Plant Biosecurity Cooperative Research Centre

Research Impact Report/Final Report

Optimising surveillance protocols using unmanned aerial systems

CRC2135

June 2018

AUTHORS

Kansas State University (KSU)
Dr. Brian McCornack
Dr. Ganesh P. Bhattarai
Mr. Trevor Witt
Queensland University of Technology (QUT)
Dr. Felipe Gonzalez
Dr. Grant Hamilton
Dr. Fernando Vanegas
Dr. Jens Froese
Mr. Juan Sandino
Victoria State Government
Dr. John Weiss
Queensland DAFF
Dr. Geoff Pegg

Project Leader contact details

Name: Brian McCornack
Address: 123 W. Waters Hall, 1603 Old Claflin Pl., Manhattan, KS 66506
P: +1 (785) 532-4729
F: +1 (785) 532-6232
E: mccornac@ksu.edu

PBCRC contact details

Plant Biosecurity Cooperative Research Centre
LPO Box 5012
Bruce ACT 2617

P: +61 (0)2 6201 2882
F: +61 (0)2 6201 5067
E: info@pbcrc.com.au
www.pbcrc.com.au

This document should be cited as: McCornack, B. P. (2018), *Optimising surveillance protocols using unmanned aerial systems*. Final report for contract PBCRC2135.

PBCRC gratefully acknowledges funding support from the Australian Government through the Cooperative Research Centres Programme.

Australian Government
Department of Industry, Innovation and Science
Business
Cooperative Research Centres Programme

Contents

1. Executive Summary

Pest and disease detection is particularly challenging when managing crops that extend for hundreds or thousands of hectares. More efficient, targeted and accurate monitoring over such vast distances offers enormous benefits concerning monitoring and early detection of pests. Research carried out in CRC National Plant Biosecurity (CRCNPB) evaluated the potential of small Unmanned Aircraft Systems (sUAS) for deployment in plant biosecurity and provided government and industry with a series of recommendations. This project is a response to one of those recommendations: to investigate the application of sUAS to detect and monitor high priority in-field plant biosecurity threats.

By combining modern digital photography with sUAS, the project team aimed to provide agricultural producers, resource managers, consultants, biosecurity personnel with the capacity to detect pests and diseases — including invasive species — before outbreaks occur. The technology is applicable across scales (plant-paddock-region), and can monitor across a range of host plants (e.g. wheat, vineyards, orchards) in diverse environments.

Targeted pests and diseases including sugarcane aphid, cereal aphids, yellow stripe rust, myrtle rust and phylloxera were used to develop a generalized decision matrix to direct biosecurity surveillance programs to better predict the likelihood of pest presence and potential areas for surveillance. This matrix is transferrable to other pests and cropping systems. Training end-users in the use and on the capacity of sUAS occurred through several workshops, crop schools, and conferences in three countries, where seven remote pilots in command (RPIC) and over 20 biosecurity staff were formally trained.

Effective and efficient biosecurity surveillance programs, and pest management in general, require increasingly sophisticated, affordable technical solutions with high levels of automation. We identified a range of scenarios where the most economical monitoring decision is independent of parameter changes to understand when and where sUAS could be deployed to monitor stripe rust. Specifically, our scenario analysis assumed that UAS monitoring adds costs but improves detection rates, and early detection results in reduced costs and increased efficacy of treatment. The extent to which UAS deployment improves detection rates was the most influential driver of net benefit. Reduced costs of UAS monitoring could make the technology economical also under much lower risk levels. In addition, supervised and unsupervised classification was undertaken of multi-spectral imagery, which can be affected by platform and pest species targeted. For example, the fixed wing 100-m altitude imagery did not have enough sufficient spatial resolution to detect changes in reflectance of individual leaves. In addition, unsupervised classification of vines was not able to differentiate “infected leaves” from either background reflectance or healthy leaves. In contrast, supervised classification, intensive visual inspection of high resolution RBG imagery from 50m altitude multi-rotor identified all infected vines but could not differentiate between 1, 2 or 4 infected leaves. Expert elicitation when used correctly can be used to estimate the likelihood of a surveillance strategy or method detecting plant pests. Our results indicated again the potential for a combined surveillance approach using sUAS to rapidly survey large areas and provide near real-time information to identify areas for on-ground inspection. Such approaches not only increase early detection of plant pests but also optimise search efforts. Results also showed that sUAS deployment strategies to survey wheat for Hessian fly will depend on land cover. More specifically, the proportion of winter wheat within a 1 km buffer explained variability in the spatial distribution of the probability of infestation in the previous growing season. These and other findings are significant contributions to understanding the utility of aircraft technologies for pest surveillance.

Reliable and affordable sUAS technologies are valuable tools for government and industry agencies involved in the planning and conduct of surveillance over both large crop production areas and/or remote natural environments. Benefits include more targeted approaches to surveillance, reductions in sampling time or improved efficiency of sampling (e.g. equivalent sampling durations but targeted to areas most at risk), which equates to cost-savings, more effective use of resources (people, equipment), and the avoided costs of control or lost production. Additionally, the project has improved awareness among end-users of the capability and benefits of using sUAS for biosecurity surveillance.

This project also showcases the need to view sUAS as a tool with multiple uses and applications—focusing on only one use limits adoption pathways and potential returns on investment. More specifically, sUAS are capable of carrying payloads designed to capture sensor-derived data but flexible enough to switch between robotic mechanisms to remotely retrieve physical samples or deploy/dispense biological solutions to designed areas Researchers developed a pipeline to process data from multiple sensors and detect and map Myrtaceae plants infected with myrtle rust through a classification algorithm using machine learning, hyperspectral imagery and a multi-rotor UAS. This required the integration of multiple sensors on a multi-rotor UAS including a high-resolution RGB, thermal, LiDAR, multispectral and hyperspectral cameras. New vegetation indices specific to phylloxera infestation on grapevines were created using the differences on spectral reflectance of infested and non-infested plants (Vanegas et al. 2018). The new indices showed higher correlations to vigour and to DVM compared to the multispectral indices. We developed a full design for a prototype device capable of performing sampling operations and collecting insects via suction in indoor bench tests (Dix et al. *in prep*). We have also presented an analysis and diagnosis of the barriers preventing the system from operating in flight. After preliminary research and concept development, a conclusion can be made that pheromone can be deployed remotely, which has implications for use in pest management programs in large-scale agriculture.

Team members gained working knowledge of sUAS in diverse systems and made this information available in a web-based knowledge tree, which can be accessed at http://www.uask.info. The primary reason for developing the tree was to direct or navigate site users (e.g., plant biosecurity personnel, program managers, researchers, graduate students, farmers, state agencies) to content that would help making informed decisions about whether sUAS was appropriate for their application or what research was needed to better understand the utility of sUAS for surveillance. Assessing whether the technology is appropriate for a given application requires a significant amount of background knowledge. The UASK.info site is designed to navigate the user to key knowledge areas, which links them use cases or keystones references to further guide uses. We also understand that new information and potential uses continue to evolve, and the web-based platform facilitates easy curation of content. The goal is not to provide all knowledge, but to prioritize questions that need to be addressed prior to investing in sUAS and related technologies.

A major recommendation moving forward, at least within plant biosecurity, is to adopt sUAS with multi-functionality as a primary driver governing adoption that maximizes return on investment. A useful finding from this project is the value of an added perspective or vantage point. Small UAS removes the need for people to enter a production area directly addresses a key biosecurity issue of how to investigate a suspect without spreading it further. In addition, the ability to provide a landscape view or new perspective across a production area in real time allows for more targeted surveillance using visual symptoms. If this can be further enhanced through sampling of those suspects using UAS, the result isquicker surveillance covering a larger area using less resources. In general, sUAS are capable of providing imagery that allow those conducting surveillance programs to see sections of a paddock or vineyard that does not require a person to physically enter that portion of the infested commodity. There may not always be added value in this added perspective, which is why such feasibility studies will need to be conducted within the targeted commodity. However, the end result should not be solely focused on early detection, as the value of the technology for aiding in surveillance could be grossly underestimated.

Professionals evaluating use of sUAS for surveillance need to realize that adoption is a continuum and heavily dependent on the invasive species of interest and related interactions with the targeted host. Surveillance independent of human interpretation will take a specific research focus within the surveillance program. More specifically, use of artificial intelligence, machine learning, and auto-recognition of data captured from flights requires sensors capable of distinguishing differences in wavelengths that are a direct result of the pest and no other competing stressors. Such a process starts with greenhouse experiments to identify signatures, which then are validated under field conditions and compared to existing practices conducted by plant biosecurity professionals.

2. Introduction

2.1 Overview. The future of effective and efficient biosecurity surveillance programs, and pest management in general, will require a higher level of automation and technical sophistication and increased dependence on affordable technologies. Reliable and effective sampling efforts are imperative to the future of plant biosecurity and food security. This project investigated sensitivities and capacity of emerging small, unmanned aircraft systems (sUAS) and sensor technologies for biosecurity surveillance in viticulture, horticultural and grains industries. The overarching aim was to investigate the use of these technologies to support claims of pest freedom and low pest prevalence compared to commonly deployed surveillance practices and utility to inform pest management decisions for established species. The project focused on the use of science-centric data (e.g., using pest biology to identify areas most likely to be infested) to inform surveillance decisions (e.g., when and where to deploy a sUAS equipped with multi-spectral cameras) made by biosecurity personnel and pest management professionals. Recent advances in sensor technologies (i.e., multi- and hyperspectral imaging and shutter speeds), affordability, and availability of sUAS in the marketplace provided a unique opportunity to evaluate the use of sUAS for detecting invasive species across different scales (region, paddock, plant). This project summarizes knowledge gained and has made it accessible to plant biosecurity professionals using an open-source content management system (CMS) to help guide decisions around whether sUAS and related technologies are cost-effective for immediate integration within existing surveillance programs, identify basic research needs for surveillance programs planning to integrate such technologies, and establish a framework to follow to successfully develop detection tools for species on varying host plants (e.g., wheat, vineyards, orchards) across diverse environments and landscapes.

2.2 Platforms and Sensors. Recent advances in remote sensed imagery and geospatial image processing using sUAS have aided in the development of rapid and ongoing monitoring tools for crop management (Marciniak, 2015; Mathews, 2015; Mulla, 2013; Zhang & Kovacs, 2012) and the detection/surveillance of insect pests. In general, sUAS can generally provide increased operational flexibility and visibility over land-based methods. In addition, this technology can provide coverage over large areas and monitor remote, dangerous or difficult to access locations and offer non-invasive monitoring approach that can target site-specific threats, which in turn allows for directed treatment and management. Tandem to the evolution of sophisticated and cost friendly platform is the advancement in research around sensor technology that are now sold fully integrated and operational onboard sUAS. For several commercially available sUAS, data analytics are offered as subscriptions. However, the utility of using such services for early detection of invasive species is not known. For use in current plant biosecurity operations, a lightweight, low cost platform and sensor combination with advanced control and guidance would be ideal to allow less restricted operation whilst reducing the safety risk and training time required to obtain useful information. Consequently, there are many challenges in adopting remote sensing technologies for pest surveillance, such as detecting early incursions of cryptic pest species or sampling across large agricultural landscapes. Therefore, we focused on sensors amenable to integration on-board sUAS under 20 kg for this project. For a more extensive background on sUAS for deployment in plant biosecurity, see the final report (CRC5055) by Gonzalez et al. (2014).

