Final Report

Advancing the delivery of national mapping applications and tools

Project leader:

Professor Andrew Robson

Report authors:

Professor Andrew Robson, Dr Moshiur Rahman, Craig Shephard, Dr Andrew Clark and Sophia Clark

Delivery partner:

Applied Agricultural Remote Sensing Centre, University of New England

Project code:

AV21006

Project:

Advancing the delivery of national mapping applications and tools (AV21006)

Disclaimer:

Funding statement:

This project has been funded by Hort Innovation, using the avocado research and development levy and contributions from the Australian Government. Hort Innovation is the grower-owned, not-for-profit research and development corporation for Australian horticulture.

Publishing details:

Published and distributed by: Hort Innovation

Level 7
141 Walker Street
North Sydney NSW 2060

Telephone: (02) 8295 2300

www.horticulture.com.au

Contents

Public summary

The Horticulture Innovation project (AV21006) ‘Advancing the delivery of national mapping applications and tools’ ensured the Australian avocado industry has access to new technologies and innovations that offer direct benefits to on farm production as well as industry-wide data collation and management. The previous levy-funded project project *Implementing precision agriculture solutions in Australian avocado production systems* (AV18002) saw the implementation of a precision agriculture solution in Australian avocado production systems and the creation of a multi-scale monitoring tool for managing Australian avocado tree crops.

To maintain the currency of these outputs, further investment was needed to maintain data, improve accuracy and extend these resources to industry.

This project has worked to deliver avocado growers with commercial tools to improve yield forecasting and mapping from the orchard block to the national scale, by:

1. Maintaining and updating the web mapping applications with improved accuracy (as well as currency of the national map of avocado orchards) and usefulness to the avocado industry.
2. Yield forecasting modelling to support other benchmarking projects and crop forecasting, and to allow investigation in the relationship between climate and yield to inform the remote sensing climate-based yield prediction model.
3. Expanding the testing and structured feedback process to allow for improved decision-making and orchard management by producers using the CropCount app as a means of improving productivity. The CropCount app will also support avocado growers who have new plantings or have no historic data (that would be used in the time series analysis).

National mapping of avocado orchards: Presented in the Australian Tree Crop Map, the location and extent of all commercial avocado orchards was most recently updated and published on 21st May 2024, and totals 19,805 hectares of avocado orchards. Analysis of the map shows that 65% of all avocado orchards in the map have been observed in 2023 or sooner (26% is current to 2024). Field validation was completed in each major growing region including Far-north Queensland, Bundaberg/Childers (twice), Northern Rivers NSW, Tristate and lastly Western Australia. Engaging with industry to contribute to the map was supported via the location-based tools developed by AARSC, which included 198 new surveys for avocado orchards received during this project. This feedback is essential for mapping new plantings which cannot be mapped with satellite imagery alone.

AARSC have developed a model to **predict planting year** based on the extent of all orchards in the map**.** The advanced methodology uses the time series of Landsat imagery (from 1988) combined with deep learning modelling to predict the planting year of avocado orchards in Australia. By comparing with a thresholding approach (originally developed for macadamia) with sophisticated models such as GRU, LSTM, and Transformer, the research demonstrates that deep learning models, especially the GRU, offer superior predictive accuracy and robustness. The GRU model, with an accuracy of ± 2.43 years, outperformed the previously used thresholding approach which had an accuracy of ± 2.82 years. The improvement using the new approach is particularly evident for recent plantings which the thresholding approach could not predict, highlighting its effectiveness in capturing temporal dependencies in the data.

Avocado yield forecasting: Accurate yield predictions play a crucial role in the avocado industry, facilitating informed decisions regarding forward selling and market access. At the orchard level, a comprehensive understanding of crop load supports growers in planning harvesting logistics and refining crop management practices efficiently. The Project AV21006 focused primarily on remote sensing data only. The project has successfully implemented two methodologies—the 'CropCount' strategy and the 'time series' method, which were originally developed in the previous Project AV18002—for pre-harvest avocado yield forecasting. One of the major limitations of time series yield prediction methodology was the alternate bearing pattern observed in avocado crops. To address this, the project began developing a remote sensing-based approach to distinguish between 'On' and 'Off' seasons, aiming to enhance the prediction accuracy. However, this effort remains ongoing as it has not been finalised due to insufficient data availability. Additionally, the project has developed a system to provide growers with a classified crop vigour map accessible through a web application (app) platform. This web app has interactive functionality, enabling growers to explore the variability of crop vigour within their orchards, and compare the performance of individual orchards to the entire farm. This can help growers to enhance their crop management practices where needed and ultimately improve the crop yields.

Expanding testing and feedback via the CropCount Mobile Application: During the 2-year project the 'CropCount: 18 tree calibration' method was further demonstrated on 6 orchards in South Australia and 7 orchards in Western Australia. The accuracies at the block level ranged from 74% to 100%. For one Western Australia farm the 18-tree methodology was altered to use the composite value of 3 rows of 6 trees—to align the calibration count with the current practice of the grower. Even with only 4 calibration points (as opposed to 18) the methodology still produced encouraging accuracies ranging from 74% to 100%.

To complement the 'CropCount' methodology, the 'time series' method was further evaluated across 69 orchards in Western Australia, and 15 orchards in South Australia, the model returned block level accuracies that ranged from 36% to 100%. At farm level accuracies ranged from 93% to 99% in the 2023–24 season. Whilst this methodology does not require in-field fruit counts, utilises freely available satellite imagery and provides predictions months before commercial harvest, it still requires additional development to better differentiate 'low' and 'high' bearing years associated with irregular bearing. To compensate for this, growers were provided with an estimate for both 'low' and 'high' years, where the most appropriate prediction could be easily selected following a visual inspection of fruit load (even as a drive through at growth stage where fruit load could be assessed).

The success of these methodologies has attracted international interest with the results requested at the World Avocado Congress in New Zealand (Auckland, 2023), alongside a keynote presentation to over 1,200 delegates. Additionally, the AARSC have been contracted by: Costa to provide forecasts for their entire Avocado crop (2022–23); Westfalia to provide prediction for all orchards across 6 countries; South African Avocado Growers Association (SAAGA); and New Zealand Avocado for close to 500 orchards. Considering Australia only produces 1% of the world's marketable avocados, this is a significant outcome for Australian research and development.

Commercialisation of the CropCount App: A significant outcome of this project was the establishment of a commercialisation plan for the avocado yield forecasting methodologies through the completion of 'Cropcount App' or via the identification of a commercial partner. The delivery of these outcomes was the requested responsibility of Hort. Innovation. Unfortunately, due to having five managers through this 2-year project, these outputs were not completed within the project timeframe.

Extension of project results: The outcomes of this project have been extended to industry through a number of forums including conferences, social media and industry magazines. The Australian Tree Crop Map Dashboard has now been visited 18,579 times. On-going updates to the map are supported by the industry engagement tools developed by AARSC, including the ATCM Survey (and Avocado Survey which is hosted on the AAL homepage) and the Industry Engagement Web App. Collectively, the contributions submitted via the location-based tools for avocado now total 922, which has greatly contributed to the accuracy and currency of the national map. The mapping has also been used for several additional applications including biosecurity (Varroa-mite), natural disaster response (Severe Weather) and water security (Murray-Darling Basin), as well as underpinning the development of the predicted planting year map.

Benefits:

- The 'time series' model was developed for 128 orchard blocks in QLD, SA and WA regions. The project combined freely available satellite data, historical orchard yield and management data and advanced machine learning approaches to enhance the accuracy of yield prediction models initially built in project AV18002. The accuracy of machine learning time series has been well received by the growers with a significant increase in engagement in the project period. Historic production data and associated farm maps have been provided by six major Australian growers in WA, SA, QLD. The project team has received direct requests from many of Australia's growers to be involved in the yield forecasting component of the project, providing sensitive historic yield data sets and tree management information.
- Further validating the 'CropCount' methodology over seven orchard blocks in WA. The relationship of canopy reflectance, measured by remote sensing technologies, to yield parameters and tree health, under Queensland growing conditions. The continued effort to better extend the project objectives to the wider avocado industry has been well received with a significant increase in grower engagement in the project period.
- Both 'CropCount' and 'time series' yield prediction models were developed and tested in QLD, SA and WA region. During the project, 10 large growers from QLD, SA, and WA participated to test and validate both the 'CropCount' and 'time series' methodologies with crops of varying ages, varieties, and historical yield and management information.
- Increased access and awareness of the 'Australian Tree Crop Map Dashboard' which has now been viewed 18,579 times at the time of writing

Technical summary

This final project report (AV21006) includes specific yield information and yield variability maps for a number of Australian growers. The predicted planting year map is currently only shared with AAL (and with their permission has been provided to the Australian Bureau of Statistics, Horticulture Statistics Working Group). Additionally, the report includes both the 'CropCount' and 'Time series' yield forecasting methodologies, and as it is hoped to commercialise these outcomes it is requested that the full report is not made publicly available.

Keywords

Avocado (Persea americana), remote sensing, WorldView, Landsat, Sentinel, yield, forecasting, prediction, tree crop map, CropCount, Minimal Viable Product, mobile application, mapping applications, biosecurity, natural disaster response.

Introduction

The total Australian avocado production in 2022/23 exceeded 115,385 tonnes with the gross value of production (GVP) estimated at $574 million. This is driven by robust expansion resulting from extensive known new plantings established over the past five years. Over the last decade, the industry has extended its production significantly from 48,715 tonnes at 2013/14 to 115,385 tonnes at 2022/23, at a value of more than AUS$21.7 million per annum (Avocados Australia, 2023a). However, the annual production is seasonally variable, with crops ranging from 78,085 tonnes in 2020/21 to 122,197 tonnes in 2021/22 (Avocados Australia, 2023a). Over the next five years, the industry is projected to expand its domestic and international markets to accommodate an extra 90,000 tonnes, surpassing double the production volume in 2021 (Hort Innovation, 2023). The production forecast indicates a robust upward trend, with an anticipated annual growth of at least 170,000 tonnes by 2026 (Avocados Australia. 2023b). Therefore, access to precise information is crucial for the avocado industry to effectively manage the projected annual growth in both production area and output volume. Reliable data ensures accurate tracking of this expansion, enabling industry stakeholders to make informed decisions regarding resource allocation, market strategies, and operational planning.

Currently, the avocado industry sources information on area of production primarily through tree census records and the Horticulture Innovation Statistics handbook, which is informed by the Australian Bureau of Statistics (ABS), projects funded by Horticulture Innovation, international trade data, and input from industry representative bodies (IRBs) (Hort Innovation, 2023). The Australian Tree Crop Map, which was first published in 2017, is built to national standards and provides the fundamental baseline information to support industry and stakeholders in understanding the current area of production and distribution of avocado orchards across Australia. The map is informed by multiple sources of evidence including industry and existing government data, remote sensing analytics, field validation and citizen science—supported by location-based tools developed by AARSC. These tools provide the support mechanism for on-going maintenance and update of the map—essential for mapping new plantings, which cannot be mapped with satellite imagery alone.

The national map provides the baseline data for location and extent of all commercial orchards > 1 hectare (ha). As a value-added application AARSC have developed a novel approach to predicting the planting year of orchards in the map, which provides the industry and stakeholders with additional metrics (e.g. bearing age). The motivation for this study stems from the industry's need to better quantify the area of newly planted orchards annually as well as locational and area trends associated with historic plantings.

Accurate measurement of orchard area and age aligns closely with the need for precise yield forecasting, particularly before harvest. This information is essential for the industry to secure market access, both domestically and internationally, and to make informed decisions regarding forward selling. For growers, such data aids in enhancing decision-making processes related to field operations, including harvest scheduling and determining the necessary resources such as pickers and bins at the time of harvest. Furthermore, it supports post-harvest decision making such as storage, handling, packing, and forward selling strategies. Additionally, the ability to map yield variability spatially and temporally at the block and farm levels through an interactive web app is invaluable. This tool assists in making decisions regarding variable rate application of inputs such as water, fertiliser, and pesticides. Moreover, it facilitates improved responses to plant diseases like Phytophthora (Salgadoe, et al., 2018; de Castro Megias et al., 2021; Poblete-Echeverría, 2023). By integrating these aspects, growers and industry stakeholders can optimise resource allocation, enhance operational efficiency, and mitigate risks, ultimately leading to improved productivity and profitability in the avocado industry.

Currently, avocado yield estimation is undertaken by the labour-intensive ‘eye-ball’ count method, involving visually assessing fruit on selected trees and extrapolating to determine average block yield. However, this approach suffers from a number of limitations such as inaccuracies due to occlusion by leaves, time and labour challenges, and limited sample size inadequately representing orchard variability (Robson et al., 2014, 2017a, 2017b). The Federal Government and Horticulture Innovation funded project (ST15002) "Multiscale monitoring tools for managing Australian tree crops: Industry meets innovation" and (AV18002) “Implementing precision agriculture solutions in Australian avocado production systems” recognised the potential of remote sensing technologies for monitoring tree health and yield forecasting using the ‘CropCount’ methodology. While global use of satellite-based remote sensing for avocado yield forecasting has been limited, promising results were observed in Australian conditions, surpassing accuracies of commercial methods. Furthermore, the combination of satellite imagery and ground-based tree calibration allowed for the derivation of yield and fruit size maps, enabling harvest segregation and variable rate input application.

Concurrent with the 'CropCount’ method lies the recognised potential of 'time series' observations derived from satellite imagery of varying resolutions for various agricultural applications such as vegetation monitoring, crop identification, land cover change detection, seasonal pattern mapping, and crop yield prediction (Rahman et al., 2022; Suarez et al., 2022, Brinkhoff and Robson, 2021). Time series analysis, as implied by its name, involves the incremental measurement of crop response over an extended temporal span, thus revealing historical crop behavior and the impacts of seasonal environmental, climatic, or management variations. Consequently, this approach offers insights into the timing of crucial phenological growth stages and their variability across different varieties, locations, and seasons. Such information proves invaluable for determining the optimal timing of essential management activities and swiftly identifying the onset of severe pest or disease outbreaks when deviations from historical growth patterns occur. Moreover, the time series method capitalizes on freely available satellite imagery sources such as Landsat and Sentinel, enabling forecasts well in advance of harvesting. Project AV21006 evaluated the accuracy of time series yield forecasting at the orchard, farm, and block levels across avocado orchards not only in Queensland region but also in South Australia and Western Australia regions to further validate the accuracy of this pioneering methodology. Moreover, eight different machine-learning models including Linear Regression, Random Forest, Decision Tree, Gradient Boosting, Ridge Regression, Lasso Regression, Support Vector and XGBoost Regression have been applied to improve the model performance and accuracy of the prediction.

One significant limitation of the 'time series' yield prediction methodology was the alternate bearing pattern in avocado crops, with 'On' and 'Off' seasons complicating accurate forecasting. To address this, the project team developed a remote sensing-based approach using machine learning classification algorithms to distinguish these ‘On’ and ‘Off’ seasons, enhancing prediction accuracy and enabling better crop management decisions. Due to insufficient data availability, the project could not finalise the methodology, so the project team ran the model twice—once for 'On' and once for 'Off' seasons—allowing growers to choose the appropriate prediction based on their on-farm visual estimates.

In conclusion, the integration of 'time series' satellite imagery with advanced machine learning models has shown significant promise in enhancing avocado yield prediction, despite challenges like alternate bearing patterns. The project demonstrated the potential of remote sensing to improve yield forecasting accuracy, surpassing traditional methods. The development of separate models for 'On' and 'Off' seasons allowed growers to make informed decisions based on their initial visual estimates, highlighting the adaptability and practical utility of the approach. While data limitations hindered the finalisation of the methodology, the promising results and innovative techniques developed underscore the value of precise data and advanced analytics in driving the future of avocado production and management.

Methodology

National map of commercial avocado orchards

Project AV21006 aimed to deliver on-going updates of the location and extent of all avocado orchards over 1 hectare (ha), as published in Australian Tree Crop Map (ATCM). The updates were managed within a national program, designed to progressively update the map by growing region, based on the 1:100K standard map-sheet tile grid. (Figure 1).

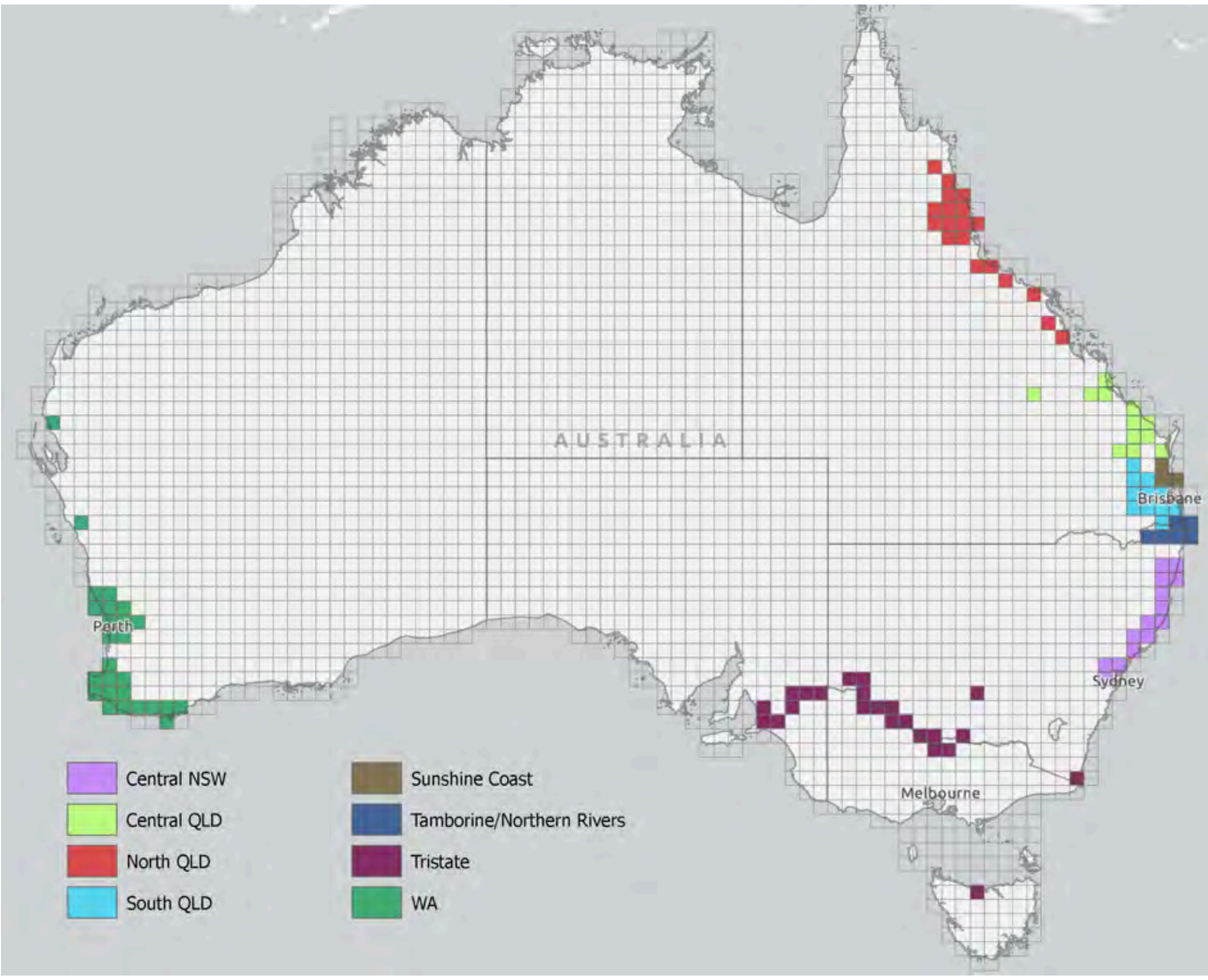

Figure 1: National mapping program by AAL growing region, managed by 1:100K map-sheet tiles

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). Orchards were mapped as polygons (location and extent) and key attributes recorded at feature level including the source and year of observation (currency)—reflecting the most recent date of observation from either imagery capture date or field observation. No personal or commercial information is contained within the map (e.g property boundaries, ownership, variety, yield, etc.), which is built to national standards of the Australian Collaborative Land Use and Management Program (ACLUMP).

Figure 2: Australian Tree Crop Map methodology

Publicly accessible (free) 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 accessed by AARSC). On occasion the currency of high-resolution imagery was very timely (< 1 year old). However, elsewhere the imagery capture date limits the currency of the map as the newly established plantings are either not visible in the imagery (small trees) or the imagery is not current enough to show the newly planted orchard and/or land use change. To overcome this challenge, we access and interpreted coarser low-resolution (but current) satellite imagery (e.g. PlanetScope) to map the new crops. This was only undertaken where other ancillary data (e.g. industry input or field observation) 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 3 presents four examples of avocado orchards showcasing how variation in tree age, variety and management practice influence the appearance of the trees in the orchard. This example clearly demonstrates the need for multiple sources of data to accurately classify avocado orchards, and that methods relying solely on imagery analysis alone (manual or automated) are not robust.

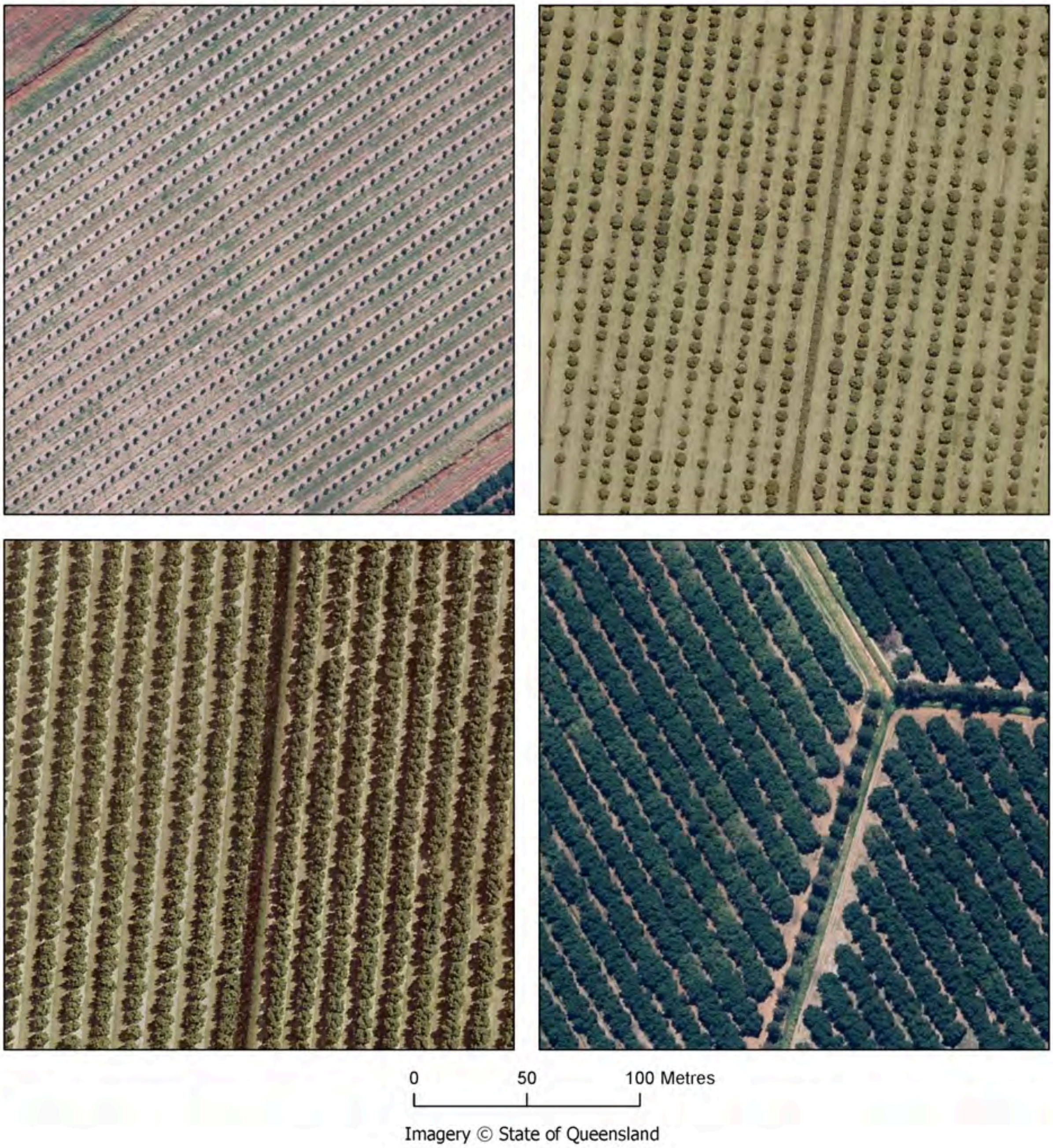

Figure 3: Avocado orchards showing variations in tree age, variety and management practice

Field validation of the map was conducted over each major growing region and targeted areas of known uncertainty in the map and/or new plantings. Fieldwork improves the accuracy and currency of the map, especially where new plantings were observed (which are not visible in imagery). As an example, Figure 4 shows the route (GPS track) covered in Comboyne, Central NSW in May 2023, which has added numerous new plantings of avocado into the map (highlighted in red).

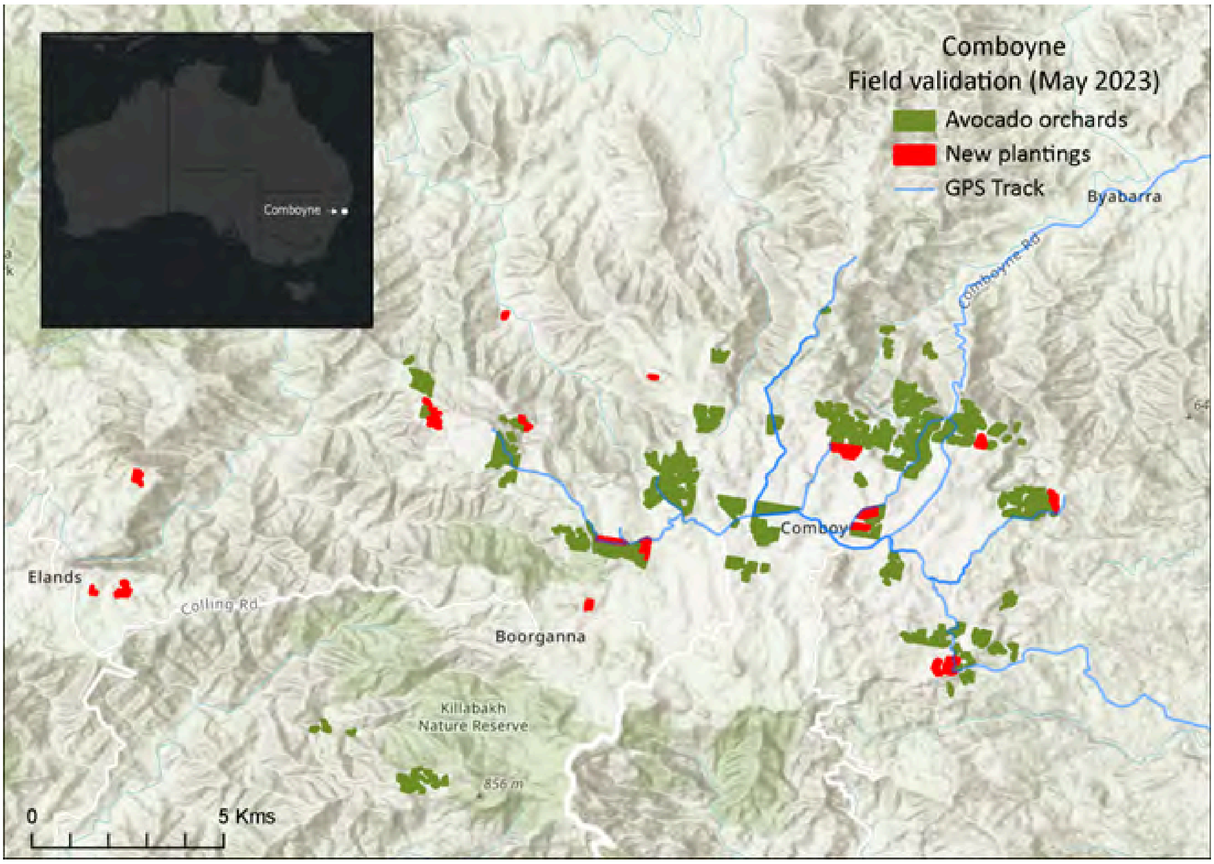

Figure 4: Field validation completed in Comboyne, NSW in May 2023, showing new avocado plantings mapped

Updates to the map are actioned ad-hoc based on the feedback received through the industry engagement tools developed by AARSC, including the ATCM Survey (Figure 5) and the Avocado Survey (Figure 6—as hosted on the AAL homepage https://avocado.org.au/). The survey forms, which are optimised for use from mobile devices (uses the GPS for location), support on-going updates of map by enabling stakeholders and growers to submit their feedback directly for the attention of the mapping team. The location information included with each survey is interpreted by AARSC and actioned as updates to the map.

