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DOCTORAL DISSERTATION
CROP AND FOREST PHENOTYPING USING REMOTE SENSING AND DATA BASED
APPROACHES

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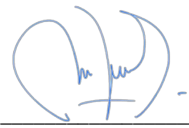
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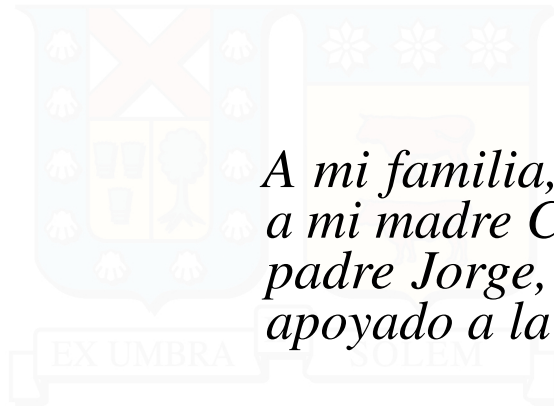
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*A mi familia, en especial
a mi madre Cecilia y a mi
padre Jorge, que me han
apoyado a la distancia...*

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RESUMEN

La agricultura es una de las actividades económicas más importantes en Chile, contribuyendo con cerca del 4.7 % del PIB del país y empleando a cerca de 350 mil personas.

Mundialmente la agricultura enfrenta varios desafíos. El crecimiento de la población demanda un incremento en la producción de alimentos, lo que exige a los productores encontrar nuevas formas de aumentar la productividad de los cultivos y un mejor manejo de los recursos. Otros problemas surgen debido al cambio climático. Áreas como la región central de Chile se ven afectadas por una sequía prolongada, y cultivos como el aguacate son intensivos en agua y están agotando los recursos hídricos del país.

En este contexto, este trabajo se centra en el uso de técnicas de teledetección, principalmente el uso de imágenes multiespectrales e hiperespectrales para la evaluación de la vegetación, enfocándose en aspectos como el contenido de agua. Dado que las imágenes hiperespectrales son datos costosos y de alta dimensión, también buscamos encontrar regiones específicas del espectro electromagnético que contengan la información más útil para la evaluación del contenido de agua en las hojas.

Para este propósito, construimos nuestro propio conjunto de datos que está compuesto por hojas de aguacate, oliva y viñedo. Las hojas fueron deshidratadas en un horno para producir 5 etapas diferentes de deshidratación. En cada etapa, se registraron imágenes multiespectrales en cinco bandas (azul, verde, rojo, borde rojo, infrarrojo cercano), reflectancia espectral en el rango de 350 a 2500 nm, peso de la hoja, contenido de agua en la hoja, contenido de clorofila en la hoja y contenido de nitrógeno en la hoja.

Utilizando este conjunto de datos, se exploraron varias opciones para evaluar el estado de la vegetación. Primero, se utilizaron redes neuronales convolucionales y algoritmos clásicos de aprendizaje automático para clasificar cada hoja según su etapa de deshidratación. Con este enfoque se verificó que utilizando solo la información espectral reducida de las imágenes multiespectrales, la clasificación fue comparable a la de usar el espectro completo de 350 a 2500 nm, con la ventaja de que registrar imágenes multiespectrales es una alternativa más barata, y puede ser utilizada junto con una plataforma robótica para la evaluación de grandes porciones de tierra, como una granja.

Con el propósito de identificar qué regiones del espectro son las más importantes para la evaluación de la vegetación, se probaron dos enfoques. Primero, se exploró la predicción de varios índices de vegetación, utilizando un espectro fuertemente muestreado. En este estudio, el espectro original de 350 a 2500 nm se muestreó cada 100 nm, luego utilizando un proceso de selección de características y algoritmos comunes de aprendizaje de máquina se predijeron un conjunto de 25 índices de vegetación. Con este enfoque, se pudo predecir con una alta correlación y bajo error la mayoría de los índices de vegetación utilizando solo el 1 % de la información de entrada original.

Otro enfoque aprovecha el uso de la inteligencia artificial explicable (XAI), para explorar regiones explícitas del espectro que se utilizan para predecir el contenido de agua en las hojas. En este estudio, se diseñó una simple red neuronal convolucional 1d con el propósito de predecir el contenido de agua en las hojas, luego utilizando el algoritmo Grad-CAM se identificaron las regiones más importantes. Luego, utilizando dichas regiones, se predijeron índices de vegetación. Los resultados de este estudio muestran que 4 regiones diferentes son las más importantes para la predicción del contenido de agua en las hojas. Además, estas regiones son suficientes para la predicción de índices de vegetación relacionados con la salud de la vegetación, con coeficientes de determinación cercanos a 0.8 en algunos casos.

Palabras clave. Estado de cultivos, aprendizaje automático, sensado remoto, imágenes multiespectrales

ABSTRACT

Agriculture is one of the most important economic activities in Chile contributing nearly 4.7 % of the country's GDP, and employing nearly 350 thousand people.

Worldwide agriculture faces several challenges. The growing population demands an increment in food production, which demands producers to find new ways to increase crop productivity and a better management of resources. Other issues arise due to climate change. Areas such as the central region of Chile is affected by a long-lasting drought, and crops such as avocados are water intensive and are depleting the country's water resources.

In this context, this work focusses on the use of remote sensing techniques, mainly the use of multispectral and hyperspectral imagery for the assessment of vegetation, focusing on aspects such as water content. Since hyperspectral imagery is a costly and high dimensional data, we also aim to find specific regions of the electromagnetic spectrum, that carry the most useful information for the assessment of leaf water content.

For this purpose we constructed our own dataset which is composed of leaves of avocado, olive and vineyard. The leaves were dehydrated in oven to produce 5 different dehydration stages. At each stage, multi-spectral images in five bands (blue, green, red, red-edge, near infrared), spectral band reflectance in the range from 350 to 2500 nm, leaf weight, leaf water content, leaf chlorophyll content and leaf nitrogen content were recorded.

Using this dataset, several options were explored to assess the status of vegetation. First, we use convolutional neural networks and classic machine learning algorithms were explored to classify each leaf according to their dehydration stage. Using this approach it was verified that using only the reduced spectral information of multi-spectral images, the classification was comparable to that of using the complete spectrum from 350 to 2500 nm, with the advantage that recording multi-spectral images, is a cheaper alternative, and it can be further used alongside a robotic platform for the assessment of large portions of land, such as a farm.

With the purpose of identifying which regions of the spectrum are the most important for the assessment of vegetation, two approaches were tested. First a study explored the prediction of several vegetation indices, using a heavily downsampled spectrum. In this study the original spectrum from 350 to 2500 nm, was downsampled up to a spectral resolution of 100 nm, meaning that the reflectance was recorded each 100 nm, then using a feature selection process, and common machine learning algorithms a set of 25 vegetation indices were predicted. Using this approach, it was able to predict with a high correlation and low error most of the VIs using only 1 % of the original input.

Another approach leverage the use of explainable AI, for exploring explicit regions of the spectrum that are used to predict leaf water content. In this study a simple 1d convolutional neural network was designed with the purpose of predicting leaf water content, then using the Grad-CAM algorithm the most important regions were identified. Then using such regions, vegetation indices were predicted. The results from this study shows that 4 different regions are the most important for leaf water content prediction. Furthermore, these regions are sufficient for the prediction of vegetation indices related to vegetation health, which achieved an R^2 of 0.8 with at least some of the identified regions.

Keywords. Crop status, machine learning, remote sensing, multi-spectral images

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1 | INTRODUCTION

1.1 Overview of Agriculture in Chile and its current challenges

Agriculture is one of the most important economic activities in Chile. It contributes to 4.7 % of the country's GDP, it generates more than 350 thousand jobs, and it is responsible for the second-largest export products of the country, after copper [3]. However, the agricultural sector in Chile faces several challenges that threaten its sustainability and productivity. These challenges include climate change, water scarcity, soil degradation, and the need for modernization and technological adoption [4, 5].

Additionally, the effects of climate change on agriculture, the severe drought that currently affects the central part of Chile, has affected the hydric resources, and they have been showing signs of exhaustion, the change in the total annual rainfall produces changes in maximum and minimum temperatures in interior regions, the frequency of high temperatures during summer season has increased, as well as polar frosts. All these symptoms have contributed to a more challenging climate for agriculture, leading to increased instability higher stress in plants, creating a more difficult environment for crop cultivation [4].

The effect of water scarcity is already being felt in the agricultural sector. Avocados, which are one of the most important cultivars in the central part of Chile, and one of the most water demanding crops, particularly in the dry regions of central Chile [6, 7], have been affected by water scarcity, and this lack of water has also affected the population of nearby towns such as the Petorca regions [8].

In this context the management of both wild lands and agricultural lands aims to reduce the negative effects of climate change and other external disturbances such as atmospheric pollution [9, 10, 11]. The characterization of vegetation includes various factors, such as leaf water content, leaf area index, pigment content, biomass concentration among others. The early assessment of these factors can lead to a better understanding of the plant's health and its response to environmental stressors, which can help farmers and land managers make informed decisions about irrigation, fertilization, and pest control [12].

1.2 Problem Statement

Vegetation assessment has been carried out recently using remote sensing techniques, which allow for the monitoring of large areas using non-destructive methods [12]. These technologies involve the use of spectral devices, whether multi-spectral or hyperspectral [1, 13], which can capture the reflectance of vegetation in different wavelengths, providing information about the plant's health and its response to environmental stressors.

The use of spectral devices has been widely used in agriculture for various purposes such as the monitoring of leaf water content (LWC), leaf area index (LAI), pigment content, and biomass concentrations to name a few [14, 15, 16, 17]. However, for some applications such as the estimation of leaf water content, the use of spectral devices can be expensive and not accessible for all farmers, especially in developing countries [1]. Therefore, there is a need for alternative methods that can provide similar information about the plant's health and its response to environmental stressors, but that are more affordable and accessible for farmers.

This dissertation focusses on alternatives that bridge the gap, between assessment of vegetation health using multi-spectral and hyperspectral devices, with the purpose of developing cost-effective and accessible alternatives that

provide similar information about the plant's health and its response to environmental stressors, with a particular focus on the estimation of leaf water content (LWC), chlorophyll content and nitrogen content.

1.3 Research Hypothesis

According to the literature review, the use of spectral devices such as multi-spectral and hyperspectral sensors can provide valuable information about the plant's health and its response to environmental stressors, which can help farmers and land managers make informed decisions about irrigation, fertilization, and pest control [12]. However, the use of these devices can be expensive and not accessible for all farmers, even though there is an intrinsic relationship between the information between multi-spectral and hyperspectral devices. Therefore, this dissertation focuses on two main hypotheses:

- The leaf spectral signature (from 350 to 2500 nm) and the derived spectral vegetation indices, describe the health status of the plant. These spectral indices are correlated with the multi-spectral images of the leaves at different drying stages, as well as information from the leaf such as chlorophyll content and the leaf water content (H1).
- There is a minimum set of wavelengths, that allows us to estimate the vegetative indices of the species under study (avocado, olive, and vines) (H2).

1.4 Research Objectives

The main goal of this work is to study the relationship between the spectral signature of leaves from different species at different drying stages, and their characterization from multi-spectral cameras and contact sensors. Hence, to model such relationships, supervised machine-learning models (Support Vector Machines, Random Forest, Artificial Neural Networks, Gaussian Process Regression), and Deep Learning architectures are used for the later evaluation of plant health.

With the purpose to accomplish the main goal of the work, the following specific objectives are pursued:

- To develop a machine learning strategy that takes as input multispectral images, chlorophyll content, nitrogen content, and the weight of avocado, olive, and vineyard leaves at different drying stages to predict the most relevant vegetation indices associated with the health of the plant. To this aim, we are going to implement different architectures using as input the five bands of the multispectral images (Red, Green, Blue, Red-Edge, Near Infrared), the chlorophyll and nitrogen content, and the weight (moisture content), the ground truth of the strategy are the spectral signature at different drying stages.
- To determine the minimum set of wavelengths that allow the estimation of the vegetation indices related to the health status of the plant with an expected accuracy of above 70%. This objective aims to find such a minimum set of wavelengths for a remote sensing implementation of the vegetation indices of the species under study.

1.5 Summary of contributions

The main contribution of this dissertation are the following.

The 'previous work' section and the research about the state of the art, focusing on machine learning, and deep learning in agricultural tasks, yielded two publications:

- **J. S. Estrada**, A. Fuentes, P. Reszka, and F. Auat Cheein, "Machine learning assisted remote forestry health assessment: a comprehensive state of the art review," *Front. Plant Sci.*, vol. 14, Jun. 2023, doi: 10.3389/fpls.2023.1139232.
- C. M. Johnson, **J. S. Estrada**, and F. Auat Cheein, "Potato plant phenotyping and characterisation utilising machine learning techniques: A state-of-the-art review and current trends," *Computers and Electronics in Agriculture*, vol. 234, p. 110304, Jul. 2025, doi: 10.1016/j.compag.2025.110304.

The creation of the dataset used for all the experiments in the dissertation resulted in a publication:

- **J. S. Estrada**, R. Demarco, C. M. Johnson, M. Zañartu, A. Fuentes, and F. Auat Cheein, “A multi-spectral and hyperspectral image dataset for evaluating chemical traits and the water status of avocado, olive and grape through leaf dehydration under laboratory conditions,” *Sci Rep*, vol. 15, no. 1, Jan. 2025, doi: 10.1038/s41598-025-85714-8.

The publications addressing H1 are listed below:

- **J. S. Estrada**, M. Zanartu, R. Demarco, A. Fuentes and F. A. Cheein, "Water Content Classification on Leaves Based on Multi-Spectral Imagery and Machine Learning Techniques for Wildfire Prevention," 2024 IEEE International Conference on Industrial Technology (ICIT), Bristol, United Kingdom, 2024, pp. 1-7, doi: 10.1109/ICIT58233.2024.10540771.
- **J. S. Estrada**, N. Cetin, K. Sacilik, B. Ulu, B. Ulu, and F. Auat Cheein, “Assessment of avocado water stress using multispectral imaging and deep learning: Toward scalable, cost-effective irrigation monitoring,” *Expert Systems with Applications*, vol. 326, p. 132688, Sep. 2026, doi: 10.1016/j.eswa.2026.132688.

The publications addressing H2 are the following:

- **J. Estrada**, N. Cetin, K. Sacilik, Z. Guo, and F. Auat Cheein, “Prediction of vegetation indices from down-sampled hyperspectral data using machine learning: A novel framework for olive crop monitoring,” *PLoS One*, vol. 21, no. 3, p. e0323158, Mar. 2026, doi: 10.1371/journal.pone.0323158.
- **J. S. Estrada** and F. A. Cheein, “Band-selection in spectroscopy information for vegetation health monitoring using explainable models,” *IFAC-PapersOnLine*, vol. 59, no. 23, pp. 108–113, 2025, doi: 10.1016/j.ifacol.2025.11.772.

The author of the thesis contributed and collaborated in research focusing on counting flowers in peach groves, the development of a new index for the comprehensive assessment of vegetation, and a framework for estimating the instantaneous power consumption using satellite information. The publications are shown below:

- **J. S. Estrada**, J. P. Vasconez, L. Fu, and F. A. Cheein, “Deep Learning based flower detection and counting in highly populated images: A peach grove case study,” *Journal of Agriculture and Food Research*, vol. 15, p. 100930, Mar. 2024, doi: 10.1016/j.jafr.2023.100930.
- Z. Guo, **J. S. Estrada**, X. Guo, R. R. Shamshiri, M. Pereyra, and F. Auat Cheein, “Integrative Nutritional Assessment of Avocado Leaves Using Entropy-Weighted Spectral Indices and Fusion Learning,” *Computation*, vol. 14, no. 2, p. 33, Feb. 2026, doi: 10.3390/computation14020033.
- F. Jorquera, **J. Estrada**, and F. Auat, “Remote Instantaneous Power Consumption Estimation of Electric Vehicles from Satellite Information,” *Robotics*, vol. 12, no. 6, p. 151, Nov. 2023, doi: 10.3390/robotics12060151.

1.6 Thesis Structure

The thesis is structure as follows:

- **Chapter 2** presents the complete literature review and the related works.
- **Chapter 3** focuses on the dataset creation for all the experiments of this thesis. The created dataset focuses on the analysis of avocado, olive and grape leaves at different dehydration states. This chapter focuses on the spectral features, and multi-spectral images that were recorded from the leaves.
- **Chapter 4** showcases the first approach for determining the water status of vegetation using multi-spectral images. This chapter shows the use of deep convolutional neural networks to classify leaves according to their dehydration stage, which serves as a proxy for leaf water content. The classification results from the multi-spectral images are compared to a classification using the complete spectrum from 350 to 2500 nm. This chapter focuses on H1.
- **Chapter 5** describes a method for the characterization of vegetation using reduce information from the spectrum. Here, machine learning algorithms were trained with downsampled spectral information, with the aim of finding the minimum spectral resolution that allows a comprehensive assessment of vegetation status. This chapter responds to H2

- **Chapter 6** focuses on the use of explainable artificial intelligence for the identification of important bands in the spectrum and their potential use as descriptors for the status of vegetation. The results of this chapter aims to respond H2.
- **Chapter 7** explores the use of multi-spectral images to replicate the assessment of vegetation that can be done through the use of hyperspectral information. The results of this chapter focuses on answering H1 and H2.
- **Chapter 8** presents the conclusions and potential future work
- **Appendix A** showcases an application of deep learning architectures for the detection and counting of flowers in peach groves, for yield prediction purposes.
- **Appendix B** presents a collaboration work made by the proponent with the purpose of estimating Instantaneous Power consumption using satellite information.
- **Appendix C** focuses on the development of a nutritional index NFI, that encompasses various vegetation parameters. This index helps of a comprehensive assessment of vegetation.

2 | Previous Work

Robotic platforms, imaging systems, lasers and remote sensing technology are currently employed to investigate and analyze vegetation and its response to external factors.

The massive amount of data that is gathered by such devices can be processed by today's computing capabilities. In this context, data driven methodologies, such as machine and deep learning algorithms, are able to capture the complex biological relationships of vegetation and features such as their optical properties reflected in the information gathered by cameras or laser imaging systems.

This chapter explores both most common equipment used for the survey of vegetation using a remote sensing approach, and the techniques used to process such data to obtain meaningful results related to vegetation.

2.1 Equipment for Remote Sensing of Vegetation

The equipment for remote sensing in vegetation can be divided into sensors and robotic platforms. Sensors are the devices capable of collecting information about the environment. In this category, elements such as regular or blue, green, red (BGR), multi-spectral, hyperspectral and infrared cameras are included, hand-held spectrometers are other devices which capture the reflectance of vegetation to an external light stimulus. Light Detection and Ranging sensors (LiDAR), besides the reflectance value at a specific wavelength also provide the distance at which the laser beam reflects, allowing for the reconstruction of 3D scenarios [18]. Figure 2.1, showcases the most common sensors for vegetation assessment and their frequency as presented in [1].

Regarding the robotic platforms, such devices are mainly used to carry the sensors and to navigate the often complex environments found in agricultural scenarios. In this category two kinds of platforms were found, unmanned aerial vehicles (UAVs) (See Fig.2.2) and terrestrial mobile platforms. Both platforms present their benefits and disadvantages. UAVs are capable of surveying large portions of land in a relatively short period of time, but sometimes their information is limited to the canopy of the vegetation, and they are also limited by their payload, being able to carry only small devices such as cameras [19, 20]. While terrestrial vehicles are more robust, can carry heavier payloads and are able to survey the understory of trees, however there are issues about the navigation in the complex terrains, and generally will cover smaller areas in longer times [21, 22].

The sensor and platform selection is highly dependent on the task to carry out, and there are no clear guidelines, such the researcher or practitioner needs to understand the problems to select the sensor or array of sensors that would suit the task properly.

2.1.1 Hyperspectral and Multi-spectral information

In the context of surveying vegetation, devices that can record reflectance in the infrared region of the electromagnetic spectrum are of great value, since various vegetation biochemical properties react in this section of the spectrum.

Within devices that record the electromagnetic spectrum beyond the visible wavelengths (450 nm to 750 nm), two kind of devices are found: multi-spectral and hyperspectral. The main difference among this two kind of devices is that multi-spectral record discrete and wide bands, often only recording a limited number of bands, ranging between 3 and 10, and in the visible to near infrared (NIR) region which ranges from 350 to 1000 nm. Two common bands

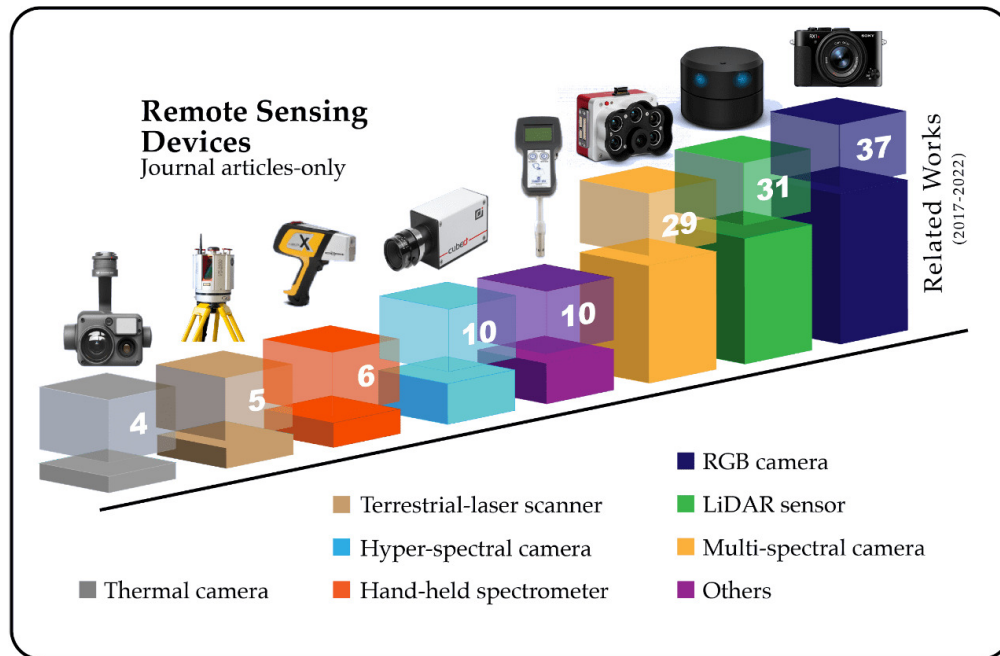


Figure 2.1: Most common sensors using for remote sensing of vegetation (Source [1]).



Figure 2.2: A UAV: a common platform to survey large portion of lands and to carry remote sensing devices (Source [1])

captured by multi-spectral devices are the NIR band which center wavelength is at 842 nm, and the red edge band with a center wavelength at 717 nm, as is the case in a Micasense RedEdge camera.

Hyperspectral devices, on the other hand, are capable of recording many bands, hundreds or even thousands, providing an almost continuous reflectance spectrum. In the case of hyperspectral devices, cameras and spectrometers are common instruments. The hyperspectral cameras, possess the advantage of capturing physical and spatial properties as well as a detailed and comprehensive spectral information, however most of these devices are limited to the NIR infrared regions. Spectrometers usually can record deeper regions of the spectrum often including the shortwave infrared (SWIR) regions ranging from 1000 nm to 2500 nm; however, these devices only record a single point in the space (a single pixel) and usually require that the probe of the instrument make contact with the desired object to measure [23]. Figure 2.3, showcases the main differences between multi-spectral and hyperspectral devices, highlighting the reduced number of bands of the multi-spectral devices and the discrete spectrum that it can produce, compared to the thousand of bands captured by multi-spectral devices, which allows a quasi-continuous reconstruction of the spectrum.

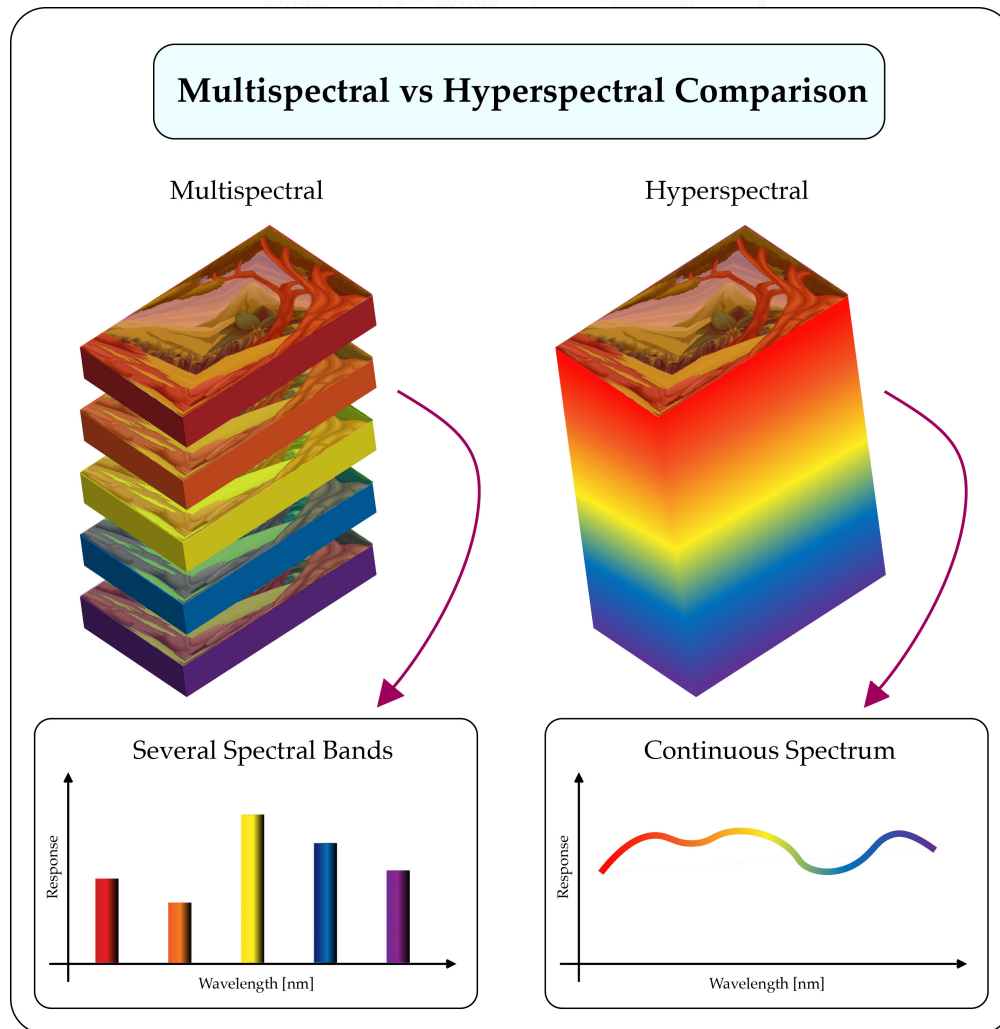


Figure 2.3: Comparison between multispectral and hyperspectral devices (Source [1])

Both multi-spectral and hyperspectral devices present advantages and disadvantages, multi-spectral devices are usually cheaper, are more portable, which allow a seamless integration in a robotic platform, thus allowing the survey of large portions of land. In contrast, hyperspectral devices are expensive and more complex equipment; their integration in an array of sensors is also more complex; furthermore, a spectrometer requires manual sampling, which is time and resource consuming; but they provide complete and comprehensive spectral information; which would allow for a better characterization of vegetation; however the complete spectral information also present additional challenges, most of the

bands provide redundant information and are highly correlated to each other, generating the need of pre-processing step that helps to identify the most important bands for a specific task. Besides, due to the large number of bands, more computing power is needed to process this information [23].

2.2 Vegetation Indices

A common way to extract meaningful features from spectral information is the computation of vegetation indices (VIs). A VI is a mathematical transformation of two or more spectral bands designed to enhance its response to a specific property of vegetation [24].

These indices are often used as input data for prediction and classification models. The reflectance values of the electromagnetic spectrum of the canopy and the leaves can be considered a distinct feature from each type of crop of tree, thus making these values important for plant and tree identification and classification [24].

Water and pigments, such as chlorophyll, from leaves present distinctive reflectance in specific bands, thus the use of VIs is suitable for tasks such as prediction of water content, chlorophyll content, nitrogen content and biomass, which is helpful to assess stress in plants, and serve as a proxy to general plant vigor, which would allow farmers and producers to take better decisions.

In the literature, there have been extensive studies about multiple vegetation indices, both using the wide-discrete bands from multi-spectral devices, and the finer hyperspectral bands; both kind of indices have been developed and tested for various applications in the assessment of vegetation.

Furthermore, there are also various studies and reviews about VIs using hyperspectral bands. Commonly these indices are classified according to their composition, ranging from simple ratios, simple differences, normalized differences, double difference, modified ratios and modified normalized indices [25]. The indices used in this thesis will be introduced later at each specific chapter.

2.3 Machine learning and deep learning overview

The large amount of data that can be gathered by the robotic platforms alongside the different array of sensors, demands an effective way to process the information and obtain meaningful results that are useful to take decisions about the agricultural practices. In this context, machine learning (ML) models have emerged as an option in the workflow of assessing vegetation, from remote sensing information. ML has been used to generalize models, and improve the precision of the parameter estimation, and provide better feature prediction in the presence of the environment variability [1, 26, 18].

In general ML is a set of algorithms that require the machine to infer and extract patterns and features from raw data. The effectiveness of the models heavily depend on the data used for training [26]. These algorithms usually can be used for regression tasks, which means to predict a specific numeric value from a set of input features. The other common task is classification, which implies the prediction of a pre-defined class according to the input features or data [27].

The process of "learning" is a key concept in machine learning, and it can be performed in the following ways: supervised learning, unsupervised learning and semi-supervised learning [27]. Supervised learning involves the use of labeled data, the model is trained to predict the label (numeric value in the case of regression or the class in the case of classification), from the input data; adjusting its parameters at each training iteration, until it achieves an optimum value [27]. Unsupervised learning aims to learn properties about the data, and how it is structured; thus it does not need a label for each set of inputs. A common task performed by unsupervised learning is to predict the statistical distribution that generated the input set, or the cluster the input feature into sets with similar characteristics [27, 28].

2.3.1 Common techniques for regression approaches

Regression tasks have been used in applications such as yield prediction, leaf water content estimation, nitrogen and chlorophyll estimation, biomass prediction and yield prediction for a wide variety of crops.

There are numerous techniques that have been used for regression tasks in agriculture, some of the most used are linear regression, random forest regression (RFR), support vector regression (SVR), partial least squares regression (PLSR), k-nearest neighbors (kNN), gradient boosting machines (GBM) and its optimized version extreme gradient boosting machines (XGBM), Gaussian process regression (GPR) and neural networks or multi-layer perceptron (MLP), among others. Figure 2.4 showcases an application of different ML algorithms for the partition of data, in a dataset from forest species.

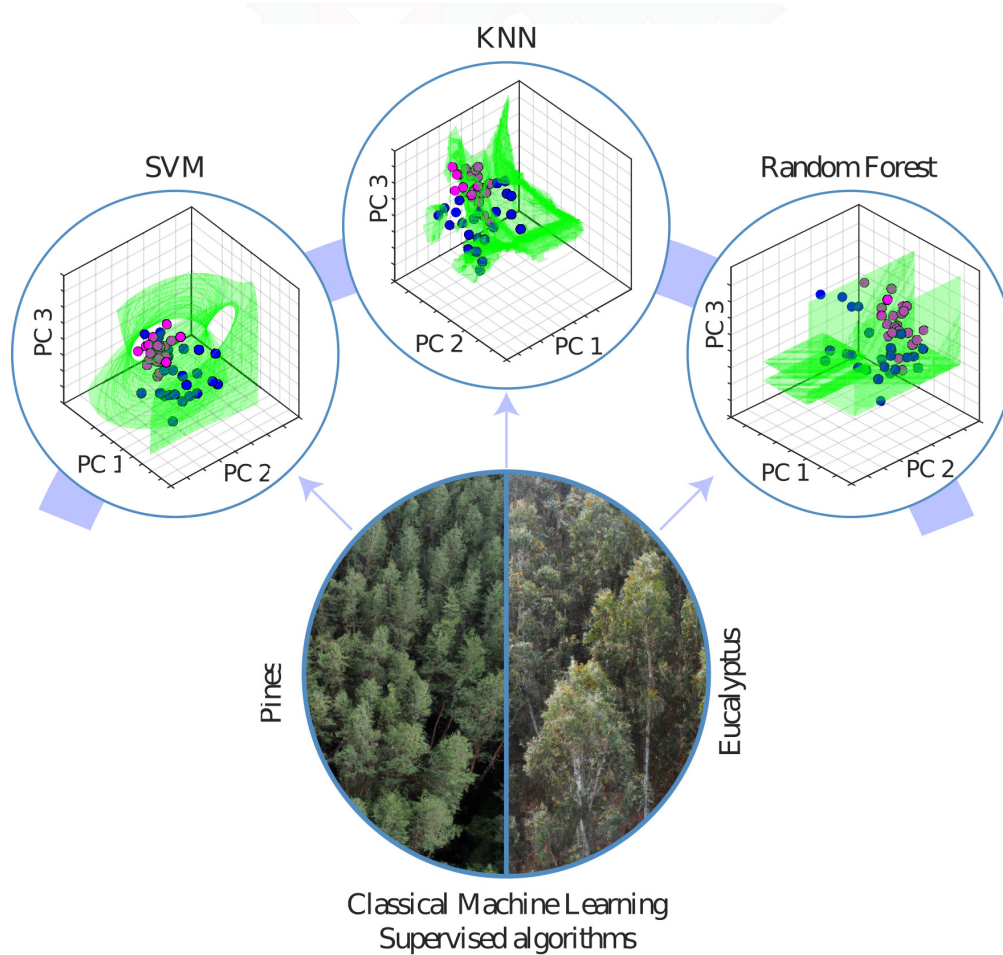


Figure 2.4: Comparison between various machine learning algorithms in a dataset of pines and eucalyptus (Source [1])

The workflow for evaluation of vegetation using remote sensing is somewhat similar in most cases. First, the task is defined, for example doing leaf water content prediction for the assessment of water stress in crops; then choosing the suitable sensors and platforms is performed, then the data collection campaign is performed, finally the data is processed, in this step machine learning models are a common trend nowadays. Finally, the models are evaluated.

Choosing the best performing algorithm and their correct hyperparameter configuration is a complex task. However, various authors often evaluate a wide variety models, with multiple hyperparameter configurations following an optimization structure, until a desirable performance is achieved. A common trend is that RF and XGB algorithms are among the best performing models, caused by the tabularity of the data in most cases.

2.3.2 Image processing and classification using Deep Convolutional Neural networks

Regular, multi-spectral and hyperspectral cameras are among the most common sensors for the remote evaluation of vegetation status. Traditional approaches for image processing involve the use of filters to extract meaningful features, or to extract texture information using techniques such as a Gray Level co-occurrence matrix. This process of "manual" feature extraction is sensitive to various factors such as variation in illumination and noise in images [28].

In this context, deep neural networks are a handy alternative to process raw unstructured data such as images. Deep learning (DL) refers to techniques that rely on multiple layers of units (neurons). These networks have the ability to automatically learn complex features and representations from unstructured and raw data. Figure 2.5, showcases some common Deep learning networks and their applications for vision tasks.

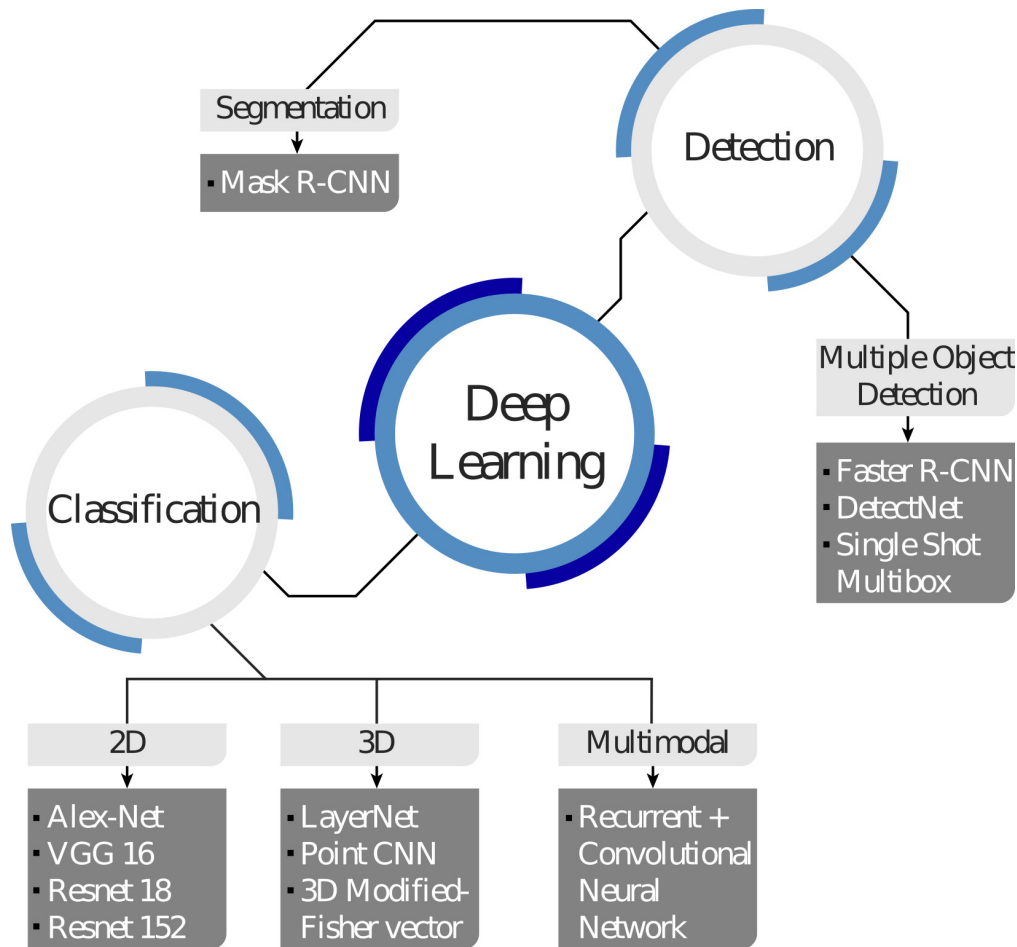


Figure 2.5: Different DL architectures and their most common application

For image analysis and processing, convolutional neural networks (CNNs) are common alternatives. In this kind of network, the algorithm automatically learns the convolution kernels that extract the most important features for a certain task. Even though, these networks are most common for processing images using 2D convolution kernels; they can be used for 1D arrays such as time series, or in the case of vegetation, 1D convolution can be used to process spectral data gathered from a spectrometer or hyperspectral camera; thus this networks is capable of learning the relationship between contiguous reflectance values.

There are numerous CNN architectures that have been successfully applied for the analysis of vegetation, in tasks such as tree recognition, tree delineation and segmentation among others. Networks such as AlexNet VGG16, ResNet50, ConvNext; which are pretrained models on large datasets, have been fine-tuned to properly suit the dataset collected for each specific task [1].

Furthermore, models such as Fast RCNN, DetectNET, Single Shot Multibox Detector (SSD), and You Only Look Once (YOLO) models, have been developed for object detection tasks; which means to detect individual objects in an image and locate them in a corresponding bounding box.

Other networks such as U-NET and Mask R-CNN perform segmentation, which is the task of classifying each pixel in an image according to their class, for example identifying which pixels are from the trees' canopy and which pixels are from the soil or background.

2.3.3 Explainable models: Grad-CAM

Deep learning algorithms are often considered black-box models, since there is no clear visualization on how these algorithms perform their decisions. In this context explainable artificial intelligence (xAI) tries to shed a light in how DL works [29].

One of the most common approaches is the use of activation maps, in this case the Gradient-weighted class activation mapping (Grad-CAM) is a powerful alternative, to investigate which exact part of the images, a certain model is looking to perform their prediction. Grad-CAM [30] is an interpretation method based on the gradients of the network at the last convolutional layer. Based on the gradients, the algorithm is capable of creating saliency maps, highlight which areas of the image or the data, are the most important for the model to make a prediction.

2.4 Machine learning and deep learning for plant assessment

This section presents some of the most important tasks that have been performed in agriculture and forest management with the aid of both robotic platforms integrated with spectral sensors and imaging systems, as well as the reviewed machine learning algorithms.

Plant phenotyping is the process of measuring or estimating plant physical, biological or chemical traits; with the purpose of using this information to enhance crop managing practices. In this context, some important phenotyping tasks, include chlorophyll, nitrogen, biomass, yield, leaf water content prediction; prediction of leaf and plant physical parameters, tree structure determination, and pest and diseases identification (see Fig. 2.5, and Fig.2.6 for the applications of ML and DL in agriculture [31])

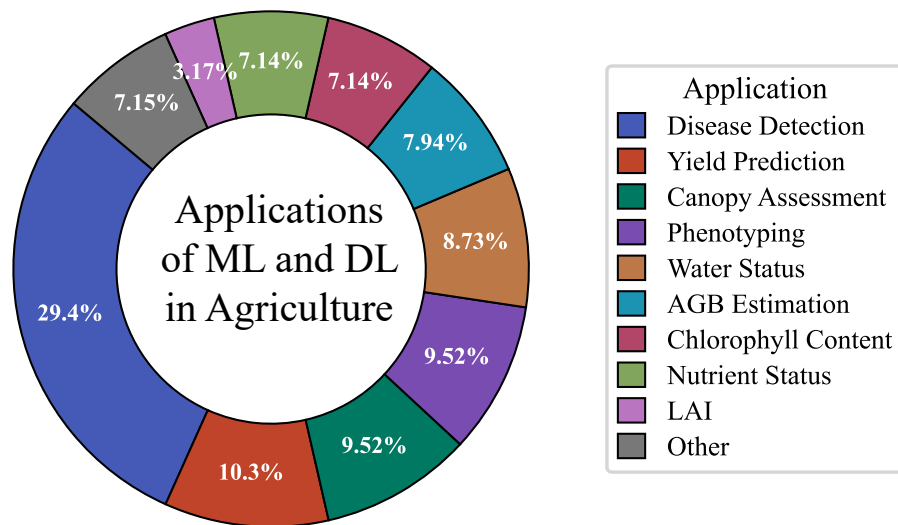


Figure 2.6: Most common applications of ML and DL in agriculture, specifically in potato phenotyping (Figure modified from [31])

2.4.1 Chlorophyll, nitrogen, biomass and yield prediction

Chlorophyll and nitrogen content is an important indicator of vigor, photosynthetic activity, fertilizer utilization, overall health status of the vegetation and as an early indicator of potential yield [1, 31]. This measurement helps farmers and producers to optimize fertilizer usage, thus reducing costs, it helps to take better choices during harvesting time, taking account the expected yield.

In this case, the use of multi-spectral imaging systems has been widely adopted. Researchers conduct flight campaigns, to survey large portions of land. Alongside the flight campaigns, land collection data is conducted by hand; furthermore, the samples collected by hand are processed to gather the ground truth (real chlorophyll, nitrogen or biomass content). The manual collection process is usually costly both in resources and time, which is why the need of using automatic approaches such as the use of remote sensing technology.

Once the remote sensing information (multi-spectral images) and the land measurements are collected; a feature extraction process starts, in this step, important features from the images are computed, which includes obtaining related VIs to the desired plant trait; or texture information; then machine learning algorithms are trained, and finally such models are evaluated. This approach has been carried out in a large variety of crops including lettuce [32], wheat [33], potato [34], oat [35], rice [36, 37], among other variety of species.