2.3 Resolutions. Smaller visual, (electro-optic), multi-spectral and hyper-spectral cameras are currently available for onboard implementation. Depending on the type of camera, multiple wavelengths may be measured simultaneously to varying degrees of spectral resolution. It is generally accepted that a finer spectral resolution can provide more information. If we can measure more detail, we can measure subtle changes and then extrapolate this to confirm the presence, absence or severity of a particle pest or disease. However, this may not be required depending on the disease to be targeted. It may be that only a particular region of the EM spectrum is required for reliable disease discrimination. This may be the visible (VIS) infrared (IR), near-infrared (NIR) or thermal-infrared (TIR) bands for example. A full review on this topic can be found in the CRC5055 final report. This project contributed novel methodologies for processing and analysing airborne visual (red-green-blue or RGB), multispectral, and hyperspectral data combined with ground-collected data with the aim to provide the foundation of a predictive detection method for crop pests. More specifically, we assessed changes in canopy vigour at varied resolutions for several of the case studies presented below.

2.4 Case study organisms. For this project to be successful, we specifically targeted pest species that challenged plant signatures in unique and challenging ways, which ranged from symptoms that were cryptic in nature to diagnostic features that were highly visible. For example, small, soft-bodied insect like aphids have the potential to cause plant chlorosis at active feeding sites. Such affects can be isolated for one aphid species but can create a whole-plant, systemic response for other aphid species on the same plant. This can be a challenge for using sUAS to detect changes when such effects potentially escape detection, since aerial perspectives, measured at different altitudes or focal distances, may not capture damage occurring on lower leaves or structures out of the view from sensors. It was also imperative that studied suitability of sUAS for biosecurity across pest types. For example, quantifying plant diseases compared to insects in relation to host plant interactions provides different logistical challenges or deployment strategies, as spread and dispersal across a field or paddock could be quite different. Having diversity in case studies required our team to assess feasibility more broadly. Plant biosecurity personnel are often required to shift expertise and adapt new protocols to survey priority pests. If sUAS is only useful or adaptable to one commodity, pest type or invasive organism, then adoption or advances in the science required to determine sUAS functionality or utility will be limited. Our goal was to inform surveillance through research, and sUAS has the potential to impact detection rates and increase efficiency, but this does not ensure that it will be equally effective and efficient across all applications. There is a need to incorporate the technology before “turn-key” solutions are fully available—biosecurity informed by science is not an immediate process. The following case studies provided investigators with a wide-range in hosts (wheat, grapes, sorghum, soybean, Myrtaceae plants) and the unique pest challenges within each crop or commodity.

2.4.1 Grape phylloxera in vineyards. Grape phylloxera is a very small insect that primarily lives underground, feeds on the roots of the grapevines, and consequently damages the root system. This impairs water and nutrient uptake to the plant, which causes stress that is expressed above-ground by impairment and changes in photosynthesis, changes in pigment ratios, reduced canopy, slow stunted growth, and reduced yield (Blanchfield et al. 2006). Grape phylloxera is currently present in most grape-growing countries, but relatively localised in wine districts in south-eastern Australia. The symptoms of infestation appear usually after two to three years, although in some instances this can be longer (Skinkis et al. 2009).

The current surveillance practice for growers is to visually inspect their grapevines (Benheim et al. 2012) or by deploying more intensive monitoring methods like traps (Powell 2012), which are usually placed at the base of suspected infested grapevines and inspected after two to four weeks. In addition, on suspected infested grapevines, the roots can be inspected for yellow galls, swellings on the older roots, and the yellow insects (Powell et al. 2009). Although these practices have been extensively used as standard methods, they are time consuming, season dependent, labour intensive and require taxonomic expertise (Giblot-Ducray et al. 2016).

2.4.2 Myrtle rust on Myrtaceae plants. *Austropuccinia psidii*, commonly referred to as myrtle rust, was detected in Australia on the NSW central coast in 2010 (Australian Government, 2017). Since then, the pathogen has spread rapidly in the mainland. It has been established along the east coast of Australia with recorded impacts across a range of ecosystems. Remote sensing efforts for the monitoring of infected vegetation by exotic pathogens has incremented gradually (Lausch et al. 2016). Standard techniques include surveys through satellite, manned and unmanned aircraft systems (Lausch et al. 2017). The environmental and economic impacts of exotic fungal species on natural and plantation forests have been historically catastrophic. Considering the rapid proliferation and deterioration rates of pathogens in hosts and prolonged periods of testing and observation of ground-based techniques have urged to seek better solutions. Remote sensing has been applied in vegetation surveys more gradually. Monitoring efforts through satellite, manned and unmanned aircraft systems (UASs) have offered novel insights of rapid estimations of vegetation conditions. However, previous research of remote sensing for the assessment of plant species has been focused on extracting biophysical conditions. Few efforts for the surveillance of forest health under impact from exotic pathogens have been reported.

2.4.3 Stripe rust on wheat. Wheat is Australia's most important crop, with a gross value of $6.2 billion and a total production area of ~110,000 km^2 (Australian Bureau of Statistics 2017a and 2017b). Wheat stripe rust (*Puccinia striiformis* f.sp. *tritici*) is a serious fungal pathogen affecting all major wheat-producing regions in Australia. It first emerged in the eastern production areas in 1979, and in the expansive Western Australian wheat belt in 2002 (Wellings 2011). Despite the ongoing development of resistant wheat varieties, this fungal disease remains a recurring and widespread problem to producers with actual average annual losses of ~$130 million, and potential yield losses of up to 80% in susceptible varieties (Murray and Brennan 2009; CropPro 2017). While such crop monitoring is mostly done from the ground (a W-shaped inspection protocol is recommended in GRDC (2015) to ensure a representative sample), the use of sUAS as part of the 'precision agriculture' revolution is expected to play an increasing role in future crop monitoring efforts (PricewaterhouseCoopers 2016; Trowbridge 2017). However, any monitoring is costly, and currently the use of UAS may still require an added investment compared to conventional, ground-based approaches, especially when both are conducted simultaneously. To efficiently target crop-monitoring resources, guidance about the spatial distribution of risk is needed.

2.4.4 Hessian fly in wheat. The Hessian fly, *Mayetiola destructor* (Say), is an important economic pest of wheat, which consistently infests a significant number of wheat fields at low levels in the US (Buntin 1999, Smiley et al. 2004, Watson 2005, Chen et al. 2009) and is a major threat to wheat production Australia. Factors affecting Hessian fly distribution within the landscape makes it difficult for producers to make informed decisions to implement Hessian fly management techniques (Schmid et al. *accepted*). Adult female Hessian flies are the primary agent of dispersal through oviposition site selection (Harris and Rose 1989), and several environmental factors affect female host selection (Harris and Rose 1990; Withers and Harris 1997; Withers et al. 1997). Landscape factors contributing to Hessian fly distribution within commercial wheat fields or the likelihood of fields becoming infested is not known but could be used as a method to prioritize fields for surveillance for traps or sUAS.

2.4.5 Russian wheat aphid on wheat. The Russian wheat aphid (RWA), *Diuraphis noxia* (Mordvilko), is a small, yellow to lime-green aphid with a distinctive football-shaped body and aphids prefer to feed in rolled leaves on the upper structures on the plant. Damage to wheat plants is visibly noticeable from a distance and populations are detectable from fixed-wing aircrafts (Mirik et al. 2007). Besides rolled leaves and trapped heads, RWA feeding can also cause purple or white longitudinal streaking on the leaves, which is visibly distinct from other aphids species found colonizing wheat. For example, leaves damaged by greenbugs (*Schizaphis graminum*) turn reddish-brown and appear scorched. When searching for the Russian wheat aphid in wheat, it is often useful to look for damage first then for the aphids. In May 2016, RWA was detected in South Australia and subsequently throughout eastern Victoria and was later detected at Barham in the Murray Region of NSW in August of 2016. The preferred time for RWA detection and estimation of area damaged is in late winter, early spring (July – August). Remote sensing approaches using multi- and hyper-spectral data are widely used in ecological studies including vegetation properties such as species identity, plant phenology, leaf chemistry, and diseases. However, spectral changes in plants associated with aphid feeding, particularly early in the infestation stage, are not well understood.

Evaluating vegetation indices that are strongly correlated to the concentration of photosynthetic pigments (chlorophylls, carotenoids, anthocyanins) and the level of aphid infestation has been well studied but effective methodologies to select relevant and robust indices for specific applications are lacking. In addition, development of vegetation indices often excludes interactions between biotic (aphid infestation) and abiotic (e.g., low-water or nutrient availability) stresses.

2.4.6 Sugarcane aphid on sorghum. Sugarcane aphid, *Melanaphis sacchari*, is a new pest species of grain sorghum (*Sorghum bicolor*) in the United States (Bowling et al. 2016; Brewer et al. 2017). It was first detected in Texas and Louisiana in 2013. In the following years, it was reported on sorghum plants in 17 states and more than 400 counties in the US. This species overwinters on annual and perennial grasses in the warmer climates of the southern US and reinvades most of its range in the northern latitudes every year, gradually migrating up the southern Great Plains of the US. As a relatively new pest species, factors influencing its long-distance dispersal, establishment and local spread are not fully understood. With ~50% yield loss, the cost of sugarcane aphid infestation on sorghum plants is severe. Furthermore, the patchy distribution of this species within a field particularly in the northern region requires substantially higher sampling effort to detect it early in the season (Elliott et al. 2017). Recent development in small unmanned aerial systems and wide range of image sensing technologies may provide a cheaper and more effective alternative in detecting aphid pest on sorghum fields. Sugarcane aphid is a migratory pest and infestations expand north from the southern regions by means of wind currents and related meteorological events (e.g., storms). More effective and efficient surveillance of this pest will required a multi-layered approach that includes predictive models that warn stakeholders of potential infestations to better documenting infestations at a paddock level, with a goal of site-specific management of this invasive species within grain sorghum.

