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RemSAGRO – Remote Sensing for Agriculture

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Master in, Telecommunications and Computer Engineering

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Co-Supervisor:
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TECNOLOGIAS
E ARQUITETURA

Department of Information Science and Technology

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Resumo

No campo da viticultura de precisão é crucial otimizar a produtividade e a sustentabilidade da vinha, especificamente à medida que as alterações climáticas representam ameaças crescentes à saúde das plantas. Este trabalho explora o desenvolvimento de um sistema de Internet das Coisas (IoT) para a avaliação e mitigação do stress térmico em plantas - com foco em vinhas, e complementado com frutos de árvores (nêspera) -, um fator de stress abiótico que pode afetar negativamente o crescimento e a produtividade.

O sistema proposto combina tecnologias de sensoriamento local e de sensoriamento remoto, que incluem a utilização de imagens de termografia, para recolher dados em tempo real sobre parâmetros como a humidade relativa do ar, a humidade do solo, a temperatura do ar/folha/solo e a luminosidade. Através da integração de diferentes canais de deteção, o estudo estabelece correlações entre os parâmetros monitorizados, permitindo uma avaliação mais abrangente do estado de saúde da vinha, no que diz respeito ao stress térmico.

Esta mistura de diferentes abordagens facilita a recolha de dados em tempo real, produzindo uma riqueza de informações vitais para o bem-estar da vinha. O sistema IoT discutido também inclui uma aplicação móvel para a monitorização dos parâmetros das culturas, permitindo que os viticultores tomem decisões informadas com o objetivo de prevenir e atenuar os desafios generalizados colocados pelo stress térmico.

Palavras-Chave: Viticultura de Precisão, Internet das Coisas, Stress Térmico, Sensoriamento Local, Sensoriamento Remoto, Termografia.

Abstract

The field of Precision Viticulture is crucial for optimizing vineyard productivity and sustainability, specifically as climate change poses increase threats to plant health. This work explores the development of an Internet of Things (IoT) system for the evaluation and mitigation of thermal stress in plants – focusing on vineyards, and complemented with tree fruits (loquat) –, an abiotic stress factor that can adversely affect growth and productivity.

The proposed system combines in-situ sensing and remote sensing technologies, which include the use of thermography imagery, to collect real-time data on parameters such as air relative humidity, soil moisture, air/leaf/soil temperature, and luminosity. Through the integration of different sensing channels, the study establishes correlations between the monitored parameters, enabling a more comprehensive assessment of vineyard health status with respect to thermal stress.

This mixture of different approaches facilitates real-time data collection, yielding a wealth of information vital to the vineyard's well-being. The IoT system discussed also includes a mobile application for the monitoring of the crops parameters, empowering viticulturists to make informed decisions aimed at preventing and easing the pervasive challenges posed by thermal stress.

Keywords: Precision Viticulture, Internet of Things (IoT), Thermal Stress, In-Situ Sensing, Remote Sensing, Thermography.

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List of Abbreviations and Acronyms

ACID – Atomicity, Consistency, Isolation, Durability

ADC – Analog-Digital Converter

ANN – Artificial Neural Network

ARH – Air Relative Humidity

AT – Air Temperature

CNN – Convolutional Neural Network

DB – Database

DSRM – Design Science Research Methodology

EM – Electromagnetic

GLD – Grapevine Leafroll Disease

GLRaV – Grapevine Leafroll-associated Viruses

GPS – Global Positioning System

GUI – Graphical User Interface

HF – High Frequency

HTTP – Hypertext Transfer Protocol

I2C – Inter-Integrated Circuit

IDE – Integrated Development Environment

IR – Infrared

IoT – Internet of Things

LCD – Liquid Crystal Display

LF – Low Frequency

LT – Leaf Temperature

LUX – Luminosity

ML – Machine Learning

NFC – Near Field Communication

NIR – Near Infrared

ORM – Object-Relational Mapping

OS – Operating System

PA – Precision Agriculture

PRISMA – Preferred Reporting Items for Systematic Reviews and Meta-Analysis

RFID – Radio-Frequency Identification

RTOS – Real-Time Operating System

SAS – Sensor Applications Symposium

SM – Soil Moisture

SQL – Structured Query Language

ST – Soil Temperature

TDR – Time Domain Reflectometry

TIR – Thermal Infrared

UAV – Unmanned Aeria Vehicle

UGV – Unmanned Ground Vehicle

UHF – Ultra High Frequency

URL – Uniform Resource Locator

USB – Universal Serial Bus

UX – User Experience

CHAPTER 1
Introduction

The integration of IoT in smart agriculture has marked a new era for precision farming, offering advanced techniques such as smart irrigation and automated equipment management. This innovation relies on sensors and data-gathering tools to collect crucial information about soil characteristics, plant health, and microclimate conditions. Subsequently, this data is meticulously processed and analyzed, facilitating targeted interventions like precise fertilizer application, pesticide use, and irrigation, all tailored to the unique requirements of individual field areas.

This increase in using remote sensing technologies over the past two decades, particularly when combined with proximal sensing, has proven to be highly efficient, benefiting precision agriculture immensely. Operating within an IoT framework, farmers access invaluable data – regarding plant's health –, empowering them to make well-informed decisions and enhance their agricultural practices.

The push for these agricultural advancements arises from the pressing need to strengthen food production and confront the challenges posed by climate change. By harnessing the potential of IoT technologies, smart agriculture systems have the capacity to revolutionize farming practices, ultimately resulting in increased crop yields, minimizing environmental impact, and overall enhancements to the agricultural industry.

This transformative approach extends beyond traditional agriculture into specialized fields like viticulture, where it aims to optimize efficiency and productivity through the adoption of innovative, sustainable, and automated technologies. One notable example is the evaluation of vineyards' responses to biotic and abiotic stress, monitored through various plant health parameters such as air, leaf, and soil temperature, soil moisture, relative air humidity, leaf color, and luminosity.

Plant growth is significantly influenced by several abiotic environmental factors, including light intensity and duration, water availability, soil nutrient content, temperature, and the presence of toxins like heavy metals and salinity. When these factors deviate from their normal ranges, plants may experience adverse biochemical and physiological effects.

To address this issue, this research work explores the effectiveness of combined technologies — In-Situ and Remote Sensing — in assessing thermal stress in vineyards. This research involves the acquisition of measurements in proximal mode using a set of smart sensors, divided into two separate sensor nodes, one fixed to the soil surface and another mobile node for assessing leaf conditions, offering a versatile approach. Furthermore, a portable thermographic imager is employed to conduct a comprehensive analysis of the vineyard's conditions, enhancing the robustness of the IoT system.

Several tests were conducted to evaluate vineyards' thermal stress with remote sensing technologies. The sensory measurements encompass two different vines within the same vineyard to introduce redundancy and are conducted at three distinct time periods throughout the day: morning, afternoon, and night. This comprehensive approach aims to establish correlations between the vine's health status and the surrounding environmental conditions, ultimately providing critical insights into thermal stress. It was also studied the evolution of thermal stress within different crop seasons. This invaluable information can be utilized to implement intelligent irrigation mechanisms designed to prevent and mitigate such constraints effectively. The implementation of a mobile application to easily integrate the visuals of the crop monitoring system is also a functionality of this project.

In this current chapter, the structure will be as follows. First, a brief contextualization will be made by providing some background, as well as motivation, to introduce this thesis subject. Second, a few research questions will be formulated to expose key aspects. Next, an objectives sub-section will address the research questions that were previously stated. Additionally, the method used in the investigation process will be exposed. Finally, the structure for this thesis will be uncovered.

1.1 Background and Motivation

According to a United Nations report from 2022, the current world population of 7,6 billion is estimated to reach 8,6 billion by 2030 and 9,8 billion by 2050 [1]. Overall, this upward trend in population size is expected to continue, thus highlighting the problems related to agricultural needs and demands. Furthermore, agriculture is highly dependent on the climate, being one of the sectors most affected by climate change, impacting agricultural productivity. Some examples of these effects are the increased temperatures, the changes in precipitation patterns and the lack of water availability [2]. Agriculture, the primary food source, holds a significant position in the worldwide economy. Therefore, it seeks an upgrade in its practices while exploring emerging technologies such as the Internet of Things and Big Data [3].

The bridge that connects agriculture and innovative technologies is nominated Precision Agriculture (PA), because it refers to the use of technology and data analysis to optimize crop production and management practices. It involves the collection and analysis of data related to soil conditions, weather patterns, and crop growth, and uses this information to make informed decisions about important actions like planting, fertilizing, watering, and harvesting. The main goals are to improve crop yields and reduce waste, simultaneously increasing efficiency, productivity, and sustainability [4].

Directly related to smart farming, the use of remote sensing technology has become an essential part of the new era of agriculture, providing all types of data about crops and the environment from a distance, typically using aerial or satellite imagery. In fact, the development of Unmanned Aerial Vehicles (UAV)-based remote sensing systems to monitor crops offers great possibilities to acquire field data in an easy, fast, and cost-effective way compared to previous methods [5]. However, due to its cost and harder access on a small-scale level project, the use of a camera with thermal imaging can be as helpful, since it provides a better understanding regarding temperature variations in more depth helping to select specific targeted areas.

In the context of thermography imaging, also known as thermal imaging or infrared imaging, this technique involves capturing the infrared radiation emitted by objects to create images that represent temperature fluctuations. Single-camera thermography imaging is highly effective for various applications, such as building and material inspections, monitor crop health, and medical diagnostics. It provides a straightforward and cost-effective way to capture thermal data, though it may have limitations in terms of depth perception or spatial information compared to multi-camera setups [6].

After being collected, this sensing data – like thermographic imaging – can be processed and analysed accordingly with the Machine Learning (ML) algorithms that best suits the application – such as random forest for crop yield prediction or reinforcement learning to optimize irrigation, for example –, allowing for proactive and targeted management strategies. ML techniques play a crucial role in developing smart agriculture solutions, providing the data analysis and decision-making capabilities needed to improve the agricultural field [7].

1.2 Research Questions

The following questions expose the key aspects which guide the analysis in this study:

- How can the use of thermal images improve the assessment of agricultural parameters?
- What communication protocols suits best in the smart farming systems?
- Which combination of sensors is the best in terms of cost-efficiency to enhance precision agriculture?
- How thermal images can be calibrated to assess thermal stress?
- Why is it valuable to use both remote and “in-situ” measurements?
- What are the most important soil characteristics to consider for smart farming applications?
- How does a group of diverse parameters impact the accuracy of "in-situ" measurements?
- What is the most suitable platform for farmers to view the data collected from the monitoring sessions?

1.3 Objectives

The main objective of this dissertation is to design and implement a system for plants health status evaluation and to determine thermal stress conditions while simultaneously seeking to mitigate this detrimental condition. These were supported using thermographic imagery provided via camera integrated with different types of air and soil sensors. This long-term goal was structured into two central tasks – medium-term goals.

First, the development of a framework that includes two measurement components: an "in-situ" measurement (hardware/sensors based) and a remote measurement (thermography/camera based). This two will be used to singularly obtain information about the field and to do correlations about their data, promoting a robust study of the culture state which includes the levels of thermal stress.

Second, the use of a software module – FLIR Tools and MATLAB – which will analyze the sensors data and the images provided by the infrared camera in remote monitoring, as well as the creation, and manipulation, of a remote database which will store the corresponding images. Associated with the software module, another important objective is the design and implementation of a mobile application for monitoring these parameters and classifying the culture's state. Moreover, it can be used to create a detailed map of fields which identifies areas that may require different management practices, such as more or less irrigation.

Concisely, some applications this thesis study aims to accomplish are:

- Culture Monitoring – "in-situ" and remotely.
- Thermal Stress Evaluation.
- Smart Irrigation Triggering.

Summarizing, the main objective is to establish correlations between the vine's health status and the air conditions in the surrounding environment, thus gaining a better understanding of thermal stress conditions. This valuable information can be visualized in a proper mobile application and then utilized to implement intelligent irrigation mechanisms aimed at preventing such constraints.

1.4 Research Method

The Design Science Research Methodology (DSRM) is a systematic approach to solving complex design problems, specifically within the field of engineering. The goal of DSRM is to create a new artefact, such as a software tool or a hardware prototype, that improves a specific situation. It can also be used to evaluate existing artefacts and identify areas for improvement [8].

The characteristics of this method – circular approach – were the reasons why it was chosen to guide this research flow. Its diagram is represented in Figure 1.1, and it was adapted to this thesis nature.

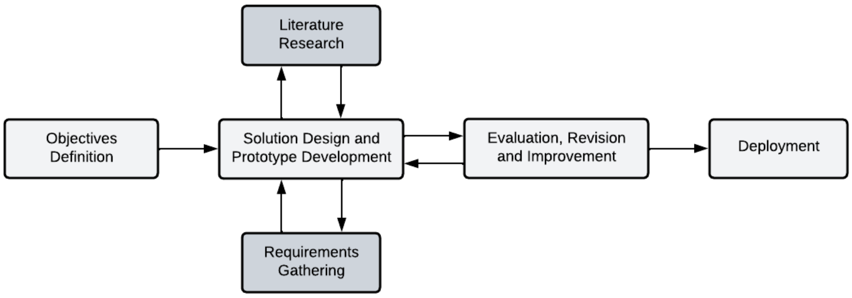

Figure 1.1 - Design Science Research Methodology

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Following the logical structure of the chosen research method, this work begins with the implementation of a problem-centred approach, as the issue to be addressed has already been identified and defined. This initial phase is reflected in the objectives section included in this dissertation report and its purpose is to define the objectives that are to be achieved with the application of the system underdeveloped.

The second stage is characterized by the design of the solution and respective prototype development. Initially through the gathering of requirements – analysing data about the problem – and defining the ideal hardware (sensors and microcontrollers) and software (FLIR Tools and MATLAB) to be used according to the constraints. After this, it's created the design that helps with the conception of the prototype to solve the problem in study. Besides that, the literature research is also helpful to give knowledge and insight into the existing solutions to similar artefacts, which can be applied to the current work, as will be shown in the next chapter of this dissertation report.

After the development and implementation of the requested prototype, it's conducted an evaluation of the model – through tests which involve feedback from manual measurements and consulting data variations over time – and subsequent revision, in the interest of finding errors to be fixed or other types of improvements to be made, as necessary. This step is bidirectional, meaning the workflow can go backwards if the evaluation is not satisfactory.

The final stage reflects the case in which the system developed is entirely functional, free of errors and accordingly to all the objectives proposed, meaning that has a positive evaluation. Hence, the artefact is ready to be implemented and deployed in a real-world setting.

1.5 Thesis Structure

The project structure consists of six chapters, which are the following.

- 1st chapter (Introduction) – introduces the investigation theme, complemented by a theoretical background and factual motivations. It presents the objectives proposed to achieve, lists the research questions which will help formulate the workflow of the research, and gives a brief description of the overall thesis structure.

- 2nd chapter (Literature Review) – discusses the literature review, which includes a systematic review – to improve the searching performance – and the related work – composed by all the topics relevant for this thesis use cases.
- 3rd chapter (System Description) – describes the IoT system in terms of its architecture, presents its functionalities, networks, and components, focusing on the sensors (hardware), the thermographic imaging, the data analysis flow, and the mobile application architecture.
- 4th chapter (Mobile Application) – visualizes the mobile application and explains its purpose, as well as its underlying structure and design, and presents the features created for the system user (farmers/viticulturists), as well as the actions they can perform.
- 5th chapter (Experimental Results and Discussion) – presents the experimental results and discusses the outputs regarding the variable/problem in study. It also illustrates the field conditions and explains sensors calibration.
- 6th chapter (Conclusion and Future Work) – concludes the investigation process giving a retrospective and discusses the future work to be developed.

Finally, in the appendix, is available the scientific paper written for the IEEE Sensor Applications Symposium 2023 international conference.

CHAPTER 2
Literature Review

The gathering of work related to the field of research addressed in this report's it's crucial to gain knowledge about the object in the study, relating different concepts and analysing the different approaches taken within a similar problem. Therefore, the literature review should be done carefully, using specific keywords to find the most suited scientific articles or conference papers accordingly to the referred subject. In this case, the most relevant keywords used were: "Thermographic Imagery", "Remote Sensing", "In-situ Sensing", "Precision Agriculture", "Thermal Stress" and "Machine Learning Models". Furthermore, having it into account, a bubble map was created to organize the main ideas and divide them into sub-categories, giving some depth and consistency to the conducted research.

This map is represented in Figure 2.1 and illustrates how the various topics intercorrelate among themselves. It starts with the main theme of this dissertation – Precision Agriculture – being in the centre, which will give a series of descendent topics important to develop a system based on implementing a PA solution. Some of them include Measurements – which help define the direction of our study –, Hardware – the tools and materials needed for the starting point –, Soil Features – knowledge about how these parameters affect PA –, Machine Learning – robustness for analysing data related to it –, and Applications – the cases of use that will work as the objectives to aim.

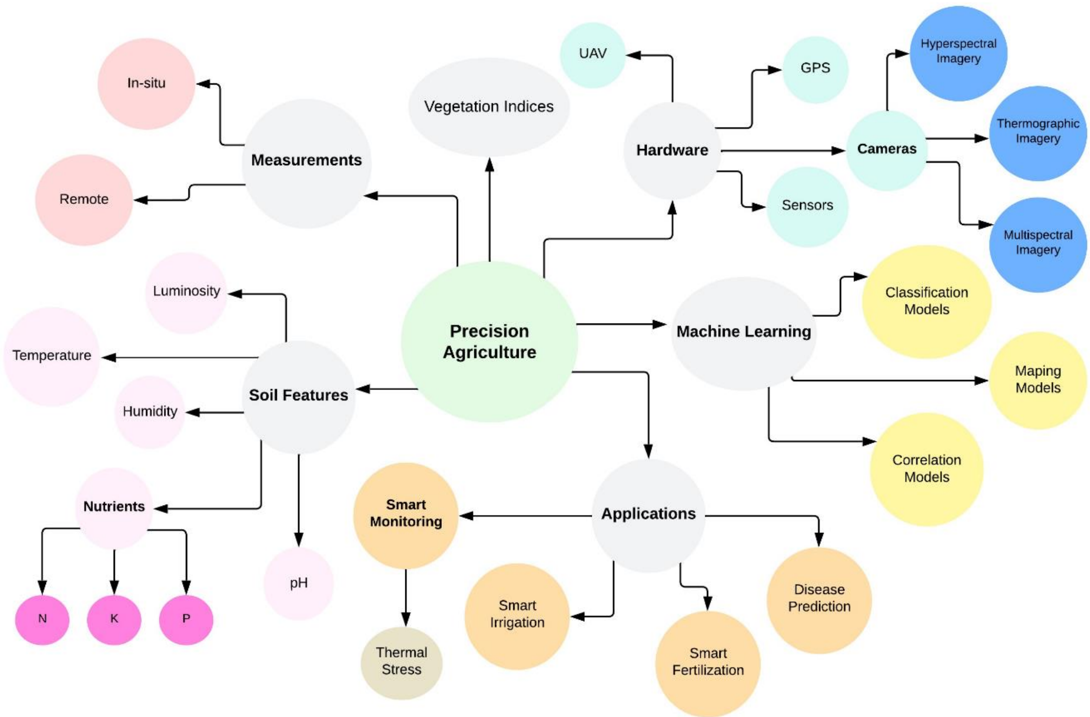

Figure 2.1 - Bubble Map with Summarized Literature Main Ideas

2.1 Systematic Review

A systematic review is a research study that involves collecting and analysing data from multiple existing studies to provide a comprehensive overview of a particular topic. With the areas of interest and principal keywords established, this research was conducted mainly in articles databases like Google Scholar, IEEE Xplore, Elsevier and MDPI.

In addition to searching these databases, a filter was also employed to pinpoint the most pertinent works between the vast array of results obtained. This filter included the following attributes.

- All types of papers related to the field of research (conferences publications, scientific reports, among others).
- Written in Portuguese and English.
- From any year, but preference for the most recent ones (2014-2023);
- Free or within ISCTE's scientific license.