The feature extraction process is not limited to multi-spectral image processing. Physical features such as estimated plant height from images, leaf area index, and vegetation cover, provide important information to perform yield prediction, such is the case presented by [38], which improved the estimation of rice yield including physical features. Furthermore, this framework has been adopted in the yield, chlorophyll, nitrogen and biomass prediction which improves the prediction from using only multi-spectral images and VI information. Such approaches have been tested in wheat [39], olive [40], black oats [41], almonds [42], sugar cane [43, 44, 45], maize [46], onion [47], potato [48], sweet potato [49], among others. In these studies, a wide variety of ML algorithms have been trained, however the most common ones are regression algorithms, with the most popular being random forest (RF), artificial neural network (ANN), multi-layer perceptron (MLP), support vector regression (SVR), gradient boosting machines (GBM) and partial least squares regression (PLSR). The most common metrics for evaluating the performance of the models are R^2 , $RMS E$ and MAE . In most studies, R^2 values higher than 0.7 are achieved, with low $RMS E$ and MAE values as well, showcasing the effectiveness of ML algorithms to predict this specific vegetation traits.

2.4.2 Leaf water content prediction

Leaf water content (LWC) prediction is important due to a variety of reasons. First it can help to the assessment of both crops and forests to water stress caused due to extended droughts. Furthermore, a timely assessment of LWC can help farmers for a better planning in irrigation practices, which would lead to saving in both water and economic resources. In forestry applications, it is associated with soil transportation of CO_2 to the atmosphere [50]. Other important tasks of LWC estimation is the assessment of wildfire risk in forested areas [51, 52, 53]. This information is necessary for land management decision-making [54].

In contrast with the prediction of chlorophyll, and nitrogen content; assessment of LWC is performed using mostly hyperspectral devices; due to the fact that water sensitive bands are located in the SWIR regions (beyond 1000 nm); thus sensors such as multi-spectral cameras, which cover only up to 1000 nm in most cases, are not capable of retrieving correct values of LWC.

LWC prediction has been performed in a dataset of *eucalyptus globulus* and *pinus radiata* leaves at different dehydration levels. [55], computed several VIs and analyzed the linear relationships between the VIs and leaf water content; this approach reached R^2 values of above 0.9. A similar study was conducted by [56], but the LWC was computed from reconstructed reflectance values, also achieving low $RMS E$ and high R^2 .

Further studies leverage the use of deep learning architectures, such as 1D CNN [57], long short term memory (LSTM) networks [58], graph neural networks [59] and transformer based architectures [60] to predict leaf water content, such networks greatly outperform approaches based on machine learning techniques such as the regression with manual extraction process such as the one presented in [61], which used fractional derivative indices and wavelet based indices for leaf water content prediction. As well, these studies were performed in a large variety of crops including blueberries [57, 60, 59], citrus [61] and oilseed rape [58].

Even though the prefer method for LWC prediction is the use of hyperspectral information in the SWIR region, there have been studies which attempt this prediction using cheaper sensors such as multi-spectral cameras. In [62], the authors attempt the construction of leaf water content maps in a forest of *eucalyptus globulus* using as input VIs, however the reconstruction only retrieved a few hyperspectral indices with R^2 of up to 0.6. Further studies leveraged as well the use of texture features, alongside the use of VIs for the prediction of LWC achieving R^2 over 0.75 in wheat [15] and in maize [63]. A similar study was conducted in cotton plants achieving similar results [64], however this study leveraged thermal information as well.

2.4.3 Tree structure and tree identification

The individual identification of trees fulfills a vital role in assessing forest health and biodiversity, in the presence of constant changes due to external factors such as droughts and climate change [65]. As well this information is needed

for forest inventory and mapping [66].

For the task of tree identification and individual tree recognition the most common approach is to use aerial images from either BGR or infrared cameras, and process this information in deep convolutional neural networks, such as VGG19 and SegNet which is used to segment each individual tree crown [67, 68, 69].

Other networks that have been trained for detecting single trees in aerial images are DetecNET, Faster R-CNN and SSD [70] and [71]. The individual tree recognition is also useful for identifying areas prone to wildfires such as is the study presented in [72], which used U-NET to identify wildfire prone areas in aerial images.

The determination of tree structure is concerned with retrieving measurements such as trunk diameter, diameter at breast height, tree height, crown height, crown volume and crown area. Such parameters are key for assessing biodiversity, forest productivity [73], and are key to assess individual tree and the total of forest vigor [74]. Since these measurements are more related to geometry and physical properties of the objects, a common approach is to rely on LiDAR measurements, to obtain 3d representations of the objects, in a point cloud [74, 75]. Regression models were used to assess such parameters from 3d point clouds gathered by LiDAR sensors [76, 77]. Such studies have been successful in retrieving such measurements achieving error below 30%.

2.4.4 Detection and counting of fruits and plant's organs

A common way for a correct assessment of yield is to directly count the number of fruits in an orchard or grove. A better yield prediction is key for farmers to allocate resources for harvesting season, and for commercialization purposes [78]. For this purpose, deep CNNs are a common approach since such networks are capable of identifying and locating multiple instances of an object within an image. Such approach was tested in [79], which used Faster RCNN and YOLOv5 for the detection and tracking of apples for yield estimation. The study in [80] used Faster RCNN to detect cherries of various sizes. Furthermore, [81] compared the identification results of two common networks, SSD and YOLOv2 for the detection of avocado, lemon and apples. Other studies such as [82], improved the YOLOv5 network for the counting of litchi fruits. Similar approaches have been tested in mango [83], which improved the YOLOv8 model for mango detection.

Another method for early yield prediction is the counting of flowers. Many flowers will develop into fruits, thus this number can be a good predictor for yield [84, 78]. Such approach has been addressed in [85], which estimated the density of litchi flowers using a multi-column deep neural network [85], this approach counted the flowers with an error of up to 10 %.

Other studies are more concerned in the individual detection of flowers as well important plant organs within the flower. This task is performed for assisted pollination efforts. In [86, 87] used YOLO models to perform multi-class object detection in kiwi flowers, whereas [84] performed cluster detection on apple flowers.

2.5 Contributions

An extensive and more in depth review of machine learning and remote sensing in forestry were published in *Frontiers in Plant Science* journal:

- **J. S. Estrada**, A. Fuentes, P. Reszka, and F. Auat Cheein, "Machine learning assisted remote forestry health assessment: a comprehensive state of the art review," *Front. Plant Sci.*, vol. 14, Jun. 2023, doi: 10.3389/fpls.2023.1139232.

The state of the art about machine learning focusing on potato phenotyping is published in *Computer and Electronics in Agriculture*:

- C. M. Johnson, **J. S. Estrada**, and F. Auat Cheein, "Potato plant phenotyping and characterisation utilising machine learning techniques: A state-of-the-art review and current trends," *Computers and Electronics in Agriculture*, vol. 234, p. 110304, Jul. 2025, doi: 10.1016/j.compag.2025.110304.

3 | Dataset Construction

Avocado, olive and grape are among the most representative, abundant and important for agriculture cultivars within the Valparaíso region. It is estimated that nearly 60 % of total Chile's avocado production comes from the Valparaíso region. Grape production is also important in the regions with production for both grape consumption and for wine production. Besides, Chile is the top grape grower in the world, with almost 30% of Chile's fruit growing area dedicated to this cultivar. While Chile is not one of the most relevant producers for olive. This crop still contributes significantly to the Chilean economy, with an export market importation of more than 12 million USD dollars. For these reasons it is important to improve practices around those crops. Thus, the remaining chapters of this dissertation is focused on these cultivars.

3.1 Sample collection

The sample collection process was as follows: Individual branches were cut directly from the trees. Then, healthy leaves were chosen based on a visual inspection; leaves with no holes and with no visible signs of visible deterioration, were chosen. If a leaf showed any of these symptoms, it was ensured that the largest part of the leaf area was unharmed. The leaves were placed in plastic bags, and were immediately carried to the laboratory within two hours of the extraction, for their analysis and the measurement process.

For the avocado leaves, the collection process occurred during April and May 2023, a total of 106 leaves were collected from different parts of the tree canopy. Olive leaves were collected during the July and August 2023, a total of 111 leaves were collected. Finally, 106 grape leaves were collected during December 2023 and January 2024. Table 3.1 shows a summary of the collection process and dates.

Table 3.1: Leaf collection process summary

Tree Species	Total leaves	Months of recollection
Avocado	106	April and May 2023
Olive	111	July and August 2023
Grape	106	December 2023 and January 2024

3.1.1 Measurement Process

For this dataset, several measurements were considered. First the spectral reflectance values from the 350 to the 2500 nm wavelengths were recorded using an ASD TerraSpec Hi-Res spectrometer. For this step, the probe light of the spectrometer was turned on for at least 15 minutes before the first measurement, with the purpose of heating up the probe, as per the vendor's recommendations. Then, the instrument was calibrated and optimized using a white Spectralon reflectance panel.

For the measurement of the leaves, each was measured three times, at different spots within its structure. For the avocado, and olive leaves the measurements were taken from one spot at the bottom, one at the middle and one at the top of the leaf. In the case of grape leaves, the three spots were chosen across the horizontal axis of the leaf. Such spots are shown in Fig. 3.1. Each leaf was placed on top of the white Spectralon reflectance panel, and the prob was placed

flush against the leaf. The final measurement was recorded as the average of the three previous measurements across the different parts of the leaf.

Next the leaf chlorophyll and nitrogen content were recorded using a TYS-4N nutrition meter. The leaves were placed inside the instrument's probe for the measurement. Again, three measurements were recorded roughly in the same spots as the reflectance values were measured. The final recorded value is the average of the three measurements.

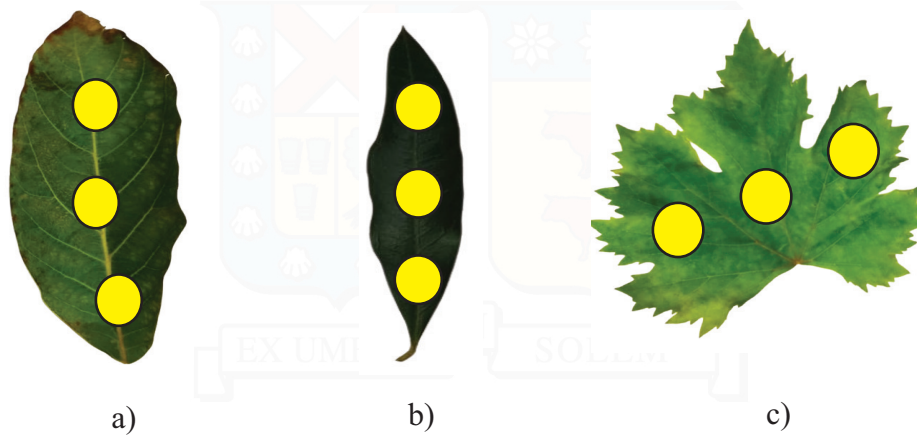


Figure 3.1: Approximate spots on the leaves where the reflectance values were recorded using the spectrometer and the nutrition meter: a) Avocado, b) olive, and c) grape (Source [2]).

Both instruments, the spectrometer and the nutrition meter were re-calibrated after a complete batch of measurements was completed: after 16 in the case of avocado and 8 in the case of grape. For the olive leaves, each complete batch consisted of nearly 32 leaves, however the re-calibration process was conducted after 16 measurements. The spectrometer was re-calibrated using the Spectralon reflectance panel, and the nutrition meter was calibrated using its own internal reference per the manufacturer's instructions.

Multi-spectral images of the leaves were taken using a Micasense Red-Edge M camera. The camera is capable of recording 5 spectral bands: Blue (B), Green (G), Red (R), Near Infrared (NIR) and Red-Edge (RE). The camera was mounted on a tripod at a height of 45 cm above the leaves, which were placed on top of a white background, made with paper sheets. Each image contains a small batch of leaves. The number of leaves was chosen the maximum number of leaves fit within a single frame of the camera: 4 leaves for avocado, 6 to 8 leaves for olive and 2 for grape leaves. To ensure consistent illumination conditions, external light sources, such as windows and doors, were blocked. The images were collected using room illumination consisting of fluorescent white lamps with a color temperature of 4100 K and a luminous flux of 2850 lumens.

Finally, the leaves were weight using a high precision Kern balance. Later, the weight measurement was used to compute the leaf water content of each leaf. The laboratory temperature was kept between 20 and 24 °C using an air condition system, the relative humidity level varied between 55 % to 70 %.

A list of all the instruments used in this study is shown if Fig.3.2 and the main features of each instrument is shown in Table 3.2

3.1.2 Dehydration Process

To evaluate the leaves at different water content levels, a dehydration process was conducted to yield five drying stages. The first stage consists of the fresh leaves, which were recently detached from the branches and brought to the laboratory.

The complete set of measurements described in the previous section was recorded with the fresh leaves. Then the leaves were placed in an oven at a 65° C, this temperature was chosen based on previous experiments, conducted to assess flammable content in leaves [55]. The leaves were placed on the oven for a period of 15 minutes. After this period, another set of measurements was recorded, yielding the second dehydration stage. This process was carried out to more times; producing two more dehydration stages, where the leaves were a total of 30 and 45 minutes inside the

Instrument	Technical Specification
Multi-Spectral camera Micasense Red-Edge M	Bands: blue (B), green (G), red (R) red-edge (RE), near-infrared (NIR)
Spectrometer ASD Terraspec 4 Hi-Res	Range: 350 to 2500 nm Resolution: 3 nm at VNIR (350 to 1000 nm) 6 nm at SWIR (1001 to 2500 nm) Reproducibility: 0.1 nm Accuracy: 0.5 nm
Balance Kern PFB 120.3	Maximum capacity: 120 g Readability: 0.001 g Reproducibility: 0.002g
Plant nutrition analyzer TYS-4N	Chlorophyll range: 00.0 to 99.9 SPAD Chlorophyll accuracy: 1.00 SPAD Nitrogen range: 00.0 to 99.9 mg/g Nitrogen accuracy: 5%

Table 3.2: Equipment used to create the dataset.

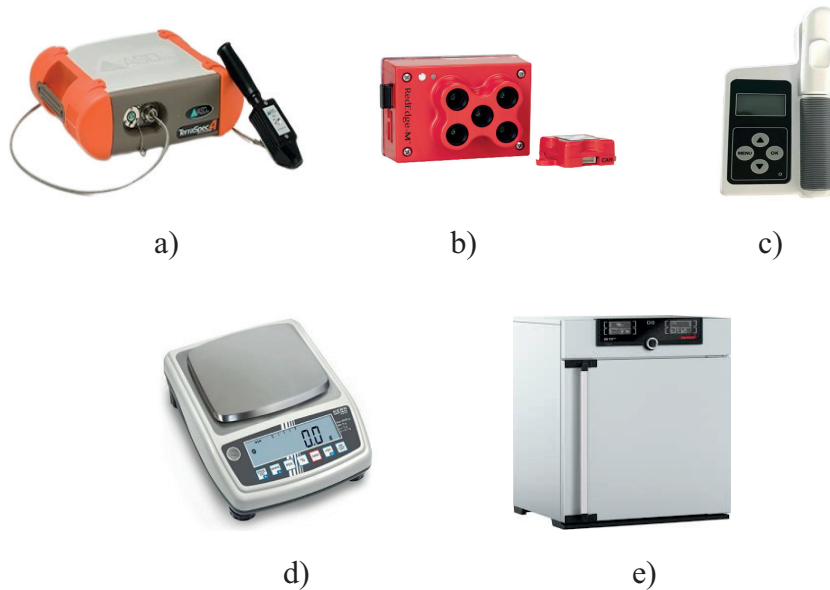


Figure 3.2: Instruments and sensors to create the dataset: a) HI-RES ASD Terraspec sensor, b) Micasense Red-Edge camera, c) TYS-4N Nutrition meter, d) Balance Kern PFB 120.3, e) Memmert U30 Oven (Source [2]).

oven. For the last dehydration stage, the leaves were left in the oven for a period of 24 hours, such long time ensures that all remaining traces of water were evaporated from the leaves.

As a result from the dehydration process, five different set of measurements were recorded, the remaining of this work names the dehydration stages as follows: Fresh stage, Dehydration Stage 1, Dehydration Stage 2, Dehydration Stage 3, and Dry Stage. Table 3.3 summarizes the dehydration stages with the complete time in the oven. The oven used in this process is a Memmert UN30 with digital PID control, and a temperature range of -5 to 100 °C with respect to room temperature. The oven can be seen on Fig.3.2.

Table 3.3: Summary of the different dehydration stages

Dehydration Stage	Total time in the oven
Fresh Stage	0 minutes (recently detached leaves)
Dehydration Stage 1	15 minutes
Dehydration Stage 2	30 minutes
Dehydration Stage 3	45 minutes
Dry Stage	24 hours

3.2 Multi-spectral image pre-processing

The Micasense Red-Edge camera records raw digital values of the five bands: B, G, R, NIR and RE. These digital values have a resolution of 16 bits, and the camera resolution is of 1.2 mega-pixels per band. To have meaningful reflectance values, a calibration process is needed. For this purpose, images of a reflectance panel provided by Micasense were recorded alongside the leaves. Using the panel images the radiometric calibration process was conducted using the free specified functions (<https://github.com/micasense/imageprocessing>)

Using the radiometric calibrated images a segmentation process was conducted with the purpose of extracting individual leaves. This process is as follows:

- The image was binarized using a simple thresholding. The threshold value was selected using Otsu's method.
- Individual contours were extracted from the binarized image.
- A masking process was conducted to extract the leaf images from the background, each leaf was masked with each contour.
- Individual leaves were extracted matching each contour to its corresponding leaf.

The algorithm was implemented using Python and OpenCV. After the automatic segmentation was performed, a visual inspection was performed on each individual image. In some cases, two or more leaves were extracted together due to their physical proximity, in other cases parts of the leaf were confused as background. In such cases, a manual segmentation was carried out using Matlab's segmenter tool.

As a result of the image segmentation process a total of 2775 images of olive, 2600 images of avocado, and 2600 images of grape leaves were recorded. The images include the five bands captured by the Micasense Red-Edge camera, at the five different dehydration stages.

A sample of all the images at all the dehydration stages are shown in Fig. 3.3. In these images we can see, the differences in reflectance across the different stages, as well the physical differences produced at each dehydration stage, such as the rolling of the leaves.

3.3 Leaf water content

Leaf water content is one of the key parameters for improving irrigation regimes, and to analyze the general health status of the vegetation. Besides water stress gets exacerbated due to climate change and drought excess. In this dataset, the analysis of leaf water content is carried out using the equations for leaf water content using a fresh basis and a dry basis:

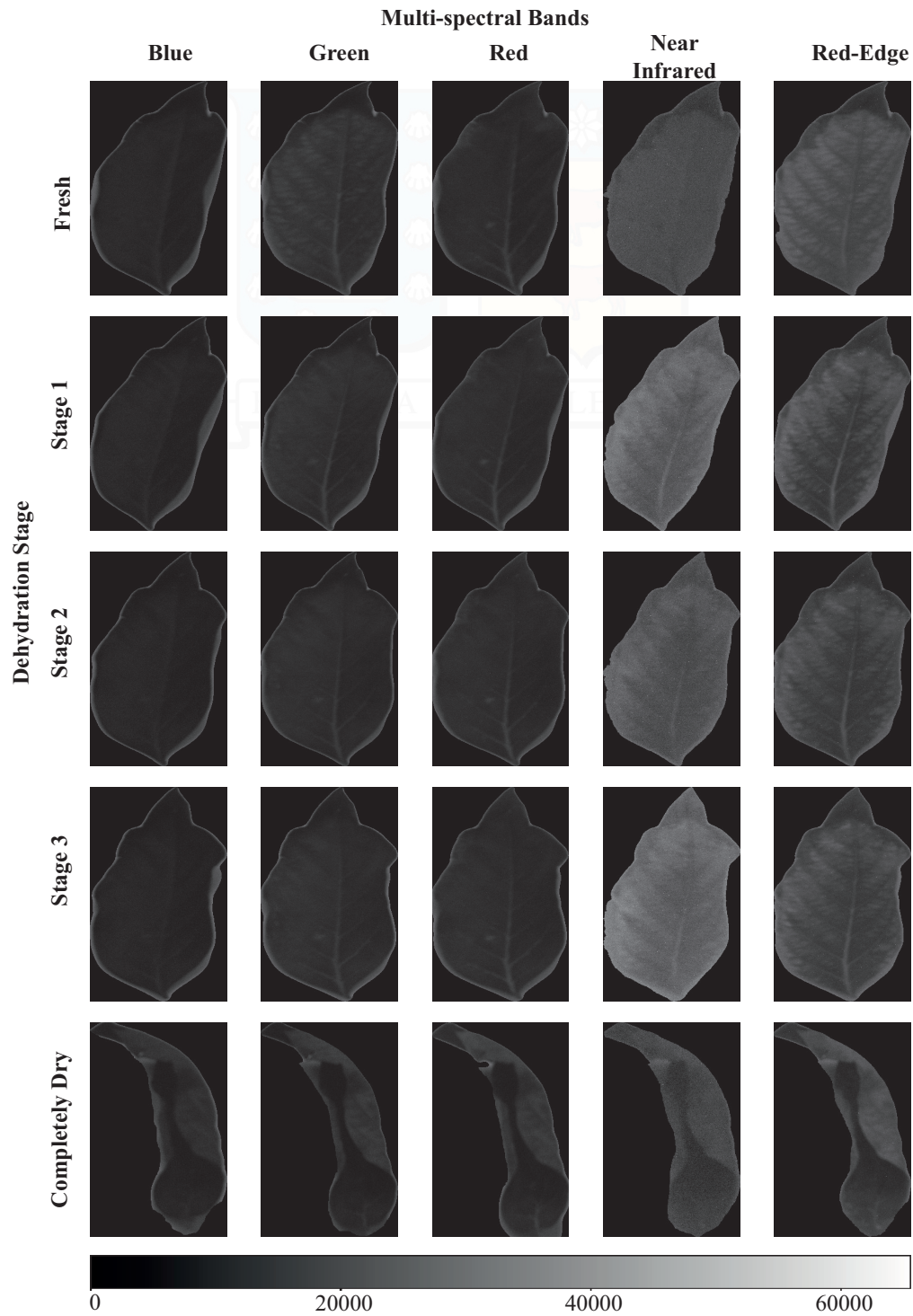


Figure 3.3: Samples from all the leaves at all dehydration stages, from all the multi-spectral bands (Source [2]).

$$LWC_f = \frac{W_{f,t} - W_d}{W_{f,t}} \times 100 \quad (3.1)$$

$$LWC_d = \frac{W_{f,t} - W_d}{W_d} \times 100 \quad (3.2)$$

Where LWC_f is the leaf water content at the fresh basis, $W_{f,t}$ is the leaf weight at the t dehydration stages W_d is the dry weight of the leaf (the weight at the last dehydration stage) and LWC_d is the leaf water content using a dry basis.

3.4 Data exploration

3.4.1 Spectral reflectance values

In figures 3.4, 3.5, and 3.6; the average reflectance values for all the species and all the dehydration stages, are shown. The bold line indicates the average values, while the shaded area indicates the span of the reflectance at the selected wavelength. In these images, it is clear that the dehydration process clearly affects the spectral response at a leaf level.

Furthermore, Figure 3.7, shows a direct comparison between the different dehydration stages and the different species. Figure 3.7, some critical bands that respond to water molecules can be distinguished. Reflectance values bands at around 975 nm, 1200 nm, 1400 nm and 1900 nm systematically increase across the drying stages. Previous studies have shown that such wavelengths respond to the vibrational bands of water molecules, thus it is expected a significant change in the reflectance values in such bands.

Another notable difference happens in the visible region of the spectrum, as the leaves, when are dehydrated, change color from green to a brown color. This effect is caused due to the lack of water which causes chlorophyll to break down, and it causes other pigments to prevail. This effect is less noticeable on olive leaves, since these are evergreen trees, due to their adaptations to extreme water stress due to the regions they were first grown [88].

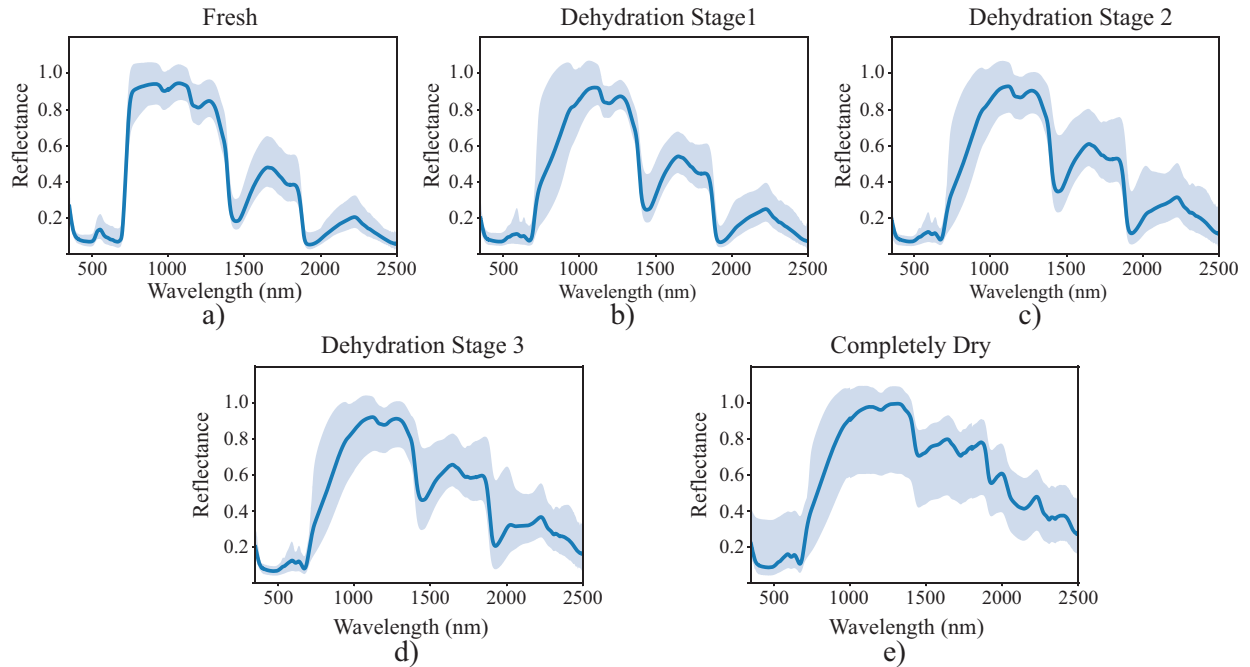


Figure 3.4: Spectral reflectance of the avocado leaves at: a) fresh stage, b) dehydration stage1, c) dehydration stage 2, d) dehydration stage 3, and e) completely dehydrated stage (Image source [2])

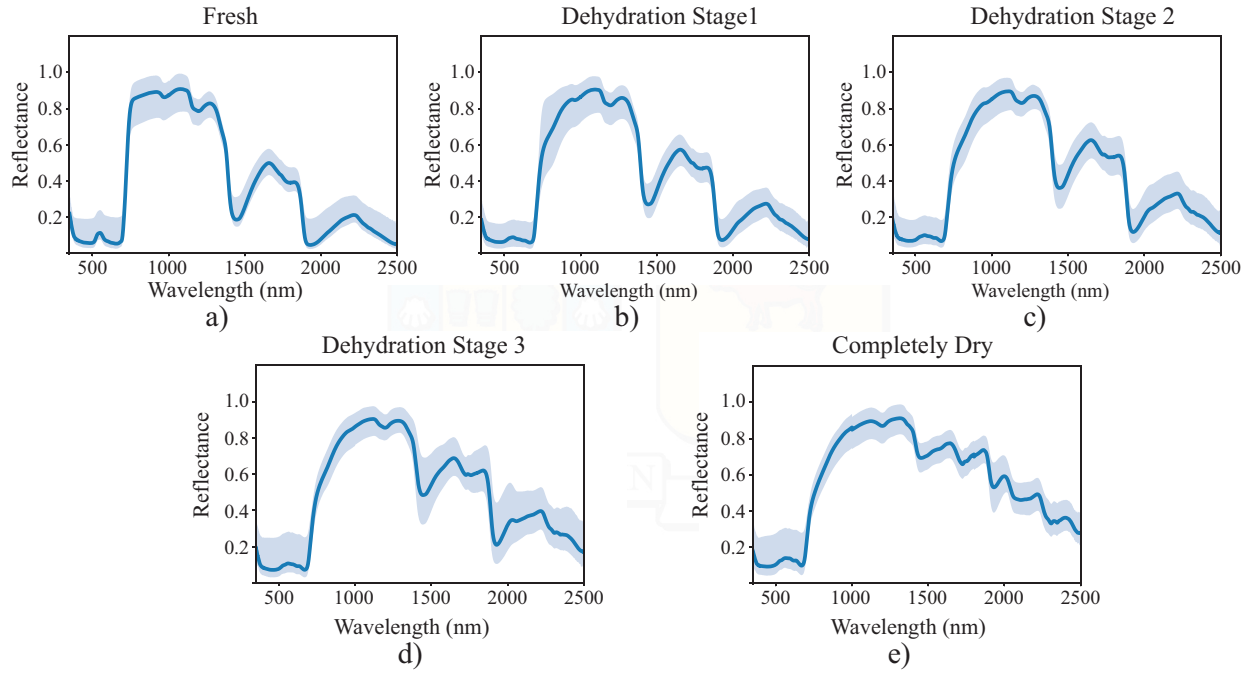


Figure 3.5: Spectral reflectance of the olive leaves at: a) fresh stage, b) dehydration stage 1, c) dehydration stage 2, d) dehydration stage 3, and e) completely dehydrated stage (Source [2]).

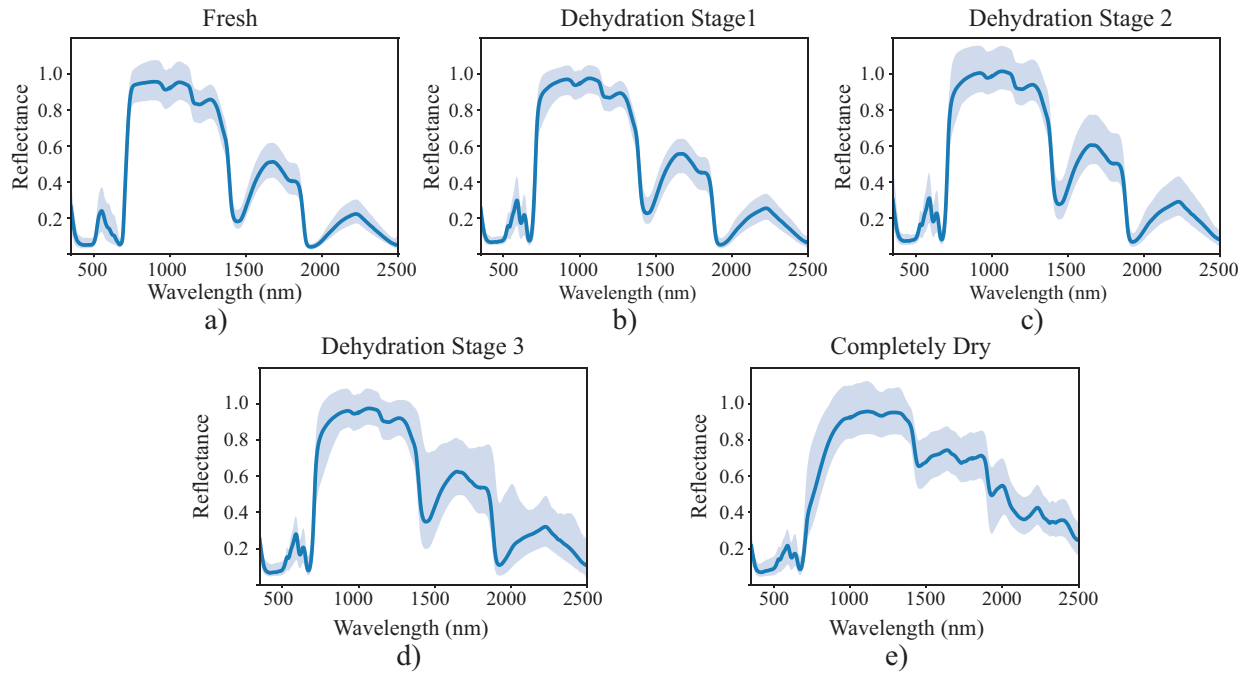


Figure 3.6: Spectral reflectance of the grape leaves at: a) fresh stage, b) dehydration stage 1, c) dehydration stage 2, d) dehydration stage 3, and e) completely dehydrated stage (Source [2]).

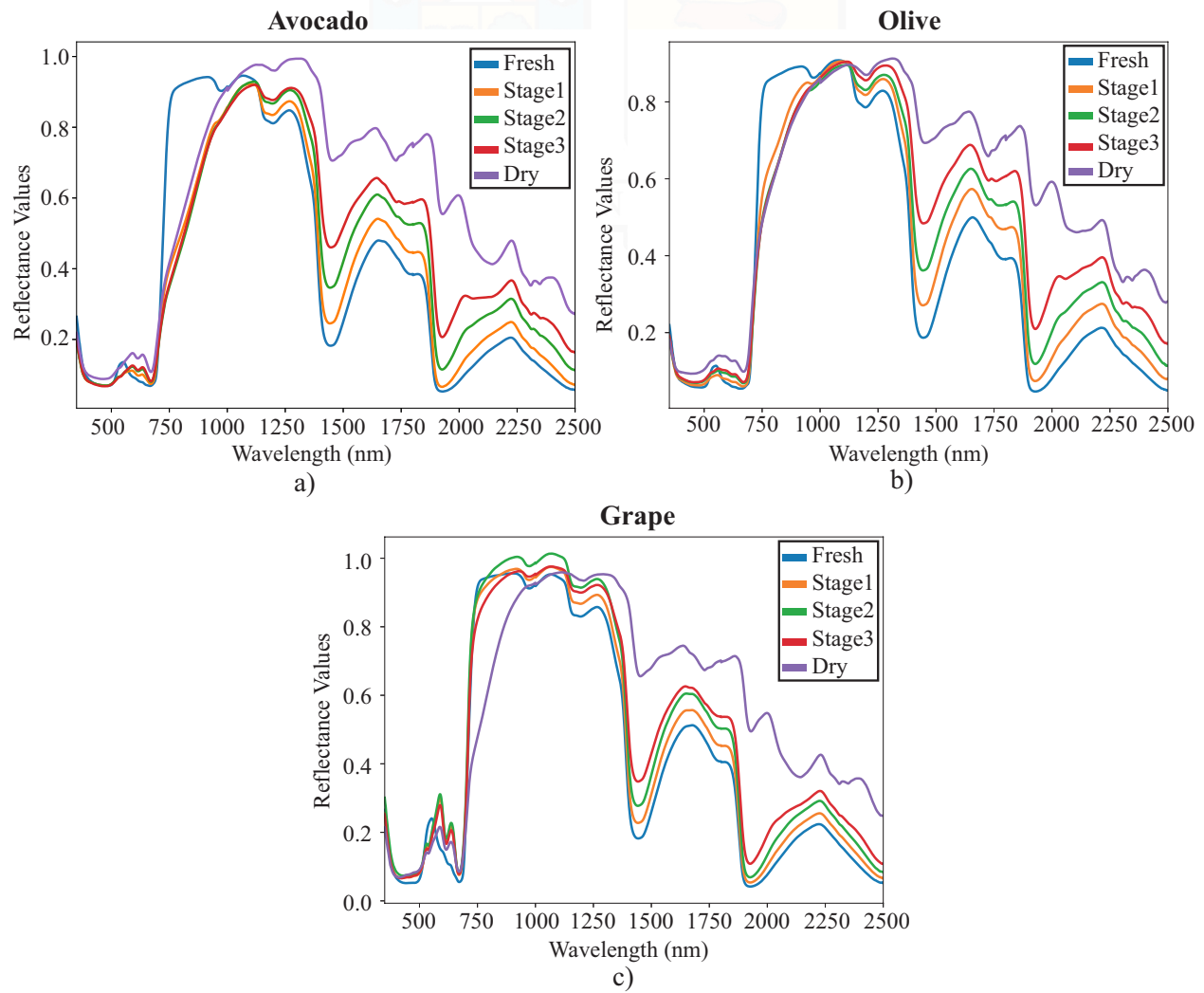


Figure 3.7: Mean reflectance across all the dehydration stages of: a) avocado leaves, b) olive leaves, and c) grape leaves (Source [2]).

3.4.2 Leaf water content

As expected, as the time in the oven increases the leaf water content (with dry or fresh basis) decreases, and reaches the zero value at the final dehydration stage. Figure 3.8, shows a dispersion graph of the leaf water content across all the species. It is clear from the graph, that clusters form according to the time the leaves were put in the oven. Table 3.4, shows the descriptive statistics of the leaf water content, including the mean values, the maximum and minimum as well as the standard deviation for all the dehydration stages.

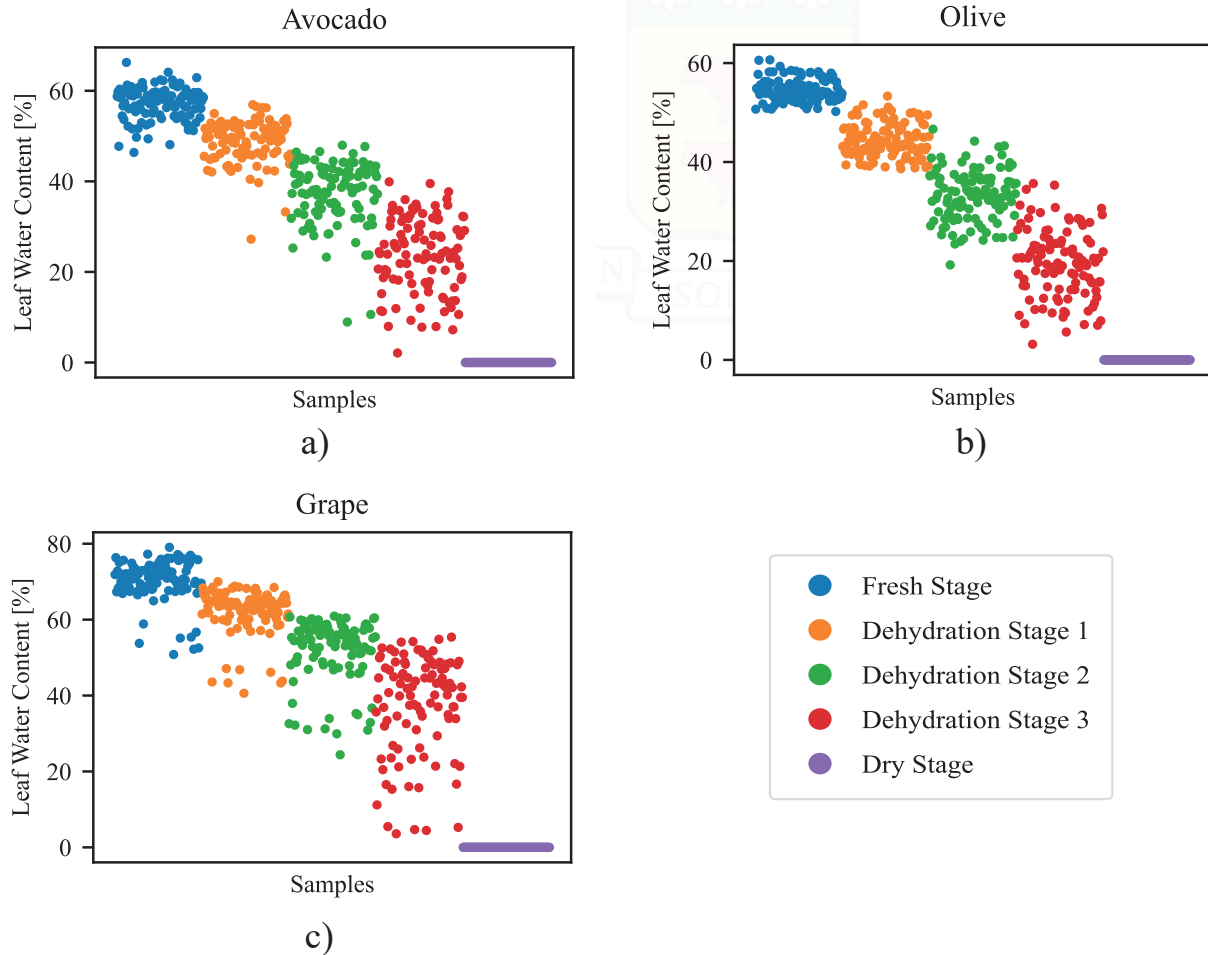


Figure 3.8: Dispersion graph of the leaf water content of: a) Avocado, b) Olive, and c) Grape.

For a better visualization of the leaf water content in both the dry or fresh basis, violin plots are shown in Figure 3.9. Besides, the figure also contains the results of a paired t-tests across the dehydration stages. The p-values show that there is a significant variation in the mean value of the leaf water content. The graph also shows the violin plots of the chlorophyll content.

3.4.3 Chlorophyll content

In Figure 3.9, the violin plots of the different chlorophyll values at the different dehydration stages are shown. Also, the paired t-tests between chlorophyll contents at the dehydration levels were performed and the p values are shown in the graph.

In contrast with the leaf water content values, there is no significant difference across most of the dehydration stages. Particularly there is a significant difference from the fresh stage of the avocado and olive to the first dehydration

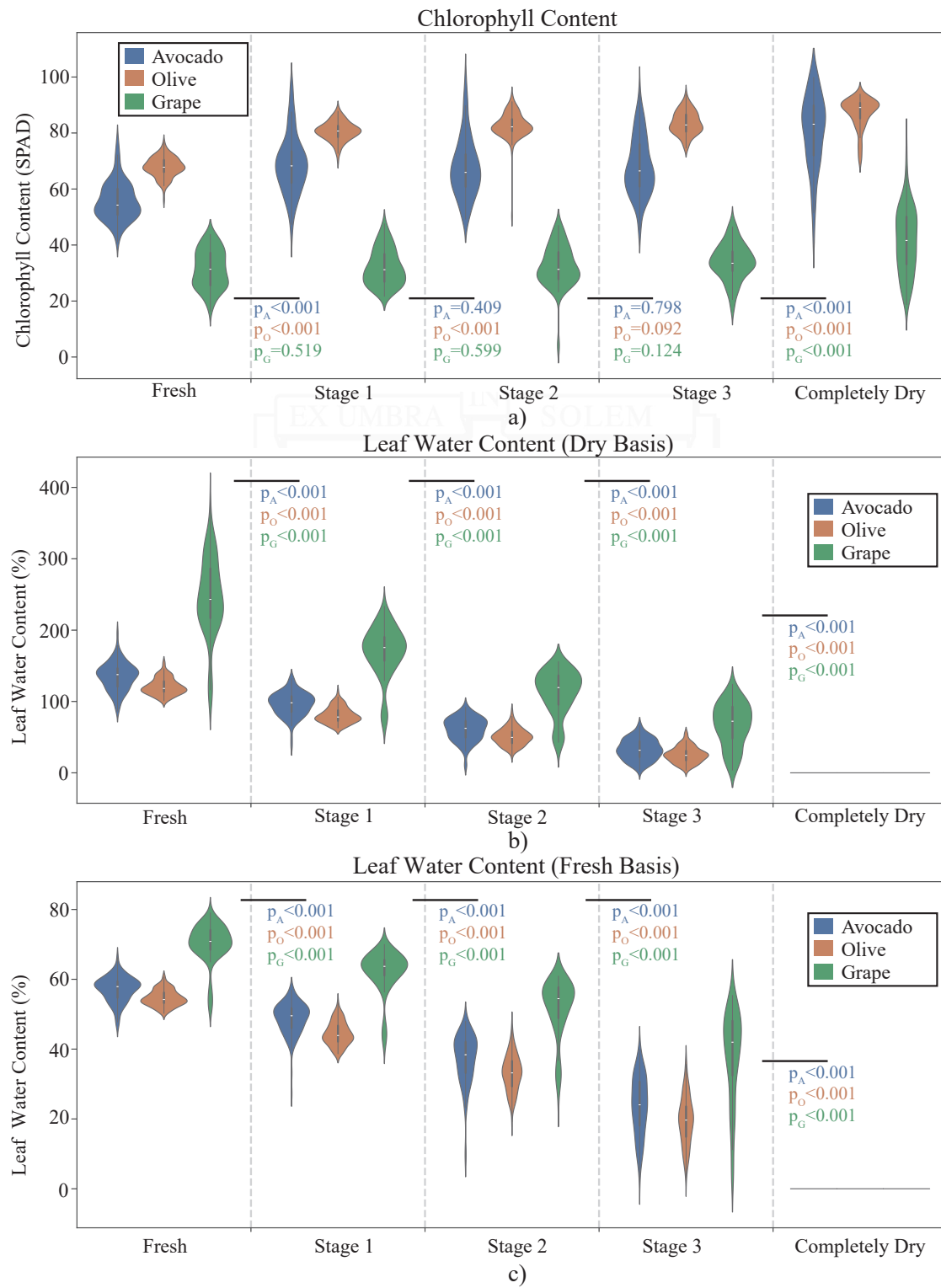


Figure 3.9: Violin plots of all the species at all the dehydration stages: a) chlorophyll content, b) leaf water content using a dry basis, and c) leaf water content using a fresh basis. (Source [2])

Species	Drying Stage	FMC_d				FMC_f			
		Mean	Max	Min	Std	Mean	Max	Min	Std
Avocado	Fresh	135.00	196.36	86.50	19.25	57.16	66.26	46.38	3.60
Avocado	Stage 1	96.48	132.21	37.42	16.32	48.73	56.93	27.23	4.60
Avocado	Stage 2	61.04	92.14	9.82	16.34	37.21	47.98	8.94	7.01
Avocado	Stage 3	32.66	66.37	2.15	14.36	23.73	39.89	2.10	8.34
Olive	Fresh	120.81	154.11	100.84	11.37	54.60	60.65	50.21	2.28
Olive	Stage 1	80.60	114.21	62.96	11.09	44.43	53.32	38.64	3.32
Olive	Stage 2	50.41	87.42	23.77	11.74	33.12	46.65	19.20	5.15
Olive	Stage 3	25.17	55.41	3.28	10.94	19.52	35.65	3.17	6.90
Grape	Fresh	246.18	377.41	103.33	54.40	70.27	79.05	50.82	5.57
Grape	Stage 1	170.50	233.33	68.35	34.70	62.28	70.00	40.60	6.03
Grape	Stage 2	113.05	155.90	32.27	30.91	51.87	60.92	24.40	8.42
Grape	Stage 3	67.24	124.20	3.70	30.74	37.89	55.39	3.57	12.98

Table 3.4: Descriptive statistics about the leaf moisture content at each drying stage

stage, the first dehydration stage of olive to the second dehydration; and from the third dehydration stage to the completely dry stage of all the species.

