

Universidad de Huelva

**Departamento de Ingeniería Electrónica, de Sistemas
Informáticos y Automática**



Remote sensing methods for detecting water and heat stress in vineyards: a contribution to their assessment

**Memoria para optar al grado de doctor
presentada por:**

Ricardo Jorge Lopes do Egipito

Fecha de lectura: 22 de mayo de 2025

Bajo la dirección de los doctores:

Juan Manuel Andújar Márquez

Arturo Aquino Martín

Huelva, 2025



Universidad de Huelva

**Programa de Doctorado de Ciencia y Tecnología
Industrial y Ambiental**

**Línea de investigación: Ingeniería Eléctrica, Electrónica,
de Control y Robótica**

**Centro de Investigación en Tecnología, Energía y Sostenibilidad
(CITES)**



**Universidad
de Huelva**

REMOTE SENSING METHODS FOR DETECTING WATER AND HEAT STRESS IN VINEYARDS: A CONTRIBUTION TO THEIR ASSESSMENT

Tesis doctoral con mención de doctor internacional presentada por:

Ricardo Jorge Lopes do Egipto

Bajo la dirección de los doctores:

José Manuel Andújar Márquez

Arturo Aquino Martín

Huelva, 2025

Dr. José Manuel Andújar Márquez, Catedrático de Universidad de la Escuela Técnica Superior de Ingeniería de la Universidad de Huelva,

Dr. Arturo Aquino Martín, Profesor Titular de Universidad de la Escuela Técnica Superior de Ingeniería de la Universidad de Huelva,

CERTIFICAN:

Que D. Ricardo Jorge Lopes do Egipto, Graduado en Viticultura e Enologia por la Universidade de Lisboa, ha realizado bajo nuestra dirección y dentro del programa de Doctorado de Ciencia y Tecnología Industrial y Ambiental (CyTIA), y en la línea de investigación de Ingeniería Eléctrica, Electrónica, de Control y Robótica, el trabajo correspondiente a su Tesis Doctoral titulada:

Remote sensing methods for detecting water and heat stress in vineyards: A contribution to their assessment

Revisado el presente trabajo, estimamos que puede ser presentado al Tribunal que ha de juzgarlo.

Y para que así conste a efectos de lo establecido por el Real Decreto 99/2011 y por la Normativa Reguladora del Título de Doctor de la Universidad de Huelva, autorizamos la presentación de este trabajo en la Universidad de Huelva.

Huelva, a 10 de febrero de 2025

ANDUJAR
MARQUEZ
JOSE MANUEL
- 29759761S

Firmado digitalmente por ANDUJAR
MARQUEZ JOSE MANUEL -
29759761S
Nombre de reconocimiento (DN):
c=ES,
serialNumber=IDCES-29759761S,
givenName=JOSE MANUEL,
sn=ANDUJAR MARQUEZ,
cn=ANDUJAR MARQUEZ JOSE
MANUEL - 29759761S
Fecha: 2025.02.13 09:36:43 +01'00'

Director: Dr. José Manuel Andújar Márquez

AQUINO
MARTIN
ARTURO -
75550883T

Firmado
digitalmente por
AQUINO MARTIN
ARTURO -
75550883T
Fecha: 2025.02.11
09:42:27 +01'00'

Director: Dr. Arturo Aquino Martín

Assinado por: **Ricardo Jorge Lopes do Egipto**
Num. de Identificação: 08277543
Data: 2025.02.11 11:24:37+00'00'

Doctorando: D. Ricardo Jorge Lopes do Egipto

Acknowledgments

I would like to express my deepest gratitude to all those who have supported me throughout my doctoral journey.

Firstly, my sincerest thanks to my Thesis Directors, Dr. José Manuel Andújar and Dr. Arturo Aquino, for their invaluable guidance, expertise, and encouragement. Your support has been essential to the success of this project, and I am incredibly fortunate to have had the opportunity to work with such distinguished mentors.

Professor Andújar, I am deeply grateful for your belief in me and for welcoming me into your Research Unit, the Centro de Investigación en Tecnología, Energía y Sostenibilidad.

A special thanks to Arturo, my mentor, and above all, if I may, my friend. There are no words to express my gratitude. You have made this possible.

I am also deeply grateful to my colleagues and fellow researchers at:

- Instituto Nacional de Investigación Agrária e Veterinária, especially Jorge Cunha, José Eduardo Eiras-Dias, and Sara Canas, for their collaboration, friendship, and constant support. The time we spent together has been integral to my growth as both a researcher and an individual. A special thanks goes to my colleague and friend, Jorge Cunha, for your invaluable encouragement. Your support has been essential to the success of this project, and I am incredibly fortunate to count you as both a friend and colleague.
- Instituto Superior de Agronomia, especially Joaquim Miguel Costa, Carlos Lopes, Ricardo Braga and Pedro Aguiar Pinto for their collaboration, friendship, and constant support. Your expertise has been indispensable in helping me navigate the more challenging aspects of my research. A special thanks goes to Joaquim Miguel Costa, my co-author, colleague, and friend. The time we spent together in the experimental field and during our discussions has been crucial to my development as a researcher.

