Final Report

Multi-scale monitoring tools for managing Australian tree crops – phase 2

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Public summary

The first phase of the 'Multi-scale Monitoring Tools for Managing Australian Tree Crops' project (Phase 1) successfully delivered on the priorities of the Rural R&D for Profit Program by producing outcomes and outputs that directly benefited a number of horticultural tree crop industries. These included the delivery of the first map of all commercial avocado, macadamia and mango orchards (> 2 ha) across Australia, an output that provides an accurate understanding of the extent (location and area) of each industry, supports improved traceability, production forecasting, infrastructure and labour planning, biosecurity preparedness and post natural disaster response.

The Phase 1 project also delivered several remote sensing (satellite, UAV, ground based) based applications including tools that provided an accurate measure of tree health spatially (across orchard blocks and entire orchards) and temporally (during the growing season and across years); improved yield forecasting and yield mapping at the orchard block level for macadamia, avocado and mango; an improved understanding of the spatial and temporal distribution of fruit quality parameters such as fruit size and maturity; and a more efficient method for measuring disease (e.g. Phytophthora) and pollination efficiency. These outcomes and outputs directly benefit growers by enabling them to make more informed decisions around forward-selling estimates for both domestic and overseas markets; to better plan logistical decisions around harvesting including labour, machinery, packaging, transport, and storage requirements; early detection of pest and disease and the adoption of targeted agronomy that directly supports the more judicious application of crop inputs including water, fertiliser and pesticides.

The Phase 1 project also delivered over 200 extension activities to the wider industry and as such the project team experienced strong industry engagement, support and most importantly adoption of some project outputs. These outcomes and outputs stimulated significant interest from other industries and as such initiated the Phase 2 project.

This Phase 2 project built on the foundations of Phase 1, by:

- Increasing the minimum mapping unit of commercial orchards from > 2 ha to > 1 ha as well as including the national mapping of all citrus, olive and banana industries;
- Quantifying the area of planting of mango and macadamia between 2017 and 2022;
- Developing a map of non-commercial mango trees within the Cape region of north Qld for the purpose of directing future surveillance of biosecurity threats coming from our northern neighbours;
- Investigating the accuracies of remote sensing technologies for measuring the spatial and temporal variation in citrus and olive tree vigour (size and health);
- Investigating the accuracies of remote sensing for predicting yield in citrus and olive orchards;
- Investigating alternative remote sensing methodologies (time series analysis, inclusion of weather variables and tree age) for the prediction of mango, citrus and macadamia yield;
- Investigating the accuracies of in-field sensors (sap flow, dendrometer, soil moisture, canopy temperature and canopy relative humidity) as well as remote sensors (satellite and airborne imagery) to determine which best identifies the early onset of water stress in olive trees;
- Identifying a reliable commercially available option for on farm connectivity to support remote access to sensors (IOT);
- Quantifying the impact of prolonged water stress on olive yield and fruit quality;
- Further extending project outcomes and outputs to the wider industries, government agencies and non-government agencies (NGOs).

Overall, the Phase 2 project has achieved significant success delivering 101 extension pieces that communicated all derived outcomes and outputs to the wider community, engaged in on-farm research across all Australian states and Territories and achieved the following awards, commercial contracting and prestigious opportunities:

- The ATCM dashboard awarded best dashboard globally at the 2021 Esri International User Conference, San Diego, USA (70,000 delegates);
- The AARSC awarded 'Best organization in imagery application' by MAXAR for the Asia Pacific and Australian regions (2020);

- The AARSC was awarded the Australian Macadamia Society: Innovation Award for 2021;
- The AARSC selected as finalists in the 2021 'Excellence in industry engagement' category: Engagements Australia excellence awards 2021;
- The AARSC selected as finalists for two industry awards at 2021 Hort Connections: Visy Industry Impact Award and Bayer Researcher of the Year;
- The AARSC has been commercially contracted by the Costa group to provide yield predictions for their entire national citrus crop;
- The AARSC has been commercially contracted by the South African Macadamia industry (SAMAC) to map all macadamia orchards across South Africa as well as to evaluate the yield forecasting methodologies under their growing environment;
- The AARSC are now mapping all Protected Cropping Structures and Truffles nationally as well as all Soybeans in Queensland;
- Associate Professor James Brinkhoff selected as one of 60 global researchers to be part of the 2022 cohort of the Google Cloud Research Innovators Program;
- Professor Robson requested to be Keynote speaker on AgTech at international avocado conference (Auckland, April 2023).
- The PhD student (mango) received the 1st Prize award of the 3MT Competition at the School/Faculty level.
- The PhD student (mango) received a Runner's up Prize of the 3MT Competition at the University level.

The 'Rural R&D for Profit Program has provided a unique opportunity for multiple industries, research, government and NGOs to work together to address common themes. This environment has enabled a range of technologies and methodologies to be tested to identify which are best suited, plus created outcomes that are relevant to multiple industries. The successes achieved by this a project are the direct result of this collaborative, well resourced, multi-industry funding model.

Forecast of tree-fruit harvest timing and volumes is critical to planning for harvest resourcing in terms of labour and materials and for marketing. This need increases in longer and larger value chains, particularly where export markets are involved. Two tools to aid forecast of harvest timing were progressed, involving: (i) heat units for mango fruit maturation, and (ii) fruit dry matter content for mango and olive. Revised Growing Degree Days (GDD) targets for harvest were proposed. An algorithm for calculation of heat that incorporates a penalty for high as well as low temperatures was implemented in context of low-cost sensor hardware with automated temperature logging. On-tree assessment of fruit dry matter content of mango and olive fruit was progressed using new chemometric approaches and implemented in instruments used by the mango industry.

For count of mango fruit in the orchard, a machine vision system mounted to a farm vehicle was developed and implemented in whole orchard fruit count exercises. Exercises were undertaken in Darwin, Katherine, Mareeba, Central Qld and South Qld growing regions. For fruit sizing, a phone app was developed that required manual acquisition of images of fruit on-tree. Additionally, a time-of-flight camera system was developed that was associated with the fruit count system, mounted to a farm vehicle. Although less accurate than caliper measurements or pack-line estimates, these tools provide for pre-harvest forecast of fruit size distribution with reduced human effort.

The foundation ability to detect fruit position was used in the development of a prototype mango fruit mechanical harvester. Improvements in gripper design and arm movements across three seasons provided increased speed and effectiveness of picking, e.g., a 5 second cycle time between assigning a pick task to an arm, movement of arm to fruit, grasping, rotation, retraction and release of the harvested fruit. An eight arm prototype was developed and deployed in field trials in central Qld and Katherine, NT.

Continuous extension activities occurred, through work on farms, presentations at grower events and articles in industry magazines. Several staff from the CQU team migrated into the mango industry in different capacities, providing a 'human resource development' outcome for the industry.

Farmers and consumers alike are expressing an increasing interest in purchasing fruit that was grown on farms employing methods that are both more productive and less harmful to the surrounding environment. Finding novel and creative approaches to get real-time field data directly into the hands of farmers so that they may make the most informed choices for their crops is an essential step in accomplishing this objective.

The agricultural sector requires a high level of resiliency, but the previous two years have presented more difficulties than most producers can remember experiencing in their careers.

Already battling through long periods of poor returns, the arrival of COVID-19 put an unprecedented level of pressure on almost every Australian banana business. Additionally, severe weather events have also taken their toll.

Additionally, the extra strain of rising farm input costs, such as ballooning prices of fertiliser, chemicals, freight, and fuel, many producers were selling fruit at rates that were substantially below the cost of production.
The supply chain of the agriculture industry as a whole is anticipated to see an increase in bottom line (profits) of several hundreds of millions of dollars as a result of digitising farm operations and applying algorithms for improved management and yield prediction.

The R&D for Profit 18-04-010 Multi-scale monitoring tools for managing Australian tree crops - phase 2 was preceded by consultation with the mango, macadamia, olive, banana, and citrous industries, a common need was identified to improve the accuracy of pre-harvest yield and fruit quality forecasting; improve surveillance of tree health including biosecurity threats; and map national production more accurately.

In order to address the gaps / shortages identified by the industry the following two objectives have been derived:

1) Improving the farm level's ability to accurately predict pre-harvest yields in order to maximise profits.
A more precise projection of the pre-harvest yield of tree crops has enormous opportunities for improvement. At the level of the farm, higher prediction accuracies support the agribusiness in making more informed decisions around forward-selling to both domestic and overseas markets. In addition**,** under an improved pre-harvest yield projection, growers would be able to better plan the logistics surrounding harvesting, including requirements for labour, machinery, packaging, transport, and storage, as well as their own capacity to meet market demands. Growers and other stakeholders in the sector could see an increase in their profitability as a result of each of these characteristics. TieUp Farming had been successful in developing and deploying a bunch tagging system in order to enable increases in the accuracy of yield forecasts.

2) Create workable tools and analysis methods that will improve the monitoring and mapping of tree health, fruit quality, and maturity levels within orchards.
In addition to improvements in pre-harvest yield forecasting and mapping, growers need tools that are both practical and adaptable for monitoring the health of trees, as well as the phenological growth stage, fruit quality, and the point at which the fruit is mature. The farm gate price is affected by a variety of maturity-related criteria, including fruit size, the amount of dry matter it contains, its shelf life, the level of blemishes it contains, etc. Therefore, the capacity to predict the ideal harvest date and to segregate crops based on their quality and maturity offer great potential economic benefit. In addition to assisting in the early detection of pest and disease outbreaks, the provision of practical tools for measuring variability in tree health can also assist in the reduction of inputs by assisting in the judicious management of water, fertiliser, and pesticides. These benefits can be realised through the application of these tools.

Tie Up Farming offers a complete software solution for the banana sector. It manages the farm operations digitally and provides a comprehensive farm management software to manage the agricultural operations (chemicals, fertilisers, labour, harvest etc.). Throughout this procedure, Tie Up Farming's primary focus was on delivering the following services:

1. Yield forecasting by utilising bunch tagging technology.
2. Mapping the yield with the help of a scale and GPS technologies.

Fruit tree crop yield and harvest timing estimation ahead of harvest can improve farm productivity by informing harvest resourcing decisions (staffing, packhouse materials, etc). Unintended benefits could also accrue through management of an orchard based on yield variability information (i.e. precision horticulture), or through selection of consistently high yielding trees (cultivar development). However, greater benefits from a yield estimation system are expected to accrue off farm, by informing marketing plans.

This project was a component of a larger Rural R&D for Profit project involving UNE, QDAF, NTDITT, CQU, NSWDPI and industry associations on 'multiscale' monitoring of mango, olive, citrus and banana crop health and fruit load, at levels from satellite to in-field. The Australian Mango Industry Association (AMIA), Queensland Department of Agriculture and Fisheries and the Northern Territory Department of Industry Tourism and Trade supported the CQU and UNE delivered components which seek to deliver tools to assist in the forward estimation of fruit harvest maturity and fruit load, to aid in harvest and marketing planning, with a focus on mango.

The project harnessed skills in in-field machine vision for fruit number and size estimation into the development of an auto-harvesting platform for mango and improve forecasting processes. The project also investigated the orchard fruit load estimations obtained from correlation to satellite-based vegetation index and canopy area estimates. The project was characterised by a high level of interaction with producers and value chains, providing a pathway for adoption of outcomes as part of the Mango Strategic Investment Plan 2022-2026.

To be better prepared for future biosecurity threats, AMIA collaborated with the Applied Agricultural Remote Sensing Centre, state (Queensland Department of Agriculture and Fisheries) and federal biosecurity agencies (Northern Australia Quarantine Strategy, Department of Agriculture, Water and the Environment) to map and publish the location of all non-commercial mango trees in the Cape York Peninsula and Torres Strait Islands. The map has been developed and is accessible here.

The Australian Mangoes team provided support to the project partners in the Northern Territory and Queensland as needed and conducted communications and extension activities to update the mango industry on the project findings and encourage growers to take up newly developed tools and technologies.

Technical summary

The following technical summary is presented as an overview of the scope of work and outcomes achieved for each of the participating industries as well as for the national mapping component.

Macadamia

Over the course of the project, grower level data was provided by 21 macadamia orchards, consisting of 204 blocks, totaling 1156 yield records from 2012-2021. This covered 1,800 hectares, approximately 5% of the Australian industry, from mid-NSW to north-QLD. The first component of the macadamia work developed a macadamia tree planting year predictor with mean absolute prediction error of 1.7 years. This was used to provide annual statistics of total macadamia area by year to the Australian Macadamia Society and Queensland Department of Agriculture and Fisheries. The second component developed a novel block level yield forecasting methodology based on the extensive amount of historic yield data collected, historic acquisitions of satellite imagery and weather variables. The resultant models generated a mean absolute prediction error of 20-25% at the **block level** (except for some severely drought effected orchards in 2020) for predicting average and total yield, and median **farm-level** production prediction errors of 8-12% (excepting 2020). These predictions were made months prior to commercial harvest, did not require infield data collection and produced accuracies that exceeded current commercial practice.

Citrus

For the citrus component of the Phase 2 project, two methodologies for improved pre-harvest yield forecasting and estimation at the farm and regional level were tested. The '18 Calibration Tree' approach (18CT) was used to provide insight of within block/orchard variability which supports harvest segregation and the more judicious use of farm inputs (water, fertiliser etc). This approach requires tree level fruit counts to be collected during the growing season to establish an empirical relationship between remote sensing data (in the form of vegetation indices – VIs) and yield (t/ha, kg/ha). In total, 51 orchards across Red Clift, Leeton and Moora (cv. Afourer Mandarin and Late Lane, Washington, Chislett and Barnfield Navels) were sampled between 2020 and 2021. The second remote sensing approach, the Time series method (TS-Citrus) was developed to provide early yield forecast at the block level that can be extrapolated to farm and region level. This approach provides yield estimates around fruit set, months before commercial harvest and does not require infield sampling. For this method, historic yield data from 2007 until 2022 was sourced from five commercial farms (FC, FH, FK, FM and FT) representing 4.7% of the total planted area of citrus in Australia, including the most common citrus types: Navel, Mandarin, and Valencia and varieties (26 in total). Specifically, 27% of planted area in the Wheatbelt region, 14% in the Riverland and 6% in the Sunraysia were analysed. From the total number of blocks included in this study, Navels represent 50% of the planted area in the Sunraysia, 64.5% in the Riverland and 75% in the Wheatbelt region and Mandarin (Valencia) represents 50% (6%), 28.3% (7.2%) and 12.5% (12.5%), respectively.

Overall prediction accuracies from the 18CT method ranged between 80% and 98% with the highest error (30%-40%) coming from orchards that experienced hailstorm damage and as such suffered major yield loss. The prediction accuracies for the TS-Citrus method at the **block level** were on average 71% and at the **farm level** 80%. The accuracies from both methods exceeded current commercial yield forecasting practices.

Olives

For the olive component of this project, groves located in Mornington Peninsula and Boort (VIC) were included. A total of 19 groves between 2020 and 2022 were sampled to test the '18 calibration tree' (18CT) methodology for yield estimation at the block level. The study demonstrated the ability of the 18CT to estimate yield one month prior to harvest with varied accuracies that were dependent on the conditions during calibration and harvest timings. Accuracies at the **block level** ranged from 63% to 99.8% with eight out of 11 groves, producing an overall accuracy of above 85% at the **farm level** (Farm 1). Lower accuracies were achieved at the two other farms (Farm 2 and Farm 3) as a result of external factors not related to the methodology (e.g. harvest losses). Overall, the remote sensing yield forecasting methodology developed through this project offers prediction accuracies higher than current commercial practice.

In addition to yield forecasting, the commencement of this project aligned with a prolonged drought that occurred across many olive growing regions and as such the industry expressed a strong need to evaluate a range of technologies to better measure water stress in olive trees and to better understand the impacts of water stress on yield, oil accumulation and final oil content (%). As such a comprehensive irrigation trial was established across 4 groves in Boort that provided water at the standard 100%, 78% and 52% of the commercial rate. This trial ran for the duration of the phase 2 project and evaluated several in field and remote sensing technologies for their ability to measure water stress based on sensitivity, responsiveness, reliability and affordability. The outcomes of this study identified that the amount of water applied could be reduced for short periods of time (1-2 seasons) without affecting crop performance. However, such decision would be seasonally dependent. It was also found that remote sensing did have the capacity to identify cumulative drought stress in olive trees but was less able to inform day-to-day irrigation management. Individual tree mounted dendrometers showed the greatest sensitivity to identifying drought stress. Dendrometers data was also the easiest to interpret.

Across both research trials (18CT and irrigation), oil accumulation within olives (during maturation) occurred at a faster rate in low vigour trees than in medium and high vigorous trees, and oil content was not highly influenced by water deficits nor fruit weight. These results provide highly beneficial insights for growers in terms of where to undertake in-season sampling to assess the maturation of olive fruit and therefore the optimal time to harvest. But also, to better understand the spatial variation in maturity across groves so that harvest segregation could be implemented to maximise oil quality. This is particularly important to medium and small groves that are paid not for volume but quality of oil.

Mango

This research investigated the accuracies of high-resolution Worldview 3 (WV3) satellite data (single capture) and the 18-tree calibration (18CT) methodology for pre-harvest mango yield prediction and yield variability mapping. This was validated over three consecutive seasons (2019/20/21), encompassing 13 farms (>250 individual orchard blocks) across four growing regions, eight mango varieties, with various tree ages and management practices. On average, an overall accuracy of ~87% at **block level** and ~94% at **farm level** was achieved in fruit count estimation using satellite data for 2019-21 seasons, a significant improvement on traditional manual yield estimation methods. In addition, the use of only 18 trees for in field calibration was significantly less than the 2-3% of trees currently counted by growers, offering significant labour and time savings for mango yield forecasting. Further evaluation of both low cost (Planet) and freely available (Sentinel-2) satellite data (over 21 blocks 4 farms in NT, NQLD and SEQLD regions for 2019/20 season) also produced comparable yield forecasting accuracies. This result is encouraging as it presents growers with a range of remote sensing cost options. A time-series yield forecasting method based from Landsat satellite imagery was also evaluated as it offers yield forecasts much earlier in the season from freely available imagery, with no infield fruit counting required. This further reduced the labour costs and time to estimate yield manually. The results for 2021-22 season were found to be highly accurate at both **farm** and **block level**, with yield prediction errors ranging from 2-15%. These accuracies again exceeded commercial practice and as such is continuing to attract more Australian mango growers every season.

As part of the mango component of this project, an on-going PhD study is evaluating a range of analytical methodologies and input variables (yield, location, variety etc) to improve the accuracies of remote sensing-based yield forecasting. Two scientific papers have been published (one in a peer reviewed journal and the other presented at two separate conferences in the USA (15th ICPA) and Australia (UNE Postgraduate Conference)). The first paper (Torgbor et al., 2022b), used Sentinel-2 derived vegetation indices to retrieve five phenology stages of mango (i.e. Flowering/Fruitset (F/F), Fruit Development (FRD), Maturity and Harvesting (M/H), Flush (FLU) and Dormancy (D)). The second paper (Torgbor *et al.,* 2022a), applied Sentinel-1-derived (SAR) radar vegetation index (RVI) in retrieving three key phenology stages of mango namely Start of Season (SoS), Peak of Season (PoS) and End of Season (EoS). Currently, an assessment of the performance of six machine learning algorithms using Landsat data in predicting mango yield in two farms of the Northern Territory is on-going. Preliminary results from this study show that the Random Forest and Support Vector Regression algorithms have some potential in predicting mango yield at the block and farm level. It was further observed that model accuracies at the farm level (>80%) are generally better than the block level (>50%) for all the models tested.

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Bananas

In addition to improvements in pre-harvest yield forecasting and mapping, growers need tools that are both practical and adaptable for monitoring the health of trees, as well as the phenological growth stage, fruit quality, and the point at which the fruit is mature. The farm gate price is affected by a variety of maturity-related criteria, including fruit size, the amount of dry matter it contains, its shelf life, the level of blemishes it contains, etc. Therefore, the capacity to predict the ideal harvest date and to segregate crops based on their quality and maturity offer great potential economic benefit. In addition to assisting in the early detection of pest and disease outbreaks, the provision of practical tools for measuring variability in tree health can also assist in the reduction of inputs by assisting in the judicious management of water, fertiliser, and pesticides. These benefits can be realised through the application of these tools.

Tie Up Farming offers a complete software solution for the banana sector. It manages the farm operations digitally and provides a comprehensive farm management software to manage the agricultural operations (chemicals, fertilisers, labour, harvest etc.). Throughout this procedure, Tie Up Farming's primary focus was on delivering the following services:

1. Yield forecasting by utilising bunch tagging technology.
2. Mapping the yield with the help of a scale and GPS technologies.

National Mapping of tree crops

The national mapping component of this project delivered the 2022 update of all commercial mango, macadamia, citrus, olive and banana orchards (> 1 ha) within the Australian Tree Crop Map (ATCM) dashboard. The ATCM has received extensive significant industry engagement during the life of the project with 4,073 ATCM surveys received, and 909 comments submitted from non-project staff actioned in the Industry Engagement Web App. All industries bodies either directly promote or present the mapping on their respective websites to provide their grower base with a direct conduit to contribute and collate industry level data, especially the planting of new orchards; additionally, the ATCM has been used for many applications, such as:

- Citrus Australia value added the national map of orchards by adding additional attribute data (citrus type, variety, productivity, grower details and a GS1 international traceability code) at block level within the ATCM polygons. This output funded by Victoria government directly improves traceability of citrus to Asian markets;
- Tree crop locations in South Australia have assisted the biosecurity fruit fly management program run by PIRSA;
- Murray-Darling Basin Authority are using the mapping for irrigation modelling;
- The locations of orchards have been overlaid with bushfire extent (2019) and multiple flood events to determine the areas of crop loss;

- The ATCM Dashboard has been used by the Federal government to coordinate the Harvest Trail program, connecting workers with farmers (https://www.dewr.gov.au/harvest-trail),
- The ATCM feature service has been used as a layer in other web map applications, such as the Queensland Government's Web-Based Agricultural Land Information (WALI) and the Nursery and Garden Industry of Queensland's mapping applications.
- The map supports the update of national catchment scale land use mapping programs, across all jurisdictions of the Australian Collaborative Land Use and Management Program (ACLUMP), and is published in national compilation of commodities data (nationalmap.gov.au);
- The Australian Bureau of Statistics (ABS) are using the map data to validate their AgCensus information and will use the data in future to support compilation of their national statistics for agriculture.

This output has also achieved significant interest from other cropping systems with the national mapping of protected cropping systems, truffles and soybeans (Qld) all commencing as well as the mapping of all macadamia orchards in South Africa. Finally, the ATCM has also achieved international acclaim by being awarded best international dashboard at the 2021 Esri International User Conference in San Diego, USA. Esri is the most widely used GIS software globally, as demonstrated by the conference having over 70,000 delegates.

A revised heat unit algorithm for mango fruit maturation (flowering to harvest maturity) incorporating a penalty for maximum as well as minimum temperatures was recommended based on comparative trials with multiple cultivars and multiple locations. Temperature sensors were established in each major growing region with data able to be accessed by growers on a real time basis.

The use of handheld near infrared spectroscopy in assessing dry matter content in context of assessing time to harvest maturity was further developed. Dry matter content is an index of starch and sugar content in mango and oil content in olive. New chemometric approaches were deployed, with a neural network model demonstrated to be more effective than a partial least squares model. This approach was adopted across the instruments used across the Australia mango industry through the annual calibration exercise undertaken by the Australian Mango Industry Association. Work with citrus fruit was less successful, as expected due to the contribution of the skin to the acquired spectra.

Technologies for estimation of mango fruit load on tree through machine vision were developed and implemented in orchards. The YOLO deep learning convolutional neural network architecture was redesigned (as 'MangoYOLO') to optimize its use for mango fruit detection. Two prototype orchard imaging systems were deployed in the major mango growing regions, viz. Darwin, Katherine, Atherton Tablelands, Bowen, Central Qld and Childers, with data returned to growers the day following imaging. In the last season, the hardware was stewarded by NT DITT and QLD DAF staff, with the imaging system used by interested mango growers. Citrus fruit detection and count was also achieved, however translation to orchard yields is compromised by the proportion of occluded (non-visible) fruit. Detection and base width estimation of banana suckers as an input to a harvest timing estimate was achieved but deemed to be impractical due to the level of trash coverage of suckers. The potential for in-orchard fruit sizing from the mobile imaging platform was also demonstrated with use of a Time of Flight depth camera. A root mean square error of 5 mm was achieved on fruit length and width measurements.

The foundation ability to detect fruit position was used in the development of a prototype mango fruit mechanical harvester. Improvements in gripper design and arm movements across three seasons and three designs provided increased speed and effectiveness of picking, e.g., a 5 second cycle time between assigning a pick task to an arm, movement of arm to fruit, grasping, rotation, retraction, and release of the harvested fruit. A fin-ray finger design was recommended within a 4 or 6 finger end effector. An eight-arm prototype was developed and deployed in field trials in central Qld and Katherine, NT.

Technology was placed into farm hands as part of the R&D exercises and extensively showcased in industry workshops and magazines. Results were formally documented within 21 refereed publications and three theses. Several staff crossovers occurred, providing human resource 'cross fertilization', e.g., two CQUni personnel moved to roles with mango production groups in roles involving crop monitoring.

Keywords

olive; citrus; macadamia; mango; banana; remote sensing; crop yield, yield forecasting; IoT, irrigation efficiency; national mapping; biosecurity; spatial analytics; satellite imagery; fruit maturity; growing degree days; heat units; near infrared spectroscopy; harvest timing; fruit load estimation precision horticulture; precision agriculture robotic harvest extension; auto-harvester

Introduction

Direct consultation with the mango, macadamia, olive, banana and citrus industries identified a common need to improve the accuracies of pre-harvest yield and fruit quality forecasting; improved surveillance of tree health including biosecurity threats and the more accurate mapping of national production. In response to these needs, the following three objectives were derived to address the requested outcomes:

1. ***Achieving improved pre-harvest yield forecasting accuracies at the national, regional and farm level.***

More accurate pre-harvest yield forecasting of tree crops offers significant benefit at a range of scales. At the national and regional scale higher prediction accuracies support the respective industry bodies in making more informed decisions around forward-selling to both domestic and overseas markets; whilst at the farm level, growers can better plan logistics around harvesting including labour, machinery, packaging, transport, and storage requirements as well as their own capacity to meet market demands. All these aspects can improve profitability for growers and industry stakeholders.

2. ***Develop practical tools and analysis methodologies that improve the within orchard monitoring and mapping of tree health, fruit quality and maturity.***

Additional to improved pre-harvest yield forecasting and mapping, growers require practical and adoptable tools for monitoring of tree health, phenological growth stage, fruit quality and maturity. Maturity related parameters such as fruit size, dry matter content, shelf life, blemish level etc. all influence farm gate price. Therefore, the ability to predict optimal harvest timing and segregation based on quality and maturity offer significant economic value. The provision of practical tools for measuring variability in tree health can also support the improved early detection of pest and disease outbreaks and water stress and therefore assist in the reduction of inputs through the judicious management of water, fertiliser and pesticides.

3. ***Develop and deliver improved detection and management tools and strategies to control future biosecurity threats and natural disasters.***

The national mapping of commercial orchards offers significant benefit to national plant biosecurity by identifying the location and distribution of all commercial orchards. In the event of an incursion, the ATCM supports the rapid deployment of surveillance staff and the establishment of exclusion zones to prevent further spread. Additionally, the mapping of all commercial orchards provides the respective industries with a much better understanding of their industry extent (location and area), annual change, supports improved traceability, market estimation and forward selling, as well as be better prepared for natural disaster response in terms or quantifying the areas of damage in near real time.

The outputs of this project also include identifying technologies and analytics that aid in the non-invasive detection of specific plant diseases as well as offer improved surveillance of targeted species in peri–urban environments and abandoned orchards (e.g. olive and mango) that may serve as hosts of plant disease and insect vectors. The development of detection tools improve the efficiency and effectiveness biosecurity preparedness, surveillance and response in the future.

Phase 1 'Multi-scale Monitoring Tools for Managing Australian Tree Crops' project successfully delivered on these priorities by producing outcomes and outputs that directly benefited several horticultural tree crop industries. These included the mapping of all commercial avocado, macadamia and mango orchards across Australia (orchards > 2 ha), an output that provides each industry with an accurate understanding of the extent and distribution of production as well as supporting improved biosecurity response and post disaster response. Additionally Phase 1 identified a range of emerging technologies that supported more accurate yield and fruit quality forecasting and mapping as well as the improved monitoring of abiotic and biotic stresses at the individual tree and orchard level.

This Phase 2 project builds on the foundations of Phase 1, by:

- Increasing the minimum mapping unit of commercial orchards from > 2 ha to > 1 ha as well as including the national mapping of all citrus, olive and banana industries;
- Quantifying the area of planting of mango and macadamia between 2017 and 2022;

- Developing a map of non-commercial mango trees within the Cape region of north Qld for the purpose of directing future surveillance of biosecurity threats coming from our northern neighbours;
- Investigating the accuracies of remote sensing technologies for measuring the spatial and temporal variation in citrus and olive tree vigour (size and health);
- Investigating the accuracies of remote sensing for predicting yield in citrus and olive orchards
- Investigating alternative remote sensing methodologies (time series analysis, inclusion of weather variables and tree age) for the prediction of mango, citrus and macadamia yield;
- Investigating the accuracies of in-field sensors (sap flow, dendrometer, soil moisture, canopy temperature and canopy relative humidity) as well as remote sensors (satellite and airborne imagery) to determine which best identifies the early onset of water stress in olive trees.
- Identifying a reliable commercially available option for on farm connectivity to support remote access to sensors (IOT);
- Quantifying the impact of prolonged water stress on olive yield and fruit quality;
- Further extending project outcomes and outputs to the wider industries, government agencies and non-government agencies (NGOs).

In terms of the requirements of the Rural R&D for Profit programme scheme, these objectives, outputs and outcomes directly offer improved productivity and profitability for primary producers, and are:

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

More specifically, the project includes outputs and outcomes that align to all four of the specified Rural Research and Development for profit program priorities.

Advanced technology: The technology assessed within this project include several commercially available remote sensing platforms including satellite, aerial and ground based; sensing technologies (multispectral, hyperspectral, and thermal); Internet of things (IOT); associated analytics including machine learning and web and phone APP development. A significant consideration of this project is to provide outputs that are currently available, cost effective, practical and therefore adoptable.

Biosecurity: This project identifies technologies and image processing methodologies that will offer improved on-farm surveillance of tree health both spatially and temporally. The national mapping of all olive, mango, macadamia, citrus and banana orchards will direct on-ground surveys and the establishment of exclusion zones in response to future biosecurity incursions. Methodologies for mapping the location of high-risk plant species within remote environments (non-commercial mango trees in the Cape) were also investigated, as well as several technologies (remote sensing, IOT) relevant to the non-invasive detection of high-risk plant diseases. The outputs, methodologies and network of expertise generated from this component will significantly benefit current and future biosecurity and plant health incursions, particularly for first responders.

Soil, water and managing natural resources: The mapping of tree health and productivity at a range of scales (individual tree, orchard, and region) assists growers in determining high, medium and low productivity areas and therefore direct targeted agronomy and the variable rate application of orchard inputs including fertiliser, fungicides, pesticides etc. Additionally, the technologies being evaluated (infield, remote sensing and IOT) have the potential for rapidly detecting the early incidence of water stress, a major concern to growing regions suffering on-going drought.

Adoption of R&D: In Phase 1, the project team developed outputs that were adopted by industry. Products included the 'The Australian Tree Crop Map dashboard' and the 'Australian Tree Crop Rapid Response Web App' (web map web app).

Phase 1 also delivered over 210 extension and adoption activities in 3 years, including industry newsletters, industry specific meetings, field days and workshops, media coverage, and field sampling campaigns with industry participants. Through direct industry engagements, Phase 2 has significantly contributed to the extension of research, has encouraged the commercialisation of results and the replication of activities by other industries (domestic and overseas).

<u>The Problem</u>

Tree fruit harvest resourcing and market distribution planning is constrained by lack of pre-harvest knowledge of crop volume and timing. For example, planning for market contracts are wasted if anticipated volumes are not delivered or delivered a week early or late. This issue can lead to poor harvest practices, e.g., harvest of less mature fruit. Thus, there is a need to quantify parameters around the decision to harvest, and to forward predict the timing and number of fruit reaching maturity, and the size distribution of those fruit.

<u>Background</u>

The current project was based on the outcomes of a Phase 1 activity (ST15005), which achieved: (i) development of a robust model for in-field estimation of mango and avocado fruit dry matter (DM) content using a hand held near infrared (NIR) spectroscopic device; (ii) development of in-field imaging capacity and an image processing pipeline for estimation of visible fruit, (iii) development of an on-line tool to display fruit load data to growers, and (iv) creation of a proof of concept mango fruit mechanical harvester based on machine vision capacity.

Phase 2 (CQU) was designed to consolidate and extend this work, to create (i) a harvest timing forecast system based on NIR-DM and 'automated' heat sums; (ii) a mango yield forecasting system based on in-field machine vision, and (iii) further development of the mango auto-harvester concept. In keeping with the R&D4Profit scheme focus on translation of research into grower use, emphasis was given in Phase 2 to grower use of the tools under development, and a search for pathways supporting commercial adoption.

<u>Topics</u>

Emphasis was placed on mango applications, with lesser activity occurring in citrus, olive and banana applications.

The Australian mango industry has adopted handheld near infrared spectroscopy (NIRS) in non-invasive assessment of fruit dry matter content, with dry matter acting as guide to fruit harvest maturity and final eating quality. However, NIRS is a secondary method, requiring development and maintenance of a prediction model. The field of NIRS continues to advance, particularly in context of chemometrics, with promise of greater module robustness, i.e., less maintenance. Work was therefore undertaken to investigate the potential of 'advanced' modelling techniques over the existing practice, Partial Least Squares Regression modeling (PLSR).

The Australian mango industry employs an algorithm for calculation of Growing Degree Days (GDD), with variation in the flowering stage (asparagus or Christmas tree) and the base temperature (Tb) used (10 and 12^{o}C). However, there is no published justification for, or consideration of:

- choice of Tb value;
- choice of the time interval used in temperature monitoring for estimation of the daily Tmin and Tmax;
- the use of an upper base temperature.
- the use of a daily temperature integral instead of a 'simple' daily Tmin and Tmax average.
- positioning of temperature sensors on farms, with some growers following the BOM specification on weather station location (in open areas) while others position sensors within trees.

Work was therefore undertaken to address these issues.

The Australian mango industry currently relies on manual (visual) estimates of flowering level and fruit load. Machine vision offers a similar direct estimate of these attributes. However, the machine vision-based system mounted on a ground vehicle developed in the Phase 1 project left a number of issues unresolved in context of scaling from a concept to a farm deployable technology. Work was therefore undertaken to address associated issues, including tracking fruit across frames, allowance for occluded fruit and sizing of fruit.

The technologies of fruit detection and camera to fruit distance measurement underpin the attempt to achieve mechanical harvest. Again, while a prototype was developed in Phase 1, commercial adoption requires greater speed. Work was therefore undertaken to improve gripper effectiveness and to increase overall speed of operation.

Methodology

The UNE AARSC engagement in this project extended across all tree crop industries (mango, macadamia, citrus, olive and banana). The information is provided as a general overview with the full methodologies provided in the appendix section (Appendix 1) of this report.

National mapping of horticultural tree crops

The Australian Tree Crop Map (ATCM) was developed under Phase 1 of the 'Multi-scale Monitoring Tools for Managing Australian Tree Crops' project, which then included all commercial avocado, macadamia and mango orchards greater than 2 ha. First published in 2017, the ATCM provided each industry with an accurate 'baseline' of the extent and distribution of production area. Under the Phase 2 project (ST19015), AARSC has built on these foundations by updating the map at greater detail (> 1 ha), and included all commercial citrus orchards, olive groves and banana plantations.

The updated map was informed using multiple sources of evidence including existing industry data, government land use mapping, remote sensing analytics, ground-based field surveys and citizen science enabled through web mapping applications.

The success of the map lies in the collaboration between industry, research and government. The support of industry bodies ensured the mapping outcomes were not perceived as an invasion of privacy and supported compilation of the map with access to existing industry data and their contribution through the industry engagement tools ensures ongoing validation of the mapping, both of which are integral to the accuracy and temporal currency of the map.

No personal or commercial information is contained in the map, which is built to the national standards of the Australian Collaborative Land Use and Management Program (ACLUMP) and is freely available. Privacy concerns are acknowledged and respected as no personal or confidential or commercial information is collected as a part of the mapping process nor contained within the mapping product.

The complete methodology of the national mapping component is provided in the Appendix section of this report (refer to Section 2.2 of Appendix 1). A summary is include here:

The national mapping program to update the map of all commercial banana, citrus, macadamia and olive crops (> 1 ha) was set, based upon known intensive growing regions across Australia (Figure 2). The workflow follows the proven methodology developed for Phase 1, with updates managed progressively through each stage, by growing region.

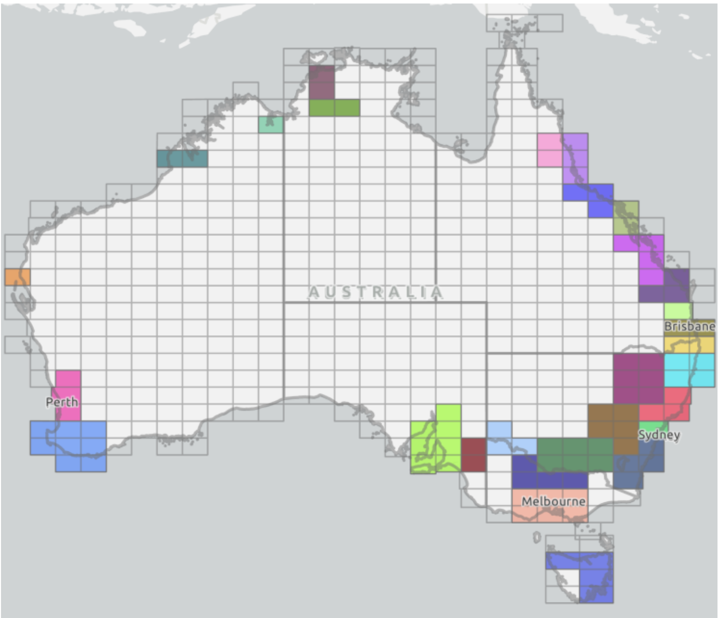


Figure 1: National mapping program

The map was informed from multiple sources including remotely sensed imagery, industry data, existing government land use information, citizen science and field-based data collection (Figure 2). Tree crops were mapped as polygons (location and extent) and key attributes recorded at feature level, which were the source of observation (either image capture date or field observation date) and year of observation (the most recent date of observation from either source).

The map includes all commercial horticulture tree crops greater than one hectare and a minimum width of 25 metres.

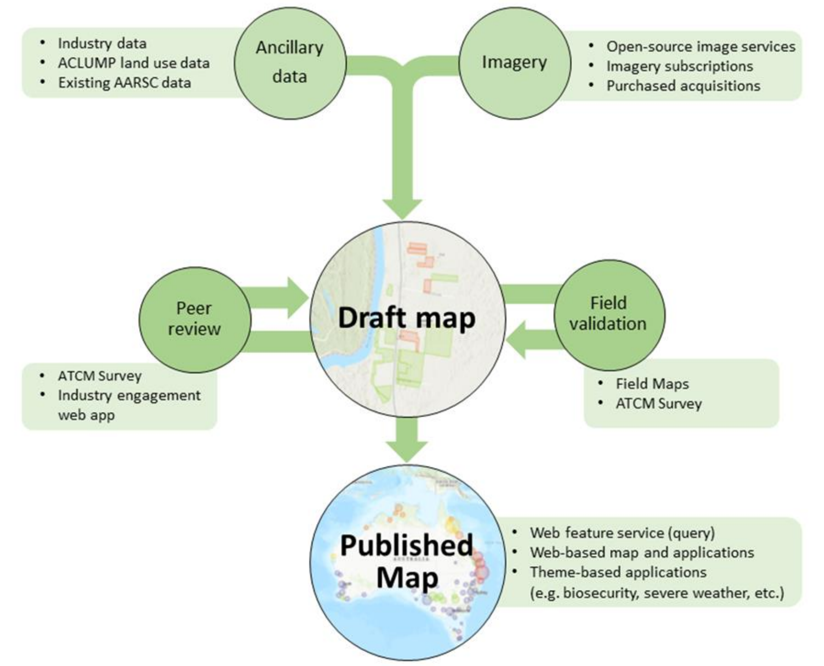


Figure 2: Mapping methodology

The recent rapid growth in horticulture tree crops in Australia raised an additional challenge for the Phase 2 mapping. The high-resolution imagery (<1.5 m pixel size) access for this work was typically freely available via open sources but in most cases is several years old. This is not a significant limitation in mapping the established crops but is when mapping new crops—as they are not visible in the open-source imagery due to its currency (age). To overcome this challenge, more recent coarser resolution imagery (e.g., PlanetScope) was used, but only where other information was available (e.g., an observation submitted through the ATCM Survey or comments in the Industry Engagement Web App). This information was used to accurately classify the newly planted tree crop type. This approach was proven to be successful particularly in the update of Bundaberg growing region, where many new tree crops have been established.

The final mapping product is derived based on numerous geoprocessing steps for data consistency, integrity, and quality relative to map scale. This effectively merges common (alike) features and removes any tree crops below the minimum mapping unit of 1 ha. The only information included in the published map (at feature level) is the tree crop type, source and year of observation and area in hectares.

Updates to the published map were completed as each growing region was drafted. These updates typically followed the field validation as draft mapping was published for peer review. During the life of the project, the published map was updated 14 times.

The ATCM is published and shared as a publicly accessible web feature service. The benefit of publishing the map as a service is that when the map is updated the changes are instantly reflected for all who access it. Note the feature service supports query operations only. The data is not available to copy, export or download.

Ancillary data

Classifying the type of tree crops accurately is more robust when informed by supplementary information as ancillary data – including geocoded industry data, publicly accessible property information and government land use information.

Industry membership information (shared confidentially by each industry body) was geocoded based on the supplied address information (Figure 3). Typically, these point locations related to postal addresses rather than actual tree crop location. As an ancillary data layer, industry data informs the mapping program (where to look for tree crops), and further aids in the image interpretation of crop type. It's especially valuable for classifying new orchards (small trees) which cannot be accurately mapped by imagery alone.