After the definition of the preferred features, a methodology like PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) was used as a reference to reduce the acquired outputs. PRISMA focuses on key aspects of a systematic review, such as the search strategy, eligibility criteria, data extraction, and quality assessment of studies, to ensure that all relevant information is reported clearly and consistently [9].

The initial search resulted in 2433 related works, so after applying the already described features to filter them, 872 pieces of literature remained. Following the process, a redundancy check was made, resulting in a total of 425 documents. The abstracts of these were then analysed, leading to the selection of 186 papers. Finally, 95 articles were thoroughly analysed, where 36 were utilized in this study. This total number of documents associated with its corresponding stage is condensed in Table 2.1.

Table 2.1 - Systematic Review Statistics

Stage	Total
Initial Search (Filtered)	872
Redundancy Check	425
After Abstract Analysis	186
Literature Review	95
Citations	36

2.2 Related Work

The current section aims to cross information between the extensive concepts and models of study, allowing a better understanding of this paper's subject and, at the same time, developing critical thinking, leading to hopefully more optimised solutions. The related works that will be presented next are a reflection and serve as inspiration for the discussion of essential key concepts and methodologies in the ongoing project. The chosen hardware platform and sensors to collect data and evaluate field conditions, the importance of using both "in-situ" and remote measurements, the types of thermographic cameras and respective imagery – and its characteristics –, the best features to have into account while studying soil and parameters related to the farming field, the machine learning models which adapt better to each application and the agricultural applications themselves, and respective constraints to be solved, are some of the ideas that will be addressed in the writing of the following sub-sections.

2.2.1 Smart Monitoring in Precision Agriculture

Smart monitoring is a key component of precision agriculture, allowing for real-time monitoring and analysis of crops and the environment. This is achieved using various sensors, hardware platforms, and other technologies, such as remote sensing, GPS mapping, and wireless networks, as will be discussed in these next subsections.

Numerous approaches can be followed to collect, process and extract data from these same devices, as well as different applications. Of the various approaches available, the following are particularly noteworthy.

2.2.1.1 Smart Fertilization and Irrigation

To begin, there are automatic and non-destructive crop monitoring systems that uses sensor data – which has integrated multispectral cameras – related to smart fertilization or/and irrigation applications. Carried out by M. C. F. Lima et al. [10], its main objective was to supervise the status of organic fertilization on tomato plants at early stages, to carry out a more responsible usage of the fertilisation chemicals, which helps reduce pollution. Their study was conducted on the correlation between vegetation indices and the data collected from the multispectral imagery, to determine the soil nutrient status.

Similarly, M. Noguera et al. [11] aimed to develop an efficient method of the nutritional soil status assessment of olive crops. This consisted of evaluating the required soil nutrients to find the right fertiliser adjusted to the number of nutrients present. Nutrients like Nitrogen (N), Phosphorus (P) and Potassium (K) are the main ones to consider when referring to soil monitoring. Due to this fact, a variety of studies were conducted with their focus being on one of these chemical parameters and the reactions of the culture to its stress. Z. Allah et al. [12] with the maize phenotyping for low nitrogen and H. Zheng et al [13] with the estimation of nitrogen accumulation in rice, are some examples.

Additionally, M. Romero et al. [14] highlighted the importance of remote sensing technology when compared to only using "in-situ" measurements, projecting a model based on the correlation between multispectral imagery collected via UAV and vegetation indices, to perform smart irrigation accordingly with the water status previously assessed in the field, which helps reduce water waste.

Moreover, P. R. Mwinuka et al. [15] combined the use of multispectral imaging based on UAV and thermal imaging – and respective evaluation of the feasibility of a mobile phone-based thermal imagery collection – with the goal of studying eggplant water status and possible yield prediction, to create an efficient smart irrigation solution, based also in humidity data collected in the leaves of the vegetable at various stages.

2.2.1.2 Disease or Anomaly Detection

Furthermore, to optimize smart monitoring while maintaining an acceptable cost-efficiency ratio in the application of disease and anomaly detection, the following work was developed.

M. Kerkech et al [16] 's objective was to obtain a faster and more precise treatment by mapping all the diseased areas in a vineyard. This method was based on combining the visible and infrared images obtained from two different sensors, which are related to multispectral cameras embedded in a UAV-based platform, as well as on deep learning segmentation approaches. On the other hand, Y. Yang et al [17] also used multispectral imaging combined with a deep learning model, but its goal was to detect multiple types of defects in potato cultures.

2.2.1.3 Parameters Study based on Field Monitoring

Continuing, besides the applications previously enunciated, other types of predictions based on the monitoring of field conditions can be performed, resulting in a complementary study which helps to understand crop performance under various constraints.

For example, crop loss assessment after an event of a hailstorm can be subjective and time-consuming, leading to inaccurate data. Hence, J. Zhou et al [18] evaluated the feasibility of accurate and fast assessment of crop damage due to simulated hailstorms using aerial multispectral imaging. The overall objective of this study was to assess the viability of a UAV-based imagery estimate of potato crop loss, being an alternative to conventional methods.

The culture's growth process is also an important matter to consider when evaluating soil quality and studying crop breeding for genetic screening to achieve its potential yield. Thus, B. P. Banerjee et al [19] developed a method for estimating wheat seedlings' emergence using multispectral images captured from a UAV. Comparably, R. H. Dehkordi et al [20] used a similar methodology – UAV-based multispectral imagery and RGB imaging additionally –, but regarding monitoring of the biochar (century-old) impact on winter wheat crop performance.

Along with it, the heterogeneity which concerns the different tree plantation distances and composition, different crop management (irrigation, pruning, weeding), and different tree attributes is a parameter to consider while monitoring cultures. So, G. Modica et al [21] followed a multiscale object-based approach to extract tree crowns from UAV multispectral imagery. His goal was to monitor vegetation vigour in heterogeneous citrus and olive orchards. Also, a method for processing vineyard image data to extract quantitative information about physical vine attributes, specifically relating to vine vigour is described by A. Hall et al [22].

2.2.2 Soil Sensors and Thermographic Cameras

Soil sensors and thermographic cameras are important tools in precision agriculture, providing valuable data to support informed decision-making and improved crop management practices. Both can be found in “in-situ” and remote measurement applications, however, it’s more common to obtain “in-situ” data from soil sensors – ground level –, while remote data is usually collected from UAV or UGV-based platforms – with cameras and GPSs modules embedded. Using both these measurements is crucial to calibrate data, introducing robustness and effectiveness.

2.2.2.1 Soil Sensors

Soil sensors measure soil properties, such as moisture, temperature, and nutrient content. This information is used to inform decisions about irrigation, and fertilization, among others. Soil sensors can be placed in the ground, providing real-time data that can be analysed to inform decision-making. However, their inability to obtain soil characteristics rapidly and inexpensively on their own remains one significant limitation of precision agriculture [23]. These sensors have been based on electrical, electromagnetic, optical, radiometric, mechanical, acoustic, pneumatic, and electrochemical measurement concepts, as illustrated in Table 2.2.

Table 2.2 - Soil Characteristics [23]

Sensors	Agronomic Soil Properties									
	Soil Texture	Soil Organic Matter	Soil Moisture	Soil Salinity	Soil Compaction	Depth Variability	Soil pH	Residual Nitrate	Other Macronutrients	Cation Exchange Capacity
Electrical and Eletromagnetic	X	X	X	X		X		X		X
Optical and Radiometric	X	X	X				X	X		X
Mechanical Acoustic and Pneumatic	X				X	X				
Electrochemical				X			X	X	X	

This dissertation focus will be on two types of sensors used for "in-situ" measurements of soil characteristics, such as soil moisture sensors – which measure the water content in soil by determining the electrical conductivity or dielectric constant of the soil –, and soil temperature sensors – which measure the temperature of the soil at different depths.

These moisture sensors can be capacitance-based sensors, which measure the change in capacitance as soil moisture changes, or time domain reflectometry (TDR) sensors, which use a pulse of energy to determine the soil moisture content. While temperature sensors can be thermistors, that change resistance with temperature, or thermocouples, that generate a voltage proportional to temperature. Examples of this sensors are illustrated in Figure 2.2

Figure 2.2 - Capacitive Moister Sensor and Thermistor Temperature Sensor (Example)

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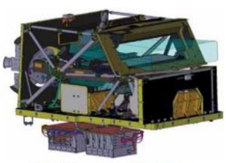
The connections between soil moisture and temperature are complex and depend on soil type, climate, and others. As an example, soil temperature can impact soil moisture by affecting evaporation. Understanding these is important for interpreting soil measurement data and making informed decisions about field management practices.

Other types of sensors which can also be used are soil porosity sensors – which measure the volume of air and water in soil –, soil nutrient sensors – which measure the concentration of nutrients, such as nitrogen, phosphorus, and potassium in soil –, and soil pH sensors – which measure the acidity or alkalinity of soil by determining the hydrogen ion concentration in soil.

2.2.2.2 UAV-based Platforms and Singular Thermographic Cameras

Unmanned aerial vehicle (UAV)-based platforms are used in precision agriculture to collect data about crops and the environment. These aerial vehicles come in various shapes, sizes, and capabilities, each designed for specific applications. Also known as drones, they are small and manoeuvrable, which allows them to fly at low altitudes and collect high-resolution data. This makes them well-suited for collecting detailed information about crops, such as plant height, leaf area, and disease symptoms – as described in [11-16]. UAVs can also be operated on demand, which can be helpful in rapid response to changing conditions. Contrarily satellites, besides offering the advantage of large-scale coverage and long-term monitoring, are being progressively less used compared to UAVs due to the necessity of having high-resolution data faster and easily. In Table 2.3 it's represented the platforms used in A. Khaliq et al [24] study regarding the comparison between Satellite and UAV-based imagery – for vineyard variability assessment.

Table 2.3 - Comparison between Satellite and UAV Platforms [24]

Platform	Satellite Sentinel-2		UAV 8-rotors custom UAV	
Sensors	 Multispectral Imager		 Parrot sequoia Multispectral camera	
Number of Channels	13		4	
Spectral Band Details	Band Name	Range	Band Name	Range
	B4-Red	650-680 nm	B2-Red	640-680 nm
	B8-NIR	785-900 nm	B4-NIR	770-810 nm
GSD per Band	B4, B8 = 10 m		5 cm	
Flight Altitude	786 km		35 m	
Field of View	290 km		70.6° HFOV	
Image Ground Dimension	100 km × 100 km		64 m × 48 m	
Number of Images to Cover Vineyard Test Site	1		> 1000	

The following Table 2.4 illustrates some differences between UAV and other manned airborne and satellite platforms in terms of range, usability, payload, cost, etc – research by S. Candiago et al [25].

Table 2.4 - Comparison between Precision Agriculture Platforms

	Spatial Resolution	Field of View	Usability	Payload Mass	Cost for Data Acquisition
UAV	0.5-10 cm	50-500 m	very good/easy	can be limited	very low
Helicopter	5-50 cm	0.2-2 km	pilot mandatory	almost unlimited	medium
Airbone	0.1-2 m	0.5-5 km	pilot mandatory	unlimited	high
Satellite	1-25 m	10-50 km			very high (high-res stereo imagery)

Every object emits infrared energy, often referred to as its heat signature. An infrared camera, or thermal imager, serves the purpose of detecting and quantifying this emitted infrared energy. It then processes this infrared data and transforms it into an electronic image, visually representing the surface temperature of the object being examined.

The camera's internal processor takes signals from each pixel and applies mathematical calculations to generate a color-coded map, displaying the estimated temperature of the object. A certain color range is assigned to represent various temperature values, creating a color-coded matrix. This matrix of colors is then stored in memory and presented visually on the camera's screen, producing a thermal image that displays the temperature distribution across an object.

In addition, many infrared cameras are equipped with a second camera that captures a standard digital image automatically each time the camera is used. This dual-capture system facilitates the correlation of potential issues in the thermal image with the actual object or area being inspected. An example of a thermal camera is displayed below in Figure 2.3 [26].

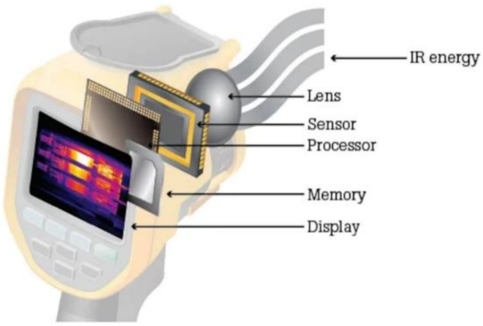


Figure 2.3 - Thermal Camera Internal Architecture

2.2.3 Multispectral and Thermal Imagery

Agricultural UAVs are specifically designed for precision agriculture and equipped with sensors and cameras that can be used to collect data about crops and the environment. This platform's most common embedded cameras can be of various kinds, such as multispectral, hyperspectral, RGB, and thermographic [27].

Multispectral imagery refers to the collection of images of the same scene or object using multiple wavelength bands, typically in the visible and near-infrared regions of the electromagnetic spectrum but can also include ultraviolet or other frequencies within the scale. These can be divided through filters allowing mapping patterns. Similarly, hyperspectral imagery is a particular case of spectral imaging, with hundreds of contiguous spectral bands being available, contrarily to multispectral which only has up to 25 accessible bands, which are discretely positioned from each other [28]. Also, RGB uses 3 channels, belonging to the visible light imaging group. Figure 2.4 shows an example of a multispectral image – containing leaves – in comparison with a regular one.

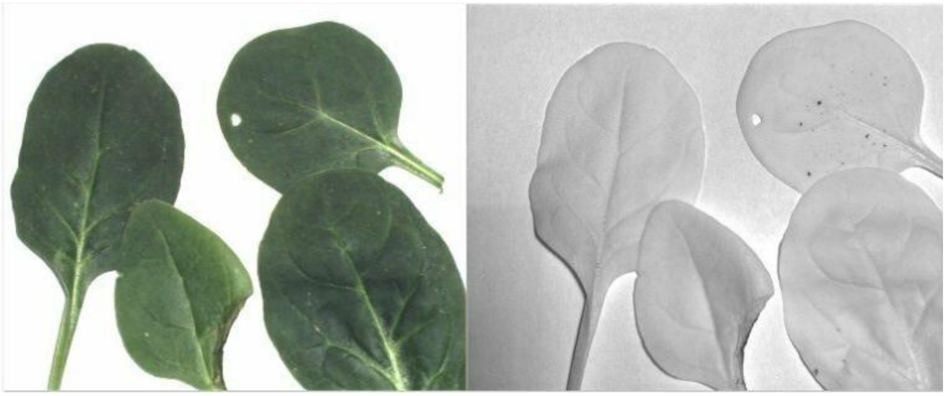


Figure 2.4 - Multispectral Imagery (Leaves Example) [28]

Thermal imagery is a representation of emitted radiation in the thermal infrared (TIR) range of the electromagnetic spectrum, which is translated into temperature data. The infrared region of the spectrum, ranging from 0.7 to 100 micrometres, is divided into two categories: reflected IR (0.7-3.0 micrometres) and TIR (3.0-100 micrometres). TIR radiation, which falls within the 3.0-14 micrometre range of the EM spectrum, is emitted by elements within a farming field such as vegetation, soil, water, and people [29]. An example of its use is illustrated in Figure 2.5.

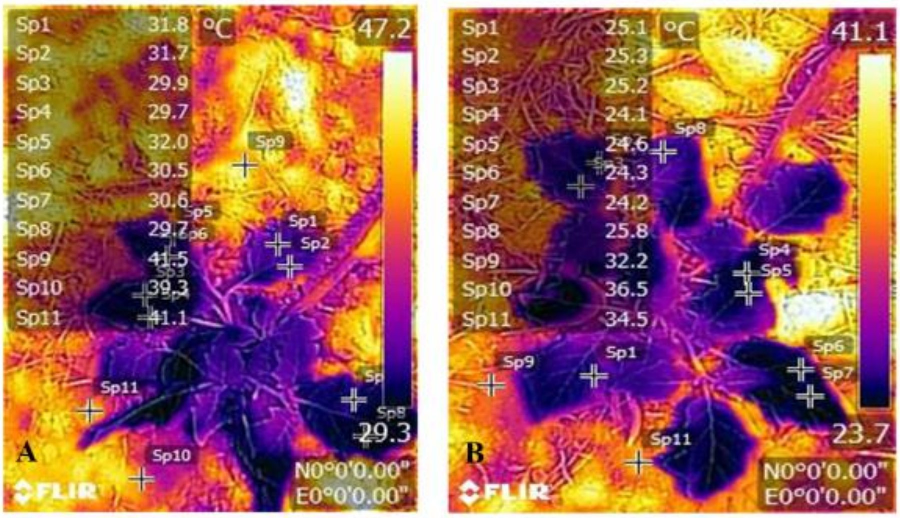


Figure 2.5 - Thermal Imagery (Leaves Example) [15]

The mentioned imagery techniques and their applications are represented below in Figure 2.6 – research by Wouter H. Maes et al [30].

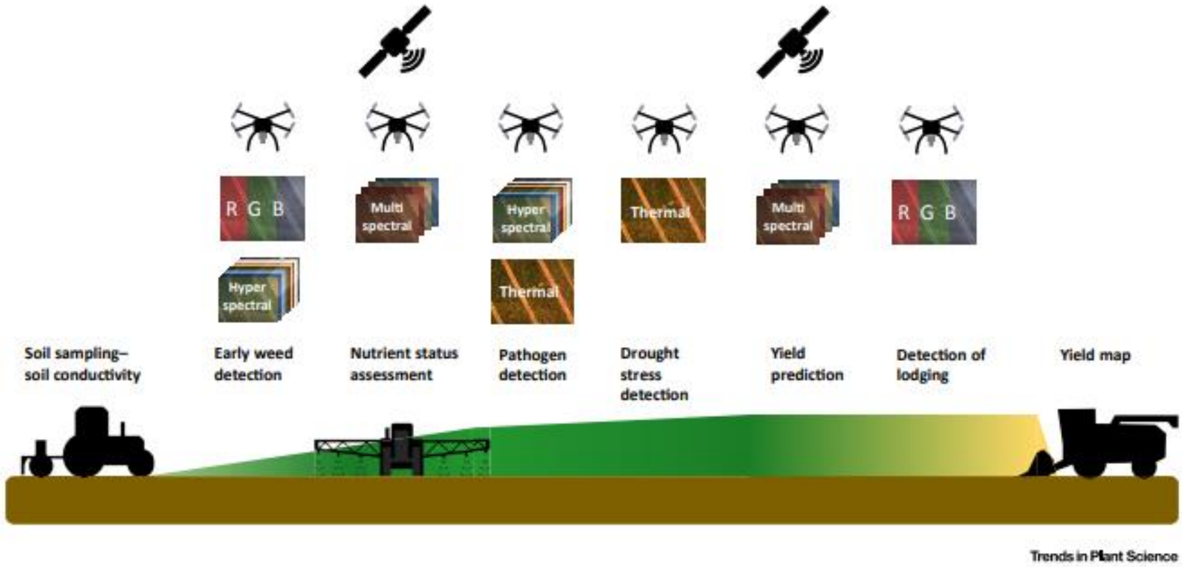


Figure 2.6 - Imagery Techniques and their Applications [30]

By analysing the figure, it's notable that the author organized the applications for precision agriculture according to its most efficient remote sensing technologies. For example, to assess early weed detection or detect lodging, the use of UAVs with RGB cameras are better, since allow to determine patterns in the soil, and crops, at a low level. However, for the cases where it's not straightforward to conclude the crop state, the use of hyper-spectral imaging allows a better understanding of the conditions of the field. Additionally, multispectral imagery enhances the nutrient status assessment and yield prediction, due to its multiple wavelength bands characteristics, while thermal imaging it's common encountered in case studies where the aim is to assess stress detection, like drought stress or thermal stress.

2.2.4 Machine Learning Models in Precision Agriculture

Precision agriculture relies heavily on machine learning techniques to increase efficiency and yield in crop production while enabling data-driven decisions. Some common applications of machine learning in precision agriculture include:

- Precision Irrigation – optimize irrigation systems by predicting soil moisture levels and crop water requirements [14-15, 27].
- Precision Fertilization – optimize fertilization based on soil nutrient levels and plant requirements [10-13, 27].
- Weed and Pest Detection – detect and identify weeds and pests in fields, allowing for targeted control and reducing the need for harmful pesticides [30].

