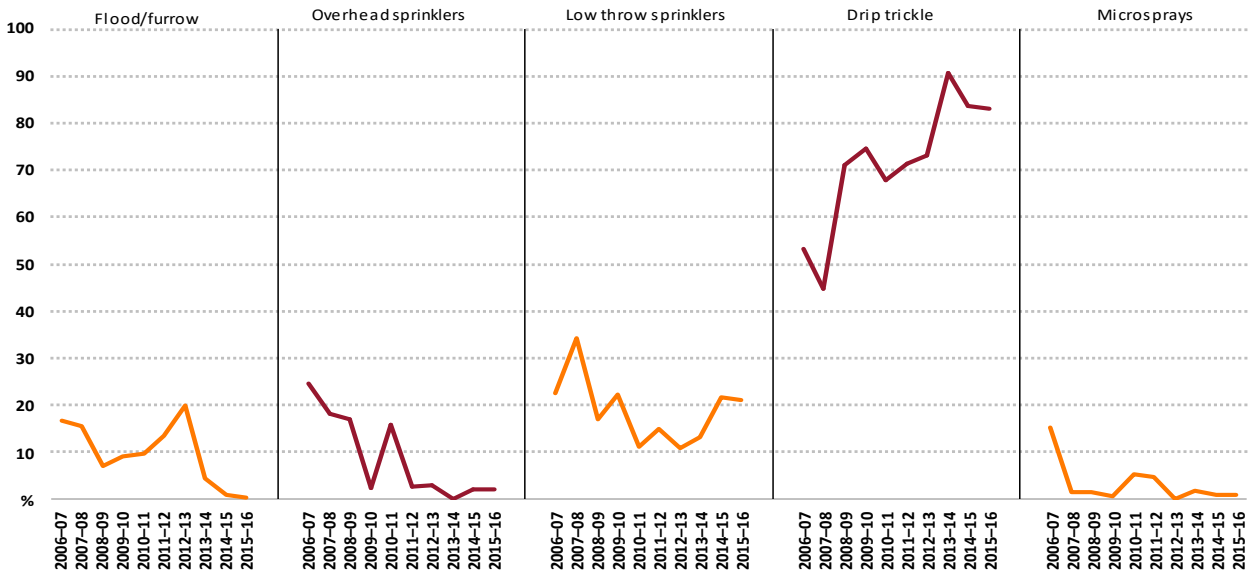


Figure 48 - Murray-Darling Basin Vineyard Irrigation infrastructure adoption (%) from 2006/07 to 2015/16. Source: ABARES (2017; Figure 10).

Finally, business returns are extremely variable, and often negative overall, which is highlighted by Figure 7 below - using Murray Valley vineyards situation in 2010-11 (which ABARES rated as an average year of business profitability for farms in the MDB).

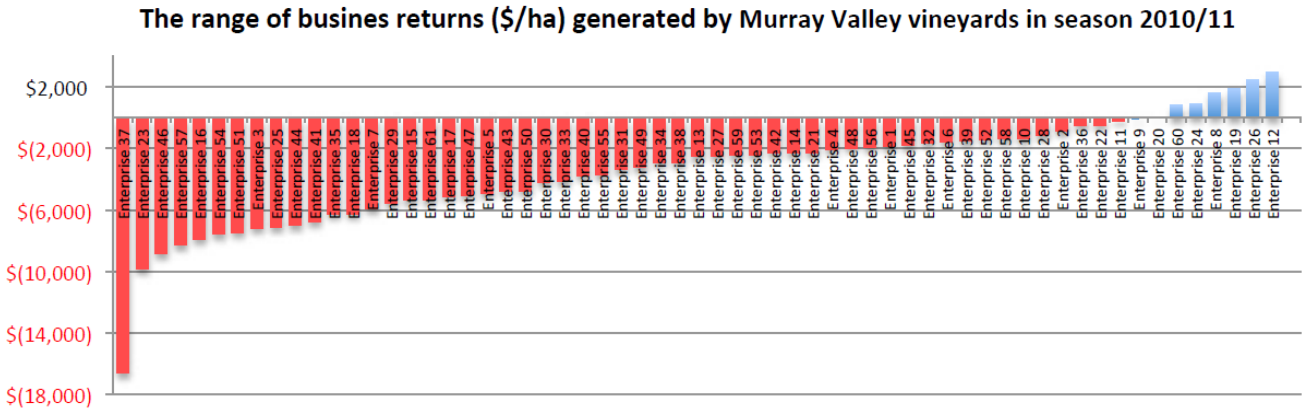


Figure 49 - Business returns $/ha in Murray Valley vineyards in 2010/11. Source: Retallack (2012; 5).

6.2. Riverland case study information

For this pilot project a case study approach was chosen to confirm some current cash and operating costs incurred by three different sized farms in the Riverland: a small farm (< 10 ha); medium farm (11-80 ha) and a large farm (80+ ha). Accounting returns ($/ha) over the past two years (2016-17 and 2018-19) were collected and averaged, and information from owners/managers on the potential for returns from different decision-making software was collected. In particular, information on costs of chemicals; fuel oil gas grease; electricity; harvesting/freight; labour hire costs; levies; machinery, plant and equipment repairs; nutrition/fertiliser; water and drainage costs; and water lease.

It is important to note that we are not suggesting that these farms are necessarily representative examples of viticultural production for the entire Riverland, and further research in this space will be needed. However, they do represent a snapshot of the current situation, and along with the previous information collected, provide some idea of the current returns and costs; and where there may be benefits from digital technologies to inform grower decision-making (hereafter referred to as 'decision-making software').

6.2.1. Small viticultural farm example < 10 ha

Our ***Small farm*** has a mix of red and white varieties and was first established in the Riverland in the early 1970s. The Small farm has made considerable investments in hard and soft technologies, including irrigation infrastructure, root stocks, new grape varieties and innovative management techniques (e.g. soil structure management and testing and fertilizer use), to address issues resulting from salinity, stony ground, soil impaction and increasing temperatures (climate change).

The ***Small farm*** can see benefits of new decision-making software for their farm in two key input areas: water and electricity use. There are a number of things that cameras and decision making software can improve related to under and overwatering issues: such as highlighting leaks, blowouts, lack of watering, fungus due to overwatering etc. Previous upgrading of water infrastructure (i.e. pump and filtration system) saved 25% in power costs, and allowed all watering to be completed at night. Given that electricity costs increased over 100% from 2017 to 2018, this was a significant saving. Additional savings on water allowed for an increase in the proceeds from leasing spare water from the farm (which represented 8.5% of gross net farm income in 2018). The percentage of various expenses in the small farm's total operating costs (an average of figures from 2016-17 and 2017-18 accounting returns) are shown in Table 25. It highlights that labour, harvesting/freight, machinery repairs are the biggest expenses incurred.

Table 25 – Breakdown of operating expenses for the small farm example

Operating Expenses	% of Total Operating costs
Chemicals	9
Fuel, oil, gas and grease	9
Electricity	4
Harvesting/freight	21
Labour hire costs	35
Levies	1
Machinery, plant and equipment repairs	10
Nutrition/fertiliser	4
Water and drainage costs	7
Water lease	0

6.2.2. Medium viticultural farm example 11-80 ha

Our ***Medium farm*** has 11 different grape varieties and also sells rootstock vine cuttings. Vines were first planted on the farm in the 1960s, and invested heavily in machinery (grape harvester) in the 1980s that, along with increased grape prices, helped clear the farm of debt and payout inheritance. Other investment in the 2000s included sheds, solar panels and irrigation drip infrastructure. Recent focus has been on improving soil health with compost and various fertiliser inputs, canopy management, becoming quality assured, buying the neighbour's property, adopting a variety of decision-making software and using the water market to buy and sell water allocations and entitlements for profit. Quality assurance has seen no reduction in quality, with increases in consistency and reliability.