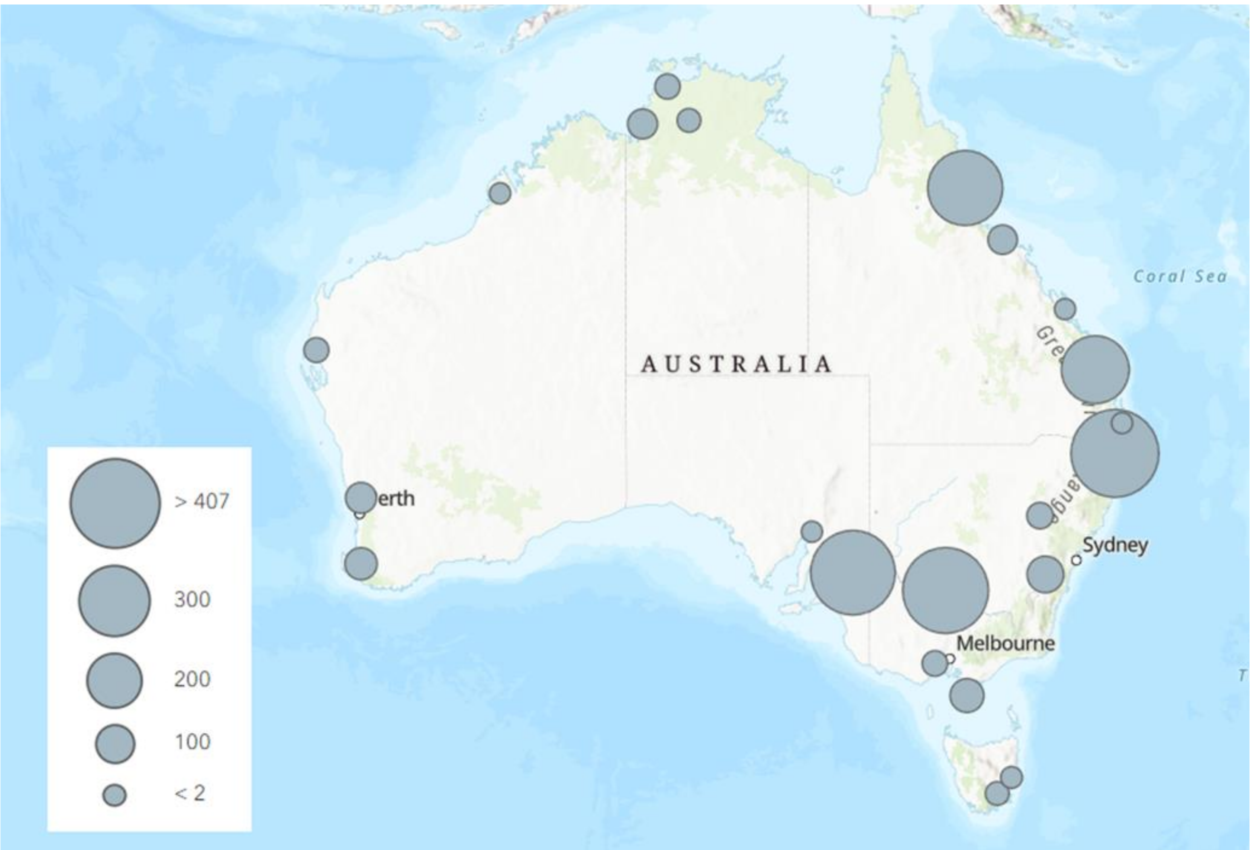


Figure 3: Geocoded industry data records

The University of New England is a partner of the ACLUMP (observer status), joining the consortium of other state and territory members and major stakeholders in the compilation of land use mapping products to national standards. Existing land use information for citrus, olives and bananas was sourced through the ACLUMP. Limitations of this information include currency (some features current to 2008), and inconsistency in scale (varies) and coverage (incomplete).

Based on sources within ACLUMP (MDBA and Victoria) we purchased existing mapping of tree crops within the Lower-Murray Darling under a Data Licence Agreement from SunRISE Mapping and Research. This data was current to 2018, but still useful for progressing the mapping updates within the Riverlands and Goulburn Valley regions.

Another source of information that informed the map was ancillary data provided by property and business internet searches. Often properties are advertised for sale through real-estate websites with location information and tree crop on the property, or the business may advertise their tree crop publicly (including area of production). This is often the case for olive groves, which may double as a tourist attraction, venue or directly sell product from the 'cellar door'.

Collectively the interpretation of multiple sources of ancillary data, in combination with imagery, field validation and peer review, greatly informs the map. It is especially valuable for informing the correct attribution of tree crop type (thematic accuracy).

Remotely sensed imagery

Publicly accessible imagery provided the primary resource of high-resolution data suitable for interpretation of tree crops (e.g., Google Earth Imagery, Esri Basemap Imagery, Google Street View and other government image services). In collaboration with ACLUMP partners, jurisdictions shared recent high-resolution imagery to inform the map, including the intensive growing region of Adelaide Hills (17cm aerial orthophotography captured in 2020, supplied by South Australia's Department for Environment and Water) and Queensland's Spatial Imagery Subscription Plan imagery, which included aerial orthophotography from 6-20cm, supplied by the Department of Environment and Science.

Generally, the currency of imagery was very timely (< 1 year old). However elsewhere the imagery capture date effectively limited the currency of the map as the newly established plantings were either not visible in the imagery (small trees) or newly planted orchard and/or land use change followed the date of image acquisition. To overcome this challenge, we accessed and interpreted coarser resolution (but very current) satellite imagery (e.g., PlanetScope) to map the new tree crops. This was only undertaken where other ancillary data (e.g., industry input or field observations) identified new plantings. This ancillary information was also used to classify the tree crop type, as it was not possible to classify new tree crops with coarse imagery alone.

Figure 4 presents four examples of citrus orchards showcasing how variation in tree age, variety and land management practices influence the appearance of trees. This example clearly demonstrates the need for multiple sources of data to accurately classify tree crops, and that methods relying solely on imagery analysis (manual or automated) are prone to error.

Figure 4: Variation in appearance of citrus orchards in imagery

Field validation

Field validation improves both the thematic accuracy and currency of the map, particularly where new plantings are found (which are not visible in imagery).

Physical field validation of the map was conducted over each major growing region and scheduled in the mapping program to immediately follow compilation of the draft map to minimise the amount of time between the desktop interpretation (image acquisition date) and the field observations. Ten separate field trips were undertaken during this project with some regions with high rates of change updated and field validated twice, given the new plantings, including Bundaberg, Wet Tropics, Mareeba and Tablelands.

Routes were pre-planned based on publicly accessible roads, with the infield recording of edits supported by the Field Maps for ArcGIS mobile mapping application.

As an example, Figure 5 shows the field validation route covered in the Tablelands growing region in far-north Queensland (September 2022), with 1,363 field observations of tree crops (including their type) captured as point locations. Post-field observation, additional edits are made elsewhere given the insights and information gathered which can further highlight omissions and misclassifications in the map, which are then resolved at the desktop.

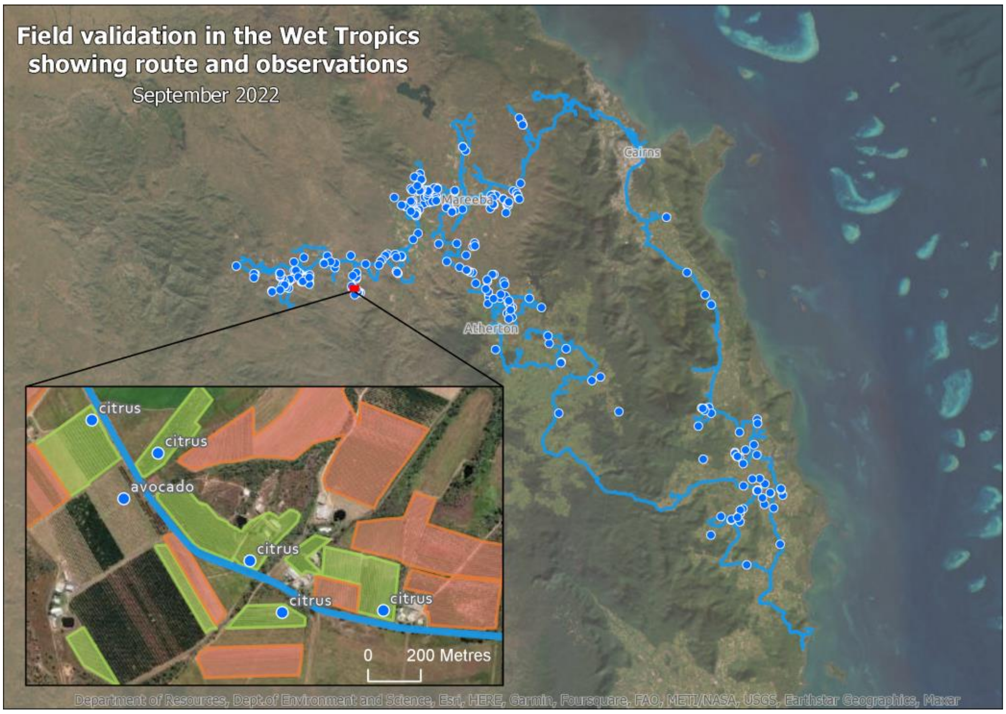


Figure 5: Field validation in the Tablelands growing region (September 2022), showing observation points collected

Peer review (Industry engagement)

Peer review or direct feedback from local experts and stakeholders in reviewing (validating) the map is extremely valuable. As defined in the mapping program, the mapping was published and updated progressively by growing region and published as draft for peer review in the publicly accessible Industry Engagement Web App (created in Phase 1). Peer review was anonymously sought through local experts across each industry, in each major growing region, to review the draft map and provide feedback as comments, either in point (location only) or as polygons (including extent). All comments were interpreted by the mapping team and actioned to update and further refine the map, including a response comment for each.

This process directly engages the industry and provides them with the tools and the opportunity to collate the information of behalf of the greater industry, it also exposes them to the concepts of spatial data. This process and direct participation improved the accuracy of the data, acceptance of the mapping by the industry, and the likelihood that the updates to the mapping will continue post project.

Draft mapping

The draft mapping was compiled at the desktop using the Esri ArcGIS Pro Geographic information System (GIS), within a service-based editing environment, hosted within the UNE ArcGIS Online organisation. All edits were compiled in a polygon feature class, with observations for tree crops recorded at feature level. The source and year of observation for each feature in the map was recorded, reflecting the most recent date of observation from the image capture date or when observed in the field. Additional attributes assigned in compilation of the draft map included the observation of management status of each feature, either: future, planted, mature, abandoned or removed. Note that only features with a management status of 'planted' or 'mature' were published in the ATCM.

Published map

To publish the final mapping product, polygon features representing the location and extent of tree crops were derived from the editing layer by aggregating and dissolving features with common attributes (tree crop, source and year of observation), relative to the map scale (minimum mapping unit of 1 ha and a width of 25 m). Figure 6 shows an example of the level of detail shown in the final mapping product (right) after the edit layer (left) is aggregated and dissolved.

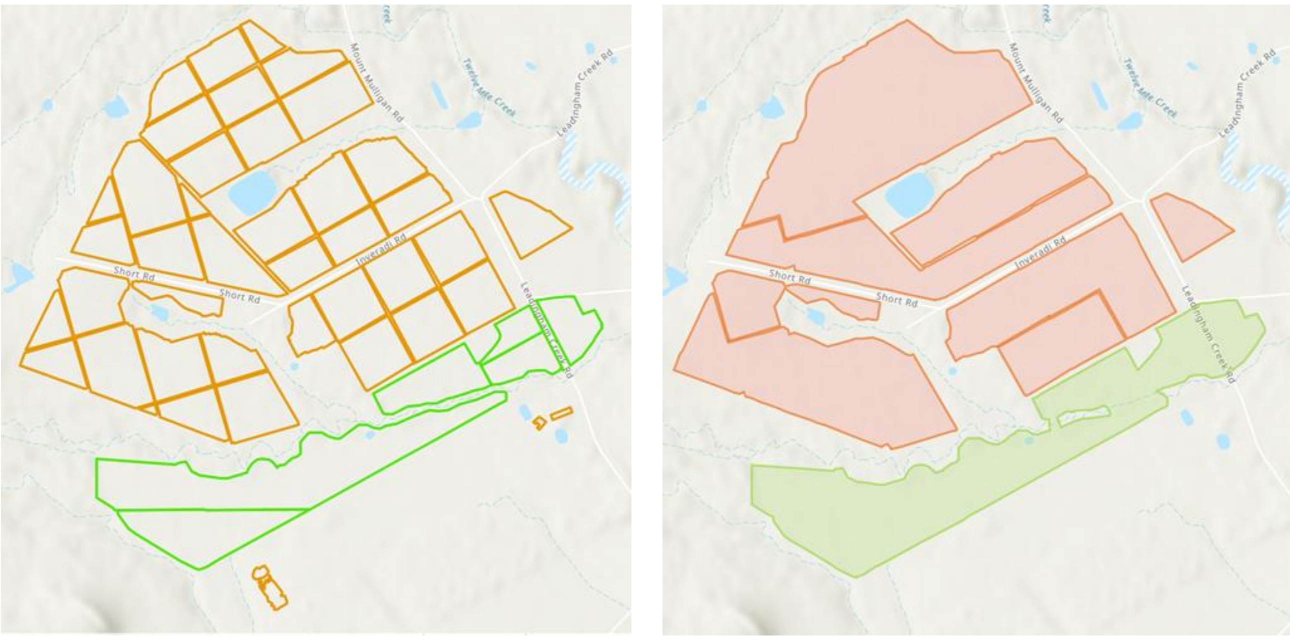


Figure 6: Blocks as mapped in edit layer (left) and derived mapping product as published (right)

Analysis at feature level (polygon) illustrates the level of detail contained in the map (edit layer) relative to the published mapping product. Figures 7 and 8 present the feature counts by tree crop type in each map respectively. Note that the edit layer also includes features for 'other' crops which are not presented in the figure. There are an additional 28,675 features labelled as 'other' tree crops mapped in the edit layer. This presents as a strong starting point for the future mapping of other commodities.

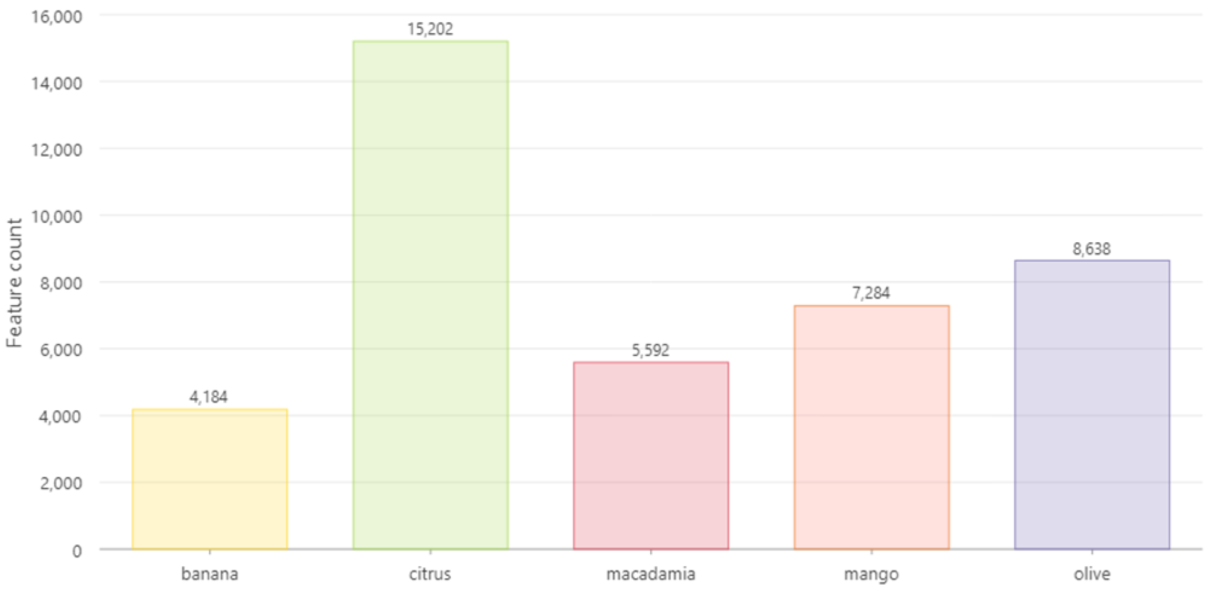


Figure 7: Feature count for edit layer

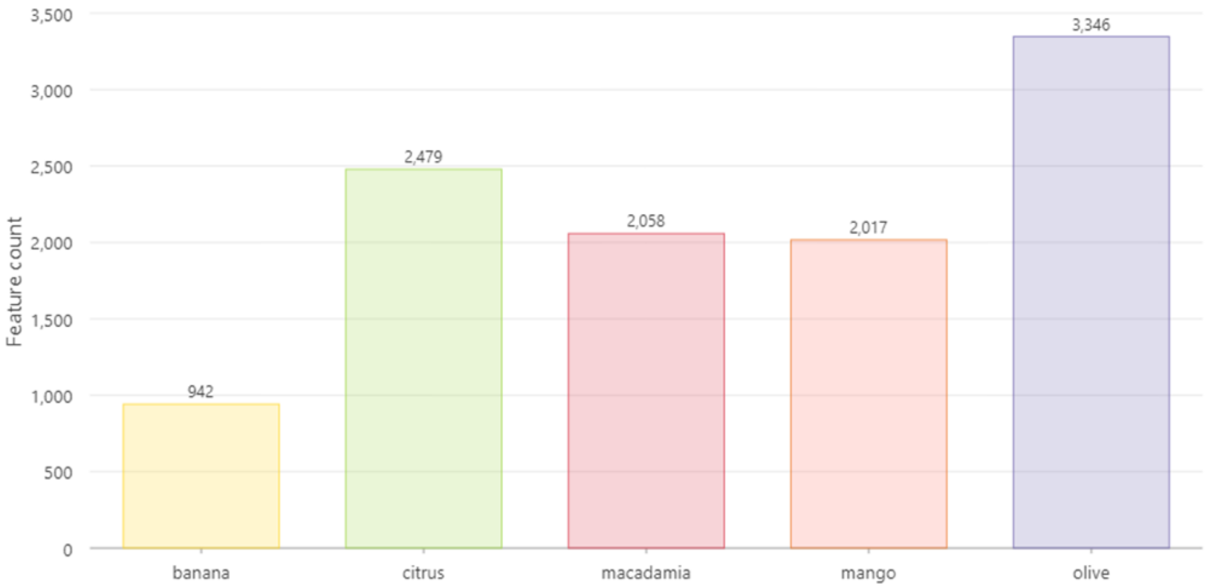


Figure 8: Feature count for derived map

The data is presented in multiple scales to aid usability. Point clusters (based on the centroid of each feature) present the map at small scale (zoomed out) which are clustered dynamically relative to the viewers zoom level. The bigger the point feature (circle) the more tree crops at that location. At large scale (zoomed in) the map is presented as polygon (area) features, showing both location and the extent of the tree crops. Presentation of the data is consistent across all maps in terms of symbology.

The functionality of the ATCM dashboard also supports the searching of location (to drive a targeted zoom) and the ability to extract summarised statistics (area of each industry) at the defined zoom area, and the local, state and national level.

Macadamia Methodology

Sites and site data

Following extensive engagement with industry (via field days, conferences, phone and email), several growers representing each of the main macadamia growing regions actively engaged in the project by providing high-quality data on tree planting statistics (year, variety, density) and annual yield at the block-level. Some of the collaborating growers only had data at the orchard level, but due to the desire to gather as much data as possible and their willingness to collaborate, this was used where possible. The locations of all collaborating orchards, who have provided data and received yield forecasts through this project, are listed in Table 8. During the life of the project, the number of participating growers has grown year-by-year, with help from consultants providing introductions to those they believed would have interest and suitable datasets. The number of yield datapoints per year, and the distribution of yields per year and growing region are shown in Figure 36. In total, there are 1156 yield datapoints from 21 orchards and 204 blocks. Generally, yields in Bundaberg (the region that has wide adoption of irrigation) are higher and relatively stable over years. Other regions (mostly non-irrigated) have quite variable inter-annual yields, of note are the lower yields in 2020 due to the 2019-2020 drought. In all cases, there is great variability between minimum and maximum yields, from close to 0 to 7 tonnes/hectare (t/ha). This presents a challenge to developing yield forecasts.

The planting year model was developed early in the project. At that stage, there were 95 block planting records for training and testing the model, from the Macksville, Ballina and Bundaberg regions.

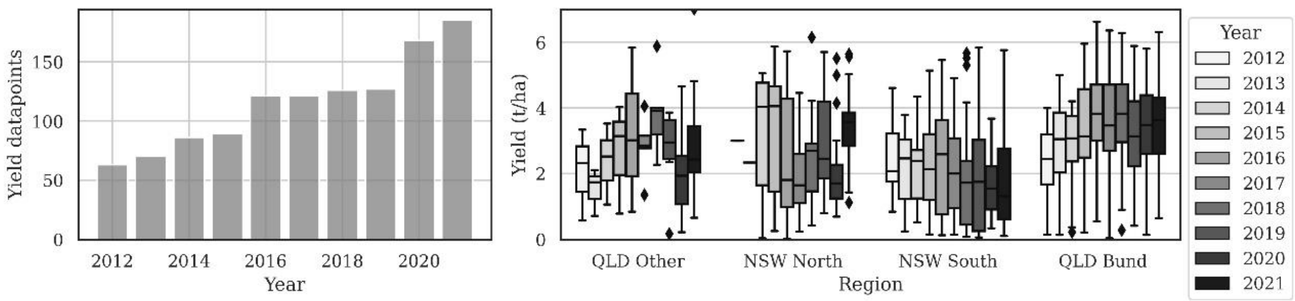


Figure 9. Yield datapoints per year (left) and yield per region per year (right)

Predictor datasets

Predictors are variables used by models to estimate, in this case tree age and yield. Most predictors used are spatio-temporal, that is they vary over both space and time. Details of the spatio-temporal dataset generation are summarised in Figure 37 (full detail is available in Brinkhoff and Robson (2021)). Google Earth Engine was used to aggregate weather and remote sensing data, all of which is available in the platform.

- *Weather information* came from the spatially interpolated (5km grid), daily, SILO dataset, which is delivered by the QLD government. Six variables were included: daily minimum and maximum temperatures, reference evapotranspiration (ETo), solar radiation, vapour pressure deficit and rainfall.
- *Remote sensing data* came from the Landsat 5, 7 and 8 satellites. The 6 reflectance bands (blue (B), green (G), red (R), near infrared (NIR), shortwave infrared 1 and 2 (SWIR1 and SWIR2)) were processed into all 15 possible normalized difference spectral indices. For example, the commonly known normalized difference vegetation index (NDVI) is defined as:

$$ND(NIR, R) = \frac{NIR - R}{NIR + R}$$

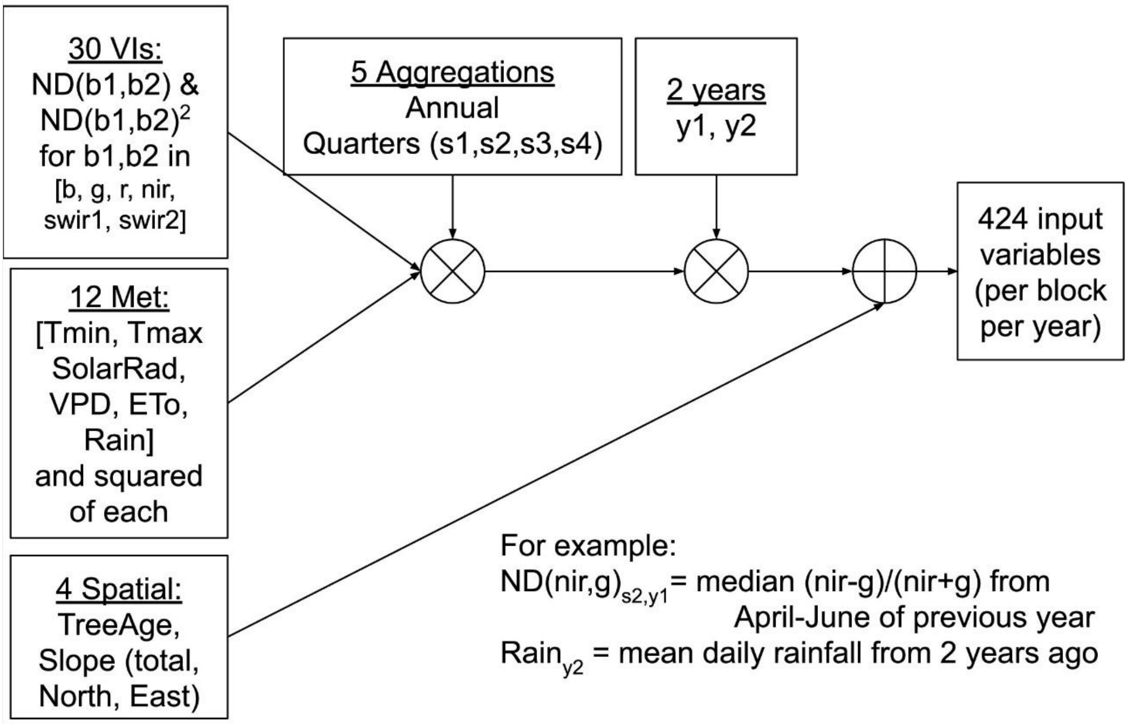


Figure 10. Collation of spatio-temporal predictors.

For the tree planting year models, remote sensing indices were aggregated per-year, then the mean of each index per-block was calculated, giving a time-series from 1990-now for each block.

For the yield models, the weather and remote sensing data (6+15=21 indices) were each squared to allow description of nonlinear relationships (additional 21 indices). These were then aggregated temporally per quarter (q1=January-March, q2=April-June, q3=July-September and q4=October-December) and per year, on a per-pixel basis. These data were then aggregated spatially per-block, finding the mean of all pixels within a block. The spatio-temporal data from the previous two years was used as predictors of the yield in the coming year. For example, $ND(NIR,R)_{q2,y2}$ is the NDVI from April-June from 2 years before the harvest year. The total number of spatio-temporal predictors is (2 years + 8 quarters) × 42 indices = 420 predictors. Four additional predictors were added, tree age (from the developed tree planting year model) and slope towards the North and East. Figure 37 shows a diagram of how these predictors were collated. Figure 38 shows an example of some of the predictor variables and the yield dataset for one of the 204 blocks.

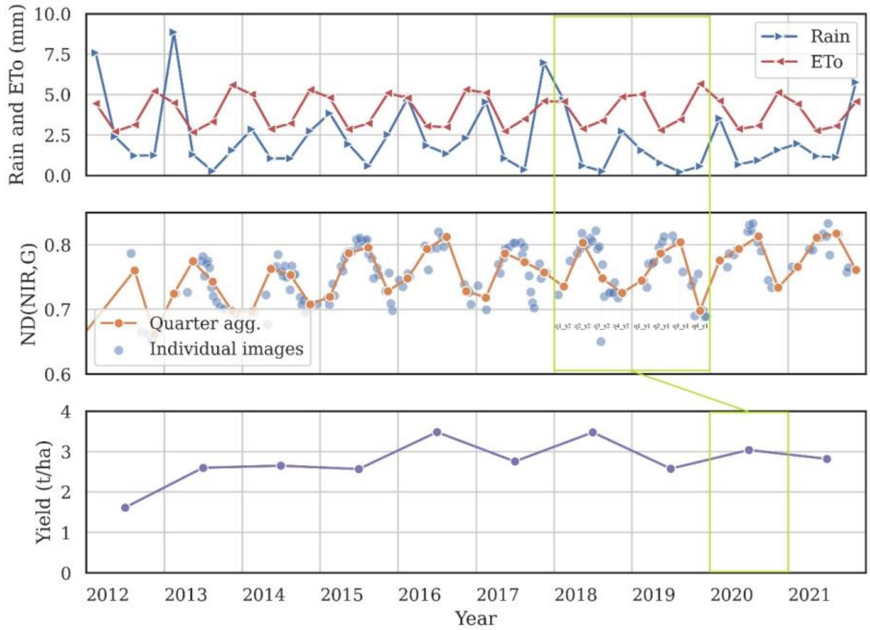


Figure 11. Example macadamia block predictor and yield dataset. The inset boxes show how two years of quarterly predictors (2018-2019) are used to forecast the following year (2020) yield

Tree planting year modelling methodology

Following the collation of the 1990-present time series of remote sensing indices for each block, the data were combined with the known corresponding planting year for each block. Several methods were trialled, with the aim of finding a characteristic in the time series data that indicated planting year. The best method was to search backwards through the time series, finding the most recent year where a remote sensing index dropped below a defined threshold (corresponding to a tree of a certain age), then subtracting a delta from that year. A comprehensive search of the 4080 possible combinations of satellite index, threshold crossing point and delta was performed. For each combination, the accuracy of planting year prediction for all 95 blocks was calculated. The algorithm with the highest accuracy was selected. A full description of the methods can be found in Brinkhoff and Robson (2020).

This algorithm was then implemented in Google Earth Engine. It was applied to all macadamia pixels (30 m resolution from the Landsat satellites) within the National Tree Crop Map. Then, for each year from 1990 to present, the total area of pixels with planting date greater than or equal to that year were summed, on a per growing region and national basis. Thus, a table of macadamia area per year from 1990-now was delivered.

Macadamia yield forecast modelling methodology

The yield forecasting models were trained using a range of machine learning (ML) algorithms commonly used for regression tasks (lasso, ridge, support vector regression, random forest), and were compared with a simple naïve model (simply estimating yield to be the average of all previous yields) and a simple linear regression model. In all experiments described below, models were trained on a subset of years, and tested on a held-out year, to give a true estimate of forecast accuracy. The ML hyperparameters (such as the regularization parameter for lasso and ridge) were optimized using leave-one-year-out cross validation in the training process.

The performance of the model was assessed using two metrics. The ability of the models to predict actual yields quantified using the mean absolute error (MAE), expressed as percentage of the mean yield. Secondly, the ability of the models to describe the variation in yields were quantified using Lin's Concordance Correlation Coefficient (LCCC), which ranges between 0-1, with an interpretation similar to R^2, except it assess how close actual vs predicted yields are to the 1:1 line (rather than simply how correlated they are).

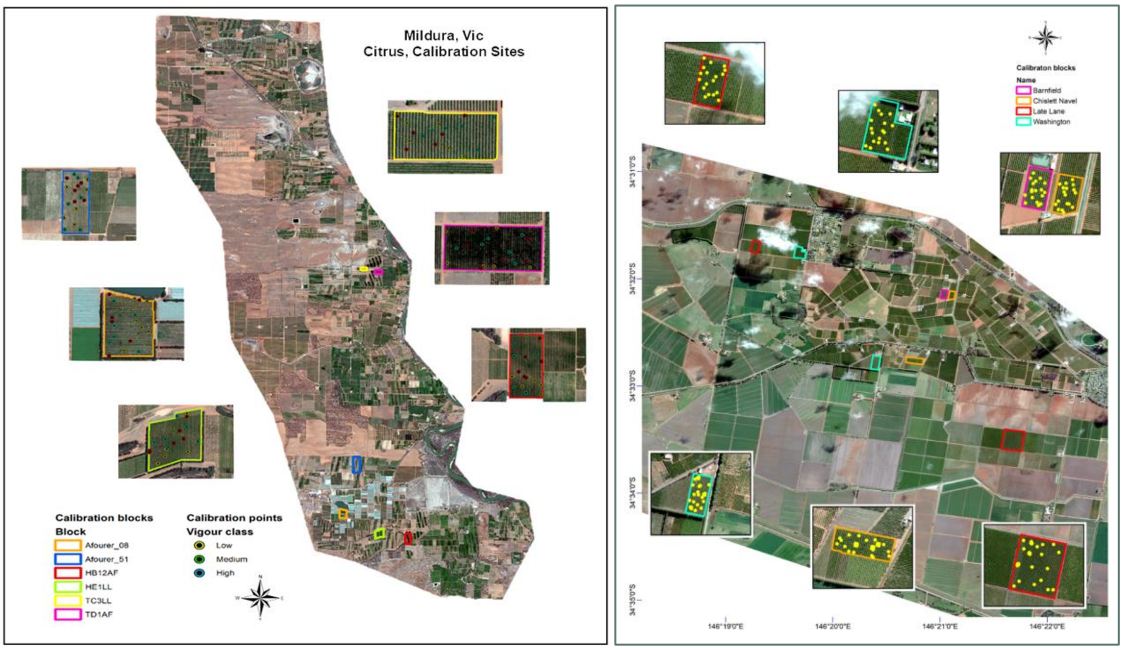
Bootstrap sampling of training data was used to estimate variability in prediction accuracy. The specified number of data points were drawn with replacement (so the same sample can be drawn multiple times), a model was trained on the sample and accuracy assessed on the independent year test data. This process was repeated 100 times to provide a distribution of prediction errors, rather than just a point estimate. This technique was used to estimate model performance as a function of predictor variables and quantity of training data.

Once the block-level yield (t/ha) was forecasted, this was multiplied by block area (ha), giving total tonnes per block. The tonnes per farm were then summed, and compared to the actual tonnes produced, as reported by the grower after commercial harvest. This procedure was used to provide farm-level accuracy metrics. This is one advantage of forecasting at the block level, errors at the farm-level are lower as positive and negative errors at the block level tend to cancel each other out. Initial investigations of scaling the forecast models to all mapped macadamia areas across the industry were performed, by producing per-pixel yield forecasts, then aggregating these pixel predictions to regional and national levels.

Citrus Methodology

Study area

For the 18 calibration tree (18CT) method for citrus yield estimation, extensive field sampling was undertaken in Moora (WA), Mildura (Vic) and Leeton (NSW). In total, 51 orchards were sampled during 2020-2021 at different growing stages to test the accuracies of the methodology early in the season and close to commercial harvest. Individual orchard (minimum reporting unit) was defined as those with similar planted year and variety. Afourer Mandarin (19 orchards in total), Late Lane (13), Washington (13), Chislett (4) and Barnfield (2) Navels were sampled. All the selected orchards were irrigated.



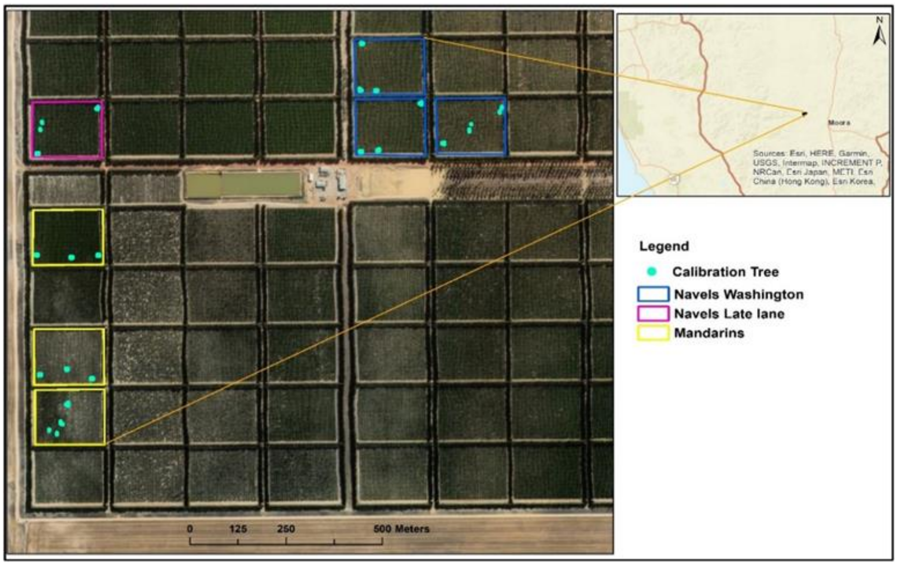


Figure 12. Locations of orchards and infield sample locations used for the 18 calibration tree yield forecasting method Mildura (a), Leeton (b) and Western Australia (c).

For the 'Time series' approach for early yield forecasting in Citrus (TS-Citrus) growers from the Sunraysia (Mildura), Wheatbelt (Moora) and South Australia (Riverland) were included (Figure 13). As this methodology relies on historical yield data, growers provided highly confidential historical yield information along with further characteristics such as planting year and variety. Growers also provided printed or digital maps that were processed and standardized for further analysis. All the yield data was provided in tons per hectare (t/ha) and the planted area was calculated by the GIS software.

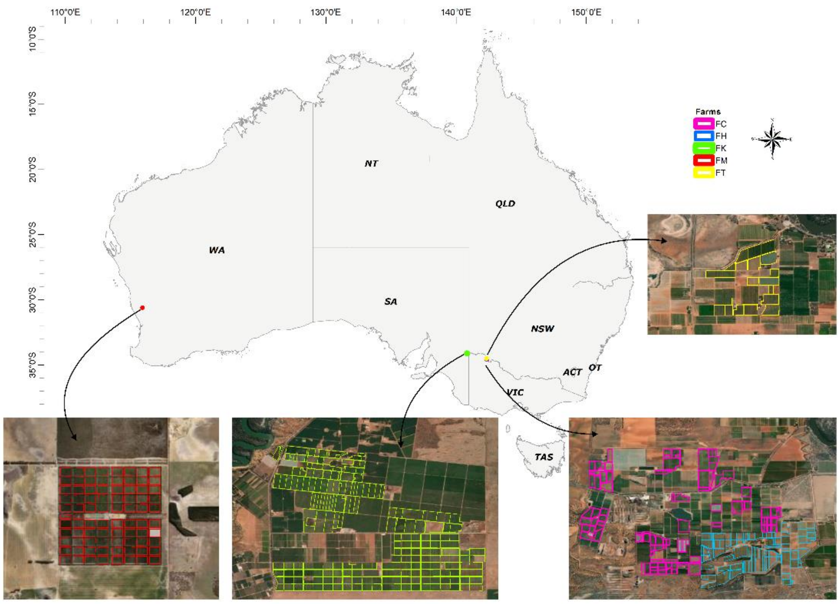


Figure 13. General location of participant growers in the time series approach. Farm's names are generic to protect grower's identity.

Calibration Tree Approach (18CT)

The sampling approach used in this project was based on the methodology reported by Robson et al. (2017) [i] which requires the selection of 18 calibration trees that represent variation in tree crop vigour (canopy size and health) across an orchard (6 tree replicates is in high, medium and low vigour regions), as defined by remote sensing (Worldview-3, Planet or airborne CERES).

For the derivation of yield models yield (fruit number) from each calibration tree was manually counted prior to commercial harvest (4-5 weeks). Once yield was collected (in t/ha and total fruit number), several VIs were calculated and the empirical relationships between yield and VIs were derived. The VI that best describes yield variability was used to transform each pixel value into a yield value allowing the yield forecasting algorithm to be extrapolated across the entire orchard block. Inter-rows were masked, hence only tree canopy was used for mapping. Yield maps were generated, and average estimated yield (t/ha, kg/ha) was calculated and provided to growers (Figure 14). This value was compared with commercial harvest (actual yield) provided by growers for assessing accuracies of the approach.

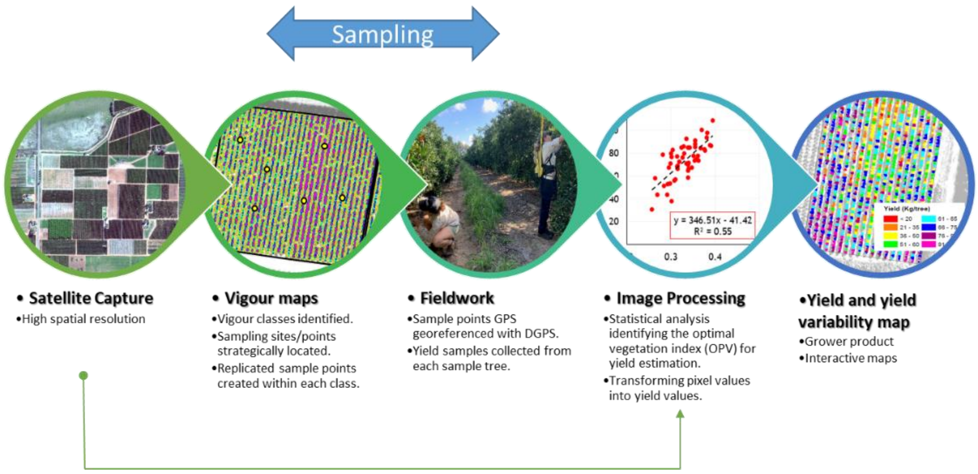


Figure 14. Illustration of main steps for the '18 calibration tree' approach

Time series for early yield forecast in Citrus

Historic yield data, extending from 2007 until 2022, was sourced from the participating growers. Five commercial farms (named as FC, FH, FK, Fm and FT) representing 4.7% of the total planted area of citrus in Australia, including the most common citrus types: Navel, Mandarin, Valencia and other varieties (26 in total) were included in this study. Specifically, 27% of planted area in the Wheatbelt region, 14% in the Riverland and 6% in the Sunraysia was analysed in this study. From the total number of blocks included in this study, Navels represent 50% of the planted area in the Sunraysia, 64.5% in the Riverland and 75% in the Wheatbelt region and Mandarin (Valencia) represents 50% (6%), 28.3% (7.2%) and 12.5% (12.5%), respectively.

The compiled dataset was highly heterogeneous with information on planting year per block (from 1998 to 2018, average tree age = 14.4), production (0.05 t/ha – 210 t/ha), harvest seasons (2007-2022), and block area (0.4 ha – 14.4 ha).

For each record (block per season), the historical block-yields of the previous three years were added to the dataset generating the time series (TS) of historical yields (HY-TS), hence only blocks with the necessary historical information available were used. Furthermore, blocks with 'no data' or 0 t/ha records were removed, reducing the number of valid records to 3986 (Table 10).

Sourcing and processing of Satellite imagery for TS analysis

The digital boundaries of all blocks were imported to Google Earth Engine (GEE) (Gorelick et al., 2017) to extract the respective spatio-temporal information at the block level. Atmospherically corrected, surface reflectance Landsat 5 TM, 7 ETM+ and 8 OLI sensors (collection 2, tier 1) at 30-meter spatial resolution from October 2006 until February 2022 were accessed from the Earth Engine Data Catalogue via GEE. Landsat satellite imagery was chosen as it provides the historical timeframe and sufficient frequency required for this study.

The cloud mask product by USGS CFMASK was applied to all imagery to remove areas under cloud cover/shadow. As this process can remove data from a capture generating gaps in the time series, a bimonthly aggregation was performed encapsulating the key developmental stages of the citrus crops. Six periods (P) were generated with the first period (1P) starting after harvest in October and finalising the following September (Table 11). For a block during a particular season, the average VI values for each period was calculated, resulting in a bimonthly spatio-temporal RS time series (TS).

Additionally, the previous three years of the RS-TS were also added creating the final TS-RS.

Table 1. Key growth stages of citrus blocks during calendar year and periods of analysis.

Month of the year	1	2	3	4	5	6	7	8	9	10	11	12
Period (P)	2	3		4		5		6		1		2
Key growth stage												
Floral induction and initiation												
Pre-bloom												
Flowering												
Stage I Fruit Growth												
Stage II Fruit Growth												
Maturation/Harvest												

The TS-RS and the TS-HY were merged resulting in a time series of two temporal resolutions: bimonthly and annual. This dataset (named L1) was used for modelling calibration and validation of results.

Modelling calibration and validation for TS

To determine the best and most accurate block-yield forecasting model, six statistical and machine learning algorithms were evaluated. As the multicollinear relationship between predictors can significantly influence model performance (Rosipal and Trejo 2002), all the models tested incorporated linear and non-linear transformations and regularization parameters. Table 2 lists the tuning parameters for each regression algorithm.

Table 2. Algorithms and tuning parameters used in this study.

