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sonke siya phambili
saam vorentoe

Experiences in digital agriculture applications with a focus on water stress monitoring

Ms Talitha Venter and Prof CA. Poblete-Echeverria
June 2024

SAGWRI South African Grape and Wine Research Institute

Image compiled by the Digital agriculture research group

Conceptual background

Digital Agriculture Research Group

Our mission is to contribute to optimizing agriculture practices through innovative digital solutions and cutting-edge research. We aim to enhance agricultural productivity, sustainability, and resilience by leveraging advanced remote and proximal sensing technologies, and modern data analysis techniques (machine vision and artificial intelligence).

SAGWRI - South African Grape and Wine Research Institute

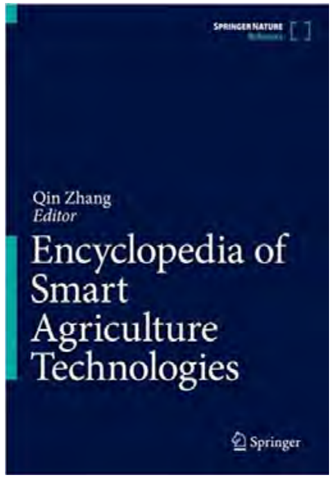
https://sagwri.sun.ac.za/

Conceptual background

Traditional agriculture practices

Uniform management: application of the same intensity or the same dose in operations such as pruning, fertilization, phytosanitary treatments, irrigation, etc., regardless of the exact location and variability.

Digital smart applications



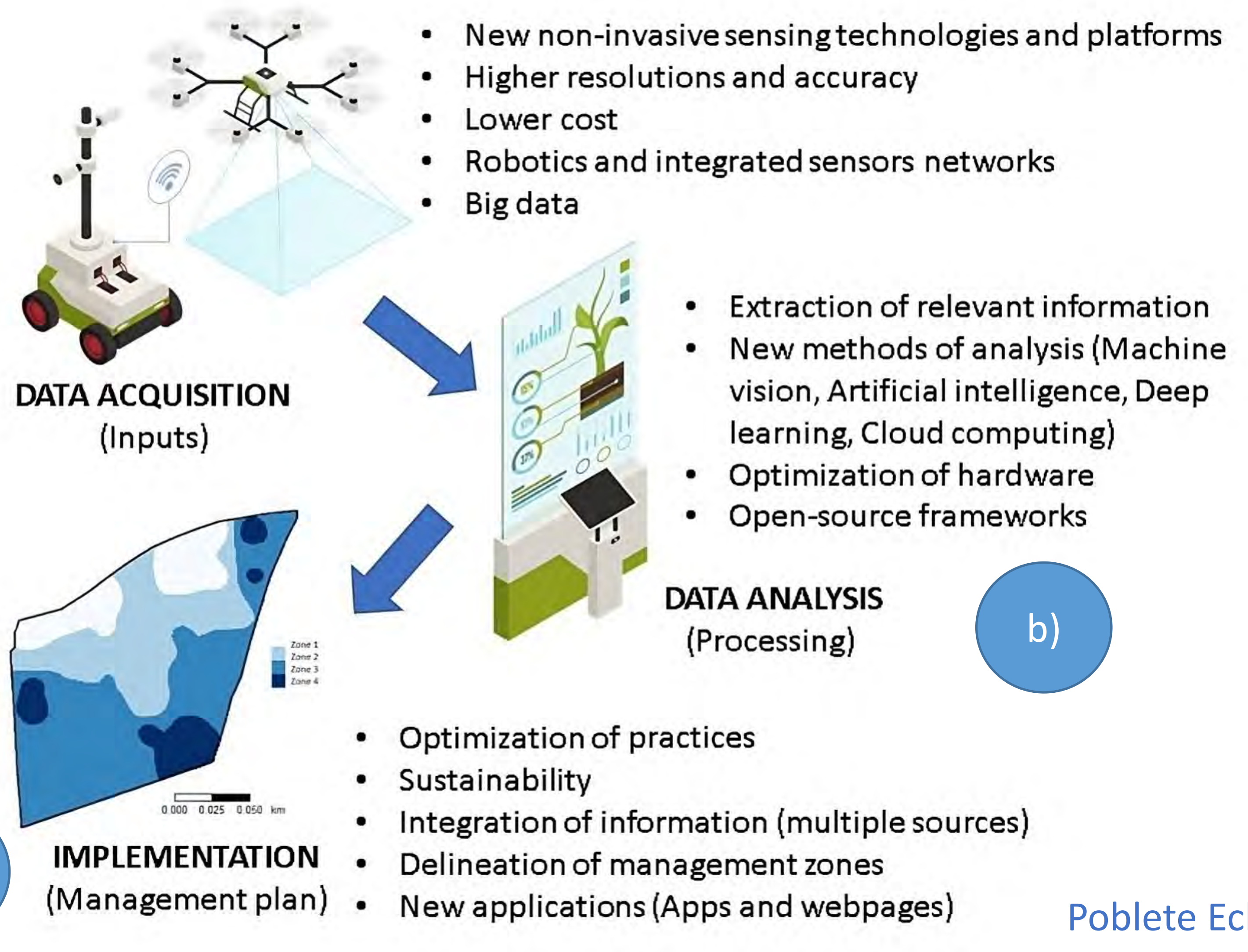
"**Digital Agriculture** can be defined as a group of new technologies (sensors, platforms, and algorithms) used to provide technology solutions to handle **spatial** and **temporal variability** of agriculture variables and site conditions in order to provide useful information for **optimizing management practices**"

- **Noninvasive Sensing Technologies (Sensors)**
- **Sensing platforms**
- **Algorithms**

Poblete Echeverria and Tardáguila (2023)

Conceptual background

a)



b)

c)

Figure 1. The adoption process of digital agriculture.

(a) Data acquisition from the vineyard;
(b) Information extraction from the acquired data;
(c) Development and implementation of a targeted management plan based on the previous data analysis.

Poblete Echeverria and Tardáguila (2023)

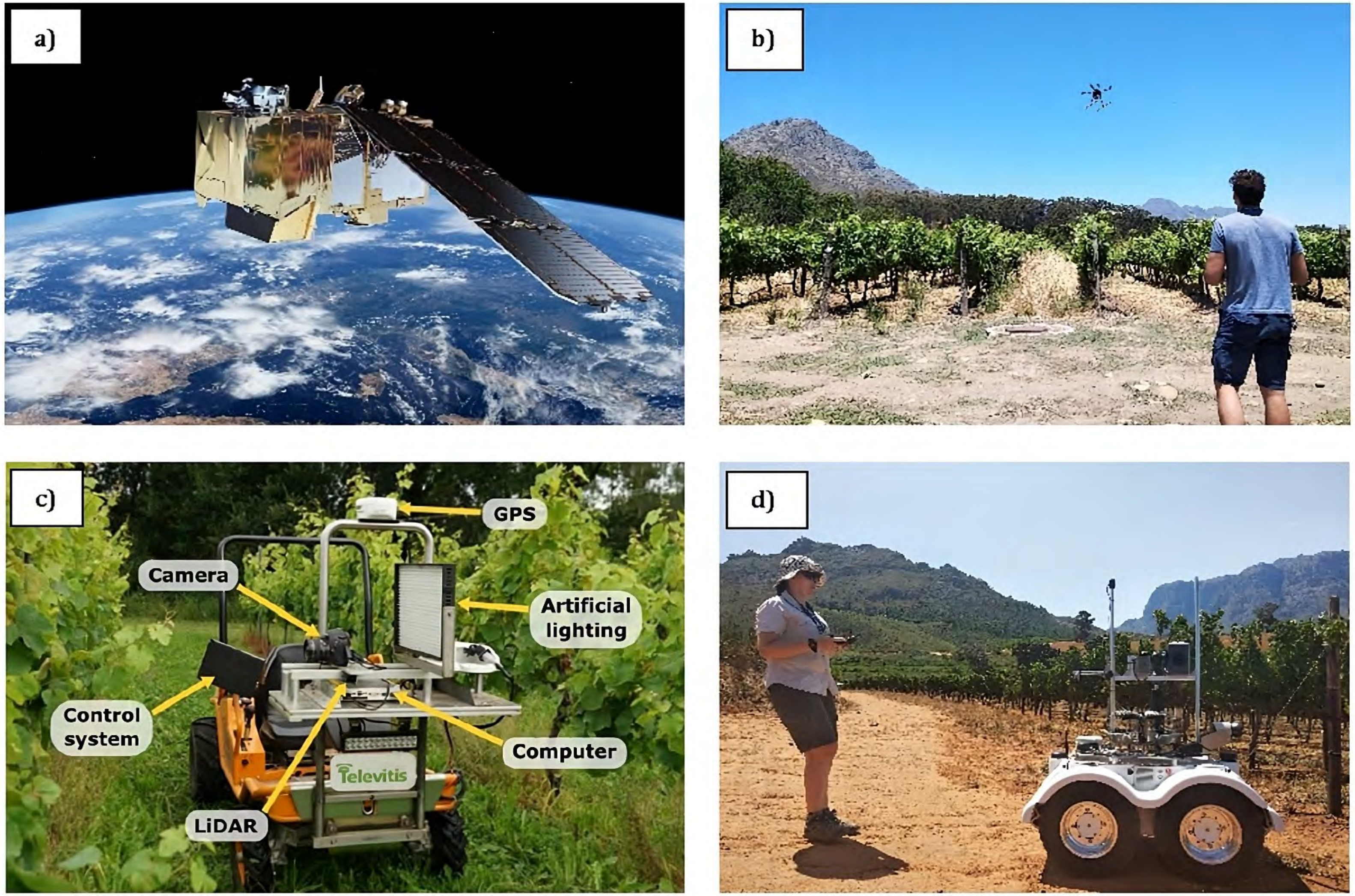
Data acquisition – Novel monitoring technologies

Non-invasive Sensing Technologies - Remote and Proximal sensing

- **RGB imaging (RGBi):** *Digital images captured by RGB cameras. These images replicate human vision, capturing light in red, green, and blue wavelengths (RGB) for accurate colour representation.*
- **Spectroscopy:** *Spectral reflectance data measured by spectrometers. VIS (400-750 nm) and NIR (750-2500 nm) spectral wavelengths are particularly important in viticulture since multiple processes are associated with these spectral signals.*
- **Multispectral imaging (MSI):** *While conventional spectroscopy usually records the response of a small 'spot' size to a continuous spectrum, MSI registers the radiation on an image with typically four or six narrow wavelengths (e.g., RGB and NIR).*
- **Hyperspectral imaging (HSI):** *The spectral resolution is the main characteristic that distinguishes HSI from MSI. HSI deals with narrower wavelengths over a continuous spectral range, thereby generating the spectra of all pixels of the object. Compared to MSI, the principal advantage of HSI is that, because an entire spectrum is recorded at each spatial position. Since HSI is a relatively new technique, the full potential of this technology has yet to be realised.*
- **Chlorophyll fluorescence:** *The principle underlying this technology is based on the various fates that light energy absorbed by Chl molecules in living plant tissues can follow.*
- **Infrared thermography (IRT):** *IRT is a technique which uses a camera to produce visible images showing the amount of infrared energy emitted by an object. This energy is converted to temperature to display an image of the temperature distribution of the targeted area.*
- **Electrical resistivity and conductivity:** *An EMI sensor allow depth-weighted average measurement of apparent soil electrical conductivity (ECa) by inducing an electrical current in the soil which is determined by the relative amounts and types of clay, salts, rock, and water in the soil.*
- **Laser imaging detection and ranging (LiDAR):** *LiDAR is a technology that measures the distance to a target by illuminating the target with pulsed laser beams and measuring the reflected pulses with a sensor. Differences in laser return times and wavelengths can then be used to make digital 3-D reconstructions of the target. LiDAR is sometimes called laser scanning or 3-D scanning and has terrestrial, airborne and mobile applications.*

Sensing platforms

- **Space-based platforms:** The traditional remote sensing approach used in agriculture is based on **satellite platforms**. There are numerous types of satellite platforms which vary according to the type of sensors, spatial resolution, revisited frequency, spectral resolution, radiometric resolution, and accessibility of the images (freely available versus paid images). All these characteristics define the potential applications of each type of satellite imagery.
- **Air-based platforms:** Aircraft operating at altitudes between 600 and 1,700 m. In more recent times, **UAVs or drones** have been used to acquire data, as well as conduct other tasks in vineyards. UAVs offer a useful alternative to satellites and aircraft in relation to flight availability and image resolution. The spatial resolution (i.e., pixel size) that can be provided by a light aircraft typically ranges from 0.1 to 0.5 m/pixel. For UAVs, ultra-high resolutions of up to 0.01 m/pixel can be achieved. A variety of UAV platforms are available, and they differ with respect to their size, shape, configuration, and flight characteristics. UAVs offer the opportunity to acquire imagery at ultra-high resolutions in near real-time, but flying permits are often required and regulations have to be followed.
- **Ground-based platforms:** Portable sensors, especially those which are GPS-enabled, have the advantage of being able to acquire geo-referenced data across large sample areas. Proximal sensors can be embedded into robots or attached to agricultural machinery such as ATVs, tractors, harvesters, and sprayers for on-the-go data acquisition. Sensors can be used for controlling machine guidance, while other sensors can be used for a range of vineyard monitoring tasks such as measuring yield during harvest operations or taking plant-based measures while they are travelling along each row of the vineyard completing other tasks.
- **Robots:** Robots are emerging ground-based platforms with great potential to change all forms of agricultural production systems, including viticulture. Autonomous robots use laser scanner technology for automation of navigation and as a safety feature. There are numerous projects in this domain and several companies and research institutions are developing robots for monitoring vineyards (e.g., VineRobot, VineScout, Dassie robot, VinBot and Phenobot).