3. Materials and Methods

3.1 Where and when should UAS be deployed? Early in this project, we understood that it would not be feasible or cost effective to send biosecurity personnel to all targeted areas (e.g., paddocks or forests) and survey using sUAS. For some context on the spatial issues associated with sUAS deployment, collecting one aerial data set across all 3.5M ha of wheat in Kansas would requires approximately 5 years to complete—this simply is not feasible or a realistic expectation of the technology. There are likely times during a growing season of greater risk of incursion and/or locations more likely to be infested, and there are several factors (biotic and abiotic) that could help prioritize surveillance or deployment strategies using sUAS. The following case studies were used to develop targeted processes to direct surveillance activities to areas and times with a higher risk of invasion. More specifically, we investigated and quantified the importance of satellite vegetation indices, environmental and landscape-scale parameters for predicting the likelihood of presence or abundance of plant pests to identify potential surveillance targets.

3.1.1 A generalized approach to using statistical risk models (Bayesian networks, BN). We adopted a spatially explicit modelling approach using BN and Geographic Information Systems (GIS). BNs are a general, flexible modelling tool and have been applied in diverse contexts, ranging from business processes to biological invasions (Fenton and Neil 2013; Smith et al. 2012). Further advantages of this approach for the purposes of sampling prioritization are further outlined in Appendix 1. Our BN model contained two conceptually distinctive parts and was implemented using *Norsys Netica v.5.12* and spatial integration in the *ESRI ArcGIS 10.5*. In our model of outbreak risk, knowledge about climatic risk factors affecting the developmental cycle of wheat stripe rust was gathered via desktop research and advantages to this approach are outlined in Appendix 1. When translating this conceptual model into a predictive BN model, we included only climatic risk factor variables for which spatial proxies were available across all wheat growing regions in Australia. The predictive BN model was calibrated using the approach suggested in Fenton et al. (2007). We represented changing levels of disease risk in a 'yield loss risk' variable, which was influenced by the predicted climatic outbreak risk as well as the resistance of the cultivated wheat variety. Secondly, our model included two 'decision nodes' representing alternative crop management decisions. Thirdly, our model included several parameters describing the effects of alternative crop monitoring and management decisions. Finally, we calculated the portion of avoided yield losses as the difference between actual and potential yield loss (we capped avoided losses at a maximum of 60%). Conditional on treatment and monitoring decisions, more yield losses may be avoided at increasing levels of disease risk, and impact (i.e. the portion of yield potentially lost). By comparing expected net benefits between ground-based and UAS monitoring, our model allows decision-makers to identify the most economical alternative in a given situation. We evaluated the sensitivity of modelled outbreak risk to changes in each climatic risk factor variable contained in the model. We used the 'sensitivity to findings' algorithm in *Norsys Netica 5.12* software, focusing on the 'variance reduction' metric recommended for numerical variables (Marcot 2012).

3.1.2 Comparative detection of simulated disease in a vineyard. We aimed to compare the performance of sUAS and existing surveillance practices (human inspection) to detect a simulated disease in a Victorian vineyard (Appendix 2).

Surround®, a compound approved for sun protection in vineyards, was sprayed on individual vine leaves to simulate the appearance of a fungal disease similar to downy mildew and a plastic paint tray behind the selected leaves to control the number of leaves affected, by reducing splash onto other vine leaves. Vine rows were randomly assigned a prevalence of 5 or 10% vines affected. Within each 200-vine row, individual vines were selected at random for the simulated disease at the assigned prevalence. An equal number of individuals within each row were assigned a disease severity of 1, 2 or 4 leaves. These leaves were selected haphazardly across the outer and upper leaves of the vine, which would be apparent to the UAVs. Four staff members with experience in biosecurity searches were recruited to individually inspect the vines. Both fixed wing and multi-rotor sUAS with the same multispectral camera were deployed over the vine blocks at 50 m for multi-rotor and 100 m altitude for fixed-wing. Unsupervised and supervised classification of the images was undertaken without prior knowledge of the location of all the "infected" plants. Consequently, this method was published a conference proceedings (Hauser et al. 2016).

3.1.3 Expert elicitation of detection rates of stem pest in grain crops with and without sUAS. An alternative to determining detection rates for specific plant pests is to utilise expert opinion on the ability of surveillance staff to detect pests (e.g., Russian wheat aphid) at a specific density given a specific search time and area to cover (Appendix 2). This component built on a Victorian and Federal Government project evaluating the CropSafe project on its ability to detect exotic pests like Russian wheat aphid and diseases at an early stage (DEDJTR 2016). This project utilised a structured approach to elicit judgments about the likelihood of CropSafe agronomists to detect key exotic plant pests and diseases. Expert elicitation is the structured process of retrieving and quantifying expert knowledge and opinion when information is poor, unavailable or difficult to acquire. The project's elicitation method used an IDEA methodology (Hanea et al. 2016, 2017; Hemming et al. 2017). The project estimated the detection rate of various crop pests at a 1% infestation level given 20 min to search 100 hectares.

3.1.4 Landscape effects on Hessian fly distribution within commercial wheat. In this study we modeled Hessian fly distribution within commercial wheat fields and examine environmental factors that may affect their distribution within and between fields. Study fields (n = 6) in Kansas were selected based on previously reported Hessian fly infestations, which occurred during the fall of 2016. Sampling points in each field were laid out in a predetermined grid and at each sampling point a 1 m row of plants (top 5 cm of roots and above ground material) was removed and plants were dissected for the presence of pupae. Cover of landscape immediately surrounding the sampled fields was also recorded at time of sampling. Generalized additive models (GAMs) were used to understand the within field and between field variability in the spatial distribution of Hessian fly pupae abundance and the number of wheat plants infested (Wood 2017). GAMs are a flexible approach that can incorporate variables such as plant resistance (e.g., table 1) and landscape-level habitat as covariates (dependent variables), but can also account for the spatial autocorrelation generated by complex spatial-temporal processes (e.g. dispersal) (Hefley et al. 2017; Wood 2017). The GAM framework allows for linear effects of covariates such as field characteristics as well as nonlinear effects that are captured by basis functions (e.g., spatial location). During the initial stages of the analysis, alternative specifications of the GAMs were fitted (e.g., using Poisson distribution instead of negative binomial), relevant model assumptions were checked, and if needed (or possible) models were improved accordingly (Ver Hoef and Boveng 2015). A full description of statistical methods is included in Schmid et al. (*in prep*).

3.2 How effective are UASs at identifying areas of interest? Once areas are selected or prioritized using available models, we set out to test the suitability sUAS to detect infested or infected areas within a targeted surveillance area. Early in the project, we evaluated factors such as altitude and flight speed to determine optimal coverage and detection rates as suggested by PBCRC5055 (data not shown). Later studies included sophisticated and replicated experimental designs to compare differences in camera technologies and associated spectral indices, as each provides data necessary to differentiate between biotic and abiotic stressors. The following case studies provide a broad basis to understand the capabilities and limitation of surveillance technologies in identifying high-risk areas, potential identification of pests, and increased chance of first detection using aerial images collected from different platforms (i.e. fixed-wing versus multi-rotor).

3.2.1 Comparisons in NDVI data derived from orbital and fixed-wing sensors. We conducted a field experiment to evaluate the relationship between Hessian fly infestation in wheat fields and changes in plant spectral reflectance throughout the growing season. In spring 2017, Hessian fly infestation was quantified for multiple (n = 15-50 per field), one-meter linear quadrats (1m row of wheat) in seven wheat fields in Kansas. All wheat plants in the linear quadrat were examined for the presence of Hessian fly pupae inside the stems and pupae number were recorded. Hessian fly infestation level for each quadrat was estimated as the product of proportion of stems infested and mean number of pupae per stem. Aerial imagery data were acquired from two remote sensing platforms, TerrAvion aircraft (https://www.terravion.com/) and Sentinel 2 satellites (https://www.esa.int/Our_Activities/Observing_the_Earth/Copernicus/Sentinel-2) for our field sites. TerrAvion deploys manned aircrafts to collect natural color and near infrared imagery from an elevation of ~2 km above the ground. Images were processed to develop Normalized Difference Vegetation Index (NDVI) maps as an indicator of plant vigor/biomass in the agricultural areas. Mean NDVI values were extracted for each quadrat in each field site for all available data sets from both platforms. Finally, the relationship between NDVI and Hessian fly infestation was examined for each platform using a separate mixed effect model. In the case of TerrAvion data, we used field as a random factor to control for the non-independence of quadrats within a site. Similarly, non-independence of data caused by repeated measures (NDVI values through time) on quadrats that are nested within the sites was controlled by categorizing field and quadrat as random effects (Bhattarai and McCornack *in prep*).

3.2.2 Sugarcane aphid and detection from fixed-wing and multi-rotors. We used two sUAS to compare the imagery collected at varying altitudes and speeds using multi-rotor (DJI S1000+) and fixed-wing (Aero) platforms. A series of images were collected using two different cameras equipped with either an electro-optical (EO) or near infrared (NIR) sensor, which were flown over sugarcane aphid infested sorghum fields in south-central Kansas. Images obtained from either platform types used the same sensors, so we could compare differences between platforms. Aerial imagery was collected on four different days between July and August and sorghum development ranged from boot to soft dough. Images from each sUAS, survey date, and sensor type were processed using Agisoft Photoscan, georectified, and stitched together to develop a series of color (EO) and NIR orthomosaics. We then developed normalized difference vegetation index (NDVI) map for the sorghum field for each imagery date and sUAS platform using ArcGIS 10.2(ESRI, Redlands, CA). For each UAS, relationship between NDVI values extracted from orthomosaics and aphid density were evaluated using a mixed-effect model with mean aphid density per leaf, survey date, and the interaction between aphid number × survey date as fixed effects and quadrat (1 m linear row of sorghum sampled per waypoint) as a random effect. Although mean honeydew secretion was positively related to mean aphid density per leaf, relationship between NDVI and honeydew secretion was also evaluated using a similar mixed model (Bhattarai and McCornack *in prep*).

3.2.3 Aerial mapping of Myrtaceae forests affected by myrtle rust. We investigated the suitability of sUAS to collect image sensor datasets to identify deteriorated plant samples (Sandino et al. 2018). The performance of the UAS was assessed to evaluate capabilities in non-optimal environmental conditions, which can significantly affect image quality. We also evaluated the utilisation of available high-resolution digital SLR, thermal, multispectral and hyperspectral cameras for identifying alterations in Myrtaceae plants by myrtle rust. This was determined by modelling optimal flying distance to target host plants for increased image quality. This information was used to develop processes and methods to compare the detection rates and benefits of directed surveillance by sUAS to existing procedures. New detection and mapping framework approaches were tested, which evaluated the vegetation condition of natural and plantation Myrtaceae forests using four primary sections including: 1) Data acquisition, 2) Data preparation, 3) Training and 4) Prediction. The system interacted directly (site-based tests) and indirectly (UASs + cameras) with the surveyed area to acquire the data, preprocess and arranges data into features, fits a machine-learning model and depicts segmented images of the studied zones. The proposed framework comprises the integration of sUAS, multiple image sensors, and data processing algorithms using machine-learning classifiers like Extreme Gradient Boosting (XGBoost). Imagery was orthorectified using third-party proprietary software due to their effectiveness and high-quality results but processed with open-source tools such as Python programming language, GDAL and Scikit-learn libraries. For supervised learning approaches, the training and prediction processes required adequate correlation of data from remote sensing technology and site-based experiments (e.g. *in situ* exclusion trials.)