To my family, I am eternally grateful for your love, understanding, and encouragement. To my parents, Manuel Filipe and Maria Luisa, thank you for your unwavering belief in me and for always pushing me to strive for excellence. Your sacrifices and support have been a constant source of motivation. To my spouse, Maria Luis, and my children, Mafalda, Filipe, Raul, and Maria, thank you for your love and patience during the long hours spent working on this thesis. You have been my rock and my greatest source of strength.

Lastly, I would like to thank all of my friends who have been by my side throughout this journey. Your friendship, humor, and perspective have made the challenges much easier to bear, and I look forward to continuing this journey together in the future.

This thesis would not have been possible without all of you. Thank you from the bottom of my heart.

Table of contents

Abstract.....	3
Resumen	5
List of abbreviations	7
1.Introduction	11
1.1. Importance of viticulture (and wine) throughout history	11
1.2. The wine market value	12
1.3. Viticulture and the Mediterranean climate	15
1.4. Vineyard precision irrigation.....	16
1.5. Assessing grapevine water status	18
1.5.1. Meteorological-based methods.....	18
1.5.2. Soil-based methods.....	20
1.5.3. Plant-based methods.....	21
1.5.4. The Energy Balance Method: An Integrative Approach to the Soil-Plant- Atmosphere System.....	44
1.6. Challenges and future perspectives	45
1.7. Motivation of the thesis	46
1.8. Scientific contributions of the thesis	47
2. Objectives.....	50
3. Experimental layout.....	52
4. Materials	54
5. Methodology.....	58
5.1. Methodology for Objective 1. Development and evaluation of a machine learning algorithm to estimate actual crop evapotranspiration (ET _c) adapted to vineyards grown under arid conditions.	58
5.2. Methodology for Objective 2. Development and evaluation of a biophysical model to predict the canopy conductance to water vapor of grapevines under arid conditions.	59
5.3. Methodology for Objective 3. Review of soil temperature effect on ecophysiological and agronomical performance in Mediterranean vineyards. Discuss the potential of imaging techniques to assess ST and vertical canopy temperature profiles.....	60
5.4. Methodology for Objective 4. Development and evaluation of a modeling framework to estimate the dynamics of energy fluxes at the soil and plant levels under arid conditions.	61
6. Results	63
6.1. Article 1	63
6.2. Article 2	80
6.3. Article 3	97
6.4. Article 4	116

7. Discussion.....	138
8. Conclusions	141
8.1. Objective 1. Development and evaluation of a machine learning algorithm to estimate actual crop evapotranspiration adapted to vineyards grown under arid conditions.	141
8.2. Objective 2. Development and evaluation of a biophysical model to predict the canopy conductance to water vapor of grapevines under arid conditions.	141
8.3. Objective 3. Review of soil temperature effect on ecophysiological and agronomical performance in Mediterranean vineyards. Discuss the potential of imaging techniques to assess soil temperature and vertical canopy temperature profiles.	142
8.4. Objective 4. Development and evaluation of a modeling framework to estimate the dynamics of energy fluxes at the soil and plant levels under arid conditions.	142
8.5. Global conclusion	142
9. Conclusiones.....	144
9.1. Objetivo 1. Desarrollo y evaluación de un algoritmo de aprendizaje automático para estimar la evapotranspiración real del cultivo adaptado a viñedos cultivados en condiciones áridas.....	144
9.2. Objetivo 2. Desarrollo y evaluación de un modelo biofísico para predecir la conductancia del dosel al vapor de agua de la vid bajo condiciones áridas.	144
9.3. Objetivo 3. Revisión de los efectos de la temperatura del suelo sobre el rendimiento ecofisiológico y agronómico en viñedos mediterráneos. Discusión sobre el potencial de las técnicas basadas en imagen para evaluar la temperatura del suelo y los perfiles de temperatura vertical de la canopia.	145
9.4. Objetivo 4. Desarrollo y evaluación de un marco de modelado para estimar la dinámica de los flujos de energía a nivel del suelo y de la planta bajo condiciones áridas.....	145
9.5. Conclusión global	146
10. References	148
List of Tables	180
List of Figures.....	181

Abstract

Vineyard precision irrigation aims to enhance productivity and grape quality while promoting the socio-economic and environmental sustainability of the sector. A critical aspect of implementing these strategies is the accurate evaluation of actual vineyard water use with high spatial and temporal resolution to optimize grapevine water stress.