Sensing platforms

Figure 2. Examples of sensing platforms:

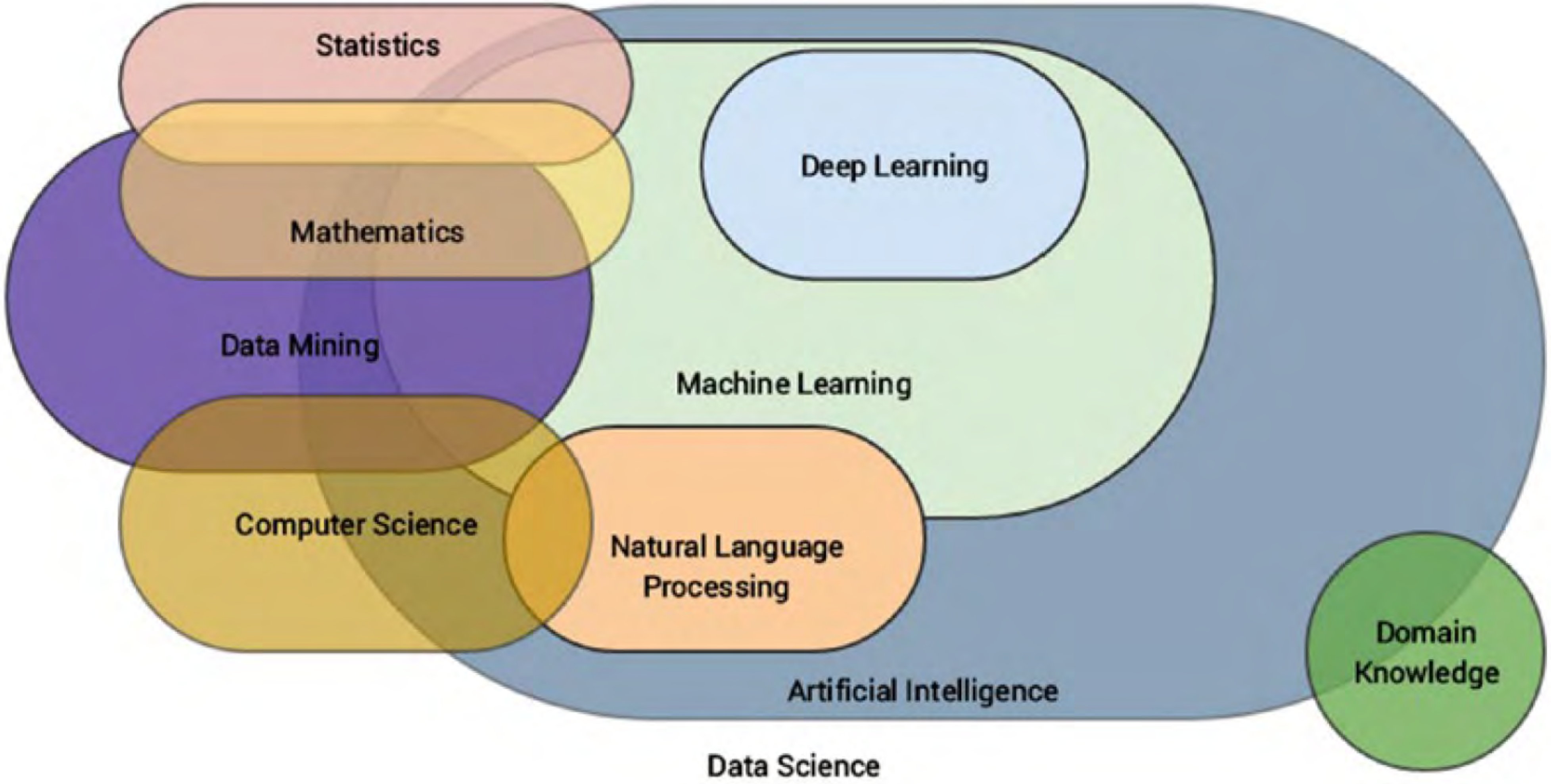
(a) Satellite (Sentinel 2);
(b) Drone;
(c) (Ground-based platform (Televitis mobile lab) and
(d) Robotic platform (Dassie robot).

Poblete Echeverria and Tardáguila (2023)

Data analysis – Processing

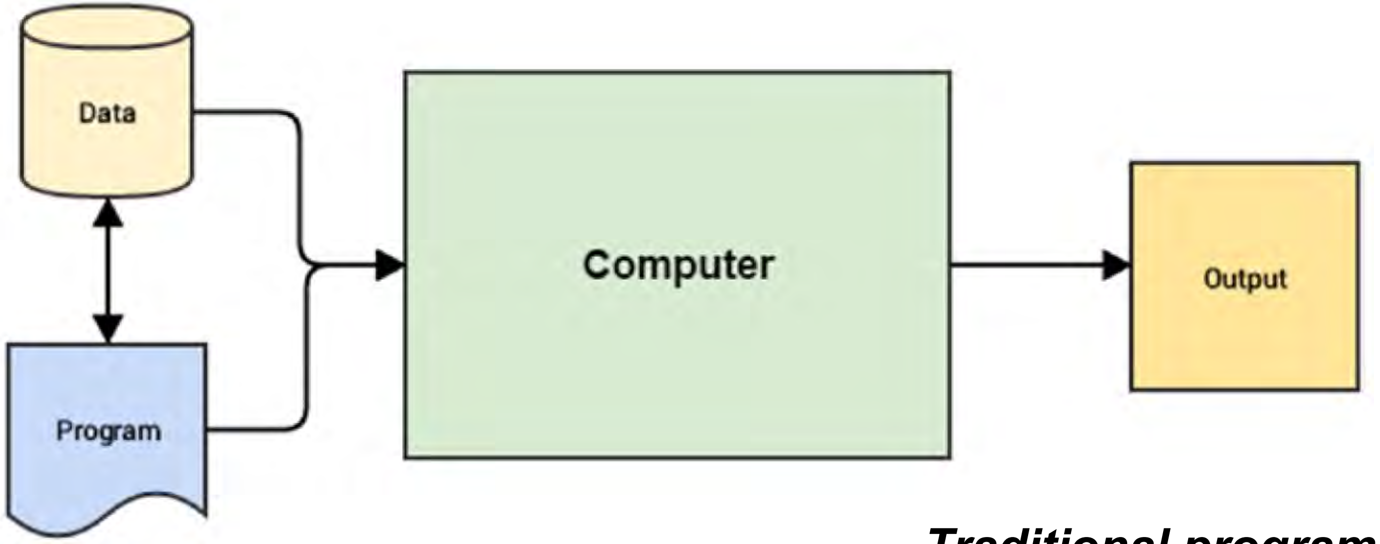
Data analysis – Processing

Machine Learning: a true multi-disciplinary field

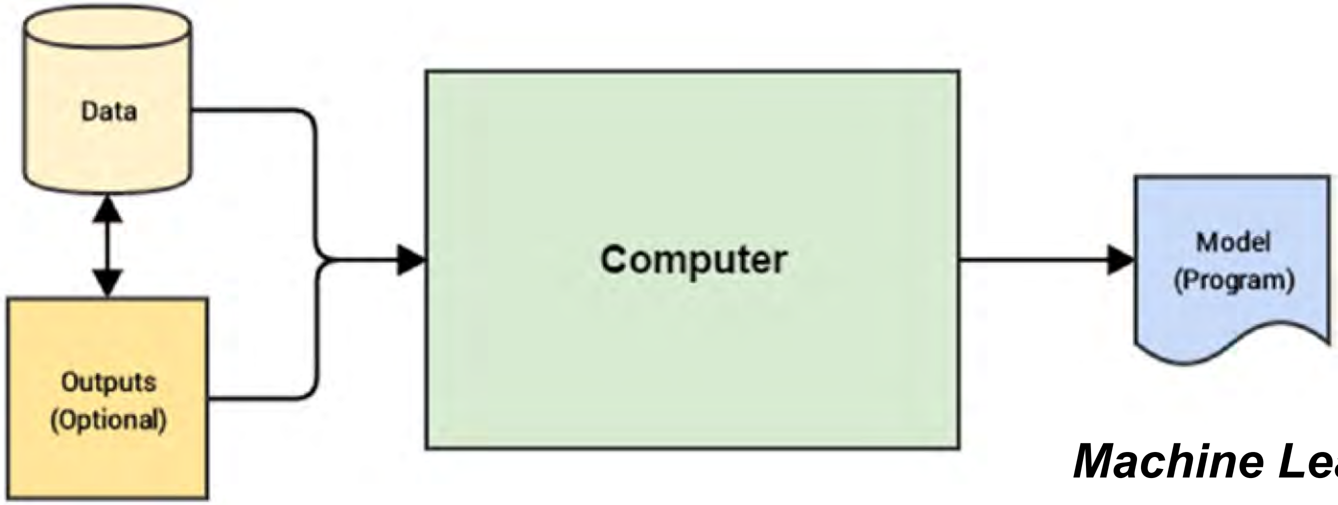


Sarkar et al., (2018)

Data analysis – Processing



Traditional programming paradigm



Machine Learning paradigm

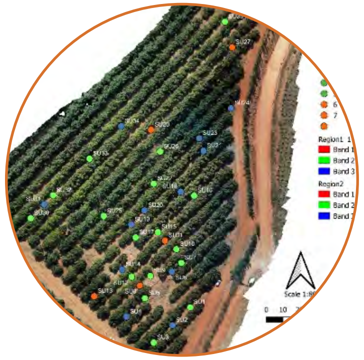
Sarkar et al., (2018)