Figure 5: ATCM Survey

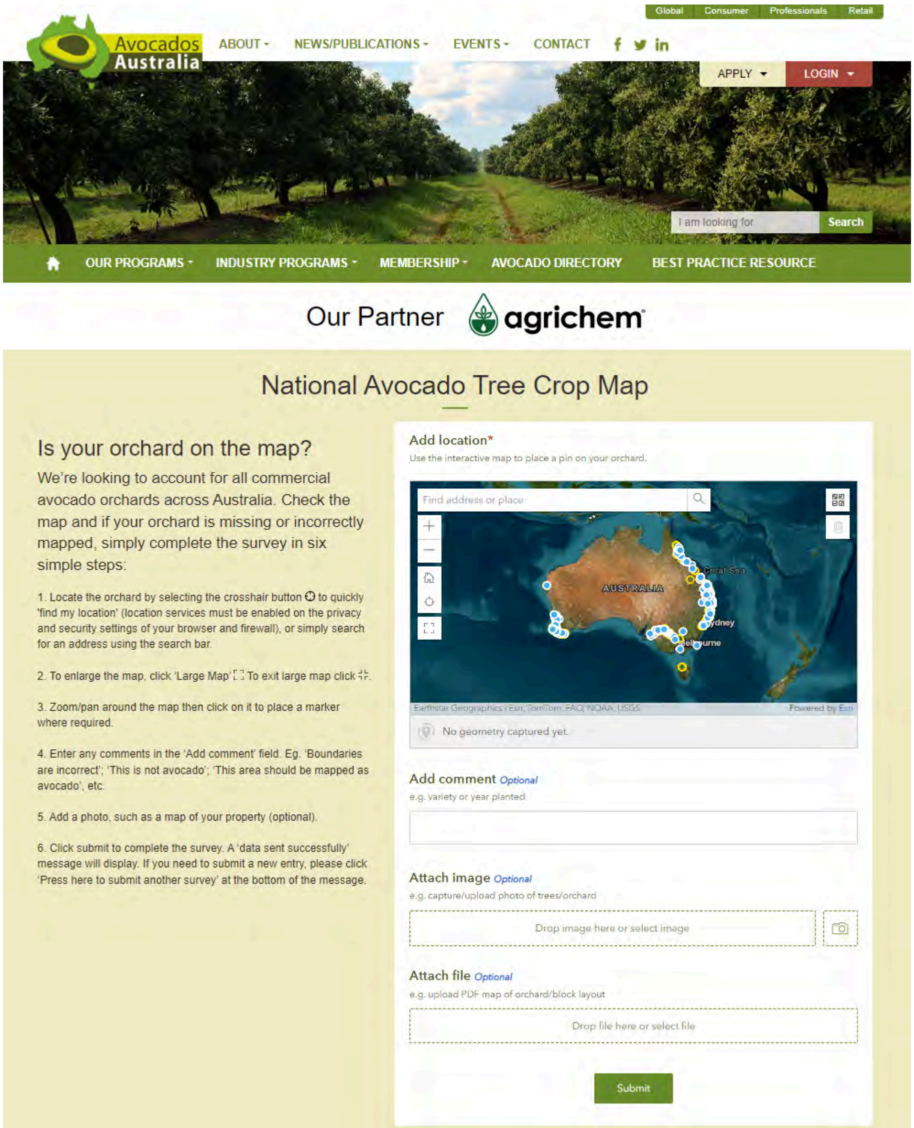

Figure 6: Avocados Australia survey (as hosted on the AAL website homepage)

Additionally, peer review of the map is supported via the Industry Engagement Web App (Figure 7). Optimised for desktop use, the app supports industry and stakeholders to review the map and provide feedback for the attention of the mapping team. This is especially useful for new plantings, which can be delineated using a polygon (area) tool to accurately inform their extent.

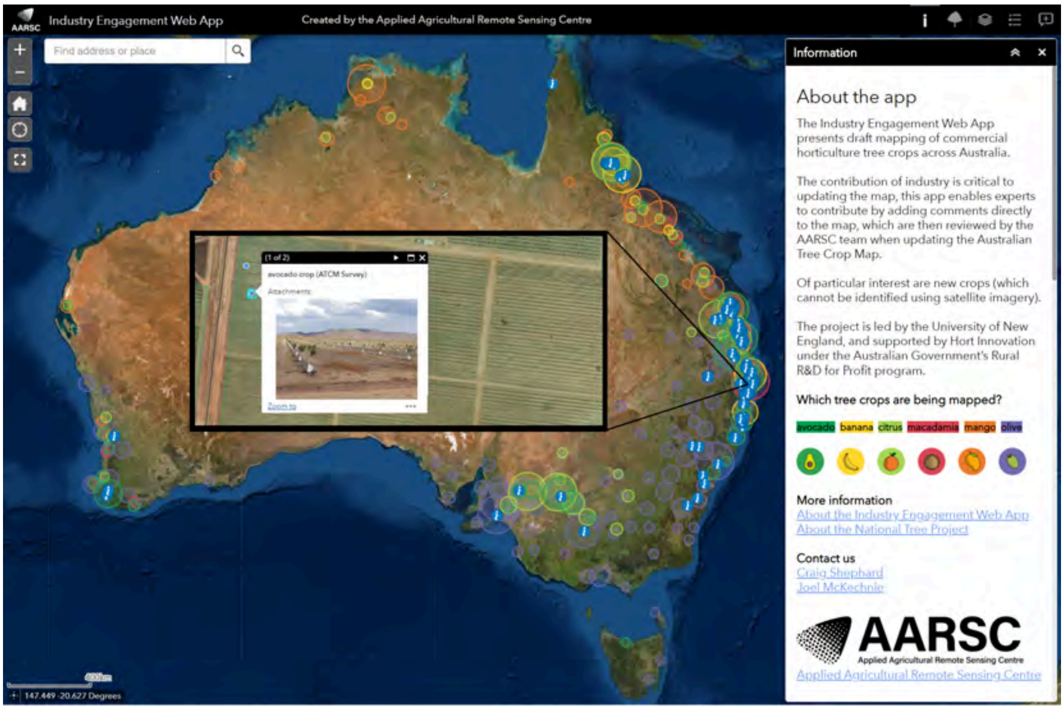

Figure 7: Industry Engagement Web App (IEWA)

To produce the mapping product (i.e the Australian Tree Crop Map), AARSC publish updates biannually (typically May and September). Polygon features representing avocado orchards were derived from the editing layer by aggregating and dissolving features relative to map scale (minimum mapping unit of 1 ha and a width of 25 m). Figure 8 shows an example of the level of detail as presented in the final map. The only information available in the mapping product at feature level is the source and year of observation, and area in hectares.

Figure 8: Avocado features as mapped in edit layer (L) and the derived mapping product as published (R)

For reference, there are 5,056 individual avocado 'features' in the edit layer—versus 2,222 in the map product. The published map is shared as a publicly accessible feature service layer, hosted in Esri ArcGIS Online (metadata is available at https://www.arcgis.com/home/item.html?id=b3933850c5e6405aa4d7b1866e26d4ce).

AARSC publish the mapping product as a feature service so that as we update it, all users who connect to the service will access the latest information. The published map is presented consistently across numerous web applications and dashboards, some of which include additional spatial analysis by AARSC using other authoritative spatial information. Each is discussed in the results section below.

Planting Year Prediction

Avocado orchards in Australia have seen significant growth over recent decades. Accurate mapping and monitoring of location and age are crucial for agricultural planning and management. This section utilises time series Landsat imagery and machine and deep learning models to predict the planting years of avocado orchards. The primary objective is to assess and compare the performance of different models in predicting planting years.

As a value-added application, AARSC has undertaken research and development to derive a predicted planting year map for orchards based on the extent of all avocado orchards mapped, with several approaches (models) developed. Each method uses the time series of Landsat satellite imagery (from 1988 to the present) to assign pixel-based classification for predicted planting year (30 m pixels).

Gaining insights into the precise location, area, and age of avocado orchards is essential for informing decision-making at the farm and industry levels. These insights have applications in biosecurity preparedness, natural disaster response and recovery, as well as contributing to the overall sustainability and profitability of agricultural industries.

The motivation for this section stems from the industry's need to better quantify the area of newly planted orchards annually, as well as locational and area trends associated with historic plantings. Additionally, tree age influences the yield potential of tree crops, and therefore, accurate knowledge of planting year for all commercial orchards can improve yield forecasting and subsequent decision-making around forward selling and market access.

This section addresses this need by assessing a diverse range of machine learning models trained using Landsat satellite imagery and avocado orchard age data. Models included traditional approaches such as Random Forest (RF) and Distributed Gradient Boosted Trees (DGBT), and deep learning approaches including Temporal Convolutional Neural Network (TempCNN), Temporal Convolutional Network (TCN), Bidirectional Recurrent Neural Network (biRNN), Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), Transformer, and Residual Network (ResNet). These models were compared against an existing method, which detected planting year using vegetation index threshold, with the limitation that recent plantings (< 3 years old) could not be predicted.

Study Area

The study area covers all Avocados Australia regions, including Central Queensland, Western Australia, Northern Territory, North Queensland, Southern Queensland, Tristate, Sunshine Coast, Tamborine / Northern Rivers, and Central New South Wales (Figure 9).

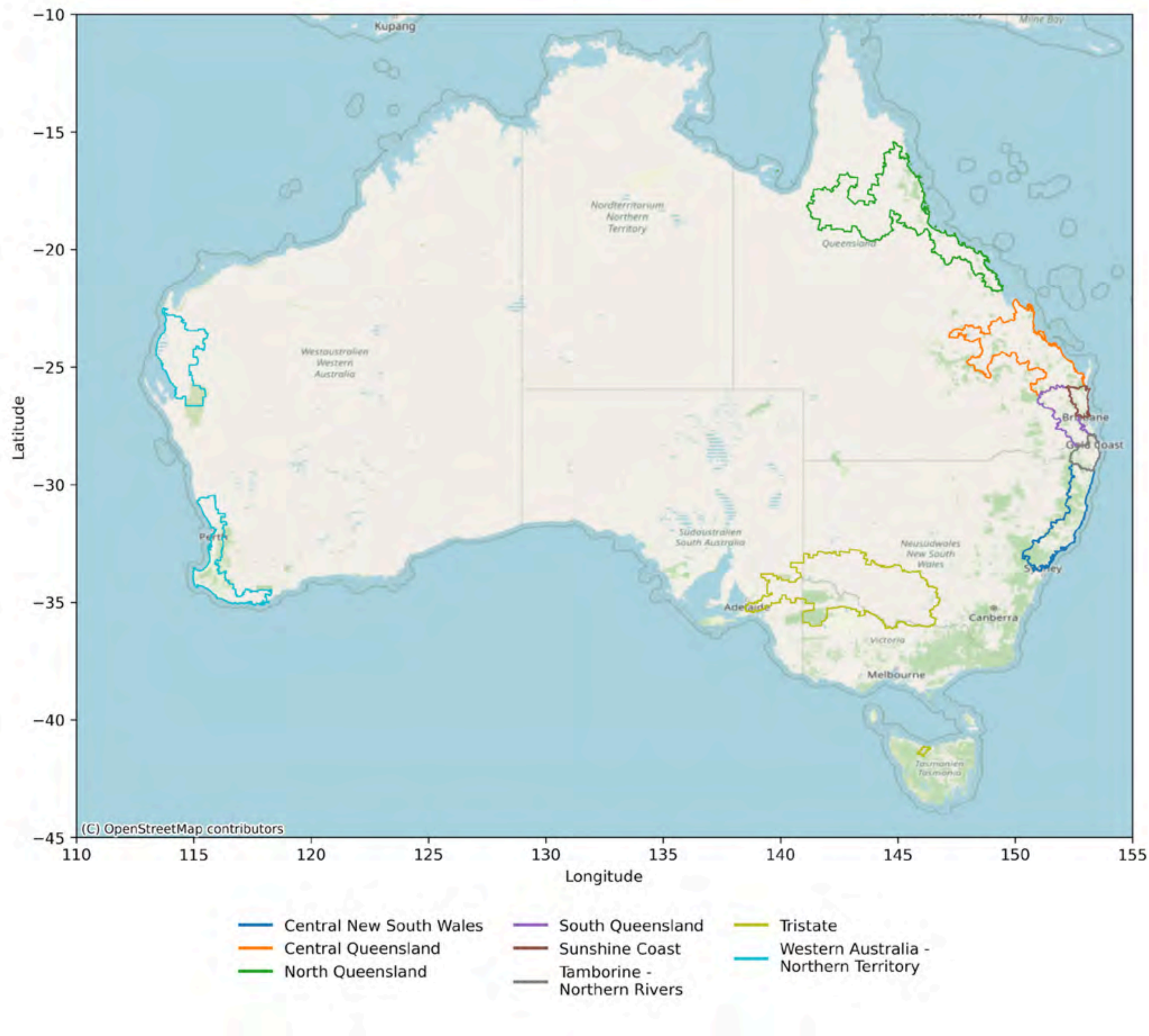

Figure 9: Geographic distribution of avocado growing regions across Australia.

Training Data

Compiling the training data for model training requires information about existing avocado block planting years (labels) and a time series of satellite data (imagery). The training data labels were derived from polygon vectors with a known planting year attribute. These data were compiled from the Australian Tree Crop Map survey data and other industry datasets. The planting year was converted into a block age, with 1 representing the most recent year. The Landsat yearly geometric median, spanning from 1988–2022, were extracted from Digital Earth Australia's Data Cube for all avocado blocks and formed the basis of the training imagery. These data consist of six spectral bands (blue, green, red, near-infrared, shortwave infrared 1, and shortwave infrared 2), and the Normalised Difference Vegetation Index (NDVI) (Rouse et al. 1974) and Green Normalised Difference Vegetation Index (GNDVI) (Gitelson et al. 1996) values were calculated. These data, along with the training labels, were provided to the models for training.

The training data were segmented into each growing region. Figure 10 shows the number of blocks within each region, in total there were 244 blocks with planting date information. The figure shows most of the training blocks are located within Central Queensland, Western Australia and North Queensland.

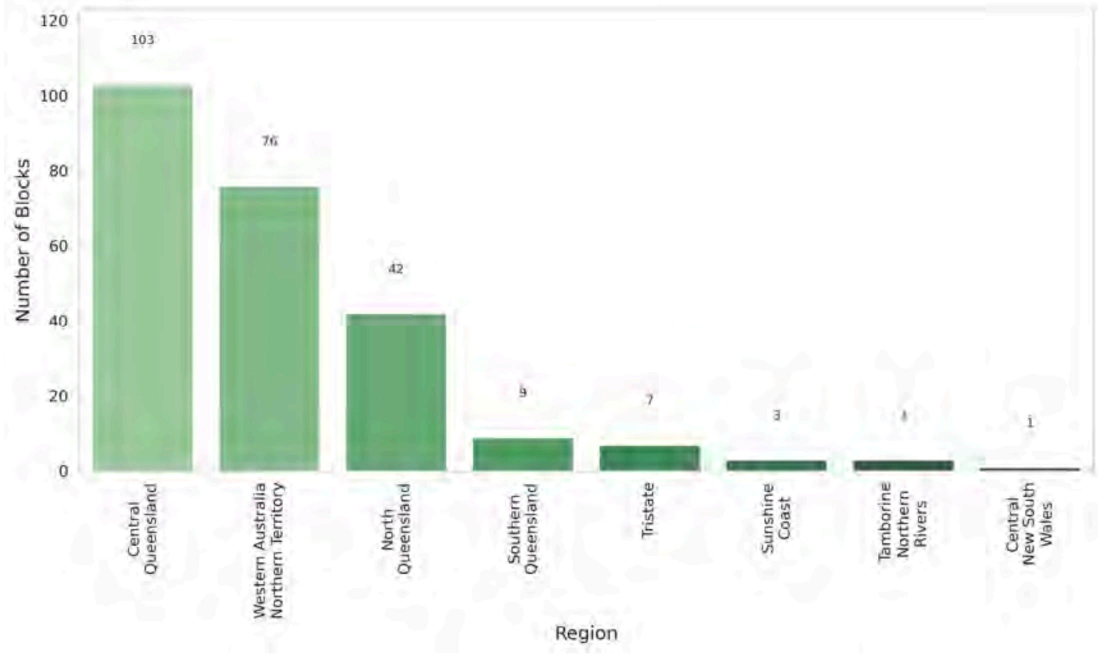

Figure 10: The number of avocado blocks in each growing region.

As deep learning models require vast amounts of data to create a generalised and robust model, we have used individual pixel values which fall within the training block boundaries. This increases the number of data points from 244 blocks to 19,406 pixels. Regions including Southern Queensland, Tristate, Sunshine Coast, Tamborine / Northern Rivers and Central New South Wales were combined for the modelling component, referred to here as 'Other Regions' (Figure 11).

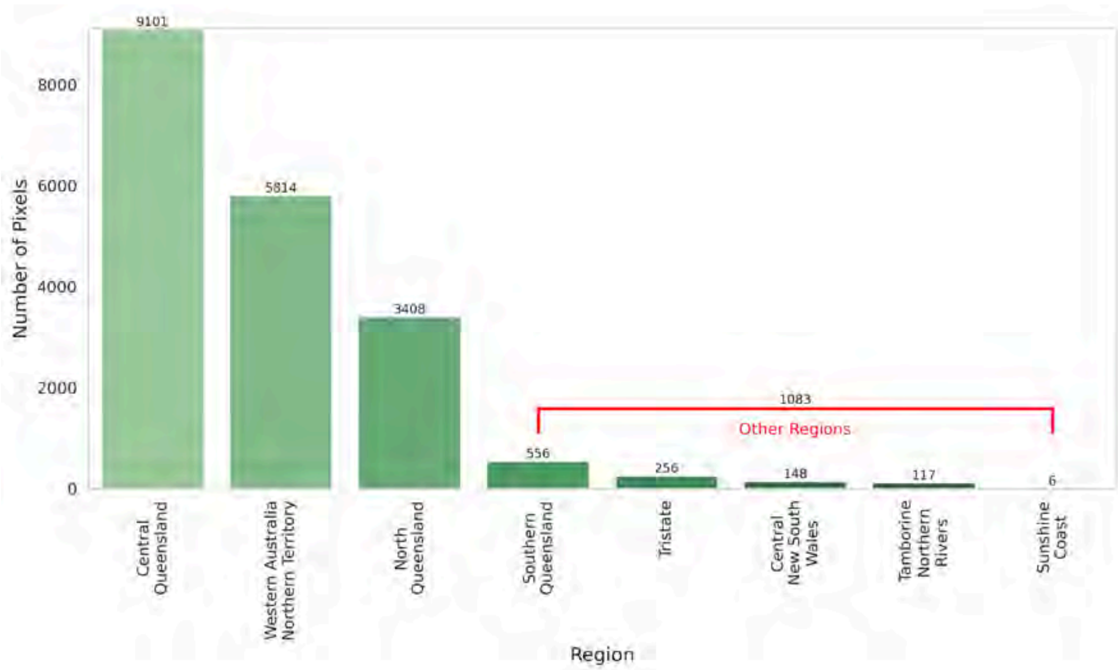

Figure 11: Number of pixels within reach growing regions.

Most of the training blocks were planted between 2003 and 2023 (Figure 12), leading to a potential bias in the models toward recent years with more abundant data. This bias could hinder the model's ability to generalise earlier planting years where data is scarce, resulting in inaccurate predictions for that period. The models may also overfit to features specific to recent satellite imagery, limiting their adaptability to older data. The lack of historical data prevents the models from capturing the full range of orchard planting variations and changes over time.

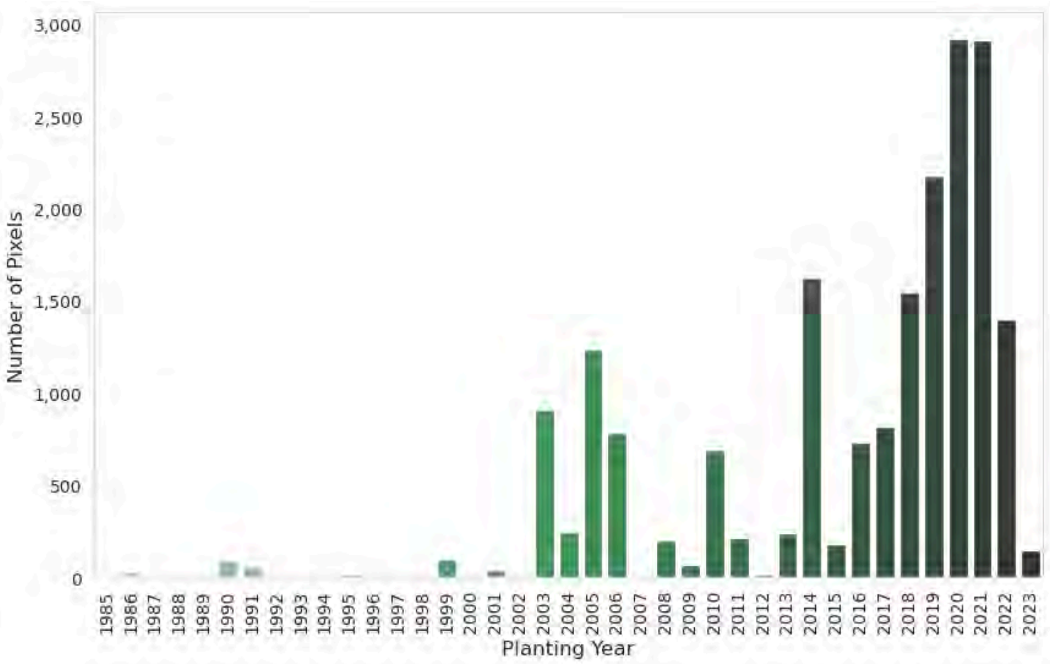

Figure 12: Temporal distribution of training dataset at pixel level by planting date.

When developing a deep learning model, it is important to ensure the model can generalise well—otherwise it will not be able to accurately predict the planting years for any data not within the training data. To ensure a generalised and robust model, a region was removed from the training data and kept for validation. This resulted in four models being trained for each model type. Each model was trained on data from all regions except the one being validated.

Figure 13 shows the distribution of training and validation pixels across different excluded regions. The figure illustrates the number of pixels used for training and validation for each region, highlighting the variability in data availability. Central Queensland and Western Australia / Northern Territory have a balanced distribution of training and validation pixels, whereas North Queensland and 'Other Regions' exhibit higher training pixel counts with comparatively fewer validation pixels. This distribution is critical for assessing model performance and generalisation across different geographic areas.

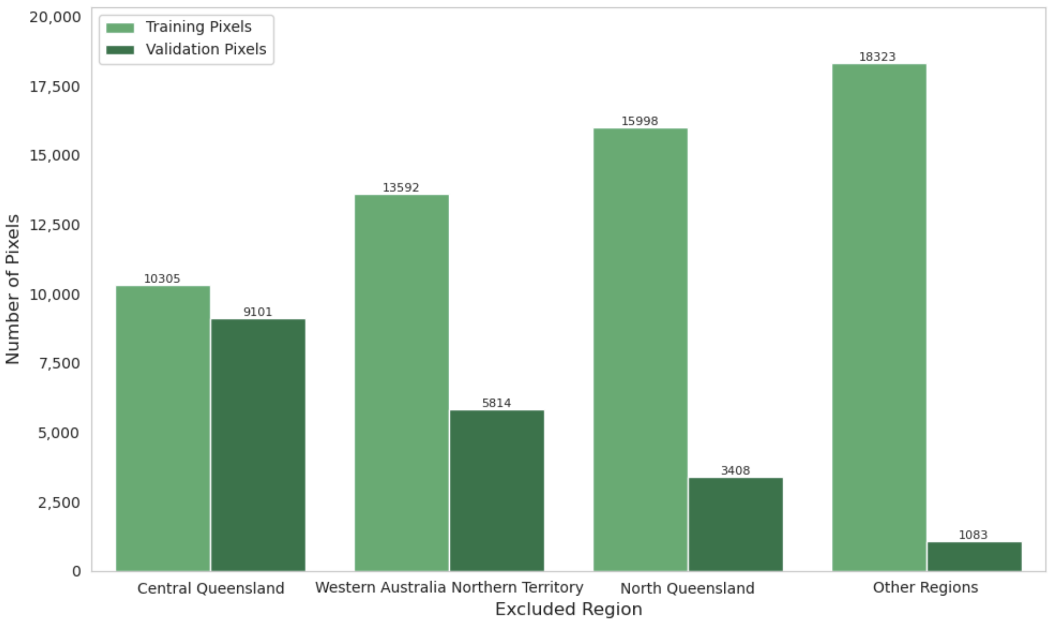

Figure 13: Distribution of training and validation pixels across different excluded regions in the study.

Analysing the training and validation data split temporally is shown in Figure 14. This figure highlights the significant lack of training and validation data for earlier years in the time series. The sparse data availability before the 2000's suggests potential challenges in accurately predicting planting years for these earlier periods, due to the limited historical data.

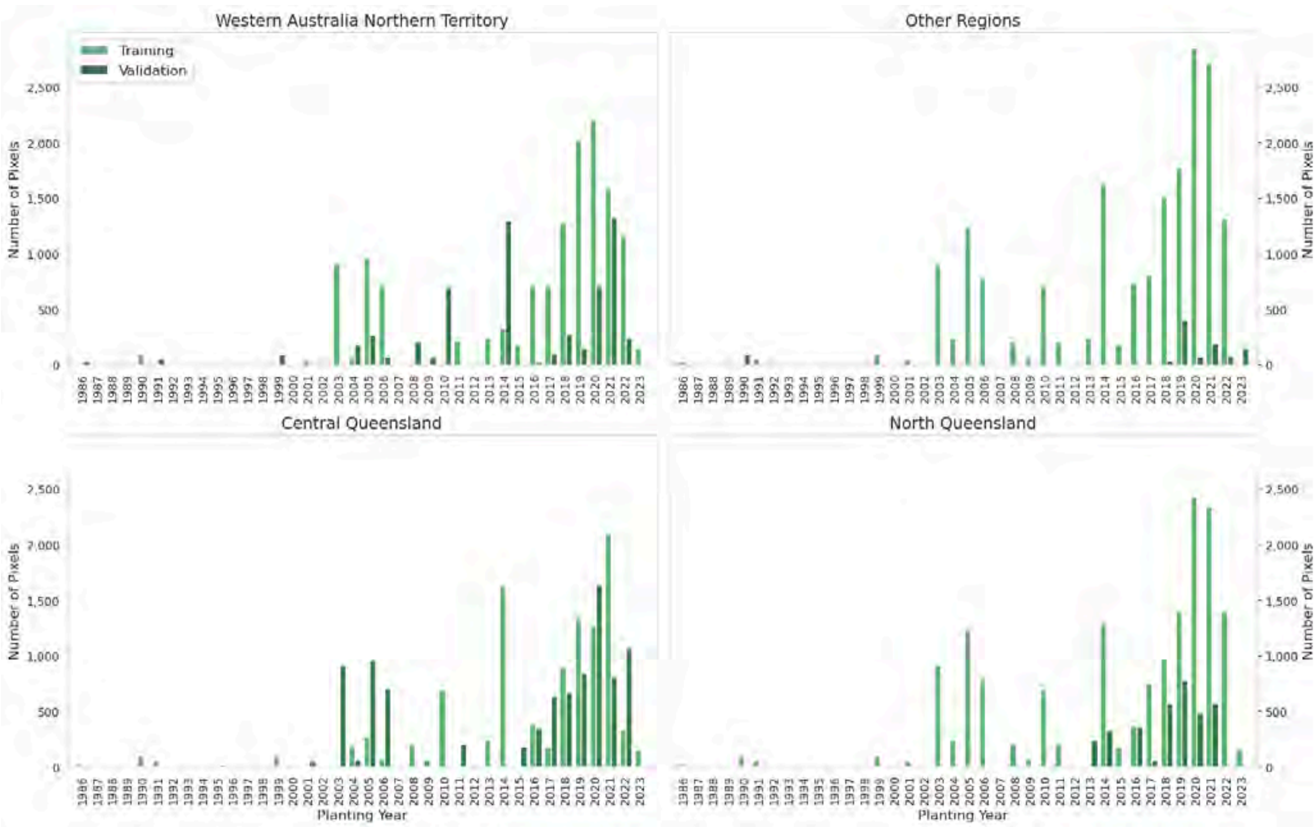

Figure 14: Temporal distribution of training and validation pixels planted each year across different regions.