One of the primary objectives of this thesis was to develop remote sensing methods for assessing grapevine water status, contributing to the advancement of precision irrigation in vineyards.

Several studies have demonstrated that stomatal conductance to water vapor (g_{sw}) and the ratio of actual crop evapotranspiration (ET_c) to reference evapotranspiration (ET_0) are closely related to grapevine water status. These metrics have also been linked to wine profiles, making them valuable tools for guiding deficit irrigation strategies.

However, despite considerable research, a universal equation for determining vine water status has not yet been established. The main challenge remains the absence of methods capable of accurately measuring vine water status at the required temporal and spatial scales. This thesis aims to address these gaps and advance precision irrigation in vineyards.

The first milestone involved developing machine learning algorithms (MLAs) that accurately estimate actual crop evapotranspiration (ET_c), positioning them as a viable alternative to the FAO-56 K_c - ET_0 method. The performance of eight state-of-the-art supervised MLAs was evaluated using three key atmospheric variables (net radiation, R_n ; wind speed, u ; and vapor pressure deficit, VPD) alongside a plant variable (leaf stomatal conductance to water vapor— g_{sw}) to predict actual ET_c . These predictions were compared to ET_c estimated using the FAO-56 K_c - ET_0 method and to actual ET_c measurements from an eddy covariance system installed in the experimental plot. Results indicated that the five best-performing algorithms explained over 89% of the variability in the measured ET_c , being, on average, 2.5 times more accurate than the FAO-56 K_c - ET_0 method.

A second milestone involved developing a biophysical model to predict the canopy conductance (g_c) to water vapor of grapevines under arid conditions. The g_c , which reflects grapevine transpiration, is highly responsive to water stress. This study aimed to develop a straightforward method for estimating g_c by combining grapevine g_{sw} with atmospheric demand for water vapor flux (R_n and VPD). The developed model accurately simulated the grapevine's response to water scarcity, increased solar irradiance, and high atmospheric water demand. The proposed model explained over 91% of the variability in g_c , as calculated by the gold standard Penman-Monteith method.

A third milestone involved conducting a state-of-the-art review of the effects of soil temperature (ST) on ecophysiological and agronomical performance of vineyards in Mediterranean climates. This review also included a discussion on the potential of imaging techniques for assessing ST and vertical canopy temperature profiles.

The third milestone set the stage for the fourth, which involved developing a modeling framework to estimate the dynamics of energy fluxes at the soil and plant levels under

arid conditions. The focus was on evaluating sensible and latent energy fluxes within the vineyard—specifically in the canopy, the soil beneath the canopy, and the interrow areas—during grapevine berry maturation. The method's reliability was tested against flux measurements from an eddy-covariance system installed in the experimental plot. When compared to the turbulent fluxes measured by the eddy covariance system, the aggregated fluxes estimated using the three-source clumped model—derived from energy fluxes measured within each compartment—accounted for 98% of the variability observed in the turbulent fluxes. The average error magnitude between the observed and estimated sensible heat fluxes remained consistently below 3 W.m^{-2} during daylight hours. Despite a slight tendency to underestimate latent heat fluxes, this study enhances the understanding of energy dynamics in vineyard ecosystems under regulated deficit irrigation practices.

The results of this research demonstrate the potential of non-destructive remote sensing techniques for evaluating grapevine water status. By estimating parameters such as actual crop evapotranspiration, canopy conductance (or its inverse, canopy resistance), and energy flux balances measured at various vineyard locations, the models and methods developed in this thesis provide valuable tools for assessing grapevine water status. These tools can also facilitate the implementation of deficit irrigation strategies.

Keywords: Grapevine, vineyard, precision irrigation, deficit irrigation, sustainability.

Resumen

El riego de precisión en el viñedo tiene como objetivo mejorar la productividad y la calidad de la uva, promoviendo al mismo tiempo la sostenibilidad socioeconómica y ambiental del sector. Un aspecto crítico para implementar estas estrategias, es la evaluación precisa del uso real del agua, con alta resolución espacial y temporal, para optimizar el estrés hídrico del viñedo.

Uno de los principales objetivos de esta tesis fue el de desarrollar métodos basados en datos de sensores remotos para evaluar el estado hídrico de la vid, contribuyendo así a la mejora del riego de precisión en los viñedos.

Diversos estudios han demostrado que la conductancia estomática al vapor de agua (g_{sw}), y la relación entre la evapotranspiración real del cultivo (ET_c) y la evapotranspiración de referencia (ET_0), están estrechamente relacionadas con el estado hídrico de la vid. Estas métricas también se han vinculado con las características del vino resultante, lo que las convierte en herramientas valiosas para guiar las estrategias de riego deficitario.