Digital agriculture – Smart applications

Digital agriculture – Smart applications

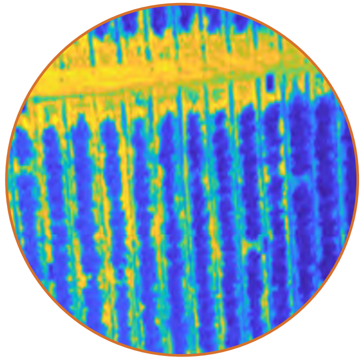
A. Fruit quality

B. Canopy assessment



C. Pest and disease and monitoring

D. Yield estimation



E. Water requirements and stress monitoring

A. Fruit quality

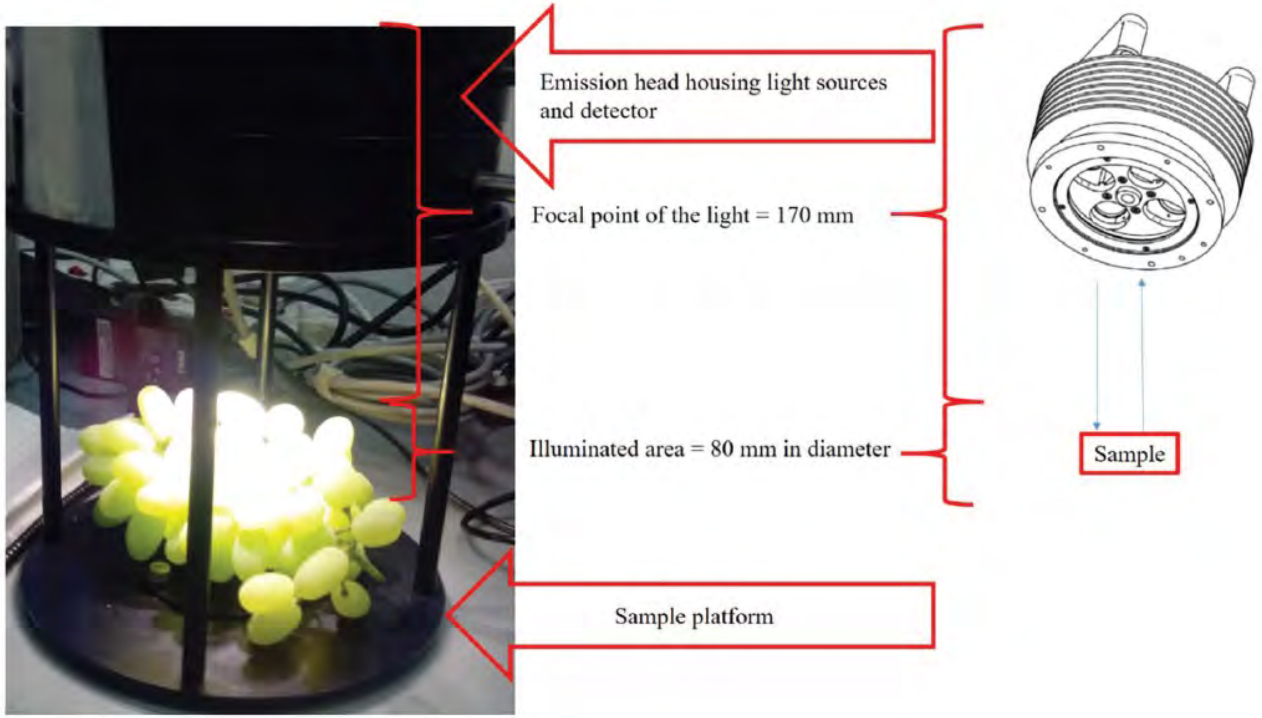


Figure 3. Contactless scanning of an intact 'Thompson Seedless' table grape bunch with the MATRIX-F NIR spectrometer (adapted from Daniels et al., 2019).

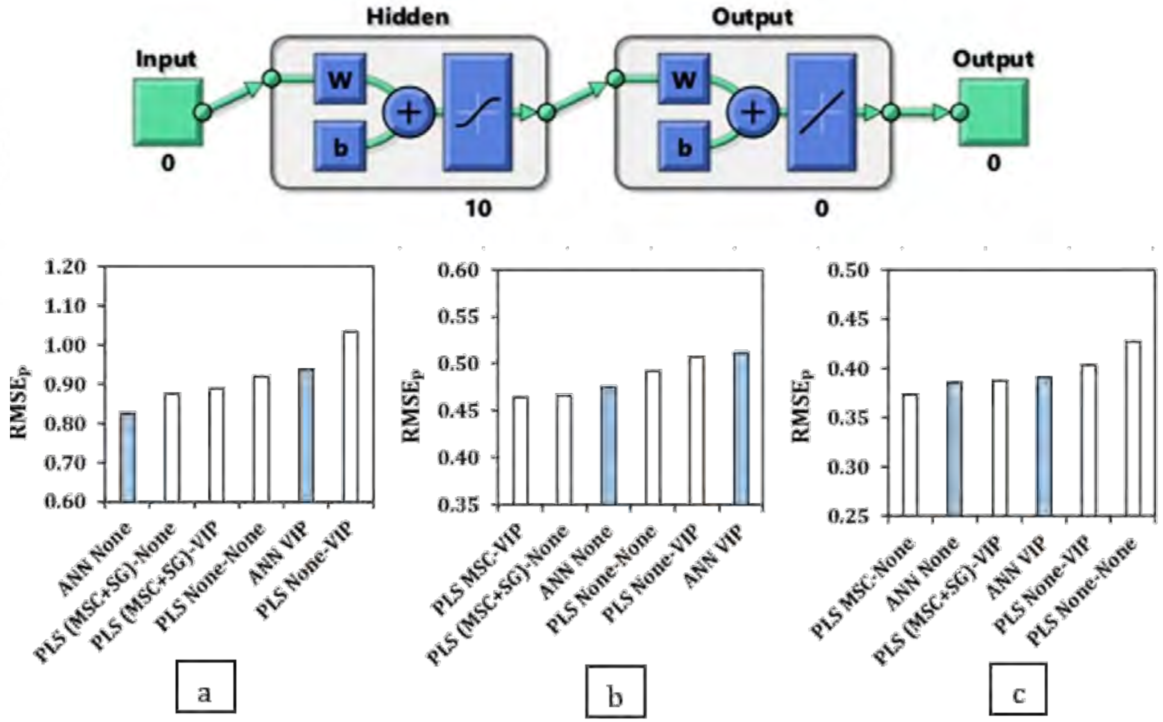
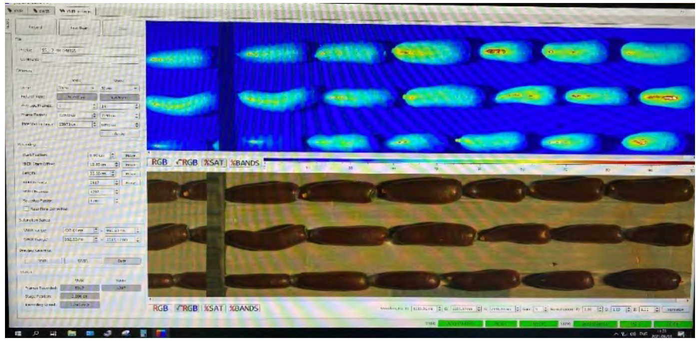
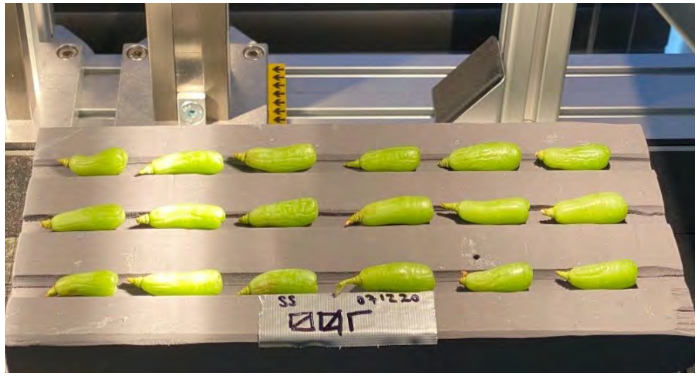


Figure 4. The prediction errors (RMSEP) that were achieved for TSS (a), TA (b) and the TSS/TA ratio (c) for ANN and PLS regression using the different spectral pre-processing methods. Light blue bars indicated the ANN models (adapted from Poblete-Echeverria et al., 2020).

A. Fruit quality

Non-destructive approach





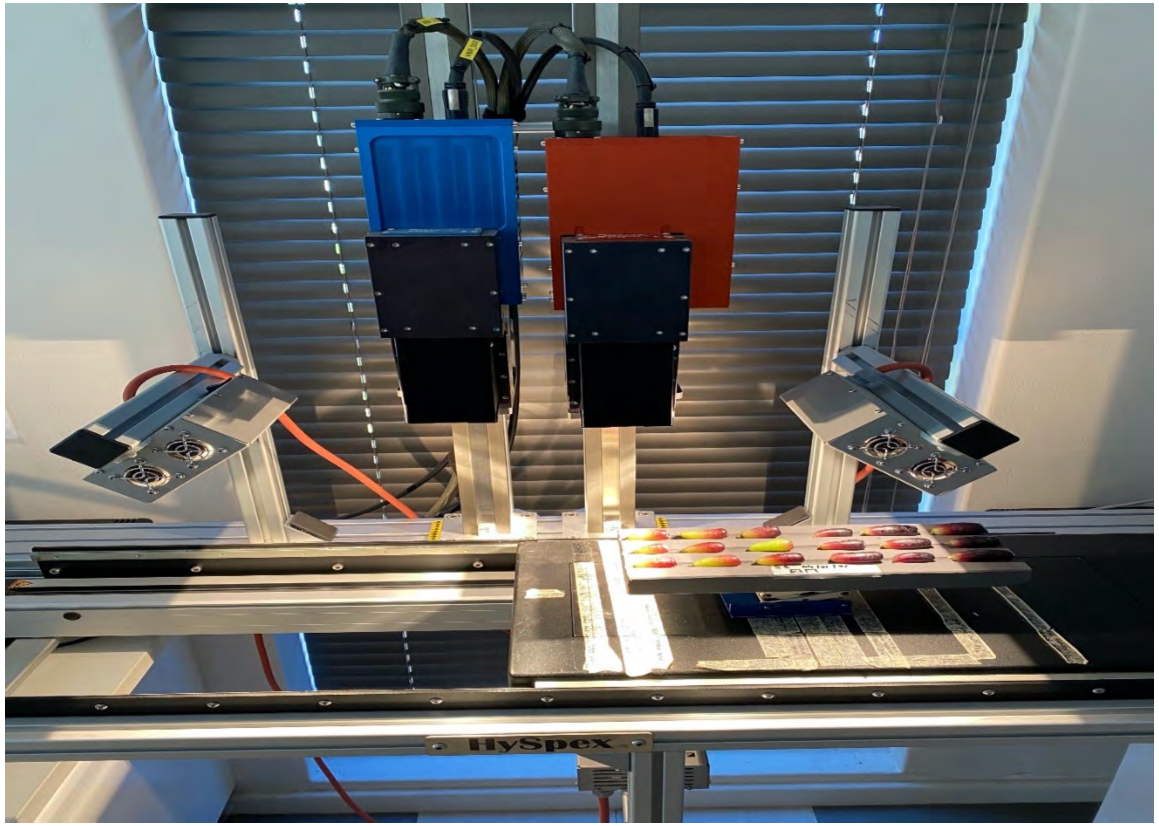


Figure 5. Example HSI and MSI collection process. SATI project "Physical and chemical bunch characterization of table grapes using machine vision".