Model	Tuning parameter(s)	Abbreviation
Partial Least Squared Regression	Number of components	plsr
Bayesian Regularized Neural Networks	Number of neurons	brnn
L2 Regularized Support Vector Machine (dual) with Linear Kernel	Cost (c) and Loss (loss) Function	svmLinear3
Support Vector Machines with Radial Basis Function Kernel	Sigma and Cost	svmRadial
eXtreme Gradient Boosting	Number of boosting iterations, L2 regularization (lambda), L1 regularization (alpha), and the learning rate (eta)	xgbLinear
Neural Networks with Feature Selection	Size (Hidden Units) and decay (Weight Decay)	pcaNNet

The L1 dataset was imported to R software for modelling calibration, validation, and assessment. For calibration purposes, the *caret* package was used. The *train* function selects the best tuning parameters that optimise model performance minimising overfitting. The Leave-Group-Out Cross-Validation (LGOCV) was used with each group representing a 'season' of the calibration dataset which we call Leave-One-Year-Out CV (LOYO CV). The algorithm was trained by LOYO CV holding-out one season at a time and fitted to the remaining seasons. Once the best tunning parameters were identified, the entire calibration dataset was used to train the final model.

The accuracies of the model were validated against the one-year forward of the calibrated model as an independent dataset (test dataset, t) which was not used in the training steps previously explained. That said, for forecasting block-yields in 2017 (t_{2017}), models were calibrated by LOYO CV with data until 2016; for forecasting yields for 2022, models were calibrated by LOYO CV with data until 2021. This process was performed 6 times for t_{2017}^{2022}. This validation approach was selected to simulate real conditions when forecasting block-yield for a new season and to provide insight about the stability of the temporal model. Figure 15 shows the general approach for modelling and yield forecasting.

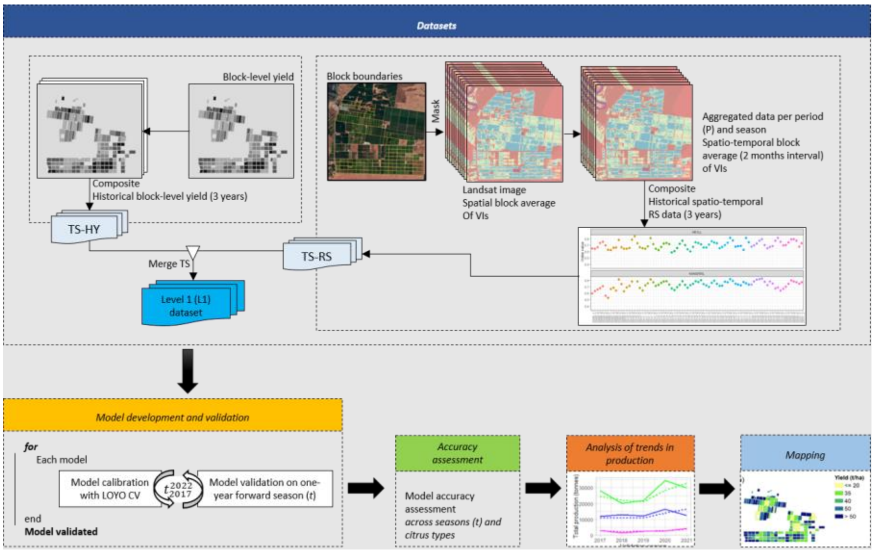


Figure 15. Flowchart of time series analysis in Citrus

Accuracy assessment

For each validated season (t), the Mean Absolute Error (*MAE, t/ha*), the Mean Bias Error (*MBE*, t/ha) and Mean Absolute Percentage Error (*MAPE*, %) were calculated following Eq. 2-4, respectively. MAE was used as it is less sensitive than RMSE to distant outliers (Perez et al. 2013). MBE is the average forecast error representing the systematic error of a forecast model to over (positive MBE), under (negative MBE) estimate or to indicate equal distribution between negative and positive values (zero MBE) (Notton and Voyant 2018; Kato 2016; Mkhabela et al. 2011). As errors tend to compensate each other, MBE is not suitable to assess errors of individual predictions. *MAPE* (Eq. 4) was used as an indication of model quality at the block level with reference to the mean of actual values, $\overline{Y}$, of the N samples contained in t.

$$MAE_t(t/ha) = \frac{1}{N} \times \sum_{i=1}^{N} \left| \overline{y}_i - y_i \right| \quad \text{(Eq. 2)}$$

$$MBE_t(t/ha) = \frac{1}{N} \times \sum_{i=1}^{N} \left(\overline{y}_i - y_i \right) \quad \text{(Eq. 3)}$$

$$MAPE_t(\%) = \frac{MAE}{\overline{Y}} \times 100 \quad \text{(Eq. 4)}$$

A temporal analysis was performed to select the most stable and reliable model across growing seasons and citrus types, followed by the estimation of the total production per citrus type and farm level with the goal to establish the optimum model to forecast future yields.

[1] Robson, A., Rahman, M., & Muir, J. (2017a). Using worldview satellite imagery to map yield in avocado (persea americana): A case study in bundaberg, Australia. *Remote Sensing, 9*(12), 1223

Mango Methodology

During the 2020/21/22 growing season, the evaluation of the accuracies of very high-resolution satellite imagery for measuring tree health and yield variability was undertaken on commercial mango orchards grown across four growing regions (NT: Acacia Hills and Katherine, Nth Qld: Dimbulah and South-east Qld: Bundaberg).

For the (2019/20) season yield estimation were carried out on 95 individual orchard blocks across the growing regions, for the 2020-21/22 season this number increased to 278 blocks (from 13 farms), to further include different mango varieties (Calypso, R2E2, KP, HG, Keitt and Parvin), tree ages and management.

Remote Sensing Data

A range of commercial and low/ free to use satellite data were investigated in this study to determine their accuracies in mango yield predictions at Tree/Block/Orchard scales. Table 3 shows the list of satellite data and their respective spatial and spectral resolutions. Commercially available Worldview3 (WV3) satellite data from MAXAR, offers 8-band multispectral data with 1.2 m spatial resolution and a 0.31 m Pan Sharpened (PS) product. Whilst the platform is being more extensively used in research and commercial applications, the very high spatial and spectral resolution does come at a cost that is likely prohibitive for large scale commercial adoption e.g. state and national level. Planetscope and Sentinel2 provide spatial resolutions of 3 m and 10 m, respectively. Whilst this resolution is not sufficient to identify individual tree crowns, their high repeat time (daily and 5 daily), and low to free cost make them increasingly attractive for identifying zonal variation in crop health across orchards and for time-series analysis.

As previously described in the citrus component of this report, the 18-calibration tree method was adopted for block level forecasting of mango yield. The classified NDVI image (derived from Worldview-3, Planet and Sentinel imagery) for each orchard was used to identify regions of high, medium and low tree vigour and the subsequent locations of the tree 18-calibration trees (6 trees each for high, medium, and low vigour). For the lower resolution images the site selection of the individual trees was first identified from very high-resolution Google Earth Imagery, which was then superimposed over the coarser imagery. All imagery was pre-processed to convert image digital number (DN) to Top-of-Atmosphere (TOA) reflectance.

Table 3. The different satellite sensors used for the mango component of this project

Satellite	Multispectral bands	Description
Worldview3 (pay to use) (MS 1.24 m resolution) 0.31m resolution	Coastal: 400-450 nm Blue: 450-510 nm Green: 510-580 nm Yellow: 585-625 nm Red: 630-690 nm Red Edge: 705-745 nm Near Infrared 1: 770-895 nm Near Infrared 2: 860-1040 nm Pan: 450-800 nm	Tree/ Block/Orchard scale mapping and tree crown delineation; Computation of spectral indices to develop mango yield prediction
Planetscope (free/low cost to use for research purpose) (MS 3 m resolution)	Blue: 455 - 515 nm Green: 500 - 590 nm Red: 590 - 670 nm NIR: 780 - 860 nm	Block/Orchard scale mapping; Extension of prediction models to low cost satellite data
Sentinel-2 (free to use) MS (10m resolution) (subset of 4 bands out of 13 bands)	Blue: 492nm (± 66 nm) Green: 559 (± 36 nm) Red: 664 (± 31 nm) NIR: 832 (± 106 nm)	Block/Orchard scale mapping; Extension of prediction models to free to use satellite data

Field Data

The GPS coordinate for each tree (with a unique tree-id) was extracted from each processed image and used to direct the infield sampling. The white circles in Figure 60 show examples of sample locations for each calibration blocks, identified on the NDVI classification maps.

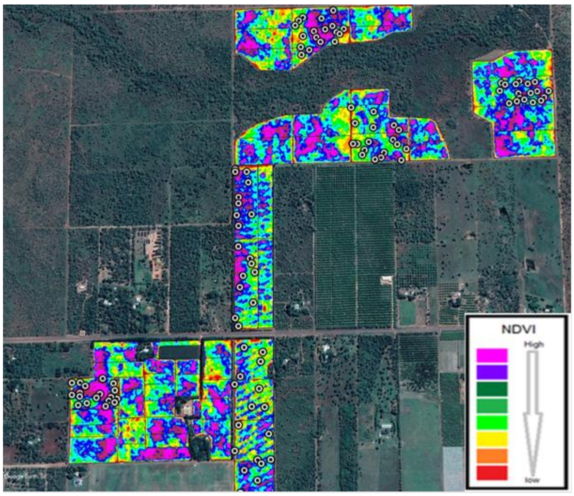


Figure 16. Classified NDVI image (Sentinel) identifying orchard regions of high, medium and low growth as well as the 18 tree sampling locations (white markers).

On-ground measures of fruit count and fruit weight (kg) (where possible) for each of the 18-sampled trees were undertaken at final fruit-set, at least 6-weeks before commercial harvest. In most cases, 2-3 persons (DAF Qld, NT DPIR staff) were engaged in fruit counting, with an average value from the respective counts used for the subsequent model development. The 18-trees calibration data within the different vigour zones (high, medium and low) were found to adequately represent the general variability in tree health and productivity across each block, and therefore aided in the accurate estimation of total block yield.

Mango Tree Crown Delineation

In this study, a Geographic Object-Based Image Analysis (GEOBIA) was used to delineate mango tree crowns in eCognition software (Blaschke et al. 2014). Recently, the method has been used successfully on a very high-resolution UAV data to delineate tree crowns in horticulture tree crop systems (Johansen et al. 2018; Yu-Hsuan et al. 2019). Figure 61 shows an example of tree crown delineated for mango trees grown in an orchard block. Crown delineation is an important process of the 18-tree calibration yield forecasting method for mango as it supports the extraction of the canopy reflectance properties of each tree as well as the calculation of Total Crown Area (TCA).

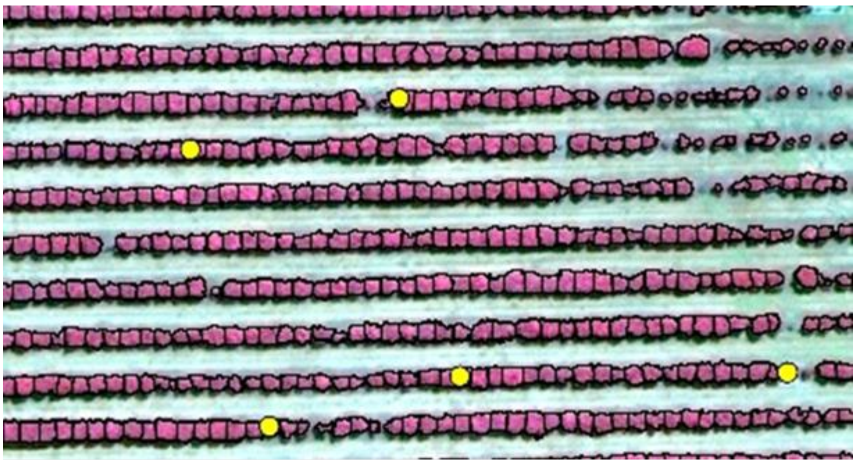


Figure 17. Tree crown area extracted for mango trees grown in orchard block superimposed over 0.3m PS multispectral WV3 imagery. The yellow points indicate the locations of the sampled trees.

Yield prediction model development and Yield variability mapping

To develop an initial yield forecasting model for each block, the canopy reflectance properties for each of the calibration trees was extracted from the relevant 1.2m multispectral WV3 image. From the extracted WV3 (TOA) 8 band reflectance image, twenty structural and pigment-based VIs were computed and their relationships with fruit numbers/Fruit wt (Kg) measured at the selected tree locations, were calculated. The VI that produced the highest regression coefficient (R2) was identified for each block and the resulting linear regression equation was then extrapolated to all image pixels to predict the average and total block yield (count or kg), as well as to derive fruit count and yield maps.

Additionally, the canopy area for each tree was also calculated and multiplied against canopy reflectance (VI) to produce an additional forecast, a method shown to be accurate by Rahman et al 2018 (Yield (VI * CA)). The calibration model prediction accuracy was determined as Root Mean Square Error (RMSE) for both fruit count and yield (kg) for the two datasets. The RMSE was computed as:

$$\text{RMSE} = \sqrt{\frac{\sum(Actual - predicted)^2}{n}}$$

The RMSE gives information on the performance of models at an individual tree level. The slope of the regression line determines the accuracy (bias) of the total block/orchard fruit load estimate. So, in addition to RMSE of the regression, it was found useful to determine the errors of the slope of the regression (slope uncertainty) for the total block/orchard estimates. The slope and intercept uncertainties for each regression model were computed using the LINEST function in MS Excel. The prediction model was modified by including the slope and intercept uncertainties in the regression equation.

Further validation was performed by comparing the actual harvest yield (e.g., packhouse data) reported by the growers against the predicted fruit counts or yield (Kg). Accuracy was defined as the ratio of predicted to packhouse data and scaled to 100%. The values above or below 100% represent over and under estimations when compared to actual packhouse data. The values ranging between ± 10% of actual packhouse data were considered high in accuracy (i.e, 90% accuracy). A comparison between the remote sensing-based predicted yield with growers' estimates was also done to determine any improvement over traditional yield estimation methods.

Figure 18 shows some examples of regression equations developed for one of the sampled blocks. The relationships between the sampled tree spectral responses (as indicated by the VI) and tree yield: (a) Fruit Count/tree; (b) Fruit Weight (Kg)/tree. The relationships between the VI x CA (tree crown area) and fruit count and fruit weight are shown in Figure 18 (c) and (d), respectively.

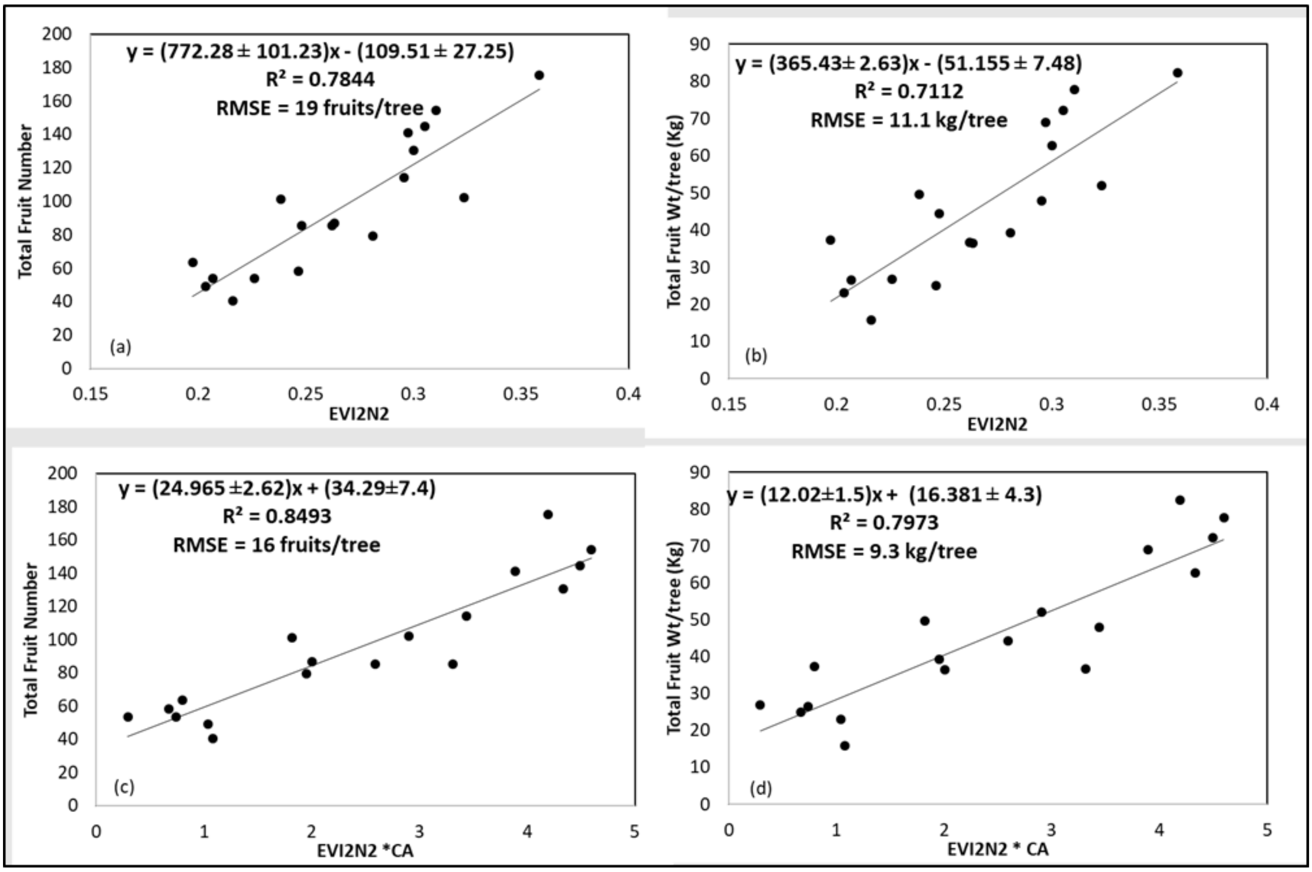


Figure 18. Relationships between canopy reflectance as optimal vegetation index and measured fruit number (a) and total Fruit Weight for tree (Kg). [EVI2N2=enhanced vegetation index from Red and NIR2 bands (EVI2N2 = (2.5*(NIR2-Red))/(1+NIR2+(2.4*Red)), where Red is Band5 of WV3) and NIR2= Near Infrared 2 (Band 8 of WV3); RMSE = root mean square estimation.

Improved Delivery of Image Products

To complement the numerical forecast of total and average yield for each orchard block, derived yield maps were also provided to the growers through a ***Web-APP***. Web-Apps do not require the growers to have any existing spatial software, with maps viewable on any device e.g., Tablets, Mobile Phone. The maps are highly intuitive with options to zoom-in/out, panning and other touch-screen commands, that allow growers to better visualise the spatial variability of their farms at individual tree - to block- the orchard level. The ***Web-APP*** development, design, look and feel is currently being assessed by participating growers with their feedback used to make further improvements.

Extension of yield prediction model from low-cost and free to use satellite data

As mentioned previously, very high-resolution imagery does come at a relatively high cost, that for some growers may be cost prohibitive and therefore a deterrent to future adoption. To address this limitation, the project team also assessed the accuracies of low cost PlanetScope (PS) and freely available Sentinel-2 (S2) data as a replacement for WV-3 in the 18-calibration tree method for yield forecasting. The PS and S2 data were acquired at dates that closely corresponded with that of WV3, to avoid any change in environmental conditions. The PS was available as surface reflectance and S2 as TOA reflectance. The tree crown area (CA) extracted from the WV3 imagery was superimposed on the two datasets and tree crown reflectance were extracted for the 18 calibration trees. Seven VIs, specific to crop biomass were computed and their relationships with yield were evaluated. The VI that produced the highest regression coefficient (R2) was identified and used to predict the average and total yield (count or kg) at the block level, as well as to derive fruit count and yield maps for each block. The results were compared with those obtained from the WV3 dataset.

Time-series mango yield prediction

Corresponding with the 18-calibration tree method, the time series method using Landsat imagery was also investigated for mango. Landsat imagery, although providing a spatial resolution coarser than Sentinel (28 m), is the only satellite that offers a long history of prior acquisition. As mentioned with citrus and macadamia research previously, the time series approach offers forecasts much earlier in the season without the need to conduct infield fruit counts to calibrate the imagery. The historic imagery, acquired monthly (depending on cloud cover), provides a very clear pattern of seasonal canopy reflectance that is influenced by growth stage or phenological growth pattern, management, variation in weather, pests, and diseases. An example of this seasonal growth pattern (provided as NDVI and GNDVI) is shown in Figure 19.

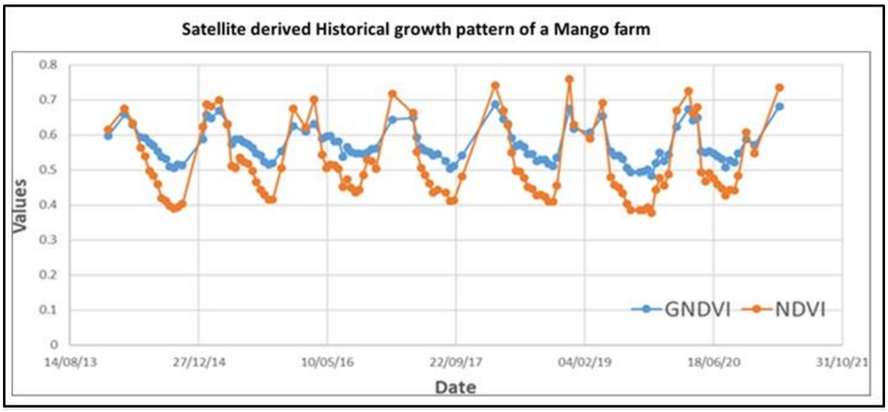


Figure 19. Time series growth profile of a mango orchard as defined by GNDVI and NDVI

To determine the relationship between the season growth curves to yield potential, historical yield data for the different orchard blocks for each of the corresponding years were obtained from the participating growers. This was used to determine what period (or periods) of the year, the canopy reflectance best correlated with final yield. By determining this, block specific time series yield models were developed and used to predict yield for following season based on the trajectory of the current seasonal growth curve. The accuracy of these predictions were determined by comparing block level yield forecasts against actual final harvested yield. This approach was tested for selected mango orchards blocks in NT and FNQLD for 2022/23 seasons.

Olive Methodology

Remote sensing trial: Improved yield estimation and quality

For this project, field sites for evaluating the 18-calibration tree (18CT) yield forecasting methodology were selected in Boort and Mornington Peninsula (Victoria) (Figure 20). Sites were also selected in the Hunter Valley, but due to COVID-19 and the associated travel restrictions, they were subsequently discontinued. The participating growers selected groves that were representative of their greater production areas in relevance to planting year, variety and management. In total, four varieties and nine groves were included in this study (Table 4). Seven groves in Boort were sampled from 2019 until 2022, except for one Picual orchard that was not be sampled in 2022 due to logistical issues. Field work in Mornington Peninsula took place for both 2020 and 2021. Unfortunately, for the latter, consistent cloud cover prevented the acquisition of very high-resolution satellite imagery during 2020, hence the methodology was only tested in 2021.

Figure 20. General site location of the 18CT in olives.

Table 4. Details of locations and the respective purpose of the sampling campaigns at harvest.

Region	Variety	# Groves	Seasons	Growers	Purpose
Boort	Picual	4	2020-2022*	2	Quality+Yield+Irrigation**
	Arbequina	3	2020-2022	2	Quality+Yield+Irrigation**
Mornington Peninsula	Leccino	1	2020-2021	1	Quality+Yield
	Frantoio	1	2020-2021	1	Quality+Yield

* One grove in 2022 was not sampled for quality and yield

** Only one grower, 4 blocks (2 Picual and 2 Arbequina)

Sampling strategy

The sampling approach was based on the methodology reported by Robson et al. (2017) [ii] where very high-resolution satellite imagery (Worldview-3 or Planet depending on availability) was used to define high, medium and low tree vigour (size and canopy health) zones within an olive grove. From these three zones, 6 individual trees were selected for targeted sampling i.e., 18-calibration trees (Figure 21).

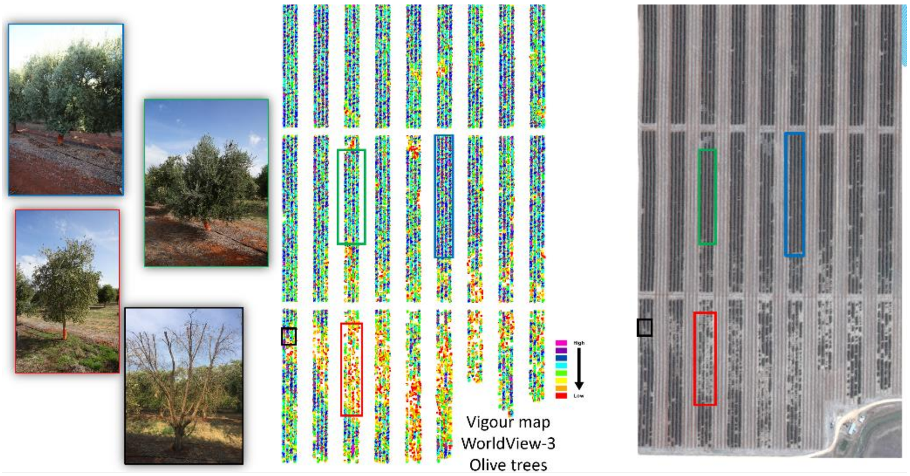


Figure 21. Vigour zones in an olive grove. Right: true colour image; middle: classified NDVI showing vigour zones in a grove; and left typical trees found on each zone. Black, red, green and blue squares represent areas with dead trees, areas of low vigour, medium and high, respectively.

The sampling included several key productivity indicators, identified by growers to be of commercial importance. These included flowering, fruit set, fruit load, oil content, fruit size, maturity and moisture content throughout the oil accumulation period (at Farm 1).

Flowering and fruit set:

To identify the spatial and temporal variability in fruit set percentage, two infield measures were conducted, the first being a measurement of the number of flowers per tree measured in late October early November (Figure 76). One branch from the North, East, South and West side of the tree was selected, with preference given to second year growth (with a branch length greater than 20 cm) where possible. The branch was marked with flagging tape, if any lateral branches were present, counting occurred after this branch. From these counts the total tree flower number per tree was calculated. The same trees and branches were then re-assessed in early December of the same year with the number of olives counted and recorded. The fruit set percentage was then calculated from the number of olives divided by the number of flowers.

Figure 22. Photo showing inflorescence counted, each red circle would be counted as one. I.e.: the score for this photo as shown would be 6, 4 are in red and 2 are hidden on the back side.

To calculate oil accumulation, samples were taken from each of the 18CT at the BB grove from February through to harvest. Each sample was refrigerated within 4 hours of being picked and processed within 30 hours. Processing consisted of weighing 25 fruit to obtain a fruit weight, scoring the fruit for maturity (Figure 23), then grinding the entire fruit sample into a past which was mixed to incorporate crushed pip and flesh to a consistent past. The paste was then placed in a NIR analyser to measure oil and moisture content.

Figure 23. Photo on left showing olive fruit past early in the oil accumulation period, photo on the right showing an olive being maturity scored late in the oil accumulation period.

To determine total yield per tree, all fruit were manually knocked off each calibration tree using a mechanical harvester, with all olives collected and weighed (Figure 78). This was undertaken prior to commercial harvest. For each tree harvested, a 1 kg subsample was taken from the harvested fruit and analysed, parameters measured included, fruit weight, fruit maturity, moisture content, cold pressed oil content, solvent extracted oil content and free fatty acid content.

Figure 24. Manual harvesting of calibration trees

High spatial resolution for mapping yield variability and yield estimation: 18CT

High spatial resolution WV-3 satellite imagery was acquired over each selected grove prior to commercial harvest and in some cases close to fruit set. Several VIs were derived from the imagery and empirical relationships between fresh yield (kg/tree, kg/ha or t/ha) and VIs were established during image processing. The VI that best describes yield variability was used to transform each pixel value into a yield value by extrapolating the relationship across the entire grove. Inter-rows were masked, hence only tree canopy was used for mapping. Yield maps were generated, and average estimated yield (t/ha, kg/ha) calculated and provided to growers. The estimated yields were compared against actual commercial harvest (actual yield) to assess accuracies. Figure 79 shows the main steps performed during the 18CT approach and Table 18 lists the dates and imagery collected during the life of this study.

Imagery also acquired over Boort at fruit set was used to explore the ability of remote sensing to map flowering and fruit set. Infield data from Farm 1 was used to fit regression equations to extrapolate values at the grove level. The approach was the same as the yield estimation described in Figure 25.

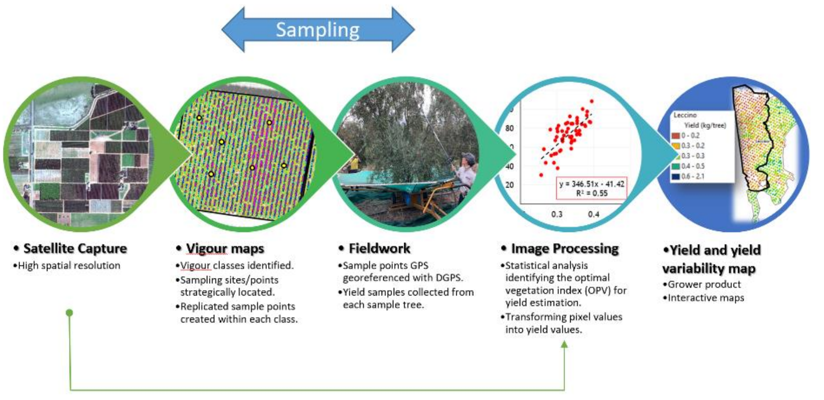


Figure 25. Illustration of main steps for the"18 calibration tree" approach

Table 5. Grove location, number of blocks, growth stage sampled, imagery source and acquisition date the 18-calibration tree yield estimation method.

Location	Growth stage	Number of Blocks	Imagery sensor	Capture
Mornington Peninsula	Harvest	2^	CERES	6May 2020
Boort	Harvest	7	World-view 3	08 June 2020
Boort	Flowering/Fruit set	7*	World-view 3	3 February 2021
Boort	Harvest	7	World-view 3	27 April 2021
Boort	Harvest	1	CERES	15 May 2022
		2	CERES	19 May 2022
Mornington Peninsula	Harvest	2	World-view 3	29 June 2021

^ Poor quality imagery prevented the analysis

***Flowering and fruit set infield data was collected on 4 groves**

Irrigation trials

Prolonged droughts present significant risks for food production and sustainability of the agricultural sector. To assess the impact of water stress on olive crop performance, irrigation deficits were applied to a commercial farm over three consecutive seasons (2020-2022) located in Boort (Figure 26 and Table 5).

Irrigation trials: experimental design

To ensure the trial was not biased by inherent variations in tree condition, a classified (Worldview 3) NDVI layer of the grove was used to locate the treatments in rows (three per treatment) that represented high or low canopy vigour. The irrigation treatments (IT) equivalent to 52%, 78% and 100% of current commercial application (based on crop evapotranspiration, ETc) were imposed from January 2020 (around fruit ripening) until just before harvesting in April 2022. Therefore, every developmental stage was under constant water deficit, except during their respective harvesting periods (April/May-August) as the grove was not irrigated. The output drip lines of each treatment-row (TR) were connected directly to the same valves as the control lines to guarantee that only the volume, and not the frequency nor duration of irrigation, varied. The trial design had variety (cv. Arbequina and Picual), IT and vigour zones (high/low) as factors, with 3 replicates of each treatment.

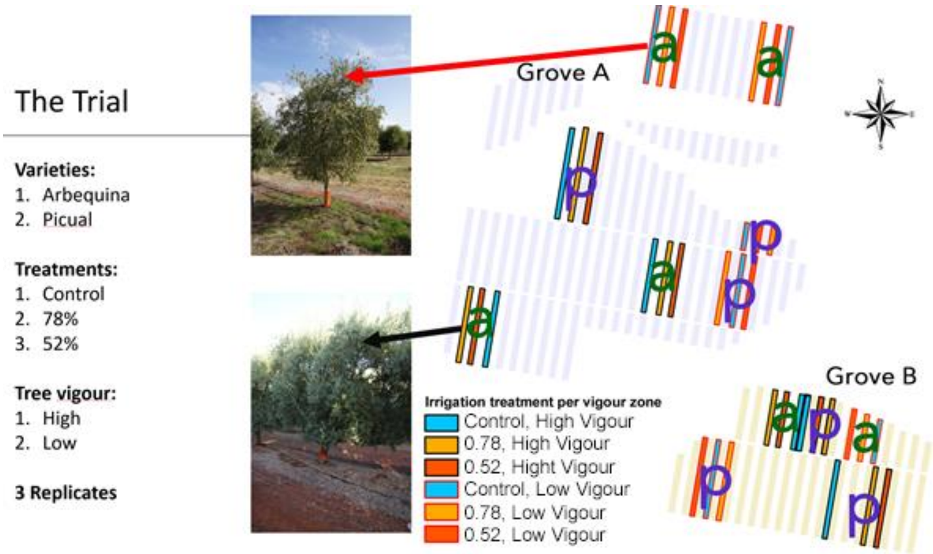


Figure 26. Experimental design and location of treatments. "a" refers to Arbequina and "p" refers to Picual. Top picture illustrates the average tree structure in low vigour areas and the bottom picture illustrates the average tree structure in the high vigour areas.

Sensors to monitor water deficits

An array of sensors was deployed to monitor water deficits. Many factors went into decisions about selecting sensors. These included:

- Cost. The cost of each sensor node and sensor was important as the trial consisted of many treatments that needed to be monitored with multiple sensor types;
- Connectivity. The aim was to collect data from every sensor at hourly intervals in real time. This required wireless connectivity to cloud databases. Tree crops present a challenging environment for connectivity, as canopies attenuate radio signals, and antennas can obstruct orchard operations. Additionally, there was a large distance between treatments, so that a wireless signal range in excess of 1 km was needed.
- Flexibility. Several sensor types from different manufacturers needed to be connected to the wireless sensor nodes, so the nodes needed to be programmable and able to interface with the standard agricultural sensor interface (SDI-12).

High frequency imagery (Planet and CERES)

Through a collaboration with Planet, a time-series of high-resolution satellite imagery was acquired over the irrigation trial site. Planet operates multiple satellite constellations, including their Dove cubesats. These acquire imagery of the whole earth's surface, at near daily frequency, and with 3-meter spatial resolution. One limitation historically has been the lack of radiometric consistency between these satellites as they are constructed using relatively inexpensive imaging hardware. Rasmus Houborg (remote sensing analysts from Planet) developed the Planet Fusion technology, which calibrates the Dove images to high quality scientific satellites, such as Landsat and Sentinel-2. The olive irrigation trial was underway just as Planet were announcing this development, so they were willing to provide Planet Fusion imagery at no cost, seeing the value of validating the imagery with the ground truth data being collected from the olive trees.

The shapefiles of the irrigation treatments were imported into Google Earth Engine, together with the Planet imagery. From there, daily vegetation indices (NDVI, GRVI, GNDVI) were extracted from each of the irrigation treatment rows. The average of the NDVI across treatments per day is shown in Figure 28, showing the phenological cycles of the olive trees (peak NDVI around the middle of the year, low NDVI during the fruit set and oil accumulation stages during summer).

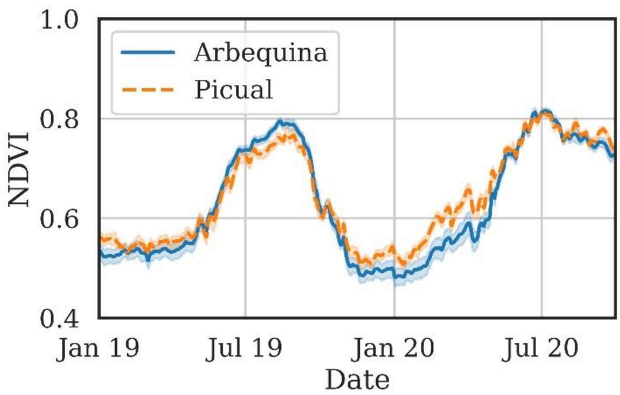


Figure 27. Planet Fusion daily NDVI, averaged across the irrigation treatments.

To quantify how effective the Planet Fusion imagery was for detecting water stress, the canopy reflectance data per treatment was normalised before the irrigation treatments were imposed (1 Jan 2020) and then again in relation to the control treatments at each date. These normalisations are described by the following equation, where VI is the vegetation index, t and t_0 are the current and start times, and a and a_0 are the irrigation treatment and control treatment areas respectively:

$$VI(t - t_0, a - a_0) = VI(t - t_0, a) - VI(t - t_0, a_0)$$

This resulted in a sensitive indicator of how the vegetation indices of each treatment area had changed over time, with respect to the control treatments. These differences were analysed on a per-day basis using ANOVA, to give a measure of the confidence that the water stressed treatments had resulted in a different vegetation index to the control treatments, indicating a real effect of the deficits on the olive tree canopies.

Tools for better identifying water stress in olives

Appendix 1 section 6.2.5 provides a full methodology of olive irrigation trial. In summary a classified (Worldview 3) NDVI layer of the grove was used to locate the treatments in rows (three per treatment) that represented historical high or low canopy vigour. The irrigation treatments (IT) equivalent to 52%, 78% and 100% of current commercial application were imposed from January 2020 (around fruit ripening) until just before harvesting in April 2022 and therefore every developmental stage was under constant water deficit, except during their respective harvesting periods (April/May-August) as the grove was not irrigated. The trial design included different varieties (cv. Arbequina and Picual), IT and vigour zones (high/low) as factors, with 3 replicates of each treatment.

Identifying the optimal technology and then subsequent brand of sensor best suited for measuring the early onset of water stress is extremely difficult to navigate for growers. As such, the project team considered a range of factors including Cost, Connectivity and Flexibility, and ultimately tested an array of sensors to monitor water deficits. For farm sensor connectivity, a low power wide area networks (LP-WAN) was selected, more specifically SigFox (provided by Australian distributor Thinxtra). DigitalMatter SensorData devices were chosen for the wireless sensor nodes. For soil moisture measurements, the project used EnviroPro capacitive sensors, with eight sensors at 10 cm intervals. To directly measure tree response to water stress, two sensor types: Dendrometers to measure trunk diameter and Sap flow sensors to measure the actual amount of water being transpired by trees, were selected. These were obtained from Edaphic,

Planet high-resolution satellite imagery as well as Planet Fusion imagery was also acquired regularly over the irrigation trial site, whilst CERES airborne multispectral and thermal imagery was acquired over the irrigation trials several times between 2020 and 2022.

To get a better understanding of tree drought stress, stem water potential (SWP) readings were taken in years two and three of the project. High stress days were targeted as well as to reference (relatively high soil moisture and low evaporative). One tree was randomly selected in each of the 36 irrigation treatments, the same trees were used throughout the project for measuring SWP. All SWP measurements were taken within 1 hour of solar noon and coincided with imagery taken by CERES.

CERES

CERES airborne imagery was acquired over the irrigation trials several times between 2020 and 2022. Reflectance data captured in the blue, green, red and NIR bands as well as thermal information was processed to compare the ability of the system to detect and monitor water stress. Imagery was processed and analysed to characterise the treatments based on the reflectance response and canopy temperature. Canopy temperature varies according to the tree vigour with low vigour trees expressing higher temperatures (less foliage for shading and transpiration). However, it cannot be assumed that a low vigour tree is suffering from water stress, it may be the result of other abiotic or biotic constraints. Therefore, a Canopy Water Stress Index was adapted to normalize the effects of vigour, so that canopy temperature variations were more likely the attributed to water deficits.

The empirical form of the crop water stress index (CWSI) is based on the linear relationship between the difference in crop canopy to air temperature (Tc − Ta) and vapor pressure deficit (VPD) of the air for a well-watered crop during the day and under homogeneous conditions and clear sky (Veysi et al. 2017). The original calculation is complex as it requires the measurement of two base lines: non-water-stressed (NWS) and no-transpiration (NT). Here, we used the NDVI to mask areas as NWS and NT and calculate the index following the equation:

$$CWSI = (T_s - T_{Cold})\ (T_{Hot} - T_{Cold})$$

Where, T_s is the LST (Canopy temperature in cropped land), T_{Cold} is the temperature of well-irrigated pixel which is almost covered fully by vegetation (Cold pixel), and T_{Hot} is the temperature of the crop covered pixel with maximum amount of water stress (Hot pixel).

Figure 28. Photo on the left of CERES taking image during SWP measurements, on the right project member taking SWP measurements

To quantify the impact of the water deficits on production, fruit samples (15-20 g/tree/sampling date) were taken from 20 randomly selected trees within the irrigation treatments. The fruit collected was analysed for fruit weight, maturity, moisture, oil accumulation and oil content. At the end of each season the entire middle row for each treatment was mechanically harvested and weighed for yield. A 1 kg subsample was taken from each row harvested and analysed for fruit weight, fruit maturity, moisture content, cold pressed oil content, solvent extracted oil content and free fatty acid content.

Full descriptions of the methodologies are provided in the appendix section of this report (Appendix 1. National Mapping of Tree Crops section 2.2, Macadamia section 3.2; Citrus section 4.2; Mango section 5.3 and Olive section 6.2)

Yield forecasting and yield mapping

Through the term of this project, the AARSC team developed remote sensing (satellite and airborne) methodologies for yield forecasting across all participating tree crop industries, other than banana. The models were developed and validated across many farms in many growing regions, providing a strong indication of robustness including the influences of location, season, variety and management (Figure 29).

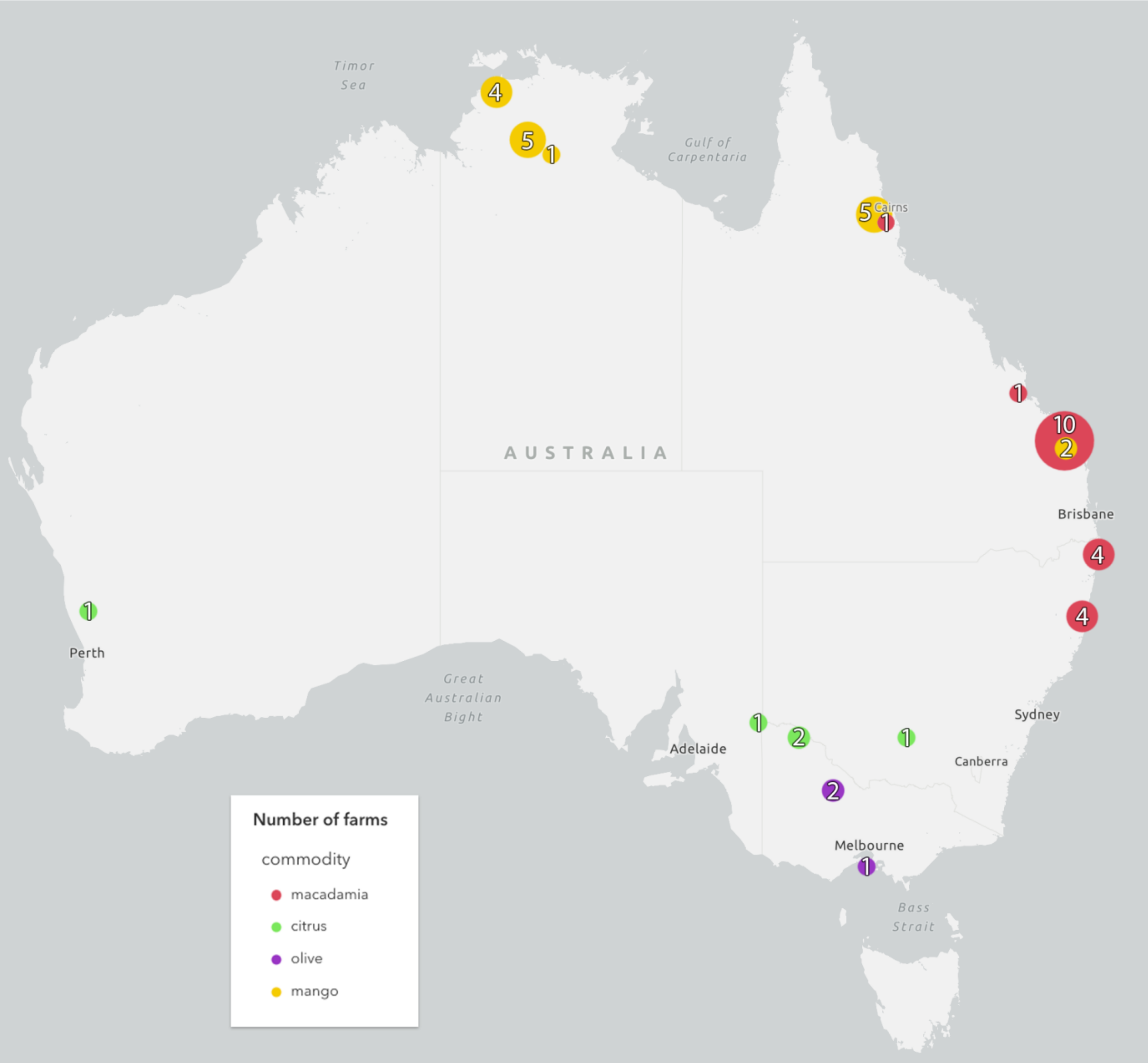


Figure 29. Locations of farms that shared field sites for the various methodologies applied during this project

The yield forecasting methodologies include two main approaches: the '**18 calibration tree' method** and the **'time series' method**.