Models Evaluated

To determine the best approach to predict the planting year of avocado orchard blocks, we evaluated a range of machine learning and deep learning models using time series Landsat imagery. The models encompass both traditional and advanced techniques, each with unique mechanisms for handling temporal data. The following section provides a detailed description of each model, including their architectures and references to foundational literature. This comprehensive evaluation aims to identify the most effective model for accurate and reliable prediction of block planting years.

Bidirectional Recurrent Neural Network

The Bidirectional Recurrent Neural Network (biRNN) (Schuster and Paliwal, 1997) involves duplicating the first recurrent layer, providing the input sequence to one layer and a reversed copy to the other. BiRNNs are frequently used in natural language processing.

Distributed Gradient Boosted Trees

DGBT is a machine learning technique for regression and classification, creating a prediction model as an ensemble of weak prediction models, typically decision trees. It builds the model stage-wise and generalises by optimizing an arbitrary differentiable loss function (Friedman, 2001).

Gated Recurrent Unit

The GRU (Cho et al., 2014) is a type of recurrent neural network (RNN) that employs gating mechanisms to control information flow between cells. GRUs, which include update and reset gates, are commonly used in sequence prediction, time series analysis, and natural language processing.

Long Short-Term Memory

The LSTM (Hochreiter and Schmidhuber, 1997) is another RNN variant designed to address long-term dependency problems. LSTMs have three types of gates: input, output, and forget, enabling them to retain or discard information over extended periods. This makes LSTMs highly effective for sequence prediction tasks.

Random Forest

RF (Breiman, 2001) is an ensemble machine learning algorithm based on Bootstrap Aggregation (bagging). It constructs multiple decision trees during training and outputs the class mode (classification) or mean prediction (regression) of the individual trees.

Residual Network

The ResNet (He et al., 2016) model, implemented using TensorFlow's Keras API, is a type of convolutional neural network (CNN) designed to train very deep networks by using skip connections to bypass certain layers, addressing the vanishing gradient problem. The 1D ResNet model used for time series data comprises a convolution layer, batch normalisation layer, ReLU activation layer, max pooling layer, residual blocks, a global average pooling layer, and a final dense layer.

Temporal Convolutional Network

The Temporal Convolutional Network (TCN) (Bai et al., 2018) architecture, used for sequence modelling, features dilated convolutions allowing large receptive fields with fewer parameters.

Temporal Convolutional Neural Network

The Temporal Convolutional Neural Network (TempCNN) (Pelletier et al., 2019) architecture is designed for sequence modeling, using 1D convolutions to process temporal data. It is suitable for tasks such as time series classification and anomaly detection.

Thresholding

Following the methodology presented in Brinkhoff and Robson (2020), NDVI and GNDVI thresholds were tested to predict the planting year across all avocado pixels in the map. Initially developed for macadamia orchards in Australia at the block level (and later applied in South Africa), we adapted this method for a per-pixel analysis consistent with the other models. This method cannot reliably predict the planting year for the most recent years as it requires the avocado trees to be at least three years old before they can be detected.

Transformer

The Transformer model (Vaswani et al. 2017), known for its effectiveness in natural language processing tasks, utilises self-attention mechanisms. The 1D version used for time series data consists of an encoder, dense layer, max pooling layer, squeeze layer, and final activation layer. The encoder includes multiple transformer layers, each containing a multi-head self-attention mechanism and a position-wise feed-forward network.

Model Training

The models were trained using a supervised learning approach where the training data included labelled examples of avocado block planting years. The training dataset was prepared by extracting pixel-level values within the boundaries of known avocado blocks from the Landsat imagery. Spectral bands from the Landsat imagery, along with calculated NDVI and GNDVI values, were used as features. These features were fed into the models to learn the relationship between the spectral data and the planting years.

Each model was initialised with its specific architecture and hyperparameters. This included defining the structure of neural networks for deep learning models and setting parameters for machine learning models like RF and DGBT. The models were trained using the training dataset, optimising the respective loss functions to minimize prediction errors. For neural network models, backpropagation and gradient descent algorithms were used, while tree-based models utilised boosting and bagging techniques.

Validation

The models were validated by evaluating their performance on excluded regions using a cross-validation approach. This method ensured that the model's performance was generalised across different geographic areas, reducing the risk of overfitting to any specific region. For each validation run, the region excluded from the training was used exclusively for validation. This process was repeated for all regions, ensuring that each region served as the validation set exactly once. The regions considered included Central Queensland, Western Australia / Northern Territory, North Queensland, and Other Regions.

By using data from excluded regions for validation, we could accurately assess the model's ability to generalise to unseen data. This step was crucial in determining how well the models performed across different geographic areas, ensuring robustness and reliability in their predictions.

The evaluation metrics used included:

- Mean Absolute Error (MAE): This metric measures the average magnitude of errors in predictions, providing a straightforward interpretation of model accuracy.
- Root Mean Square Error (RMSE): RMSE measures the square root of the average squared differences between predicted and actual values, giving higher weight to larger errors. It is useful for understanding the model's performance in terms of variance.

- Coefficient of Determination (R^2): This metric assesses how well the predicted values explain the variability of the actual values. An R^2 value closer to 1 indicates a better fit of the model to the data.

The performance metrics from each validation run were aggregated to provide an overall assessment of each model's performance. This aggregation involved calculating the mean and standard deviation of the MAE, RMSE, and R^2 across all regions, giving a comprehensive view of the model's effectiveness.

The aggregated performance metrics were used to compare the different models. This comparative analysis helped identify the models that consistently performed well across different regions, as well as those that showed variability in performance depending on the region.

By using a cross-validation approach that excludes regions, the validation process helps to identify any regional biases in the models. If a model performs significantly better in some regions than others, this may indicate that the model has learned region-specific features that do not generalise well.

The cross-validation approach used in this study ensures that the models are robust and generalisable across different geographic regions. By rigorously assessing each model's performance using MAE, RMSE, and R^2, we can confidently identify the most effective models for predicting the planting year of avocado blocks. This validation strategy not only enhances the reliability of the models but also provides insights into their applicability across diverse agricultural landscapes.

Model Application

After validation, the next step involved applying the trained models to the entire dataset of avocado orchards to generate predictions for planting years. The full dataset, encompassing all avocado orchards in the Australian Tree Crop Map was prepared for model application. This dataset included the pixel-level values for each orchard, derived from the same time series Landsat imagery used in the training stage. Each model, having been trained and validated, was applied to the pixel-level data of the avocado orchards. Predictions were made for each pixel within the orchard boundaries, to derive the predicted planting year map.

One of the limitations of a per-pixel model is the variation within individual blocks. To reduce this variation and improve the accuracy of the predictions, a 3x3 median filter was applied. This filter helps to smooth the output by averaging the values of each pixel with its eight neighboring pixels, thereby reducing noise and minor inconsistencies.

Additionally, any area with a clump of 15 pixels or less (1.35 ha) with the same planting year was merged into the dominant surrounding planting year. This step was crucial for eliminating artefacts such as the edges of fields or small areas that may have been predicted differently from the rest of the block. For example, a small area predicted as the year 2000 within a larger block predicted as 1999 would be adjusted to match the surrounding majority, thus smoothing out the overall prediction map.

To ensure the accuracy and reliability of the predicted planting years, the output classifications were visually inspected against higher-resolution data. This inspection involved comparing the model predictions with high-resolution satellite imagery and existing knowledge of avocado block age. By overlaying the predicted planting years on the high-resolution images, any inconsistencies or anomalies were identified and flagged for further review. This step ensured that the model outputs were not only statistically accurate but also visually consistent with known data, thereby enhancing the overall credibility of the predictions.

Results

Figure 15 presents a comparison of the machine learning and deep learning models in predicting the planting year of avocado pixels. Each subplot corresponds to a different model and includes a scatter plot of predicted versus actual planting years, with a diagonal line indicating perfect prediction. The colour intensity reflects the density of data points, and marginal histograms show the distribution of actual and predicted planting years. The figure highlights the variability in predictive accuracy and generalisation performance across different models.

Models such as the GRU, Transformer, and TCN exhibit tighter clustering of points along the diagonal line, indicating that these models provide more accurate predictions, closely matching the actual planting years. The RF and DGBT models also show reasonable clustering around the diagonal but with more variability compared to the high accuracy models. The Thresholding model shows a reasonable clustering of points along the diagonal, indicating moderately accurate predictions, although with some variability, particularly for recent planting years. Notably, the machine and deep learning models, especially the GRU and Transformer, have the capability of predicting the planting year for very recent plantings, whereas the threshold approach requires the plantation to be at least two to three years old.

The scatter plots for models like ResNet and TempCNN show a wider spread, suggesting these models may be capturing different temporal features but with less accuracy. Outliers are present in all models, where the predicted planting year deviates significantly from the actual year. These outliers may indicate specific challenges within the dataset or limitations of the models in capturing certain temporal features.

The marginal histograms reveal that most of the planting year data is concentrated between 2003 and 2023. Limited training data for avocado planting year likely contributed to poorer accuracy, particularly for earlier planting years, due to the bias towards more recent plantings.

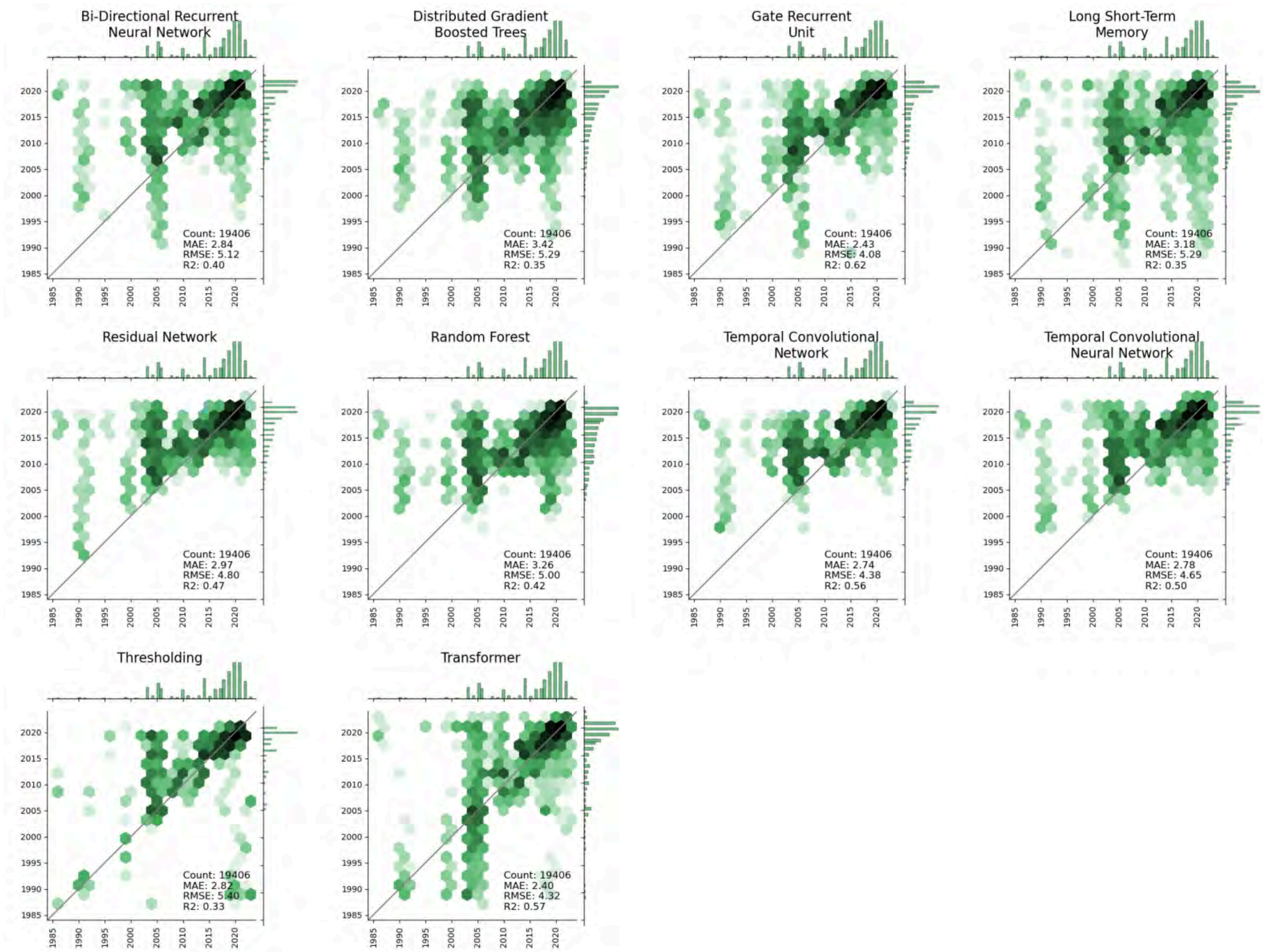

Figure 15: Scatter plots comparing predicted versus actual planting years for various models. The plot compares the performance of various machine learning and deep learning models, including Bidirectional Recurrent Neural Network (biRNN), Distributed Gradient Boosted Trees, Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), Residual Network (ResNet), Random Forest, Temporal Convolutional Network

(TCN), Temporal Convolutional Neural Network (TempCNN), Thresholding, and Transformer. The diagonal grey line indicates perfect prediction. Colour intensity reflects data point density, and marginal histograms show the distribution of actual and predicted planting years.

The plot results indicate that models such as GRU (MAE: ± 2.43 years), Transformer (MAE: ± 2.40 years), TCN (MAE: ± 2.74 years), and TempCNN (MAE: ± 2.78 years) are the most effective in predicting the planting year of avocado pixels with high accuracy. The RF (MAE: ± 3.26 years) and DGBT (MAE: ± 3.42 years) models show moderate performance. ResNet (MAE: ± 2.97 years) and biRNN (MAE: ± 2.84 years) exhibit reasonable accuracy but with more variability. The LSTM (MAE: ± 3.18 years) shows moderate accuracy, and the Thresholding model (MAE: ± 2.82 years) provides moderately accurate predictions with some variability, particularly for recent planting years.

Figure 16 presents the MAE for each model, offering a quantitative comparison. The box plot highlights that the GRU, LSTM, and Transformer models have the lowest MAE, indicating their superior predictive accuracy. The RF and DGBT models show moderate MAE values, while models like ResNet, TempCNN, TCN, and Thresholding exhibit higher MAE values, confirming their lower predictive accuracy as shown in Figure 15. This comprehensive comparison provides a robust evaluation of model performance, essential for understanding their applicability in predicting avocado orchard planting years.

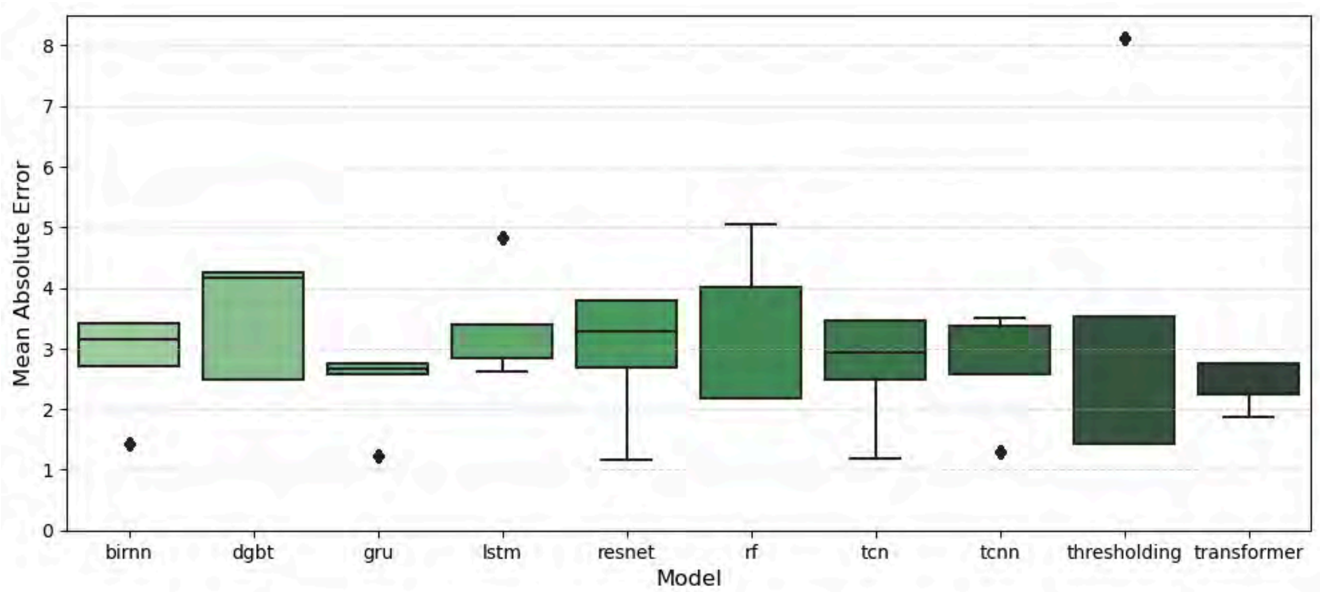

Figure 16: Box plot showing the Mean Absolute Error (MAE) for each model. The plot compares the performance of various machine learning and deep learning models, including Bidirectional Recurrent Neural Network (biRNN), Distributed Gradient Boosted Trees, Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), Residual Network (ResNet), Random Forest, Temporal Convolutional Network (TCN), Temporal Convolutional Neural Network (TempCNN), Thresholding, and Transformer. Lower MAE values indicate better predictive accuracy.

The thresholding approach, originally used for this work, relies on the vegetation indices to determine the planting year. This method was initially developed for macadamia orchards and later applied to avocado orchards. While the thresholding approach is straightforward and computationally efficient, it has significant limitations, particularly in predicting planting years for very recent plantings. The thresholding method requires avocado blocks to be at least two to three years old to make reliable predictions, limiting its applicability and accuracy for recent data.

In contrast, the GRU model can predict planting years for recent plantings more effectively. The GRU model demonstrated a tighter clustering of points along the diagonal in scatter plots, indicating closer alignment with actual planting years.

Additionally, the GRU model exhibited lower MAE values compared to the thresholding approach, further highlighting its predictive accuracy.

The GRU model's performance was evaluated using MAE, RMSE, and R^2. These metrics showed that the GRU model outperformed the thresholding approach, particularly in regions with more recent plantings where the thresholding method struggled.

The cross-validation approach used in this study, where models were validated on excluded regions, ensured that the GRU model was robust and generalisable across different geographic areas. This validation strategy not only helped to identify any regional biases but also provided a comprehensive assessment of the model's performance. The GRU model consistently showed better generalisation compared to the thresholding approach, which was more prone to overfitting specific regional characteristics.

Figure 17 presents the cumulative avocado planting areas by year and growing region, as predicted by the GRU model. The plot shows a clear trend of increasing avocado planting areas over time, with significant growth observed from the early 2000’s onward. This growth trend indicates the expansion of avocado orchards in Australia, reflecting the rising demand and popularity of avocados. There is a noticeable acceleration in the planting of avocado orchards starting around 2010. The cumulative area increases steeply, highlighting a period of rapid expansion in the avocado industry.

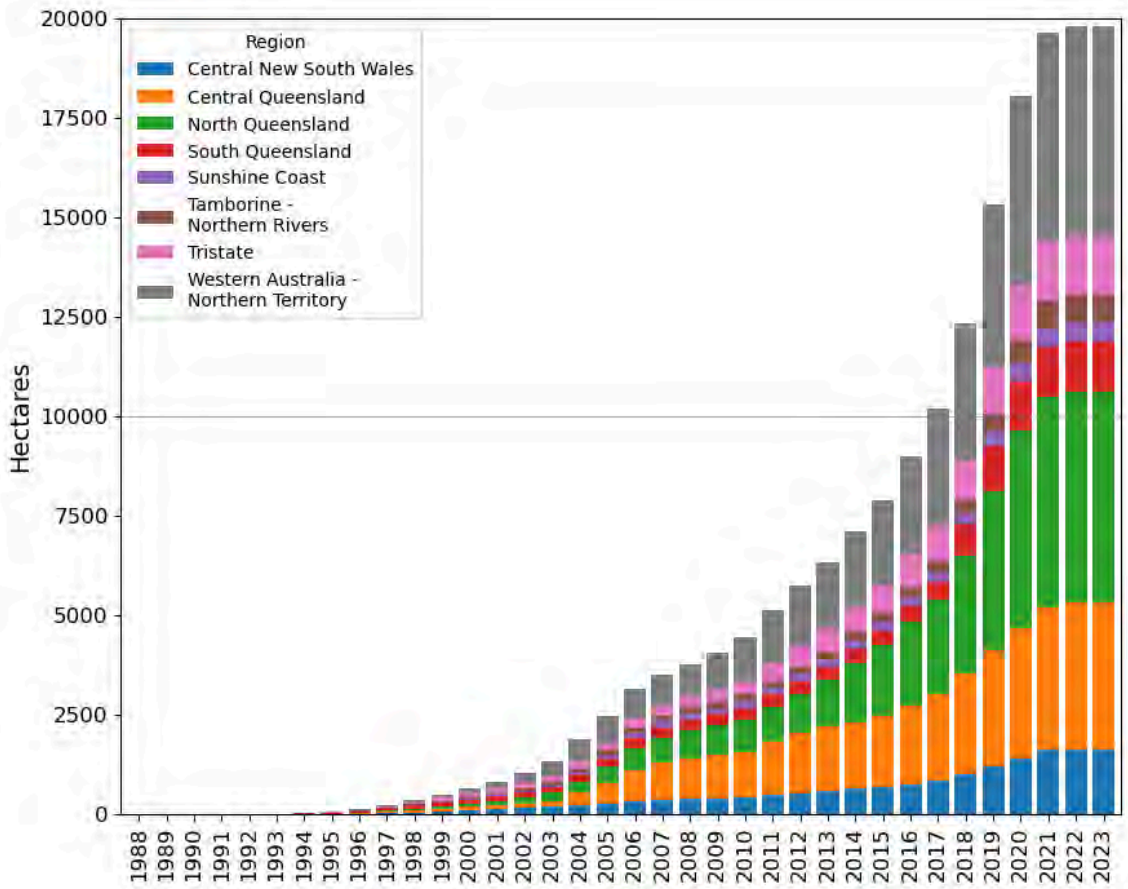

Figure 17: Cumulative Avocado Planting Area by Growing Region (1988-2023) Predicted by the GRU Model. The x-axis represents planting years from 1988 to 2023, while the y-axis shows the cumulative planting area in hectares. The plot includes only orchards in the map, excluding those that have been removed, and demonstrates a bias towards more recent planting years due to the availability of training data.

The training data is biased towards more recent years, as indicated by the concentration of planting year data between 2003 and 2023. This bias could affect the model's accuracy in predicting earlier planting years due to the limited representation of older data. Consequently, the plot predominantly reflects the growth in more recent years, potentially underestimating the planting activity in earlier in the time series.

The plot reveals significant contributions from Central Queensland and North Queensland to the overall avocado planting area, with substantial growth from the early 2000's to 2023. South Queensland and Sunshine Coast also exhibit notable growth, particularly from the mid-2000's onward. Western Australia / North Territory and Tristate, while contributing to the overall planting area, have relatively smaller cumulative areas compared to Central and North Queensland. Central New South Wales and Tamborine / Northern Rivers show a gradual increase in planting areas over time, contributing to the diversity of avocado production regions.

The most recent years (2018–2023) continue to see substantial increases in planting areas across all regions, especially in Western Australia. This suggests a sustained and robust expansion in the avocado industry. However, the approach only considers avocado orchards that are shown in the ATCM. Any avocado blocks that have been removed over-time are not represented in the plot. This means the cumulative areas shown do not account for historical orchards that were planted and subsequently removed, potentially leading to an underestimation of the total planting activity over the years.

Additionally, some avocado blocks may have been removed and then replanted. This replanting activity may not be fully captured in the plot, as the cumulative area only increases without reflecting instances where blocks were removed and later replanted. This could contribute to an overestimation of the total orchard area in recent years. Blocks known to have been 'stag-horned', where significant portions of the tree canopy are removed were accounted for in the model which retained the original planting year, rather than the land management practice intervention event.

Overall, the plot demonstrates the effectiveness of the GRU model in capturing the temporal dynamics of avocado planting across different regions, while also highlighting the limitations and biases inherent in the data and modelling approach. The cumulative growth trends provide valuable insights into regional planting patterns and the industry's expansion in Australia over the past three decades.

Conclusion

This study demonstrates the effectiveness of using time series Landsat imagery and various machine learning and deep learning models to predict the planting years of avocado orchard blocks, across multiple regions in Australia. By leveraging extensive satellite data and advanced modelling techniques, we have developed a robust methodology for accurately mapping the age of avocado orchards. The models evaluated, including both traditional machine learning approaches like RF and GBT, as well as deep learning models such as TempCNN, TCN, biRNN, GRU, LSTM, Transformer, and ResNet, along with the existing thresholding approach, provide valuable insights into their predictive capabilities and limitations.

The findings indicate that deep learning models, particularly GRU (MAE: ± 2.43 years), Transformer (MAE: ± 2.40 years), and TCN (MAE: ± 2.74 years), offer superior predictive accuracy compared to traditional methods and simpler thresholding approaches. These models demonstrate tighter clustering around the diagonal in scatter plots and lower MAE values, highlighting their effectiveness in capturing the temporal dynamics of avocado orchards. However, the study also acknowledges the challenges posed by limited historical data, which can introduce biases towards more recent planting years and affect model generalisation for earlier periods.

The GRU model was selected for its superior ability to handle time series data, its higher predictive accuracy, and its robustness across diverse regions. The comparison with the thresholding approach underscores the advancements and benefits of using deep learning models for predicting the planting years of avocado pixels, ultimately leading to more accurate and reliable agricultural planning and decision-making.

Implementing data augmentation techniques could address the bias towards more recent planting years. By artificially synthesising avocado pixel data for earlier periods, we can create a more balanced training dataset, improving model performance for older planting years. This augmentation could involve generating synthetic satellite imagery and corresponding planting year labels, simulating the spectral and temporal characteristics of historical orchards. Such an approach would help in reducing bias and enhancing the generalisability of the models.

Additionally, moving from a pixel-based analysis to a patch-based analysis can further improve the accuracy of planting year predictions. A patch-based approach considers the broader context of the surrounding area, rather than relying solely on individual pixels. This context-aware method can capture spatial patterns and relationships that are critical for accurate mapping of orchard ages. By analysing patches of pixels, the models can better understand the landscape context, leading to more robust and reliable predictions.

