Kiwifruit leaf water content detection using Synthetic Aperture Radar (SAR) satellite technology

Report for Toitū te Whenua, Toiora te Wai - Our Land and Water National Science Challenge Rural Professionals Fund 2021-2022

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Funding: This work was funded by the New Zealand Ministry for Business, Innovation and Employment's Our Land and Water (Toitū te Whenua, Toiora te Wai) National Science Challenge, contract 21/22RPF031, as part of the 'Rural Professionals' programme.

Cover photo: Matapihi orchards, Tauranga, Istvan Hajdu 2022

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Executive summary

Managing water resources sustainably is crucial to New Zealand's horticultural sector. It is apparent that these resources must be managed by optimising the use of rainfall and applied water to avoid water stress in crops. Orchardists are being required to monitor their use of water and many now use soil moisture measurement (through probes in the ground) as a means of better informing their irrigation management. While this is a major step forward and accurate information can be provided for the point measured, it is also recognised that orchard soils are often highly variable and further methods need to be implemented to create a cost-effective measurement network.

The emergence of new spaceborne remote sensing instruments offer possibilities for optimised irrigation scheduling. Synthetic Aperture Radar (SAR) satellites, which is a form of microwave sensing, orbit over New Zealand on a very regular basis providing several advantages over conventional optical means. SAR is not affected by cloud cover, and it captures images day or night. Therefore, the '*Kiwifruit leaf water content detection using Synthetic Aperture Radar (SAR) satellite technology*' research project investigated the capability of SAR to acquire a series of spatial foliar water level maps of kiwifruit during the growing season The graphical summary of the project is presented in Figure 1.

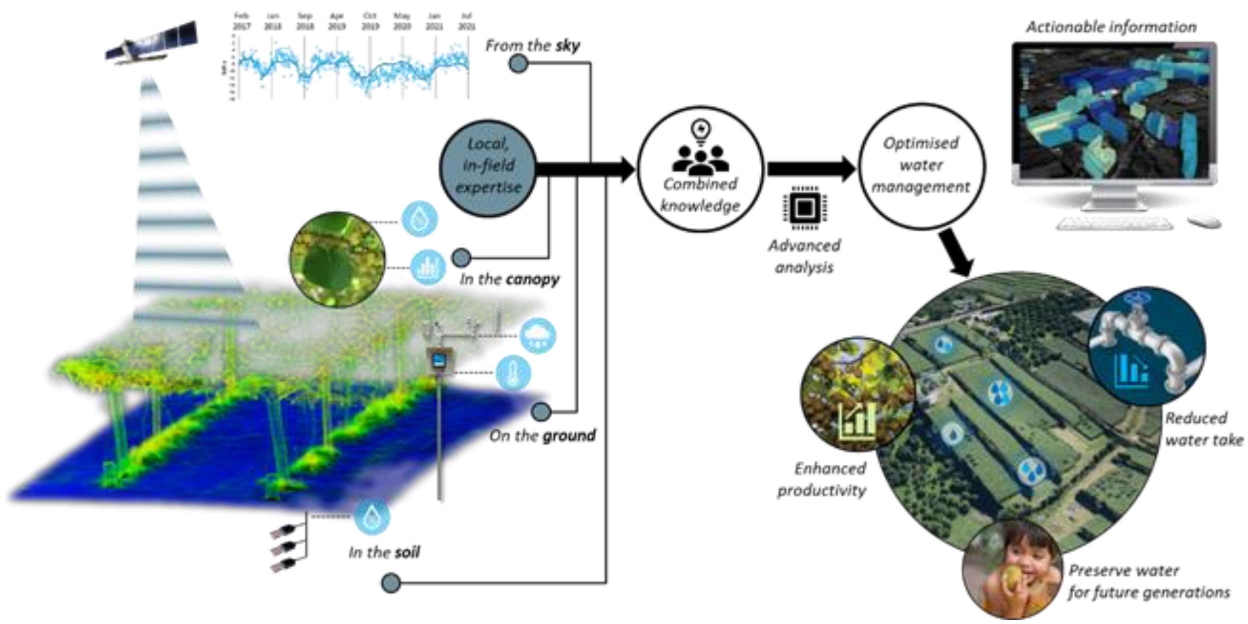


Figure 1 Graphical project abstract

The trial site was set up on the Māori owned Ngai Tukairangi Trust's orchards situated at Matapihi, Tauranga. Two Hayward (HW) and four Gold (GA) actively managed kiwifruit blocks were monitored with a wireless sensor network to collect soil moisture readings at 300- and 600-mm soil depths. To assess soil moisture response to rainfall, daily climatic data was acquired from a weather station at Tauranga Airport, situated 3.2 km from the orchard.

To create ground truth data from the canopy, eight sampling campaigns were completed to collect kiwifruit leaves at 3 sampling points within in each of the selected six blocks. The samples were processed and dried to obtain leaf water content (LWC expressed as %) in Eurofins analytical laboratory.

This study relied on SAR instruments on board the Sentinel-1 satellite between 1st November 2021 and 20 April 2022 with the addition of ICEYE satellite from 22 February 2022. The selected period overlapped with a significant portion of the seasonal foliar development cycle leading up to harvest. The Sentinel-1 SAR datasets and image collections were acquired through Google Earth Engine, a planetary-scale cloud-computing platform. The ICEYE images were received directly from the satellite operator and the pre-processing was completed using an open-source software package. Three methods were tested for data extraction from SAR images regarding the spatial aggregation of pixel values, i.e., point-scale, zonal-scale, and block-scale.

Rainfall, soil moisture, foliar water content and SAR datasets were stacked as vertical layers and loaded into a geographical information system (GIS) to store, manage and analyse the data stack. The focus of this project was to develop a better understanding of the relations between the various data layers, to reveal the underlying spatial and temporal patterns, and to visualise the generated information in a meaningful way. Therefore, to address these objectives, the presented work was organised into five focus areas.

1) Exploratory data analysis of the laboratory results to unfold the patterns in the laboratory results of LWC as a function of cultivars and time.
2) A comparison of the fluctuation of LWC and soil moisture over time.
3) The analysis of the sensitivity of SAR to LWC changes at various spatial scales for two satellites.
4) Model development to generate a series of LWC maps from SAR and hydrological variables.
5) A dashboard-driven visualisation of the generated time series information.

Key findings and conclusions

It was observed that HW kiwifruit leaves stored lower amount of water compared to GA based on the lab results. These findings were consistent across the monitored blocks. In general, the results revealed a decreasing LWC trend as the season progressed for both cultivars.

For each block, a moderate positive linear relationship was observed between soil moisture and LWC. LWC followed the soil moisture fluctuations over time, however, soil moisture levels were not homogenous across the orchard. This was unexpected as previous field observations and information from existing soil databases indicated that the soil cover and soil properties were mostly homogenous across the Matapihi orchards.

Pair plots, statistical distributions and density curves were generated to capture the relationship between the SAR data and LWC measurements as a function of variety. The fundamental SAR backscatter response to the water contained by the target was confirmed by this study. HW variety with lower LWC resulted in lower backscatter intensity while higher SAR values were observed for the GA variety with generally higher LWC. In general, increasing LWC resulted in increased SAR backscatter intensity, indicating a positive linear correlation. These findings suggest that SAR was sensitive to the dielectric properties of the foliage governed by LWC changes and variety was a principal factor.

However, SAR is also affected by other physical characteristics of the canopy, such as geometry, density, structural elements, surface roughness and biomass. The assessment of the effects of these features on SAR intensity was out of the scope for this study.

Several statistical models were developed and tested to predict LWC from SAR. A simple multivariate linear regression approach was chosen to create the final model and generate the spatial layers of LWC for each Sentinel-1 satellite pass over at Matapihi.

The best model performance and lowest uncertainty occurred at the block-scale using Sentinel-1 data with the addition of hydrological variables, i.e., rainfall, soil water deficit and soil moisture. This process resulted in an R^2 of 0.77 and 0.85 and root mean squared error (RMSE) of 0.99 and 1.04 % when evaluated using the Leave-One-Out and repeated K-fold cross-validation methods, respectively. Although the ingestion of hydrological attributes led to marginal improvements in correlation, the error values were reduced by a considerable 0.1 % LWC at the block level.

The accuracy of Sentinel-1 based LWC predictions at the zonal and point-scale delivered R^2 of 0.67 and 0.74 and RMSE of 1.48 and 1.49 % for the K-fold and Leave-One-Out cross-validation, respectively. These results indicate that sub-block level LWC mapping would introduce higher error rates and more uncertainty compared to the block-scale approach. This is likely to be caused by the noise contained in the 10x10 m pixel size SAR data. Hence, the appropriate spatial averaging of SAR pixels is key for reliable LWC mapping. From an irrigation management point of view, block-scale information would be suitable for most growers as most irrigator systems are not equipped with variable rate capability within a given block.

The LWC prediction from ICEYE delivered lower error levels but lower correlation as opposed to Sentinel-1 predictions at the zonal scale. Due to the number of image captures and data points, ICEYE data-based modelling was only completed at the zonal scale. LWC was predicted with R^2 of 0.59 and 0.64 and RMSE of 1.22 and 1.37 as a result of K-fold and Leave-One-Out cross validation, respectively. The assessment suggests that ICEYE SAR contains valuable information for LWC mapping and with a daily revisit cycle it can be a powerful tool to capture LWC changes over time with high temporal and spatial granularity.

This study presented a workflow and a GIS-assisted methodology that allows the development of a geospatial dashboard to demonstrate how a series of LWC maps can be utilised by growers as a decision support tool. The operational online dashboard integrated the spatial layers and visualised LWC in an actionable way so it can be easily interpreted and accessed by the end users.

The outcomes of this work revealed the spatial and temporal variability of LWC over 6 monitored kiwifruit orchard blocks during a 5-month period. The research found that Sentinel-1 and ICEYE SAR satellite data carry useful information for foliar water content mapping which can inform irrigation management and orchard management. Due to the weather and daylight independent feature of SAR, the presented approach can be further improved by better models and more input data, and it should be implemented in the near future to detect water stress and to avoid over-irrigation events.

In summary, the findings of this project, the adoption of remote sensing, IoT and geospatial technologies directly feed into the development of advanced tools for kiwifruit growers. These data-driven platforms enable orchardists to make better decisions around increasing yield, preserving freshwater resources, and reducing fruit value variability within the orchard. Ultimately, the proposed solution will help the users to tailor their precision irrigation strategies to eliminate both under and over-irrigation thereby preserving freshwater resources.

Challenges, limitations, and recommendations

- The conducted LWC measurements were useful and satisfactory to prove the proposed concept. However, relative LWC measurements could provide even more valuable information. The relative LWC method can determine the amount of water a leaf compared to what the leaf can hold at full turgidity or saturation level.
- A larger and more dense ground truth dataset related to more SAR images would likely improve model performance and reduce uncertainty.
- There was no straightforward way to extract irrigation management data from RICADO's online platform, thus irrigation was not included in the analysis or the modelling.
- SAR signals (backscatter) showed sensitivity to biomass; therefore, this effect will need to be considered by introducing other remote sensing products or by creating a biomass indicator metric from SAR.
- As SAR is sensitive to the geometric characteristics of the foliage, it is recommended to assess and quantify these impacts with further research for more accurate predictions. This would lead to the development of a clearer picture of the fundamental interactions between SAR signal and the foliage.
- Following the anomaly of Sentinel-1B satellite, Sentinel-1A SAR ensured data availability through the crop growing season with a 12-day repeat cycle. The replacement of Sentinel-1B will be launched in the first half of 2023 which will reinstate the 4–6-day revisit time over New Zealand.
- On account of the spatial resolution and the noise contained in Sentinel-1 images the best prediction results were delivered at the block-scale. Sub-block level LWC information would be valuable, although to address that orchardists would be required to develop sub-block level irrigation management capability.
- The results presented in this report proves and supports the value of Sentinel-1 and ICEYE backscatter measurements for vegetation monitoring and LWC estimation. However, to develop a viable irrigation support system SAR and optical satellite data fusion is recommended. This combined approach would require a more complex workflow and data fusion process. On the other hand, the recommended method would increase the frequency of image acquisitions and provide several spectral bands as additional input variables for the models.
- The ingestion of rainfall, soil water deficit and soil moisture into the modelling improved the model performance, it limits the methodology to be used only in areas where these datasets are available.
- Since soil moisture is correlated to the foliar water levels, IoT soil moisture data can help to site specifically calibrate the LWC model, hence improved accuracy can be achieved.
- The generation of a universal kiwifruit water stress index would make the interpretation of the results more straightforward for growers. However, to achieve that a better understanding of LWC at saturation, stress and wilting point levels will be necessary from plant water dynamics and plant physiology perspectives.
- Based on the reported results and the potential of remote sensing in foliar water monitoring, the collaborators recommend extending the presented project and complete more detailed research on LWC at the regional scale. A regional scale project would be able to create improved, robust models and find solutions to the challenges and limitations revealed during this trial.

Introduction

Aotearoa New Zealand's kiwifruit sector contributed 38%, by far the highest value to horticultural exports in 2020 (Horticulture New Zealand, 2020). The current outlook sees global trade volumes continuing to rise by 45% by 2025 and by 2030, the sector's GDP contribution will double. As a response, a further 2800 hectare is being licensed to kiwifruit production in the next few years (New Zealand Kiwifruit Growers Incorporated, 2020). However, water access has been identified as one of the main risk factors that investors will face (ANZ, 2019).