- The 18-tree approach better describes yield variability within the orchard level. It is ideally suited for growers with young orchards or growers that do not have historic productivity information. It requires high resolution imagery and manual counts of fruit.
- The 'time series' method is suitable for forecasting yield at the block, farm, regional and national level. It utilizes free imagery (Landsat and Sentinel), requires no field work and can provide predictions months before harvest.

Locations

Equipment development and reference analyses occurred at the CQUniversity 'CQIRP' campus in Rockhampton. A 20 (mango) tree planting on campus facilitated initial evaluation work. Trial work was farm based, with activity occurring on farms that spanned the mango production areas of Australia, from NT Top End to SE Qld. Additional work occurred on citrus, olive and banana farms.

Research findings are broadly applicable across all growing districts of the respective commodities.

This section presents a 'high-level' overview of the methods employed, with detail provided in appendices and in journal publications. This project involved the development and testing of equipment and protocols for assessment of harvest timing and fruit load (fruit number and size), primarily in context of mango, but also with citrus, olive and banana. A mechanical harvester for mango fruit was also further developed and tested.

Forecast of harvest maturity

Three technologies were involved in estimation of optimum timing of harvest:

(i) assessment of fruit dry matter (DM) using handheld near infrared spectroscopy,

(ii) the non-invasive assessment of flesh colour using handheld visible region spectroscopy and

(iii) heat sums calculated from in-field temperature sensors.

(i) NIRS-DM

Detail of methodology can be found in Anderson et al. (2020) and Anderson et al. (2021).

From Anderson et al. (2021): Briefly, spectra were collected using F750 and F751 Produce Quality Meters (Felix Instruments, Camas, USA). Each mango fruit was scanned twice on the shoulder of each cheek immediately before destructive analysis involving sampling of a 29×10^{-3} m diameter core of flesh from the fruit cheek. The skin of the fruit core was removed with a peeler and the core was cut from the seed side to $\sim 10 \times 10^{-3}$ m in length. The core was weighed, then quartered and dehydrated for 48 h at 65 °C in a commercial air-forced oven (UltraFD1000, Ezidri, Beverley, Australia) for estimation of dry matter content (DMC) calculated as dried weight as a percentage of fresh weight.

The mango work involved fruit of mango cultivars 'Calypso™', 'Honey Gold', 'Keitt', 'Kensington Pride', 'Lady Grace', 'Lady Jane', 'R2E2' and National Mango Breeding Program (NMBP) lines 1201, 1243 and 4069 were collected over four seasons for a total of 112 unique populations, 4675 mango samples with reference values and 11,691 spectra after removal of 143 spectral outliers. Other work was undertaken

Samples sets (calibration, tuning and test sets) were as reported in Anderson et al. (2020). Spectra associated reference values and meta data of the fruit populations involved in each set are also available at: https://data.mendeley.com/datasets/46htwnp833/2.

RStudio (RStudio Team, Boston, USA), The UnScrambler (Camo, Sweden) and the online platforms were used in model building. The RStudio based models were compared in model build and prediction time, using an Intel® Core™ i5−7300U CPU with 16 GB RAM.

Various spectra pretreatment and modeling types, including local (LOCAL, LOVR, LPLS, LPLS-S, MBL, SBL), non-linear (ANN, GPR, SVR) and rule based (Cubist) techniques were compared to a global PLSR model. Cubist models were developed using the R package 'Cubist' (v0.2.3; Kuhn et al., 2020). SVR models were developed using the R package 'e1071' (v1.7−3; Meyer et al., 2019). ANN models were developed using the R package 'nnet' (v7.3–13; Ripley and Venables, 2020). GPR was performed using the R package 'kernlab' (V0.9–29; Karatzoglou et al., 2019). LOCAL was performed using the three methods proposed by Shenk et al. (1997) for prediction of samples using a local model. In one method (LOCALA), the prediction was based on a local PLSR using a set maximum LV (10, 12, … 40). MBL and SBL was developed from the R package 'resemble' (v1.2.2; Ramirez-Lopez and Stevens, 2016) and was tuned based on the same parameters as LOCAL. An ensemble result was created by averaging the prediction results from the three top performing individual models from dissimilar modelling methodologies (e.g., local, kernel regression and neural network) described above, chosen on the basis of RMSEP of tuning set prediction. Two cloud-based packages were trialed, Hone Create (Hone, Newcastle, Australia) and DataRobot (Sydney, Australia) were employed. The autopilot feature was used in DataRobot's Automated Machine Learning platform (https://app.datarobot.com/docs/modeling/build-basic/model-ref.html#summary-info), and the software was provided only with the pre-processed data in this. In Hone Create, pre-processed data was run through five families of algorithms: (i) Linear Model (GLM), (ii) Distributed Random Forest (DRF), (iii) Gradient Boosting Machine (GBM), (iv) Deep Learning (Neural Networks), and (v) XGBoost. Combinations (i.e., 'Stacked Ensembles').

Parallel work was undertaken with olives, with method detail documented in Sun et al. (2020), and citrus (Aryal, 2022, Ch. 7) (Fig. 30).The citrus work involved a comparison of three portable instruments. The F750 and SunForest units operate a wavelength range to 1000 nm and are purpose built for use with fruit. The SunForest unit was citrus specific. The F750 offers an internal referencing procedure, applied with every measurement, to cope with ambient light variation, i.e., outside conditions. The MicoNIR (Viavi, USA) unit was a generic spectrometer, portable rather than handheld, operating to 1700 nm.

Figure 30. **F-750 (left) SunForest (middle) and MicroNIR (right) devices (from Aryal, 2022).**

(ii) Vis-NIRS - Flesh colour

Greater detail on methodology can be found in Amaral (2022, Ch. 6). A condensed version of that documentation follows:

Fruit were sourced from several growing districts (Table 6). Panicles were tagged at asparagus stage and harvests were made in each of the two weeks prior to, and two weeks after, the GDD predicted harvest maturity date. CIE B values were assessed of cut cheeks using a CR400 (Minolta, Japan). Fruit were assigned to three maturity stages (i.e., immature, mature and over-mature classes) using CIE B; for Calypso: <28; >28<39; > 39; Honey Gold: <30, >30<43, > 43; Keitt: <48, >48<58, > 58; respectively, with a minimum DMC of 14% for all cultivars). Ripened fruit were also assessed. Tree-ripened Honey Gold and Keitt fruit were collected from orchards and four store fruit of both KP and R2E2 cultivars were exposed to 10 ppm ethylene and allowed to ripen at 20 °C until soft to touch. Two sides of each fruit were assessed, with a total of 434 Honey Gold samples (217 fruit), 242 Keitt samples (121 fruit) and 24 Calypso samples (12 fruit) processed.

Table 6. Fruit populations used in carotenoid determinations.

Cultivar	Stage	Location	Fruit #	Season	Comment
Honey Gold	hard green fully ripen	CQ	217	2020	5-10 fruit harvested weekly 03/12/2020 to 14/01/2021
Keitt	hard green	CQ	121	2020	5-10 fruit harvested weekly 03/12/2020 to 14/01/2021
Calypso	hard green fully ripe	FNQ	29	2021	of these, 5 fruit exposed t ppm ethylene

Honey Gold	fully ripe	FNQ	9	2021	5 fruit exposed to ethylene at 10 ppm, 4 tree ripened
Keitt	fully ripe	CQ	5	2021	4 fruit exposed to ethylene at 10 ppm and one tree ripe
R2E2	fully ripe	*Retail store*	4	2022	
KP	fully ripe	*Retail store*	4	2022	

Vis-NIR interactance spectra (330 – 1100 nm) were collected from each side of the fruit using a F750 handheld spectrometer (Felix Instruments, Camas, WA, USA). The fruit was weighed and then a 20 mm diameter core taken from the equator of each cheek. The skin was removed from the core and the core was trimmed to 10 mm length, resulting in a sample of approximately 7 g. The colour of the inside cut was assessed visually by comparison with colour cards for the Keitt and Calypso cultivars, respectively, and CIE LAB colour space measured with a Konica Minolta Chroma Meter (CR-400, Konica Minolta Sensing Inc., Osaka, Japan).

Dry matter content (DMC) was assessed using one half of the cores from the weight change after placement in a dehydrator (UltraFD1000, Ezidri, Beverley, Australia) at 65 °C for 48 h. The other half of the cores were frozen and stored at -20 °C for later assessment of carotenoid content. For carotenoid estimation, frozen samples were freeze-dried (-45°C/ 200 mT) (Flexi dry MP freeze-drier, FTS Systems, USA) to constant weight, i.e., for approximately 36 h. Soluble sugar content (SSC) of filtrate was measured with a Bellingham and Stanley RFM320 digital refractometer and titratable acidity (TA) assessed of a 10 mL sample of juice using 0.1 N NaOH as a titrant and 1% w/v citric acid as a reference.

Samples frozen at -20 °C were freeze dried (-45 °C, 200 mT) (Flexidry MP freeze drier, FTS Systems, USA) for approximately 36 hours, then crushed in a ceramic mortar and pestle. Approximately 0.1 g of subsample was placed into 15 mL of acetone, then sonicated for 30 min and centrifuged. Total carotenoids were determined by A450 nm measurement of tissue extracts using a UV-Vis spectrometer. Separation of component compounds in the acetone extracts representative harvest-mature and fully ripened fruit of each cultivar was undertaken using a HPLC-based protocol. The retention time of a β-carotene standard was 13 min in 2021 trials and 11 min in 2022 trials. A β-carotene standard curve (slope 157.9, intercept 9.5117 and R^2 of 0.99) was based on A450 nm of β-carotene standards of 0, 0.03, 0.33, 0.64, 1.40, and 3.33 mg/L.

One-way ANOVA statistical analysis was undertaken using the RStudio 4.1.2 statistical software module 'agricolae'. A significance p-value < 0.05 was adopted. Population results were expressed as mean + SD.

The Unscrambler (CAMO, Sweden) was used for chemometrics. Spectra were pre-treated using standard normal variate (SNV) treatment followed by a Savitzky-Golay second derivative. A PLSR model for total carotenoid content was developed using vis-NIR spectra trimmed to 500 - 975 nm, using data of one population of Honey Gold mango fruit (n = 152), and tested on data of another population of fruit of the same cultivar (n = 226).

(iii) Heat units

Greater detail on methodology can be found in Amaral (2022; Ch. 3). A condensed version of that documentation follows:

Locations

Temperature was logged on a range of farms in the growing regions of Darwin and Katherine in the Northern Territory (NT), Dimbulah, Bungundarra and Childers in Far North, Central and South Queensland, and Petrolina in Brazil, during the 2018/19, 19/20, 20/2021 and 21/22 seasons.

Sensor hardware

The selection criteria on a remotely logged field temperature sensor were cost, field ruggedness, battery life and transmission range. The SensorHost (Rockhampton, QLD; sensorhost.com) LoRa (945 MHz) based field temperature sensor and associated repeater and gateways were evaluated. The device is based on a thermistor (Si7051, Silicon Labs, Austin, USA) with manufacturer specification of ±0.01 °C accuracy) mounted on an electronics board, with protection offered by a conformal coating (Figure 31). Sensors were housed in a mini-Stevenson screen mounted 1.2 m above ground (Figure 31b). If required to improve LoRa signal transmission, a 4 m extension cable was used, with the antenna raised above the tree canopy. The gateway was connected to farm Wi-Fi with data logged to a database and displayed to a website. GoogleEarth elevation profiles between sensor and gateway location were used to guide sensor location (Figure 32).

Figure 31. (a) SensorHost electronics board; (b) Stevenson screen mounted at 1.2 m height on a star picket; (c) repeater unit; (d) gateway.

Figure 32. Example ground elevation profiles from GoogleEarth between sensor location and gateway location (packshed). The aerial position was 3 m higher than ground level for sensors, and 6 m higher for gateways.

Several exercises were undertaken to evaluate sensor performance. In one exercise, six sensors were placed together in an incubator operated to a range of temperatures. In another exercise, temperature was logged using sensors in weather screens placed in pairs inside and outside the tree canopy on a NT and a CQLD farm. Temperature variation within three farms was also assessed, with sensors placed in different management zones of the farms. Other exercises were undertaken to consider the effect of Stevenson screen design, and of colour change due to ageing of the screens.

<u>Heat unit algorithm</u>

Heat unit calculations were based on temperature measurements acquired on farms in Darwin and Katherine between flowering and commercial maturity. Comparison was made between: (i) GDD estimate based on a Tb of 12 °C (Eqn. 1) based on daily Tmin and Tmax extracted from 15 minute interval logged data; (ii) GDD estimate based on Tmin and Tmax extraction from hourly logged measurements using Eqn. 3; (iii) GD15 min estimate based on a daily temperature integral using 15 minute interval data (Eqn. 2), using Tb = 12; (iv) GDD estimate involving an upper temperature (TB) limitation (Eqn. 4.4-4.7), with Tb = 12 and TB = 32 °C; and (v) GDD estimate using Tb = 10 and 13 °C (for a winter period between flowering at Groves Grown farm – this being the site with lowest temperatures, with temperatures below the Tb thresholds).

Standard method (as used in the Australian industry currently):

$$\mathrm{GDD} = \frac{\mathrm{Tmax+Tmin}}{2} - Tb \qquad \text{Eqn. 1}$$

Integral methods:

$$\mathrm{GD15min} = \frac{\sum_{n=1}^{96}(Ti - Tb)}{96} \qquad \text{Eqn. 2}$$

$$\mathrm{GDH} = \frac{\sum_{n=1}^{24}(Ti-Tb)}{24} \qquad \text{Eqn. 3}$$

Upper temperature method (allows for slowing of physiological processes at high as well as low temperatures):

If TB>Tb>TM>Tm; then GDD = 0. Eqn. 4

If TB>TM>Tm>Tb; then GDD = $\left(\frac{TMax-Tmin}{2}\right) + (Tmin - Tb)$ Eqn. 5

If TB>TM>Tb>Tm; then GDD = $\frac{(TMax-Tb)^2}{2*(TMax-Tmin)}$ Eqn. 6

If TM>TB>Tm>Tb; then GDD = $\frac{2*(TMax-Tmin)*(Tmin-Tb)+(TMax-Tmin)^2-(TMax-Tb)^2}{2*(TMax-Tmin)}$ Eqn. 7

If TM>TB>Tb>Tm; then GDD = $\frac{1}{2} * \left[\frac{((TMax-Tb)^2-(TMax-TB)^2)}{TMax-Tmin}\right]$ Eqn. 8

where TB is Upper base temperature, Tb is Lower base temperature, Tmax is maximum daily temperature and Tmin is minimum daily temperature.

To optimize the Tb and TB values used in the GDD calculation, Tb values from 1 to 20 °C at intervals of 1 °C were used in equation 4.1, and TB from 25 to 37 °C at intervals of 1 °C were used in equations 4.4 to 4.8. For the Tb exercise, temperature data from four different flowering events at a southern location (in Yeppoon, QLD) was used. For the TB exercise, data of flowering events of northern sites (two near Darwin, NT, and one event at Katherine, NT) was used (Table 7). The sites and periods were chosen for low temperatures in assessment of Tb and high temperatures in assessment of TB.

Table 7. Farm locations and range of temperature values used for Tb or TB in Tb/TB optimisation.

Location (farm)	Tb	TB	Method	Period
Darwin , NT Orchard 1	12	23 to 37	Eqn 4-8	15/06/2021-20/10/2021
Darwin, NT Orchard 2	12	23 to 37	Eqn 4-8	15/06/2021-20/10/2021
Katherine, NT Orchard 1	12	23 to 37	Eqn 4-8	15/06/2021-20/10/2021
Yeppoon, CQLD Orchard 1	1 to 20		Eqn 1	07/07/2020-23/12/2020
Yeppoon, CQLD Orchard 2	1 to 20		Eqn 1	07/07/2020-23/12/2020
Yeppoon, CQLD Orchard 3	1 to 20		Eqn 1	07/07/2020-23/12/2020

The Coefficient of Variation (CV) was calculated for GDD values estimated across three sites for each Tb or TB values, i.e., n=3 for both Tb and TB calculations. The Tb or TB value with the lowest CV was chosen as the most reliable Tb or TB.

Estimation of cultivar GDD for fruit maturation

Daily minimum and maximum temperatures were used in calculation of daily GDD using a Tb = 12 °C, and TB = 32 °C, using Eqn. 4.4 to 4.8. Panicles were tagged on 9 orchards, with populations of panicles at asparagus stage (Figure 33) tagged in each of several weeks to give a total of 22 populations, where each population is specific in location and date (Table 8). The resulting fruit were destructively sampled at weekly intervals around the harvest maturity date anticipated from the currently recommended GDD for a given cultivar, with measurement of DMC, SSC, TA, flesh colour (CIE LAB, hue) and carotenoid levels, using methods described in the Vis-NIR Flesh Colour section. GDD units between the stages of asparagus, Christmas tree and harvest maturity were calculated for Calypso, Honey Gold and Keitt cultivars. A flesh colour specification for Honey Gold was also established using the existing GDD specification. The thirteen 2021 populations were used to validate the recommended target by destructive assessment of fruit when the fruit reached the target GDD.

Table 8. Panicle tagging exercises. All panicles were tagged at asparagus stage except as noted.

Pop (#)	Cultivar	Farm	Tagging date	Panicle (#)	Fruit (#)	Retention (%)	harvest dates
2018							
1	Calypso	Darwin 1	29-May	269	95	35	20/09
2A	Honey Gold	Yeppoon	10-Jul	201	31	15	18/12, 27/12, 31/12
2B	Honey Gold	Yeppoon	17-Jul	291	73	25	18/12, 27/12, 31/12
2C	Honey Gold	Yeppoon	26-Jul	92	47	51	18/12, 27/12, 31/12
2D	Honey Gold	Yeppoon	4-Aug	280	30	11	18/12, 27/12, 31/12
2E	Honey Gold	Yeppoon	18-Aug	138	28	20	18/12, 27/12, 31/12
2019							
3A	Calypso	Darwin 1	22-May	50	12	24	4/10
3B	Calypso	Darwin 1	29-May	50	24	48	4/10
3C	Calypso	Darwin 1	5-Jun	50	15	30	4/10
3D	Calypso	Darwin 1	12-Jun	50	11	22	4/10
3E	Calypso	Darwin 1	19-Jun	50	9	18	4/10
3F	Calypso	Darwin 1	26-Jun	50	21	42	4/10
3G	Calypso	Darwin 1	3-Jul	50	1	2	4/10
4A	Honey Gold	Yeppoon	16-Jul	113	16	14	20/12
4B	Honey Gold	Yeppoon	25-Jul	60	10	17	20/12
4C	Honey Gold	Yeppoon	2-Aug	18	7	39	20/12
4D	Honey Gold	Yeppoon	14-Aug	30	13	43	20/12
4E	Honey Gold	Yeppoon	30-Aug	24	2	8	20/12
2020							
5A	Honey Gold	Yeppoon HG1 FE 1	5-Jul	600	55	9	03/12, 10/12, 17/12, 23/12, 28/12/2020, 07/01, 15/01/2021
5B	Honey Gold	Yeppoon HG1 FE 2	5-Aug	600	57	10	03/12, 10/12, 17/12, 23/12, 28/12/2020, 07/01, 15/01/2021
6A	Honey Gold	Yeppoon HG4 FE1	5-Jul	600	58	10	03/12, 10/12, 17/12, 23/12, 28/12/2020, 07/01, 15/01/2021
6B	Honey Gold	Yeppoon HG4 FE2	13-Aug	600	47	8	03/12, 10/12, 17/12, 23/12, 28/12/2020, 07/01, 15/01/2021
7	Keitt	Yeppoon 1	5-Aug	300	71	24	22/12, 29/12/2020, 07/01, 13/01, 20/01, 29/01, 04/02/2021
8	Keitt	Yeppoon 2	25-Aug	200	49	25	20/01, 29/01, 04/02, 11/02, 10/03/2021
9	Keitt	Brazil 1	6-Aug	300	81	27	28/12, 31/12/2020, 05/01/2021
2021							
10	Calypso	Darwin 1	4-Jun	100	44	44	28/09, 01/10, 04/10

11	Calypso	Darwin 1	4-Jun	100	27	27	23/09
12	Honey Gold	Darwin 2	8-Jul	50	13	26	27/10
13	Honey Gold	Katherine 1	2-Jul	100	40	40	26/10
14	Calypso	Katherine 2	15-Jun	100	9	9	20/10
15	KP	Katherine 3	15-Jun	50	13	26	7/10
16	Calypso	Collins Cal	30-Jun	100	29	29	25/11, 29/11
17	Honey Gold	Collins HG	30-Jun	100	20	20	29/11
18	Keitt	Brazil 2	16-Jun	100	32	32	8/11
19	Keitt	Brazil 3	18-Jun	100	24	24	15/11
20	KP	Yeppoon	5-Jul	50	2	4	1/12
21	Honey Gold	Yeppoon HG3	24-Jun	100	5	5	8/12
22	Keitt	Yeppoon	5-Jul	100	5	5	5/01

Figure 33. Flowering development stages in Honey Gold cultivar of asparagus (D), Elongation (E), Christmas tree (G).

The CR-400 colorimeter was also used to measure colour values of printed versions of commercially available mango maturity colour cards.

Linear correlations between parameters, ANOVA LSD and Tukey mean comparison tests were performed using RStudio (Boston, USA), using P <0.05.

Forecast of fruit load

Fruit count

A common set of field locations and reference counts was employed in the testing of the technologies employed in the current study and the satellite imagery-based technology of UNE. A manual count of fruit on 18 trees per site was undertaken by staff from CQU, Qld DAF, NT DITT and AMIA.

Three technologies were involved in estimation of mango fruit load in-orchard: (i) farm pack house harvest records, (i) a manual count of fruit on tree, using a statistically valid sampling strategy and sample number, per orchard; (iii) a machine vision-based estimate using an in-field rig driven at 5 k/h with an image processing pipeline for fruit identification and count; and (iv) a machine vision-based estimate of flowering level.

(i) Farm packhouse records

Farm records were sourced as 'reference' values to benchmark forecasts against.

(ii) Manual count

Currently, commercial farms either 'eyeball' fruit load, or, in best practice, count fruit on a sample of trees. However, the sampling procedure used is not based on a statistical consideration of sampling need, and typically involves s ample of trees encountered in a straight line walk across an orchard block.

A statistical consideration was given to this application, in terms of sampling strategy and sample number. Method detail can be found in Walsh et al. (2021) and Anderson et al. (2021).

(iii) Machine vision estimation – fruit count

The in-orchard machine vision hardware was further developed, with the addition of an uninterruptible power supply (UPS) and improvements in housing and frame. The image processing pipeline was also improved, with the further development of a tracking algorithm, as described in Wang et al. (2019). This allowed count of fruit across frames, from video acquired at 5 frames per second. Fruit were 'counted' when not identified in seven consecutive frames.

Fruit size estimation

Fruit size at harvest can be estimated from measurements made in earlier weeks given knowledge of the rate of fruit growth. Fruit were tagged and measured by caliper at weekly intervals to establish a method for forecast of size at harvest. Detail is provided in Marcelo and Walsh (2022).

Given detection of fruit in a colour (RGB) image, fruit dimensions can be calculated in terms of number of pixels. Conversion of this measurement to an actual measurement requires knowledge of camera to fruit distance. Once approach to this is the use of a camera for both RGB and depth (RGB-D). RGG-D cameras can operate using stereo vision, structured light, or a time-of-flight principle. Several low-cost cameras were characterized in context of the application of fruit sizing in orchard at day or night. Assessment criteria included measurement accuracy and performance under varied light conditions. Further documentation of the methods followed can be found in Neupane et al. (2021).

The object detector used in counting fruit was used, however many fruit imaged on a tree canopy are partly occluded, and inappropriate for sizing estimation. Therefore, a system for segmentation of fruit related pixels and rejection of partly occluded fruit was developed. Further documentation of the methods followed can be found in Neupane et al. (2022).

Flowering estimation

A YOLO based deep learning detector for detection and classification of mango panicles to three maturity levels (Fig. 5) was trained and deployed in field trials. Details of associated methodology can be found in Koirala et al. (2020).

Data display

Supporting all of the above tasks, a web-app based decision support system was further developed to display data on fruit load, size and harvest timing to both farm managers and value chain decision makers. The web-app was designed around a hierarchy of users, e.g., farm owner, manager, consultant, with both manual and automated (API) data import. Farm set up involves input of block boundaries and crop details. Data inputs include temperatures, estimates of flowering times and fruit load, fruit size and fruit DM. An API was created for extraction of data to other farm management systems. An Agile software development method was adopted, given feedback from multiple users (growers) came within the fruit maturation period each year. Details of methodology with software architecture can be found in Appendix 2.

Mechanical harvester

Phantom fruit

Trials were undertaken to develop a cost-effective protocol for production of non-perishable 'phantom' fruit, for use in comparative trials of gripper function. Moulds were created of real fruit using a number of materials, e.g., Plaster of Paris and silicone (polydimethylsiloxane, PDMS), and phantom fruit were cast using various materials, e.g., formulations of PDMS and starch. Two phantom stalks were also trialed, one based on a piece of dowel, the other on magnets. The phantom fruit were benchmarked to actual mango fruit on the characters of density and firmness, while the phantom stalk was benchmarked in terms of force required to detach the fruit from the stalk. Detail is provided in Goulart et al. (2022; provided as Appendix 3).

Harvester

The 'Mk 1' prototype mechanical harvester system of the Phase 1 project was further developed in terms of (i) improved end-effector (gripper) design and function; (ii) improved conrol of operation. Performance was documented in terms of gripper success rate, harvest efficiency (% of fruit picked) and postharvest injury.

(i) Gripper design

Comparative trials of multiple gripper designs were undertaken to evaluate grasping and picking efficiency, with the candidate robotic grippers tested in an artificial but reproducible scenario, and under field (orchard) conditions. Gripper design evolved in terms of finger type, length, spacing and orientation within the 'hand' (Figure 34), and the pressure used to close the gripper.

Figure 34. **Example of grippers used in trials.**

A grasp was considered successful if the fruit was held through the detachment process, i.e., through wrist rotation and arm retraction, with placement of the detached fruit in an allocated receiving area. Failures were characterised in terms of (a) grasping, (b) rotation and (c) retraction of fruit, for fruit varying in weight and shape, and with variation in the position of the fruit relative to the axis of the harvester's arm. These exercises defined the effective 'picking volume' for each gripper for each fruit size and gripper design.

Gripper design evolved based on the results of the iterative trials. Gripper parts were designed in Fusion and 3D printed using a Flash Forge Guider II 3D printer using Tecor ABS printer filament.

(ii) Control software

A redesign of the system control software was undertaken to allow more control of individual and collaborative gripper functions and to decrease cycle times was also undertaken. The redesign followed the waterfall software development life cycle (SDLC) using the programming paradigm of object-oriented programming (OOP). Waterfall SDLC was chosen because the uncertainty of this proposed project is low (i.e., requirements are well defined), and the software complexity is low.

The GUI was developed using Qt Quick framework and Python. The vision system was also written in Python. The software executed by a Beckhoff PLC (programmable logic controller) to control the actuators was written in Structured Text (ST) and Function Block Diagram (FBD) as per IEC 61131 standard. Performance of the vision system was benchmarked to the existing system in terms of frames per seconds and CPU utilisation.

Harvest effectiveness was assessed in terms of the percentage of fruit harvested and time taken to harvest. Laboratory trials using phantom fruit were used to develop 'operational rules', around scenarios for collaborative arm function, and acceptable grasping points, e.g., vertical and horizontal displacement of the fruit centroid from gripper centre.

The two best performing designs were further tested in field trials. Field trials were undertaken at Martos Mangoes on R2E2 fruit, Groves Grown and Tropical Produce on Honey Gold fruit, Groves Grown on Keitt fruit and Niceforo Group farms on Calypso fruit.

Banana digital solutions

The initial part of the first year of the project was dedicated to an investigation of the instruments that are already being utilised by producers in the banana business. This investigation led to the conclusion that the first thing that needed to be digitised on the farm was the labour management system, followed by the fertiliser and chemical management systems. Designing a digitised system to manage the labour and the chemicals and fertilisers involved having numerous conversations with farmers about the various ways in which they apply inputs on their farms.

The project also mapped out the current solution in the market although there weren't many and in some cases, there were none. During the life of the project, our team created the software that is necessary to manage such facets on a farm level for banana growers in all sizes.

Once we reached the next stage in the life of the project, we did software implementations on the farm with the help of a dedicated staff member. The project team used various messaging channels as the primary means of communication between the teams working on the farm and the team working on Tie Up Farming. The frequency of this contact ranged from once per week to twice every month.

In the second year, the Tie Up Farming project started developing a technique for bunch tagging using QR barcodes and a technology using global positioning system (GPS) at its core. Bringing together a group of engineers to work on the development and installation of the tagging system that was used on the farm's vehicles. At first, it was believed that the GPS technology would be the most efficient method for identifying the bunches of bananas in their precise location on the field. Following our finding regarding the GPS efficacy, we were able to determine that the use of QR barcodes does not give the level of accuracy and resilience that is necessary for tags to endure in such a demanding environment. Installing scanners on the farm vehicles and scanning the tags when the user is at the spot where they are supposed to put the tag on the banana bunch using RFID technology was the preferred method after rigourous testing accuracies and robustness of tags.

The packing shed management that was refined for the banana growers was completed during the third year of the project. Tie Up Farming did not have a commercial rollout of the packing shed through the life of the project.
In the pack house, we were able to track the number of banana bunches that were taken from each block and the total weight of those bunches. In addition to this, we provided a comprehensive yield mapping for each block by identifying the tags that were attached to the bunches through the use of RFID scanners.

Tie Up Farming experimented with a few different approaches to scan QR barcodes in the packing shed, but were unable to get a success rate of more than 90% in that area. We were able to obtain a 99% tags scanned success rate with the RFID fixed scanner that we deployed in the packing shed.

This work was carried out by a member of staff (excluding hardware installations in the packing shed) who, relocated to Queensland during the second year (2020). This team member worked on the farms to instal the technology and train others how to make the use of it and getting feedback on how to improve it.

The software development team was responsible for the software development, and with dedicated personnel for this project situated in Queensland were responsible for the implementation of the product. There were instances when we dispatched personnel to support the implementation of hardware as well as the creation and installation of new hardware.

Throughout the process, growers had decided not to participate in the project for a variety of reasons (COVID-19 related reasons were the main ones).

Extension

Extension activity was undertaken in a 'public' space through collaboration with AMIA, NTDIT, Qld DAF and the grower groups, supporting industry events and publications, and in a 'private' space through interaction with the commercial groups seeking to adopt the technology.

Support provided to CQU, UNE

The Australian Mango Industry Association (AMIA), Queensland Department of Agriculture and Fisheries and the Northern Territory Department of Industry Tourism and Trade supported the CQU and UNE delivered components which seek to deliver tools to assist in the forward estimation of fruit harvest maturity and fruit load. Support consisted of ground truthing, connecting the team with interested growers, calibration assistance, material troubleshooting.

Communications and Extension activities

Australian Mangoes reported or provided a platform for project partners to report on the project findings and showcase the tools/technologies which were developed as part of this project for the Mango Industry (see media section for details and links).

Communication and extension activities included presentations at the Australian mangoes' pre-season roadshows, hosting field days and webinars, developing promotional and tutorial videos, articles in Australian Mangoes' newsletter and magazine, webpages and social media posts.

Impact of the Covid-19 pandemic

Due to COVID-19 lockdowns, there were restrictions to deliver stakeholder face-to-face gatherings and industry field days. Unfortunately, Australian Mangoes' North QLD pre-season roadshows were cancelled in 2021. A remote sensing webinar was hosted on 31 August 2021 instead.

Having regionally based Industry development officers and departmental staff was critical to ensure project activities could continue during the COVID-19 lockdowns.

Results and discussion

KPI 3.3 Develop improved pre-harvest yield forecasting accuracies at the national, regional and farm level for macadamia, mango, olive and citrus.

The full results achieved against this KPI can be found in the Appendix 1. section of this report (National Mapping of Tree Crops section 2.3, Macadamia section 3.3 Citrus section 4.3, Mango section 5.4, Olive section 6.3). In brief,

Macadamia

Over the course of the project, grower level data was provided by 21 macadamia orchards, consisting of 204 blocks, totalling 1156 yield records from 2012-2021. This covered 1,800 hectares, approximately 5% of the Australian industry, from mid-NSW to north-QLD. The first component of the macadamia work developed a macadamia tree planting year predictor with mean absolute prediction error of 1.7 years. This was used to provide annual statistics of total macadamia area by year to the Australian Macadamia Society and Queensland Department of Agriculture and Fisheries. The second component developed a novel block level yield forecasting methodology based on the extensive amount of historic yield data collected, historic acquisitions of satellite imagery and weather variables. The resultant models generated a mean absolute prediction error of 20-25% at the **block level** (except for some severely drought effected orchards in 2020) for predicting average and total yield, and median **farm-level** production prediction errors of 8-12% (excepting 2020). These predictions were made months prior to commercial harvest, did not require infield data collection and produced accuracies that exceeded current commercial practice.

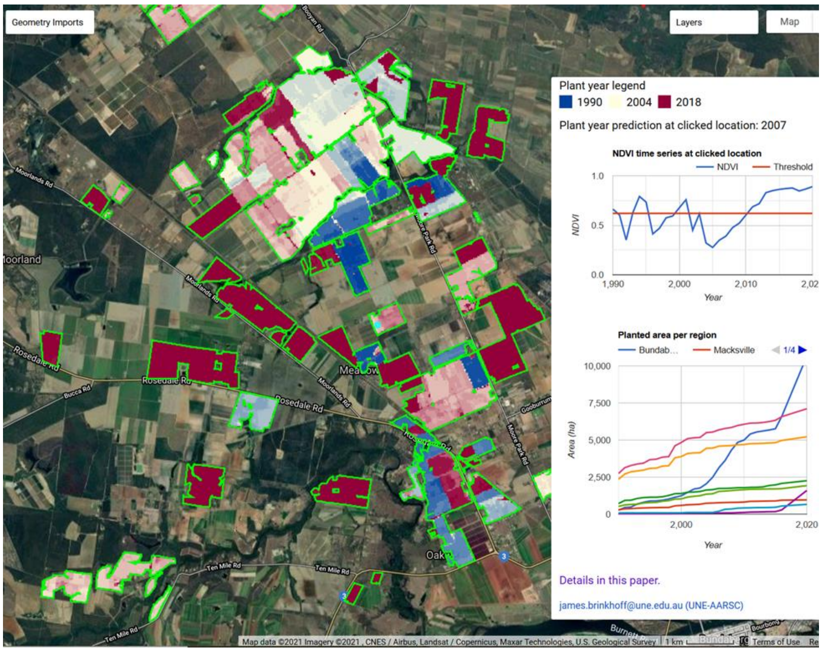


Figure 35. Per-pixel planting year predictions near Bundaberg, supplied as a web application to the Australian Macadamia Society.

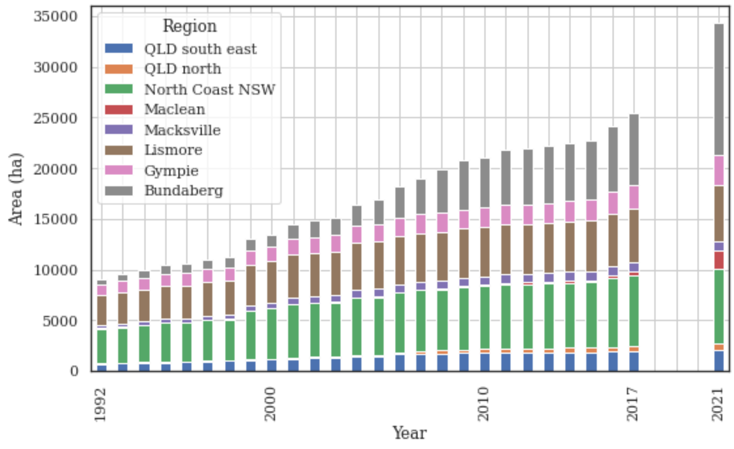


Figure 36. Planted macadamia area per region, per year.

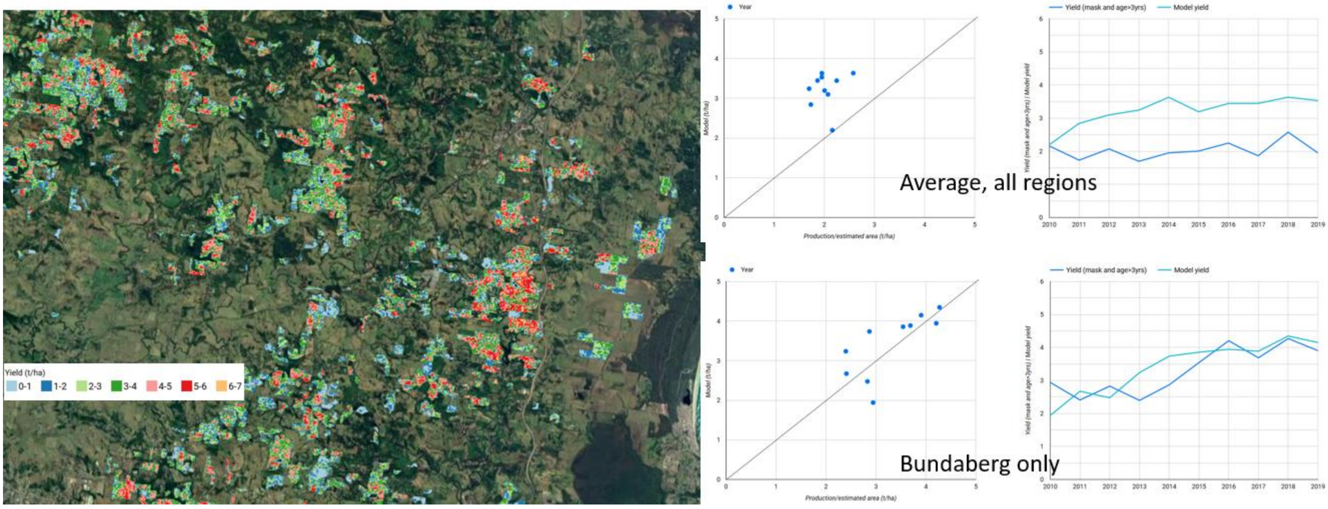


Figure 37. Per-pixel yield forecast across the whole Australian tree crop map, and accuracy for all regions (top right) and only Bundaberg (bottom right).

Citrus

For the citrus component of the Phase 2 project, two methodologies for improved pre-harvest yield forecasting and estimation at the farm and regional level were tested. The '18 Calibration Tree' approach (18CT) was used to provide insight of block/orchard variability which supports harvest segregation and the more judicious use of farm inputs (water, fertiliser etc). This approach requires tree level fruit counts to be collected during the growing season to establish an empirical relationship between remote sensing data (in the form of vegetation indices – VIs) and yield (t/ha, kg/ha). In total, 51 orchards across Red Clift, Leeton and Moora (cv. Afourer Mandarin and Late Lane, Washington, Chislett and Barnfield Navels) were sampled between 2020 and 2021. The second remote sensing approach, the Time series method (TS-Citrus) was developed to provide early yield forecast at the block level that can be extrapolated to farm and region level. This approach provides yield estimates around fruit set, months before commercial harvest and does not require infield sampling. For this method, historic yield data from 2007 until 2022 was sourced from five commercial farms (FC, FH, FK, FM and FT) representing 4.7% of the total planted area of citrus in Australia, including the most common citrus types: Navel, Mandarin, and Valencia and varieties (26 in total). Specifically, 27% of planted area in the Wheatbelt region, 14% in the Riverland and 6% in the Sunraysia were analysed. From the total number of blocks included in this study, Navels represent 50% of the planted area in the Sunraysia, 64.5% in the Riverland and 75% in the Wheatbelt region and Mandarin (Valencia) represents 50% (6%), 28.3% (7.2%) and 12.5% (12.5%), respectively.

Overall prediction accuracies from the 18CT method ranged between 80% and 98% with the highest error (30%-40%)

coming from orchards that experienced hailstorm damage and such suffered major yield loss. The prediction accuracies for the TS-Citrus method at the **block level** were on average 71% and at the **farm level** 80%. The accuracies from both methods exceeded current commercial yield forecasting practices.

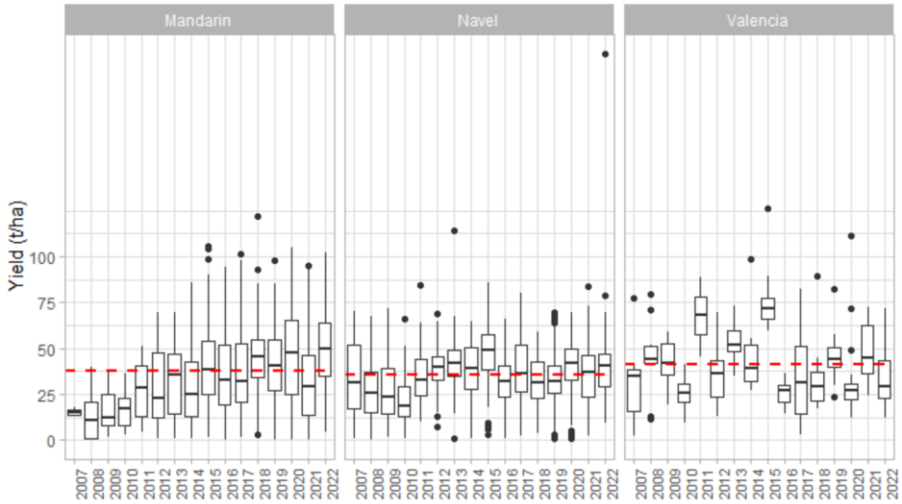


Figure 38. Historical production of citrus blocks according to citrus type: Navel, Mandarin, and Valencia

Yield forecasting using the 18CT methodology

Obtaining an accurate yield forecast based on the 18CT method relies heavily on the ability to get accurate counts (and weights) of fruit on the 18 calibration trees. If this is done poorly, then the extension of those 18 trees to all trees in the orchard will be inaccurate. From the field work conducted, it was identified that fruit counts taken at final fruit set (mid-way through the growing season) were inaccurate mainly due to an inability to see the fruit within the canopy (fruitlets were about 10-15 mm diameter).