The application of cross-validation techniques, where models were validated on excluded regions, ensured the robustness and generalisability of the models across diverse geographic areas. This approach not only helped identify region-specific biases but also provided a comprehensive assessment of each model's performance.

In conclusion, the predictive models developed in this study hold significant potential for enhancing agricultural planning, yield forecasting, and decision-making processes within the avocado industry. The integration of these models into a dashboard-style mapping application, as well as collaboration with industry stakeholders for expanding training data, will further refine and improve the accuracy of planting year predictions. The insights gained from this research will contribute to the overall sustainability, profitability, and resilience of the avocado industry in Australia.

Yield forecasting

The project AV21006 concentrated on updating and validating two remote sensing-based approaches: the 'CropCount' and the 'time series' for yield forecasting mainly in Northern Queensland, South Australia and Western Australia region.

‘CropCount’ methodology

The 'CropCount' methodology, initially developed by Robson et al. (2014, 2017a, 2017b) and further refined by Rahman et al. (2019) in Project ST15016 and AV18002, showcased the effectiveness of yield forecasting and mapping for individual avocado blocks. This method utilised high-resolution WorldView3 (WV3) satellite imagery (1.24 m spatial resolution and 0.31 cm pan sharpened) to derive 20 different vegetation indices (VIs). By correlating these VIs with targeted samples of fruit number and weight from 18 representative trees across high, medium, and low vigor regions of the orchard, accurate yield predictions were achieved. Project AV21006 extended this evaluation across one farm in Queensland, three farms in South Australia and four farms in Western Australia. The study locations are provided in Figure 18.

Figure 18: Study locations where the 'CropCount' and 'Time Series' methodologies were applied

Instead of using 8-band multispectral WV3 imagery, the AV21006 project opted for 6-band multispectral Pleiades Neo imagery (1.2 m spatial resolution and 30 cm pan-sharpened) due to the more affordable cost. Figure 19 shows an example location of Pleiades NEO image acquired over 87 km² in WA on 24th and 30th September 2022.

The imagery was subsetted according to the orchard or farm boundary and determined the classified Normalized Difference Vegetation Index (NDVI) of 8 classes, depicting variations in tree vigour. Six replicate trees were then selected from each NDVI region to represent high, medium, and low vigour areas, totaling 18 trees. Additionally, the clustered sampling technique developed in project AV18002 was evaluated again in AV21006, where clusters of six replicate trees from each block's high, medium, and low NDVI regions were chosen. This clustered approach proved to be more efficient and less labor-intensive compared to the original 18-tree sampling method.

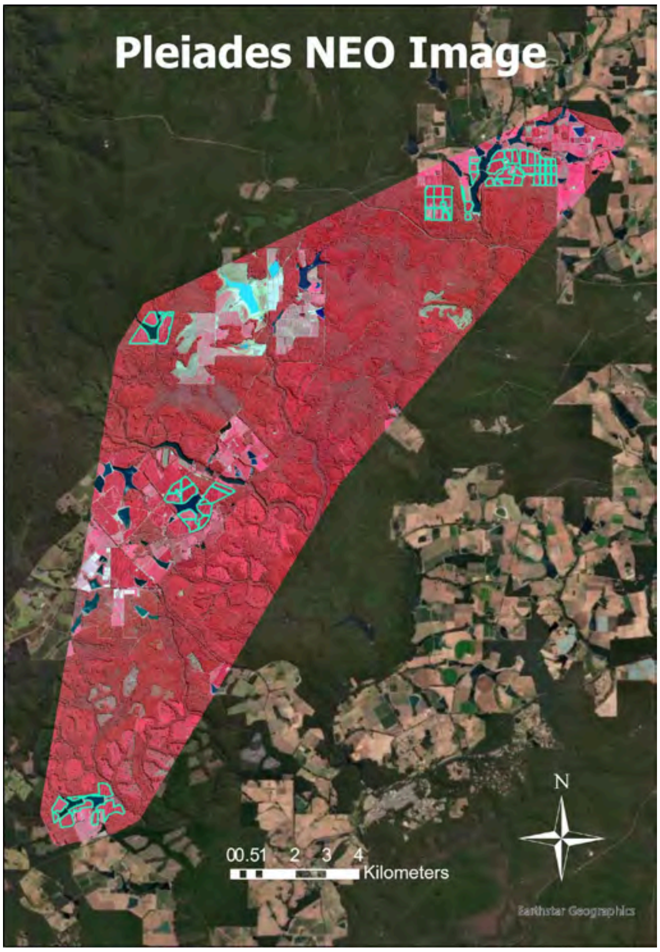

Figure 19: Acquired Pleiades NEO-3 image for testing 'CropCount' methodology over 5 farms in Western Australia (24th and 30th of September 2022)

To precisely locate selected trees within the orchard, block, row, and tree numbers were manually counted from pan-sharpened Pleiades Neo images. Moreover, to better align with the current practices of the participating growers in WA, the original methodology was modified for seven farms in the current project. This included measuring the yield from only nine trees instead of 18 in two of the orchards (Figure 20). In the other five orchards, growers used a 'panel' count method, where the yield of six trees was combined in four different locations across the orchard (Figure 21). Although both methods reduced the number of calibration points (n=9 and n=4 per orchard), the accuracies achieved exceeded the growers' current estimation practices. Using handheld Trimble DGPS devices, the exact positions of each tree centre was recorded. In some cases, the tree or panel locations were determined manually using Google Earth imagery, to plan the targeted sampling—before the commencement of actual harvest. Manual harvesting of the selected trees typically coincided with commercial harvesting, with all harvested fruits counted and weighed to determine total fruit yield per tree or per panel.

The locations of each sampled tree or the panel were overlaid onto the Pleiades Neo images (30 cm panchromatic band) using ArcGIS Pro 10.8.1 (Environmental Systems Research Institute, Redlands, CA, USA). For each tree or panel location, a polygon was created according to the tree canopy or tree canopies for the panels. This ensured that the extracted pixel values were specific to the selected tree canopies or panels and excluded any pixels influenced by shade or ground cover in the inter-rows. Using the open-source software Starspan GUI (Rueda et al., 2005) and QGIS 3.34.4 (QGIS.org (2023)), each area-of-interest (AOI) was used to subset the 6-band spectral information for each tree canopy or panels location from the non-pan-sharpened multi-spectral imagery. From the extracted data, 13 structural and pigment-based vegetation indices (VIs) specific to crop biomass and yield parameters were derived (Table 1) and regressed against total fruit weight (kg/tree). This analysis was performed separately for each block.

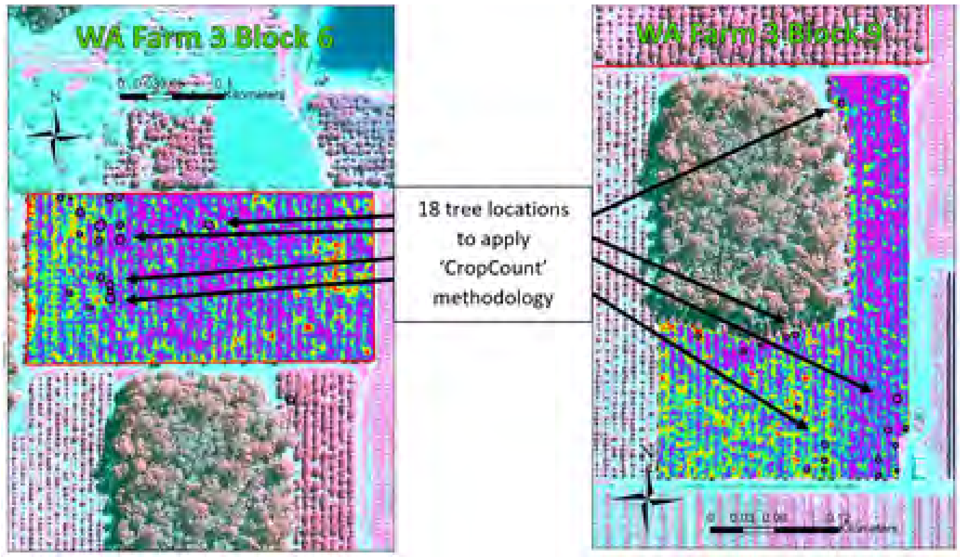

Figure 20: Example of 18 tree locations in two blocks in one farm in Western Australia to develop yield forecasting models using 'CropCount' methodology.

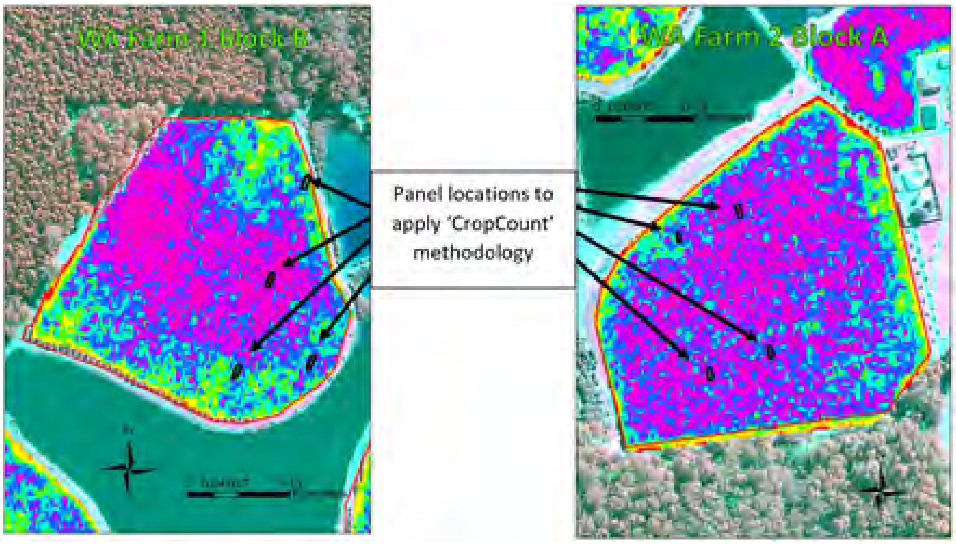

Figure 21: Example of panel locations in two blocks in two farms in Western Australia to develop yield forecasting models using 'CropCount' methodology. Panel locations are show with black boundary in the image.

Table 1: Vegetation indices used in this study

	Name	Formula	References
1	Normalized Difference Red-edge/Red (NDVI red-edge)	(RE − R)/(RE + R)	(Gobron et al., 2000)
2	Transformed Chlorophyll Absorption Reflectance Index (TCARI)	3 × ((RE − R) − 0.2 × (RE − G) × (RE/R))	(Haboudane et al., 2002)
3	Structure Insensitive Pigment Index (SIPI)	(NIR − B)/(NIR + R)	(Penuelas et al., 1995)
4	Coastal Blue Structure Insensitive Pigment Index (CB SIPI)	(NIR − CB)/(NIR + CB)	(Penuelas et al., 1995)
5	Normalized Difference Red/Red-edge Index (R/RENDVI)	(NIR − R)/(NIR + RE)	(Gitelson et al., 1996b)
6	Green Normalized Difference Vegetation Index (GNDVI)	(NIR − G)/(NIR + G)	(Gitelson et al., 1996a)
7	Modified Simple Ratio (MSR)	(NIR/R − 1)/(SQRT((NIR/R) + 1))	(Chen, 1996)
8	Ratio Vegetation Index (RVI)	NIR/R	(Jordan, 1969)
9	Normalized Difference Vegetation Index (NDVI)	(NIR − R)/ (NIR + R)	(Rouse et al., 1974)
10	Normalized difference Red-edge Index (RENDVI)	(NIR − RE)/ (NIR + RE)	(Fitzgerald et al., 2010)
11	Renormalized difference Vegetation Index (RDVI)	(NIR1 − R)/(SQRT (NIR1 + R))	(Roujean & Breon, 1995)
12	Transformed Difference Vegetation Index (TDVI)	1.5 × ((NIR − R)/ (SQRT(NIR^2 + R + 0.5))	(Bannari et al., 2002)
13	Non-Linear Index (NLI)	(NIR^2 − R)/(NIR^2 + R)	(Goel & Qin, 1994)

Several statistical methods were applied to identify the VI most strongly related to yield parameters such as fruit number and total fruit weight (kg/tree). This included principal component analysis (PCA) and non-linear regression, performed using R software (R Development Core Team, 2023). While PCA is typically used to eliminate redundancy among many variables, in this study, it served as a variable reduction technique to select the two optimal VIs from the 13 most related to yield parameters. The VI with the highest coefficient of determination (R^2) and the lowest root mean square error (RMSE) was selected as optimal.

To extrapolate the linear relationships identified between the selected 18 trees and the optimal VI for each block to all trees within those blocks, non-canopy related pixel information (e.g., inter-row vegetation, soil, shading) was removed. This was achieved by isolating pixels specific to individual tree canopies and creating a 'mask' to subset the imagery. The linear algorithm developed between the optimal VI and yield parameter for each block was then applied to the subsetted pixels, converting reflectance to the respective yield parameter units. Alongside the creation of classified yield maps, the average yield for each block was calculated by applying the average pixel reflectance value of all tree canopies into the corresponding block yield algorithm. Figure 22 provides a flowchart detailing the process for algorithm development, derivation of block-level yield maps, and prediction of block-level yield parameters. The average and total yield for each block were then compared to the actual harvested yield.

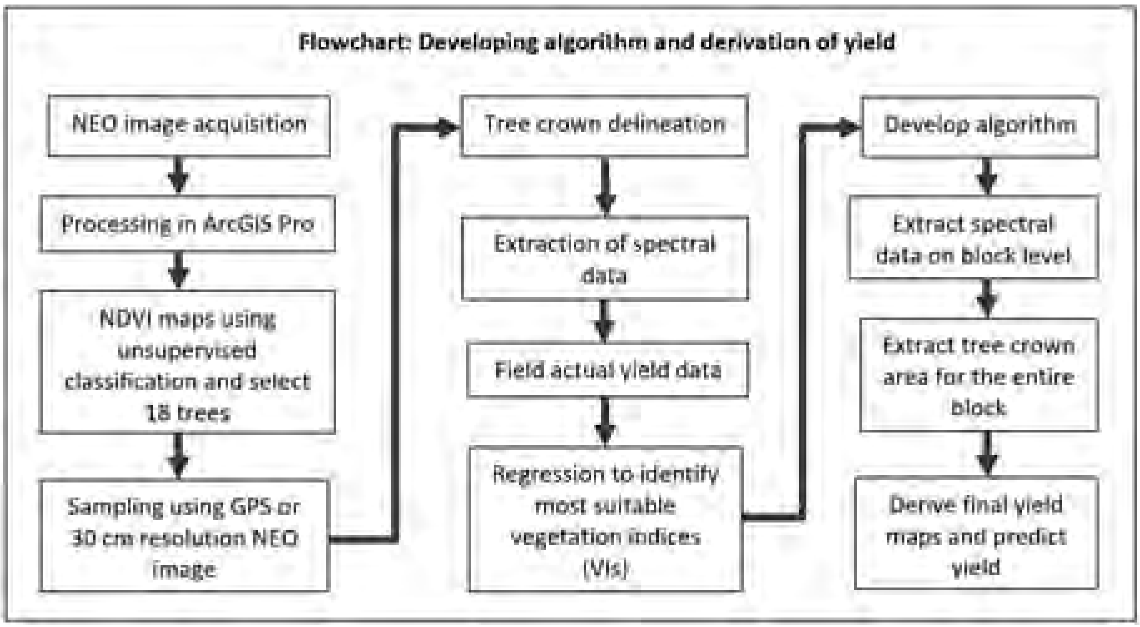

Figure 22: The flowchart of developing algorithms and derivation of block level yield maps.

In the 2021/22 season, the 'CropCount' methodology was applied in four orchard blocks in Western Australia. For the 2022/23 season the methodology was again evaluated over seven orchards across four farms in Western Australia. The list of blocks, image capture dates and sampling dates where the 'CropCount' methodology was applied is shown in Table 2.

Table 2: The list of Avocado farms and blocks, NEO image capture date and sampling date in 2021/22 and 2022/23 seasons

Year	*Farm*	*Block*	*Image capture date*	*Sampling date*
2021/22	*Farm 1, WA*	Block 1	25 September 2022	15 December 2022
		Block 2	25 September 2022	15 December 2022
	Farm 2, WA	Block 3	25 September 2022	13 October 2022
		Block 4	25 September 2022	13 October 2022
2022/23	*Farm 1, WA*	Block 1	21 September 2023	22 October 2023
		Block 2	21 September 2023	22 October 2023
	Farm 2, WA	Block 3	21 September 2023	22 October 2023
		Block 4	21 September 2023	22 October 2023
	Farm 3, WA	Block 5	21 September 2023	22 October 2023
	Farm 4, WA	Block 6	21 September 2023	26 October 2023
		Block 7	21 September 2023	26 October 2023

'Time Series' methodology

For the 'time series' methodology, historical Sentinel-2 and Landsat imagery were used to plot the annual growth profiles of selected avocado crops. This approach provides valuable insights into the seasonal effects of management practices, location, and weather conditions on tree vigour (health, size, density) and the timing of key phenological growth stages. In Project AV21006 'time series' methodology was applied over three farms (35 blocks) in Queensland; three farms (15 blocks) in South Australia and eight farms (69 blocks) in Western Australia. The historical block-level yield data spanning 7 to 10 years was obtained from participating avocado farms from all three states. Corresponding cloud-free Landsat 7, 8, and Sentinel-2A, 2B imagery were acquired from Google Earth Engine (GEE) (Gorelick et al., 2017) for these farm regions to develop the 'time series' models. Canopy reflectance for each orchard block, identified by the normalised difference vegetation index (NDVI), plotted over time, reveals seasonal and cross-seasonal growth trends. Figure 23 illustrates this output for an orchard, showing each season's peak in vigour in June and troughs in January. Four different VIs derived from satellite images on temporal resolution and the corresponding annual yields (t/ha) allowed for the identification of past relationships, which were then used in eight different machine learning (ML) models to develop time series ML models to predict yield (t/ha) on block level. The procedures for data acquisition, pre-processing, cleaning, and machine learning model development are illustrated in Figure 24.

To enable a comprehensive evaluation of the best performed ML model, three metrics were employed: coefficient of determination (R^2), mean absolute error (MAE) and root mean squared error (RMSE). The model with the highest R^2 value and the lowest MAE and RMSE values was considered as the best performing model and selected for the prediction of yield.

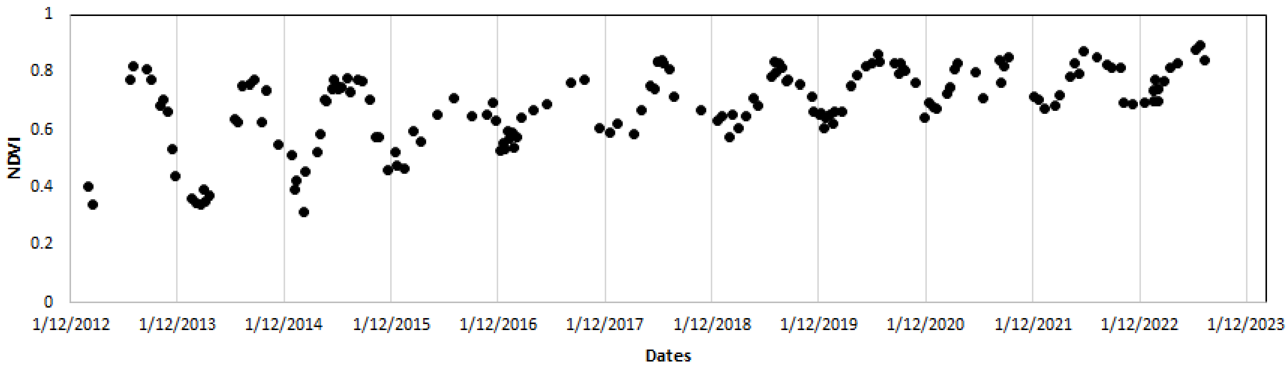

Figure 23: Time series GNDVI data derived from Landsat images for an avocado block

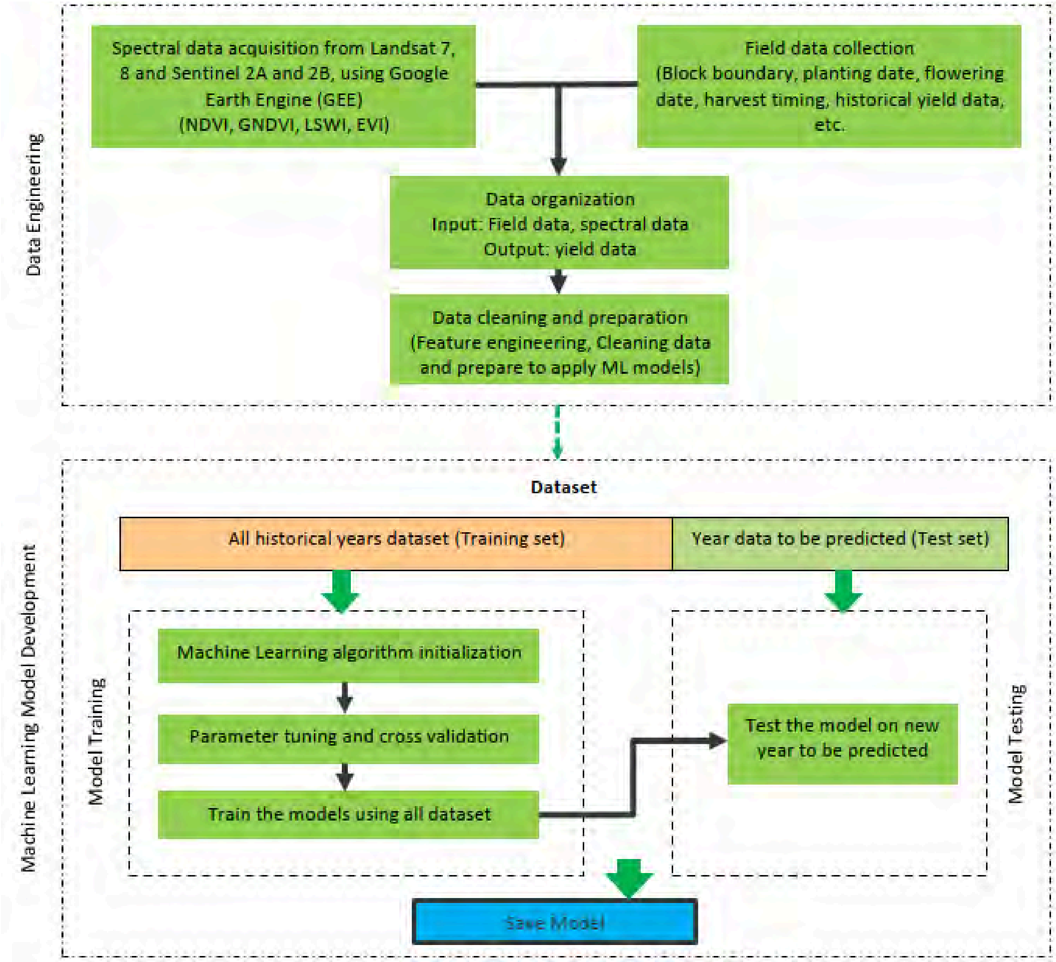

Figure 24: The overall approach including data engineering and machine learning model development

One significant limitation identified in the 'time series' yield prediction methodology was the alternate bearing pattern observed in avocado crops. This pattern, characterised by fluctuating yields between 'On' and 'Off' seasons, posed a challenge to accurate yield forecasting. To address this issue, the project initiated the development of a remote sensing-based approach aimed at distinguishing between these alternating seasons, thereby improving the yield prediction accuracy, which was presented in World Avocado Congress 2023 (Rahman and Robson, 2023).

The methodology involved analysing satellite imagery and other historical productivity data to identify patterns and markers indicative of the different seasons using seven ML classification algorithms. The flowchart of data acquisition, preprocessing, cleaning and machine learning model development are illustrated in Figure 25. By distinguishing these seasonal variations, the project aimed to refine the predictive models used for yield estimation. This approach promised to deliver more precise and timely information to growers, enabling them to make better-informed decisions regarding crop management and resource allocation.

However, the project encountered challenges that have prevented the finalisation of this approach. The primary obstacle has been the insufficient availability of data. Accurate and reliable remote sensing-based predictions require extensive and high-quality data sets, covering multiple seasons and various conditions. The limited data availability has constrained the projects ability to validate and fine-tune the methodology effectively. In the 2022/23 season, the project provided predicted yield data in both 'On' and 'Off' formats for some blocks. This approach allowed growers to choose the predictions with their initial visual estimates and determine whether the season was likely to be 'On' or 'Off.' This dual-format prediction aimed to assist growers in making more informed decisions based on their on-farm observations.

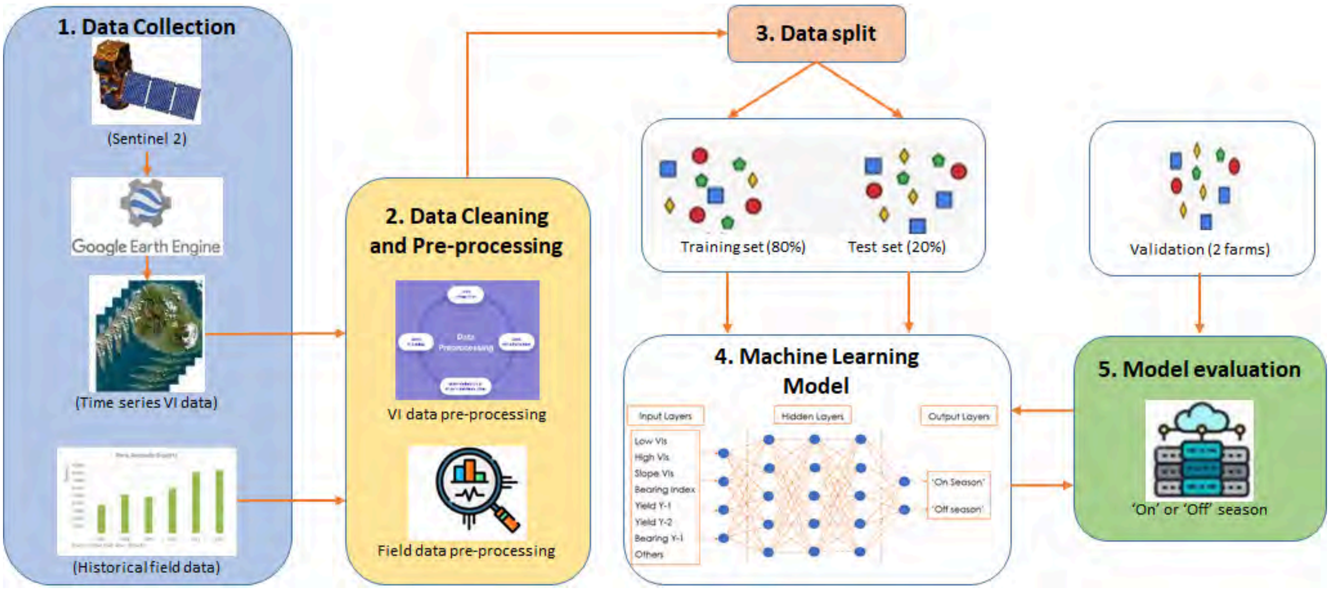

Figure 25: The overall approach of alternate bearing season prediction using ML models

Photos/images/other audio-visual material

World Avocado Congress NZ 2023: (Figure 26 includes L-R: Moshiur, Andrew and Craig)

- **Dr Muhammad Moshiur Rahman**: Better predicting the irregular bearing of avocado crops using sentinel 2 derived time series enhanced vegetation index. Presentation link.
- **Prof. Andrew Robson**: How to navigate 'AgTech' for tree crops. Presentation link.
- **Craig Shephard**: Industry meets innovation: Building the national avocado tree crop map in Australia and ensuring its ongoing maintenance through engagement with industry. Presentation link.