Since the principal aim was not to artificially change the chlorophyll content of each leaf, any changes are caused by the loss of water, and the changes in reflectance values. The SPAD value used as proxy for chlorophyll, is a spectral index computed using the transmittance values in the wavelengths 650 nm (red light) and 940 nm (infrared light). Such value can vary due to several factors including illumination conditions, nitrogen treatments and water stress. It is reasonable to expect changes in this value due to the artificially induced water loss. Besides from figures 3.7 we can see variations in the wavelengths that compose the SPAD value, which explain its variation. A detailed description of the SPAD values is shown in Table 3.5.

Species	Drying Stage	Mean	Max	Min	Std
Avocado	Fresh	55.63	77.53	41.13	6.78
Avocado	Stage 1	68.85	96.97	43.83	10.26
Avocado	Stage 2	67.65	99.90	49.23	10.56
Avocado	Stage 3	80.32	68.02	95.50	10.35
Avocado	Dry	80.33	99.90	12.20	14.24
Olive	Fresh	67.85	76.60	56.10	11.37
Olive	Stage 1	80.69	88.80	70.10	11.09
Olive	Stage 2	82.62	92.80	50.40	11.74
Olive	Stage 3	83.62	93.90	74.60	10.94
Olive	Dry	87.14	93.90	70.20	5.42
Grape	Fresh	31.33	43.80	16.40	6.86
Grape	Stage 1	32.01	47.60	21.70	6.40
Grape	Stage 2	32.51	47.00	3.70	7.36
Grape	Stage 3	34.00	48.60	16.60	6.48
Grape	Dry	41.41	76.00	6.48	11.53

Table 3.5: Descriptive statistics about the chlorophyll content at each drying stage

3.5 Use of vegetation indices

Furthermore, to corroborate the usability and validity of the dataset, we computed three common vegetation indices used for the assessment of leaf water content and for water stress in plants. Such indices are Leaf Water Index (LWI), Double Difference Index (DDI), and Normalized Difference Water Index (NDWI1). These indices were taken from [55], both LWI and DDI, presented high coefficient of determination R^2 , while NDWI1 presented the worst performance from the three and from several other indices found in the same work. Equations 3.3, 3.4 and 3.5 show the formulas for LWI, DDI and NDWI1 respectively.

$$LWI = \frac{R_{1300}}{R_{1450}} \quad (3.3)$$

$$DDI = 2R_{1530} - R_{1005} - R_{2055} \quad (3.4)$$

$$NDWI1 = \frac{R_{860} - R_{1240}}{R_{860} + R_{1240}} \quad (3.5)$$

The results of the linear regression analysis are shown in Table 3.6 in the form of $y = mx + b$ where y is the respective vegetation index and x is the leaf water content using the fresh basis (LWC_f). Additionally, Table 3.6 shown the Root Mean Squared Error (RMSE) as a performance metric. The linear regression results are shown in Fig. 3.10

Species	VI	Linear Model	R^2	RMSE
Avocado	LWI	$y = 0.0578x + 0.9613$	0.82	0.562
Avocado	DDI	$y = -0.00835x + 0.1337$	0.84	0.079
Avocado	NDWI1	$y = 0.002253x - 0.2112$	0.11	0.120
Olive	LWI	$y = 0.05598x + 0.9219$	0.84	0.489
Olive	DDI	$y = -0.00794x + 0.1159$	0.92	0.048
Olive	NDWI1	$y = 0.001943x - 0.1213$	0.47	0.042
Grape	LWI	$y = 0.04393x + 1.21$	0.84	0.507
Grape	DDI	$y = -0.00583x + 0.02765$	0.86	0.064
Grape	NDWI1	$y = 0.001745x - 0.06844$	0.77	0.026

Table 3.6: Linear regression results for the prediction of fuel moisture content using different vegetation indices.

Comparing the results from Table 3.6 and those found in [55], it is heavily implied that there is a strong correlation between the tested indices and LWC_f , particularly using LWI and DDI. However, the results in this study presented lower R^2 values. This can be attributed to different reasons, for example the variability in the reflectance values due to the measuring process, variation in illumination, and the variability introduced by the different tested species; even though the applied dehydration process was similar. Another notable result is that NDWI1 was the least performing index.

3.6 Contributions

The proposed methodology and the results of the dataset were published in the multidisciplinary journal Scientific Reports.

- Estrada, J.S., Demarco, R., Johnson, C.M. et al. A multi-spectral and hyperspectral image dataset for evaluating chemical traits and the water status of avocado, olive and grape through leaf dehydration under laboratory conditions. Sci Rep 15, 2973 (2025). <https://doi.org/10.1038/s41598-025-85714-8>

The files of the dataset can be found in the following public repository:

- Estrada, Juan Sebastian (2024). A multi-spectral and hyperspectral image dataset for evaluating the health status of avocado, olive and vineyard. figshare. Dataset. <https://doi.org/10.6084/m9.figshare.26950660.v2>

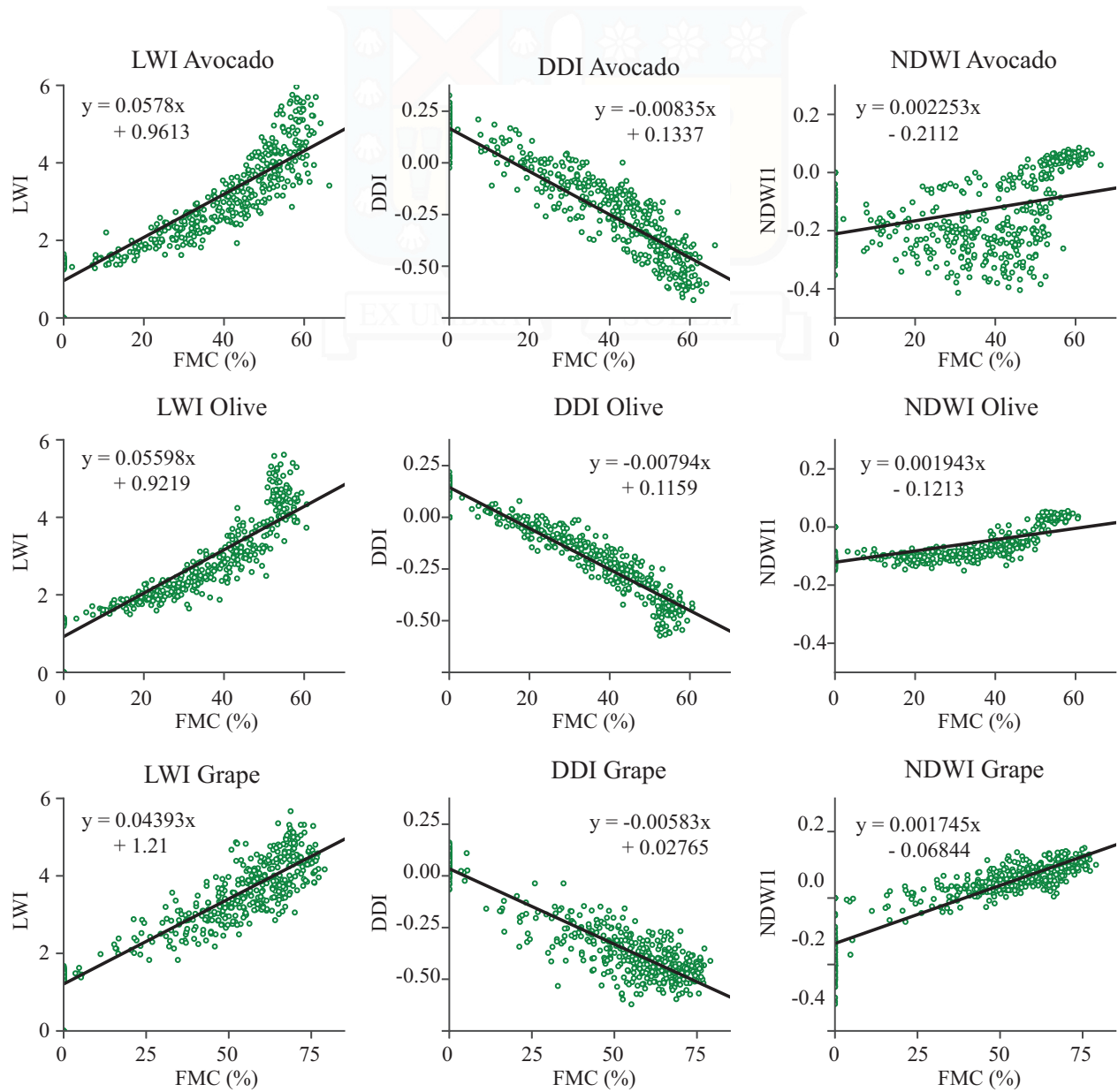
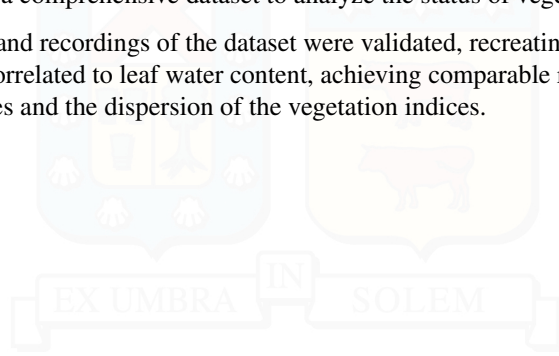


Figure 3.10: Linear regression results for the tested VIs for prediction of leaf water content. (Source [2])

3.7 Conclusion

This section presents the data collection process of the samples that were used in the next chapters of this dissertation. The dataset is composed of 106 samples of avocado, 111 samples of olive and 106 samples of olive leaves. Each leaf underwent a dehydration process resulting in five different dehydration stage. From each sample at each dehydration stage the reflectance values ranging from 350 to 2500 nm, multi-spectral images in five bands: blue, green, red, red-edge and near infrared, weight and chlorophyll content were recorded. Using the weight values, the leaf water content was computed. This process created a comprehensive dataset to analyze the status of vegetation.

Furthermore, the results and recordings of the dataset were validated, recreating the results presented by [55]; in which vegetation indices were correlated to leaf water content, achieving comparable results, with acceptable variations caused by variation in the species and the dispersion of the vegetation indices.



4 | Classification of leaves according to their dehydration stage

4.1 Introduction

Leaf water content prediction is an important indicator of leaf health, water stress and to assess evotranspiration in vegetation. This parameter can be used to improve irrigation regimes by automatically detecting which trees or crops are suffering water stress, thus focusing irrigation efforts in those areas.

Furthermore, detecting leaf water content on forested areas, can serve as an important mapping tool to identify fire risk areas, which are an important tool for fire risk prevention.

LWC assessment is usually a complex task, that can be performed remotely using spectral information; however the spectral information, usually needs to cover the SWIR region (1000 to 2500 nm). Such information is difficult to obtain, usually from hyperspectral devices, or from satellite imaging, hyperspectral devices are costly and their integration in a robotic platform is complex compared to other sensors such as multi-spectral cameras, thus not allowing the survey of large portions of land in short amounts of time.

The exploration of LWC using multi-spectral devices remains relatively unexplored, for example [62], used multi-spectral images to retrieve VIs related to leave water content; this approach did not achieve a great performance achieving R^2 0.18 using machine learning regressors. Other approaches focusing on the prediction of LWC using aerial multi-spectral images are the ones presented by [15, 64, 63], which leverage various features from multi-spectral images to detect LWC, achieving R^2 values above 0.7. Even though these latest approaches are encouraging, they still do not reach the results for LWC prediction using hyperspectral devices, which usually achieve R^2 values over 0.9 [57, 59, 60].

Therefore, this section focuses on an alternative way to assess LWC, using multi-spectral images and deep learning architectures. In this approach, instead of predicting the exact value of LWC, the leaves will be classified according to their dehydration status. For this purpose the created dataset, contains samples at 5 different dehydration stages, thus the aim of this chapter is to classify each sample according to that stage. For this purpose, 2D-CNN architectures are employed. The selected architectures are ResNet, which has been extensively used in agriculture to detect stressed in vegetation [89], by detecting rolled leaves, and the detection of pests [90]. Lightweight architectures, such as MobileNet has been used in similar tasks, [91], employed this network to for biotic stress classification in coffee leaves, and [92] detected diseases in olive leaves. Finally, ConvNext, a CNN inspired by transformer's architecture [93], has been used to classify soybean leaf diseases [94]. To compare the classification results using the multi-spectral images, the same task was carried out, but using as input the complete reflectance values (from 350 to 2500 nm). This input is considered tabular data, thus simple ML models were evaluated using this data, a wide variety of models were employed including: RF, kNN, SVM, MLP, decision trees (DT), reduced error pruning trees (REPTree), classification trees (SimpleCART), bayesian networks (BayesNet), linear discriminant analysis (LDA) and logistic regression (LR). The models were evaluated using common metrics including accuracy, precision, recall, F1-score, receiver operating characteristics (ROC) curves, area under the curve (AUC), and confusion matrices, ensuring a comprehensive assessment of the classification effectiveness.

4.2 Methodology

The general overview of the implemented architecture for this chapter is shown in Fig. 4.1. First, from the dataset, both the spectral signature and multi-spectral images for the vegetation are collected. The data is classified according to their dehydration stage (fresh stage, dehydration stage 1, dehydration stage 2, dehydration stage 3, and completely dry stage). The multi-spectral images underwent a pre-processing step, which consisted on resizing the images, scaling between the values 0 to 1, and creating matrices from the 5 files. Then, using the two kinds of data (multispectral images and complete spectrum), the set of deep learning architectures and machine learning algorithms were trained. Finally, the models were evaluated using the same metrics.

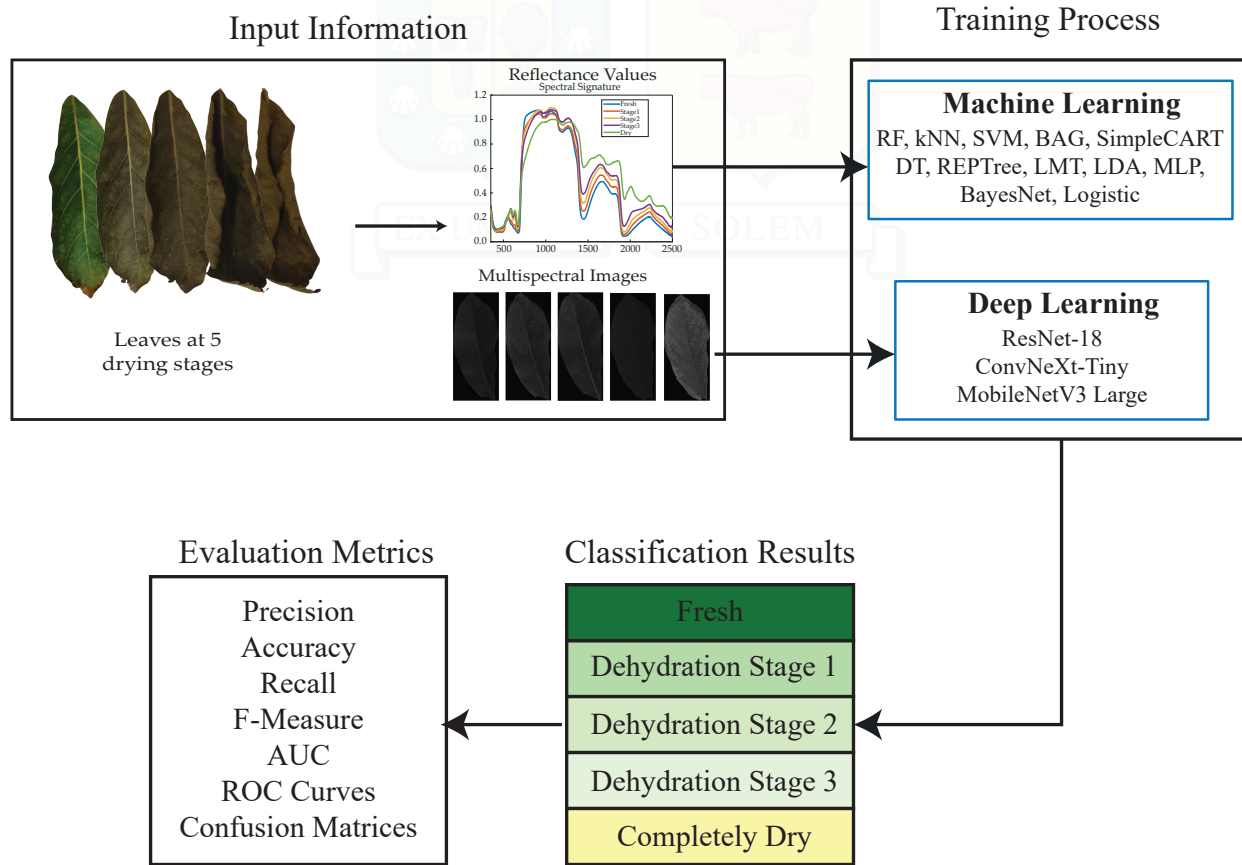


Figure 4.1: Architecture implemented for the classification of leaves according to the dehydration stage (Figure modified from [95]).

4.2.1 Multispectral image pre-processing and deep learning architectures

The images from the dataset are radiometrically calibrated, and are adjusted to a resolution of 16 bits; thus, to normalize the values from 0 to 1, each image was divided by 65 535. Furthermore, all the images were resized to a standard size of 401×210 , this value was chosen based on the average size of the images. Afterward, all the .tiff files corresponding to each sample were read, and matrices of size $401 \times 210 \times 5$ were created.

The three deep learning architectures chosen to process the multi-spectral images are the following: ResNet18, which is a well established network used for image classification in agricultural and vegetation settings, this version of ResNet presents fewer layers which results in lower computational requirements and faster training times [96]. The ConvNext-Tiny network combines CNN with deep learning techniques inspired by transformer architectures [97]. Finally, MobileNetV3 is an optimized for devices with limited computation capabilities, thus this is a lightweight network, with similar performance to other more complex networks. This model is suitable for potential deployment in mobile devices and in-field operations.

The three selected models were trained and designed for three-channel images (RGB), thus the input layer was modified so it can receive the five input channel. Due to the size of the dataset, some strategies were adopted to prevent overfitting, dropout and weight-decay were added, and the models were trained for 15 epochs. The Adam optimizer was chosen for all the models. For the learning rate an adaptive strategy was adopted. The hyperparameter selection is summarized in Table 4.1. A complete overview of the image preprocessing scheme and the training process is shown in Fig. 4.2

Table 4.1: Hyperparameter selection for the deep learning models

Parameter	ResNet18	ConvNeXt-Tiny	MobileNetV3
Learning rate	0.001–0.0001	0.00001–0.0001	0.0001–0.001
Batch Size	32	32	32
Weight Decay	0.01	0.01	0.01
Optimizer	Adam	Adam	Adam
Epochs	15	15	15
Dropout	0.5	0.5	0.5

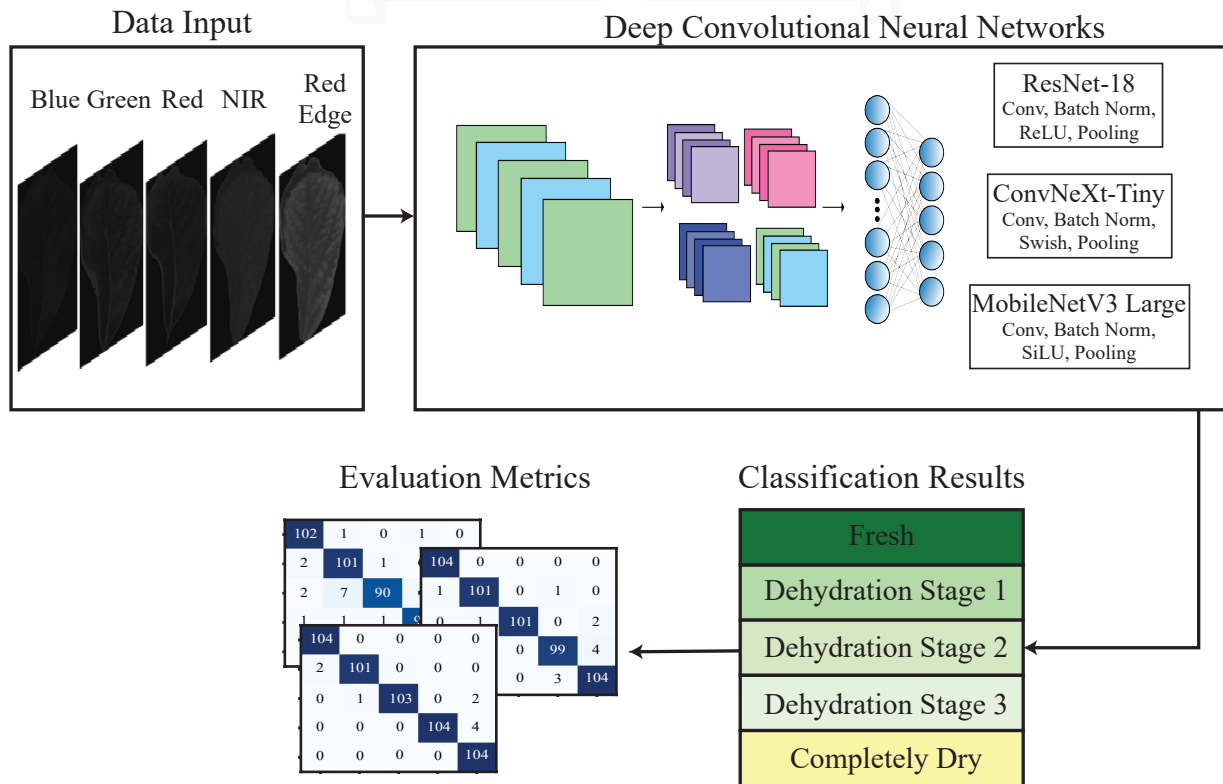


Figure 4.2: Steps for the training and validation of the deep learning architectures (Source [95]).

4.2.2 Machine learning models

The spectral information can be considered a vector of 2151 elements, containing the reflectance values ranging from 350 to 2500 nm at a resolution of 1 nm. No further pre-processing or feature selection model was performed to the spectral raw data, this is done to correctly assess a fair comparison with almos raw unprocessed data. Performing a feature or band selection algorithm, would create a positive bias towards the classification using this spectral data. For the classification process, eleven machine learning algorithms were chosen, RF, kNN, SVM, BAG, DT, REP-Tree, SimpleCART, BayesNET, LMT, LDA, LR, and MLP. The model configuration and parameters are shown in Table 4.2.

Table 4.2: Hyperparameters of the machine learning classifiers

Algorithms	Hyperparameters
RF	breakTiesRandomly: False; debug: False; maxDepth:0 numExecutionSlots: 1; numIterations: 100; seed: 1
k-NN	k:5; distanceWeighting: No distance Weighting; nearestNeighbourSearchAlgorithm: LinearNNSearch (distanceFunction: EuclideanDistance)
SVM	c: 1.0; calibrator: Logistic debug: False; epsilon: 1.0E-12 ; filterType: Normalize training data; kernel: PUK; randomSeed:1; toleranceParameter: 0.001
BAG	bagSizePercent: 100; calcOutOfBag: False; classifier: REPTree; numExecutionSlots:1; numIterations: 10; seed: 1
DT	binary splits: False collapseTree:True; confidenceFactor: 0.25; numFolds:5; reducedErrorPruning: False; seed: 1; useLaplace: False; useMDLcorrection: False
REPTree	initialCount: 0.0; maxDepth: -1; minVarianceProp: 0.0001; noPruning: False; seed: 1; spreadInitialCount: False
SimpleCART	heuristic: True; minNumObj: 2.0; numFoldsPruning: 5; seed: 1; sizePer: 1.0; useOneSE: False; usePrune: True
BayesNet	estimator: SimpleEstimator; searchAlgorithm: K2; useADTree: False
LMT	fastRegression: True; minNumInstances: 15; numBoostingIterations: -1; splitOnResiduals: False; useAIC: False; weightTrimBeta:0.0
LDA	batchSize: 100; debug: False; ridge: 1.0E-8
Logistic	batchSize: 100; debug: False; maxIts: -1; ridge: 1.0E-6; useConjugateGradientDescent: False
MLP-1	hiddenLayers: a ((attribs + classes) / 2); momentum: 0.1; learningRate: 0.3; NominalToBinaryFilter: True; normalizeAttributes: True; trainingTime (epochs): 100; seed: 0; validationThreshold: 20; activation function: sigmoid
MLP-2	hiddenLayers: a ((attribs + classes) / 2); momentum: 0.1; learningRate: 0.3; NominalToBinaryFilter: True; normalizeAttributes: True; trainingTime (epochs): 300; seed: 0; validationThreshold: 20; activation function: sigmoid

Furthermore, to ensure model generalization and to avoid overfitting, a 5-fold cross validation analysis was performed in all the deep learning and machine learning models

4.2.3 Performance metrics

First the deep learning models were assessed using common metrics, mainly accuracy, precision, recall and F1 Score. Furthermore, since the models are not trained on a large dataset, additional robust performance metrics are added to this study. The robust metrics are as follows:

- **Balanced Accuracy:** It is the average of recall obtained at each class. This metric is appropriate for datasets with unbalanced classes.
- **Matthews Correlation Coefficient (MCC):** This metric takes into account all the elements of a confusion matrix, thus providing a better understanding of the classification and the contribution of each class. This value ranges from -1 to 1; with 1 being a perfect prediction, 0 is a model that does not improve a random guess, and -1 means a complete disagreement between the model and the correct prediction.
- **Cohen's Kappa:** This coefficient measures the agreement between two classifiers. To assess the multi-class classification problem, this coefficient helps understand how the model performs against a random classifier.

Besides all the metrics listed, the confusion matrices for all the models are used to analyze the capabilities of the

models to classify each leaf according to each class.

4.3 Results

In this section, the classification results are presented for all the trained models, including the machine learning and deep learning models.

4.3.1 Deep learning classification results

The training results are shown in Fig. 4.3. All the models reached a stable result at around 15 epochs, so the results were capped at that value, up until that point; the training and validation results both in accuracy and loss function did not diverge from one another, proving that no overfitting occurred during the training stage. The training graphs also show the evolution of the accuracy and the error rate, showing how the performance increases and become stable as the training epochs progress.

To improve the training performance, a variable learning rate strategy was applied to all the models, the graphs for the evolution loss across the variable learning rate, based on this graph, the learning rates were chosen in the midpoint of the steepest slope as suggested by the documentation of FastAI. The variation of the loss function according to the learning rate is shown in Fig.4.4.

The metrics for the three deep learning architectures are shown in Table 4.3. Here, the micro average per class metrics for accuracy, precision, recall and F1 score are shown, alongside the standard deviation obtained for all the models in the 5-fold split cross validation. For the robust metrics, the results are shown in Table 4.4. The results of this metrics support the claims that the models do not overfit, and present a good performance in the classification of all the leaves.

Table 4.3: 5-Fold Cross-Validation Results for Deep Learning Models

Model	Accuracy	Precision	Recall	F1-Score
ResNet-18	98.0	98.0	98.0	98.0
ConvNeXt-Tiny	99.0	98.0	99.0	99.0
MobileNetV3	98.0	98.0	98.0	98.0

Table 4.4: Robust metrics for the deep learning models

Model	Balanced Accuracy	MCC	Cohen's Kappa
ResNet-18	0.980	0.973	0.973
ConvNeXt-Tiny	0.980	0.973	0.973
MobileNetV3	0.990	0.990	0.990

Furthermore, to evaluate the interclass classification results, the confusion matrices for the deep learning models are shown in Fig.4.8. In the confusion matrices, it is clear that the major amount of error are shown in the intermediate dehydration stages, with an almost perfect classification results in the completely dehydrated stage, and the fresh stage.

4.3.2 Comparison between machine learning and deep learning

The deep learning classification approach for leaves according to the dehydration stage using reduced multi-spectral information, was compared against lighter models (machine learning approaches), but using as input the complete spectral information from 350 to 2500 nm. As stated in the previous section, no data preprocessing or feature selection analysis was performed in the complete spectral information, to avoid any bias towards the machine learning approaches.

The macro-average accuracy is summarized in the radial plot presented in Fig. 4.5. In this graph, it is clear that the deep learning approach outperforms the classification results achieved by the classic machine learning algorithms,

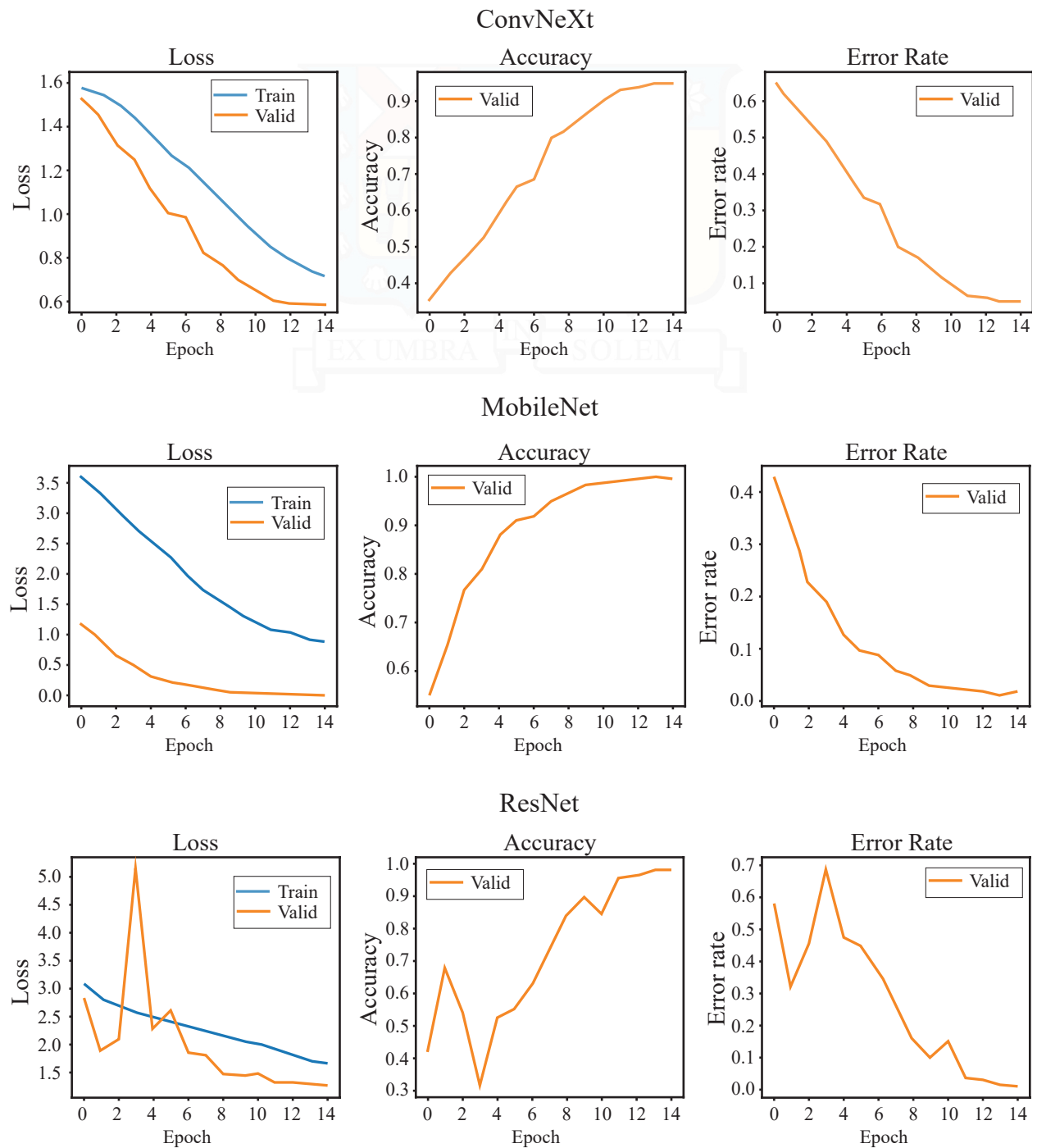


Figure 4.3: Training results of all the tested deep learning architectures. The graph include both the loss function and the evaluation metrics of accuracy and error rate (Source [95]).

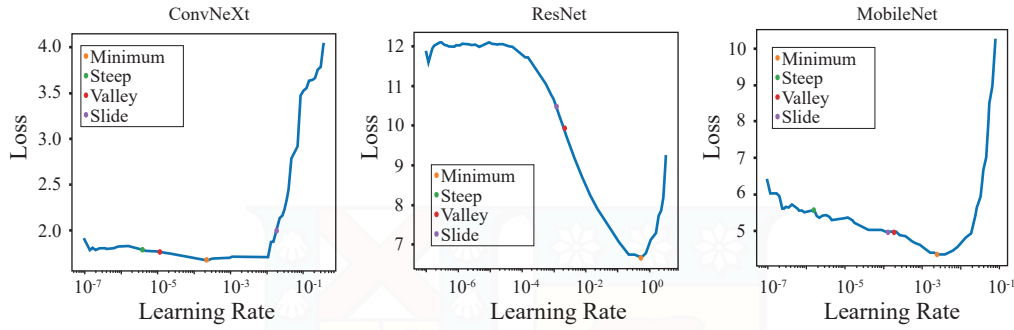


Figure 4.4: Evolution of the loss function according to the learning rate for all the three tested networks (Source [95]).

both the MobileNetV3 and the ResNet-18 achieve accuracies above 98% while the ConvNext-Tiny model achieves an accuracy of 94%.

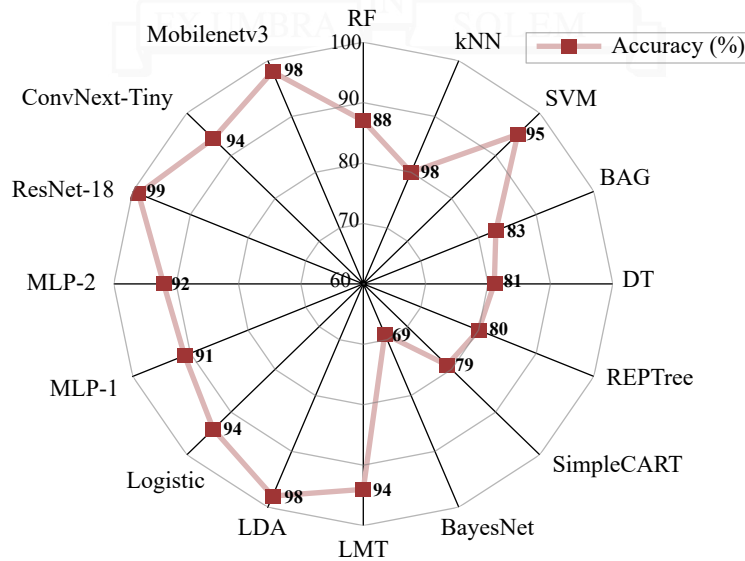


Figure 4.5: Accuracy results for the machine and deep learning models (Source [95]).

Comparing among the machine learning algorithms, the best performing one is the LDA algorithm reaching an accuracy of 98%, followed by the SVM algorithm achieving 95%, finally both the LMT and Logistic regression algorithm achieved both 94% accuracy. The least performing algorithm is the BayesNet which only achieved an accuracy of 69%. In general all the models achieved an acceptable performance of above 70% except for the BayesNet.

Furthermore, a list for all the metrics including Precision, Recall, F1 Score and Area under Curve (AUC) is shown in Fig.4.6. These metrics follow a similar pattern to Fig.4.5. Here, the best performing models are still the deep learning approaches, while the other models achieve similar results particularly the LDA, LMT, SVM and Logistic Regression. For a complete description of the models all the macro-averaged metrics are shown in Table 4.5.

Furthermore, all the confusion matrices are shown in Fig.4.7 and Fig.4.8. Here the performance of the models can be assessed in a class by class case, rather than using a single metric.

4.4 Discussion

In this chapter various machine and deep learning models were trained with the objective of classify leaves according to their dehydration stage, as a method to assess the current water status of vegetation, which is a valuable tool for

Model	Precision	Recall	F1-Score
RF	0.866	0.865	0.866
kNN	0.803	0.804	0.802
SVR	0.947	0.946	0.947
BAG	0.825	0.829	0.825
DT	0.808	0.810	.808
REPTree	0.799	0.802	0.800
SimpleCART	0.795	0.793	0.793
BayesNet	0.687	0.690	0.688
LMT	0.941	0.940	0.940
Logistic	0.938	0.937	0.937
MLP-1	0.909	0.908	0.908
MLP-2	0.923	0.923	0.923
ResNet-18	0.994	0.994	0.996
ConvNext-Tiny	0.942	0.940	0.940
MobileNetv3	0.982	0.980	0.982

Table 4.5: Metrics obtained by the different machine and deep learning models in the classification task.

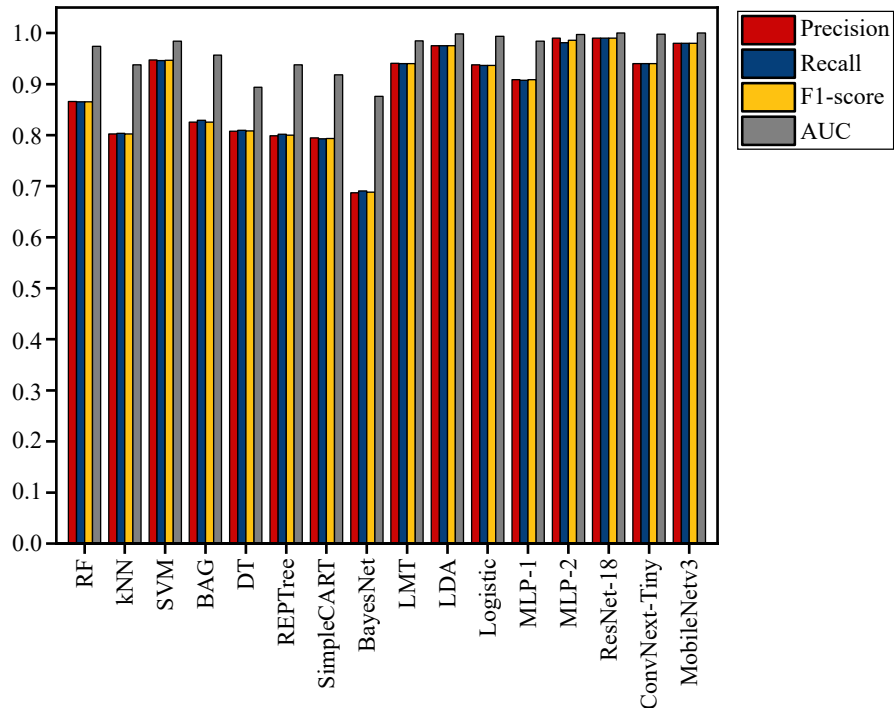


Figure 4.6: Macro averaged metrics for all the machine and deep learning models in the classification task. The metrics include precision, recall, F1-score and area under roc-curve (Source [95]).

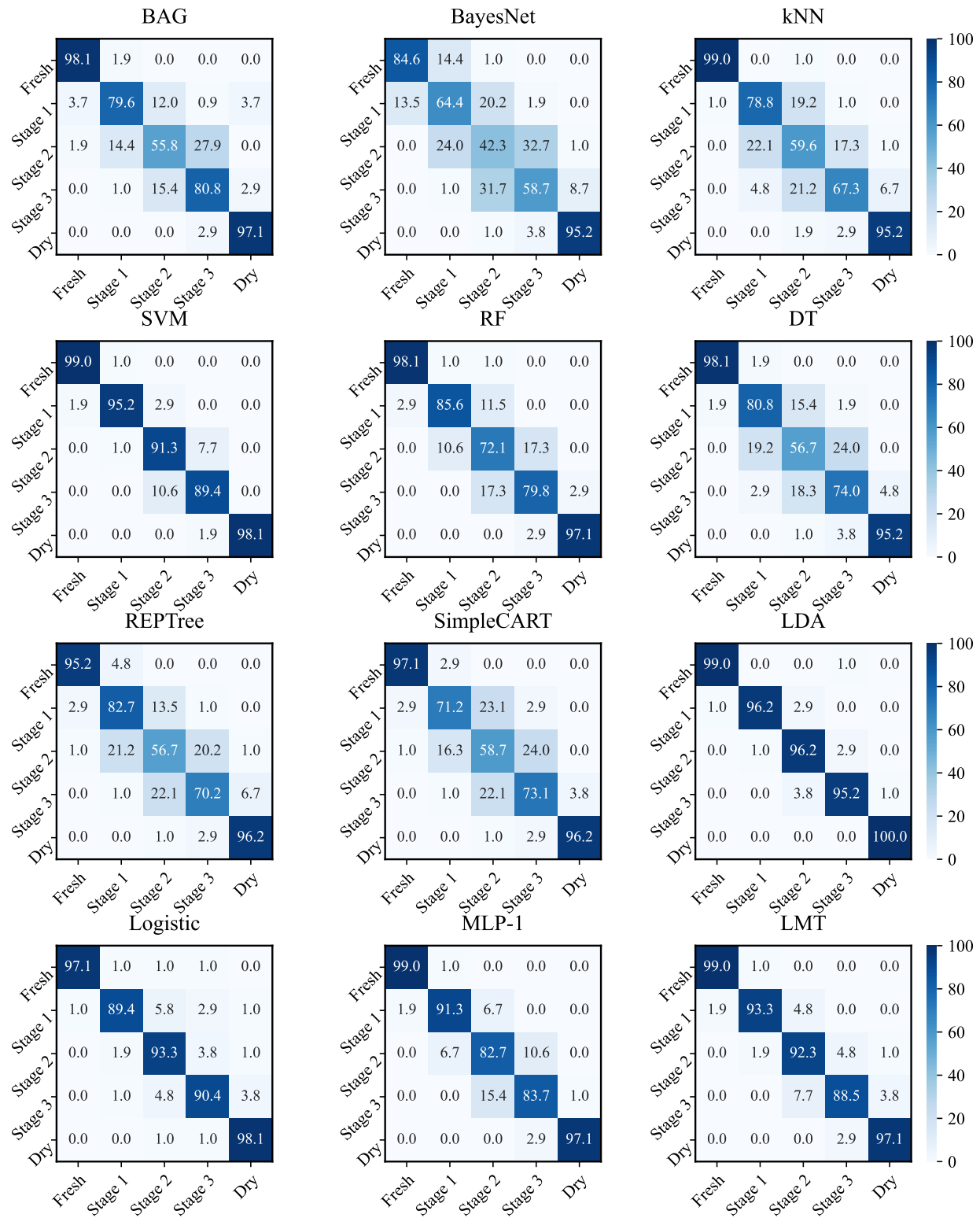


Figure 4.7: Confusion matrices of the machine learning models (source [95]).