It is estimated that the current decision-making software has saved considerable amounts of electricity, water and labour time. In particular, detecting water leaks much faster has improved yields (estimated at 2-4% reduced yield loss across property, for a gross revenue increase of between $10,000 and $20,000), as well as the automatic detector for frost switching on watering and reducing potential damage. In addition, it was estimated that there was four hours of operator labour saving time a week, adding up to a month's time

of labour over a year. Additional benefits are seen as possible in terms of predicting yield and downy mildew.

The percentage of various expenses in the medium farm's total operating costs (an average of figures from 2016-17 and 2017-18 accounting returns) are shown in Table 26. It highlights that machinery repairs, harvesting/freight, water and drainage costs and electricity are the biggest expenses incurred.

Table 26 - Breakdown of operating expenses for the medium farm example

Operating Expenses	% of Total Operating costs
Chemicals	7
Fuel, oil, gas and grease	7
Electricity	11
Harvesting/freight	20
Labour hire costs	7
Levies	0
Machinery, plant and equipment repairs	28
Nutrition/fertiliser	4
Water and drainage costs	15
Water lease	0

6.2.3. Large viticultural farm example 80+ ha

Our ***Large farm*** in the Riverland has been established for decades, and has a number of red and white varieties. Considerable investment in viticultural technology has been incurred. The large farm does not see that investment in the decision-making software will lead to a decrease in costs at all, especially labour, as in their view those costs as fixed and non-changeable. They see two possible potential uses of the technology, namely 1) to allow more optimisation of inputs (especially fertiliser and water) to produce more consistency in yields from low vigour versus high vigour plants; and 2) allow better planning of truck deliveries from vineyard to winery to stop overloading issues (which have flow on implications for wine quality). The ***Large farm*** believes that a 10% increase in yield from improved optimisation is possible, which represents a potential increase (given current year yields and average prices received) of over $220,000 in gross revenue.

The percentage of current various expenses in the large farm's total operating costs are shown in Table 27. It highlights that labour, water lease, machinery repairs, fuel/oil/gas & electricity are the biggest expenses incurred.

Table 27 - Breakdown of operating expenses for the large farm example

Operating Expenses	% of Total Operating costs
Chemicals	5
Fuel, oil, gas and grease	10
Electricity	10
Harvesting/freight	5
Labour hire costs	30
Levies	0
Machinery, plant and equipment repairs	13
Nutrition/fertiliser	6
Water and drainage costs	1
Water lease	20

Figure 50 illustrates that overall labour, machinery repairs, harvesting/freight are the biggest expenses incurred by farms.

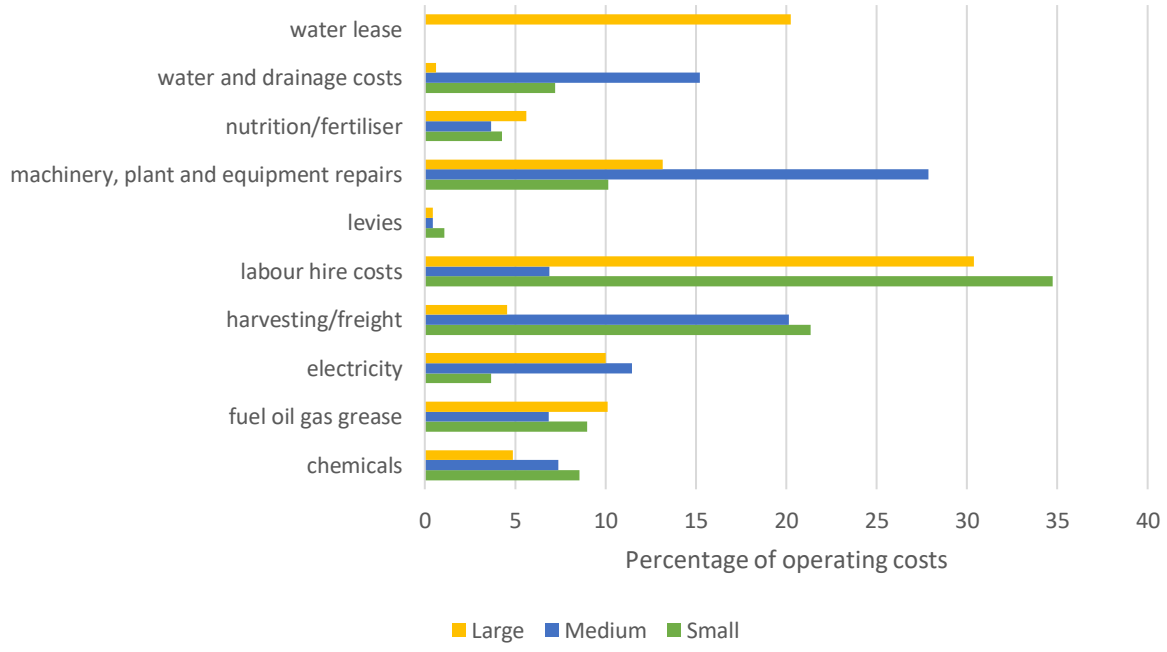


Figure 50 - Percentage of Operating Costs incurred by the Three Case Study Farms – $/ha averaged over 2016-17 and 2017-18

6.3. Benefit Cost Analysis

Benefit cost analysis (BCA), an economic analysis tool for decision making project evaluation was chosen as the most appropriate economic method to use for this project. BCA is used to determine whether a project is justified on economic grounds. It is a widely used tool for comparing alternative courses of action by reference to the *net benefits* that they produce, and comparing a base case (no change or control) with the proposed option.

An important feature of the analysis is that costs and benefits are, as far as possible, expressed in money and hence are directly comparable with one another. Because a dollar available for spending (or investing) today is more valuable than a dollar that will not become available until a later period, it is necessary to discount future benefits and costs so they are comparable with current benefits and costs.

A benefit-cost ratio (BCR) provides an indication of the result achieved from a particular activity. For example, a benefit cost ratio above one indicates that a positive economic return was achieved, and a benefit cost ratio below one indicates that a negative economic return resulted.

In conducting the benefit cost analyses, we used the Federal (Department of Finance 1991) and South Australian (Department of the Treasury 1990) Guidelines.

6.3.1. Assumptions made within the benefit cost analyses

The following assumptions were made in the BCAs:

- Benefits and costs were assumed to accrue over the life of the decision-making software, with the exception that no benefits are assumed to occur in Year One (a conservative assumption given that potential benefits of detecting leaks and reducing yield penalties in vines would probably be realized in year one). The BCA was conducted over a period of 5 years and used a discount rate of 7%;
- Benefits and costs are calculated on a $/ha basis, using an average of the costs incurred by the small/medium/large viticultural case study farms, and ABS/AWRI data to calculate an average size of a Riverland viticultural farm (30 hectares); volume water applied (6.6 ML/ha); yield received (22 tonnes/hectare); grape prices received ($304/tonne average for all varieties – a conservative estimate based on 2016 prices);
- Fixed technology costs were incurred in the first year (this includes dashboard, data online and satellite data costs, IoT network/sensors, tractor mounted cameras for $614/ha). It was assumed that they would have a life expectancy of five years, with no salvage value. An extra assumption on additional technical costs was also included as a sensitivity test (an addition $72/ha);
- Only variable software and data costs (and or benefits) influenced by technology applications were assumed to occur every year (at $27/ha), all other costs remained the same;
- Case study, focus group and interview findings suggest that there is a potential for electricity savings, fuel savings, labour savings as a result of informed and quicker decision making. Some of our case studies identified improvements of up to 50% (e.g. in electricity), however, we assumed conservative improvements of 10% improvements. Nothing was assumed for chemical savings, nor for harvesting/freight (as the increase in costs associated with more yield would offset the improvements in costs) and for yield improvements we assumed a conservative 5% improvement across the farm (which would come from improved optimization of inputs and reduced yield loss in vines from detecting water leaks faster). Also, increase revenue from selling surplus water (or saving in reduced water leas costs) (from the 10% of saving) was included in the benefits of the technology;
- Additional sensitivity testing including no values from water saving (to reflect periods where water trade values are low, unlike the 2016-17 and 2017-18 situation) was also conducted.