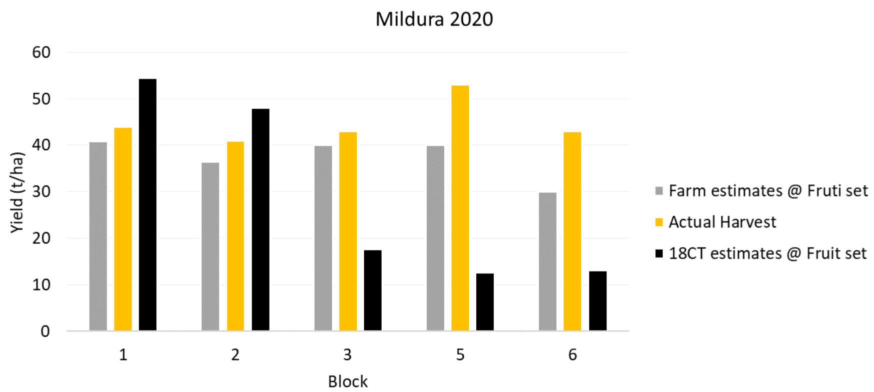


Figure 39. Comparison between farm estimated yield, 18CT estimates at fruit set and actual harvested yield

Fruit counts/ weights collected 4 to 5 weeks prior to harvest resulted in much more accurate results (refer to Figure 39). Once the fruit is bigger and it is possible to clearly see them, accuracies improved. When 18CT was tested between 1-2 months prior commercial harvesting, the differences between actual harvest and estimated yield were significantly reduced. Overall accuracies ranged between 80% and 98% (Figure 52) with the highest discrepancies (30%-40%) coming from orchards that experienced hailstorm damage that altered the expected yield (potential yield).

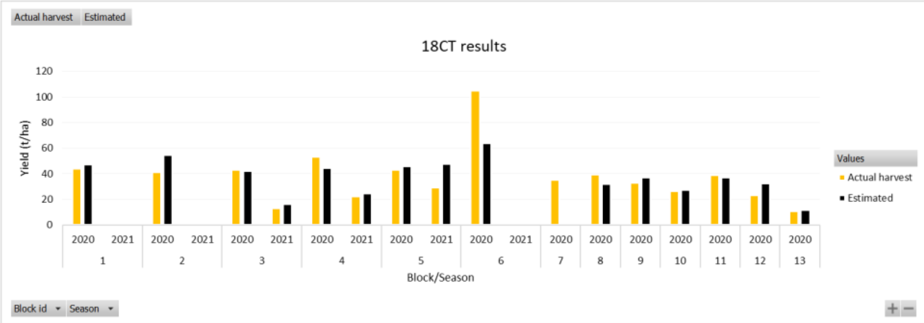


Figure 40. Comparison between farm estimated yield, 18CT estimates at pre-harvest and actual harvested yield.

Olives

For the olive component of this project, groves located in Mornington Peninsula and Boort (VIC) were included. A total of 19 groves between 2020 and 2022 were sampled to test the '18 calibration tree' (18CT) methodology for yield estimation at the block level. The study demonstrated the ability of the 18CT to estimate yield one month prior to harvest with varied accuracies that were dependent on the conditions during calibration and harvest timings. Accuracies at the **block level** ranged from 63% to 99.8% with eight out of 11 groves, with an overall accuracy of above 85% achieved at the **farm level** (Farm 1). Lower accuracies were achieved at the two other farms (Farm 2 and Farm 3) as a result of external factors not related to the methodology. Overall, the remote sensing yield forecasting methodology developed through this project offers prediction accuracies higher than commercial practice.

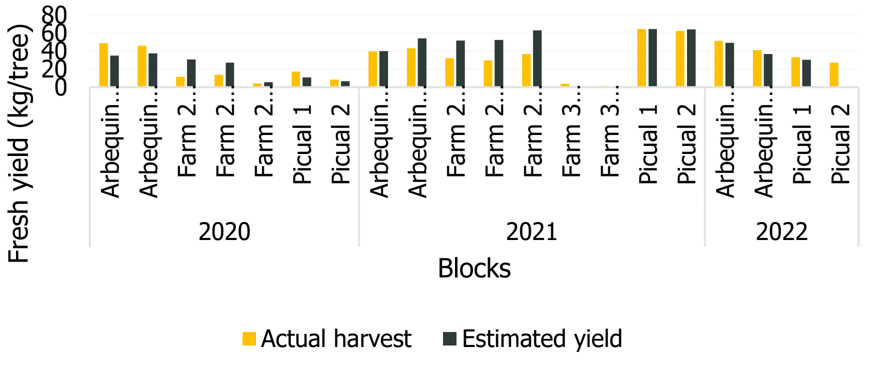


Figure 41. Comparison of yield values reported by the grower (Actual (commercial) harvest), and estimated yield from 18CT approach.

Mango

This research investigated the accuracies of high-resolution Worldview 3 (WV3) satellite data (single capture) and the 18-tree calibration (18CT) methodology for pre-harvest mango yield prediction and yield variability mapping. This was validated over three consecutive seasons (2019/20/21), encompassing 13 farms (>250 individual orchard blocks) across four growing regions, eight mango varieties, with various tree ages and management practices. On average, an overall accuracy of ~87% at **block level** and ~94% at **farm level** was achieved in fruit count estimation using satellite data for 2019-21 seasons, a significant improvement on traditional manual yield estimation methods. In addition, the use of only 18 trees for in field calibration was significantly less than the 2-3% of trees currently counted by growers, offering significant labour and time savings for mango yield forecasting. Further evaluation of both low cost (Planet) and freely available (Sentinel-2) satellite data (over 21 blocks 4 farms in NT, NQLD and SEQLD regions for 2019/20 season) also produced comparable yield forecasting accuracies. This result is encouraging as it presents growers with a range of remote sensing cost options. A time-series yield forecasting method based from Landsat satellite imagery was also evaluated to develop a model that provided yield forecasts much earlier in the season and with no infield fruit counting required. This further reduced the labour costs and time to estimate yield manually. The results for 2021-22 season were found to be highly accurate at both **farm** and

block level, with yield prediction errors ranging from 2-15%. These accuracies exceeded commercial practice and as such is continuing to attract more Australian mango growers every season.

Time-series model prediction – Landsat data

Figure 42 shows an example of 2020 prediction accuracies (actual verses predicted) of the time-series yield model approach developed from historic canopy reflectance (derived from Landsat satellite data) and corresponding annual yield data from several mango orchards grown in Katherine, NT. The model was developed from 2013-2019 yield data and the spectral response of respective blocks and included two mango varieties KP and R2E2. The prediction accuracy was found to be extremely high with R2= 0.82 and RMSE = 9892 Kg. The model was then used to predict yields for the 2021-22 season for the same orchard blocks.

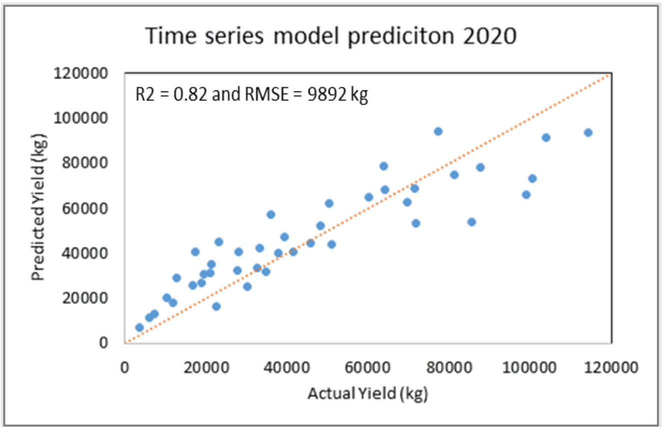


Figure 42. Performance of time-series model prediction accuracy for 2020 season for orchard blocks in Katherine.

For the 2021-22 season, the time series approach again produced forecasting accuracies that exceeded those from current commercial practice (between 2-15% better) for 30 KP blocks and 10 R2E2 blocks grown in Katherine, NT. Although some variability in accuracy was observed at the block level, the farm level prediction was between 97% for KP to 103% for R2E2 blocks, when compared to packhouse data (Figure 43). The model was further refined for the 2022-23 season by including yield and spectral data from the 2021-22 season. Using this updated model, predictions were provided to the grower mid-July, 2.5 months earlier than the actual harvest (scheduled in late September 2022). Unfortunately, the final yield data has not been supplied by the grower in time for the submission of this report.

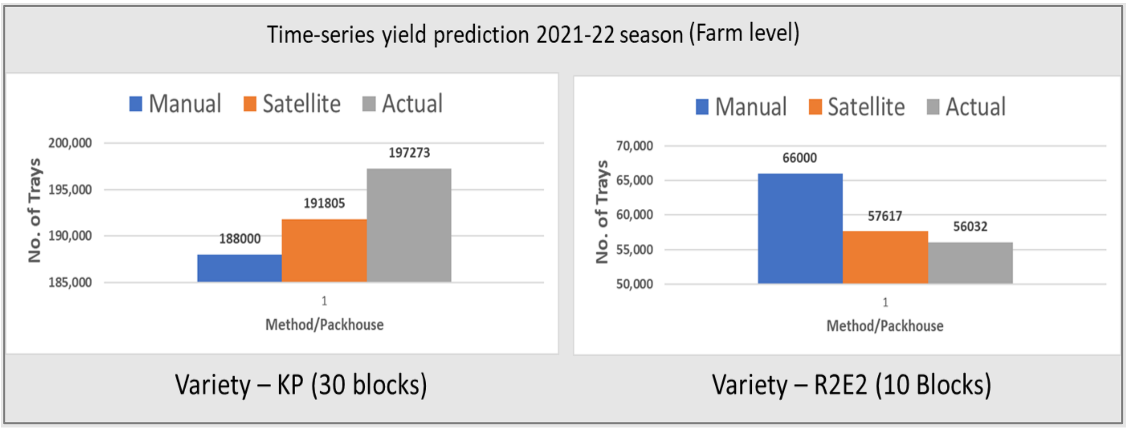


Figure 43. Comparison of time-series based yield predictions with grower's manual estimates and actual harvest data for the 2021-22 season for Katherine farm.

As part of the mango component of this project, an on-going PhD study is evaluating a range of analytical methodologies and input variables (yield, location, variety etc) to improve the accuracies of remote sensing-based yield forecasting. Two scientific papers have been published (one in a peer reviewed journal and the other presented at two separate conferences in the USA (15th ICPA) and Australia (UNE Postgraduate Conference)). The first paper (Torgbor et al., 2022b), used Sentinel-2 derived vegetation indices to retrieve five phenology stages of mango (i.e. Flowering/Fruitset (F/F), Fruit Development (FRD), Maturity and Harvesting (M/H), Flush (FLU) and Dormancy (D)). The second paper (Torgbor et al., 2022a), applied Sentinel-1-derived (SAR) radar vegetation index (RVI) in retrieving three key phenology stages of mango namely Start of Season (SoS), Peak of Season (PoS) and End of Season (EoS). Currently, an assessment of the performance of six machine learning algorithms using Landsat data in predicting mango yield in two farms of the Northern Territory is on-going. Preliminary results from this study show that the Random Forest and Support Vector Regression algorithms have some potential in predicting mango yield at the block and farm level. It was further observed that model accuracies at the farm level (>80%) are generally better than the block level (>50%) for all the models tested.

All tree crops

A main goal of Phase 2 project was to develop remote sensing-based yield forecasting methodologies for each of the participating industries. The development of the 18-control tree and 'time series' models have achieved this outcome at the block and farm level.

The pros for the 18-tree method:

- provides a more accurate measure of yield variability at the within orchard block level;
- does not require historic yield data;
- accounts for biannual/ irregular bearing;
- can be calibrated for fruit size, maturity, disease.

The cons for the 18-tree method:

- requires very high-resolution imagery that can be expensive;
- requires infield fruit counts to calibrate the imagery;
- generally, predictions can only be provided around commercial harvest time;
- not scalable to regional and national level.

The pros for the 'Time-series' method:

- uses freely available satellite imagery;
- can provide predictions months before commercial harvest;
- does not require infield fruit counts;
- can be scaled to regional and national level;
- can be automated to form predictions on mass.

The cons for the 'Time-series' method:

- image resolution not able to differentiate individual tree crowns;
- unable to form predictions at the within orchard level;
- susceptible to error from irregular bearing or unusual events (storms, disease, pest);
- requires at least 5 years of historic yield data.

In terms of yield forecasting at the regional and national level, macadamia and citrus are the most progressed. This is the result of extensive grower production data being supplied from multiple regions, and growing seasons. The collation of this data with the existing time series yield models will allow regional forecasts as well as the forecasting of farms without historic yield data to be made.

KPI 3.4 Develop practical tools and analysis methodologies that improve the within orchard monitoring and mapping of tree health, fruit quality and maturity.

Throughout the Phase 2 project, remote sensing has been demonstrated as a highly accessible and accurate tool for identifying variation in tree vigour (health and size) across orchards within a growing season and across years. Planet, Sentinel, Landsat and Worldview satellite imagery as well as airborne imagery from CERES were all shown to be useful for this purpose and as such present as a wide range of resolutions (temporal, spatial, spectral and radiometric) as well as cost option for end users. The provision of tree vigour maps (through Web- Apps, pdfs or other format) directly inform growers on where poor and high performing areas are occurring in their orchards. Simply knowing where and when to conduct targeted agronomy can help growers better understand what biotic and abiotic factors are driving orchard variability in terms of tree health as well as productivity, maturity, quality and phenological growth stage.

For olive, the evaluation of a range of technologies to better measure the impacts of water stress on tree vigour, yield, oil accumulation and final oil content (%), directly respond to requirements of this KPI. The evaluation of a range of technologies, identified dendrometers as being the most sensitive to drought stress. These sensors are commercially available and can be deployed with remote access (LP-WAN) to improve grower accessibility. The broader observation that the current levels of irrigation could be significantly reduced without reducing yield potential and quality (particularly during low bearing years), presents significant benefit for reducing water costs for growers and environmental impact. The further identification that olive trees from areas of low vigour accumulated oil at a faster rate than trees of higher vigour, offers significant benefit to growers in terms of more accurately determining when to harvest (based on optimal fruit maturity) as well as the opportunity of employing a segregated harvest to ensure optimal fruit maturity.

For mango, the PhD study identified that utility of frequently acquired, historic satellite imagery for 'benchmarking' seasonal growth as well as indicating the impacts of extreme weather events. The study has determined the relationship between these annual growth profiles with the timing of key phenological growth stages (i.e. Flowering/Fruitset (F/F), Fruit Development (FRD), Maturity and Harvesting (M/H), Flush (FLU) and Dormancy (D)), outcomes that can greatly assist growers in better timing orchard management activities, including the timely application of crop inputs. These results have been published in a peer reviewed journal as well as presented at two separate conferences in the USA (15th ICPA) and Australia (UNE Postgraduate Conference)).

As mentioned previously, the analysis of historic time series satellite data in conjunction with the national map of orchards was used to calculate orchard planting dates for macadamia. For citrus, the focus of Phase 2 was building a better understanding of the relationship between tree canopy reflectance properties and yield.

KPI 3.5 Develop and deliver improved detection and management tools and strategies to control future biosecurity threats and natural disasters.

The phase 2 project produced several outcomes that are relevant to the improved preparation, surveillance and response to biosecurity threats. The national mapping of tree crops identifies the location of all commercial orchards over 1 ha (ATCM Dashboard). This information is essential in the event of a high-risk incursion as it directly informs first responders on where to conduct targeted ground surveillance and where to apply exclusion zones to prevent spread. Having a spatial context, the tree crop map can be overlaid with roads, water courses, walking tracks, topography etc. to better determine high risk movement scenarios and therefore assist in defining where exclusion zones should be implemented. The ability to undertake these two actions in near real-time can be the difference between containment and spread.

National mapping applications summary

The following section presents the mapping applications developed through project ST19015 that support both the development and extension of the Australian Tree Crop Map (ATCM) to industry.

The ATCM is shared across a range of location-based web applications, all available for access from the AARSC Industry

Applications and Maps Gallery webpage (www.une.edu.au/webapps). (Figure 44).

Each app is designed for simplicity (ease-of-use) for the capture and/or sharing of location-based information.

- ATCM Dashboard
- ATCM: Severe Weather App
- Bushfire Rapid Response Map
- ATCM Survey
- Industry Engagement Web App

Finally, several value-added mapping applications developed through this project are also presented.

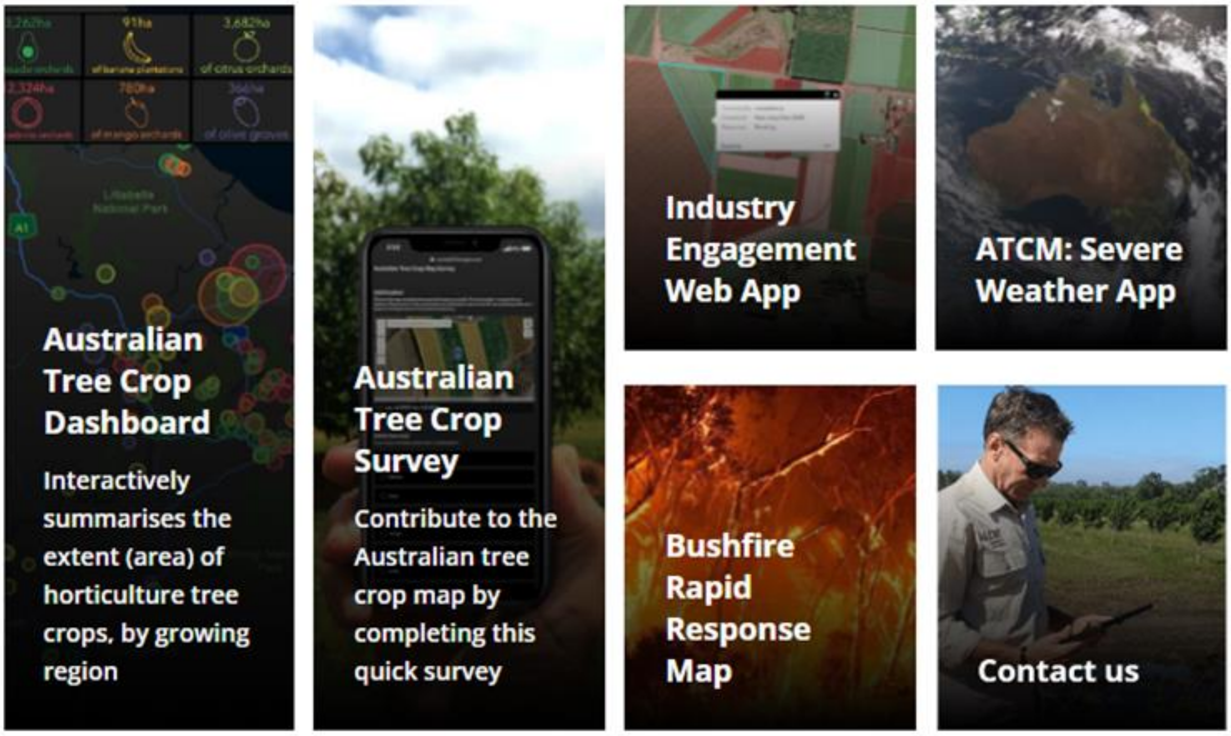


Figure 44. AARSC Industry Applications and Maps Gallery

Australian Tree Crop Map Dashboard

This dashboard-style web application features the latest map from the ATCM and presents metrics for avocado, mango, macadamia, citrus, olive, banana and truffle orchards (area of production in hectares) based on the zoom/view extent of the user. The dashboard includes the functionality to return metrics by state and territory and local government area (LGA) in a pop-up window as well as interactively based on the view extent of the user. Navigation around the map can be undertaken using the bookmark tool, or the user can simply type an address or place name into the search box and/or simply pan and zoom the map, which the dashboard will update the statistics for each tree crop (at bottom) on-the-fly, based on the map view extent. (Figure 45).

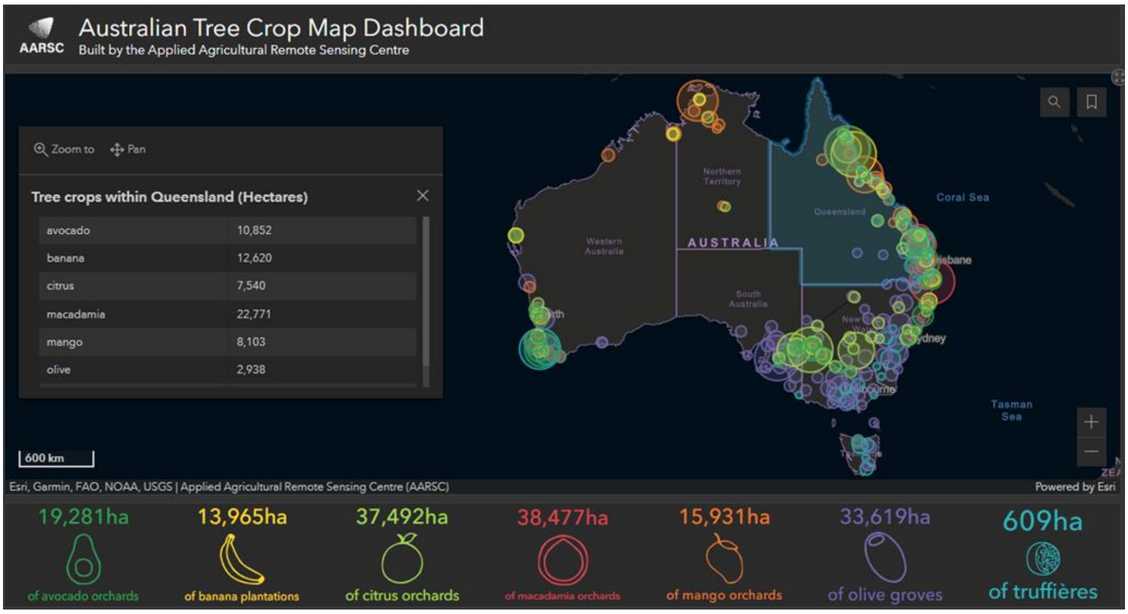


Figure 45. Australian Tree Crop Map Dashboard

The dashboard has been viewed (opened) 22,879 times. Significantly the dashboard was awarded first place as 'Best dashboard' application in the map gallery at the 2021 Esri International User Conference. This conference was attended by 70,000 delegates and as such the award is considered highly prestigious within the international mapping community. The dashboard has also been included in Esri's Living Atlas as authoritative data.

Industry Engagement Tools

The location-based tools described below have successfully supported the peer review and on-going (ad-hoc) updates of the map. These tools continue to be an invaluable resource to inform updates of the map, especially for new plantings. Each observation received is interpreted by the mapping team and actioned as updates to the map, including a response. This information validates existing data and can highlight omissions in the map which are then resolved, improving both the accuracy and currency of the map.

Australian Tree Crop Map Survey

The survey (built using Esri Survey123 for ArcGIS) has been configured to run in any browser on any device – mobile, tablet or desktop. (Figure 46). Users do not need to download or install any third-party software to use it. The survey provides an xtremely reliable and efficient means of engaging with industry and stakeholders to contribute to the mapping. Point observations submitted via the survey include location information, crop type and optionally a photo. The map to capture location information within the survey form includes both existing (submitted) survey observations and the ATCM to orientate the user.

Figure 46. ATCM Survey app

This information is interpreted at the desktop, it is extremely valuable in correctly classifying tree crops from one-another and essential for mapping new crops. Each ATCM survey was interpreted and actioned in the updated map, Figure 47 shows an example of survey observation submitted for a new macadamia orchard (including photo), since been actioned and updated in the map with the extent of the new macadamia orchard shown.

Figure 47. shows one example of new macadamia orchard (and photo) received via the ATCM Survey App

Analysis of the survey data shows a total of 2,781 new surveys were submitted during this project (Phase 1 total was 1,292). The total number of surveys submitted during both phases—including the non-featured crops (e.g., avocado, lychees, stone fruit, etc.) now totals 4,073. (Figure 48).

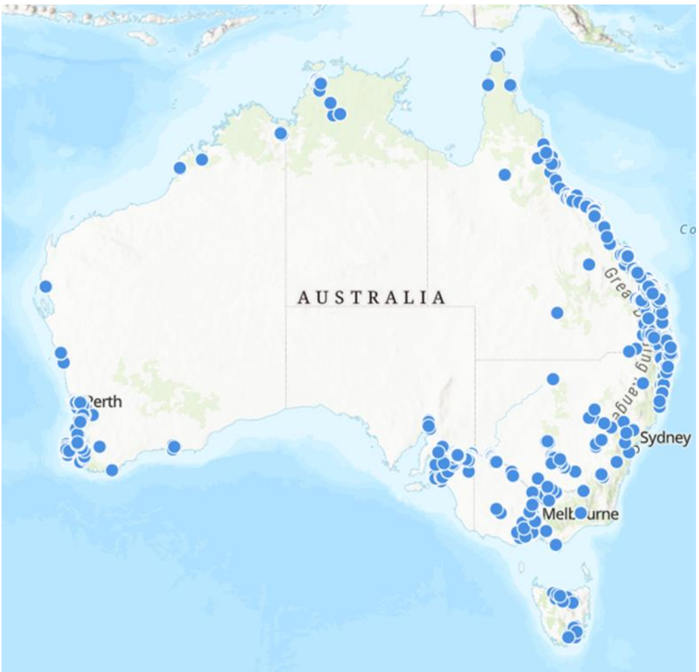


Figure 48. ATCM Surveys (showing all observations)

Summary analysis of the survey observations submitted during phase 2 is presented in Table 9. Other surveys include all non-featured crops (e.g., avocado, lychee, pecan, etc), note these have not been analysed for the area added or removed as generally 'other' tree crops are not explicitly mapped.

Table 9. ATCM Surveys summary (during Phase 2)

Tree Crop	Surveys (count)	Area added or confirmed (hectares)	Area removed (hectares)
Banana	96	318	50
Citrus	263	810	28
Macadamia	226	3,123	21
Mango	429	1,433	73
Olive	225	1,597	24
Other	1,542	Not available	Not available
Total	**2,781**	**7,271 ha**	**196 ha**

Industry Engagement Web App

The app presents draft mapping and enables comments to be added directly (anonymously). The app includes simple web-GIS capabilities that allow anyone to add (draw) a feature (as a point or polygon) on the draft map (Figure 49). AARSC interpret the information submitted and action updates to the map, which supports both the addition (and confirmation of existing) features in the map and removal of features either misclassified or removed. This application is critical to inform the mapping of new and crops, which cannot be mapped with satellite imagery alone.

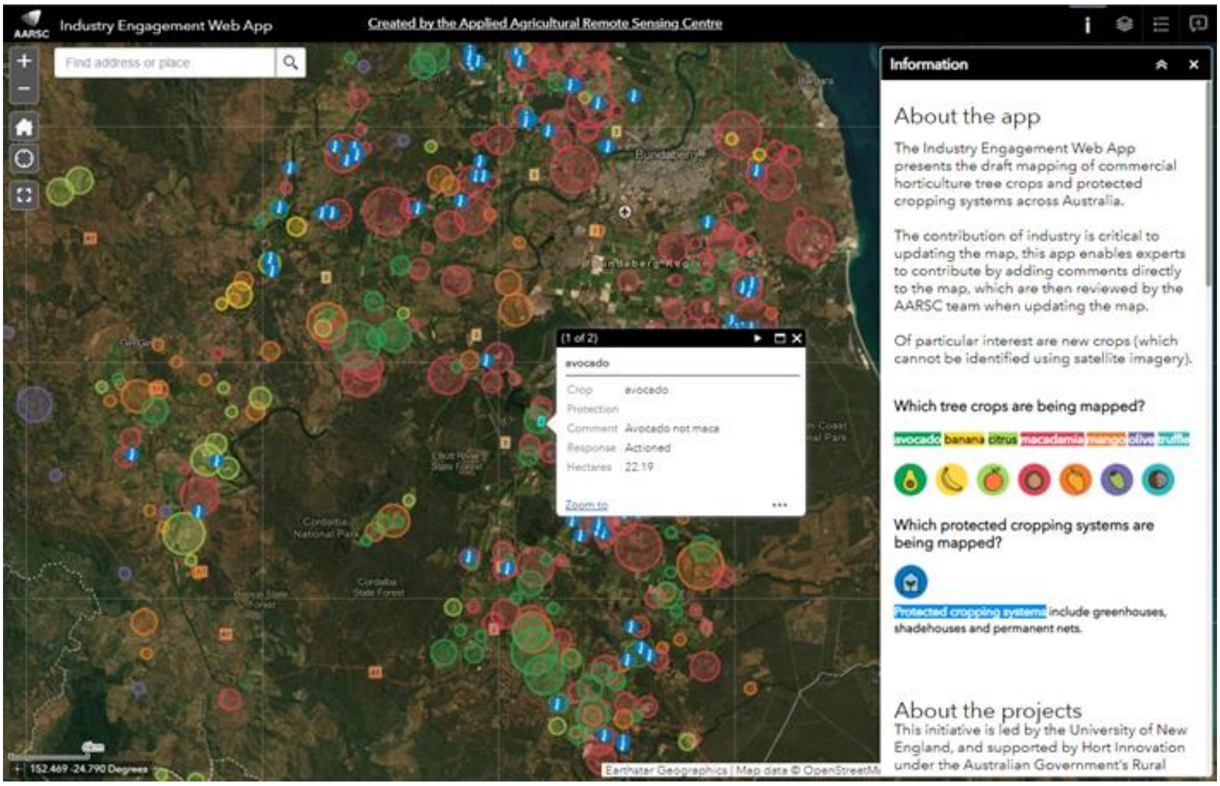


Figure 49. Industry Engagement Web Application, showing comment for a misclassified feature in Bundaberg

The Industry Engagement Web App has now been viewed a total of 6,225 times. Comments provided by participating growers include both point (location) and polygon (extent) observations. The total number of comments received (for all observations) through this tool is 909. Figure 50 shows the distribution of features in the map that were informed by peer review comments.

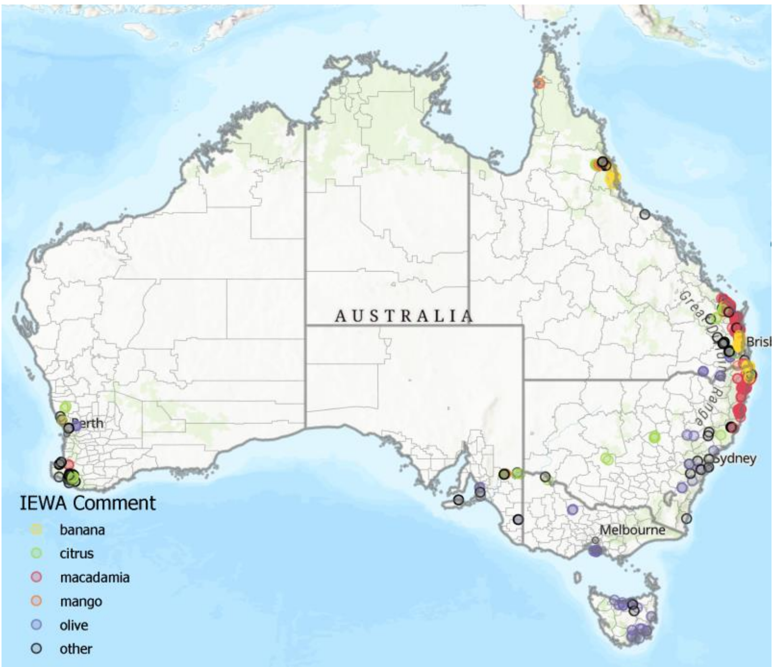


Figure 50. Distribution of features in the map informed by peer review comments

Analysis of the comments received is presented in Table 10. Additional comments were received associated with commodities outside the scope of this project report (e.g., avocado, lychee, etc) and are presented in a single class of 'other'. There has been significant engagement from all industries, resulting in a total of 10,609 ha of additions or confirmations and 2,001 ha of crops removed from the map. The most impact was seen in macadamia industry (9,027 ha added or confirmed) due to the extensive expansion of new plantings and the contribution by grower liaison officers at the Australian Macadamia Society in peer review.

Table 10. Peer review comments submitted in the IEWA

Tree Crop	Comments (count)	Area added or confirmed (hectares)	Area removed (hectares)
Banana	90	156	548
Citrus	96	589	1,016
Macadamia	500	9,027	67
Mango	57	59	370
Olive	99	778	0
Other	63	Not available	Not available
Total	**909**	**10,609 ha**	**2,001 ha**

Industry engagement in peer review is especially valuable for mapping new plantings, the response demonstrates the adoption of this output by industry, and further enables and supports on-going updates of the map in future.

To further assist the mango industry in being better prepared for future biosecurity threats, particularly those coming from our northern neighbours, the AARSC, together with the Australian Mango Industry Association (AMIA), state (Department of Agriculture and Fisheries) and federal biosecurity agencies (Northern Australia Quarantine Strategy, Department of Agriculture Water and the Environment), undertook a challenging project to map all non-commercial mango trees in the Cape York Peninsula. The area-of-interest included the Cape York Peninsula and Torres Strait Islands NRM regions, once developed the mapped location of non-commercial mangoes can be monitored (both on-ground and using remote sensing) for potential biosecurity threats. The project commenced with the collation and geocoding of existing data, which included some 1,580 locations of mango trees. This information was interpreted against high-resolution imagery (provided by the Queensland Government's Spatial Imagery Subscription Program), in combination with other ancillary data, to compile a draft baseline map. The draft Cape Mango Map was published in June 2021 and currently shows 8,969 non-commercial mango trees. Stakeholders have been encouraged to review the draft and contributed to the peer review and provide feedback. (https://arcg.is/0KLH1q).

The remote sensing analysis undertaken within the Phase 2 project also offers highly beneficial insights and outcomes relevant to biosecurity surveillance. The single capture of satellite and / or airborne imagery and the subsequent classification of tree health across an orchard can indicate individual trees that are underperforming or suffering from a constraint, including pest and disease. This output alone can direct where growers and surveillance teams should undertake infield assessment to identify the cause via visual assessment, PCR testing etc. As the imagery has a spatial context, GPS locations of sick trees can be extracted from the imagery to direct infield observation and similarly field observations can be linked back to the mapping layer to better understand distribution and spread of a particular threat. The time series analysis also provides a highly beneficial output. The establishment of a historic seasonal measure of canopy vigour can be used a 'benchmark' of usual tree, block, farm and even regional tree condition. Any rapid variation from this benchmarked performance may indicate the onset of a biosecurity incursion. This method can be automated to better inform growers and biosecurity agencies of 'where' and 'when' to look for possible incursions.

The full description of these methodologies are provided in the Appendix section of this report

Phase 2 (CQU) was designed to progress work on: (i) a harvest timing forecast system based on NIR-DM and 'automated' heat sums; (ii) a mango yield forecasting system based on in-field machine vision, and (iii) further development of the mango auto-harvester concept.

Forecast of harvest maturity

Two approaches were considered in the forecast of optimum harvest time: (i) the use of NIRS, and (ii) heat units (also known as Growing Degree Days, GDD).

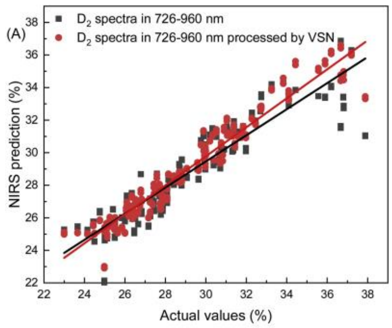
NIR-DM

Reviews

Three reviews were produced on the topic of the use of NIRS in assessment of fruit quality. Walsh *et al.* (2020a) provides a technical assessment of the strengths and limitations of this technology in context of fruit quality assessment. The existing literature is critiqued in terms of demonstration of the robustness of recommended optical configurations and modelling techniques, with many papers failing to demonstrate use beyond the harvest populations from which the training set was drawn. Walsh *et al.* (2020b) provides a consideration of the uptake of this technology in several value chains, with consideration of drivers and barriers. Anderson *et al*. (2022c) provides a review of the evolution in chemometrics methods occurring in this application area.

Application to olive

NIRS was successfully applied to estimation of dry matter content of intact olive fruit, as documented in Sun *et al.* (2020b). The developed model performed well in prediction of independent populations, with a slight improvement recorded with use of the variable sorting for normalization treatment (Fig. 51).



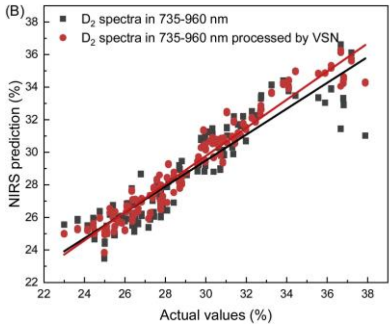


Figure 51. Prediction results for PLSR models based on second derivative and variable sorting normalization treated second derivative spectra, for instrument 16048 (A) and 17057 (B). Models were developed on populations 1–3 and used in prediction of population 4.

However, discussions with Boundary Bend revealed a weak use case for the technology. At present approximately 20 fruit are collected, brought to laboratory, macerated and assessed using a bench top NIRS unit for assessment of both moisture and oil content. The handheld unit allows assessment of fruit in orchard, with the advantage of rapid assessment compared to the laboratory assessment and could have some utility in guiding irrigation decisions. However, given the low cost of fruit and the centralized nature of quality control operations, the driver for adoption of a field portable, non-invasive technique is low.

Application to citrus

The three devices were calibrated using a population of 120 fruits and tested in prediction of SSC of a fourth population of fruit. The best cross validation and prediction results were achieved with the SunForest unit (Table 11. However, the SunForest device could not function in direct sunlight (data not shown). Further, the result of the prediction of the independent test set (R^2 of 0.62 and RMSEP of 1.16 %SSC) was poor in context of the variation expected in future test populations (SSC SD was <2 %SSC in 4 of 5 populations assessed in this study). Further documentation can be found in Aryal (2022, Ch. 7).

Table 11. PLSR cross validation (CV) and prediction (p) statistics for a model developed for each device (120 cv Imperial fruit calibration population, 30 fruit prediction population). Fruit were scanned in laboratory conditions ~20^{0}C) or in diffuse sunlight. Predict pop SD was 1.72 %SSC.

Device	Rcv^2	Rp^2
Condition	room	room
F-750	0.78	0.36
SunForest	0.86	0.62
MicroNIR	0.86	0.39

In conclusion, this technology has documented value in harvest maturity and or quality assessment of thinner-skinned fruit types, such as stonefruit, pomefruit and mango, but its use with mandarin or other citrus fruit is not recommended. The poor result is ascribed to the optical 'interference' of the relatively thicker skin of mandarin.

Application to mango

Experimental activity focused on demonstration of the robustness of DM models across fruit varying in temperature (Sun *et al.*, 2020a) or sourced from different growing conditions or cultivars (Anderson *et al.*, 2020, 2021).

From Anderson *et al.* (2021): Models were developed on a data set collected across three seasons (n = 10,243) and tested on that of a fourth season (n = 1,448). Model types included Artificial Neural Network (ANN), Gaussian Process Regression (GPR), Local Optimized by Variance Regression (LOVR), Local Partial Least Squares Regression (LPLS), Local PLS Scores (LPLS-S) and Memory Based Learner (MBL), with manual tuning of parameters undertaken. Additionally, two commercially available cloud-based chemometric packages for automated model development were trialed. Models were compared both on prediction results and on resources required for model building and implementation (Table 12). All of these models gave a better result than use of a global PLS model (the current industry practice). The best result (lowest RMSEP) was achieved with an ensemble of ANN, GPR and LPLS-S, with the best individual model result achieved by LOVR, with RMSEP of 0.839 % and 0.881 %, respectively, compared to the global PLS result of 1.014 %. The best precision was achieved with the LPLS model, with a SEP of 0.846 %, compared to the global PLS result of 1.012 %. LOVR was twice as fast as a generalized latent variable selection method LPLS-S-cv in prediction of independent validation set (at 58.7×10^{-3} s compared to 163×10^{-3} s). The ANN model was satisfactory in all categories (prediction speed, model build speed, and prediction statistics) and insensitive to tuning, e.g., 33 of the 70 parameter combinations were within 0.05 units of RMSEP of the minimum combination. However, the ANN learning rate was low. For applications that require 'real-time' prediction, such as fruit pack-lines, use of ANN and GPR models was recommended. For non-cloud based handheld NIR devices lacking the computational power to perform local modelling, ANN was recommended.

Table 12. Time to build models and time to predict per sample (seconds) per modelling technique. Handcrafted models were built on an Intel® Core™ i5-7300U CPU with 16 GB RAM. DR-LGB, DR-E and Hone-E were computed on their respective cloud servers. and not by the computer as specified in the above caption.

Time	ANN	SVR	SBL	PLS	MBL
sample (s)	0.01×10^{-3}	2.37×10^{-3}	21.55	0.01×10^{-3}	0.35
model build (s)	15.3	83.2	153	1.4	0.02
Time	LOVR	LPLS	LPLS-S-cv	LOCAL	LPLS-S
sample (s)	58.70×10^{-3}	25×10^{-3}	0.16	19.9×10^{-3}	25×10^{-3}
model build (s)	1.4	1.4	1.4	1.4	1.4
Time	GPR	Cubist	DR-LGB	DR-E	Hone-E
sample (s)	0.99×10^{-3}	0.95×10^{-3}	1.46×10^{-3}	6.0×10^{-3}	67.7×10^{-3}
model build (s)	810	216	210	8000/ 690	6000

Models used: Artificial Neural Network (ANN), Support Vector Regression (SVR), Spectrum Based Learner (SBL), Partial Least Squares (PLS), Memory Based Learner (MBL), Local Optimized by Variance Regression (LOVR), Local Partial Least Squares (LPLS), Local Partial Least Squares with latent variables selected by cross-validation (LPLS-cv), Shenk LOCAL, Local Partial Least Squares Scores (LPLS-S), Gaussian Process Regression (GPR), Cubist, DataRobot Light Gradient Boosting (DR-LGB), DataRobot ElasticNet Ensemble (DR-E) and Hone Create Stacked Ensemble (Hone-E).

The (large) mango data set underpinning this study was publicly released as (https://data.mendeley.com/datasets/46htwnp833/2) and has been accessed by multiple other groups. These groups have demonstrated use of other modelling approaches, notably 1D convolutional networks (CNN). A Masters candidate has been started, tasked with the comparison of those and like approaches to the ANN models developed by Anderson *et al*. (2022).

An artificial neural network model was used in preference to the existing Partial Least Squares regression model and deployed through AMIA onto instruments used across the mango industry in the Australian 2021 and 2022 seasons.