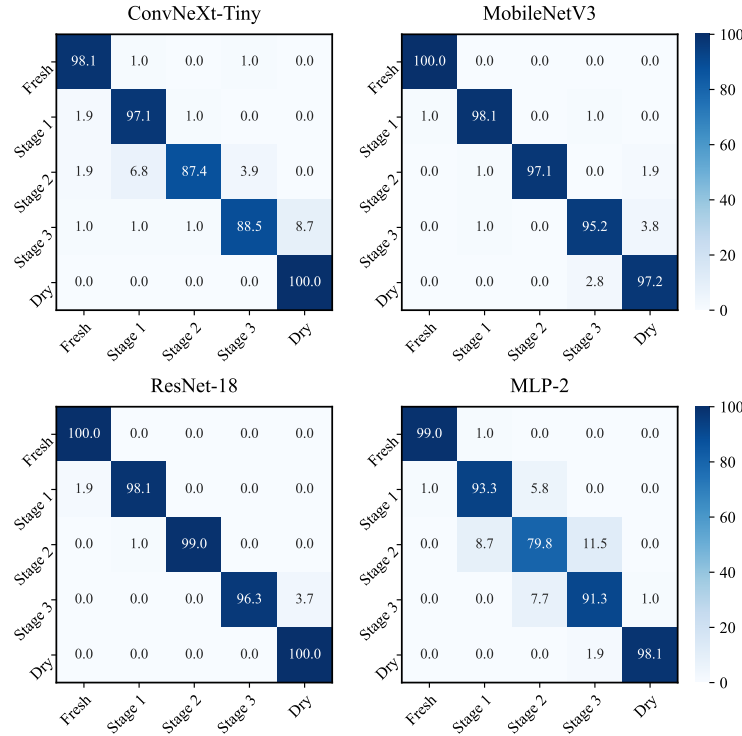


Figure 4.8: Confusion matrices of the deep learning models (and MLP2)(Source [95]).

optimizing irrigation regimes [98]. The classic machine learning models were trained using as input the complete spectral information, while the deep learning architectures were trained using multi-spectral images in five bands (B, G, R, NIR, RE). The chosen DL architectures are deep 2D-CNNs, these models are useful to extract important features from unstructured data, such as images, and have been applied to various agricultural tasks such as disease detection and classification [96, 97, 99].

The metrics shown in the previous section showcase the capabilities of the deep learning models to classify the leaves according to their dehydration stage, achieving accuracies of above 0.99 in the case of ResNet18, and MobileNetV3, while the ConvNext-V2 achieve an accuracy of 0.94 which is still a very high value. Comparing the results, with the obtained by the modelling using the complete information, the deep learning models clearly outperform most of the machine learning algorithms. The machine learning algorithms particularly the LDA and Logistic regression achieved similar performances to the DL approach, with accuracies above 0.9. For the rest of the ML models, the accuracies were also acceptable with values over 0.70, except for the BayesNet model, which achieved an accuracy of 0.69. When comparing using other macro-averaged metrics (Precision, Recall and F1-Score), the performance of the models is still similar, with the DL models clearly outperforming the ML alternatives.

Analyzing the confusion matrices of the models, it also showcases that the DL models present very few misclassifications, with values of under 1% in most cases. Most notably, the misclassifications occur in the intermediate dehydration stages (Stages 1 trough 3). There are various explanations for this phenomenon, first the drying was carried out in an oven, and even though the oven has temperature control, areas of the oven might dehydrate the leaves at different rates due to differences of temperature within the oven. Furthermore, there might not be a clear distinction between this intermediate dehydration levels [56].

The trend of misclassifying leaves in the intermediate stages of dehydration, is more clear when analyzing the ml models' confusion matrices. In these models it is more clear that near perfect classification rates are achieved, in the fresh and completely dehydrated stages, due to the fact that this stages present the more distinct features, both spectral and physical. The misclassifications clearly occur in the intermediate dehydration stages. However, the best performing models (LDA, LMT, SVM and Logistic Regression), still present very few misclassifications, with values near 1%, and the majority of samples classified correctly.

As the leaves undergo the dehydration process, there are visible changes in its physical structure; thus, spectral information such as the one recorded by the spectrometer is not capable of capturing such changes. A multi-spectral image, is able to capture both spectral features and the physical features; and a 2D CNN is capable to extract the needed features for the classification purposes. Under extreme water stress as the leaves present physical modifications such as size contraction, and rolled edges [89]. Such differences allow for a better classification of the leaves, principally in the fresh and completely dehydrated stages.

The results of both the classification using multi-spectral images and the complete spectral information, support the claim that a quick assessment of water status, can be performed using only the reduced bands that can be recorded by a multi-spectral camera; in fact, in combination with deep learning architectures, the classification results outperform the ones obtained using most of the machine learning algorithms using the complete spectral information. Thus enabling further studies that rely solely on the use of multi-spectral cameras for the assessment of water status at a large scale, using robotic platforms such as UAVs.

4.5 Contributions

The results of these experiments have led to the publication and presentation at ICIT 2024:

- **J. S. Estrada**, M. Zanartu, R. Demarco, A. Fuentes and F. A. Cheein, "Water Content Classification on Leaves Based on Multi-Spectral Imagery and Machine Learning Techniques for Wildfire Prevention," 2024 IEEE International Conference on Industrial Technology (ICIT), Bristol, United Kingdom, 2024, pp. 1-7, doi: 10.1109/ICIT58233.2024.10540771.

Furthermore, an extended version, using the comparison with hyperspectral values, is considered for publication at the journal Expert Systems with Applications:

- **J. S. Estrada**, N. Cetin, K. Sacilik, B. Ulu, B. Ulu, and F. Auat Cheein, "Assessment of avocado water stress using multispectral imaging and deep learning: Toward scalable, cost-effective irrigation monitoring," Expert Systems with Applications, vol. 326, p. 132688, Sep. 2026, doi: 10.1016/j.eswa.2026.132688.

4.6 Conclusion

The deep learning architectures are able to perform the leaf classification task according to their dehydration level. These architectures outperform the classification using machine learning algorithms that process the whole input. The ResNet-18 and MobileNetv3 achieved accuracies of 0.99 with very few misclassifications; such results are comparable to the LDA, LMT and SVM. The performance of the MobileNetv3 architecture is notable, because this is a light model that can be deployed in cheaper and portable devices for on-field exploration.

The success of these experiments suggest that an early assessment of crop water status can be performed using multi-spectral cameras rather than with hyperspectral devices that record the NIR and SWIR region. Further work should focus on adjusting and retraining the models, so the models can still perform the classification task with minimal errors even in the presence on noise and background interference induced by the harsh ambient conditions.

5 | Prediction of vegetation indices using down-sampled data

5.1 Introduction

Health status of vegetation is predicted using spectral information, which is used to compute vegetation indices that are correlated to various vegetation features, including leaf water content, chlorophyll content, various pigments, and biomass concentration [18]. Such approach has been tested in various cultivars including rice [37, 36], soybean [100], cotton [101], onion [47], sweet potato [49], sugarcane [44], wheat [102], corn [103] among others. These applications highlight the potential of vegetation indices as predictors of vegetation health status.

Even though the information from hyperspectral devices is rich and comprehensive, such devices present major drawbacks. Devices such as spectrometers exhibit low spatial resolution (they can record a single point in the space), require manual sampling process (the probe needs to keep contact with the sample), and present difficulties in coupling with robotic platforms such as UAV, besides the high cost compared to multi-spectral devices. These practical limitations-high cost, restricted coverage, and complexity in deployment, present significant barriers to large-scale monitoring [104].

Due to the drawback from using hyperspectral devices, there have been various studies trying to replicate the complete information from hyperspectral devices using a reduced set of bands. For example the study in [105, 106], explores the reconstruction of the NIR band and Red-edge band from multi-spectral cameras, by using as input the bands in the visible spectrum (Blue, green, red). For this purpose, the authors trained a hyperspectral deep convolutional neural network (HSCNN-R), furthermore in [107] the authors propose the use of a generative adversarial network (GAN) with the same purpose. Similar networks have been tested, but with the purpose of reconstructing multiple bands and not only the NIR and RE bands. Then using this reconstructed bands, the authors analyzed the capabilities of such bands to assess the quality of tomatoes [108].

The authors in [109] use shallow learning approaches, relying on coupled dictionaries and sparse representation of matrices, for the prediction of multi-spectral bands while employing lighter models, compared to deep convolutional neural networks.

The previous studies focus on rebuilding bands in the near infrared region, however for applications such as leaf water content prediction, reflectance values in the SWIR region are needed, since these are more sensitive to water molecules. Studies such as the one in [56], use the reflectance in the visible and NIR regions (350 to 1000 nm) to replicate reflectance values in the SWIR region. Then, the predicted region was used to evaluate the leaf water content on a dataset composed of *Eucalyptus globulus* leaves.

The success of these studies suggest that there exists a fundamental set of wavelengths, which would allow a complete characterization of vegetation. Finding such set of wavelengths, would allow the construction of cheaper sensors focused only on recording the needed wavelengths for its agricultural purpose, such devices would also be smaller, more accessible and their integration in another platform would be easier.

Thus, this chapter is focused on finding the minimum wavelength sampling, that allow the prediction of various vegetation indices related to various plant parameters. For this purpose we use the spectral reflectance values from 350 to 2500 nm with a resolution of 1 nm, and systematically downsampled its resolution up to 100 nm. Using the

downsampled information, machine learning algorithms were trained, including random forest, artificial neural network, support vector machine and k-nearest neighbors. Previous the training of the models, a correlation based feature selection algorithm was performed to select only a few bands for each vegetation index. Each model was evaluated using the coefficient of determination R^2 and the $RMS E$ metrics.

5.2 Methodology

Figure 5.1, showcases the general framework implemented in this section. We used the samples from our constructed dataset. In this case we only used the reflectance values in the 350 to 2500 nm, recorded using the spectrometer. The spectrometer allows a reconstruction of the spectrum with a 1 nm resolution. Then this information was systematically downsampled, meaning that only a few selected wavelengths with the higher correlation factor are used to train the machine learning models. Then four common machine learning algorithms: random forest (RF), multilayer perceptron (MLP), support vector regression (SVR) and k- nearest neighbors (kNN) were trained to predict each vegetation index. Afterward, the models were evaluated using two common metrics R^2 and $RMS E$.

5.2.1 Vegetation indices

We analyzed 25 different vegetation indices that have been tested for various plant tasks, including leaf water content prediction, chlorophyll prediction, pigment concentration and biomass concentration.

The complete list of the indices is shown in Table 5.1, where R_x shows the reflectance value at the x wavelength.

Table 5.1: Vegetation indices used in this section for the prediction using downsampled spectral information

Name	Acronym	Equation
Theme Mapper 57	TM57	R_{1650}/R_{2220}
Fractional Water Band Index	FWBI	$R_{900}/\min(R_{930} - R_{980})$
Leaf Water Index	LWI	R_{1300}/R_{1450}
Shortwave Infrared Water Stress Index	SIWSI	$\frac{R_{1640}-R_{888}}{R_{1640}+R_{888}}$
Vogelmann Red Edge Index	VOG1	R_{740}/R_{720}
Structure Insensitive Pigment Index	SIPI	$\frac{R_{800}-R_{445}}{R_{800}+R_{680}}$
Optimal Vegetation Index	VOPT	$(1 + 0.45) \cdot \frac{R_{800}^2 + 1}{R_{670} + 0.45}$
Transformed Chlorophyll Absorption Reflectance Index	TCARI	$3(R_{700} - R_{670}) - 0.2(R_{700} - R_{550}) \cdot \frac{R_{700}}{R_{670}}$
Soil Adjusted Vegetation Index	SAVI	$1.5 \cdot \frac{R_{800}-R_{670}}{R_{800}+R_{670}+0.5}$
Simple Ratio 800-500	SR800550	R_{800}/R_{550}
Chlorophyll Index Red Edge	CIIRE	$R_{750}/R_{710} - 1$
Leaf Chlorophyll Index	LCI	$\frac{R_{850}-R_{710}}{R_{850}+R_{680}}$
Anthocyanin Reflectance Index	ARI	$1/R_{550} - 1/R_{700}$
Simple Pigment Ratio Index	SPRI2	R_{750}/R_{556}
Blue Red Pigment Index	BRI	R_{400}/R_{690}
SPAD Index	SPADI	R_{650}/R_{940}
Gitelson and Merzylak Index 1	GM1	R_{750}/R_{550}
Ration Vegetation Index 1	RV11	R_{750}/R_{705}
Carotenoid Reflectance Index	CRI1	$1/R_{510} - 1/R_{550}$
Red-Edge Vegetation Stress Index	RVSI	$0.5(R_{772} + R_{763}) - R_{753}$
Normalized Difference Vegetation Index	NDVI	$\frac{R_{750}-R_{680}}{R_{750}+R_{680}}$
Normalized Difference Vegetation Index	NDVI3	$\frac{R_{780}-R_{715}}{R_{780}+R_{715}}$
Normalized Difference Vegetation Index	NDVI6	$\frac{R_{800}-R_{700}}{R_{800}+R_{700}}$
Pigment Specific Normalized Difference B	PSNDB	$\frac{R_{800}-R_{680}}{R_{800}+R_{680}}$
Lichtenhaler Index 2	LIC2	$\frac{R_{790}-R_{680}}{R_{790}+R_{680}}$

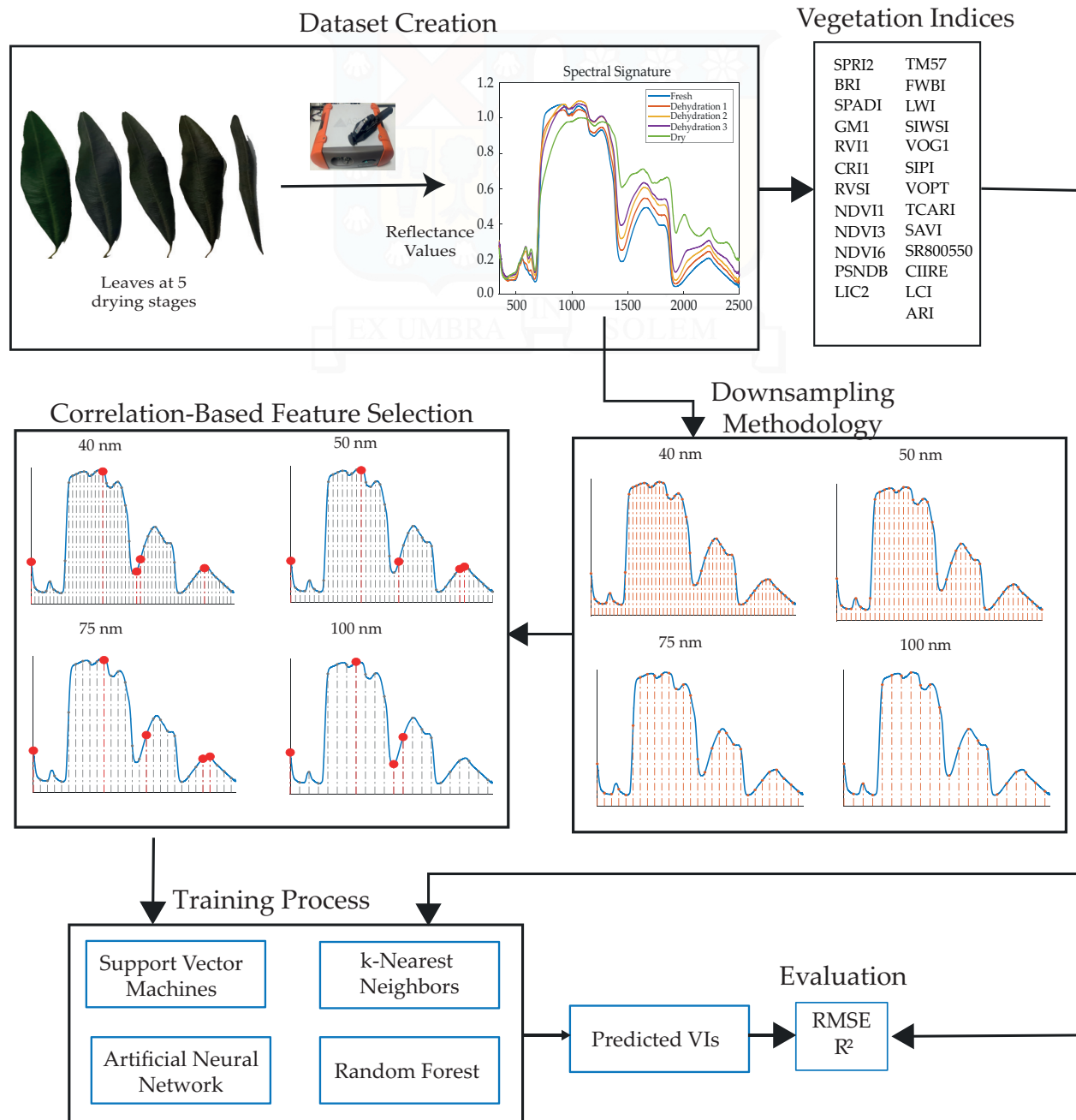


Figure 5.1: Proposed architecture for the prediction of vegetation indices using downsampled spectral information (Image modified from [110]).

5.2.2 Downsampling Methodology

The precision of the ASD Terraspec enables the reconstruction of the spectral signature of the samples at a resolution of 1 nm, producing 2151 reflectance values ranging from 350 to 2500 nm.

Since the intent is to find the minimum set of wavelengths, the spectral resolution was reduced systematically up to 100 nm per point in the spectral reflectance values. Bands were selected at intervals of 10, 20, 30, 40, 50, 75, and 100 nm. The number of points and the sampling period is shown in Table 5.2. Furthermore, figure 5.2, shows a comparison between the complete reflectance values, and a downsampled curve, using a simple linear interpolation, between the points. It is clear from figure that some features (such as peaks and curves) are lost, when reconstructing the spectral values sampling at 75 nm.

Table 5.2: Downsampling periods and the number of wavelengths.

Sampling wavelength	Total Wavelengths	Percentage of Information
1 (original)	2151	100%
5	431	20%
10	216	10%
20	108	5%
30	72	3.35%
40	54	2.51%
50	44	2.05%
75	29	1.35%
100	21	1.02%

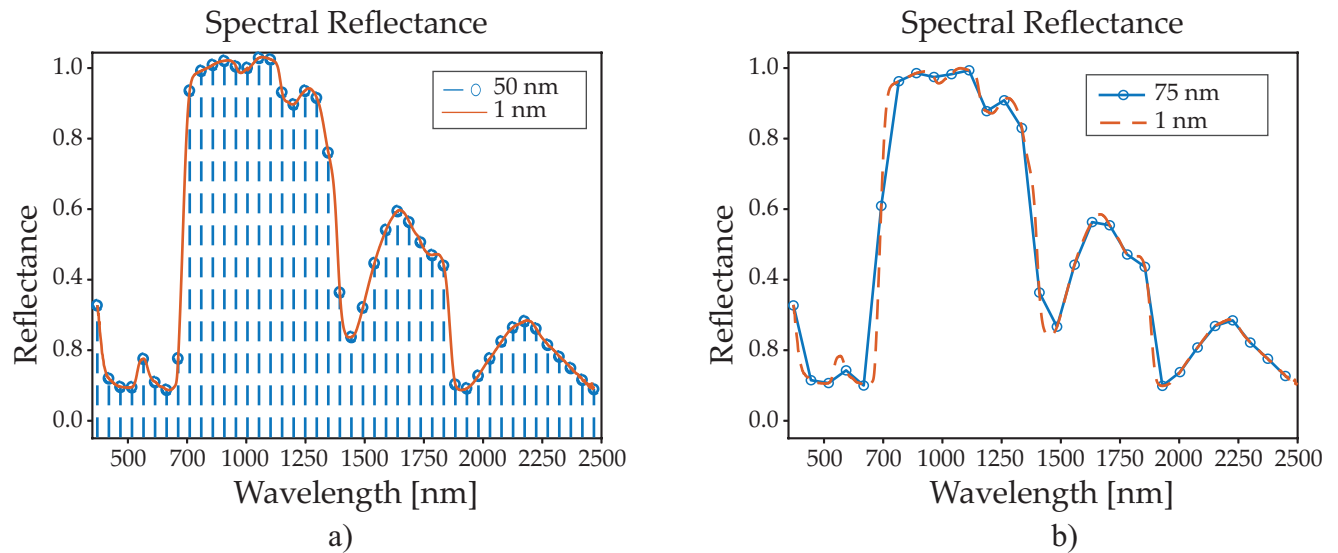


Figure 5.2: Downsampled spectral reflectance values in the range from 350 to 2500 nm: a) showcases the individual points with a resolution 50 nm, and b) linear reconstruction using a resolution of 75 nm (Source [110]).

5.2.3 Machine Learning methods

The selected techniques to predict the different vegetation indices were four common machine learning regression algorithms, that have been significantly tested for agricultural tasks, these algorithms are as follows:

- *Support vector regression (SVR)*: the Pearson VII (PUK) was used as kernel for the SVR.
- *Multi Layer Perceptron (MLP)*: Custom layers were implemented were, the number of hidden neurons was twice the number of input features. The sigmoid activation function was used at the final layer, with a total of 500

epochs. For the optimizer a learning rate of 0.3 was chosen with a momentum of 0.2.

- *K-nearest neighbors (k-NN)*: The number of n was set to five, and the Euclidean distance rule was used in the search process.
- *Random Forest (RF)*: The number of estimators was set at 500, the maximum depth at 25.

After training, the models were evaluated using the coefficient of determination R^2 and the root mean squared error (RMSE). The use of these metrics, first evaluates the strength of the linear relationship between the predicted and the true vegetation indices, while RMSE and MAE quantifies prediction accuracy in absolute terms, capturing both bias and random error.

For the training process a 10-fold strategy was adopted, meaning that the training set was split in a 9:1 proportion, and at each trial the algorithms were trained in the 9 splits, and 1 was left out for testing purposes.

Previous the training models, a correlation based feature selection process was carried out. In this process, the correlation factor of each individual feature was computed against the target variable, then the top ranked features were selected as predictors for the model.

5.3 Results

This section presents the results of the proposed methodology, first we evaluate the feature selection algorithm. Then, the performance of the machine learning models was discussed.

5.3.1 Feature Selection analysis

Depending on the composition of the vegetation index, different wavelengths on different regions of the electromagnetic spectrum were chosen. As well as the dehydration stages changed, there were slight variations in the chosen features as input for the models.

For better visualization, Figure 5.3, shows the histograms showcasing the number of bands that were selected for all the models. From this figure, it is shown that most features fall in the range from 500 to 1000 nm regardless of the sampling interval. One factor that contributes to this fact, is that the composition of most indices, includes at least one band in this region of the spectrum (see Table 5.1).

Furthermore, in Figure 5.4, the specific bands at the different dehydration stages, for 3 vegetation indices are shown. In this case LWI, LCI and NDVI, were chosen as sample indices for the figure, due to the different regions that compose such indices; showcasing a great diversity in wavelengths and regions of the spectrum.

5.3.2 Machine learning algorithms

As stated in the previous sections, the performance of the ML algorithms was evaluated using R^2 and $RMSE$. Four models were trained to predict the 25 vegetation indices used for different assessment of vegetation tasks.

All the algorithms at the different dehydration stages produced similar metrics, thus we averaged those values. The results are shown in Figure 5.5 for the R^2 value, and $RMSE$ is shown in Figure 5.6.

As shown in both figures, the reconstruction of the vegetation indices was carried out successfully even with the heavily downsampled information of 100 nm. Generally, all four regressors presented a similar performance; however the RF algorithm performed slightly better than the rest.

As expected the reconstruction of the indices using the more complete information (1 and 5 nm sampling periods), has the better performance, since it does not eliminate most of the information; and the downsampled information from 75 and 100 nm, present lower metrics results as expected. However, the heavily downsampled information stills presents R^2 values of over 0.9 in most indices.

Comparing the results across the dehydration stages, the training results for all combined stages, present the better metrics. A larger dataset, would allow capturing the relationships across the different wavelengths to produce more robust models. The dehydration stage 1, presented the lower metrics in comparison.

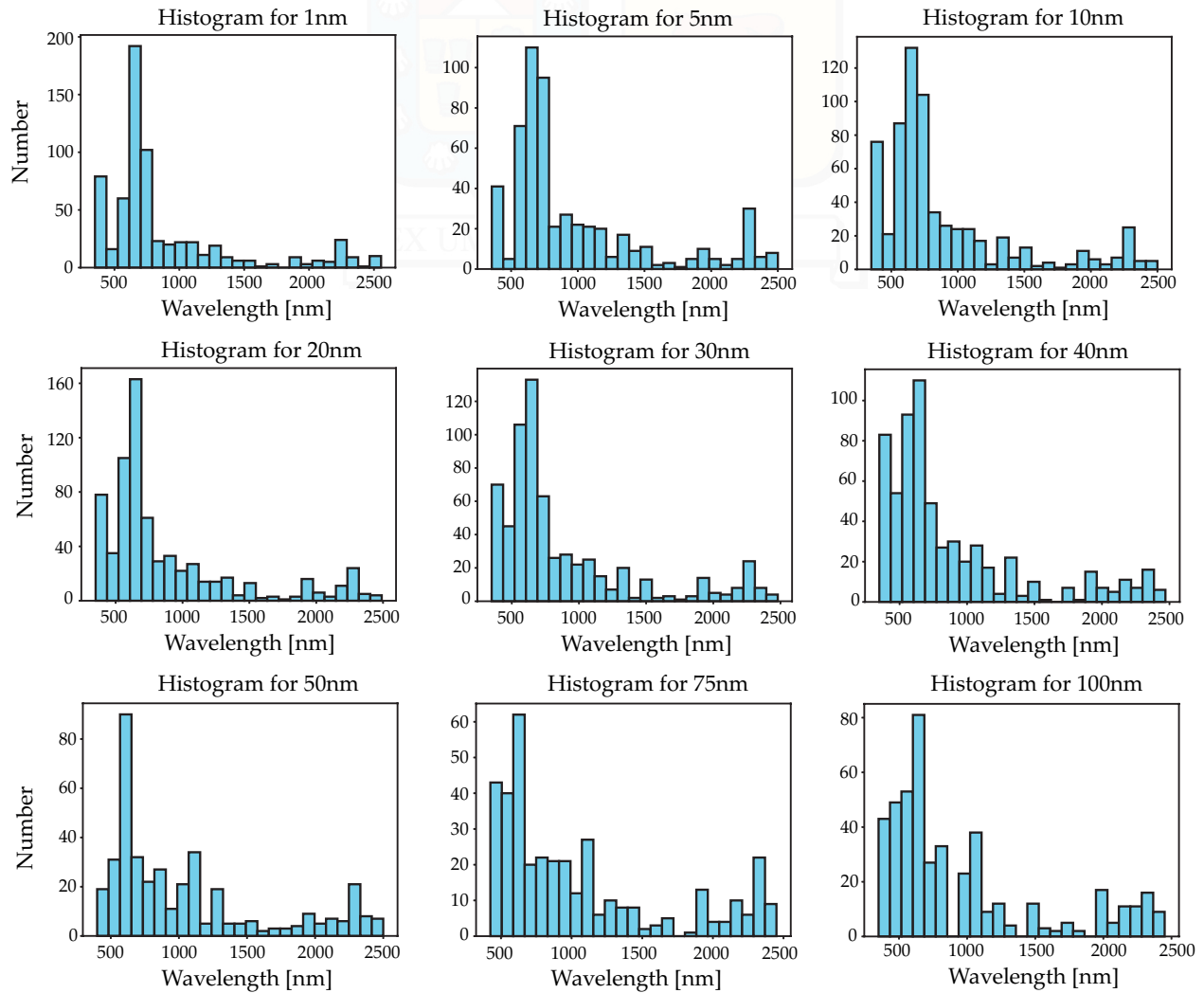


Figure 5.3: Histogram with the number of selected bands, from the correlation selection algorithm. From top to bottom it shows the results for all the downsampling periods (Source [110]).

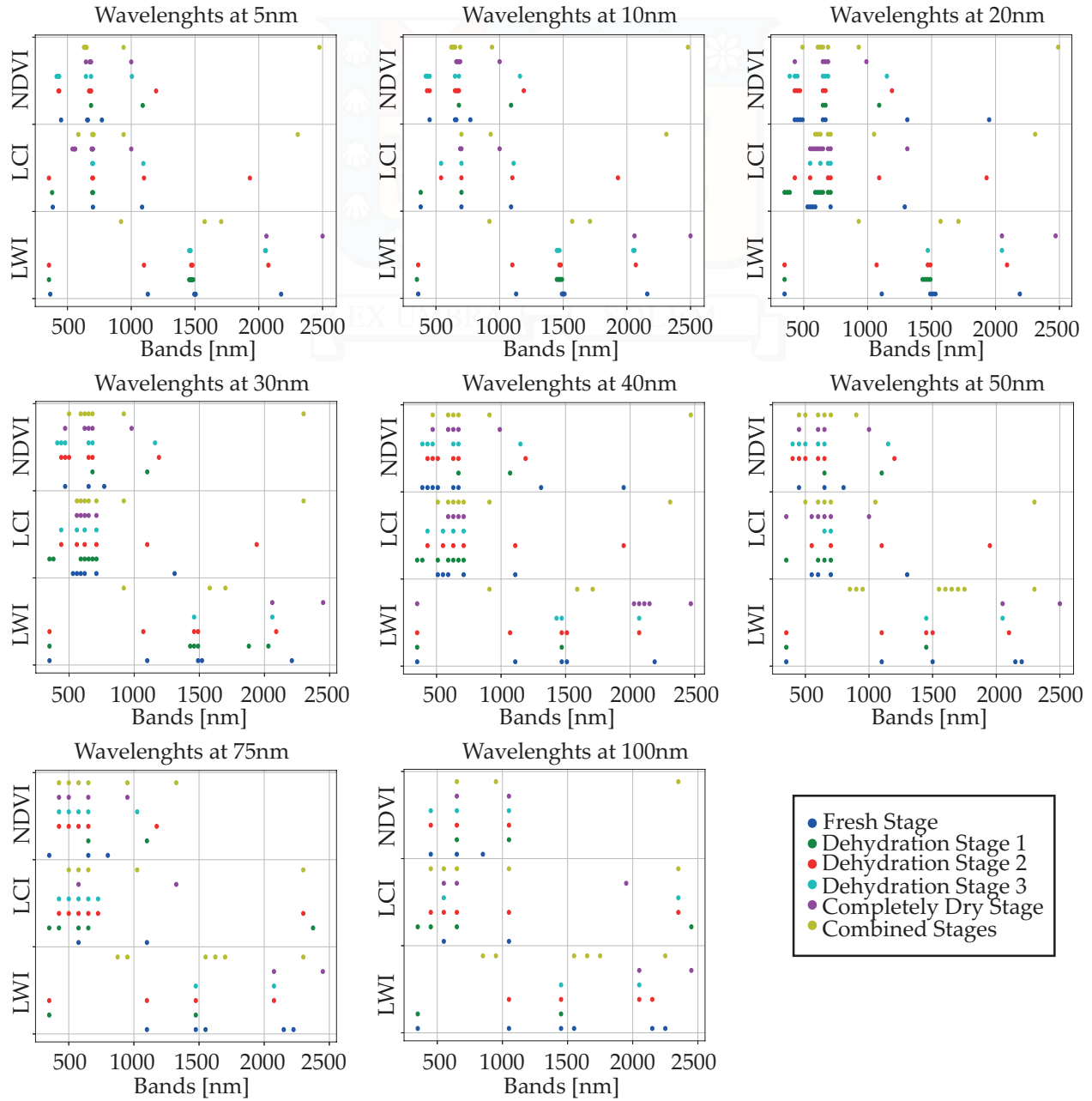


Figure 5.4: Specific examples of wavelengths chosen by the correlation based algorithm. This figure showcases three vis as examples: LWI, DDI and NDVI (Source [110]).

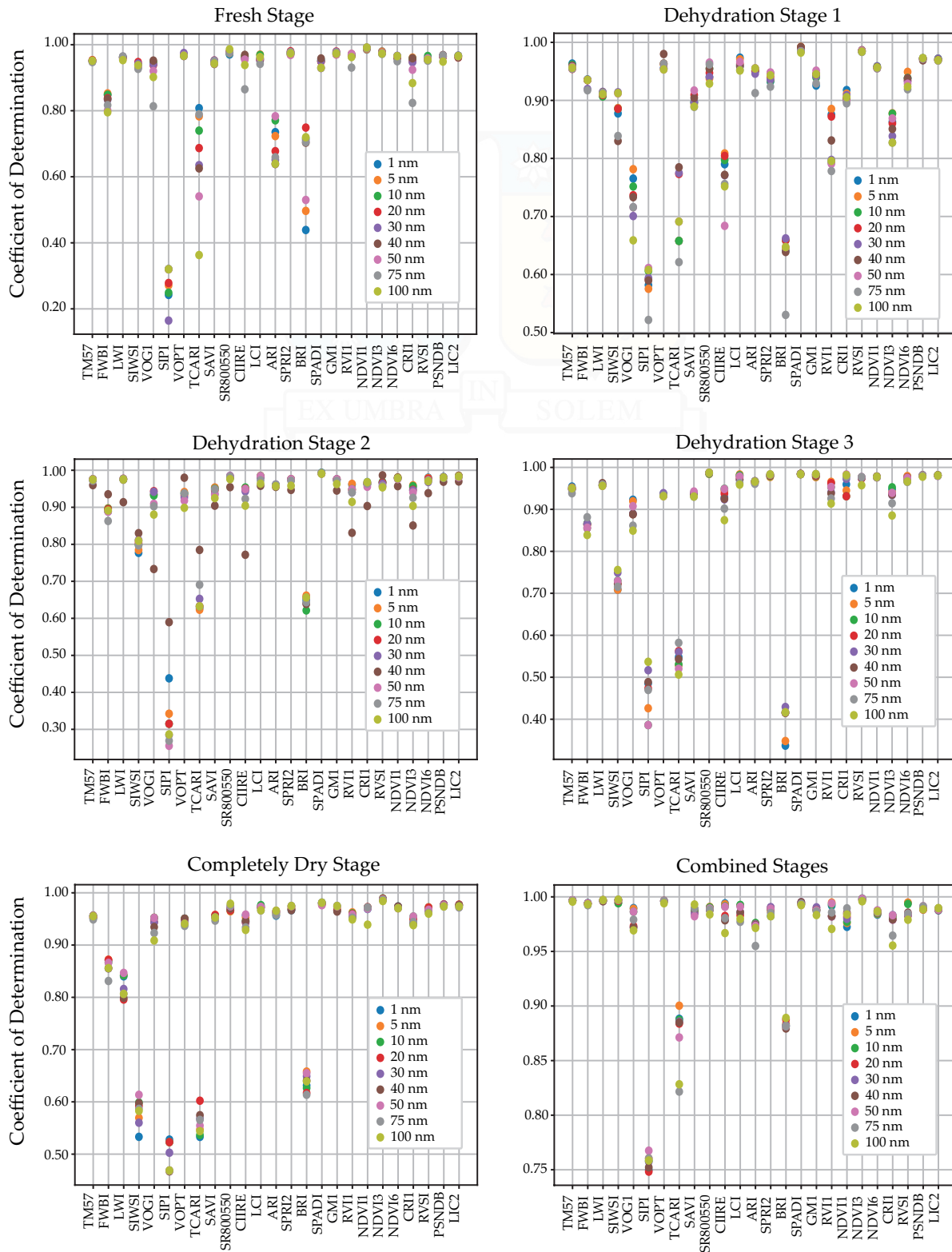


Figure 5.5: Averaged correlation coefficient obtained by the machine learning algorithms, for all the downsampled periods (Source [110]).

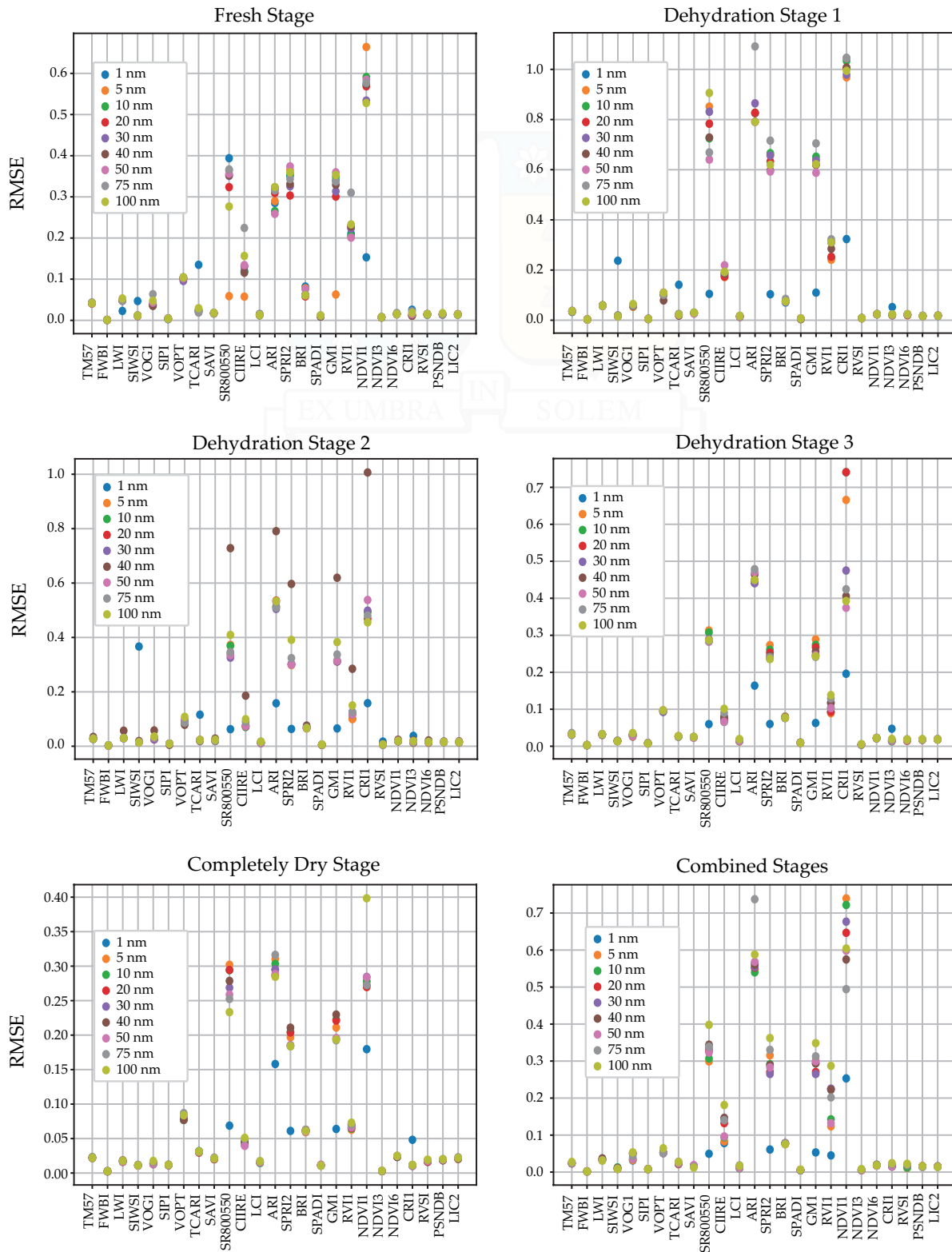


Figure 5.6: Averaged root mean squared error obtained by the machine learning algorithms, for all the downsampled periods (Source [110]).

Comparing the specific indices the best performing ones in both R^2 and $RMSE$ are NDVI based indices, SAVI, LCI, SPADI and RVSI; which present low $RMSE$ and high R^2 across all the dehydration stages and the downsampling methodology, showcasing robustness even when lacking complete spectral information.

One notable poor performing index is the SIPI index, which presented the lower R^2 in all the stages, and with all the downsampling methodology. However, this index presented a minor improvement when training the models using all the information from the different dehydration stages.

5.4 Discussion

The analysis of the selected features based on correlation, showcases that for most indices, at least one band within the visible and near infrared regions, is needed for the reconstruction of most indices, this fact corroborates the findings from [56], which predicted moisture from reconstructed spectral values, using mostly reflectance values in the visible and NIR region of the spectrum. Both studies provide the theoretical foundation for compressing hyperspectral data into compact informative subsets. This also confirms the strong relationship between the VNIR and SWIR regions, particularly in indices related to leaf water content such as LWI, FWBI and SIWSI.

The strong correlation between the predicted indices using machine learning algorithms and the real values, even with the heavily downsampled data. These results favor the notion that contiguous band in the spectrum are heavily correlated among between each other, which is corroborated by various previous studies. Indices such as NDVI, SAVI and water related indices, in their composition are dependent on wide stable bands in the spectrum. In contrast, pigment-sensitive indices such as ARI, CRI1 and GM1 present higher errors ($RMSE$), and their composition relies on finer spectral features, and are more susceptible to the loss of information.

As expected using almost complete information (1 nm, 5 nm and 10 nm wavelength sampling), produce better prediction results, achieving coefficient of determination of 0.99. However, this performance did not degrade when using the downsampled information. Such performance suggest the possibility of in-field measurement process using simpler spectral devices rather than a spectrometer or a hyperspectral camera. Also, these findings have practical applications in sensor design, indicating that specific filters can be applied for a complete characterization of vegetation.

Comparing the results from across the stages, the models perform better when a larger sample, and more variability in the spectral reflectance. The increased dataset size, with more diverse spectral features, and different dehydration levels help the models to learn the distinct spectral features and the different relations between distant regions of the spectrum; thus improving the performance of the models compared to the only using spectral values of a single stage.

5.5 Contributions

The results of this section have resulted in the following publication on the journal PLOS One:

- **J. Estrada**, N. Cetin, K. Sacilik, Z. Guo, and F. Auat Cheein, “Prediction of vegetation indices from down-sampled hyperspectral data using machine learning: A novel framework for olive crop monitoring,” PLoS One, vol. 21, no. 3, p. e0323158, Mar. 2026, doi: 10.1371/journal.pone.0323158.

5.6 Conclusions

In this section the results of using down-sampled spectral information for the prediction of vegetation indices was analyzed. We demonstrated that most of the selected VIs, were predicted with coefficient of determination of above 0.9 even when using heavily downsampled information at every 100 nm, which accounts for roughly 1.21% of the total initial information. However, as expected using more complete information (sampling every 5 and 10 nm), produce better prediction results.