3.3 Can multi-rotor UASs be deployed to identify and collect plant pests? Deployment of sensors or collection of higher-resolution data can be further refined to identify pests using various methods. The primary focus of this objective was to investigate the suitability of multi-rotor UASs to collect high-resolution images and specific signatures to identify infected or infested plant parts (e.g., wheat tiller, leaf, or grain). The performance of fine resolution, multi-rotor sUAS was assessed to evaluate relative capability in varying environmental conditions, which will affect image quality and development of meaningful surveillance indices. Multi-rotor sUAS were used to capture images using different camera technologies (digital SLR, multispectral, hyperspectral) at plant and sub-plant levels within the same paddocks and expanded to test systems in other industries including horticulture (vineyards) and forestry (Myrtaceae plants). We also explored optimal flying distances to target host plants in select row-crops for increased image quality and their ability to identify pests. This information was used to compare the detection rates and benefits of directed surveillance by multi-rotor UAS to existing procedures. Detection rate and accuracy of sUAS was also determined under a variety of field conditions (e.g., drought, fertility, host phenology). Lastly, a physical sample is always required for correct identifications, especially reported incursions that can affect international trade; however, access to sampling areas (tree tops, hillsides, stored grain) may prevent biosecurity personnel from collecting specimens. Therefore, we investigated the feasibility of building robotic elements (widgets, grasping/collecting devices) that can be attached to a multi-rotor sUAS, which would allow for the collection of physical samples, specimens, and materials for identification by experts.

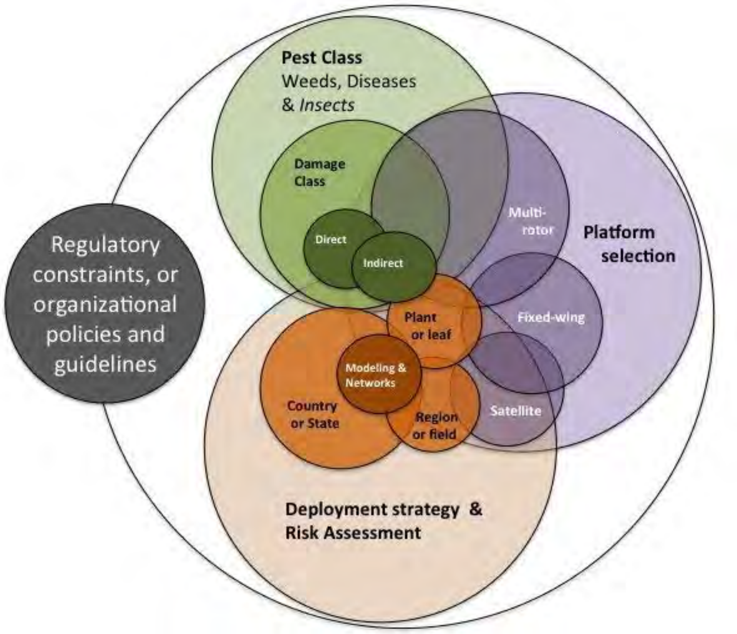
3.3.1 Improved plant pest surveillance in vineyards and crops using airborne and spatial data. The overall aim of this sub-objective was to generate novel methods to collect and process remotely sensed hyperspectral and multispectral imagery and to combine the processed data with available ground data to develop predictive models for pest infestation. A novel methodology was developed to improve plant pest surveillance in vineyards and crops using airborne and spatial data, which consisted of four main stages. The development of this methodology is described in Vanegas et al. (2018). The first stage of the 4-step process is data collection. Next, multispectral and hyperspectral images are processed to obtain radiance and reflectance values, which are then used to first generate a DVM, which is based on RGB imagery, a digital surface model, and a digital terrain model. Lastly, all of the multiple sources of data are combined into a single information system. Attribute table created during this process contain the extracted values for several published vegetation indices (Vanegas et al. 2018), expert vigor assessment classes, and values estimated from a DVM. The table populated with georeferenced data from multiple sources was used to run a correlation analysis. This analysis highlighted the most significant vegetation indices, spectral bands and spatial data that are the foundation for the development of a preliminary phylloxera detection model; see Appendices 7 and 8 for full description of methods.

3.3.2 Automated collection of insect samples using suction. This publication presents an alternative method by which a sample collection device can be deployed directly from the sUAS. Designing an airborne apparatus with the capability to capture and hold insect samples presents many challenges. We determined two main requirements that we had to adhere to in the design process in order to build a successful prototype. One of the main limitations was the weight restriction inherent to any airborne design. Another challenge faced in the design process was the air currents that are produced by the S1000 rotors. As a result, another major design requirement was that the apparatus must be capable of sampling from distances greater than seven feet, meaning it must also be able to recognize and regulate its distance from the canopy. A full description of the design can be found in Dix et al. (*in prep*). We constructed a small indoor testing apparatus that suspends the attachment approximately one meter above the ground for indoor functionality testing. We performed our outdoor testing at a KSU research farm.

3.3.3 Autonomous pheromone lure deployment using sUAS. The process for development of a more efficient and cost-effective method of pheromone deployment began with the concept to use small unmanned aircraft systems (sUAS). The technology has progressed to the point of carrying payloads large enough for practical applications. UAVs for the application make sense in that they are able to cover large fields effectively and accurate enough to place the pheromone tabs where needed. A full description of the design can be found in Flippo et al (*in prep*). To control this prototype system a myRIO-1900 (National Instruments Corporation) computer was used running LabVIEW 2013. The program waited for a signal from the pilot (via sUAS radio receiver) to index the drum until the encoder measured a confirmed drop. Figure 2 shows the control flowchart. This design proved to be an efficient method of deployment as nearly every strip was properly ejected with a very low rate of doubles or skips. The prototype was designed to attach to a DJI S1000+. This allowed the sUAS pilot to control the drop action of the prototype to be mapped to a switch on the handheld controller console. For the field deployment trial, the drop interval was adjusted to 100 meters. In other words, once the sUAS travelled 100 meters, a signal was sent to the prototype using Pixhawk to drop a pheromone tab. A flight plan was set up to the aircraft travelled over an isolated, gravel road; observers were positioned on either end of the flight path to ensure a safe and unobstructed flight. The flight plan was approximately 400 m long, which resulted in four total drops.

3.3.4 Sub-canopy sampling methods to assess pest presence. An inherent challenge to using aerial images is the inability to detect changes to host plants that are located, especially for pest species that preferentially feed on lower plant structures. One approach is to determine whether the spectral responses can be detected on distal leaves or structures, which we determined under greenhouse and field conditions using a hand-held leaf spectrometer (McCornack 2018). However, we also tasked sUAS to provide the mechanism to capture presence/absence of pests on structures not visible when sensors are attached directly to the aircraft. We simplified the design to test whether sUAS was capable of collecting images of aphids on lower canopy leaves in sorghum. We used a 3 m section of PVC that was cut in half and re-connected with a small metal hinge. A plastic T-joint was secured to one end of the pole, which was used to secure the entire apparatus to the DJI S1000+ and provided a mechanism by which the camera pole could pivot. On the opposite end of the pole, a Go-Pro Hero Session 4 camera was attached using a standard clip and enclosed with a plastic protective housing; this allowed the apparatus to penetrate and exit the canopy without getting stuck or adding unnecessary force to the aircraft. The two, hinged positions allowed the sUAS to lift the two 1.7 m sections in sequence and provided the pilot with more control during take-off and landing.

3.4 Synthesise the practical lessons learned from Objectives 1-3 using UAS technology for detection of a high priority plant pest. An underlying theme across the above objectives was whether the use of sUAS was practical, not only to those in plant biosecurity but also to those making management decisions. We realized early in this project that adoption of this technology was possible, but likelihood of adoption was directly related to the return on investment. There were no defined methodologies associated with this objective, rather investigators integrated the predictive modelling, imaging and flying capacity developed throughout the project to evaluate the utility of UASs for improved detection at a farm level, specifically for the pest management of yellow striped rust in wheat. Given that these methods have the potential to provide a substantial boost for the detection of invasive species, where possible we also aim to work with project CRC2100 and CRC2063 led by Hamilton (Decision Making for Eradication and Quarantine Zones) and Pegg (Managing myrtle rust and its impacts in Australia) to trial them in incursion responses and to improve management. In addition, our team also realized that knowledge gained from this research would be of great value to those not sure where sUAS would be useful within existing surveillance programs. Therefore, we developed a web-based knowledge tree (right) to capture our knowledge about sUAS, related sensors, and structured content using an open source content management system. The Unmanned Aircraft System Knowledge (UASK or "you ask") tree can be accessed at http://www.UASK.info.



4. Aims

The aim of this project was to use predictive models combined with high-resolution detection technologies to increase sampling efficiency and improve first detection rates. Objectives include:

1) Modeling region-wide environmental changes to identify criteria for selecting high-risk surveillance areas and compare these predictors to current selection methods deployed by biosecurity personnel;

2) Prioritize sampling times and areas within targeted areas to direct surveillance efforts and increase rate of first detection using higher-resolution surveillance technologies (fixed-wing UAVs) and unique spectral signatures;

3) Evaluate utility of higher-resolution cameras and robotic technologies on multi-rotor UASs to categorize and/or collect target pests on different plant structures for identification by trained diagnosticians; and

4) Synthesise modeling and improved UAS technologies to demonstrate a practical application for surveillance of high priority plant pests in commercial crops.

Detection of plant pests will be significantly improved by region-wide modelling the likelihood of biosecurity threats and utilising UASs to gather and analyse spectral indices to maximise the probability of accurate detection of biosecurity incursions at smaller scales. Three specific issues were addressed: 1) does spatiotemporal prioritisation of sampling areas using environmental and landscape-scale parameters maximise the likelihood of pest detection?, 2) can UAS and spectral indices be used to locate established species under different environmental conditions?, and 3) to what extent can UAS technologies improve sampling efficiency (e.g., more area sampled with fewer resources) and detection rates?