It is important to note that not all the benefits of the software are included in the quantitative benefit cost analysis. Namely, possible increases in prices due to improved grape quality, increased carbon levels, improvements in vine nutrition, soil quality, water quality and biological factors have been excluded. No benefits from improvements in year one were included either, nor did we include any value for reduced

operator labour in the economics (either by reducing it as a benefit of the software, or the time it would take for an operator to learn the new decision-making software).

6.3.2. Results of the benefit cost analysis

There were considerable quantitative economic net benefits from software decision-making application for viticultural grape production in Riverland over the five year period accessed.

For example, a BCR of 3.38 was obtained, indicating that for every dollar the grower invested, they received a return of about $3.38 dollars.

Additional sensitivity analysis was conducted, by a) increasing technology fixed costs (e.g. if growers do not have access to available IoT gateways, and have to pay extra in fixed technology costs) and b) eliminating any water lease savings to account for low values in water markets, then the return drops to $2.24 for every dollar invested.

We believe the above is a very conservative estimate of the economic return, because it does not consider:

- Reduced operator labour time on farms, which was predicted to add up to a month a year;
- Far greater reductions in certain outputs (electricity, fuel/oil/gas, labour) could be achieved than our estimates;
- Average prices for 2016-17 and average yields were used, and no increase in premiums were also assumed, hence some farms will receive much higher benefits from investment;
- There may be some salvage value from the technology investment, and it may also last longer than 5 years;
- Yield improvements in the first year were possible;
- No allowance for improved health and safety operating issues (identified as a benefit in our case studies) were allowed for; and
- No improvements in grape, soil, water, vine quality were allowed for.

Future economic research is highly warranted in this space, given the lack of information on representative gross margins, and influences on farm business returns and profitability.

7. Project outcomes

This pilot project provides the foundational work to test key components of a digital vineyard guidance system that is designed to facilitate costs-of-production savings for Riverland growers. The emphasis of the pilot has been on review and documentation of key technologies required for translating data and information streams into actionable guidance for growers as well as the proof-of-principle testing of key system elements. A preliminary economic analysis was also conducted to identify potential focus areas for the digital technology, combined with a benefit-cost analysis to estimate likely return on investment of the technology to growers. A summary of primary project outcomes is given below:

1. An assessment was conducted of the 'technology readiness level' of a range of technology solutions that can potentially be incorporated into a digital viticulture guidance system, including a review of sensor systems, connectivity solutions, algorithms and modelling solutions. The assessment found a high level of maturity *of in-situ* sensors (principally for measuring weather, environmental variables, soil moisture and salinity, plant development and on-farm infrastructure), but less maturity in other data acquisition systems (e.g. vision data, financial data, records of grower management actions). Commercial adoption of algorithms and computational models that 'value add' on data remains low in the viticulture industry, and integrated solutions that translate data streams to advice and decision recommendations are limited.

2. A targeted review of space-borne data acquisition streams showed a high level of technological maturity in terms of spatial, temporal and spectral resolution, yet only a small subset of potential use-cases have thus far been commercialised within a viticultural context. Potential applications of space-borne data streams in the pilot successfully demonstrated the detection of spatial anomalies in vigour using a range of satellite products with different resolutions, temporal frequency, record lengths and pricing structures.

3. A proof-of-principle mobile ground-based image retrieval system was developed and demonstrated to work in-field for a range of realistic operating conditions (i.e. realistic tractor speed, vibrations and light conditions), with high potential for cost-effective 'incidental' data capture. The system is currently tractor-mounted and uses a multi-camera system to provide visual spectrum imagery (i.e. high resolution image photos) and photogrammetric information that provides information on canopy size, volume and density. Further development could accommodate different visual sensors (multi- or hyper-spectral, infrared, LiDAR), and mounting on other mobile systems such as quad-bikes and/or autonomous vehicles.

4. Long-range wide area network (LoRaWAN) technology was selected as the demonstration communications technology due to its low cost, long range and increasing breadth of compatible sensor options. A LoRa base station ('gateway') was installed and operationalised as part of the pilot at the Loxton Research Centre, is capable of handling data from between 1000-10,000 sensors (depending on data volumes) and with a demonstrated range of up to 18 km (directionally dependent, based on line-of-sight). The LoRaWAN technology was demonstrated using set of meteorological, soil moisture and plant sensors at the Sherwood Estates Vineyard, located 3.5 km from the Loxton research centre.

5. Computer vision technology was applied to detect bunches within a canopy, and segment key canopy elements such as bunches, canopy, trunk, and green shoots. An assessment of potential future applications of machine learning to enable monitoring of canopy indicators, flowers, berries, bunches, diseases, weeds and water shoots is provided.

6. Conceptual approaches to numerically modelling physical and biological processes in the context of vineyards were identified, focusing on models that (i) estimate and predict vine development; (ii) predict grape quality; (iii) estimate and predict yield; (iv) estimate and predict disease risk; and (v) simulate on-farm operations. The review included both machine learning and process-based

(biophysical) modelling approaches. Pathways to develop systems that provide guidance and advice by building on existing research platforms were reviewed.

7. The creation of an open-source data storage and visualisation (i.e. dashboard) system that presents real-time data feeds to growers, including:

    - 'internet of things' data (soil moisture sensors, weather station data, plant status);
    - satellite data;
    - ground-based imagery from the tractor-mounted camera system;
    - historical water pricing information; and
    - management records (e.g. spray records).

    Although the pilot focuses on data visualisation, these data feeds ultimately will provide the foundation for developing various 'apps' in stage 2 that provide advice and operational decision support to growers as part of the longer-term development plan.

8. Preliminary estimates of grower costs highlighted significant year-to-year operating cost variations across vineyards, with the largest incurred costs being hired labour, followed by contracts, interest payments, water, and repairs and maintenance. A scenario-based assessment using a small (<10 ha), medium (11-80 ha) and large farm (>80 ha) highlighted areas of pre-existing technology investment, and identified potential areas for digital technologies to save water, electricity, fuel and/or labour costs, as well as the potential to increase overall farm yield.

9. Preliminary benefit-cost estimates found considerable quantitative economic benefits from digital agricultural solutions that targeted decision making, with a benefit-cost ratio conservatively estimated to be 3.38, indicating that for each dollar invested, the grower would receive a return of $3.38.

Beyond outcomes related to technological development, a critical outcome was the formation of an interdisciplinary team (comprising economics, computer scientists, spatial scientists, engineers and viticulturists) across the University of Adelaide, and the adoption of a 'producer-led' approach to technological development comprising multiple meetings, field trips and other forms of engagement with Riverland growers. This strong engagement model has proved highly valuable in focusing the project outcomes, and establishes excellent foundations for future development of the technology.