Sin embargo, a pesar de la considerable investigación llevada a cabo hasta la fecha, aún no ha sido posible establecer una ecuación universal para determinar el estado hídrico de la vid. El principal desafío sigue siendo la falta de métodos capaces de medirla con precisión a las escalas temporales y espaciales requeridas. Esta tesis tiene como objetivo abordar estas lagunas existentes y avanzar en la mejora del riego de precisión de los viñedos.

El primer hito consistió en el desarrollo de modelos de aprendizaje automático supervisado (MLA) para estimar la ET_c con precisión, como alternativa viable al método FAO-56 K_c - ET_0 . Para ello, se evaluó el rendimiento de ocho MLAs, alimentándolos con tres variables atmosféricas clave (radiación neta, R_n ; velocidad del viento, u ; y déficit de presión de vapor, VPD), y con una variable vegetal, g_{sw} . Las estimaciones obtenidas por los modelos fueron comparadas con la ET_c estimada utilizando el método FAO-56 K_c - ET_0 , y con las mediciones reales de ET_c obtenidas con un sistema de *eddy covariance* instalado en la parcela experimental. Los resultados indicaron que los cinco modelos de mejor rendimiento explicaron más del 89% de la variabilidad presente en la ET_c medida, siendo en promedio 2.5 veces más precisos que el método de referencia FAO-56 K_c - ET_0 .

Un segundo hito consistió en desarrollar un modelo biofísico para predecir la conductancia del dosel (g_c) al vapor de agua de la vid bajo condiciones áridas; la g_c , la cual refleja la transpiración de la vid, responde de manera altamente sensible al estrés hídrico. Este estudio tuvo como objetivo desarrollar un método sencillo para estimar la g_c , combinando la g_{sw} de la vid, con la demanda atmosférica de flujo de vapor de agua (R_n y VPD). El modelo desarrollado simuló con precisión la respuesta de la vid a la escasez de agua, el aumento de la irradiancia solar, y la alta demanda atmosférica de agua. El modelo propuesto logró explicar más del 91% de la variabilidad presente en g_c , calculada esta mediante el método estándar de referencia de Penman-Monteith.

El tercer objetivo de esta tesis consistió en la realización de una revisión sistemática de la bibliografía relativa a los efectos de la temperatura del suelo (ST) sobre el rendimiento ecofisiológico y agronómico de los viñedos en climas mediterráneos. Esta revisión también incluyó una discusión sobre el potencial de las técnicas basadas en imágenes para evaluar la ST y los perfiles de temperatura vertical del dosel.

El trabajo anterior estableció las bases para la definición y el abordaje del cuarto objetivo de esta tesis, que consistió en el desarrollo de un marco de modelado para la estimación de la dinámica de los flujos de energía, a nivel del suelo y la planta, bajo condiciones áridas. El enfoque se centró en evaluar los flujos de energía sensible y latente dentro del viñedo, específicamente en el dosel, en el suelo bajo el dosel, y en las áreas de entre las hileras, durante la maduración del fruto. La fiabilidad del método se probó comparando su desempeño con las mediciones de flujo obtenidas de un sistema de *eddy covariance* instalado en la parcela experimental. Al comparar los flujos turbulentos medidos con el sistema *eddy covariance*, los flujos agregados estimados mediante el modelo desarrollado de tres fuentes agrupadas, derivados de los flujos de energía medidos en cada localización, se alcanzó a explicar el 98% de la variabilidad observada en los flujos turbulentos. El error promedio entre los flujos de calor sensible observados y estimados permaneció consistentemente por debajo de $3 \text{ W} \cdot \text{m}^{-2}$ durante las horas diurnas. A pesar de una leve tendencia a subestimar los flujos de calor latente detectada, este trabajo proporciona una mejora de la comprensión de la dinámica energética de los ecosistemas de viñedos gestionados con prácticas de riego deficitario regulado.

Los resultados de esta investigación demuestran el potencial de las técnicas no destructivas, basadas en datos de sensores remotos, para la evaluación del estado hídrico de la vid. Al estimar parámetros como la evapotranspiración real del cultivo, la conductancia del dosel (o su inversa, la resistencia del dosel), y los balances de flujo de energía en diversas ubicaciones del viñedo, los modelos y métodos desarrollados en esta tesis proporcionan herramientas valiosas para evaluar el estado hídrico del viñedo. Estas herramientas también facilitan la implementación, basada en datos, de estrategias de riego deficitario.

Palabras clave: vid, viñedo, riego de precisión, riego deficitario, sostenibilidad.