Figure 26: AARSC presented at the World Avocado Congress NZ 2023

National avocado dashboard map: AARSC have created a demonstration video (Figure 27) to support users to access and view the dashboard (https://experience.arcgis.com/experience/4137ef7d53f741c7bf1475ecfbfe371e). The video (which is available as a link in the header) also features a demonstration of the ATCM Survey. The video is hosted on YouTube (https://youtu.be/2eqnbcU06QA?si=j2JTHcdNex7BSsrg).

Figure 27: National avocado map (Demonstration video)

Results and discussion

National Mapping

The final update of the national map of avocado orchards was published into the Australian Tree Crop Map Dashboard on the 21st May 2024. **The total area of commercial avocado orchards mapped across Australia is 19,805 ha**. Analysis for currency shows that 26% of all orchards in the map are current (mapped in year) to 2024 and 65% are current to at least 2023.

Figure 28 presents the national map of avocado orchards summarised by Local Government Areas (LGA). Total figures for production area are presented (labelled) for each State. At state-level, Queensland has the largest area of avocado orchards with 10,878 ha (55%), followed by Western Australia with 5,283 ha (27%).

Bundaberg is the largest LGA with 3,444 ha (17% of the national total) followed by Manjimup with 3,350 ha (17%). Mareeba has 2,672 ha (13%) and Tablelands has 2,483 ha (13%).

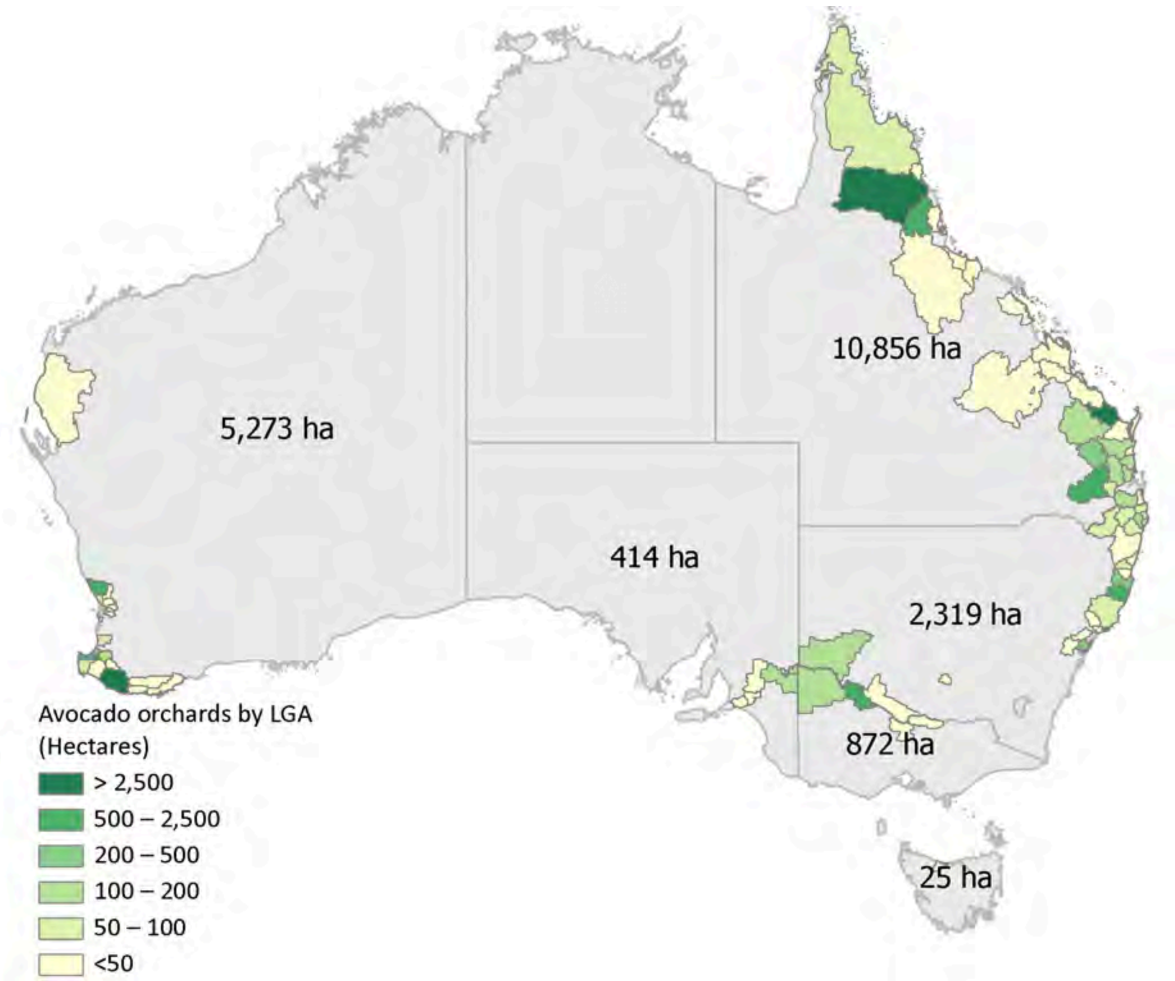

Figure 28: Avocado orchards (total area) by Local Government Area (LGA). Labels shown are State totals (hectares)

Table 3 and Figure 29 presents summary analysis of the map by AAL region. North Qld has the largest area of production with 5,283 ha (or 27%) just exceeding the WA/NT with 5,312 ha (26%), followed by Central Qld with 3,678 ha (19%).

Table 3: Area of production by AAL region

AALRegion	Area (Hectares)	Area (%)
Central NSW	1,629	8%
Central QLD	3,678	19%
North QLD	5,312	27%
South QLD	1,245	6%
Sunshine Coast	508	3%
Tamborine/Northern Rivers	682	3%
Tristate	1,467	7%
WA/NT	5,283	27%
Grand Total	**19,805**	**100%**

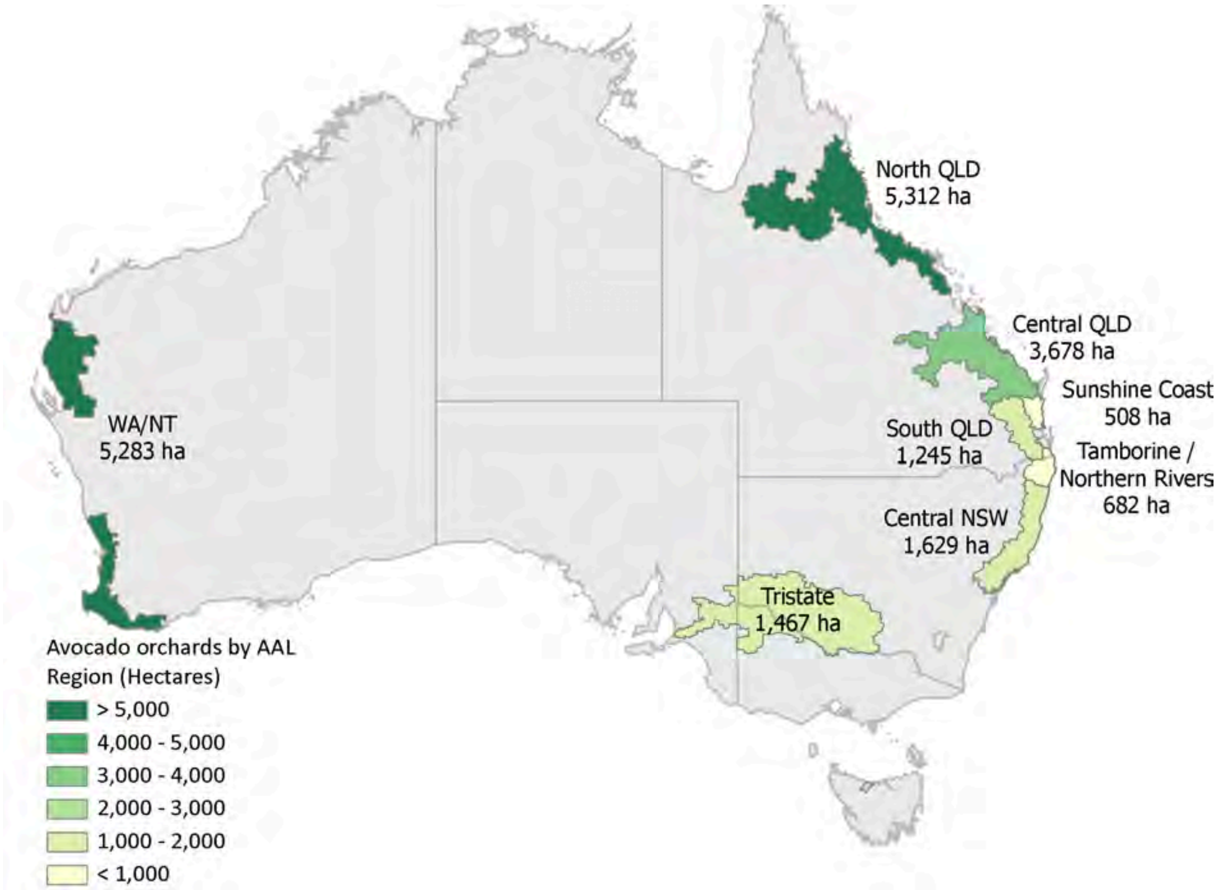

Figure 29: Avocado orchards (total area) by AAL Region (hectares)

Analysis of changes in total area of production (areal) by State is presented in Table 4, reflecting previous milestone reporting for map updates. Be aware that changes in the mapping methodology influence these results (e.g. increasing the minimum mapping unit from 2 ha (Phase 1) to 1 ha (Phase 2 and on-going), as well as 'improvements' to the map where misclassifications are corrected (e.g. incorrect tree crop class). Changes between each state/territory reflect targeted updates as per the mapping program where updates are prioritised by growing region (across states).

Table 4: Total area of production by State, based on mapping milestones timeline (hectares)

State / Territory	Phase 1 (Dec 2017)	AV18002 Phase 2 (Apr 2022)	AV21006 MS103 (Nov 2022)	AV21006 MS104 (May 2023)	AV21006 MS105 (Nov 2023)	AV21006 MS190 (May 2024)
ACT	0	0	0	0	0	0
NSW	1,642	2,295	2,300	2,325	2,280	2,332
NT	0	0	0	0	0	0
QLD	9,044	9,766	10,852	10,850	10,829	10,878
SA	177	406	409	402	415	415
Tas	4	18	18	18	25	25
Vic	555	981	993	970	856	873
WA	1,714	4,669	4,709	4,680	4,854	5,283
Grand Total	**13,136**	**18,136**	**19,281**	**19,223**	**19,259**	**19,805**

Applications Summary

Mapping products:

- Australian Tree Crop Dashboard (https://arcg.is/9n95e)

This dashboard-style web application features the latest map and includes metrics for avocado, mango, macadamia, citrus, olive, banana and truffle orchards (area of production in hectares). At national scale, clicking the map will return the total area of orchards by state and territory in a pop-up (Figure 30), while zooming in to the map will show Local Government Areas (LGA). Navigation around the map can be achieved by 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. The dashboard will update the summary statistics for each tree crop (at bottom) on-the-fly, based on the map view extent. The ATCM dashboard has been viewed (opened) 18,579 times.

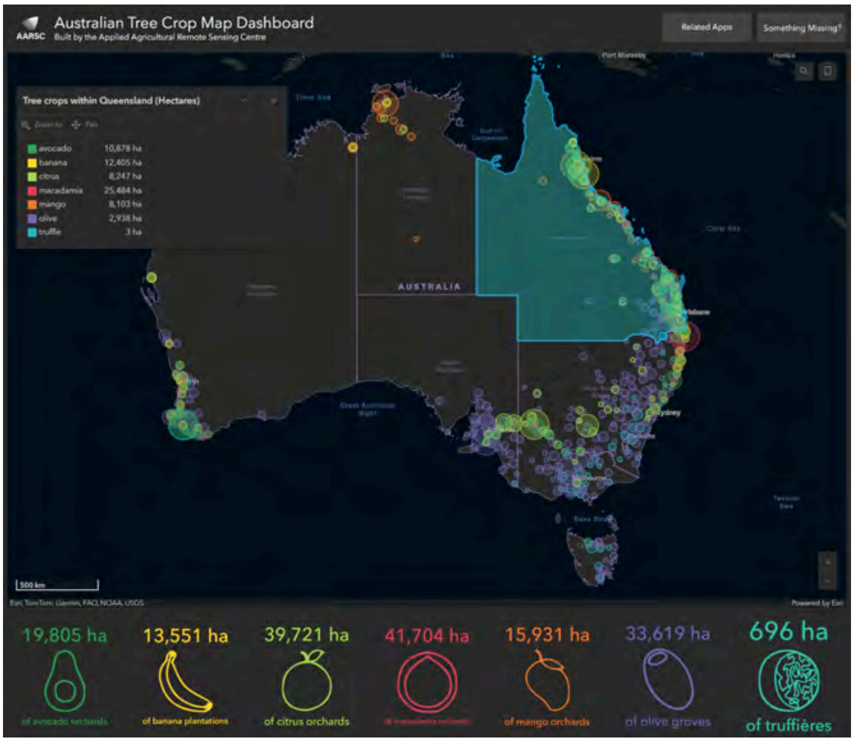

Figure 30: ATCM Dashboard showing total production area in Qld in a pop-up (May 2024)

- Avocados Australia Dashboard Map
  https://experience.arcgis.com/experience/4137ef7d53f741c7bf1475ecfbfe371e

AARSC built the 'avocado-only' dashboard-style mapping application (Figure 31) which presents the same information as shown in the ATCM Dashboard—but only includes avocado orchards. Summary statistics of total production area are available for query (in a pop-up) by State/Territory, AAL growing region and Local Government Area (LGA). The dashboard includes a tool to summarise the map by any area-of-interest. Figure 32 shows the result of an area defined by drawing directly on the map, which in this example includes 132 ha of avocado orchards. AARSC have also included within the header (as buttons which function like hyperlinks) to launch the ATCM Survey for feedback, and a demonstration video.

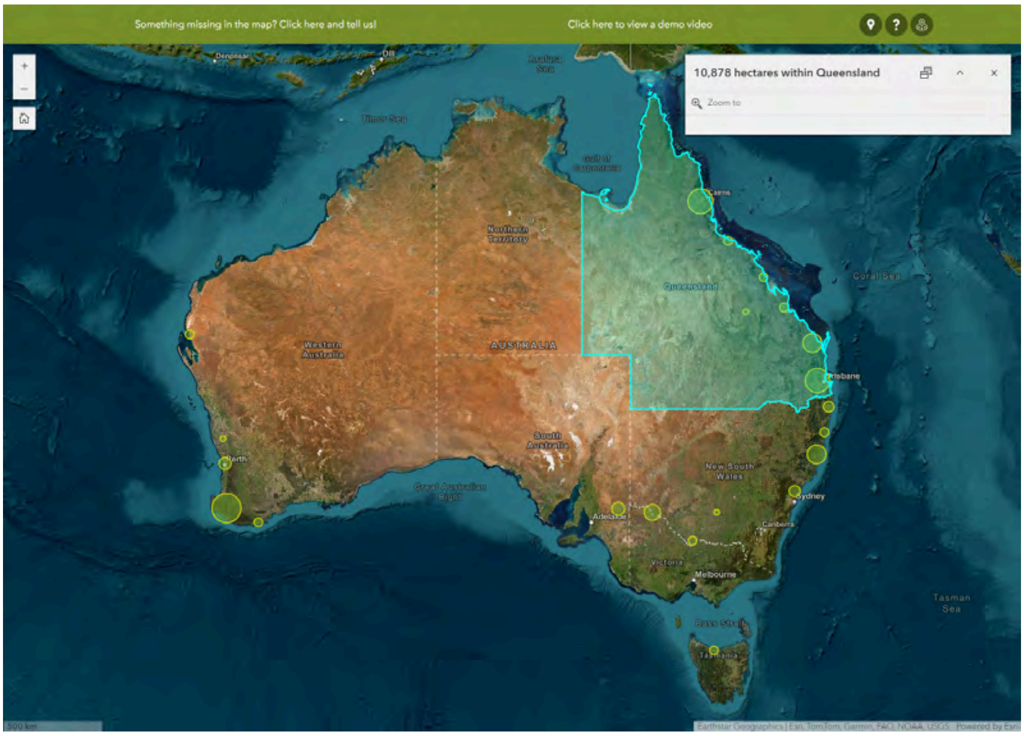

Figure 31: Avocados Australia Dashboard Map (showing total production area in Qld in a pop-up)

Figure 32: Avocados Australia Dashboard Map includes a Summarise area tool

The Avocados Australia Dashboard Map has been shared with AAL, with the suggestion to feature it on their website—potentially to replace the current Avocado Survey form. It has been viewed 243 times.

- ATCM: Severe Weather App (https://arcg.is/0C5LqC0)

With much of Australia's most lucrative avocado orchards concentrated in small geographical regions, the impact of a single severe weather event can be significant. The AARSC have developed spatial and temporal tools that support industry preparedness, response and recovery to severe weather events, including tropical cyclones, severe thunderstorms (hail) and bushfires.

AARSC have recently rebuilt the ATCM: Severe Weather App, which is updated in near-real time with authoritative weather information sourced from the Bureau of Meteorology (BoM)—under annual subscription. The data includes real and near-real time information, including: satellite imagery (Himawari-8), tropical cyclones and severe thunderstorms (hail). Updated with additional analysis by AARSC, the application supports industry with understanding potential impacts from severe weather events and where to prioritise recovery assistance. Additionally, the app now includes information for bushfires, based on the burnt area extent.

– include examples of potential impacts to avocado orchards for detected severe weather events, including: TC Jasper which crossed the Queensland coastline on 13th December 2023; a bushfire detected near Gingin (WA) on 14th January 2024; and a severe thunderstorm cell detected on the Sunshine Coast (Qld) on 4th March 2024.

The ATCM: severe weather app has been viewed 801 times.

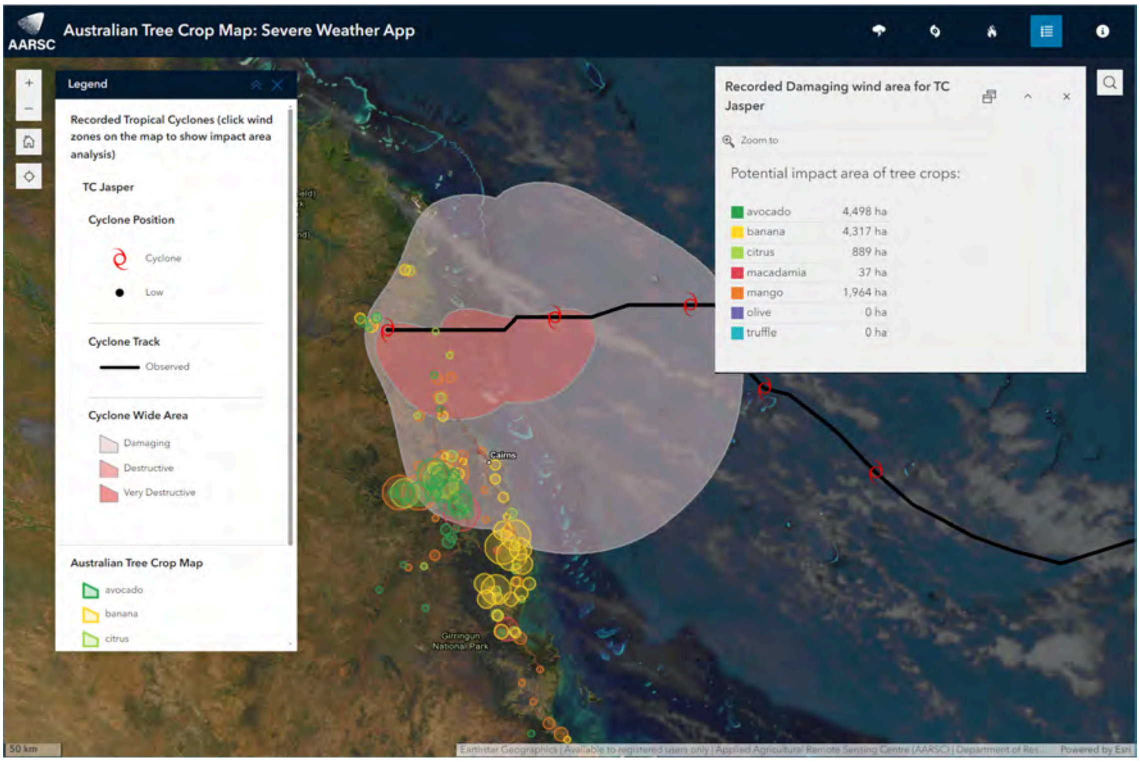

Figure 33: ATCM: Severe weather App, showing TC Jasper's damaging wind area zone in pop-up

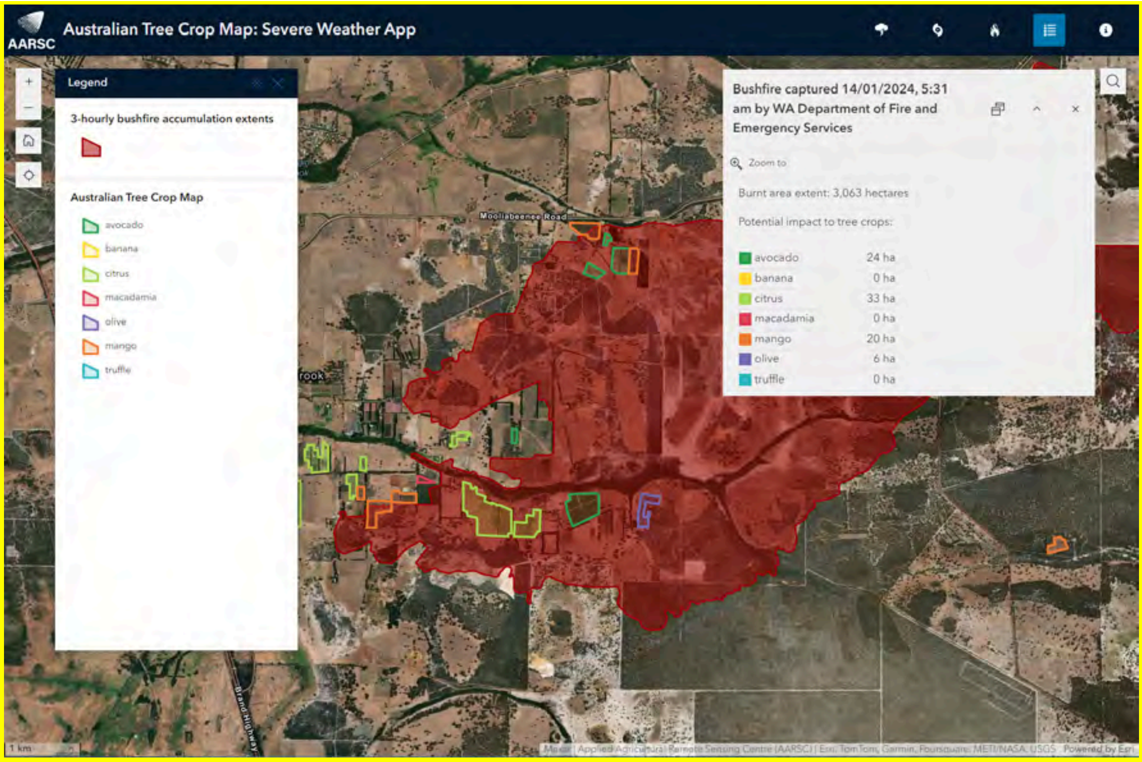

Figure 34: ATCM: Severe weather App, showing bushfire event near Gingin, WA, detected 14th January 2024

Figure 35 shows a severe thunderstorm cell detected on 4th March 2024 on the Sunshine Coast. When analysed for potential impacts to tree crops, this event showed 100 ha of avocado orchards are within the detected thunderstorm cells impact area. The analysis of thunderstorm cells is currently restricted (by BoM) to the metropolitan doppler radar. AARSC are seeking to have the coverage expanded to include rural radars.

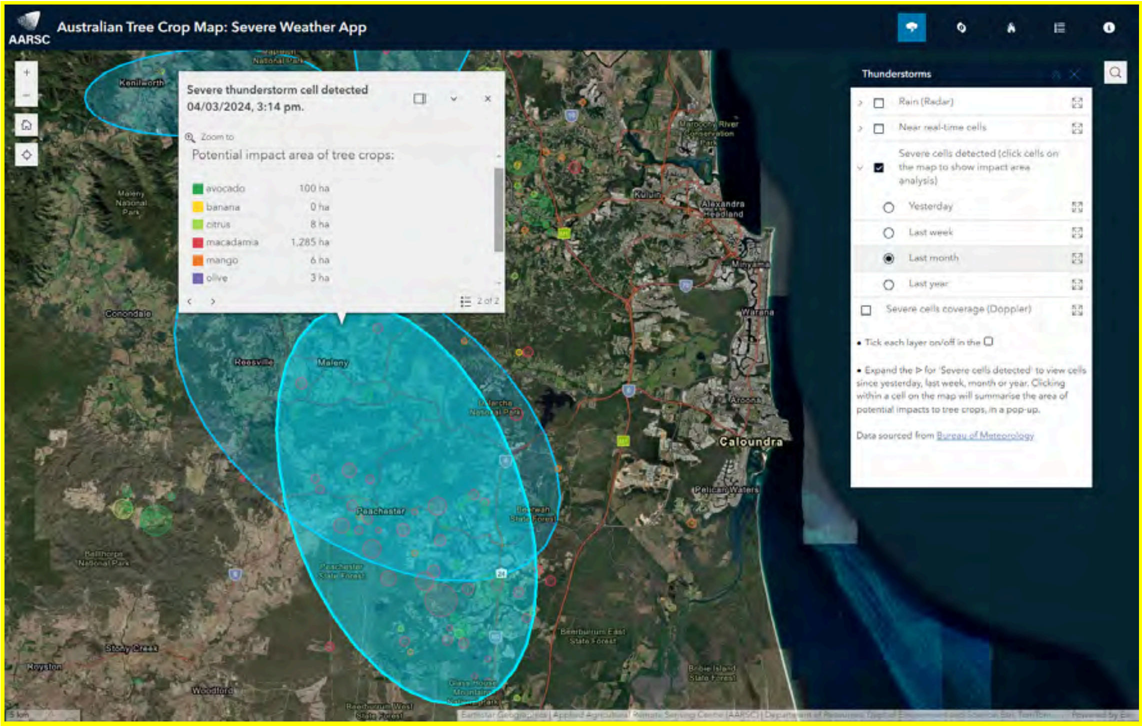

Figure 35: ATCM Severe Weather App, showing a thunderstorm cell detected 4th March, 2024

- Varroa Mite Rapid Response Map (https://experience.arcgis.com/experience/9b9812e3fc294bd49ad8b0671a987415/?org=UNE-2351)

The Varroa Mite incursion detected in NSW in 2023 provided a further demonstration of the significant benefits an established national map of avocado orchards offers industry. AARSC built the Varroa Mite Rapid Response Map, a web application leveraging the national map of tree crops and protected cropping systems, together with analysis based on the NSW DPI eradication and surveillance (management) zones. The app was updated live (as the DPI zones changed). Clicking each zone on the map interactively returns charts (pop-up), presenting the total area of crops within that zone. In this example shown in Figure 36, some 220 ha of avocado orchards are within the eradication zone (10km of detected hives) and a further 162 ha were located within the surveillance zone (25km).