- Crop Stress Detection – detect plant stress by analysing images and data from sensors in the field [16-17, 30].
- Crop Yield Prediction – predict crop yields based on various factors such as weather patterns, soil data, and plant health [23-24, 30].

Machine learning algorithms can be applied to both image data and numeric data. Accordingly with the type of the data, this can use different algorithms based on supervised and unsupervised learning. In supervised learning, the algorithm is trained on labelled data, where input data and corresponding output are provided. The algorithm learns to make predictions or classifications based on this labelled training data. On the other hand, in unsupervised learning, the algorithm is given input data without explicit output labels. Therefore, it seeks to discover patterns or relationships within the data, without prior knowledge of what to expect. Clustering and dimensionality reduction are some of the most common tasks [31].

To perform the previous applications, models should be designed accordingly to their specific tasks, as well as data regarding vegetation indices, "in-situ" measurements and historical data should be stored to be correlated with the data extracted from the soil sensors and remote sensing platforms.

For numerical data, machine learning models include linear regression, logistic regression, decision trees, random forests, and neural networks. These models are used to perform tasks such as regression (predicting a numeric value as soil moisture), classification (predicting a categorical value as detecting heat/water stress), and clustering (grouping similar data points as pest detection).

For image data, computer vision techniques such as convolutional neural networks (CNNs) are commonly used. These models are designed to handle large amounts of image data and can perform tasks such as image classification – detecting crop stress and disease detection –, object detection – anomalies detection –, and semantic segmentation – differentiating between soil, crop, and weed pixels. A. Milioto et al. [32] proposed a tool, which addresses the fragmentation problems - unavailability of more straightforward software - by building a higher abstraction that is specific to the semantic segmentation tasks in the robotic field. As C. Potena et al. [33] presented a system for agriculture robotics with the aim to automatically perform, in real-time, the crop/weed detection and classifications tasks. Using Unmanned Ground-based equipped with a multispectral camera, his approach considered two different CNNS – a lightweight one for segmentation and a deeper one to perform classification – applied to Near Infrared (NIR) images.

Table 2.5 displays some of the most used vegetation indices, that are derived from remote sensing data, typically captured by satellites, drones, or other sensors, and they provide valuable information about the health, growth, and conditions of vegetation. These are explained in greater detail by R. H. Dehkordi et al. [20].

Table 2.5 - Vegetation Indices [20]

Index Name	Index Acronym	Formula
Normalized Difference Vegetation Index	NDVI	$(R_{NIR}-R_{red})/(R_{NIR}+R_{red})$
Weighted Difference Vegetation Index	WDVI	$WDVI = R_{NIR} - a.R_{red}$ $with\ a = \left(\frac{R_{NIR}}{R_{red}}\right)\ of\ the\ soil$
Normalized Difference Red Edge Index	NDRE	$(R_{NIR} - R_{rededge})/(R_{NIR} + R_{rededge})$
Optimized Soil Adjusted Vegetation Index	OSAVI	$1.16 \times (R_{NIR} - R_{red})/(R_{NIR} + R_{red} + 0.16)$
Chlorophyll Vegetation Index	CVI	$(R_{NIR}/R_{green}) \times (R_{red}/R_{green})$
Enhanced Vegetation Index	EVI	$2.5 \times (R_{NIR} - R_{red})/(R_{NIR} + 6 \times R_{red} - 7.5 \times R_{blue} + 1)$
Chlorophyll Index Red	CI-red	$\left(\frac{R_{NIR}}{R_{red}}\right) - 1$
Simplified Canopy Chlorophyll Content Index	s-CCCI	$NDRE/NDVI$

Table 2.6 organizes information about the analysed related works regarding the machine learning models applied.

Table 2.6 - Machine Learning Models and their Applications

Model	Application	Reference
Supervised MLR	Estimating Wheat Seedlings' Emergence	[19]
	Predicting Rice Yield	[23]
	Nutritional Status Assessment	[11]
	Vineyard Water Status Assessment	[14]
ANN	Predicting Rice Yield	[23]
	Nutritional Status Assessment	[11]
	Vineyard Water Status Assessment	[14]
Classification, Segmentation and Object Detection CNNs	Monitoring Plant Status + Smart Fertilization	[10]
	Detection of Multi-type Defects	[17]
	Vineyard Disease Detection	[16]
	Crop and Weed Identification	[33]

2.2.5 Thermal Stress Assessment

Thermal stress assessment is a valuable tool in the domain of plant health and environmental monitoring, offering insights that empower us to adapt and thrive in an ever-changing climate. Therefore, when exploring IoT systems specifically designed for monitoring plant stress through thermal imaging or other remote and in-situ sensing measurements, there are several approaches available for encompassing, processing, and extracting data from these devices.

2.2.5.1 Solely Remote Sensing Technologies

Beginning with thermography as a key component, notable studies by Stoll et al. [34], Jones et al. [35], and Leinonen et al. [36] have employed it to measure leaf temperature for diagnosing and evaluating plant stress. The study in [34] had into consideration the solar exposure factor and made the measurements of leaf characteristics in shaded areas, while the authors in [35] expanded on this by combining thermography with spectral sensing analysis to mitigate errors introduced by multiangular solar radiation and irregular backgrounds. Similarly, the study in [36] used visible imagery for the same purpose. However, these authors acknowledged the limitations associated with relying solely on a single method when working with thermography imagery.

In Figure 2.7 is illustrated how the solar emissivity affect thermal imaging [37]. As it was stated previously, the sunlight – the heat source – affects the measurements of the object in study, introducing errors, due to the irradiation of both the reflected sunlight and the radiated energy from the target to measure. This combination of energetic waves is detected simultaneously by the thermal camera, which leads to the output temperature of the target being different from the temperature effectively measured.

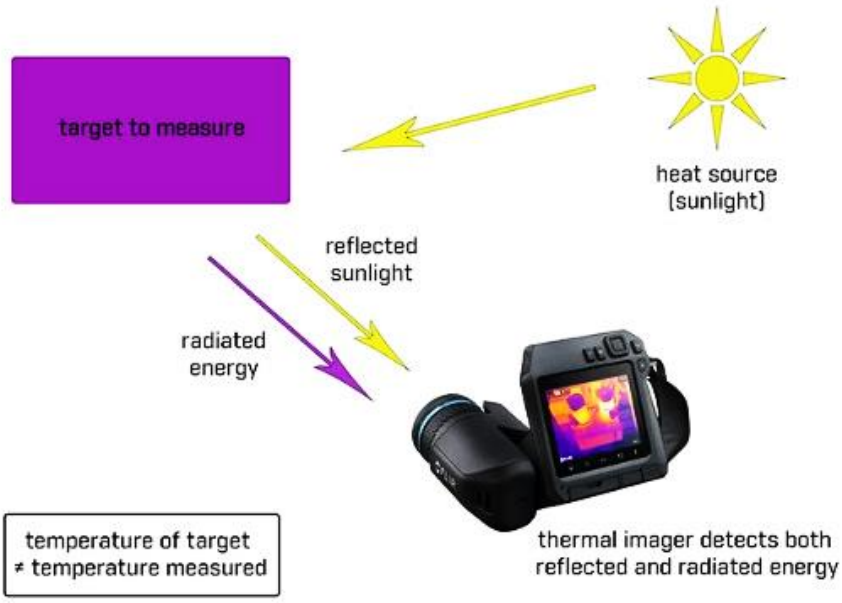


Figure 2.7 - Effects of solar emissivity in thermal imaging

In this thesis case, luminosity and color temperature were among the parameters required for the study. Consequently, all measurements were conducted under normal ambient conditions, disregarding solar exposure. Furthermore, this IoT system not only incorporates remote sensing technologies but also in-situ sensing capabilities, which helps mitigate errors introduced by radiation. This approach provides an additional perspective to the project by enhancing its robustness and redundancy.

2.2.5.2 In-Situ and Remote Sensing Technologies

The current experiment is conducted in a vineyard, but plant thermal stress can occur in any type of culture, as highlighted by Burke et al. [38] and Waqas et al. [39]. These authors conducted their investigation in cotton and maize crops, respectively, and emphasized the importance of establishing efficient measurement techniques accordingly. Similarly, Mendes et al. [40] and Dhillon et al. [41], similarly to our research, employed a combination of remote and “in-situ” measurements.

However, both Mendes's and Dhillon's IoT systems had limitations regarding soil characteristics measurements. This occurs because their primary focus was on "in-situ" sensing, using sensors that measure air and leaf characteristics - given their emphasis was predominantly on detecting and diagnosing diseases.

The Figure 2.8 explains the influence of thermal stress on reproductive development in a maize. This experiment conducted by Waqas demonstrates how the corn crop reacts when it's put through thermal stress, having two different conditions in study – a stress tolerance plant and a stress sensitive plant. As expected, the stress tolerant plant offers more resistance, being able to be germinated, and consequently, fertilized. While the stress sensitive plant becomes sterile, and it is not able to be fertilized.

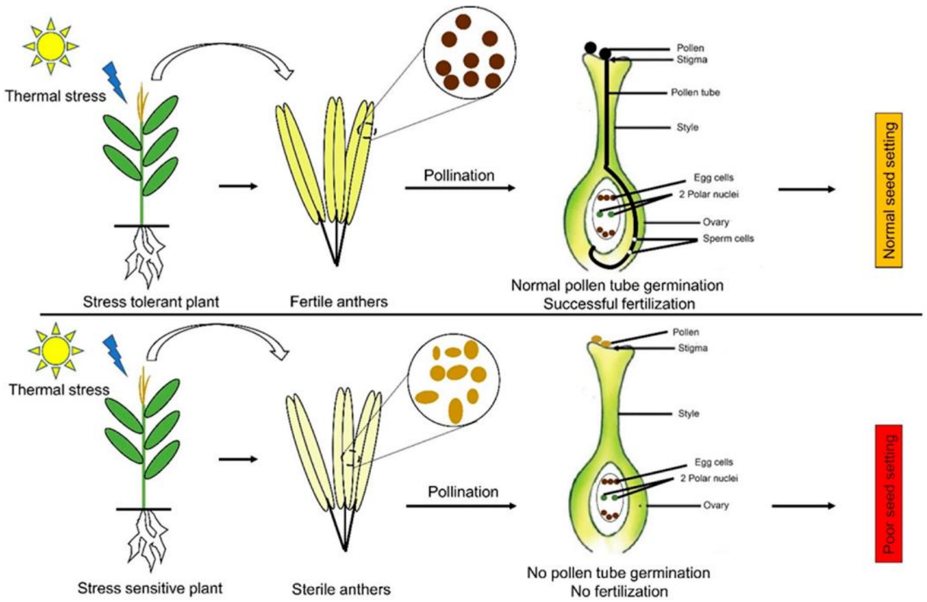


Figure 2.8 - Study of plants thermal stress in different conditions [39]

Nevertheless, it is crucial to acknowledge the significance of integrating measurements from diverse plant characteristics such as air, soil, and leaves. This integration forms the foundation of our paper, emphasizing the importance of a complete system. Also, the fusion of in-situ and remote sensing technology emerges as another key aspect introduced in our research.

CHAPTER 3

System Description

A smart IoT-based vineyard monitoring and analysis system was successfully designed and implemented. This system integrates a variety of carefully chosen technologies to gather, process, and assess data related to the vineyard's surroundings. These technologies encompass a wide range of parameters, including air and soil temperature, relative humidity, and soil moisture. Furthermore, specific vineyard attributes, such as leaf color and leaf temperature, are assessed through a combination of in-situ and remote sensing solutions. The Figure 3.1 illustrates the system cover in terms of its hardware box prototype.

Figure 3.1 - IoT System Box Prototype

The system includes advanced thermographic imaging, using a FLIR E60 camera, with data analysis conducted through the FLIR Tools Software [42] and Matlab Tools like Data Acquisition Toolbox [43]. This combination enables efficient and accurate monitoring of vineyard conditions and detection of thermal stress in plants.

The data of the developed embedded system, that is characterized by ESP32-PICO microcontroller, is then stored in a remote SQL-type database – in the cloud –, as the information is transmitted through Wi-Fi, to ensure security and real-time communication. The distributed measurement system is designed with flexibility and modularity in mind, achieved with fixed and mobile sensor nodes.

This approach ensures optimized data collection and aids in the early detection of potential issues, ultimately contributing to the overall health and productivity of the vineyard. To accomplish this, two ESP32 microcontrollers, corresponding to each node, were chosen as the preferred solution, since they have an embedded Wi-Fi module which allows a straightforward connection to the sensors used and for remote sensing monitoring due to its versatility and wireless connectivity.

Furthermore, a mobile application with a couple of features has been developed to enhance user-side visualization for crop monitoring. This specific architecture will be explored further on chapter 4 – Mobile Application. The overall architecture of the implemented IoT system is depicted in Figure 3.2.

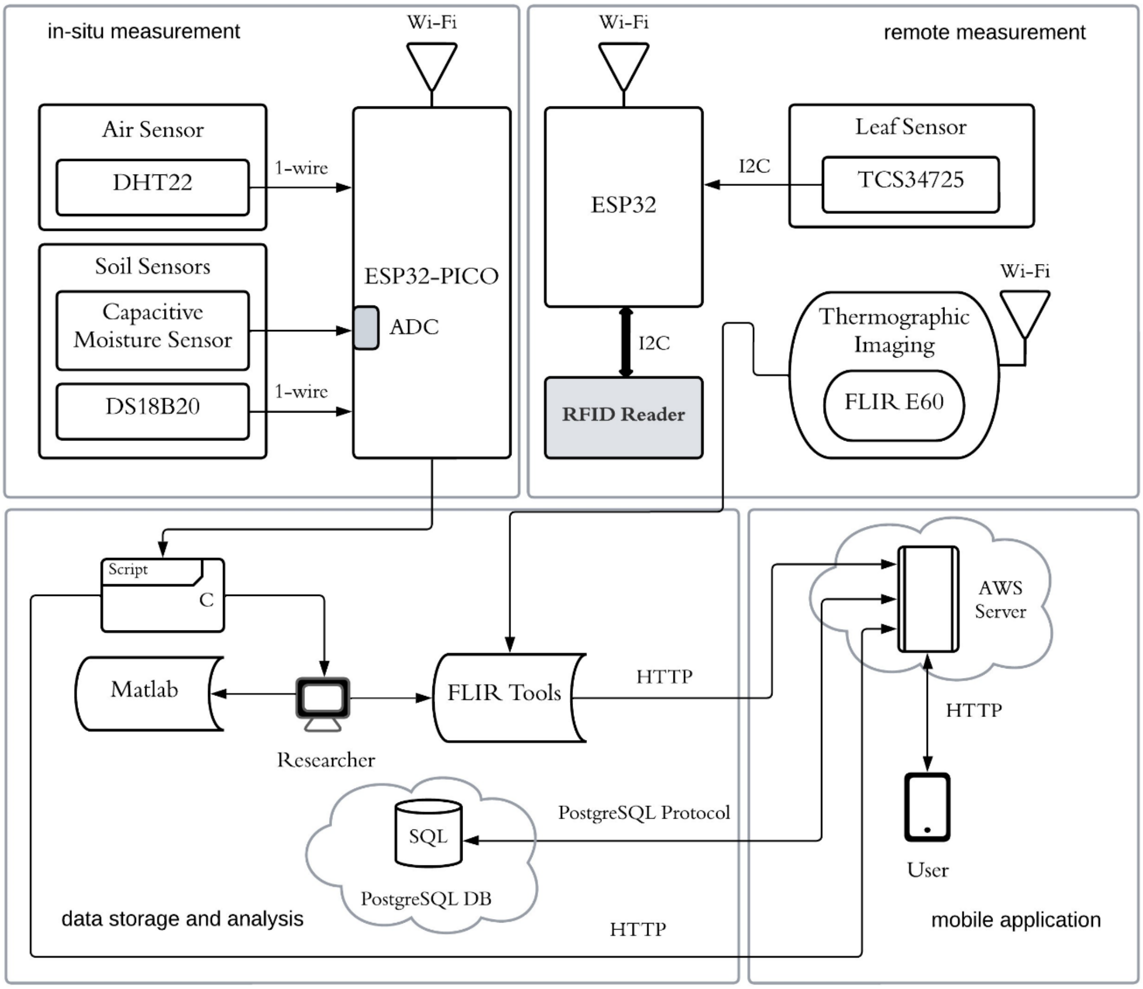


Figure 3.2 - System's Architecture: Hardware and Software Components

3.1. Communication Protocols

In the realm of agriculture, the utilization of different communication protocols is essential for efficient data transmission and comprehensive farm management. These protocols, which include RFID (Radio-Frequency Identification), Wi-Fi – IEEE 802.11 – (short-range), and LoRa (long-range), each offer unique advantages that tailor to the specific needs of agricultural applications. Notably, they address the limitations of relying solely on USB connections, which are neither scalable nor practical for the dynamic and extensive environments of modern agricultural fields.

The chosen communication protocol in this project is Wi-Fi, since it presents several advantages when used as a standalone in agriculture. It enables real-time data transmission within the farm network, facilitating decision-making and enhancing precision agriculture. Additionally provides extended bandwidth for transmitting data, which is particularly beneficial for streaming data from various sensors and devices, offers a stable communication infrastructure, that reduces data dropouts and ensures a consistent flow of information, and integrates with a wide range of IoT devices, making it a versatile choice for connecting sensors, and monitoring equipment around the experimental field.

In fact, Wi-Fi was preferred over LoRa for this smart agriculture practices, due to its specific application requirements. Some of them include reduced latency – for applications that require low-latency communication, like remote control of irrigation systems, where rapid response to changing conditions is critical –, higher data throughput – need to transmit large volumes of data quickly, such as real-time images from the thermal camera –, and interoperability – easier to integrate with various devices and sensors [44].

On the other hand, RFID plays a complementary role when combined with Wi-Fi in agricultural contexts. RFID (Radio-Frequency Identification) systems use radio waves to identify and track objects equipped with RFID tags, which helps identify specific crops of the different vineyards in the study, as well as stores their location. There are various types of RFID systems, categorized based on frequency range, power source, and application [45].

- Low-Frequency (LF) RFID – typically around 125-134.2 kHz – is used for access control, and tracking.
- High-Frequency (HF) RFID – typically around 13.56 MHz – its applications are contactless smart cards and NFC (Near Field Communication) technology for mobile payments and data transfer.
- Ultra-High-Frequency (UHF) RFID – typically around 860-960 MHz – is used in inventory tracking, supply chain management, and logistics.
- Active RFID have an internal power source (battery) that enables them to transmit signals over longer distances. They are used for real-time location tracking and monitoring.
- Passive RFID do not have an internal power source and are activated by the reader's signal. They are used in management, access control, and tracking applications.

The RFID system used in this dissertation was the passive RFID and a representation of its components is presented in Figure 3.3.

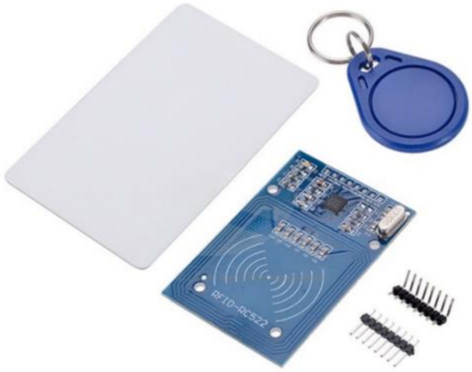


Figure 3.3 - Passive RFID System

3.2. Sensors

This subsection focuses on the physical layer of the system and provides a description of the sensors used in this IoT system. These sensors belong to the branch of in-situ sensing technology and their technical schematic can be seen below in Figure 3.4.

