ANDRE MIRANDA MAIA

ENHANCING AGRICULTURE MONITORING THROUGH ANOMALY DETECTION OF IOT SENSOR DATA

UNIVERSIDADE DO ALGARVE
Instituto Superior de Engenharia
2024

ANDRE MIRANDA MAIA

ENHANCING AGRICULTURE MONITORING THROUGH ANOMALY DETECTION OF IOT SENSOR DATA

Master's Degree in Electrical and Computer Engineering

(Specialty in Power and Control Systems - SEC)

Work carried out under the guidance of:

Pedro Jorge Sequeira Cardoso

Jorge Filipe Leal Costa Semião

UNIVERSIDADE DO ALGARVE

Instituto Superior de Engenharia

2024

ENHANCING AGRICULTURE MONITORING THROUGH ANOMALY DETECTION OF IOT SENSOR DATA

Declaration of authorship of the work

I hereby declare to be the author of this work, which is original and unpublished. Authors and works consulted are properly cited in the text and included in the reference list.

(ANDRE MIRANDA MAIA)

Dedicated to my wife,
Ana Paula Cunha Maia,
& my daughter,
Aurora Cunha Maia

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my advisors, Professors Pedro J. S. Cardoso and Jorge Filipe Leal Costa Semião, for their unwavering support, guidance, and insightful advice throughout the research and writing of this thesis. Their expertise and encouragement have been invaluable in every step of this journey, and their dedication to my academic and professional growth has been deeply appreciated. I also wish to extend my sincere thanks to the Instituto Superior de Engenharia (ISE) for providing an enriching academic environment and access to specialized knowledge that has been crucial for my development in this field. The learning opportunities and resources offered at ISE were instrumental in shaping both my research and my future career path. My heartfelt appreciation goes to the ATTENTIA project team, which played a central role in this research. The contributions and insights from this project have significantly enhanced the scope and impact of my work. I would also like to acknowledge the Visual Computing Lab team for their camaraderie, knowledge sharing, and positive work environment.

Finally, I would like to express my deepest gratitude to my wife, Ana Paula Cunha Maia, for providing me with unwavering support and encouragement throughout this journey. Her love, patience, and belief in me have been fundamental in helping me achieve this milestone. I also extend my heartfelt thanks to my parents, my brother, and my sister-in-law for their steadfast support and for being by my side every step of the way.

To my colleagues, your support and motivation have been invaluable throughout this journey, and I am deeply grateful for your presence.

RESUMO

Este trabalho propõe um aprimoramento no monitoramento agrícola por meio da detecção de anomalias utilizando dados de sensores IoT, aplicados especificamente em plantações de citros. O projeto investiga a integração de redes de sensores e técnicas de aprendizado de máquina para monitorar variáveis ambientais críticas, como evapotranspiração e a resistência interna do tronco das plantas. Ao incorporar dados meteorológicos da IPMA e de sensores instalados diretamente nas árvores, foi desenvolvido um sistema de monitoramento com o objetivo de detectar anomalias no uso da água e identificar reações anômalas das plantas em meio a condições ambientais adversas. Este sistema está atualmente em fase de coleta intensiva de dados, sendo que, no futuro, esses dados serão utilizados para retreinar os algoritmos de aprendizado de máquina, otimizando os processos de irrigação e minimizando o desperdício de recursos hídricos. Uma parte central do projeto foi a criação de um *dashboard* interativo, projetado para facilitar o acesso em tempo real às informações coletadas e processadas. Esse *dashboard* exibe dados ambientais e agrícolas, incluindo indicadores chave como evapotranspiração e consumo de água, fornecendo *insights* valiosos para os agricultores. O *dashboard* foi desenvolvido com tecnologias modernas de visualização de dados, permitindo personalização por localização geográfica e condições climáticas, e oferecendo uma plataforma prática para o gerenciamento de operações agrícolas em diversas regiões de Portugal. Os resultados preliminares indicam que o uso de algoritmos de detecção de anomalias é promissor para entender os padrões e as reações das árvores cítricas diante de mudanças climáticas, demonstrando potencial significativo para melhorar a eficiência no manejo da irrigação. Esse avanço pode representar uma contribuição importante para a sustentabilidade das operações agrícolas, reduzindo o desperdício de água e aumentando a resiliência das plantações em face das condições ambientais variáveis.

ABSTRACT

This work proposes an enhancement in agricultural monitoring through anomaly detection using IoT sensor data, applied specifically to citrus plantations. The project investigates the integration of sensor networks and machine learning techniques to monitor critical environmental variables, such as evapotranspiration and internal trunk resistance of plants. By incorporating meteorological data from IPMA and sensors installed directly on the trees, a monitoring system was developed to detect anomalies in water usage and identify anomalous reactions of plants to adverse environmental conditions. The system is currently in an intensive data collection phase, with plans to use these data in the future to retrain machine learning algorithms, optimizing irrigation processes and minimizing water resource waste. A central component of the project was the creation of an interactive dashboard, designed to provide real-time access to the collected and processed information. This dashboard displays environmental and agricultural data, including key indicators such as evapotranspiration and water consumption, offering valuable insights for farmers. The dashboard was developed using modern data visualization technologies, allowing customization by geographic location and weather conditions, providing a practical platform for managing agricultural operations across different regions of Portugal. Preliminary results indicate that the use of anomaly detection algorithms shows promise in understanding the patterns and reactions of citrus trees in the face of climate changes, demonstrating significant potential to improve irrigation management efficiency. This advancement may represent an important contribution to the sustainability of agricultural operations by reducing water waste and increasing the resilience of plantations in response to changing environmental conditions.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

ACRONYM	Meaning
ACF	Autocorrelation Function
AES	Advanced Encryption Standard
CSS	Chirp Spread Spectrum
DSS	Decision Support System
DSSS	Direct Sequence Spread Spectrum
ETc	Crop Evapotranspiration
ETo	Reference Evapotranspiration
FAO	Food and Agriculture Organization
GSM	Global System for Mobile Communications
IPM	Integrated Pest Management
IPMA	Instituto Português do Mar e da Atmosfera (Portuguese Institute for Sea and Atmosphere)
IoT	Internet of Things
Kc	Crop Coefficient
LoRaWAN	Long Range Wide Area Network
LPWAN	Low Power Wide Area Network
MC	Moisture Content
NB-IoT	Narrowband Internet of Things
OFDM	Orthogonal Frequency-Division Multiplexing
OWM	OpenWeatherMap
RF	Radio Frequency
SC-FDMA	Single Carrier Frequency Division Multiple Access
TDMA	Time Division Multiple Access
WAN	Wide Area Network
Wi-Fi	Wireless Fidelity
WLAN	Wireless Local-Area Network
WPA	Wi-Fi Protected Access
WPAN	Wireless Personal Area Network

1

INTRODUCTION

This Master of Science project is centered on developing a methodology to analyze IoT sensor data within the agricultural sector, focusing particularly on citrus plantations. This endeavor forms a part of the ATTENTIA project, which seeks to innovate in the monitoring of citrus orchards using an integrated system of IoT sensors and mobile robots. The primary goal of this project is to harness machine learning techniques, specifically anomaly detection, namely to detect irregular patterns in the data.

The importance of this project stems from its potential to significantly enhance agricultural practices through the precise monitoring of critical variables such as the growth of fruits, the efficiency of irrigation systems, and overall plant health. By implementing an IoT sensor network, along with the integration of data from various APIs and databases, this project aims to establish a robust data collection framework. The sensor network includes the monitoring of a critical variable in the citrus plant, the resistivity of the internal part of the trunk, which gives some knowledge about the quantity of fluids that are being transferred inside the plant. All this data will serve as the backbone for developing and refining machine learning models that can effectively identify anomalies in the plant plasticity and plant response to ambient changes, but also to forecast key agriculture parameters, such as evapotranspiration.

1.1 SCOPE AND OBJECTIVES

The work presented in this project will specifically focus on the phases of data acquisition, storage, retrieval, and analysis. Furthermore, it will delve into the development of machine learning models tailored for anomaly detection. The initial phase of the thesis will involve a comprehensive review of the current state of the art in machine learning techniques applicable to anomaly detection. Following this theoretical exploration, practical methods will be formulated, and computational tests will be conducted to pinpoint anomalies within the gathered data. The project will focus on monitoring key environmental variables such as evapotranspiration rates, and the data collected will be used to support improved decision-making in agricultural practices.

This project not only aims to contribute to the academic field by advancing the application of machine learning in agriculture but also seeks to offer tangible improvements in the monitoring and management of citrus plantations, thus supporting the broader goals of the ATTENTIA project.

Through this research, the project aspires to demonstrate the efficacy of integrating advanced data analysis techniques in enhancing the sustainability and productivity of agricultural operations. The detailed objective aimed in this project are described below:

- Bibliographic review of works/projects/technologies relevant to the investigation of the proposed topic of study.
- Calculation of reference evapotranspiration and crop evapotranspiration, based on environmental data available from IPMA platform [1].
- Calculation of reference evapotranspiration and crop evapotranspiration, based forecast environmental data available from OWM platform [2].
- Implementation of an experimental sensor network in one orange tree targeted for study in Bela Curral.
- Implementation of a dashboard that will support the control of the citrus irrigation process across the entire Portuguese territory, which will be expandable to other locations available in database.
- Implementation and analysis of a machine learning algorithm with the main objective of suggesting improvements in the irrigation process of citrus trees. The main input data for this algorithm includes:
  - Environmental data from the IPMA platform.
  - Crop evapotranspiration values calculated using the Penman Monteith method [3].
  - Data collected from the internal trunk resistance sensor.
  - Irrigation event data.

In achieving these objectives, the project aims to provide a comprehensive framework for precision agriculture, leveraging modern technologies and data-driven approaches to optimize irrigation practices, thereby increasing the overall efficiency and sustainability of citrus production.

1.2 PROJECT CONTEXT

This Master of Science project is part of the ATTENTIA project, which focuses on the development of innovative monitoring systems for citrus orchards using IoT sensors and mobile robots. The primary goal of the ATTENTIA project is to enhance the efficiency and sustainability of citrus farming by leveraging real-time data collection and advanced analysis techniques. These IoT sensors monitor key environmental variables such as soil moisture, temperature, and humidity, allowing for a precise understanding of the agricultural environment. This data is then used to optimize irrigation and resource management, ensuring that citrus plants receive the necessary care while minimizing waste. By integrating mobile robots and IoT technology, the ATTENTIA project aims to create a system that automates and improves the monitoring process, reducing the need for manual interventions. This approach will help farmers detect anomalies, such as irregularities in water usage or potential pest infestations, early on, ensuring a more efficient response to these issues.

In summary, the ATTENTIA project contributes to the advancement of precision agriculture by developing and implementing smart monitoring solutions for citrus orchards, improving overall crop management and sustainability [4].

1.3 DISSERTATION OVERVIEW

The current chapter has introduced the main theme of this project report, presenting its scope, objectives, and primary contributions. The report explores the development and application of machine learning techniques, specifically anomaly detection, to enhance agricultural monitoring, with a focus on citrus agriculture.

Chapter 2 provides an in-depth literature review, surveying the state of the art in sensor technology, IoT communication protocols, and the crucial role of reference evapotranspiration (ETo) in precision agriculture. It outlines the importance of meteorological data platforms and Decision Support Systems (DSS) in improving water management practices and irrigation efficiency. The chapter also explores the integration of various IoT protocols, such as LoRaWAN and NB-IoT, into agricultural networks, highlighting their potential to facilitate large-scale data collection and transmission.

Chapter 3 discusses the experimental work carried out, including the implementation of an IoT sensor network for data collection in a citrus tree, data analysis methodologies, and the integration of machine learning models for anomaly detection. Additionally, the chapter presents the development and implementation of a customized dashboard for real-time data visualization, which assists farmers in making informed decisions based on current environmental conditions.

Chapter 4 focuses on the experimental results obtained from the integration of the IoT sensor network with the ThingSpeak platform. It validates the data collected from the sensors by comparing it with publicly available data from IPMA and other platforms. Furthermore, it examines the reliability and accuracy of the implemented machine learning models in detecting anomalies and predicting agricultural outcomes.

Finally, Chapter 5 provides a discussion on the key findings of the research, offering conclusions and recommendations for future work. The chapter highlights the impact of integrating advanced data analysis techniques into agricultural monitoring systems and suggests potential areas for improvement in precision agriculture through further refinement of machine learning models and sensor networks.

This dissertation demonstrates the effectiveness of leveraging IoT and machine learning technologies to enhance agricultural monitoring, paving the way for more sustainable and efficient farming practices.

2

LITERATURE REVIEW

This chapter delves into the state of the art of technologies crucial for revolutionizing agricultural monitoring practices. It methodically explores various advanced technologies and methodologies that significantly impact agricultural productivity and sustainability. The structure of the subchapters is outlined in the summary below.

Building on this technological foundation, Subsection 2.1 explores the impact of sensor technology on citrus agriculture. Citrus cultivation is a sector with a rich heritage and global significance but is fraught with challenges and complexities. Farmers must navigate environmental variables such as soil quality, weather patterns, pests, and diseases like citrus greening. These challenges emphasize the need for precision agriculture technologies. This subsection also highlights the integration of specialized sensors, such as soil moisture and electrical conductivity sensors, that can help optimize irrigation, manage soil salinity, and monitor overall plant health. Advances in sensor technologies, such as leaf surface temperature and humidity sensors, enable real-time monitoring of plant water stress and disease onset, providing actionable insights that enhance citrus farming efficiency and sustainability.

Subsection 2.2 delves into various IoT protocols that facilitate efficient data transmission across agricultural settings. Protocols like LoRaWAN and NB-IoT are evaluated for their effectiveness in expansive and remote farm environments. This discussion extends to these protocols' energy efficiency, scalability, and capability to support a robust network of agricultural sensors, which are crucial for real-time data collection and analysis.

Additionally, Subsection 2.3 explores how the calculation of reference evapotranspiration (ETo) is vital for effective water resource management in agriculture. Employing methods, such as the Penman-Monteith method, is integral for determining the water needs of crops, which supports precise irrigation scheduling. This is particularly relevant in citrus agriculture, where optimal water management is crucial to maintaining fruit quality and productivity.

Furthermore, Subsection 2.4 highlights the importance of meteorological data platforms that provide essential weather information for agricultural planning and operations. These platforms, which offer open access to data, are invaluable for integrating weather forecasting and real-time climate data into agricultural decision-making processes, enhancing the ability to effectively respond to climatic changes.

To conclude, Subsection 2.5 examines how Decision Support Systems (DSS) integrate sensor data, IoT protocol information, and meteorological insights to provide comprehensive decision-making support. DSS are transforming agricultural management by leveraging data to provide actionable insights that enhance crop production, optimize resource use, and reduce environmental impact, advancing the sustainability and productivity of agricultural practices.

By weaving together these technological advancements, Chapter 2 sets the stage for demonstrating how anomaly detection of IoT sensor data can be effectively applied to monitor and enhance agricultural practices, ensuring sustainability and efficiency in modern agriculture.

2.1 IMPACT OF SENSOR TECHNOLOGY ON CITRUS AGRICULTURE

Citrus cultivation is a sector with a rich heritage and global significance, yet it is fraught with challenges and complexities. Farmers must navigate an array of environmental variables that can impact growth, from soil quality to weather patterns. Pests and diseases, such as citrus greening, pose a persistent threat, requiring vigilant management and innovative solutions. The reference [5] addresses citrus greening, highlights the negative impact of the disease on production efficiency, including reduced yield, increased mortality, and higher production costs. Additionally, the citrus market demands adherence to high standards of fruit quality and production efficiency to remain competitive

The labor-intensive nature of citrus farming, combined with the need for precision in nutrient management and harvesting, adds further layers of complexity. Water management is particularly critical; both drought and excessive moisture can lead to diminished crop quality or yield. These complexities underscore the need for advanced approaches to cultivation that can adapt to the dynamic needs of citrus plants [6].

In the current landscape of precision agriculture, the incorporation of specialized sensors in citrus cultivation is becoming a game-changer for improving the efficiency and sustainability of agricultural practices. Soil moisture sensors, for example, are essential for intelligent irrigation management, avoiding both scarcity and excess water, which is crucial for the health of citrus plants [7].

Measuring soil electrical conductivity is also essential for evaluating soil salinity, a factor that directly affects the health and growth of citrus plants. Electrical conductivity sensors provide accurate data that enable farmers to identify areas of high salinity and apply appropriate management strategies, such as differentiated irrigation or the application of correctives, to mitigate the harmful effects of salinity on plants. This precise monitoring contributes to maintaining soil quality and maximizing nutrient absorption by plants, resulting in higher quality fruits and optimized agricultural yields [8]. Recent research has explored several approaches for monitoring the health of citrus plants using soil electrical conductivity sensors. For example, the study carried out by Vanella et al. [9] highlighted the use of electrical resistivity imaging to identify soil-plant interactions in a mixed-age orange orchard, demonstrating the relationship between soil electrical resistivity and changes in soil water content, as well as the influence of tree age in this relationship.

Furthermore, another range of sensors that has proven to be efficient in monitoring plant health are leaf surface temperature and humidity sensors. Sensors capable of measuring these parameters in real time enable efficient irrigation management, ensuring that plants receive the ideal amount of water. Monitoring leaf temperature is also crucial for early detection of diseases, many of which alter leaf surface temperatures before manifesting visible symptoms. Consequently, the use of these sensors allows quick and specific interventions, reducing the spread of diseases and minimizing production losses. Recent advances in sensor technology provide new opportunities for accurate, real-time monitoring of plant health. A study by Peng et al. [10] describes the development of a wearable capacitive sensor for monitoring the moisture status of leaves, highlighting the importance of accurate moisture detection for the assessment of plant water stress. Furthermore, Son et al. [11] presented the practical application of leaf temperature sensors to optimize photosynthetic efficiency, especially in tomatoes, increasing production in controlled environments.

An IoT-based system for monitoring weather conditions during the flowering period in fruit plantations was explored by Hristov [12], demonstrating how accurate monitoring of temperature and humidity can positively influence future harvest.

2.2 SENSOR NETWORK AND IOT PROTOCOLS

The Internet of Things (IoT) revolutionizes traditional farming practices by introducing smart, connected technologies into the agricultural domain. IoT encompasses a network of sensors, devices, and systems that communicate and share data, enabling precise monitoring and management of agricultural environments. This transformative approach to agriculture leverages IoT protocols to enhance crop yields, optimize resource use, and minimize environmental impacts, marking a significant step toward sustainable and efficient farming practices. Through real-time data collection and analysis, IoT technologies empower farmers with actionable insights for informed decision-making, showcasing the potential of digital innovation in advancing the agricultural sector.

The authors of the various works described in this subchapter evaluated some of the main IoT communication protocols, known worldwide, taking into account in their analysis of advantages, some important comparison criteria such as – range, energy consumption and scalability – and their disadvantages, criteria such as data rate limitations and implementation costs. Based on this work, we list below some of the main advantages and disadvantages.

2.2.1 LONG RANGE WIDE AREA NETWORK (LORAWAN)

LoRaWAN stands out as a pivotal IoT protocol, specifically tailored for the expansive needs of modern agriculture. It ueses a long-range, low-power wireless platform, making it an ideal solution for spanning large agricultural areas with minimal energy consumption. This protocol supports the deployment of a vast network of sensors across farmlands, enabling detailed monitoring of soil moisture, crop health, and environmental conditions. Its unique architecture facilitates deep penetration in dense environments, ensuring reliable data transmission even in remote or obstructed areas, thus fostering a more informed and responsive farming approach. However, LoRaWAN's low data rate may limit its use in high-bandwidth applications. Nonetheless, its ability to support a wide sensor network remains invaluable for comprehensive monitoring of soil moisture, crop health, and environmental conditions in modern agriculture.