Fundamental plant processes and fruit expansion are intolerant of water stress, implying that even short periods of water limitation can exert severe, irreversible effects on the final fruit value (Judd et al., 1986; Judd and McAneney, 1987). Additionally, with forecasted longer and more frequent droughts, higher evapotranspiration in summer will effect water availability, influencing the establishment of new blocks as well as the viable operation of kiwifruit orchards (Masson-Delmotte, V., P. Zhai, A. Pirani, S. et al., 2021; Tait et al., 2018). With strong worldwide demand for production growth, changing climate and dependency on sufficient water supplies, irrigation will become an even more essential part of orchard management.

The volume of water stored within the soil available to the plant at a point in time (i.e., plant available water) is provided by rainfall, or by irrigation systems extracting water from surface and ground. Net depletion of ground water can occur when water use is not optimised (Deurer et al., 2011). In the past, irrigation has exceeded local resources and led to community based irrigation schedules to ensure economic production (Judd et al., 1989). Recently, lower than normal precipitation resulted in declined ground water levels which was further depleted by irrigation. In 2021, the prolonged rainfall deficit triggered the longest water restriction in recent history in the Bay of Plenty, which is responsible for 80% of the country's kiwifruit export. Irrigated orchards coped better with dry conditions and generally produced higher yields compared to non-irrigated orchards. Most assessments of the sector's current and future water footprint support the overall conclusion that a substantial increase in irrigation will drive the greater water use, which will likely exceed allocable resources (Aqualinc Research, 2007; Hume and Coelho, 2011; Tait et al., 2018; White et al., 2009).

Beyond the importance of freshwater for horticulture, local biodiversity and aquatic habitats are dependent on sufficient water quality. Therefore, protecting waterways' base flow is essential to preserve their healthy, environmental, and cultural values. Since irrigated land use has already been increasing, council plans are concentrated around increased reporting of water takes, declined consents and cultural impact assessments directed by the National Policy Statement for Freshwater Management (Ministry for the Environment, 2020).

For the reasons listed above, growers are progressively required to justify their water take through rigorous reporting depending on the use of surface water, ground water or community water schemes. Some orchards are separated into irrigation stations while others apply a single irrigator, meaning that blocks may receive water regardless the plant's demand causing over- and/or under-watering, contributing to the risk of nutrient leaching. Ultimately, growers will need to be more efficient with water use to maintain market edge, to achieve compliance and to conserve freshwater resources while facing the projected competition for water from other users.

Despite kiwifruit plants' significant water demand, they are also sensitive to waterlogging as a result of extreme rainfall events or excessive water use, causing reduced productivity (Bardi, 2020). On the other hand, growers often induce controlled water stress to increase the amount of dry matter and sugar content in the fruit for higher returns. Consequently, to reduce water use while enhancing economic value and productivity, the sector would benefit from an optimised water allocation strategy that is driven by orchard specific water demand.

It is generally accepted that to optimise the use of water resources, a continuous monitoring of the water status in plant-soil systems is critical. Delineating orchard zones that are well hydrated or under various degrees of water stress can guide irrigation management to avoid unnecessary overirrigation. One way to help grower's decision making is through systematic leaf water content (LWC) observations. Analysing LWC indicates the underlying stresses by reflecting the integrated status of plant water, plant physiology, and environmental conditions (e.g., soil water and evaporative demand) (Jain et al., 2021; Jin et al., 2017; Quemada et al., 2021; Zhang and Zhou, 2019). LWC correlates well to changes in soil moisture triggered by rainfall or irrigation, thus capturing the evolution of LWC across the orchard can deliver valuable information for growers. Despite the proven value of LWC, to our knowledge, kiwifruit LWC monitoring at scale has never been investigated in New Zealand.

Traditional thermogravimetric LWC measurements require leaf samples detached from the plants before the tests. In contrast, LWC can be estimated by collecting reflectance in optical (visible, near-infrared, and short-wave infrared) domains of the electromagnetic spectrum using hand-held spectrometers directly on the plant [16]–[19]. While these methods are highly accurate and commonly used to collect ground truth, they suffer from the point-scale nature of the information, repeatability, cost, and labour limitations.

As a proxy for LWC, soil moisture can be used to validate LWC estimations and vice versa (Gao et al., 2013; Lyons et al., 2021). Soil water potential and dielectric soil moisture sensing techniques have been receiving growing interest in precision agriculture and horticulture to guide irrigation scheduling. To bridge the gap between field and catchment scale observations, spatially distributed sensors are connected through wireless networks or Internet of Things (IoT) for automated data collection. IoT supplies reliable, timeseries type information at specific locations, however, it is labour intensive and expensive to deploy dense sensor networks over large orchards or across regions.

Since the detection of canopy characteristics is of great importance across broad geographic scales, airborne and spaceborne optical sensors have been utilised to estimate spatiotemporal changes in the foliage (Lyons et al., 2021). However, the acquisition of spectral information through optical satellites is undermined in New Zealand. The sensor's dependency on reflected sunlight from the land surface and the frequent cloud cover present major disadvantages for LWC monitoring.

To overcome these challenges, Synthetic Aperture Radar (SAR) satellite technology has been increasingly utilised for Earth observation. SAR is an active microwave sensor; it is known to be an "all weather" and "24 hour" instrument because it can acquire data through clouds, and it does not require sunlight for capturing imagery. Consequently, these unique characteristics make SAR ideal for frequent vegetation monitoring. Several studies have indicated that phenological stages can be captured using SAR, and there is a significant correlation between LWC and SAR data (El Hajj et al., 2019; Han et al., 2019; Khabbazan et al., 2019; Quemada et al., 2021). This is mainly due to the well-known sensitivity of microwaves to the dielectric properties of the vegetation closely relating to the water mass in the above-ground plant components (Konings et al., 2019).

The cost of monitoring seasonal soil moisture and canopy vigour has been a major constraint for orchardists and there is no currently available tool that provides imagery based spatial information on a systematic basis. This proposal aims to fill this void and develop a scalable, LWC mapping tool that is centred around a unique fusion of highly accurate IoT observations, the water sensitivity of SAR, and invaluable horticultural expertise.

The projected outcome has the potential to revolutionise how we manage land and water by quantifying plant-soil-water interactions and improved irrigation scheduling nationwide. Furthermore, kiwifruit canopies present an ideal scenario for microwave-based satellite observations since the short wavelength SAR instrument will primarily pick up the signal from the foliage. Since New Zealand has diverse landscapes and soil types, a novel IoT and public SAR imagery driven management tool will enable growers and rural professionals to map out and address LWC variations adequately to save water and enhance orchard performance.

The specific aims of the proposed project considering OLW's strategic plans are:

- to create benefit for orchardists, Māori landowners and the community in general by creating a scalable solution.
- to reduce water usage to preserve our freshwater resources while enhancing productivity
- to leverage and expand sensor data by the support of remote sensing to monitor kiwifruit LWC with the aim of generating more consistent high returns across landscapes
- to co-develop a practically useful, interpretable, and actionable tool to provide LWC information on a regular basis in a form of spatial dashboards distinctly designed with growers for growers

Methodology

Site description and experimental design

This work was carried out on Ngai Tukairangi Trust's orchard blocks situated on Matapihi Peninsula (S 37.69995, E 176.19556) in Tauranga. The orchards were established on highly productive, well-drained loam textured soils formed on mainly flat to undulating terrain. According to the New Zealand Soil Classification system, the main soil order is Allophanic on the peninsula providing ideal soil depth wand non-restricting layers for kiwifruit root development (Lilburne et al., 2012).

These orchards are well-managed and have been monitored for several years via RICADO's automated remote data system. Orchard maps, block outlines and cultivar information were provided by Ngai Tukairangi Trust's managers. To monitor soil moisture and foliar water content six orchard blocks were selected with the assistance of orchard managers. Within each of the six selected blocks, leaf samples were collected from three spatially distributed sampling sites (Figure 2).

The soils and the foliage were monitored from 1 November 2021 to 28 March 2022. This period overlaps with the critical phenological development stages of the kiwifruit, including leaf formation, flowering, fruit set and fruit growth leading up to harvest. During this 5-month period the role of water management is critical to achieve high returns which is driven by yield, fruit size and weight, sweetness, and dry matter. Therefore, the detection of water stress and the management of variable water demand are essential during the canopy and fruit development cycle, especially during the summer months.

Figure 2 Location of leaf sampling sites and soil moisture sensors at Matapihi orchards

The blocks represent Hayward green (HW) and gold (GA) kiwifruit cultivars with various maturity stages and variable characteristics (Table 1). One of the blocks was chosen from an area covered by hail netting to investigate the potential effect of plastic net on the satellite signal.

Table 1 Specifications of the monitored orchard blocks at Matapihi

Block number	Eurofins ID	Variety	Description
40	1	HW	No irrigation
109	2	GA	Organic
12	3	HW	Mature vines
30-31b	4	GA	Old, mature vines
33	5	GA	Young vines
77	6	GA	Mature vines with hail protection cover

Soil moisture network

In the centre of each of these blocks Teros 10 soil moisture sensors were installed at 300 mm and 600 mm depths in October 2021 (Figure 3). To convert raw sensor readings to volumetric soil moisture, a generic calibration formula was applied that are suitable for most mineral soils and offer an accuracy of 3 % or 0.03 m^3m^{-3} as per the manufacturer's guidelines. The sensors were connected to RICADO's IoT network and online platform which provided near-real time data access. The soil moisture readings were extracted with a 15 min interval.

Figure 3 Installation of Teros 10 soil moisture sensors, the telemetry unit in the field and the Teros 10 sensor.

Foliar leaf water content (LWC) data collection

LWC, often expressed as percentage, is one of the appropriate measures of plant water status as it reflects the physiological consequences of cellular water conditions. Traditionally, LWC represents the weight change between fresh and oven dried leaves and often expressed as a percentage (Jin et al., 2017). During the study period, 8 sampling campaigns were conducted to build a LWC timeseries for the selected sampling sites to capture a season-wide variation of LWC. A total of n=144 leaf samples were collected, n=48 from HW blocks and n = 96 from GA blocks by technicians from Eurofins Laboratory, New Zealand.

The sampling site positions were recorded with a high accuracy GNSS device (Trimble TDC600 with Trimble correction service) and marked with physical markers to ensure repeatability for regular sampling. From each sampling site, 20 random leaves of various sizes were collected, bulked, and given a unique ID. The sampling sites corresponded to a bay, which can be approximated with a 3x4 m rectangle shape. The leaves were placed in self-sealing plastic bags to avoid water loss (Figure 4).

Figure 4 Leaf sampling by a Eurofins technician and an example of the bulked sample containing 20 leaves

The sampling campaigns were timed as closely as possible to expected satellite pass over times. Leaf samples were collected early in the morning when the leaves were rehydrated. Once collected, the samples were cool stored in polystyrene boxes and sent to the lab on the same day to determine LWC. The samples were weighed and then dried in at 65°C for 48 h to a constant weight. In this study, LWC can be defined as the proportion of water (%) of the total fresh weight calculated as per Eq. 1.

$$LWC\ (\%) = \frac{Fresh\ weight\ (g) - dry\ weight(g)}{Fresh\ weight\ (g)} \times 100 \qquad \textit{Eq. 1}$$

Weather data

Daily rainfall and soil water deficit datasets were obtained from the nearest weather station located at Tauranga Airport through NIWA's CliFlo climate database. CliFlo is an open-access online platform that provides access to New Zealand's National Climate Database. The climate station is situated about 3.2 km north of the main office building at Matapihi orchards. To retrieve the datasets the *clifro* R package was utilised (Seers and Shears, 2015).

Remote sensing data

Initially, the project was designed to use the SAR instruments on board the Sentinel-1 satellites. The Sentinel-1 constellation comprises of two polar-orbiting satellites, namely Sentinel-1A and Sentinel-1B. The Sentinel-1 mission has been collecting data since 2016 as part of ESA's Copernicus program which facilitates full and open license to all Sentinel data through an open access hub for research. Sentinel-1 satellites are mounted with C-band (wavelength = 5.6 cm) SAR and provide imagery with an unprecedented 4-6-day repeat cycle when both satellites are considered. Based on the last five years of operation over Matapihi, they provided data every 4.5 days as average. Figure 5 depicts the Sentinel-1 acquisition segments, sensor view directions and image footprints overlapping the Matapihi peninsula.

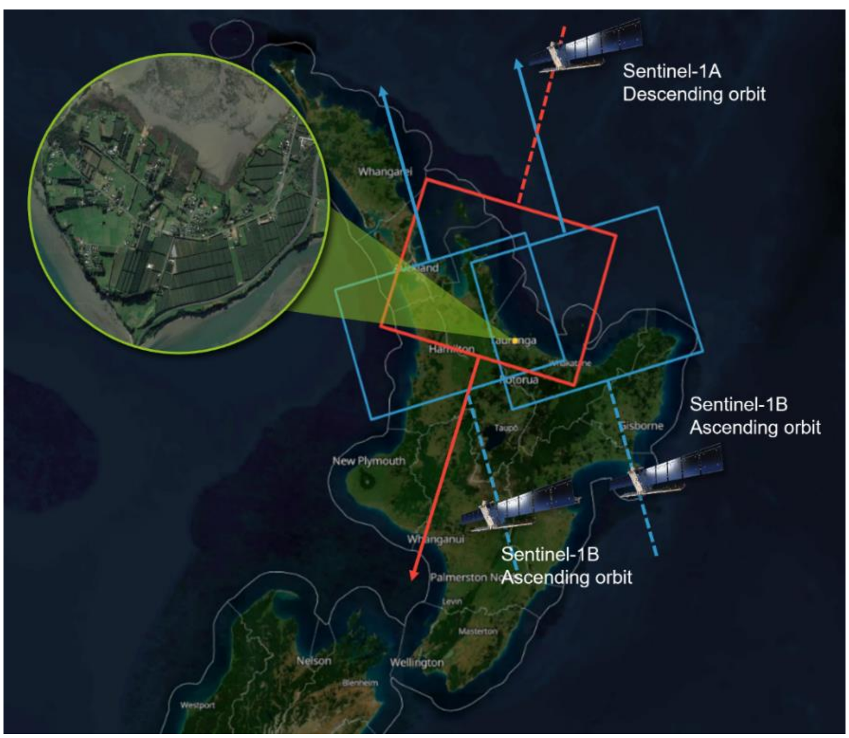


Figure 5 Sentinel-1 orbits and the location of Matapihi orchards within the satellite footprints

However, due to a malfunction of Sentinel-1B occurred on 23 December 2021, the revisit time dropped to 12 days with only Sentinel-1A acquiring data (Figure 6). Therefore, the major body of the analysis and modelling was executed only using Sentinel-1A images. Even though the frequency of acquisitions decreased, the amount of data collected was adequate to evaluate the potential of the proposed methodology.