List of abbreviations

ABA	Abscisic Acid
AVA	American Viticultural Areas
BCE	Before Common Era
CO ₂	Carbon dioxide
CT	Computed Tomography
CWSI	Crop Water Stress Index
DI	Deficit Irrigation
DSS	Decision Support System
EC	Eddy Covariance
E _c	Vine Transpiration
EP	Electrical Potential
ERT	Ensemble of Regression Trees
ET	Evapotranspiration
ET ₀	Potential Evapotranspiration
ET _c	Crop Evapotranspiration
ET _{c act}	Actual Crop Evapotranspiration
EWT	Equivalent Water Thickness
FAO	Food and Agriculture Organization
FAO-56-K _c -ET ₀	Crop Evapotranspiration under Standard Conditions (FAO 56 method)
FD	Fruit Diameter
FDR	Frequency-Domain Reflectometry
Fv/Fm	Maximum Quantum Yield
G	Soil Heat Flux
g _c	Canopy Conductance
GCM	General Circulation Model
GI	Geographical Indication
GPR	Gaussian Process Regression
g _s	Stomatal Conductance
g _{sw}	Stomatal Conductance to Water Vapor
g _{s max}	Maximum Daily Stomatal Conductance
H	Sensible Heat Flux
H _{bs}	Sensible Heat Flux from bare soil between rows
H _c	Sensible Heat Flux from the canopy
HPV	Heat Pulse Velocity
H _{uc}	Sensible Heat Flux under the canopy

IPCC	Intergovernmental Panel on Climate Change
IQR	Interquartile Range
IR	Infrared
K_c	Crop Coefficient
K_{cb}	Basal Crop Coefficient
K_e	Soil Evaporation Coefficient
kha	Thousand hectares
K_s	Stress Coefficient
K_{sx}	Xylem Hydraulic Conductivity
LAI	Leaf Area Index
LDVT	Linear Variable Displacement Transducers
LE	Latent Heat Flux
MDS	Maximum Daily Shrinkage
Mhl	Million hectolitres
Mha	Million hectares
MLA	Machine Learning Regression Algorithm
NIR	Near-Infrared
NDWI	Normalized Difference Water Index
PDO	Protected Designations of Origin
PGI	Protected Geographical Indication
PLC	Percentage Loss of Conductivity
PM	Penman-Monteith
PRD	Partial Root Drying
PSII	Photosystem II
qP	Photochemical Quenching
RDI	Regulated Deficit Irrigation
R_n	Net solar radiation
SDI	Sustained Deficit Irrigation
SDV	Stem Diameter Variation
SGR	Stem Growth Rate
SPAC	Soil-Plant-Atmosphere Continuum
ST	Soil Temperature
SVM	Support Vector Machine
SWIR	Short-Wave Infrared
TDR	Time-Domain Reflectometry
T_{dry}	Dry Surface Temperature
TTB	Alcohol and Tobacco Tax and Trade Bureau

List of abbreviations

T_{wet}	Wet Surface Temperature
u	Wind Speed
UAV	Unmanned Aerial Vehicles
UGV	Unmanned Ground Vehicles
WABI	Water Balance Index
WI	Water Index
WUE	Water Use Efficiency
VI	Vegetation Indice
VRI	Variable Rate Irrigation
Z_r	Reference height
$\delta^{13}\text{C}$	Carbon Isotopic Discrimination
θ_{stem}	Stem Water Content
ϕPSII	Effective Quantum Yield
Ψ_l	Leaf Water Potential
Ψ_{mid}	Midday Leaf Water Potential
Ψ_{PD}	Pre-Dawn Leaf Water Potential
Ψ_{stem}	Stem Water Potential
Ψ_{TLP}	Turgor Loss Point

1.Introduction

1.1.Importance of viticulture (and wine) throughout history

The cultivation of grapevines and the practice of winemaking have profoundly shaped human societies for thousands of years, influencing agriculture, culture, religion, and economies worldwide (Campbell and Guibert, 2007). The domestication of grapevines (*Vitis vinifera* ssp. *Sylvestris*) began roughly 11,000 years ago in Western Asia and the Caucasus, giving rise to varieties used for table grapes and wine (Dong et al., 2023). From Western Asia, domesticated grapevines spread into Europe, where they interbred with ancient wild ecotypes and diversified along human migration routes (Dong et al., 2023). The Phoenicians, through their expansive and enduring trade network, introduced viticulture throughout the Mediterranean Basin (Estreicher, 2019), laying the foundations of an economically and culturally cohesive Mediterranean that the Greeks, and later especially the Romans, would continue to develop (Bentley, 1999). Both the Greeks and Romans played significant roles in disseminating viticulture, with the Romans extending vineyard cultivation into newly conquered territories across Europe, moving viticulture beyond the Mediterranean coast (Estreicher, 2019; Bouby et al., 2013).