Echoing the initial project brief, a more detailed summary of specific project outcomes is summarised in Table 28.

Table 28 - Summary of the outcomes of the 'Integrated Vineyard Precision Control System Pilot'

Planned Tasks	Outcomes
Prototype dashboard platform	Development of open-source architecture concept (consideration of multiple data streams, data formats, cloud storage solutions) (Sections 4.2 and 5.3.2).
	Exploration of dashboard technologies & engagement with growers on design specifications (Section 5.3).
	An assessment of established numerical models that simulate physical and biological processes was provided that (i) estimate and predict vine development; (ii) predict grape quality; (iii) estimate and predict yield; (iv) estimate and predict disease risk; and (v) simulate on-farm operations. This review included including identification of key data streams, decision variables (i.e. management strategies), and outputs (e.g. yield, quality, growth, disease risk) for a range of available empirical and bio-physical models, including an evaluation of licensing options (see Section 5.2).
	Proof-of-principle dashboard integrating multiple data sources developed for test vineyard site (see Section 5.3.1), including: - 'Internet of things' data (soil moisture sensors, weather station data, plant status);

	- Satellite data; - Ground-based imagery from the tractor-mounted camera system; - Historical water pricing information; and - Management records (e.g. spray records).
A pilot network of IoT sensors and infrastructure	Review and guidance provided on appropriate IoT technologies for different grower contexts (see Sections 3.1 and 4.1), including an evaluation of range, data rates, wireless standards and other properties of each solution.
	Prototype LoRa network installed in Loxton (see Section 4.1.2), comprising: - LoRa gateway; - Stem dendrometer; - Multi-depth soil moisture sensors; - Soil temperature, electro-conductivity and volumetric water content; and - Weather station (12 observations).
Knowledge of the most economical technology options for effective airborne and space borne remote sensing for crop health and growth indicators	Review of remote sensing products has been completed including an analysis of technology readiness level relative to opportunity, and recommendations on the best technologies for different applications are provided (see Sections 3.2.2)
	Multiple remote sensing products for different spatial, temporal and spectral resolutions have been collated for the vineyard test site period. A demonstration using this data that examines the utility of remotely sensed vegetation vigour for grape growers is also presented (See Section 3.2.3).
A prototype vision based sensing system and processing algorithm.	A proof-of-principle mobile ground-based image retrieval system was developed and demonstrated to work in-field for a range of realistic operating conditions (i.e. realistic tractor speed and light conditions), with high potential for cost-effective 'incidental' data capture. The system is currently tractor-mounted and uses a multi-camera system to provide visual spectrum imagery (i.e. high resolution image photos) and photogrammetric information that provides information on canopy size, volume and density (see Section 3.3).
	Due to the delay in project commencement, data was collected both towards the end of the growing season and post-harvest using the developed vision system for a range of vine varieties at two vineyards (see Section 0)
	Computer vision technology was applied in a proof-of-principle manner to detect bunches within a canopy, and segment key canopy elements such as bunches, canopy, trunk, and green shoots (see Section 5.1).
A business case for and the value to the grower of the technologies and strategies developed in this project	Audit of farm processes and farm management strategies (or grower 'intervention options') was conducted to target crop interventions (Section 6.1).
	Preliminary estimates of grower costs highlighted significant year-to-year operating cost variations across vineyards, with the largest incurred costs being hired labour, followed by contracts, interest payments, water, and repairs and maintenance. A scenario-based assessment using a small (<10 ha), medium (11-80 ha) and large farm (>80 ha) highlighted areas of pre-existing technology investment, and identified potential areas for digital technologies to save water, electricity, fuel and/or labour costs, as well as the potential to increase overall farm yield (see Section 6.2).
	Preliminary benefit-cost estimates to identify quantitative economic benefits from digital agricultural solutions that targeted decision making (see Section 6.3).

8. Potential Applications of the Digital Vineyard Guidance System

Key concepts

- The overarching aim of Vitivisor is to create an open-source platform that collates a wide variety of information to support on-farm decision making, increase information transferability, transparency and ease-of-access, and improve farm outcomes (e.g. gross margins/profitability and sustainability measures).
- The focus of system development is to create a step-change in digitally recording the following data streams across the Riverland:
    - Vineyard outcomes (e.g. gross margins/profitability, yield, quality measures, sustainability measures), representing the outcomes likely to be of most interest to growers;
    - Grower decisions/management actions (e.g. irrigation management, water trading, disease management, canopy management), representing 'levers' available to growers to modify vineyard outcomes;
    - Within-season measures of vineyard development (e.g. canopy development, soil status, disease risk, infrastructure performance), representing information streams that are used to inform grower decisions/management actions, and are indicators for end-of-season outcomes;
    - External factors (e.g. weather/climate, water markets factors and energy prices), representing factors with a material impact on vineyard outcomes over which growers do not have control.
- Building on this digital foundation, four layers of system use and value are identified, each complementing the others and with benefits to growers increasing over time.
- The project's design includes consideration of training and extension to improve adoption and use of the platform across the Riverland.

8.1. Long-term vision of the digital vineyard guidance system

The long-term vision of the proposed digital guidance system is to develop an open-source platform that builds on the rapid advancement of a range of data acquisition, communications and storage technologies to provide a 'one-stop-shop' for key digitised elements of vineyard operations. This represents a departure from a range of existing commercial platforms that take in a relatively small subset of available data (e.g. *in-situ* soil moisture sensors, satellite-based NDVI), and are typically devoted to one or several specific use-cases, and with a focus on information display. Although not questioning the value of these existing platforms, it is argued herein that *the next major technological advance in agriculture will arise through the systematic integration of a larger set of differentiated but complementary data streams into a single platform (or set of interoperable platforms)*. There are at least two 'high level' benefits of such an integrated system:

- Reduced redundancy of aligned systems and enhanced interoperability, to allow growers to continually develop their vineyard digitisation efforts without unnecessary duplication costs and/or concern regarding 'lock-in' to specific technology providers; and
- Enhanced capacity for the system to 'learn' over time, as data collection systems become increasingly sophisticated and are applied across an increasingly large number of vineyards. This would be applied both from the same vineyard over time, and from other vineyards from which parallel data streams are collected.

In order to achieve the ultimate vision of providing advice and guidance into the hands of growers—rather than just display of information—the system needs to digitise the answers to two key questions:

- What management actions are undertaken on the vineyard?
- What are the outcomes of those actions?

A simplified schematic of such a proposed approach is provided in Figure 51 below. Here, the emphasis is placed on gross margin and/or profitability as the primary outcome desired by the grower, which is a function of revenue minus the costs and labour. Intermediate outcomes that influence revenue, such as per-hectare yield and various quality measures (e.g. baume, pH, temperature, anthocyanins), can also be recorded—as can key vineyard sustainability metrics to avoid focusing on short-term objectives (e.g. with-year profit maximisation) at the expense of longer-term vineyard viability. Collectively, these information streams would represent a digital record of key aspects of vineyard performance.

To improve overall vineyard performance, growers have a set of 'levers' that are referred to in this document as management actions (e.g. water management, nutrient management, canopy management, disease and weed management, soil management; see Table 20). For the purposes of this illustration, only with-season operational decisions are considered, and new plantings or other significant works are considered fixed. As illustrated in the diagram, these 'levers' influence performance both in terms of influencing biophysical outcomes (i.e. yield, quality measures and so on) and in determining the costs of production (e.g. consumption of water, energy, nutrients, pesticides, labour, machinery and so forth). Thus, any digital platform that seeks to provide guidance to growers on improving vineyard outcomes must consider the set of levers available to growers to modify system function.