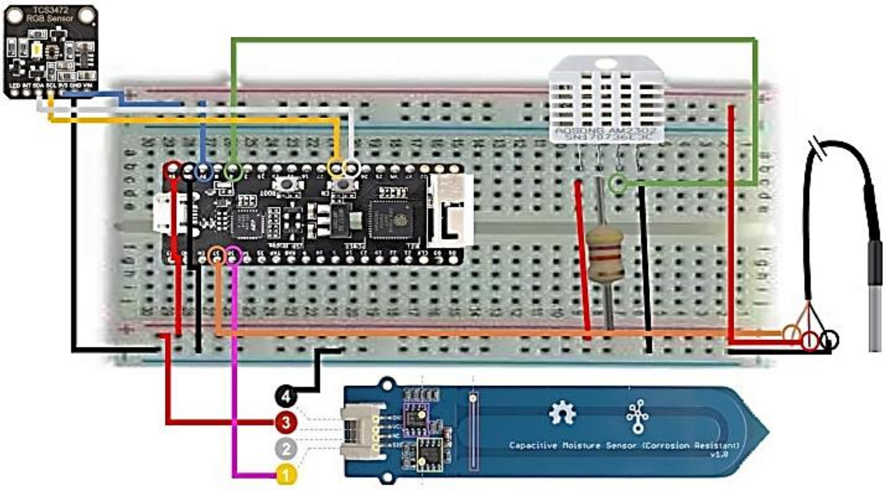


Figure 3.4 - Sensors Technical Schematic

To effectively monitor the vineyard parameters, it is crucial to consider factors such as air temperature and air relative humidity that may give insights about the soil moisture – as well as influence the thermographic images. To assure air parameters measurement a DHT22 1- wire sensor was included in the system. This 1-wire digital sensor is based on a thermistor and a capacitive humidity sensor to measure the temperature and RH of the air and can transmit this information to a microcontroller, such as the ESP32-PICO. The DHT22 sensor has four pins: VCC, Data, NC (No Connect), and GND. The Data pin is connected to the RTC_GPIO10 and the VCC is powered with 5V, assuring connectivity. This sensor has high accuracy and reliability, measuring humidity in a range of 0-100% with an accuracy of ±2%, and temperature in a range of -40°C to 80°C with an accuracy of ±0.5°C [46].

The soil characteristics measurement is based on M5Stack capacitive moisture sensor. This type of sensor – capacitive – was selected due to its balance of accuracy, energy efficiency, non-destructiveness, low-latency, and cost-effectiveness – when compared to other types of soil moisture sensors, such as resistive and TDR (Time-Domain Reflectometry). Its connection to the microcontroller is made through the GPIO38 pin, also powered at 5V. Additionally, a waterproof digital soil temperature sensor called DS18B20 is utilized. The measuring electrodes are based on capacitive design, which helps to avoid the issue of corrosion during use, by comparison with two resistive moisture sensors [47]. Its connection to the microcontroller is made through the GPIO37 pin but powered with 3.3V. The DS18B20 also has an accuracy of ±0.5°C over a temperature range of -10°C to +85°C and a single wire interface which allows a reduction in the system's complexity, with lower power consumption [48].

Furthermore, the previously described sensors are part of a sensor node fixed at the soil level. In contrast, the sensors which will be described next are incorporated into a mobile sensor node. This distinction is made to optimize data collection since the first node is used to measure soil and air characteristics, whereas the second node is used to measure leaf properties. Each one of the nodes has its own microcontroller to increase efficiency, allowing synchronism between the data collected from soil/air sensors and the one from leaf sensors. This data is next stored in a remote database, communicating directly by Wi-Fi – HTTP messages.

To monitor the plant's exposure to light and accurately measure the RGB color of its leaves, a TCS34725 color sensor was implemented to measure the following parameters: RGB code, color temperature and luminous flux. Its communication with ESP32 is made through the RTC_GPIO8 and RTC_GPIO9 pins, respectively associated with SCL and SDA, while powered with 3.3V. The TCS34725 is a digital sensor and uses the I2C communication protocol, being highly accurate in identifying a wide spectrum of colors – accuracy of ΔE00 = 1.57. Its mode of operation involves capturing the intensity of red, green, blue, and clear (unfiltered) light with photodiodes and subsequently converting these measurements into digital data [49]. However, it is important to notice that the sensor's sensitivity is quite reduced because of light absorption, and as a result, this parameter was not considered in this study. Also, the redundancy added by this RGB color parameter doesn't compensate the error introduced.

3.3. Thermographic Imaging using FLIR Tools Software

The current section focuses on describing the technology used and explaining the imaging processing behind the developed system.

The remote sensing technology based on portable thermographic camera, FLIR E60 was considered – represented in Figure 3.5 – and has some fine characteristics, that will be listed as follows. It's highlighted the high thermal sensitivity of 0.05°C, for temperature range of -20°C to 650°C, and a

320 x 240-pixel resolution infrared detector, used to measure leaves temperature. Other notable features include a 3.5-inch color LCD touchscreen display, interchangeable lenses with auto-calibration, and a laser pointer for easier targeting. The camera has bluetooth and wi-fi connectivity capabilities, allowing the transferring of image wirelessly. It also offers multiple measurement modes and analysis tools for image interpretation [50].

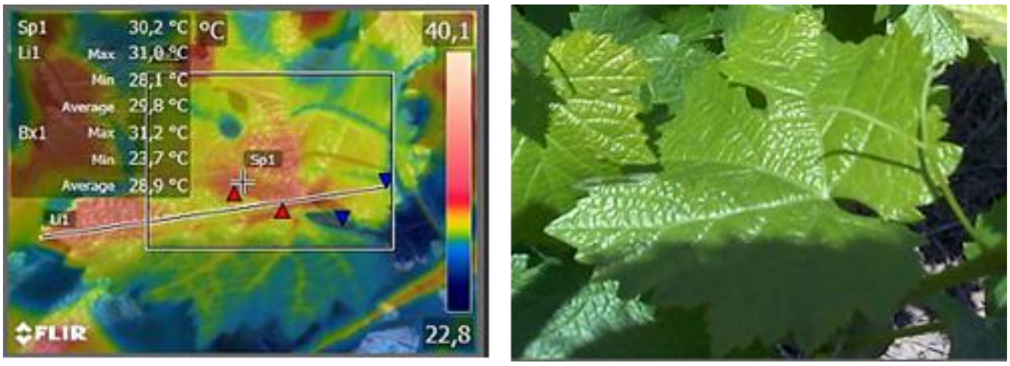
Figure 3.5 - Thermal Camera (FLIR E60)

Furthermore, the FLIR E60 camera is accompanied by compatible software denominated FLIR Tools, which was used for the analysis and reporting of thermal imaging data, as well as to export data to Matlab for further analysis. To ensure consistency and minimize variables and errors in the analysis, all images were captured at the same distance and angle. The baseline parameters for the camera in terms of emissivity and distance are, respectively, 0,98 and 0,50 cm.

The image analysis process had in its core three types of processes: line, ellipse, and box measurement tools. The line tool assesses temperature gradients by measuring the temperature profile along a straight line, revealing hot or cold spots and temperature changes between two points. The ellipse tool focuses on round or curved objects by measuring temperature distribution within an elliptical shape, providing quantitative analysis for non-rectangular areas. The box tool evaluates temperature variations across flat or rectangular surfaces by defining a rectangular region of interest, displaying minimum, maximum, and average temperatures within that area. Therefore, these tools work together to provide a comprehensive understanding of temperature patterns and anomalies, enabling users to identify underlying issues and areas of concern in thermal images.

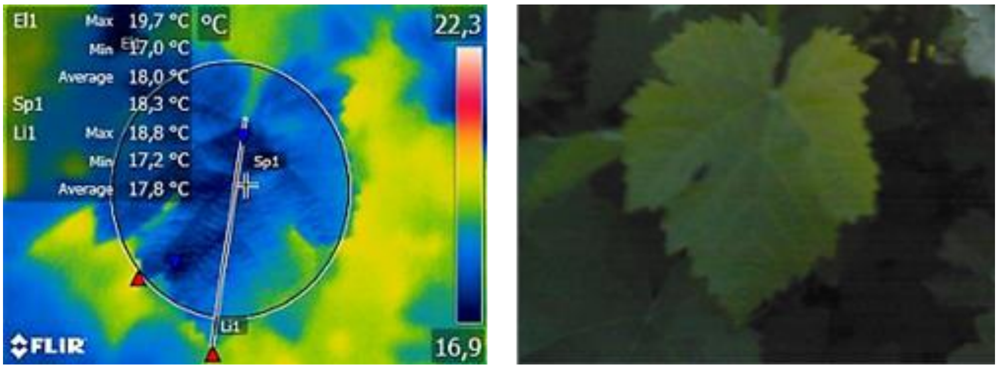
During the field thermographic imaging experiments, it was important to specify the image capture procedure, to introduce the smallest number of errors deviation. This process involved stablishing a fixed distance where the camera would have an equal distance from each target object – around 50cm –, and similar angle – around 30°. Also, it was considered the radiation sources – sunlight –, whose influence is a problem highlighted in the related work chapter. This effect was reduced by taking the thermal images against the sunlight, avoiding much as possible the direct radiation.

The Figures 3.6 and 3.7 illustrate two examples from this thesis study of imaging analysis conducted using FLIR Tools Software. These examples capture thermal images taken to a healthy vineyard during the afternoon and night periods, respectively.



a) b)

Figure 3.6 - Afternoon Thermal Imaging; a) Leaf Analysis using Linear and Box Measurement Tools from FLIR Tools; b) Leaf Image Taken in the Afternoon



a) b)

Figure 3.7 - Night Thermal Imaging; a) Leaf Analysis using Linear and Ellipse Measurement Tools using FLIR Tools; b) Leaf Image Taken at Night

3.4. Data Analysis

Matlab Data Acquisition Toolbox serves as a valuable instrument for intermediate visualizing and examining information, in the point of view of the researcher. The Data Acquisition add-on facilitates importing, displaying, and evaluating real-time data from external devices, including microcontrollers such as ESP32-PICO. The bridge between the two software is straightforward because the board programmed with the Arduino IDE uses a C compiler.

The ESP32-PICO is a microcontroller module that includes the ESP32 chip, which is part of the Espressif ESP32 series. Its firmware is the primary code that runs on the ESP32-PICO and performs the intended functions of our project. It is written in languages like C and is responsible for tasks such as data processing, sensor communication, and device control. It also runs an RTOS (Real-Time

Operating System) to manage tasks and ensure real-time performance and comes with built-in Wi-Fi capabilities, including protocol stacks needed to manage wireless communication.

Moreover, the inverse characteristics of the moisture sensor is unknown and requires the necessity of calibration. Therefore, this calibration process was conducted to establish a linear unit measure equivalent to a percentage. First, the ADC values were converted into voltage values. Subsequently, the calibration process considered the levels of maximum saturation and maximum erosion. The sub-section 5.1 explains in more detail the calibration process and the results obtained. To simplify and approximate a linear relation, a formula (1) was developed and employed for converting the voltage output (x) from the sensor into a percentage (y).

$$y = \lfloor -137x + 0{,}5 \rfloor + 351 \tag{1}$$

Posteriorly, all the information regarding air relative humidity, air/leaf/soil temperature, soil moisture and luminosity had to be analyzed based in some metrics. These classify the vineyard in the study as in a stress state or not, and which factor(s) are causing it. These limit metrics are the following according to the literature:

- for leaf temperature, the temperature should be between [15°C -30°C] [14].
- for soil temperature the [10°C -24°C] range, it's more suitable [15].
- for luminosity should not be higher than 25000 [16].
- depending on the air relative humidity values, the air temperature should not be greater than 32°C (high humidity) or 23°C (medium humidity) [17].

The flowchart represented in Figure 3.8 illustrates the thermal stress analysis procedure.

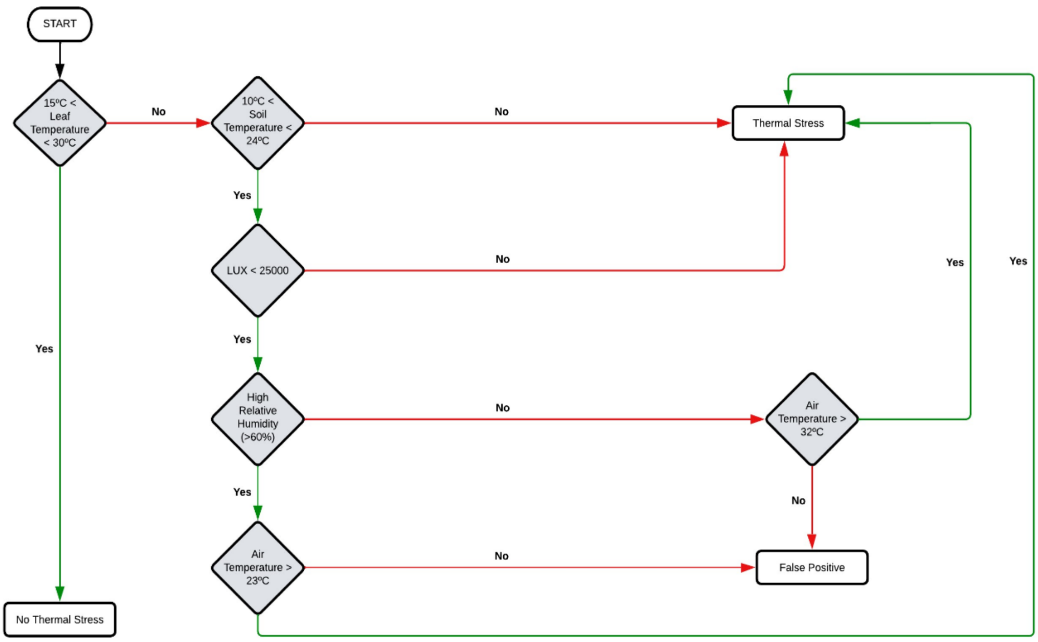


Figure 3.8 - Thermal Stress Analysis Procedure Flowchart

To summarize, the algorithm starts by comparing the leaf temperature to its reference threshold, which leads to two possible outcomes: either there is no thermal stress, or the flow continues. The leaf temperature was identified as the primary parameter in this analysis, as it plays a crucial role in determining plants' thermal stress. Following the charts flow, the remaining environmental health parameters are compared to their respective baseline threshold. Accordingly, depending on the path taken, it can be concluded that the plant is indeed under thermal stress and what parameter is causing it, or that it was a false positive. The algorithm for estimating thermal stress was implemented using C programming language and Arduino IDE on the ESP32-PICO microcontroller.

CHAPTER 4
Mobile Application

A mobile application was created, developed, and implemented due to the necessity of having a platform designated to visually monitor vineyards parameters and its status. This app was designed thinking about the user experience (UX), in this case farmers and their struggle to know in real-time what are the needs of their crops, allowing a faster targeted decision-making, which continuously can lead to the increase of crop productivity and consequently decrease of crop thermal stress situations.

The mobile application system developed and described in this dissertation is composed by five components. It has a server in the cloud – AWS – built in Node.js, – in a demo testing stage – designated by RemMonitor. The system uses Docker, which is responsible for ensuring portability, consistency, and scalability [51]. RemMonitor function is to support the mobile application by ensuring communication and connectivity between the client/user and the PostgreSQL remote database, where all the data is located regarding vineyards. Plus, the mobile application uses a JavaScript framework denominated React Native, which was used for the front-end creation and implementation. Finally, this information origin come from the sensors, which are in the field collecting all the invaluable data. In Figure 4.1 is represented the mobile application architecture in more detail.

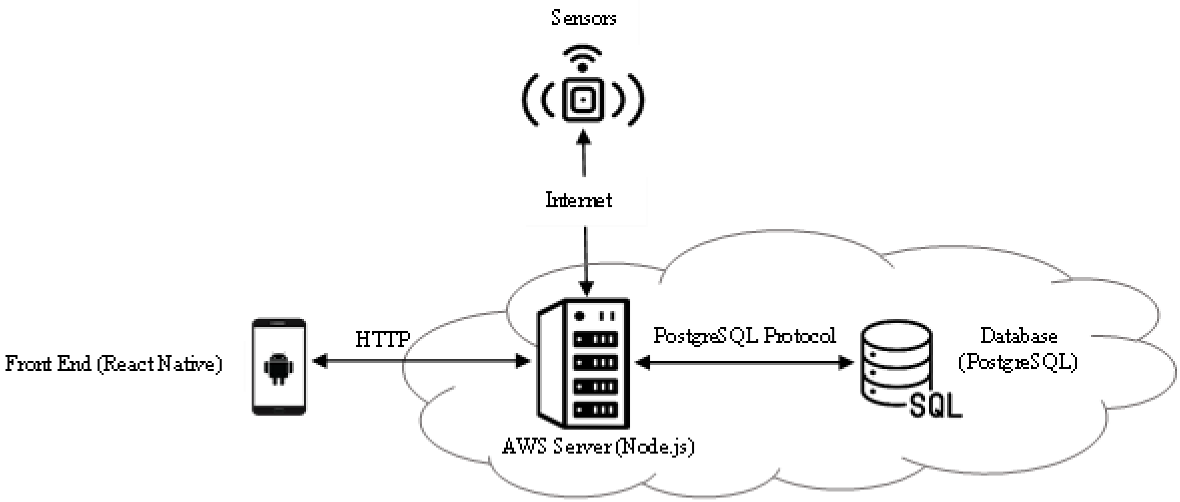


Figure 4.1 - Mobile Application Architecture

The communication protocol dominant in this architecture it is HTTP, since it’s the most used in interactions between the various components in a mobile-based system design, including the server, front-end, and the database. HTTP operates using a client-server model, where the React Native mobile app, and the server (Node.js), communicate through HTTP. Afterwards, the server processes the requests from the client and sends responses back. When the mobile app needs to send a request to the server or retrieve data, it constructs an HTTP request. This request includes a method (GET, POST), a URL specifying the endpoint on the server, headers, and an optional message body. The client sends this HTTP request to the server over the internet, and on the server, the Node.js application is set up to listen for incoming HTTP requests. It receives the request, processes it according to the requested action (fetching data from the database), and generates an HTTP response. If the server needs to interact with the database (PostgreSQL), it makes use of a ORM (Object-Relational Mapping) to construct and send SQL queries to the database, using PostgreSQL Protocol. Then, the database processes the query, retrieves the data, and sends back a response to the server [52].

The database chosen is PostgreSQL, a relational database, which means it organizes and stores data in tables with rows and columns. It follows the principles of the relational model, offering data integrity, consistency, and structured data storage. It is also open-source and follows the ACID (Atomicity, Consistency, Isolation, Durability) compliance [53]. It is a remote database connected to the cloud.

Regarding the front-end, React Native is an open-source framework for building mobile applications using JavaScript and React (JavaScript library). It allows developers to create mobile apps for multiple platforms – hybrid applications –, such as iOS and Android, using a single codebase. It has an efficient development process, strong community support, and access to native components, reason why it was chosen to be implemented in this project [54].

For the server, Node.js, which refers to a server application or process that is built using Node.js, a runtime environment that allows to run JavaScript on the server side. It is known for its non-blocking, event-driven architecture, which makes it particularly well-suited for building high-performance, scalable server applications [55]. In this project architecture, the Node.js application is running within a Docker container on the AWS server.

4.1. Application Characteristics and Requirements

During the IoT system development was clear the need of an application to easily display the vineyards sessions data. The data displayed should have three parts, one associated with real-time data, the other with an history, where they would be transformed into statistical data, and the last one with the thermal captured images. Besides that, it should be presented a signalling object that would correspond to the state of the vineyard – according to the thermal stress condition or not. These were the main basic functional requirements for the construction of the application.

Continuing, in terms of the application itself, it should be mobile – due to the need to be used in agriculture contexts (field testing) –, simple – because its users tend to have a higher age range and can have low technological skills –, and broad – to have the higher number of users possible without limitations of age, OSs (operating system) and platform. In this respect, was decided to develop a mobile application, due to mobile phones being the device with more consumers around the world [56], as shown in Figure 4.2, with React Native, a hybrid framework which allows multiple OS – Android and iOS.