The origin of wine can be traced back to the domestication of grapevines (Estreicher, 2017) and early winemaking likely emerged as humans settled into agricultural lifestyles, recognizing that grapes could be fermented into a stable, palatable beverage (Renfrew, 2002). Archaeological evidence suggests systematic grape harvesting and wine production as early as the 6th millennium Before Common Era (BCE) in Iran and the 5th millennium BCE in northern Greece (Valamoti, 2018; Estreicher, 2017). The winemaking traditions spread across the Mediterranean, and later becoming central to ancient civilizations such as those of Egypt, Greece, and Rome (Estreicher, 2019). These cultures revered wine as more than just a beverage, seeing it as a symbol of communal bonding, celebration and spirituality, often associating it with gods like Bacchus and Dionysus (Dodd, 2022; Osborne, 2014). It served as artistic inspiration, a component in medical practices (Varriano, 2022; McGovern, 2003a), a marker of social status (Dodd, 2022; Estreicher, 2019) and a highly valued commodity (McGovern, 2003b). Religiously, wine has held symbolic importance for centuries. In both Jewish and Christian traditions, wine is used to represent holiness and sacrifice in rituals like Passover and communion, connecting individuals to their faith in a tangible way (Joy et al., 2020; McGonigle, 2019). As an evocative symbol of blood, it was used in temple ceremonies, occupying the heart of the Eucharist (McGovern, 2003b). As civilization developed, wine transitioned from a spiritual instrument to a dominant economic force, influencing trade, warfare, and technological advancements (Pellechia, 2006).

The significance of viticulture extends well beyond cultural symbolism. Early winemaking practices fostered advancements in agricultural techniques, including soil management, irrigation, pruning, and fermentation science (Berg et al., 1980). Such developments set the groundwork for more sophisticated agricultural systems. Roman society refined viticultural techniques and developed storage methods like amphorae and barrels allowing wine to be transported across vast distances (Bouby et al., 2013). The ability to store wine for extended periods made it a valuable trade commodity, fostering economic connections among Mediterranean civilizations (Renfrew, 2002). Wine also served as a catalyst for significant historical advancements, including the rise of maritime trade, the development of glassblowing, and the early practices of advertising (Pellechia, 2006).

Wine has historically held a main place in social and religious practices, symbolizing connection, artistry, and a respect for the land. From ancient feasts and religious ceremonies to political gatherings and family celebrations, wine has been a medium of socialization and cultural expression (Harutyunyan and Malfeito-Ferreira, 2022). In ancient Egypt, wine was a staple at royal feasts and was buried with pharaohs to accompany them into the afterlife (McGovern et al., 2009). In Greece, wine was central to the *symposium*, a social institution where intellectual debates took place (Dodd, 2022; Lantos et al., 2020; McGovern et al., 2017; Osborne, 2014). In Rome, wine became a marker of wealth and social status, with the elite enjoying fine, imported wines while more modest varieties were consumed by the lower classes (Bouby et al., 2013).

Today, wine maintains its cultural, economic, and social relevance (Campbell and Guibert, 2007). The term *terroir* originated from the Latin word *territorium*, meaning land or territory became central to winemaking philosophy, eventually spread by the French winemakers to other wine-producing regions worldwide. The term *terroir* encompasses not just land but the combination of natural factors—such as soil, climate, and topography—that influence wine (Ballantyne et al., 2019; Wilson, 2001). Over centuries, French winemakers began to emphasize *terroir* to explain how specific environmental conditions and human practices plays a crucial role in shaping a wine's flavor, aroma, acidity, and body imparting a "sense of place" unique to each wine (Joy et al., 2021; Ballantyne et al., 2019). In France, *terroir* has become the organizing principle of the wine industry, tied to economic protection and classification systems (Fourcade, 2012). *Terroir's* significance extends beyond wine, linking gastronomy to cultural mythology, agriculture, and philosophy, elevating fine wines to an art form and heritagization, and has played a role in framing France's national identity (Joy et al., 2021; Parker, 2015).

The concept of *terroir* extends beyond wine, reconnecting people with their land and ancestral heritage in response to globalization (Hammer, 2011). This connection to place and identity significantly shapes modern foodways and cultural experiences (Hammer, 2011). Today, wine represents both heritage and economic strength, blending tradition, community, and craftsmanship. It reflects humanity's respect for the land, leaving a legacy that connects shared history with cultural identity (Harvey et al., 2014).

1.2. The wine market value

The global wine industry is characterized by diverse regional influences and evolving market dynamics. Consumer choice in retail settings is primarily driven by previous experience and recommendations, with variations in factors like brand, food pairing, and origin across different markets (Goodman, 2009).