The results obtained in this section suggests that for plant monitoring tasks, simpler spectral devices can be utilized, instead of complex spectrometers or hyperspectral cameras. Besides, based on this results the design of simpler devices can be performed, focusing on obtaining wide bands instead of finer bands.

The correlation based feature analysis showcases that for most of the indices, bands in the visible and near infrared regions are needed, this is due to the fact that the composition of the indices include bands in such regions, and also in cases of water stress or dehydration, there are significant changes in the spectral response in these regions.



6 Identification of important areas in the spectrum for leaf water content prediction

6.1 Introduction

Spectral information in the range of 350 to 2500 nm is a great tool for evaluating various aspects of plant health, including yield prediction [38, 100, 47], chlorophyll and nitrogen prediction [111, 37, 44], and leaf water content [55, 112, 61] in a wide range of crops.

Even though, the complete spectrum provides comprehensive information, which allows a complete phenotyping of vegetation, the large volume of data (particularly if it is a hyperspectral image), makes processing the information more difficult, requiring more advance hardware and more computing power. Besides adjacent bands usually are highly correlated, thus, such bands do not provide useful information for training prediction models, and could induce worst results [113]. Thus, a first step of identifying relevant bands is key, when processing hyperspectral information.

Furthermore, studies such as [56, 114] predict different bands of the spectrum from information related to LWC; suggesting that there is a fundamental set of wavelengths needed for this task, and that important spectral information can be inferred from LWC.

Since the continuous spectrum can be considered unstructured data in 1 dimension, CNNs are a powerful alternative to process this data, and make predictions useful for phenotyping purposes. For example, [57], propose a convolutional architecture for LWC results, in a set of blueberry leaves. A 1D convolution, as well as any ML architecture, at first can be considered a black box model lacking interpretability on how the model makes the prediction, in this context xAI, help to better understand the decisions made by the model [115]. GRAD-CAM is an xAI alternative that works well, with CNN, creating saliency maps, highlighting important areas of the input data, which are focused by the model to make a prediction. These models have been used extensively used with time-series information and in the medical field [116, 29, 117], however its use remains unexplored with the use of hyperspectral information, particularly in agricultural settings [115].

In this context, a simple 1d CNN is proposed for the leaf water content prediction task, furthermore; Grad-CAM is used to locate the most important wavelengths or sets of wavelengths that contribute the most for the network's final decision. Then, using these identified areas were used to predict hyperspectral VI, related to various plant properties; with the objective of testing the capabilities of such areas to predict the general status of vegetation.

6.2 Methodology

The general overview of the work is shown in Fig. 6.1. First a simple 1d CNN is used to perform regression of LWC. Applying the Grad-CAM method, the saliency maps of the input spectrum are generated. Using the areas with a great importance in the prediction are selected and isolated from the original input set. Furthermore, the similar architecture for the leaf water prediction task, were trained using the reduced input for the prediction of hyperspectral VIS.

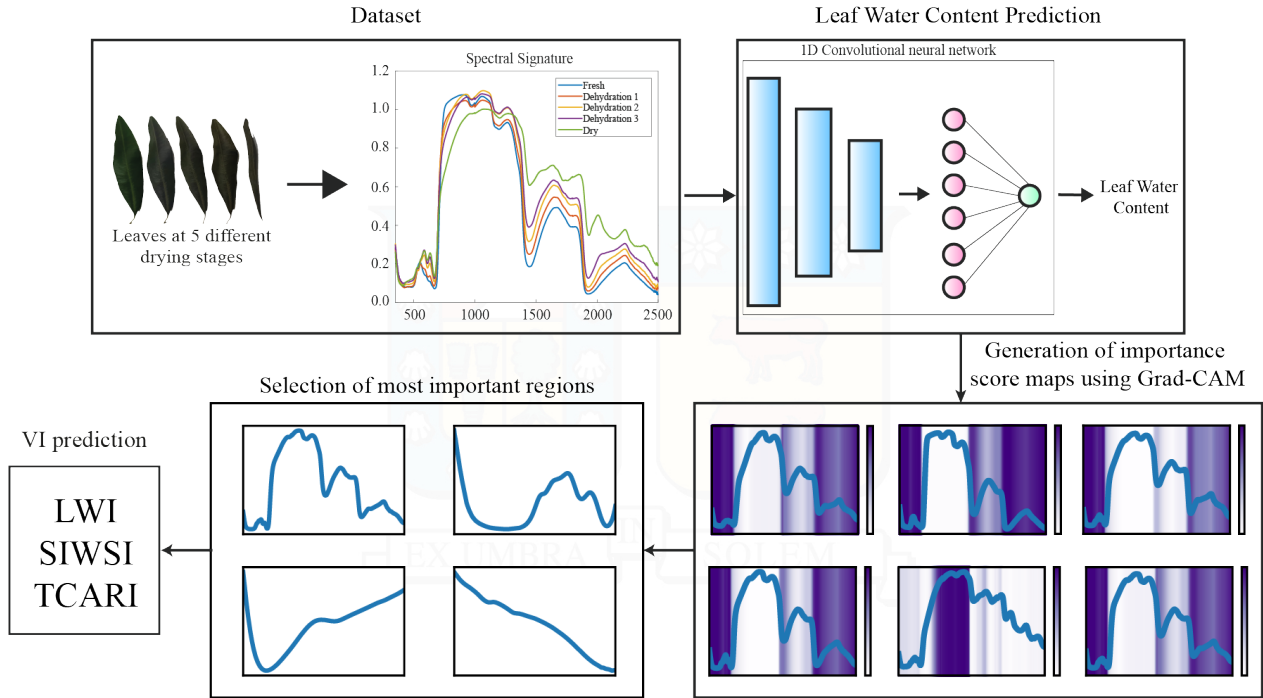


Figure 6.1: Proposed methodology for the identification of important areas in the spectrum for leaf water content prediction, using a 1d CNN and the Grad-CAM algorithm (Source [118]).

6.2.1 Leaf water content prediction using convolutional neural networks

1D convolutional neural networks are suitable for spectral information due to their ability to automatically learn and extract features and relationships among adjacent bands, without a prior feature engineering process [119, 57]. In this section, a simple 1D CNN is proposed for the task of leaf water content prediction. Following a similar structure of AlexNet [120], the network is composed by two convolutional blocks followed by a max-pooling block, and a batch normalization block to prevent overfitting. After the convolutional blocks, global average pooling is used to linearize the feature map, followed by two fully connected layers with a ReLU activation function; the output layer is a single neuron, using a linear activation function, that maps the last features to the desired output. A complete description of the network and the layers parameters are shown in Table 6.1. A representation of the network is shown in Fig. 6.2. The loss function was the mean-squared error (MSE).

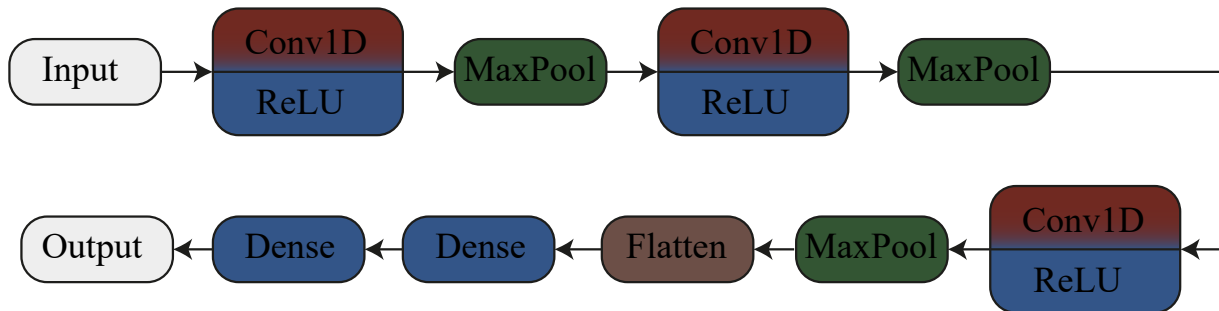


Figure 6.2: Representation of the proposed 1d CNN for leaf water content prediction.

Table 6.1: Layers and parameters of the proposed 1-D convolutional neural network for the leaf water prediction task

Layer	Parameters
Input	Size: (2151,1)
1-D convolution	Kernel Size: 3 Filters: 32 Activation: ReLU
Max Pooling	Stride: 2
1-D convolution	kernel Size: 3 Filters: 64 Activation: ReLU
Max Pooling	Stride: 2
1-D convolution	kernel Size: 3 Filters: 64 Activation: ReLU
Flatten	
Dense	Neurons: 128 Activation: ReLU
Dense (output)	Neurons: 1 Activation: Linear

6.2.2 Explainable AI: Grad-CAM

Grad-CAM is an interpretation method based on the gradients of convolutional layers, and it is capable of generating localization maps that highlight the contribution of each band to the final prediction results [30, 29]. In this case we use Grad-CAM to identify the wavelengths or set of wavelengths that are most important for the LWC prediction task.

Furthermore, these important wavelengths have been linked to the general status of vegetation [114, 56]; thus these regions are used as input for models that predict vegetation indices that have been linked to other parameters of vegetation, such indices are discussed in the following section.

6.2.3 Prediction of important VIs with selected areas of the spectrum

This section uses three hyperspectral indices, to evaluate the feasibility of predicting general health status of vegetation using the identified regions by the Grad-CAM algorithm. These indices are as follows: Leaf water index (LWI) used to identify the leaf water content in leaves, shortwave infrared water stress index (SIWSI) used to assess water stress in canopy, and chlorophyll absorption reflectance index (TCARI) which is used to assess chlorophyll content in leaves. The equations for such indices are shown in Table 6.2. Besides the usefulness of these indices in assessing the status of vegetation, their spectral composition consists of bands in different regions of the spectrum, further showing the capabilities of the selected wavelengths to predict vegetation features represented by a wide range of spectral features.

Table 6.2: Vegetation indices used in this study

Name	Equation
LWI	$\frac{R_{1300}}{R_{1450}}$
SIWSI	$\frac{R_{1640} - R_{858}}{R_{1640} + R_{868}}$
TCARI	$3(R_{700} - R_{670}) - 0.2 \left(R_{700} - R_{550} \frac{R_{700}}{R_{670}} \right)$

6.2.4 Hardware and training considerations

All the models were implemented in a Python 3.10.9 environment, using the Tensorflow-keras framework. The training was performed on a computer with an Intel Core Ultra 9 Processor CPU, with an NVIDIA GeForce GTX 4080 Ti with 8 GB VRAM GPU, and 32 GB of RAM, running the Windows 10 operating system. Other systems include CUDA 11.7 and cuDNN 4.0.

The dataset was partitioned with 70/20/10 for training, testing and validation purposes; using the 'adam' optimizer for a total of 100 epochs for each model. The mean average error was used as an evaluation metric.

6.3 Results

6.3.1 Leaf water content prediction

First, the training results for the leaf water content prediction task using the custom 1d CNN are evaluated. The training history is shown in Fig. 6.3. The model converges at around 40 epochs of training, both the training and the testing curves follow the same trend, showing that the model does not overfit. The training achieved a loss function value of 0.0013 while the MAE reached a value of 0.02. Furthermore, Fig. 6.4, shows the linear relationship between the predicted LWC and the measured LWC in the laboratory; the trend shows a strong correlation between both values with an R^2 of 0.979. These metrics showcase the effectiveness of the custom 1d-CNN for the task of LWC prediction.

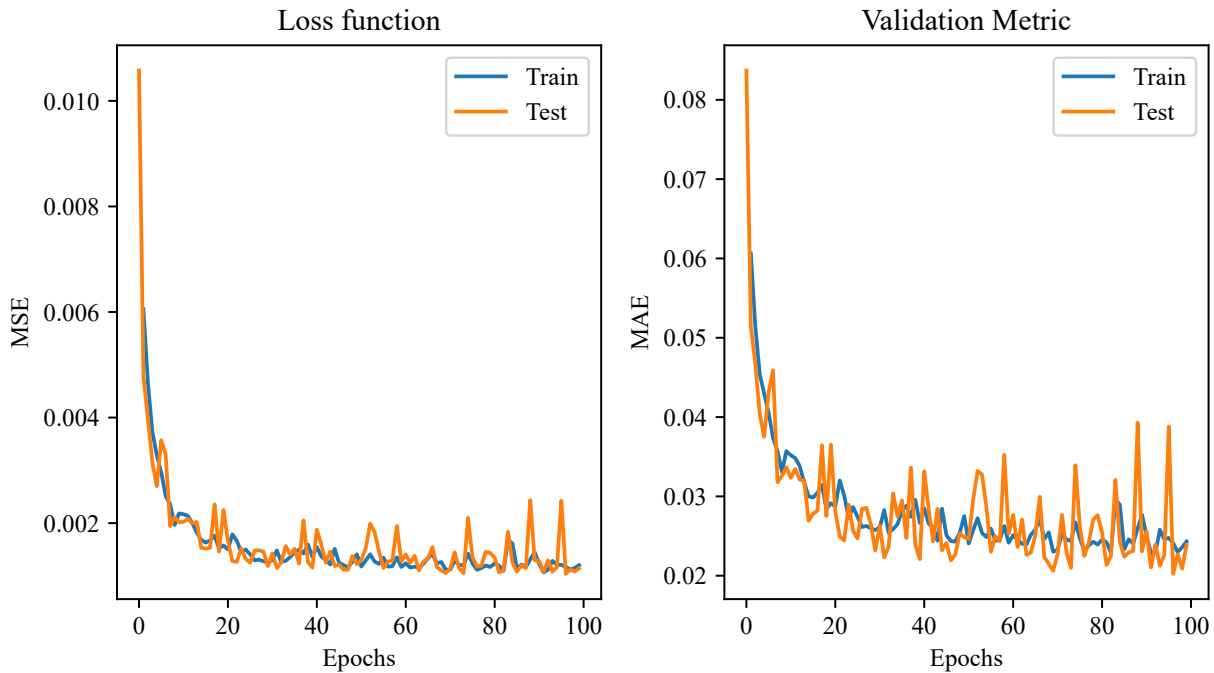


Figure 6.3: Training history of the 1d-CNN for leaf water content prediction (source [118])

6.3.2 Selection of important areas using a Grad-CAM

Generally the Grad-CAM algorithm allows for the prediction of a single sample. To get meaningful results, the saliency map for every sample in the testing set, then we averaged the score for every wavelength.

Furthermore, the test sample was divided into every different dehydration stage found, in the dataset. The resulting saliency maps are shown in Fig.6.5. A clear outlier in the saliency maps is the one created using only the data in the completely dehydrated stage, which clearly only looks at the region between 900 and 1400 nm in the spectrum, while the other maps present a more diverse range of wavelengths.

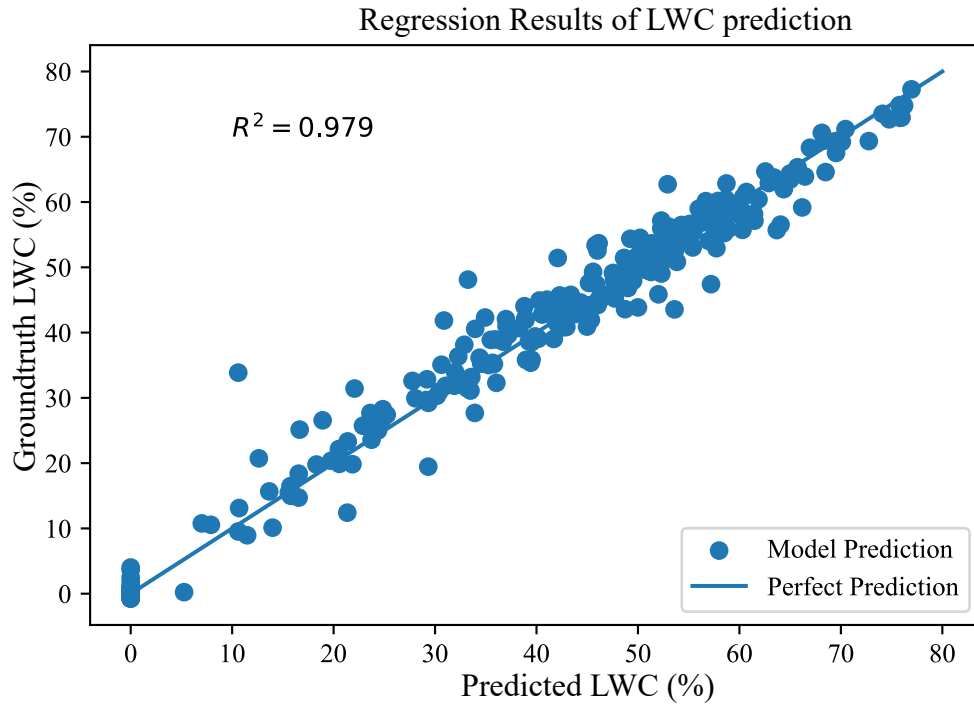


Figure 6.4: Linear relationship between predicted and measured leaf water content (source [118]).

To separate the most important regions, a threshold of 0.7 was applied; thus the wavelengths or regions of wavelengths with an importance score equal or above 0.7 were chosen as the most important regions. Using this threshold in the average heatmap for all the data, three regions were identified as the most important, the first region ranges from 350 to 688 nm, the second region from 1886 to 2180 nm and the third region from 2260 to 2500 nm.

6.3.3 VIs prediction using selected regions

In this section, the prediction results for the three selected VIs are shown. A total of seven models were trained for each vegetation index, each model was trained using a different region or a combination of region. In the results, R0 refers to the region ranging from 350 to 688 nm, R1 refers to 1886 to 2180 nm and R2 refers to the region that ranges from 2260 to 2500 nm. R01 refers to the combination of regions R0 and R1, R02 is the combination of regions R0 and R2, R12 considers the concatenation of regions R1 and R2 and finally R012 considers the union of all the regions. To create the final input vector for the multiple regions, the vectors from each region were simply concatenated in the same dimension. The training history for the different VIs is shown in Fig.6.6 and Fig.6.7 In this figure, only the training results for the R012 input are shown. The training history shows that the models converge at around 40 epochs, with a similar trend for the training and testing curves, showing that the models do not overfit.

The prediction results are summarized in Table 6.3, for the evaluation of each VI, R^2 and $RMSE$ are shown for the testing dataset. Finally the regression plots for the three indices using the R012 input are shown in Fig. 6.8. The regression plots show a strong correlation between the predicted and measured values for the three indices, with R^2 values of 0.977, 0.946 and 0.847 for LWI, SIWSI and TCARI respectively.

6.4 Discussion

The LWC prediction task was carried out successfully using a simple a lightweight 1d-CNN, this approach reached an R^2 of 0.98 which greatly outperforms other approaches using only single VIs such as the study presented in [55], which reached an R^2 of 0.90 using some indices. The network presented in this study also outperforms the model presented by

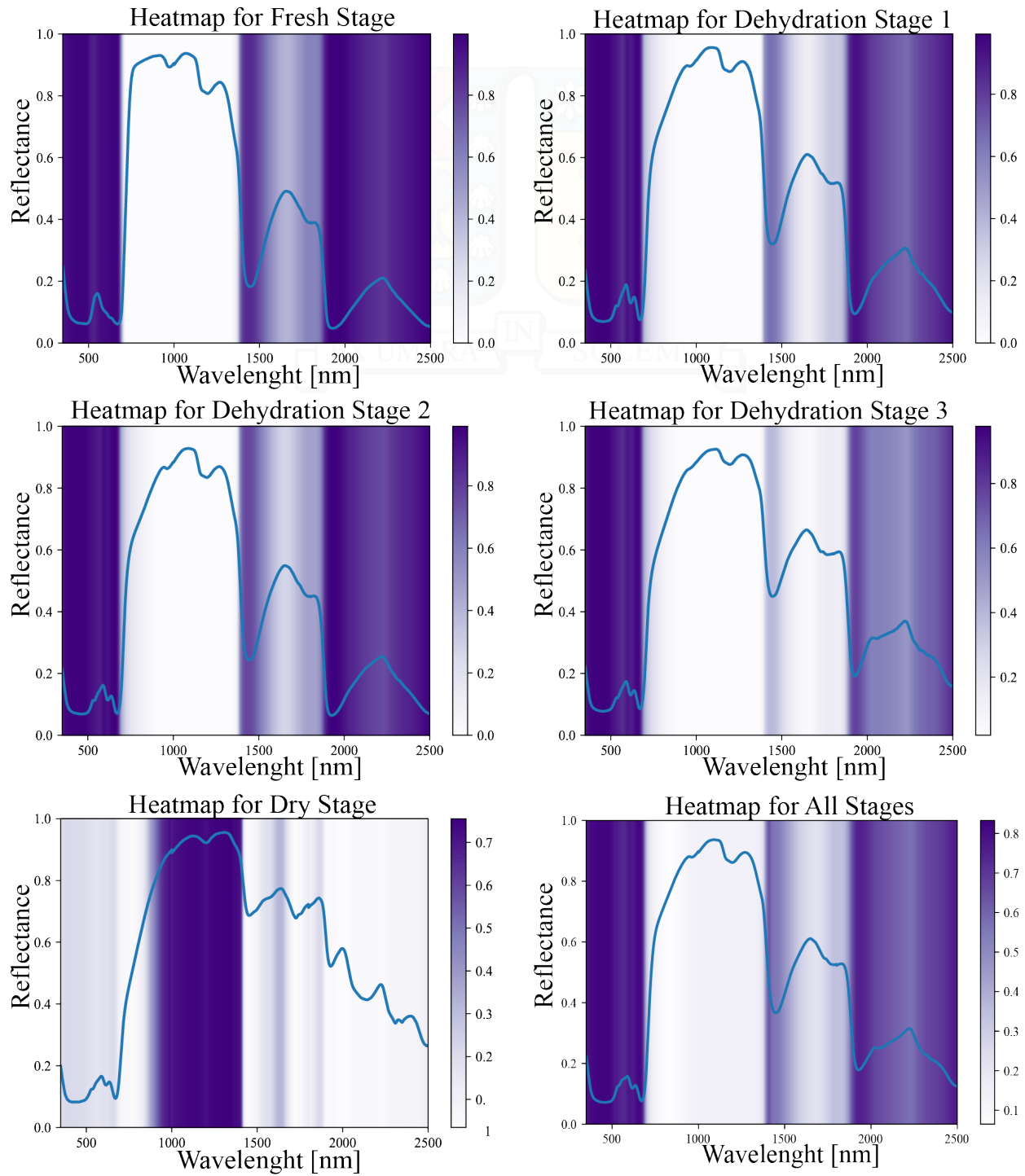


Figure 6.5: Saliency maps generated by Grad-CAM algorithm in the leaf water content prediction.

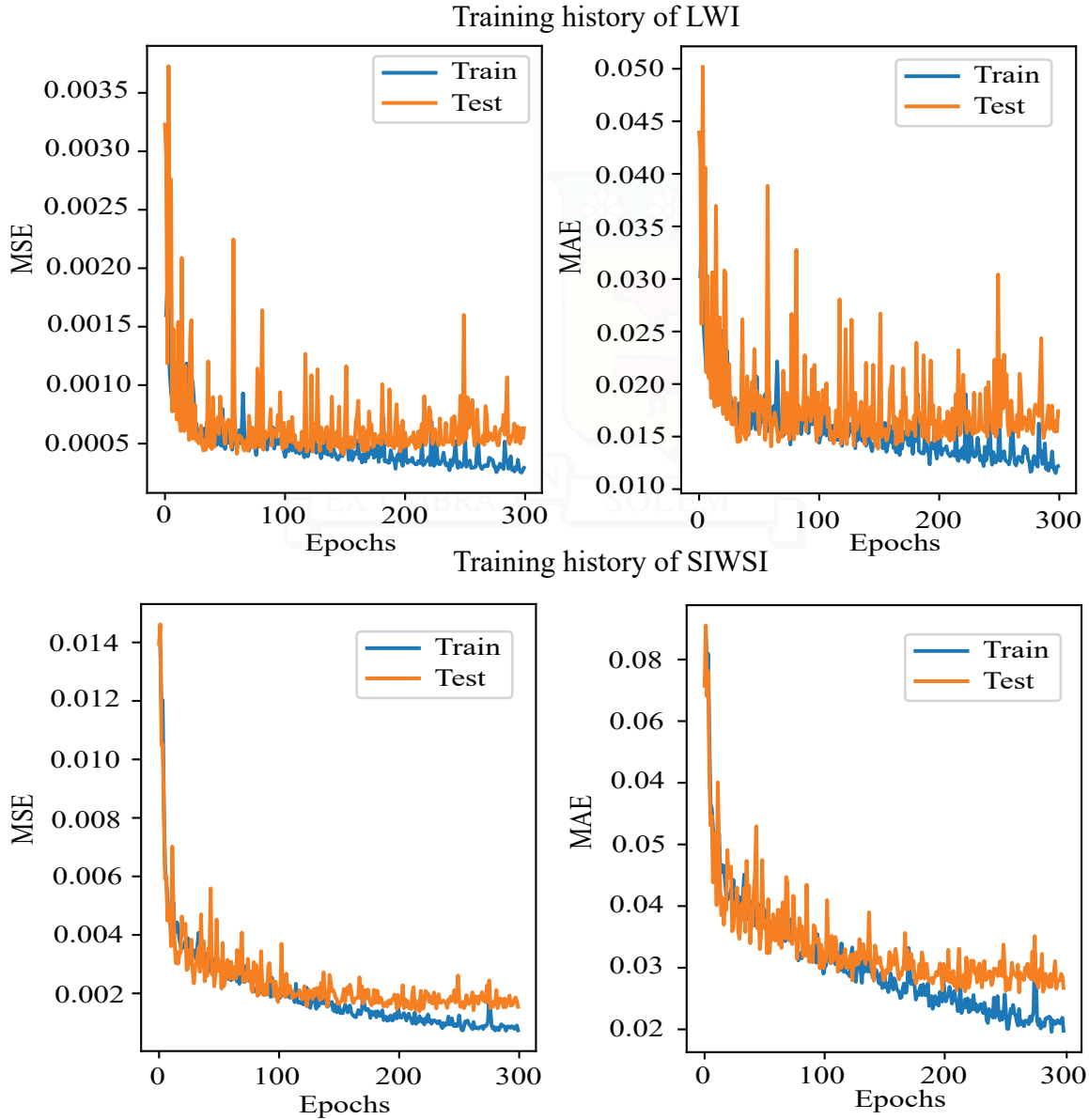
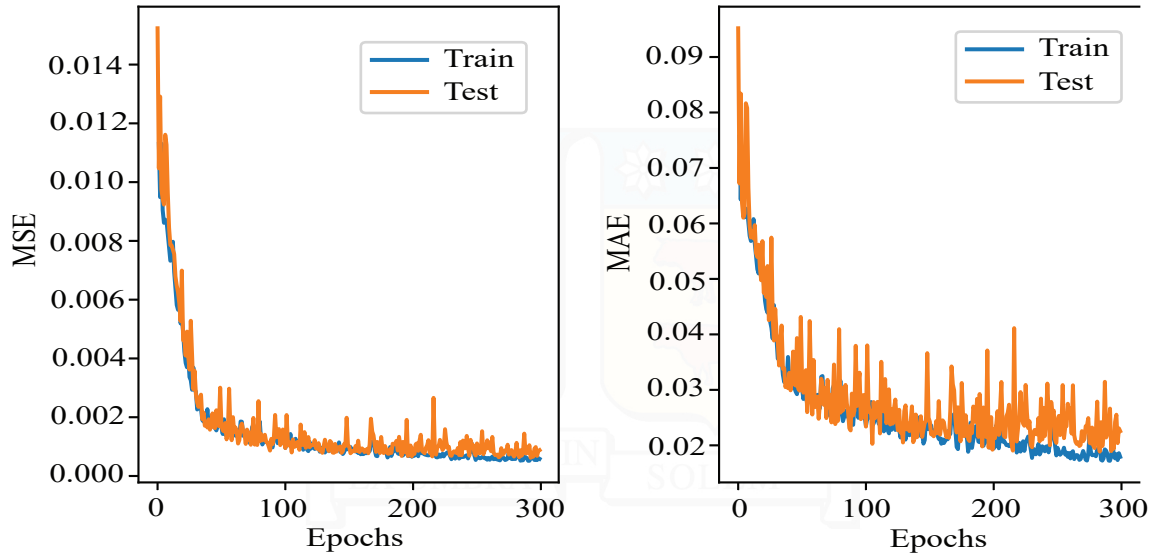
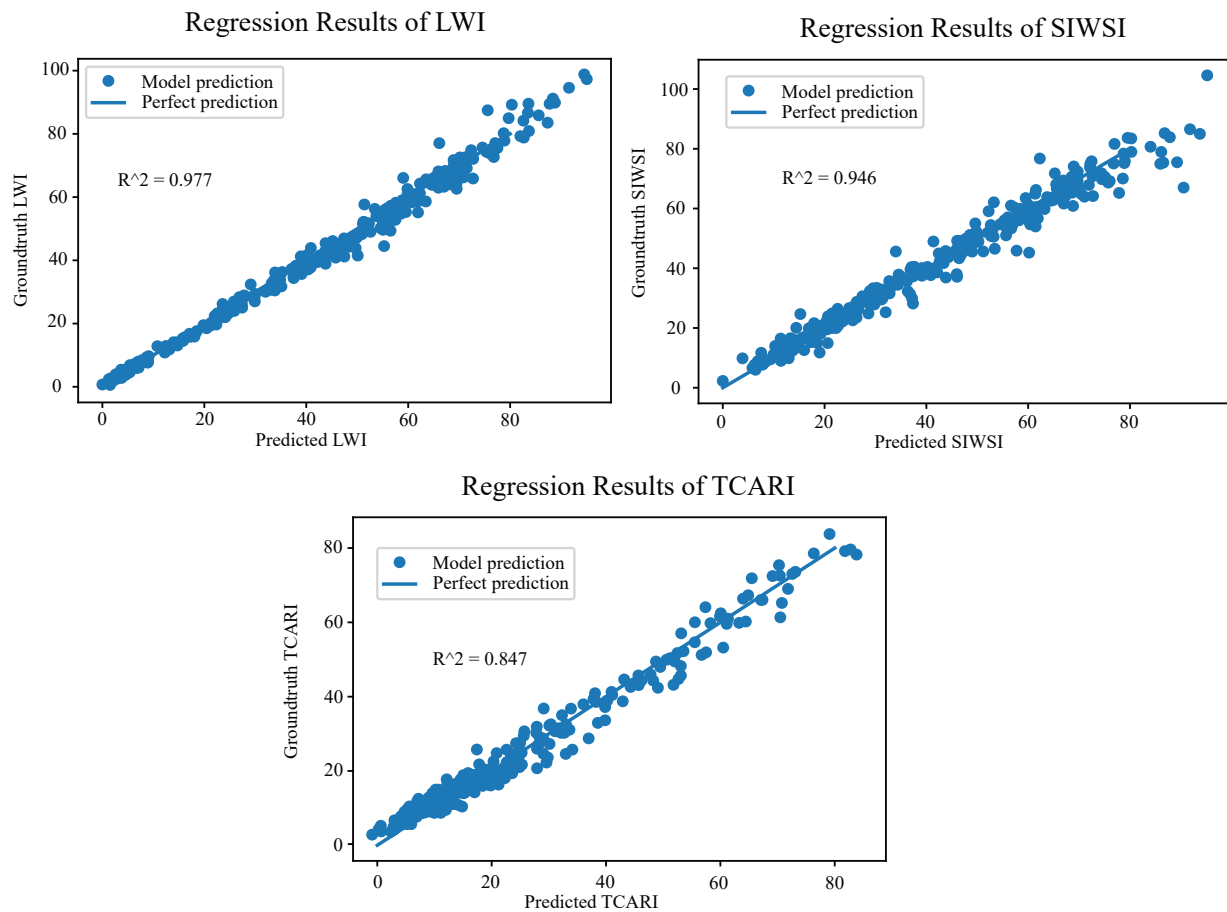


Figure 6.6: Training results of the tested vegetation indices: LWI, SIWSI (Only the training history for the R012 input is shown).

Table 6.3: Evaluation metrics of the models for predicting vegetation indices, using as input the most important regions identified by the Grad-CAM algorithm

Region	LWI		SIWSI		TCARI	
	R^2	$RMSE$	R^2	$RMSE$	R^2	$RMSE$
R0	0.710	0.123	0.867	0.078	0.795	0.077
R1	0.978	0.038	0.660	0.117	-0.824	0.180
R2	0.973	0.042	0.956	0.047	-0.264	0.160
R01	0.973	0.042	0.943	0.053	0.930	0.049
R02	0.961	0.050	0.956	0.047	0.842	0.068
R12	0.978	0.038	0.718	0.109	0.160	0.145
R012	0.977	0.039	0.946	0.051	0.847	0.070

Training history of TCARI

**Figure 6.7:** Training results of TCARI (Only the training history for the R012 input is shown).**Figure 6.8:** Regression results for the three tested indices: LWI, SIWSI and TCARI (Only the results for the R012 input is shown).

[57], which consider ResNet blocks on its architecture; however it is important to notice, [57] tested their network on a dataset with data in a single dehydration stage; thus having less variability in their data, so the model possibly could not capture all the nuances across different stages, besides this network was tested on a single species, while the proposed network was tested with data of multiple vegetation species.

Even though the LWC prediction results are encouraging, the main focus of this chapter is to analyze the most important regions of the spectrum, that could potentially model the complete health status of the vegetation. According to the saliency maps produced by the Grad-CAM algorithm, three regions are the most important for the LWC prediction task. The first region: 350 to 680 nm, roughly corresponds to the visible light spectrum wavelengths (380 to 750 nm); visibly leaves change their color as they become more dehydrated, thus it is expected that this region greatly affects the prediction of leaf water content. The next two regions 1886 to 2180 nm and 2260 to 2500 nm; contain known bands within the SWIR region that are known to react to the vibrational bonds of water contained in the leaf, particularly the bands around 1900 nm [121].

Furthermore, as suggested by [56], regions of the spectrum related to leaf water content, can represent different properties of vegetation, being some kind of fundamental set of wavelengths; thus three different vegetation indices were predicted using as input the different sets of regions identified by the xAI algorithm. The three indices: LWI, SIWSI and TCARI were successfully predicted with R^2 of over 0.8, with at least one input set. As expected, the index prediction obtained higher metrics when using the combination of all the regions; however there are still successful cases using only a single input set. Notably, the TCARI index prediction works when using R0 or a combination including this region; this can be attributed to the composition of the index, which involves mostly bands up to 1000 nm.

A notable finding is that all the indices were retrieved by using only R0, which is the regions that overlaps with the visible spectrum; thus opening the possibility of doing plant phenotyping using only devices in the visible spectrum. This finding aligns with the ones presented by [114], which suggested that a reconstruction of the spectrum using only the visible and the NIR regions can be used for LWC prediction. Another consequence of this finding is that, for some aspects of vegetation health assessment, only devices that record the visible spectrum are needed such are BGR cameras. However, more studies are still needed.

By combining all the regions, it was possible to retrieve all the tested indices with R^2 above 0.9, highlighting that there is no need to use the full spectrum from 350 to 2500 nm to predict a wide variety of vegetation properties, and not only a few selected regions are needed; thus encouraging the development of devices focused on specific regions that are useful for vegetation health assessment.

6.5 Contribution

The results of these experiments were published and presented on the 8th IFAC conference on Sensing, Control and Automation Technologies for agriculture, AGRICONTROL 2025. The article was published in:

- **J. S. Estrada** and F. A. Cheein, “Band-selection in spectroscopy information for vegetation health monitoring using explainable models,” IFAC-PapersOnLine, vol. 59, no. 23, pp. 108–113, 2025, doi: 10.1016/j.ifacol.2025.11.772.

6.6 Conclusion

LWC was successfully predicted using a 1d CNN, using as input the reflectance values between 350 and 2500 nm. Furthermore, Grad-CAM was applied to the model to investigate which areas of the spectrum are the most important for the LWC prediction task.

Three distinct regions were identified from the average maps, for all the testing samples at all the dehydration stages. The regions were: 350 to 688 nm, 1886 to 2180 nm, and 2260 to 2500 nm. Notably, the first region corresponds to the visible spectrum, and the other two contain bands that react to the water vibrational bonds.

Using as input the reduced set of wavelengths, the three tested indices were retrieved with R^2 values of 0.9 using at least one combination of the selected regions. This suggests that a complete representation of the vegetation can be retrieved with a reduced set of the spectral reflectance values. Notably, all the indices were retrieved with an R^2 of at

least 0.7 using only the first regions, which suggest that the use of devices that capture only the visible region of the spectrum might be useful for predicting various vegetation traits.



7 | Assessment of vegetation health using multi-spectral images

7.1 Introduction

Hyperspectral vegetation indices are a common method for assess vegetation status. Various indices have been developed to predict vegetation traits such as LWC, chlorophyll content, nitrogen content and to detect stressed vegetation [122, 55]. In general, hyperspectral devices allow for a complete characterization of vegetation [123, 23, 124].

Similar tasks can be carried out using only multi-spectral devices, and their derived indices from wider bands, such approach has been tasted in various crops such as wheat [125], maize [126], rice [127, 36, 38], potato [48], sweet potato [49], onion [47], cotton [101], and soybeans [100] to name a few. For this purpose, features such as the derived vegetation indices and texture features are used to train regression models and predict the desired task [17, 16, 128].

Even though the use of multispectral information has been widely used in agriculture, for some tasks such as LWC, the use of hyperspectral information is still preferred [59, 60, 57, 55], because water absorption bands are located in the NIR and VNIR regions of the spectrum [55, 56]. Some efforts to predict LWC have been attempted to with only the use of multi-spectral devices with the aid of machine learning algorithms [129, 15, 64, 63], however the models present worse performance than models trained with hyperspectral information.

Due to the advantages and disadvantages of hyperspectral and multispectral information, this chapter focuses on a methodology to bridge the gap between the comprehensive assessment of hyperspectral devices, with the information that can be gathered by the use of multi-spectral devices. For this purpose, a methodology using color, texture and predicted features from multi-spectral images, as input for ML models with the objective of predicting hyperspectral derived VIs is proposed.

7.2 Methodology

The proposed framework is shown in Fig.7.1. First, from the dataset the multi-spectral images are collected, from these images various features are obtained, first color features are obtained, as the computation of various vegetation indices, texture features from the gray-level co-occurrence matrix (GLCM), and predicted leaf water content; are obtained. These features are used input for training and later testing common machine learning approaches. This section testes four models: random forest, support vector machine, extreme gradient boosting machine, and multi-layer perceptron. The objective of the machine learning is to predict vegetation indices derived from the complete spectrum of the leaf from 350 to 2500 nm. The chosen VIs for this purpose were chosen based their ability to predict various vegetation tasks such as leaf water content, chlorophyll content and nitrogen content. Finally, the results are evaluated using R^2 and $RMSE$.

7.2.1 Vegetation indices for health assessment derived from hyperspectral information

This section focuses on the selection of various vegetation indices derived from hyperspectral information. In the literature there have been numerous vegetation indices reviews [130, 131, 132], which show their capabilities to the

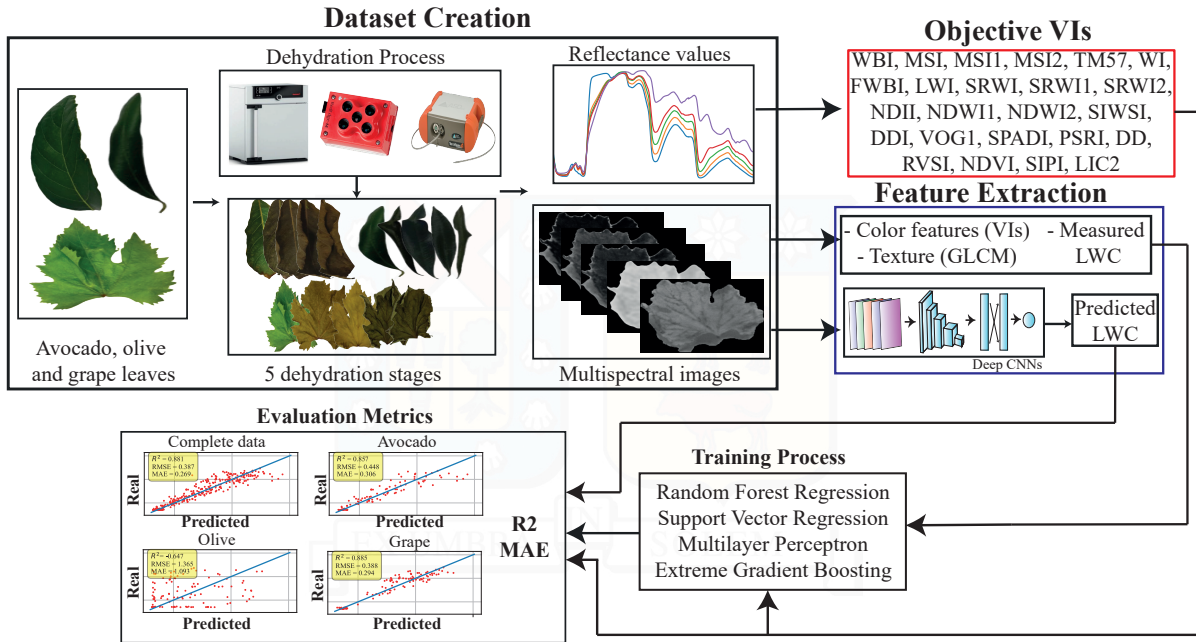


Figure 7.1: Conceptual framework for the prediction of hyperspectral derived vegetation indices using multi-spectral information.

assessment of vegetation. For this section, a list of 24 vegetation indices were chosen based on their use in the prediction of leaf water content, chlorophyll content and assessment of water stress. Besides, the indices also show a wide range of spectral bands, thus showing the robustness of predicting indices whose composition is not explicitly involve in the bands obtained by the multi-spectral cameras. The list of the 24 VIs is shown in Table 7.1.

7.2.2 Feature engineering process

As stated in the introduction, for this chapter several features from the multi-spectral images are extracted. First color features which are color indices computed with the reflectance of the vegetation indices. For this purpose, 43 indices were compiled from the literature. The complete list of the indices can be seen in Tables 7.2 and 7.3. In these tables B, G, R, NIR and RE indicates the reflectance values at their respective bands.

Computing the spectral indices directly in the images generates multiple values, corresponding to the number of leaf pixels present in the image; thus, to generate meaningful features from these indices, representative statistics were chosen as the input features. Three descriptive statistics were chosen, which are: mean, median and mode. It is worth nothing that for the computation of these values, the background pixels were not taken into account.

The same descriptive statistics were applied to the original five multi-spectral bands. As a result, a total of 144 color features were created: $43 \text{ VIs} \times 3 \text{ metrics} + 5 \text{ bands} \times 3 \text{ metrics} = 144 \text{ features}$.

The second set of features are texture descriptors obtained from the GLCM of each band. This set of features have been successfully used to predict various vegetation properties [17, 16, 128]. To obtain the GLCM the images were normalized to 8 bits (0 to 255), as a standard procedure, then focusing on the region of interest (pixel leaves), the GLCM was extracted. Once the matrix was obtained 10 descriptors were extracted: contrast, dissimilarity, homogeneity, angular second moment (ASM), energy, correlation, entropy, mean, variance and standard deviation. As a result of this process a total of 50 features were extracted: $5 \text{ bands} \times 10 \text{ texture descriptors}$.