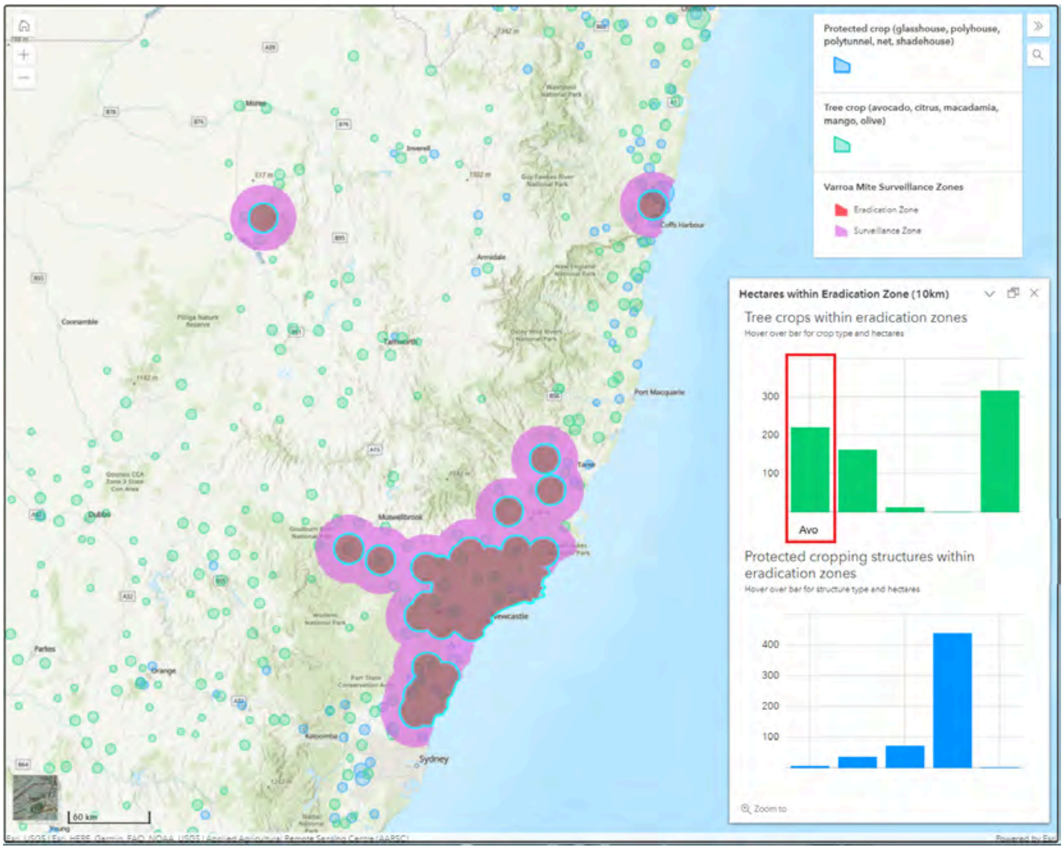

Figure 36: Varroa Mite Rapid Response Map, showing impacted crops within the NSW DPI eradication zone. The chart shown in pop-up presents total area of crops within the eradication zone (220 ha of avocado orchards)

Since launch on 28th March 2023 the Varroa Mite Rapid Response Map was viewed 1,542 times.

- Murray-Darling Basin (MDB) Rapid Response Map (https://experience.arcgis.com/experience/01bb068a277843e696a1c45ce0e59801)

Applications of the map continue to inform industry with accurate information based on the extent of the Murray-Darling Basin (MDB)—essential data that has been requested by both industry and the Federal government in the current debate over the water buy-back scheme. AARSC have built the Murray–Darling Basin Rapid Response Map, a web map application leveraging the national map of tree crops. Clicking the MDB on the map will interactively return chart and metrics (pop-up), presenting the total area of crops within that zone. Some 1,514 ha of avocado orchards are within the MDB (Figure 37). Since launch on 1st December 2023 and shared on LinkedIn (post achieved 4,906 impressions and 83 reactions), the map has been viewed 127 times.

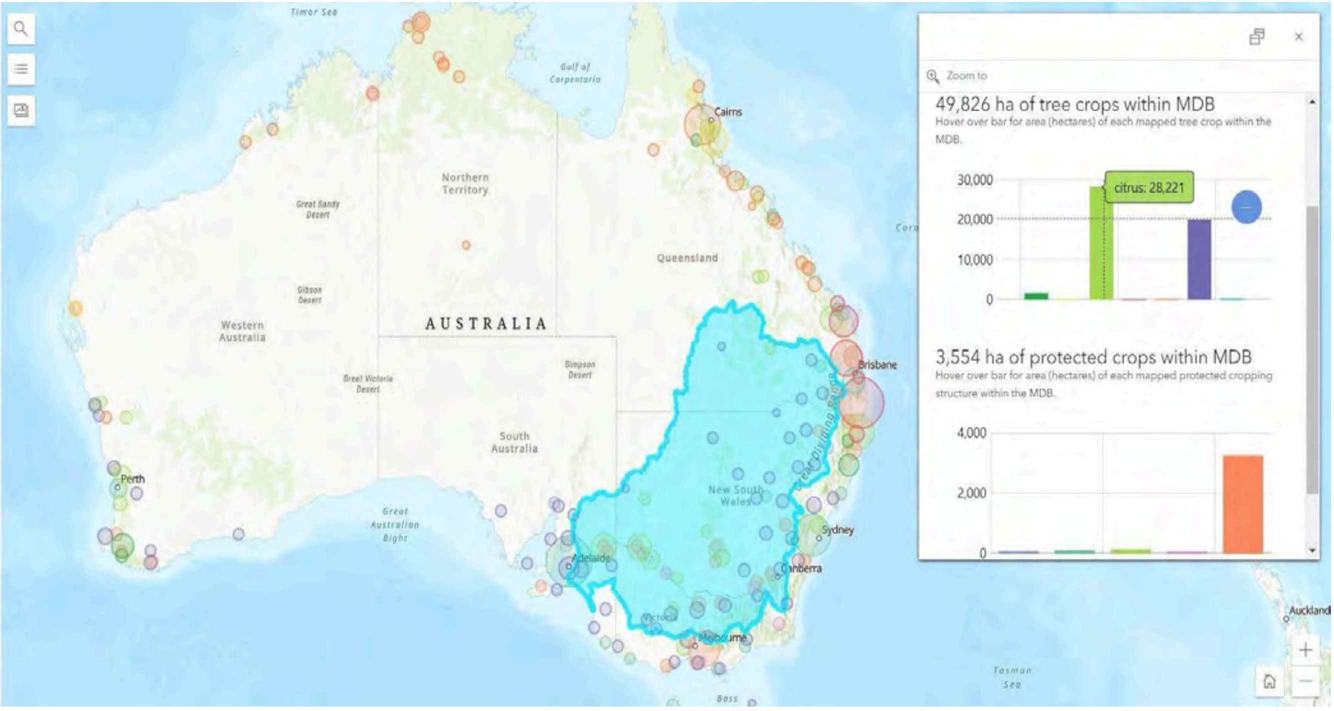

Figure 37: Murray-Darling Basin Rapid Response Map

- AAL Predicted Planting Year Dashboard
(https://experience.arcgis.com/experience/4470c3e4c49546a8bb4a68dcf53a7b12/page/Main-page/)

AARSC has developed the AAL Predicted Planting Year Dashboard mapping application to present and analyse the planting year prediction map. The dashboard interactively summarises the map by planting year, based on the view extent of the user (Figure 38).

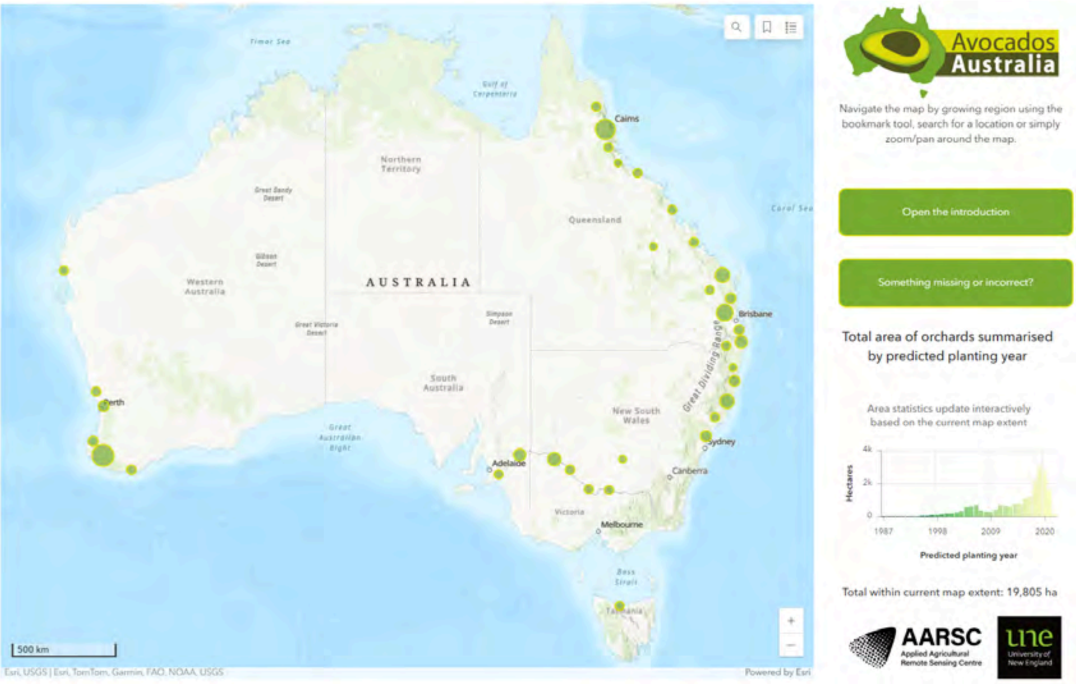

Figure 38: AAL Predicted Planting Year Dashboard

Additional analysis is supported through pop-ups which will return summary metrics by AAL Region, including a 'hover-over' chart which shows planting year and area (ha). Figure 39 shows the result for Central QLD region, which includes 3,378 ha of avocado orchards, the chart shows the distribution of predicted planting year, with 274.8 ha planted in 2021.

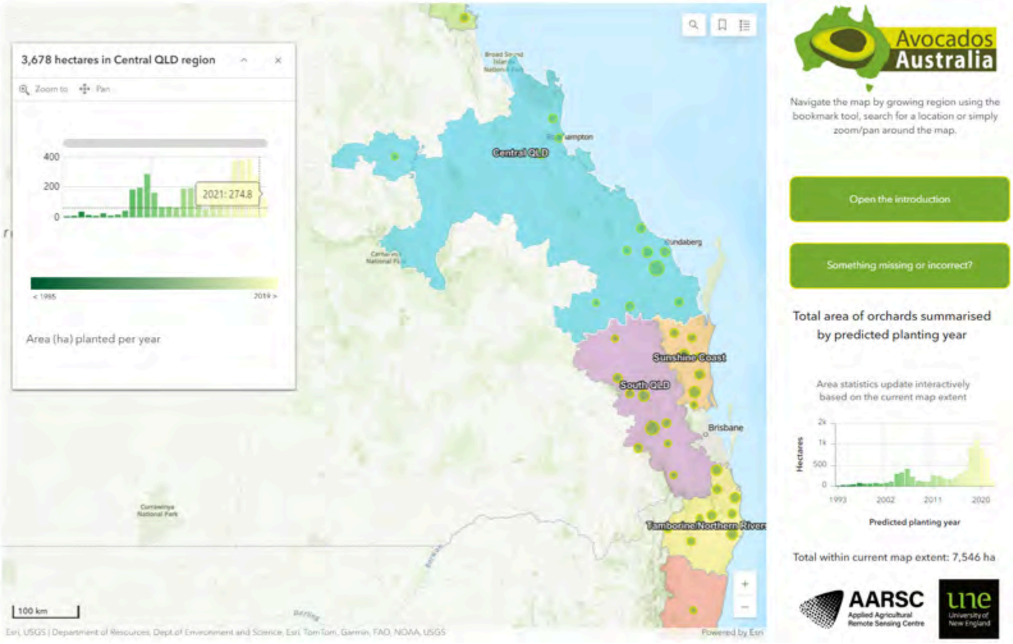

Figure 39: AAL Predicted Planting Year Dashboard showing analysis for Central QLD region (pop-up)

Zooming into local scale the predicted planting year map will display as features, presented in 5-yearly intervals (across 8 classes). Dark green features represent old orchards and lighter features are young (Figure 40).

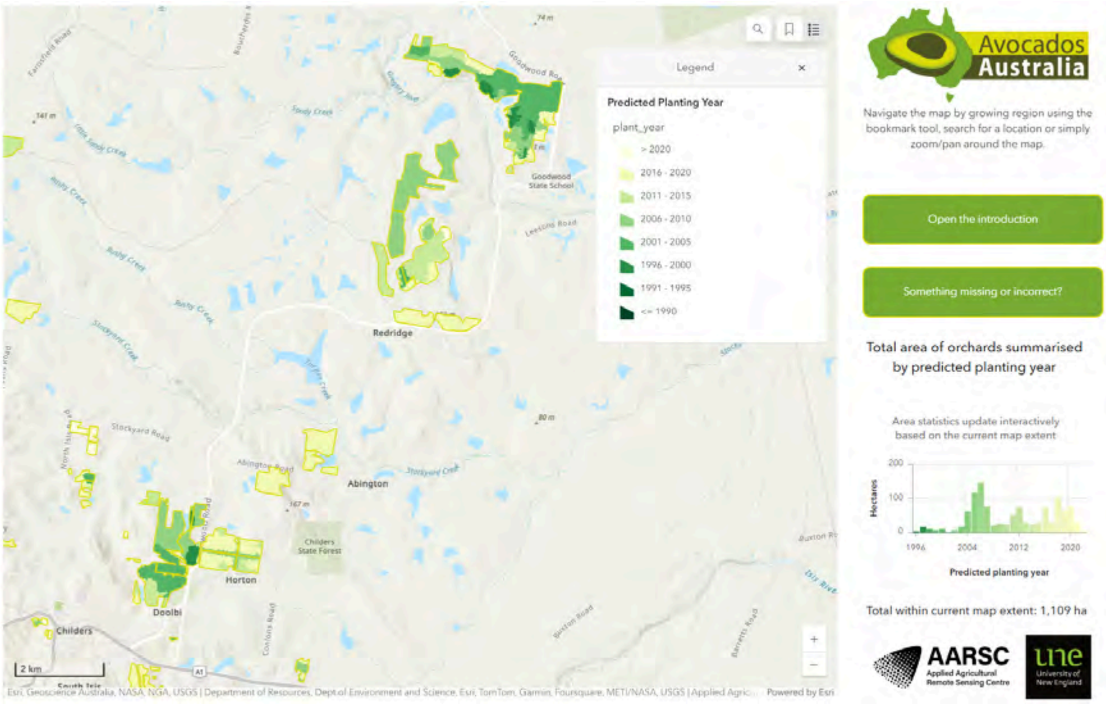

Figure 40: AAL Predicted Planting Year Dashboard showing predicted planting year map

AARSC is actively supporting the Australian Bureau of Statistics (ABS) campaign “Modernising ABS agricultural statistics”. The ATCM is informing the working group for horticulture tree crop statistics and our recent R&D to derive a planting year prediction map for all avocado orchards in the ATCM (summarised by growing region) has been shared with the Horticulture Statistics Working Group.

Industry engagement tools:

- Australian Tree Crop Survey (https://arcg.is/1W4Kie1) and Avocados Australia Survey

Engaging industry and stakeholders in contributing feedback (especially for new plantings) is supported by the ATCM Survey (Figure 5) and additionally through an 'avocado-only' survey form (Figure 6)—which is hosted on the Avocados Australia website homepage (https://avocado.org.au/). The ATCM survey is optimised for mobile devices (it uses the GPS). Anyone can complete a survey in a few simple steps:

1. Add location of the orchard by clicking on the embedded map:
    - either select the cross-hair button to quickly 'find my location' or search for an address.
    - place the pin on the orchard by clicking the map and continue the survey (from a mobile device confirm the location by selecting either the ✓ or the back arrow (<) button in the top-left corner to continue the survey).
2. Select tree crop type and optionally attach a photo.
3. Click submit to complete the survey!

The total number of ATCM surveys received is 4,396—with 699 surveys specifically for avocado (Figure 41). Since the 30th April 2022 (under project AV21006), 198 new avocado surveys have been received. Analysis of this survey data during this project shows 480 ha of new avocado plantings were added, 1,322 ha was confirmed as avocado and updated for currency, whilst 65 ha of avocado was removed from the map.

AARSC acknowledge the generous support of AAL, who in undertaking their annual tree census campaign (OrchardInfo), encouraged members to check their orchard was in the map, and provided instructions and link to complete a survey.

Figure 41: ATCM surveys (showing avocado only). Labels show the total number of suverys received in that location

As an example, Figure 42 shows an ATCM survey observation received near Pemberton, WA for a new avocado orchard planting, which also includes a photo. As a mechanism to inform on-going updates, the survey tool is proving very successful.

Figure 42: Survey observation for avocado planting including photo at X, with direction arrowed (Pemberton, WA)

- Industry Engagement Web App (https://arcg.is/1WyWDa0)

The app features the ATCM and enables feedback comments to be added directly for the attention of AARSC (anonymously). The app includes simple web-GIS capabilities that allow anyone to add (draw) a feature (as a point or polygon) on the map. AARSC interpret the information submitted and action updates to the ATCM. This application is critical to inform the mapping of new plantings.

As an example, Figure 43 shows a feedback comment which delineated a new planting, north of Gingin in WA. This information has added 171 ha of new avocado orchard to the map. The imagery shown (Esri Basemap, captured 24th December 2022), shows newly prepared rows north of the mapped area—which are yet to have trees planted. AARSC will continue to revisit this area, pending the availability of more recent high-resolution satellite imagery we can further extend this orchard when trees are planted.

Figure 43: Feedback comment (dashed white polygon) submitted via the IEWA showing new avocado orchard (171 ha) added to the map

The Industry Engagement Web App—which was first published in 2019, has been viewed 7,572 times. Comments submitted include both point (location) and polygon (extent or area) observations, which specifically for avocado, total 28 and 195 respectively. The total number of comments received (for all tree crop observations) through this location-based tool is 1,028.

Yield forecasting of Avocado using both the 'CropCount' and 'Time Series' methodologies:

As outlined in the methodology section, the 'CropCount' and 'time series' yield forecasting methodologies were applied across a number of orchards in Queensland, South Australia and Western Australia during Project AV21006.

Yield forecasting using 'CropCount' Method

In the 2021/22 season, 3 farms were selected (Kangara, Yandilla and Solora farms) in South Australia and six farms were selected (West Pemberton, Treen Brook, North Pemberton, Southern Forest, Rose and Rob Farms) in Western Australia to evaluate the 'CropCount' methodology. However, due to the early harvest of crops, 'CropCount' methodology was not tested in South Australia. In Western Australia, the 'CropCount' methodology was tested partially in four orchard blocks, since the growers in other farms could not harvest their crops from 18 calibration trees separately before the commencement of actual block level harvest.

As a first step, the classified Normalized Difference Vegetation Index (NDVI) was generated using Pleiades NEO-3 image and shared in a web application (app) to the growers to select 18 sample trees from their orchard blocks (Figure 44). This tool enabled them to select 18 sample trees from their orchard blocks, with six trees chosen from low, medium, and high-performing regions, with the interactive functionality of the app. However, in two orchard blocks the growers provided yield data from only nine instead of the 18 trees, and in another two orchards growers used 'panel methodology'—where they harvested avocados in a 'panel' (combined of six trees) and provided three panels (n=3 points) data to support the development of the prediction models. Although this was a variation of the original methodology (to better suit the current practice of the growers), the accuracy achieved in all four orchards ranged from 74% to 98%—which was higher than the grower's estimation (Figure 45).

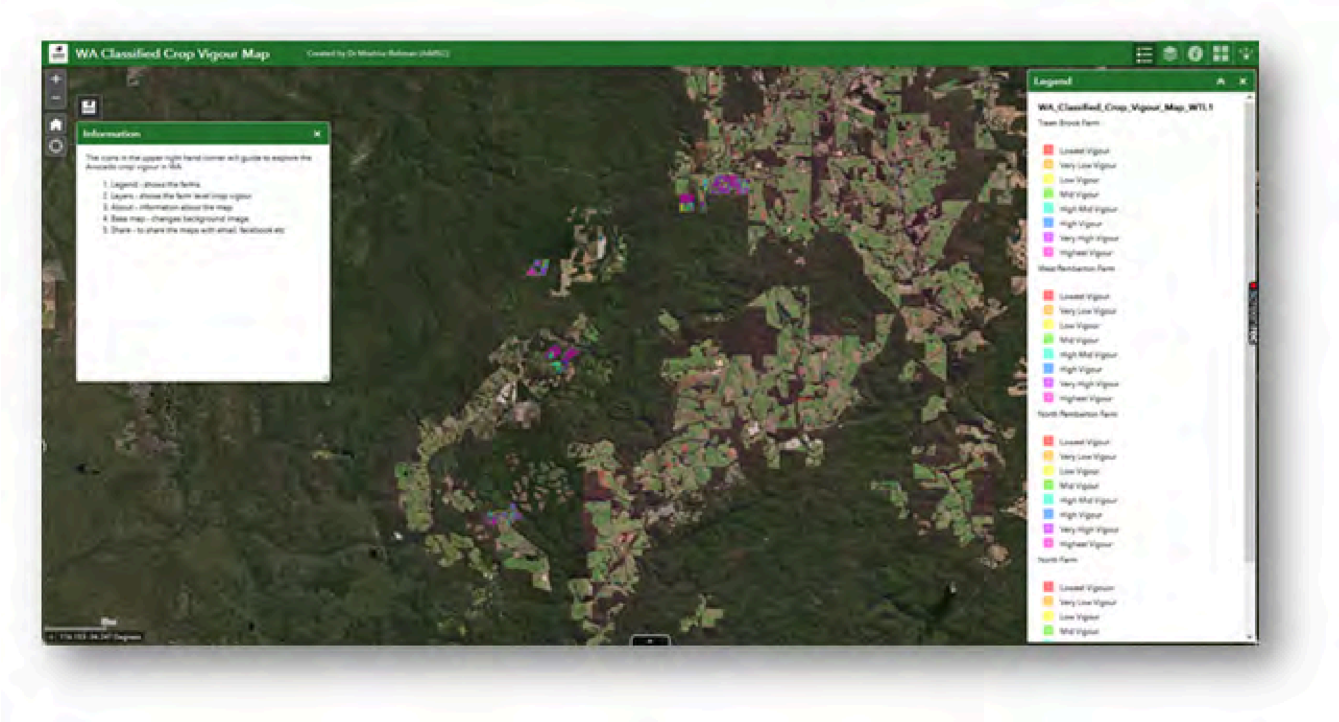

Figure 44: Classified Normalized Difference Vegetation Index (NDVI) map generated from Pleiades NEO-3 image and provided as web app to select 18 calibration trees for 'CropCount' methodology.

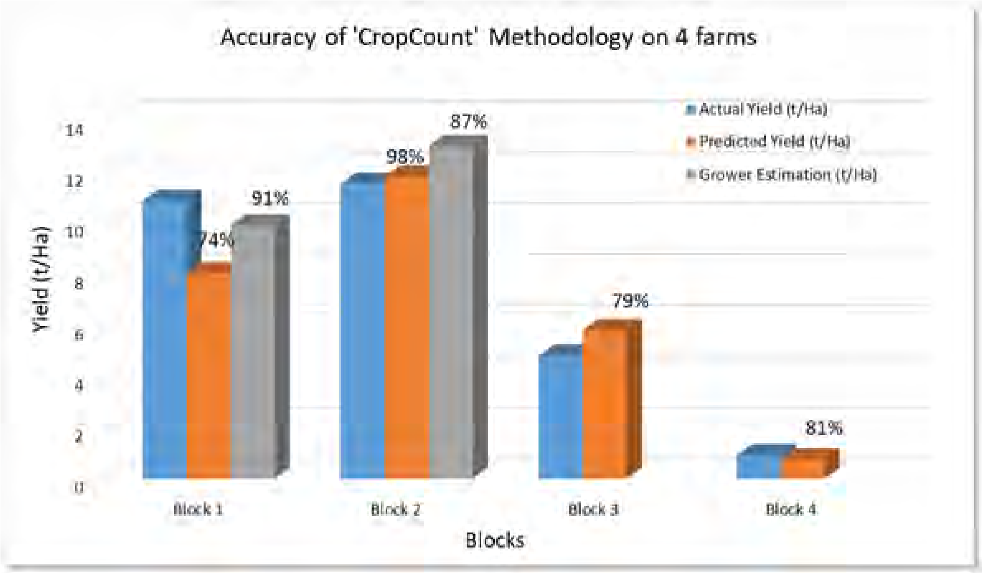

Figure 45: Accuracy of 'CropCount' methodology on 4 orchards in Western Australia in 2022/23 season

In the 2022/23 season, the 'CropCount' methodology was again planned to trial across two farms (six orchard blocks) in South Australia and five farms (seven orchard blocks) in Western Australia. Pleiades NEO-3 imagery (30 cm 6-band panchromatic and 1.2 m 6-band multispectral) was acquired over a 100 km² in South Australia on August 15, 2023, and over 87 km² in Western Australia on September 21, 2023. The classified NDVI map from the Pleiades NEO image was developed as a web app and provided to growers (Figure 34). As mentioned earlier, one grower in Western Australia adapted this targeted sampling methodology by selecting four locations and hand-picking six trees per row (referred to as a panel count) for sampling. For all orchard blocks in SA and WA, a form was provided that allowed the growers to record the row number, tree number and fruit number per tree for 18 sample trees (kg/tree). A separate form was provided to the grower who adopted the 'panel methodology'—asking the information of panel location, row number, number of trees per panel, starting point of tree, direction and production of fruits per panel (kg/panel). This form was based on the data collection process developed in Project AV18002.

Although the 18 calibration tree locations map has been provided for SA region, unfortunately, the yield data (kg/tree) of those blocks were not received from the growers to develop models and predict yield for those orchard blocks. The calibration data for all four farms (seven blocks) in WA were received, and the yield prediction models were developed for 2022/23 season. The comparison between 'CropCount' model predicted yield (t/ha) and the actual harvest yield (t/ha) has been shown in Figure 46 and Figure 47 below. The accuracy achieved in all seven orchards ranged from 79% to 100%, which was again higher than the grower's estimation.