Some interesting areas of application of the protocol were noted, for example, the study [13] proposed the development of an IoT-based smart irrigation system, which could increase water savings in rice production by up to 64% compared to conventional methods. This approach uses LoRa-based systems to optimize water delivery directly to plant roots, improving water efficiency in agriculture. Another interesting area of application was described by [14], the study highlighted LoRaWAN for its energy harvesting capabilities in remote agriculture monitoring and how the technology can be used to improve sustainable agricultural production, enabling effective and efficient monitoring of critical parameters such as soil moisture, temperature and nutrients, contributing to increased productivity and sustainability in agriculture.

2.2.2 NARROWBAND INTERNET OF THINGS (NB-IOT)

Following the transformative impact of IoT in agriculture, NB-IoT emerges as a crucial protocol, enhancing connectivity even in challenging environments. It's distinguished for its deep penetration capabilities and low power consumption, ensuring reliable data transmission from remote or underground sensors [15]. NB-IoT's robust coverage extends to vast agricultural lands, supporting efficient resource management and precise monitoring, thus embodying a key technological advancement in sustainable farming practices. This protocol's integration within the agricultural sector illustrates a forward leap in achieving high-efficiency, data-driven farming operations, reinforcing the sector's adaptation to modern digital innovations. However, its advantages of exceptional connectivity and low power requirements come with considerations such as higher setup costs and reduced data rates compared to alternatives like LoRaWAN, influencing its deployment in precision farming strategies.

Several promising applications of the protocol can be found in literature, for example [16] focus on comparing existing wireless protocols and their impact on implementing IoT-Wireless Sensor Network in smart agriculture. The study highlights the energy consumption states of technologies such as LoRa WAN, Zigbee, Sigfox and NB-IoT in the context of smart agriculture, indicating how NB-IoT can contribute to more efficient and sustainable agricultural solutions.

2.2.3 ZIGBEE

Zigbee is specifically designed to meet the needs of low-data rate, low-power consumption applications [15], making it an excellent choice for sensor networks in agricultural settings. It supports mesh networking, which enhances the reliability and extends the range of IoT devices by allowing data to hop from one device to another until it reaches its destination. This capability is particularly useful in monitoring vast and complex agricultural environments, where direct communication between devices and the central system might not be feasible due to distance or obstructions. Zigbee's efficiency in power usage and its mesh networking capability contribute significantly to creating sustainable and resilient agricultural monitoring systems. Despite its strengths in mesh networking and power efficiency, it is important to note that Zigbee's range is more limited compared to other IoT protocols such as LoRaWAN and

NB-IoT [15], which can present challenges in covering larger agricultural areas without the deployment of additional repeaters or nodes.

Tang, Aridas, and Talip [17] investigated the development of a wireless sensor network for agricultural greenhouses based on the improved Zigbee protocol. Their study proposed an enhanced protocol, EMP-ZBR, which demonstrated significant improvements in energy efficiency and network performance compared to traditional Zigbee routing protocols. This advancement enhances data monitoring systems in agricultural greenhouses by reducing energy loss and congestion, making it a pivotal contribution to the efficient collection and management of environmental data for agricultural production. The study [18] proposed to improve communication in smart agriculture in mountainous areas by adjusting the number of repeaters to expand the network and increase communication efficiency using the protocol ZigBee. This study addressed specific challenges faced in hillside agriculture, such as signal limitations due to rugged terrain, and demonstrated how adjustments to network infrastructure can lead to significant improvements in agricultural data communication.

2.2.4 RADIO FREQUENCY PROTOCOLS INTEGRATED IN ARDUINO PLATFORM

Integrating the RF protocol with Arduino presents a dynamic approach within the IoT framework, especially relevant in the agricultural sector. This combination offers a practical and cost-effective solution [19] for creating sensor networks capable of monitoring various environmental parameters critical to farming operations. Leveraging the flexibility of Arduino's programmable platform alongside the RF protocol's simplicity in communication, this setup enables the development of customized agricultural applications aimed at enhancing crop management, irrigation efficiency, and overall farm productivity. This method stands out for its ability to be tailored to specific agricultural needs, bridging the gap between advanced technology and practical, on-the-ground farming practices. The RF protocol, when used with Arduino modules, is known for its low power consumption, which is beneficial for IoT devices that require long battery life [19]. However, the RF protocol in combination with Arduino does face limitations such as interference and limited range in environments filled with numerous RF signals or physical barriers. Additionally, when compared to more advanced technologies like 5G [20], the data rate offered by RF communication is lower, potentially hindering its application in scenarios demanding high bandwidth. These factors necessitate careful consideration when implementing RF and Arduino in agricultural IoT solutions.

The authors of the OpenGreenEnergy.com page described an interesting project "Solar Powered Arduino Weather Station" [21], which implements a self-sustaining solar-powered weather station by combining Arduino and RF modules to transmit environmental data. This system allows you to monitor essential climate variables remotely, contributing to more informed and efficient agricultural practices.

2.2.5 GLOBAL SYSTEM FOR MOBILE COMMUNICATIONS

Incorporating Global System for Mobile Communications into IoT applications represents a fundamental shift towards enhancing connectivity in various sectors, including agriculture. GSM, a standard developed to describe protocols for second-generation digital cellular networks used by mobile phones, offers the advantage of widespread global coverage and established infrastructure [22]. The GSM protocol allows easy integration with various IoT devices, making it versatile for multiple applications [23]. GSM also provides reliable data transmission over long distances, supporting IoT devices in remote or rural agricultural settings where other forms of connectivity may be limited. Its integration into IoT applications facilitates real-time monitoring and data collection, vital for precision agriculture practices that demand constant and reliable communication channels. Nevertheless, it is important to note that GSM's data transmission rates are not as high as those provided by newer networks such as 4G or 5G [22], which could limit its effectiveness in data-intensive IoT applications. Moreover, while GSM modules themselves are generally affordable, the operational and data consumption costs can accumulate [23], representing a significant factor in budget planning for IoT projects.

2.2.6 WIRELESS FIDELITY (WI-FI)

Wi-Fi is widely recognized for its prevalence not only in residential and business environments but also within the IoT, particularly in agriculture. Operating primarily on 2.4 GHz and 5 GHz bands, Wi-Fi offers high data transfer speeds and convenient integration with existing networks, making it an appealing choice for IoT deployments that require substantial data throughput within the coverage area of standard Wi-Fi networks [24].

One of the major advantages of using Wi-Fi in IoT applications is its high data rate, supporting data transfer rates up to several gigabits per second, especially with the advent of Wi-Fi 5 (802.11ac) and Wi-Fi 6 (802.11ax) [24]. This capability is crucial for applications that need to transmit large amounts of data in real time. Additionally, the established infrastructure of many facilities already equipped with Wi-Fi allows for easy integration of IoT devices without the need for additional networking equipment, simplifying setup and reducing costs. However, Wi-Fi also presents some disadvantages. Typically, Wi-Fi networks have a limited range, approximately 50 meters indoors, which can be restrictive for agricultural applications spread over large areas unless repeaters or additional access points are used. Moreover, Wi-Fi devices generally consume more power compared to other IoT protocols like LoRaWAN or NB-IoT. This can be a significant drawback in scenarios where devices need to operate on battery power for extended periods, potentially limiting their usability in remote or difficult-to-access areas without regular maintenance. The use of Wi-Fi in IoT applications, particularly in precision agriculture, highlights its potential to enhance efficiency and sustainability despite these challenges.

2.2.7 SUMARY OF IOT PROTOCOLS

Table 2.1 offers a comprehensive comparison of various IoT protocols, delineating their network type, power consumption, frequency bands, data rates, range, spreading techniques, and security measures. This summary is based on [12], [24]and [25], and allows us to evaluate the suitability of each protocol for specific agricultural applications.

Table 2.1 - Sumary of IoT protocols

Characteristics	ZigBee	LoRaWAN	NB IoT	RF (combined with Arduino Module)	GSM LTE 3.9G Release 8	Wi-Fi
Network	WPAN	WAN	LPWAN	WAN / WPAN	WAN	WLAN
Topology	Star, mesh, tree	Star	Star	Star, mesh, tree	Star	Mesh
Power	Low	Ultra-low-power	Ultra-low-power	Low	Medium	Medium
Frequency Bands	2.4 GHz	869/915 MHz	10 - 90 Mhz	433MHz	20 MHz	2.4 / 5 / 6 GHz
Data Rate	250 kbps	50 kbps	26 Kbps (downlink) / 66 kbps (uplink)	800 bps	300 Mbps	11-9600 Mbps
Range	10–100 m Short Range	Urban (2–5 km) suburban (15 km)	Urban (1 Km) Suburban (10 km)	30 m (5V)	-	Indoor: 45 m / Outdoor: 90 m (2.4 GHz Wi-Fi)

						Indoor: 30 m / Outdoor: 60 m (5 GHz Wi-Fi)
Spreading	DSSS	CSS	SC-FDMA / OFDM	DSSS / CSS	TDMA / FDMA	DSSS
Security	AES-128	AES-128	AES-128	AES-128	A5/1 or AES-128	WPA 2 / 3
Operator Dependency	No	No	Yes	No	Yes	No

2.3 THE ROLE OF REFERENCE EVAPOTRANSPIRATION IN PRECISION AGRICULTURE

The critical challenge in modern agriculture, particularly in precision farming practices, lies in the efficient management of water resources. Understanding and calculating reference evapotranspiration (ETo) is paramount in this context, as it plays a vital role in water management, directly influencing irrigation scheduling and crop health. As pointed by [26], ETo estimates the amount of water lost through evaporation from the soil and transpiration from plants, providing a basis for determining the actual water needs of crops at different growth stages.

The Penman-Monteith method has emerged as the most scientifically robust method for calculating ETo, especially for citrus cultivation which requires precise water management due to its sensitivity to both over and under-watering. Recognized globally by the Food and Agriculture Organization of the United Nations (FAO) [3], and extensively validated in various climatic conditions, the Penman-Monteith method considers a variety of environmental factors including temperature, humidity, solar radiation, and wind speed. This comprehensive approach enables it to provide more accurate and reliable estimates of ETo compared to simpler methods like the Hargreaves equation, which mainly depends on temperature data and is often used when other environmental data are not available.

The superiority of the Penman-Monteith method in various microclimatic conditions is supported in [27] and further described in [28], highlighting its ability to adjust to local weather variations, which is crucial for precision agriculture. The detailed data required by this method, while initially seeming as a barrier due to the need for complex and potentially expensive sensor systems, can now be more readily sourced from modern IoT-based agricultural sensor networks. These networks facilitate the real-time collection of environmental data necessary for the accurate application of the Penman-Monteith method, enhancing the sustainability and productivity of agricultural operations by optimizing water usage and reducing waste.

This understanding of ETo, and particularly the application of the Penman-Monteith method, aligns closely with the evolving needs of citrus agriculture as detailed in Section 2.1. As evapotranspiration is directly tied to plant and soil health, and thus to the overall yield and quality of the produce, precision in its calculation is not merely beneficial but necessary [26]. It allows for tailored irrigation practices that meet the exact requirements of citrus plants, promoting better growth conditions and helping to mitigate the impacts of varying environmental stresses.

In essence, the integration of accurate ETo calculation into citrus farming practices offers a pathway to achieving higher efficiency in water use, a critical factor in the sustainability and economic viability of agriculture in arid and semi-arid regions where water scarcity is a prominent challenge.

2.4 OVERVIEW ON METEOROLOGICAL DATA PLATFORMS

Weather data platforms are essential for a wide range of applications, offering valuable information ranging from daily forecasts to long-term climate analysis. The Portuguese Institute of the Sea and Atmosphere (IPMA) is the national reference in Portugal, providing detailed meteorological data and services, forecasts, and alerts [29]. Globally, the European Center for Medium-Range Weather Forecasts (ECMWF) [30] and the World Meteorological Organization (WMO) [31] are also key resources, with climate models and observational data covering the Portuguese region. Another notable feature is OpenWeatherMap (OWM), which offers a comprehensive suite of weather services, including data on temperature, humidity, weather forecast, and more, with an open access option that can be especially useful for developers and weather enthusiasts looking to integrate weather data in your projects or applications. The combination of these platforms provides comprehensive weather coverage that is indispensable for professionals across different industries and the general public.

For more detailed information, including direct URLs and specific data, it is recommended to consult directly the IPMA [29], ECMWF [30], OpenWeatherMap [32], and WMO [31] platforms to access the mentioned resources.

Table 2.2 offers a comprehensive comparison between OpenWeatherMap, IPMA, and Meteomatics focusing on showing specific characteristics regarding the data request and other functionalities, as well as displaying the coverage of the parameters necessary to calculate the reference evapotranspiration.

Table 2.2 - Sumary of weather data platforms

Platform	Penman-Monteith parameter coverage	Other features
OpenWeatherMap	✓ Min. temperature ✓ Max. temperature ✓ Relative humidity ✓ Solar radiation ✓ Wind speed	API calls: 60 calls/minute -1,000,000 calls/month Availability (Uptime): 95.0% Weather API data update: < 2 hours License for maps, APIs, and other products: CC BY-SA 4.0 License for data and database: ODbL Tech support: Helpdesk
IPMA	✓ Min. temperature ✓ Max. temperature ✓ Relative humidity ✓ Solar radiation ✓ Wind speed	Weather warnings for up to 3 days Daily weather forecast up to 5 days aggregated by location Daily weather forecast for up to 3 days, aggregated per day Seismic information, Arch. Azores, Continente and Arch. Madeira Sea state forecast for up to 3 days, aggregated per day Fire risk forecast for up to 2 days, aggregated per day Ultraviolet risk forecast for up to 3 days (Ultraviolet Index) Meteorological observation (hourly data, last 24 hours) Weather observation of stations, last 3 hours (GeoJSON format)
Meteomatics	✓ Min. temperature ✓ Max. temperature ✓ Relative Humidity ✓ Solar Radiation ✓ Wind speed	Up to 500 queries per day 15 basic weather parameters Forecast period of up to 10 days Historical data for the past 24 hours Global resolution of 1 hour and 90 meters Global resolution of 1 hour and 90 meters Support available via e-mail

2.5 OVERVIEW ON DECISION SUPPORT SYSTEMS

Decision Support Systems (DSS) are sophisticated information systems designed to assist decision-makers in making informed and data-driven decisions. These systems integrate data, analytical tools, and models to help users evaluate complex situations, predict outcomes, and choose optimal solutions. In agriculture, DSS are becoming increasingly important due to the sector's reliance on timely and accurate information to manage resources efficiently, enhance productivity, and mitigate risks associated with climate variability and market fluctuations. In recent years, the application of DSS in agriculture has grown exponentially, driven by advancements in technology and the increasing availability of data. Modern DSS leverage Cloud Computing, Data Mining, Machine Learning, and Artificial Intelligence to process vast amounts of information from various sources, including satellite imagery, weather forecasts, soil sensors, and crop models. These technologies enable DSS to provide actionable insights that help farmers optimize irrigation schedules, apply fertilizers more effectively, and protect crops from pests and diseases.

As described by [33], Decision Support Systems (DSSs) have been introduced in agriculture primarily to combat the adverse effects of climate change on production and to promote more sustainable agricultural practices that increase the quantity and quality of production while conserving water, energy, and reducing the use of fertilizers and pesticides. This supports the adoption of precision farming technologies. In the last decade, the application of DSSs in agriculture has expanded significantly, fueled by the emergence of new technologies such as Cloud Computing, Data Mining, Machine Learning, Artificial Intelligence, and substantial investments from numerous research organizations and governments worldwide. More recently, Acharya et al. [34] discussed the use of IoT-based technologies like the Internet of Things and Low Power Wide Area Networks in DSSs, highlighting the technology's impact on enhancing agricultural productivity and decision-making processes by focusing on regional parameters and optimizing decisions through distributed hierarchical systems [34]. This reflects a trend toward more interconnected, responsive, and smart agricultural decision-making frameworks.

One practical application of DSS in agriculture is the Smart Water Management Platform (SWAMP) project [35], which employs IoT-based methods for precision irrigation. The project addresses issues such as water wastage in irrigation systems by using data analytics and autonomous devices to ensure efficient water management. By integrating IoT, Big Data, Cloud/Fog computing, and drones, the SWAMP project enables precise water application, reducing both under-irrigation and over-irrigation.

Another critical application of DSS is in pest and disease management. Systems like the Integrated Pest Management (IPM) DSS combine data on pest populations, weather conditions, and crop health to predict pest outbreaks and suggest timely interventions. This helps farmers apply pesticides more efficiently, reducing both costs and environmental impact. An example of this is the DSS developed by the European Union's ENDURE Network, which provides farmers with real-time pest and disease forecasts and management advice [36].

Decision Support Systems (DSS) have become indispensable tools in modern agriculture, providing farmers with the ability to make more informed, data-driven decisions. By integrating technologies such as Cloud Computing, Machine Learning, and IoT, DSS enable more efficient resource management, improved crop protection, and optimized irrigation practices. The rapid advancement and adoption of these systems in the agricultural sector are helping to mitigate the effects of climate change, enhance sustainability, and promote precision farming techniques. The practical applications of DSS, such as the SWAMP project for water management and Integrated Pest Management for pest control, demonstrate the tangible benefits of these systems in real-world scenarios. As agriculture continues to evolve, the role of DSS in supporting smarter, more responsive decision-making frameworks will only become more critical.

3

DEVELOPMENT OF THE WORK DONE

This chapter outlines the key developments and methodologies implemented throughout the course of this research. The primary focus is on the design, setup, and execution of the experimental work, including the deployment of sensor networks, data collection, and the subsequent analysis of environmental and plant-specific data. The work presented here is essential for understanding how advanced sensor technologies and data analytics can be applied to optimize agricultural processes, particularly in precision farming.

Each section of this chapter details specific stages of development, starting from the installation and calibration of sensors, to the integration of real-time data into the monitoring dashboard. The chapter also covers preliminary tests and performance evaluations, which have contributed to refining the methodology and improving data accuracy. Additionally, the investigation of trunk resistance sensors, and the application of machine learning techniques for anomaly detection are discussed as part of the broader effort to enhance irrigation management and crop health assessment.

By detailing the experimental processes and challenges encountered, this chapter sets the foundation for the results and analyses presented in the following sections, highlighting both the progress made and areas identified for future improvements.

3.1 PRESENTATION AND ANALYSIS OF EVAPOTRANSPIRATION DATA COLLECTED AND ESTIMATED

The seamless transition from the theoretical foundations laid out in Chapter 2, particularly in Section 2.4, provides a robust groundwork for the empirical analysis presented in this chapter. The preceding discussions have established the critical role of weather data platforms like the

IPMA, which offers an extensive range of meteorological services and data essential for agricultural monitoring and management. This data, accessible through platforms noted for their openness and detailed coverage, such as IPMA, ECMWF, OpenWeatherMap, and WMO, serve as pivotal resources in the quest for enhanced agricultural productivity through advanced data analytics. As we delve into the practical application of these data sources, this chapter focuses on a specific aspect of agricultural data analytics with focus on evapotranspiration (ETo).

ETo is a fundamental metric in precision agriculture, providing crucial insights into the water requirements of crops, which is pivotal for optimizing irrigation practices and ensuring sustainable water use. The analysis of evapotranspiration data, especially those collected from IPMA, is instrumental in refining our understanding of crop water needs under varying climatic conditions. This not only aids in the precise scheduling of irrigation but also plays a significant role in the broader context of water resource management in agriculture.

The rationale for an in-depth data analysis as a precursor to the application of machine learning and artificial intelligence algorithms lies in the necessity to understand and prepare the data fully before it can be used effectively. Data analysis helps in identifying patterns, anomalies, and underlying trends, which are crucial for developing accurate predictive models. It ensures that the input data fed into machine learning algorithms is of high quality and significantly representative of the real-world conditions, thereby enhancing the reliability and accuracy of the predictions made by such models.