To mitigate the long-term impact of Sentinel-1B anomaly in the future and the feasibility of the proposed methodology, the use of other SAR satellites was considered. The commercial Earth Observation company ICEYE (Finland) operates a fleet of SAR satellites. ICEYE was integrated into the Third-Party Mission data portfolio of the European Space Agency (ESA) which allows the distribution of ICEYE images for sponsored research programs free of charge. Thus, a proposal was submitted to ESA to gain access to ICEYE satellite tasking. The application was accepted on 15th February 2022, and the project was awarded with access to a limited number of ICEYE scenes.

The ICEYE constellation consists of 16 X-band (wavelength = 3 cm) SAR satellites as of the beginning of 2022. The constellation will continue to grow offering sub-daily revisits for a given location. In this study, the images were captured in Strip Mode that provides a ground range resolution of 2.24x2.24m in vertical-vertical (VV) polarisation.

The data collection timeline (Figure 6) presents all available Sentinel-1 image acquisition dates, the captured ICEYE image dates alongside with soil moisture sensor installation and foliar sampling campaigns.

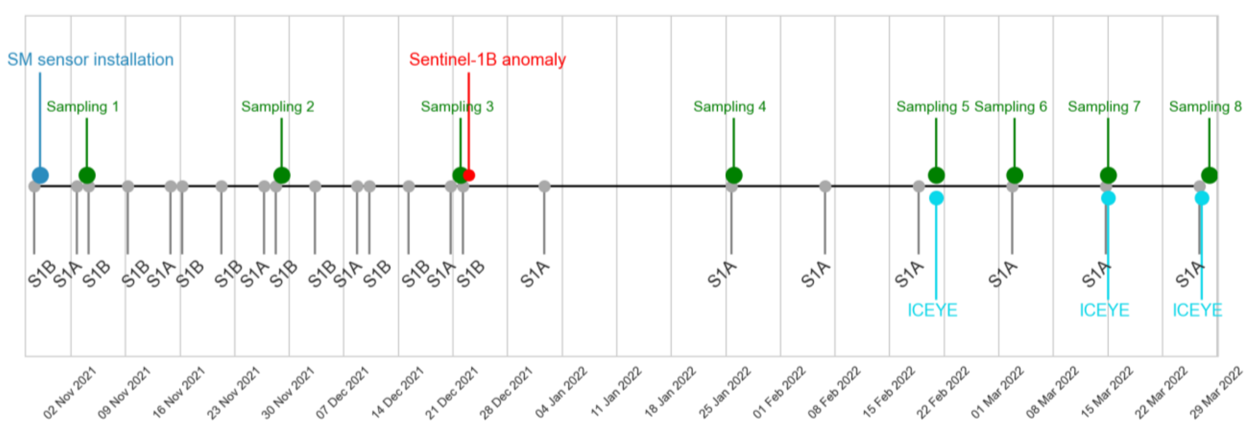


Figure 6 Data collection timeline

SAR image access and pre-processing

Downloading and processing a series of Sentinel-1 satellite imagery is a time-consuming task that requires large amount of storage and computing power for executing the pre-processing and analysis. Therefore, to generate a consistent and extendable dataset, the Google Earth Engine (GEE), a cloud-based, geospatial computing platform was utilised in this study (Gorelick et al., 2017).

The Sentinel-1 satellite data was obtained through GEE's Python API and the *GEEMAP* Python package implemented in Jupyter Notebooks (Wu, 2020). This approach ensured the generation of a consistent, analyses-ready image collection from GEE's pre-processed Sentinel-1 ground range detected image catalogue (S1_GRD). GEE's standard pre-processing includes orbit metadata updates, border noise removal, thermal noise removal radiometric calibration and terrain correction. The steps are described in more detail in the documentation of GEE based on the Sentinel-1 toolbox (“Sentinel-1 algorithms,” 2021). In this study, as an additional step, a mono-temporal Refined Lee speckle filter was applied to reduce speckle noise in individual scenes (Mullissa et al., 2021, p. 1).

The raw ICEYE images were pre-processed using the Sentinel Application Platform (SNAP), an open access and free software environment made available by ESA (SNAP, 2018). The pre-processing followed the workflow recommended by the ICEYE user guide, including radiometric calibration, terrain correction and speckle filtering which produces a comparable, analysis ready image. A visual comparison of Sentinel-1 and ICEYE images is shown in Figure 7.

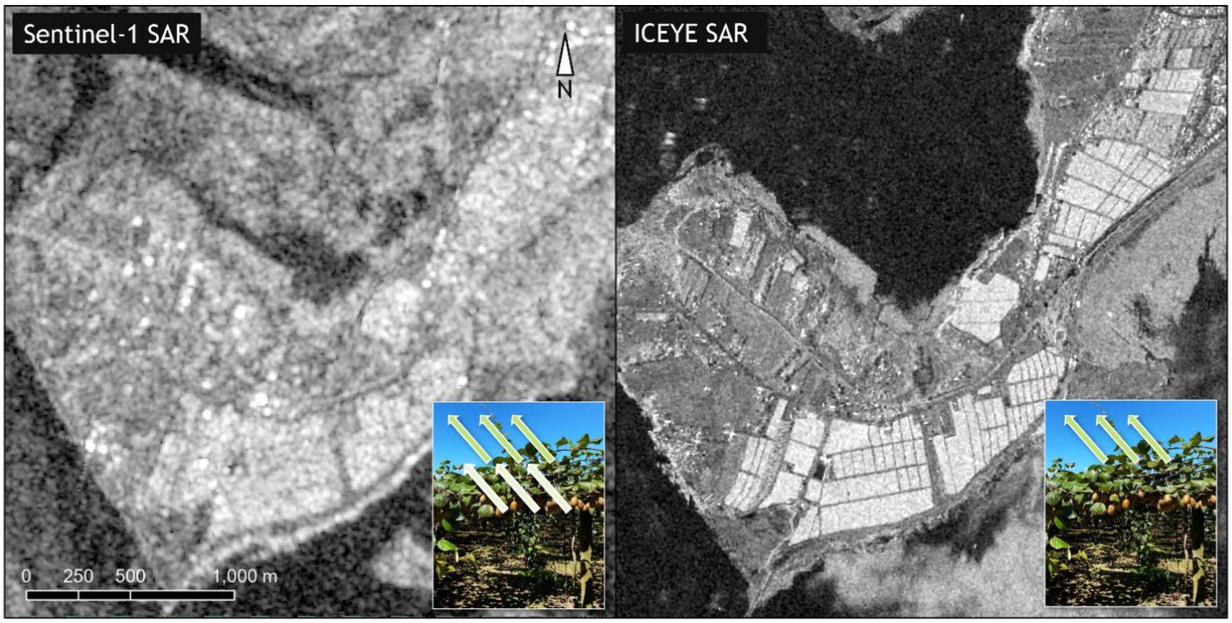


Figure 7 A visual comparison of Sentinel-1 and ICEYE images over Matapihi. Images in the bottom right illustrate the expected penetration depth of the two different microwave signals, i.e., C-band for Sentinel-1 and X-band for ICEYE.

SAR backscatter and data extraction methods

Active microwave platforms, including SARs, measure the magnitude of artificially generated energy that is reflected, scattered back from the land surface or the targeted objects (Schmugge et al., 2002; Seneviratne et al., 2010). SAR image pixels represents measurements of physical processes, expressed as the backscattering coefficient that quantifies signal intensity and the power loss caused by the interaction with the target. Due to its wide dynamic range, the backscatter is usually converted to decibels (dB).

To obtain more information from the target, some SARs can operate in various polarisation modes, such as co-polarised (HH or VV) or cross-polarised (VH or HV) (Ulaby et al., 1996). The first letter denotes to the polarisation of the transmitted wave whereas the second letter refers to the polarisation of the received wave (V-vertical, H-horizontal). As a result of data extraction from dual polarised Sentinel-1 SAR images, two variables were gained, namely VV and VH backscatter with 10x10 m pixel size.

The measured backscatter value is primarily governed by the dielectric constant of the vegetation canopy. The dielectric property of the foliage is a function of the free water content of the leaves. Fundamentally, increased vegetation water content will result in an increase in free water and therefore greater dielectric constant. If other backscatter affecting factors are not taken into account, higher vegetation water content leads to higher backscatter values which enables the use of SAR for monitoring the changes in vegetation water content.

However, vegetation exerts a significant effect on the backscatter by causing a complex scattering mechanism. Consequently, the total backscatter of the kiwifruit canopy is a result of several contributions from various parts of the foliage. The additional controlling factors are the size, shape and orientation of canopy elements, surface roughness, the growth stage and biomass (Dobson and Ulaby, 1986; Mattia et al., 2003). Both Ferrazzoli et al. (1992) and Toan et al. (1992) found that σ^0 increases with increasing amount biomass until a saturation point. The detailed understanding of these controlling factors is beyond the scope of this project; therefore, this report focuses on the effect of LWC on the backscatter.

An added amount of uncertainty is present in the image interpretation as SAR remote sensing (and active systems in general) inherently suffers from a phenomenon called speckle or noise. The effect can be reduced by statistical noise modelling or averaging and filtering techniques. Due to the noise contained by SAR images, three methods were used for extracting pixel values from the SAR images (Figure 8). These data extraction approaches allowed the assessment of whether the various spatial resolution SAR images are suitable to derive block or sub-block scale LWC information.

Method-1 used the coordinates of the leaf sampling points to extract the values of the overlapping SAR pixel, meaning that no spatial averaging was applied during data extraction. This method gained n=144 observations at will be referred to as point-scale.

Method-2 used buffer zones around the leaf sampling points with a given radius depending on the satellite platform to compute the spatial mean of image cell values intersecting with the individual zonal buffers. This method resulted in n=144 observations and will be referred to as zonal scale.

Method-3 generated spatially averaged block level observations by aggregating the LWC lab results from the 3 sampling points and obtaining the average of all pixel values within the block outline. The pixels were considered if the pixel centroids fell within the block outline. This method will be referred to as block-scale.

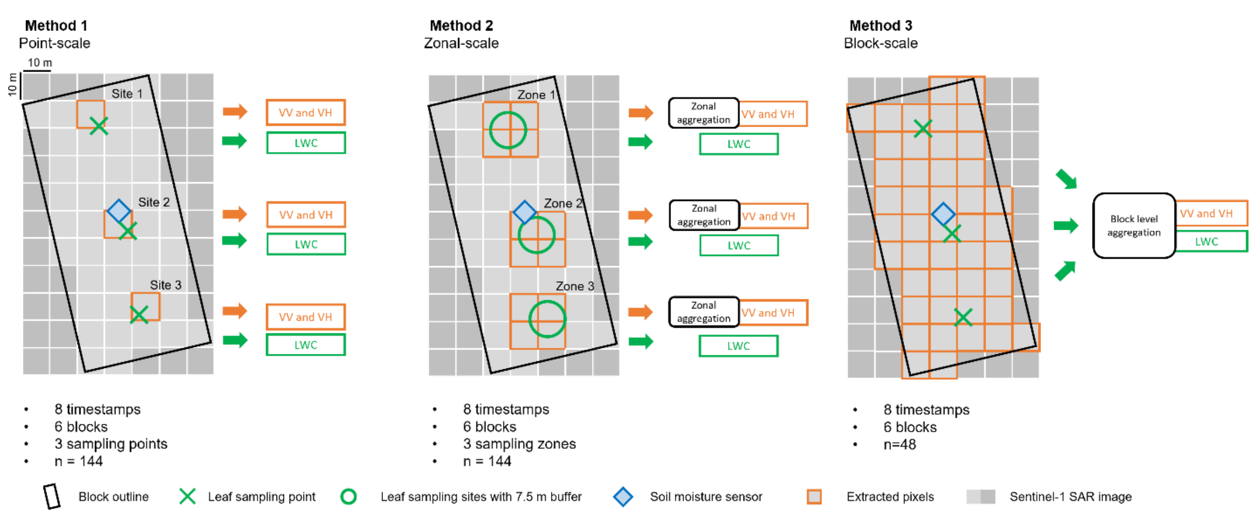


Figure 8 Data extraction methods from SAR images at three spatial aggregation scales

All three methods were applied to the Sentinel-1 image collection; Method-2 was applied with a 7.5 m radius buffer zone. As the pixel size of ICEYE images is 2.24x2.24m, the mean VV values were calculated on a zonal basis using Method-2 with a 3 m buffer radius.