There are also a number of external factors (including weather, water and energy pricing) as well as a set of assumptions (e.g. grapevine variety, crop factor, row spacing, trellising) that, within the context of with-season operational decision making, are outside of grower control. Finally, there are set of intermediate variables (e.g. within-season plant water stress and other water balance measures, measures of canopy development, soil salinity, disease incidence) that provide proxy measures for end-of-season outcomes and can provide immediate feedback to the grower (e.g. whether to reduce or increase irrigation or spray rates), thus representing a key information stream on which to optimise production.

Clearly this diagram could be conceptualised in many different ways, depending on grower objectives, constraints (e.g. whether planting a new vineyard or optimising an existing vineyard), and other factors. Regardless of the specific details, the central message is that the primary concern of the proposed digital system is to support growers to optimise their activities by focusing on the things within the control of the grower (i.e. the management actions listed in Figure 51), in order to achieve outcomes that are considered desirable to the grower (e.g. gross margins, sustainability metrics), subject to the internal and external constraints that are outside of grower control.

8.2. Strategies for operationalising a digital vineyard guidance system

To capture the full potential benefits of the system, it will be necessary for the digital system to be scaled and deployed across a large number (e.g. 100s) of vineyards within a region such as the Riverland, or even across multiple regions, and be adopted over a number of years. Such a system would allow any grower who opts in to benchmark their management actions and outcomes with those of other growers (and/or against their own vineyard across a set of historical seasons). These data streams also provide the foundation for biophysical models and/or machine learning approaches (or, likely, a combination of the two) that can continually learn and improve the predictions and guidance provided to growers.

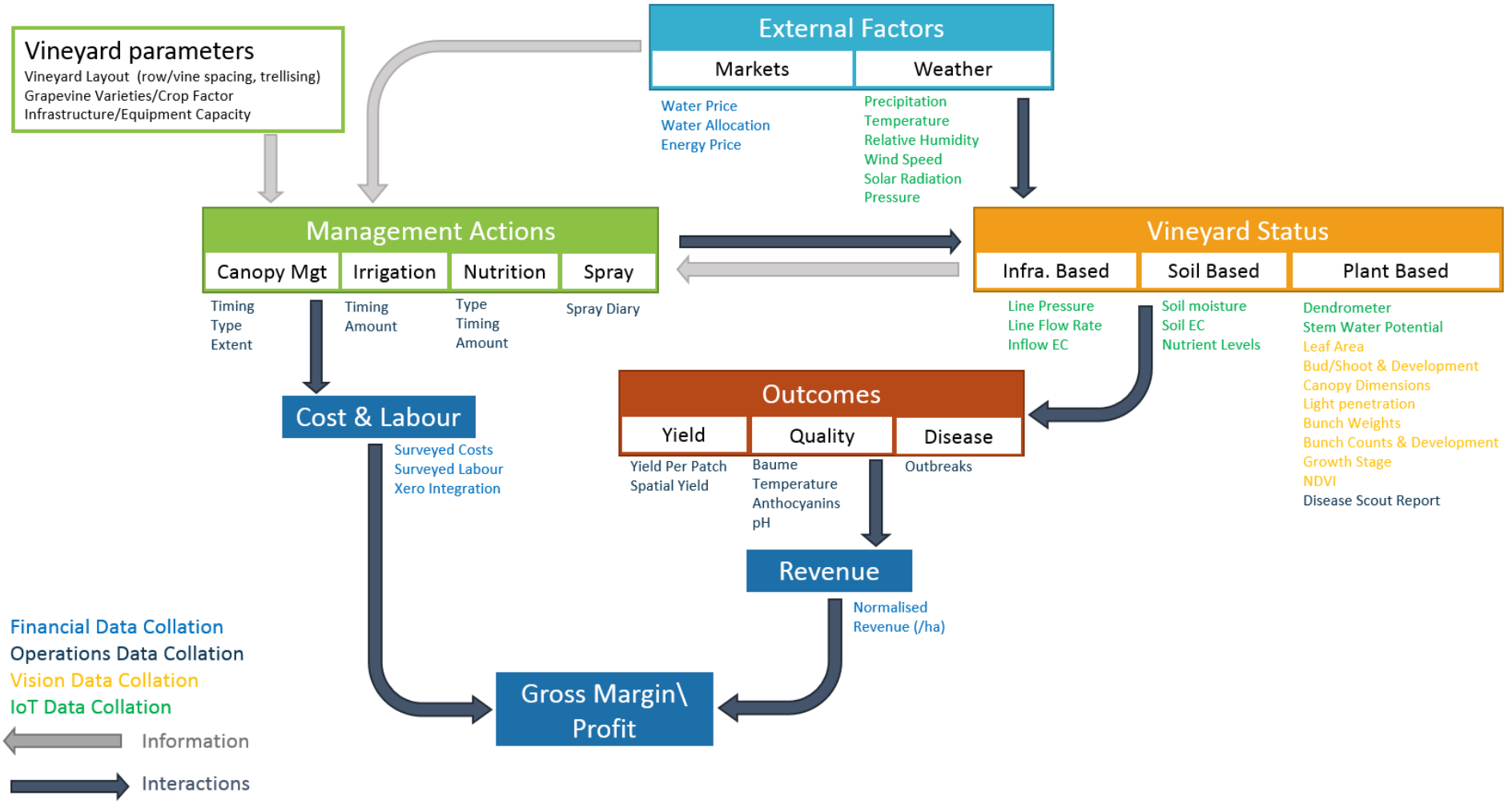


Figure 51 – Schematic of proposed approach. Colour coding of the text refers to the 'source' of the datasets to be collected as part of system design.

A primary challenge is that the initial cost of establishing such a system is potentially high, both in terms of development costs (e.g. building the digital system in the first place) and in terms of deployment (as growers may need to invest in new sensing technologies, connectivity solutions and so on). In the initial period as the system is being built, the value to grower is also potentially low, as the system has yet not begun to achieve the learning that is obtained through widespread deployment over a period of multiple years. This scenario is illustrated conceptually in Figure 52, in which the marginal increase in operating costs reduces as the digital vineyard system is developed (e.g. the marginal cost of a single additional sensor is relatively lower than the first sensor), whereas the marginal increase in benefit to growers continues to increase. Note the specific shape of these curves is unknown and requires further investigation as part of any future cost-benefit analyses.