3.1.1 IPMA DATA RELEVANT FOR RESEARCH

IPMA provides a comprehensive range of meteorological data essential for agricultural research and other scientific applications. This includes everything from daily weather forecasts to historical observational data, crucial for long-term climate analysis. The data is available in various formats, including JSON and CSV, which facilitates integration with automated data analysis systems. For this specific study, two sets of data from the IPMA platform were selected: hourly data from the last 24 hours, available through their API [37], and daily data [1].

The hourly data encompasses essential information such as wind intensity, air temperature, wind direction, accumulated precipitation, relative humidity, atmospheric pressure, and solar radiation. Parameters provided on an hourly basis are:

- **YYYY-mm-ddThh:mi:** Date and time of the observation.

- **idEstacao**: Identifier of the station
- **intensidadeVentoKM**: Wind intensity recorded at a height of 10 meters (km/h).
- **temperatura**: Air temperature recorded at a height of 1.5 meters, average for the hour (°C).
- **idDireccVento**: Class of the predominant wind direction recorded at a height of 10 meters (0: no direction, 1 or 9: "N", 2: "NE", 3: "E", 4: "SE", 5: "S", 6: "SW", 7: "W", 8: "NW").
- **precAcumulada**: Precipitation recorded at a height of 1.5 meters, hourly accumulated amount (mm).
- **intensidadeVento**: Wind intensity recorded at a height of 10 meters (m/s).
- **humidade**: Relative humidity of the air recorded at a height of 1.5 meters, hourly average (%).
- **pressao**: Atmospheric pressure, reduced to mean sea level (MSL), hourly average (hPa).
- **radiacao**: Solar radiation (kJ/m^2).

These metrics are instrumental for conducting detailed analyses and for swiftly adapting to changes in weather conditions that can directly affect agricultural practices. In this research, particular attention was given to the hourly data from the Olhão meteorological station (ID 1210881), situated at latitude 37.033, longitude -7.821. This station was selected due to its proximity to the field study in Bela Curral, Olhão, Portugal. Ensuring the meteorological data collected are reflective of the local climatic conditions faced by the considered agriculture. However, the Olhão station does not provide data on solar radiation, a crucial parameter for in-depth agricultural studies. Thus, to maintain the completeness and accuracy of our analyses, solar radiation data from the nearby Faro meteorological station (ID 1200554, latitude 37.016579, longitude -7.971953) was also used, providing comprehensive coverage of all necessary climatic parameters for the region being studied. Namely, the Penman-Monteith method was employed for the estimation of ETo, which relies on accurate solar radiation data to ensure reliable results.
Building on the analysis of hourly data, the study also focused on daily data, which is essential for calculating reference evapotranspiration and other important agronomic analyses. The IPMA platform provides a historical record of the last 90 days with the following parameters:

- **Daily total precipitation by county** [38]**:** Crucial for understanding the natural water input, which directly impacts irrigation needs.
- **Daily minimum and maximum temperature by county** [39], [40]**:** These data are vital as they directly influence evapotranspiration and soil water dynamics.
- **Daily reference evapotranspiration by county** [41]**:** Provides the necessary basis for determining the water needs of crops.

The CSV files structure these measurements into several columns that detail the date, minimum and maximum values, daily range, average, and standard deviation for each county. This structure not only facilitates temporal and spatial analysis but also allows for direct correlations with agronomic needs. For example, the typical structure of a CSV file is shown in Figure 3.1. The file shown in Figure 3.1 represents the daily maximum temperature data for Olhão county [40]. Therefore, the most crucial column to consider in this file is the "maximum" column. Another file also exists for daily minimum temperature data [39], following the same structure. In this case, the key column to focus on is the "minimum" column.

	A	B	C	D	E	F
1	date	minimum	maximum	range	mean	std
2	26/11/2023	17.36367607	17.59372139	0.230045319	17.44691411	0.045230353
3	27/11/2023	18.24620056	18.42856026	0.182359695	18.35022926	0.050032127
4	28/11/2023	18.63507271	18.91725349	0.282180786	18.75062113	0.072705517
5	29/11/2023	20.53256226	20.70484924	0.172286987	20.61969359	0.035591317
6	30/11/2023	20.38985252	21.06982803	0.67997551	20.69235058	0.188701068
7	01/12/2023	18.58975601	19.30898285	0.719226837	18.96661891	0.188373604
8	02/12/2023	16.48060989	16.72030258	0.239692688	16.61527523	0.067507135
9	03/12/2023	16.12255478	16.2276516	0.105096817	16.16717968	0.025668988
10	04/12/2023	17.31116295	17.54891396	0.237751007	17.45408654	0.061191049
11	05/12/2023	13.8184185	14.34907341	0.530654907	14.11058328	0.14122897
12	06/12/2023	16.1685276	16.74410057	0.575572968	16.53403939	0.15190993
13	07/12/2023	18.37243462	18.45210266	0.079668045	18.39830444	0.0165631
14	08/12/2023	19.03126335	19.11428833	0.083024979	19.07170742	0.019158707
15	09/12/2023	19.13829422	19.27647591	0.138181686	19.18844869	0.026539927
16	10/12/2023	19.6944828	20.35259247	0.658109665	20.01363853	0.179235076
17	11/12/2023	20.26669312	21.10343361	0.836740494	20.70956345	0.224405351
18	12/12/2023	20.25362396	20.62140274	0.367778778	20.43530887	0.098912171
19	13/12/2023	17.2578125	17.9278698	0.670057297	17.63107078	0.174364989
20	14/12/2023	15.91125011	16.63090324	0.71965313	16.32153274	0.186606792
21	15/12/2023	18.13394737	18.2554493	0.121501923	18.20349893	0.029408239

Figure 3.1. Daily maximum temperature of Olhão

This comprehensive data enables detailed and accurate analysis of climate conditions, essential for efficient water management and sustainable agricultural practices.

3.1.2 DATA AQUISITION AND CONSOLIDATION

During the development of the project, Python scripts were developed to automate the collection of the previously mentioned hourly data. These scripts leveraged powerful libraries such as ‘requests’ for making HTTP requests, ‘json’ for handling data in JSON format, ‘csv’ for reading and writing CSV files, and ‘datetime’ for managing and processing dates and times. This combination allowed for efficient automation of data acquisition and storage.

The developed script follows an efficient programmatic logic to ensure that data are collected, processed, and stored without interruptions. It begins with defining variables for setting file names and access paths, then proceeds to request data from the IPMA API using requests.get(). The structure of the generated JSON file is shown Figure 3.2.


```json
{
    "2024-05-17T19:00": {
        "1210881": {
            "intensidadeVentoKM": 11.2,
            "temperatura": 22.3,
            "radiacao": -99.0,
            "idDireccVento": 8,
            "precAcumulada": 0.0,
            "intensidadeVento": 3.1,
            "humidade": 42.0,
            "pressao": -99.0
        },
        "1210883": {
            "intensidadeVentoKM": 21.6,
            "temperatura": 22.2,
            "radiacao": -99.0,
            "idDireccVento": 9,
            "precAcumulada": 0.0,
            "intensidadeVento": 6.0,
            "humidade": 39.0,
            "pressao": 1011.9
        },
        "1200533": {
            "intensidadeVentoKM": 30.6,
            "temperatura": 16.8,
            "radiacao": -99.0,
            "idDireccVento": 8,
            "precAcumulada": 0.0,
            "intensidadeVento": 8.5,
            "humidade": 63.0,
            "pressao": 1013.9
        },
        "1210865": {
            "intensidadeVentoKM": 20.5,
            "temperatura": 19.1,
            "radiacao": -99.0,
            "idDireccVento": 8,
            "precAcumulada": 0.0,
            "intensidadeVento": 5.7,
            "humidade": 47.0,
            "pressao": 1012.0
```

Figure 3.2. IPMA meteorological station readings in JSON

Upon confirming a successful response, the script converts the received data into JSON format. With the data in JSON, the script then proceeds to open and write to various CSV files, structuring columns to include relevant information such as date, station ID, wind intensity, temperature, radiation, wind direction, accumulated precipitation, humidity, and atmospheric pressure. Multiple functions were implemented to manipulate and filter the data, writing them into separate files based on the station ID, which facilitates specific analyses by location. For example, a separate file is created for data from the Olhão station, ensuring that the collected data are representative of the climatic conditions in the study area in Bela Curral, Olhão, Portugal.

To complement this data collection process and enhance the accuracy of our analyses, we employed the Ref-ET software [42]. Ref-ET is a specialized tool developed by the University of Idaho's Kimberly Research and Extension Center, designed to compute ETo and crop evapotranspiration (ETc) using weather data inputs. The software is extensively used in agriculture to estimate the water requirements of crops, facilitating effective irrigation management. By providing accurate ETo calculations, Ref-ET helps in determining the precise amount of water needed to optimize crop growth, which is crucial for sustainable water resource management in agriculture. As already mentioned in this research, Ref-ET was a significant contributor to validating the calculations of ETo and ETc, ensuring the accuracy and reliability of our evapotranspiration calculations, which are fundamental for developing effective irrigation schedules.

To further refine our approach, we used the methodology outlined in ‘Chapter 6 - ETc - Single crop coefficient (Kc)’ from the FAO guidelines [3] was used. The chapter provides detailed instructions on calculating ETc from ETo using the crop coefficient. The process involves:

1. **Calculating ETo:** Using weather data inputs, Ref-ET calculates the ETo, which represents the evapotranspiration rate from a reference surface, typically a well-watered grass field.
2. **Selecting Kc Values:** Kc is selected based on the specific crop and its growth stage. For this study, focusing on an orange plantation (Citrus, no ground cover 21 / - 50% canopy), a Kc value of 0.60 was chosen [3].
3. **Calculating ETc:** ETc is then calculated by multiplying ETo by the selected Kc (ETc = ETo × Kc).

This structured approach allows for precise estimation of crop water requirements, tailored to the specific conditions and crop type of the study area.

3.1.3 DATA ANALYSES

The importance of exploratory data analysis cannot be overstated, as it provides critical insights that guide further research and analysis. With the data at hand, we then embarked on an exploratory analysis of the same. The first analysis conducted aimed to verify whether the graphical profile of the radiation data collected by the meteorological station aligns with the expected behavior of sunlight throughout the day. The data exhibited a satisfactory profile, adhering to the sinusoidal shape expected for solar radiation during the day, see Figure 3.2 and Table 3.1. This observation confirms the sensor's effectiveness in tracking solar intensity variations influenced by daily and seasonal solar trajectories. Furthermore, during winter dates, a reduced radiation emission was observed, consistent with the shorter daylight hours and lower solar angle.

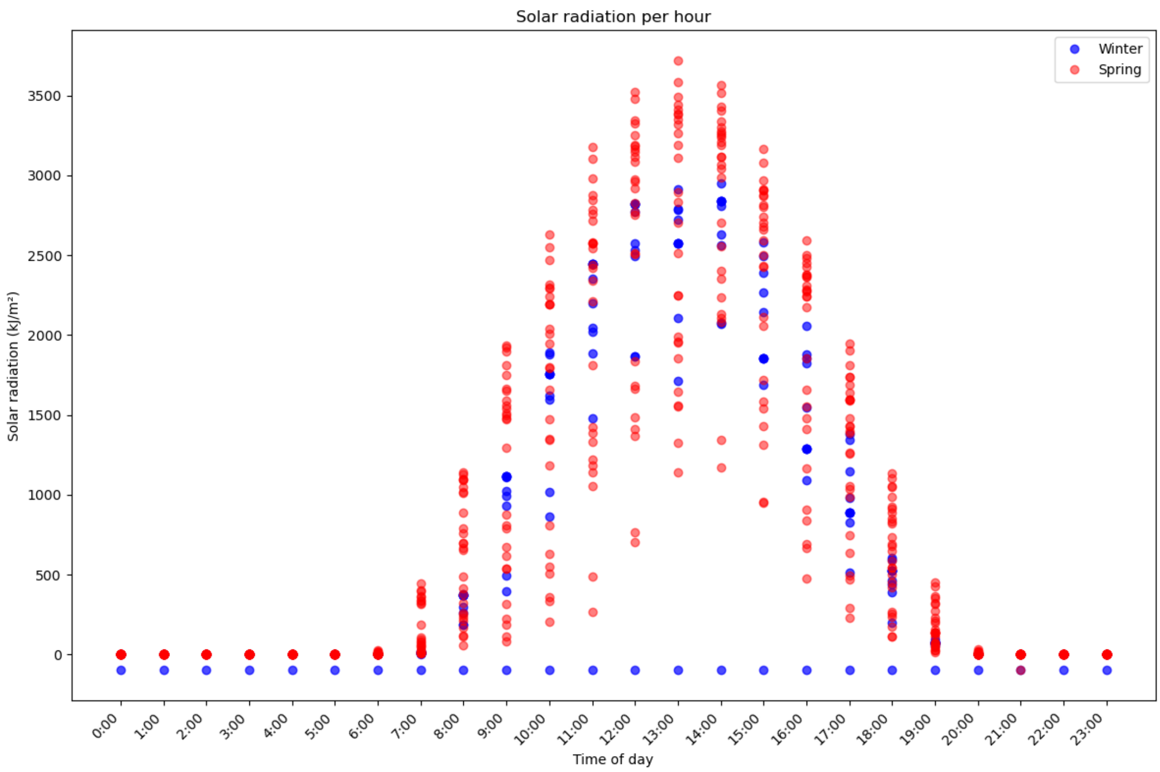
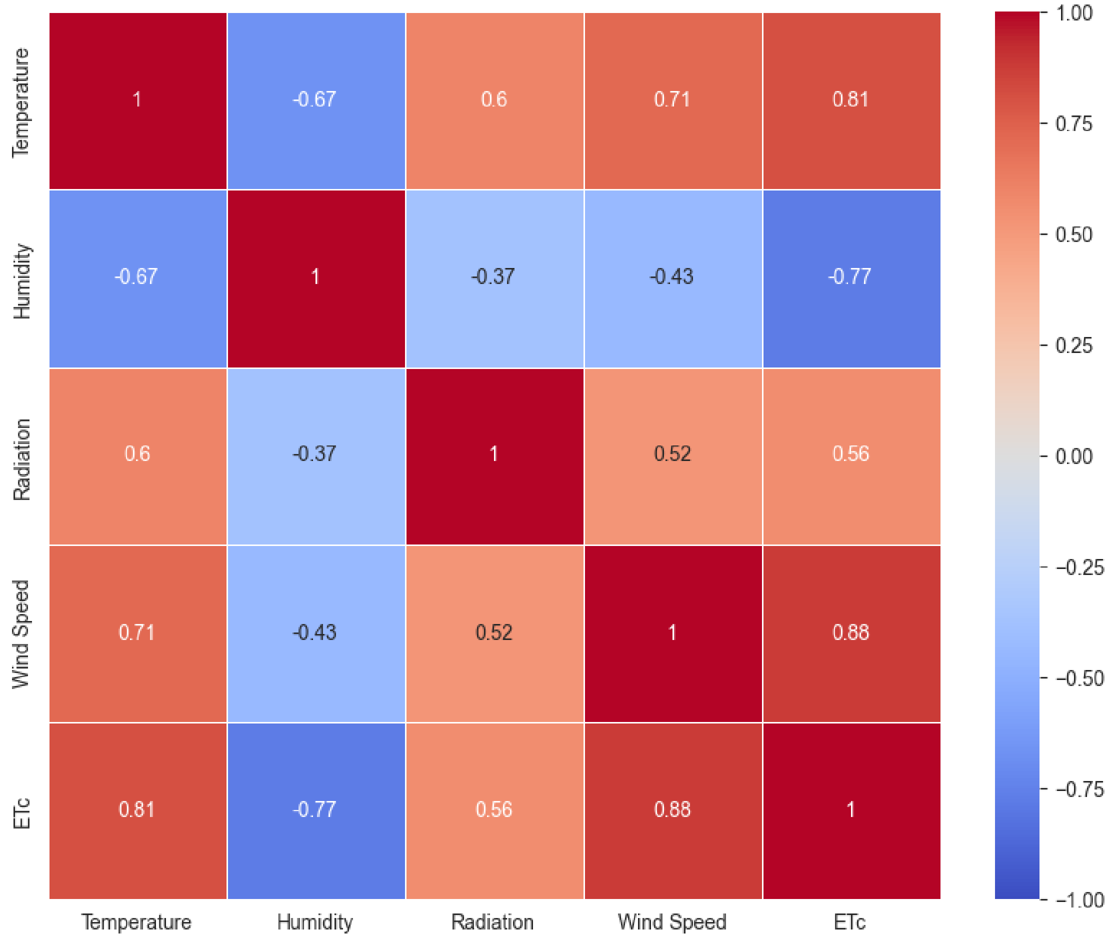


Figure 3.3. Solar radiation per hour – Winter and Spring comparison

In this analysis, it was also noted that there were some missing data on specific days, which were identified as problematic data points. These gaps in the data could potentially affect the accuracy of trend analysis and predictions, underscoring the need for careful data management and possibly the implementation of techniques to handle missing data in further analyses. This highlights the importance of robust data collection processes and the potential need for redundancy in data acquisition systems to ensure comprehensive data coverage over time.

The second major analysis focused on comparing the profile of calculated ETc against the variation of other natural variables, beginning with solar radiation, see Figure 3.3 and Table 3.1. Solar radiation is a crucial factor influencing ETc as it directly affects the energy available for the evaporation and transpiration processes in plants. Higher solar radiation increases the energy input, leading to higher ETc values. Conversely, lower radiation levels, typical during cloudy or winter days, result in lower ETc.

Table 3.1 - Correlation matrix – IPMA Data & ETc



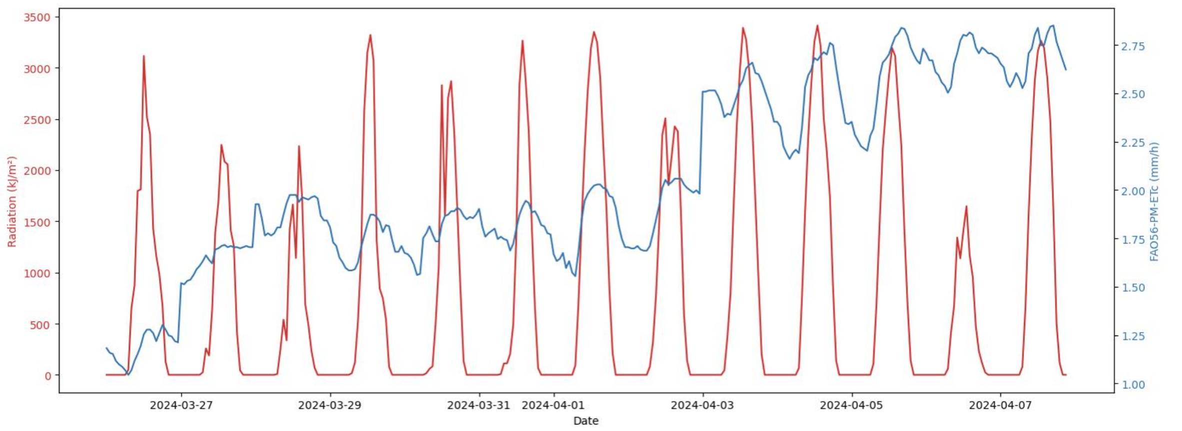


Figure 3.4. ETc profile against solar radiation

This comparison is vital for understanding how changes in solar radiation throughout the day and across different seasons impact the water requirements of crops. Figure 3.4 demonstrates a clear correlation between increased solar radiation and higher ETc values, reinforcing the importance of solar radiation as a driving force behind evapotranspiration rates. At the same time, we can also observe a difference in ETc for similar radiation patterns, as seen on the days 26/03 and 2/04, which suggests that other factors might influence ETc. This observation is corroborated by the temperature variation, which we analyze next. Ambient temperature plays a significant role in evapotranspiration as it affects both the saturation vapor pressure and the plant's transpiration rate. Higher temperatures generally enhance the evapotranspiration process, leading to increased ETc, while lower temperatures can suppress this process.