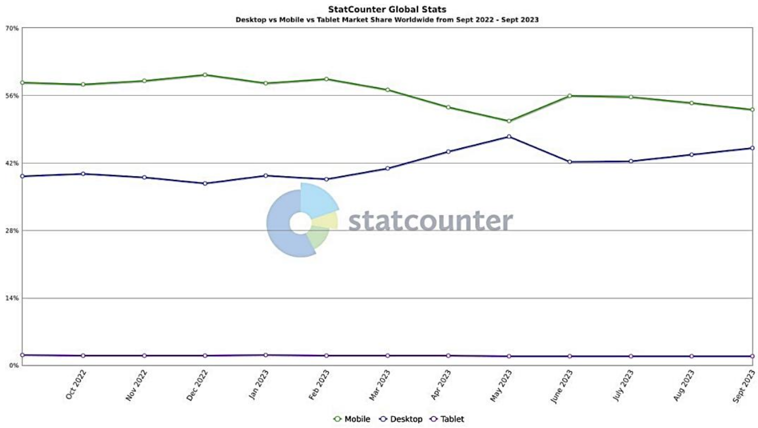


Figure 4.2 - Devices with More Users in the World [56]

Besides that, the application characteristics are also a fundamental topic before the implementation of the mobile app and will be listed and explain below, according to our system requirements.

- Application Login – to use the application, the user is required to be registered in the system, to be able to login. This registration is made manually by the administrator in the application back-end. Basically, this is achieved by sending a curl command from the back-end script dedicated to the sign-up to an endpoint in the database. The password is then encrypted, and the farmer user is created. To perform the login in the mobile application, the registered user should enter its credentials (username and password), as shown in the Figure 4.3.
- Remote Database – additionally to the real-time component, there is a section on the database designated to offline access of the data previously stored, to not be exclusively dependent on the internet. It is used the PostgreSQL database since it's integration with mobile applications is easy-accessible and consistent. This characteristic will allow for the integration of persistence in the application, and at the same time access to statistical data regarding of the time when the app was previously online – depends on the information stored in the database.

- Graphical Design – the application uses a library named "react-native-gifted-charts" [57] which creates and draws all the different charts that are available in the dashboard related to the statistical data. These charts can be of different types – bar, line, area, stacked bar, etc –, being the preferred choice for this application the line and area graphs. This library **additionally allows to select points in the chart to see more information – exact values.**

Figure 4.3 - Login Functionality

4.2. System Functionalities and Application Flow

Once established the application requirements and characteristics, the system functionalities – operations users can execute to interact with the application –, and the flow of the application – detailed step-by-step paths in the app that can be performed, to activate the systems functionalities – can be defined, considering that this is an app designed for farmer users.

Starting with the system functionalities, this group of actions, that can be executed by the user in the mobile applications, has eight acts in total. The system is composed by the login, the visualization of several components such as: the vineyards associated to the user, the last data measurements, the statistical data, the thermal images, and the vineyards status which reflects its condition – thermal stress assessment –, and the choosing or creation of a specific vineyard. These acts have the potential to:

- The login action was detailed in the previous subsection, and in terms of functionality basically consists in the fulfilment of two fields – the username and the password –, which must be beforehand associated with a user account registered in the database.
- The visualization of the vineyards associated with the user account, as the name suggests, is an action whose output is the list of all the vineyards being monitored by the farmer user.

- The creation of a specific vineyard is an action in which the user can create its vineyard through the fulfilment of a form with the required parameters such as: the vineyards name, location, and logotype.
- The choosing of a particular vineyard allows for the selection of one of the previously listed vineyards, which will guide the user to the next actions mentioned.
- The visualization of the last measured data is an action which should be associated to a specific vineyard, so its data is the one being displayed – the system can be online (real-time value) or offline (last stored value).
- The visualization of the statistical data has the same specifications as the last point, distinguishing by the presentation of the data in the charts format, to enable some analysis and historical context.
- The visualization of the vineyards conditions is basically associated with a flag, which informs the user if its vineyard is in thermal stress or not (vineyard status).
- The visualization of the captured thermal images it must be associated with a vineyard, as well as with a specific time domain – to organize the images and have knowledge about the moment where the picture was taken.

In the Figure 4.4 it is presented all the beforementioned system functionalities, which corresponds to the diagram’s use cases.

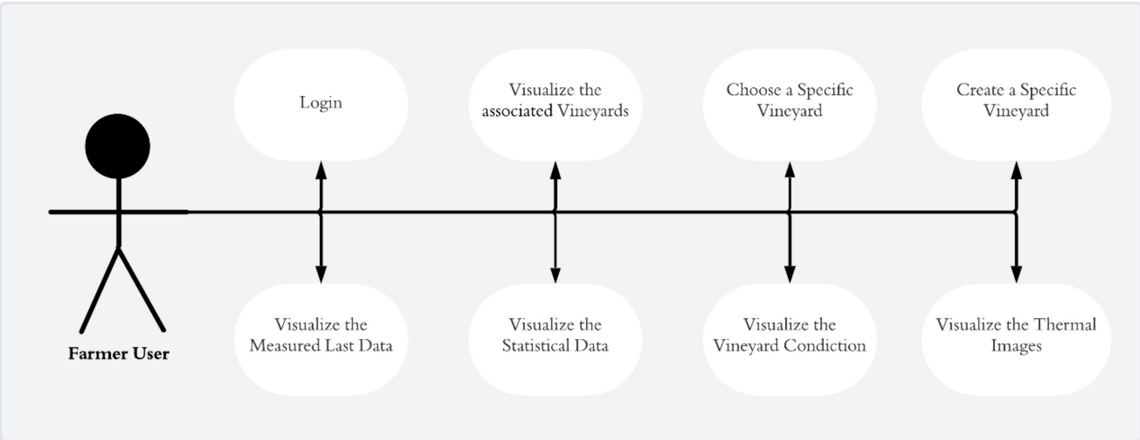


Figure 4.4 - System Functionalities Use Cases Diagram

Following to the application flow, this is a comprehensive sequential procedure within the app that should be followed to enable the system's features and contains several stages with a couple of features, which will be now explained.

Beginning with the starting point of this flowchart, the Login. It’s a state where the user only truly enters if it is already registered, being this the first conditional block encountered by the user. If the condition is true, the farmer can proceed to the following stage, the block containing the Vineyards Information. If not, he returns to the Login state, where it won't come out unless the administrator creates an account for him.

Admitting the user is now in the Vineyard Information stage, he has five possible paths. The first one consists of logging out of its account, a decision which will send him to the beginning stage – Login. The second doesn't change nothing, the user remains in its current stage. The third involves selecting a vineyard out of the list of vineyards associated with this user, which will lead him to the Vineyard Dashboard stage. The next one is related to the creation of a new vineyard – which will require the fulfilment of a formulary appeared via pop-up. And the last consists in erasing a chosen vineyard.

In the Vineyard Dashboard block there are four possible outcomes. One is the possibility of coming back to the prior stage, the Vineyard Information. Another one is simply the stage remaining in the same point. The third consists of choosing to switch the current chart – containing statistical data regarding some vine health parameter – into other available graph, which will take the user to a different, yet similar stage denominated Vineyard Dashboard Plus – due to the additional modification. This state has a level of similarity so high that at a certain point can be considered the Vineyard Dashboard stage again. At last, the fourth offers the possibility to check the vine condition. If yes, the user is lead to the Pop-up stage, where will be displayed the information regarding the vineyards thermal stress status. After this, the user can remain in that stage or accept the condition Leave, to leave the pop-up and return to the Vineyard Dashboard stage.

The Figure 4.5 illustrates the user functionalities flowchart according to the mobile application developed.

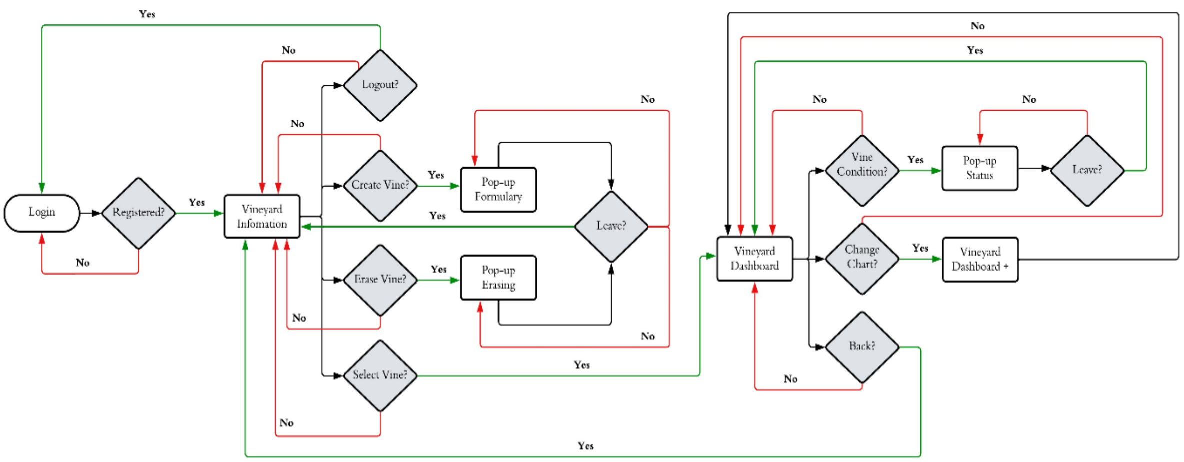


Figure 4.5 - Flowchart of the User Functionalities in the Mobile Application

4.3. Graphical User Interface (GUI)

The application name is RemSAGRO, and its correspondent logotype is illustrated in Figure 4.6. This sub-section is reserved for the display of the dashboards created for the application – GUI –, as well as the respective explanations of all the components and features that compose it.

Figure 4.6 - RemSAGRO Logotype

The mobile application consists of three main dashboards, and a few complementary event-actions. The objective was to implement the described monitoring system based on the requirements and characteristics previously stated, to offer the farmers an adequate monitoring system.. Its initial user interface is the login page, already illustrated in Figure 4.3. This page contains the logo, shown in Figure 4.6, at the top, followed by the box components where the user will fill with the required information – username and password. While writing the password, the characters will be encrypted, so it will only be seen some asterisks. Right bellow there is the login button, that when triggered will lead the user to the next page. Finally, at the bottom is presented the ISCTE logotype. This page is fully represented in Figure 4.7.

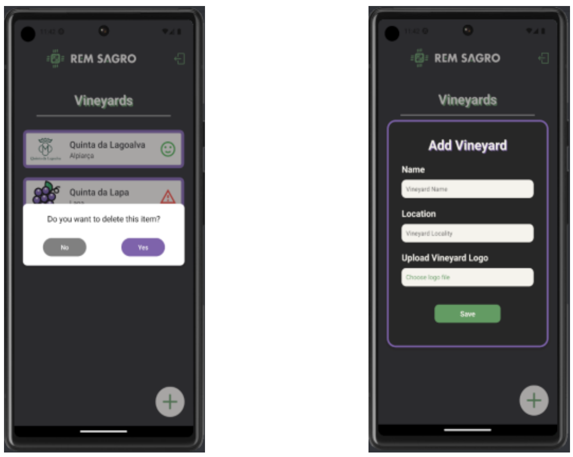
Figure 4.7 - Mobile Application Login Dashboard

The following GUI is the vineyard information page and is represented in Figure 4.8. This dashboard has in its header the system logotype and an action – represented by the door icon – which is associated with the logout. Above, it's shown the list of the active vineyards being monitored by the current farmer user.

This list is composed of two farms, where each one of them has elements like its name, and below its location. Plus, at the left side of this information, is illustrated the farms logotype and, at the right side, the state of the vineyard regarding thermal stress. Each icon means a status, the top one, demonstrated by a smiley face, is associated with no thermal stress, while the alert icon intuitively shows that the vineyard is experiencing thermal stress. By clicking on one of the vineyards, the next dashboard will be displayed.

Figure 4.8 - Mobile Application Vineyard Information Dashboard

However, the user can also have two extra functionalities, within this dashboard, which are: create and delete. To delete one of the vineyards the user must continuously press the desired vineyard, until it appears a pop-up that will reassure the user of its action. The farmer must then select “yes” or “no” accordingly. The second action consist of creating a vineyard, where its function is triggered by pressing the “plus” button presented at the bottom right of the dashboard. After that, a pop-up with a formulary will be displayed showing fields to be completed like the vineyard name, location, and logotype. These functionalities are represented in Figure 4.9.



a) b)

Figure 4.9 - Mobile Application Vineyard Information Dashboard; a) Delete Vineyard Functionality; b) Create Vineyard Functionality

The third and final dashboard is the vineyard dashboard, the page where all the data regarding the vineyards monitoring is displayed. Represented in Figure 4.10, the vineyard can have two conditions. The first one is not having data available to display. Or in the second case, the contrary. Within this last condition, the page has in its header, at the left side, a feature which enables the user to return to the previous dashboard, represented by the left arrow icon, and at the right side, the app logo. Right above, there's component with the information of the chosen vineyard – name, location, and logotype.

Continuing, there's a button denominated Thermal Stress with the icon representative of the vineyard status and a note – in case the farmers want to know more details about the crop status –, that when clicked will lead to a pop-up, appearing with its information in a tabular format. These include the health parameters and its conditions, as well as a message with the status. Following, it is a component box with the last values measured by the field sensors and the date of the measurements. These parameters are composed by air temperature and humidity, luminosity and soil temperature and moisture, and are also represented in Figure 4.10.

a) b) c)

Figure 4.10 - Mobile Application Vineyard Dashboard; a) No Data Available; b) Last Measured Values; c) Pop-up with Thermal Stress Status

Proceeding in this dashboard, is still a set of functionalities to be explored that are connected to the statistical data components and are represented in Figure 4.11. Below the last measured values box, it is presented an array of five elements, each one of them corresponding to a different measurement, and consequently a different chart. These icons are representative of the parameters in the study. In the charts, the higher areas are fill with warmer tones than the lower areas, and its axis are adjustable according with the data delivered to the database.

a) b)

Figure 4.11 - Mobile Application Vineyard Dashboard; a) Air Temperature Chart; b) Soil Moisture Chart

To conclude the functionalities of this dashboard, the last function is attached to the thermal imaging component, and it is represented in Figure 4.12. Underneath the statistical data charts, it is presented a label informing the user of the thermal image's placement. These images are related to the associated vineyard and have a date stamp. It is also possible to scroll by the set of pictures moving the cursor to the left/right.

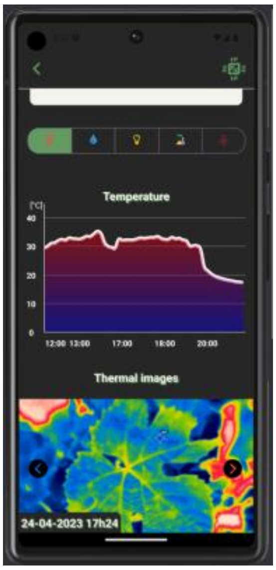


Figure 4.12 - Mobile Application Vineyard Dashboard – Thermal Images

CHAPTER 5
Experimental Results and Discussion

The current section starts with a dedicated subsection to soil moisture sensor calibration, since it was a challenge to obtain an equation accurate for this parameter, due to a lack of documentation for this type of sensor data. Its subject already was introduced in the Sensors subsection of the System Description chapter.

Continuing, this chapter's goal is to present and demonstrate the results of a continued research during two sessions of experimental field measurements in vineyards, and one session regarding measurement in fruit trees. These experiments were made to evaluate thermal stress in multiple conditions –different time and crop stages, and additionally how it affects fruits. The first study session resulted in the publication of one scientific article, which can be found in Appendix A. This article was accepted and presented in the IEEE Sensor Applications Symposium 2023 conference, at Ottawa, Canada.

Both the field experiments were conducted at "Quinta da Lagoalva de Cima" [18], a prestigious Portuguese farm located in Alpiarça, Santarém – with the corresponding coordinates 39°17'45.53"N, 8°33'46.62"W. The chosen vineyards, for the assessment of thermal stress, were of the variety Sauvignon Blanc – Vitis Vinifera – and were planted in clayish soil. It is worth mentioning that prior to the commencement of this experiment, the vineyards had a couple sets of treatments, one of the reasons why weren't encountered any diseases or anomalies associated.

These measurements were taken in April 2023, specifically during the fruit set stage of the grapevines, and in September 2023, while it had already been harvested. This period was chosen due to the contrast of crops stage, which will be reflected in the measured values in a more evidently way. Additionally, to have a contrast about how other types of cultures react to thermal stress, a set of tests were conducted in fruit trees like pear, loquat, and fig trees. This last study is important to introduce some diversity to this set of experiments, and to fully uses the thermal imaging potential in other evaluations besides leaves temperature.

5.1. Soil Moisture Calibration Results

The well-functioning of the proposed IoT system is essential to elaborate models of study and obtain the desirable results with truthful data, to provide veridic information. Consequently, the absence of documentation for the reading of the soil moisture sensor couldn't be an excuse to disseminate false data. Therefore, a process of calibration was made and will be presented in this subchapter.

To begin, besides the sensor introduced in the "Sensors" subsection – M5 Stack Moisture Sensor –, another one was used to do this calibration by comparison, which is the LSE01-8 sensor, shown in Figure 5.1. This sensor has other parameters, but the only one used in this calibration was the soil moisture. Its measurements go from [0-100] %, which is the ideal range for the moisture sensor.

Figure 5.1 - LSE01-8 (Soil Moisture & EC Sensor)

Continuing, a few standard measurements were performed to extract the values read by each one of the sensors. These tests used a vase with soil, previously dried. Before starting the measurements with the exact defined water quantities to irrigate the earth soil in time slots of 20 minutes, to give the soil some time to absorb all the water given, this were the default categorized measurements: erosive (35°C-42°C) and ambient (30°C-35°C). The tests will end once the soil saturates, which means the percentage should be equivalent to 100%.

In Figure 5.2 it's presented the sensor calibration curve between the two sensors enunciated above and its respective equation and error deviation. As displayed, this relation isn't linear, and its best approximation was a polynomial function of the sixth degree (2), also presented below.

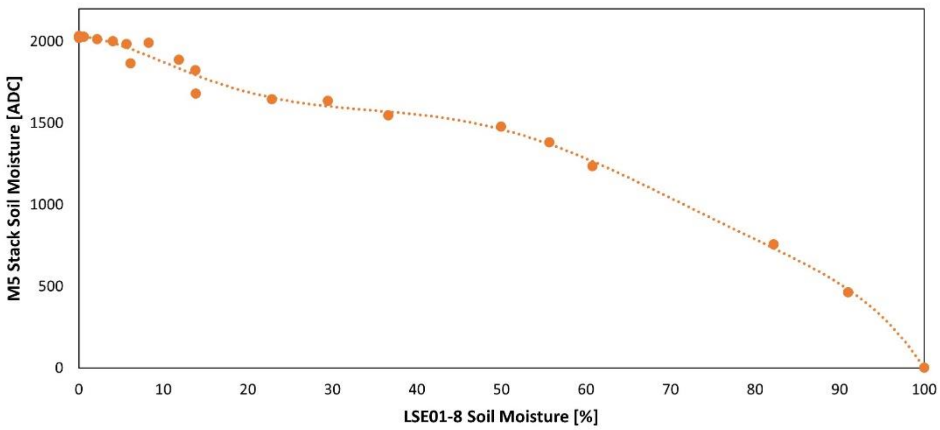


Figure 5.2 - Sensor Calibration between LSE01-8 (Reference Sensor) and M5 Soil Moisture Sensors

$$y = (-8 \times 2{,}71828 - 08)x^6 + (2 \times 2{,}71828 - 05)x^5 - 0{,}0025x^4 + 0{,}1215x^3 - 2{,}3295x^2 - 2{,}1564x + 2030{,}6 \quad (2)$$

Additionally, in Figure 5.3 it's illustrated the Reverse Characterization of the same sensors, in order to facilitate the conversion of one non-defined value to a percentage value. This relation also had applied for estimation a polynomial function (3), but this used one of the fifth degree.