Two SAR indices were also calculated and used in the modelling as they allow the integration of information gained from the various polarisation configurations into a single variable. Cross ratio (CR, Eq. 2) and Radar Vegetation Index (RVI, Eq. 3) were observed to correlate well with vegetation water content and biophysical parameters in other crops (Khabbazan et al., 2019; Nasirzadehdizaji et al., 2019; Shorachi et al., 2022). Thus, these two indices were derived from Sentinel-1 VV and VH backscatter using the formulas below:

$$CR = \frac{VH}{VV} \qquad \text{Eq. 2}$$

$$RVI = \frac{4\mathrm{VH}}{\mathrm{VV} + \mathrm{VH}} \qquad \text{Eq. 3}$$

Results and discussion

Soil moisture and rainfall

The dynamic sensor response to the timing and magnitude of daily rainfall events, drying cycles and the temporal trends was observed to be reasonable during the 5-month observation period (Figure 9). The response to rainfall events was more pronounced in the 300 mm layer. During the study period, three large precipitation events occurred, each of them reaching 50 mm daily accumulated rainfall.

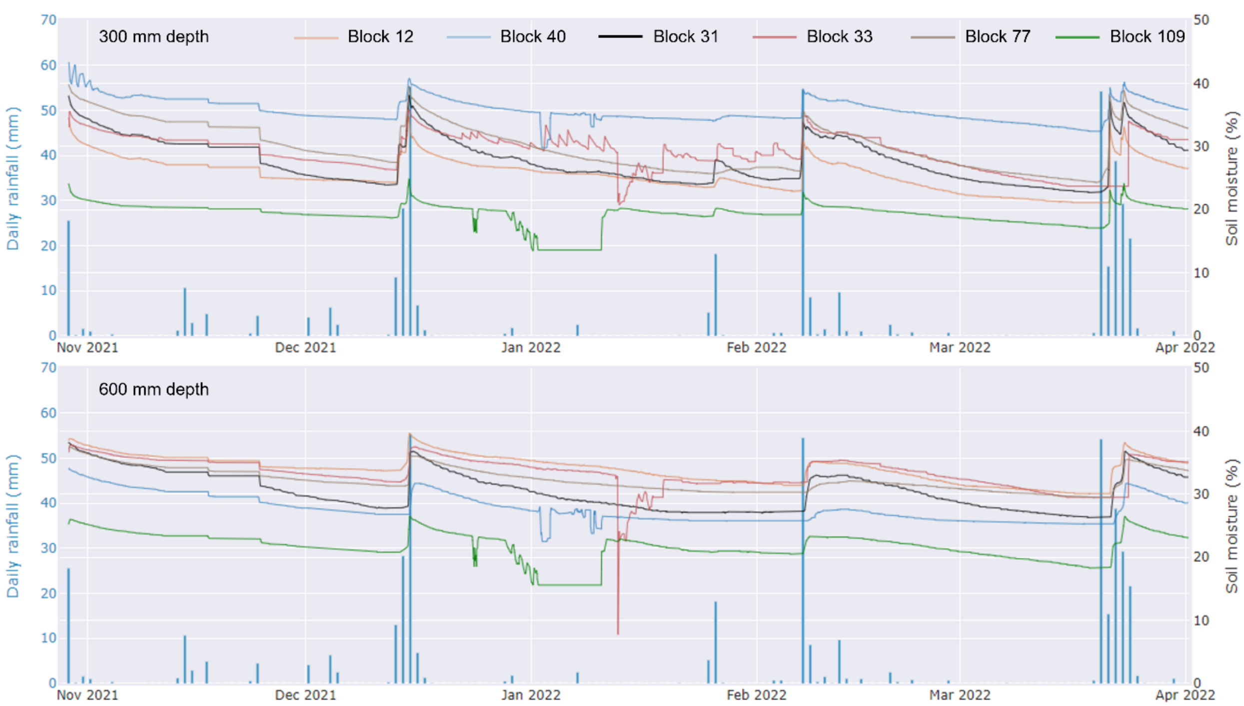


Figure 9 30-min soil moisture timeseries at 300 mm and 600 mm soil depths with daily rainfall as bars

These events triggered increased soil moisture levels along the monitored soil profile. As expected, the soil moisture variability and fluctuation were greater at the 300 mm soil depth than at the 600 mm depth due to meteorological factors. Except for Block 40, the 600 mm soil depth contained more soil moisture as compared to the 300 mm depth. Irrigation patterns can be observed in Block 33 during the summer months. LWC responded well to soil moisture changes as shown in Figure 10. In general, the study period can be characterized with a decreasing trend regarding soil moisture. This trend was reflected by the LWC measurements, although some instances show increases due to a rainfall event prior to leaf sampling.

This response and relationship between LWC and soil moisture was expected which supports the hypothesis investigated in this project. The C- and X-band SAR signals are not able to penetrate the canopy to acquire information from the soil, hence these SARs dominantly acquire information from the foliage. As soil moisture and the LWC levels are highly correlated, the capability to use SAR to monitor LWC allows the characterisation and enhanced understanding of the dynamics and process of the soil-foliage water system.

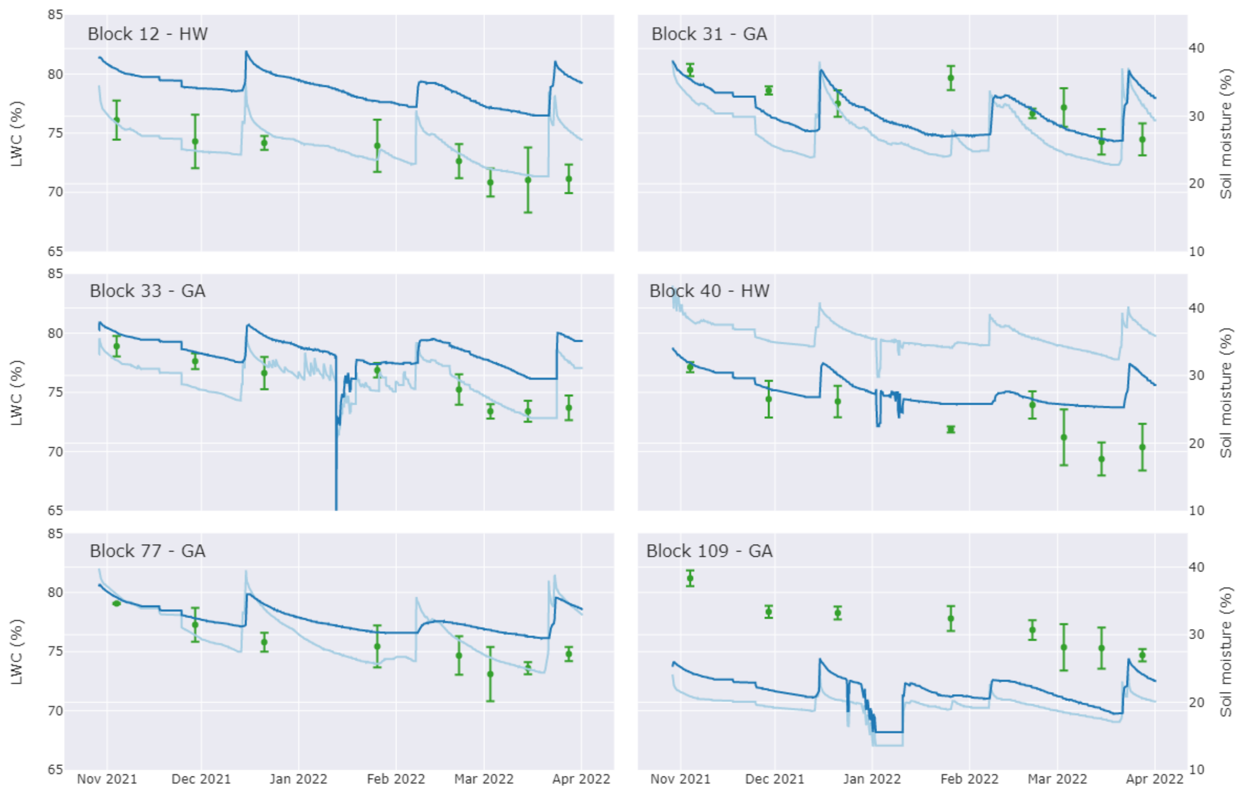


Figure 10 Soil moisture traces and the evolution of leaf water content over time. Light blue lines indicate soil moisture at 300 mm depth, dark blue marks soil moisture at 600 mm depth while green dots with error bars depict mean leaf water content and standard deviation within a block.

Exploratory data analysis of laboratory results

The histograms and density distribution charts in Figure 11 reveal that there was a significant difference between the cultivars in terms of the measured LWC. The LWC ranged between 67.8 and 77.6 % with a mean of 72.9 % and standard deviation of 2.5 % for HW. These results show similarities with results of Miller et al. (1998) in terms of water content of leaves during a water stress experiment on HW kiwifruit vines. Their observed range was 68-74 % over a 200-day monitoring period. In case of GA, LWC varied between 71.4 and 81.9 % with a mean of 76.4 % and standard deviation of 2.3 %.

HW variety stored lower amount of water in the leaves than the GA cultivar regardless of management and whether the blocks were irrigated or not. These results suggest that the two cultivars can be characterised with different water storing capacity in the foliage. Therefore, this attribute will be a significant factor for deriving LWC from satellite images.

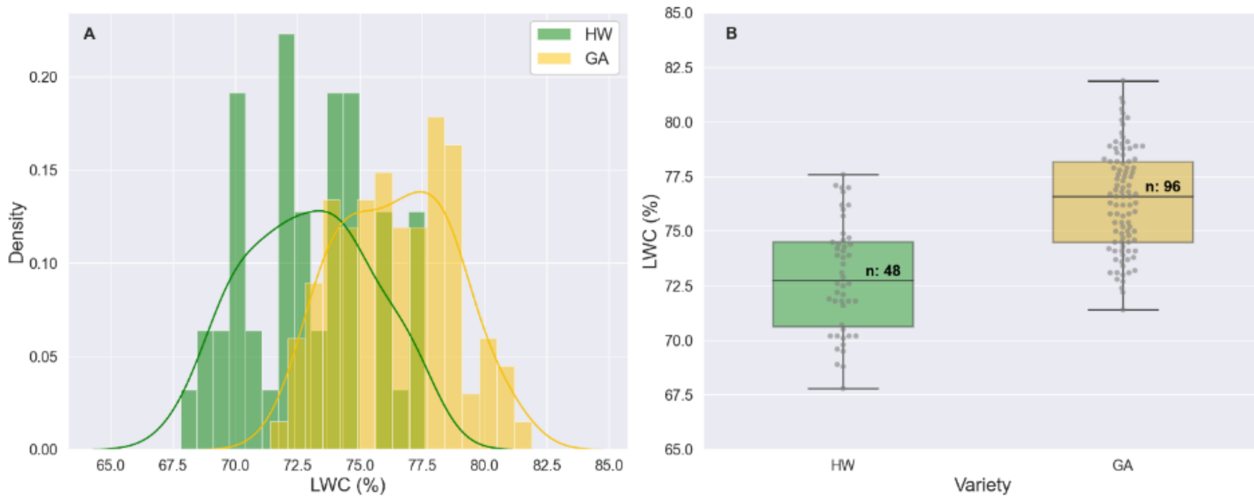


Figure 11 Leaf water content (LWC) histogram and density curves (A) and boxplots represent the value ranges for the Green (HW) and Gold (GA) varieties.

The method used to derive LWC is rapid, simple, and low-cost. The laboratory observations provided valuable information on the ratio of leaf dry matter and water content and their change over time. While the generated LWC dataset is sufficient to rapidly test the proposed remote sensing methodology, it poses a number of limitations.

For instance, the chosen LWC method is not sufficient to quantify the maximum water holding capacity of the leaves which would allow the calculation of relative LWC. Relative LWC estimates the water content of the leaves at a given time as a function of maximum water the leaf can hold at the fully hydrated stage, i.e., at full turgidity (Barrs and Weatherley, 1962). Secondly, the relative LWC approach would also allow the calculation of water content on a surface area basis or mass basis (Féret et al., 2019).

Despite the mentioned advantages, the relative LWC method is more time consuming, more expensive and more labour intensive than the presented LWC extraction method. Therefore, we recommend the consideration of relative LWC techniques or the investigation of other advanced methods in the next phase of this research.

Temporal LWC patterns

Figure 12 displays the temporal change in LWC at each block on a multiple time-series plot. In each facet, the block mean is presented by coloured lines according to variety, while the corresponding standard deviation is depicted by shaded areas. In the background, the LWC time series of every sampling site is plotted one by one as grey lines. This visualisation enables the investigation of the spatial variability across all monitored sampling sites over time.