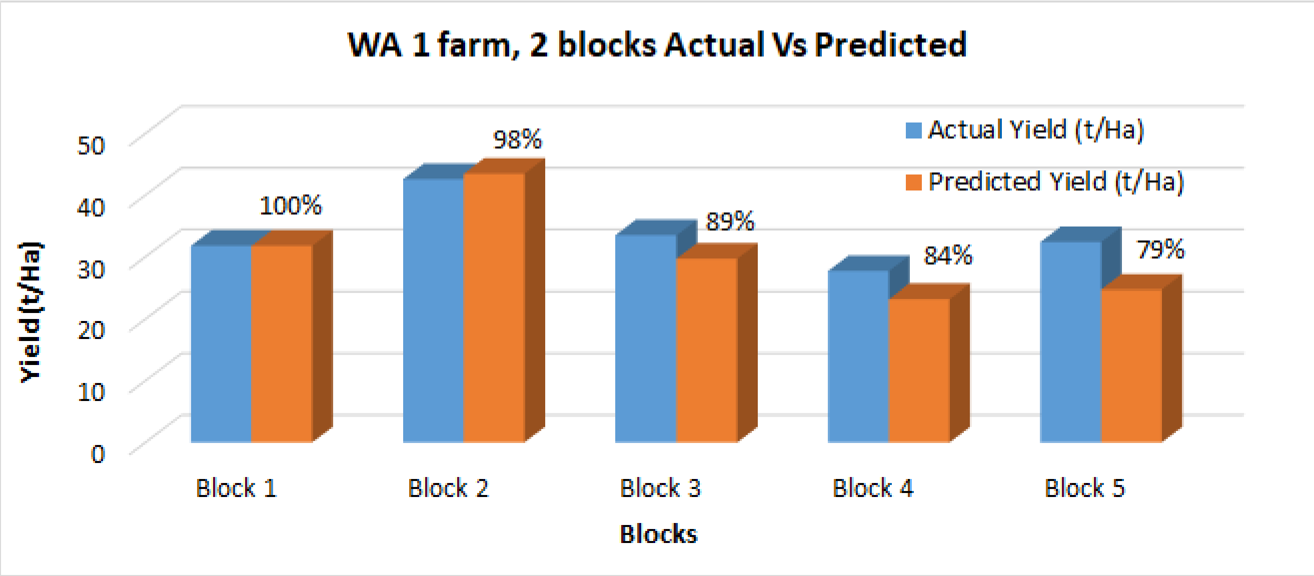

Figure 46: Comparison between actual yield (t/ha) and predicted yield (t/ha) from the 'CropCount' methodology for 5 orchards from 3 farms in Western Australia

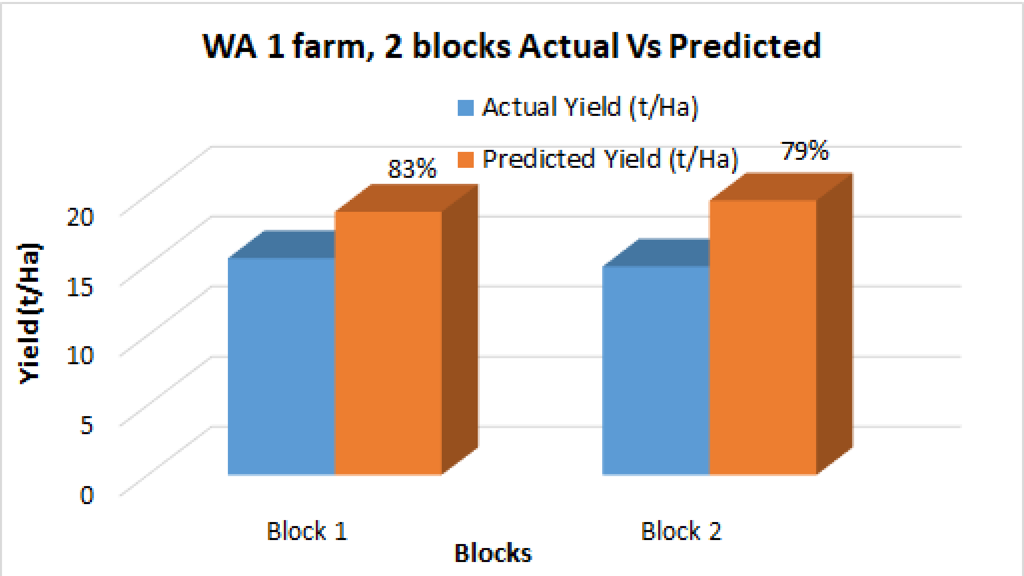

Figure 47: Comparison between actual yield (t/ha) and predicted yield (t/ha) from the 'CropCount' methodology for 2 orchards from 1 farm in Western Australia

The results achieved from 'CropCount' methodology was encouraging, producing accuracies that exceeded current commercial methods. The following discusses the pros and cons of this method:

'CropCount' Methodology:

- Pros:
    - More responsive to extreme events, including incidences of irregular bearing, pest, disease and natural disasters;

    - Can be used when no historic data is available e.g. young orchards or those recently purchased;
    - Incorporates current commercial 'eye ball' estimation method, but greatly reduces the number of trees required;
    - Able to map yield variability at the within orchard level;
    - Can be applied to satellite, airborne or UAV imagery.

- Cons:
    - Requires high-resolution imagery, that does come at cost to growers;
    - Requires in field counting of fruit that can be time and labour intensive;
    - Predictions can only be made once fruit is of a size that can be seen and accurately counted;
    - Provides a measure of yield as fruit number per tree, unless fruit weight is also measured, or a default fruit weight is applied.

Yield forecasting using 'Time Series' Method

The project AV21006 has evaluated the 'time series' approach across 128 individual orchard blocks, including 69 in Western Australia (WA), 35 in Queensland (Qld), and 24 in South Australia (SA).

In the 2021/22 season, 'time series' methodology, initially developed in project AV18002, was evaluated across 35 blocks in Queensland, 24 blocks in South Australia and 23 blocks in Western Australia. Although the accuracy achieved in Queensland (overall 93%), South Australia (overall 86%), and one farm in Western Australia (overall 87%) (Figure 48, Figure 49 and Figure 50) is highly encouraging, there were significant discrepancies observed in two other farms in Western Australia (Figure 51 and Figure 52). The error percentages for these farms were 210% and 134%, respectively. These high errors can be attributed primarily to the alternate bearing nature of the crops—a phenomenon where the yield varies significantly between 'On' and 'Off' seasons. The models used in the study were not adequately trained to differentiate between these seasonal variations, leading to substantial prediction inaccuracies.

To address this issue, future efforts should focus on enhancing the models to recognise and adapt to the alternate bearing patterns. This could involve incorporating additional training data that captures the cyclical nature of yield variations or developing new algorithms specifically designed to handle these fluctuations. By improving the models in this way, it will be possible to achieve more reliable yield predictions across all regions, including those with alternate bearing crops.

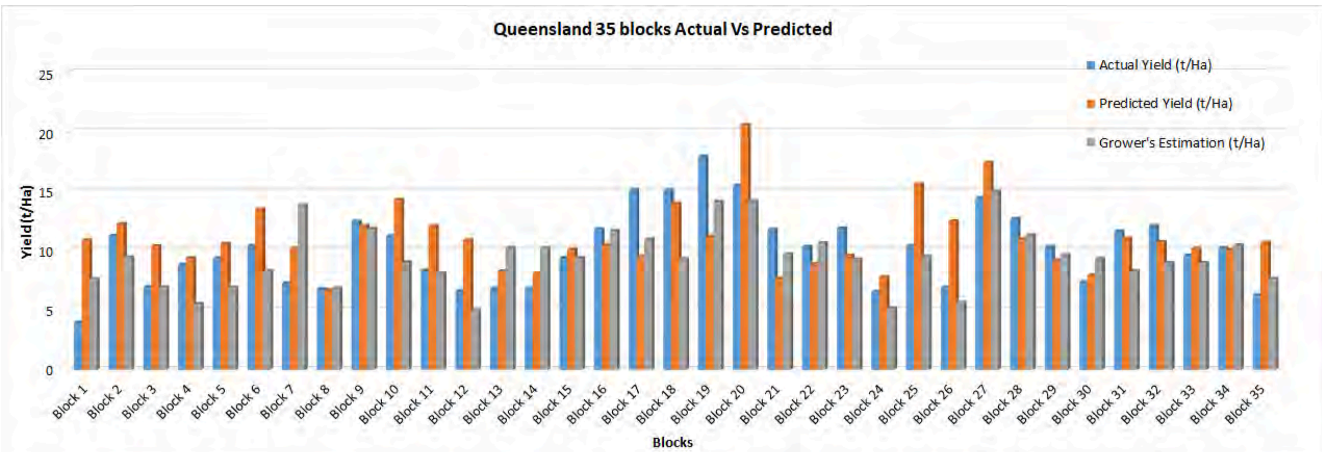

Figure 48: Comparison between actual yield (t/ha) and predicted yield (t/ha) from the 'time series' methodology for 35 orchards in Queensland in 2021/22 season.

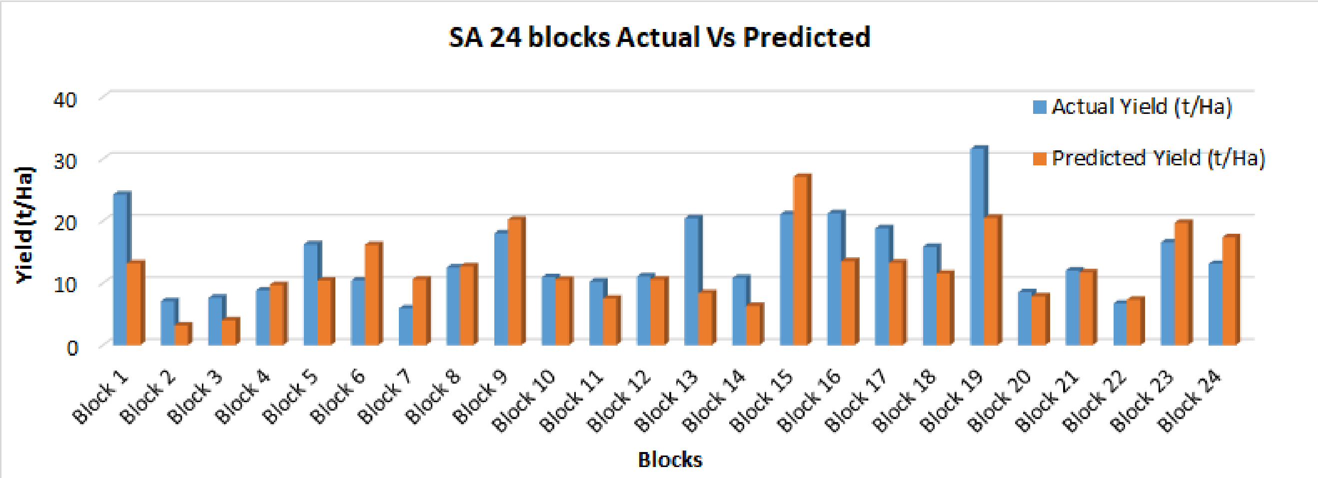

Figure 49: Comparison between actual yield (t/ha) and predicted yield (t/ha) from the 'time series' methodology for 24 orchards in South Australia in 2021/22 season

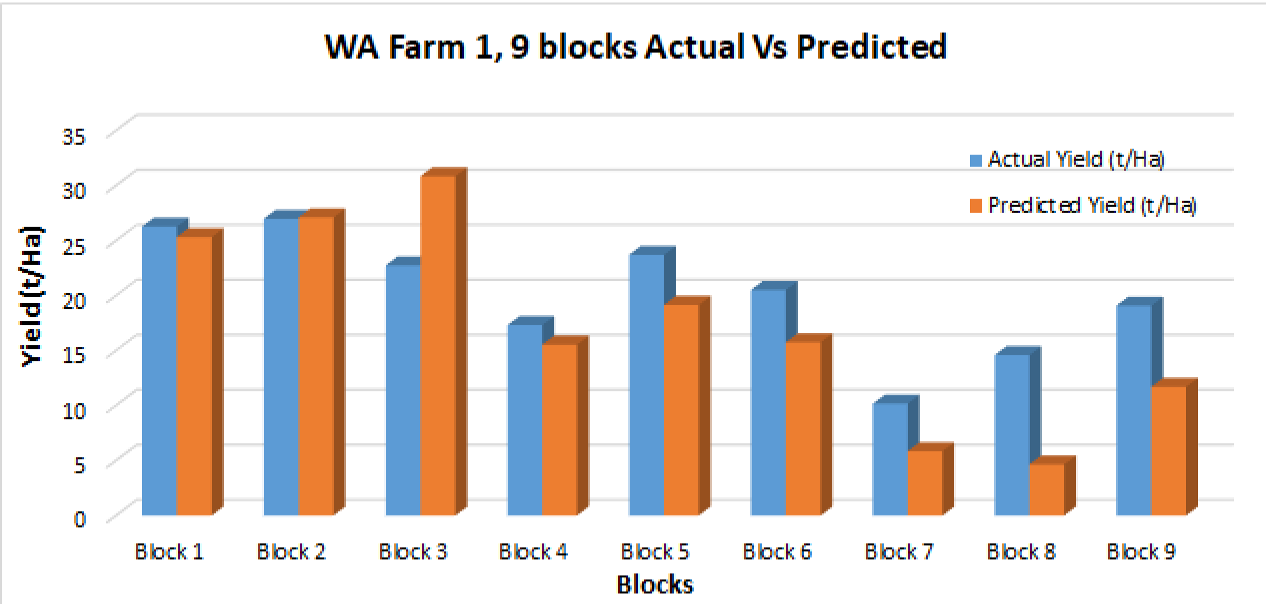

Figure 50: Comparison between actual yield (t/ha) and predicted yield (t/ha) from the 'time series' methodology for 9 orchards in one farm in Western Australia in 2021/22 season

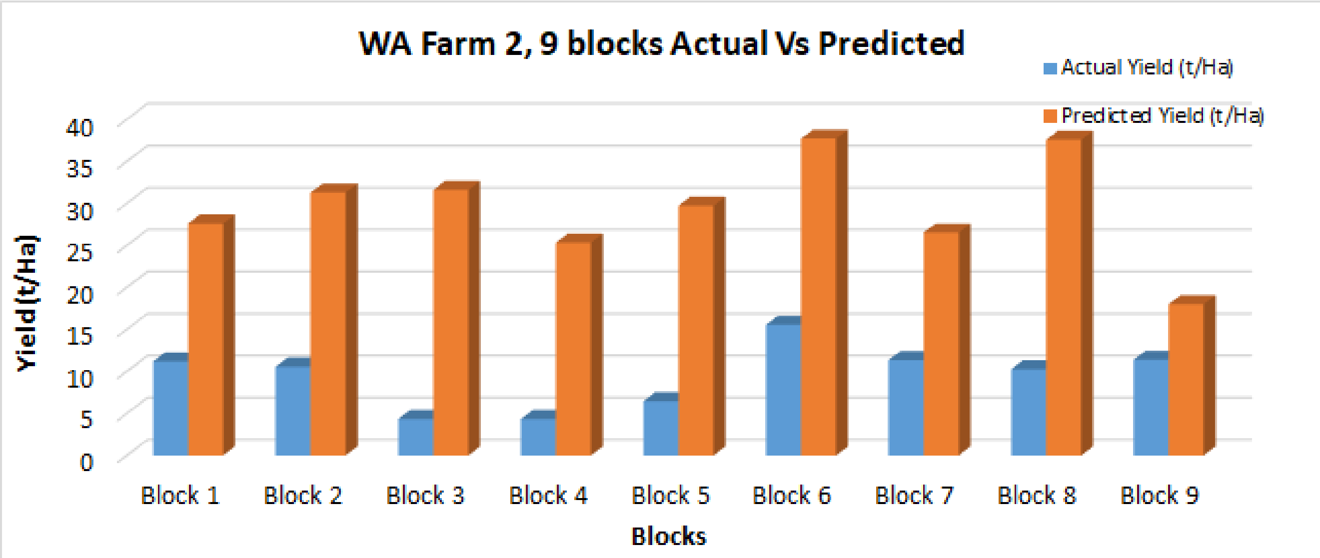

Figure 51: Comparison between actual yield (t/ha) and predicted yield (t/ha) from the 'time series' methodology for 9 orchards in second farm in Western Australia in 2021/22 season

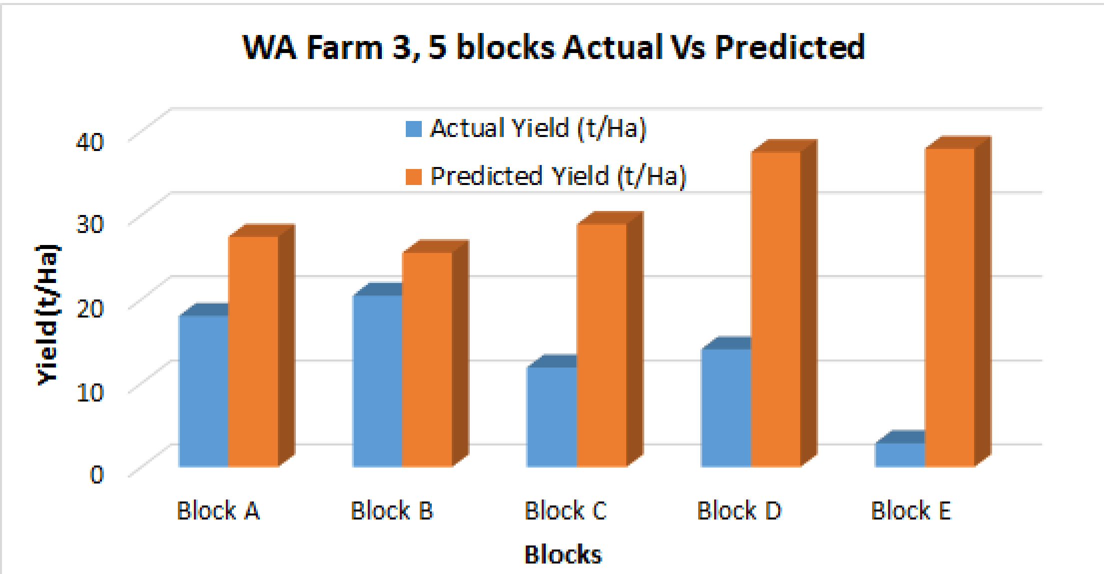

Figure 52: Comparison between actual yield (t/ha) and predicted yield (t/ha) from the 'time series' methodology for 5 orchards in third farm in Western Australia in 2021/22 season

In the 2022/23 season, the 'time series' methodology was enhanced by integrating eight different machine learning approaches with remote sensing data. This improved approach was evaluated across 35 blocks in Queensland, 15 blocks in South Australia, and 69 blocks in Western Australia. Unfortunately, we did not receive the actual yield data from 35 blocks in Queensland and from 32 blocks across four farms in Western Australia. In South Australia, the overall accuracy achieved from the 15 blocks was over 99% (Figure 53). However, the accuracy results from the three other farms in Western Australia were more varied, with accuracies of 63%, 56%, and 86%, respectively (Figure 54, Figure 55 and Figure 56). The lower accuracies observed in some Western Australian farms can be attributed to the alternate bearing issues present in certain blocks.

To address the challenge of alternate bearing, the project team initiated a strategy to run the machine learning models twice—once for 'On' season and once for 'Off' season. This approach aims to provide yield predictions at an early stage of crop growth. By doing so, growers have the opportunity to visit their orchards early in the season and determine whether it is likely to be an 'On' season or an 'Off' season. Based on their observations, they can then select the appropriate yield prediction. This early prediction method allows growers to make informed decisions regarding their crop management and planning, improving overall yield forecasting accuracy and operational efficiency.

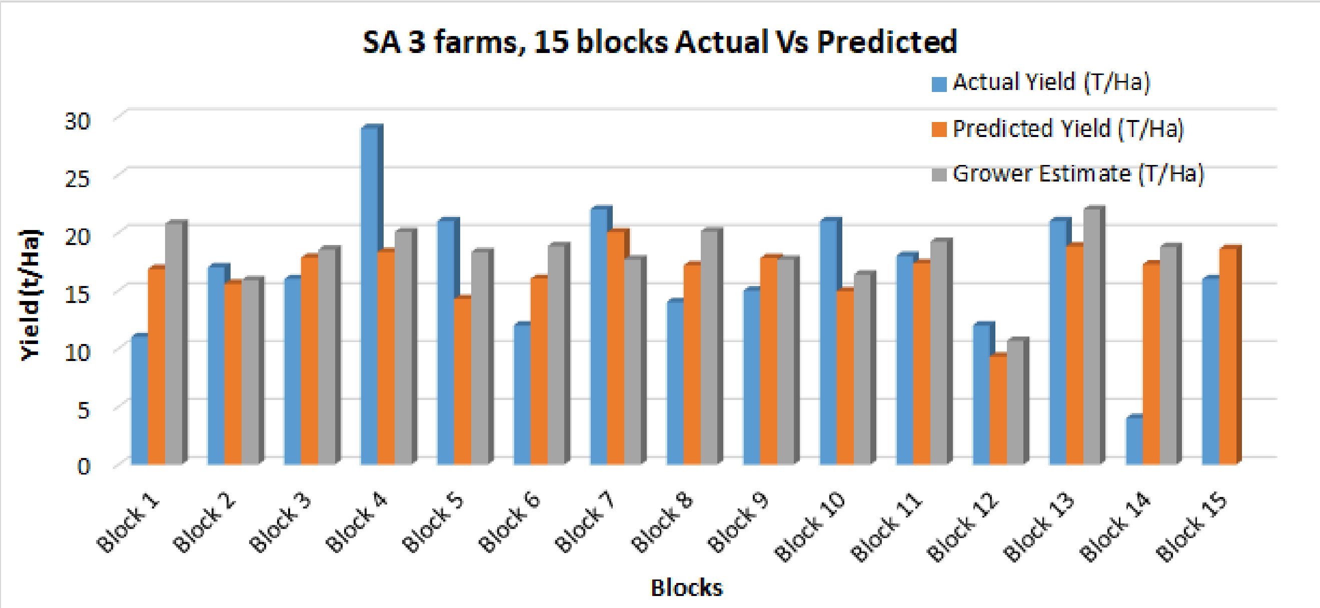

Figure 53: Comparison between actual yield (t/ha) and predicted yield (t/ha) from the 'time series' methodology for 15 orchards in three farms in South Australia in 2022/23 season

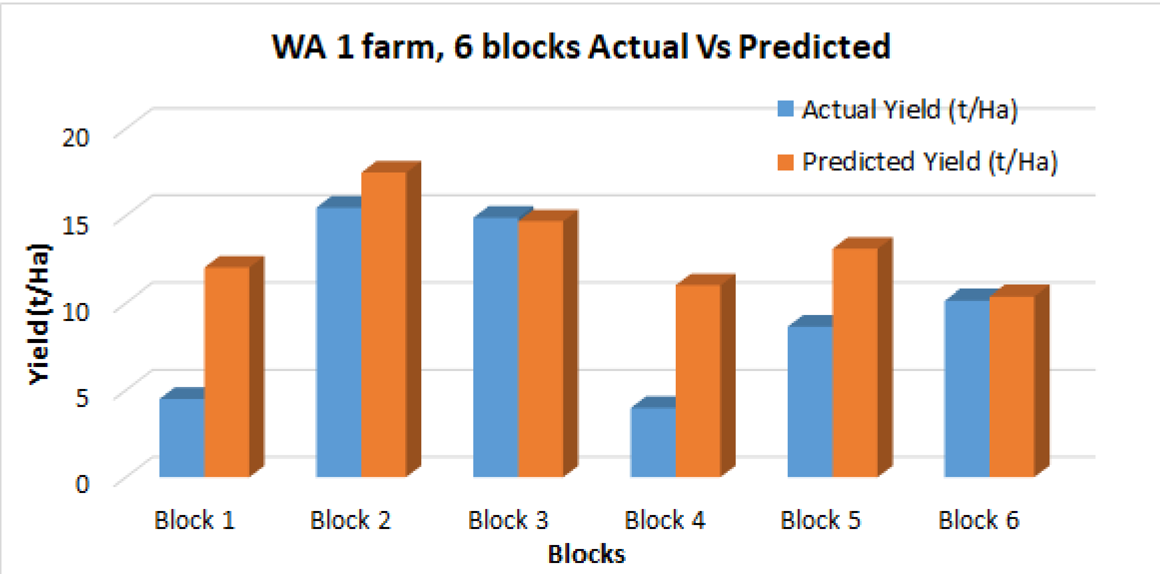

Figure 54: Comparison between actual yield (t/ha) and predicted yield (t/ha) from the 'time series' methodology for 6 orchards from one farm in Western Australia in 2022/23 season

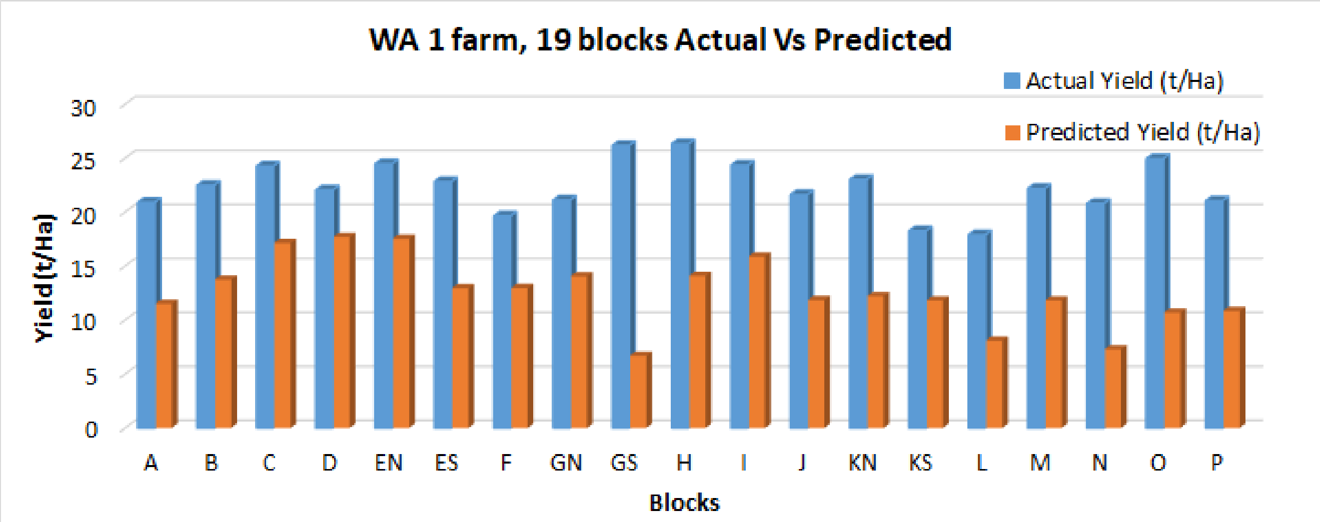

Figure 55: Comparison between actual yield (t/ha) and predicted yield (t/ha) from the 'time series' methodology for 19 orchards from second farm in Western Australia in 2022/23 season

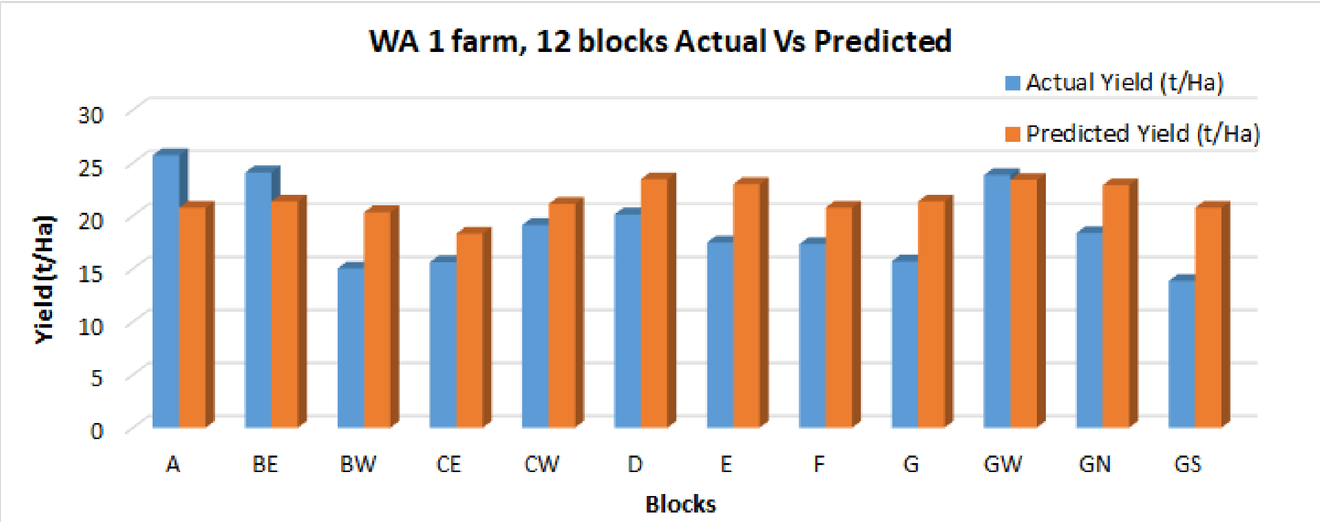

Figure 56: Comparison between actual yield (t/ha) and predicted yield (t/ha) from the 'time series' methodology for 12 orchards from third farm in Western Australia in 2022/23 season

The results obtained from the 'time series' method were highly encouraging, demonstrating accuracies that, in most cases, surpassed those of current commercial practices. The following discusses the pros and cons of 'time series' methodology:

- Pros:
    - Uses freely available imagery;
    - Requires no infield fruit counting;
    - Provides forecasts many months before harvest;
    - Model can be developed and applied in a relatively short time;
    - Provides forecasts at the block, farm and possibly regional level.