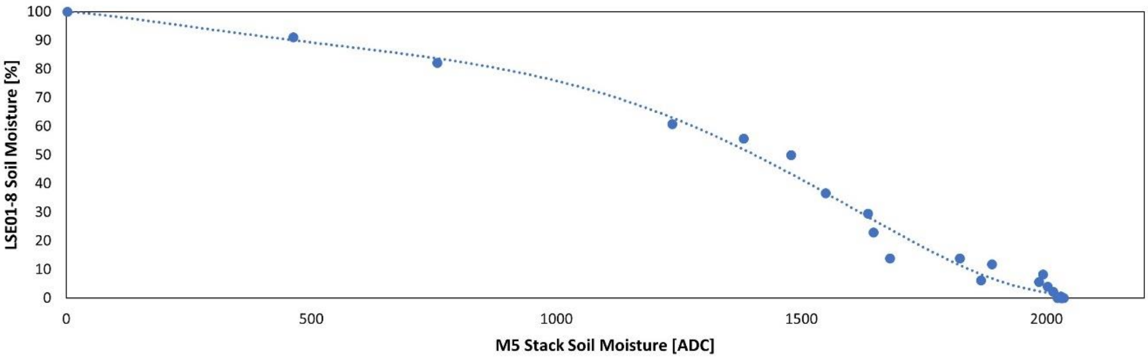


Figure 5.3 - Soil Sensors Inverse Characterization

$$y = 2E - 14x^5 - 9E - 11x^4 + 1E - 07x^3 - 5E - 05x^2 - 0{,}0147x + 100{,}14 \quad (3)$$

5.2. First Set of Measurements in Vineyards (April)

The specifications related to the weather conditions in which the monitoring took place for each of the grapevines considered in the study, such as meteorologic, spatial and time features, are presented in Table 5.1.

Table 5.1 - Information of Experimental Environment and Ambient Conditions (April)

		Vineyard 1	Vineyard 2
Time	Morning	[12:48:56-13:16:26]	[13:28:55-13:45:46]
	Afternoon	[17:42:52-18:16:43]	[18:24:38-18:41:28]
	Night	[20:33:03-20:50:56]	[20:51:16-21:14:59]
Coordinates		39°17'52.6"N, 8°33'20.9"W	39°17'52.6"N, 8°33'20.7"W
UV Radiation		UV8	
Air Temperature		29,2°C	
Air Relative Humidity		55%	

To evaluate the system's performance, experiments were conducted in a vineyard, focusing on two specific grapevines, throughout the day. These measurements aimed to test a hypothesis of how the system should behave during the three moments of the day, while in the fruit set stage. The ESP32-PICO microcontroller was programmed to transmit sensory data to the portable computer at regular intervals of every 40 seconds since this type of data has a high relevance due to its quick variation.

Firstly, it is important to note that two grapevines were used as a control method to introduce redundancy. However, comparing them is not relevant due to the closely aligned values they produced. Also, the time ranges which delimitate morning, afternoon and night are, respectively, [12:48- 13:45], [17:42- 18:41] and [20:33- 21:14] [hh:mm]. In Figures 5.4-5.6 are represented analyses of the data – regarding air relative humidity, soil moisture, light luminosity, and air/leaf/soil temperature – collected from both the remote and in-situ sensors throughout the day, being possible to observe the distinct stages of the day and how the data oscillates for the various plant health parameters.

In the first case, considering the thresholds, the air relative humidity (RH) parameter shows a gradual increase throughout the day. During the morning, it ranges between 35%-50%, 40%-50% in the afternoon and 50%-70% at night. Contrarily, soil moisture decreases at a faster rate and on a non-linear scale until the afternoon, measuring values between 10% and 50%, while at night increases until reaching 30%, as seen in Figure 5.4.

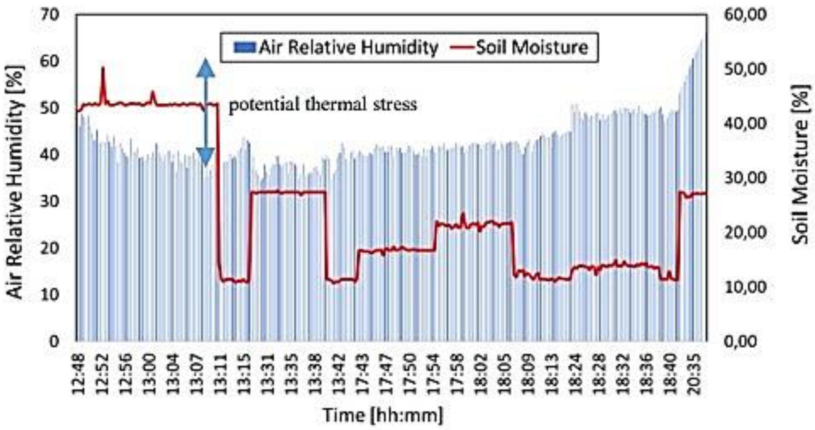


Figure 5.4 - Relation between Air Relative Humidity and Soil Moisture during the Different Stages of the Day

On the other hand, the second case involves three different variables, all related to temperature, as shown in Figure 5.5. As expected, due to the surface temperature characteristics, air and leaf temperature are similar and behave in a similar way, decreasing their values over the day. However, it's important to re-highlight that the leaf temperature values were measured with the thermal camera, while the air temperature values come from the DHT22 sensor. In contrast, soil temperature demonstrates an opposing trend, steadily increasing and maintaining a relatively stable range of values – and were measured by the M5 soil moisture sensor.

At night, the values of Air RH are high since they surpass the 60% line. However, its corresponding temperature is below the 23°C mark, leading us to conclude that there was no thermal stress during this moment of that exact day. On the other hand, during the morning and afternoon moments, the outputs for Air RH are between [40%-60%] which means the plant could be experiencing thermal stress if the air temperature goes above 32°C. As observed in the temperature chart, it is a condition that is met, especially after 13:00 until 18:00, approximately – the highest heat period. Related to leaf temperature, whose limit range is between [15°C-30°C], during the same period, thermal stress is also observed.

Contrarily, for the soil temperature, the threshold is not surpassed, meaning that soil characteristics are not a reason that causes the vineyard to experience thermal stress.

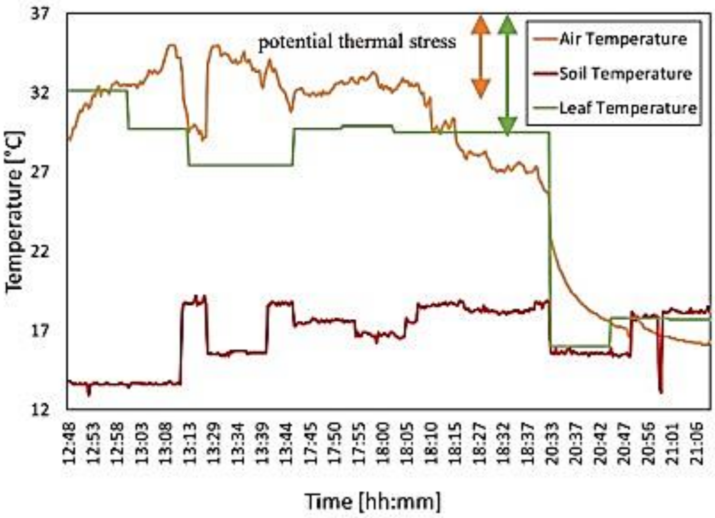


Figure 5.5 - Air/Soil/Leaf Temperature Variation during the Different Stages

It is also noteworthy that the green liner representing the leaf's temperature values may exhibit slight errors in its outputs due to various factors, being underlined by the sun's orientation and the solar radiation absorbed. Therefore, when considering the temperature thresholds, a deviation of approximately ±1°C should be considered [2-3].

Finally, the third case illustrated in Figure 5.6 represents the variation in luminosity for different moments of the day. It can be concluded that due to the surpassing of the 25000 LUX threshold in the morning stage, there is a higher probability to exist thermal stress related to the heat in that time when compared to the others, which was confirmed with the previous data.

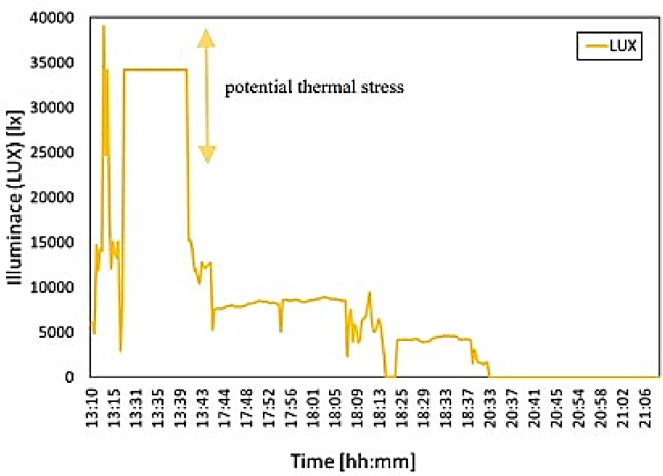


Figure 5.6 - Luminosity Variation for the Different Moments of the Day

These results indicate an inverse relationship between relative humidity and air temperature, suggesting that as relative humidity increases, air temperature tends to decrease. Similarly, an inverse relationship is observed between soil moisture and temperature, indicating that higher soil moisture levels are associated with lower temperatures. This correlation is depicted in Figures 5.7-5.8 and has been previously stated by Stull et al. [19].

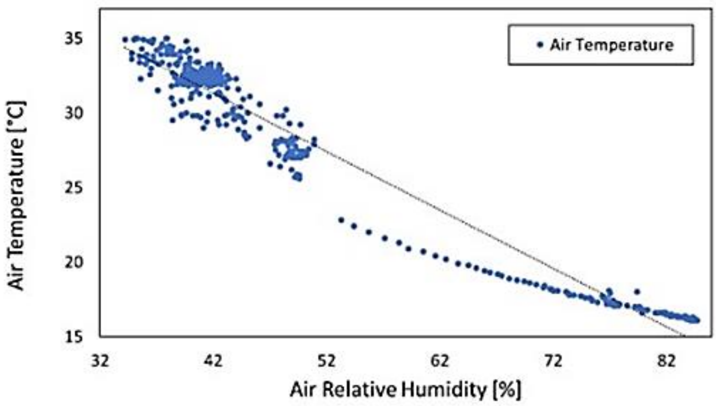


Figure 5.7 - Correlation between Air Relative Humidity and Air Temperature

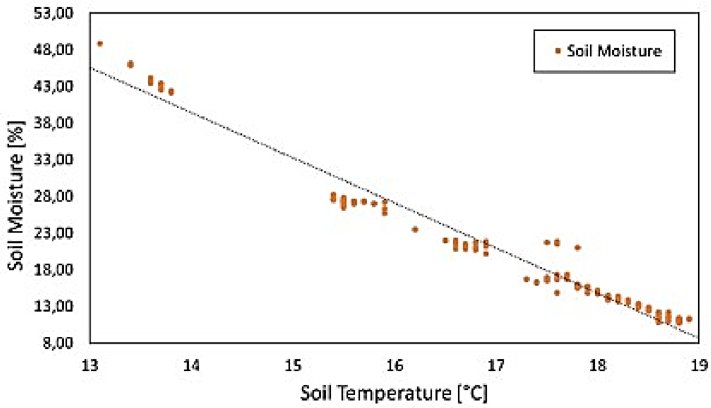


Figure 5.8 - Correlation between Soil Temperature and Soil Moisture

Considering this relationship, the accuracy of measurements and predictions related to various environmental conditions can be improved, including heat indexes. This can be achieved through the utilization of mathematical models or algorithms, as acknowledged by Anderson et al. [20].

The proposed system was designed to incorporate both “in-situ” and remote measurements, aiming to provide enhanced reliability and minimize errors that may arise from relying solely on individual technologies. The leaf’s temperature is one of the principal characteristics when assessing thermic stress. Thermography on its own can detect whether the plant is experiencing thermal stress, but it does not reveal the underlying causes. In this case, the inclusion of sensors complements the study by offering robustness and effectiveness on a smaller scale. Table 5.2 represents a correlation matrix showcasing the interrelationships among the significant parameters considered in this study.

Table 5.2 - Correlation Matrix of all Measured Plant Health Metrics (ARH: Air Relative Humidity; AT: Air Temperature; LUX: Luminosity; ST: Soil Temperature; SM: Soil Moisture; LT: Leaf Temperature)

	ARH	AT	LUX	ST	SM	LT
ARH	1,000					
AT	-0,973	1,000				
LUX	-0,541	0,566	1,000			
ST	0,137	-0,195	-0,070	1,000		
SM	-0,164	0,227	0,028	-0,988	1,000	
LT	-0,878	0,896	0,312	-0,078	0,144	1,000

5.3. Second Set of Measurements in Vineyards (September)

This set of measures aimed to redirect the focus of the variables in study, to give a complementary view and more deep understanding of thermal stress in multiple conditions. Therefore, the measurements were conducted only during the afternoon in the previously referred two vineyards, where the variable is the state of the crop.

The specifications concerning the environmental conditions during the monitoring of each grapevine included in the study, encompassing meteorological, spatial, and temporal characteristics, are detailed in Table 5.3.

Table 5.3 - Information of Experimental Environment and Ambient Conditions (September)

		Vineyard 1	Vineyard 2
Time	Afternoon	[17:31:08-17:52:55]	[18:01:42-18:20:08]
Coordinates		39°17'52.6"N, 8°33'20.9"W	39°17'52.6"N, 8°33'20.7"W
UV Radiation		UV10	
Air Temperature		33,6°C	
Air Relative Humidity		51%	

These measurements were conducted with the objective of testing a hypothesis regarding the system's performance under different conditions. The variations in system behaviour were investigated during the afternoon, with a focus on two distinct stages: the fruit set stage in the first study and the grape harvest set stage in the second study.

Primarily, it is important to note that once again two grapevines were only used as a control method to introduce redundancy. Also, the time ranges which delimitate the afternoon are [17:31- 18:20] [hh:mm]. In Figures 5.9-5.11 are illustrated the analyses of the data collected from both the remote and in-situ sensors, being possible to observe the different crop stages and how the data oscillates for the various plant health parameters.

In the first study case, considering the thresholds of the second set of measurements, the air relative humidity (RH) parameter shows a gradual non-linear decrease throughout the afternoon. These values oscillate between [32-42] %. Comparatively with the first set of measurements, the thresholds decrease at a faster rate and its values are approximately 5% smaller, as seen in Figure 5.9. This occurs not only because the two sets of measurements were taken in different seasons, but mostly due to the evapotranspiration of the vineyards, which is more accentuated when a culture is growing its fruits than when is entering a drought season.

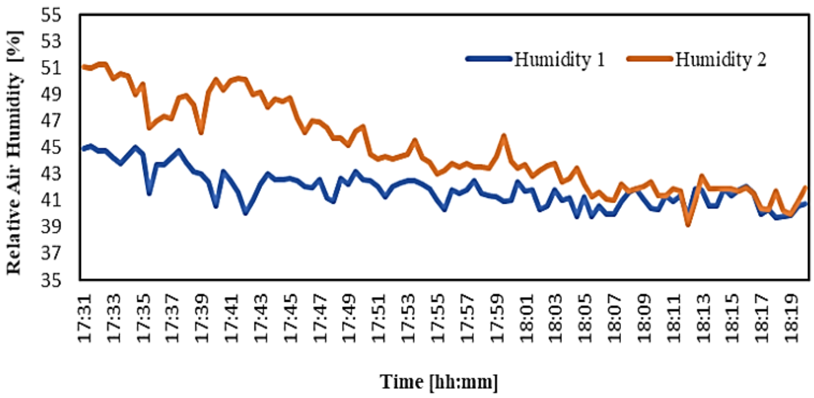


Figure 5.9 - Relative Air Humidity Variation during the Different Season Stages of the Crop; Humidity 1 – Fruit Set Stage; Humidity 2 – Harvest Set Stage

Following that, the second study case compares both crop sets, this time relating it to soil moisture, which can give us a complementary view of what was observed in Figure 5.9. As expected, due to the air relative humidity characteristics, the curves of both crop sets are directly dependent of their respectively studies. Plus, it can be observed in Fig 5.10 that grape harvest crop increases almost in a linear format, which can be explained by the low fluctuations of temperature during the afternoon in September, when compared to April.

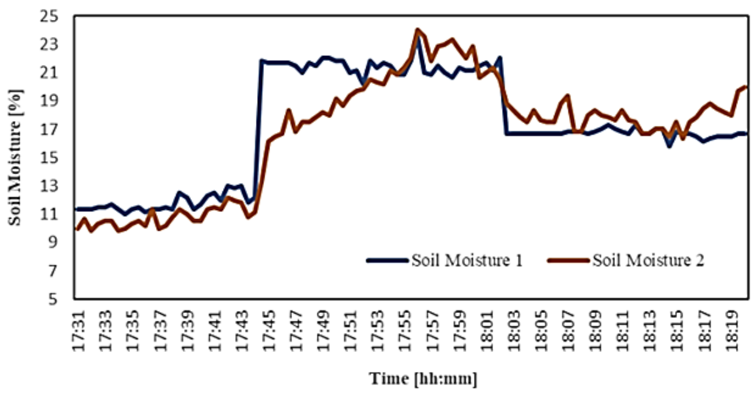


Figure 5.10 - Soil Moisture Variation during the Different Season Stages of the Crop; Soil Moisture 1 – Fruit Set Stage; Soil Moisture 2 – Harvest Set Stage

Finally, the third case illustrated in Figure 5.11 represents the comparison of the different crop stages for the soil temperature parameter. In fact, this data is directly proportional with the one registered in Figure 5.9 and inversely proportional to the previous curves in Figure 5.10, a conclusion that had already been taken in the last subsection. This happens since the soil temperature increases due to environmental favorable conditions – high temperatures – and the lack of irrigation and/or plants perspiration cycle, which has a higher rate in the development stage of the crop set – for example, the fruit crop set –, and lower rate in the ending stage of the crop set – the grape harvest crop.

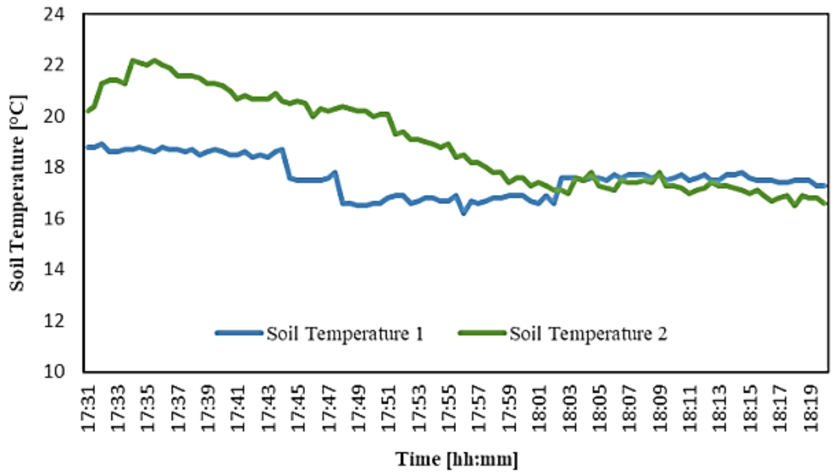


Figure 5.11 - Soil Temperature Variation during the Different Season Stages of the Crop; Soil Temperature 1 – Fruit Set Stage; Soil Temperature 2 – Harvest Set Stage

It's also noteworthy to mention that the grape harvest crop is more susceptible to thermal stress than the fruit set crop, since it has less mechanisms to defend itself from the excessive heat/cold received, as it can be seen in Figures 5.12-5.13.