Vis-NIR - Flesh colour

Flesh colour is a useful measure of fruit maturity, but it is currently assessed by cutting the fruit, i.e., a destructive measurement. In consequence, relatively few fruit per orchard will be assessed in a commercial practice. An attempt was made to use a non-invasive method (detail is available in Ch 7 in Amaral, 2022).

The best wavelength range for assessment of flesh CIE B was 522 to 909 nm (R^2=0.81 and RMSEP of 5.5, Figure. 52) for the 2018-2020 populations used, although starting wavelengths up to 633 nm and end wavelengths from 873 to 987 gave comparable results (data not shown). Wavelength ranges covering just the visible region of the spectra gave poor results. ANN and SVR models returned only slightly better results with RMSEP of 5 to 7 units. This level of precision is inadequate for harvest maturity estimation, given the need to distinguish between CIE B levels of 32 and 36 for Australian cultivars, and between 51 and 56 for Florida cultivars around harvest maturity.

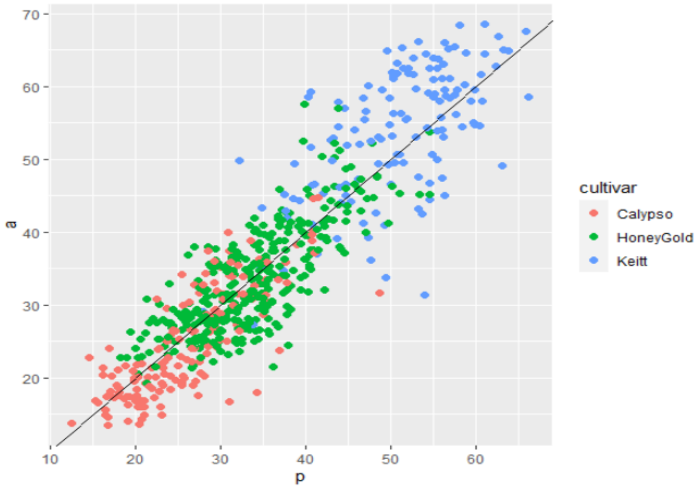


Figure 52. Scatter plot of actual (a) plotted against cross validation predicted (p) values for CIE B (right panel) using a PLSR model based on the range 522 - 909 nm (R^2 of 0.81, RMSEP of 5.5 % w/w), colour coded by cultivar.

Future research could attempt direct NIRS prediction of fruit GDD values from fruit spectra using non-destructive weekly data before, during and after commercial harvest.

<u>Orchard use of DM measurements</u>

The DM content of fruit is directly correlated to ripened fruit Brix, and thus eating quality. Specifications have thus been developed in this context, e.g., minimum 14% DM for KP fruit. DM content of fruit increases while fruit are on tree, as carbohydrates accumulate, and thus can be used as a gauge of fruit maturation, however the absolute level associated with harvest maturity will vary, associated with growing condition. There is, however, some confusion in industry between the eating quality specification and a harvest maturity specification. There is some confusion around the use of the DM quality specification as a harvest specification.

The following recommendation is made: As harvest GDD approaches, the non-destructive measure of NIR-DMC should be used to select fruit of a range of DMC values, and thus maturities, from an orchard. These fruit should be cut to assess flesh colour. The NIR-DMC of fruit at the harvest maturity flesh colour, as evaluated by comparison to colour charts, can then be established. That NIR-DMC value can be used in non-destructive assessment of fruit harvest maturity for orchards with similar growing conditions.

Heat units

The use of heat units in estimation of fruit maturation is well known, however the practice is not well established in the mango industry, and, when used, often compromised in practice. For example, the NT Government provides a calculator that allows use of temperature records of a 'local' BoM station (https://nt.gov.au/__data/assets/pdf_file/0009/267678/heat-sum-instructions.pdf). However, such stations are often at some distance from farms, with potentially different temperature regimes. Farms may have a temperature record from a weather station, but these stations are often compromised in location, e.g., adjacent to packhouse or on a farmhouse balcony, being reliant on a Wi-Fi connection. One farm recognized temperature variation across the farm and employed temperature loggers at various locations across the farm. These loggers require manual downloading for transfer of data, and annual battery change. On one farm, loggers were positioned within tree canopies rather than in the standard BoM position (open area, 1.2. m height, grass or mulch underneath). A need was identified for a 'set and forget', reliable, robust, low cost and accurate temperature sensor for heat unit estimation at multiple locations on farm, and for guidelines on placement of sensors on farm.

<u>Sensor evaluation</u>

Desired criteria for a temperature sensor were set as: (i) low cost hardware, i.e. <$200 per station , (ii) low cost on-going fee for data management, i.e., <$100 year), (iii) access to data; (iv) connectivity across the farm to allow automated data access, with multiple connectivity options, e.g., 4G or LoRa to 4G or wifi enabled gateway, (v) low power consumption, allowing operation for > 2 years unattended. Multiple units were evaluated on documented material, withT Logic (China), Senso Hive (Denmark), Monnit (USA) and SensorHost (Australia) evaluated physically. SensorHost was chosen for further evaluation based on match to specifications.

Sensor repeatability and accuracy was assessed by placing sensors adjacent to each other in three controlled temperature spaces for approximately 14. Across 168 temperature records collected at 15 min intervals, the mean and SE of the maximum absolute difference between the 6 sensors at each record time was 0.15 ± 0.01 ^{o}C. This result is consistent with the manufacturer specification on measurement accuracy of 0.1 °C.

The manufacturer recommended replacement of the two AA batteries (3.0 V when new) when at 2.4 V, although units were observed running with a battery voltage of 1.9 V. With the transmission rate set to 1 min intervals, battery voltage dropped from 3.1 to 2.4 V over 6 months, while remaining functional. Simplistically, this result suggests that at a 15 min logging interval the battery replacement period might be 15x6 months or 7.5 years, if voltage loss is linear with time. In Field use, sensor battery voltage dropped over 18 months of use from 3.1 to 3.0 V, at a 15 min logging interval. Any battery replacement period of over two years represents an acceptably low level of maintenance that farm management would support.

For sensors in Stevenson screens, the mean and SE of the maximum absolute difference between the paired sensors in screens located in adjacent positions in the field was 0.38 ± 0.05 ^{o}C, across 192 temperature records collected at 15 min intervals. In a comparison of stations in aged (yellowish) and new (white) screens (Figure 4.4b, the mean and SE of the maximum absolute difference between paired sensors in screens at the same field locations was 0.20 ± 0.06 ^{o}C, based on 192 temperature records collected at 15 min intervals. In a comparison of Stevenson screens of different designs (Figure 4.4a) using 96 temperature records collected at 15 min intervals, the mean and SE of the maximum absolute difference between the paired sensors was 0.56 ± 0.03 ^{o}C with the older screen having higher temperatures. These results indicate consistency between screens of a given type in terms of internal environment, even despite two years of field aging of the screen.

LoRa signal was good (-90 RSSI) for a clear line-of-sight of 500 m between sensor and gateway aerials, although consistent data transmission occurred at distances of up to 3 km, with signal as low as -100 RSSI. Data transmission also occurred at signal strengths as low as -120 RSSI. Atmospheric conditions impact signal transmission, so a system operating at -120 RSSI will likely fail at certain times of day, resulting in collection of less than 96 values per day when logging at 15 min intervals. Operation at RSS as low as -110 RRS is recommended.

The robustness in use, long battery life support and consistency between stations support a recommendation in favour of use of these stations for in-orchard use. Being LoRa signal dependent, sensors need to be placed in a relatively clear line-of-sight to the gateway aerial, with operations at signal strengths above -110 RSSI recommended.

Sensor canopy position

The outside of canopy sensor logged lower minimum temperatures and higher temperatures than an inside of canopy sensor in one orchard, while in another orchard there was less difference between the two positions (Figure 53). The difference is ascribed to the density of the canopy and/or surrounding soil cover characteristics, with creation of microclimate differences.

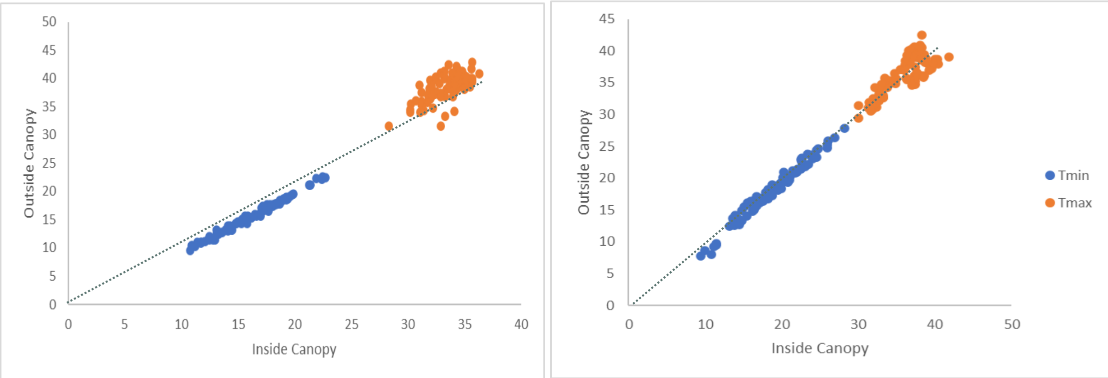


Figure 53. Scatter plot between outside and inside canopy measurements of maximum and minimum temperatures of a Darwin farm (left panel) and Katherine farm (right panel). Line of slope 1 is shown.

Accumulated GDD across the flowering to harvest period was higher for the outside of canopy sensor compared to the inside of canopy sensor, equivalent to 18, 1, and 5 days earlier harvests for the Darwin, Katherine and Yeppoon sites, respectively (Table 13).

Table 13. GDD accumulated over a one-week period in winter and summer and for the flowering to harvest total period at three sites. GDD was calculated from temperature records of paired sensors located inside a tree canopy and at an adjacent outside canopy position. Flowering to harvest periods were 04/06/2021-01/10/2021 for the Darwin farm, 10/07/2020-06/10/2020 for the Katherine farm and 07/07/2020-28/12/2020 for the Yeppoon farm. Data is presented for the difference between inside and outside sensors for GDD accumulated across the flowering to harvest period with associated calendar days equivalent, and the GDD calculated using Upper T method for the outside canopy sensor.

Site	flowering to harvest	flowering to harvest	difference (calendar days equivalent)	flowering to harvest (Upper T)
	inside	outside		outside
Darwin	1687	1960	273 (18)	1743
Katherine	1341	1351	11 (1)	1296
Yeppoon	1861	1925	64 (5)	1895

At all sites, the GDD-TB estimate was closer to the inside canopy estimate, consistent with the effect of canopy on Tmax (Table 14). The GDD-TB estimate is based on the premise that physiological processes slow at high as well as temperatures (see section on GDD Algorithm).

Vegetative terminals and panicles are largely on the outer part of the canopy. Depending on canopy architecture and position of panicles, the weight of the developing fruit may result in fruit development within the canopy, but fruit placement on the outside of the canopy is preferred, as this results in better quality fruit. Overall, measurement of ambient (outside canopy) temperature rather than inside canopy microclimate is recommended.

Sensor position on farm

Differences in (outside of canopy) temperatures existed between sites on a given farm (Table 13). These differences were significant in terms of fruit maturation GDD requirements, e.g., 1640 units from asparagus to harvest for Calypso. Site differences were greatest on the farm that had the greatest altitudinal variation between sites.

Table 14. GDD accumulated between flowering and actual harvest date season using temperature data from each of three locations on each of three farms. GDD calculated using the standard calculation (Eq. 1) and Tb = 12.

Farm - location #	GDD
Darwin-1	1950
Darwin -2	1960
Darwin -3	1798
Max difference	*163*
Kat-M1	1419
Kat-M2	1351
Kat-M3	1368
Kat-M4	1429
Max difference	*77.7*
Yeppoon-1	1925
Yeppoon-2	1861
Yeppoon-3	2147
Max difference	*286*

GDD, GD-15 min and GDH

The industry accepted GDD calculation is based on daily Tmax and Tmin and ignores the rest of the daily data. Thus, a day on which a temperature spiked to 35 °C for only 10 min will yield the same Tmax as a day where temperatures sat at 35 °C for 6 hours (Figure 54). An integral of temperature may provide a more relevant index of temperature in context of plant physiological processes.

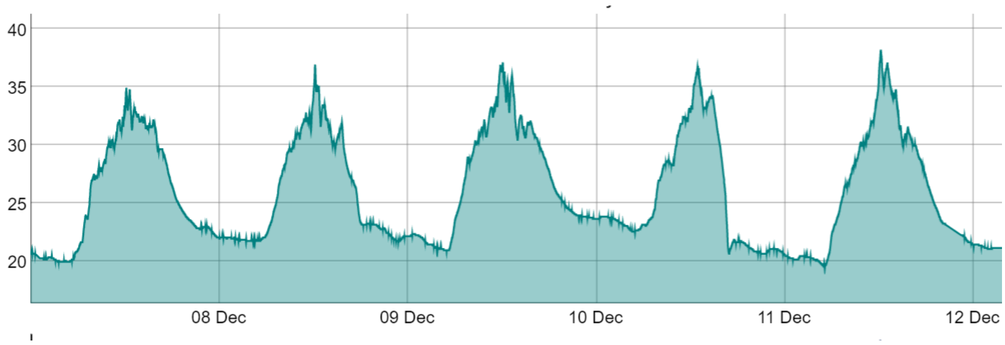


Figure 54. Temperature record for a site showing 'spikes' in daily high temperatures. Data logged at 2 min intervals.

For all three cases (winter week, summer week and whole season) and all locations, the GD-15 min and GDH temperature integral measurements were equivalent, and both gave lower values than the GDD calculation (data not shown). The use of GDD and GDH requires a different numerical target than GDD. The use of the GD-15 min and GDH therefore seems unwarranted except for sites that experience within-day temperature volatility. Further consideration of how often this condition occurs is recommended.

<u>On-line calculator</u>
A web app was established to provide an easy to use GDD calculator, Users enter flowering date and relevant cultivar GDD target, select their region or specific sensor and receive a forecast harvest date. This forecast is based on the current season daily maximum and minimum temperature to the current date, and a 10 year average for forecast purposes. A DAF prepared video introducing the site is available at
https://www.youtube.com/watch?v=4kvftGiK5qY.

<u>GDD-conclusions</u>
For the use of GDD in estimation of harvest timing, it is recommended that:

- GDD be based on local temperature monitoring, with multiple monitoring sites recommended for larger farms or farms with elevation variations that create microclimates.
- to aid the decision on number and placement of stations, monitoring of a large number (e.g., one per management zone) of stations over a one winter week and one summer period is recommended,
- temperature should be monitored outside the tree canopy, using the BOM standard of placement 1.2 m above a ground surface covered with vegetation or mulch.
- GDH is equivalent to GD-15 min and can be used for an integral GDD calculation, with both measures usually resulting in lower GDD accumulation values compared to the standard average of Tmax and Tmin calculation. However further work is required to demonstrate which calculation better represents the physiological maturation process.
- a Tb = 12 °C and TB = 32 °C (Upper T method) be used in calculation of GDD.
- the Upper T temperature method relative to the standard method should be further evaluated in terms of estimation of harvest maturity, particularly for northern sites.

It is also recommended that a single colour card set be used across all cultivars, including Keitt. Cards with scores of 11, 13 and 15 could be added to the existing 'Calypso' card set (QDAF 2019 print), with CIE B values of 43.0, 51.0 and 58.0, as illustrated in Table 15.

Table 15. Proposed fruit maturity colour swatches and associated CIE LAB values, as collected using Konica Minolta (CR-400) chromameter. CIE L have two proposed values separated by slash (/), the first one set for printing purposes based on a digital representation, the second one is the expected CIE L reading from a fruit using Konica Minolta (CR-400).

3 CIE L = 97.00/85.00 CIE A = -4.40 CIE B = 18.00	**5** CIE L = 97.00/85.00 CIE A = -5.20 CIE B = 26.00	**7** (Calypso/KP) CIE L = 97.00/85.00 CIE A = -5.70 CIE B = 32.00	**9** (Honey Gold) CIE L = 95.00/84.00 CIE A = -5.90 CIE B = 36.00
11 CIE L = 95.00/84.00 CIE A = -4.70 CIE B = 43.00	**13** (Keitt) CIE L = 92.00/83.00 CIE A = -3.80 CIE B = 51.00	**15** CIE L = 92.00/83.00 CIE A = -1.08 CIE B = 57.00	**17** CIE L = 88.00/80.00 CIE A = 1.60 CIE B = 62.00

Forecast of fruit load

Forecast of tree fruit yield requires prediction of both fruit size and fruit number at the time of harvest.

Fruit count

<u>Packhouse record</u>

Packhouse fruit data was sourced as 'reference' data for comparison of fruit load estimations. However, the most 'meticulous' farms suffered the following issues:

- Fruit not harvested. For example, in the 2022 season high heat caused fruit to mature early, before marketable sizes were reached. One major farm reported harvesting less than one third of the crop due to sizing issues.
- Fruit harvesting pattern does not align to block boundaries. For example, to avoid frequent turning at end of rows, a harvest aid may continue across orchard blocks. Even if fruit bins are tagged, there will be a mixed-block bin at each row end.
- Field bins not identified by block, so if several blocks are harvested over a short period, bins may be mixed by time of entry to packline.
- Bins do not 'clear' in packline. Bins are typically tipped into a water tank before carriage into the conveyor system. Fruit are not totally cleared before dumping of the next bin, leading to mixing of fruit at the changeover between blocks. In other cases, field bins from various blocks are mixed in storage, and not identified by block during the packing process.
- Un-marketable fruit are not packed. Marketable fruit are packed to trays of set sizes (number of fruit per tray), allowing an accurate count of pieces of marketed fruit. Other fruit pass to a field bin. Fruit number can be estimated based on assumptions of field bin weight and average fruit weight.
- Packhouse records are not available. In a surprising number of cases, packhouses either do not keep records on a per block basis, or the data is difficult to extract (with harvests spread across multiple dates and multiple blocks). One (large) farm estimated a person-week was required to retrieve data. Data may also be compromised by periods of packing line difficulties during the season.

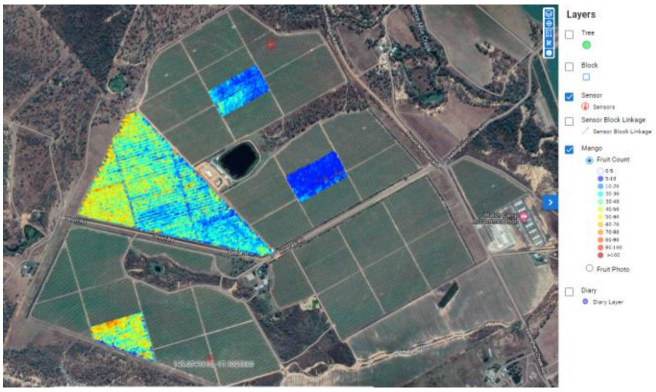
These errors can be very large and affect both whole farm and block level estimates. The conclusion is 'buyer beware' – a packhouse count can be a very good reference value, sometimes.

<u>Machine vision</u>

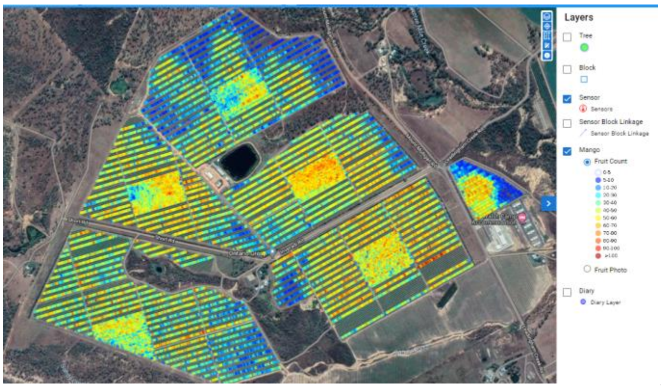
The orchard imaging system evolved over the three-year project period (Figure 55. In the first season, CQU research staff drove the imaging system on farms and processes data to return data the following day. In the second season, CQU research staff delivered the imaging system to farm, farm staff operated, and data was processed and delivered the following day. In the last season, the hardware was left in stewardship of NT DIT and QLD DAF in Darwin/Katherine and Mareeba, respectively, with farmers collecting and using on farm. Again, data was processed and returned within a day.

Figure 55. Orchard imaging system in orchard.

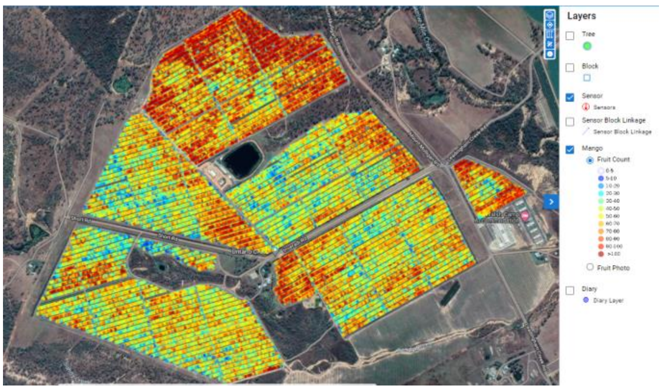
The machine-vision estimated fruit counts can be used to create 'heat maps' of flower count or fruit load for orchards with a consistent canopy architecture (Figure 56). Such maps provide an insight to farm production not otherwise available to the farmer.



2019/20 season



2020/21 season



2021/22 season

2022/23 season

Figure 56. **Display of fruit load (blue to red scale is low to high fruit count per tree spacing. In order of top to bottom panels, data is of 2019/20, 2020/21, 2021/22 and 2022/23 seasons. In the first year of the project, only part of the farm**

was imaged.

For example, Figure 57 provides an example of imagery that captured the impact of an agronomic event in 20/21 that impacted fruit set (blue areas are low fruit set). The affected areas returned high fruit loads in the subsequent year, suggesting that a 'biennialty' in production was triggered. However, this phenomenon was avoided, with uniform production in the 2022/23 season. Heat maps of flowering (Figure 60) allow for planning of the order of harvest of orchard blocks.

Figure 57. Display of flowering levels (blue to red scale) in 2022/23 season.

Detail of the performance of the system, relative to manual counts of a sample of trees and to packhouse counts, is available at Anderson *et al*. (2021). In brief, estimate error was ascribed to double counting, i.e, over-estimation, associated with view of fruit from both sides of the canopy in trellised trees, and to greater occlusion of fruit associated with planting density and cultivar (Figure 58).

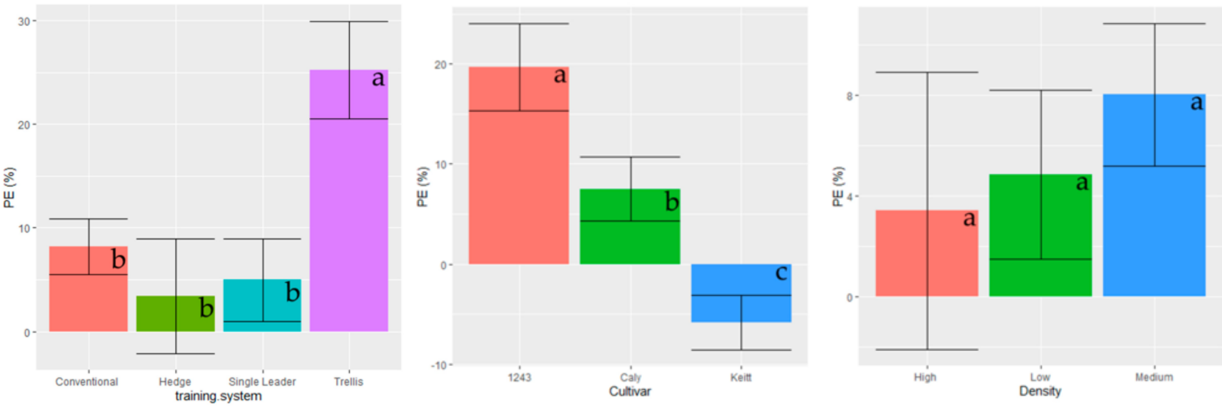


Figure 58. (from Anderson *et al.*, 2021). **Average percentage absolute error of machine vision-based count of fruit per tree relative to harvest count, presented by training system for all cultivars and densities (top panel); by tree density, for all cultivars and training systems except trellis (middle panel); and by cultivar, for all densities and training systems except trellis (bottom panel). Bars represent ± SD, significant differences denoted with letters a, b and c to $p < 0.05$.**

An unsuccessful attempt was made to estimate % of fruit occluded using machine vision, based of the proportion of all visible fruit that were partly occluded (as reported in Koirala *et al.*, 2020). Estimation of actual fruit number can thus be achieved in orchards with open canopies, in which all fruit are visible during a 'drive past'. For canopies with occluded fruit, a correction factor for occluded fruit can be estimated from machine vision values and manual counts of selected trees. Further work is required to optimize a sampling method for estimation such a correction factor, in terms of minimizing effort but maintaining statistical validity.

Repeated measurements of fruit load on a given block provided information of the spear of fruit maturation (Figure 59).

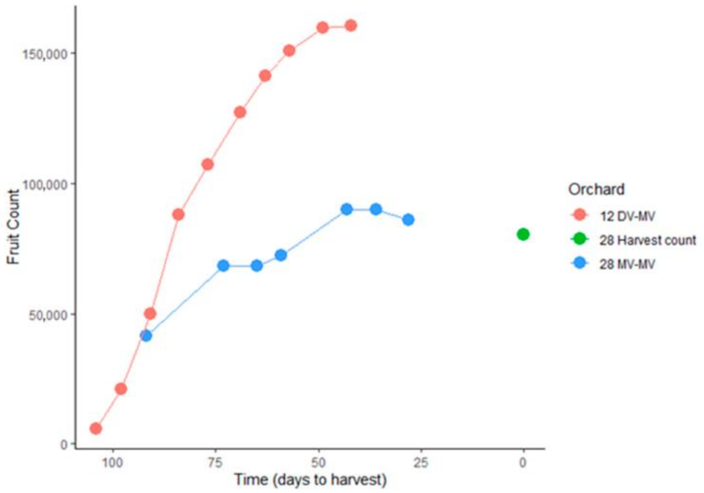


Figure 59. Time course of fruit count estimated in repeated machine vision imaging events in two orchards. Fruit associated with a later flowering cause a second 'wave' for orchard 28 (blie line). Harvest occurred 6 and 4 weeks after the last assessment orchards 12 and 28 orchards, respectively. Packhouse count for orchard 28 is shown at time 0.

Across multiple orchards, the average percentage error on machine vision of fruit counts was 11%, relative to packhouse count in the 2019-20 season, and 24% in 2020-21 (Table 15). Error was high in the 20-21 season as there was a late second flowering. Fruit from this second flowering was not of a size at the time the orchards were imaged. The late flowering impacted manual (human) counts as well, with the assumption that the second flowering fruit would 'drop'. However, the manual count were taken at a later date than the machine vision, resulting in improved forecast for the manual counts. In such a case, a second count is required. This should be easier to implement using a machine vision system than for a manual count data (Figure 60), indicating a consistent proportion of fruit were derived from the later flowering event.

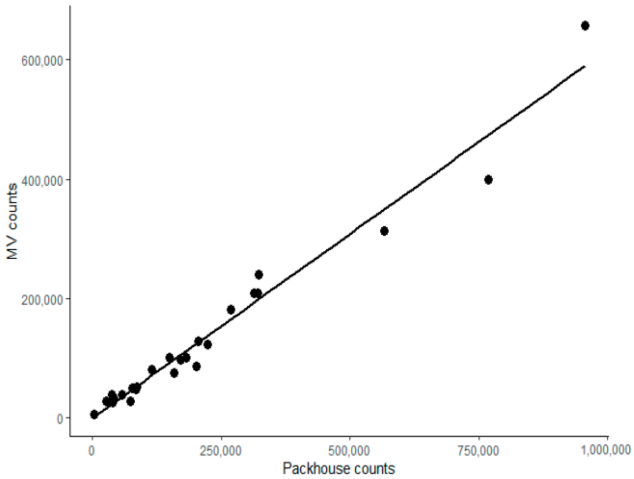


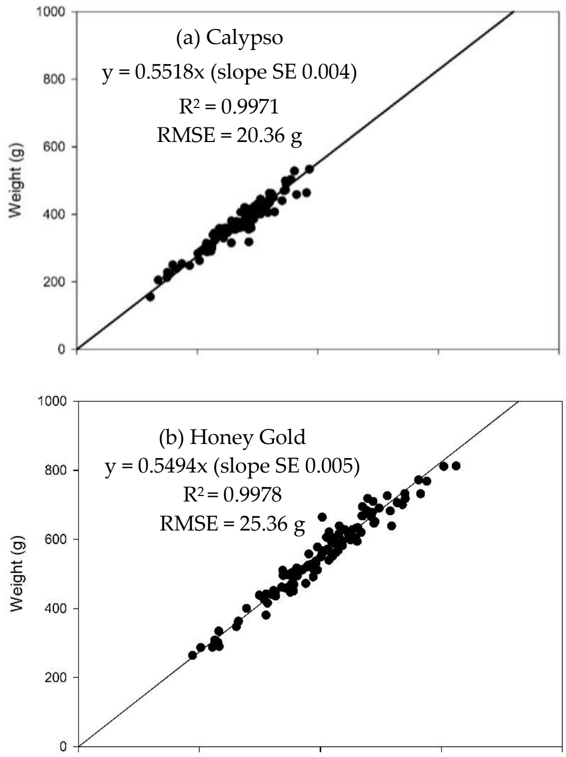
Figure 60. From Anderson *et al.* (2021): **2020–2021 season multi-view machine vision count of fruit per orchard fruit plotted against packhouse fruit count for 20 orchards from one farm. Data is fitted by a linear regression model, R^2 = 0.97, slope = 0.62, p < 0.001.**

Down-sampling to imaging of every third inter-row was recommended as a compromise between required effort and acquisition of information on spatial variation in fruit load across the orchard.

Fruit size estimation

From [Amaral and Walsh (2022):](#) Mango fruit mass (M) can be estimated from correlation to measurements of fruit length (L), width (W) and thickness (T). On-tree measurements of individually tagged fruit were undertaken using callipers at weekly intervals until the fruit were past commercial maturity, as judged using growing degree days (GDD), for mango cultivars 'Honey Gold', 'Calypso' and 'Keitt' at four locations in Australia and Brazil during the 2020/21 and 21/22 production seasons. Across all cultivars, the linear correlation of fruit mass to LWT was characterized by a R^2 of 1.00, RMSE of 23.9 g and slope of 0.5472 g/cm^3 (Figure 64), while the linear correlation of fruit mass to L (((W+T))/2)2, mimicking what can be measured by machine vision of fruit on tree, was characterized by a R^2 of 0.97, RMSE of 25.0 g and slope of 0.5439 g/cm^3.

A procedure was established for prediction of fruit size at harvest based on measurements made five and four or four and three weeks prior to harvest (approx. 514 and 422 GDD, before harvest, respectively). Linear regression models on weekly increase in fruit mass estimated from lineal measurements were characterized by a R^2 > 0.88 for all populations, with an average slope (rate of increase) of 19.6 ± 7.1 g/week, depending on cultivar, season and site. The mean absolute percentage error for predicted mass compared to harvested fruit weight for estimates based on measurements of the earlier and later intervals was 16.3 ± 1.38.and 4.5 ± 2.4%, respectively. Measurement at the later interval allowed better accuracy on prediction of fruit tray size distribution (Figure 62). A recommendation was made for forecast of fruit mass at harvest based on in-field measurements at approximately 400 to 450 GDD units before harvest GDD and one week later.



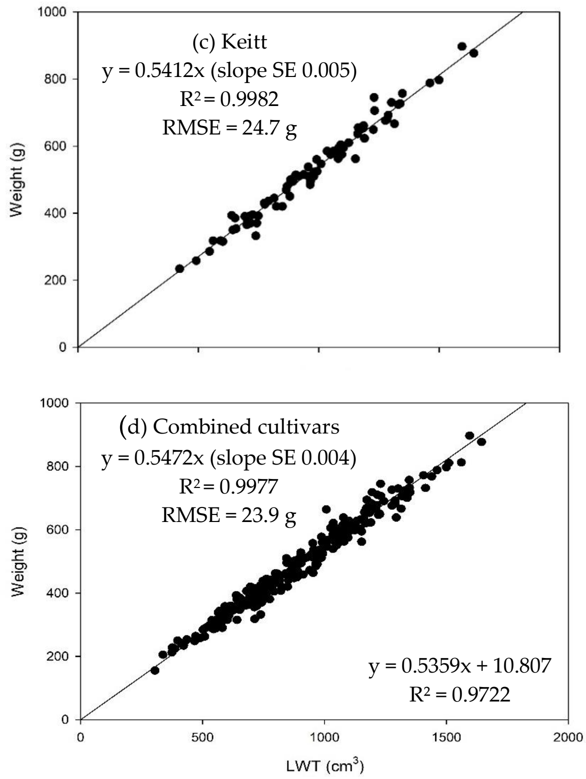


Figure 61. Scatter plots of fruit mass (g) against LWT (cm^3) for (a) Honey Gold (populations 1a, 1b, 2a, 2b and 8 n=110) (top panel), (b) Keitt (populations 3, 4 and 9, n = 75); (c) Calypso (population 5, 6 and 7, n = 100), and (d) all populations, i.e., combined cultivars (n = 285). Pearson's linear regression fit, equation with SE of slope, R^2 and RMSE are shown. Mean and SD of fruit mass of Calypso, Honey Gold and Keitt populations were 369 ± 74, 553 ± 118, and 524 ± 148.5 g, respectively.

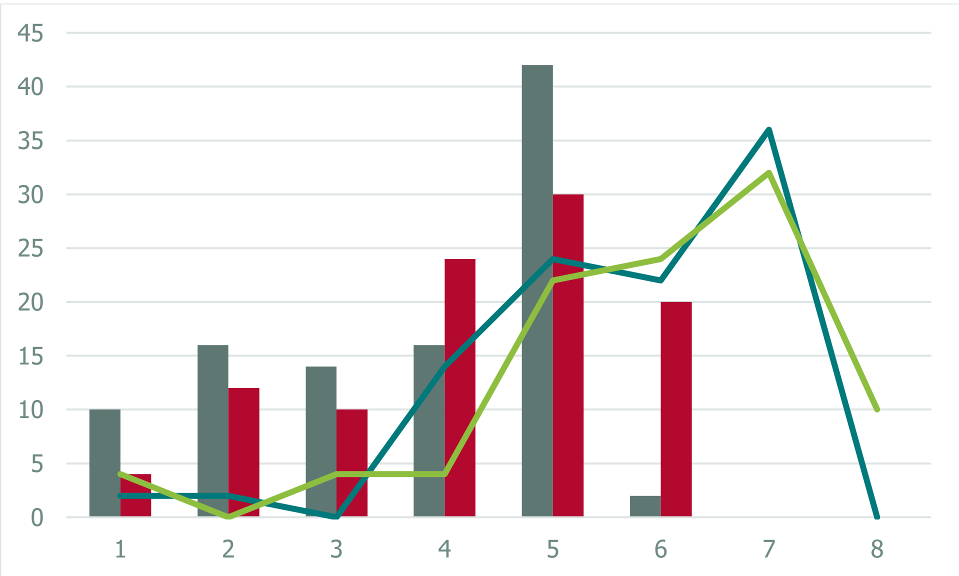


Figure 62. kLWT estimate. Frequency (% of total fruit number) for fruit mass ranges equivalent to tray sizes for Populations 1 (top), 5 (middle) and 9 (bottom), i.e., example Calypso, Honey Gold and Keitt populations, respectively. Each panel displays a distribution for four and three weeks before harvest (bars), and for the forecast and actual fruit size at harvest (lines). Forecast size was based on a growth rate of 23.2, 32.7 and 25.1 g/week (as estimated from the mass change between weeks 4 and 3) for populations 1, 5 and 9, respectively. Fruit mass was calculated using fruit L, W

and T (eqn. 1).

As manual measurement of the dimensions of fruit on tree is tedious, the potential for use of a depth camera in 'automation' of the measurement was assessed. As detailed in Neupane *et al.* (2021) eight depth cameras varying in operational principle were assessed (stereoscopy: ZED, ZED2, OAK-D; IR active stereoscopy: Real Sense D435; time of flight (ToF): Real Sense L515, Kinect v2, Blaze 101, Azure Kinect). The ToF cameras achieved the desired specification of a bias-corrected root mean square error of 20 mm for a camera-to-fruit distance of 2 m and operation under sunlit field conditions. The use of the Blaze 101 or Azure Kinect was recommended in terms of operation in sunlight and in orchard conditions. For a camera-to-fruit distance of 1.5 m in sunlight, the Azure Kinect measurement achieved an RMSE of 6 mm, a bias of 17 mm, an SD of 2 mm and a fill rate of 100% for depth values of a central 50 × 50 pixels group.

To enable inter-study comparisons, it is recommended that future assessments of depth cameras for this application should include estimation of a bias-corrected RMSE and estimation of bias on estimated camera-to-fruit distances at 50 cm intervals to 3 m, under both artificial light and sunlight, with characterization of image distortion and estimation of fill rate.

As detailed in Neupane et al. (2022), the use of depth cameras for in-orchard estimation of fruit size was then considered, addressing the challenge of the removal of partly occluded fruit from consideration. Three approaches were compared (Fig. 22), being: (i) refined bounding box dimensions of a YOLO object detector; (ii) bounding box dimensions of an instance segmentation model (Mask R-CNN) applied to canopy images, and (iii) instance segmentation applied to extracted bounding boxes from a YOLO detection model. YOLO versions 3, 4 and 7 and their tiny variants were compared to an in-house variant, MangoYOLO, for this application, with YOLO v4-tiny adopted within a processing pipeline (Figure 63). Criteria developed to exclude occluded fruit by filtering based on depth, mask size, ellipse to mask area ratio and difference between refined bounding box height and ellipse major axis.

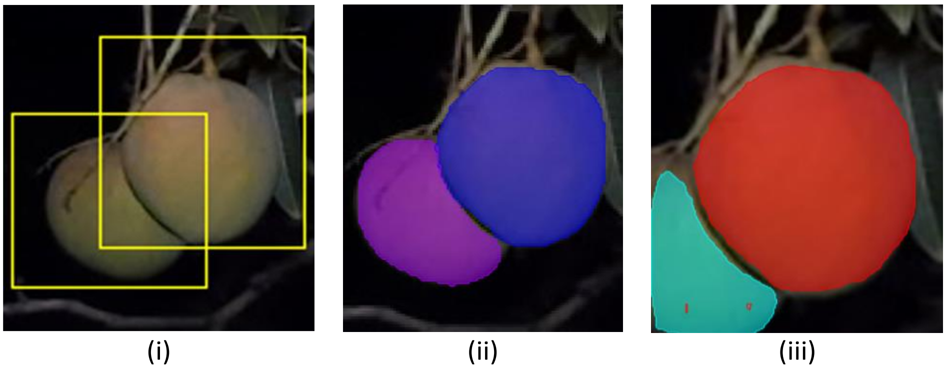


Figure 63. Example of model outputs for: (i) YOLOv4-tiny bounding box on detected fruits; (ii) Mask R-CNN instance segmentation on image tile; (iii) instance segmentation applied to bounding box produced by a YOLOv4-tiny detection model.

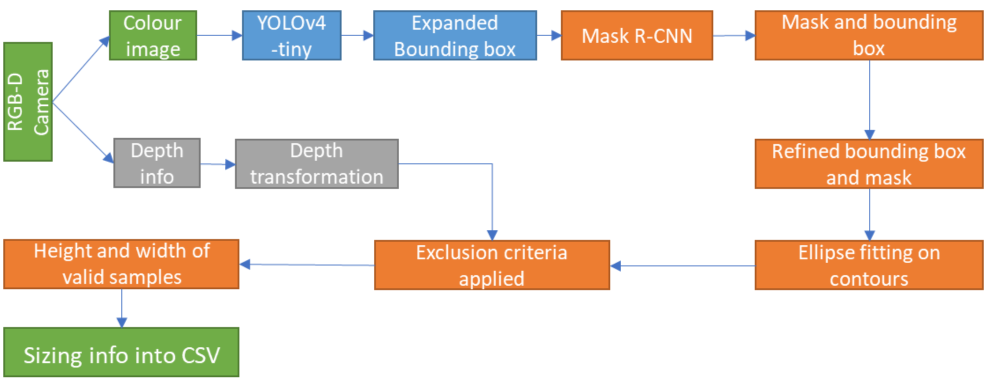


Figure 64. Method 3 – Mask R-CNN segmentation within YOLOv4-tiny detected bounding boxes.67

The lowest root mean square error (RMSE) of 4.7 mm and 5.1 mm on the lineal length dimensions of a population (n = 104) of Honey Gold and Keitt varieties of mango fruit, respectively, and the lowest fruit exclusion rate was achieved using method (ii), while the RMSE on estimated fruit weight was 113 g on a population weight range between 180 and 1130 g (Table 16).

Table 16. Statistics of RMSE, R^2 and Bias on estimation of fruit length using three methods (M1: YOLOv4-tiny with Otsu's thresholding; M2: Mask R-CNN segmentation method; M3: YOLOv4-tiny bounding box + instance segmentation) and two criteria. Units of RMSE and bias are mm. best result for each population and metric is bolded.

		HG	Keitt
Criteria-A	RMSE	**5.2**	7.8
	R^2	**0.8**	0.9
	Bias	2.0	-3.8
Criteria-B	RMSE	**4.7**	**5.1**
	R^2	**0.9**	0.9
	Bias	3.1	-2.4

Flowering estimation

As detailed in Koirala et al. (2020), automated assessment of the number of panicles by developmental stage can provide information on the time spread of flowering. A pixel-based segmentation method for the estimation of flowering level from tree images was confounded by the developmental stage. Therefore, the use of a single and a two-stage deep learning framework (YOLO and R2CNN) was considered, using either upright or rotated bounding boxes. For a validation image set and for a total panicle count, the models MangoYOLO(-upright), MangoYOLO-rotated, YOLOv3-rotated, R2CNN(-rotated) and R2CNN-upright achieved weighted F1 scores of 76.5, 76.1, 74.9, 74.0 and 82.0, respectively. For a test set of the images of another cultivar and using a different camera, the R^2 for machine vision to human count of panicles per tree was 0.86, 0.80, 0.83, 0.81 and 0.76 for the same models, respectively. Thus, there was no consistent benefit from the use of rotated over the use of upright bounding boxes. The YOLOv3-rotated model was superior in terms of total panicle count, and the R2CNN-upright model was more accurate for panicle stage classification. To demonstrate practical application, panicle counts were made weekly for an orchard of 994 trees, with a peak detection routine applied to document multiple flowering events (Figure 65).