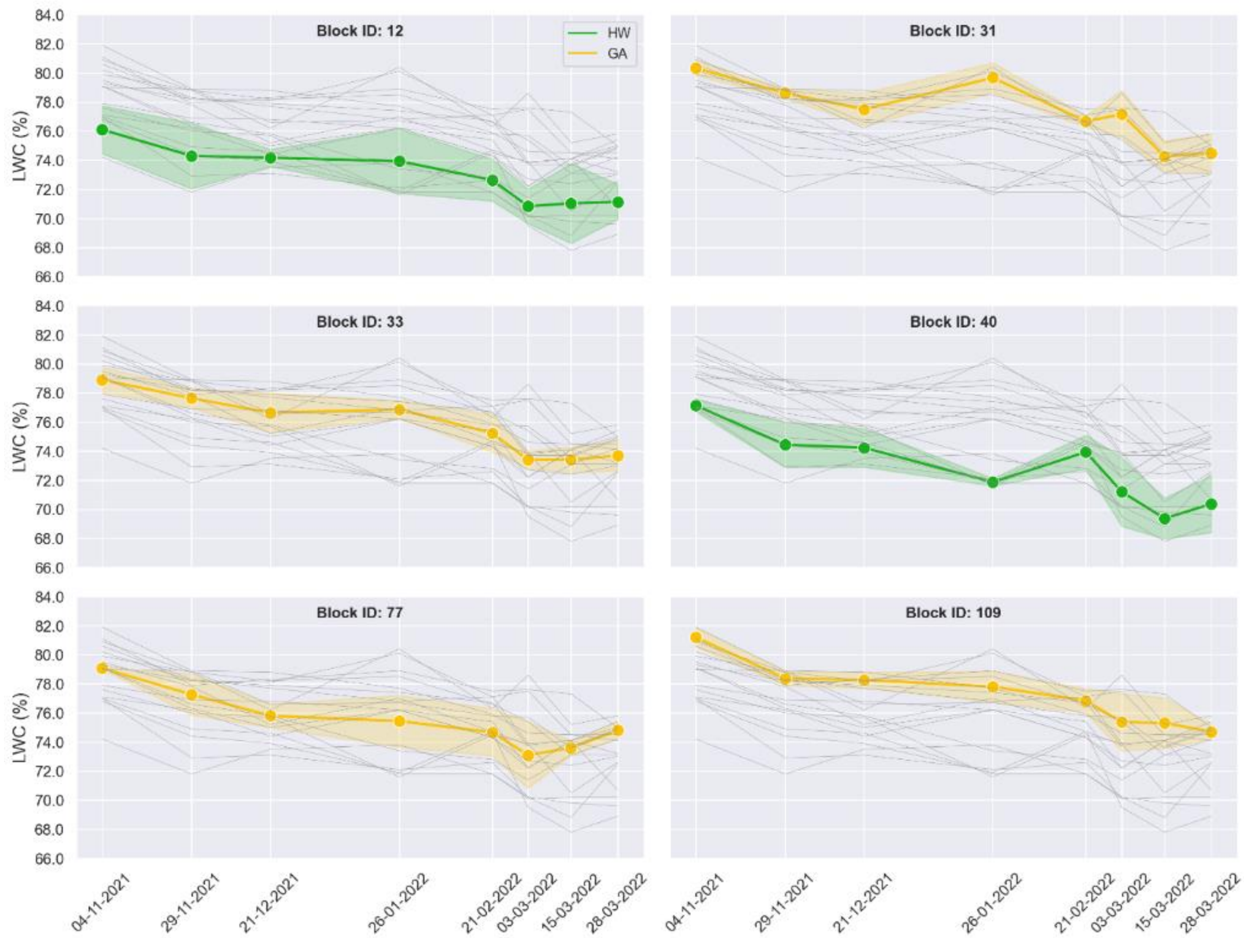


Figure 12 Temporal evolution of leaf water content at each block. Block mean and standard deviation is represented by the coloured bold lines and shaded areas, respectively. On each subplot, grey lines mark the LWC timeseries at each sampling point.

Figure 12 also reveals position of mean LWC levels of a particular block positioned relative to the entire range observed over the monitored blocks. Block 40 planted with HW cultivar occupied the lowest levels of LWC due to the non-irrigation. Even though Block 12 was irrigated Blocks 31 and 109 showed elevated level of LWC whereas Blocks 33 and 77 were situated around the middle range. The temporal change of standard deviation indicates that the variability within each block was dynamic during the growing season.

SAR and LWC relationship

To understand the basic relationships, distributions, and patterns hiding in this dataset, LWC measurements were related to VV, VH as well as the two derived indices in pair plots. Similar patterns were given by plotting point-scale, zonal scale, and block-scale data points. Figure 13 was generated at the zonal scale to visualise a larger number of data points as opposed to the number of data points at the block-scale. The observations were coloured by cultivars.

The previously described different LWC holding characteristics of HW, and GA cultivars resulted in observable differences in VV and VH backscatter response and inherently in the behaviour of the derived SAR indices, i.e., CR and RVI. The backscatter values from HW foliage were generally lower than in GA blocks for all SAR derived variables.

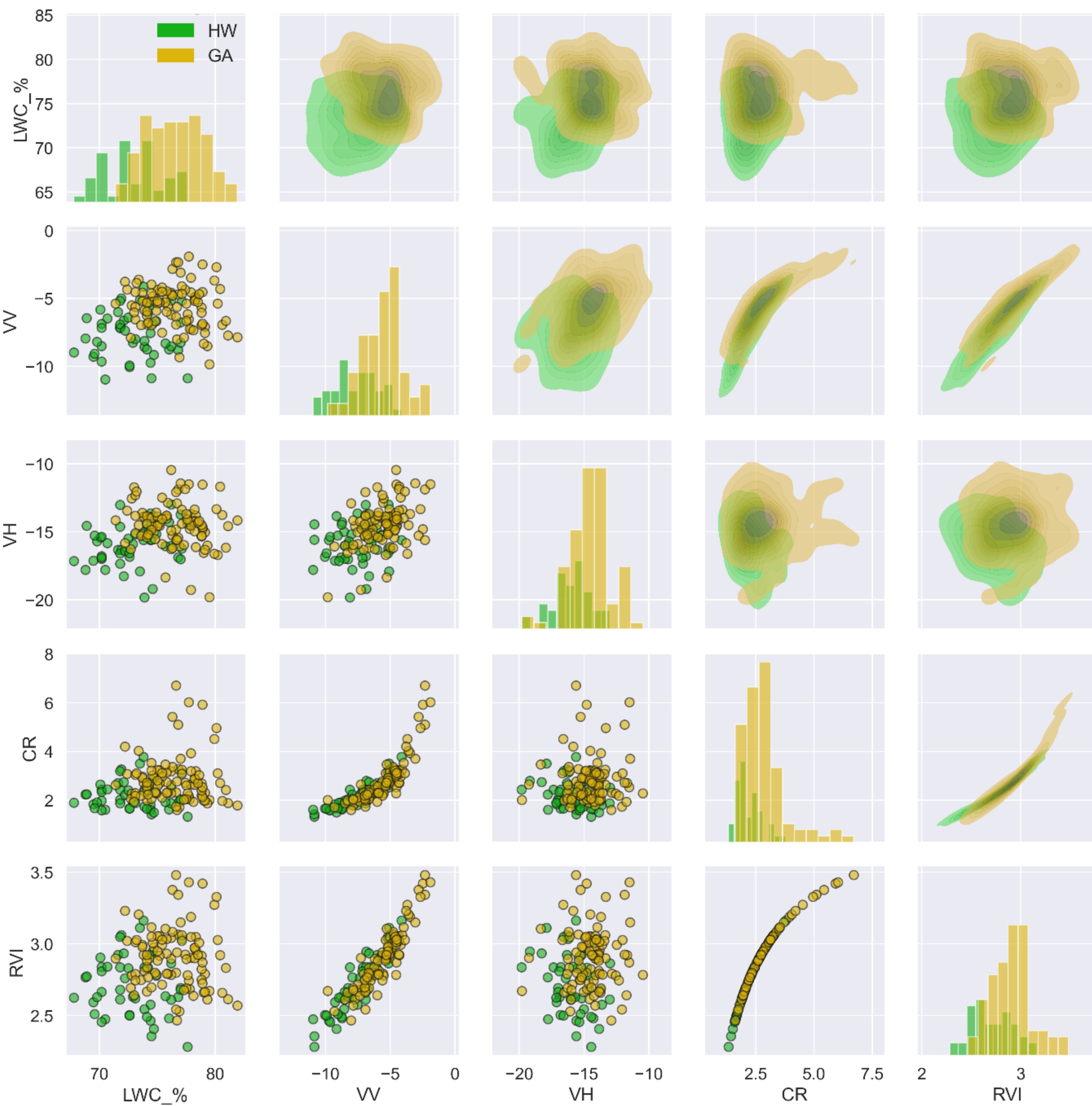


Figure 13 Pair plots to reveal the relationships between leaf water content and SAR derived data at the zonal scale.

These differences resulted in a formation of two distinguishable clusters shown by the kernel density estimate plots in the upper triangle of Figure 13. These observed stratification patterns confirm the previously introduced fundamental relationship between the dielectric properties of the target and the SAR backscatter. This means, that as the water content of the foliage increases, the intensity of the microwave signal also increases resulting in greater backscatter values for well hydrated foliage. The apparent correlation between LWC and SAR backscatter implies that response follows a certain level of embedded positive linearity which could be exploited during modelling.

Modelling LWC from SAR

The modelling was considered as a multivariate regression problem. Due to the low number of independent variables and observations, a simple multivariate linear regression approach was chosen to fit a model and predict LWC. Several other more sophisticated and complex algorithms, such as decision trees and partial least square regression, were tested but their performance did not show significant accuracy improvements as compared to a multivariant linear approach. Some of the tested methods can suffer from over fitting and the interpretation of the model performance can be challenging when the number of observations is low. Therefore, it was found that a simple linear and common type of predictive analysis tool was adequate to prove the concept presented in this report.

The prediction results were validated against the ground truth using two common methods, i.e., repeated K-fold cross-validation (3 repeats and 10 random folds) and Leave-One-Out (LOO) cross-validation. There was no observation removed from the dataset during the analysis and fitting. To evaluate the regression model, root mean squared error (RMSE) and mean absolute error (MAE) were calculated to quantify the residuals. The coefficient of determination score (R^2) was chosen to represent the goodness of fit between observed and the predicted values and it also indicates the amount of variation explained by the model.

Sentinel-1 predictions

To develop analytical models and predict LWC, a total of seven variables were generated. Two SAR variables were chosen, namely *VV (1)* and *VH (2)* as the two polarisations. As the SAR indices were poorly correlated with LWC, they were not included in the model development.

Soil moisture, soil water deficit and precipitation data were fed into the model in specific formats to investigate their effect on model performance. As a group, these variables will be referred to as hydrological variables in this study. The *Mean soil moisture (3)* variable was calculated by averaging the soil moisture readings at 300 mm and 600 mm depths. The precipitation data was summed for each 8-day period prior to sampling events, providing the *8-day cumulative rainfall (4)* variable as model input. Finally, *Soil water deficit (5)* derived from Tauranga Airport weather station was added. The models were developed with and without rainfall and soil water variables included.

The model was provided with *Variety (6)* information and *Week number since 1 Oct (7)* as numeric features. Since the SAR signal is affected by biomass, the *Week number since 1 Oct* variable was created to support the model to account for the temporal component of the canopy development cycle.

While this approach is not intended as a final solution, the addition of *Week number since 1 Oct* significantly improved the model performance. Several alternative ways can be investigated to account for biomass changes, including the implementation of growth models, ingestion of additional weather information, the use of optical remote sensing imagery or the development of biomass indicators using a data fusion approach.

In case of Sentinel-1 predictions, the highest model performance and lowest RMSE was achieved at the block-scale with soil moisture and rainfall information included. This model resulted in a mean R^2 of 0.77 and an RMSE of 0.99 % as the outcome of K-fold cross validation. The LOO cross-validation resulted in R^2 of 0.85 and a 1.04 % RMSE. Table 2 and

Table 3 summarise the model performance measures for the two satellites with and without the use of rainfall and soil moisture variables. Both Sentinel-1 zonal scale and point-scale data extraction methods delivered R^2 values of 0.65 and RMSE of 1.5%.

Overall, the model performance comparison revealed that a multivariate linear regression captured a large amount of the variation in the dataset regardless of the data extraction and aggregation method.

However, these results indicate that slightly higher predictive accuracy and model performance can be achieved at the block-scale compared to a zonal-scale or point-scale approach. Due to the lowest uncertainty, reduced error rates and highest R^2 achieved by the modelling at the block-scale, only that method will be detailed in this section. Figure 14 presents the linear relationship between observed and predicted LWC values derived from the LOO cross-validation at the block-scale. For comparison, histograms and density curves were generated to reveal the shape and distribution of the observed and predicted block mean LWC values. The density curves showed a generally close alignment between observed and predicted values considering their shapes and value ranges. Minor differences can be observed at 75% and 80% LWC values which indicate slight overestimation and underestimation, respectively.