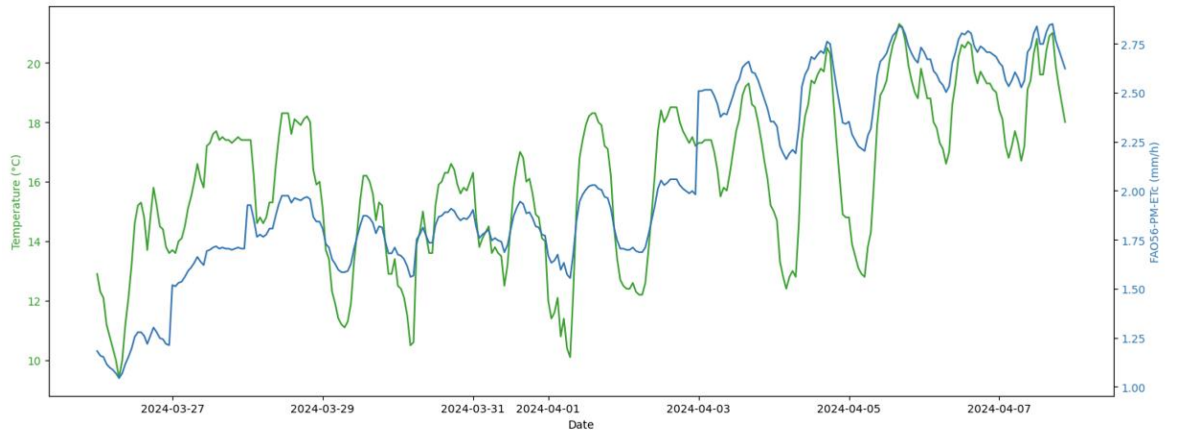


Figure 3.5. ETc profile against ambient temperature

Figure 3.5 shows ETc against ambient temperature, it suggests a positive correlation, where ETc values tend to rise with increasing temperatures. This relationship is crucial for predicting water requirements during warmer periods and highlights the need for efficient irrigation practices to manage higher water demand during hot weather conditions. In summary, these analyses underscore the critical interplay between solar radiation, ambient temperature, and crop evapotranspiration. Understanding these relationships enables better prediction and management of water resources in agricultural practices, ensuring optimal crop growth and sustainability.

Continuing with the previous analysis, we now delve into the specifics of the relationship between wind speed and ETc.

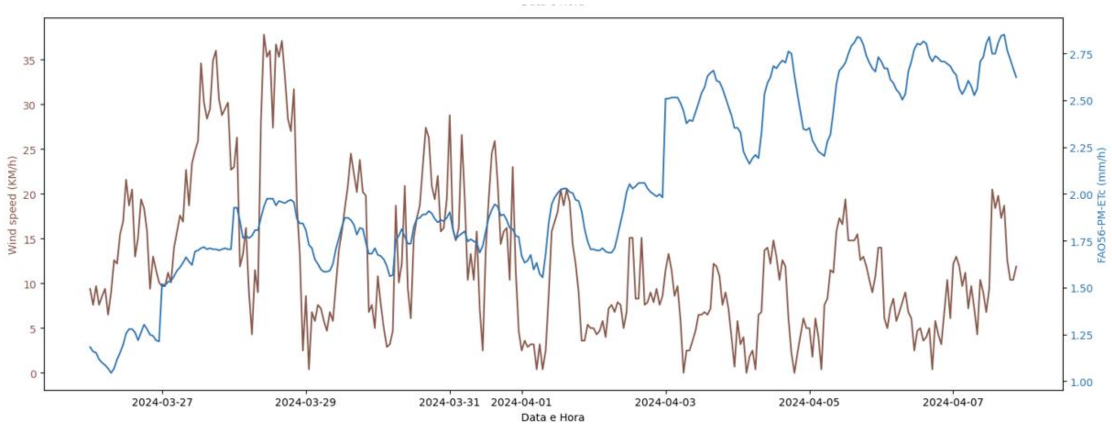


Figure 3.6. ETc profile against wind speed

Figure 3.6 shows the relationship between wind speed (in KM/h) and ETc (in mm/h) during a period from the end of March to the beginning of April 2024. The analysis suggests a positive correlation where the fluctuations in wind speed often coincide with changes in ETc values. Higher wind speeds are generally associated with increased ETc, demonstrating this positive correlation between the two variables, see Table 3.1. Throughout the period, significant variability in wind speed is observed, with some days showing peaks of up to 35 km/h. Likewise, ETc values also show an upward trend, peaking in response to higher wind speeds. On the other hand, during periods of lower wind speed, ETc values tend to stabilize or decrease, indicating a reduction in evaporation and transpiration rates.

In summary, Table 3.1, showing the correlation matrix between the mentioned variables, corroborates that ETc is positively correlated with parameters such as temperature and wind speed, and negatively correlated with humidity values.

Overall, these comprehensive analyses highlight the critical interplay between solar radiation, ambient temperature, and wind speed in determining crop water requirements. By understanding these relationships, agricultural practices can be better optimized to predict and manage water resources, ensuring efficient water use, optimal crop growth, and sustainable farming operations. The findings from this subchapter lay a robust foundation for developing precise and adaptive irrigation strategies tailored to varying climatic conditions, ultimately supporting the sustainability and productivity of agricultural systems.

3.2 SENSOR DATA COLLECTION

The collection of sensor data is a critical component in the development of agricultural monitoring systems, particularly for precision agriculture. In this study, a sensor network was implemented at Hubel's orange orchard to gather real-time environmental data that would contribute to the understanding of crop water needs and plant health. The primary goal of this phase was to collect reliable data from the field, which could then be used to analyze the behavior of citrus trees in relation to environmental factors such as temperature, humidity, solar radiation, precipitation, wind speed, among relevant other factors.

This section presents the process of setting up the sensor network, detailing the IoT architecture employed, and discusses the experimental tests conducted to evaluate the performance of soil moisture sensors when repurposed for monitoring internal trunk resistance in citrus trees. The experimental setup aimed to assess whether these low-cost, widely available sensors could be effectively used to monitor tree health, thereby providing valuable insights into the internal water dynamics of the trees without significant disruption.

By leveraging IoT technology, this sensor network facilitates continuous, automated data collection, allowing for detailed analyses of plant-environment interactions and supporting the development of advanced, data-driven agricultural practices.

3.2.1 IOT NETWORK IMPLEMENTATION

To allow the sensor data collection in Hubel's orange orchard, an experimental IoT network architecture was implemented, as shown in Figure 3.7.

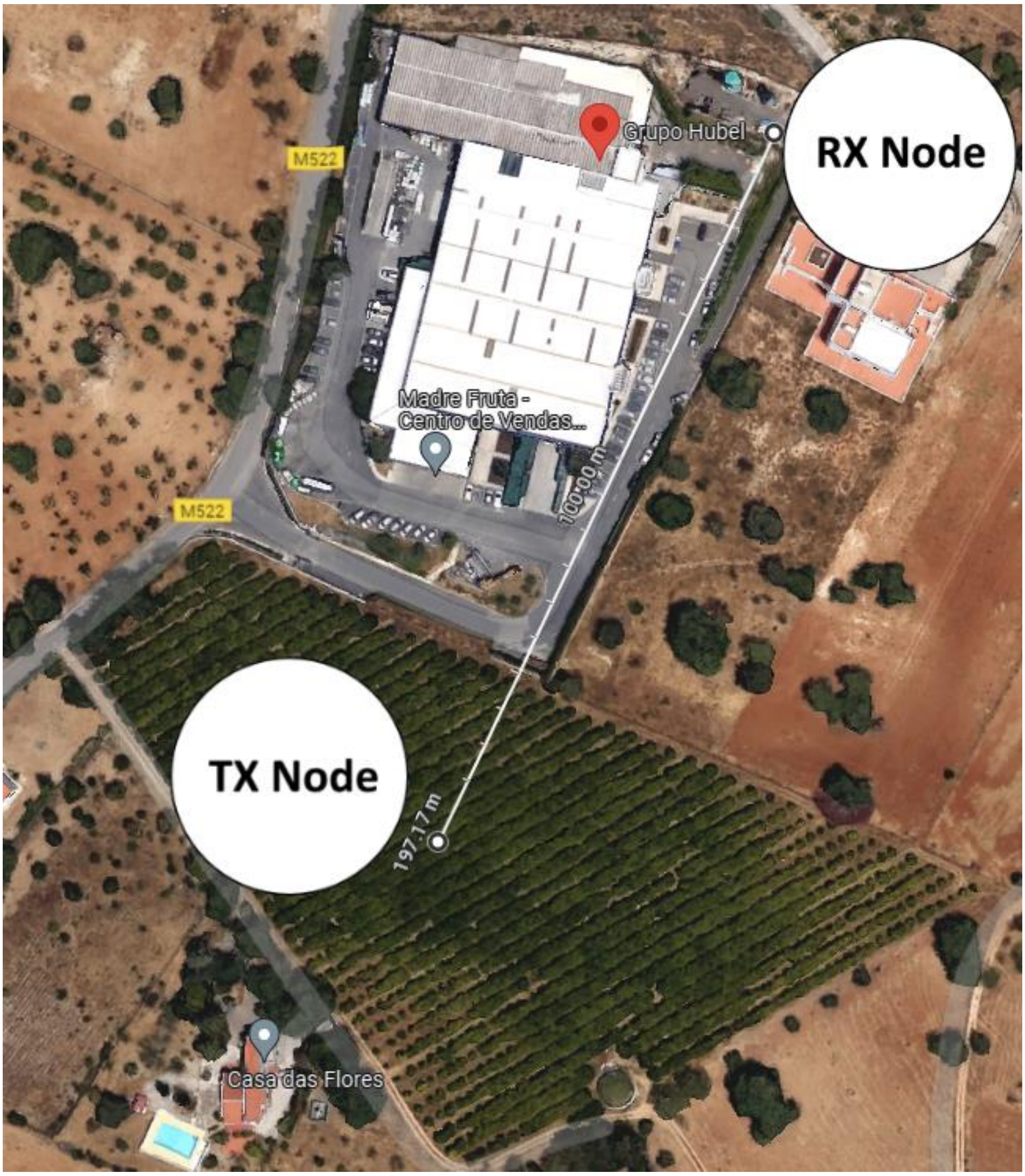


Figure 3.7. Aerial view showing the locations of the Tx and Rx nodes – Arquitecture 1

The initial network architecture (Architecture 1) was composed of two network nodes. One node was installed near the target orange tree, and the other was placed near the company's office. The necessity for two nodes appeared due to the distance between the orchard and the office, as there was no WiFi connectivity in the orchard. WiFi connectivity was essential for transmitting the collected data to the cloud platform ThingSpeak. Table 3.2 describes an overview of implemented components for Architecture 1.

Table 3.2 - Network component overview for archtecture 1

Components	TX Node	RX Node
ESP32: A powerful microcontroller with integrated WiFi capabilities, ideal for IoT applications.	✓	✓
NRF24: A radio frequency communication module used for wireless data transmission.	✓	✓
Batteries: A set of four 9900 mAh batteries from GTF.	✓	✓

The primary function of the TX node is to collect data from the sensors and transmit it to the RX node using the NRF24 module. The ESP32 module serves as the processing unit, aggregating data from the sensors and handling the communication with the NRF24 module. It is important to highlight that the ESP32 module used in the TX node was deployed primarily for testing purposes. The integrated WiFi functionality of the ESP32 was redundant in this setup, as the TX node communicated with the RX node exclusively via the radio frequency protocol. In retrospect, other microcontroller modules without WiFi capability could have been employed to perform the same function at a relatively lower cost. The RX node's main role is to receive data from the TX node via the NRF24 module, establish a WiFi connection, and upload the data to the ThingSpeak platform. The ESP32 module manages the reception, processing, and transmission of the data to the cloud. The choice of ESP32 for the RX node was essential due to its WiFi capabilities, which were necessary for connecting to the internet and transmitting the data to the cloud platform.

The communication test conducted in the field showed satisfactory results regarding the interaction between the TX and RX nodes. The data transmission between the nodes was performed well, and the subsequent function of uploading the data to the cloud platform ThingSpeak was executed successfully. This confirmed that the communication architecture was functioning as intended, ensuring reliable data transfer from the orchard to the cloud. However, a significant issue was observed with the battery performance. Despite the use of four 9900 mAh batteries, the nodes exhibited a shorter-than-expected operational duration.

This limitation posed a challenge for long-term, continuous data collection, necessitating frequent battery replacements or recharges, which is impractical for a sustainable monitoring solution.

Some techniques could be applied to reduce battery consumption, such as disabling the Wi-Fi module or putting all components into sleep mode during periods when data readings are not being transmitted. However, these strategies were not the primary focus of this work. To ensure continuous data collection, the modules were connected to the electrical grid, thus eliminating concerns about battery life.

Furthermore, there was a second issue with the access to Hubel's WIFI network from the field implementation. Therefore, in order to not jeopardize the results to this project, a second sensor was used, with the same architecture and set-up replicated, in a lime tree, with access to a WIFI network and also located in Faro. This setup aimed to validate the sensor readings in a more controlled environment, where the amount of irrigation applied is precisely known. The goal of this step was to closely examine the internal electrical resistance of the tree trunk and its relationships with environmental factors and irrigation events.

It is important to note that by measuring the resistivity of the internal part of the trunk, we have some knowledge about the quantity of fluids that are being transferred inside the plant. This normally happen as a response from the plant to the environment changes, like temperature, causing fluids transfer as a way to balance the temperature in all the plant. If the fluids' transfer occur synchronized with some ambient parameters' changes, it means that the plant's plasticity is good, i.e., that the plant's response to external and ambient changes is good and is in perfect functional operation. On the contrary, if plant's response is delayed or altered, it may indicate that the plant is not fully functioning and a deeper analysis should be made by an agronomist (a desease is maybe the cause, or an aging characteristic, or other type of problem).

3.2.2 SENSOR EXPERIMENTAL TESTS

The investigation into the viability of using a soil moisture sensor in a novel application, by embedding it within the trunks of citrus trees, such as orange and lemon trees, stems from the growing need to enhance agricultural monitoring techniques. Traditional methods of assessing plant health often involve invasive or indirect measures, which can be resource-intensive or provide limited real-time data. The integration of IoT technology in agriculture presents an opportunity to overcome these challenges by allowing continuous and precise monitoring of plant conditions. Specifically, soil moisture sensors, which are traditionally used to measure moisture content in soil, are being investigated in this study for their potential to estimate moisture content (MC) within the trunk of a tree. This exploratory approach aims to assess whether these low-cost, readily available sensors can effectively gather critical data about plant health, even with a small intrusive approach to the plant's trunk. The results of this investigation will determine if these sensors can indeed be repurposed for this novel application, and the findings will be discussed in detail in the conclusion of this chapter.

In the previous subchapter, the architecture of the IoT network was discussed, highlighting its role in enabling seamless communication between various sensors and the central data collection system. With the IoT network operational, experimental tests with sensors were initiated to assess the health of the plants by measuring various parameters, including trunk's resistivity. This application leverages the network's capability to transmit real-time data, which is crucial for timely interventions in agricultural practices.

One of the primary motivations for conducting this feasibility test with the soil moisture sensor is to explore whether it can reliably estimate the MC within the trunk, thus providing insights into the plant's health. The study [43] provides a relevant context for this objective. The study evaluated the efficiency of the Electrical Resistivity Tomography (ERT) tool in detecting wetwood and estimating the mean MC of silver fir trunks, demonstrating a significant correlation between MC and electrical resistivity (ER). This research underlines the importance of accurately estimating MC to assess tree health. Inspired by this, our study aims to verify the feasibility of using a low-cost soil moisture sensor for similar purposes in citrus trees. The goal is to determine if such a sensor can provide a cost-effective alternative to more sophisticated tools like ERT, while still offering valuable insights into the moisture dynamics within the tree trunk and, by extension, the overall health of the plant.

To achieve this, the implementation of an operational IoT network was a critical step, enabling seamless data collection and analysis across various environmental conditions. With this network in place, we could proceed to the experimental phase, where the practical application of the sensors would be rigorously tested. The first sensor selected for investigation was a soil moisture sensor illustrated in Figure 3.8. This selection was strategic, as the sensor's capacity to detect variations in electrical resistance directly correlates with changes in moisture content, making it a promising candidate for this innovative application within the trunks of both orange and lemon trees.

Figure 3.8. Moisture Sensor

The initial steps involved laboratory testing to determine the sensor's maximum and minimum reading points before saturation. Known resistance values were connected between the sensor's probes to observe the analog readings from the ESP32 module, which has a 12-bit ADC scale ranging from 0 to 4095. These tests verified the sensor's linearity and established reference points for maximum and minimum saturation. Table 3.3 and Figure 3.9 illustrate the resistor values used, along with the linearity between resistance and analog readings.

Table 3.3 - Moisture sensor test results

Applied Resistance (ohms)	log10R	Analog Reading	Interpolation
2.67E+04	4.426511	173	-91.51307814
3.28E+04	4.515874	213	76.34414836
5.06E+04	4.704151	430	430
1.01E+05	5.004321	860	993.8360732
5.69E+05	5.755112	2512	2404.109519
1.00E+06	6	2997	2864.102669
3.32E+06	6.521138	3843	3843
3.92E+06	6.593286	3938	3978.521603
4.77E+06	6.678518	4039	4138.620596

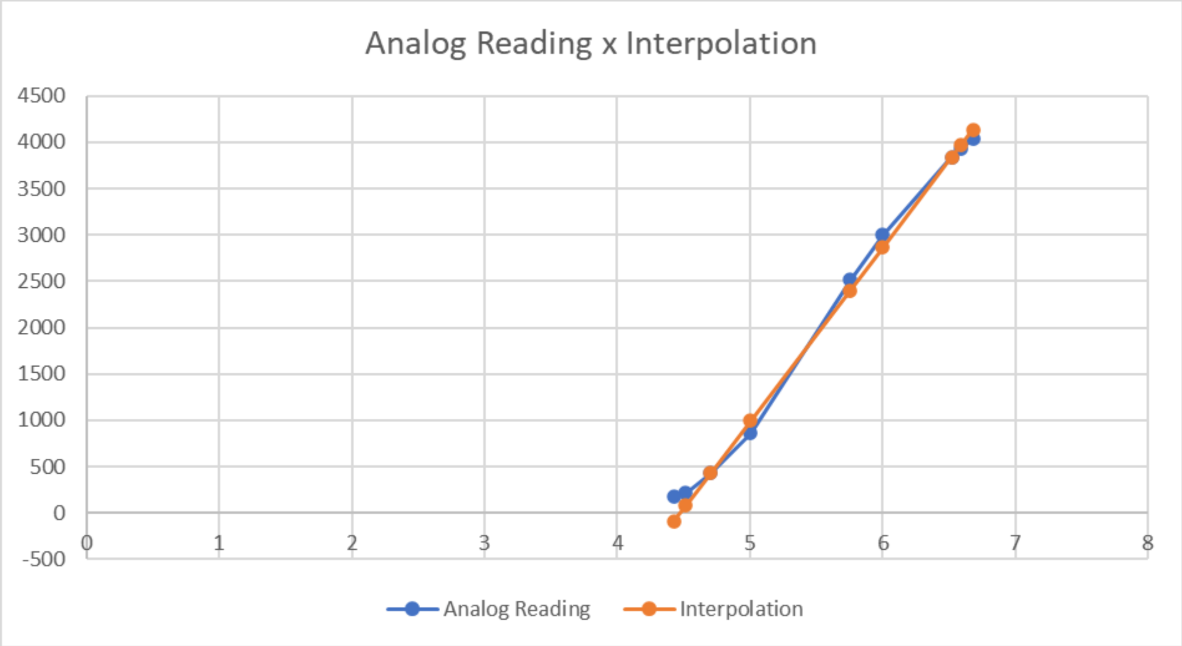


Figure 3.9. Moisture Sensor - Analog Reading x Interpolation

The blue graph shows real sensor measures obtained with known resistors in laboratory. As we can see, the sensor's response is linear for a base 10, logarithmic-scale, of resistances. The graph also shows in the orange plot the interpolation of measured values to obtain a linear function for the resistance, using a linear regression.