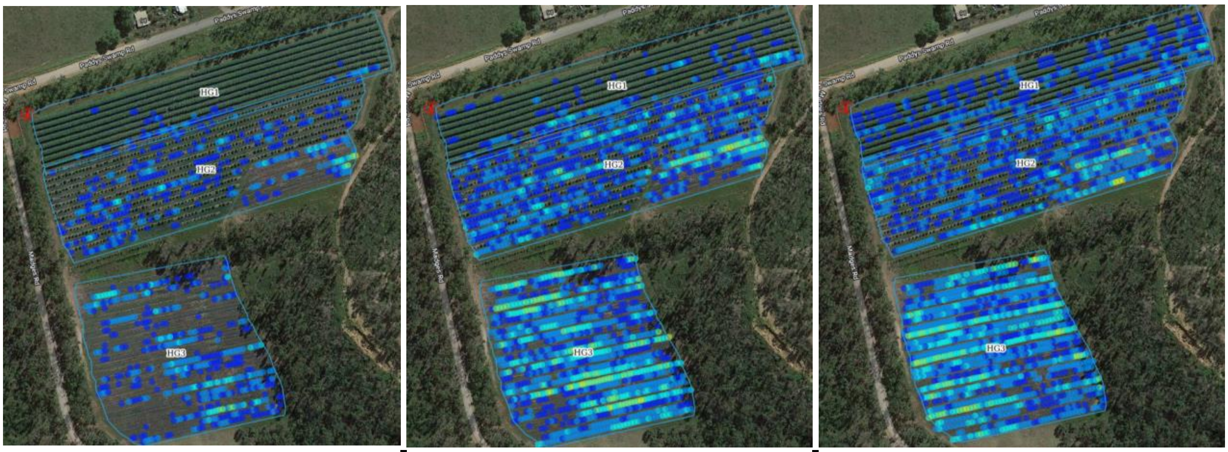


Figure 65. Example of 'heat map' of flowering assessed at time intervals during the flowering period. Colours refer to panicle count (brighter colours associated with higher panicle counts).

Mechanical harvester

Phantom fruit

Different protocols and materials were trialed for production of 'phantom' fruit and stalk (Figure 66), as detailed in Appendix 3. A commercially available silicone material was recommended for production of fruit moulds, and a 60:40 mixture of silicone and starch was recommended for production of phantom fruit with fidelity to actual fruit shape and weight.

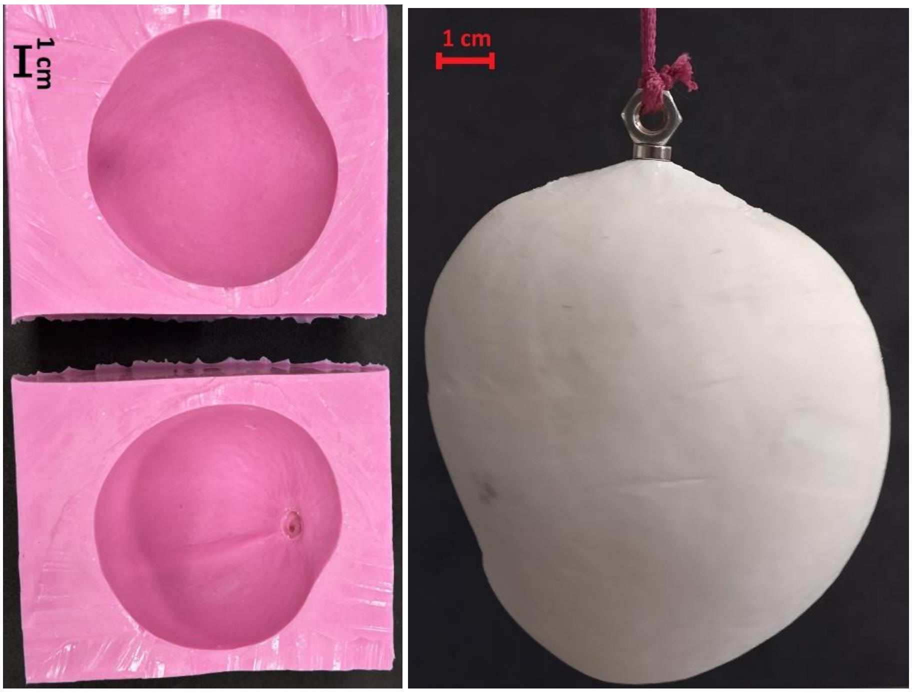


Figure 66. Mould of mango fruit (left panel) and cast with magnetic stalk (right panel).

Two methods for creation of a phantom fruit stalk were developed and trialed, one involving a wooden dowel and the other a magnetic latching. The magnetic system was recommended for ease of use, enabling rapid gripper trials.

Harvester

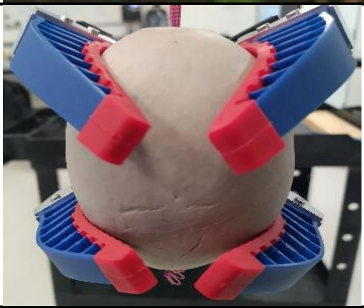
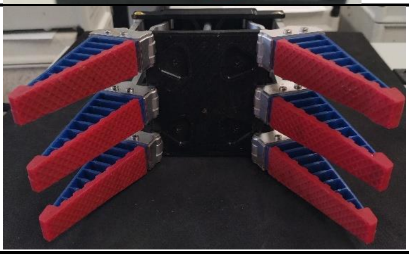
The Mk 1 prototype from the Phase 1 project was evolved through the course of the current project, but the basic design remained unchanged. This design consisted of an elevating platform carrying a set of belt-driven linear actuators equipped with stepper motors. Arm movements involved acceleration to a velocity of 1 m/s. These actuators deliver a gripper to the desired position. Following gripper closure, the arm is rotated 180° to detach the fruit from the stalk, the arm is retracted to the home position, and the fruit is released.

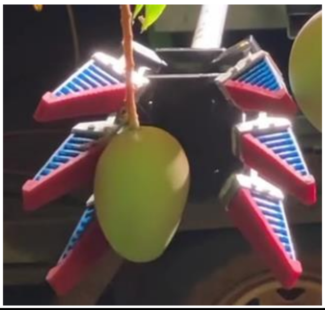
Over the course of the project, the mechanism of the gripper closure and arm rotation movements were modified from electric motor control to pneumatic actuator control, to decrease response times and increase effectiveness in detaching the fruit from its stalk. Other work focussed on the design of the gripper and its control.

<u>Gripper design</u>

The starting design was a commercially available two-finger gripper used in pole harvest of tree fruit (Table 17). Iterative designs were influenced by performance observations. Required parts were designed in AutoDesk Fusion 360 and printed using a Flashforge Glider II 3D printer using ABS filament (Flashforge, 1.75mm diameter).

Table 17. Gripper designs.

Design	Image	Characteristics
1. Two flat jaws		Commercially available. Closure by tension from winding cord onto an electrically actuated drum, opening due to spring. Limited harvest 'volume', i.e., fruit alignment to gripper was critical.
2. Two articulated jaws		3D printed. Closure activated by tension on cord created by winding cord onto an electrically actuated drum, opening due to spring. Larger picking 'volume'.
3. Four finray fingers		3D printed base plates, commercially available fingers. 4 finger design, with 'straight' fingers Improved picking volume
4. Four finray fingers with angles		4 finger design, with fingers at 30° angle from vertical Improved picking volume but with failures for smaller fruit (fruit slip between fingers)
5. Six finray fingers		6 finger design, with straight fingers Poor performance with top and bottom fingers having little engagement with fruit

6. Six finray fingers with angles		Top and bottom fingers at 30° angle from vertical. Good picking volume but fails in collaborative picks (when two arms move together)

<u>Gripper laboratory trials</u>

The 'picking volume' of the end effector designs were compared, using a set of phantom fruit varying in mass (378, 512, 636 and 836 g). Phantom fruit were suspended from a frame that allowed movement of phantom horizontally and vertically in 10 mm increments. The frame was shifted in 20 mm increments in relation to the distance to the end effector, i.e., depth. The 'picking volume' of an end effector was defined as the volume of space that a fruit could occupy relative to the axis of the harvester's arm and be successfully harvested.

Fruit position was defined with reference to the mid-point of the top of the fruit, while end effector position was defined with reference to the mid-point of the top of the palm of the end effector. Grasp was considered successful if the fruit was held through the detachment process, i.e., through wrist rotation. These trials did not consider the presence of interfering materials, such as leaves, branches or other fruits.

An example performance evaluation is provided in Figure 67, illustrating a 2D slice of the harvest volume of two gripper designs, for a given fruit size.

	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8
-5	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
-4	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
-3	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
-2	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
-1	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
0	NOK	NOK	OK	OK	OK	OK	OK	OK	<u>OK</u>	OK	OK	OK	OK	OK	OK	NOK	NOK
1	NOK	NOK	OK	OK	OK	OK	OK	OK	NOK	OK	OK	OK	OK	OK	OK	NOK	NOK
2	NOK	OK	OK	OK	OK	OK	OK	OK	NOK	OK	OK	OK	OK	OK	OK	OK	NOK
3	NOK	NOK	OK	OK	NOK	NOK	OK	NOK	NOK	NOK	OK	NOK	NOK	OK	OK	NOK	NOK
4	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
5	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
6	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
7	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK

	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9
-5	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
-4	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
-3	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
-2	NOK	NOK	NOK	NOK	NOK	OK	OK	OK	OK	OK	OK	OK	OK	OK	NOK	NOK	NOK	NOK	NOK
-1	NOK	NOK	NOK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	NOK	NOK	NOK
0	NOK	NOK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	NOK	NOK
1	NOK	NOK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	NOK	NOK
2	NOK	NOK	NOK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	NOK	NOK	NOK
3	NOK	NOK	NOK	NOK	NOK	NOK	NOK	OK	OK	OK	OK	OK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
4	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
5	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
6	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
7	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK

	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9
-5	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
-4	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	OK	OK	OK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
-3	NOK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	NOK
-2	NOK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	NOK
-1	NOK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	NOK
0	NOK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	NOK
1	NOK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	NOK
2	NOK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	NOK
3	NOK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	NOK
4	NOK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	NOK
5	NOK	OK	OK	OK	OK	NOK	OK	OK	NOK	NOK	NOK	OK	OK	NOK	OK	OK	OK	OK	NOK
6	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK
7	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK	NOK

Figure 67. Score card of gripper success for fruit positions varied in context of the arm position for two gripper designs. X and Y scales are in units of cm. This trial involved a 636 g phantom placed 0 mm away from the palm of the gripper. Top, middle and bottom panels present results for gripper 2, 3 and 6 from Table 11. Relative picking volumes were 45 : 70 : 151 for the three designs, respectively.

<u>Gripper field trials</u>

Of the five candidate end effectors, the two best performing designs (the 4 finger no angle, and the 6 finger, 30° angle) were evaluated in an orchard setting, for fruit on-tree. In an on-tree environment, targeted fruit can be partly occluded by leaves, branches or other fruit. The four-finger design gave a 9% performance benefit over the 6 finger design in picking trials of harvest of Calypso fruit (average weight 350 g).

<u>Control system</u>

A two-camera system was implemented, with both cameras operating in the same spatial co-ordinate frame, and with fruit detection achieved from the output of both cameras. Fruit were tracked as the harvester moved, allowing for harvest attempt of fruit occluded by leaves when the arm is in harvesting position, given earlier detection.

Changes in elevator and arm behavior were trailed and implemented sequentially. At end of 2023 trials, the 8 arm (1.4 m wide) system (Fig. 68) was traversing 3 m vertical height of canopy in 90 seconds, while achieving a 76% success rate of fruit harvest attempts.

Figure 68. Autoharvester MkIII in field trials in Katherine NT, 2022/23 season.

A video of harvester operation can be seen at https://www.youtube.com/watch?v=9P5fJBoxip4 (AMIA, 2022).

Activity 2 – Project planning and management

KPI 3.1 - Provide a summary of project planning and management activities

Four levels of planning occurred throughout the life of the project. (i) Planning and management of the overall project was led by UNE and Hort Innovation and occurred through regular Zoom and face-to-face meetings and emails. (ii) Groups involved in the mango sub-component of the project (CQU, AMIA, QDAF, NTDITT and UNE) also met regularly by Zoom, communicated by phone, text and email for project planning, and met face-to-face to conduct project activities. (iii) Planning meetings occurred with farm management for each of the farms on which activity has occurred. Finally, (iv) briefings also occurred with the mango marketing groups Pinata, Manbulloo and Perfection Fresh.

Activity 3 – Communication and extension

KPI 3.2 - Provide a summary of communication and extension activities.

Communication and extension activities included presentations at the Australian mangoes' pre-season roadshows, hosting field days and webinar, developing promotional and tutorial videos, articles in Australian Mangoes' newsletter and magazine, webpages and social media posts. We estimate that at least 90% of the industry is aware of the project and of the project's tools and technologies developed to better predict fruit load and harvest timing.

The project team also raised awareness of the project when speaking with growers or other relevant stakeholders such as local farming groups and connected project partners with producers interested in participating in the project and testing the technology.

During the 2020/21 and 2021/22 seasons, the machine vision yield mapping system was made available to the broader industry and growers were encouraged to trial the imaging rig on their own farm. AMIA worked closely with Martina Matzner, consultant for CQU, to spread awareness on the machine vision rig and the heat sum online platform and encourage growers to try the technology. This was achieved through the creation of a promotional video on forecasting technologies (see Outputs section below), as well as farm visits for one-on-one conversations with growers. The field days were also key as they allowed growers to familiarise themselves with this new technology and equipment. NTDITT, QDAF and AMIA assisted growers with transporting the machine and processing and analysing the data. As a result, In the NT, 52% of the industry (in volume) has used the machine vision rig in the lead up to harvest for the 2022-2023 season. The uptake was particularly successful in Katherine with 91% of the industry (in volume) trialling the technology. In Far North Queensland, we estimate that 60% of the industry has used the machine vision rig. The growers who used the rig were able to provide feedback to CQU and the company commercialising this technology to ensure the next version is better suited to the mango industry's needs.

See Output section for details and links.

Activity 5 – Research activities

KPI 3.3 Develop improved pre-harvest yield forecasting accuracies at the national, regional and farm level for mango

In consultation with project lead and partner organisations, the scope of the project activities for each mango harvest season in the NT and QLD was defined. Specific activities to acquire data of ground truthing for improving the predictability of the remote sensing technologies were scheduled.

Accordingly, the NT DITT and QDAF project teams coordinated the project data acquisition schedule with the project partners – including the UNE and commercial mango farms in the NT and QLD. The commercial farms in the NT included Acacia Hills Farm, Manbulloo Farm, Ballongilly Farm, NTLD Farm, Nutrano Farm and Pinata Farm. Those in QLD included Ontario farms, Blushing Acres, Manbulloo farm, JPK farming, Marto's Mangoes, Groves Grown farm and Dorrian Farm.

NT DITT project team coordinated with the project partners from UNE to align the schedule of ground truthing with the satellite imaging acquired by the UNE partners. The identification of the selected blocks and trees in each orchard was facilitated by UNE colleagues. Data of the ground truthing were acquired by the NT DITT team.

The methodology, observations and relevant statistics of ground truthing were reviewed and agreed by the project team.

All the data were shared with UNE colleagues for developing pre-harvest yield forecasting accuracies at the national, regional and farm levels for mango.

A detailed description of developing improved pre-harvest yield forecasting accuracies at the national, regional and farm level for mango is included in the milestone report produced by UNE.

KPI 3.4 Develop practical tools and analysis methodologies that improve the within orchard monitoring and mapping of tree health, fruit quality and maturity.

As noted above, in consultation with project lead and partner organisations, the scope of the project activities for each mango harvest season in the NT and QLD was defined. Specific activities to acquire data of machine vision for improving the predictability of the remote sensing technologies were scheduled.

Accordingly, the NT DITT and QDAF project teams coordinated the project data acquisition schedule with the project partners - including the CQU and commercial mango farms in the NT. The commercial farms include Acacia Hills Farm, Manbulloo Farm, NTLD Farm, Nutrano Farm and Pinata Farm. Those in QLD included Ontario farms, Blushing Acres, Manbulloo farm, JPK farming, Marto's Mangoes, Groves Grown farm and Dorrian Farm.

NT DITT project team coordinated with the project partners from CQU to align the schedule of ground truthing with machine vision studies. Data of the machine vision tools and analysis methodologies to improve the within mango orchard monitoring and mapping of tree health, fruit quality and maturity were captured by CQU with support from NT DITT.

A detailed description of developing practical tools and analysis methodologies that improve the within orchard monitoring and mapping of tree health, fruit quality and maturity is included in the milestone report produced by CQU.

The Australian Mangoes team provided support to CQU, NTDITT, QDAF and UNE as required.

The support provided included NIR devices calibration and troubleshooting assistance, ground truthing work, installing and troubleshooting temperature data loggers, etc.

AMIA continued to provide a NIR dry matter testing service to assist growers with tracking their fruit maturity. In-field assessment of fruit maturity using NIR technology has been widely adopted with 71% of the industry (by volume) using the Felix Produce Quality Meters. On-farm testing is generally conducted by the IDOs but farming businesses have begun investing in their own machines, where AMIA assisted with technical support and the calibration procedure.

AMIA and QDAF collaborated to write a review of existing yield estimation tools and forecasting strategies used by the Australian mango industry (see Appendix 4).

KPI 3.5 Develop and deliver improved detection and management tools and strategies to control future biosecurity threats and natural disasters.

To be better prepared for future biosecurity threats, AMIA has been collaborating with the Applied Agricultural Remote Sensing Centre, state (Queensland Department of Agriculture and Fisheries) and federal biosecurity agencies (Northern Australia Quarantine Strategy, Department of Agriculture, Water and the Environment) to map and publish the location of all non-commercial mango trees in the Cape York Peninsula and Torres Strait Islands.

The map has been developed and is accessible here.

The following is a screenshot of the preliminary data that was gathered during our field tests on the farms.
The first thing that needed to be done was to create a method for tagging the banana bunches, validate the location accuracy, and figure out how this can be done in a way that is both operationally feasible and efficient.

In order to properly install a system that allows for the accurate capture of information regarding the banana bunches, it was important for the field workers to effectively handle the tags and scan the tags in the most time-effective manner possible. Growers are not going to agree to the adoption of such a system if it can't be operated in the field in a speedy and uncomplicated manner.

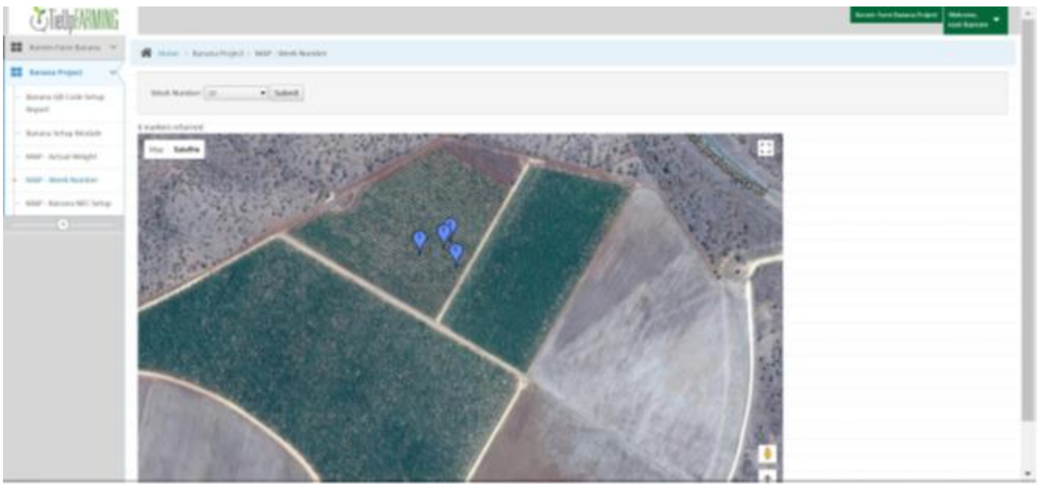


Figure 69. showing random tag scans from the plantation – measuring the accuracy of the GPS device. Tagging bunches.

Figure 70. **Testing tags on farm to insert directly into the stem of the banana bunch**

Figure 71. **Testing different type of tagging bunches.**

This method was identified as not practical from operation point of view. Takes a couple of scans to tie the zip around the stem.

Figure 72. Identifying banana bunch tagging process.

The process of putting bags on the banana bunches was identified as the best way to tag bunches.

Figure 73. Field trial number 2.

With improved GPS accuracy and an added function to enter the actual weight of a bunch, this demonstrated what the end result would be.

Figure 74. **Trialled RFID tagging and NFC technology tagging (see below figure 78).**

Figure 75. Near-field communication (NFC) trials

During the initial stage, the project team attempted to integrate tagging banana bunches with harvest management. Unfortunately, this strategy was unsuccessful. The team also attempted to use the NFC (near-field communication) tagging technology, which does not require any further equipment aside from a mobile phone, but were unable to achieve the level of accuracy that was required. Following this, the team started testing in the one block where each and every tag was placed throughout the initial campaign.

During the second season, we were able to attain the requisite level of precision, and the deployment aligned with the commercial practice.

Table 18. Measuring and comparing different type of tags against pre-defined criteria.

	Number of Tags deployed	GPS accuracy achieved	GPS accuracy required	Tag information recorded	
RFID	1000	10 cm	10 cm	GPS location	
NFC	5	3 meters	10 cm	GPS location | Picker details	

For the second season, they have "closed the loop" with satellite imagery and ground-based data capturing tagging tools.

Figure 76. The weight was gathered in the packing shed using an A&D scale. The scale is positioned on the conveyer belt where the banana bunches are hanged.

The project team install an RFID reader and a computer at the point of weighting and linked the two sets of data together to provide the above info.

Outputs

Table 19. Output summary

Output	Description	Detail

Further development of the National Tree Map Platform.	Delivery a freely available national map of commercial olive groves and citrus orchards over 1 ha. This will provide the respective industry bodies with a more accurate measure of the distribution and extent of national production as well as serving as an essential tool to assist biosecurity response and post disaster monitoring.	• The Australian Tree Crop Map (ATCM) was updated during the phase 2 project to include all mango, macadamia, citrus, olive and banana orchards (> 1 ha) (https://www.arcgis.com/apps/dashboards/f6dd44763f0b476e8a1c2f0504fc8779)
		• The map developed directly with the respective industry bodies, is built to national Australian mapping standards, and is freely available
		• 4,073 ATCM surveys received, and 909 comments actioned in the Industry Engagement Web App
		• The mapping of all commercial orchards has provided each industry with a more accurate understanding of extent (location and area) of their tree crops, critical baseline information to better quantify annual change, traceability, infrastructure and labour requirements, production estimates and forward selling, and for better preparedness and response to biosecurity threats and natural disasters.
		• In terms of industry statistics, the mapping of tree crops is summarised in the following metrics:
		    ○ 13,965 ha of banana plantations
		    ○ 37,492 ha of citrus orchards
		    ○ 38,477 ha of macadamia orchards (27% increase over Phase 1)
		    ○ 15,931 ha of mango orchards (18% decrease since Phase 1)
		    ○ 33,619 ha of olive groves
		• Mapping completed in 2017 compared to 2022, identifies an increase in production area of 27% in macadamia orchards (up from 28,178 ha), whilst mango have decreased by 18% (down from 18,806 ha) nationally;
		• The map is published within the ATCM Dashboard and available in industry-specific dashboard applications (hosted on industry websites)
		• The ATCM dashboard was awarded best dashboard at the 2021 Esri International User Conference (San Diego, USA)
		• For further evidence refer to the impact and legacy section in Appendix 1 of this report.

Further development of and commercialisation of tools ('Fruitmaps App', NIR, satellite, airborne and UAS remote sensing, barcoding) that assist growers in identifying the spatial and temporal variability of fruit quality, size,	Outcomes will support optimal harvest timing and harvest segregation as well as the more judicious application of crop inputs i.e., fertiliser, herbicides, water etc. and the associated savings of labour and fuel costs (mango, citrus, olive, and banana).	• Within the phase 2 project, classified maps of tree vigour variation across orchard blocks and whole farms (for mango, citrus and olive orchards) derived from satellite imagery were provided to participating growers via industry engagement Web Apps. These maps assist growers in better understanding variability across orchards that can better direct in field assessments of fruit quality, size and maturity as well as direct the targeted application of cop inputs. These were well received as the growers are not required to have any existing spatial software, the maps are highly intuitive with maps viewable on any device e.g., Tablets, Mobile Phone (refer to Appendix 1, section 6.4.4.). • A web interface (Google Data Studio visualisations) was developed for participating olive growers to provide real-time access to infield

maturity, oil content, Brix etc.		sensors deployed for the irrigation trial (sap flow, dendrometer, canopy temperature and relative humidity).
Develop platforms that support the commercialisation of yield forecasting and yield mapping technologies and methodologies, i.e., remote sensing, and barcoding.	Outcomes will support improved decision-making around forward selling and harvest logistics including transport and labour requirements (mango, olive, citrus and banana).	• Collaborating macadamia growers were provided interactive yield analysis and forecast reports in January each year, 3 months prior to harvest. These were delivered as web apps and html files and showed historic and forecasted yields for all blocks along with previous forecast accuracies, a map of block forecast yield for the coming season, and weather data related to yield. • Classified maps of derived yield maps across orchard blocks and whole farms (for mango, citrus and olive orchards) derived from satellite imagery were provided to participating growers via industry engagement Web Apps.
Further development and adoption of tools that support the improved monitoring of tree health I.e., abiotic, and biotic constraints, biosecurity threats.	Outcomes will support the more judicious application of inputs and rapid detection of biosecurity incursions.	• For the olive component of this project, a range of commercial technologies (sap flow, dendrometers, soil moisture, soil conductance, canopy temperature and relative humidity, satellite and airborne imagery) were assessed for their capacity to measure the early onset of water stress. These assessments included accuracy, responsiveness, affordability and reliability of these technologies as well as connectivity. For the latter the SigFox-Thinxtra network was selected with live updates of the sensors provided to growers through a web interface (refer to Figure 105, in the full project report, Section 6.3.3.4). By navigating through a wide range of technologies, identifying the most responsive sensors as well as a commercially relevant connectivity option offers significant benefit to growers within drought prone areas. • As mentioned previously, classified maps of derived yield maps across orchard blocks and whole farms (for mango, citrus and olive orchards) derived from satellite imagery were provided to participating growers via industry engagement Web Apps. • The national mapping of crops through the ATCM and the mapping of non- commercial mango trees in the Cape York region both directly support improved biosecurity preparedness and response.
	Platform to assist with the improved regional and national yield forecasting and yield mapping via the culmination of climate models (where available), total crop area provided by the national tree map, and newly develop methods for estimating yield at the individual tree level.	Outcomes will support accurate forward selling decisions, and monitor spatial and temporal variation in orchard performance, i.e., varietal performance, disease, and pest incidences etc. (mango and macadamia). For macadamia, spreadsheets, charts and web apps showing the results of analysis of macadamia planted area vs year (using remote sensing algorithms) were provided to Queensland Department of Agriculture and Fisheries and the Australian Macadamia Society to support regional yield forecasting and industry growth analyses. Whilst for citrus, mango and olive block and farm level yield forecasts were provided to the many participating growers across Australia (refer to Table 1) via a range of formats. With the significant amount of data now collated and ever-increasing grower engagement, the development of regional models is achievable, with the continuing PhD study on mango already including this component.
Improved detection and monitoring of specific target species to prevent future biosecurity threats from northern	Outcomes will support state and federal biosecurity agencies and the mango industry to be better prepared for future biosecurity threats entering Australia from neighbouring	Through collaboration with Federal and state biosecurity agencies the project team collated and spatially referenced all existing data that identified the location of non- commercial mango trees in the Cape. Additional image analysis of remote sensing data identified other mango tree locations that were shared with the agencies for validation. The result of this engagement was a map of mango locations in the Cape (refer to Figure 23, in the full project report, Section 2.3.4.2) https://arcg.is/0KLH1q

neighbours i.e., abandoned mango orchards in the Cape York; as well as individual citrus tree and host risk host of citrus trees.	islands in the north.	
Identify optimal sensor, connectivity, and platform options for the deployment of strategically located IOT that will assist with improved delivering essential information about crop performance such as modelling maturity and growth rate, risk of frost, pest and disease incidences and irrigation efficiency. UNE will also evaluate a number of commercial platforms such as EnviroEYE to determine that best suited for delivering the information to end users.	Outcomes provided olive growers with a better understanding of what sensors and on farm connectivity options are most sensitive to early water stress. The collation of information was provided to growers in an integrated platform	Olives: After analysis of the many available options, the project selected SigFox IoT networks, which provided the necessary connectivity across the olive irrigation trial, with lowest cost and minimal maintenance and configuration requirements. Irrigation monitoring sensors were deployed including weather, soil moisture, sap flow and dendrometer sensors, which provided wireless updates every hour. EnviroEye provided visualisation of the data in the first 1.5 years but did not have resources to continue this. UNE stored and processed all sensor data and provided Google Data Studio visualisations to end users.
The project will deliver a number of newsletters, scientific publications, and PhD thesis.	The project achieved extensive communication via a range of media, direct communication and engagement. The impact of project extension can be clearly seen by the number of growers engaged in each project component, the contribution to the mapping, the now commercialisation of some of the outcomes and the awards received by the research team.	103 media pieces that communicated the project and progress were captured from July 2020 to the conclusion of the project, December 2022 (refer to Appendix1 section 7.1 within full project report, Table 22) 3 Journal Articles and 3 Chapters in a book or paper in conference proceedings have been published in relation to the project (details provided below). PhD thesis titled '*Integrating Remote Sensing and Meteorological Variables for Yield Forecasting of Horticultural Tree Crops' due* for submission in 2023.
Theses	Masters of Science (2); PhD (1)	Available in Trove and CQU library website, see links in Publications section
Scientific publications	Refereed articles (21)	Available online, see links in the Publications section. Google Scholar records rising citation rates on app papers, e.g., the MangoYOLO paper on design of a deep learning architecture optimized for mango fruit detection has 242 citations. CI Walsh H index stands at 39 (Scopus)

Scientific webinar	1, general public access on-line	https://agronomy-1.sciforum.net/
Industry publications	Articles in Tree Fruit magazine Mango industry magazines Hort Innovation	The Australian mango harvest aid—a story in the making. Australian Tree Crop Magazine, August/September 2022 Reproduced in https://www.industry.mangoes.net.au/cmsb/uploads/mm-spring-2022-final-(web)-revised.pdf World first – mango autoharvester. Australian Tree Crop Magazine, November 2021 https://www.treecrop.com.au/news/world-first-mango-auto-harvester/, See AMIA report "A tool we now couldn't see our operation operate without" P 8 Mango Fund Annual report 2021/22 https://www.horticulture.com.au/globalassets/hort-innovation/levy-fund-financial-and-management-documents/fund-annual-report-pdfs-202122/hort-innovation-far-mango-2021-22.pdf
Industry events	Presentations	See industry Association reports. Citrus Technical Workshop, Olive Seminar, AMIA roadshow events 9multiple places and years, including hosting on CQU campuses in Rockhampton and Bundaberg).
General media	Various articles also appeared i other media, undertaken with intent to reach the wider ecosystem of Australian tree fruit production	Type 'mango autoharvester' in Google search.
Heat units	Temperature sensors established in 7 mango growing regions, with publicly available data	See image below and www.fruitmaps.info This resource enables grower forecast of harvest date based on a regional temperature sensor and input of flowering date
NIR	Neural network model for mango DM developed (replacin PLS model)	Model utilized by AMIA in NIR-DM assessments of Australian mango from 2021/22 season
Orchard imaging, mango harvester	Website	Used in display of imaging data (flowering and fruit load) to growers
Orchard imaging, mango harvester	MoU CQU and Freelance Robotics Nov 2021 for commercialization of tech	Awaiting Hort Innovation to CQU license
Fertiliser and chemical management through improved on-farm data monitoring and intelligence.	Developed and enhanced a full digitized Spray Dairy including fertilizer and chemical inventory module.	During the course of the project, we made modifications to the Spray Dairy in order to better accommodate the requirements that banana farmers have about the application of fertiliser on their farms. Offline functionality was introduced to the mobile app in order to accommodate locations with poor reception, and we included capability for cost capture in order to encourage accurate data entry.
QR barcode system to manage labour through improved on-farm data monitoring and intelligence achieved through digitalisation.	A full labor management module to track workers productivity and harvest information.	The labour management component of the TieUp Farming programme has been further expanded and improved by our team. We combine a variety of methods that growers can use to collect information on their labour.

Tagging bunches system to enable digitalisation.	Digitalisation through scales and RFID scanner system for analyzing RFID tags and bunch weight analysis.	Banana growers now have access to a complete RFID system that makes use of RTK technology and can be used to tag bunches of bananas. We linked the scale and RFID scanner in the packing shed to a computer so that the appropriate data could be uploaded to the cloud. The RTK was installed on the bagging equipment machinery together with the RFID scanner so that the bunches could be uniquely identified.
Spatial mapping data of tree productivity.	Map view of banana bunch tagged and harvest information on the map.	Our satellite view map displays, on a block-by-block or patch-by-patch basis, the productivity of the banana plants based on the number of bunches that are being produced by the individual plant.
Packing Shed management system including an Allocation module between Sales Order module to Storage inventory management module enabling the digitalisation of the operation.	A full packing shed management module for banana growers.	A piece of software that will help manage the outputs of the packing shed and will digitise the processes.
Industry events	Australian Mangoes' pre-season roadshows (16)	The project's progress, tools and technologies were presented at Australian Mangoes' pre-season roadshow events.
Industry events	Webinar (2)	Australian Mangoes Remote Sensing Webinar held on 16 September 2020. Recording available here. 29 attendees + 133 views on YouTube. Australian Mangoes R&D Update Webinar held on 31 August 2021. Recording available here. 36 attendees + 64 views on YouTube.
Industry publications	Articles in Australian Mangoes quarterly magazine – Print and online (8)	AMIA's Mango Matters Autumn 2020 edition, p22-23 "How many mangoes do I have?" AMIA's Mango Matters Spring 2020 edition, p26-27 "Mango fruit yield estimation from satellite data" AMIA's Mango Matters Summer 2021 edition, p22-26 "National tree crop mapping – Queensland updated" and "Australian mango industry crop forecasting – how is it going?" AMIA's Mango Matters Autumn 2021 edition, p31 "Picking a mechanical winner" AMIA's Mango Matters Spring 2021 edition, p13 "Mango map now up on website" AMIA's Mango Matters Autumn 2022 edition, p23 "Mango yield mapping field walk" AMIA's Mango Matters Winter 2022 edition, p22 "When do I harvest – heat units the easy way using Fruitmaps" AMIA's Mango Matters Spring 2022 edition, p22-24 "The Australian mango harvest aid—a story in the making"
Industry publications	Articles in Australian Mangoes eNewsletters (12)	My Mango – 21 January 2020 (in relation to bushfire map) My Mango – 29 January 2020 (in relation to bushfire map)

		The Slice – July 2021 edition My Mango – 7 September 2021 My Mango – 26 October 2021. Fruit mapping article and Mango Yield Mapping Field Walk advert. Event also advertised 2 November 2021. My Mango – 29 March 2022 The Slice – July 2022. Publication of the video "An introduction to the National Mango Tree Crop Map Dashboard" (1) and article on the Fruitmaps platform (2) My Mango – 20 September 2022. Publication of the video "Adoption technology to predict your crop". My Mango – 27 September 2022 (video included again) My Mango – 4 October 2022 (advertisement of the auto-harvester field demo) My Mango – 11 October 2022 (article on the auto-harvester field demo)
Industry publications	Articles in Australian Tree Crop (1)	Australian Tree Crop - 22 Sept 2021 "Satellites helping with NT mango harvest"
Videos	4	An introduction to the National Mango Tree Crop Map Dashboard, 4/7/2022. This video sees AMIA Industry Development Manager, Marine Empson discuss the National Mango Tree Crop Map Dashboard and why it is important to industry. (341 views on YouTube, 1771 views on LinkedIn) Adopting technology to predict your crop, 20/09/2022. The video features Martina Matzner, Tech Adoption Advisor and previous mango grower, who talks about the range of tools and technologies available to assist growers in predicting their crop numbers and harvest timing, and how these technologies will contribute to the exciting future of the mango industry. (234 views on YouTube, 2694 views on LinkedIn) Mango forecasting with machine vision: how it works, Nov, 2021. This video is a promotional video explaining the machine vision technology. It was used as a promotional video at Roadshows to encourage growers to trial the technology on their farms for the 2021/2022 and 2022/2023 seasons. (600 views on YouTube) Fruitmaps.info heat units calculator for mango, Dec 2021. This video demonstrates the open access version of the fruitmaps.info heat units calculator. It shows users how to input peak flowering dates from their farm and provides an estimated harvest date, based on historical temperature data from the BOM. These data are updated with the current season's data from locally placed temperature sensors as the season progresses. (842 views on YouTube)

Media appearances	Press and TV (5)	NT News Freshplaza Foodmag Sydney News Today Australian Online News Network
Report	1	AMIA and QDAF collaborated to write a review of existing yield estimation tools and forecasting strategies used by the Australian mango industry (see Appendix 4)
Project poster	Poster and newsletters (4)	Project poster ‘Facilitating the adoption of multiscale monitoring tools for managing Australian mango crops’ displayed at TropAg from 31 October 2022 to 01 November 2022. 800+ registered delegates. Project poster displayed at Berry Springs Mango Market on 31 October 2021. Multiscale monitoring tools for managing Australian tree crops’ in NT Farmers Association magazine. An article ‘NT growers using satellite images for mango yield forecasting’ published in Territory Rural Review November 2021 Issue. NT growers using satellite images for mango yield forecasting - Department of Industry, Tourism and Trade
Scientific conference presentations/ Stakeholder forums, meetings	3	Project update presented at International Symposium of Tropical Fruits of the TFNet on 28 September 2021. https://www.youtube.com/watch?v=e3QEUuV8ckY&list=PLKxiDl17HlWvQaMITh2S7BNNrVtPS3feo&index=2 ‘Satellite based mango yield prediction for NT farms’ presented at 2021 Developing Northern Australia Conference on 18 August 2021. Mango yield mapping field walk, 4/11/2021, 40 attendees, Professor Kerry Walsh presented the machine vision technology at Manbulloo’s Pin Road farm. A Mango Matters article was also published about the event. Dr Geoff Dickinson presented at the Northern Australia Food Futures on the benefits, economics and technology that will support the transition to mango orchard intensification, 20/05/2021, 50 attendees.