5. Results

5.1 Where and when should UAS be deployed?

5.1.1 Generalized approach to using statistical risk models (Bayes nets). In our model, the risk of a stripe rust outbreak occurring was most sensitive to spore dispersal from infected plants (25% variance reduction). Our model reasonably assumed that infection is unlikely to occur if spores are not available, even under otherwise favourable climatic conditions. If spores were available, sporulation temperature and pre-infection rainfall conditions were most influential in determining outbreak risk (7% and 5% variance reduction, respectively). Infection temperature and humidity conditions affecting leaf adhesion contributed only 3% and 1%, respectively, to reducing the variance in modelled risk. We applied the predictive risk model to a recent stripe rust outbreak in Western Australia. Mapped outbreak risk from the initial two detections, subsequent two detections, and averaged outbreak risk from all four detections corresponded well to all subsequent detections in 2015, which were all recorded in 'high' or 'moderate risk areas (Appendix 1). There was considerable uncertainty in most of the cost/benefit parameters contained in our crop monitoring decision model. Therefore, we explored model behaviour under changing parameter values using a scenario analysis approach. Our focus was on comparing the expected net benefit between UAS deployment and ground-based crop monitoring. We identified a range of scenarios where the most economical monitoring decision is independent of parameter changes. Specifically, our scenario analysis assumed that UAS monitoring adds costs but improves detection rates, and early detection results in reduced costs and increased efficacy of treatment. Currently UAS deployment is likely conducted in conjunction with ground-based efforts and therefore requires added investments. In this context cost-effectiveness was highly dependent on disease risk. In fact, with most parameter combinations expected net benefit increased non-linearly, with a positive return on investment only emerging at moderate to high-risk levels in all scenarios. In situations where disease impacts are already effectively managed using an available treatment option and monitoring is currently receiving little attention (scenario A), UAS deployment was rarely economical. In situations where effective disease management is highly reliant on early detection surveillance (scenario B) a different picture emerged. Here, UAS monitoring proved economical under all tested parameter combinations; at least where disease risk was high. The level of risk at which added costs were likely offset by added benefits, and the extent of benefits, varied strongly. Finally, in scenario C, which represented a less heavily monitored and managed pest or disease system, we found that improved UAS performance resulted in both larger economic benefits and lower risk thresholds at which deployment yielded positive returns on investment. The extent to which UAS deployment improves detection rates was the most influential driver of net benefit. Reduced costs of UAS monitoring (here we assumed $15 per hectare) could make the technology economical also under much lower risk levels.

5.1.2 Comparative detection of simulated disease in a vineyard. Surveillance staff detected all the different levels of disease severity (1, 2 or 4 leaf) but with different levels of detection (Appendix 2). The average detection rate for 1 infected leaf was 76.8%, 89.7% for 2 infected leaves and 96.9% for 4 leaves. The time spent per vine also affected the detection rates for 1 or 2-leaf infections. As the time per vine increased so did the probability of detection. To have a 95% confidence of finding the simulated disease at a 1 or 2 leaves infected, the searcher has to spend 1.75 seconds per vine. In contrast the 4-leaf infected plant had an almost 100% detection rate even at the fastest inspection time (slightly less than 1.5 seconds). In a vineyard with approximately 10,000 vines, insuring a 95% probability of detecting a single vine with the "disease" would require 5 hours of inspection time. Supervised and unsupervised classification was undertaken of the multi-spectral imagery. The fixed wing 100-m altitude imagery was found not to have sufficient spatial resolution to detect changes in reflectance of individual leaves. In addition, unsupervised classification of vines was not able to differentiate "infected leaves" from either background reflectance or health leaves. In contrast, supervised classification, intensive visual inspection of high resolution RBG imagery from 50m altitude multi-rotor identified all infected vines but could not differentiate between 1, 2 or 4 infected leaves.

5.1.3 Expert elicitation of detection rates of stem pest in grain crops with and without sUAS. Expert elicitation when used correctly can be used to estimate the likelihood of a surveillance strategy or method detecting plant pests (Appendix 2). When provided with a case study utilising UAV imagery to identify regions of aphid feeding damage, the mean expert estimate of detection of a similar stem pest, significantly increased from 0.4 to 0.78 with a higher level of confidence. These results indicate again the potential for a combined surveillance approach using UAVs to rapidly survey large areas and provide near real-time information to identify areas for on-ground inspection. This approach would not only increase the early detection of plant pests but also optimise search effort. Use of hyperspectral data to detect stem pests like Russian wheat aphid were further explored under greenhouse conditions to determine whether sensor data was capable of detecting differences between different cereal aphid species (Bhattarai and McCornack *in prep*). In general, leaf reflectance data using hyperspectral data can be used to detect aphids on wheat. Vegetation indices associated with leaf pigments, specifically chloropylls, are most predictive at determing aphid-infested plants; however, a combination of indices related to pigments, moisture, nutrients, and other physical properties will be more useful to distinguish between aphid species.

5.1.4 Landscape effects on Hessian fly distribution within commercial wheat. Results show that host plants (wheat and grasses) adjacent to fields did not affect the distribution of pupae or plants infested within the field. Instead, the proportion of wheat within 1 km around the fields affected Hessian fly infestation within the fields. The results of this study show previously unknown distribution of Hessian fly infestation within commercial wheat fields, which produce new hypotheses about Hessian fly management in agroecosystems. In addition, the proportion of winter wheat within a 1 km buffer explained variability in the spatial distribution of the probability of infestation in the previous growing season. The GAM fit to the number of pupae shows that the expected abundance varies within and between fields (Schmid et al. *in prep*). Directing deployment of sUAS surveillance strategies over fields or paddocks most likely to be infested based on proportion of land cover, in this case the number of ha planted to wheat, requires further investigation. However, these results contribute to the growing study of landscape effects on pest populations, and how analysis of the landscape can help predict areas at higher risk for pest outbreaks (Margosian et al. 2009, O'Rourke et al. 2011, Mazzi and Dorn 2012, Tonnang et al. 2017).

5.2 How effective are UASs at identifying areas of interest?

5.2.1 Comparisons in NDVI data derived from orbital and fixed-wing sensors. NDVI values estimated from either aerial platform declined with increasing Hessian fly infestation. For satellite data, NDVI decreased with pest infestation. A significant negative relationship between NDVI and pest infestation was evident as early as early November that increased in intensity across the growing season. Similarly, NDVI values from the fixed-wing aircraft were also negatively related to Hessian fly infestation; as number of pupae per sample point increased, NDVI values or total vegetation decreased. Furthermore, NDVI values derived from fixed-wing and orbital sensors, in this case TerrAvion and Sentinel 2 platforms, respectively, were strongly correlated (Bhattarai and McCornack *in prep*).

5.2.2 Sugarcane aphid and detection from fixed-wing and multi-rotors. Aphid numbers on sorghum plants increased exponentially over the course of the study, where populations were at or below action thresholds at prior to data collection and exceeded treatable densities at the time of final flights. In this study, mean NDVI for sampled quadrats did not differ between multi-rotor and fixed-wing sUAS. As indicated by a significant aphid number by date interaction, change in NDVI between survey dates differed between sUAS. For the DJI S1000+ system, NDVI increased substantially from 26 July to 1 August but it did not change for fixed-wing system, which used the same sensor as the multi-rotor platform. The relationship between NDVI and aphid infestation was not consistent between the sUAS used in this study. More specifically, NDVI increased significantly with the aphid number when using the multi-rotor system, and percent cover of honeydew, which has a direct correlation to aphid density, over but these patterns appear to be primarily driven by survey dates. In contrast, no significant relationship between NDVI and aphid number was observed when using the fixed-wing platform; however, NDVI using images captured from our fixed-wing platform showed a significant negative relationship when detecting honeydew within each quadrat sampled (Bhattarai and McCornack *in prep*).

5.2.3 Aerial mapping of Myrtaceae forests affected by myrtle rust. Researchers developed a pipeline to process data from multiple sensors and detect and map Myrtaceae plants infected with myrtle rust through a classification algorithm using machine learning, hyperspectral imagery and a multi-rotor UAS. This required the integration of multiple sensors on a multi-rotor UAS including a high-resolution RGB, thermal, LiDAR, multispectral and hyperspectral cameras. The latter required the design of a customised gimbal, built using 3D printing technology, to maximise the quality of acquired data for orthorectification and stitching pre-processing techniques, noise reduction and distortion attenuation. The absence of public databases of spectral signatures to detect and map myrtle rust on Myrtaceae plant species, as well as singularities presented at specific regions (e.g. southeast coastal Queensland, Australia), required the use of exclusion trials and glasshouse experiments with selective paperbark tea tree samples. The developed assessment tool is capable of segmenting physical deterioration zones of forest trees affected by myrtle rust. Detailed results and discussion are presented in Appendices 6 and 12.

5.3 Can multi-rotor UASs be deployed to identify and collect plant pests?

5.3.1 Improved plant pest surveillance in vineyards and crops using airborne and spatial data. An expert visual assessment of the vineyard vigour was conducted. In this assessment the expert classified the vigour of groups of five to six vines into classes ranging from 1 to 5 were 1 corresponds to a dead plant and 5 corresponds to a healthy plant. This assessment found some areas affected by Phylloxera, which showed lower vigour. The plants were also classified into the five classes based on a Digital Vigour Model (DVM), generated based on aerial RGB imagery. Pearson correlation between DVM and expert vigour assessment was (0.414) for the area at site 1 and (0.52) site 2. These values of correlation demonstrate an adequate correlation and validity of the novel remote sensing method. Full results from the mean spectral signature analysis are presented in Vanegas et al. (2018b), Vanegas et al. (2018c), and Vanegas et al. (2017). In general, infested grapevines showed higher reflectance in the visible region, and lower reflectance in the near infrared (NIR) region. Furthermore, infested vines have higher levels of reflectance at the chlorophyll well around 670 nm, with the healthy grapevines absorbing more light around this wavelength. Spectral signatures also show higher differences between infested and non-infested grapevines for the February 2017 imagery. New vegetation indices specific to phylloxera infestation on grapevines were created using the differences on spectral reflectance of infested and non-infested plants (Vanegas et al. 2018). The new indices showed higher correlations to vigour and to DVM compared to the multispectral indices. This is case study, hyperspectral camera with a higher spectral resolution allowed us to distinguish specific bands or wavelengths of interest, and thus generate indices that were not possible to create with the multispectral camera, which has fewer bands.

5.3.2 Automated collection of insect samples using suction. We developed a full design for a prototype device capable of performing sampling operations and collecting insects via suction in indoor bench tests (Dix et al. *in prep*). We have also presented an analysis and diagnosis of the barriers preventing the system from operating in flight. Future work should focus on reducing the impact of environmental EMI from the UAS. One possible solution is to create an EM shield to protect the circuitry in the device from EMI. An alternative solution is to reduce the weight of the system and thereby reduce the load on the UAS motors; this will reduce the current draw and therefore reduce the EMI generated by them. The solution most likely to be successful will incorporate both of these strategies to minimize the system's sensitivity to EMI.

5.3.3 Autonomous pheromone lure deployment using sUAS. After preliminary research and concept development, a conclusion can be made that pheromone can be deployed remotely, which has implications for use in pest management programs in large-scale agriculture (Flippo et al. *in prep*). The concept is at early stages of development, and further research needs to be conducted, but with the use of sUAS, the idea of deploying pheromones across a large area becomes more feasible. Use of small autonomous platforms is gaining momentum in agriculture, allowing previous labour-extensive tasks to be done autonomously and with little human intervention.