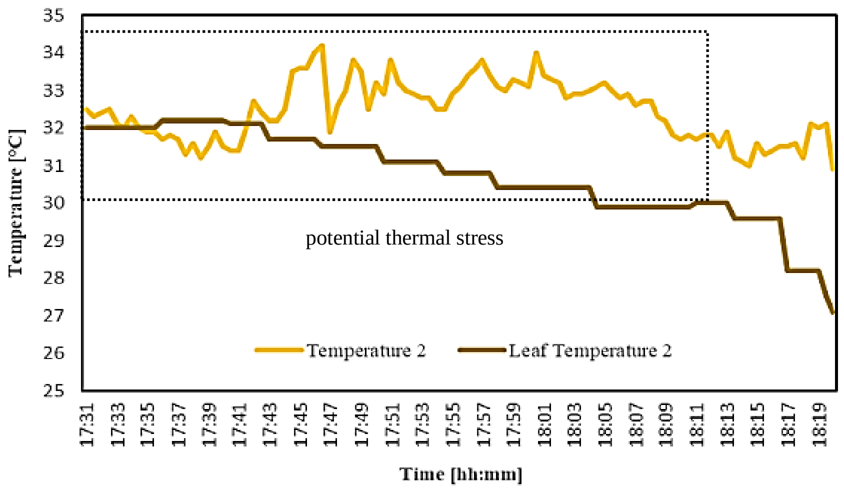


Figure 5.12 - Thermal Stress Assessment in the Harvest Set Crop Stage; Air Temperature 2 – Harvest Set Stage; Leaf Temperature 2 – Harvest Set Stage

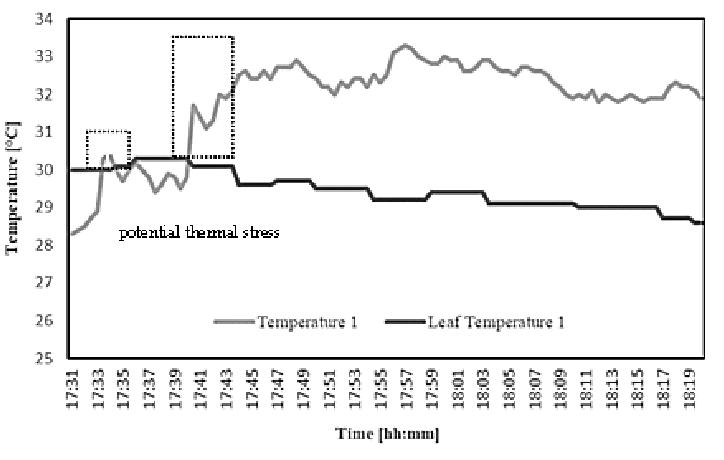


Figure 5.13 - Thermal Stress Assessment in the Fruit Set Crop Stage; Air Temperature 1 – Fruit Set Stage; Leaf Temperature 1 – Fruit Set Stage

5.4. Extra Set of Thermal Measurements (April)b

The tests for this extra set of measurements were conducted to give a new view of thermal stress in multiple crop cultures, as well as to visualize the differences between a healthy and an unhealthy vineyard. Thus, the measurements were conducted during the span of 5 minutes in each crop, to stabilize the sensors, and in the same region has the vineyards. The unhealthy vineyard chosen was encountered while doing a monitoring testing in the field. While the fruit trees in study were randomly chosen, being a peer tree, a fig tree, and a loquat tree.

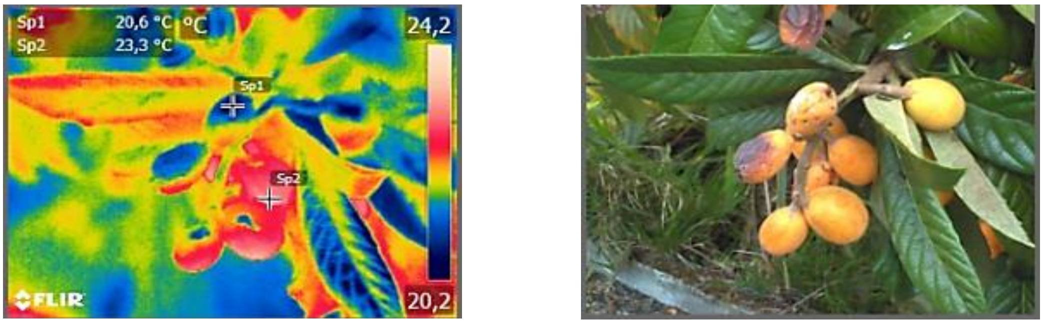
Due to the similarities between the tree fruits, and to avoid redundancy, the loquat tree was the chosen one to show some results, since it was also the only one with fruits already – blooming crop set. This was a selector factor, since it was crucial to visualize the influence of the fruit in the thermal images, as will be seen in Figures 5.14-5.15.

In Figure 5.14, it's shown that there's a big red area in the leaves – which indicates higher temperature values –, however, due to the direct sunlight exposition, these values cannot be considered with the veracity of the previous measurements, being one of the reasons why it was made an elliptical mean measurement. According to it, the average leaf temperature was 29,2°C, which indicates no thermal stress.

a) b)

Figure 5.14 - Loquat Tree Thermal Imaging; a) Leaf Analysis using Box Measurement Tools from FLIR Tools; b) Leaf Image Taken in the Afternoon

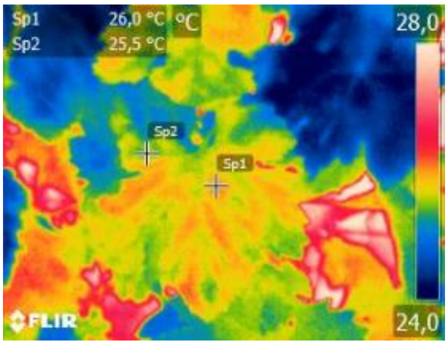
In the previous figure was already possible to see that the fruit was easily detected by the thermal camera, due to its heat emissivity, regardless of the direct exposition to the sun. Therefore, in Figure 5.15 it can be visualized with more detailed this difference, since the second shot was taken in the shadow. Additionally, there are rotten and ripe loquats, so it will be also possible to take some conclusions about the influence of fruits – and its state – in thermal imaging. The healthy fruit has an instant measure of 23,3°C, while the unhealthy fruit has 20,6°C. A variance of approximately 3°C that makes all the difference on the fruit state.



a) b)

Figure 5.15 - Loquat Thermal Imaging; a) Loquat Analysis using Point Measurement from FLIR Tools; b) Loquat Image Taken in the Afternoon

Additionally, an unhealthy vineyard – with the Grapevine leafroll disease – thermal image was collected, and it is represented in Figure 5.16. The grapevine leafroll disease (GLD), also known as grapevine leafroll-associated viruses (GLRaV), is a viral disease that affects grapevines, particularly in vineyards and grape-growing regions [58]. It is characterized by the appearing of reddish/purplish irregular spots near the leaf's nerves and edges, as it can be observed. The corresponding thermal imaging allows to analyse that the spots in the original picture correspond to the orange stain in the thermal capture – register 26°C, a difference of ±0.5°C when compared to a leaf area with no visible spots. This can be a sign that the virus is spreading through the leaves.



a)

b)

Figure 5.16 - Unhealthy Vineyard Thermal Imaging (GLD); a) Thermal Imaging using Point Measure from FLIR Tools; b) Unhealthy Vineyard Image Taken in the Afternoon

CHAPTER 6
Conclusion and Future Work

In this chapter will be presented some conclusions, going from the big picture until the more particular ones. Additionally, will be looking back to the limitations encountered while developing this master thesis work, and looking forward to the future work to be developed in the continuation of the presented dissertation.

Thermal Stress is one type of abiotic stress which commonly affect plants' health, leading to short growth and, consequently, poor productivity, or in extreme conditions, death. To detect the thermal stress, an IoT system was designed and implemented. Thus, the thermal stress in vineyards was monitored with the aim of developing a smart irrigation mechanism that can prevent or mitigate thermal stress and optimize water consumption. In fact, with the real-time monitoring of various parameters related to the plant and its environment, considering in-situ and remote sensing technologies, it was possible to extract data and establish correlations between the parameters in the study, such as air relative humidity, soil moisture, air/leaf/soil temperature and luminosity. These correlations are useful for demonstrating the importance of irrigation to decrease thermal stress caused by heat, and inversely to show the importance of sun luminosity in cold thermal stress. Additionally, the impact of air temperature on soil/leaf temperature at different levels is influenced by on-air relative humidity as well. The usage of different types of sensors allows the analysis and diagnosis of the vineyard’s health status. Thus, thermal stress conditions can be estimated in an accurate mode.

6.1. Conclusions

In a more particular view, the following closing points were crucial to inference the major conclusions and to respond to the research questions enunciated in the starting chapter of this dissertation, which guided the whole process of investigation and development of this project.

To begin, the combined use of in-situ and remote sensing technologies allows not only to assess thermal stress, but mostly to determine the underlying causes of it. Therefore, in-situ measurements are essential to connect the agricultural parameters values to its corresponding thermal images, coming from remote measurements, which is representative of the plant conditions.

Continuing, it is important to integrate the measurements from diverse plant characteristics such as air, soil, and leaves, to have a complete study of the system. In fact, the more parameters are presented, the completest the study will be. However, the basic parameters – such as humidity, temperature, and luminosity – already deliver accurate conclusions, which can even help predict the remaining parameters. Additionally, these main parameters sensors are affordable, highlighting a cost-effective IoT system.

Following, the preferred communication protocol for this type of smart agriculture practices is Wi-Fi, at least in the spectrum of this project system, due to its advantages as a standalone technology with simple processes, enabling real-time data transmissions and straightforward IoT devices integration – something crucial for this systems application – and without data loss, which ensures a consistent flow of information.

Also, focusing on the conclusions taken from the previous results chapter, the air relative humidity and the soil moisture values have an inversely proportional relation. While the air and leaf temperature are directly proportional, being inversely proportional to soil temperature. As it can be concluded, the values for soil parameters use to behave contrary to the values for air parameters.

In terms of thermal stress – having in consideration the environmental conditions of the region during the conduction of this study (warm summer) and the stage of the crop (blooming season) –, this factor was shown to be higher during the morning/afternoon due to high luminosity and/or high air temperature, causing heat stress which can be fought with the application of smart irrigation.

Additionally, the assessment of lower humidity and higher temperature on a culture in the harvest stage comparatively to the fruit set stage is explained by its lower rate of evapotranspiration. This means that the grape harvest crop is more vulnerable to thermal stress than the fruit set stage, since it has less mechanisms to regulate its own temperature – which is triggered by evapotranspiration.

To conclude, in thermal imaging, the presence of fruits is detectable, and its state can be identified by its color. For example, a reddish or white color usually means the fruit is ripe, while the color blue is associated with a rotten fruit.

6.2. Limitations

In retrospective, some challenges and limitations appeared along the path of this project development, which will be highlighted in the current subsection.

The camera used to acquire thermal imaging have limitations in terms of depth perception and spatial information compared to multi-camera setups which includes multispectral features. This is a limitation since it was supposed to be used parallelly a UAV drone, that unfortunately wasn't possible to acquire, due to external reasons.

6.3. Future Work

As part of future work, the points listed below represent all the improvements that would take this project to the next level.

- Employment of intelligent irrigation techniques as a solution to fight heat stress, for example.
- Acquisition of multispectral imaging through remote sensing technology, integrated via a UAV and UGV-based system, for introduction of multispectral imaging and multi-level measurements.
- Incorporation of sensors that measure soil conductivity, pH levels, and nutrient concentrations such as NPK, for example, on behalf of a completer study by managing more correlations between these metrics.
- Hybrid solution with LoRa to upgrade the communication protocol of the IoT system, for the cases where it's not possible to access Wi-Fi or where it's not necessary to have data real-time updates.
- Implementation of machine learning models – like thermal stress assessment based on classification algorithms – and use of embedded artificial intelligence to evaluate study cases at a higher level – to determine within a higher precision how to solve a thermal stress condition.
- Improvement of the mobile application by adding new functionalities – like statistical values display, and sign-up.

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APPENDIX

<u>Article: Vineyard Thermal Stress Assessment through the Combination of In-Situ and Remote Sensing Technology</u>

This article was accepted and presented in SAS (2023 IEEE Sensors Applications Symposium International Conference), a conference organized by Carleton University in cooperation with IEEE Instrumentation Measurement Society, at Ottawa, Canada.

The article acceptance e-mail, sent by the organization committee, is presented below.

[SAS 2023] Your paper #1570910797 ("Vineyard Thermal Stress Assessment through the Combination of In-Situ and Remote Sensing Technology")

S2

EDAS Conference Manager <help@edas.info> em nome de SA!

Para: Teresa Felício;

seg, 05/06/2023 20:57

Octavian Adrian Postolache <octavian.postolache@gmail.com>;

Mariana Jacob Rodrigues; Pedro Sebastião <pedro.sebastiao@lx.it.pt>

Dear Mrs. Teresa Felício:

Congratulations - we are pleased to inform your #1570910797 ("Vineyard Thermal Stress Assessment through the Combination of In-Situ and Remote Sensing Technology") has been accepted for presentation at 2023 IEEE Sensors Applications Symposium (SAS) and publication in the Conference Proceedings.

Also, the conference program, specifically the one containing the special session 7 – Smart Sensing and IoT for Precision Agriculture.

16:00 - 17:40
Special Session: Smart Sensing and IoT for Precision Agriculture
Session Chairs: Alessandro Depari and Juan Campo Rodriguez
Room: Theater

16:00
Assessment of Leaf Phosphorus for Multiple Crop Species using an Electrical Impedance Spectroscopy Sensor
Rinku Basak and Khan A Wahid (University of Saskatchewan, Canada)

16:15
LoRaVine: using LoRaWAN for smart vineyards microclimate monitoring
Davide Botturi, Alessandro Depari, Paolo Ferrari, Alessandra Flammini and Simone Pasinetti (University of Brescia, Italy); Matteo Soprani (Prospecto, Italy); Emiliano Sisinni (University of Brescia, Italy)

16:30
A Performance Comparison of Two Portable NIRS Technologies for Olive Oil Adulteration
Ana Soldado Cabezuelo, Jose Manuel Costa Fernandez, Candela Melendras García, Patricia Lozano Fernández, Juan C Campo Rodriguez, Marta Valledor, Alberto López Martínez and Francisco Ferrero Martín (University of Oviedo, Spain)

16:45
Wireless sensing in the woodlands: preliminary tests for LoRaWAN transmission in vegetated areas
Irene Cappelli (University of Siena, Italy); Giacomo Peruzzi, Alessandro Pozzebon and Edoardo Scarpel (University of Padova, Italy)

17:00
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Vineyard Thermal Stress Assessment through the Combination of In-Situ and Remote Sensing Technology

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***Abstract*— Precision viticulture is crucial for optimizing vineyard productivity and sustainability, particularly as climate change poses increasing threats to plant health. This work explores the development of an Internet of Things (IoT) system for the evaluation and mitigation of thermal stress in vineyards, an\ abiotic stress factor that can adversely affect growth and productivity. The proposed system combines in-situ sensing and remote sensing technologies, which also include the use of thermography imagery, to collect real-time data on parameters such as air relative humidity, soil moisture, air/leaf/soil temperature, and luminosity. Through the integration of different sensing channels, the study establishes correlations between the monitored parameters, enabling a more comprehensive assessment of vineyard health status with respect to thermal stress.**

Keywords*— *Precision Viticulture, Internet of Things (IoT), Thermal Stress, Abiotic Stress, In-Situ Sensing, Remote Sensing, Thermography Imagery

I. Introduction

The integration of IoT in smart agriculture enables the implementation of diverse advanced techniques, including precision farming, such as smart irrigation, and automated equipment management. Precision farming utilizes sensors and other data-gathering tools to collect information on soil characteristics, plant health, and microclimate conditions. Subsequently, this data is processed and analyzed, allowing targeted interventions, such as precise application of fertilizers, pesticides, and irrigation, customized to the specific requirements of each field area.

Over the past two decades, there has been a noticeable increase in utilizing remote sensing technologies to collect data on various agricultural parameters. The combination of remote sensing with proximal sensing has proven to be highly efficient, which is why precision agriculture greatly benefits from the integration of these two technologies. By relying on an Internet of Things (IoT) framework, farmers gain access to crucial data that enables them to make well-informed decisions and enhance their agricultural practices simultaneously.

The drive for advancements in agriculture stems from the necessity to enhance food production and address the challenges presented by climate change. By harnessing the potential of IoT technologies, smart agriculture systems have the capacity to revolutionize farming practices, resulting in increased crop yields, minimized environmental impact, and overall improvements in the agricultural industry. Similarly, smart viticulture focuses on enhancing efficiency and productivity through the adoption of innovative, sustainable, and automated technologies. An example of this is the assessment of the vineyards' response to biotic and abiotic stress. This is accomplished by monitoring different plant health parameters, including air/leaf/soil temperature, soil moisture, relative air humidity, leaf color and luminosity.

The plants' growth is influenced by several abiotic environmental factors, such as light (intensity and duration), water (soil availability and humidity), soil nutrient content, temperature, and the presence of toxins like heavy metals and salinity. When these abiotic factors deviate from their normal ranges, plants may undergo adverse biochemical and physiological effects [1].

To address this issue, this paper aims to investigate the effectiveness of combined technologies – In-Situ and Remote Sensing – in assessing thermal stress in vineyards. In order to achieve this, proximal measurements were collected using a set of smart sensors, which were divided into two separate sensor nodes: one fixed to the soil surface and another mobile node to gather information on leaf conditions, resulting in a versatile approach. Additionally, a portable thermographic imager was employed, enabling a comprehensive analysis of the vineyard's conditions, and enhancing the robustness of the IoT system. The sensory measurements were conducted on two different vines within the same vineyard to introduce redundancy. Furthermore, measurements were taken during three time periods throughout the day – morning, afternoon, and night – to study thermal stress under various conditions. One of the primary objectives is to establish correlations between the vine's health status and the air conditions in the surrounding environment, thus gaining a better understanding of thermal stress conditions. This valuable information is then utilized to implement intelligent irrigation mechanisms aimed at preventing such constraints.

The structure of this paper is organized as follows: Section II provides additional perspectives on the problem under investigation and presents related works. Section III discusses the materials and methods employed in this study. Subsequently, Section IV presents and extensively discusses the results. The paper concludes with Section V, which outlines the conclusions drawn from the study and discusses potential avenues for future research.

II. Related Work

When exploring IoT systems specifically designed for monitoring plant stress through thermal imaging or other remote and in-situ sensing measurements, there are several approaches available for encompassing, processing, and extracting data from these devices. Among the multitude of designs, the following ones stand out as noteworthy examples.

Beginning with thermography as a key component, notable studies by Stoll et al. [2], Jones et al. [3], and Leinonen et al. [4] have employed it as a means to measure leaf temperature for diagnosing and evaluating plant stress. The study in [2] had into consideration the solar exposure factor and made the measurements of leaf characteristics in shaded areas, while the authors in [3] expanded on this by combining thermography with spectral sensing analysis to mitigate errors introduced by multiangular solar radiation and irregular backgrounds. Similarly, the study in [4] used visible imagery for the same purpose. However, these authors acknowledged the limitations associated with relying solely on a single method when working with thermography imagery.

In this paper's particular case, luminosity and color temperature were among the parameters required for the study. Consequently, all measurements were conducted under normal ambient conditions, disregarding solar exposure. Furthermore, this IoT system not only incorporates remote sensing technologies but also in-situ sensing capabilities, which helps mitigate errors introduced by radiation. This approach provides an additional perspective to the project by enhancing its robustness and redundancy.

On the other hand, it is worth noting that while this paper's experiment is conducted in a vineyard, plant thermal stress can occur in any type of culture, as highlighted by Burke et al. [5] and Waqas et al. [6]. These authors conducted their investigation in cotton and maize crops, respectively, and emphasized the importance of establishing efficient measurement techniques accordingly. Similarly, Mendes et al. [7] and Dhillon et al. [8], like this paper, employed a combination of remote and "in-situ" measurements. However, both Mendes's and Dhillon's IoT systems had limitations when it came to sensors measuring soil characteristics. This occurs because their primary focus is on "in-situ" sensing, using sensors that measure air and leaf characteristics. Given their emphasis is predominantly on detecting and diagnosing diseases. Nevertheless, it is crucial to acknowledge the significance of integrating measurements from diverse plant characteristics such as air, soil, and leaves. This integration forms the foundation of our paper, emphasizing the importance of a complete system. Also, the fusion of in-situ and remote sensing technology emerges as another key aspect introduced in our research.