Nowadays, viticulture holds a central place in the agricultural and economic systems of many regions worldwide. Not only does it contribute significantly to national and local economies, but it also shapes social and cultural identities and plays a crucial role in environmental stewardship. The economic importance of viticulture is underscored by its contribution to the global wine market, valued at over €36 billion in wine export in 2023, the second highest ever recorded (OIV, 2024). Three EU countries account for 63% of the total global export value, with France the highest-value exporter at 11.9 billion €, followed by Italy at €7.7 billion, and Spain at €2.9 billion (OIV, 2024). The wine and wine-based products represent 8% of total European agri-food value exported in 2023, only surpassed by cereal preparations and milling products, and dairy products that respectively represented 11% and 9% of total European agri-food value exported (EC,

2024). Together, the five largest non-European wine producers—Chile (€1.41 billion), Australia (€1.24 billion), South Africa (€0.57 billion), the United States (€1.13 billion), and Argentina (€0.63 billion)—contributed approximately 13.8% to the global wine export value. Notably, despite being the 12th largest exporter by volume, New Zealand's wine exports were valued at €1.2 billion in 2023 (OIV, 2024).

Despite a decrease of 6.3% in respect to 2022, global wine export volume in 2023 ascended to 99.3 million hectolitres (Mhl) (OIV, 2024). Together, Italy, Spain, and France exported 54.9 Mhl, accounting for 56% of 2023 world wine exports in volume (OIV, 2024).

Global wine production in 2023, excluding juices and musts, is estimated at 237 Mhl, with the vinified production in the EU estimated at 144.5 Mhl, approximately 61% of the global total (OIV, 2024). By country, France, the world's leading wine producer in 2023, achieved an estimated volume of 48 Mhl, representing 20% of the global total. Italy, the second-largest wine-producer, experienced historically low production levels in 2023, with a notable 23.2% decrease, totaling 38.3 Mhl. Spain also faced a notable decline, reaching its lowest production since 1995, with an estimated output of 28.3 Mhl (OIV, 2024). In contrast, the five largest non-European wine producers accounted for approximately 26.5% of world wine production in 2023. The United States, the fourth-largest global producer, generated an estimated 24.3 Mhl, followed by Chile with 11 Mhl, Australia with 9.6 Mhl, South Africa with 9.3 Mhl, and Argentina with 8.8 Mhl, ranking as the eighth-largest global producer (OIV, 2024).

In 2023 the world's vineyard surface area was estimated at 7.2 million hectares (Mha), encompassing winegrape, table grape, juice grape and raisin varieties (OIV, 2024). Approximately 45.8% (3.3 Mha) of the world's vineyards are in Europe, with the three greatest volume and value wine producers accounting for approximately 34 % of world vineyard area in 2023. Spain, the largest vineyard in the world, accounts for 945 thousand hectares (kha), France, with the second largest area under vines, accounting for 792 kha, and Italy reaching 720 kha. Other European countries like Romania, with 187 kha, and Portugal, with 182 kha, respectively the fourth and fifth largest EU vineyards, are followed by Germany with 104 kha, and Greece with 94 kha (OIV, 2024). The five largest non-European wine producers collectively account for 14.5% of the world's vineyard area. Viticulture supports millions of jobs and provides livelihoods for rural communities across Europe.

In the 17th and 18th centuries, Bordeaux winemakers faced significant competition from the growing wine industries of Spain, Portugal, and Italy, particularly in terms of price. In response, they sought to distinguish their wines by emphasizing their perceived quality. Smaller vineyards were consolidated into larger estates, often associated with nearby châteaux. This linkage conferred an air of aristocratic prestige and sophistication to wines (Ulin, 2009). These early marketing strategies laid the foundation for the enduring prestige and premium prices that Bordeaux wines command today.

The 1855 Bordeaux classification is widely regarded as a precursor to modern systems of Geographical Indications (GIs) and Protected Designations of Origin (PDOs), which are now enshrined in international treaties and enforced by the European Union (Inglis, 2015). The contemporary concept of PDOs emerged later in France and was subsequently adopted more widely across Europe (Inglis, 2015). The European Union's current PDO framework, established in the 1990s, was designed to strengthen the protection of regional and traditional products, ensuring consistent quality and facilitating market differentiation (Porter, 2024). In this context, wine PDOs represent a refined form of GI, specifically intended to convey the concept of terroir within the wine market (Candiago et al., 2022;

Porter, 2022; Belletti et al., 2017; Lee and Sumner, 2013; Delmastro, 2005). The framework sets quality benchmarks and assurance programs that regulate production and farming practices, including factors such as grape variety, yield, aging requirements, cultivation methods, and alcohol content. By legally linking the quality of wines to specific geographic regions and traditional production methods, it helps maintain the integrity and reputation of wine PDOs (Candiago et al., 2022), helping to distinguish wines based on their unique terroir and production methods (Gomis-Bellmunt et al., 2022; Barrio-Galán et al., 2020). Moreover, because the true quality of wine is only fully revealed after consumption, its market perception and economic value is significantly influenced by the reputation of its PDO or the collective reputation of the region (Porter, 2024; Barham, 2003). Nowadays the European wine sector operates within a well-established system of PDOs and Protected Geographical Indications (PGIs) (Meloni et al., 2019).