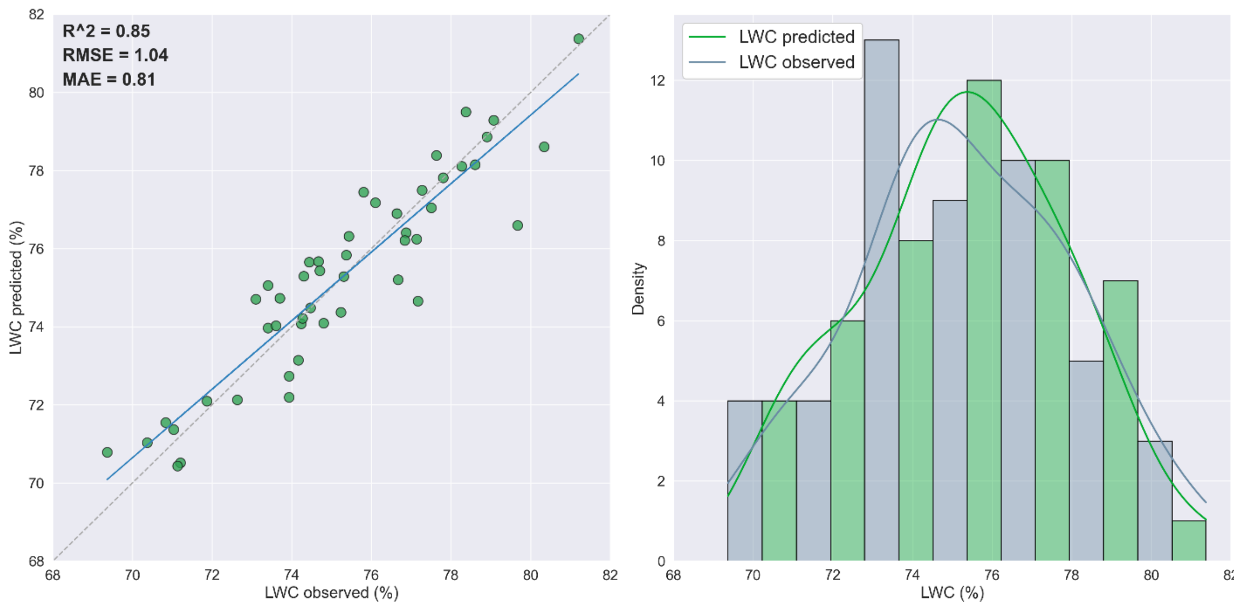


Figure 14 Model performance and histogram comparisons of observed and Sentinel-1 predicted LWC values at the block-scale

ICEYE predictions

Considering the higher spatial resolution of ICEYE images compared to Sentinel-1, and the resulting low number of observations n=18 at the block-scale, the modelling was completed at the zonal scale with n=54 observations. ICEYE imaging radars operate only in VV polarisation mode, therefore the number of input variables were reduced to six, i.e., *VV (1)*, *Variety (2)* and *Week number since 1 Oct (3), Mean soil moisture (5), 8-day cumulative rainfall (5),* and *Soil water deficit (6)* for this task.

the relationship between observed and predicted values as a result of LOO cross-validation is presented in Figure 15. The validation results are provided in Table 2 and Table 3 whereas a visual comparison of correlation and error metrics grouped by validation method, metric and satellite were plotted in Figure 16. The scale and whether hydrological variables were included in the analysis is specified on the x-axis.

The previously introduced multivariate linear approach delivered 0.64 R^2 and 1.37 % RMSE as a result of LOO cross validation with the hydrological variables included. The correlation coefficient and error metrics obtained from K-fold cross validation were slightly lower than the Sentinel-1 prediction results at the zonal scale, giving 0.59 R^2 and 1.4 % RMSE without the addition of hydrological variables. The standard deviation of RMSE and MAE calculated though K-fold cross validation were greater as compared to the results delivered by Sentinel-1 based predictions.

Several factors may be responsible for the declined model performance compared to the modelling results from Sentinel-1 images. These potential reasons may be the low number of data points, the aggregation at the zonal scale, the single polarisation of ICEYE sensors. Another plausible factor is the narrow range of LWC values used to train the models. This issue originates from the three ICEYE image acquisitions starting from the end of February. Consequently, these images were captured across the lower end of the LWC value range missing the well-hydrated status of the foliage that occurred in the early stage of the season.

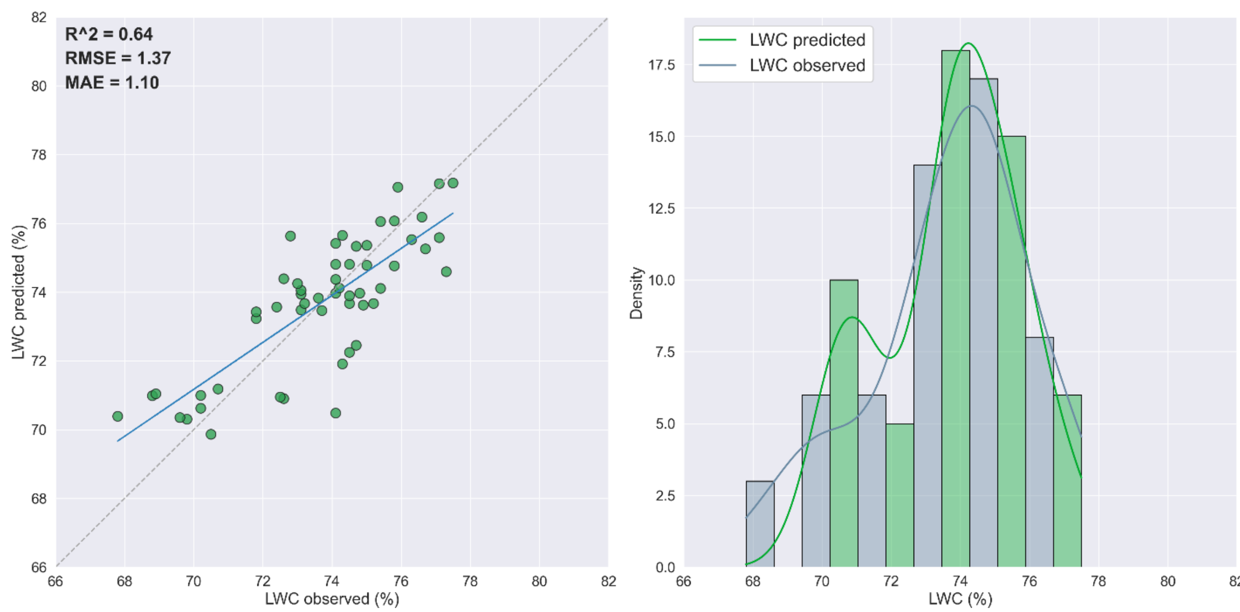


Figure 15 Model performance and histogram comparisons of observed and ICEYE predicted LWC values at the zonal scale

Despite the above-described limitations, and the low number of input variables, the modelling results indicate that ICEYE images are likely to serve as an alternative to Sentinel-1 in the context of foliar water content mapping. Aggregation at the block-scale could further improve the prediction accuracy, although that would require a larger collection of data points than the currently available dataset.

Table 2 Summary of modelling results for Sentinel-1 and ICEYE datasets. The values in brackets indicate standard deviation generated from repeated K-fold cross validation. LOO – Leave-One-Out

Cross-validation	Metric	**Sentinel-1**			**ICEYE**
		Block-scale	Zonal scale	Point-scale	Zonal scale
K-Fold	R^2	0.74 (0.17)	0.65 (0.16)	0.66 (0.15)	0.59 (0.2)
	RMSE (%)	1.07 (0.32)	1.54 (0.21)	1.53 (0.22)	1.4 (0.47)
	MAE (%)	0.91 (0.29)	1.26 (0.18)	1.25 (0.19)	1.22 (0.41)
LOO	R^2	0.83	0.72	0.72	0.54
	RMSE (%)	1.11	1.54	1.54	1.54
	MAE (%)	0.9	1.25	1.24	1.26

Table 3 Summary of modelling results for Sentinel-1 and ICEYE datasets including hydrological variables. The values in brackets indicate standard deviation generated from repeated K-fold cross validation. LOO – Leave-One-Out

Cross-validation	Metric	Sentinel-1			ICEYE
		Block-scale	Zonal scale	Point-scale	Zonal scale
K-fold	R^2	**0.77** (0.2)	0.67 (0.17)	0.67 (0.16)	0.59 (0.27)
	RMSE (%)	**0.99** (0.35)	1.49 (0.21)	1.48 (0.2)	1.22 (0.43)
	MAE (%)	**0.83** (0.29)	1.21 (0.17)	1.2 (0.17)	1.05 (0.38)
LOO	R^2	**0.85**	0.74	0.74	0.64
	RMSE (%)	**1.04**	1.49	1.49	1.37
	MAE (%)	**0.81**	1.19	1.19	1.1

Concerning these reasons, only the Sentinel-1 datasets were used to model LWC changes over time which will be discussed in the following section.

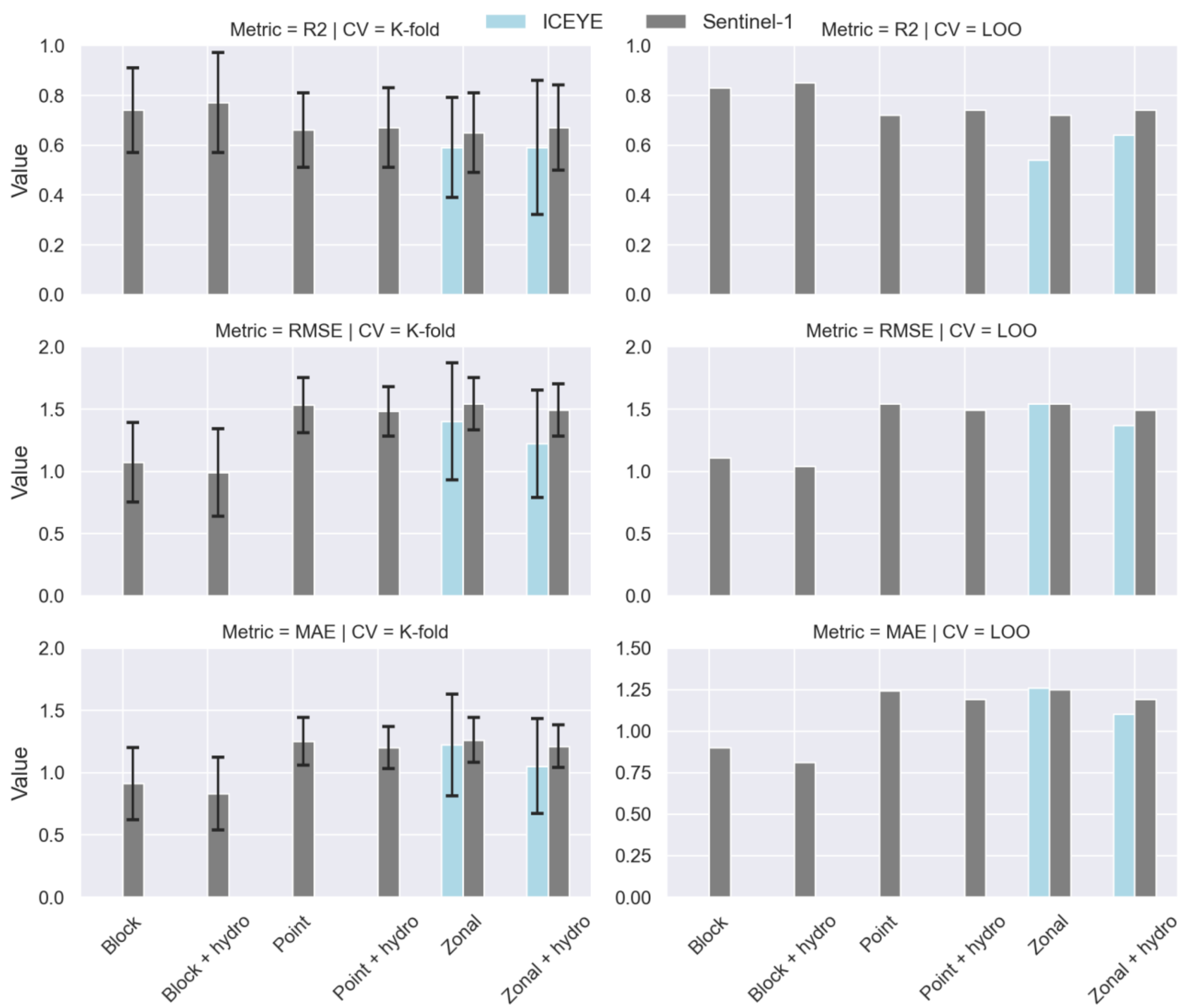


Figure 16 Plot of correlation and accuracy metrics as a results of multivariate linear regression approach. Error bars indicate standard deviation generated from repeated K-fold cross validation.

Timeseries of LWC predictions from Sentinel-1 data

The trained model was executed on each Sentinel-1 image captured between November 2021-April 2022 to generate time series dataset for each monitored block to assess whether the modelled LWC followed the trends returned by the lab analysis (Figure 17). In total, 14 Sentinel-1A SAR images were used in this analysis. The continuous lines coloured by variety show the evolution of predicted block mean LWC. The ground truth is represented by the black markers indicating the mean as points and standard deviation as error bars calculated from the lab results at the three sampling sites in each block.

It can be observed that the long-term decreasing trend was followed by the predictions in each block. In general, the predictions errors were the largest in Block 31 and 77. Interestingly, the model predictions persistently overestimated the observed LWC values in Block 77, which is covered by hail netting.

The different ranges of LWC between HW and GA varieties were captured well by the model and most predicted values were found within the error bars, i.e., within the standard deviation of LWC within a specific block. The modelled values were mostly in close agreement with the lab results and followed the trends between November and March. However, in March the predictions often showed under-or over estimation. There could be several reasons and factors affecting the predictions in different stages of the growing season. Increasing biomass, the crop load, the developing thickness of the foliage layer, irrigation can all contribute to the SAR response.