III. System Description

A smart IoT-based vineyard monitoring and analysis system was successfully designed and implemented. The system incorporates different technologies selected to collect, process, and analyze data concerning the vineyard environment. This includes parameters such as air and soil temperature, relative humidity, and soil moisture. Additionally, vinery-specific characteristics like leaf color and leaf temperature are measured using in-situ and remote sensing solutions, respectively.

The system includes advanced thermographic imaging, using a FLIR E60 camera, with data analysis conducted through the FLIR Tools Software and Microsoft Excel plugin Data Streamer. This combination enables efficient and accurate monitoring of vineyard conditions and detection of thermal stress in plants. The data collected by the microcontrollers is initially stored in a local database on a portable computer, as the information is transmitted offline. However, the intention is to later store this data in a cloud-based MySQL database. The distributed measurement system is designed with flexibility and modularity in mind, achieved through the use of fixed and mobile sensor nodes. This approach ensures optimized data collection and aids in the early detection of potential issues, ultimately contributing to the overall health and productivity of the vineyard. To accomplish this, two microcontrollers, corresponding to each node, were chosen as the preferred solution. The architecture of the implemented IoT system is depicted in Fig. 1*.

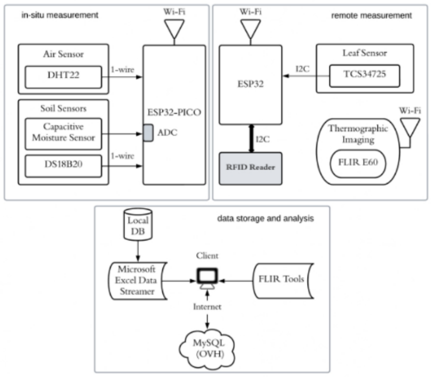


Fig. 1. System's Architecture: Hardware and Software Components

In the realm of agriculture, the utilization of different communication protocols, such as RFID, Wi-Fi (short-range), or LoRa (long-range), can provide numerous advantages in terms of data transmission and overall farm management. This is because relying solely on USB is neither scalable nor practical in agricultural fields. In fact, an alternative solution involving RFID is currently being explored to store all the plant health parameters data, effectively replacing the conventional USB connection.

This section presents an in-depth overview of the primary components of the plant thermal stress monitoring system. It begins by outlining the hardware components and their implementation, providing detailed information on their integration into the system. The section then processes to explains the thermographic imaging techniques employed. Finally, the software elements utilized in the development and analysis of the system are discussed.

A. Sensors

This subsection focuses on the physical layer of the system and provides a description of the sensors used in this IoT system. These sensors belong to the branch of in-situ sensing technology.

To effectively monitor the vineyard parameters, it is crucial to consider factors such as air temperature and air relative humidity that may give insights about the soil moisture. To assure air parameters measurement a DHT22 1-wire sensor was included in the system. This 1-wire digital sensor is based on a thermistor and a capacitive humidity sensor to measure the temperature and RH of the air and can transmit this information to a microcontroller, such as the ESP32-PICO. The DHT22 sensor has high accuracy and reliability, measuring humidity in a range of 0-100% with an accuracy of ±2%, and temperature in a range of -40°C to 80°C with an accuracy of ±0.5°C [9].

The soil characteristics measurement is based on M5Stack capacitive moisture sensor. Additionally, a waterproof digital soil temperature sensor called DS18B20 is utilized.. The measuring electrodes are based on capacitive design, which helps to avoid the issue of corrosion during use, by comparison with two resistive moisture sensors [10]. The DS18B20 also has an accuracy of ±0.5°C over a temperature range of -10°C to +85°C and a single wire interface which allows a reduction in the system's complexity, with lower power consumption [11].

Furthermore, the previously described sensors are part of a sensor node fixed at the soil level. In contrast, the sensors which will be described next are incorporated into a mobile sensor node. This distinction is made in order to optimize data collection since the first node is used to measure soil and air characteristics, whereas the second node is used to measure leaf properties. Each one of the nodes has its own microcontroller in order to increase efficiency, allowing synchronism between the data collected from soil/air sensors and the one from leaf sensors. This data is next stored in a local database located on a portable computer, communicating through a USB cable, due to the lack of Wi-Fi connection caused by the vineyard location.

To monitor the plant's exposure to light and accurately measure the RGB color of its leaves, a TCS34725 color sensor was implemented to measure the following parameters: RGB code, color temperature and luminous flux. The TCS34725 is a digital sensor and uses the I^2C communication protocol, being highly accurate in identifying a wide spectrum of colors. Its mode of operation involves capturing the intensity of red, green, blue, and clear (unfiltered) light with photodiodes and subsequently converting these measurements into digital data [12]. However, it is important to notice that the sensor's sensitivity is quite reduced because of light absorption, and as a result, this parameter was not considered in this particular study. Also, the redundancy added by this RGB color parameter doesn't compensate the error introduced.

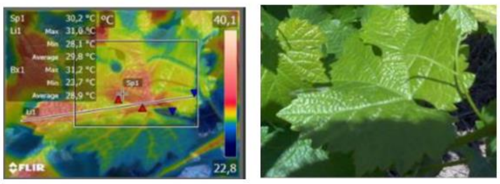
B. Thermographic Imaging using FLIR Tools Software

The current section focuses on describing the technology used and explaining the imaging processing behind the developed system. The remote sensing technology based on portable thermographic camera, FLIR E60 was considered. Some characteristics of used camera are high thermal sensitivity of 0.05°C, for temperature range of -20°C to 650°C, and a 320 x 240-pixel resolution infrared detector, used to measure leaves temperature. Other notable features of it include a 3.5-inch color LCD touchscreen display, interchangeable lenses with auto-calibration, and a laser pointer for easier targeting. The camera also has the ability to transfer images via Bluetooth and Wi-Fi connectivity, offering multiple measurement modes and analysis tools for image interpretation [13].

Furthermore, the FLIR E60 camera is accompanied by compatible software denominated FLIR Tools, which was used for the analysis and reporting of thermal imaging data, as well as to export data to Microsoft Excel for further analysis. To ensure consistency and minimize variables and errors in the analysis, all images were captured at the same distance and angle. The baseline parameters for the camera in terms of emissivity and distance are, respectively, 0,98 and 0,50 cm.

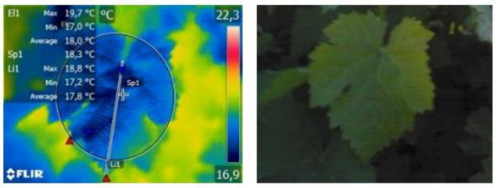
The image analysis process had in its core three types of processes: line, ellipse, and box measurement tools. The line tool assesses temperature gradients by measuring the temperature profile along a straight line, revealing hot or cold spots and temperature changes between two points. The ellipse tool focuses on round or curved objects by measuring temperature distribution within an elliptical shape, providing quantitative analysis for non-rectangular areas. The box tool evaluates temperature variations across flat or rectangular surfaces by defining a rectangular region of interest, displaying minimum, maximum, and average temperatures within that area. Therefore, these tools work together to provide a comprehensive understanding of temperature patterns and anomalies, enabling users to identify underlying issues and areas of concern in thermal images.

The Fig. 2 and Fig. 3 illustrate two examples from this paper's study of imaging analysis conducted using FLIR Tools Software. These examples capture thermal images taken during the afternoon and night periods, respectively.



a) b)

Fig. 2. Afternoon Thermal Imaging; a) Leaf Analysis using Linear and Box Measurement Tools from FLIR Tools; b) Leaf Image Taken in the Afternoon;



a) b)

Fig. 3. Night Thermal Imaging; a) Leaf Analysis using Linear and Ellipse Measurement Tools from FLIR Tools; b) Leaf Image Taken at Night;

C. Data Analysis

Microsoft Excel serves as a valuable instrument for visualizing and examining information. The Data Streamer add-on facilitates importing, displaying, and evaluating real-time data from external devices, including microcontrollers such as ESP32-PICO. The bridge between the two software is straightforward because the board programmed with the Arduino IDE uses a C compiler.

Moreover, the ADC output values of the soil moisture sensor were not initially calibrated. Therefore, a calibration process was conducted to establish a linear unit measure equivalent to a percentage. First, the ADC values were converted into voltage values. Subsequently, the calibration process considered the levels of maximum saturation and maximum erosion, resulting in a range between [1500-2100]. To simplify and approximate a linear relation, a formula (1) was developed and employed for converting the voltage output (x) from the sensor into a percentage (y).

$$y = \lfloor -137x + 0{,}5 \rfloor + 351 \tag{1}$$

Posteriorly, all the information regarding air relative humidity, air/leaf/soil temperature, soil moisture and luminosity had to be analyzed having as baseline their thresholds. These metrics classify the vineyard in the study as in a stress state or not, and which factor(s) are causing it. These limit metrics are the following: for leaf temperature, the temperature should be between [15°C -30°C] [14], while for soil temperature the [10°C -24°C] range, it's more suitable [15]. The luminosity should not be higher than 25000 [16], and depending on the air relative humidity values, the air temperature should not be greater than 32°C (high humidity) or 23°C (medium humidity) [17]. The flowchart represented in Fig. 4 illustrates the thermal stress analysis procedure.

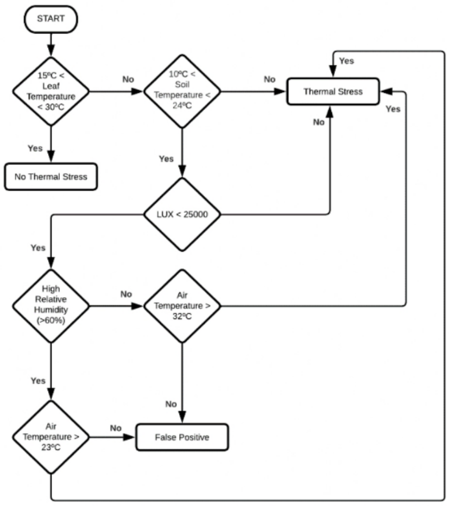


Fig. 4. Thermal Stress Analysis Procedure Flowchart

To summarize, the algorithm starts by comparing the leaf temperature to its reference threshold, which leads to two possible outcomes: either there is no thermal stress, or the flow continues. The leaf temperature was identified as the primary parameter in this analysis, as it plays a crucial role in determining plants' thermal stress. Following the charts flow, the remaining environmental health parameters are compared to their respective baseline threshold. Accordingly, depending on the path taken, it can be concluded that the plant is indeed under thermal stress and what parameter is causing it, or that it was a false positive. The algorithm for estimating thermal stress was implemented using C programming language and Arduino IDE on the ESP32-PICO microcontroller.

IV. Experimental Results and Discussion

The field experiments were conducted at "Quinta da Lagoalva de Cima" [18], a prestigious Portuguese farm located in Alpiarça, Santarém – with the corresponding coordinates 39°17'45.53"N, 8°33'46.62"W. These measurements were taken in April 2023, specifically during the fruit set stage of the grapevines. The chosen vineyard was of the variety Sauvignon Blanc – Vitis Vinifera – and was planted in clayish soil. It is worth mentioning that prior to the commencement of this experiment, the vineyard had undergone three sets of treatments. In Table I are presented all the specifications related to the conditions in which the monitoring took place for each of the grapevines considered in the study, such as meteorologic, spatial and time features.

TABLE I. INFORMATION OF EXPERIMENTAL ENVIRONMENT AND AMBIENT CONDITIONS

		Vineyard 1	Vineyard 2
Time	Morning	[12:48:56-13:16:26]	[13:28:55-13:45:46]
	Afternoon	[17:42:52-18:16:43]	[18:24:38-18:41:28]
	Night	[20:33:03-20:50:56]	[20:51:16-21:14:59]
Coordinates		39°17'52.6"N, 8°33'20.9"W	39°17'52.6"N, 8°33'20.7"W
UV Radiation		UV8	
Air Temperature		29,2°C	
Air Relative Humidity		55%	

To evaluate the system's performance, experiments were conducted in a vineyard, focusing on two specific grapevines, throughout the day. These measurements aimed to test a hypothesis of how the system should behave during the three moments of the day. The ESP32-PICO microcontroller was programmed to transmit sensory data to the portable computer at regular intervals of every 40 seconds since this type of data has a high relevance due to its quick variation.

Firstly, it is important to note that two grapevines were used as a control method to introduce redundancy. However, comparing them is not relevant due to the closely aligned values they produced. Also, the time ranges which delimitate morning, afternoon and night are, respectively, [12:48-13:45], [17:42- 18:41] and [20:33- 21:14] [hh:mm]. In Fig. 5-7* are represented analyses of the data collected from both the remote and in-situ sensors throughout the day, being possible to observe the distinct stages of the day and how the data oscillates for the various plant health parameters.

In the first case, considering the aforementioned thresholds, the air relative humidity (RH) parameter shows a gradual increase throughout the day. During the morning, it ranges between 35%-50%, 40%-50% in the afternoon and 50%-70% at night. Contrarily, soil moisture decreases at a faster rate and on a non-linear scale until the afternoon, measuring values between 10% and 50%, while at night increases until reaching 30%, as seen in Fig. 5.

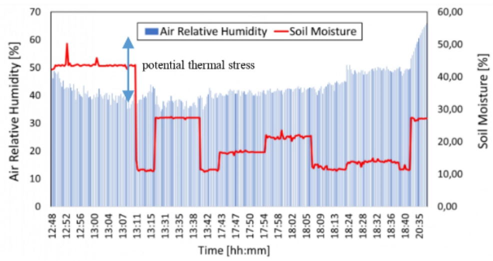


Fig. 5. Relation between Air Relative Humidity and Soil Moisture during the Different Stages of the Day

On the other hand, the second case involves three different variables, all related to temperature. As expected, due to the surface temperature characteristics, air and leaf temperature are similar and behave in a similar way, decreasing their values in the course of the day. In contrast, soil temperature demonstrates an opposing trend, steadily increasing and maintaining a relatively stable range of values.

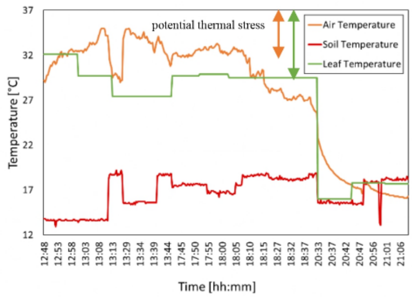


Fig. 6. Air/Soil/Leaf Temperature Variation during the Different Stages of the Day

At night, the values of Air RH are high since they surpass the 60% line. However, its corresponding temperature is below the 23°C mark, leading us to conclude that there was no thermal stress during this moment of that exact day. On the other hand, during the morning and afternoon moments, the outputs for Air RH are between [40%-60%] which means the plant could be experiencing thermal stress if the air temperature goes above 32°C. As observed in the temperature chart, it is a condition that is met, especially after 13:00 until 18:00, approximately – the highest heat period. Related to leaf temperature, whose limit range is between [15°C-30°C], during the same period, thermal stress is also observed. Contrarily, for the soil temperature, the threshold is not surpassed, meaning that soil characteristics are not a reason that causes the vineyard to experience thermal stress.

It is also noteworthy that the green liner representing the leaf's temperature values may exhibit slight errors in its outputs due to various factors, being underlined by the sun's orientation and the solar radiation absorbed. Therefore, when considering the temperature thresholds, a deviation of approximately ±1°C should be considered [2-3].

Finally, the third case illustrated in Fig. 7 represents the variation in luminosity for different moments of the day. It can be concluded that due to the surpassing of the 25000 LUX threshold in the morning stage, there is a higher probability to exist thermal stress related to the heat in that time period when compared to the others, which was confirmed with the previous data.

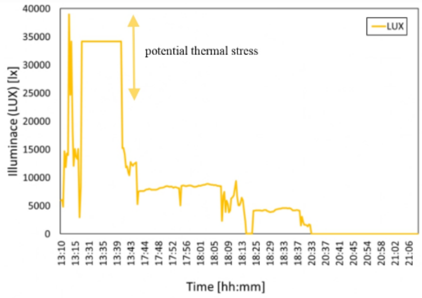


Fig. 7. Luminosity Variation for the Different Moments of the Day

These results there indicates that is an inverse relationship between relative humidity and air temperature, as well as between soil moisture and temperature. This correlation is depicted in Fig. 8 and 9 and has been previously stated by Stull et al. [19].

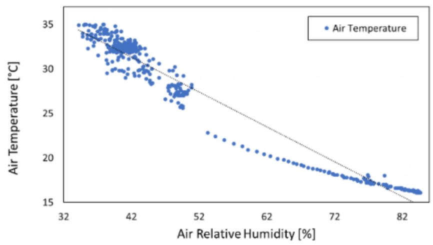


Fig. 8. Correlation between Air Relative Humidity and Air Temperature

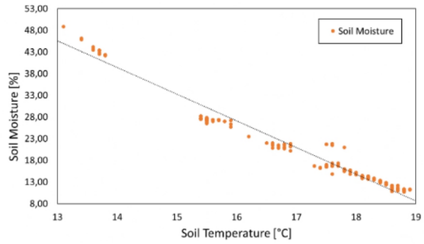


Fig. 9. Correlation between Soil Temperature and Soil Moisture

Taking this relationship into account can enhance the accuracy of measurements and predictions related to various environmental conditions, including heat indexes. This can be achieved through the utilization of mathematical models or algorithms, as acknowledged by Anderson et al. [20].

The proposed system was designed to incorporate both "in-situ" and remote measurements, aiming to provide enhanced reliability and minimize errors that may arise from relying solely on individual technologies. The leaf's temperature is one of the principal characteristics when assessing thermic stress. Thermography on its own can detect whether the plant is experiencing thermal stress, but it does not reveal the underlying causes. In this case, the inclusion of sensors complements the study by offering robustness and effectiveness on a smaller scale. Table II represents a correlation matrix showcasing the interrelationships among the significant parameters considered in this study.

TABLE II. CORRELATION MATRIX OF ALL MEASURED PLANT HEALTH PARAMETERS (ARH: Air Relative Humidity; AT: Air Temperature; LUX: Luminosity; ST: Soil Temperature; SM: Soil Moisture; LT: Leaf Temperature)

	ARH	**AT**	**LUX**	**ST**	**SM**	**LT**
ARH	1,000					
AT	-0,973	1,000				
LUX	-0,541	0,566	1,000			
ST	0,137	-0,195	-0,070	1,000		
SM	-0,164	0,227	0,028	-0,988	1,000	
LT	-0,878	0,896	0,312	-0,078	0,144	1,000

V. Conclusion and Future Work

Thermal Stress is one type of abiotic stress which commonly affect plants' health, leading to short growth and, consequently, poor productivity, or in extreme conditions, death. To detect the thermal stress, an IoT system was designed and implemented. Thus, the thermal stress in vineyards was monitored with the aim of developing a smart irrigation mechanism that can prevent or mitigate thermal stress and optimize water consumption.

In fact, with the real-time monitoring of various parameters related to the plant and its environment, considering in-situ and remote sensing technologies, it was possible to extract data and establish correlations between the parameters in the study, such as air relative humidity, soil moisture, air/leaf/soil temperature and luminosity. These correlations are useful for demonstrating the importance of irrigation to decrease thermal stress caused by heat, and inversely to show the importance of sun luminosity in cold thermal stress. Additionally, the impact of air temperature on soil/leaf temperature at different levels is influenced by on-air relative humidity as well.

The usage of different types of sensors allows the analysis and diagnosis of the vineyard's health status. Thus, thermal stress conditions can be estimated in an accurate mode.

As part of future work, the acquisition of multispectral imaging through remote sensing technology is being considered, which will be integrated with a UAV-based system. Moreover, incorporating sensors that can measure soil conductivity, pH levels, and nutrient concentrations such as NPK would be a valuable enhancement of the system. Models and embedded artificial intelligence implementation will be considered as part of future precision agriculture for vineyards.

Acknowledgement

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