Following the laboratory tests, the soil moisture sensor was installed in the trunk of a lemon tree with minimal invasion, and in the trunk of a lemon tree as exemplified in Figure 3.10. As shown in Figure 3.10, part of the sensor was insulated using a rubber heat-shrink sleeve to ensure that only 3 cm of the sensor made contact with the tree.

Figure 3.10. Moisture sensor installation – lemon tree

This installation method was crucial for two main reasons: firstly, the shallow installation minimized the invasive impact on the tree, reducing potential harm. Secondly, as indicated by the study by [43], the outer zones of the trunk, such as the S zone highlighted in the study, show a direct proportionality between moisture content (MC) and electrical resistance (ER). The charts correlating MC, ER, and Distance to pith of tree can be found in the mentioned work.

With the sensor installed, data collection began by connecting the sensor to the architecture setup described in Subsection 3.2.1.

3.3 DASHBOARD IMPLEMENTATION

In the evolving landscape of agricultural technology, the ability to monitor and respond to environmental anomalies is crucial for optimizing crop yield and resource management. This chapter introduces a tailored dashboard designed specifically for citrus agriculture in Portugal. The dashboard serves as an invaluable tool for farmers, enabling them to make informed decisions based on real-time environmental data. By leveraging the daily data provided by the IPMA, which encompasses information from 203 weather stations across the country, this dashboard offers a comprehensive overview of various climatic factors that impact citrus farming.

The dashboard was developed with a generic approach to ensure its applicability across all available weather stations. This design decision was driven by the extensive dataset from

IPMA, which provides daily updates on various environmental parameters. These parameters include, but are not limited to, temperature, humidity, wind speed, and precipitation. The generic nature of the dashboard allows for scalability and adaptability, catering to the diverse needs of farmers across different regions of Portugal. Furthermore, the dashboard integrates calculations for Evapotranspiration (ETc) and estimates of water loss over specified periods, aiding farmers in efficient water management practices.

The implementation of this dashboard used several advanced libraries such as Bokeh (bokeh.plotting and bokeh.models) [44], Matplotlib (matplotlib.pyplot) [45], and Windrose [46], which together enabled the creation of a feature-rich and user-friendly interface. These libraries were chosen for their robust capabilities in data visualization and interactivity, providing users with intuitive and dynamic graphs and charts that depict critical agricultural data.

In today's technologically advanced agricultural sector, leveraging such data is not just beneficial but essential for sustainable farming practices. This dashboard acts as a crucial intermediary between complex data sets and practical agricultural decisions, providing users with accessible insights that can lead to improved crop yield, resource efficiency, and overall farm management.

The functionalities of the dashboard are designed with a clear focus on user-friendliness and adaptability. Each feature aims to simplify the decision-making process for farmers, allowing them to tailor data analysis to their unique agricultural needs. By doing so, the dashboard bridges the gap between technology and traditional farming practices, offering seamless integration that enhances productivity and sustainability. This section explores the primary functionalities of the dashboard, including the Location Selection Menu, Environmental Data Presentation, Crop Evapotranspiration per Hour, Water Loss Estimation, and Outlier Detection. Each of these components plays a vital role in the comprehensive monitoring system provided by the dashboard. Below, an image of the current version of the dashboard is displayed in Figure 3.11.

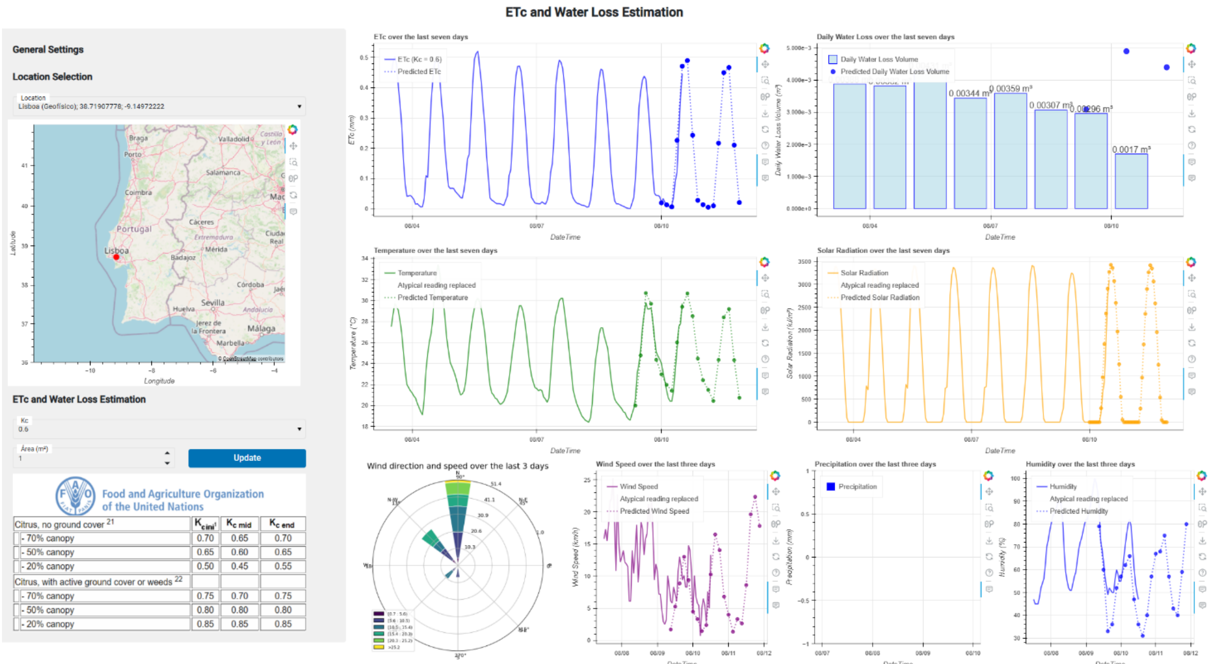


Figure 3.11. Dashboard overview – Location: Lisboa – Date: 10/08/2024

3.3.1 LOCATION SELECTION MENU

This feature offers users the ability to customize their experience based on geographic preferences, ensuring that the data presented is highly relevant to their specific region. By selecting from a range of locations, farmers can access localized data that reflects the unique climatic conditions of their area. Situated on the left-hand side of the interface for intuitive access, the menu allows users to select their desired location from a dropdown list, with "Faro" pre-set as the default location. Upon selecting a new location, the dashboard dynamically updates the relevant calculations and visualizations using callback functions such as @pn.io.with_lock. This ensures users receive the most current and relevant data for their selected area, facilitating precise agricultural planning and decision-making.

The importance of this feature lies in its ability to provide hyper-localized data, essential for addressing the diverse climatic conditions across Portugal. By offering a tailored view of environmental data, the Location Selection Menu enables farmers to adapt their strategies to the specific conditions of their region, ultimately leading to better resource management and crop optimization.

3.3.2 ENVIROMENTAL DATA PRESENTATION

By aggregating data from 203 IPMA weather stations, this feature provides a panoramic view of climatic variables crucial for citrus farming. Users can access detailed information on temperature, humidity, wind speed, and precipitation, enabling them to make informed decisions based on real-time environmental conditions. The dashboard presents comprehensive environmental data from all 203 weather stations available through the IPMA API, covering the entire mainland of Portugal and the islands. This broad and inclusive dataset reflects diverse climatic conditions, allowing users to obtain localized and accurate environmental information pertinent to their specific agricultural needs.

For each meteorological variable, including temperature, solar radiation, wind speed, precipitation, and humidity, forecasts for the current and the next day are obtained through OpenWeatherMap APIs, as previously introduced in Chapter 2.4. These forecasts are displayed as dotted lines on each respective graph, as shown in Figure 3.12.

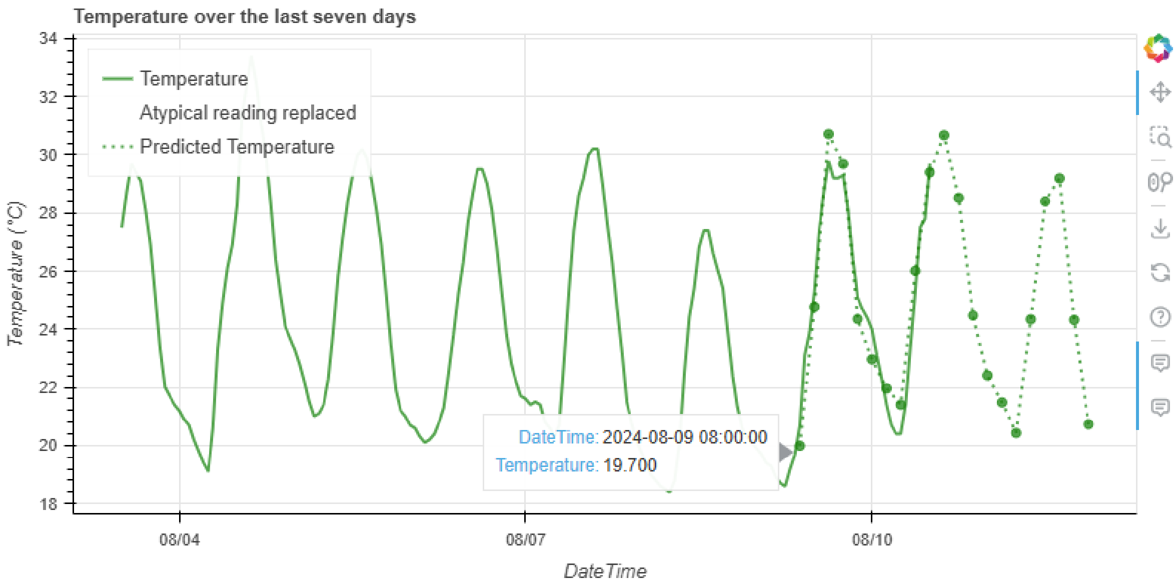


Figure 3.12. Temperature data overview – Location: Lisboa – Date: 10/08/2024

The importance of these forecasts cannot be overstated, as they provide farmers with anticipatory insights that can guide proactive measures to mitigate potential adverse effects on crop health. By visualizing this data through intuitive graphs and charts, the dashboard transforms complex information into actionable insights, empowering farmers to make informed decisions based on real-time environmental conditions.

3.3.3 CROP EVAPOTRANSPIRATION

This functionality initially provides the traditional daily calculation of crop evapotranspiration (ETc), which is essential for determining the overall water needs of crops over a 24-hour period. Building on this, an advanced feature of the dashboard enables the precise calculation of ETc on an hourly basis. This more granular approach is critical for optimizing irrigation schedules, ensuring that crops receive the right amount of water at the most appropriate times throughout the day. The hourly ETc calculation is based on real-time meteorological data and employs the Penman-Monteith method. The variations in the Penman-Monteith formulas for hourly calculations were adapted from [47].

Moreover, an additional and highly significant functionality has been implemented: the calculation of crop evapotranspiration based on weather forecasts for the next day. This predictive approach, which uses reliable weather forecast source from OpenWeatherMap, allows for an estimation of water loss for the upcoming day. By applying these forecasted ETc values, farmers are equipped with foresight into their crops' water needs, enabling more effective irrigation planning and water conservation. This feature not only enhances water use efficiency but also supports broader sustainability and environmental stewardship goals in agriculture.

3.3.4 WATER LOSS ESTIMATION

Water Loss Estimation is a crucial feature that significantly enhances the dashboard's utility by enabling users to calculate potential water loss in their agricultural fields. This calculation is deeply intertwined with the daily ETc (Evapotranspiration) values discussed in chapter 3.5.3 Crop Evapotranspiration. The daily ETc values serve as the primary input for estimating daily water loss, offering a comprehensive understanding of water requirements and potential deficits. An example of the daily water loss estimation graph is displayed in Figure 3.13.

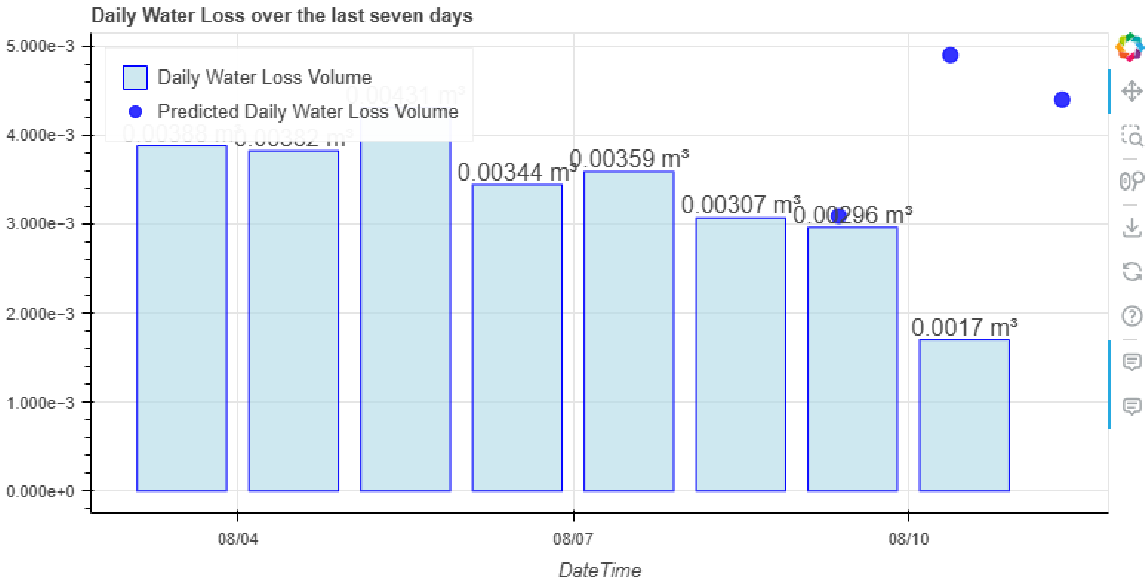
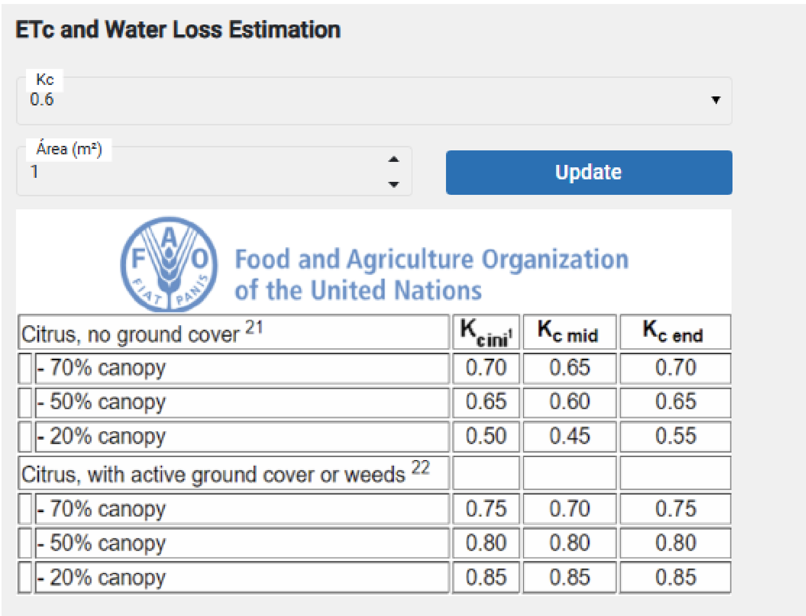


Figure 3.13. Daily water loss overview – Location: Lisboa – Date: 10/08/2024

Figure 3.13 not only shows the daily water loss volume but also incorporates predictions for water loss on the current day and the next day, based on weather forecasts. This predictive capability is particularly valuable as it allows farmers to adjust their irrigation schedules in real-time, ensuring that crops receive the precise amount of water needed today, while also preparing for the next day's water requirements. Such foresight is vital for optimizing water usage and mitigating risks associated with water scarcity. Additionally, the "ETc and Water Loss Estimation" menu in the dashboard includes options for users to select the crop coefficient (Kc) based on values provided in the FAO-56 guidelines for citrus agriculture.



Citrus, no ground cover [21]	$K_{c\,ini}$	$K_{c\,mid}$	$K_{c\,end}$
- 70% canopy	0.70	0.65	0.70
- 50% canopy	0.65	0.60	0.65
- 20% canopy	0.50	0.45	0.55
Citrus, with active ground cover or weeds [22]			
- 70% canopy	0.75	0.70	0.75
- 50% canopy	0.80	0.80	0.80
- 20% canopy	0.85	0.85	0.85

Figure 3.14. Daily water loss overview – Location: Lisboa – Date: 10/08/2024

As shown in Figure 3.14, an image of the Kc table is integrated into the dashboard to assist users in making accurate selections. The default Kc value is set at 0.6, as mentioned in the section 3.1.2. This Kc value is crucial for calculating ETc using the Penman-Monteith method, with the selected Kc triggering updates to ETc calculations and visualizations in real-time whenever it is modified. Moreover, as presented in Figure 3.14, the dashboard allows users to input the area, in square meters, for which they wish to estimate water loss. Initially set to $1m^2$, this field is customizable to reflect the size of the user's agricultural field, providing precise water loss estimates for irrigation purposes. This flexibility is particularly beneficial for farmers aiming to optimize their water usage and maintain efficient irrigation practices across diverse field sizes.

Importantly, the water loss estimation also accounts for precipitation values—both actual and forecasted for the upcoming day. By integrating real-time and predictive meteorological data, including precipitation, the dashboard provides a robust tool for managing water resources effectively. This comprehensive approach not only promotes the efficient use of water but also aligns with broader goals of sustainability and environmental stewardship in agriculture. As illustrated in Figure 3.13, the dashboard's dual visualization of daily water loss estimation and predictions for the current and next days empowers farmers with actionable insights. This capability enables them to adjust their irrigation practices promptly, ensuring that crops receive the precise amount of water required today while also preparing for the following day's needs. This foresight is crucial for optimizing water usage, especially in regions facing water scarcity, and significantly contributes to sustainable farming practices.

3.3.5 ATYPICAL READING REPLACEMENT FOR FAILED IPMA DATA

The detection of atypical readings is an essential functionality implemented in the dashboard to ensure the accuracy and reliability of the data used in various calculations, including evapotranspiration and water loss estimates. Atypical readings, such as failed or missing IPMA data, can significantly distort these calculations, leading to erroneous conclusions and suboptimal irrigation practices. To mitigate these risks, the dashboard includes mechanisms to effectively detect and replace atypical readings.