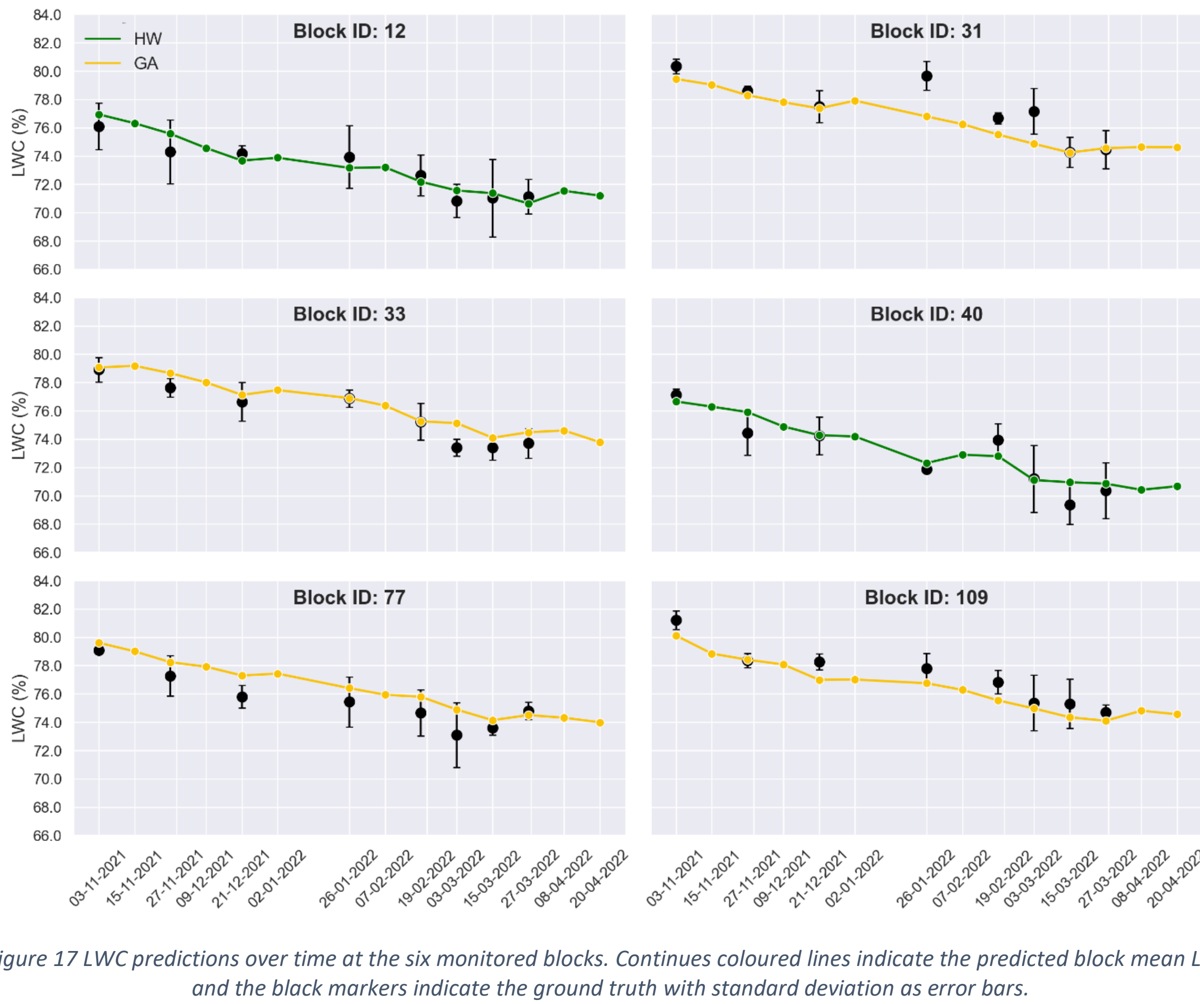


Figure 17 LWC predictions over time at the six monitored blocks. Continues coloured lines indicate the predicted block mean LWC and the black markers indicate the ground truth with standard deviation as error bars.

Overall, the model performance can be considered reasonably high for all time stamps with ground truth data. These results suggest that a simple linear model was able to predict LWC over time with acceptable accuracy.

To generate LWC maps, several geospatial tools were used including GIS-assisted techniques and open-source geospatial Python packages. The orchard blocks were represented by georeferenced polygons which were used for data extraction and aggregation. Geospatial zonal statistics was applied to extract block-scale mean SAR data from each available Sentinel-1 image for all blocks presented in Figure 2. The SAR dataset was populated with variety information and the corresponding LWC results for modelling. To create a vector-based visualisation, the centroid of each block was created. The modelled LWC values from each Sentinel-1 image were assigned to the centroids generating an attribute table with time stamps.

To provide a visually meaningful spatial modelling output the modelled LWC values were represented by vertically extruded cylinders and presented as a static 3D view. A series of 3D scenes were generated for each variety separately, as shown in Figure 18.

This allows the tracking of LWC changes in each block over time and to get insights about the spatial variability within Matapihi orchards. However, due to the numerous timestamps considered in this analysis, the modelled results were fed into an online dashboard for interactive mapping which process will be described in the following section.

Interactive dashboard development

The modelling was completed for 100 selected blocks with known variety as presented in Figure 2. Once all maps were produced, the outputs were uploaded to the hosting servers of ArcGIS Online. In the next step an operational ESRI ArcGIS Dashboard was developed to create an interactive visualisation interface to explore the spatial and temporal trends.

Dashboards enables users to visualise and aggregate information from various sources via an intuitive interface. Geospatial dashboards often centralised around a web-map that displays GIS layers which can be used as input for plots placed around the map widget. The purpose of this dashboard is to provide access to complex data sets and to provide benefits over static map content. This is essential for generating actionable information from highly dynamic environmental variables, such as LWC. Moreover, the cloud-based platform offers a scalable solution, it can be updated with new predictions from SAR and the spatial region of interest is extendable.

A screenshot of the dashboard is presented in Figure 19. The dashboard comprises of widgets, or elements which allow cross-filtering of a dataset by variety, orchard block identifier, or date. The dashboard features a map in the centre displaying the generated geospatial layers. The map is the core element of this dashboard, and the map layers are interlinked with all the other widgets for real time interaction.

In the left, category selectors assist with filtering the dataset based on calendar day or variety. Right beside the selector panel, a ranked bar chart provides variety specific insights about which blocks are the most hydrated or show the lowest LWC levels on a selected date.

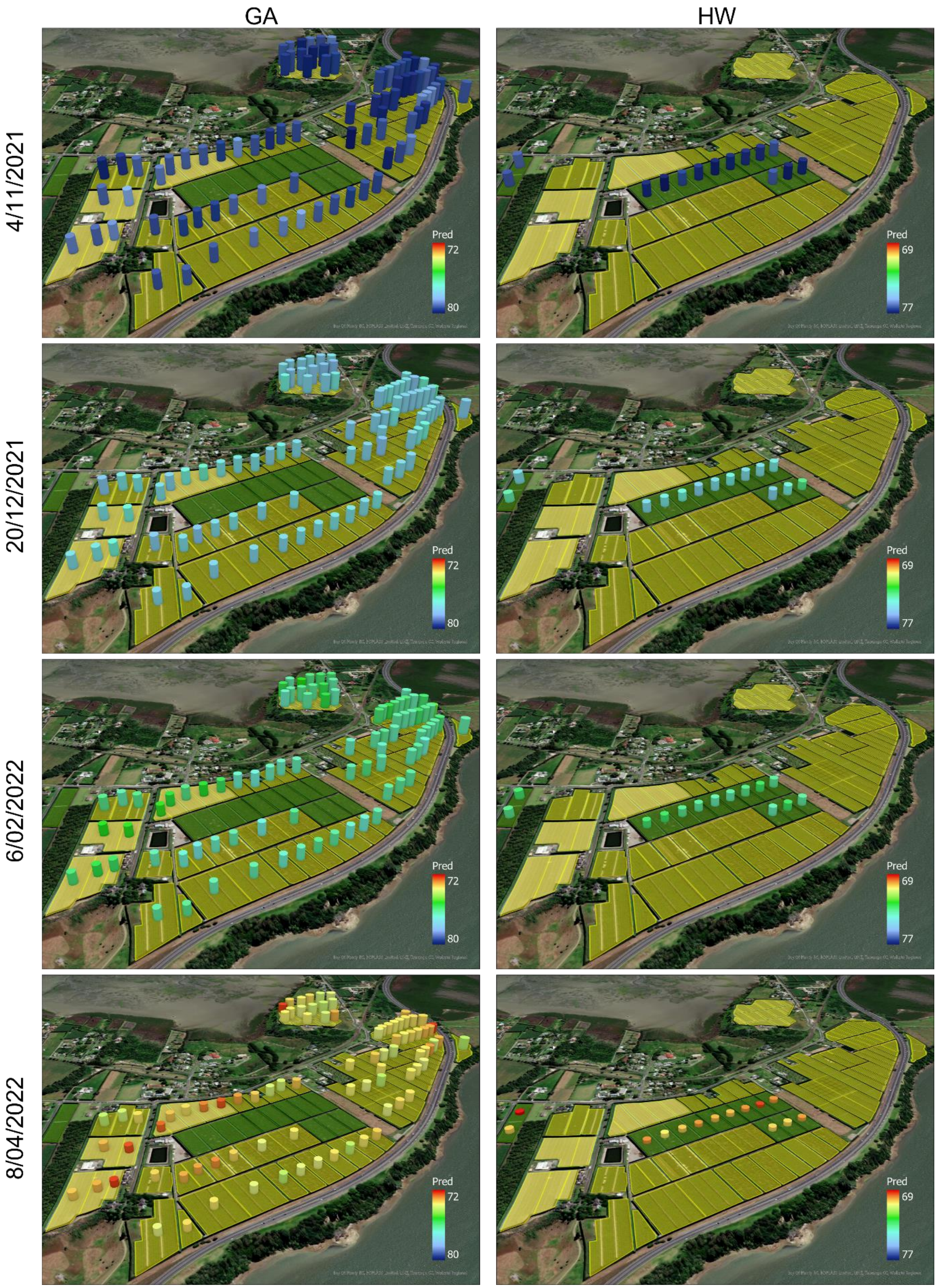


Figure 18 A series of spatial maps of block-scale LWC levels at Matapihi

Figure 19 A snippet from the developed ESRI ArcGIS Operational Dashboard for LWC monitoring

Below the map element, two gauges display the LWC values for selected blocks which can be done by clicking on a block on the map. For the sake of this demonstration, arbitrary low, optimal and high LWC thresholds were added to the gauges which could facilitate easier interpretation for the users. These thresholds could indicate whether a block is over- or under-irrigated or the blocks are at the optimum LWC level. To track changes over time, a timeseries plot situated in the bottom right visualises LWC values on all available dates for a selected block. For LWC time series comparison purposes, multiple blocks can also be selected and displayed on this plot.

In the top right a map legend is given informed by the underlying spatial layers. As the result of the current filter settings the map widget displays the block-scale values derived from the Sentinel-1 LWC prediction on the 15 November 2021. Up and down arrows and a chosen red-blue colour scheme illustrates whether the blocks' LWC levels are above or below the given thresholds. For demonstration purposes, an arbitrary value of 76 and 73 % were chosen for HW and GA cultivars, respectively.

The chosen LWC thresholds will need to be determined precisely with further research that considers the relationship between foliar water content dynamics, yield, fruit development and where the stress point is for both varieties.

As a further improvement, point-scale soil moisture information from IoT devices or climatic variables can also be incorporated into the dashboard and visualised real-time to inform water management decisions.

The combination of GIS and an interactive operational dashboard allows growers to turn complex, large datasets into insights. By adopting these visual analytics toolkits, the end users can extract actionable information and relate that to a specific location. A geospatial dashboard provides a useful platform for growers for the identification of potentially water stressed areas and for the tracking of LWC changes and it can help to optimise water usage.

Communication, written articles, and press releases

Several channels have been used to engage with the members and the wider community to enhance the value of the generated knowledge, to share project updates and to introduce the idea of a combined technology driven solution for optimising irrigation. These updates included a newsletter, a science conference presentation, internal and external meetings, a magazine article, and a downloadable case study. Here we provide a timeline detailing these updates.

21 September 2021

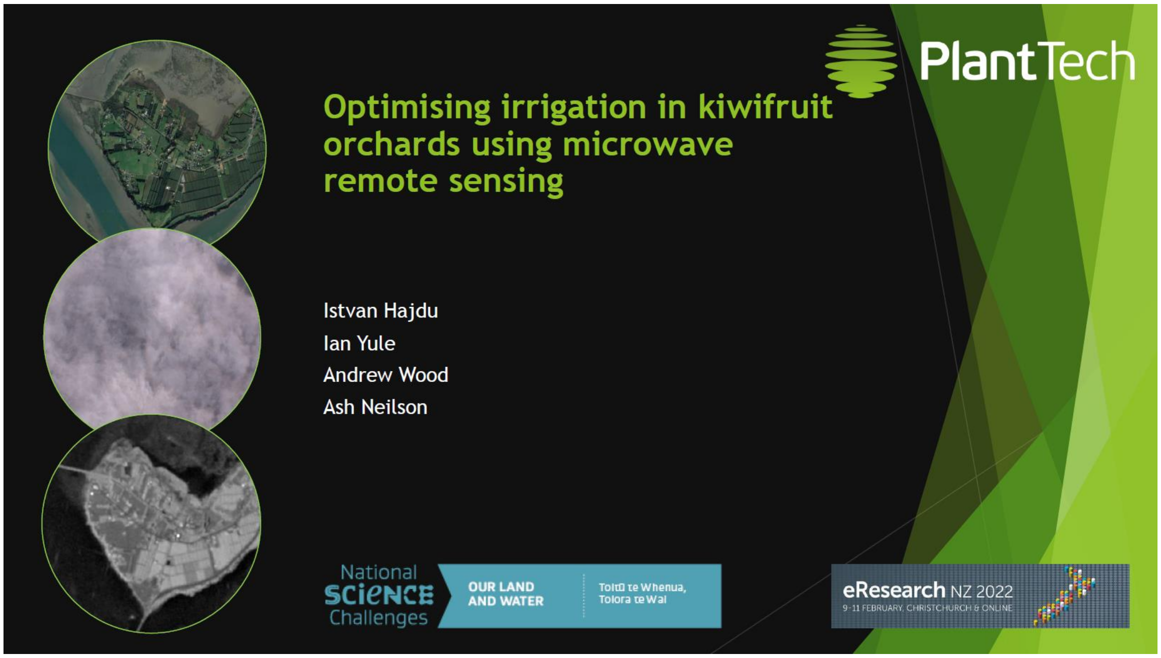
PlantTech newsletter “On the Vine” announcing the proposal success, members, and general description of the project.