5.3.4 Sub-canopy sampling methods to assess pest presence. The initial test flight was successful, as the sUAS travelled several meters while hovering over the soybean canopy with the sub-canopy sampling apparatus securely attached to the platform. The primary application for this design was to quickly view inside the crop canopy, which would result in sub-samples or RBG images to detect pests colonizing at a known location (i.e., GPS of aircraft and timestamp from image captured). A sub-sample consists of dropping the sensor into the canopy and triggering the camera remotely. However, dragging the sensor through the canopy will cause significant force on the aircraft, which may lead to overloaded motors, instability, and increased likelihood of losing control of the sUAS. In a follow-up pilot study, we sampled over 300 locations using the above device. Here, 66% of images were clear and in focus and 35% of the plants sampled had detectable aphid colonies as well as provided evidence of natural enemy colonization (McCornack 2018). Spectral signatures captured from aerial perspectives could be attributed to several factors, but sUAS equipped with similar sub-canopy sensors are realistic solutions to ground truth remotely sensed data.

5.4 Synthesise the practical lessons learned from Objectives 1-3 using UAS technology for detection of a high priority plant pest. The knowledge tree (http://www.uask.info) is organized into four main "branches." The first focuses on regulatory concerns associated with sUAS. Such regulations are country specifics and understanding the rules before purchasing and flying sUAS is imperative to avoid expensive fines and, more importantly help improve safety and continued use of this technology within government entities. It is also imperative that those interested in using sUAS for surveillance understand the potential issues or regulations that exist within their respective institutions. The remaining three branches are divided into the following categories or questions: 1) What is your research problem or question?; 2) What is your knowledge of on sUAS technology?; and 3) What is your knowledge on pest risk and management? Content or knowledge within each of these categories is further sub-divided using guiding questions or statements. At any point through the knowledge clave, site users can easily switch between branches. In addition, content is also connected using taxonomy terms or "keywords" that links together content between different branches. The primary reason for developing the tree was to direct or navigate site users to content that would help making informed decisions about whether sUAS was appropriate for their application or what research was needed to better understand the utility of sUAS for surveillance. Assessing whether the technology is appropriate for a given application requires a significant amount of background knowledge. The UASK.info site is designed to navigate the user to key knowledge areas, which links them use cases or keystones references to further guide uses. The goal is not to provide all knowledge, but to prioritize questions that need to be addressed prior to investing in sUAS and related technologies.

5.4.1 What is your research problem or question? The main focus in this branch is to get the user to become aware of key literature or pest-plant interactions that will direct decisions on platforms that are more effective for surveillance. If the research goal is to detect incursions early, before they're visible, then symptoms or plant signatures must be detected before visually observed. This would guide the user to resources that could be used to develop spectral signatures. In other cases, a visual symptom is more appropriate, and cost effective due to a smaller platform and RBG sensor. Here, the goal is not early detection but rather to document overall occurrence of a known infestation across a wider area. Time saved here is sampling or not having to go into infected areas to confirm what is already known using ground-truth data.

5.4.2 What is your knowledge of sUAS technology? In this branch, the expectation is that the end user knows very little about platforms, but does have a broader understanding of the specific tasks that are required to complete a specific surveillance task. Prompting questions or statement includes identification of key tasks (measuring, delivering, retrieving) or basic consideration for sUAS selection or best practices for data collection (spatial control, spectral and optical calibration).

5.4.3 What is your knowledge on pest risk and management? Deployments strategies will be integral to the integration of sUAS into surveillance programs, especially when attempting to quantify returns on investment. Quite simply, it is not cost effective to deploy sUAS everywhere, for every use case. Instead, this branch makes the user aware of different modeling strategies that can be used to select areas of interest, or to focus deployment to areas where the incursion is most likely to occur. Questions or statements are further refined to direct site visitors to different modeling approaches, including those in this report, but also directing to other projects funded by the PBCRC. Since it is a dynamic CMS, it will allow our project investigators to expand the knowledgebase as new information becomes available or expand authorship to include researchers as the needs for content arises. Lastly, the design of the UASK.info site allows for the easy addition of new knowledge branches, which provides flexibility and mechanism to restructure content as needed while providing a better user experience.

5.4.4 Platforms and sensors galleries. Underlying the above branches are designated pages that showcase sUAS and related sensors. This supporting content includes more specific details about platforms, generalized costs, flight times, and other important features. Most of this content will change rapidly as the industry continues to grow exponentially. Therefore, we designed these to be standalone entities in the knowledge tree, which allows for quick updating or replacement of platforms across multiple landing pages. AS new platforms are added by partnering institutions, new knowledge nodes are easily created and integrated to other content on the site.

6. Discussion & Conclusion

A development deployment strategy for sUAS requires a balance between efficiency and effectiveness. Foundational data is required to model risk and apply such knowledge to select regions or situations where sUAS should be deployed. To answer the "when and where" question, team members developed a spatially explicit model to support on-farm monitoring decisions using wheat stripe rust in Australia as a model system. The climatic outbreak risk model was most sensitive to knowledge about spore dispersal from infected plants across a wheat-growing region. Our framework may be applied to different study regions simply by changing spatial proxies linked to each model variable, or adjusted to different pest or disease systems by identifying alternative life / infectious cycles and developmental stages, and their respective influential climatic variables. As there was considerable uncertainty in most of the cost/benefit parameters contained in our crop monitoring decision model, we explored model behaviour using a scenario analysis approach. The expected net benefit (measured in $ per hectare) of UAS monitoring over current approaches was strongly dependent on the level of disease risk. In low risk conditions, UAS deployment was rarely economical because the disease is likely absent, and added monitoring costs were therefore not offset by any benefits of improved early detection. However, as UAS technology becomes cheaper, or replaces more expensive alternatives altogether, it may prove economical also under much lower risk levels. As outbreak risk increased, added costs of UAS monitoring were often justified, as long as detection rates were sufficiently improved compared to alternative monitoring approaches. Better UAS performance resulted in both larger economic benefits and lower risk thresholds at which deployment yielded positive returns on investment.

We also presented the results of comparing a digital vigour model of the vineyard to an expert visual assessment. We found that the two assessments correlate positively indicating that the developed method is a correct approach for generating vigour assessments in vineyards. Geo-referenced results give a number of advantages over standard expert-based assessments: much more spatially accurate localisation (<0.02 m), individual tree assessment rather than panel (groups of five or six vines) approximation, and the ability to detect subtle trends that are unnoticeable due to inaccurate references used for visual assessment, such as the height of the poles. One of the most important advantages is the shorter time required to assess a large area. However, the inability to detect early symptoms of the disease and occasional irregular behaviour of the affected grapevines (early infested grapevines sometimes demonstrate abnormal intense vigour for a short time) are the known limitations of the DVM method. Nevertheless, the DVM method could provide insight to the expert to select candidate zones to revisit for closer and more detail inspections. We generated vegetation indices to highlight possible symptoms of phylloxera infestation, such as changes in the reflectance/absorption of light indicating a reduction in the chlorophyll content in the grapevines. This could be done remotely using both the multispectral and hyperspectral collected and treated imagery. Furthermore, we identified mean spectral signatures for different levels of infestation for the Chardonnay variety at two different times of the year which helped us find regions of interest in the spectrum in order to generate new vegetation indices to highlight grape phylloxera infestation.

In addition to the development of new indices, results from our work also indicated that commonly used vegetation indices derived from various aerial platforms can provide valuable information about plant health and biomass in agricultural systems and potential causes for the problems including pest infestation. Significant relationship between NDVI values derived from various aerial platforms and insect infestation in the field suggests the possibility for aerial monitoring system for pest infestation and management in agricultural systems. Furthermore, these aerial data may also be useful in developing predictive models for insect infestation in agricultural areas. Although this experiment could not provide a strong evidence of the relationship between NDVI and the measurements of aphid infestation in sorghum field, it highlights the potential for the use of small UAVs and remote sensing technology in pest detection and management in agricultural systems. Our results were most likely suffered from various limitations such as small number of sites, small number of survey dates, and the lack of wide range of pest infestation. In spite of these limitations, NDVI showed a significant negative relationship with the levels of honeydew secretion for the fixed-wing UAV. Furthermore, NDVI values derived from this platform remained more consistent between the survey dates than the octocopter.

For adoption of sUAS to be practical and cost effective, it is imperative that future research focuses on comparing the use of these technologies with existing strategies. For example, cost of flights and post processing of sUAS imagery for the simulated disease study was approximately $185per hectare. Conversely, estimated cost of surveillance staff for inspections at 95% confidence level is $50/hour with 1 hectare encompassing approximately 1500 vines (15 rows of vines, 200m long with vine spacing at 2m per vine). This would take approximately 45 min. In this case, the cost of on-ground inspections by surveillance staff is cheaper than sUAS imagery with the additional benefit of immediate feedback about possible infected vines. However, when the detectability of the plant pest is lower, or the time spent per inspection per plant increases then UAVs could become more cost-effective. In addition the combined use of UAVs to fly over large areas and to identify regions or parts of the crop that require more detailed inspection by ground staff could be more effective. Understanding feasibility is only the first step, and surveillance programs aiming to adopt sUAS technologies must consider all aspects, including understanding potential returns on investment.

7. Recommendations

7.1 Case studies and future research. The various cost and benefit parameters contained in our decision model can be easily adjusted “on the fly.” When specific farm level parameter values are known, the decision model allows comprehensive evaluation of the economic benefits of UAS monitoring under range of risk scenarios. In general, one should explore all possible available data.

We also demonstrated that hyperspectral imagery has the potential to detect grape phylloxera before it is apparent to visual inspection. The next stage is to determine if these hyperspectral indices have the potential to be adapted to the multispectral data without a loss in correlative power. Future work should focus on deriving predictive models (utilising these indices) and testing their accuracy in predicting the presence/abundance of the plant pest. One important aspect in order to validate a remote sensing technique is the accuracy of the ground data in terms of geographical reference and the resolution of the collected data sets. Novel techniques for collecting ground data with accurate geo-referencing could be further explored.

Expert visual assessments performed on the ground is time-consuming and sparse i.e., vigour assessment is done for panel or groups of five to six vines and is done using mostly qualitative data that is then translated into five levels or classes of vigour. This technique might not be reliable enough to generate statistical data and might be susceptible to error. In general, faster ground vigour assessments could be implemented using more technological methods such as georeferenced cameras and computer vision to increase the accuracy and resolution of the ground vigour assessment estimation.

The reflectance calculation could be more accurately and efficiently calculated with the help of a supporting sensor that estimates the solar irradiance while flying and collecting data. A mechanism to attach such sensor to the platform should also be developed. Moreover, inertial measurement sensors or systems, which have higher accuracy, could improve the ortho-rectification process for the hyperspectral data which shows some drifting due to the type of sensor used which is a push broom scanner.