SATI
South African Table Grape Industry

B. Canopy assessment

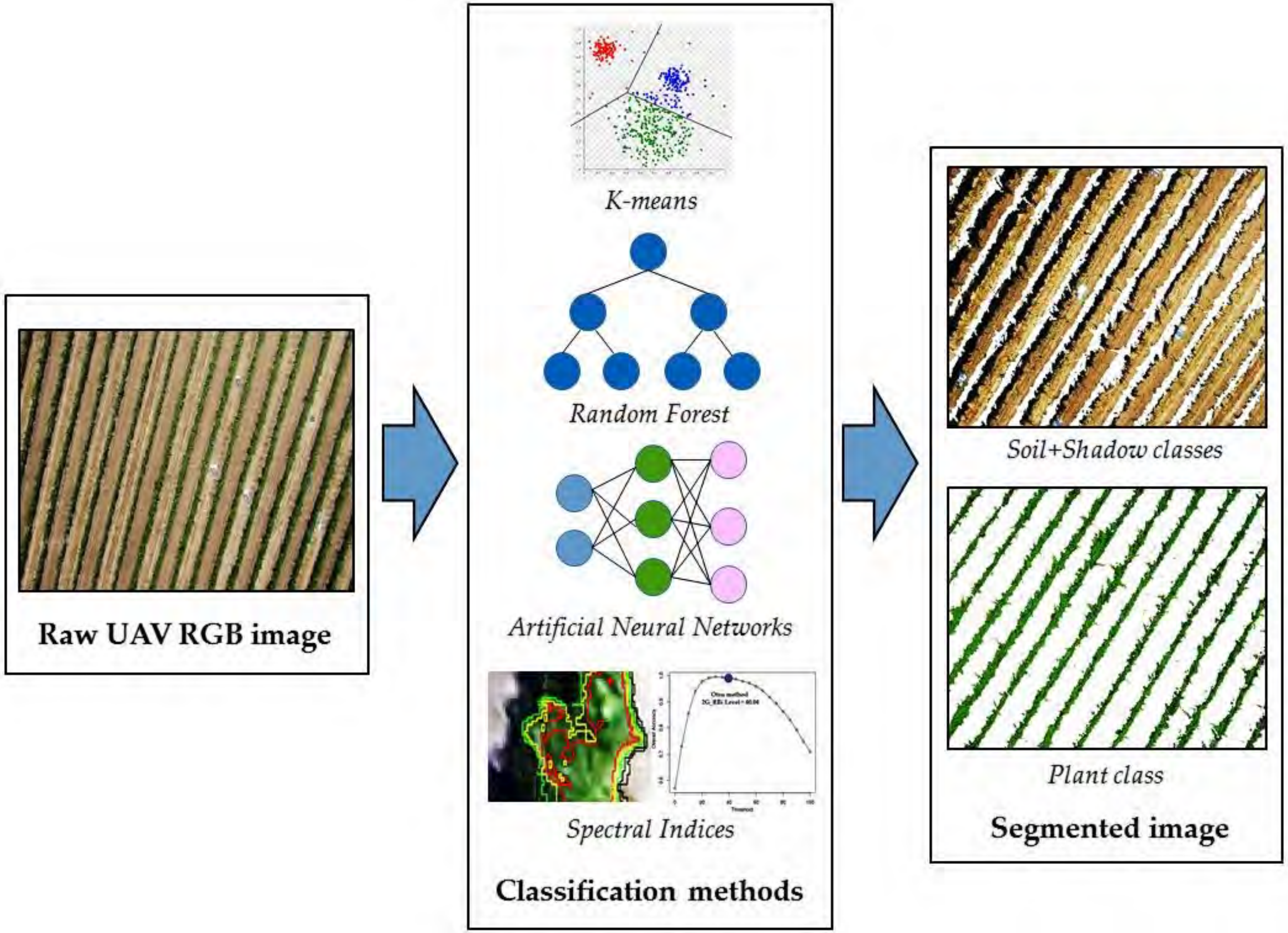
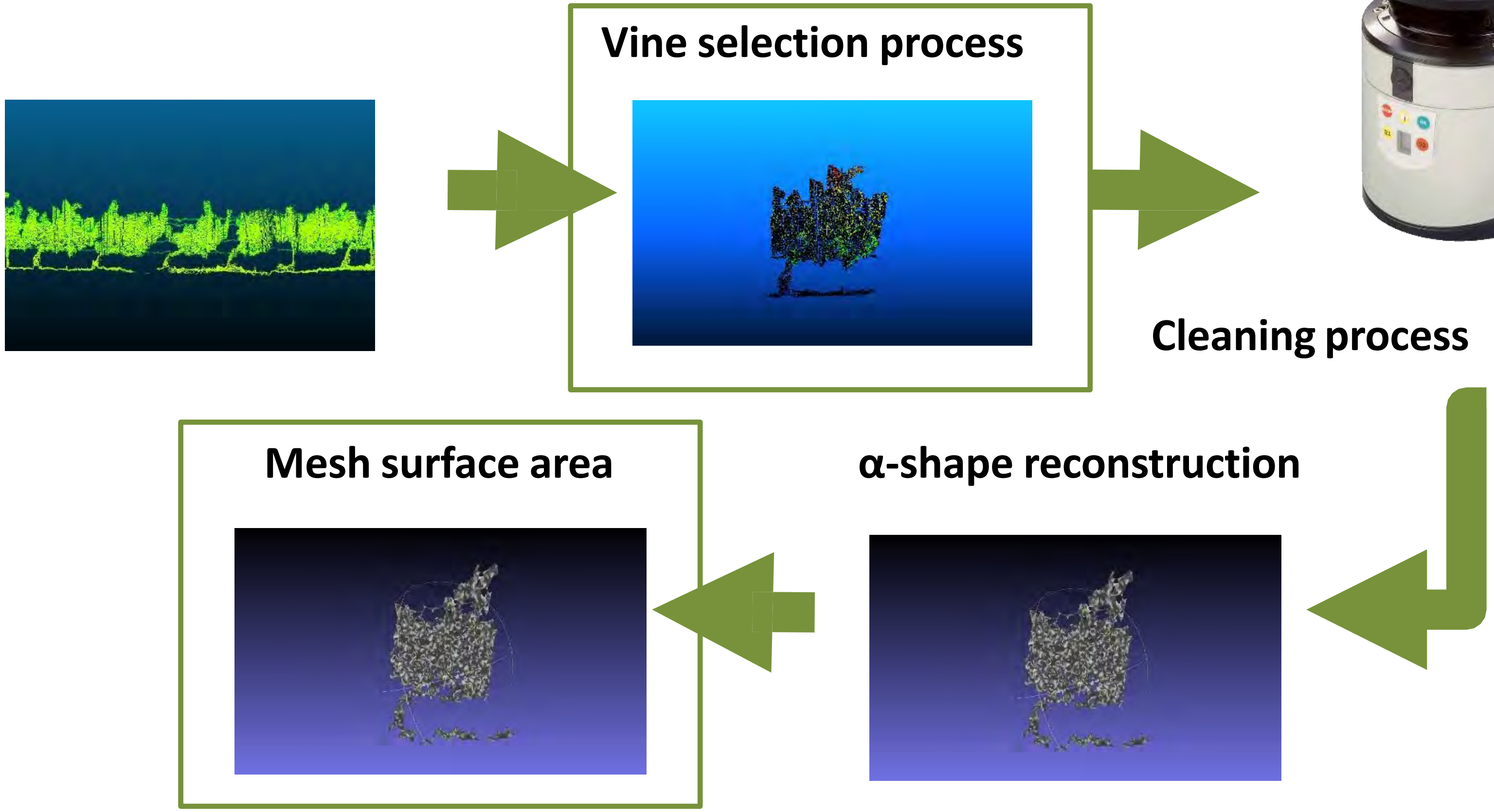


Figure 6. Canopy segmentation using different classification methods (K-means, Random forest, ANNs and spectral indices)

Poblete-Echeverria et al. (2020).

B. Canopy assessment

Mesh surface area (MSA)



- LiDAR measurements
- RTK GPS
- Canopy temperature
- Multispectral images

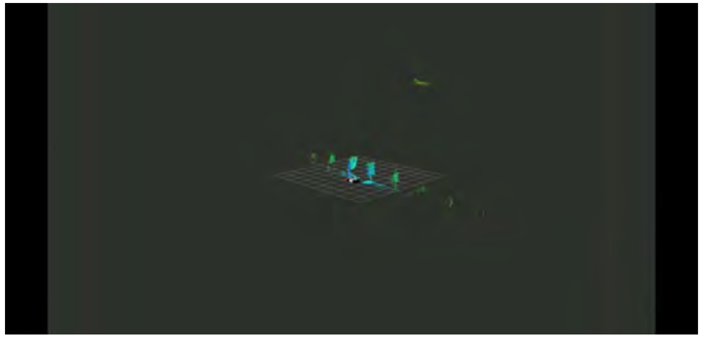
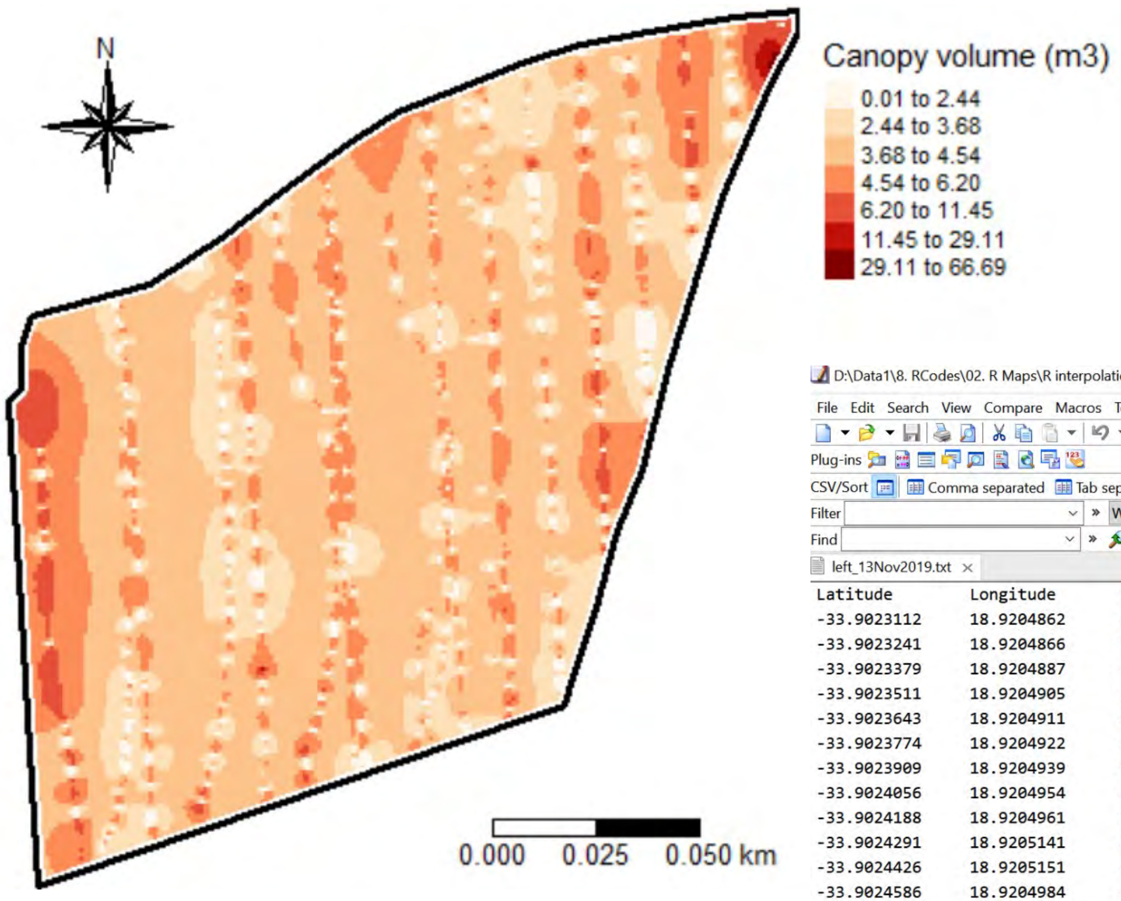
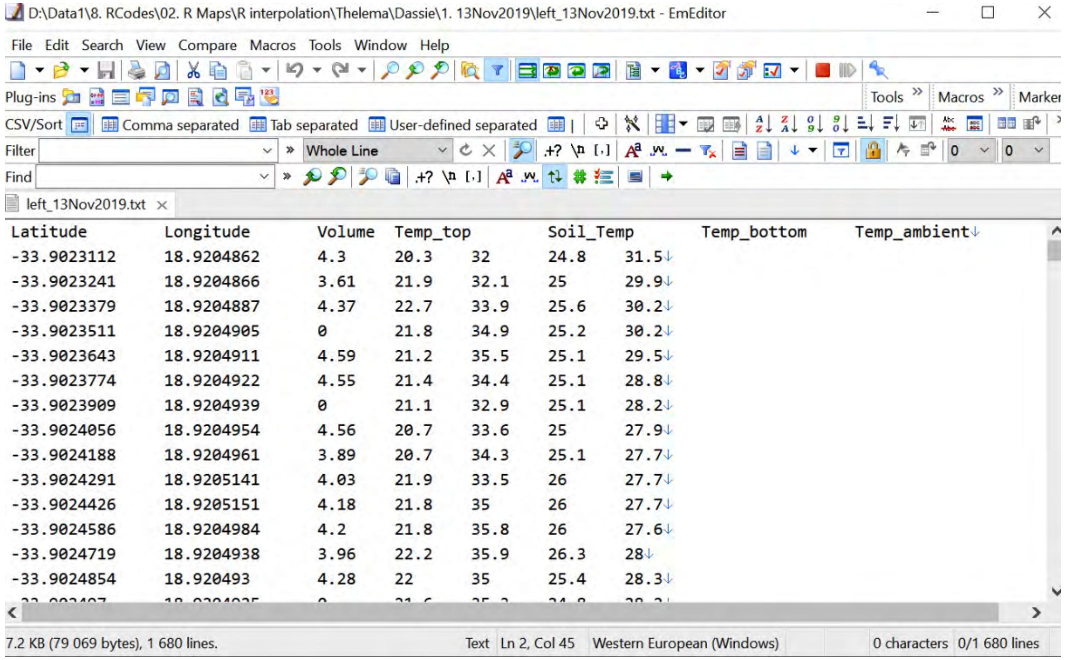


Figure 7. 3d LiDAR point cloud for canopy assessment. Adapted from Poblete-Echeverria et al. (2020).