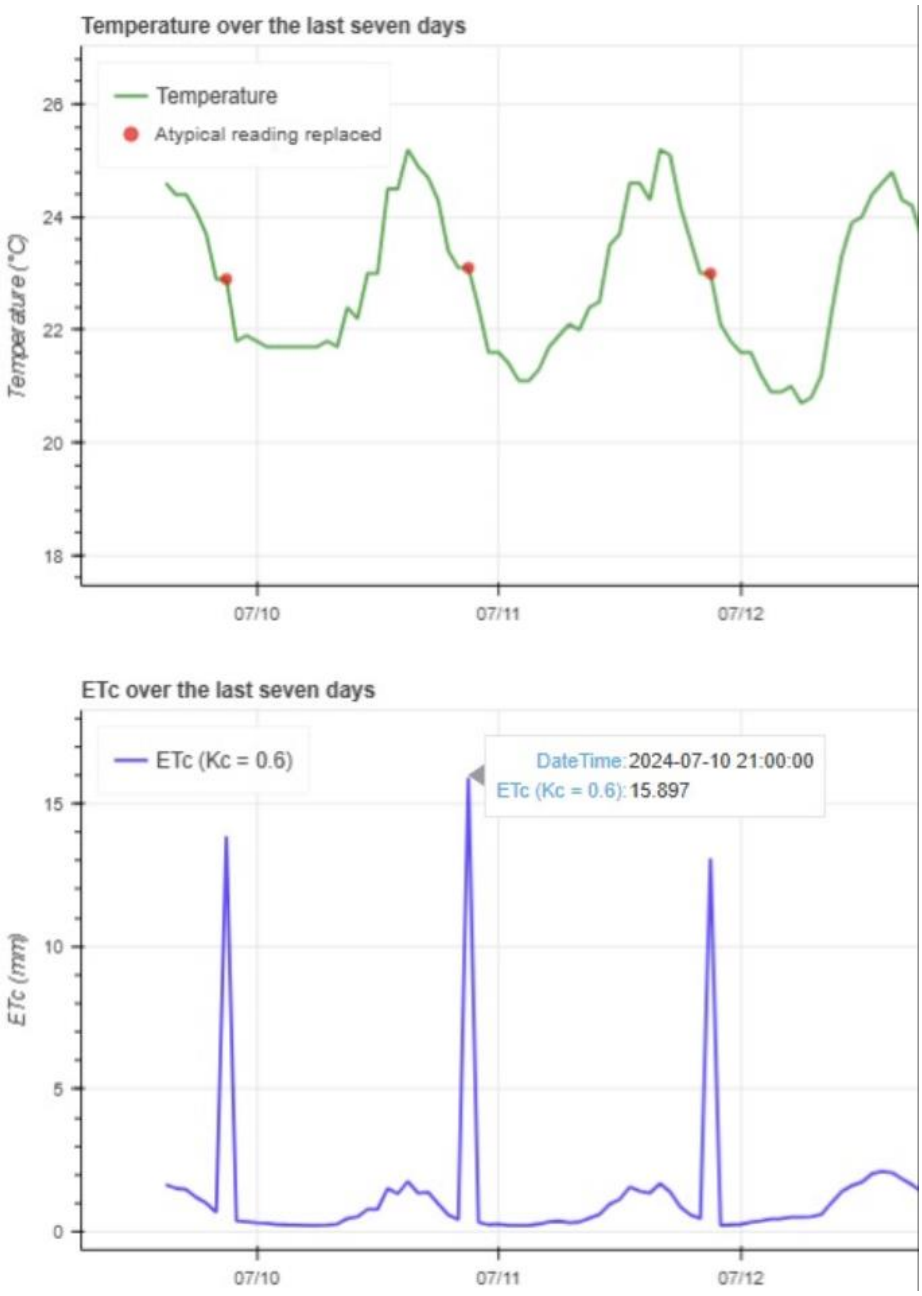


Figure 3.15. Atypical reading replacement – Location: Porto Santo – Date: 12/07/2024

Figure 3.15 illustrates the initial stage of identifying atypical readings, where these data points have been flagged but not yet replaced for calculation purposes. This identification process is crucial for isolating erroneous data, particularly in temperature and solar radiation measurements, which are vital inputs for evapotranspiration calculations. The presence of such atypical readings is significant because evapotranspiration plays a key role in determining water loss and irrigation requirements. Once atypical readings are identified, the dashboard employs a substitution technique to ensure data integrity. When data is flagged as invalid by the IPMA, it is temporarily substituted with the value "-99" to mark it as an atypical reading. To maintain the accuracy of the calculations, the dashboard then replaces these invalid readings with the most recent valid reading for the same parameter. Other solutions were considered, such as applying interpolation to the data, replacing the invalid readings with mean or median values, etc. However, due to the data variability and the frequency of missing data points, using the most recent valid data proved to produce the best results.

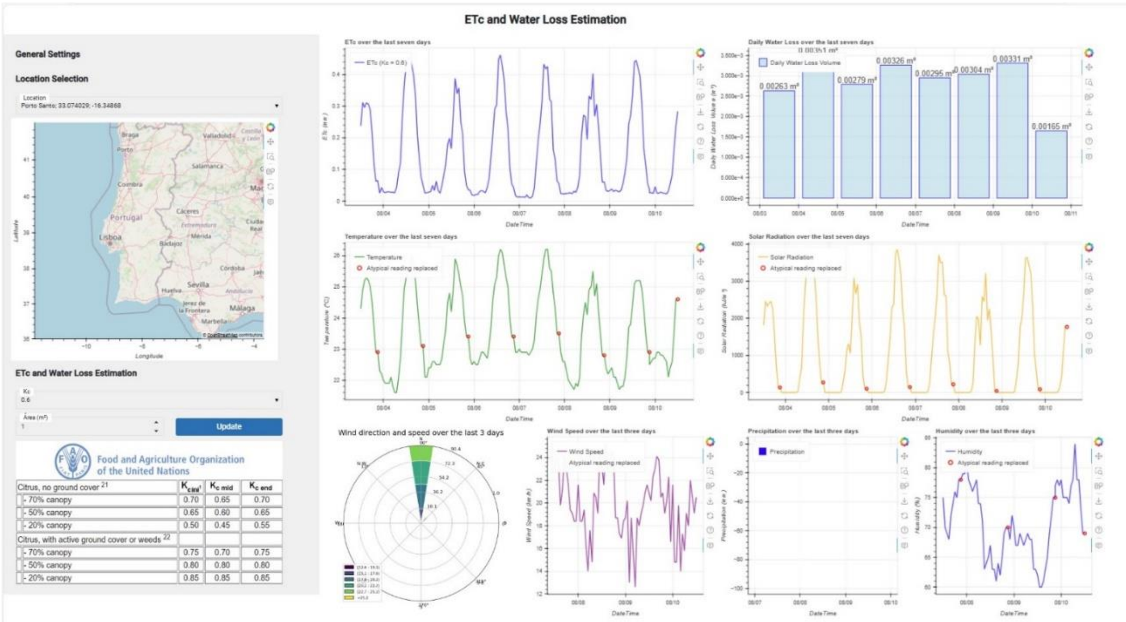


Figure 3.16. Dashboard showing an atypical reading replacement along the remaining graphical elements – Location: Porto Santo – Date: 10/08/2024

Figure 3.16 demonstrates a scenario where the atypical readings have already been replaced, ensuring that they no longer negatively impact the calculations. This replacement leads to more accurate and realistic estimates, closely reflecting the actual environmental conditions. By using the most recent valid data for substitution, the dashboard maintains continuity and reliability in its calculations, ensuring that evapotranspiration and water loss calculations align with real-world conditions. The effectiveness of the atypical reading detection and replacement process showcases the dashboard's commitment to delivering accurate data for decision-making. By addressing the challenges posed by faulty or missing data, the dashboard strengthens its role as a reliable tool for optimizing agricultural practices and improving water management efficiency.

These functionalities, among others, exemplify the dashboard's dedication to improving agricultural practices through precise data analysis and presentation. By equipping farmers with these tools, the dashboard not only supports effective decision-making but also promotes the adoption of innovative strategies that enhance the sustainability and efficiency of farming. The integration of advanced data visualization, real-time analytics, and predictive forecasting ensures that farmers are empowered with the insights needed to adapt to changing environmental conditions, ultimately leading to better crop yields and improved resource management.

3.3.6 COST IMPLICATIONS

The financial aspects of implementing and maintaining the dashboard are essential considerations for ensuring its long-term viability and accessibility for users. One of the key advantages of the dashboard is that all instantaneous and historical data displayed are sourced directly from the IPMA platform. This means that there are no associated costs for accessing this data, which is a significant benefit. The IPMA provides comprehensive environmental data, including temperature, humidity, wind speed, and precipitation, across 203 weather stations in Portugal. By leveraging this freely available resource, the dashboard can offer detailed environmental insights without incurring any recurring expenses for data acquisition related to past or current conditions. A major positive aspect of this characteristic is that the dashboard does not impose any monthly fees for acquiring data necessary for calculating ETc or estimating water loss based on instantaneous or past environmental data. This cost-free access ensures that farmers can continuously monitor and optimize their agricultural practices without the burden of ongoing expenses, making the dashboard an economically sustainable tool for the agricultural community.

However, when it comes to acquiring weather forecast data, the situation is more nuanced. The dashboard's ability to predict future ETc and water loss relies on two key APIs, both provided by OpenWeatherMap. The first API, which is responsible for gathering general weather forecast data, is freely accessible. This API can be accessed via [2], and it provides essential information such as temperature, humidity, and wind speed forecasts at no cost. This free access is particularly beneficial, as it allows the dashboard to continue providing valuable predictive insights without additional financial outlays.

The second API, however, deals with the acquisition of solar irradiation forecast data and is a paid service. Solar irradiation data is critical for accurately determining ETc, as discussed in "3.1.3 Data Analyses." This API, available at [48], incurs a cost of 0.11 EUR per API call. There are no limits on the number of API calls that can be made, and the service operates on a "pay-as-you-call" basis. To provide a clear picture, if one API call is made daily for a single location throughout the year, the annual cost would be approximately 40.15 EUR per location. This charge represents the only current bottleneck preventing the dashboard from being entirely free, including the provision of water loss predictions. While the IPMA and general weather forecast data can be accessed without cost, the acquisition of solar irradiation forecast data introduces an ongoing expense. Despite efforts to find free alternatives, all other contacted providers, such as [49], [50], [51], also charge for API access to solar irradiation data. These costs underscore the challenge of offering a fully free dashboard, though the expense is relatively modest compared to the potential benefits provided by accurate ETc and water loss predictions. However, other alternatives exist, such as estimating ETc based on the remaining meteorological data, as seen, for example, in several studies for example [52], and [53], that successfully employed such methods.

In conclusion, while the dashboard is largely cost-effective, especially with its free access to IPMA data and general weather forecasts, the requirement to pay for solar irradiation forecast data remains the only significant expense. However, this cost is necessary to ensure the accuracy and reliability of ETc calculations, ultimately contributing to better water management and sustainable agricultural practices.

4

EXPERIMENTAL RESULTS

This chapter delves into the experimental results obtained during the development and validation of the dashboard system for estimating ETo using the Penman-Monteith method, and its comparison with established datasets, particularly those provided by IPMA. This comparison is essential to evaluate the accuracy and reliability of the predicted ETo values presented in the dashboard, which is critical for agricultural monitoring and irrigation management.

In addition to the comparison of ETo values, this chapter expands on experimental insights obtained from exploratory analyses of internal trunk resistance in citrus trees. By embedding soil moisture sensors into tree trunks, this novel application aims to assess internal moisture levels as an indicator of tree health and water status. A time series decomposition of trunk resistance data, as well as autocorrelation analyses, are discussed to identify temporal patterns and the relationship between environmental factors such as temperature, radiation, and irrigation events.

The experimental results from both the dashboard validation and the internal trunk resistance analysis provide a comprehensive evaluation of the methods and technologies employed, laying the groundwork for future enhancements in precision agriculture monitoring systems.

4.1 VALIDATION OF DASHBOARD DATA AGAINST IPMA

In order to ensure the reliability and accuracy of the dashboard's values presented in Subsection 3.3, it is imperative to compare the ETo values presented by the dashboard with those provided by a trusted and established source like the IPMA. Table 3.3 and Table 3.4

present a comparison between the ETo values presented by the dashboard in this context and those provided by IPMA [54] for two different locations, Faro and Lisboa.

Table 3.3 - Comparison of IPMA data and ETo estimated values for Faro over a period of 15 days

Date	IPMA - Faro	ETo Estimated by PM Formula - Faro (Airport)		Absolute Error
	ETo (mm/day)	ETo (mm/day)	Water Loss (m3 /day)	
18/08/2024	8.04	7.53	0.00452	0.50667
17/08/2024	6.88	6.48	0.00389	0.39667
16/08/2024	7.01	6.35	0.00381	0.66000
15/08/2024	6.46	6.05	0.00363	0.41000
14/08/2024	5.99	5.65	0.00339	0.34000
13/08/2024	7.26	6.72	0.00403	0.54333
12/08/2024	5.83	5.37	0.00322	0.46333
11/08/2024	4.58	4.12	0.00247	0.46333
10/08/2024	5.98	5.75	0.00345	0.23000
09/08/2024	5.67	5.30	0.00318	0.37000
08/08/2024	6.02	5.72	0.00343	0.30333
07/08/2024	6.38	6.15	0.00369	0.23000
06/08/2024	6.32	5.87	0.00352	0.45333
05/08/2024	6.19	5.93	0.00356	0.25667
04/08/2024	6.27	5.80	0.00348	0.47000

Table 3.4 - Comparison of IPMA data and ETo estimated values for Lisboa over a period of 15 days

Date	IPMA - Lisboa	ETo Estimated by PM Formula – Lisboa		Absolute Error
	ETo (mm/day)	ETo (mm/day)	Water Loss (m3 /day)	
18/08/2024	6.17	5.63	0.00338	0.53667
17/08/2024	7.52	7.30	0.00438	0.22000
16/08/2024	8.23	8.02	0.00481	0.21333
15/08/2024	7.92	7.60	0.00456	0.32000

14/08/2024	5.52	5.25	0.00315	0.27000
13/08/2024	5.62	5.28	0.00317	0.33667
12/08/2024	6.09	5.55	0.00333	0.54000
11/08/2024	5.58	5.15	0.00309	0.43000
10/08/2024	6.33	6.60	0.00396	0.27000
09/08/2024	5.44	5.12	0.00307	0.32333
08/08/2024	5.44	5.98	0.00359	0.54333
07/08/2024	6.31	5.73	0.00344	0.57667
06/08/2024	6.45	7.18	0.00431	0.73333
05/08/2024	7.07	6.37	0.00382	0.70333
04/08/2024	6.81	6.47	0.00388	0.34333

The comparison between the ETo values calculated by the dashboard and those provided by IPMA reveals a high degree of similarity, as evidenced by the small absolute error between the daily values. This close alignment underscores the accuracy of the algorithms used to calculate the ETo values shown in the dashboard.

However, it is important to highlight that some differences were expected. The dashboard is designed to provide precise hourly calculations tailored to the specific location of each weather station. In contrast, the IPMA focuses on providing daily ETo accumulations at the municipal level. According to information available on the IPMA's website, their calculations involve interpolating data from multiple stations to consolidate a representative value for the entire municipality. This methodological difference can account for the slight variations observed between the dashboard and IPMA’s data.

In short, the "Absolute Error" columns in Tables 3.3 and Table 3.4 further validate the reliability of the dashboard as a practical tool for farmers. The low error between ETo values demonstrate that the variations between the dashboard's ETo calculations and those provided by IPMA are minimal, highlighting the precision of the algorithms used for the dashboard.

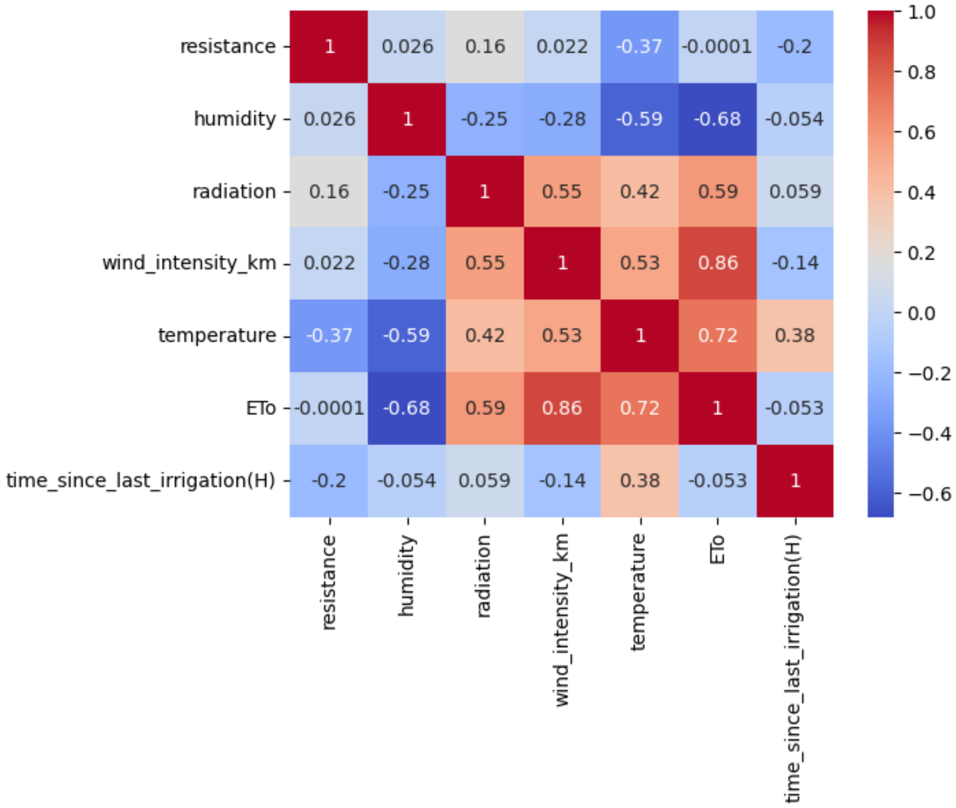
4.2 EXPLORATORY ANALYSIS OF INTERNAL TRUNK RESISTANCE

The motivation for using sensors in novel applications, diverging from their originally intended purpose of measuring soil moisture, was discussed in detail in Subsection 3.2.2. In this section, we focus on embedding these sensors within the trunk of citrus trees, such as lemon and orange trees, as part of a preliminary study.

Concerning sap flow, there are two distinct types of sap within the plant's vascular system: xylem sap and phloem sap. Xylem sap, primarily composed of water and dissolved minerals, is responsible for transporting these substances from the roots to the aerial parts of the tree. On the other hand, phloem sap carries the products of photosynthesis, such as sugars, from the leaves to other parts of the plant for growth and storage. These two saps travel through separate channels: the xylem, located closer to the outer layers of the trunk, and the phloem, located in the inner bark layers. As shown in [55], xylem sap exhibits significant diurnal variations in flow volume, particularly in the earlywood regions of the trunk, in response to changes in water potential, whereas phloem sap flow remains more stable, with less variation over time. This finding supports the hypothesis that the sensors placed near the outer trunk layers are most likely measuring xylem sap. As discussed further below, this repurposed sensor likely measures xylem sap, the sap that primarily transports water and mineral salts from the roots to the aerial parts of the tree. Following the installation of the sensor, an exploratory data analysis was initiated to assess the sensor's performance and behavior in a lemon tree, covering the period from September 5, 2024, to September 20, 2024. This analysis provides preliminary insights into the sensor’s behavior and its correlation with environmental factors. Future analyses will include data collected from the orange tree installation, also discussed in Subsection 3.2.2, to validate and compare findings between the two citrus species and, obviously, a larger period of observation.

It is important to note that the data collected on September 5, 2024, was excluded from the analysis due to the significant noise present in the dataset. Upon further investigation, the primary cause of this noise was identified as suboptimal contact between the sensor probes and the internal surfaces of the lemon tree’s trunk. At the time of installation, the two sensor probes were not fully embedded within the grooves of the trunk, preventing stable and reliable measurements. Once this issue was addressed, the analysis proceeded by studying correlations between trunk resistance and various environmental factors resulting in the matrix presented in Table 3.5.