7.2 Added perspective and multi-tasking widgets. A useful finding from this project is the value of an added perspective or vantage point. Small UAS removes the need for people to enter a production area directly addresses a key biosecurity issue of how to investigate a suspect without spreading it further. In addition, the ability to provide a landscape view or new perspective across a production area in real time allows for more targeted surveillance using visual symptoms. If this can be further enhanced through sampling of those suspects using UAS, the result isquicker surveillance covering a larger area using less resources. In general, sUAS are capable of providing imagery that allow those conducting surveillance programs to see sections of a paddock or vineyard that does not require a person to physically enter that portion of the infested commodity. There may not always be added value in this added perspective, which is why such feasibility studies will need to be conducted within the targeted commodity. However, the end result should not be solely focused on early detection, as the value of the technology for aiding in surveillance could be grossly underestimated. Incorporating hyperspectral technologies for example is a significant investment in sensors, suitable platforms to carry such a sensor, and personnel to process, analyse and interpret data. Conversely, seeing symptoms in an image captured from a smaller, more portable system allows for quick assessment of infestation at remote areas of a paddock or orchard. Both have value and require investment in human capital; however, capabilities and limitations will be cropping system specific. Therefore, goals should be clearly defined prior to investment in technology, which is why the UASK.info resource was developed.

Most of the recent focus in use of sUAS for pest detection, especially from an industry perspective, has been on providing stitched images or an orthomosaics to derive vegetation indices for the entire sampling universe (paddock, orchard). Consequently, such information can also be derived from satellite data or other commercially available platforms. In this case, use of sUAS should be evaluated based on temporal limitations to currently available data like satellite, where frequencies in sensory deployment or data capture may not meet the needs of the surveillance program and targeted pest.

Professionals evaluating use of sUAS for surveillance need to realize that adoption is a continuum and heavily dependent on the invasive species of interest and related interactions with the targeted host. Surveillance independent of human interpretation will take a specific research focus within the surveillance program. More specifically, use of artificial intelligence, machine learning, and auto-recognition of data captured from flights requires sensors capable of distinguishing differences in wavelengths that are a direct result of the pest and no other competing stressors. Such a process starts with greenhouse experiments to identify signatures, which then are validated under field conditions and compared to existing practices conducted by plant biosecurity professionals.

Another perspective this project offers is that sUAS should be viewed as a multi-tool. More specifically, we demonstrated that sUAS are capable of carrying payloads designed to capture sensor-derived data but flexible enough to switch between robotic mechanisms to remotely retrieve physical samples or deploy/dispense biological solutions to designed areas. A major recommendation moving forward, at least within plant biosecurity, is to adopt sUAS with this multi-functionality mind and all potential uses cases should be explored prior to adopting the technology in order to maximizes return on investment. We have demonstrated that sUAS selection is important to successful integration into surveillance programs, but only focusing on imaging is underutlizing the potential this technology has to offer.

8. References

ABS / Australian Bureau of Statistics. (2017a). Agricultural commodities, Australia 2015-16.

ABS / Australian Bureau of Statistics. (2017b). Value of Agricultural Commodities Produced, Australia 2015-16.

Australian Government (2017) Myrtle rust (Puccinia psidii) | Department of the Environment and Energy. Available at: http://www.environment.gov.au/biodiversity/invasive-species/diseases-fungi-and-parasites/myrtle-rust (Accessed: 25 September 2017).

Benheim, D., Rochfort, S., Robertson, E., Potter, I. D., & Powell, K. S. (2012). Grape phylloxera (Daktulosphaira vitifoliae) - A review of potential detection and alternative management options. *Annals of Applied Biology*, *161*(2), 91–115. https://doi.org/10.1111/j.1744-7348.2012.00561.x

Bosem Baillod, Aliette, Teja Tscharntke, Yann Clough, and Péter Batáry (2017). Landscape-Scale Interactions of Spatial and Temporal Cropland Heterogeneity Drive Biological Control of Cereal Aphids. Journal of Applied Ecology 54 (6): 1804–13. https://doi.org/10.1111/1365-2664.12910.

Blanchfield, A. L., Robinson, S. A., Renzullo, L. J., & Powell, K. S. (2006). Phylloxera-infested grapevines have reduced chlorophyll and increased photoprotective pigment content - Can leaf pigment composition aid pest detection? *Functional Plant Biology*, *33*(5), 507–514. https://doi.org/10.1071/FP05315

Buntin, G. D. 1999. Hessian fly (Diptera : Cecidomyiidae) injury and loss of winter wheat grain yield and quality. J. Econ. Entomol. 92: 1190-1197.

Bowling, Robert D., Michael J. Brewer, David L. Kerns, John Gordy, Nick Seiter, Norman E. Elliott, G. David Buntin, et al. (2016). Sugarcane Aphid (Hemiptera: Aphididae): A New Pest on Sorghum in North America. *Journal of Integrated Pest Management* 7 (1). https://doi.org/10.1093/jipm/pmw011.

Brewer, Michael J., John W. Gordy, David L. Kerns, James B. Woolley, William L. Rooney, and Robert D. Bowling (2017). Sugarcane Aphid Population Growth, Plant Injury, and Natural Enemies on Selected Grain Sorghum Hybrids in Texas and Louisiana. *Journal of Economic Entomology* 110 (5): 2109–18. https://doi.org/10.1093/jee/tox204.

Chen, M.-S., X. Liu, H. Wang, and M. El-Bouhssini. 2009. Hessian fly (Diptera: Cecidomyiidae) interactions with barley, rice, and wheat seedlings. J. Econ. Entomol. 102: 1663-1672.

CropPro. (2017). Stripe rust of wheat. Retrieved from State Government of Victoria, http://www.croppro.com.au/crop_disease_manual/ch02s07.php

Elliott, Norm, Mike Brewer, Nick Seiter, Tom Royer, Robert Bowling, Georges Backoulou, John Gordy, B. McCornack et al. (2017). Sugarcane Aphid Spatial Distribution in Grain Sorghum Fields. *Southwestern Entomologist* 42 (1): 27–35. https://doi.org/10.3958/059.042.0103.

Fenton NE, Neil M and Caballero JG. (2007). Using ranked nodes to model qualitative judgments in Bayesian networks. IEEE Transactions on Knowledge and Data Engineering 19(10): 1420-1432. doi: http://dx.doi.org/10.1109/tkde.2007.1073

Giblot-Ducray, D., Correll, R., Collins, C., Nankivell, A., Downs, A., Pearce, I., … Ophel-Keller, K. M. (2016). Detection of grape phylloxera (Daktulosphaira vitifoliae Fitch) by real-time quantitative PCR: development of a soil sampling protocol. *Australian Journal of Grape and Wine Research*, *22*(3), 469–477. https://doi.org/10.1111/ajgw.12237

Hanea, A. M., McBride, M. F., Burgman, M. A. and Wintle, B. C. (2016) 'Classical meets modern in the IDEA protocol for structured expert judgement', Journal of Risk Research, 1-17.

Hanea, A. M., McBride, M. F., Burgman, M. A., Wintle, B. C., Fidler, F., Flander, L., Twardy, C. R., Manning, B. and Mascaro, S. (2017) 'I nvestigate D iscuss E stimate A ggregate for structured expert judgement', International Journal of Forecasting, 33(1), 267-279.

Harris, M. O., and S. Rose. 1989. Temporal changes in the egg-laying behavior of the Hessian fly. Entomol. Exp. Appl. 53: 17-29.

Harris, M. O., and S. Rose. 1990. Chemical, color, and tactile cues influencing oviposition behavior of the Hessian fly (Diptera, Cecidomyiidae). Environ. Entomol. 19: 303-308.

Hauser, CE, Weiss, J, Guillera-Arroita, G, McCarthy, MA, Giljohann, KM, Moore, JL R. Randall, S.Lloyd, C Borger (Eds) (2016) 'Designing detection experiments: three more case studies, Proceedings of the 20th Australasian Weeds Conference.' Perth, Western Australia. (Weeds Society of Western Australia.

Hefley, T. J., K. M. Broms, B. M. Brost, F. E. Buderman, S. L. Kay, H. R. Scharf, J. R. Tipton, P. J. Williams, and M. B. Hooten. 2017c. The basis function approach for modeling autocorrelation in ecological data. Ecology 98: 632-646.

Hemming, V., Burgman, M. A., Hanea, A. M., McBride, M. F. and Wintle, B. C. (2017) 'A practical guide to structured expert elicitation using the IDEA protocol', Methods in Ecology and Evolution, n/a-n/a.

Lausch, A. et al. (2016) 'Understanding forest health with remote sensing-Part I-A review of spectral traits, processes and remote-sensing characteristics', Remote Sensing. doi: 10.3390/rs8121029.

Lausch, A. et al. (2017) 'Understanding forest health with Remote sensing-Part II-A review of approaches and data models', Remote Sensing. doi: 10.3390/rs9020129.

Marciniak, M. (2015). Use of remote sensing to understand the terroir of the Niagara Peninsula. Applications in a Riesling vineyard. *Journal International Des Sciences de La Vigne et Du Vin*, *49*(1), 1–26. https://doi.org/10.20870/oeno-one.2015.49.1.97

Marcot BG. (2012). Metrics for evaluating performance and uncertainty of Bayesian network models. Ecological Modelling 230: 50-62. doi: http://dx.doi.org/10.1016/j.ecolmodel.2012.01.013

Mathews, A. J. (2015). A Practical UAV Remote Sensing Methodology to Generate Multispectral Orthophotos for Vineyards : Estimation of Spectral Reflectance. *International Journal of Applied Geospatial Research*, *6(4)*(October-December 2015), 65–87. https://doi.org/10.4018/ijagr.2015100104

Mirik, M., G. J. Michels Jr., S. Kassymzhanova and N. C. Elliott (2007). Reflectance characteristics of Russian wheat aphid (Hemiptera: Aphididae) stress and abundance in winter wheat. Computers and Electronics in Agriculture 57: 123-134.

Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems Engineering*, *114*(4), 358–371. https://doi.org/10.1016/j.biosystemseng.2012.08.009

Murray GM and Brennan JP. (2009). The current and potential costs from diseases of wheat in Australia. Grains Research and Development Corporation, Barton.

Powell, K. (2012). *A Holistic Approach to Future Management of Grapevine Phylloxera*. *Arthropod Management in Vineyards: Pests, Approaches, and Future Directions* (Vol. 9789400740). https://doi.org/10.1007/978-94-007-4032-7

Powell, K. S., Korosi, G. A., & Mackie, A. M. (2009). Monitoring grape phylloxera populations using simple non- destructive trapping systems. *Acta Horticulturae*, *816*, 29–34.