B. Canopy assessment





Latitude	Longitude	Volume	Temp_top	Soil_Temp	Temp_bottom	Temp_ambient
-33.9023112	18.9204862	4.3	20.3	32	24.8	31.5
-33.9023241	18.9204866	3.61	21.9	32.1	25	29.9
-33.9023379	18.9204887	4.37	22.7	33.9	25.6	30.2
-33.9023511	18.9204905	0	21.8	34.9	25.2	30.2
-33.9023643	18.9204911	4.59	21.2	35.5	25.1	29.5
-33.9023774	18.9204922	4.55	21.4	34.4	25.1	28.8
-33.9023909	18.9204939	0	21.1	32.9	25.1	28.2
-33.9024056	18.9204954	4.56	20.7	33.6	25	27.9
-33.9024188	18.9204961	3.89	20.7	34.3	25.1	27.7
-33.9024291	18.9205141	4.03	21.9	33.5	26	27.7
-33.9024426	18.9205151	4.18	21.8	35	26	27.7
-33.9024586	18.9204984	4.2	21.8	35.8	26	27.6
-33.9024719	18.9204938	3.96	22.2	35.9	26.3	28
-33.9024854	18.920493	4.28	22	35	25.4	28.3

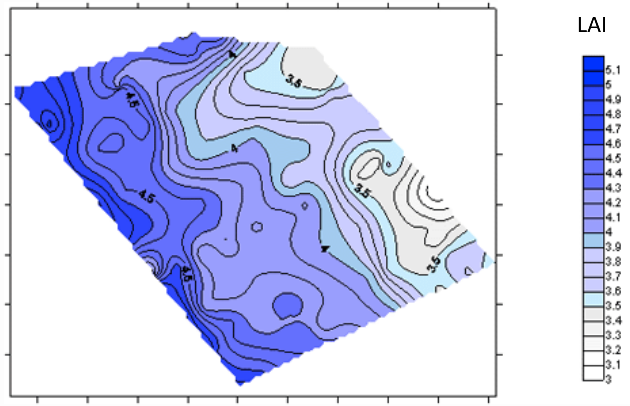
Figure 8. Example of canopy volume map.

B. Canopy assessment

Estimate canopy vigor using cover photography

Example of an upward-looking image obtained by the App

Data gathered can be sent as a csv file and mapped to assess spatial variability of vigor within a field



http://www.irrigateway.net/tools/du/

App developed to analyze cover photography of canopies and outputs stored.

B. Canopy assessment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Sensors **2015**, *15*(2), 2860-2872; doi:10.3390/s150202860

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Article

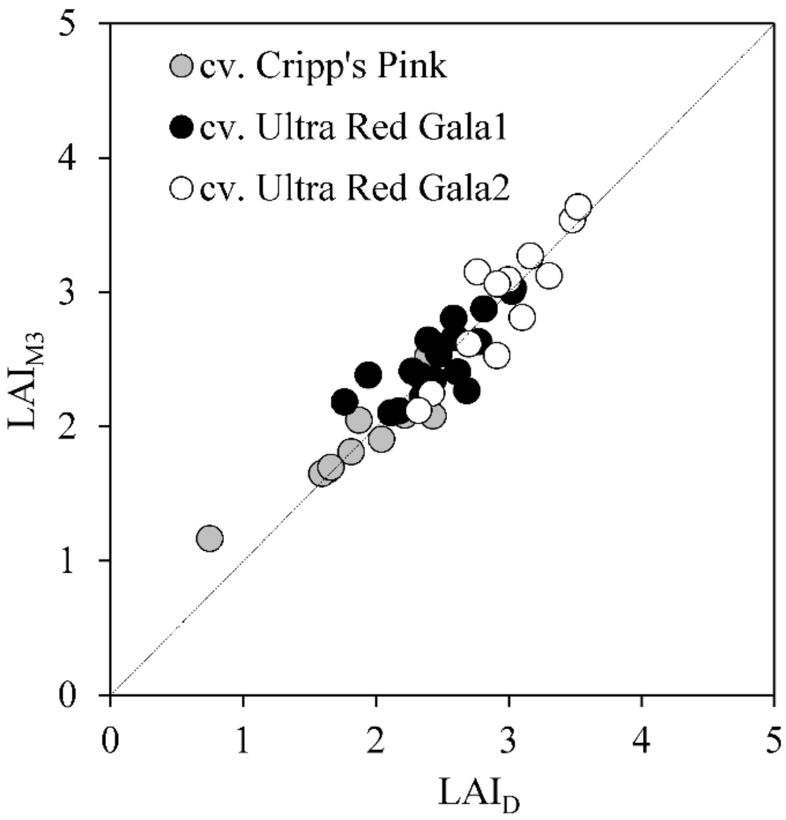
Digital Cover Photography for Estimating Leaf Area Index (LAI) in Apple Trees Using a Variable Light Extinction Coefficient

Carlos Poblete-Echeverria [1,*], Sigfredo Fuentes [2], Samuel Ortega-Farias [1], Jaime Gonzalez-Talice [3] and Jose Antonio Yuri [3]

+ Authors' affiliations

Received: 7 August 2014 / Accepted: 10 December 2014 / Published: 28 January 2015

(This article belongs to the Special Issue Agriculture and Forestry: Sensors, Technologies and Procedures)



Poblete Echeverria et al., (2015)

C. Pest and disease and monitoring

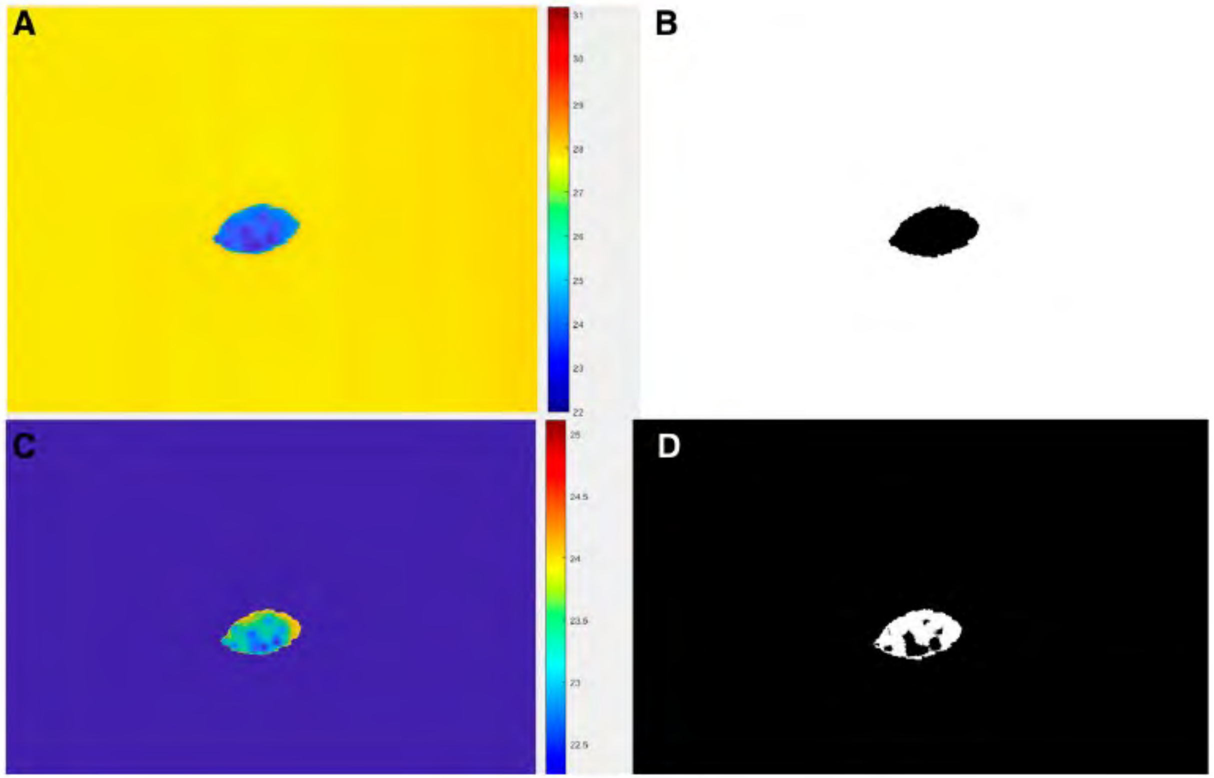


Figure 9. Illustration of the two-step process used for isolating apple leaf background from Venturia inaequalis infections sites during the thermographic infrared image analysis process.

Rebel et al. (2022)

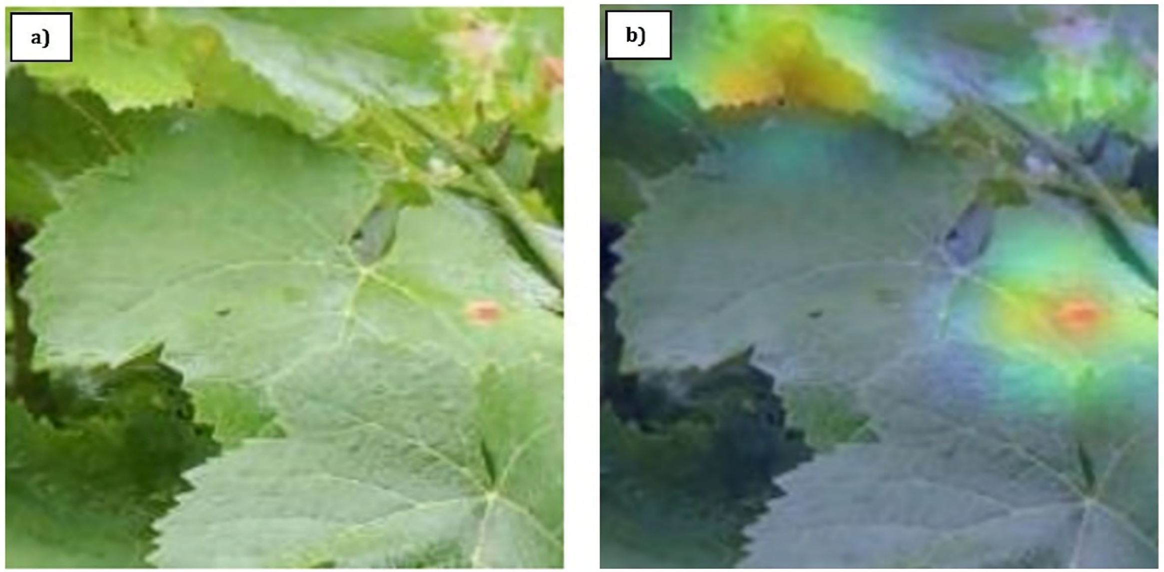


Figure 10. Automatic disease detection using artificial intelligence: Comparison between (a) RGB images and (b) proceeded images with the automatic detection of the downy mildew symptoms (AI algorithm) in grapevine leaves.