Table 3.5 - Correlation matrix – IPMA & internal trunk resistance (lemon tree)



The correlation study aimed to explore potential relationships between internal trunk resistance readings and environmental variables such as radiation, temperature, humidity, wind intensity, and irrigation events. As detailed in Table 3.5, the strongest correlations observed were:

- **Temperature vs. Trunk Resistance:** A moderate negative correlation was found between ambient temperature and trunk resistance. As temperatures rise, the internal moisture content of the tree likely increases, leading to a decrease in trunk resistance. This supports the hypothesis that the tree absorbs more water at higher temperatures to manage internal cooling.
- **Radiation vs. Trunk Resistance**: Although a low positive correlation was observed between solar radiation and internal trunk resistance, no direct relationship was found between the radiation curve, which follows a sinusoidal pattern, and the resistance graph. However, a noticeable shift in the resistance trend was identified, directly linked to the presence or absence of radiation. This interaction will be further detailed in Subsection 4.2.1, where the nuances of this phenomenon are explored in more depth.

- **Period since last irrigation vs. Trunk Resistance:** A negative correlation was found between the elapsed time since the last irrigation and trunk resistance. As more time passes without irrigation, the moisture content inside the tree decreases, resulting in increased trunk resistance.

Figure 4.1. Trunk internal resistance (lemon tree) & temperature

The data from the temperature versus trunk resistance correlation is visually supported by the trends shown in Figure 4.1. In the first chart, we observe an apparent inverse relationship between trunk internal resistance and temperature. As temperature peaks, the resistance tends to decrease, which aligns with the previously discussed negative correlation between these two variables. Periods of lower temperature correspond with higher internal resistance, suggesting that the internal moisture content decreases as external temperatures drop, maintaining a higher resistance value.

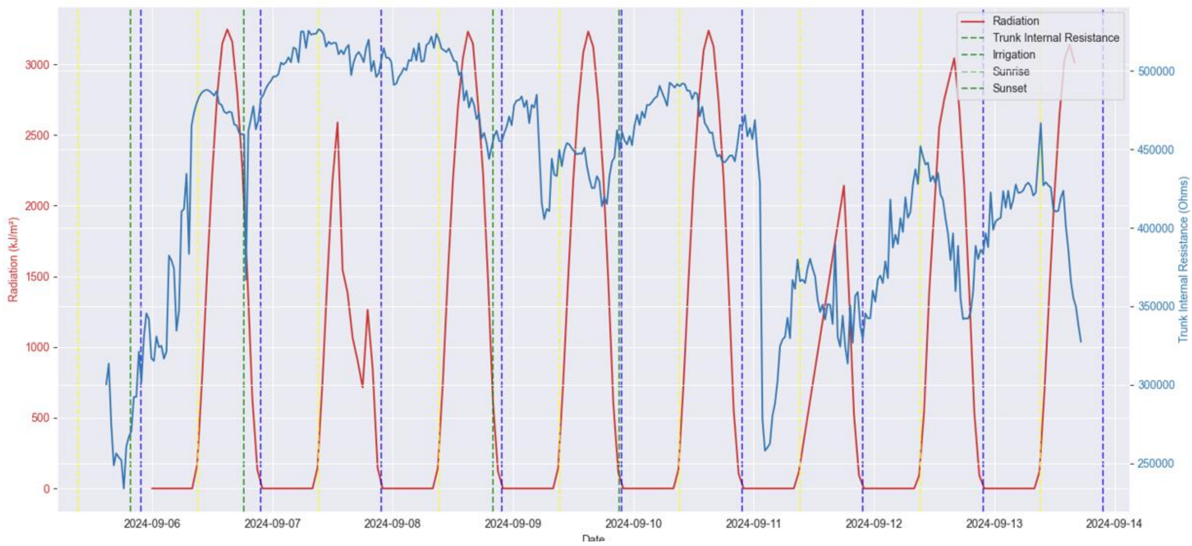


Figure 4.2. Trunk internal resistance (lemon tree) & radiation

In Figure 4.2, the interaction between trunk internal resistance and radiation is shown, alongside sunrise and sunset times. While the radiation curve follows a sinusoidal pattern during the day, with distinct peaks, the trunk resistance trend does not exhibit a direct relationship with these peaks.

Figure 4.3. Trunk internal resistance (lemon tree) & air humidity

Upon examining Figure 4.3, we can observe a similar trend of minimal correlation between humidity and trunk resistance, supporting the previously discussed weak relationship. The graph shows fluctuations in humidity levels, but these changes do not seem to correspond closely with significant shifts in trunk resistance. In some instances, humidity appears to rise or fall without producing a clear, proportional effect on the trunk's internal resistance. This behavior reinforces the hypothesis that humidity does not strongly influence the internal trunk resistance, further suggesting that the sensor might be more reactive to other environmental factors like temperature or radiation. Interestingly, the sensor's performance appears less stable in periods of high humidity, where spikes are visible in the data. These fluctuations suggest that the sensor may be picking up external moisture, particularly during more humid conditions, which distorts the internal trunk resistance measurements. This possibility of external atmospheric interference presents a challenge for obtaining accurate data on internal trunk moisture levels, which is crucial for analyzing the health of the tree.

Given these observations, the need for enhanced insulation around the sensor becomes even more apparent. By improving the sensor's insulation to block out external humidity, future applications could ensure more reliable readings that focus solely on internal trunk conditions. This would eliminate the interference seen during periods of high atmospheric humidity and lead to more accurate assessments of trunk moisture levels.

Therefore, the graph reinforces the conclusion that the current design may be vulnerable to external environmental factors, and insulation improvements could resolve this issue, leading to more accurate data collection.

4.2.1 ANALYSIS OF TRUNK INTERNAL RESISTANCE IN RELATION TO THE SOLAR CYCLE AND TIME SERIES DECOMPOSITION

To further expand the analysis of the sensor, data related to sunrise and sunset times in Faro were incorporated, represented by the orange and blue dashed lines, respectively, in Figure 4.4. These sunrise and sunset times were obtained from [56]. This comparison provided intriguing insights into the behavior of the tree's internal trunk resistance in relation to the solar cycle. As shown in Figure 4.4, a clear shift in the trunk resistance trend can be observed at the times corresponding to sunrise and sunset. These trends, signaled by red lines for declining resistance and green lines for rising resistance, highlight the plant's physiological response to the start and end of the photosynthesis process. At sunrise, the trend shows a decline in trunk resistance, which is likely due to the tree beginning to photosynthesize as it "wakes up" with the sun. This aligns with the observation that tree moisture content tends to increase when photosynthesis begins, as more water is drawn into the trunk to support this process, leading to a decrease in internal trunk resistance due to the higher moisture content.

The observed behavior is consistent with other studies on moisture dynamics during photosynthesis. As the tree absorbs water through the xylem to support photosynthesis, the internal moisture content increases, causing the trunk resistance to drop. This suggests that the sensor is primarily measuring xylem sap, which is responsible for water transport from the roots to the upper parts of the tree. Studies such as [55] further support this, as they demonstrated that xylem sap exhibits significant diurnal variation due to environmental factors like water potential.

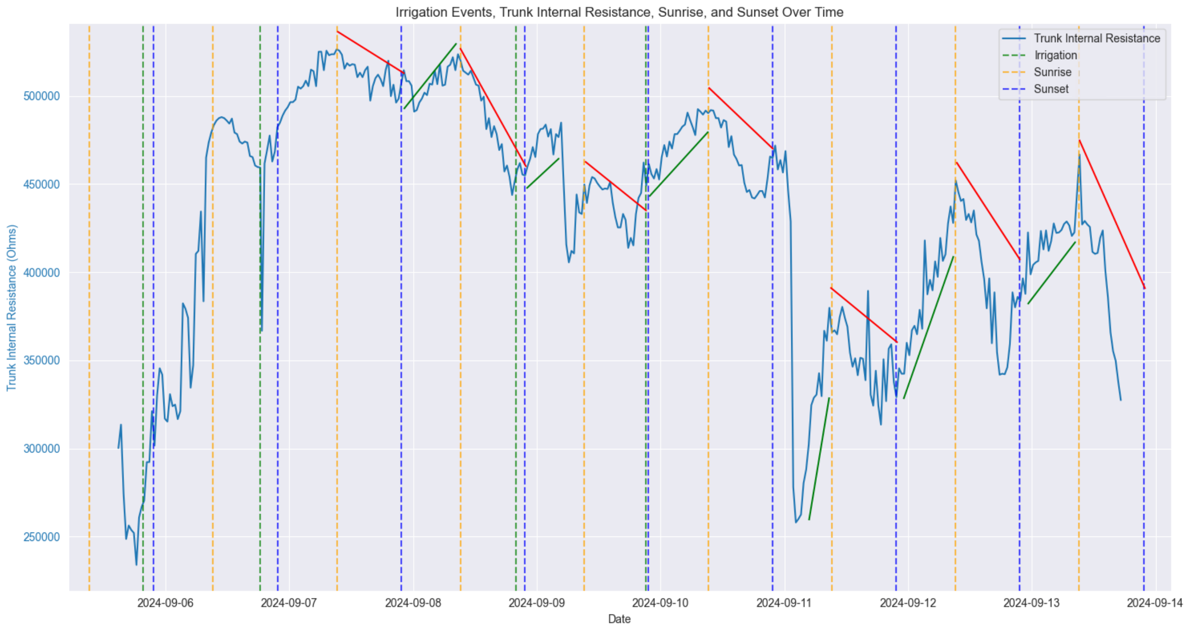


Figure 4.4. Trunk internal resistance (lemon tree) & sunrise & sunset

This finding aligns well with the observed behavior in the trunk resistance data, where resistance decreases as the tree starts photosynthesizing during the day, indicating a rise in moisture content within the trunk.

Continuing from the earlier analysis, a new approach was undertaken to examine the trunk internal resistance by applying a time series decomposition method. This analysis decomposed the data into its key components: observed data, trend, seasonal variation, and residuals, which help isolate long-term trends from daily cyclical patterns and random fluctuations.

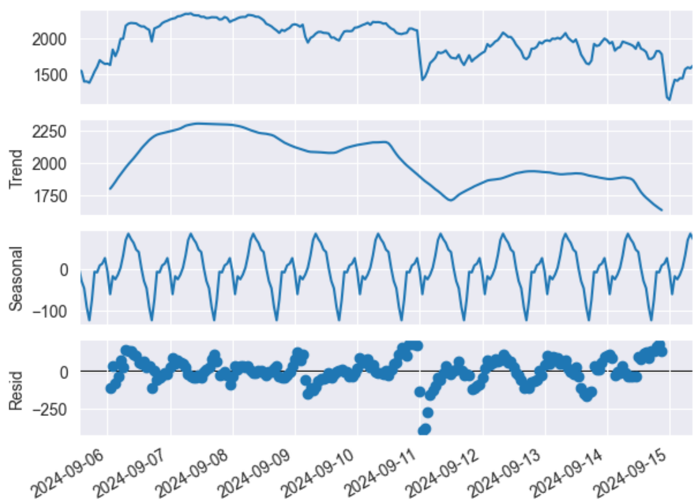


Figure 4.5. Decomposition analysis of trunk internal resistance (lemon tree)

The raw time series, presented in the first plot of Figure 4.5, exhibits significant fluctuations between 1500 and 2250, with notable peaks and troughs at specific points throughout the day. This reflects the daily variation in trunk resistance, which is influenced by environmental factors such as temperature and moisture. The decomposition of the original time series was then made into:

- **Trend:** The second plot isolates the trend, showing a general increase in trunk resistance at the start of the observation period, peaking towards the middle, followed by a gradual decrease. This suggests a shift in the internal conditions of the tree, potentially linked to changes in moisture content, soil conditions, or atmospheric factors. The long-term decrease may indicate reduced moisture absorption over time, possibly due to environmental stress or seasonal changes.
- **Seasonal Component:** The third plot highlights the cyclical, repeating nature of the trunk resistance on a daily basis, with periodic peaks and troughs. This strong seasonal cycle likely corresponds to daily temperature fluctuations, which drive moisture changes within the tree. These cycles are consistent in both magnitude and timing, suggesting stable and predictable patterns of internal trunk resistance.
- **Residual:** The residual component represents random noise that isn't captured by the trend or seasonal patterns. Although the residuals generally fluctuate around zero, some deviations suggest minor environmental factors or experimental noise that were not accounted for in the decomposition model.

To obtain the decomposition results, the data was first smoothed and resampled into hourly averages to ensure that it was more clean and representative of broader trends. An additive decomposition model was then applied, which allowed the time series to be broken down into its core components. This approach provided insights into the evolution of trunk resistance over time, isolating daily cycles from long-term trends.

This finding aligns well with the observed behavior in the trunk resistance data, where resistance decreases during the day, indicating a rise in moisture content within the trunk. The cyclical nature of the seasonal component reinforces the notion that this daily pattern is driven by external environmental factors, such as sunlight, temperature, humidity, and evapotranspiration, which affect the tree's internal moisture dynamics. These relationships suggest that the sensor can be effectively used to monitor the normal functioning of the plant. Any detected anomalies, such as a deviation in fluid transfer or moisture response, may indicate that the plant is no longer displaying normal plasticity, thus losing its ability to regulate internal conditions in response to external environmental factors.

This decomposition analysis provides a detailed view of how the tree's internal resistance behaves, supporting the preliminary hypothesis that internal moisture levels rise during the day, contributing to the observed decrease in resistance. Another remarkable aspect of this analysis is the behavior observed at sunset. As the tree transitions from photosynthesis to its nocturnal state, a noticeable increase in resistance can be seen in the residual components, likely due to the diminishing of moisture intake and the redistribution of water within the tree.

4.2.2 AUTOCORRELATION ANALYSIS OF INTERNAL TRUNK RESISTANCE

Following the decomposition of internal trunk resistance data, a further analysis was conducted to explore the autocorrelation patterns observed in the time series data. Autocorrelation measures the relationship between the current value of the series and its own past values at different time lags, helping us understand the underlying temporal dependencies.

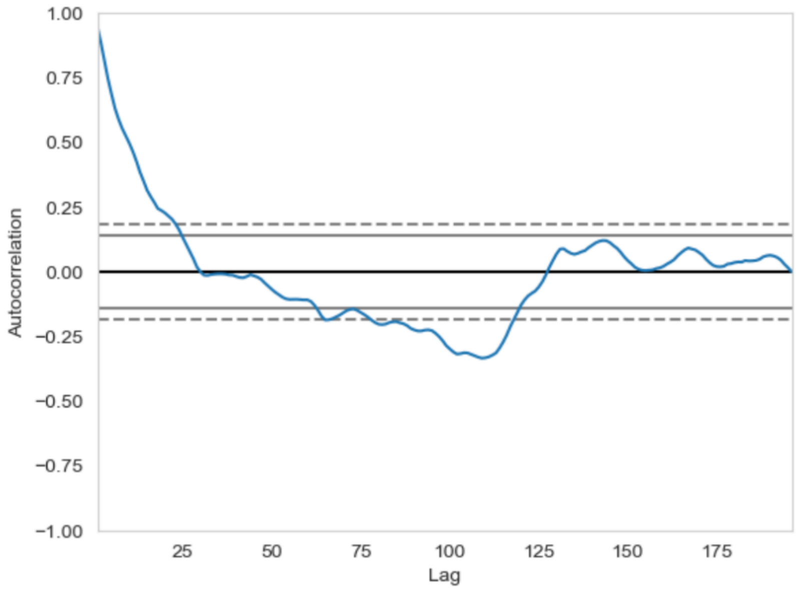


Figure 4.6. Autocorrelation plot of internal trunk resistance (lemon tree)

Figure 4.6 presents the autocorrelation function (ACF) of the resampled trunk resistance data over a period of 150 lags, providing insights into the persistence of internal resistance over time. The code used for this analysis computes the autocorrelation coefficients of the internal resistance data. In Figure 4.6 we observe that the correlation at lag 0 is 1, as expected, since any time series is perfectly correlated with itself at lag 0. The autocorrelation quickly decreases within the first few lags, and after around 10 lags, the autocorrelation falls below 0.5, indicating that the series exhibits low memory beyond this point.

Insights from the Autocorrelation Plot:

- **Short-Term Memory:** The autocorrelation falls significantly after the first few lags, suggesting that trunk resistance is primarily influenced by short-term factors. This aligns with the hypothesis that internal trunk resistance is highly responsive to daily environmental changes such as moisture intake, which shows high variability throughout the day.
- **Lag 30 Analysis:** The autocorrelation at lag 30 is close to zero, suggesting a lack of significant relationship between the current value of the series and its value 30 readings earlier. This suggests that after 30, the internal resistance data loses most of its memory, and current values are independent of those recorded 30 lags earlier.
- **Decreasing Autocorrelation:** Beyond lag 10, the autocorrelation remains below 0.5, confirming that the tree's internal trunk resistance does not exhibit strong periodicity within the sampling window analyzed. The decreasing trend in autocorrelation highlights the lack of long-term dependencies in the series.

It is important to note that the number of readings available for this analysis might still be insufficient to derive more robust conclusions. Expanding the data collection over longer periods and capturing more events, such as irrigation cycles and environmental changes, would provide a more comprehensive understanding of the autocorrelation patterns in trunk resistance. Overall, this autocorrelation analysis offers a preliminary look into the temporal dependencies of internal trunk resistance. Future work should aim to gather more data and refine the sampling process to further validate these findings and better understand the role of external factors in influencing trunk resistance.

At this stage, the current dataset is insufficient to draw definitive conclusions about the mechanisms underlying these observations. It remains uncertain whether these trends are driven by seasonal changes, environmental conditions, data acquisition errors, or other factors not yet considered. As such, ongoing data collection and more comprehensive analyses will be essential to validate these initial findings and better understand the broader implications for agricultural monitoring and tree health management.

4.3 ANOMALY DETECTION IN TRUNK INTERNAL RESISTANCE DATA

In this section, the preliminary analysis of anomaly detection in trunk internal resistance data using the Isolation Forest algorithm is presented. The primary objective of this analysis is to identify unusual patterns or outliers in the collected data, which may suggest irregularities in tree physiology or environmental conditions.

The Isolation Forest algorithm, a machine learning technique tailored for anomaly detection, was selected due to its efficiency in isolating anomalies through random partitioning. This method is particularly suited for identifying rare events or data points that significantly deviate from the norm [57]. Unlike traditional algorithms that build profiles of normal data, the Isolation Forest isolates anomalies by recursively partitioning the dataset through random splits, creating "isolation trees" where outliers are more likely to be isolated early, as they tend to be located further from dense clusters of regular data.

Previous works, such as, [58], [59] have demonstrated the effectiveness of the Isolation Forest algorithm in diverse fields, highlighting its scalability and robustness when applied to anomaly detection tasks.

4.3.1 DATA PREPROCESSING AND TREATMENT

The core dataset used for this analysis consisted of internal trunk resistance data, collected at 30-minute intervals. Given that the environmental data, such as temperature, radiation, and wind speed, were collected at 1-hour intervals, it was necessary to align both datasets to a common timeline. To achieve this, resampling techniques were applied to ensure that all data, including resistance and environmental variables, adhered to the same temporal resolution. This adjustment involved resampling the environmental data to match the 30-minute intervals of the trunk resistance data, ensuring that all data points were synchronized in time and preventing any inconsistencies in the model training process due to misaligned data.

4.3.2 DATA AND FEATURES FOR TRAINING

For training the Isolation Forest model, the following key variables were used:

- **Internal trunk resistance:** The primary focus of the analysis, serving as an indicator of tree moisture content (MC).
- **Environmental data:** Variables such as temperature, solar radiation, wind speed, and humidity were included in the model to provide context on external factors affecting tree physiology.
- **Irrigation events:** These events were incorporated into the model to distinguish between normal fluctuations in trunk resistance and irrigation-induced changes.

The model was trained using this dataset to detect anomalies over sliding windows of 6 hours, which helped to capture time-dependent behaviors and evolving trends in the data.

A sliding window approach was applied to enhance the detection of dynamic changes in the dataset. By dividing the data into 6-hour overlapping intervals, the model was able to monitor short-term anomalies, while also capturing longer-term deviations that could signal environmental stress or physiological changes in the trees. This method allowed for the continuous tracking of evolving trends over time, significantly improving the model's ability to differentiate between normal fluctuations in trunk resistance and more critical irregularities that may require further investigation or intervention.