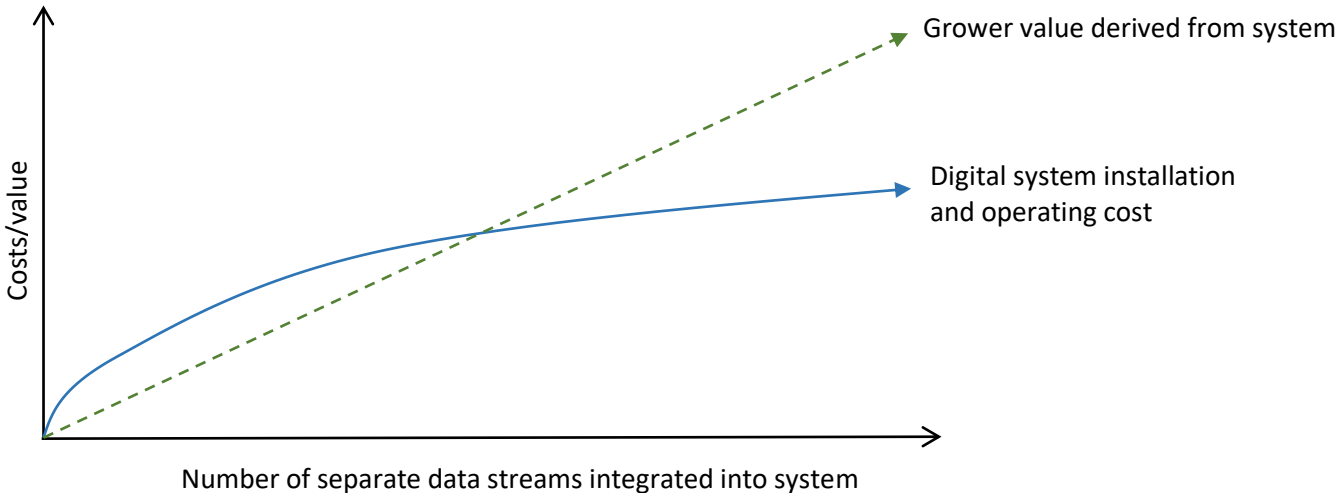


Figure 52 - Hypothetical trade-off between the installation and operation costs an integrated digital vineyard guidance system, and the value of such a system to growers, plotted against the number of data streams integrated into the system

Therefore, in order to accelerate development of the technology, it will be necessary to develop a sequential strategy that:

- Minimises initial operational costs of the system
- Maximises the initial value of the system

Potential strategies to achieve this are given below.

8.2.1. Strategy 1: Reduce costs of data acquisition

There are many data streams that are currently being captured (to various degrees of rigour) by growers as part of current business operations, that could serve as potential data streams to be integrated with a digital vineyard system with relatively little additional cost. For example, irrigation use is increasingly recorded digitally (e.g. via Outpost Central) to provide a record of actual on-farm water consumption, and water pricing data (e.g. via WaterFind or H_2OX) provides insight into likely cost of water purchase. Growers also regularly maintain spray diaries that provide information on spray application. Although accounting systems are different, modern accounting software (e.g. Xero, MYOB, QuickBooks), when linked to a common chart of accounts, provides potential opportunities to streamline collection of major grower costs, without imposing additional workflow onto the grower.

Other data streams, particularly those measuring relatively standard biophysical vineyard measures, are also increasing becoming very low-cost and widely available. Examples include satellite systems that measure variables such as NDVI, and the acceleration of 'internet of things' technologies such as weather stations, soil

moisture monitors, irrigation line monitors (flow rate and pressure), dendrometers, and so forth. As articulated in this report, each of these have relatively high 'technology readiness' and most are already being applied in commercial settings, and thus have the potential to be either already deployed on existing vineyards, or available at competitive prices for inclusion into an integrated digital guidance system such as proposed in this report.

Ground-based vision data represents a new data stream that was developed in this pilot, and has the capacity to capture high-quality photographic and photogrammetric imagery of vine development throughout the growing season. The new nature of these data streams, and significant data volume requirements, are likely to lead to comparatively higher costs relative to other data sources. However, deployment of this technology not only has the potential to provide insight into vine development, disease risk, incidence of weeds and so forth, but also could potentially detect management actions (particularly related to canopy management, such as pruning, tipping) that may otherwise not be recorded as standard practice by growers. To manage costs, strategies such tractor mounting to enable incidental capture (thereby reducing acquisition costs by only collecting imagery when the tractors pass through the vineyard, eliminating labour costs), and using low-cost camera systems, have been carefully considered in the project design. Furthermore, as the technology matures, it is highly likely that future tractors and other on-farm vehicles will contain camera systems that collect a range of imagery (e.g. visible, LiDAR, etc.) as a standard feature. Therefore, there is a reasonable likelihood that ground-based vision technology will become increasingly affordable and 'mainstreamed' in the future, enabling this information to be integrated into the vision system.

8.2.2. Strategy 2: Maximise benefits through initial focus on information display, and system 'hot-start' by integration of existing models and algorithms

Whereas the ultimate vision is to transition from information to predictive services and advice, initial efforts should focus on targeted information display to support sharing and learning amongst growers and between growers and advisors. This is discussed further in 'use case 1' below, and not only represents a foundational step towards an integrated digital advisor, but is likely to have value as a stand-alone product to the grower. In particular, peer-to-peer benchmarking (for example a grower knowing their nitrogen or water application per hectare, or yield per hectare, and comparing to an anonymised set of 'similar' growers), has the capacity to facilitate substantial identification of opportunities for cost savings or other efficiencies.

In parallel, it is possible to 'hot start' prediction and advice functions by focusing on existing algorithms that can be supported by mature data streams, and thus do not assume large volumes of new data or machine learning technology. A detailed review on existing models and algorithms that can predict vine development, yield, quality measures and disease was provided in Section 5.2, and provides a significant level of intellectual capital from earlier research that can be integrated into a guidance system with relatively low overall costs—certainly when compared to the costs of the original fundamental research on which such models and algorithms were based. Although it is possible that aspects of the models and algorithms may ultimately be superseded by sophisticated data-driven machine learning algorithms, the capacity to blend existing biophysical knowledge with machine learning technology allows the system to provide credible predictions early in its development, while gradually improving predictive performance as the system is deployed more widely.

8.2.3. Other considerations

In addition to a direct focus on maximising value and minimising operating costs of a digital advisory tool, there are multiple significant challenges that need to be overcome before a fully integrated digital advice system can be widely adopted by industry. These include at least three inter-related issues:

- Commercial models both for the integrated system, and system sub-components (e.g. data acquisition). This will require careful consideration of issues such as digital rights management, licensing and IP management.

- Interoperability with existing data acquisition efforts. This extends beyond the facilitation of common sensor and communication protocols, but also includes challenges such as how to share data across different technology providers while preserving commercial models.
- Data ownership, privacy and security. Maximum sector-wide benefits are likely to be derived through growers sharing data on management actions and outcomes; however increased sophistication of data capture also increases the need to carefully consider issues related to data ownership, privacy and security.

Although these issues are likely to be critical for wide-spread adoption, they are not viewed as limiters for development of proof-of-principle and pilot-level systems that demonstrate system benefits and advance current systems to TRL 6 (i.e. pre-commercial stage). For example, while issues of data privacy are likely to be of concern both to system development and commercial deployment, the use of University of Adelaide ethics protocols provides a structured way for a single technology provider (i.e. a University) to engage with a community of growers (e.g. via Riverland Wine), and thus for the purpose of future project stages, issues of data privacy can be addressed throughout a standard research and development process. Similarly, in the short term research and development activities will focus on 'early adopter' vineyards that already have technologies (e.g. *in-situ* sensors) with a high degree of interoperability with the proposed system design. Thus, although these are indeed significant issues to overcome, it is recommended that sector-wide discussions regarding these issues be conducted in parallel with specific technology development as part of any future stage in this project.

8.2.4. Next steps

Although there are multiple challenges to overcome in achieving the overall project vision, the review of technologies, existing data streams as well as models and algorithms as part of the pilot provides confidence that significant progress can occur by building on solid scientific and technological foundations. Furthermore, the progress that could be made in the pilot in a 5.5 month timeframe (with most of the specific sub-elements being developed over even shorter timeframes) highlights the feasibility of achieving the overarching project vision.