Adapted from Hernandez et al. (2023)

C. Pest and disease and monitoring

Sensing technique	Category	Distance to the target/resolution	Acquisition mode
Infrared thermography	Proximal	3 m and 0.5 m	Manual
RGB (Red, Green, Blue)	Proximal	3 m	Manual
NGB (NIR, Green, Blue)	Proximal	3 m	Manual
RGB (Red, Green, Blue)	Remote	60 m	Drone
Multispectral (MSI)	Remote	60 m	Drone
Multispectral (MSI)	Remote	Various resolutions will be tested	Satellite
Hyperspectral imaging (HSI)	Proximal	30 cm	Lab. conditions

Figure 11. SAAGA project: Study of Remote Sensing Techniques for mapping the severity of Phytophthora Root Rot (PRR) Disease in Avocado Orchards. Poblete Echeverria and McLeod (2021)

D. Yield estimation

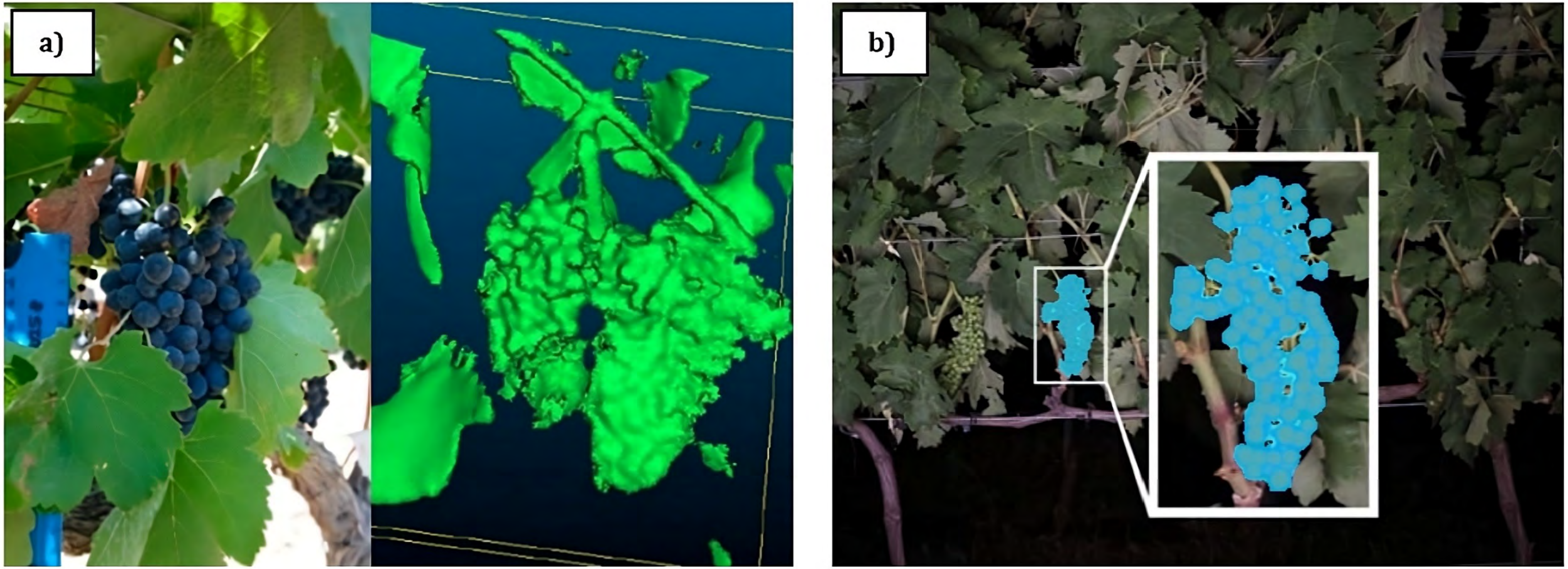


Figure 12. Yield components assessment: (a) Example of using 3-D proximal sensing bunch reconstruction Adapted from Hacking et al. (2019); (b) Example of inflorescence segmentation. Adapted from Palacios et al. (2020).

D. Yield forecast

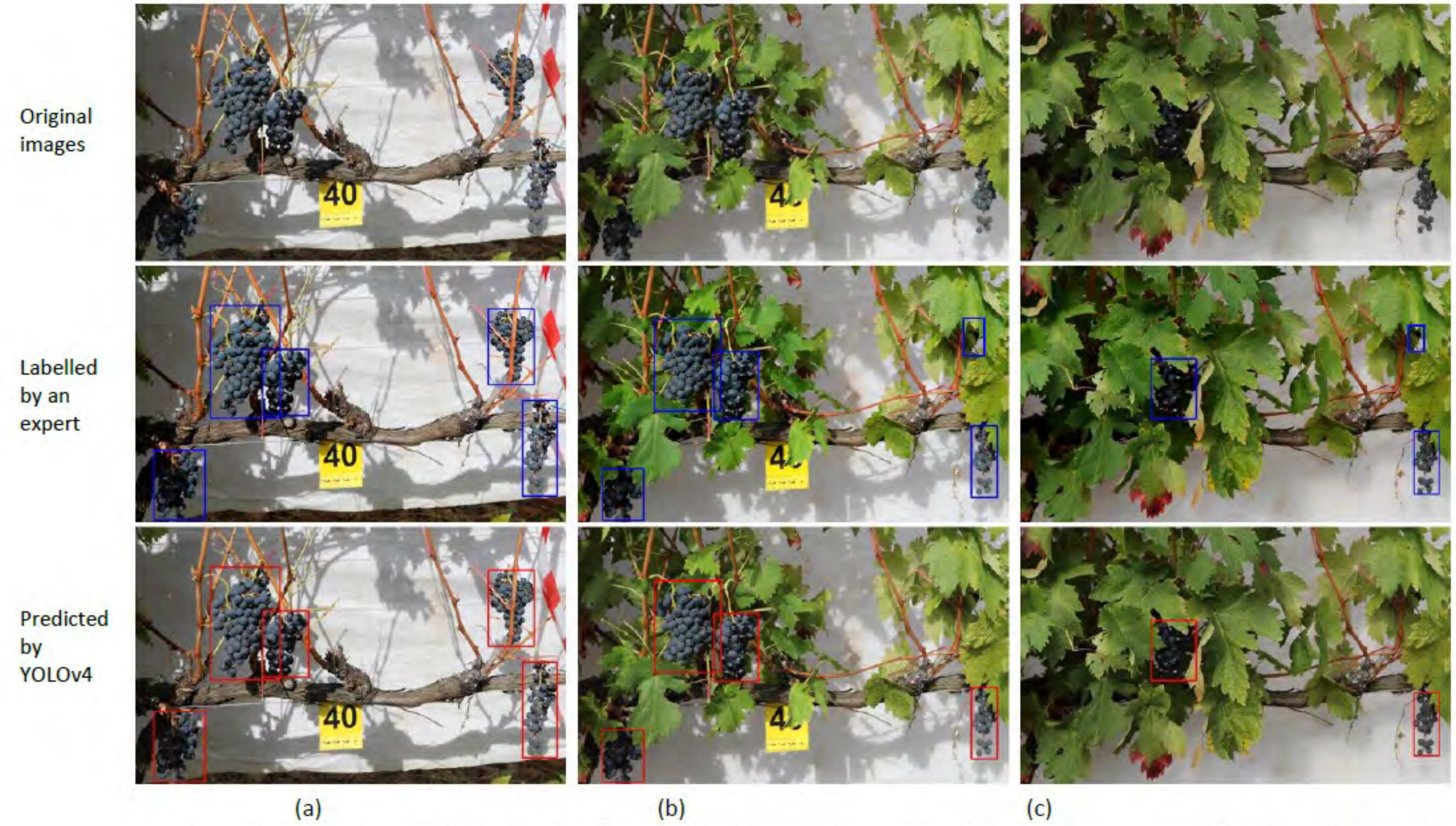
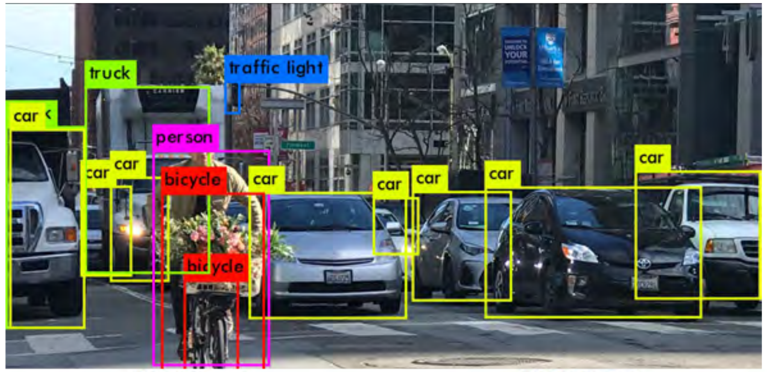
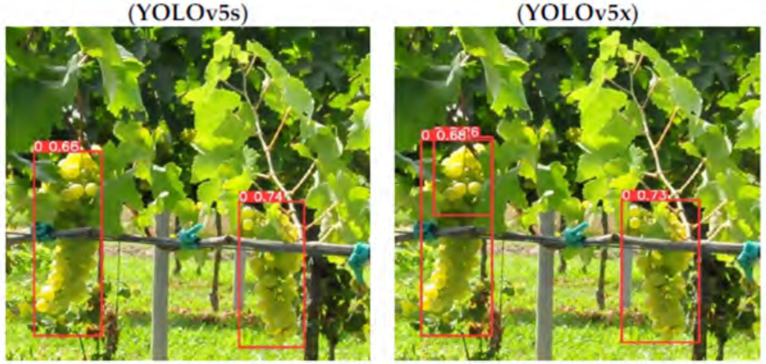


Figure 14. Comparison of the number of visible bunches in an original image, detected and labelled by an expert (blue bounding boxes) and predicted bunches using YOLOv4 (red bounding boxes) in full defoliation (a), partial defoliation (b) and no defoliation (c).

Artificial intelligence

YOLO "You Only Look Once"





Iñiguez et al. (2024) Submitted

E. Water requirements and stress monitoring

Anais XVI Simpósio Brasileiro de Sensoriamento Remoto - SBSR, Foz do Iguaçu, PR, Brasil, 13 a 18 de abril de 2013, INPE

Estimación de la evapotranspiración de un huerto de manzanos mediante el modelo de coeficiente dual FAO-56 asistido por imágenes satelitales

Carlos Poblete-Echeverria[1] Magali Odi[1], Samuel Ortega-Farias[1]

[1] Centro de Investigación y Transferencia en Riego y Agroclimatología (CITRA) Universidad de Talca, Chile.
cpoblete@utalca.cl

remote sensing

MDPI

Article

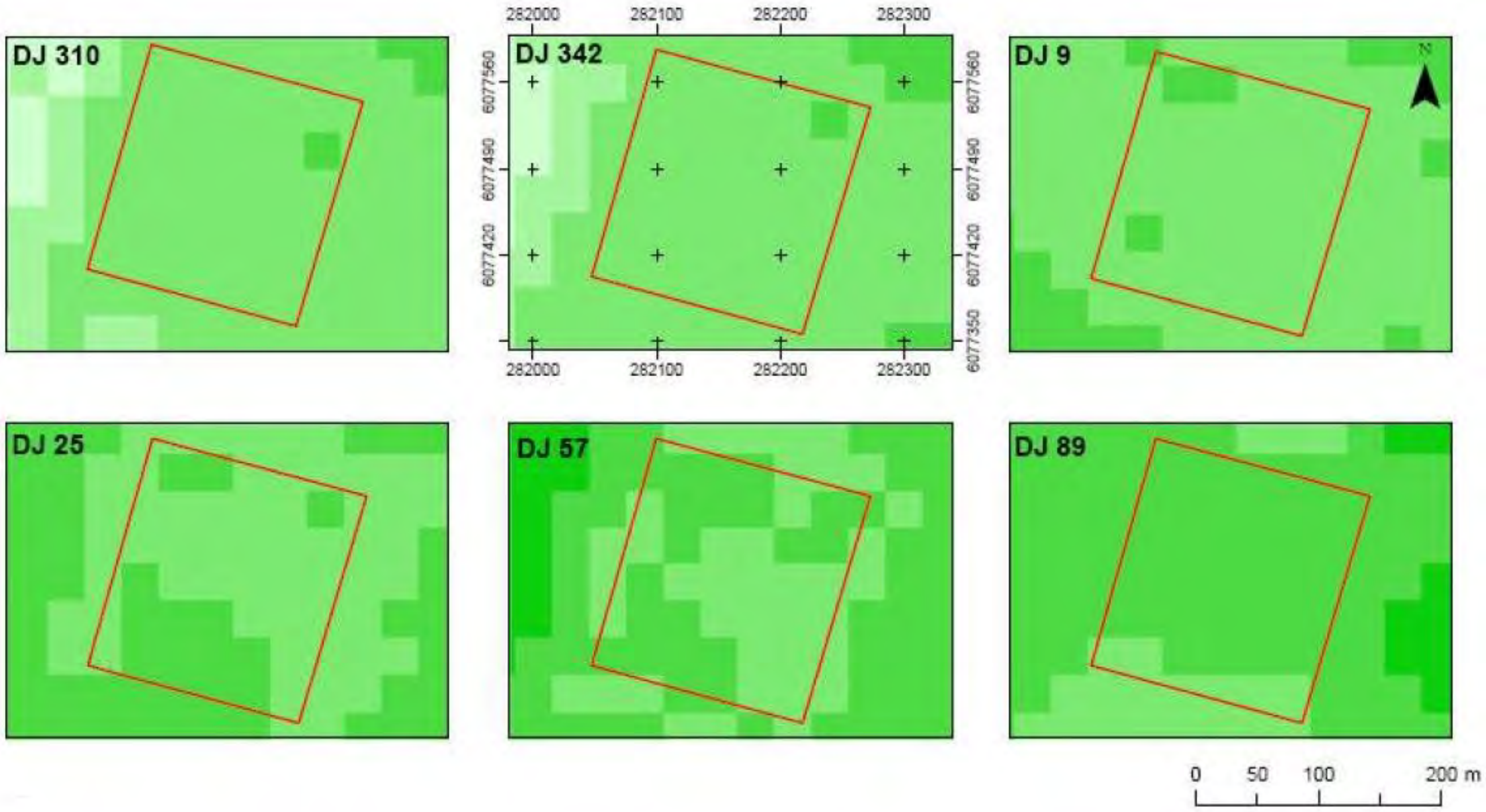
Estimating Evapotranspiration of an Apple Orchard Using a Remote Sensing-Based Soil Water Balance

Magali Odi-Lara [1,*], Isidro Campos [2], Christopher M. U. Neale [2], Samuel Ortega-Farías [1,*], Carlos Poblete-Echeverría [3], Claudio Balbontín [4] and Alfonso Calera [5]

Palabras clave: Teledetección, Landsat 7 ETM+, Sistema de flujos turbulentos, coeficiente dual.