2021 ISTF Conference Proceeding	1	An update on tropical fruit RDE in Australia.
Case study	1	Case study on Ray Courtice, FNQ grower developed by Hort Innovation and published in the Mango Annual Report and summer edition of MangoMatters, 2023 (yet to be published).
Web page	2	National mango tree crop map dashboard published on the AMIA website on 2 September 2021 A new user-friendly version of fruitmaps.
Social media presence		Events and communication also on our Facebook page and LinkedIn page to extend communication. Queensland Agriculture Facebook post, 3/12/2020 'Mango Mania'

Outcomes

Table 20. Outcome summary

Outcome	Alignment to fund outcome, strategy and KPI	Description	Evidence
Achieving improved pre-harvest yield forecasting accuracies at the national, regional and farm level.	***KPI 3.3 Develop improved pre-harvest yield forecasting accuracies at the national, regional and farm level for macadamia, mango, olive and citrus.***	More accurate pre-harvest yield forecasting of tree crops offers significant benefit at a range of scales. At the national and regional scale higher prediction accuracies support the respective industry bodies in making more informed decisions around forward-selling to both domestic and overseas markets; whilst at the farm level, growers can better plan logistics around harvesting including labour, machinery, packaging, transport, and storage requirements as well as their own capacity to meet market demands. All these aspects have the ability to improve profitability for growers and industry stakeholders.	**Macadamia** Over the course of the project, grower level data was provided by 21 macadamia orchards, consisting of 204 blocks, totalling 1156 yield records from 2012-2021. This covered 1,800 hectares, approximately 5% of the Australian industry, from mid-NSW to north-QLD. The first component of the macadamia work developed a macadamia tree planting year predictor with mean absolute prediction error of 1.7 years. This was used to provide annual statistics of total macadamia area by year to the Australian Macadamia Society and Queensland Department of Agriculture and Fisheries. The second component developed a novel block level yield forecasting methodology based on the extensive amount of historic yield data collected, historic acquisitions of satellite imagery and weather variables. The resultant models generated a mean absolute prediction error of 20-25% at the **block level** (except for some severely drought effected orchards in 2020) for predicting average and total yield, and median **farm-level** production prediction errors of 8-12% (excepting 2020). These predictions were made months prior to commercial harvest, did not require infield data collection and produced accuracies that exceeded current commercial practice. **Citrus** For the citrus component of the Phase 2 project, two methodologies for improved pre-harvest yield forecasting and estimation at the farm and regional level were tested. The '18 Calibration Tree' approach (18CT) was used to provide insight of block/orchard variability which supports harvest segregation and the more judicious use of farm inputs (water, fertiliser etc). This approach requires tree level fruit counts to be collected during the growing season to establish an empirical relationship between remote sensing data (in the form of vegetation indices – VIs) and yield (t/ha, kg/ha). In total, 51 orchards across Red Clift, Leeton and Moora (cv. Afourer Mandarin and Late Lane, Washington, Chislett and Barnfield Navels) were sampled between 2020 and 2021. The second remote sensing approach, the Time series method

			(TS-Citrus) was developed to provide early yield forecast at the block level that can be extrapolated to farm and region level. This approach provides yield estimates around fruit set, months before commercial harvest and does not require infield sampling. For this method, historic yield data from 2007 until 2022 was sourced from five commercial farms (FC, FH, FK, FM and FT) representing 4.7% of the total planted area of citrus in Australia, including the most common citrus types: Navel, Mandarin, and Valencia and varieties (26 in total). Specifically, 27% of planted area in the Wheatbelt region, 14% in the Riverland and 6% in the Sunraysia were analysed. From the total number of blocks included in this study, Navels represent 50% of the planted area in the Sunraysia, 64.5% in the Riverland and 75% in the Wheatbelt region and Mandarin (Valencia) represents 50% (6%), 28.3% (7.2%) and 12.5% (12.5%), respectively. Overall prediction accuracies from the 18CT method ranged between 80% and 98% with the highest error (30%-40%) coming from orchards that experienced hailstorm damage and such suffered major yield loss. The prediction accuracies for the TS-Citrus method at the **block level** were on average 71% and at the **farm level** 80%. The accuracies from both methods exceeded current commercial yield forecasting practices. **Olives** For the olive component of this project, groves located in Mornington Peninsula and Boort (VIC) were included. A total of 19 groves between 2020 and 2022 were sampled to test the ‘18 calibration tree’ (18CT) methodology for yield estimation at the block level. The study demonstrated the ability of the 18CT to estimate yield one month prior to harvest with varied accuracies that were dependent on the conditions during calibration and harvest timings. Accuracies at the **block level** ranged from 63% to 99.8% with eight out of 11 groves, with an overall accuracy of above 85% achieved at the **farm level** (Farm 1). Lower accuracies were achieved at the two other farms (Farm 2 and Farm 3) as a result of external factors not related to the methodology. Overall, the remote sensing yield forecasting methodology developed through this project offers prediction accuracies higher than commercial practice. **Mango**

			This research investigated the accuracies of high-resolution Worldview 3 (WV3) satellite data (single capture) and the 18-tree calibration (18CT) methodology for pre-harvest mango yield prediction and yield variability mapping. This was validated over three consecutive seasons (2019/20/21), encompassing 13 farms (>250 individual orchard blocks) across four growing regions, eight mango varieties, with various tree ages and management practices. On average, an overall accuracy of ~87% at **block level** and ~94% at **farm level** was achieved in fruit count estimation using satellite data for 2019-21 seasons, a significant improvement on traditional manual yield estimation methods. In addition, the use of only 18 trees for in field calibration was significantly less than the 2-3% of trees currently counted by growers, offering significant labour and time savings for mango yield forecasting. Further evaluation of both low cost (Planet) and freely available (Sentinel-2) satellite data (over 21 blocks 4 farms in NT, NQLD and SEQLD regions for 2019/20 season) also produced comparable yield forecasting accuracies. This result is encouraging as it presents growers with a range of remote sensing cost options. A time-series yield forecasting method based from Landsat satellite imagery was also evaluated to develop a model that provided yield forecasts much earlier in the season and with no infield fruit counting required. This further reduced the labour costs and time to estimate yield manually. The results for 2021-22 season were found to be highly accurate at both **farm** and **block level**, with yield prediction errors ranging from 2-15%. These accuracies exceeded commercial practice and as such is continuing to attract more Australian mango growers every season.
Develop practical tools and analysis methodologies that improve the within orchard monitoring and mapping of tree health, fruit quality and maturity.	***KPI 3.4 Develop practical tools and analysis methodologies that improve the within orchard monitoring and mapping of tree health, fruit quality and maturity.***	Additional to improved pre-harvest yield forecasting and mapping, growers require practical and adoptable tools for monitoring of tree health, phenological growth stage, fruit quality and maturity. Maturity related parameters such as	Throughout the Phase 2 project, remote sensing has been demonstrated as a highly accessible and accurate tool for identifying variation in tree vigour (health and size) across orchards within a growing season and across years. Planet, Sentinel, Landsat and Worldview satellite imagery as well as airborne imagery from CERES were all shown to be useful for this purpose and as such present as a wide range of resolutions (temporal, spatial, spectral and radiometric) as well as cost option for end users.

		fruit size, dry matter content, shelf life, blemish level etc. all influence farm gate price. Therefore, the ability to predict optimal harvest timing and segregation based on quality and maturity offer significant economic value. The provision of practical tools for measuring variability in tree health can also assist with the early detection of pest and disease outbreaks and assist in the reduction of inputs through the judicious management of water, fertiliser and pesticides.	The provision of tree vigour maps (through Web-Apps, pdfs or other format) directly inform growers on where poor and high performing areas are occurring in their orchards. Simply knowing where and when to conduct targeted agronomy can help growers better understand what biotic and abiotic factors are driving orchard variability in terms of tree health as well as productivity, maturity, quality and phenological growth stage. For olive, the evaluation of a range of technologies to better measure the impacts of water stress on tree vigour, yield, oil accumulation and final oil content (%), directly respond to requirements of this KPI. The evaluation of a range of technologies, identified dendrometers as being the most sensitive to drought stress. These sensors are commercially available and can be deployed with remote access (LP-WAN) to improve grower accessibility. The broader observation that the current levels of irrigation could be significantly reduced without reducing yield potential and quality (particularly during low bearing years), presents significant benefit for reducing water costs for growers and environmental impact. The further identification that olive trees from areas of low vigour accumulated oil at a faster rate than trees of higher vigour, offers significant benefit to growers in terms of more accurately determining when to harvest (based on optimal fruit maturity) as well as the opportunity of employing a segregated harvest to ensure optimal fruit maturity. For mango, the PhD study identified that utility of frequently acquired, historic satellite imagery for ‘benchmarking’ seasonal growth as well as indicating the impacts of extreme weather events. The study has determined the relationship between these annual growth profiles with the timing of key phenological growth stages (i.e. Flowering/Fruitset (F/F), Fruit Development (FRD), Maturity and Harvesting (M/H), Flush (FLU) and Dormancy (D)), outcomes that can greatly assist growers in better timing orchard management activities, including the timely application of crop inputs. These results have been published in a peer reviewed journal as well as presented at two separate conferences in the USA (15^{th} ICPA) and Australia (UNE Postgraduate Conference)). As mentioned previously, the analysis of historic time series satellite data in conjunction with the

			national map of orchards was used to calculate orchard planting dates for macadamia. For citrus, the main focus of Phase 2 was building a better understanding of the relationship between tree canopy reflectance properties and yield.
Develop and deliver improved detection and management tools and strategies to control future biosecurity threats and natural disasters.	***KPI 3.5 Develop and deliver improved detection and management tools and strategies to control future biosecurity threats and natural disasters.***	The national mapping of commercial orchards offers significant benefit to national plant biosecurity by identifying the location and distribution of all commercial orchards. In the event of an incursion, this freely available mapping layer supports the rapid deployment of surveillance staff and the establishment of exclusion zones to prevent further spread. Additionally, this layer can determine the areas of each industry impacted by natural disaster, in near real time. The outputs of this project will also include technologies and analytics that aid in the non-invasive detection of specific plant diseases (Panama) as well as offer improved surveillance of targeted species in abandoned orchards (e.g., olive and mango) that may serve as hosts of plant disease and insect vectors. The development of	The phase 2 project produced several outcomes that are relevant to the improved preparation, surveillance and response to biosecurity threats. The national mapping of tree crops identifies the location of all commercial orchards over 1 ha (ATCM Dashboard). This information is essential in the event of a high risk incursion as it directly informs first responders on where to conduct targeted ground surveillance and where to apply exclusion zones to prevent spread. Having a spatial context, the tree crop map can be overlaid with roads, water courses, walking tracks, topography etc. to better determine high risk movement scenarios and therefore assist in defining where exclusion zones should be implemented. The ability to undertake these two actions in near real-time can be the difference between containment and spread. To further assist the mango industry in being better prepared for future biosecurity threats, particularly those coming from our northern neighbours, the AARSC, together with AMIA and state (Department of Agriculture and Fisheries) and federal biosecurity agencies (Northern Australia Quarantine Strategy, Department of Agriculture Water and the Environment), undertook a challenging project to map all non-commercial mangoes in the Cape York Peninsula. The area-of-interest included the Cape York Peninsula and Torres Strait Islands NRM regions, once developed the mapped location of non-commercial mangoes can be monitored (both on-ground and using remote sensing) for potential biosecurity threats. The project commenced with the collation and geocoding of existing data, which included some 1,580 locations of mango trees. This information was interpreted against high-resolution imagery (kindly provided by the Queensland Government's Spatial Imagery Subscription Program), in combination with other ancillary data, to compile a draft baseline map. The draft Cape Mango Map was published in June 2021 and currently shows 8,969 non-commercial mango trees. Stakeholders have been encouraged to review the draft and contributed to the peer review and provide feedback. (https://arcg.is/0KLH1q).

		improved detection analytics will improve the efficiency and effectiveness of the surveillance component of control and containment programs (e.g., banana) offering significant savings in labour costs for any managed response to biosecurity incursions.	The remote sensing analysis undertaken within the Phase 2 project also offers highly beneficial insights and outcomes relevant to biosecurity surveillance. The single capture of satellite and / or airborne imagery and the subsequent classification of tree health across an orchard can indicate individual trees that are underperforming or suffering from a constraint, including pest and disease. This output alone can direct where growers and surveillance teams should undertake infield assessment to identify the cause via visual assessment, PCR testing etc. As the imagery has a spatial context, GPS locations of sick trees can be extracted from the imagery to direct the infield observation and similarly field observations can be linked back to the mapping layer. The time series analysis also provides a highly beneficial output. The establishment of a historic seasonal measure of canopy vigour can be used a 'benchmark' of usual tree, block, farm and even regional tree condition. Any rapid variation from this benchmarked performance may indicate the onset of a biosecurity incursion. This method can be automated to better inform growers and biosecurity agencies of 'where' and 'when' to look for possible incursions.
Increased mango grower awareness and use of heat units for forecast of time of harvest	**OUTCOME 4 – Improved industry sustainability and management of risks**	Easy to use heat unit calculator resource, with improved algorithm	Observed grower use of sensors and calculator
Improved use of mango NIR-DM	**OUTCOME 1 – Increased industry productivity through increased yields and reduced costs per hectare**	Implementation of neural network over PLS models, with improved instrument performance	AMIA quality control (calibration) exercises at start of season
Increased instrument supplier base to mango industry	**OUTCOME 1 – Increased industry productivity through increased yields and reduced costs per hectare**	temperature sensor hardware for heat unit estimation. machine vision-harvester system commercialization path	SensorHost now providing temperature sensor hardware targeting heat unit estimation. MoU signed for commercialization of machine vision-harvester system.

Personnel migration from research project into mango industry	***OUTCOME 3 – Increased R&D and extension capacity and resources supporting industry development***	Two research staff/students have entered employment in mango industry	Contact employers
Digital solution for the banana growers to enable better decision making and better management, mainly in the farm, packing shed and marketing levels.	***Growers or a business user utilising project output to forecast yield and carry out yield mapping for better farm management.***	We have observed the growers' use of the programme and asked them for continuous input during the duration of the study. The process of digitising agricultural operations is a difficulty for most growers and agribusinesses. Time and precise timing are required for its implementation. The way this this is relevant to the fund is by providing real-time, digitise information, more granular data, and improved insights on the crop and what was applied to it are some of the benefits that come with "digitising" the farm once it was done during the life of the project (better access to data). Putting everything together help to provide a yield mapping and enhance the yield forecasting algorithm.	The primary method of gathering evidence consisted of conducting interviews with the farmers and gaining a knowledge of the requirements they had. We also conducted interviews with a variety of stakeholders within the agribusiness in order to gain a better understanding of their requirements. For instance, we spoke with the marketing department of one of the agribusinesses in order to gain insight into how they currently collect data and act upon it, as well as how they would describe their ideal scenario for making use of the data. We devote a significant amount of time to analysing the farmers' usage of the program as well as the data that is being collected. We collect information from the growers and many stakeholders about how they will characterise the most effective approach to provide the data in order to make better decision. In light of the findings presented above, we took the necessary steps to devise an appropriate tools, digital capabilities and set of reports for the use of the agribusinesses.
The management of the packing shed, GPS systems, bunch tagging, and other aspects of the banana farm's operations are all up and running	***GPS system, bunch tagging, packing shed management and banana farm operation is all linked, set-up and complete.***	The implementation of this system is one of the most important aspects of this project for the banana sector. The result is a comprehensive system that is immediately ready for commercial use and can	During our first campaign, we attempted to combine tagging banana bunches with harvest management. Unfortunately, this strategy was unsuccessful. We also tried NFC (near – field communication) tagging method which requires no equipment other than cell phone, but we could not attain the necessary precision to tag banana bunches. During the first campaign we deployed all tags on to the 1 block. On the second season, we were able to achieve the

and fully functional.		be adopted by both individual growers and major agribusinesses. The system is robust and easy to use (still few tweaks might be needed for better tag insertion). This is relevant to the fund as the tagging technique will assist in identifying individual bunches/plant as well as the total weight of each bunch. This will provide an early indicator about the health of the plant as well as how the block is preforming on a granular basis (plant basis). This is the first step in understanding how activities on the farm and weather events effect each plant individually. Soil, water and managing natural resources: The spatial mapping of productivity at a range of scales (individual tree, orchard, and region) assist growers in determining high, medium and low productivity areas that assists with targeted agronomy and the variable rate application of plantation inputs including fungicides, pesticides etc.	required level of accuracy, and we performed a deployment that was more commercial in nature. Following an analysis of the machinery that we chose to install in the packing shed and on the farm, we have begun testing and putting into operation the machinery required to carry out the relevant tests. A high-precision GPS device, a unique overhead scale in the packing shed, and a complicated system of RFID scanners on the farm and in the packing shed are some of the pieces of technology that we have installed. Alongside this, there were also technological advancements made to the software that was used for data collecting. During the time period in question, we carried out a number of farm visits, in addition to training and work on implementation on the farm itself.
Reduced traffic and erosion along the interrow	***Growers or a business user utilising project output to forecast yield and carry out yield mapping for better farm management.***	As soon as the bunch was tagged, the banana producers were able to despatch the appropriate team to the appropriate location in order to perform the necessary agro-technical operations on the bunch. Additionally, the producers were able to send the harvest crew directly to the place where their services were	We observed a few growers at work on blocks that had some tags implemented to the bunches in it. They were working on the block. We watched them looking at the map to identify the place, and we also witnessed how, based on the location that was displayed on the TieUp Farming app, they carried out the operation at hand, which included harvesting and sending workers to the precise spot. In addition, we conducted interviews with farmers, and it became very evident that this provides them with visibility about how to more effectively manage their blocks.

		required, which contributed to an increase in both the level of safety on the farm as well as the level of efficiency achieved with regard to the labour.	
Increased industry awareness of the new tools and technologies available or in the process of being commercialised to predict crop yield and harvest timing.	***Outcome 3: Extension and capability*** ***Improved capability and an innovative culture in the Australian mango industry will maximise investments in productivity and demand.***	Roadshows, field days, grower visits, promotional video delivered practical information to mango growers.	Website visits and stakeholder responses to project surveys, grower engagement and feedback
Increase industry awareness of the new auto-harvester being developed and the associated needs regarding orchard design and canopy management.	***Outcome 3: Extension and capability*** ***Improved capability and an innovative culture in the Australian mango industry will maximise investments in productivity and demand.***	Roadshows, field demonstration, grower visits, promotional video delivered practical information to mango growers.	Website visits and stakeholder responses to project surveys, grower engagement and feedback
Increased grower skills and adoption of the machine vision rig.	***Outcome 3: Extension and capability*** ***Improved capability and an innovative culture in the Australian mango industry will maximise investments in productivity and demand.***	During the 2020/21 and 2021/22 seasons, the machine vision yield mapping system was made available to the broader industry and growers were encouraged to trial the imaging rig on their own farm.	Grower participation and feedback.
Time series modelling using lower resolution satellite imagery	***Outcome 3: Extension and capability*** ***Improved capability and an***	UNE investigated and demonstrated that time series modelling can accurately predict crop yield. This	UNE report and presentation. Feedback from Industry and the AMIA board.

alongside farm historical yield data was proven to be an accurate methodology to predict crop yield.	***innovative culture in the Australian mango industry will maximise investments in productivity and demand.***	methodology doesn't require calibration trees. Industry and some farming businesses have expressed interest in pursuing this approach further.	
Access to a more user-friendly version of Fruitmaps using more accurate temperature data	***Outcome 3: Extension and capability*** ***Improved capability and an innovative culture in the Australian mango industry will maximise investments in productivity and demand.***	A new version of fruitmaps was developed by CQU, with temperature data loggers installed in the main mango growing regions. Growers were encouraged to use the platform through communications and tutorial and promotional videos.	Website visits, number of views
Increased industry capability to more accurately predict crop yield and timing of harvest.	***Outcome 3: Extension and capability*** ***Improved capability and an innovative culture in the Australian mango industry will maximise investments in productivity and demand.***	A range of tools have been developed to assist growers predict crop yield and harvest timing. The project team and the mango industry gained knowledge and skills on how to use them.	Project reports and activities
Increased industry capability to more accurately map and identify orchard variability.	***Outcome 3: Extension and capability*** ***Improved capability and an innovative culture in the Australian mango industry will maximise investments in productivity and demand.***	The tools developed as part of this project can also be used to map orchard variability and tailor management practices (precision agriculture).	Case study, project reports
Increased collaboration between research	***Outcome 3: Extension and capability***	The direct involvement of NTDITT, QDAF, AMIA, UNE and CQU has allowed for a more	Meeting attendance and minutes, supporting activities undertaken

partners and extension service providers	***Improved capability and an innovative culture in the Australian mango industry will maximise investments in productivity and demand.***	effective collaboration between state and territory departments, universities and peak industry bodies.	
Increased industry's biosecurity preparedness	***Outcome 2: Industry supply, productivity and sustainability*** ***The Australian mango industry has increased profitability, efficiency and sustainability through innovative R&D, sustainable BMPs and pollination.***	Map of abandoned orchards in Cape York is available.	Website visits
Better access to industry data	***Outcome 4: Business insights*** ***Measure industry supply (production) and demand (consumer behaviour) data and insights to inform decision-making.***	The existing mango map was updated with ground truthing work from UNE and review from AMIA.	Updated national tree crop map.

Monitoring and evaluation

Table 21. Key Evaluation

End of Project Outcomes (PLF)	Project Component	Outcome delivery	Insights	Continuous improvement opportunities
1.2 Improved awareness and adoption of tech 1.3 Improved detection of biosecurity threats **1.4** Improved mapping of commercial orchards	National Mapping	Updated maps for Macadamias and Mango. New maps for Banana, Olive and Citrus. Significant level of adoption by industry Use of maps as decision support tool - biosecurity, infrastructure, disaster response & recovery	Use of three different levels of satellite imagery made it more cost effective for growers Relied on 'champions' who can facilitate input from various industries and regions to support 'ground truthing' / validation of the data Project drove unified approach to tree cropping mapping in Australia Tree Crop map has become the 'gold standard'; recognised both nationally and internationally. Provides a common platform to capture and aggregate grower data. Used to inform Federal and State Government investment and planning Biggest supporters are industry and bigger growers. National maps are a useful decision support tool enabling evidence-based decisions. Aligning with National mapping standards have been really valuable in adding credibility as a 'trusted source' for maps. Having regionally based staff allowed work to continue through COVID Greatest supporters are industry and the larger growers.	Would like to see integration of other data into national maps e.g. flood zone layers Not leveraging full use of the national map unless connected to other data. Lack of compatibility with mapping data exists between some jurisdictions. Maintaining map will be real challenge. Who will pay for continuity? Know technology really well now and how it interacts with various crops. Opportunity to include Almond industry and wine grapes. Tool evolution possible – quantify individual grower area as % of region, regional branding, land use planning, infrastructure, logistics planning Data security concerns among some growers (eg: where is the data going to? Who can access it?) Keep industry engagement: easy, uncomplicated, and inexpensive
1.1 Improved forecasting **1.2** Improved awareness and adoption of tech	Time series forecasting model 18-Tree	Time series modelling developed using 5yrs of satellite imagery and yield data – good accuracy at farm level – olives, citrus, macadamias Good collaboration	Hugely innovative and beneficial: addresses a commercial need for growers. Nothing else does this Growers surprised with	Time series data modelling not as accurate at block level. Fee for service model (commercialization) opportunities – imagery is free, individual models still

	forecasting model	outcomes with research partners. The 18-tree approach describes yield variability within the orchard level. It is ideally suited for growers with young orchards or growers that do not have historic productivity information. It requires high resolution imagery and manual counts of fruit. In terms of yield forecasting at the regional and national level, macadamia and citrus are the most progressed.	accuracy (90%). Growers delighted and surprised that technology was accessible and could be applied so readily. Key decision tool and timely. Improved value if explored earlier and considered for regional level. Project has provided opportunities to engage with new industry (macadamia) and develop relationships and build trust in 'research' Geographical scope of project was large. Time and logistic involved weren't well understood at start. Difficult to include some of the smaller growers as one of the project criterion was participants needed 500 trees of a single variety. Inability to capture some remote sensing images across some orchards [EG Mornington Peninsula].	need to be built, data needs to be processed in model. AMIA would like to develop regional industry model. Attraction of PhD students to assist with the research is extremely difficult. Need to rethink attraction and retention strategies.
1.1 Improved forecasting **1.2** Improved awareness and adoption of tech	Irrigation Trial (Olives)	Hugely beneficial for assisting growers to make investment decisions regarding yield production Significant data capture on tree response to water stress and the impact on fruit quality and yield Historically testing on olives has been hard to achieve	Learning: minimise crop loss during drought using remote sensing Legacy of equipment provides opportunity for more data collection. Great for small industry to have such a large block of work.	Needs further time to collect more data and analyse. Future questions – resilience of trees in 3-5 years? How well will trees recover from water stress? Opportunity for traceability of product to assist with quality insurance for table olives
1.1 Improved forecasting **1.2** Improved awareness and adoption of tech	Banana Yield Forecasting	RFID tag technology deployed on farm to improve forecasting of banana production. Tags contain information about GPS point on the fields, date, time and who is scanning it. A 10cm accuracy is constantly achieved for bunch	Diversity of banana crops makes it difficult to do yield forecasting. AgTech companies face difficulties in research space – business idea focused, no industry contacts, don't understand crop.	The banana research resulted in limited large scale demonstration and testing of forecasting accuracy. Only two farms were part of the final research – this is not enough to be conclusive on the

		location. Yield mapping system involves GPS system, bunch tagging, packing shed management and banana farm operation has been successfully installed, linked, and operational. Scanned data is stored in Tie-Up Farming cloud based software and used by the algorithm (ML) to forecast yield.	Cost of tags could be a barrier to adoption Further improvements to equipment needed – waterproofing of head unit	applicability to farms at a general level. Requires good access to reliable internet coverage. Further trials are required to demonstrate the logistical feasibility and benefits arising from this technology.
1.1 Improved forecasting **1.2** Improved awareness and adoption of tech	Mango Imaging System & Harvester	Imaging system is operational and being used by growers with minimal support. Harvester prototype developed. Commercialisation not finalized. Terms of IP license have been negotiated but license is yet to be issued. MOU in place with commercial partner. High industry awareness	This project funding allowed for this technology development to 'get legs'. Unexpected levels of collaboration with government departments in NT and Queensland. Assumed this technology could be applied to other crops e.g. olives, bananas. Realised that it is not as applicable due to crop characteristics such as amount of leaf litter. New technology is tending to be picked up by younger generations. Growers are interested in what else the technology can do. Role of an Industry Development Officer (Martina) has been critical to project success. Onboarding a commercial partner at an earlier stage would have been beneficial.	Built up a team that is effective and they will disappear when the project ends. What does this mean for longevity of the tech? Data needs to be downloaded and then sent to processing computer. Requires reliable power. Commercial version will need to include UPS. Opportunity to shift to autonomous/ self-propelled systems. Potential for harvester to influence orchard design (tree size, planting density) Funding has enabled extra 3-year focus on advancing technology. Continuity brings time to build up relationships with growers. What are the 'use cases' for these technologies? – exploring complementary applications
Foundational	Project Management	Project managed effectively. Project team collaborates effectively to deliver project outcomes.	Strengthening the project ecosystem thinking from the get-go… making valid connections and joining people up and promoting new talent and opportunities for 'rising	Design individual project contracts with clearly articulated activities and or KPIs Create an Onboarding / Induction process for

			stars’ Project partner capacity to operate in a research environment can vary and capacity building may need to be considered and supported. It isn’t always well understood that Hort Innovation invest in R&D outputs by procuring the services of qualified delivery partners rather than undertaking research inhouse.	commercial partners (particularly first-time partners) to familiarise them with evaluation and reporting expectations. Federal Government to offer a Contract buffering process that incorporates a timely/well communicated contractual negotiation period.

Recommendations

National mapping of tree crops:

The development of the national map of commercial orchards has set a new benchmark for whole of industry data collation, accessibility, interoperability and adoption. It has also demonstrated how industry can work directly with researchers to establish an output of such significant impact. This output has been used not only to provide a measure of industry extent (location and area of orchards) but also for natural disaster response (cyclones, floods and droughts), biosecurity preparedness, water security, labour allocation, mapping of tree age and yield forecasting. The mapping has received international award at the highest technological level (ESRI) and has initiated additional commodity mapping (protected cropping structures, truffles and soybeans in Australia and macadamias in South Africa), as well as a value adding e.g., traceability project with Citrus Australia (funded by Agriculture Victoria) adding grower level data and GS1 coding to the citrus polygons.

There is however a need to establish a mechanism that supports the ongoing updating of the national map for all participating industries, otherwise the currency of the map will become outdated and therefore no longer relevant (especially with the high level of new planting that is occurring). The AARSC has investigated a range of options to find ongoing funding to keep the mapping updated annually (with the respective industry bodies), but this has been challenging as the industry bodies themselves do not have funding to achieve this (estimated to be $30,000 dollars per industry annually). Also, applications to the Federal government traceability and biosecurity grant funding have been unsuccessful. Currently, the AARSC and the macadamia, citrus, banana and avocado industry bodies have a project application with the Future Food Systems CRC to continue the annual maintenance of the map, as well as to increase the level of information within each orchard polygon (variety, tree age, productivity, grower information etc.) which will significantly benefit traceability and biosecurity needs. This project will also provide training to each industry body so that they obtain inhouse capacity to update the mapping into the future.

The AARSC has also worked to see the mapping outcome expanded to include all Australian agricultural industries. This has included the running of three workshops with Earth Observation Australia (‘A unified approach to national crop class mapping’) to determine what commodity mapping products currently exist (and to what standard), what end users require from the outcome and what is the optimal structure to derive, manage and deliver this product. The workshops were well attended and thus far the conversation is continuing with the Federal government with support from ABARES, ABS, Plant Health Australia, Earth Observation Australia, Citrus Australia and Hort. Innovation.

Based on the success of this project it is hoped that a pathway forward is identified to continue the commodity mapping for not only the industries involved, but for all Australian agricultural industries.

Macadamia:

Within the Phase 2 project, the remote sensing outcomes and spatial analytics developed for the macadamia industry have been substantial. The development of a tree planting age map for all orchards has directly benefitted the industry by clearly defining where new plantings are occurring, a significant outcome for better understanding and planning future production, marketing, water, transport, labour and processing requirements. It has also greatly improved the regional yield forecasting being undertaken by the Department of Agriculture and Fisheries Queensland (DAF Qld). The development of the yield forecasting methodologies for the orchard and farm level have also been supported by many growers, with accuracies produced exceeding current practice. This outcome has resulted in an increasing level of grower participation, a follow-up regional yield forecasting project with DAF Qld and the further evaluation of the methodologies in South Africa. This yield forecasting work as well as the mapping of macadamia led to the AARSC winning the Australian Macadamia Society research innovation award in 2021.

Whilst the outcomes and outputs have been extremely encouraging and well received, they have identified additional avenues for further research and development. The influence of variety and irregular bearing on yield forecast models has not yet been investigated. Literature suggests causes for this including carbohydrate cycling and pollination effects and interaction with variety. This project has noted that the variable inter-annual yield patterns have been predicted well for some orchards, but not for other. Therefore, some additional investigation is warranted. The prediction accuracy of the models was also influenced by the 2019 drought in some non-irrigated orchards, therefore an improved method (such as the use of thermal satellite imagery) should be investigated to better predict and then account for. Growers and advisors have noted that nut size is often a driver of yield, rather than nut count. Future work could seek to model nut size and count separately to give a more accurate expectation of total nut yield. This work has focused on nut-in-shell yield, but there is also great interest in predicting quality parameters, such as sound kernel recovery (SKR), as this impacts the selling price of macadamia. Scaling yield forecasts from block to regional and national level, making use of the remote sensing methodologies and data engineering developed in this project, should be further investigated, possibly contributing to accuracy of existing climate-based regional yield forecasting efforts.

Citrus:

Within the Phase 2 project, the AARSC achieved strong engagement in evaluating the capacity of remote sensing for measuring variability in citrus tree heath and for the prediction of yield at the orchard block and farm level. Grower participation included the provision of highly sensitive historic productivity information as well as on farm access for individual tree sampling. The forecasting accuracies from both the '18 CT' and 'time series' method was well received with accuracies exceeding current commercial practice. The outcomes have resulted in the Costa Group commercially contracting the AARSC for the forecasting of all their commercial citrus orchards as well as the further evaluation of the methodologies in Peru with ProCitrus (funded by COALA). Additionally, Melbourne University have partnered with the AARSC to further evaluate the accuracies of remote sensing for differentiating specific diseases in citrus.

As with macadamia. Further development of the models in terms of variety, location and season may improve forecasting accuracies (especially at the block level). Further development is required to extrapolate the models to regional, state and national forecasting which is highly achievable considering the accuracies derived from the time series model, the level of industry support including the provision of highly sensitive farm level data and the ability to integrate the models with the national map of orchards. Additionally, the further evaluation of remote sensing for predicting and mapping variability in crop maturity, water stress (with the integration of infield sensing), quality (fruit size, storm damage etc) and disease (Albedo breakdown, HLB, Canker) would offer significant benefit to growers.

Mango:

A large amount of 18 tree data has been collected during the first and second phase of this project that now encompasses 6 growing season, four growing locations, multiple tree ages and varieties. There is significant opportunity to run a full analysis of this data with the inclusion of other parameters such as weather variables to determine if yield variability can be better explained at the tree level from canopy reflectance properties, and if a more generalized model can be derived that would allow the prediction of individual tree yield without the need for infield fruit counting. Additionally, the time series methodology may be significantly improved by the inclusion of other variables such as tree age, variety, weather variables etc. The current PhD study is investigating both opportunities as well as determining if the development of block level models over a greater number of orchards can result in the development of more generic regional, state and national forecasting algorithms. This will require the collection of more grower level data. The study is also determining how accurately remote sensing can distinguish the phenological growth patterns of mango, an important outcome for better understanding seasonal growth patterns, particularly under a changing climate as well as to direct growers with the timing of critical crop management decisions.

Additionally, the further evaluation of the capacity of remote sensing to predict and map variability in crop maturity, water stress (with the integration of infield sensing), quality (fruit size, storm damage etc) and disease would offer significant benefit to growers.

Olive

The olive component of the Phase 2 project successfully demonstrated the capacity of remote sensing for measuring variation in tree vigour cross orchard blocks and farms, for the prediction of yield (at the block and farm level) and for measuring water stress (satellite and airborne imagery). These results were received well by industry as demonstrated by grower engagement and the opportunity to present results at several olive industry forums.

The results achieved thus far also indicate the opportunity to further investigate the accuracies of the 'time series' method for forecasting block and farm level yield, and to better understand the influence of variety, tree age, location and season on the relationship between canopy reflectance properties and yield. These findings will support the extrapolation of farm level forecasts to the regional, state and national level. As with the other tree crops there is the additional opportunity to better understand the accuracies of remote sensing for predicting and mapping variations in fruit quality, phenological growth cycle, nutrition and the incidence of pest and disease. A survey of growers identified an interest in being able to better quantify harvest efficiencies including the ability to determine the amount of fruit left on the trees post-harvest. This output would aid in early detection of incorrectly calibrated equipment or other losses in the harvest process in a timely manner so fixes could be implemented, and losses reduced. Another grower identified an interest in evaluating the accuracies of remote sensing for quantifying the impact of severe weather events.

For the irrigation trial, there was an extensive amount of data collected from infield sensors (dendrometers, sap flow, soil moisture, soil conductance, temperature, relative humidity), remotely sensed imagery (satellite and airborne multispectral and thermal), measures of tree health (stem water potential and light interception) and productivity (flower number, fruit number, oil accumulation and oil concentration) over the duration trial. The results indicated some beneficial outcomes such as the potential to reduce water application in 'off' biannual producing seasons, the differing rate of oil accumulation between trees of different vigour and dendrometers were the most responsive 'real time' measure of water stress. However, an initial failure to find PhD students to support this project, meant that the greater opportunity to analyse this extensive amount of data was not realised. It is therefore recommended that an opportunity is found to analyse this data as the outcomes will offer significant benefit to olive (and other tree crop) growers on what optimal sensors, connectivity and water scheduling is required to maximise mater use efficiencies with reducing yield and quality. Fortunately, a student is starting right as the project is ending, and has attracted a government scholarship, therefore we anticipate further insights will come from this project in the coming years.

Overall, the research team are extremely encouraged by the accuracies, practicalities and commercial readiness of the remote sensing-based yield forecasting outcomes achieved in this project. In order to commercialise these outcomes a commercialisation plan, business model and marketing of the technologies will be required. These outcomes are a world first for mango and it is envisaged that the adoption of the methodologies will occur both domestically and internationally.

The 'legacy and impact' of all project outcomes are provided in the summary section of the Appendices (see Appendix 1). These include the practical applications developed from the Phase 2 project.

Licensing

Phase 2 was undertaken with the intent of seeing Technologies emerging from phase 1 developed to a level to support sustainable commercial development. Without involvement of a commercial partner, project outcomes remain 'academic' and likelihood of engaging a partner decrease if research group expertise scatters post project funding.

It is recommended future Projects look to expedite commercialisation arrangements within the term of the Project.

Industry practice

A number of recommendations are made for industry practice:

Mango NIR-DM estimation

- *A neural network model is recommended for adoption in NIR-DM assessment*.
- *The specification on minimum DM for eating quality should be differentiated from the minimum DM for harvest maturity*, as the latter will vary with growing conditions. It is recommended that growers use NIR-DMC to select fruit of a range of DMC values from an orchard as harvest GDD approaches. The fruit can then be cut to assess flesh colour, and the NIR-DM value associated with fruit at the harvest maturity as evaluated by flesh colour in comparison to colour charts can then be established. That NIR-DMC value can be used in non-destructive assessment of fruit harvest maturity for orchards with similar growing conditions.

Heat units

For the use of GDD in estimation of harvest timing, it is recommended that:

- *GDD be based on local temperature monitoring*, with multiple monitoring sites recommended for larger farms or farms with elevation variations that create microclimates.

- To aid the decision on number and placement of stations, monitoring of a large number (e.g., one per management zone) of stations over a one winter week and one summer period is recommended,
- *temperature should be monitored outside the tree canopy*, using the BOM standard of placement 1.2 m above a ground surface covered with vegetation or mulch.
- *For ease of implementation, use of automatically logged temperature sensors and an automated calculator is recommended*, such as the 'fruitmaps.info' resource.
- *The Upper T temperature method* (using a Tb = 12 °C and TB = 32 °C) *is recommended*, relative to the standard method, particularly for northern sites, although further confirmatory work is also recommended.

The following minimum maturity specifications are recommended (with GGD measured from asparagus stage of flowering):

- *Calypso: GDD of 1728*, CIE B of 32 (card 7), DMC of 16.0%, TA < 1.1 and SSC:TA > 6.5
- *Honey Gold: GDD of 1740*, CIE B of 36 (card 9), DMC of 18.0%, TA < 1.1 and SSC:TA > 6.5
- *Keitt: GDD of 2185*, CIE B of 51 (possible card 13), DMC of 16.0%, TA < 1.1 and SSC:TA > 6.5
- *Kensington Pride: GDD of 1600*, CIE B of 32 (card 7), with further work required to confirm this recommendation.

The GDD from Christmas tree to harvest maturity can be calculated by subtraction of 180 from the asparagus target for Australian cultivars, and 240 for Keitt, resulting in a GDD of 1540 for Calypso, 1560 for Honey Gold, 1420 for Kensington Pride and 1936 for Keitt.

It is recommended that a single colour card set be used across all cultivars, including Keitt. Cards with scores of 11, 13 and 15 could be added to the existing 'Calypso' card set (QDAF 2019 print), with CIE B values of 43.0, 51.0 and 58.0, as illustrated in Table 9.

Table 22. (repeated) Proposed fruit maturity colour swatches and associated CIE LAB values. CIE L have two proposed values separated by slash, the first one set for printing purposes, the second being the expected CIE L reading from a fruit using Konica Minolta (CR-400).

3 CIE L = 97.00/85.00 CIE A = -4.40 CIE B = 18.00	**5** CIE L = 97.00/85.00 CIE A = -5.20 CIE B = 26.00	7 (Calypso/KP) CIE L = 97.00/85.00 CIE A = -5.70 CIE B = 32.00	**9** (Honey Gold) CIE L = 95.00/84.00 CIE A = -5.90 CIE B = 36.00
11 CIE L = 95.00/84.00 CIE A = -4.70 CIE B = 43.00	**13** (Keitt) CIE L = 92.00/83.00 CIE A = -3.80 CIE B = 51.00	**15** CIE L = 92.00/83.00 CIE A = -1.08 CIE B = 57.00	**17** CIE L = 88.00/80.00 CIE A = 1.60 CIE B = 62.00

Fruit sizing

Mango fruit size at harvest can be estimated from lineal measurements of L, W and T made up to four weeks before harvest. For practical implementation, it is recommended that a first measurement of fruit size be made at a GDD associated with stone hardening stage, i.e., at the harvest target GDD minus around 400 to 450 units for Calypso, Honey Gold and Keitt (Chapter 5). A second measurement should then be made one week later.

In-orchard imaging

The following recommendations are made for the use of the in-orchard imaging technology:

- During the flowering period, imaging of several rows per block could be undertaken. The time of peaks in counts of panicles at 'Christmas tree' stage can be used as the dates of flowering 'events' and used in GDD estimates of harvest timing.
- An early season fruit load estimate can be achieved from the average total count of panicles per tree as estimated by machine vision and a manual count of the total number of terminals per tree. The latter can be estimated by a manual count of terminals within a meter square frame multiplied by canopy area as estimated from canopy height, width and thickness. Panicle count is expressed as a percentage of total terminal count and multiplied by the maximum yield expected for the site, viz. with 100% of terminals flowering. Further work is required to consider sampling requirements for estimation of terminal number per tree. This method provides an estimation of maximum yield, which can be decreased by later flower or fruit loss.
- For manual count of orchard fruit load, the use of a systematic sampling strategy is recommended over a random sampling method, to lessen time and uncertainty in the location of sample trees.
- Estimates of fruit load will require correction for late flowering events, or a second count closer to harvest.
- Machine vision count of fruit will require correction for fruit occlusion or double counting. For estimation of the correction factor, manual count can be made of trees in areas of consistent low, medium and high fruit load, as estimated by machine vision and visualised as a heat map of fruit load.

Continued R&D (&C)

Commercialisation

To achieve commercial sustainability, an ag-technology must create value for both the user and the manufacturer/supplier. As a generalization, the Australian market size for ag-tech is small, due to the small size of the Australian industry and the fragmented nature of horticulture, i.e., the market is divided across many commodities with different needs. For example, handheld NIRS has been well adopted into the Australian mango industry, serving to reinforce dry matter content standards. However, the entire Australian mango industry, including retailers and R&D sectors, is served by less than 20 units. Further, the ag-technology field is characterized by continual technical advancements providing potential improvements in hardware and software, necessitating continued development by providers. However, it is recognized that industry levy funds (as opposed to R&D4Profit funds) are unlikely to be directed to ag-tech development.

These challenges are relevant to the technologies of the current project, with commercial viability of all the Technologies of the Project being low if left 'as is'. Two responses are possible: (i) the ag-tech must create a significant increase in grower profitability, and the grower-user must be willing to share that with the technology provider, i.e., pay a high price for the equipment/service; or (ii) an expanded range of application areas must be found for the ag-tech, e.g., other fruit commodities, and/or overseas markets must be developed. Strategy (i) carries the risk that competitor product will be developed overseas and, supported by a large international market, sell a lower price point in the Australian market.

It is recommended that in Hort Innovation increase activity supporting networking within the hort-tech commercialisation ecosystem.

R&D

The performance of an ag-technology is often tied to the specifics of the production system. In the case of tree crops, a major factor is tree architecture. For example, performance of the technologies for fruit load estimation and for harvesting is tied to canopy architecture, with better performance achieved with narrow, open canopies than the traditional wide canopies. Success of these technologies therefore lies part in engineering improvements and part in changes in tree architecture.

It is recommended that there is scope for industry levy funded R&D on the implementation of commercialized ag-technology, e.g., in context of the interface between harvester and canopy structure.

R&D topics building on the foundation provided by the current project include:

- *Developments in deep learning should be evaluated in context of NIR-DM assessment.*
- *Attempt to use NIR in a direct assessment of days to harvest.*

- *Determination of heat units for fruit maturation of further (new) cultivars and development of new indices based on the available temperature sensor network, e.g., chill units for flowering.*
- *Continued development of the heat units web app to app other functionalities, e.g., chill units for flower initiation.*
- *Consideration of the use of GDH and GD-15 min in an integral GDD calculation in comparison to the current practice of using only daily Tmin and Tmax.*
- *Further consideration of the levels of β-carotene (the dominant carotenoid) and the 'other' carotenoids noted in Keitt and R2E2 samples, around promoting 'functional food' value of mango.*
- *Development of new applications for the orchard imaging technology beyond flowering and fruit count.*
- *Continued development of the web-app for presentation of data of machine vision counts of panicles and fruit, fruit size and DMC, following the adage that 'data is not information', i.e., that data needs to be presented in a form that time poor managers can easily interpret.*
- *A review of available Orchard Farm Information Management Systems should be undertaken*.

<u>Human resource development</u>

There is a divide between government, university, and industry. This can be beneficial, with each able to access different resources, but it can also hinder the appropriate focusing and translation of research. The movement of two personnel from university into industry roles from this project was an 'exception to the rule'. Movement of personnel between these sectors is recommended.

The establishment of specific support packages to encourage staff movement between the 'three sectors', akin to the AusIndustry Innovation Connections (research in business, or business in research) program, is recommended.

Utilization of the Technology in the Future There are a Few Areas Where It Will Be Applied.
The technology will be utilised in the following areas:

1. In the system's long-term plans, a forecasting component will be included to determine how many bananas will be required in various regions of the country and how much of that total quantity should be planted.

2. By utilising the system we developed (mainly the tagging system), the Marketing managers of large agriculture organisations will be able to guarantee that they are always aware of the figure that is anticipated to be attained in order to keep the pricing of the product in control.

3. Farmers: The system will be used to compute the number of harvest workers required for the farm based on the data provided by the yield forecast tool.

4. When farming operations become dependent on machinery and, more precisely, when they become autonomously based, then this technology will be very important for guiding the operating to the correct spot where harvesting or agro-technical activity will be required.

5. In the packing shed, more research and development projects will be able to be carried out as a direct result of this project. Through the utilisation of computer vision technology, which includes cameras, RFID tags, and RFID scanners, the objective is to establish a connection between the banana bunches and the puckouts. This will make it possible to additionally calculate the net kilograms that come out of the block as well as the precise position of the bunch. Additionally, it will be possible to evaluate the quality of a single banana and relate that quality to the precise spot where it grew. Understanding its carbon foot print and the resources investment in growing a single piece of fruit.

- The industry should keep the momentum going and continue the extension and adoption efforts, enhancing the accumulated information and strengthening the relationships and capacity between growers, AMIA and project partners, especially around the use of fruitmaps and temperature sensors and the use of the imaging rig.
- The industry should continue to support its extension assets and capability particularly the regionally based Industry

Development Officers and the departmental extension officers who have fostered strong industry relationships.

- RD&E efforts should continue to improve and validate the time series modelling. This yield estimation methodology, developed by UNE as part of this project, uses satellite imagery and past yield data and has shown very promising results. Currently, the process used by industry to develop a crop forecast at the beginning of the season is very tedious and time-consuming. Being able to accurately predict volumes at a regional level using the time-series method would streamline the process and ensure we can keep informing in-season market planning and supply strategies.

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On-tree mango instance segmentation data is accessible via https://doi.org/10.25946/21655628

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[1] Robson, A., Rahman, M., & Muir, J. (2017a). Using worldview satellite imagery to map yield in avocado (persea americana): A case study in bundaberg, Australia. *Remote Sensing, 9*(12), 1223

Intellectual property

Project IP: Each project partner has provided a detailed summary of all Project Intellectual Property (IP) using Hort Innovation's IP Register, outlining previous (background) IP and that which has been developed during the life of the program.

Two patents were granted from work arising from phase 1 of the project:

- Walsh, K.B. Apparatus for harvesting fruit. Australian Innovation Patent 2020102993 granted 24 Oct 2020
- Walsh, K.B. Method and Apparatus for Estimating Tree Fruit Load and Harvesting Time. Australian Innovation Patent 2021104829 granted 2 Aug 2021

Licensing of IP from Hort Innovation to CQUniversity has been finalised.
Licensing of IP from Hort Innovation to UNE AARSC is under negotiation at the time of writing this report.

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