- Cons:
    - Requires historic yield data (at least 5 years);

- Less responsive to extreme events, including incidences of irregular bearing, pest, disease and natural disasters. Especially extremes that have not occurred historically;
- Not designed to predict within orchard yield variability.

Considering their respective advantages and disadvantages, both yield forecasting methods are complementary. The 'time series' method allows growers to obtain an early season prediction without the expense of imagery or the need to enter the orchard. This early forecast can help guide harvesting logistics and forward-selling decisions well before the harvest begins. After the final fruit set, growers can use the 'CropCount' method to more accurately quantify yield variability (fruit number per tree) across the orchard, as well as assess fruit size and the incidence of diseases such as phytophthora.

CropCount MVP (Minimal Viable Product)

A notable achievement of this project was the formulation of a commercialisation plan for the avocado yield forecasting methodologies, either through the development of the 'CropCount App' or by securing a commercial partner. This initiative aimed to ensure that the innovative yield prediction tools developed during the project would be accessible and beneficial to the avocado industry at large. The responsibility for delivering these outcomes was assigned to Hort Innovation. However, due to the turnover of five different managers over the two-year duration of the project, these crucial outputs were not finalised within the expected timeframe. This high managerial turnover led to delays and discontinuities in project execution, hindering the completion of the commercialisation strategy. Despite these challenges, the groundwork laid by the project provides a strong foundation for future efforts to bring these advanced yield forecasting methodologies to market. It is essential to address the managerial continuity issues and ensure consistent leadership to successfully commercialise these innovative tools, ultimately benefiting growers by providing them with accurate, reliable, and user-friendly yield prediction solutions.

Outputs

The following Table has been included to detail the outputs achieved by project AV21006

Table 5: Output summary

Output	Description	Detail
Block and farm level yield forecasting models derived from the 'time series' model.	The 'time series' yield forecasting models were developed for QLD, SA and WA regions. Historical yield data were obtained from all participating growers and the corresponding satellite imagery spanning 5 to 10 years were acquired over these regions to develop machine learning time series yield prediction models.	The 'time series' yield forecasting models were developed for five growers, covering 14 individual farms and 128 orchards across QLD SA, and WA regions. Historical yield data was collected from all participating growers in these regions and high temporal resolution Landsat and Sentinel data were acquired to develop the machine learning based time series yield prediction models. However, to maintain confidentiality, the models predicted yield data was shared exclusively with the corresponding growers.
Web app of individual avocado blocks and farms.	Classified crop vigour or NDVI maps generated, presented in a web app and provided to the growers to select 18 calibration trees or best suited panel locations to apply 'CropCount' yield prediction methodology.	Classified crop vigour or NDVI maps generated using ArcGIS Pro and ArcGIS online and created a web app to distribute among the growers. This allowed growers to choose the best location for selecting 18 calibration trees or panel locations for applying 'CropCount' yield prediction methodology.
Delivery of complete, functional 'CropCount App', with associated, marketing and training guides; note long term this may require additional marketing resources to disseminate and educate depending on industry/grower uptake (this need identified post GATE2020 and as part of the Stop/Go).	The delivery of these outcomes was the requested responsibility of Hort. Innovation. Unfortunately, due to having five managers through this 2-year project, these outputs were not completed within the project timeframe.	
National update of 'The Australian Tree Crop Map Dashboard' and associated Avocado specific map to be hosted on the Australia avocado website;	Four updates of the national map were published, presented across a range of web applications, including: 1. ATCM Dashboard 2. National Avocado Map Dashboard 3. Avocado Predicted Planting Year dashboard 4. ATCM: Severe Weather App 5. Varroa-mite Rapid Response	The mapping applications developed are presented across a range of location-based web applications, all available and freely accessible via the AARSC Industry Applications and Maps Gallery (www.une.edu.au/webapps). Additionally, AAL has hosted the avocado survey app on their home page (https://avocado.org.au/) to encourage engagement and

	Map 6. Murray-Darling Basin Rapid Response Map Industry Engagement to contribute on-going updates to the map is supported by the location-based tools: 7. ATCM Survey 8. Avocado Survey 9. Industry Engagement Web App	participation from growers. AARSC is providing support to AAL to include both the National Avocado Map Dashboard and the Avocado Predicted Planting Year dashboard on their website.
Project extension materials to be presented at grower field days, conferences, industry communication channels and magazines, and social media.	Promotion and extension of project outputs and outcomes to industry and stakeholders by AARSC, through numerous print, online and conference media.	Project outcomes communicated through industry eNews, magazine (Talking Avocados), workshops, and conferences, including the World Avocado Congress 2023. This event alone generated significant interest in the project outcomes, including New Zealand, Spain and South Africa.

Outcomes

Table 6: Outcome summary

Outcome	**Alignment to fund outcome, strategy and KPI**	**Description**	**Evidence**
The ‘time series’ model was developed for 128 orchard blocks in QLD, SA and WA regions. The project combined freely available satellite data, historical orchard yield and management data and advanced machine learning approaches to enhance the accuracy of yield prediction models initially built in project AV18002.	Align with the Fund outcome 1, the 'time series' model development allows growers from all regions to participate easily in this project. The provision of historic yield information coupled with historical satellite imagery will allow yield forecasting models specifically developed for each farm in rapid time. Creating participation, industry engagement, technological awareness and ultimately, a comprehensive 'industry-wide' production data set.	The participating growers have gained understanding of the yield forecasting process through their testing of ‘time series’ methodology. The accuracy of the time series models generally exceeded the growers' current estimations. As the model utilizes freely available satellite imagery, it offers significant cost savings for growers. Moreover, it provides an excellent means to understand crop performance within an orchard, thereby supporting better management decisions.	The accuracy of machine learning time series has been well received by the growers with a significant increase in engagement in the project period. Historic production data and associated farm maps have been provided by six major Australian growers in WA, SA, QLD. The project team has received direct requests from many of Australia’s growers to be involved in the yield forecasting component of the project, providing sensitive historic yield data sets and tree management information.
Further validating the ‘CropCount’ methodology over seven orchard blocks in WA. The relationship of canopy reflectance, measured by remote sensing technologies, to yield parameters and tree health, under Queensland growing conditions.	Align with the Fund outcome 2, the analysis of historic imagery alone will provide highly beneficial insights into the influence of location, season, variety and management on the seasonal canopy growth profiles. Additionally, how those profiles relate to production, the timing of key phenological growth stages, irregular bearing, and potentially the incidences of pests and disease.	Produce yield forecasting accuracies that exceed current commercial practice (~80%) The Pleiades NEO satellite imagery derived optimal vegetation indices (VIs) provided a positive relationship to total fruit number and fruit weight (kg/tree) to develop yield prediction models in both 2021/22 and 2022/23 seasons. The technique can be used for the orchards that does not have enough historic yield information to build ‘time series’ models or are too young to have the range of yields needed.	The continued effort to better extend the project objectives to the wider avocado industry has been well received with a significant increase in grower engagement in the project period.

Both 'CropCount' and 'time series' yield prediction models were developed and tested in QLD, SA and WA region.	Align with the Fund outcome 3, growers will have the opportunity to choose which methodology, i.e. 'time series' or 'CropCount', best meets their forecasting requirements, access to historical information, availability of labour and financial resources, hence offering adoption access points for all levels of the industry.	The participating growers gained an understanding of both methodologies and adopted them based on the relevance to crop ages and the associated historical yield and management information.	During the project, 10 large growers from QLD, SA, and WA participated to test and validate both the 'CropCount' and 'time series' methodologies with crops of varying ages, varieties, and historical yield and management information.
Increased access and awareness of the 'Australian Tree Crop Map Dashboard' which has now been viewed 18,579 times at the time of writing.	Spatial data (location and extent) for understanding the current production area and distribution of commercial avocado orchards across Australia. Fundamental 'baseline' information to support industry at multiple-scales (national, state and regions).	The map is delivered across a range of web apps (access via the UNE industry web applications gallery) and also through the Avocados Australia website, which features the Avocado Survey on the homepage. This has increased the awareness and acceptance in the map, and trust in spatial technologies and data collation as a whole. The further development of value-added applications (e.g Varroa mite Rapid Response Map, Predicted Planting Year Dasbaord) which are all built on the national map, will ensure on-going contribution by industry to update and maintain it in the future.	Metrics for views to each web app are recorded, based on opening (access). The Australian Tree Crop Dashboard has been viewed 18,579 times.

Monitoring and evaluation

Table 7: Key Evaluation Questions

Key Evaluation Question	Project performance	Continuous improvement opportunities
1. To what extent has the project achieved its expected outcomes?	National map updated (new plantings added) and timeliness (currency) of existing features updated. The project achieved significant advancements in yield forecasting, offering valuable tools for growers to improve crop management, resource allocation, and operational planning, ultimately leading to enhanced productivity and profitability in the avocado industry.	AS23000 will continue to maintain and update the ATCM, with additional data developed for industry (at block-level). Both 'CropCount' and 'time series' yield prediction models should be developed for all blocks, farms, regional, and national scales. User-friendly tools or apps with real-time analysis capabilities could be created to facilitate more informed decision-making.
2. How relevant was the project to the needs of intended beneficiaries?	Industry metrics supported at mutliple-scales (national, regional and local) for production area and age of orchards (predicted planting year). Both the complementary models, 'CropCount' and 'time series', were highly relevant to the needs of the intended beneficiaries, including avocado growers, industry stakeholders, and agricultural planners. By providing more accurate and timely yield forecasts, the models addressed critical issues such as efficient resource allocation, improved crop management, and enhanced market access strategies. The ability to predict yields with greater precision allowed growers to optimize inputs, reduce costs, and plan better for harvest and post-harvest activities.	Baseline information for production area and tree age, delivered at multiple-scales to inform decision-making. The planting year model would benefit from additional training data especially for older orchards (< 2000). More growers need to be engaged to improve the data access and thus improve the machine learning time series yield prediction model accuracy.
3. How well have intended beneficiaries been engaged in the project?	Location-based tools developed by AARSC have proven success in informing updates to the map, e.g. Avocado Survey (as hosted on the AAL webpage), encouraging growers to check their orchard is in the map and complete a survey if required. During project AV21006, 10 prominent growers from QLD, SA and WA participated in testing and	These tools will be maintained under AS23000, as support mechanism for on-going updates to the ATCM. Greater involvement of industry representatives/experts by directly contributing to the map using bespoke tools. Increased engagement of growers is essential to enhance data access and consequently improve the accuracy

	validating the 'CropCount' and 'time series' methodologies. These methodologies were applied to crops of different ages and varieties, incorporating historical yield and management data. The participation of these growers was crucial for refining the methodologies and demonstrating their practical value in real-world agricultural settings.	of the machine learning time series yield prediction model. By involving more growers, a broader and more diverse dataset can be obtained, providing a richer source of information for model training and validation. This expanded participation ensures that the model captures a wider range of factors influencing avocado yield, such as varying management practices, environmental conditions, and regional differences.
4. To what extent were engagement processes appropriate to the target audience/s of the project?	Yes, via project reference group meetings, industry newsletters, publications, and various forms of media (see appendix).	

Recommendations

National Mapping

The national mapping of tree crops has established a new standard for the adoption of spatial data for horticulture industries in Australia. The success is a result of direct collaboration between industry (in contributing to the map) and research. Regular maintenance of the map is required to maintain accuracy and currency (to map new plantings) and the most sustainable way to continue to update and maintain this valuable resource for all users. As such AARSC continues to look for opportunities to ensure the on-going update of the map (ideally annually).

Under a new project 'Spatially enabling tree crop production practice' (funded by the Future Food Systems CRC, Hort Innovation, UNE, Avocados Australia Ltd, Australian Banana Growers Council, Australian Macadamia Society and Citrus Australia) the Australian Tree Crop Map will be taken to the next level as a high value industry-only data collation, analysis and presentation tool.

Each industry body will work with their respective grower base using an AARSC developed 'Block-Builder' application (app) to assign information to orchards at block level (e.g. variety, planting date, management, etc.). AARSC will provide in-house training to each industry body to facilitate this data collection. Industry-only maps can capture more detailed spatial and temporal data that will further support improved decision-making around processes such as forward selling, traceability and biosecurity. Importantly, the Block-Builder app and all data within is managed and secured by AARSC under strict sign-in access for AAL only. The app will also be supported through a mobile data collection tool which runs on a tablet device (iPad).

This map supports AAL to make more powerful and informed decisions for their industry, beyond the limits of the ATCM which only includes the location and extent of avocado orchards. Within this project on-going updates for the publicly accessible ATCM will also be maintained. Mapping updates will be managed by growing region, with updates published into the ATCM biennially (scheduled for May and November) till project end in 2026.

AARSC continue to pursue on-going discussions with the Federal government and others to kick-start the 'unified approach to crop mapping'. This opportunity has been presented at multiple forums in the last year and direct meetings between the Federal Department of Agriculture, Horticulture innovation, Department of Agriculture and Fisheries Qld, Australian Bureau of Statistics, ABARES and numerous industry bodies.

Yield forecasting

The project AV21006 has done extensive research on developing 'CropCount' and machine learning based 'time series' avocado yield prediction methodologies, therefore it is recommended that the avocado industry, including growers, stakeholders, and other relevant parties, adopt both methodologies to significantly enhance avocado crop production systems. The 'CropCount' method, which combines satellite imagery with ground-based calibration, has proven to deliver highly accurate yield predictions on both block and farm-level, without the need for any historical yield or management information. This approach not only provides detailed yield maps highlighting variations within orchards, but also offers significant cost savings by reducing the need for extensive field sampling. Such precise yield mapping is invaluable for making informed decisions about variable rate applications of inputs like water, fertilisers, and pesticides, thereby optimising resource use and enhancing overall crop management.

Additionally, the 'time series' model leverages historical crop reflectance data from satellite imagery to predict yields with greater accuracy. This method is particularly beneficial for understanding the impacts of seasonal, environmental, climatic, and management variations on crop performance. By providing insights into the timing of critical phenological growth stages, the 'time series' model helps growers optimise the timing of essential management activities. Moreover, the model's ability to detect deviations from historical growth patterns enables early identification of severe pest or disease outbreaks, facilitating prompt and effective responses.

A significant challenge encountered in the 'time series' yield prediction methodology is the alternate bearing pattern in avocado crops, which results in fluctuating yields between 'On' and 'Off' seasons. To address this, the project team developed a remote sensing-based approach using machine learning classification algorithms to distinguish between these seasons. This innovation can significantly improve yield prediction accuracy and support better-informed crop management decisions. Due to data limitations, the project team adopted a practical solution by running the model twice—once for 'On' and once for 'Off' seasons—allowing growers to choose the most accurate prediction based on their initial on-farm visual estimates. This dual-model approach enhances the model's adaptability and practical utility in real-world applications.

The application of freely available satellite imagery sources like Landsat and Sentinel ensures that these methods are cost-effective and accessible, providing significant savings for growers. By embracing these innovative technologies, the avocado industry can achieve substantial improvements in productivity, operational efficiency, and sustainability. The adoption of 'CropCount' and the 'time series' model represents a forward-thinking approach that leverages cutting-edge remote sensing and machine learning techniques to drive the future of avocado production and management.

To maintain the currency of these outputs, further investment was needed to maintain data, improve accuracy and extend these resources to industry.

Refereed scientific publications

Journal article

Rahman, M.M.; Robson, A.; Brinkhoff, J. 2022. Potential of Time-Series Sentinel 2 Data for Monitoring Avocado Crop Phenology. *Remote Sensing*, 14, 5942. https://doi.org/10.3390/rs14235942

Chapter in a book or paper in conference proceedings

Rahman M., Robson, A. (2023). Better predicting the irregular bearing of avocado crops using sentinel 2 derived time series enhanced vegetation index. 10th World Avocado Congress, New Zealand. Presentations - New Zealand Avocado (nzavocado.co.nz).
https://az659834.vo.msecnd.net/eventsairseasiaprod/production-tcc-public/2af3b5ce693b4bc687ba50a69d43cb88

Shephard, C., Mckechnie, J., Robson, A. (2023). Industry meets innovation: Building the national avocado tree crop map in Australia and ensuring its ongoing maintenance through engagement with industry. 10th World Avocado Congress, New Zealand,
https://az659834.vo.msecnd.net/eventsairseasiaprod/production-tcc-public/f227ebadfd6b4545900495d76ee6de4c

References

Avocado Australia. (2023a). Facts at a Glance for the Australian avocado industry - 2022/23. Retrieved 10/05/2024 https://avocado.org.au/wp-content/uploads/2023/10/2022-23_AAL-Facts-at-a-glance.pdf

Avocado Australia. (2023b). Avocado Strategic Investment Plan 2022-2026. Retrieved 10/05/2024 (https://www.horticulture.com.au/globalassets/hort-innovation/levy-fund-financial-and-management-documents/sip-2022-2026-pdfs/hort-innovation-sip-2022-26-avocado.pdf)

Brinkhoff, J., & Robson, A. J. (2021). Block-level macadamia yield forecasting using spatio-temporal datasets. *Agricultural and Forest Meteorology*, *303*, 108369. https://doi.org/10.1016/j.agrformet.2021.108369

Hort Innovation. (2023). Australian Horticulture Statistis Handbook. Retrieved 10/05/2024 (Hort Innovation | Australian Horticulture Statistics Handbook 2022/23).

de Castro Megías, A. I., Pérez-Roncal, C., Thomasson, J. A., Ehsani, R., López-Maestresalas, A., Yang, C., Jaren, C., Wang, T., Cribben, C., Marin, D., Isakeit, T., Urrestarazu, J., Lopez-Molina, C., Wang, X., Nichols, R., Santesteban, G., Arazuri, S., and Pena, J. (2021). Applications of Sensing for Disease Detection. In: Kerry, R., Escolà, A. (eds) Sensing Approaches for Precision Agriculture. Progress in Precision Agriculture. Springer, Cham. https://doi.org/10.1007/978-3-030-78431-7_13

Gitelson, A.A., Kaufman, Y.J., Merzlyak, M.N. (1996). Use of a green channel in remote sensing of global vegetation from EOS-MODIS. Remote Sensing of Environment, 58(3), 289-298. https://doi.org/10.1016/S0034-4257(96)00072-7

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote sensing of Environment*, *202*, 18-27. https://doi.org/10.1016/j.rse.2017.06.031

Salgadoe, A.S.A.; Robson, A.J.; Lamb, D.W.; Dann, E.K.; Searle, C. (2018). Quantifying the Severity of Phytophthora Root Rot Disease in Avocado Trees Using Image Analysis. Remote Sensing, *10*, 226. https://doi.org/10.3390/rs10020226.

Poblete-Echeverría, C., Duncan, S.J. and McLeod, A. (2023). Detection of the spectral signature of Phytophthora root rot (PRR) symptoms using hyperspectral imaging. Acta Horticulturae. 1360, 77-84. https://doi.org/10.17660/ActaHortic.2023.1360.10

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot M., & Duchesnay, É. (2011). Scikit-learn: Machine learning in Python. *the Journal of machine Learning research*, *12*, 2825-2830.

Rahman, M.; Robson, A.; Salgadoe, S.; Walsh, K.; Bristow, M. (2019). Exploring the Potential of High-Resolution Satellite

Imagery for Yield Prediction of Avocado and Mango Crops. In Proceedings of the 29th International Horticultural Congress, Brisbane Convention and Exhibition Centre, Brisbane, Australia, *36*, 154. https://doi.org/10.3390/proceedings2019036154

Rahman, M.M.; Robson, A.; Brinkhoff, J. Potential of Time-Series Sentinel 2 Data for Monitoring Avocado Crop Phenology. *Remote Sens.* **2022**, *14*, 5942. https://doi.org/10.3390/rs14235942

R Development Core Team (2023). R: A Language and Environment for Statistical Computing (Version 3.34.4); R Foundation for Statistical Computing: Vienna, Austria. https://www.R-project.org

Robson, A.J.; Petty, J.; Joyce, D.C.; Marques, J.R.; Hofman, P.J. (2014). High resolution remote sensing, GIS and Google Earth for avocado fruit quality mapping and tree number auditing. In Proceedings of the 29th International Horticultural Congress, Brisbane Convention and Exhibition Centre, Brisbane, Australia, 17–22 August 2014; pp. 589–595.

Robson, A., Rahman, M. 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.

Robson, A., Rahman, M. M., Muir, J., Saint, A., Simpson, C., & Searle, C. (2017b). Evaluating satellite remote sensing as a method for measuring yield variability in Avocado and Macadamia tree crops. *Advances in Animal Biosciences, 8*(2), 498-504. http://doi.org/10.1017/S2040470017000954

Rouse, J.W., Haas, R.H., Schell, J.A., Deering, D.W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. In: Proceedings of the Third Earth Resources Technology Satellite-1 Symposium, vol. 1, NASA SP-351, Washington, DC, pp. 309–317.

Rueda, C., Greenberg, J., & Ustin, S. (2005). StarSpan: A tool for fast selective pixel extraction from remotely sensed data. *Center for Spatial Technologies and Remote Sensing (CSTARS), University of California at Davis, Davis, CA*.

QGIS Development Team (2023). QGIS Geographic Information System. Open-Source Geospatial Foundation Project. http://qgis.org

Suarez, L. A., Robson, A., & Brinkhoff, J. (2023). Early-Season forecasting of citrus block-yield using time series remote sensing and machine learning: A case study in Australian orchards. *International Journal of Applied Earth Observation and Geoinformation*, *122*, 103434. https://doi.org/10.1016/j.jag.2023.103434

Intellectual property

Part 1 -Pre-Existing/Background IP (BGIP) and Third Party IP (TPIP) to be used in the Project

Previous projects of the Parties:

BACKGROUND INTELLECTUAL PROPERTY (BGIP) AND THIRD PARTY INTELLECTUAL PROPERTY (TPIP) REGISTER								
No	Date (ie date on which details were initially listed and/or modified)	Owner(s) of BGIP or TPIP (If TPIP - list the name of the organisation which provided it)	IP Category (eg plant variety, gene, formulation, software, thesis, report, data etc)	Specific Description of IP	Nature of IP (eg copyright, patent, trade mark, design, PBR) Form in which the IP subsists (eg device, process, formulation, document)	Registration/ application details (if registered) (eg registration number, date of registration and expiry)	Intended purpose and value of the IP that is provided	Used or may be used for Commercialisation of Project IP (yes/no) and, if **yes**, how it is used
1	BASED ON PROJECT START DATE AND SCHEDULE	TPIP - MAXAR	SOFTWARE AND DATA	CLOUD PLATFORM USED FOR RUNNING ANALYTICS ON SATELLITE DATA	COPYRIGHT			YES – LICENCES ARE AVAILABLE. THIS MAY BE USED FOR RUNNING SCRIPTS ON WV3 SATELLITE IMAGERY TO PRODUCE RESULTS AT A CHEAPER COST COMPARED WITH THE PURCHASE OF IMAGERY AND THEN RUNNING SCRIPTS ON THE PURCHASED IMAGERY.
Details of restrictions on use (eg licence conditions, security conditions, encumbrances, confidentiality requirements, including any restrictions on publication of the BGIP/TPIP as part of publication of Project results and use of BGIP/TPIP which is part of Project IP): The IP can be used for commercial purposes with an appropriate licence issued by Digital Globe.								
2	BASED ON PROJECT START DATE AND SCHEDULE	TPIP – PLANET LAB	SATELLITE DATA API SOFTWARE AND DATA	API FOR ACCESSING SATELLITE DATA CAPTURED BY PLANET LAB	COPYRIGHT			YES – LICENCES ARE AVAILABLE. USED TO SEARCH AND DOWNLOAD APPROPRIATE SATELLITE DATA FOR ANALYSIS.
Details of restrictions on use: Use is determined by the type of account subscribed to.								
3	BASED ON PROJECT START DATE AND SCHEDULE	TPIP – EUROPEAN SPACE AGENCY	SATELLITE DATA API SOFTWARE AND DATA	API FOR ACCESSING SATELLITE DATA CAPTURED BY THE ESA	COPYRIGHT			YES – LICENCES ARE AVAILABLE. USED TO SEARCH AND DOWNLOAD APPROPRIATE SATELLITE DATA FOR ANALYSIS.
Details of restrictions on use:								
4	BASED ON	BPIP – UNE, AUSTRALIAN	FORMULATIONS,	NATIONAL , REGIONAL	COPYRIGHT			YES – LICENCES ARE

	PROJECT START DATE AND SCHEDULE	FEDERAL GOVERNMENT AND HORT INNOVATION AUSTRALIA	PUBLICATIONS	AND SUB REGIONAL ALGORITHM DEVELOPMENT OF YIELD FORECASTING MODELS FROM REMOTE SENSING AND SITE SPECIFIC WEATHER DATA. : METHODOLOGY FOR THE 'ON- THE-FLY' CALCULATIONS OF YIELD AT THE INDIVIDUAL CROP LEVEL AS WELL AS THE DERIVATION OF YIELD AND FRUIT SIZE MAPS.				AVAILABLE
Details of restrictions on use:								

Acknowledgements

The project team acknowledge the extensive industry support and engagement in this project from Avocados Australia Ltd and many associated growers and the greater AARSC project team for the hard work and support of each other to see the delivery of this project. More specifically Dr Andy Clark and Associate Professor James Brinkhoff (planting year prediction), Dr Moshiur Rahman and Benjamin Torgbor (yield forecasting), Craig Shephard, R. Blake Morrison and Abbie Rankin (mapping), Casey Naughton and Sophia Clark (business management, extension material, contracting, report writing). Finally, the project team acknowledge Hort Innovation for funding the project.

Appendices

Project Media Captured

Press Type	Publication	Article	Publication Link
SOCIAL MEDIA	LINKEDIN	Field validation of Avocados in WA	https://www.linkedin.com/company/28872527/admin/feed/posts/
INDUSTRY MAGAZINE	Talking Avocados	Avocado R&D Investment Overview	Winter 2023, Volume 34, No.2 (page 66)
INDUSTRY MAGAZINE	Talking Avocadoes	Mapping trees - Why do we do it	Winter 2022 edition page 19
SOCIAL MEDIA	LinkedIn	Validation of fieldwork underway in WA	https://www.linkedin.com/feed/update/urn:li:activity:6917707874915823616
INDUSTRY MAGAZINE	Talking Avocadoes	Orchard Census Update	Summer 2022 edition page 17
SOCIAL MEDIA	TWITTER	Avocado project fieldwork June 2023	https://twitter.com/jamesbrinkhoff
SOCIAL MEDIA	TWITTER	Avocado project fieldwork June 2022	https://twitter.com/jamesbrinkhoff
SOCIAL MEDIA	TWITTER	Avocado project fieldwork June 2021	https://twitter.com/jamesbrinkhoff
SOCIAL MEDIA	LINKEDIN	World-first yield forecasting technology offers avocado growers 93% accuracy	https://www.linkedin.com/feed/update/urn:li:activity:6806448196102041600
ONLINE ARTICLE	TREDE FARM MACHINERY.COM.A		https://www.tradefarmmachinery.com.au/product-news/2105/yield-accuracy-boost-in-avocado-app
e-news	UNE STAFF NEWS 'PULSE'	Revolutionising avocado yield estimates	
SOCIAL MEDIA	LINKEDIN	World-first yield forecasting technology offers avocado growers 93% accuracy	https://www.linkedin.com/posts/andrew-robson-9666a658_world-first-yield-forecasting-technology-activity-6804681407122812928-lPxs
ONLINE ARTICLE	GrowAG	World-first yield forecasting technology offers avocado growers 93% accuracy	https://www.growag.com/highlights/article/world-first-yield-forecasting-technology-offers-avocado-growers-93-accuracy?mkt_tok=NjQzLU5PRy0zMDAAAAF9TtErVYsu_6xNvHedIsKa8ZI2sZ9SAMT34MRGGKSLYMmCXAIIqKfleOF6GCinvKr4DIyq03Iv8SOdENxt9SY8HnZOjufGb9wNcuAq