Odi-Lara et al. (2016)

Estimation of ET in an apple orchard using dual crop coefficient approach of FAO assisted by satellite images



Poblete-Echeverria et al. (2013)

E. Water requirements and stress monitoring

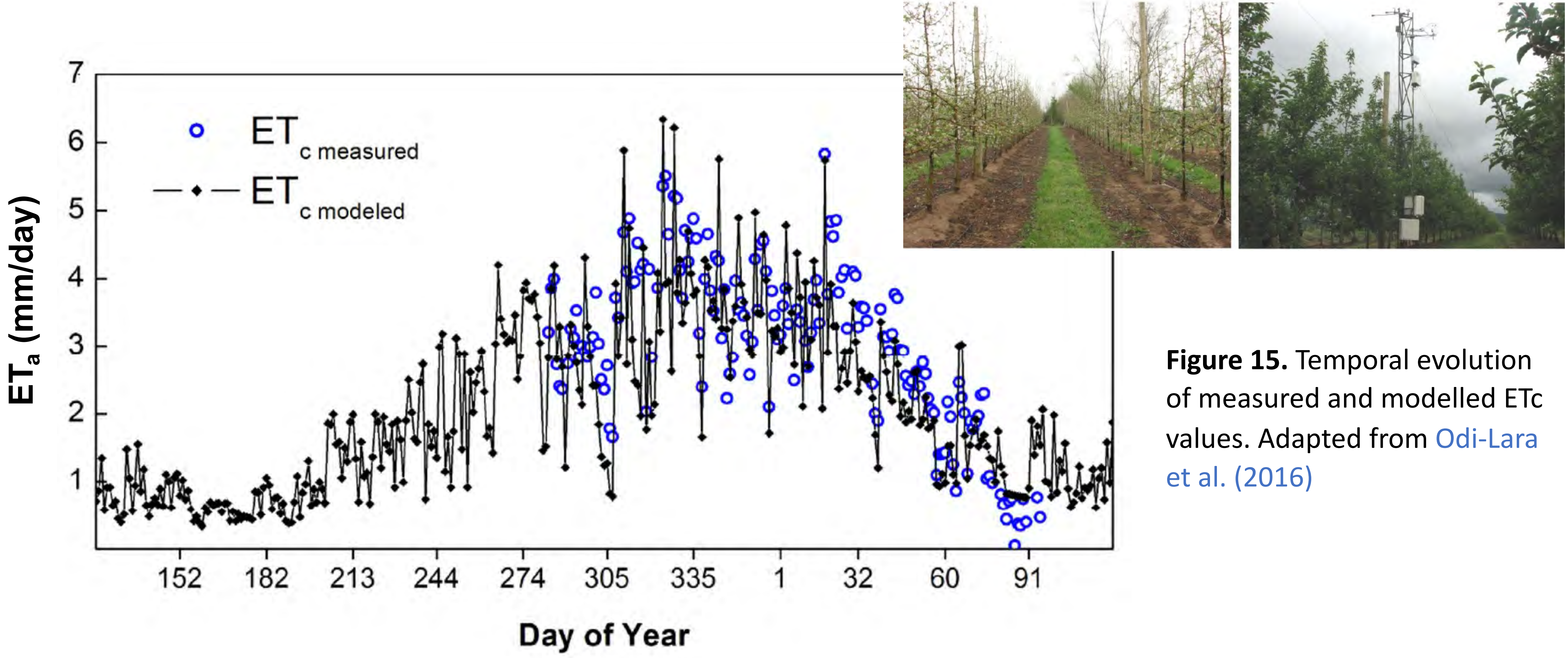


Figure 15. Temporal evolution of measured and modelled ETc values. Adapted from Odi-Lara et al. (2016)

E. Water requirements and stress monitoring

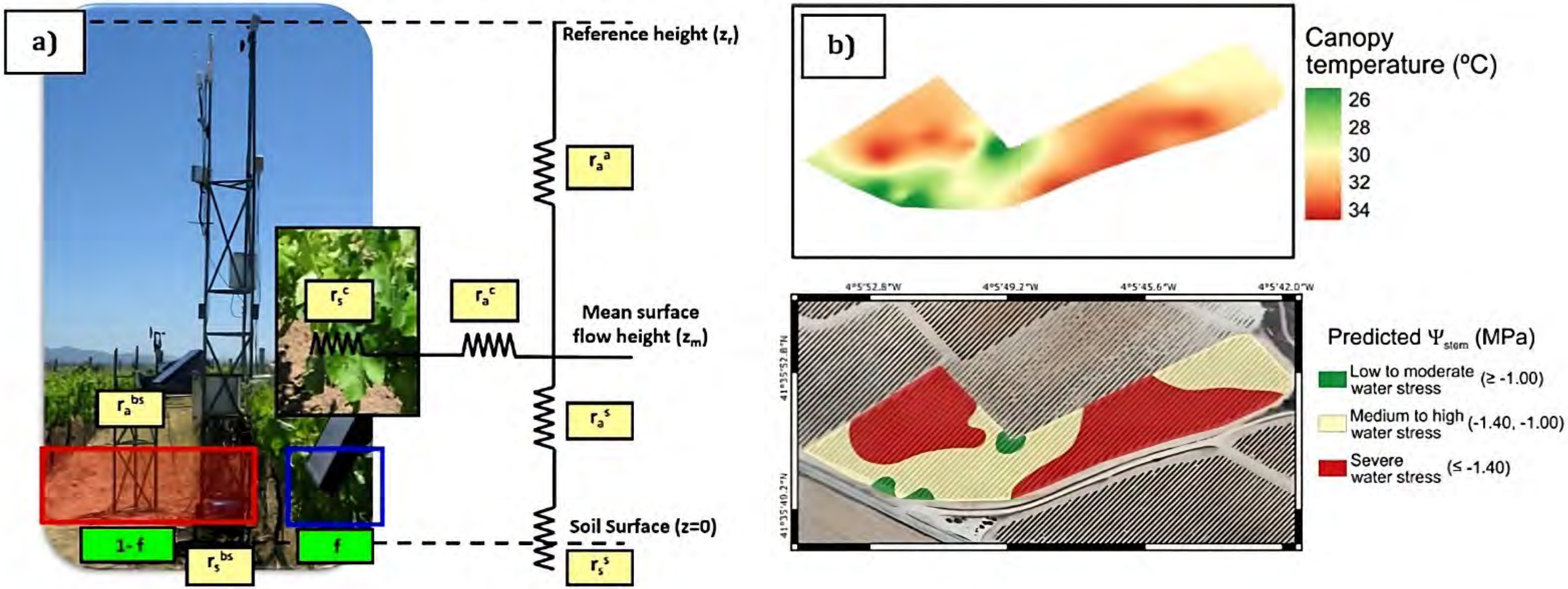


Figure 16. (a) Representation of a model for estimating evapotranspiration in vineyards. Adapted from Poblete-Echeverria and Ortega-Farias (2009); (b) Canopy temperature used for predicted stem water potential. Adapted from Gutierrez et al. (2021).

E. Water requirements and stress monitoring

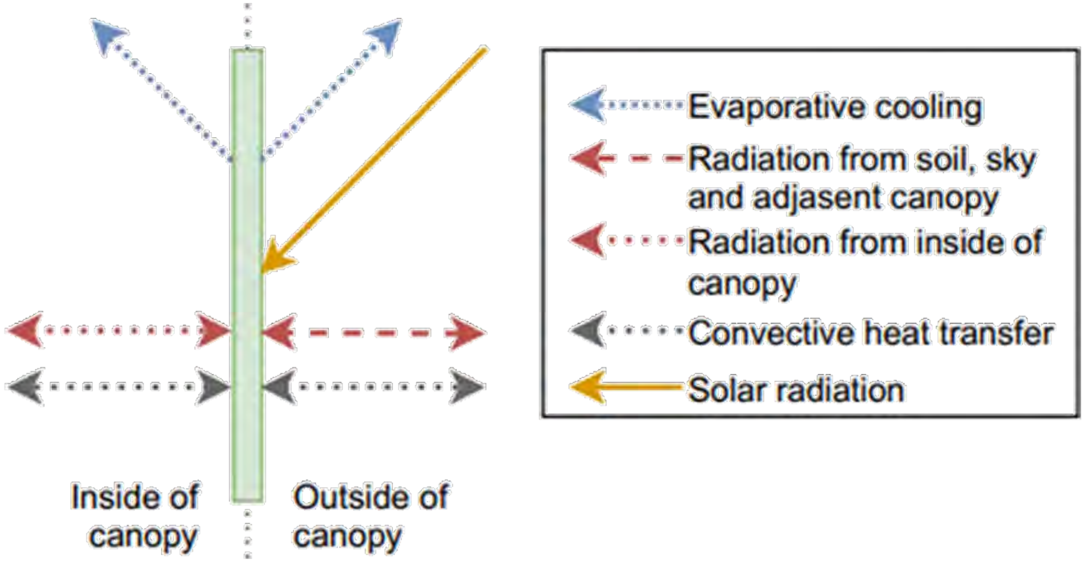


Fig. 17. Schematic of heat transfer components.

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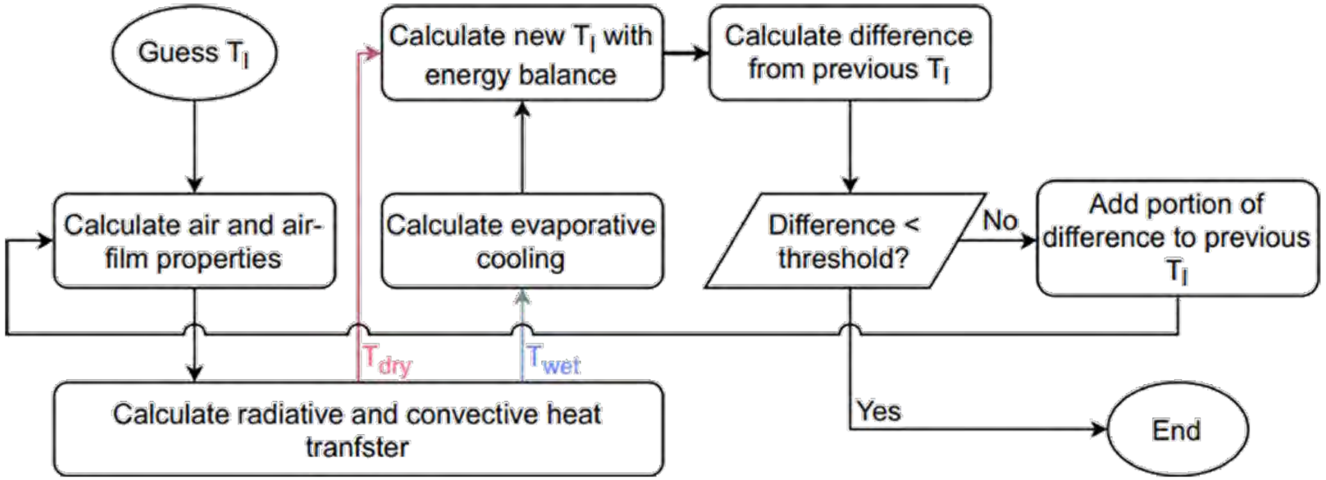
journal homepage: www.elsevier.com/locate/compag