7.2.3 Leaf water content

Various of the indices tested are used to predict leaf water content. The constructed dataset focuses on five dehydration stages. Thus, to enhance the prediction capabilities of the machine learning models, the measured LWC was added to

Table 7.1: Vegetation indices derived from hyperspectral information used as objectives in this study

Name	Acronym	Equation
Water Band Index [55]	WBI	R_{970}/R_{900}
Moisture Stress Index [129]	MSI	R_{1600}/R_{820}
Moisture Stress Index 1 [129]	MSI1	R_{1650}/R_{1230}
Moisture Stress Index 2 [129]	MSI2	R_{1650}/R_{830}
Thematic Mapper Band 5 to 7 [129]	TM57	R_{1650}/R_{2220}
Water Index [129]	WI	R_{900}/R_{970}
Floating-position Water Band Index [129]	FWBI	$R_{900}/\min(R_{930} - R_{980})$
Leaf Water Index [129]	LWI	R_{1300}/R_{1450}
Simple Ratio Water Index [129]	SRWI	R_{860}/R_{1240}
Simple Ratio Water Index 1 [129]	SRWI1	R_{1350}/R_{870}
Simple Ratio Water Index 2 [129]	SRWI2	R_{880}/R_{1265}
Normalized Difference Infrared Index [129]	NDII	$\frac{R_{850} - R_{1650}}{R_{850} + R_{1650}}$
Normalized difference Water Index 1 [129]	NDWI1	$\frac{R_{860} - R_{1240}}{R_{860} + R_{1240}}$
Normalized difference Water Index 2 [129]	NDWI2	$\frac{R_{870} - R_{1260}}{R_{870} + R_{1260}}$
Shortwave Infrared Water Stress [129]	SIWSI	$\frac{R_{1640} - R_{858}}{R_{1640} + R_{858}}$
Double Difference Index [129]	DDI	$2R_{1530} - R_{1005} - R_{2055}$
Vogelman Red Edge Index 1 [122]	VOG1	$\frac{R_{740}}{R_{720}}$
Normalized Difference Vegetation Index [122]	NDVI1	$\frac{R_{750} - R_{680}}{R_{750} + R_{680}}$
Datt Derivative [122]	DD	$\frac{R_{850}}{R_{710}}$
Plant Senescence Reflectance Index [122]	PSRI	$(R_{680} - R_{500})/R_{750}$
Red-Edge Vegetation Stress Index [122]	RVSI	$0.5(R_{722} + R_{763}) - R_{733}$
SPAD Index [122]	SPADI	$\frac{R_{640}}{R_{940}}$
Structure Insensitive Pigment Index [122]	SIPI	$\frac{R_{800} - R_{445}}{R_{800} - R_{680}}$
Lichtenthaler Index [122]	LIC2	$\frac{R_{790} - R_{680}}{R_{790} + R_{680}}$

Table 7.2: Mutispectral VIs used as input features (Part A)

Name	Acronym	Equation
Normalized Difference Vegetation Index [133]	NDVI	$\frac{NIR - R}{NIR + R}$
Green normalized difference vegetation index [133]	GNDVI	$\frac{NIR + R}{NIR - G}$
Normalized difference red edge index [133]	NDRE	$\frac{NIR + G}{NIR - RE}$
Structure insensitive pigment index [133]	SIPI	$\frac{NIR + RE}{NIR - B}$
Normalized green blue difference index [134]	NGBDI	$\frac{NIR - R}{G - B}$
Normalized green red difference index [134]	NGRDI	$\frac{G + B}{G - R}$
Green red difference index [134]	GRDI	$\frac{G + R}{G - R}$
Normalized blue-green vegetation index [134]	NBGVI	$\frac{B - G}{B + G}$
Normalized excessive green index [134]	NEGI	$\frac{2G - R - B}{2G + R + B}$
Modified Green Blue Vegetation Index [135]	MGRVI	$\frac{G^2 + R^2}{G - B}$
Modified Visible Atmospheric Resistant Index [135]	MVARI	$\frac{G + R - B}{G^2 - B * R}$
Red-Green-Blue Vegetation Index [135]	RGBVI	$\frac{G^2 - B * R}{G - 0.39R - 0.61B}$
Triangular Greenness Index [135]	TGI	$\frac{G - R}{G + R - B}$
Visible atmospheric resistant index [135]	VARI	$\frac{G}{G + R - B}$
Green red ration index [103]	GRRI	$\frac{R}{R}$
Normalized redness intensity [103]	NRI	$\frac{R + G + B}{G - R}$
Green Red Vegetation Index [103]	GRVI	$\frac{G + R}{NIR - (2R - B)}$
Atmospherical Resistant Vegetation Index [103]	ARVI	$\frac{NIR + (2R - B)}{NIR - (2R - B)}$
Simple Ratio [136]	SR	$\frac{NIR}{R}$
Soil Adjusted Vegetation Index [136]	SAVI	$1.5 \frac{NIR - R}{NIR + R + 0.5}$
Chlorophyll index [136]	CI	$\frac{RE}{R - G} - 1$
Plant Sense Reflectance Index [136]	PSRI	$\frac{RE}{R - G}$
Modified canopy chlorophyll content index [136]	M3CL	$\frac{NIR + R + RE}{NIR - RED + RE}$
Shadow Index [43]	SI	$\frac{R + G + B}{NIR}$
Modified Simple Ratio Index [137]	MSR	$\frac{3}{(NIR/R - 1) + (NIR/R + 1)^{\frac{1}{2}}}$

the input feature vector used to train and test the ML models. Thus, a vector of a total 195 features was used for training purposes 144 color features + 50 texture features + 1LWC = 195total features

As stated previously, measuring LWC precisely requires a destructive method (dehydration in an oven and measuring the weight after a manual sampling campaign), or to get an estimated value, a measurement with hyperspectral devices. However, the purpose of this chapter is to create a framework that functions completely remotely, using only features from a multispectral device; an estimated LWC from the multi-spectral images is obtained through the use of deep convolutional neural networks.

Table 7.3: Multispectral VIs used as input features (Part B)

Name	Acronym	Equation
Optimized Soil Adjusted Vegetation Index [137]	OSAVI	$\frac{1.16(NIR - R)}{NIR + R + 0.16}$
Ratio Vegetation Index [137]	RVI	$\frac{NIR}{G}$
Triangular Vegetation Index [137]	TVI	$60(NIR - G) - 100(G - R)$
Enhanced Vegetation Index [137]	EVI	$2.5 \frac{NIR - R}{NIR + 6R - 7.5B + 1}$
Green Index [137]	GI	$\frac{G}{R}$
Transformed Chlorophyll Absorption in reflectance Index [137]	TCARI	$3[(RE - R) - 0.2(RE - G)\frac{RE}{R}]$
Simple Ratio Pigment Index [137]	SRPI	$\frac{B}{R - B}$
Normalized Pigment Chlorophyll Index [137]	NPCI	$\frac{R + B}{G - B}$
Normalized Difference Vegetation Index 2 [137]	$NDVI_{GB}$	$\frac{G + B}{G - R}$
Plant Senescence reflectance Index 2 [137]	PSRI	$\frac{G}{B - R}$
Color Index of vegetation extraction [137]	CIVE	$0.44R - 0.81G + 0.39B + 18.79$
Near Infrared Reflectance of Vegetation [138]	NIR_V	$NIR * NDVI$
Difference Vegetation Index [62]	DVI	$\frac{NIR - R}{NIR + R}$
Modified Soil Adjusted Vegetation Index [139]	MSAVI	$[2NIR + 1 - \sqrt{2NIR + 1 - 8(NIR - R)})/2$
Chlorophyll Absorption Reflectance Index [139]	CARI	$\frac{RE - R - 0.2(RE - G)}{NIR/RE - 1}$
Red Edge Modified Simple Ratio [139]	REMSR	$\frac{\sqrt{NIR/RE + 1}}{NIR - RE}$
Red Edge Normalized Difference Vegetation Index [139]	RENDVI	$\frac{NIR + RE}{NIR - RE}$
Leaf Chlorophyll Index [62]	LCI	$\frac{NIR + RE}{NIR + R}$

Table 7.4: Parameter grid search the ML models

Model	Parameter	Search Values
RFR	Number of trees	100, 200, 500, 1000
	Max depth	None, 10, 20, 30, 40
	Minimum samples	2, 5, 7, 10, 15, 20
	Regularization (C)	0.1, 1, 10, 100
SVR	Epsilon (E)	0.01, 0.05
	Gamma	1, 5, 10
	Kernel	Linear, Radial Basis Function (RBF)
MLP	Hidden layers/neurons	1/100, 2/(50,50)*
	Penalty term (A)	0.0001, 0.001, 0.01
	Learning rate	0.001, 0.01
	Activation function	Linear, tahn, ReLU
XGB	Number of estimators	100, 500, 1000
	Max depth	3, 5, 7, 10
	Learning rate	0.1, 0.2, 0.5
	Row sampling	0.2, 0.6, 0.8
	Feature sampling	0.8, 1.0

* 1 hidden layer with 100 neurons, and 2 hidden layers with 50 neurons each.

In this case we use the two best performing networks from the previous sections. ResNet-18 and MobileNetV3. The network first layer was adapted so it accepts a 5 channel input; then the final layer was changed to a single neuron, with a linear activation function so it performs the regression task, and the loss function was the mean-squared error (MSE).

7.2.4 Machine learning algorithms

In this section, four common machine learning algorithms for regression were tested: RFR, SVR, MLP and XGB. These algorithms have been tested extensively for various agricultural tasks [140]. To achieve the best possible results, a hyperparameter optimization process was performed using an extensive grid-search. The parameters of the search are shown in Table 7.4

All the software was developed using a Python 3.9.0 environment using the Scikit-Learn (scikit-learn.org) library and the Pytorch (pytorch.org) framework. The training was conducted on a computer with an Intel Core i7 7th Gen Processor CPU, NVIDIA GeForce GTX 1080 Ti 8 GB GPU, and 16 GB of RAM, running on the Windows 10 operating system.

7.2.5 Data preprocessing, feature selection and training considerations

All the features from the different sets (color, texture and LWC) underwent a normalization process, using min-max scaling to ensure that all values range between 0 and 1; thus favoring the training of the machine learning algorithms. The normalization was also conducted in the raw files from the multi-spectral images. Originally the images show the reflectance value scaled to a 16 bit value (ranging from 0 to 65535). Thus, for training the deep learning architectures, the values were scaled to a factor of 65535 thus generating images in the same range from 0 to 1.

The computation of the GLCM in 16 bits might result in significant efforts for the computation capabilities, thus the values were standardized between the values from 0-255 which is a common process for analyzing 16 bit resolution, for the computation of the GLCM. A correlation based feature correlation was conducted on the total vector feature, since the great number of features that were recollected from the multi-spectral images. Then the top 50, with the highest importance rank were used to assess the optimum number of features.

A 5-fold cross validation scheme was used to ensure robustness of the models and to provide an accurate generalization estimate. The 5 number of folds was chosen to ensure that 80% was used for training, leaving 258 samples for validation at each split. Additionally, a 20% of the original dataset was left out for validation purposes.

7.3 Results

This section focuses on the results obtained by the training results. First, the feature selection results are analyzed, then the training results are presented. As stated, various sets of models were trained. The first set of models included all the features, a second set of models used only VIs and texture features, the third set of models using only the information from the VIs, and the final set of models used only texture features for training purposes.

7.3.1 Features selection analysis

The correlation feature based selection was performed to reduce the number of unnecessary features. The graph shown in Fig. 7.2. Show the summary of the most used features across all the models for all the vegetation indices, the graph also shows the most used bands, using only the vegetation indices and the texture features from the bands. A notable result, is that LWC is a common feature present in most of the indices which is expected, since most of the VIs analyzed in this study, are heavily correlated with this feature [55]. Furthermore, the diverse combination of indices which in its composition involves the use of the bands in the visible and NIR regions, showcases the need for the use of the whole spectrum to perform a comprehensive analysis of the plant's health.

7.3.2 Machine learning algorithms

The evaluation metrics for the validation dataset are shown in Table 7.5, for all the models and all the combination of input features. From the table the best performing vegetation index is the DDI index, using the XGB regressor, and in general, using all the features (VIs+Texture+LWC), yields the better performance. Comparing the performance from all the regressors, in general there is not a big drop in performance across the RFR, SVR, and XGB; however the XGB presents a better performance using the three sets of features, in all the other input sets (VIS+Texture, VIs, Texture), the SVR algorithm performs the best for the majority of the tested indices. A representation of the coefficient of determination is shown in Fig. 7.3, which allows the comparison of the performance of all the training models. Another notable results, is that the MLP regressor performs the worst in all the tested indices, reaching values of 0 or negative (In the figure, all the negative values were maintained at 0 for better visualization.).

The results in Figure 7.4, showcases the results grouped by regressor, thus allowing a better visualization according to the input type. According to this graph, it is clear that the models perform the best when using all the training features, including the LWC; in some cases the performance is far superior, for example in the LWI and DDI indices, the removal of the LWC produces a significant drop in the R^2 value, which goes from 0.9 to below 0.7. Using only the texture features produces the worst results overall.

7.3.3 Leaf water content prediction

The two models of LWC, were optimized using an exhaustive grid-search approach, the best hyperparameters are shown in Table 7.6. The grid-search focused on hyperparameters such as batch-size (BS), learning rate (LR) and dropout rate. Besides, Table 7.6 also show the resulting metrics: the testing Loss (MSE) and the R^2 . The two models were trained using an early stopping strategy, with a maximum number of 300 epochs. Both models converged around 30 epochs each, reaching loss functions of 119.2 and 125.6 for the ResNet and MobileNet models respectively. Even though these results can be considered good, the prediction of LWC using hyperspectral information outperforms this methods reaching values over 0.9 [57, 60, 59, 55]. Furthermore, Figure 7.5, showcases the comparison of the predicted LWC with the measured LWC, revealing that the largest contributors to error are the samples from the completely dehydrated stage (LWCI is 0).

7.3.3.1 Prediction of VIs using as input predicted LWC

The results shown in the previous sections showcases that the combination of LWC+VIs+Texture features, perform the best to recover the various tested vegetation indices. Thus, this section focuses on the performance variation, when replacing the measured LWC using the weight method, with the predicted LWC obtained through the deep learning architectures.

Table 7.7 showcases the results when replacing the measured LWC, in the best performing models for the prediction of each VI. The table presents the results, and the comparison among the real (measured) LWC, and the

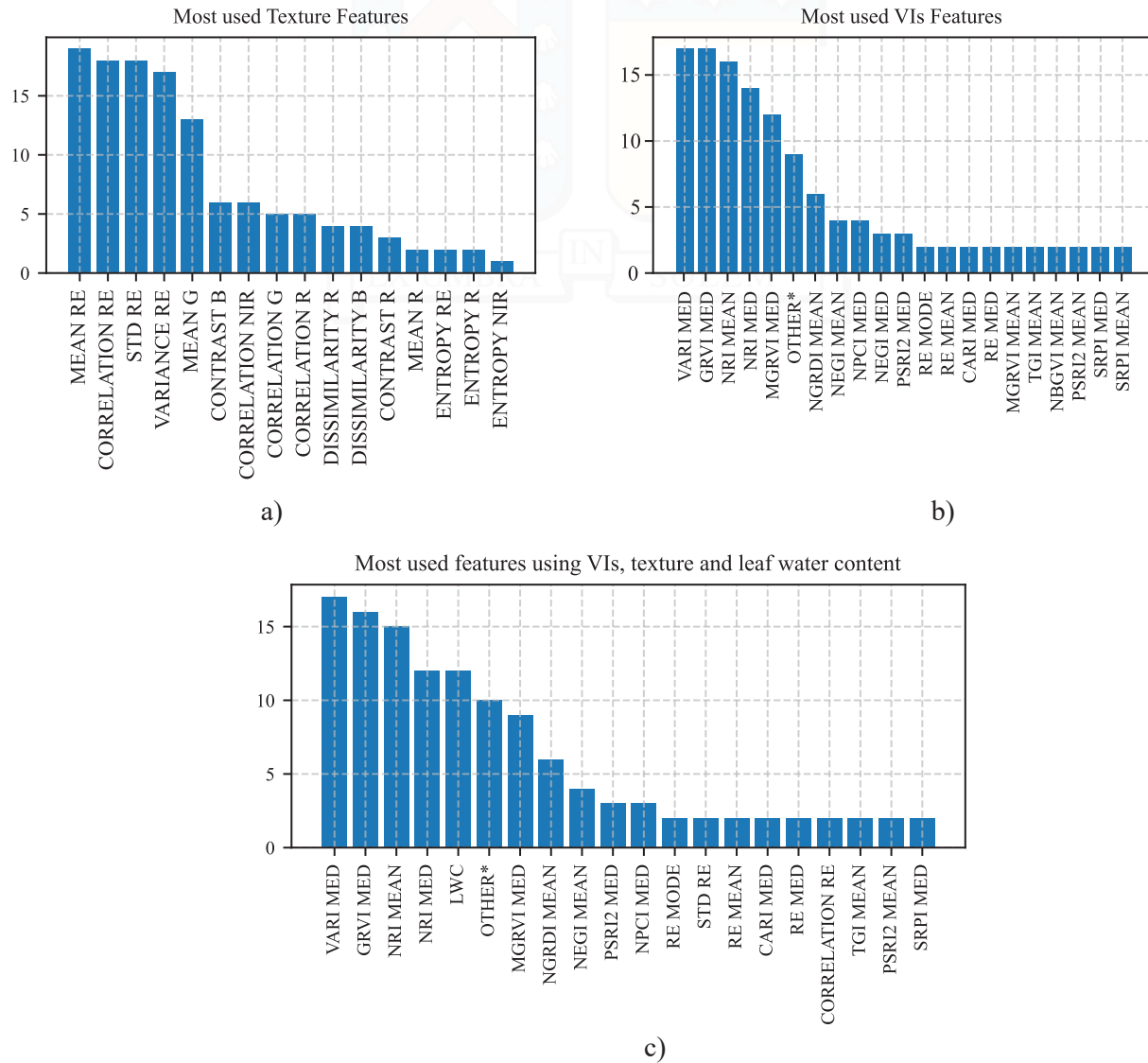


Figure 7.2: Summary of the most used features across all the models for all the vegetation indices: a) shows the histogram of the most used texture features, b) shows the histogram of the most used VIs color features, and c) shows the histogram of the most used bands using the combination of all features.

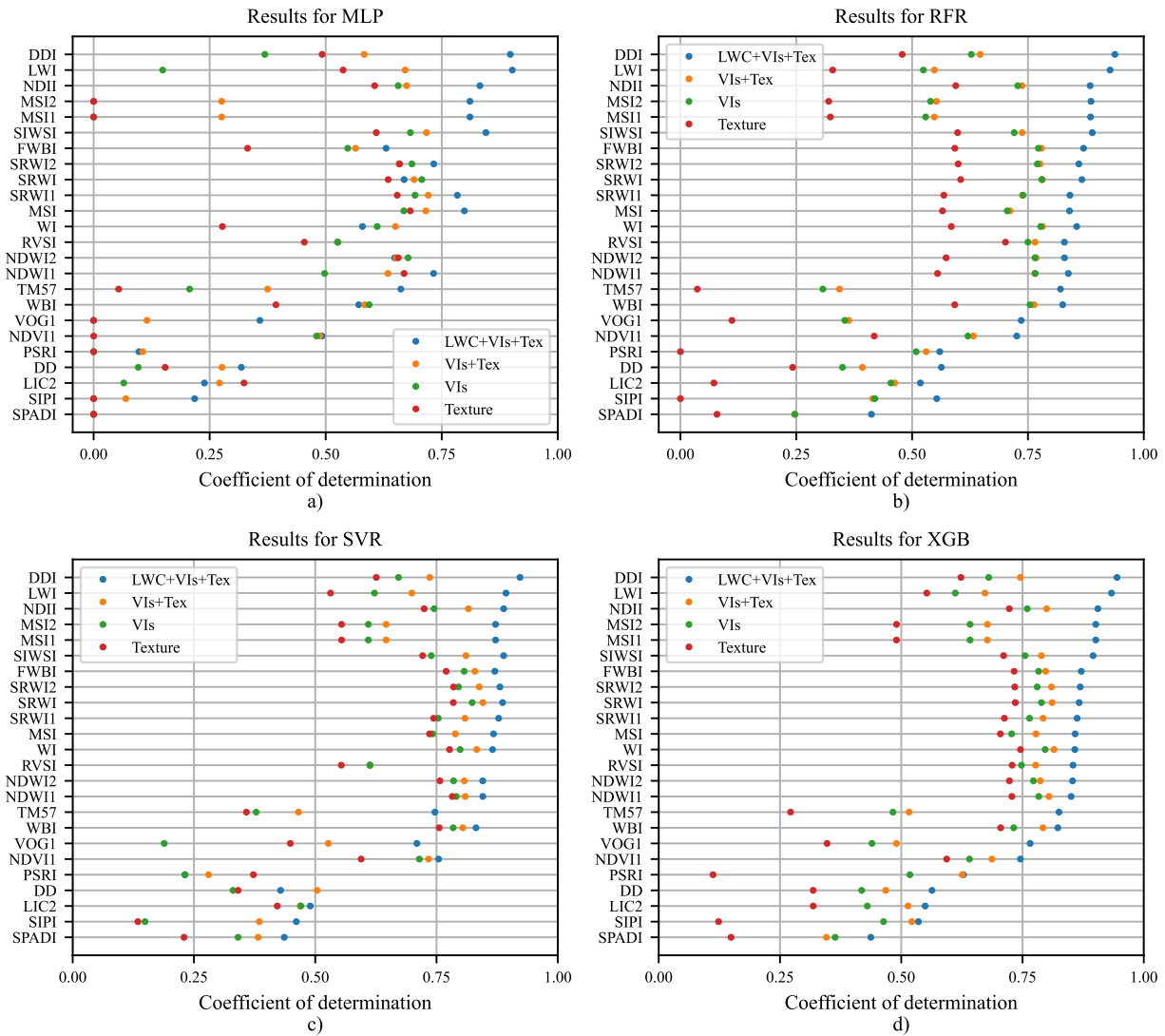


Figure 7.3: Coefficient of determination grouped by types of input features: a) LWC+VIs+Texture, b) VIs+Texture, c) VIs, and d) Texture.

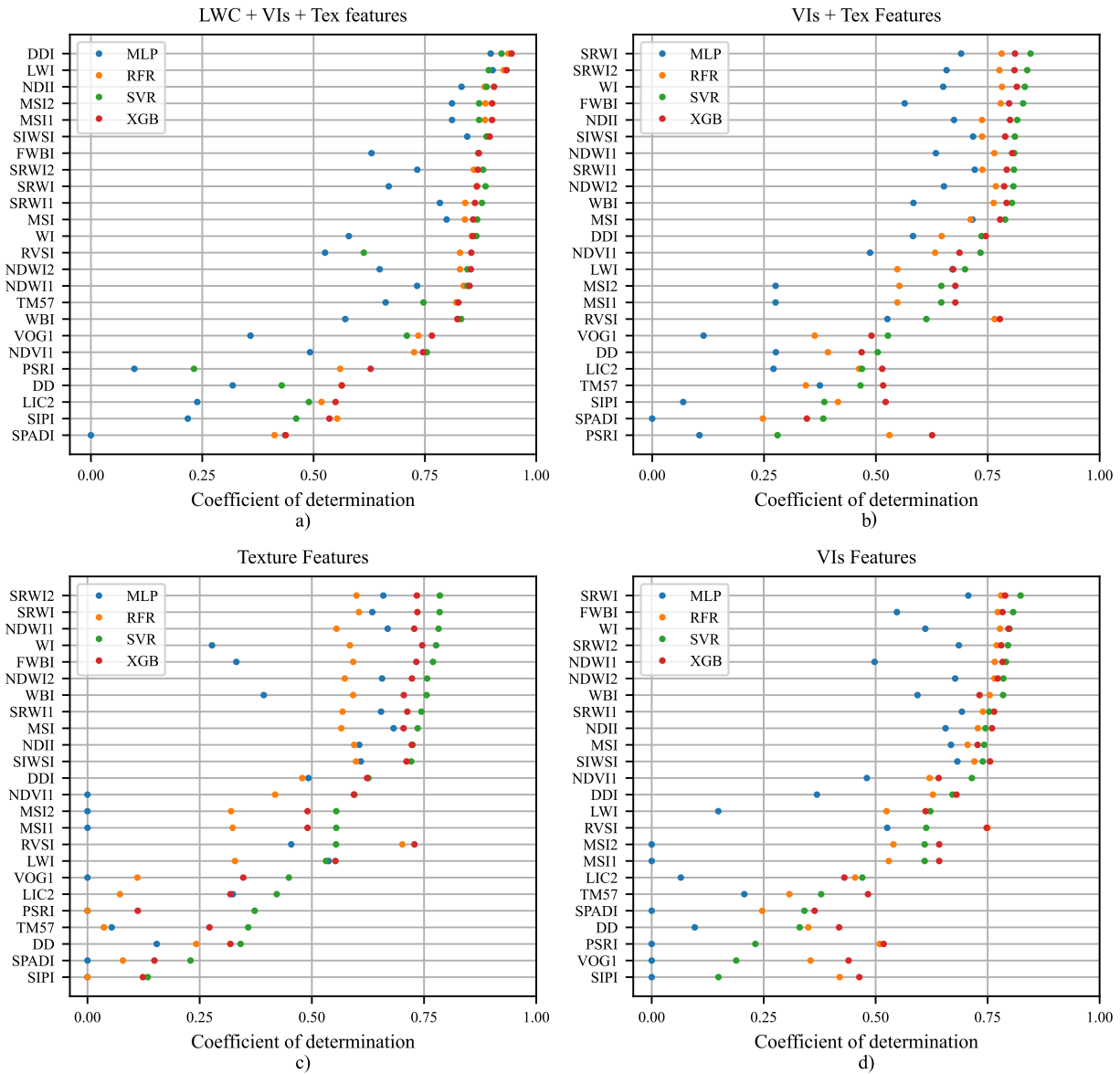


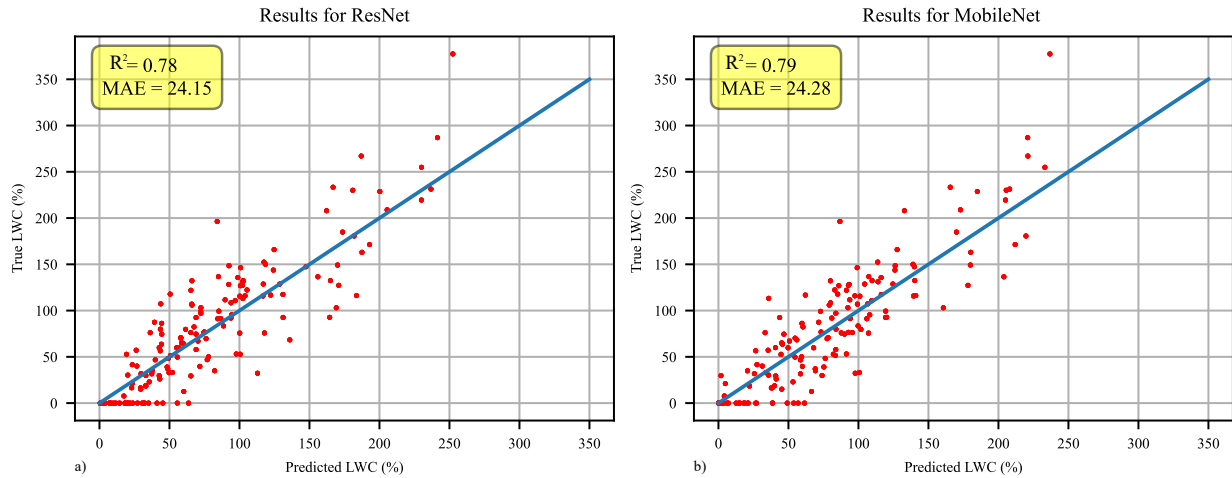
Figure 7.4: Coefficient of determination grouped by regressor: a) MLP, b) RFR, c) SVR, and d) XGB.

Table 7.5: Metrics for the prediction results using the different input combinations

Index	LWC+VIS+TEX			VIS+TEX			VIS			TEX		
	ML*	MAE**	R ²	ML	MAE	R ²	ML	MAE	R ²	ML	MAE	R ²
DD	XGB	0.27 ± 0.36	0.56	SVR	0.31 ± 0.40	0.50	XGB	0.31 ± 0.41	0.42	SVR	0.33 ± 0.44	0.34
DDI	XGB	0.03 ± 0.04	0.94	XGB	0.06 ± 0.08	0.75	XGB	0.06 ± 0.05	0.68	SVR	0.08 ± 0.10	0.63
FWBI	XGB	0.01 ± 0.02	0.87	SVR	0.01 ± 0.02	0.83	SVR	0.01 ± 0.02	0.81	SVR	0.02 ± 0.02	0.77
LIC2	XGB	0.04 ± 0.07	0.55	XGB	0.04 ± 0.06	0.51	SVR	0.05 ± 0.06	0.47	SVR	0.05 ± 0.07	0.42
LWI	XGB	0.21 ± 0.30	0.93	SVR	0.45 ± 0.59	0.70	SVR	0.48 ± 0.33	0.62	XGB	0.46 ± 0.61	0.55
MSI	SVR	0.07 ± 0.12	0.87	SVR	0.10 ± 0.14	0.79	SVR	0.11 ± 0.13	0.74	SVR	0.11 ± 0.16	0.74
MSI1	XGB	0.02 ± 0.03	0.90	XGB	0.03 ± 0.05	0.68	XGB	0.04 ± 0.03	0.64	SVR	0.04 ± 0.05	0.55
MSI2	XGB	0.02 ± 0.03	0.90	XGB	0.03 ± 0.05	0.68	XGB	0.04 ± 0.03	0.64	SVR	0.04 ± 0.05	0.55
NDVI1	SVR	0.02 ± 0.02	0.75	SVR	0.02 ± 0.03	0.73	SVR	0.02 ± 0.03	0.71	SVR	0.02 ± 0.03	0.59
NDI1	XGB	0.03 ± 0.05	0.91	SVR	0.04 ± 0.06	0.82	XGB	0.05 ± 0.05	0.76	SVR	0.05 ± 0.08	0.72
NDWI1	XGB	0.02 ± 0.04	0.85	SVR	0.03 ± 0.04	0.81	SVR	0.03 ± 0.04	0.79	SVR	0.03 ± 0.05	0.78
NDWI2	XGB	0.02 ± 0.03	0.85	SVR	0.03 ± 0.04	0.81	SVR	0.03 ± 0.04	0.79	SVR	0.03 ± 0.04	0.76
PSRI	XGB	0.01 ± 0.02	0.63	XGB	0.01 ± 0.02	0.63	XGB	0.01 ± 0.02	0.52	SVR	0.01 ± 0.02	0.37
RVSI	XGB	0.00 ± 0.00	0.85	XGB	0.00 ± 0.01	0.78	RF	0.00 ± 0.01	0.75	XGB	0.00 ± 0.01	0.73
SIPI	RF	0.01 ± 0.02	0.55	XGB	0.01 ± 0.02	0.52	XGB	0.01 ± 0.02	0.46	SVR	0.01 ± 0.02	0.13
SIWSI	XGB	0.03 ± 0.05	0.90	SVR	0.04 ± 0.06	0.81	XGB	0.05 ± 0.05	0.76	SVR	0.05 ± 0.07	0.72
SPADI	XGB	0.02 ± 0.03	0.44	SVR	0.02 ± 0.03	0.38	XGB	0.02 ± 0.03	0.36	SVR	0.03 ± 0.04	0.23
SRWI	SVR	0.04 ± 0.06	0.89	SVR	0.05 ± 0.06	0.85	SVR	0.05 ± 0.06	0.82	SVR	0.06 ± 0.08	0.78
SRWI1	SVR	0.05 ± 0.09	0.88	SVR	0.07 ± 0.11	0.81	XGB	0.08 ± 0.10	0.76	SVR	0.08 ± 0.12	0.74
SRWI2	SVR	0.03 ± 0.05	0.88	SVR	0.04 ± 0.06	0.84	SVR	0.05 ± 0.06	0.80	SVR	0.05 ± 0.07	0.79
TM57	XGB	0.08 ± 0.11	0.83	XGB	0.12 ± 0.16	0.52	XGB	0.12 ± 0.11	0.48	SVR	0.14 ± 0.18	0.36
VOG1	XGB	0.06 ± 0.09	0.77	SVR	0.08 ± 0.11	0.53	XGB	0.08 ± 0.09	0.44	SVR	0.09 ± 0.12	0.45
WBI	SVR	0.02 ± 0.03	0.83	SVR	0.02 ± 0.03	0.80	SVR	0.02 ± 0.03	0.78	SVR	0.03 ± 0.04	0.76
WI	SVR	0.02 ± 0.03	0.87	SVR	0.02 ± 0.03	0.83	SVR	0.02 ± 0.03	0.80	SVR	0.02 ± 0.03	0.78

*ML shows the best performing ML model for the selected VI and input feature combination.

**The MAE also includes the standard deviation of the error.

**Figure 7.5:** LWC prediction using as input deep convolutional neural networks.**Table 7.6:** Prediction of LWC using Deep CNN approaches.

Model	BS	LR	Dropout	Loss (MSE)	R ²
MobileNetV3	16	0.001	0.3	125.6	0.78
ResNet18	16	0.001	0.0	119.2	0.79

predicted using the two tested models. In all the cases the best performing model is still the one that uses the measured LWC. Replacing the LWC drops the performance in some cases, for example in the LWI and DDI models, which suffer the most. However, other indices such as SIWSI, RVSI, WI, and NDWIE still showcases a strong performance with the addition of the estimated LWC.

For a better comparison, Fig.7.6, showcases the comparison from table 7.7; where it is clear which indices show the worst performance when replacing the measured LWC with the predicted LWC from the deep learning architectures.

Table 7.7: Metrics obtained using as input the real value of LWC, and the predicted values obtained through ResNet18 and MobileNetV3.

Index (Model)	Real LWC		ResNet18 LWC		MobileNetV3 LWC	
	R^2	MAE	R^2	MAE	R^2	MAE
DDI (XGB)	0.94	0.03 ± 0.04	0.74	0.06 ± 0.07	0.82	0.05 ± 0.06
LWI (XGB)	0.93	0.21 ± 0.30	0.79	0.37 ± 0.44	0.82	0.34 ± 0.43
NDII (XGB)	0.91	0.03 ± 0.05	0.85	0.04 ± 0.05	0.85	0.04 ± 0.05
MSI1 (XGB)	0.90	0.02 ± 0.03	0.70	0.03 ± 0.04	0.77	0.03 ± 0.04
MSI2 (XGB)	0.90	0.02 ± 0.03	0.70	0.03 ± 0.04	0.77	0.03 ± 0.04
SIWSI (XGB)	0.90	0.03 ± 0.05	0.84	0.04 ± 0.06	0.84	0.04 ± 0.06
SRWI (SVR)	0.89	0.04 ± 0.06	0.87	0.04 ± 0.06	0.87	0.04 ± 0.06
SRWI2 (SVR)	0.88	0.03 ± 0.05	0.86	0.04 ± 0.05	0.86	0.04 ± 0.05
SRWI1 (SVR)	0.88	0.05 ± 0.09	0.84	0.06 ± 0.09	0.85	0.06 ± 0.09
FWBI (XGB)	0.87	0.01 ± 0.02	0.80	0.01 ± 0.02	0.80	0.01 ± 0.02
MSI (SVR)	0.87	0.07 ± 0.12	0.82	0.09 ± 0.13	0.83	0.09 ± 0.12
WI (SVR)	0.87	0.02 ± 0.03	0.85	0.02 ± 0.03	0.85	0.02 ± 0.03
RVSI (XGB)	0.85	0.00 ± 0.00	0.84	0.00 ± 0.00	0.85	0.00 ± 0.00
NDWI2 (XGB)	0.85	0.02 ± 0.03	0.81	0.02 ± 0.04	0.80	0.02 ± 0.04
NDWI1 (XGB)	0.85	0.02 ± 0.04	0.81	0.03 ± 0.04	0.81	0.02 ± 0.04
WBI (SVR)	0.83	0.02 ± 0.03	0.81	0.02 ± 0.03	0.82	0.02 ± 0.03
TM57 (XGB)	0.83	0.08 ± 0.11	0.68	0.11 ± 0.13	0.70	0.10 ± 0.13
VOG1 (XGB)	0.77	0.06 ± 0.09	0.66	0.07 ± 0.10	0.67	0.07 ± 0.10
NDVI1 (SVR)	0.75	0.02 ± 0.02	0.73	0.02 ± 0.02	0.74	0.02 ± 0.02
PSRI (XGB)	0.63	0.01 ± 0.02	0.59	0.01 ± 0.02	0.62	0.01 ± 0.02
DD (XGB)	0.56	0.27 ± 0.36	0.52	0.29 ± 0.38	0.51	0.29 ± 0.38
LIC2 (XGB)	0.55	0.04 ± 0.07	0.49	0.05 ± 0.07	0.51	0.05 ± 0.07
SIPI (RF)	0.49	0.01 ± 0.02	0.41	0.01 ± 0.02	0.43	0.01 ± 0.02
SPADI (XGB)	0.44	0.02 ± 0.03	0.35	0.02 ± 0.03	0.37	0.02 ± 0.03

7.4 Discussion

This chapter focused on the prediction of VIs computed from hyperspectral information, which are used for a comprehensive assessment of vegetation health status, including leaf water content, chlorophyll prediction, nitrogen prediction and biomass estimation. For the prediction of such indices, the main focus is to use features extracted from devices such as multi-spectral cameras, which are cheaper than spectrometers, and present advantages such as faster sampling times, which would allow monitoring in real time, and the surveying of larger portions of land.

The initial input vector for training ML models includes measured LWC, color and texture features from the multi-spectral images. As stated previously, the main objective is to use as input only the multi-spectral images, thus an estimated LWC replaced the measured LWC replaced the measured value in the models.

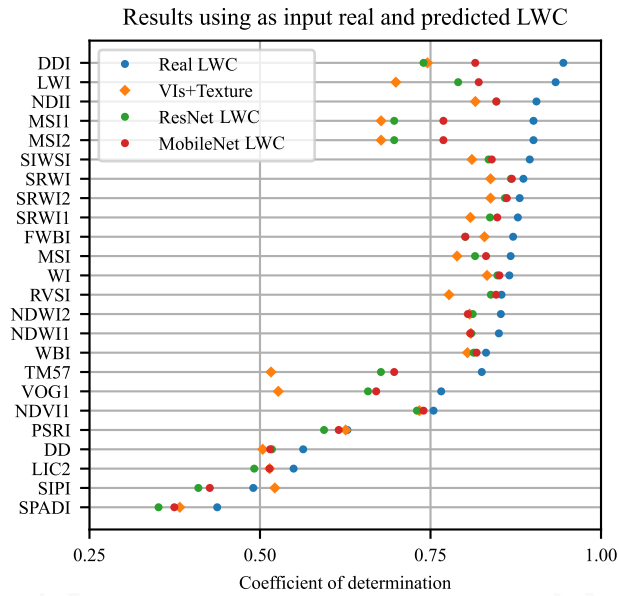


Figure 7.6: Comparison of the performance of the models when replacing the measured LWC with the predicted LWC from the deep learning architectures.

7.4.1 Feature selection

The initial step for training the models included a feature selection based on a correlation analysis. In this step each feature was analyzed with its correlation to the respective target VI. As a result from this correlation analysis, one of the most used feature is the measured or predicted LWC. This is expected since various of the tested VIs are highly related to the analysis of water or water stress in the plants [55].

When analyzing the most used multi-spectral vegetation index the best most used vegetation index, is the VARI index; this index has been extensively studied and is shown to have a strong correlation with live fuel moisture [141], it also has been applied to determine tree structure, biomass concentration and nitrogen concentration [103, 142]. It is important to mention that this index is composed by the bands in the visible part of the spectrum (B, G, R). Other indices that are also relevant include the GRVI, MGRVI, NGRDI, NEGI, PSRI2, NPCI, SRPI and TGI; these indices are composed by bands in the visible spectrum, which suggests that this bands can be an important factor to determine some aspects of plant vegetation [143]. However, another important features are derived from both the RE and NIR band, thus the analysis of health vegetation, needs the reflectance in all these bands.

Comparing both the VIs+Texture models, it is clear that VIs are the most used features for the assessment of vegetation status, while Texture features participate in a minor part. This also explain the poor performance of the trained models, using only the Texture features.

7.4.2 VI prediction

The best metrics obtained in this section are shown in Table 7.5. This table showcases that the models achieve the best when using the complete input set including the color, texture and LWC features. Some indices achieve R^2 of above 0.9, specifically the indices WI and DDI. Both of these indices have been used extensively to analyze LWC [55], thus it is expected to achieve larger coefficient determination values when using additional spectral information and not only the LWC value.

Analyzing the results and the performance of the different ML models, using the complete feature vector the XGB model performs the best, however the improvement from the other models is minimal. The clear outlier is the use of the MLP, or the neural network model, which performs the worst for all the models; in this chapter only two configurations of MLP were tested, only 1 hidden layer with 100 neurons, and two hidden layers with 50 neurons each; an MLP is a highly customizable model, with different number of layers and different number of neurons. However,

increasing the number of parameters of the MLP will increase the inference time and would make the model to use a larger computation power.

The next best performing set of features in all the tested target VIs, is the color (multispectral VIs) and texture features. Using only this combination of features the best performing indices are: SRWI, FWBI, WI, SRWI2, NDII, SIWSI, NDWI1, NDWI2, WBI, and MSI which achieve R^2 above 0.75, diminishing its performance in the R^2 metric in 0.1 or 0.2. In contrast, the LWI and DDI indices, when removing the LWC feature, the performance significantly decreases from approximately 0.9 to 0.58 and 0.67 respectively.

A further examination of the SRWI, FWBI, WI, SRWI2, NDII, SIWSI, NDWI1, NDWI2, WBI, and MSI indices, showcases that these indices are composed by bands in the NIR region (specifically in the range from 850 to 950 nm), while the second band is located in the SWIR region (for instance, MSI present the second band at 1650 nm). The combination of these bands suggest that it is possible to reconstruct some information in the SWIR region, using only information from a multi-spectral camera (visible and NIR region), as corroborated in [56, 107]. Indices such as LWI and DDI are composed by bands completely in the SWIR region, this composition helps them to predict with low error LWC [55], but predicting these indices using only information in the NIR regions, remains a challenge, as showcased by the drop in performance when removing the LWC feature.

The other indices which are not related to LWC (VOG1, DD, LIC2, TM57, SIPI and SPADI), consistently displayed the poorest performance with all the models, and with all the input feature sets, reaching only R^2 of 0.7 in the best cases. The analysis of the spectral composition of such indices show that they are built using only regions below 1000 nm, and with narrow spectral separation (e.g., LIC2: 790 and 680 nm, VOG1: 740-720 nm). This suggests that spectral features defined by bands that are relatively close to one another are difficult to reproduce using only the broad bands of a multispectral camera.

7.4.3 LWC prediction and performance of the models using the predicted LWC

The two deep learning architectures reached relatively acceptable R^2 of 0.78 and 0.79, these results are comparable to other machine learning frameworks which employ texture and color features from multi-spectral images [15], however these results are still worse than those obtained using the hyperspectral information [55, 60, 59]. An alternative to improve these results is to apply more robust models such as transformer based networks [60], however this model would need a sufficiently large dataset for a reliable training process and a reliable result [144].

When replacing the predicted LWC in the input feature vector for the models trained used the LWC+VIs+Tex features, the performance understandably decreases. However, comparing these results with the VIs+Texture models, the performance of the models increase. Notably, the models for the DDI and LWI indices which have an R^2 of 0.75 and 0.70 from VIs+Texture, improve the performance to 0.82 in both cases. Models that are not as affected by the removal of LWC (SRWI, FWBI, WI, SRWI2, NDII, SIWSI, NDWI1, NDWI2, WBI, and MSI), still see an improvement in performance when using the predicted LWC, but it is not as impactful as the indices mentioned above. Increasing the performance of the LWC prediction pipeline, and replacing this improved value of LWC in the models would generate an improved performance on the prediction of the vegetation indices.

7.5 Contributions

The results of these experiments are under revision for the journal IEEE Transactions on AgriFood Electronics.