4.3.3 PRELIMINARY OBSERVATIONS

Figure 4.7 shows the results of the anomaly detection analysis, with outliers flagged within the trunk resistance data. Several anomalies were identified during periods of rapid resistance decrease, particularly following irrigation events. These anomalies appear as deviations from expected resistance ranges and are marked in the figure.

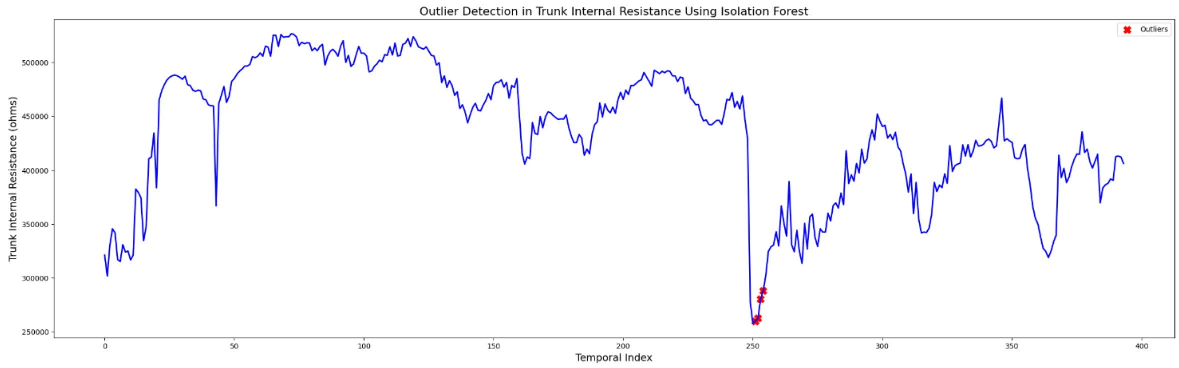


Figure 4.7. Anomaly detection in trunk internal resistance (lemon tree)

Anomalies detected in the lower resistance ranges (around 250,000 ohms) are particularly noteworthy. These outliers coincide with periods following irrigation, indicating irregular moisture absorption during or after these events. This finding aligns with earlier observations that internal resistance tends to drop sharply after irrigation events. However, the cause of these anomalies is not yet fully understood, and further investigation is needed to determine whether they are related to environmental factors or intrinsic tree behavior.

The application of the Isolation Forest algorithm has yielded promising preliminary results, detecting several potential anomalies in the trunk resistance data. These detected anomalies may serve as early indicators of changes in tree health or environmental conditions, providing valuable insights for future monitoring and management efforts.

Nevertheless, these conclusions are preliminary due to the limited amount of data currently available. As additional data is gathered, further analysis will refine the model, explore the underlying causes of the detected anomalies, and enhance the accuracy of anomaly detection in relation to tree moisture content and overall physiological behavior. Additionally, expanding the dataset with more environmental variables and refining the sliding window technique will further improve the model's robustness.

5 CONCLUSIONS AND FUTURE WORK

This dissertation presented a comprehensive study on enhancing agricultural monitoring through anomaly detection, focusing on the application of IoT sensor data in monitoring internal trunk resistance and evapotranspiration (ETo) in citrus trees. The research combined advanced methodologies for data collection via IoT technology and machine learning algorithms to detect anomalies in tree physiology and environmental conditions. The study's main findings include:

- **Validation of ETo values:** A comparison between the ETo values calculated for the implemented dashboard and those provided by IPMA demonstrated the dashboard's accuracy. While minor variations were identified due to differences in data sources (local weather stations vs. interpolated municipal data), the dashboard's performance was validated as a reliable tool for precision agriculture.
- **Preliminary insights on internal trunk resistance:** Initial findings indicated that sensors commonly used for soil moisture measurements could be adapted to monitor the internal trunk resistance of citrus trees. The analysis revealed correlations between trunk resistance and environmental factors such as temperature and radiation, suggesting the potential of this method to assess tree health and moisture content.
- **Anomaly detection:** The application of the Isolation Forest algorithm yielded promising results in detecting anomalies in trunk resistance data, particularly following irrigation events. This indicates potential irregularities in water absorption, highlighting the importance of monitoring tree responses to environmental stimuli.

5.1 ANALYSIS OF WORK DONE

The primary focus of the study was on real-time monitoring of citrus trees using IoT technology and machine learning techniques. Chapter 4 provided a detailed analysis of the experimental results, validating the reliability of the developed dashboard in calculating ETo values and exploring the relationship between internal trunk resistance and environmental variables.

The ETo data comparison between the dashboard and IPMA demonstrated a high level of accuracy, confirming that the dashboard can serve as a valuable tool for irrigation management. Furthermore, the exploratory analysis of trunk resistance indicated a significant relationship between environmental factors and trunk moisture content. Anomaly detection using the Isolation Forest algorithm effectively identified irregularities in water uptake following irrigation events, suggesting the potential of this method for early detection of tree stress factors.

However, the study encountered limitations, particularly concerning the scope of data collection. The dataset used for internal trunk resistance measurements was limited to a short time frame, which restricted the depth of analysis. As a result, some conclusions remain preliminary, and further data collection is required to fully validate the findings.

5.2 FUTURE WORK

There are several key areas for future research and development to expand upon the findings of this dissertation:

- **Long-term monitoring and dataset expansion:** Future work should involve continuous monitoring across multiple seasons, environmental conditions, and citrus species to further validate the trends observed in this study. Additionally, other tree species could be analyzed in parallel, allowing for a broader application of the anomaly detection algorithm across diverse agricultural contexts. Expanding the dataset will also enhance the robustness of the anomaly detection algorithm, improving its accuracy in identifying physiological changes in trees. In the same way, other species may also be analyzed simultaneously in future studies, providing richer comparative data and enabling more nuanced conclusions.
- **Integration with irrigation systems:** Combining trunk resistance measurements with ETo data and other environmental variables can be integrated into automated irrigation systems. Developing a decision support system that optimizes irrigation based on real-time data would help farmers reduce water usage and improve crop health by responding more effectively to environmental stressors.
- **Scaling the dashboard and improving sensor technology:** Future efforts should focus on scaling the dashboard to monitor other crops and expanding its application to different geographic regions. Additionally, improving sensor design, particularly by addressing issues related to sensor insulation and external interference, would enhance the accuracy of internal trunk resistance measurements.

By addressing these areas, future research could further advance the capabilities of IoT-enabled agriculture, moving towards a fully autonomous, data-driven farming system. This work represents a crucial step towards more sustainable and efficient agricultural practices, with the potential for wide-ranging applications in global food production.

REFERENCES

[1] "API IPMA Daily." Accessed: May 08, 2024. [Online]. Available: https://api.ipma.pt/open-data/observation/climate/precipitation-total/faro/

[2] "OWM forecast API", Accessed: Aug. 26, 2024. [Online]. Available: https://api.openweathermap.org/data/2.5/forecast

[3] "FAO56 guidelines ." Accessed: May 09, 2024. [Online]. Available: https://www.fao.org/4/X0490E/x0490e0b.htm

[4] "ATTENTIA Project." Accessed: Sep. 07, 2024. [Online]. Available: https://cisca.ualg.pt/en/index.php/projeto-attentia/

[5] T. H. Spreen and J.-P. Baldwin, "Citrus Greening and Citrus Tree Planting in Florida," *EDIS*, vol. 2014, no. 1, 2014, doi: 10.32473/edis-fe937-2014.

[6] "Precision Agriculture Technologies in Citrus", Accessed: May 18, 2024. [Online]. Available: https://citrusindustry.net/2019/06/04/precision-agriculture-technologies-in-citrus/

[7] "Using Soil Moisture Sensors for Citrus Irrigation", Accessed: May 18, 2024. [Online]. Available: https://citrusindustry.net/2018/07/10/using-soil-moisture-sensors-for-citrus-irrigation/

[8] "A Guide To Soil Electrical Conductivity (EC): Description, Importance & Soil EC Maps", Accessed: May 18, 2024. [Online]. Available: https://atlas-scientific.com/blog/soil-electrical-conductivity/

[9] D. Vanella, J. M. Ramírez-Cuesta, G. Longo-Minnolo, D. Longo, A. D'Emilio, and S. Consoli, "Identifying soil-plant interactions in a mixed-age orange orchard using electrical resistivity

imaging," *Plant Soil*, vol. 483, no. 1–2, 2023, doi: 10.1007/s11104-022-05733-6.

[10] B. Peng, X. Liu, Y. Yao, J. Ping, and Y. Ying, "A wearable and capacitive sensor for leaf moisture status monitoring," *Biosens Bioelectron*, vol. 245, p. 115804, 2024, doi: https://doi.org/10.1016/j.bios.2023.115804.

[11] K. H. Son, H. S. Sim, J. K. Lee, and J. Lee, "Precise Sensing of Leaf Temperatures for Smart Farm Applications," *Horticulturae*, vol. 9, no. 4, 2023, doi: 10.3390/horticulturae9040518.

[12] H. I. Hristov, B. T. Ganev, and L. B. Laskov, "Using an IoT system for monitoring climatic conditions during flowering in fruit plantations," in *2023 XXXII International Scientific Conference Electronics (ET)*, Sep. 2023, pp. 1–4. doi: 10.1109/ET59121.2023.10278739.

[13] S. S. Islam, M. M. Hasan, M. R. Islam, and M. F. Hossain, "Performance Analysis of IoT Based Solar Operated Smart Water Management System for Irrigation Field," in *3rd International Conference on Electrical and Electronic Engineering, ICEEE 2021*, 2021. doi: 10.1109/ICEEE54059.2021.9718794.

[14] S. Madasamy, "Analysis of Long-Range Wireless Area Network Enabled Smart Agriculture for Sustainable Food Production," *Asian Journal of Research in Computer Science*, vol. 16, no. 3, 2023, doi: 10.9734/ajrcos/2023/v16i3359.

[15] M. Mansour *et al.*, "Internet of Things: A Comprehensive Overview on Protocols, Architectures, Technologies, Simulation Tools, and Future Directions," 2023, *MDPI Energies Journal*. doi: 10.3390/en16083465.

[16] S. Bhatia, Z. A. Jaffery, and S. Mehfuz, "A Comparative Study of Wireless Communication Protocols for use in Smart Farming Framework Development," in *2023 3rd International Conference on Intelligent Communication and Computational Techniques, ICCT 2023*, 2023. doi: 10.1109/ICCT56969.2023.10075696.

[17] R. Tang, N. K. Aridas, and M. S. Abu Talip, "Design of Wireless Sensor Network for Agricultural Greenhouse Based on Improved

Zigbee Protocol," *Agriculture (Switzerland)*, vol. 13, no. 8, 2023, doi: 10.3390/agriculture13081518.

[18] P. Uarchoojitt, S. Pothongkham, T. Kongnarong, W. Boonsong, C. Samakee, and T. Inthasuth, "The Communication Link Analysis of ZigBee Mesh Networks Using Received Signal Strength Indicator (RSSI) for the Agricultural Slope Environment," in *2023 International Conference on Electronics, Information, and Communication, ICEIC 2023*, 2023. doi: 10.1109/ICEIC57457.2023.10049953.

[19] G. P. N. Hakim, M. H. I. Hajar, A. Firdausi, and E. Ramadhan, "Benchmarking In Microcontroller Development Board Power Consumption For Low Power Iot Wsn Application," *Jurnal Teknologi Elektro*, vol. 13, no. 1, 2022, doi: 10.22441/jte.2022.v13i1.005.

[20] Y. Wang, Z. Su, K. Huang, J. Yan, S. Wang, and W. Ye, "Research on Pulse Power Wireless Communication Network Based on LoRa Technology," in *Journal of Physics: Conference Series*, 2023. doi: 10.1088/1742-6596/2433/1/012003.

[21] "SOLAR-POWERED-ARDUINO-WEATHER-STATION/." Accessed: Apr. 02, 2024. [Online]. Available: https://www.instructables.com/SOLAR-POWERED-ARDUINO-WEATHER-STATION/

[22] T. G. Durand, L. Visagie, and M. J. Booysen, "Evaluation of next-generation low-power communication technology to replace GSM in IoT-applications," *IET Communications*, vol. 13, no. 16, pp. 2533–2540, 2019, doi: https://doi.org/10.1049/iet-com.2019.0168.

[23] K. J. Somaiya, "IoT based Intruder Detection System Using GSM," 2020. [Online]. Available: https://ssrn.com/abstract=3572326

[24] "Wi-Fi Alliance ", Accessed: May 18, 2024. [Online]. Available: https://www.wi-fi.org/discover-wi-fi/internet-things

[25] A. Maskooki, G. Sabatino, and N. Mitton, "Analysis and performance evaluation of the next generation wireless networks,"

in *Modeling and Simulation of Computer Networks and Systems: Methodologies and Applications,* 2015. doi: 10.1016/B978-0-12-800887-4.00021-3.

[26] S. Wanniarachchi and R. Sarukkalige, "A Review on Evapotranspiration Estimation in Agricultural Water Management: Past, Present, and Future," 2022, *MDPI Hydrology Journal*. doi: 10.3390/hydrology9070123.

[27] R. G. Allen, L. S. Pereira, D. Raes, M. Smith, and a B. W, "Crop evapotranspiration - Guidelines for computing crop water requirements - FAO Irrigation and drainage paper 56," *Irrigation and Drainage*, 1998, doi: 10.1016/j.eja.2010.12.001.

[28] P. J. M. V. Martins, "Smart irrigation platform based on machine and deep learning," masterThesis, Universidade do Algarve., 2022. Accessed: Sep. 29, 2024. [Online]. Available: http://hdl.handle.net/10400.1/18945

[29] "Instituto Português do Mar e da Atmosfera 2024." Accessed: Mar. 30, 2024. [Online]. Available: https://www.ipma.pt/pt/index.html

[30] "European Centre for Medium-Range Weather Forecasts." Accessed: Mar. 30, 2024. [Online]. Available: https://www.ecmwf.int/

[31] "2024 World Meteorological Organization (WMO)", Accessed: Mar. 30, 2024. [Online]. Available: https://wmo.int/

[32] "2012 — 2024 OpenWeather", Accessed: Mar. 30, 2024. [Online]. Available: https://openweathermap.org/

[33] G. Fenu and F. M. Malloci, "DSS LANDS: A Decision Support System for Agriculture in Sardinia," *HighTech and Innovation Journal*, vol. 1, no. 3, 2020, doi: 10.28991/HIJ-2020-01-03-05.

[34] B. K. Acharya, A. K. Timalsina, B. Joshi, and B. T. Magar, "IoT based Distributed Framework for Agricultural Decision Support System," in *2023 7th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*, Oct. 2023, pp. 83–93. doi: 10.1109/I-SMAC58438.2023.10290206.

[35] "Smart Water Management Platform (SWAMP)", Accessed: May 25, 2024. [Online]. Available: https://cordis.europa.eu/project/id/777112

[36] "ENDURE, a resource for Integrated Pest Management (IPM) projects", Accessed: May 25, 2024. [Online]. Available: http://www.endure-network.eu/endure/endure_a_resource_for_ipm_projects2

[37] "API IPMA Hourly." Accessed: May 08, 2024. [Online]. Available: https://api.ipma.pt/open-data/observation/meteorology/stations/observations.json

[38] "Precipitation - IPMA." Accessed: Sep. 29, 2024. [Online]. Available: https://api.ipma.pt/open-data/observation/climate/precipitation-total/

[39] "Minimum Temperature - IPMA." Accessed: Sep. 29, 2024. [Online]. Available: https://api.ipma.pt/open-data/observation/climate/temperature-min/

[40] "Maximum Temperature - IPMA." Accessed: Sep. 29, 2024. [Online]. Available: https://api.ipma.pt/open-data/observation/climate/temperature-max/

[41] "Evapotranspiration - IPMA." Accessed: Sep. 29, 2024. [Online]. Available: https://api.ipma.pt/open-data/observation/climate/evapotranspiration/faro/

[42] "Ref - ET", Accessed: May 09, 2024. [Online]. Available: https://www.uidaho.edu/cals/kimberly-research-and-extension-center/research/water-resources/ref-et-software

[43] L. Martin, H. Cochard, S. Mayr, and E. Badel, "Using electrical resistivity tomography to detect wetwood and estimate moisture content in silver fir (Abies alba Mill.)," *Ann For Sci*, vol. 78, no. 3, 2021, doi: 10.1007/s13595-021-01078-9.

[44] "bokeh library." Accessed: Sep. 27, 2024. [Online]. Available: https://docs.bokeh.org/en/latest/

[45] "matplotlib documentation." Accessed: Sep. 27, 2024. [Online]. Available:

https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.plot.html

[46] "WindRose Library." Accessed: Sep. 27, 2024. [Online]. Available: https://python-windrose.github.io/windrose/

[47] D. Feitosa, F. Hernandez, C. Neale, A. Teixeira, and G. Santos, "Evapotranspiração de Referência Cálculada à intervalos De Dados Horários E Diário," Dec. 2009. Accessed: Aug. 26, 2024. [Online]. Available: https://www2.feis.unesp.br/irrigacao/pdf/Conird_2011/FEITOSA.pdf

[48] "OWM solar irradiance API", Accessed: Aug. 26, 2024. [Online]. Available: https://api.openweathermap.org/energy/1.0/solar/data

[49] "Soda - is (solar radiation forecast)", Accessed: Aug. 26, 2024. [Online]. Available: soda-is.com

[50] "Solar webservice." Accessed: Aug. 26, 2024. [Online]. Available: https://solarwebservices.ch

[51] "Solcast webservices." Accessed: Aug. 26, 2024. [Online]. Available: https://solarwebservices.ch,

[52] P. J. Vaz, G. Schütz, C. Guerrero, and P. J. S. Cardoso, "A Study on the Prediction of Evapotranspiration Using Freely Available Meteorological Data," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2022. doi: 10.1007/978-3-031-08760-8_37.

[53] P. J. Vaz, G. Schutz, C. Guerrero, and P. J. S. Cardoso, "Hybrid Neural Network Based Models for Evapotranspiration Prediction Over Limited Weather Parameters," *IEEE Access*, vol. 11, 2023, doi: 10.1109/ACCESS.2022.3233301.

[54] "IPMA - Evapotranspiração ETo ." Accessed: Sep. 04, 2024. [Online]. Available: https://www.ipma.pt/pt/agrometeorologia/et/

[55] Y. Terada, Y. Horikawa, A. Nagata, K. Kose, and K. Fukuda, "Dynamics of xylem and phloem sap flow in an outdoor zelkova tree visualized by magnetic resonance imaging," *Tree Physiol*, vol. 40, no. 3, 2020, doi: 10.1093/treephys/tpz120.

[56] “Horas do nascer e do pôr do sol em Faro.” Accessed: Sep. 15, 2024. [Online]. Available: https://nascerepordosol.com/pt/faro

[57] Y. Chabchoub, M. U. Togbe, A. Boly, and R. Chiky, “An In-Depth Study and Improvement of Isolation Forest,” *IEEE Access*, vol. 10, 2022, doi: 10.1109/ACCESS.2022.3144425.

[58] T. Mendes, P. J. S. Cardoso, J. Monteiro, and J. Raposo, “Anomaly Detection of Consumption in Hotel Units: A Case Study Comparing Isolation Forest and Variational Autoencoder Algorithms,” *Applied Sciences (Switzerland)*, vol. 13, no. 1, 2023, doi: 10.3390/app13010314.

[59] M. U. Togbe, Y. Chabchoub, A. Boly, M. Barry, R. Chiky, and M. Bahri, “Anomalies detection using isolation in concept-drifting data streams,” *Computers*, vol. 10, no. 1, 2021, doi: 10.3390/COMPUTERS10010013.