Automating reference temperature measurements for crop water stress index calculations: A case study on grapevines

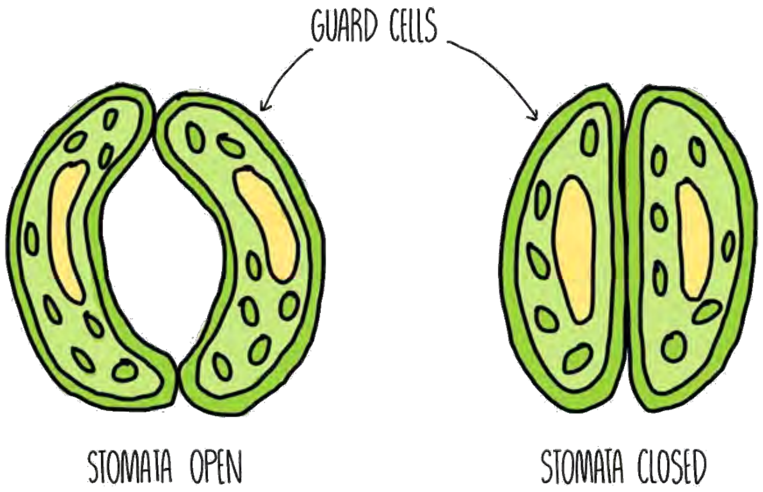
Jaco Luus[a], Danie Els[a], Carlos Poblete-Echeverría[b,*]

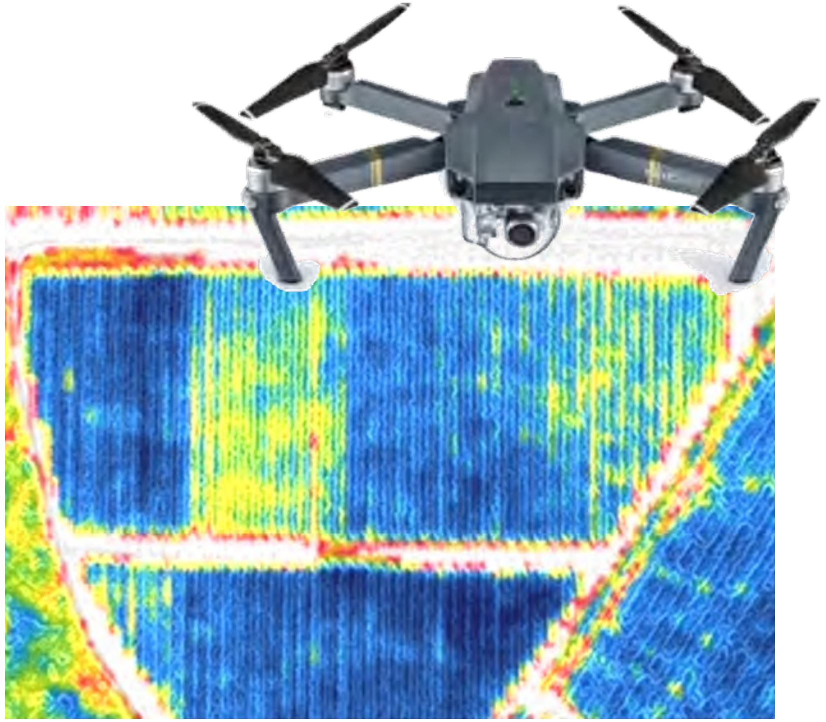
[a] Department of Mechanical and Mechatronic Engineering, Stellenbosch University, Stellenbosch, South Africa
[b] Department of Viticulture and Oenology, South African Grape and Wine Research Institute (SAGWRI), Faculty of AgriSciences, Stellenbosch University, Stellenbosch, South Africa



Luus et al. (2022)

E. Water requirements and stress monitoring





Water Stress

Stomatal closure

Leaf temperature increase

Digital agriculture – Smart applications

Stellenbosch University Iyunivesithi Universiteit
SAGWRI South African Grape and Wine Research Institute

A study of the use of drone-based imagery for mapping water stress in a commercial apple orchard

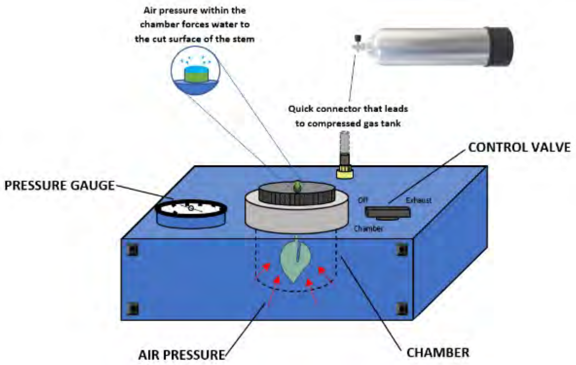
MSc Thesis – Karin Clüver (Feb 2024)

Field experiments

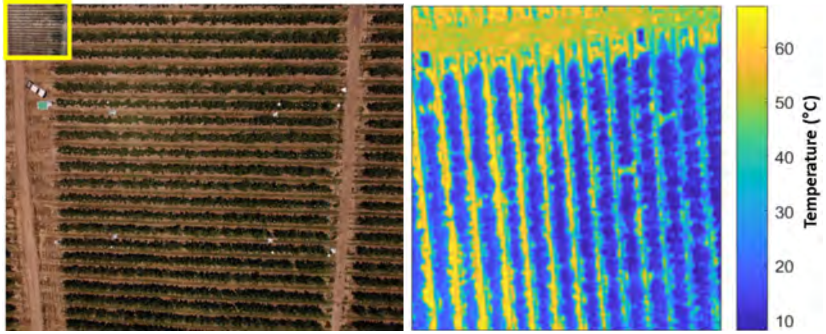
2 seasons

Reference measures

- Stem water potential
- Stomata conductance
- Soil moisture
- Soil analysis



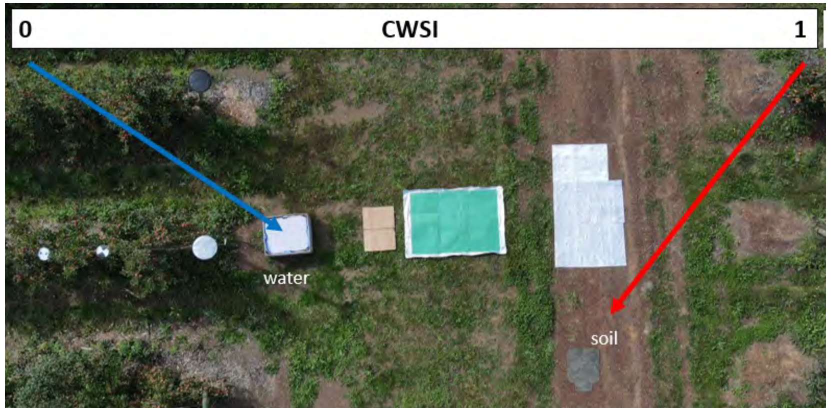
New methods of data analysis

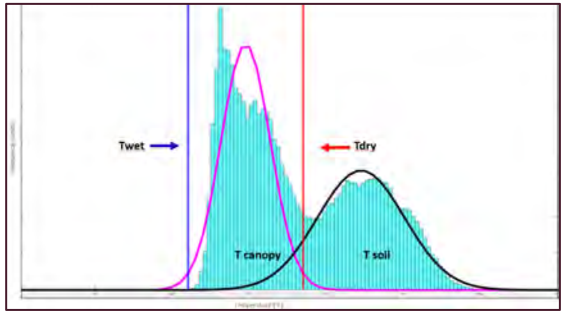


Original visible image (RGB)

Thermal image

Development of a Pipeline for working with thermal data

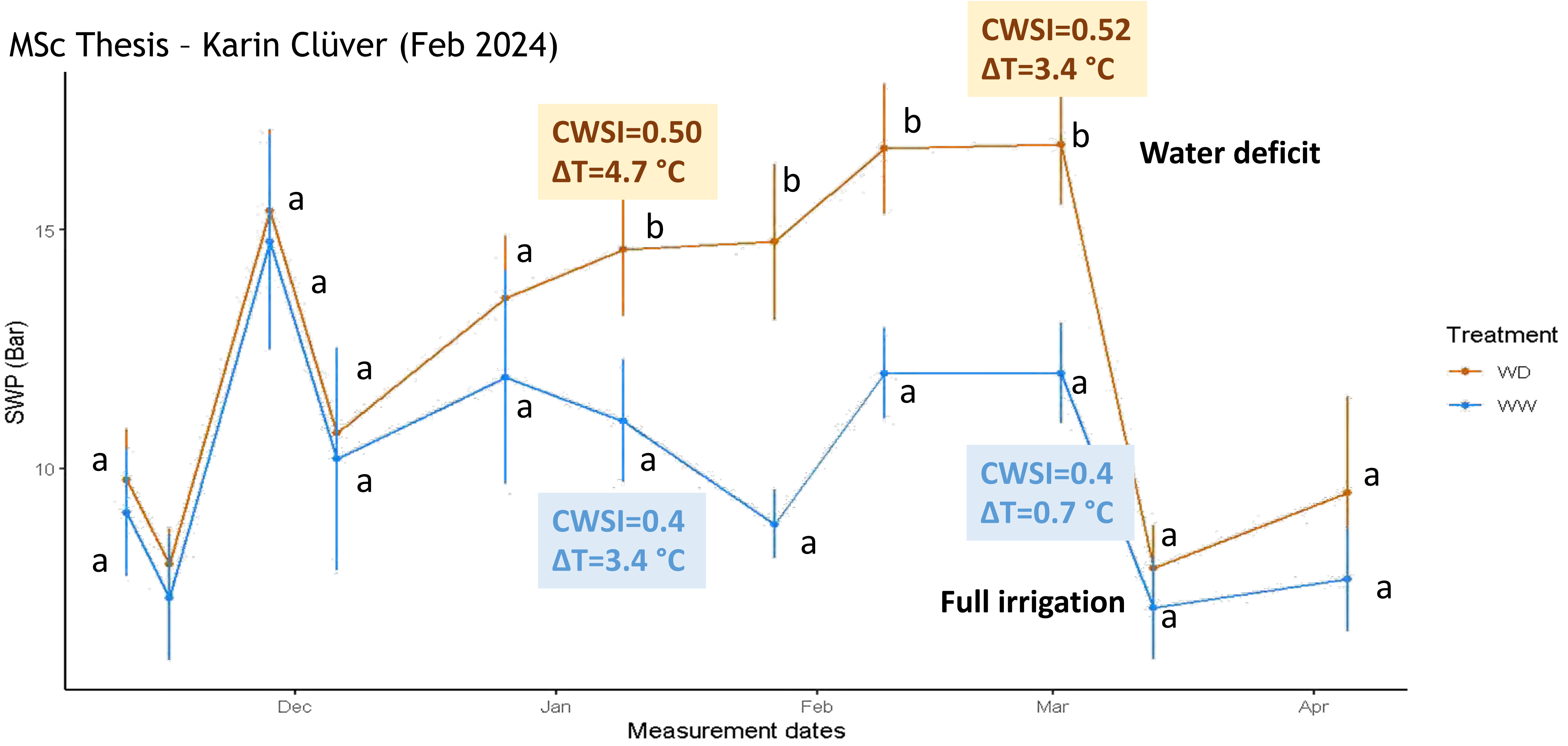




New methods to determine CWSI

A study of the use of drone-based imagery for mapping water stress in a commercial apple orchard

MSc Thesis – Karin Clüver (Feb 2024)



Digital agriculture – Future perspectives

- Supporting current traditional agricultural practices with the latest technologies for data capturing and analysis can improve performance, quality and productivity capacity of the agriculture sector.
- New concepts and ideas (smart applications) can be implemented to optimize management practices and solve technical problems.
- AI and mechanistic models should be trained/calibrated and tested properly before being released for practical use.
- The collection, digitalization, storage, visualization, and management of historical data, together with modern data analysis tools (AI, machine vision, modelling techniques), can reduce decision-making uncertainties.
- Collaboration among growers, service providers, and research institutions can accelerate the implementation and adoption of new technologies by the agriculture industry.

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Experiences in digital agriculture applications with a focus on water stress monitoring

Ms Talitha Venter and Prof CA. Poblete-Echeverria
June 2024

SAGWRI South African Grape and Wine Research Institute

Thanks for your attention

Image compiled by the Digital agriculture research group