"Nutritional Assessment of Crops: Bridging the Gap Between Hyperspectral and Multispectral Imagery using Machine and Deep Learning Approaches"

7.6 Conclusion

In this chapter, the reconstruction of 24 hyperspectral VIs used for assessing vegetation health status was analyzed. As input, features extracted from multi-spectral images were used, including color information (VIs derived from five bands: B, G, R, NIR, and RE) and texture features derived from the GLCM. Additionally, the LWC value, measured via manual sampling, was included as an input feature. The prediction task was carried out by four ML models: MLP, SVR,

RFR, and XGB. Using this approach, R^2 values of over 0.9 for indices such as DDI and LWI were achieved. However, when using only features from the spectral images, the best R^2 values reached 0.75 for indices such as SRWI, SRWI2, WI, and FWBI.

To overcome the need for manual sampling to obtain LWC, two deep CNN architectures (ResNet50 and MobileNetV2) were trained to predict LWC using only multi-spectral images. By using the predicted LWC as an input feature alongside VIs and texture features, the performance of the models improved considerably, achieving R^2 values of around 0.8 for indices such as DDI and LWI.

Notably, indices that combine bands in the range of 800 to 950 nm with a second band in the SWIR region were the best performing when using only features from multi-spectral images. Furthermore, these indices were the least affected when the LWC feature was removed from the inputs, and adding the predicted LWC only slightly improved their performance.

Indices exhibiting high correlation with LWC, notably DDI and LWI, were most sensitive to the exclusion of the LWC feature. Integrating the CNN-predicted LWC significantly restored their performance, implying that future enhancements in LWC prediction accuracy will directly translate to improved model results.

8 | Conclusion and Future Works

This chapter summarized the main findings and conclusions made in this dissertation. Furthermore, suggested future work is presented in the research field.

8.1 Conclusions

The experiments and procedures performed in this thesis, supported the hypothesis that for a comprehensive assessment of vegetation status, it is sufficient to use information from spectral devices, whether there is a multispectral (multispectral camera) or hyperspectral (Terraspec ASD spectrometer) device. Even though the assessment of vegetation can be performed more precisely using hyperspectral information, shown by a highly accurate prediction result in the LWC parameter, a coarser, yet effective, method of assessing water stress can be performed using only multispectral images, by classifying leaves according to their dehydration stage. Furthermore, in this thesis two methods were tested to reduce the number of bands in the electromagnetic spectrum, with the objective to find the minimum number of bands or sets of bands that would allow for a complete assessment of the plant's health. The first method consists of systematically reduce the spectral resolution from 1 nm to 100 nm, which maintains only 1.02 % of the initial information. Using the reduced spectral reflectance values, and a machine learning strategy, various vegetation indices were predicted with coefficient of determination above 0.9. The other approach consists on identifying key regions, through the use of xAI models. Using this approach, three regions were identified as the most useful for predicting leaf water content; then these regions were used to predict vegetation indices related to other vegetation parameters. The main contributions per chapter are described below:

- Chapter 4 focuses on the classification of leaves according to their dehydration stage, using both multi-spectral images in conjunction with deep convolutional neural networks, and hyperspectral information using machine learning approaches. The results show that the deep learning approaches (MobileNetv3 and ResNet18) outperforms most of the ML approaches, reaching accuracies of 0.98; thus showcasing that for a quick assessment of water status in plants, there is no need of the full spectrum in the 350 to 2500 nm.
- In chapter 5, the reduction of a spectral resolution of 1 nm to 100 nm was performed. This reduction means that only 1.02 % of the original information was kept. Then using this reduced information 25 vegetation indices related to various parameters of vegetation indices was conducted using machine learning algorithms. Using machine learning algorithms, and the reduced information, various of the tested indices were retrieved with R^2 above 0.9. However, as expected the performance of the models reduces with the downsampled information.
- Chapter 6 focuses on the identification of important regions of the spectrum for the prediction of leaf water content. For this purpose, a simple 1d CNN was trained, with the objective of predicting LWC, then using Grad-CAM (an xAI algorithm), the most important regions were identified. The 1d-CNN predicted LWC with an R^2 of 0.91 and the identified regions were 350 to 658 nm, 1886 to 2180 nm and 2260 to 2500 nm. These regions were able to retrieve three indices with an R^2 of above 0.9; showcasing the capabilities of these regions for the assessment of plant health status. Notably using the first region, 350 to 658nm, which corresponds to the visible spectrum; predicted the tested indices with an R^2 of 0.7, suggesting that some parameters of vegetation status can be predicted using only the visible part of the spectrum, thus the necessary sensors can be regular cameras, instead of infrared devices.
- In chapter 7, a methodology for the evaluation of health status of vegetation through the prediction of VIs is

proposed. Various features from multispectral images were computed, including descriptive VIs and texture features were computed, additionally LWC was predicted from the images through the use of deep learning. This approach showcased that using VIs+Texture + measured LWC, can predict indices with R^2 of 0.9 and above. However, when eliminating the LWC, the performance of the models significantly drops, reaching values of 0.7. Furthermore, a deep CNN trained to predict LWC, was able to achieve this task with R^2 of 0.78, using this predicted LWC in the input vector for the VIs+Texture+LWC models, improves the performance from the VIs+Texture models reaching again values of 0.8 in indices such as LWI and DDI, which are heavily correlated with LWC.

8.2 Future Works

The results presented in this dissertation corroborate that the use of multi-spectral imagery is heavily correlated to the more comprehensive and in-depth information provided by the hyperspectral devices such as the spectrometer. However, this approaches still need validation in real field conditions, and algorithms need to be proposed to overcome the harsh environmental conditions that could hinder the performance of the models.

First, a remote sensing platform should be developed. For this instance a UAV mounted with the multi-spectral camera is the most common approach. Furthermore, a field that has been externally induced to various stress factors need to be surveyed; for this purpose, crops which have been intentionally under irrigated provide the necessary conditions to test the algorithms for the prediction of leaf water content prediction. Alongside the survey of land using the remote sensing platform, the groundtruth is needed; for this purpose a land sampling campaign is carried out. The manual sampling, involves the collection of spectral reflectance values using the spectrometer, in the same environmental conditions as the multi-spectral images. Leaf sampling needs to be carried out as well, so meaningful insights of the plant can be recorded. With both the hyperspectral individual values, and the multi-spectral aerial images; an adapted framework from this thesis can be tested.

The new data collected, particularly the multi-spectral images, do not represent only useful information from leaves; the images would also contain background, blur induced by the movement of the platform, and interference and occlusion from other elements, such as branches from the same trees. Therefore, algorithms that overcome this issues need to be applied to the images, so the performance of the models are not as affected by this external factors.

Furthermore, whether the robotic platform is ground based or aerial based, the camera can only record information from the surface; thus elements from inside the tree are still invisible; thus, a complete characterization of vegetation is incomplete using only information from cameras, cannot recover the complex geometrical features from canopy, that would allow the measurement of physical parameters from vegetation, that are also important for the assessment of current crop health. Therefore, the integration of passive sensors such as cameras, with active sensors that can capture spatial and 3D features, to create complete models of vegetation, would allow a more in-depth assessment of both physical and biochemical features from the plants. Furthermore, state-of-the-art deep learning methodologies such as 3D gaussian splatting, are capable of performing reliable 3D reconstruction using as input images from different points of view of an object. The combination of both, multi-spectral sensing technology and the newly developed 3D reconstruction models, opens up the possibility of creating a digital model of vegetation, and furthermore the incorporation of weather information into the models allows the construction of digital twins of vegetation.

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A | Counting of flowers in densely populated images

A.1 Introduction

During the blooming period, various flowers will undergo the pollination process, thus converting into fully developed fruits. Thus, counting flowers during the blooming period can be an early predictor for fruit yield, without considering other factors such as climate hazards [84, 78].

Currently, research is focused on the counting of fully developed fruits including cherries [80], apples [79], avocados, lemons [81] and litchis [82]; using various deep learning architectures such as YOLO, Fast RCNN, and Single Shot Detector (SSD), and tracking networks. These approaches have shown great success detecting up to 90% of the fruit in images. However, these methods can be applied once the fruit is either fully developed or in its early stages, thus it is not suitable for an early prediction of yield.

In contrast, the detection and counting of flowers is still highly unexplored. For instance, [84] used YOLO for the detection of apple flower clusters, [145, 87] used YOLO networks for the identification of kiwi flowers and their different organs for artificial pollination purposes. Even though these approaches have presented high accuracies, they still do not focus on the problem of high density objects. The first work focusing on high-density detection is the one presented by [85], where a multi-column network is used to predict the density of flowers and not to detect each individual instance in a dataset of litchi plants. This approach can count up to 90% of total flowers in the image, greatly outperforming the counting by detection of each individual instance. This work leverages the multi-column approach used for crowd counting [146, 147, 148, 149].

In this chapter, the focus is to perform the flower counting task in peach groves, which present high flower density, occlusion and interference from background trees and elements. The two most common techniques for counting were tested. First, the flower density prediction was applied using a similar network presented by [85], but a color filter was implemented for an early segmentation of flowers, with the purpose of reducing the interference from the background. The second approach involves the use of different YOLO versions for counting each individual flower. The counting results were evaluated using the Root mean squared error (RMSE), MAE and error percentage.

A.2 Methodology

In this section, the peach grove dataset is introduced, the data preparation and image annotation strategies are presented. Next, flower-density prediction networks are detailed, as well as the YOLO networks used for detection, finally the evaluation metrics are introduced. The overall architecture of this chapter is shown Fig.A.1

A.2.1 Dataset

The dataset is comprised by frames extracted from videos recorded in peach groves located in the region of Catalonia, Spain. The videos were recorded using a camera from an iPhone 5 cellphone. The features of the camera are presented in Table A.1. The camera was carried by hand and walking across the peach-groves.

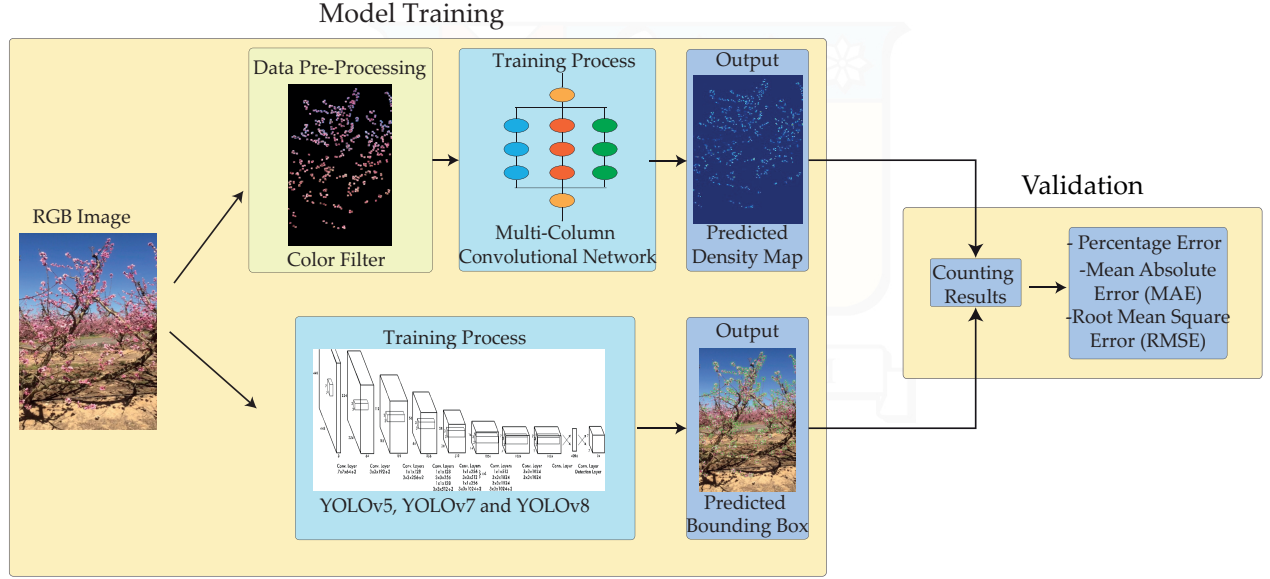


Figure A.1: Proposed architecture for the counting of flowers in peach groves. The architecture is divided into two main branches, the first branch focuses on the prediction of density maps, while the second branch focuses on the detection of each individual flower using YOLO networks (source [150]).

Table A.1: Features of the camera used to generate the dataset

Feature	Value
Resolution	8 Mega Pixels
Focal Length	33 mm
Maximum Aperture	f/2.4
Sensor Size	1/3.2"
Pixel Size	1.4 μm
Video Quality	1080p@30fps

Three videos were recorded at a resolution of 1280×720 pixels. From the videos, a total of 500 frames were extracted. Each frame presents a full tree, with no blurring. Additionally, a set of 100 images was separated and annotated for validation purposes.

This dataset poses several challenges for the counting task. The high density of elements, the occlusion and overlapping between objects, and the interference from similar objects, present real challenges to overcome using deep learning architectures. Figure A.2 showcases some of the scenarios present in the dataset. Furthermore, Table A.2 present the most important features of the dataset, including the total number of instances and other significant statistics about the dataset.

Table A.2: Dataset description

Feature	Value
Training images	400
Testing images	100
Validation images	100
Total images	600
Total flowers	235640
Average number of flowers	423.81
Maximum number of flowers in an image	887
Minimum number of flowers in an image	134

A.2.1.1 Image annotation

For the prediction of density maps, a dot annotation is needed [146, 151, 85], while counting by detection using YOLO networks need box annotations [84]. Annotations were made with the LabelMe tool [152]. Every flower, including those experiencing occlusion, were considered. Only the first row of trees were annotated, since the background rows of trees are not considered objects of interest, and could interfere with the desired flowers. Examples of dot annotations are shown in Fig.A.3.

A.2.2 Prediction of Density Maps

If the primary task is to count the objects, then the exact position of each instance is not relevant; thus, the density prediction becomes a useful alternative when dealing with highly populated images [146, 153, 151, 85]. This approach can be considered a regression task instead of a classification task.

The ground truth generation for the density maps involves using a Gaussian kernel in the dot-annotated image map. The resulting density map represents the spatial distribution and the intensity of the objects in the image.

For the prediction task, the multi-column networks presented by [85] is used, with a few modifications. First the head is modified to accept BGR images instead of gray-scale images; this was done to leverage the distinct color features from peach flowers, and to minimize the interference of similar background objects, and the branches' shadows. The complete network is shown in Fig.A.4. The main feature of the network is its multi-column approach. Each column creates a feature map, trough convolutional kernels of different sizes, with the purpose of capturing flower of different sizes present in the image. The first column uses a kernel of size 11×11 across the 5 columns it reduces its size by a reason of 2×2 , until reaching a size of 3×3 . The feature map generated by each column is then concatenated, and a final 1×1 kernel is applied. The final layer uses a linear activation function to generate the final prediction. Figure A.5 showcases an annotated image with its generated density map, using a Gaussian kernel of 5×5 .

After the final prediction a threshold was applied to eliminate false positives. The final counting result is obtained by integrating the image values (adding up all the pixel values, normalized between 0 and 1).

A.2.3 Counting by detection

In recent years, YOLO architectures [154, 155, 155] have been widely used for various detection tasks in agricultural environments, including the detection of fruits and flowers [79, 80, 81, 145, 87, 84]. The single-stage approach of



a)



b)



c)

Figure A.2: Samples of the peach trees found in the dataset: a) shows a tree spanning the whole frame, b) shows a tree with high density of flowers and interference from the background, and c) presents a tree with a different flower distribution but with similar interference from the background (source [150]).

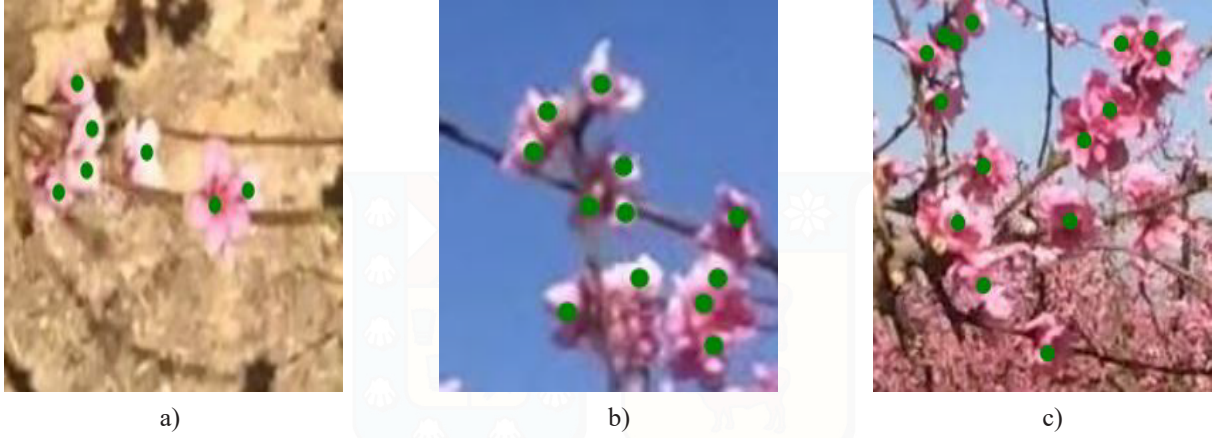


Figure A.3: Different flower annotation in the dataset: a) flowers with soil in the background, b) flowers with the sky in the background, and c) flowers with interferencia with background trees and flowers (source [150]).

YOLO enables the model to be faster and smaller compared to other detection algorithms.

In this chapter, YOLOv8, YOLOv7, YOLOv6 and YOLOv5 networks were trained, with the purpose of assessing which network would yield better results. With each version of YOLO, various sizes of the network are released; each size was tested as well.

A.2.4 Color Filter in The HSV space

To minimize the interference of the background trees, the sky, tree branches, and other objects, a color filter is proposed. The flowers in the dataset present a clear distinct color. Such color is accentuated in the *hue*, *saturation*, *value* color space. Then, a threshold was found in order to preserve the largest amount of flowers while reducing the number of pixels in the background.

The models were trained on both, the images with the filter and without the filter. The result of applying the filter are shown in Fig.A.6.

A.2.5 Evaluation metrics

YOLO networks are evaluated using common metrics for classification algorithms including Precision, Recall and mean average Precision (mAP) To evaluate the counting results, RMSE, MAE and percentage error are considered. The equations for such metrics are presented below, where y is the real number of flowers, $\hat{y}$ is the estimated number of flowers, and n is the total number of samples.

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(\hat{y}_i - y_i)^2}{n}} \quad (A.1)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i| \quad (A.2)$$

$$\%Err = \frac{1}{n} \sum_{i=1}^n \frac{|\hat{y}_i - y_i|}{y_i} \times 100 \quad (A.3)$$

A.2.6 Hardware and training considerations

The density map prediction algorithm was implemented in Python 3.9 using TensorFlow 2.0. The training was conducted on a computer with an Intel Core i7 7th Gen Processor CPU, NVIDIA GeForce GTX 1080 Ti 8 GB GPU, and 16 GB of

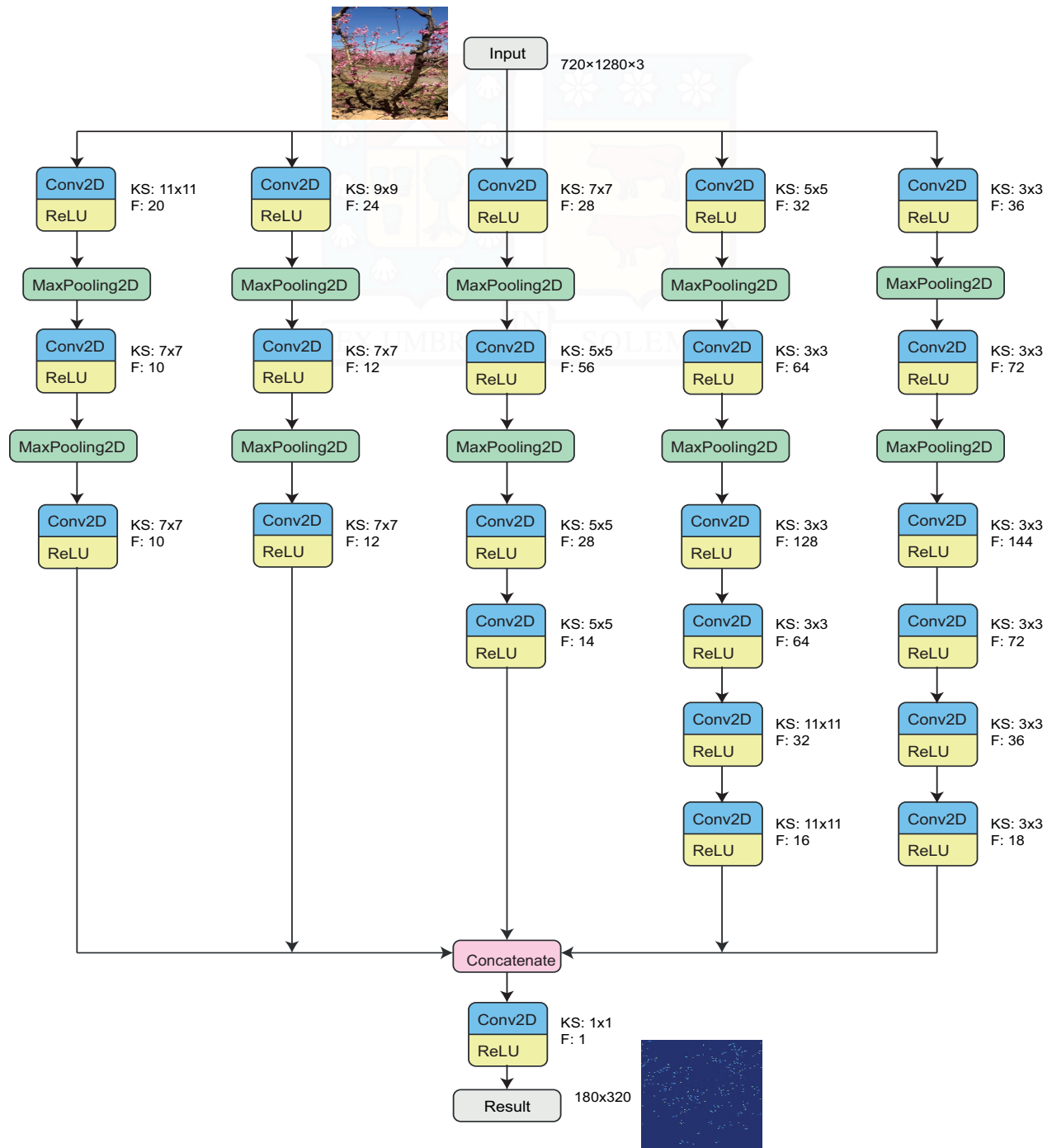


Figure A.4: Proposed multi-column network for the prediction of flower density maps (source [150]).

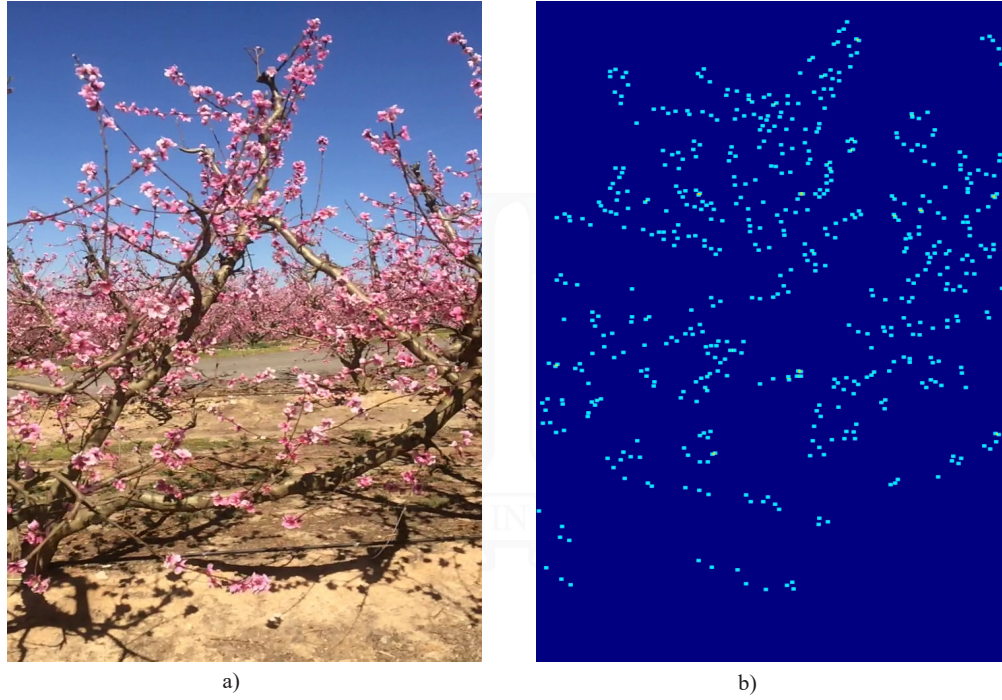


Figure A.5: Generated density map: a) Original image, b) Density map (source [150]).

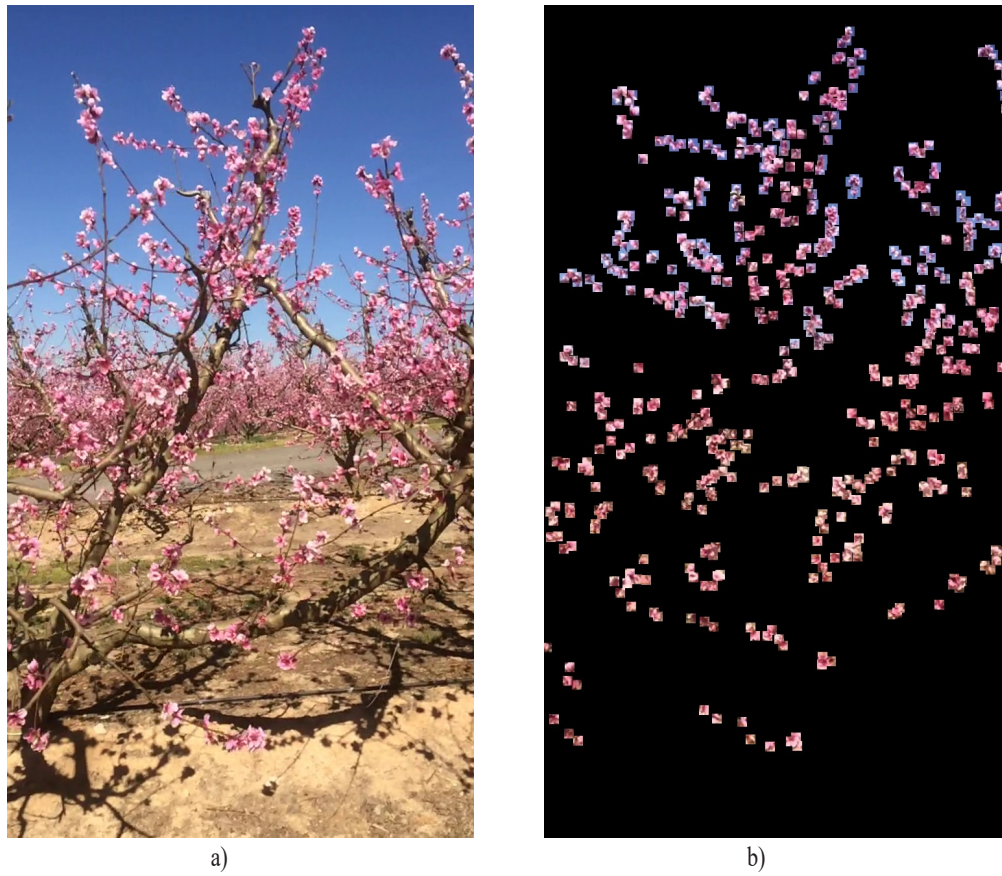


Figure A.6: Proposed color filter: a) original image , and b) after applying the proposed filter (source [150]).

RAM, running on the Windows 10 operating system. Other software tools utilized include CUDA 11.7 and cuDNN 4.0.

The dataset was split with 0.8 of the samples for training and 0.2 for validation purposes. Apart, the additional 100 images were used for evaluation purposes.

A.3 Results

In this section, the counting results for both the density prediction and detection using YOLO are presented.

A.3.1 Counting by predicting density maps

To obtain the best performing hyperparameter configuration, various combinations were tested changing the size of the Gaussian kernel used to generate the ground truth, the batch-size and the learning rate. Also, the algorithm was trained with and without the proposed HSV color filter. The algorithms were trained with a maximum of 1000 epochs, however the models converged at around 300 epochs.

The metrics obtained in the evaluation dataset are shown in Table A.3. This table showcases all the tested hyper-parameter configurations including Gaussian Filter size (GS), batch size (BS), learning rate (LR), and threshold value (TR) that yielded the best results. The table also showcases if the color filter (F) was used or not.

Table A.3: Results of the density prediction map, with different hyperparameter configuration during the training process

Hyperparameters						Metrics		
Model	F	GS	BS	LR	TR	MAE	RMSE	%Err
1	N	7	1	0.001	0.0005	38.63	59.8	10.95
2	N	7	1	0.005	0.0005	105.27	131.46	24.024
3	N	7	1	0.01	N/A	N/A	N/A	N/A
4	N	7	4	0.001	0.0005	109.59	143.84	25.48
5	N	7	4	0.005	0.0005	109.59	143.84	25.48
6	N	7	4	0.01	N/A	N/A	N/A	N/A
7	N	15	1	0.001	0.0005	83.75	106.61	19.63
8	N	15	1	0.005	0.000725	48.66	76.06	14.27
9	N	15	1	0.01	N/A	N/A	N/A	N/A
10	N	15	4	0.001	0.0005	86.707	118.11	22.25
11	N	15	4	0.005	0.0005	138.73	161.34	45.48
12	N	15	4	0.01	N/A	N/A	N/A	N/A
13	Y	7	1	0.001	0.0005	61.83	88.83	15.33
14	Y	7	1	0.005	0.0005	88.52	119.64	21.16
15	Y	7	1	0.01	N/A	N/A	N/A	N/A
16	Y	7	4	0.001	0.0005	92.92	124.31	22.17
17	Y	7	4	0.005	0.0005	81.77	113.82	20.86
18	Y	7	4	0.01	N/A	N/A	N/A	N/A
19	Y	15	1	0.001	0.0005	39.13	69.69	9.98
20	Y	15	1	0.005	0.00054	77.41	109.86	19.1
21	Y	15	1	0.01	N/A	N/A	N/A	N/A
22	Y	15	4	0.001	0.0005	183.38	213.34	42.1
23	Y	15	4	0.005	0.0005	109.72	152.7	26.22
24	Y	15	4	0.01	N/A	N/A	N/A	N/A

According to the results in Table A.3, the best performing model uses a Gaussian Filter of size 15×15 , a batch size of 1, and a learning rate of 0.001, using the proposed HSV color filter. This model reached a counting percentage error of 9.98%, which is on par to the results obtained by [85]. In all cases the largest learning rate (0.01) failed to

predict any result. The inference using this hyperparameter configuration, simply produced an image with all values capped at 0.

Furthermore, for a qualitative and visual evaluation of the algorithms, examples of the inference are shown in Fig.A.7. These images showcase the effectiveness of the model in various cases. In the image, the results are obtained with the best model, according to table A.3

A.3.2 Counting by detection

For the training of the YOLO models, the total number of epochs was set at 1000 however the models converge at around 300 epochs. All the sizes of YOLO were tested for all the versions (YOLOv8, YOLOv7, YOLOv6 and YOLOv5), YOLOv5 presents the following sizes: nano (n), small (s), medium (m), large (l), extra Large (xl). YOLOv7 present the following sizes: tiny, standard (s), large (x), w6 and e6, both of the last models modify and scale the input for improved performances. Finally, YOLOv8 presents the same sizes as YOLOv5.

The detection results for the YOLO models are evaluated using the Precision, Recall and mean Average precision, while the counting task is evaluated using the same metrics as the prediction of density maps. The metrics are shown in Table A.4.

Table A.4: Evaluation metrics for the YOLO models, trained to predict the number of flower in peach groves

Model	Precision	Recall	mAP	MAE	rMSE	%Err
YOLOv5n	0.65	0.4	0.5	198	252.7	39.4
YOLOv5s	0.66	0.4	0.51	215.4	277.8	48.4
YOLOv5m	0.7	0.4	0.52	204.2	266.8	40.8
YOLOv5l	0.71	0.4	0.52	208.5	273.6	41.5
YOLOv5x	0.71	0.42	0.54	198.0	252.7	39.4
YOLOv7 tiny	0.62	0.36	0.41	173.5	240.3	36.8
YOLOv7m	0.656	0.3805	0.282	161.7	229.4	34.2
YOLOv7x	0.78	0.52	0.39	152.7	212.9	29.7
YOLOv7d6	0.71	0.42	0.33	160.4	227.3	33.5
YOLOv7e6	0.71	0.43	0.34	162.8	225.4	32.6
YOLOv8n	0.752	0.442	0.61	170.8	244.5	35.8
YOLOv8s	0.754	0.451	0.62	169.2	248.6	34.5
YOLOv8m	0.756	0.442	0.6	173.3.2	245.8	35.8
YOLOv8l	0.751	0.596	0.44	166.5	242.5	33.2
YOLOv8x	0.779	0.456	0.615	160.39	221.0	31.4

Visual examples of the detection achieved by the YOLO networks are shown in Fig. A.8. In these examples, the first column showcases the flowers detected by YOLOv5x, the next column show YOLOv6x, and the final column shows YOLOv8x. In this case, only the results of the size x models are presented because they obtained the better metrics according to Table A.4.

Finally, the main results of the counting task, comparing both the YOLO and prediction models are shown in Fig.A.9. This figure clearly demonstrates that counting by predicting the density map, greatly outperforms counting by detection using YOLO.

A.3.3 Background error

The greatest source of error for the models, is over-counting due to the interference of background trees, as they possess similar features with the desired objectives. The error caused by this source is quantified and showed in Tables A.5 and A.6. In these tables, the total average flowers in the background are counted (AvBF) and the relative background flowers compared to the total number of detected flowers (%BF).

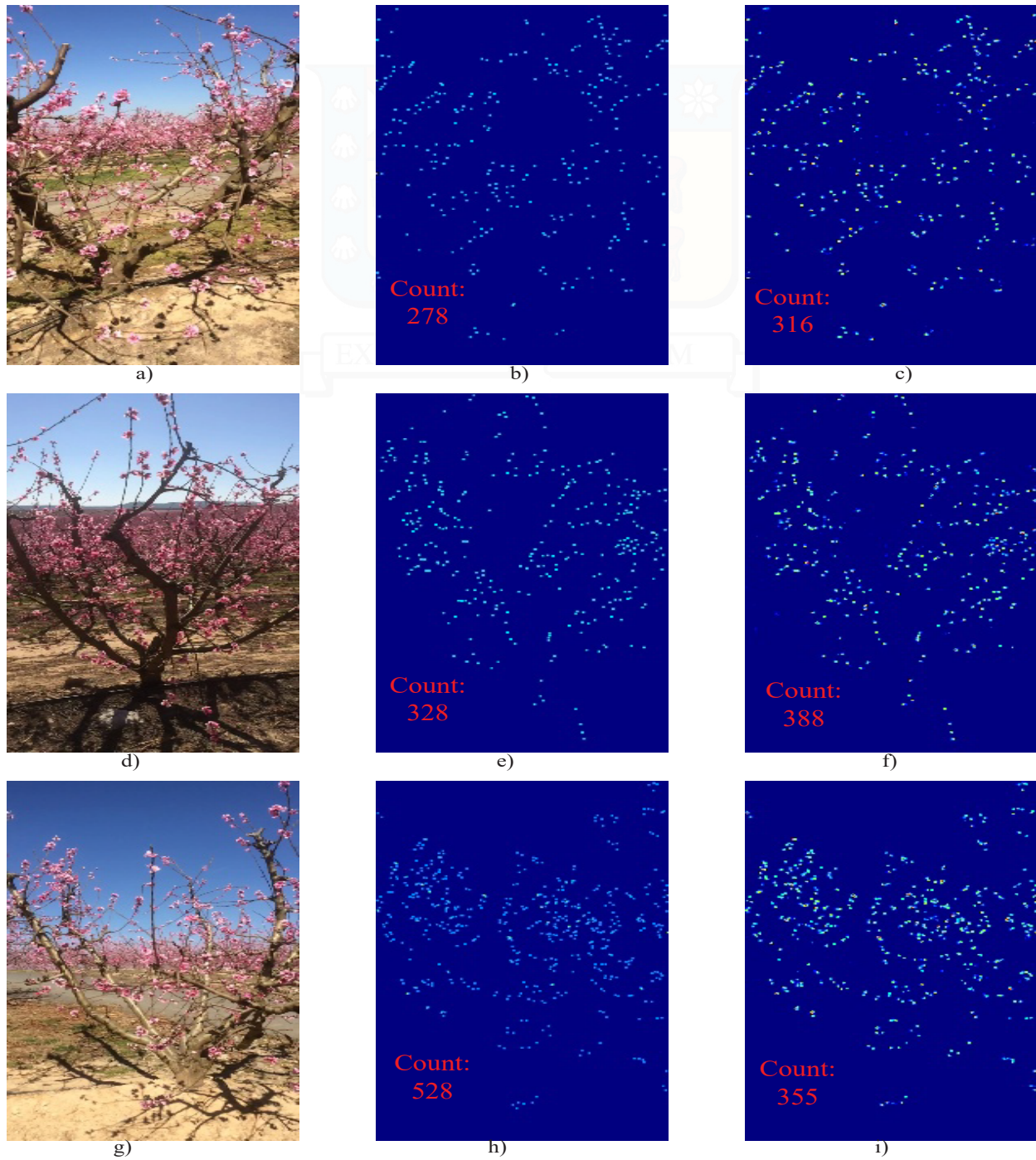


Figure A.7: Samples of the predicted density maps: a), d) and g) show original RGB images, b), e) and h) show the groundtruth density maps, and c), f) and i) show the predicted density maps (source [150]).

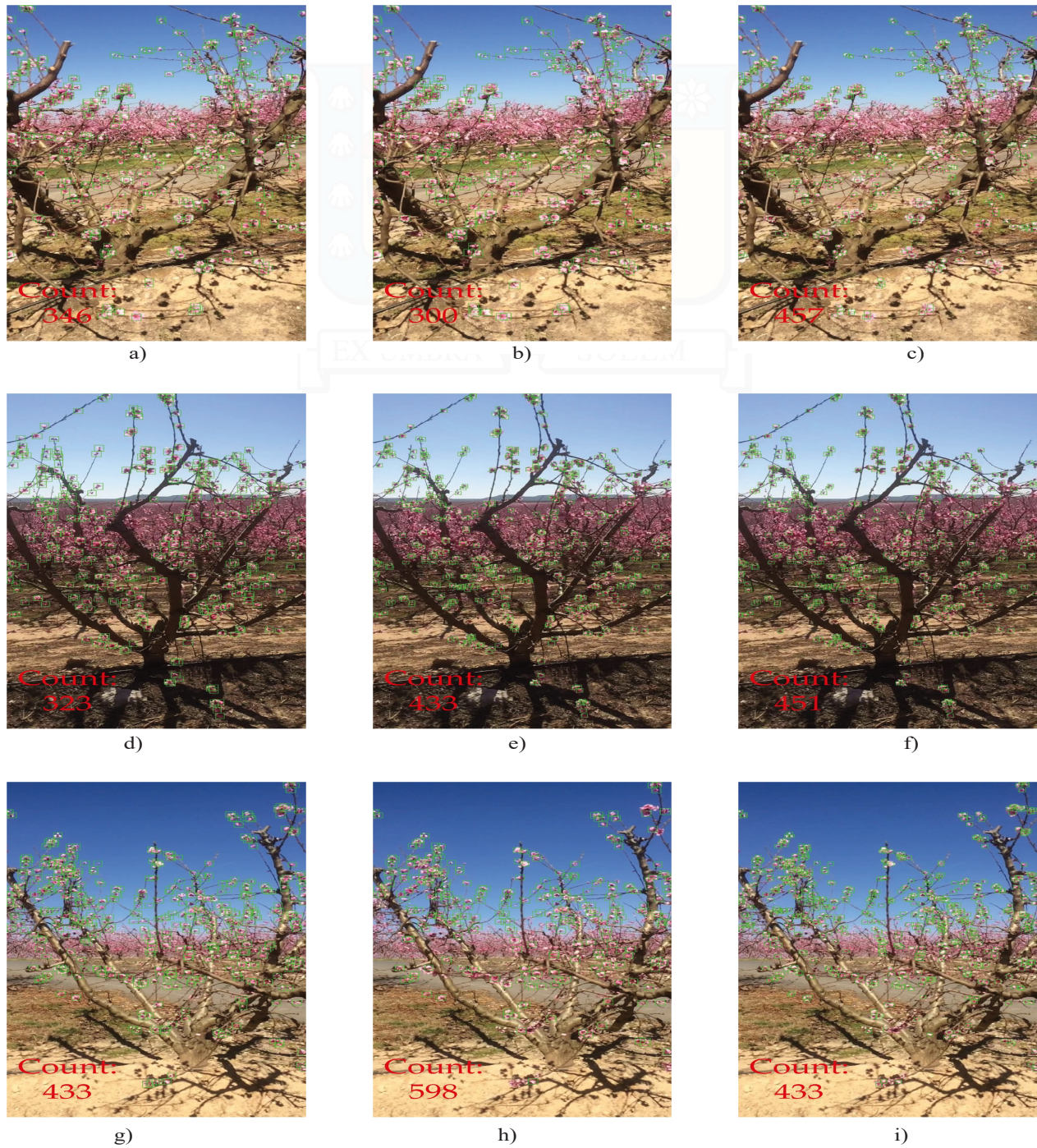


Figure A.8: Samples of images and the different YOLO predictions: a), d), g) show YOLOv5x, b), e) and h) show the predicted bounding boxes by YOLOv7x, c), g) and f) show the predicted bounding boxes by YOLOv8x, (source [150]).

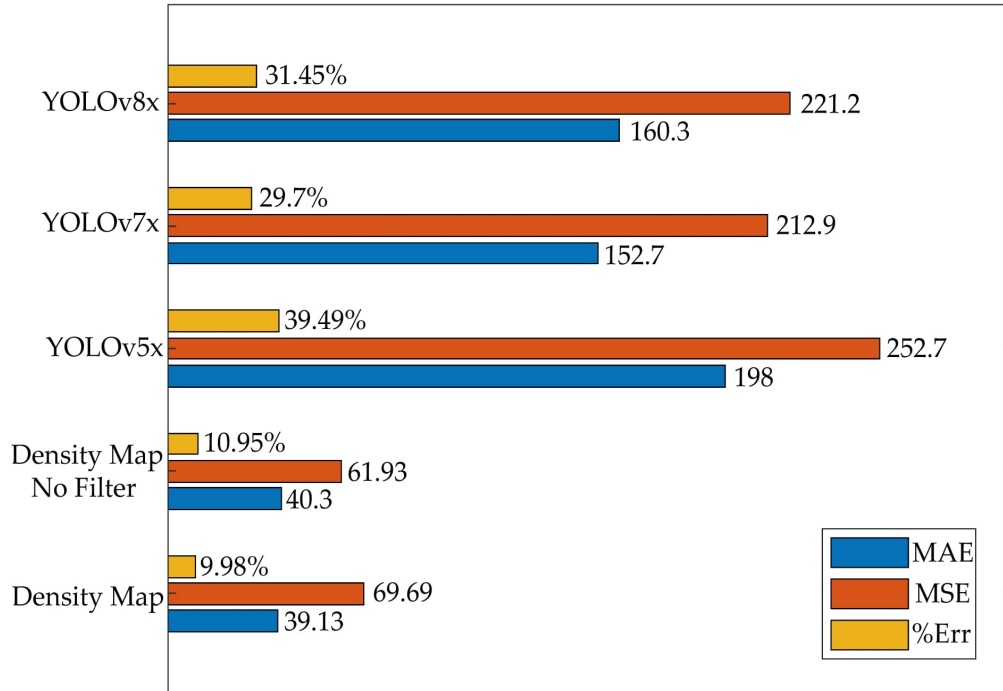


Figure A.9: Comparison of the counting results obtained by the density prediction and the YOLO models (source [150]).