To ensure success, it is recommended that future stages follow an iterative and producer-led approach, in which growers are closely integrated into the development process and future projects are managed using 'agile' approaches with rapid feedback loops between growers and technology developers. This provides the greatest likelihood of ensuring that tools that are developed meet grower needs, identifying and building existing solutions to problems (rather than reinventing solutions) where possible, and therefore having a system that can be deployed and start 'learning' from real-world operating environments as rapidly as possible.

In parallel, in the short term it is recommended to work with a small number of 'early adopters' who have interest in experimenting with the tool and providing feedback. Once a tool has been developed to a sufficient level of maturity, training and extension activities in the Riverland are then recommended to increase grower familiarity with the tool, and also provide the opportunity to solicit grower feedback for further improvements.

Lastly, the focus on an open-source community development environment is also critical to address issues around commercial models and data ownership, given the significant need to achieve grower trust in, and ownership of, the system. This is particularly pertinent for aspects such as integration of financial datasets, as the resolution of issues around ownership, privacy and security will be critical to obtain grower trust, which in turn is essential to have the widespread adoption needed for the system to achieve its full potential.

Having discussed overall system design principles and potential strategies for reducing system cost and maximising system benefits, four layers of system use and value are now described, each designed to complement the others, and with benefits to growers increasing over time

8.3. Use Case 1: 'VitiView' – A Digital Vineyard Platform for Information Collation, Visualisation, Benchmarking and Communication

The systematic digitisation of the vineyard is the precursor to higher-value digital services such as prediction and advisory services. However grower feedback during the pilot highlighted concern with the large number of tools and lack of a centralised portal, suggesting the value of creating a 'one-stop-shop' for all key data streams relevant for grower decisions. Following the conceptualisation in Figure 51, these data streams can be grouped into the following four categories:

- Vineyard outcomes (e.g. gross margins/profitability, yield, quality measures, sustainability measures), representing the outcomes likely to be of most interest to growers;
- Grower decisions/management actions (e.g. irrigation management, water trading, disease management, canopy management), representing 'levers' available to growers to modify vineyard outcomes;
- Within-season measures of vineyard development (e.g. canopy development, soil status, disease risk, infrastructure performance), representing information streams that are used to inform grower decisions/management actions, and are indicators for end-of-season outcomes; and
- External factors (e.g. weather/climate, water markets factors and energy prices), representing factors with a material impact on vineyard outcomes over which growers do not have control.

Ensuring ready access to these data streams is likely to have direct value in reducing time for data acquisition (e.g. having access to a data stream on a grower's phone, rather than having to manually drive and check meter readings), but more importantly this system enables systematic recording of vineyard operation for later retrieval and analysis. Importantly, much of the information identified in Figure 51 is already being collected by growers; the challenge is to digitise and automate the integration of these data streams into a common system.

These records can be shared between growers working within a vineyard, or collaborating across multiple vineyards, as well as between growers and advisors. Finally, widespread use of the system by multiple growers would then unlock another, potentially powerful benefit: the capacity to benchmark performance on a vineyard against an anonymised pool of 'similar' vineyards (in terms of scale or other measures). For example data on irrigation amount per hectare, spray volume per hectare, nitrogen application per hectare, yield per hectare, and various quality measures (e.g. baume, pH, temperature, anthocyanins) could all be benchmarked in some manner and facilitate comparison between growers. Each of these potential benefits are summarised in the box below.

Potential Benefits of Use Case 1 ('VitiView')

- The ability to track key management actions and vineyard outcomes over time
- 24/7 access to a summary of historical and near-real-time management actions and vineyard outcomes, accessible from anywhere in the world
- The ability to share key vineyard information with other growers both within a single vineyard operation (i.e. with colleagues), and through collaboration across grower groups
- The ability to benchmark management actions (e.g. kg nitrogen applied per hectare) and outcomes (yield, objective measures of quality) with other 'similar' growers
- A platform to enable targeted and cost-efficient agronomic advice, by reducing need for travel to vineyard and improving the quantity and integrity of information available to advisors
- Potential application for communication with banks and financial advisors when considering on-going viability of vineyard enterprises (e.g. annual reviews)

8.4. Use Case 2: An 'app store' to provide growers with point-of-decision access to the latest research outputs

There is a substantial body of viticulture research that is articulated in journal papers and industry reports, and/or embedded in various in research-grade models and algorithms. The focus of this use case is therefore on identifying pathways that can ensure existing research (e.g. advice, models and algorithms) can be contextualised to grower-specific conditions, and made available in a suitable form at point-of-decision for the grower.

Models and algorithms that can predict vine development, yield, quality measures and disease were provided in Section 5.2, and a subset of these would provide a natural foundation to 'hot start' a prediction and advisory service based on the data streams embedded in Use Case 1. Examples of potential applications include:

- Irrigation advice based on estimated plant water demand, soil moisture, soil salinity, nutrient applications and/or other relevant considerations;
- Disease risk indices based on local weather conditions;
- Yield predictions based on bio-physical vine models, soil characteristics, seasonal climate forecasts and related data; and
- Water market strategies based on water ownership, projected irrigation demand, allocations and water prices

Each of the above applications require further scoping and co-development with Riverland growers, but would rest on significant scientific foundations that already exist in the literature. The increasing availability and accessibility of key data streams required to apply the underlying models, together with the emphasis on visualisation as part of Use Case 1, provide much of the enabling infrastructure that ensures this is possible. Potential benefits to growers and the wider viticulture industry are articulated in the box below.

Potential Benefits of Use Case 2

- A focus on 'value adding' to existing research, by focusing on increasing accessibility of research to growers in a suitable format at point-of-decision
- The capacity to contextualise existing research by using the significant data streams acquired as part of Use Case 1 to specific grower conditions
- The ability to 'hot start' a prediction and advisory system during the period when limited data exists to enable machine learning
- Predictions and advice provide return on investment by enabling the tailoring and optimising management actions to specific objectives (e.g. cost of production, sustainability measures, etc.).
- A mechanism for future research outcomes to be integrated into a platform for rapid integration into grower decision pathways

8.5. Use Case 3: A data-driven system that learns over time

Whereas Use Case 2 focuses on building on existing research, machine learning technologies represent a fundamentally different proposition whereby algorithms can be developed that relate the vast amounts of data now being collected about all aspects of the vineyard to specific grower outcomes (e.g. yield, quality measures). Importantly, as the digital viticulture guidance system begins to be adopted and the scale of the data ingestion increases, it becomes possible for machine-learning based predictions to become increasingly accurate over time.

Ultimately, the potential exists for such models to usurp more traditional approaches, although the relative advantages and disadvantages of machine learning approaches relative to biophysical approaches remains an open research question. A complementary approach to machine learning that blends traditional approaches with the increasing availability of relevant data streams is known as 'data assimilation', which enables biophysical modelling approaches to be regularly updated by using localised data streams so that the models become increasingly accurate over time. Regardless of the precise approach (and it is likely that a mixed approach will be most successful), the significant emphasis of the project on the collation of large volumes of data means that data-driven techniques will be capable of providing increasingly accurate predictions and advice that is specifically tailored to individual growers as the system matures.

Potential Benefits of Use Case 3

- The ability of the system to continually learn and improve its predictions and advice over time
- Highly precise predictions and advice provides clear return on investment by enabling the tailoring and optimising management actions to specific objectives (e.g. cost of production, sustainability measures, etc.)
- A mechanism for future research outcomes to be integrated into a platform for rapid integration into grower decision pathways

8.6. Use Case 4: A rich data repository for research

While the emphasis of the previous use-cases have been on direct value to growers and their advisors, a final use-case relates to the capacity to transform research opportunities, through insights gained via 'big data'. In contrast with the 'control trial site' approach to scientific research in which all possible factors are controlled (e.g. variety, soil type, management strategy) except for the specific factor of interest, the collation of vast amounts of data across a large number (e.g. 100s or 1000s) of operational vineyard provides the opportunity to develop a fundamentally different approach to viticulture research.