PricewaterhouseCoopers. (2016). Clarity from above: PwC global report on the commercial applications of drone technology. Retrieved from PwC, https://www.pwc.pl/en/publikacje/2016/clarity-from-above.html

Schmid, R. B., A. E. Knutson, K. L. Giles, and B. P. McCornack. Hessian fly (Diptera: Cecidomyiidae) biology and management in wheat. Journal of Integrated Pest Management (*accepted*).

Skinkis, P., Walton, V., & Kaiser, C. (2009). Grape Phylloxera, Biology and Management in the Pacific Northwest. *Oregon State University, Extension Program*, (June), 7–9.

Smiley, R. W., J. A. Gourile, R. G. Whittaker, S. A. Easley, and K. K. Kidwell. 2004. Economic impact of Hessian fly (Diptera : Cecidomyiidae) on spring wheat in Oregon and additive yield losses with fusarium crown rot and lesion nematode. J. Econ. Entomol. 97: 397-408.

Smith CS, van Klinken RD, Seabrook L and McAlpine C. (2012). Estimating the influence of land management change on weed invasion potential using expert knowledge. Diversity and Distributions 18(8): 818-831. doi: http://dx.doi.org/10.1111/j.1472-4642.2011.00871.x

Trowbridge G. (2017). The drone revolution and Australian agriculture part two: case studies and practical benefits. Retrieved from Directions International Pty Ltd, http://www.droneremotesensing.com/vegetation-indicies/drones-in-precision-agriculture/

Vanegas, F., Bratanov, D., Powell, K., Weiss, J., & Gonzalez, F. (2018). A Novel Methodology for Improving Plant Pest Surveillance in Vineyards and Crops Using UAV-Based Hyperspectral and Spatial Data. *Sensors*, *18*(1), 260. https://doi.org/10.3390/s18010260

Ver Hoef, J. M. V., and P. L. Boveng. 2015. Iterating on a single model is a viable alternative to multimodel inference. J. Wildl. Manage. 79: 719-729.

Watson, S. 2005. Hessian fly problems have been increasing in recent years in the Central Plains. Wheat Farmer/Row Crop Farmer 9: 4-5.

Wellings CR. (2011). Global status of stripe rust: a review of historical and current threats. Euphytica 179(1): 129-141. doi: https://doi.org/10.1007/s10681-011-0360-y

Withers, T. M., and M. O. Harris. 1997. Influence of wind on Hessian fly (Diptera: Cecidomyiidae) flight and egglaying behavior. Environ. Entomol. 26: 327-333.

Withers, T. M., M. O. Harris, and C. Madie. 1997. Dispersal of mated female Hessian flies (Diptera : Cecidomyiidae) in field arrays of host and nonhost plants. Environ. Entomol. 26: 1247-1257.

Wood, S. N. 2017. Generalized Additive Models: An Introduction with R, 2nd ed. CRC press, Boca Raton, FL.

Yang, Long, Yingda Zeng, Lei Xu, Bing Liu, Qian Zhang, and Yanhui Lu. 2018. Change in Ladybeetle Abundance and Biological Control of Wheat Aphids over Time in Agricultural Landscape. Agriculture, Ecosystems & Environment 255 (March): 102–10. https://doi.org/10.1016/j.agee.2017.12.013.

Zhang, C., & Kovacs, J. M. (2012). The application of small unmanned aerial systems for precision agriculture: A review. *Precision Agriculture*, *13*(6), 693–712. https://doi.org/10.1007/s11119-012-9274-5

9. List of Appendices

Appendix 1

Small UAS deployment strategies using wheat stripe rust as a case study:

Froese, J. G., J. Eldridge, G. Hamilton (2018). Case study: Monitoring for wheat stripe rust using unmanned aerial systems: a risk-based decision framework. PBCRC 2135 Report.

Appendix 2

Progress report:

Weiss, J. (2017). Milestone Report – November 2017: Optimizing surveillance protocols using unmanned aerial systems. Department of Economic Development, Jobs, Transport & Resources, Victoria.

10. List of Outputs

Bhattarai, G. and B. McCornack (a). Detecting insect pests in agricultural fields using remote sensing: Hessian fly as a case study. Journal of Insect Science (*in prep*).

Bhattarai, G., and B. McCornack (b). Detecting sugarcane aphid infestation using small unmanned aircraft systems (sUAS). Sensors *(in preparation*).

Bhattarai, G., and B. McCornack. 2017. Using hyperspectral data to detect insect pests in an agricultural system. Ecological Society of America, National Meeting, Portland, OR, USA.

Dix, P. Applications of Unmanned Aerial Systems in Automated Collection of Insect Samples. Kansas State University, Department of Biological and Agricultural Engineering, Thesis. Committee members: Drs. B. McCornack, D. Flippo, and A. J. Sharda (in prep).

Flippo, D., R. Patcha, T. Witt, and B. McCornack. Autonomous Pheromone Deployment for Lure and Kill Management of Agricultural Pests. (*in prep*)

McCornack, B. 2018. Optimising surveillance protocols using unmanned aircraft systems: the power of perspective. Science Protecting Plant Health (SPPH) Conference, co-sponsored by the Plant Biosecurity Cooperative Research Centre, Brisbane Australia.

Sandino, J., Pegg, G., Gonzalez, F., Smith, G. (2018) *Aerial Mapping of Forests Affected by Pathogens using UAVs, Hyperspectral Sensors and Artificial Intelligence*. Sensors 2018, 18, 944.

Schmid, R. B., T. Hefley, R. Lollato, and B. P. McCornack. Landscape effects on Hessian fly, *Mayetiola destructor* (Diptera: Cecidomyiidae), distribution within six Kansas commercial wheat fields. Journal of Economic Entomology (*in prep*)

Vanegas F., Pegg G., Kok J., Sandino J., Gonzalez F. (2017a) UAS remote sensing efforts for Myrtle rust management. In *Science Protecting Plant Health 2017*. Brisbane, Australia. (https://eprints.qut.edu.au/117032/)

Vanegas, F., Bratanov, D., Powell, K., Weiss, J., & Gonzalez, F. (2018b). A Novel Methodology for Improving Plant Pest Surveillance in Vineyards and Crops Using UAV-Based Hyperspectral and Spatial Data. *Sensors*, *18*(1), 260. https://doi.org/10.3390/s18010260

Vanegas, F., Bratanov, D., Powell, K., Weiss, J., & Gonzalez, F. (2017b). The use of UAS obtained imagery to detect early stages of pest incursions: case study of grape phylloxera in vineyards. *In* Science Protecting Health 2017.

Vanegas, F., Bratanov, D., Weiss, J., Powell, K., & Gonzalez, F. (2018a). Multi and Hyperspectral UAV Remote Sensing : Grapevine Phylloxera Detection in Vineyards. In *2018 IEEE Aerospace Conference Proceedings* (pp. 1–9). (*Approved for presentation*)

11. Abbreviations/glossary

Insert list of abbreviations of acronyms (for example)

ABBREVIATION	FULL TITLE
PBCRC	Plant Biosecurity Cooperative Research Centre
EPP	Emergency plant pest
BN	Bayesian Networks
NDVI	Normalized Difference Vegetation Index

11. Plain English website summary

Please complete table using plain English. This information will be published on PBCRC's website for a public audience.

CRC project no:	CRC2135

Project title:	Optimising surveillance protocols using unmanned aerial systems
Project leader:	Dr. Brian McCornack
Project team:	Drs. Felipe Gonzalez, John Weiss, Grant Hamilton, and Geoff Pegg
Research outcomes:	A development deployment strategy for sUAS requires a balance between efficiency and effectiveness. Foundational data is required to model risk and apply such knowledge to select regions or situations where sUAS should be deployed. The climatic outbreak risk model was most sensitive to knowledge about spore dispersal from infected plants across a wheat-growing region. Our framework may be applied to different study regions. We also presented the results of comparing a digital vigour model of the vineyard to an expert visual assessment. We found that the two assessments correlate positively indicating that the developed method is a correct approach for generating vigour assessments in vineyards. We generated vegetation indices to highlight possible symptoms of phylloxera infestation, such as changes in the reflectance/absorption of light indicating a reduction in the chlorophyll content in the grapevines. This could be done remotely using both the multispectral and hyperspectral collected and treated imagery. In addition to the development of new indices, results from our work also indicated that commonly used vegetation indices derived from various aerial platforms can provide valuable information about plant health and biomass in agricultural systems and potential causes for the problems including pest infestation. For adoption of sUAS to be practical and cost effective, it is imperative that future research focuses on comparing the use of these technologies with existing strategies.
Research implications:	The various cost and benefit parameters contained in our decision model can be easily adjusted "on the fly." When specific farm level parameter values are known, the decision model allows comprehensive evaluation of the economic benefits of UAS monitoring under range of risk scenarios. In general, one should explore all possible available data. Future work should focus on deriving predictive models (utilising these indices) and testing their accuracy in predicting the presence/abundance of the plant pest. One important aspect in order to validate a remote sensing technique is the accuracy of the ground data in terms of geographical reference and the resolution of the collected data sets. Novel techniques for collecting ground data with accurate geo-referencing could be further explored. The most useful finding from this project is the value of an added perspective or vantage point. In general, sUAS are capable of providing imagery that allow those conducting surveillance programs to see sections of a paddock or vineyard that does not require a person to physically enter that portion of the infested commodity. There may not always be value in this added perspective, which is why such feasibility studies will need to be conducted within the targeted commodity. However,

	the end result should not be solely focused on early detection, as the value of the technology for aiding in surveillance could be grossly underestimated. In this case, use of sUAS should be evaluated based on temporal limitations to currently available data like satellite, where frequencies in sensory deployment or data capture may not meet the needs of the surveillance program and targeted pest. Professionals evaluating use of sUAS for surveillance need to realize that adoption is a continuum and heavily dependent on the invasive species of interest and related interactions with the targeted host. Surveillance independent of human interpretation will take a specific research focus within the surveillance program. Another perspective this project offers is that sUAS should be viewed as a multi-tool. More specifically, sUAS are capable of carrying payloads designed to capture sensor-derived data but flexible enough to switch between robotic mechanisms to remotely retrieve physical samples or deploy/dispense biological solutions to designed areas. A major recommendation moving forward, at least within plant biosecurity, is to adopt sUAS with multi-functionality as a primary driver governing adoption that maximizes return on investment.
Research publications:	Vanegas, F., Bratanov, D., Powell, K., Weiss, J., & Gonzalez, F. (2018). A Novel Methodology for Improving Plant Pest Surveillance in Vineyards and Crops Using UAV-Based Hyperspectral and Spatial Data. *Sensors*, *18*(1), 260. https://doi.org/10.3390/s18010260.

Plant Biosecurity
Cooperative Research Centre

Level 2, Building 22, Innovation Centre
University Drive, University of Canberra
Bruce ACT 2617

LPO Box 5012
Bruce ACT 2617

P: +61 2 6201 2882
F: +61 2 6201 5067
E: info@pbcrc.com.au
www.pbcrc.com.au