A.4 Discussion

This annex focused on the counting of flowers in peach groves, with the purposes of making an early prediction of total yield. The dataset presents serious challenges; first the images showcase various rows of trees, however only the first row of trees is the regions of interest; due to the similarity of colors and shapes, the background elements might interfere with the prediction of the deep learning models. Second, the images are populated with numerous flowers in a small spaces; furthermore, the flowers present occlusion, varying sizes, and changes in illumination; such dataset demands special care compared to other studies such as the litchi flower dataset [85], which presents only the flowers in a single plant not in a row of trees, or the kiwi flower dataset [145], which clearly presents a single flower, or reduced number of flowers, with the purpose of identifying each individual organ of the flower instead of getting the raw number of flowers in the image.

As shown, Tables A.4, this method of counting is poor compared to the results of density prediction. The detection metrics, are also not ideal since Precision, and mAP only reach values of 0.7 and 0.60 in the best scenario, which are poorer compared to the results presented by [85], which achieves 0.9. However, the obtained results are consistent with research focused on the identification of small objects, where the detection algorithms underperform [156, 157].

Since the desired task is to obtain the raw number of flowers and not the precise location of each individual instance; the prediction of density maps was proposed. This method has been successful in various counting tasks, such as flower [85], crowds [146] and animals [158]. This approach, clearly outperforms counting by detection as shown by Fig.A.9, where the error by prediction of density maps reaches values of 9.98 % and the counting by detection using YOLOv7x reaches an error of 29.7%.

Even though the application of the color filter reached the best metrics from all the models; the improvement is not significant. However, hyperparameter selection is a key factor in the performance of the models. Particularly the selection of the Learning rate, showed to have a great impact in the performance of the models. A very high LR of 0.01 proved to produce no results, showcased by predicting a totally black density map.

Regarding the counting using YOLO models, even though YOLOv8 is the latest tested version of the model, it did not achieve the best metrics. In our case, YOLOv7 achieved the best metrics, showcasing the need of testing

Table A.5: Background error produced in the prediction of density maps.

Hyperparameters						Metrics	
Model	F	GS	BS	LR	TR	%BF	AvBF
1	N	7	1	0.001	0.0005	5.38	14.9
2	N	7	1	0.005	0.0005	7.32	22.45
3	N	7	1	0.01	N/A	N/A	N/A
4	N	7	4	0.001	0.0005	11.7	33.57
5	N	7	4	0.005	0.0005	16.26	48.53
6	N	7	4	0.01	N/A	N/A	N/A
7	N	15	1	0.001	0.0005	4.64	12.13
8	N	15	1	0.005	0.000725	11.99	36.58
9	N	15	1	0.01	N/A	N/A	N/A
10	N	15	4	0.001	0.0005	16.89	48.54
11	N	15	4	0.005	0.0005	18.8	55.08
12	N	15	4	0.01	N/A	N/A	N/A
13	Y	7	1	0.001	0.0005	9.86	30.38
14	Y	7	1	0.005	0.0005	16.48	50.44
15	Y	7	1	0.01	N/A	N/A	N/A
16	Y	7	4	0.001	0.0005	12.89	37.57
17	Y	7	4	0.005	0.0005	16.80	49.65
18	Y	7	4	0.01	N/A	N/A	N/A
19	Y	15	1	0.001	0.0005	6.71	21.51
20	Y	15	1	0.005	0.00054	8.59	25.15
21	Y	15	1	0.01	N/A	N/A	N/A
22	Y	15	4	0.001	0.0005	10.6	29.84
23	Y	15	4	0.005	0.0005	21.33	63.90
24	Y	15	4	0.01	N/A	N/A	N/A

Table A.6: Error caused by background interference in the results YOLO models

Model	%BF	AvBF
YOLOv5n	42.3	199.2
YOLOv5s	41.12	192.5
YOLOv5m	41.21	192.2
YOLOv5l	40.58	190.13
YOLOv5x	40.16	185.57
YOLOv7tiny	38.97	160.21
YOLOv7m	37.56	153.55
YOLOv7x	34.25	145.81
YOLOv7d6	37.86	152.84
YOLOv7e6	36.55	150.27
YOLOv8n	38.16	166.15
YOLOv8s	38.02	165.22
YOLOv8m	38.56	166.52
YOLOv8l	38.12	162.38
YOLOv8x	37.51	159.62

the different versions of the model to achieve the better results. Comparing the sizes of the models, as expected, the largest size of YOLO in all its versions (YOLOv5x, YOLOv7x, and YOLOv8x), produced the better results; which is expected; since the larger number of parameters, and that in all datasets this versions of YOLO outperforms the smaller sizes. However, the improvement is still not significant, and it is important to take into account the higher hardware

requirements to run the heavier YOLO models, when deploying on field equipment.

A visual analysis of the counting prediction using YOLO in Fig.A.8, showcases that the YOLO models present difficulties detecting each individual flower within a cluster, leading to lower accuracies and increasing counting errors. Another error source is the under detection of occluded flowers. These issues highlight the challenges that still present detection algorithms particularly when the target objects are small and present occlusion.

The error quantization showcased in Table A.5, shows that a significant portion of the error is present due to the interference of the background objects. In the peach flower dataset, it is a major source of error, because the background present similar color and similar shapes.

Future work, involves the improvement on metrics using more recent networks based of vision-transformer. Besides, the use depth cameras or stereo vision, to reduce the interference of background objects from a distance threshold, would reduce the error caused by the interference of such objects.

A.5 Contribution

The results of the experiments conducted in this annex are published in the Journal of Agriculture and Food Research. The results are found in the article:

J. S. Estrada, J. P. Vasconez, L. Fu, and F. A. Cheein, “Deep Learning based flower detection and counting in highly populated images: A peach grove case study,” Journal of Agriculture and Food Research, vol. 15, p. 100930, Mar. 2024, doi: 10.1016/j.jafr.2023.100930.

A.6 Conclusion

In this section, two approaches for counting flowers in highly populated images are presented, first the counting by prediction of density maps, and the detection of each identified instance is shown. The dataset of peach flowers, presents serious challenges, a high number of instances, heavy occlusion among objects, and interference of background trees.

In the conducted experiments, counting by predicting the density maps produces better results, counting the flowers with an average error of 9.98% in the best performing model. A color filter was proposed to reduce the interference of background objects, and even though the best performing model employs the filter, it only presents a slight improvement in the metrics.

The detection of small objects using YOLO models, still presents difficulties, and the precision reaches values of 0.7 in the best cases. Furthermore, even though YOLOv8 was the latest tested model, YOLOv7x was the model that reached the higher metrics, showcasing the importance of testing various models for the specific task.

The background is a great source of error in the dataset, since these are objects located away from the main target, a distance threshold with the help of stereo cameras, or other instruments would help to reduce the error caused by the interference of the background.

B | Remote instantaneous power consumption estimation of electric vehicles from satellite information

B.1 Summary

This work focuses on the prediction of instantaneous power consumption (IPC) of electric vehicles from satellite information, in various terrain conditions. For this work, an electric car was driven under three distinct terrain conditions: pavement, gravel and grass.

In each trial, the data recorded from the electric car, includes the time and position recorded by an RTK device, and the IMU sensor. To compute the real IPC, a sensor was developed that measures the voltage and current in the electric engine of the car.

Since the objective is to measure IPC only from satellite information, a model for IPC was constructed using only the acceleration obtained from the RTK device, the model is shown below, where μ_{rr} is the friction coefficient, which depends on the terrain, m is the car's mass, g is the gravity, ϕ is the slope angle, and v is the instantaneous speed.

$$IPC_t = (\mu_{rr,t}m_t g \cos\phi_t + m_t g \sin\phi_t + m_t a_t)v_t \quad (B.1)$$

The main results are shown in Fig.B.1, which showcase that estimating the IPC using satellite information, is comparable to the results measured directly from the batteries. It also showcases the differences between the consumption in the different terrains; where the gravel performed the worst compared to the other algorithms.

B.2 Contribution

The results of these experiments were published in the Robotics journal. The reference is listed below:

F. Jorquera, **J. Estrada**, and F. Auat, "Remote Instantaneous Power Consumption Estimation of Electric Vehicles from Satellite Information," Robotics, vol. 12, no. 6, p. 151, Nov. 2023, doi: 10.3390/robotics12060151.

B.3 Conclusion

This study presented a novel study that leverages the use of satellite information (a series of position points in time) to predict the IPC. This approach was tested in different terrain conditions: pavement, gravel and clay. Despite the challenges encountered, particularly in the case of gravel terrain, this research significantly contributes to the field of IPC estimation for electric vehicles. The utilization of satellite data and field experiments showcases the potential of the proposed methodology. The observed discrepancies in gravel terrain underscore the complexities associated with dynamic terrains, emphasizing the need for refinement and adaptation of the methodology to address specific challenges presented by such conditions.

Comparison of computational experiment, field experiment and measures

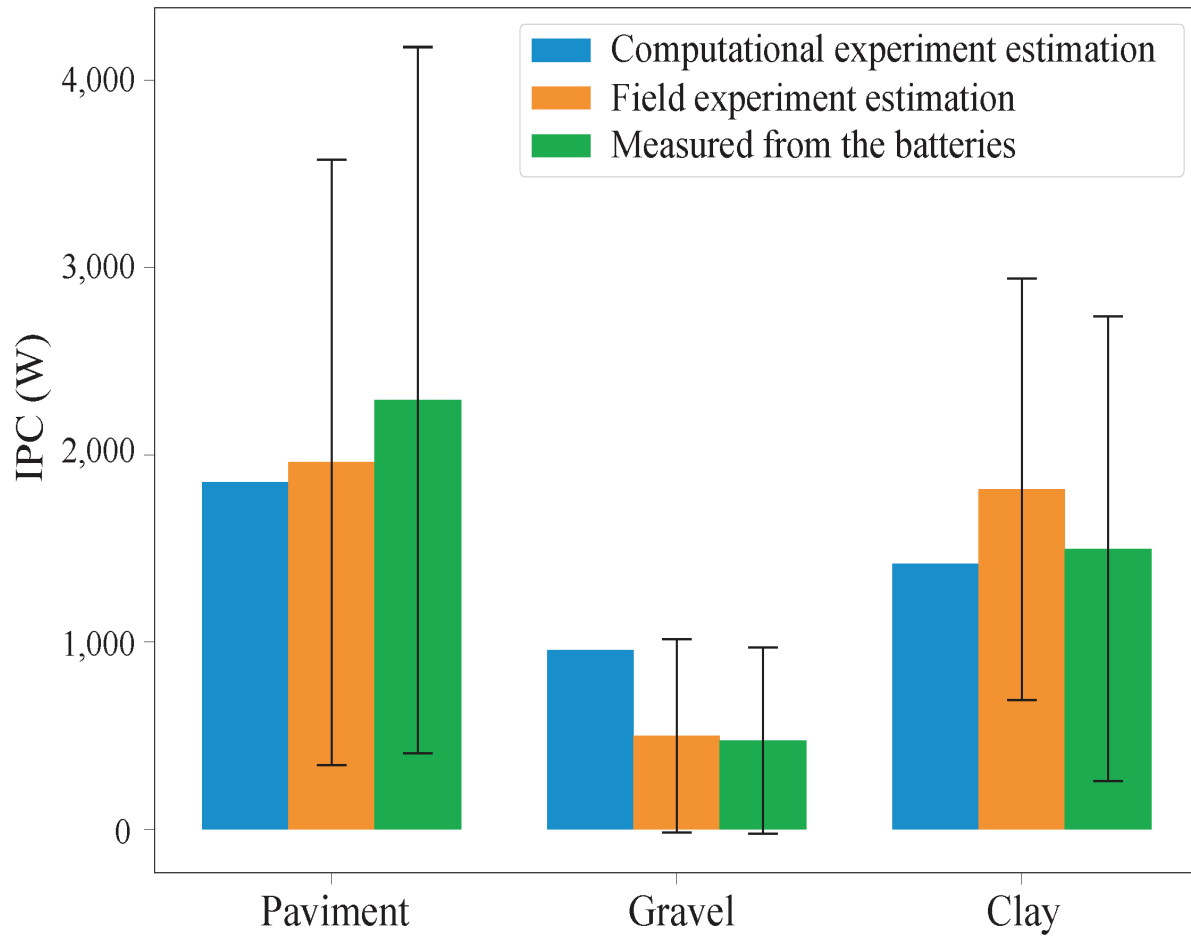


Figure B.1: Comparison of the real IPC measured from the batteries and the predicted IPC from satellite information, for the three different terrains: pavement, gravel and grass (source [159]).

C | Integrative index for evaluation of vegetation health

C.1 Summary

This annex focuses on the creation of an integrative index for the assessment of avocado leaves. The nutritional function index NFI, is constructed using an entropy-weighted approach. This index focuses on the integration of the three vegetation parameters from our dataset: leaf water content, chlorophyll content and nitrogen content. Furthermore, to improve the prediction capabilities of this index, specialized VIs are constructed based on exhaustive screening of the spectrum.

Also, feature wavelengths chosen by successive projections' algorithm (SPA), and competitive adaptive reweighted sampling (CARS), further enhanced the prediction performance.

C.2 Methodology

The overview implemented is shown in Fig.C.1. The architecture focuses the features extracted from the dataset, the construction of the NFI, encompasses the union of moisture content, nitrogen content and SPAD values which serve as a proxy for chlorophyll content. Later, spectral features including specialized VIs obtained through exhaustive screening of wavelengths. Furthermore, using CARS and SPA, selected wavelengths, obtained through data-driven techniques, were chosen. Both, the constructed indices and the selected wavelengths were used as input for machine learning models with the objective of predicting NFI.

C.2.1 Nutritional function index construction

The aim of NFI is to construct an index for the assessment of plant's health, but focusing on various parameters, instead of a single one such as LWC or chlorophyll content. For this purpose, an entropy-weighted multi-criteria decision-making (MCDM) framework is proposed [161]. Before NFI computation, all the indicators (LWC, nitrogen and SPAD) were normalized. The detailed construction of NFI is detailed in [162].

Let x_{ij} denote the normalized value of the i -th indicator for the j -th sample. The entropy e_i of each feature was calculated using the Shannon entropy formula:

$$e_i = -k \sum_{j=1}^n p_{ij} \ln(p_{ij}) \quad (C.1)$$

where:

$$p_{ij} = \frac{x_{ij}}{\sum_{j=1}^n x_{ij}} \quad (C.2)$$

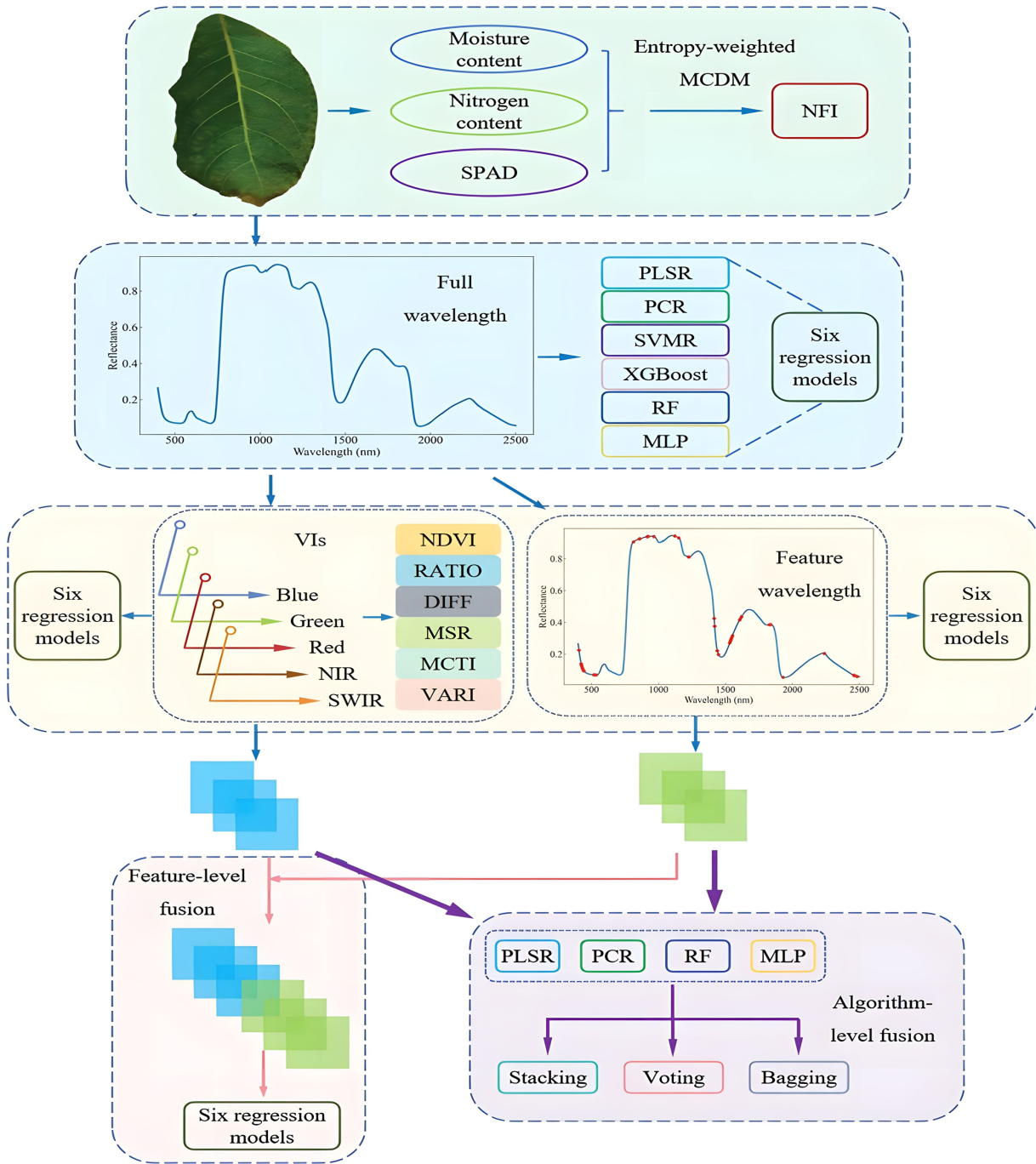


Figure C.1: Proposed architecture for the construction and prediction of NFI. This architecture encompasses the construction of the NFI, the construction of VIs based on correlation to NFI, and the selection of feature wavelengths using CARS and SPA. Finally, all the constructed features are used as input for machine learning models for the prediction of NFI (source [160]).

$$k = \frac{1}{\ln(n)} \quad (C.3)$$

Here, p_{ij} represented the proportion of the i -th feature for the j -th sample across all samples, and k was a normalization constant ensuring $0 \leq e_i \leq 1$. A higher entropy value implies greater uniformity, thus contributing less weight in the final index. Based on the entropy redundancy $(1 - e_i)$, the weight w_i for each feature was derived as follows:

$$w_i = \frac{1 - e_i}{\sum_{j=1}^n (1 - e_i)} \quad (C.4)$$

This formulation ensured that features exhibiting greater variability were assigned higher weights, thereby emphasizing more informative indicators. The final NFI score for the j -th sample was computed as a weighted sum of normalized indicators:

$$NFI_j = \sum_{i=1}^m w_i \cdot x_{ij} \quad (C.5)$$

Using this process, NFI is able to balance the 3 vigor indicators present in the dataset.

C.2.2 Vegetation indices

Various indices were constructed and tested for the prediction of the NFI. First, normalized difference vegetation index (NDVI) is defined as the ration between the difference and the sum of two spectral bands [163], the ratio indices are defined as the ratio of two wavelengths, DIFF is the difference between wavelengths.

To reduce spectral redundancy and enhance the efficiency of predictive modeling, two selection wavelengths are proposed, CARS and SPA. SPA is a straightforward variable selection method designed to minimize collinearity among selected wavelengths [164]. The other algorithm CARS, is an adaptive and robust method for wavelength selection, this method employs Monte Carlo sampling in conjunction with partial least square regression (PLSR) to iteratively eliminate uninformative variables [165].

C.2.3 Machine learning algorithms and data fusion approach

To evaluate the predictive potential of selected VIs and feature wavelengths, a series of regression models were implemented and compared. PLSR was applied as a linear multivariate method that projected both predictors and response variables onto a lower-dimensional latent space, principal component regression (PCR) was constructed by combining PCA for dimensionality reduction with a standard linear regression model [166]. Support vector machine regression (SVMR) with a radial basis function (RBF) kernel was employed as a nonlinear model capable of capturing complex, non-linear relationships between features and response variables [167]. XGBoost, a gradient-boosted tree ensemble algorithm, was used for its robustness and capability to model feature interactions [168]. Random Forest (RF), another ensemble-based method, built multiple decision trees using random subsets of data and features, and aggregated their predictions to reduce overfitting and variance [169]. A multi-layer perceptron (MLP) regressor was employed to capture nonlinear feature interactions through a feed-forward neural network [170].

Furthermore, to increase the prediction capabilities of the models and the features, both sets of features were combined into a single input feature vector; then a combination of the models was introduced. The regression models (PLSR, PCR, RF, MLP) were trained in parallel with the same dataset, then a stacking strategy was used. In this case all the prediction results from the individual learners were used as input for a new meta-model for a final prediction. The next method, voting, simply averages the results from each individual regressor, enhancing the stability of the models. Finally, bagging was implemented by training multiple-instances of the base learners and aggregating their outputs, which reduces model variance and overfitting [171].

C.3 Results

C.3.1 NFI construction

Figure C.2, showcases the distribution of NFI across all the samples at all different stages, this figure also showcases a basic analysis of the features from the dataset.

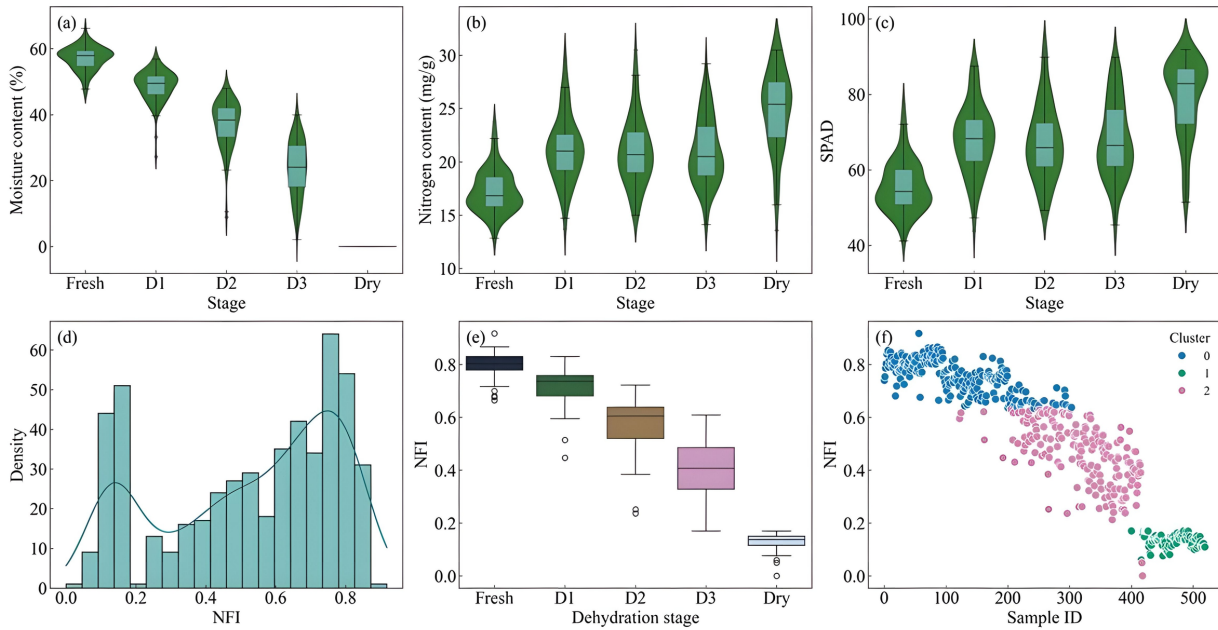


Figure C.2: Nutritional and spectral variation across the different stages of dehydration: a) leaf water content, b) nitrogen content, c) spad distribution, d) histogram of the NFI across the samples, e) NFI variation across the different stages of dehydration, f) clustering of NFI (source [160]).

The construction of the NFI using the entropy-weighted approach showcases that the weights for LWC, nitrogen and SPAD, are 0.83, 0.09 and 0.08. These results indicate that moisture content contributed the majority of information variability across the dehydration stages, and that SPAD and nitrogen content were used as complementary information. The importance of LWC in the creation of NFI is expected, due to the nature of the dehydration process, which in fact creates more variability across the stages. Even though, nitrogen and SPAD also change, the variation is not as pronounced as is the case for LWC.

As shown in Fig.C.2 the value of NFI decreases in a similar rate to dehydration. Specifically, the mean values at each dehydration stage follow the pattern: fresh stage (0.80 ± 0.04), dehydration stage 1 (0.72 ± 0.06), dehydration stage 2 (0.57 ± 0.09), dehydration stage 3 (0.41 ± 0.10), and dry stage (0.13 ± 0.03). This progression closely mirrored the physiological degradation of leaf tissue under drying conditions, validating the biological significance of NFI in quantifying dehydration severity and overall physiological health. To further elucidate unsupervised patterns within NFI data, Gaussian mixture model (GMM) clustering was performed. As shown in Figure C.2(f), the NFI data were divided into 3 clusters. Cluster 0 had a high mean NFI of 0.75, corresponding to fresh or early-stage dehydration. Cluster 1 showed an intermediate mean NFI of 0.46, indicating moderate dehydration. Cluster 2 had a low mean NFI of 0.13, reflecting severe dehydration or complete dryness.

C.3.2 Construction of indices based on correlation to NFI

With the purpose of identifying optimal indices, all the combinations of two bands were computed against each other with the indices in the form of NDVI, RATIO and DIFF. The correlation was measured between all the indices and the newly constructed NFI. The top-ranking spectral regions prominently clustered around specific absorption features, notably at wavelengths 1446, 1455, 1465, 1865, and 1937 nm. These wavelengths corresponded to known water absorption bands

(1450 nm, 1930 nm) and structural biochemical features in plant tissues, underscoring their physiological relevance to NFI. The distribution and the number of appearances of each band is showcased in Fig.C.3.

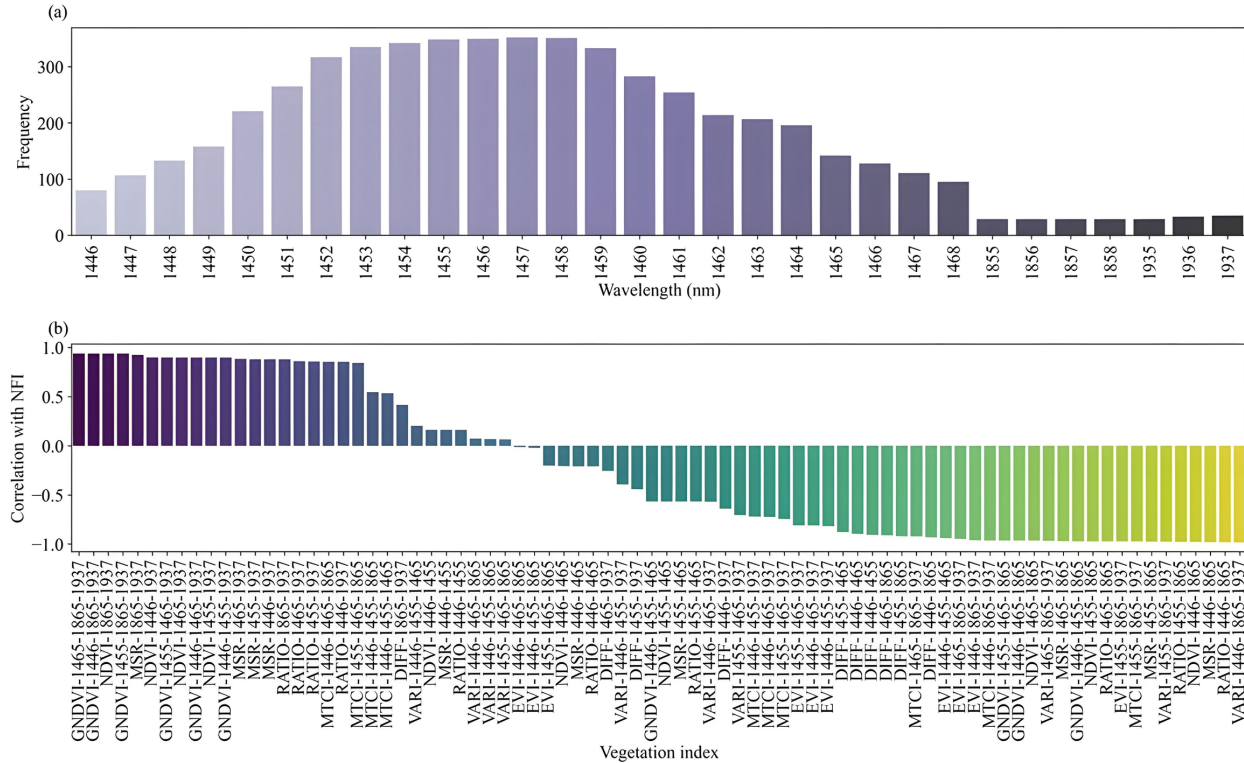


Figure C.3: Summary of informative wavelengths and most relevant VIs: a) showcases the histogram of the most used bands, and b) showcases the best VIs according to the correlation coefficient (source [160]).

To test the SPA and CARS algorithm, both methodologies were applied to detect the best bands for the prediction of LWC, SPAD and nitrogen. The direct comparison to NFI is avoided with the purpose of not inserting biases in the later prediction of NFI. The selected wavelengths from both algorithms are shown in Fig.C.4. The majority of selected wavelengths were situated prominently around the NIR and SWIR regions, especially around 970, 1450, and 1930 nm. These wavelengths corresponded precisely to known absorption peaks of water molecules, reflecting O-H stretching and bending vibrations [2].

C.3.3 Prediction of NFI

The prediction results are shown in Table C.1. In this table first the results, from each individual dataset, full-wavelengths VIs indices, SPA and CARS selected indices. In this table the metrics shown are the correlation coefficient (R^2), root mean squared error (RMSE) and mean average error (MAE), the results are shown for the training (Tr) dataset and the validation dataset.

The results of testing the algorithm fusion model are shown in Table C.2, in this case all the features were stacked and not a single dataset compared to the results shown in Table C.1. This new table showcases that the prediction results, using the three strategies of combining the all the regressor produce better results in the validation dataset. Particularly the stacking approach, produces the better prediction for the NFI prediction according to the R_V^2 . However, the performance of all the tested approaches, with all the tested indices, indicates that improvement is minimal, since the performance for the NFI prediction achieve R^2 above 0.9 in all the cases. This study confirms, that for the prediction of vegetation features and health status, the use of spectral information in the NIR and SWIR region produces the better results.

Finally the comparison between the predicted and real NFI values are showcased in Fig.C.5, and Fig.C.6. This

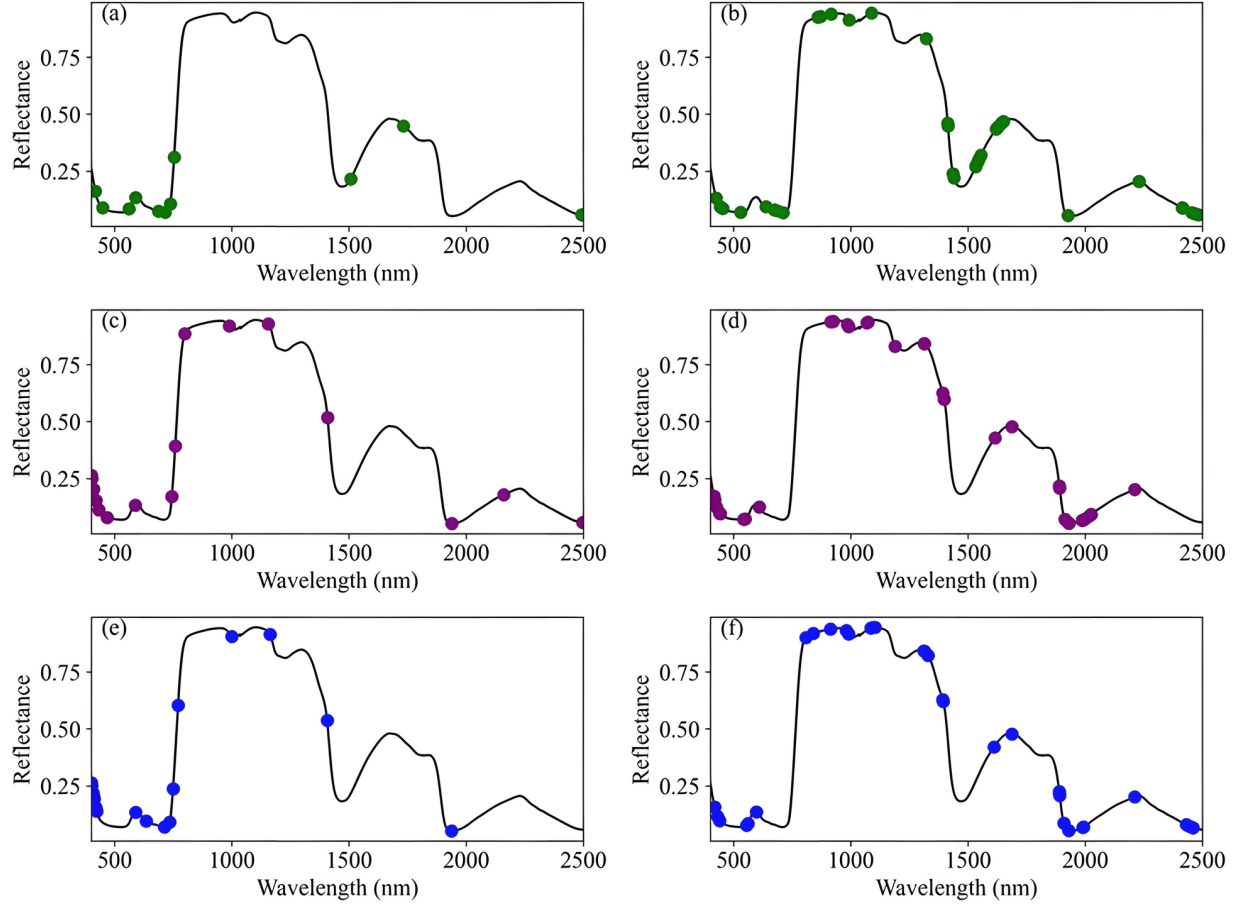


Figure C.4: Wavelengths selected by SPA and CARS for the prediction of different vegetation traits: a) SPA for LWC, b) CARS for LWC, c) SPA for SPAD, d) CARS for SPAD, e) SPA for nitrogen, and e) CARS for nitrogen (source [160]).

Table C.1: Model performance based on FW and feature wavelengths selected for NFI.

Dataset	Model	R^2_{Tr}	$RMS E_{Tr}$	MAE_{Tr}	R^2_V	$RMS E_V$	MAE_V
FW	PLSR	0.974	0.038	0.027	0.979	0.039	0.028
FW	PCR	0.968	0.042	0.030	0.978	0.040	0.028
FW	SVMR	0.943	0.057	0.045	0.949	0.060	0.048
FW	XGBoost	0.999	0.006	0.001	0.975	0.043	0.033
FW	RF	0.993	0.020	0.014	0.979	0.039	0.029
FW	MLP	0.907	0.073	0.055	0.926	0.072	0.056
SPA	PLSR	0.968	0.043	0.031	0.974	0.043	0.031
SPA	PCR	0.965	0.045	0.032	0.974	0.043	0.031
SPA	SVMR	0.945	0.056	0.044	0.954	0.057	0.044
SPA	XGBoost	0.999	0.006	0.001	0.977	0.040	0.032
SPA	RF	0.993	0.019	0.014	0.978	0.040	0.030
SPA	MLP	0.930	0.063	0.048	0.944	0.063	0.048
CARS	PLSR	0.974	0.039	0.028	0.979	0.039	0.028
CARS	PCR	0.968	0.043	0.031	0.978	0.040	0.028
CARS	SVMR	0.942	0.057	0.045	0.947	0.061	0.049
CARS	XGBoost	0.999	0.006	0.001	0.975	0.042	0.032
CARS	RF	0.993	0.020	0.014	0.976	0.041	0.030
CARS	MLP	0.931	0.063	0.047	0.940	0.065	0.050

Table C.2: Model performance based on algorithm level data fusion for NFI.

Model	R^2_{Tr}	$RMS E_{Tr}$	MAE_{Tr}	R^2_V	$RMS E_V$	MAE_V
PLSR	0.974	0.038	0.027	0.985	0.033	0.025
PCR	0.970	0.042	0.029	0.981	0.037	0.027
SVMR	0.933	0.062	0.049	0.943	0.063	0.050
XGBoost	0.999	0.007	0.001	0.980	0.037	0.028
RF	0.994	0.019	0.012	0.981	0.037	0.027
MLP	0.926	0.065	0.047	0.942	0.064	0.046
Stacking	0.984	0.031	0.021	0.986	0.032	0.023
Voting	0.976	0.037	0.026	0.979	0.038	0.028
Bagging	0.986	0.028	0.019	0.981	0.036	0.027

figure also showcases the prediction capabilities for all the models in the NFI prediction.

C.4 Contribution

The results of these experiments are published in the Computation journal, which can be found in the next reference:

Z. Guo, **J. S. Estrada**, X. Guo, R. R. Shamshiri, M. Pereyra, and F. Auat Cheein, “Integrative Nutritional Assessment of Avocado Leaves Using Entropy-Weighted Spectral Indices and Fusion Learning,” *Computation*, vol. 14, no. 2, p. 33, Feb. 2026, doi: 10.3390/computation14020033.

C.5 Conclusion

This study showcases an innovative index NFI, to evaluate the health of vegetation. This index encompasses three vigor parameters: LWC, SPAD and nitrogen content. Due to the nature of the dataset, NFI is heavily influenced by LWC.

Various wavelength selection algorithms were tested, with the objective of constructing various indices related to NFI. Furthermore, SPARS and CARS was applied to eliminate redundant and uninformative wavelengths.

To test the predicting capabilities of the constructed indices, in conjunction with the wavelengths from SPA and CARS, 6 regression algorithms were tested, namely. PLSR, PCR, SVR, RF, MLP, and XGBoost. Furthermore, three algorithm combination strategies were tested: stacking, voting and bagging. All the tested algorithms, achieved high R^2 values on the validation dataset, with values above 0.9. However, the best performing algorithm is the stacking with an R^2 of 0.986.

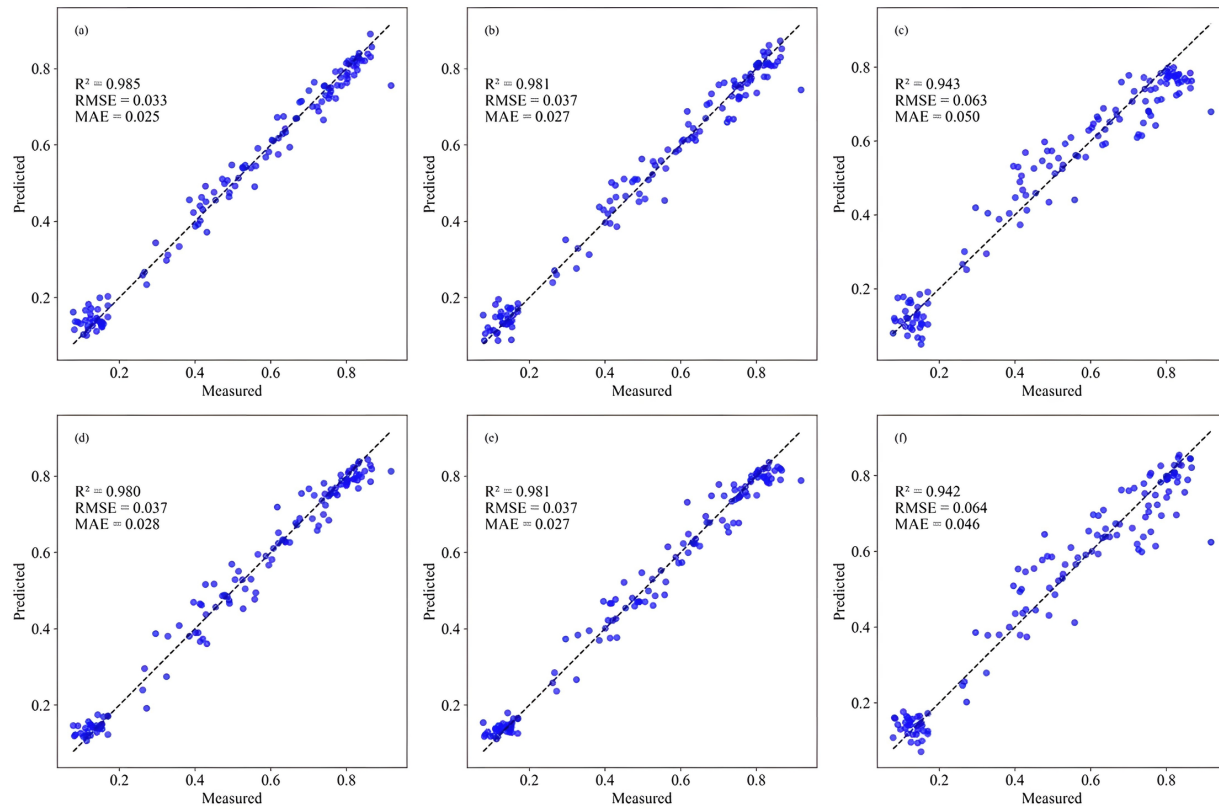


Figure C.5: Regression results for the NFI and the different algorithms: a) PLSR, b) PCR, c) SVR, d) XGBoost, e) RF, and f) MLP (source [160]).

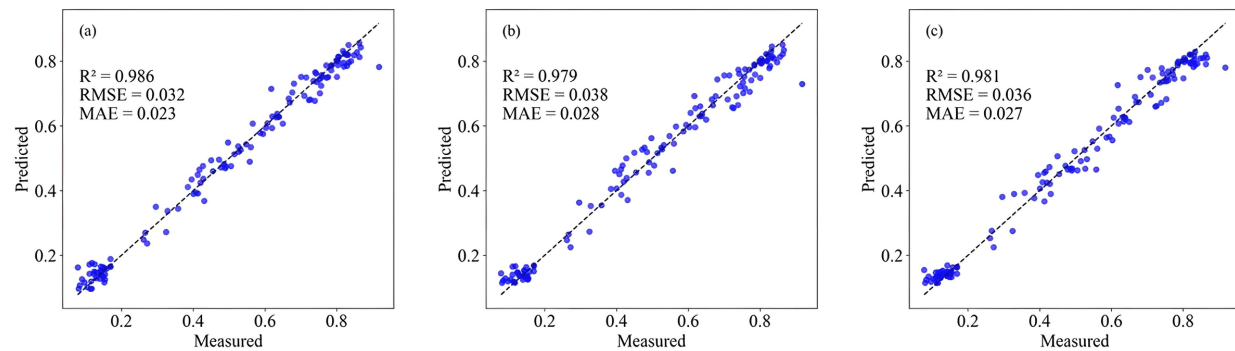


Figure C.6: Regression results for the fusion of algorithms: a) stacking, b) voting and c) bagging (source [160]).