The key challenge of such an approach is that, unlike control sites, numerous 'confounding factors' exist which make it difficult to isolate cause from effect. However, the proposed system described above is designed to measure and record a range of possible confounding factors, and sophisticated statistical and machine learning approaches exist to isolate those factors and isolate cause and effect. Although this approach is in no way suggested to replace the use of carefully developed control sites, widespread adoption of this tool (and the significant data collection efforts that would occur through adoption) would provide a powerful dataset to support future research efforts in the viticulture industry.

Potential Benefits of Use Case 4

- 'Large sample' research in real-world growing conditions provides a unique platform for research and development
- The capacity of the system to measure and record a large number of variables related to individual vineyards provides potential opportunities to remove confounding factors and identify cause-and-effect relationships

9. Recommendations

This project presents foundational work for an integrated platform to deliver information, prediction and advisory services to wine grape growers in the South Australian Riverland. This platform is predicated on the emerging opportunity to drive a step-change in digitally integrating a range of key data streams that collectively can help increase information transferability, transparency and ease-of-access, support on-farm decision making, and create a return on investment both to growers and the Riverland viticulture industry as a whole through improving gross margins and profitability.

The foundational work demonstrated the viability of all the 'critical technology elements' needed to create such an integrated solution; traversing the information value chain from data acquisition (e.g. in-situ and remote sensing, as well as human entered data such as spray diaries) to communications (e.g. LoRaWAN), analysis (e.g. empirical, machine learning and bio-physical models) and ultimately to visualisation and display. It is recommended that the next phase continue to build the open-source software tool, with the following elements in mind:

- A visualisation platform that provides a 'one-stop-shop' for all key data streams relevant for grower decisions, with a focus on ease-of-access and display;
- A benchmarking app that enables growers to compare key on farm attributes (e.g. resource utilisation per ha, yield per ha, etc.) with anonymised 'similar' vineyards; and
- A series of prediction services focusing on yield, objective quality measures and disease risk;
- A series of advisory services, focusing on infrastructure management (e.g. adequacy of irrigation infrastructure design, and any infrastructure malfunction such as leaks and blockages), irrigation requirements, water market investments, canopy management, nutrient management and spray management.

The above elements represent sequentially higher value services (from information display to prediction and advice), with each building on the one before. Importantly, feedback from growers and from Riverland Wine during the pilot suggested that there is significant value embedded in the first two elements to justify a sequential approach, with the latter elements layered onto these earlier elements.

In order to develop the proposed information, prediction and advisory platform, the following recommendations are provided:

> **Recommendation 1:** That Riverland-wide data collection efforts be accelerated and ingested into a digital platform across four primary data categories: within-season measures of vineyard development, grower decisions/management actions, vineyard outcomes and external factors. These should be based on existing data streams rather than commissioning new data streams where possible.
>
> **Recommendation 2:** That to the extent possible, efforts be placed on ensuring data streams are developed in such a way so as to reduce cost of data acquisition and enable automated integration into digital platforms, through use of APIs and other agreed protocols for data management.
>
> **Recommendation 3:** That an early emphasis be placed on benchmarking efforts across similar groups of growers, to assess current practice and identify 'best practice' activities.
>
> **Recommendation 4:** That issues related to data ownership, privacy and security be considered carefully in future project phases with close engagement of growers, given the premium on grower trust in creating the proposed system.
>
> **Recommendation 5:** That research and development activities continue in relation to ground-based imagery collection and analysis, given the substantial potential for real-time monitoring, record keeping and alerts.

Recommendation 6: That prediction and advisory functionality be 'hot-started' using existing models and algorithms (e.g. some of those reviewed in Section 5.2), operating in parallel with data assimilation and machine learning approaches that will become increasingly valuable as usage increases and the volume of ingested data accelerates.

Recommendation 7: That future project designs include consideration of training and extension components to improve adoption and use of the tool throughout the Riverland.

Recommendation 8: That costs and benefits of key digital platform elements be evaluated in parallel with technology development, to guide R&D prioritisation.

Recommendation 9: That an 'agile' development approach be undertaken to speed up the development cycle and enable functionality to be developed in a step-wise and iterative manner, rather than seek to design a complete system at the outset of the project.

Recommendation 10: That each of the above recommendations proceed with close engagement and integration with Riverland growers, to ensure a producer-led approach to maximise likelihood of adoption.

Appendix 1 – Communication

This project focused on the 'road-testing' and development of a range of technologies including a sensor network, vision acquisition system, computer vision algorithms (i.e. segmentation of key vine features) and a proof-of-principle dashboard to enable the integrations and display of key data streams over the 2018-19 growing season. Communication to and engagement with industry has been an integral part of this project. The short duration of this foundational project and the nature of the project activities have precluded publication of journal articles. Project details and results have been presented to scientific, industry and generalist audiences via presentations and radio interviews to date as follows:

- Workshop with Riverland grape growers at The University of Adelaide (North Terrace Campus) - 8 April 2019
- Presentation to Riverland Wine General Meeting, Banrock Station - 4 February 2019
- Presentation to American Geophysical Union Fall Meeting 2018 - 12 December 2018
- Radio interview on Radio Adelaide Subatomic - 27 November 2018
- Workshop with Riverland grape growers at the Loxton Research Centre - 21 November 2018
- Radio interview on ABC Riverland SA, Renmark (Rural Report) - 8 November 2018

Appendix 2 – Intellectual Property

Intellectual property generated rests as per the Project Agreement. However, outputs of this project have been developed with open-source principles in mind as stated in the project proposal. Open-source tools and frameworks have been used where possible and the proof-of-principle dashboard made freely available (code accessible at GitHub: https://github.com/hzadl/wine-dashboard). Technical knowledge arising from the project has been disclosed in this report.

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Appendix 4 – Staff

Name	Role	Organisation
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Dr Vinay Pagay	Investigator (Task Lead)	School of Agriculture, Food and Wine, Faculty of Sciences, University of Adelaide
Associate Professor Qinfeng (Javen) Shi	Investigator (Task Lead)	Australian Institute for Machine Learning, University of Adelaide
Professor Sarah Wheeler	Investigator (Task Lead)	Centre for Global Food and Resources, Faculty of Professions, University of Adelaide
Dr Kenneth Clarke	Investigator	School of Biological Sciences, Faculty of Sciences, University of Adelaide
Minming Qian	Investigator	Australian Institute for Machine Learning, University of Adelaide
Dr Ramesh Raja Segaran	Investigator	Unmanned Research Aircraft Facility, University of Adelaide
Thomas Rowntree	Investigator	Australian Institute for Machine Learning, University of Adelaide
Dr Zygmunt Szpak	Investigator	Australian Institute for Machine Learning, University of Adelaide
Kiet To	Investigator	Australian Institute for Machine Learning, University of Adelaide
Professor Wendy Umberger	Investigator	Centre for Global Food and Resources, Faculty of Professions, University of Adelaide
Hao Zhang	Collaborator	AMI Fusion Pty Ltd
Steven Andriolo	Technical Officer	Unmanned Research Aircraft Facility, University of Adelaide
Dr Paul Dalby	Advisor	Australian Institute for Machine Learning, University of Adelaide