> “ “ “
>
> ***Rural Professionals Fund***
>
> *PlantTech has submitted a funding bid to the Rural Professionals Fund run by Our Land and Water. The aim is to stimulate collaboration between research organisations and rural professionals.*
>
> *“The rural professional in this context is a company called RICADO, based in Te Puke. They provide a range of IoT monitoring solutions for orchards such as weather stations and soil moisture sensors,” says lead researcher Istvan Hajdu.*
>
> *RICADO and PlantTech are working with iwi organisation Ngai Tukairangi, the biggest Māori-owned producer of kiwifruit in New Zealand. The objective is to look at the use and management of water. One of the solutions that RICADO offers is soil moisture sensors.*
>
> *Istvan explains that there are satellite systems that can give growers information about moisture on the ground. They’re different from satellite imagery systems because these systems use radar.*
>
> *“They are sending out a signal and looking at what bounces back. These systems don’t need the sun so they can work both day and night.”*
>
> *Istvan says the signal will go through clouds, so it doesn’t matter if it’s clear or cloudy.*
>
> *“The upshot of that is you know you are getting a satellite image when it comes over. The data comes through every seven to 10 days,” says Istvan.*
>
> *This project is looking at how PlantTech can combine IoT soil sensors, that give very detailed information about one point, with satellite data that gives the user a comprehensive picture every week. The objective of that is to create tools that RICADO can make available for their customers to allow them to be more efficient with the use of water.*
>
> *“This project all comes back to managing our water resources efficiently and effectively, ensuring that we can continue to produce the highest quality delicious fruit whilst preserving the quality of New Zealand’s precious environment,” says Mark.*
>
> “ “ “

10 February 2022

Presentation at the eResearch NZ 2022 conference

The event was co-hosted by New Zealand eScience Infrastructure (NeSI), REANNZ, and Genomics Aotearoa, and delivered in partnership with Te Whare Wānanga o Waitaha University of Canterbury (UC). The Rural Professionals framework and the strategy of Our Land and Water resonated well with the theme of this conference, Building Capability Together / Waihanga Āheitanga Kotahitanga. The 20 min oral presentation was given within the Āheitanga / Capability session, highlighting the collaboration between project members and how this project can help to manage our water resources better. The first slide of the presented talk and the accepted abstract is presented below.



“ “ “

Aotearoa New Zealand’s kiwifruit sector contributed 38%, by far the highest value to horticultural exports in 2020. The current outlook sees global trade volumes continuing to rise by 45% by 2025 and by 2030, the sector’s GDP contribution will double. As a response, a further 2800 hectare is being licensed to kiwifruit production in the next few years. However, water access has been identified as one of the main risk factors that investors will face. Furthermore, growers are already progressively required to justify their water take through rigorous reporting depending on the use of surface water, ground water or community water schemes.

Therefore, managing water resources sustainably is crucial to New Zealand’s horticultural sector. We know we must manage these resources by optimising the use of rainfall and applied water to avoid water stress in crops. Irrigators are being required to monitor their use of water and many now use soil moisture measurement (through probes in the ground) as a means of better informing their irrigation management. While this is a major step forward and accurate information can be provided for the point measured, it is also recognised that orchard soils are often highly variable and further methods need to be implemented to create a cost-effective measurement network.

This project uses Synthetic Aperture Radar (SAR) which is a form of microwave sensing to provide a series of spatial maps of canopy water status to monitor water stress. The first crop it will be used in is kiwifruit. Microwave remote sensing technology can offer a viable method of capturing plant stress variability over individual orchards and blocks, with a high level of granularity and regularity. This granular information can be readily integrated with the accurate point source data from soil moisture probes to create a very effective measurement network. Microwave satellites orbit over New Zealand on a very regular basis providing a number of advantages over conventional optical means, it is not affected by cloud cover, and it captures images day or night.

This removes some of the major limitations of optical satellite systems and provides a means of having highly regular and reliable measurement.

The outcomes of this project feed into the development of digital tools for growers utilising this technology that will enable them to make better decisions around increasing their harvestable yield and reducing fruit value variability within the orchard. This project is being run with the cooperation of the industry, including growers and technology providers. Since SAR imagery is available nationwide, the developed tools will ultimately help the wider grower community and assist with precision irrigation strategies that can be applied to eliminate both under and over-irrigation.
" " "

May 2022

Press release in "The Orchardist" magazine. The article was reviewed and permitted by Our Land and Water. Screenshots of the article are attached below.

YOUR INDUSTRY

Soil moisture sensors have been measuring water levels in Ngai Tukairangi Trust orchards at two depths via RICADO's wireless remote monitoring network. Images supplied by PlantTec

Guidance from above for orchard management

Satellites may soon help kiwifruit growers monitor how well vines in different parts of their orchards are hydrated and whether the plants experience water stress. By Elaine Fisher.

A project to prove the efficacy of the concept is already underway in the Bay of Plenty and PlantTech Research Institute scientist Dr Istvan Hajdu of Tauranga says early results are promising.

Researchers are accessing data from two satellites regularly orbiting over New Zealand which contain microwave technology that can sense the water content of plants from above. The project uses Synthetic Aperture Radar (SAR), a form of microwave sensing, to provide spatial maps of kiwifruit canopy water status to help optimise irrigation strategies.

The project is funded by Our Land and Water (Toitū te Whenua, Toiora te Wai), one of the National Science Challenges. PlantTech won funding for the project under the Rural Professionals Fund programme, with partner RICADO Remote Data Systems Group of Te Puke, working alongside Ngai Tukairangi Trust, one of the leading Māori-owned kiwifruit growers at Matapihi near Tauranga.

The Rural Professionals Fund tests innovative ideas that could lead to significant improvements in farming systems while preserving the most fundamental resources, land, water and associated ecosystems. It allows researchers, farmers and rural professionals to empower and build deeper relationships with Māori agribusiness.

Istvan says two satellites began providing data from the Ngai Tukairangi Trust orchards in October last year. "These satellites have their own energy source and do not need sunlight to capture useful data making them operational 24/7. They are able to see through cloud cover, which means the images we receive are mostly independent of weather conditions in Aotearoa New Zealand. Indications are that the signal can also penetrate through hail nets, which is quite a benefit.

"The satellites transmit down microwave signal pulses which interact with the canopy. Some portion of the signal is scattered away or absorbed, and some goes back towards the satellite's antenna which provides the data we use."

To verify the accuracy of the information satellites are gathering, researchers have been 'ground truthing' the findings, using data from the nearby Tauranga Airport weather station and information from RICADO soil moisture meters and the results of laboratory leaf testing.

To date the correlation between the satellite and 'ground truth' data is pleasing, which is giving researchers confidence that eventually applications can be developed allowing growers to use satellites to remotely sense how well their vines respond to rainfall events and irrigation management.

Istvan says the data was not homogenous over the entire orchard. "From the images you can see that green and gold kiwifruit store different amounts of water in their leaves."

Images recorded at the end of January showed that a green block within the Ngai Tukairangi Trust orchard was drying out while other gold blocks remained well hydrated due to frequent irrigation.

> **"If the research could be translated to technology which growers could use daily as an early warning system of the water stress levels of individual orchard blocks, it would be extremely useful**

In March Istvan presented his findings to date via an online forum to Andrew Wood (Ngai Tukairangi Trust), Scott Whitwell (RICADO general manager), John Huntingdon (RICADO hardware technician), fellow researcher Professor Ian Yule (PlantTech), Dr Mark Begbie (PlantTech chief executive), and Rob Bensley (PlantTech commercial director).

He displayed the complex data from the satellites in 2D and 3D image form using different colours to denote differences in plant hydration. The images are similar to what growers may see if a commercial 'dashboard' programme is developed for their use.

Andrew Wood said he was excited about the possibilities the research was opening up. If it could be translated to technology which growers could use daily as an early warning system of the water stress levels of individual orchard blocks, it would be extremely useful.

Istvan joined PlantTech in 2020 after arriving in New Zealand in 2015 and completing his PhD at Massey University, Palmerston North. His scientific career started in Hungary where he achieved master's degrees in geography and earth science engineering at the University of Miskolc.

"There are great scientists in our PlantTech group. I consider myself a geospatial data scientist but collectively, we're combining all our different skills and experiences to create something new that has never been done before in New Zealand, especially in horticulture."

In scientific circles, geospatial data is called the 'golden thread' that links many datasets together. The work involving artificial intelligence (AI) technology and machine learning that is carried out by PlantTech enables the institute to process complex datasets that many other organisations cannot manage. By adding a geospatial component to the analyses, Istvan says PlantTech is able to see new patterns of information and answer questions that haven't yet been asked.

"It's about understanding all the connections and modelling those virtually. I really enjoy translating all the outputs from these complex models into something that is understandable by a client or someone who is not an expert in data science.

> **"From the images you can see that green and gold kiwifruit store different amounts of water in their leaves**

"Nowadays, we have a large selection of tools to visualise data interactively, such as GIS (Geographic Information Systems) assisted dashboards, 3D models, or we can use animation to tell a story over time."

Orchards are examples of places where geospatial data can be applied in new and revealing ways. "Production blocks are often viewed as isolated entities, but we can use geospatial data to view them as part of a wider catchment, and view and compare all the different regions to see how they react to various management practices. Using this data, we have the capability to build up a big picture that is meaningful for growers, packhouses and other clients, but it's just the tip of the iceberg.

"This sort of approach will have a huge impact on the horticultural industry and PlantTech is aiming to be a pioneer in this field." ●

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A case study was published on PlantTech Research Institute's website to share the project outline and the main findings with the general public from a business challenge, technology challenge and project value perspective. Screenshots of the case study are attached below; which can also be accessed following this URL:https://www.planttechresearch.com/case-studies/2022/7/27/kiwifruit-leaf-water-content-mapping-using-microwave-remote-sensing.

Case Study: Kiwifruit leaf water content mapping using microwave remote sensing

PlantTech partnered with RICADO and Ngai Tukairangi Trust to develop a pilot for a scalable irrigation mapping solution. The solution models leaf water content across the whole orchard to save water and improve yields for kiwifruit growers. It combines the Internet of Things (IoT), satellite data and horticultural expertise for localised analysis.

The Business Challenge

Global trade volumes for kiwifruit reached four million tonnes in 2021 with production expected to continue growing. Kiwifruit plantings are growing but this increases demand on regional water reserves and alongside climate-change risks, are driving the need for optimised irrigation.

A single Hayward kiwifruit requires 42 litres of water to reach harvest maturity. Even short periods of water stress can create irreversible effects on kiwifruit production and final fruit value. Water shortages during the rapid growth stage of kiwifruit can cause wilting, leaf browning, and reduced yield. The issue of overcompensating for the water stress risk results in over-irrigation that can bring harm to the root system, propagate disease, and wastes water reserves.

PlantTech partnered with RICADO of Te Puke, Bay of Plenty, New Zealand, and Ngai Tukairangi Trust based in Matapihi, Bay of Plenty, New Zealand to develop a pilot scalable leaf water content mapping solution to optimise water usage across 60 hectares of kiwifruit orchard. The solution aimed to reduce overall irrigation water requirements and reduce the risk of plant stress.

The Technology Challenge

IoT devices provide accurate local information for farm and orchard diagnostics but covering a whole orchard with many IoT devices is costly and inefficient. Remote sensing from satellite provides large scale and even regional understanding of the environment. Bringing these two datasets together creates an opportunity for horticulturalists to receive information that combines IoT monitoring with scalable remote sensing technologies.

Satellite mounted Synthetic Aperture Radar (SAR) is a form of microwave sensing that when coupled with analytical models can capture plant water availability in the leaves as an indicator of water stress.

SAR satellites regularly orbit over New Zealand, meaning new data every six-to-twelve days enabling a library of analysis is possible over a whole growing season. Microwave sensing from space unlike visible light sensors can image through cloud cover, during day or night, so is a reliable data source for crop analytics.

Technical Solution

IoT soil probes provide automated, accurate data at points of collection while SAR sensing monitors whole orchards with a high level of granularity and regularity. These tools complement leaf water content sampling and grower knowledge to meet each orchard's unique water needs (Figure 1).

To build the SAR analytical model, leaf samples were taken, and were sent to a laboratory. This process trained the model, enabling targeted kiwifruit block monitoring for specific cultivars.

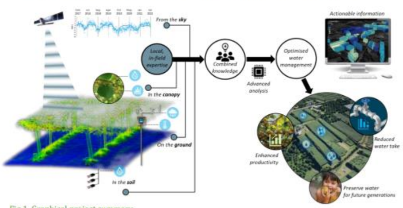

Fig 1. Graphical project summary

Technical Outcome

Model outputs were represented as a series of leaf water content maps over the growing season across the Ngai Tukairangi Matapihi orchards.

Fig. 2 Leaf water content (LWC) variations at the Matapihi orchards

This pilot study showed a strong model performance with an average correlation R^2 result of 0.8 and mean absolute error of 0.9% when compared between observed and predicted values.

This strong model allowed Ngai Tukairangi orchardists to track the leaf water content levels of individual orchard blocks (Fig. 2) and decide when and where water application was needed.

Project Value Outcome

This pilot project revealed that SAR satellite data carries useful information for foliar water content mapping which can inform irrigation management and orchard management. The adoption of SAR remote sensing technology in kiwifruit (and other horticultural crops) will lead directly to less water use, improved yields and less fruit quality variability within the orchard. PlantTech is looking at implementing this capability at scale to develop geospatial dashboards as decision support tools for growers to eliminate both under- and over-irrigation.

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