In 2019, France had approximately 320 PDOs and 73 PGIs. Notable PDO regions include Bordeaux (Médoc, Graves, Sauternes, Saint-Emilion, Pomerol), Alsace, Burgundy (Beaujolais, Chablis, Côte de Nuits, Hautes-Côtes de Nuits), Champagne, Jura, Languedoc-Roussillon, Provence, Loire Valley and Rhône Valley (INAO, 2019; INAO, 2017).

Spain boasts 101 PDOs, and 43 PGIs. Notable PDO regions in Spain include Ribera del Duero, La Mancha, Valdepeñas, Rioja, Priorat, Cariñena, Utiel-Requena, Jerez, Condado de Huelva, and Montilla-Moriles (Barrio-Galán et al., 2021; Barrio-Galán et al., 2020; Sinisterra-Solís et al., 2020).

Italy has approximately 470 PDO and 120 PGI wine regions (Raimondo et al., 2020; Zambon et al., 2018). Some prominent Italian wine PDO regions include Lombardy, Veneto (Prosecco, Lugana), Piedmont (Asti, Barbaresco, Barolo), Emilia-Romana, Tuscany (Chianti, Brunello di Montalcino), Apulia, Sicily and Sardinia (Slaghenaufer et al., 2021; Pappalardo et al., 2019).

Portugal accounts for 31 PDOs and 14 PGIs distributed by 14 wine regions, including the emblematic Madeira wine, Oporto, Vinho verde, Carcavelos and Douro regions (DGADR, 2025; IVV, 2025).

In summary, the European Union quality policy aims to protect the names of specific products to promote their unique characteristics, linked to their geographical origin as well as traditional know-how (EC, 2023).

Outside of Europe, the tradition of winemaking does not carry the same cultural and historical significance. Wine production is a relatively recent phenomenon in many regions, resulting in less regulation of the sector compared to European counterparts. For instance, in the United States, wine grape-growing regions—designated as American Viticultural Areas (AVAs)—have their boundaries defined by the Alcohol and Tobacco Tax and Trade Bureau (TTB), based on petitions submitted by wineries, vineyards, or other stakeholders. If a wine is designated with the name of an AVA, federal regulations require that 85 percent or more of the wine is derived from grapes grown within the boundaries of that TTB-established AVA and that the wine is fully finished within the state or one of the states in which the AVA is located. Certain states have stricter standards for the use of the name of an Appellation/AVA on wine labels. (TTB, 2025)

Since December 1996, the boundaries of Australia's wine GIs have been defined by legislation. Australian GIs are included in the Register of Protected Geographical Indications and Other Terms, which is maintained by Wine Australia. GIs are categorized

into Zones, Regions and Sub-regions. Zones are large areas encompassing the entirety of Australia, while Regions and Sub-regions are defined based on criteria related to the similarity of grapegrowing characteristics within the specified boundaries (Bramley and Ouzman, 2021). These definitions are determined through an application process submitted to the Geographical Indications Committee. Grapes cannot be grown outside of a designated GI zone in Australia (Wine Australia, 2025).

Overall, GI systems play a crucial role in protecting the origin and quality of wines worldwide, enabling consumers to identify unique regional characteristics (Giacomarra et al., 2020; Belletti et al., 2017). Currently, the EU recognizes approximately 3000 GIs for wine and an additional 2000 for food products (Meloni et al., 2019). Agri-food and beverage products whose names are protected as GIs within the EU account for a total sales value of €74.76 billion, with over one-fifth of this amount derived from exports outside the EU (EC, 2020).

1.3. Viticulture and the Mediterranean climate

As previously stated, viticulture and winemaking are pivotal to the economy, culture, and environment of Mediterranean regions but face substantial challenges due to climate change. Mediterranean climates occur in five global regions: California, Chile, South Africa, southwestern Australia, and the Mediterranean Basin (Mooney et al., 2001; Acevedo et al., 1999; Dallman, 1998). These regions share similar climatic characteristics, including winter-dominant rainfall and summer temperatures that vary from cool to hot (Acevedo et al., 1999). Winter precipitation variability in these areas is largely driven by internal atmospheric dynamics (Seager et al., 2019), with long-term trends indicating a drying pattern across all Mediterranean-type climate zones (Dinis et al., 2022; Seager et al., 2019). Mediterranean atmospheric warming has been exceeding global average rate since 1980's, with future annual and summer warming rates 20 to 50% larger than the global annual average (Ali et al., 2022; Lionello and Scarascia, 2018). Temperature extremes and heat waves have been increasing in intensity, number and length in recent years, and Intergovernmental Panel on Climate Change (IPCC) projections point to continue increasing (Ali et al., 2022; Cherif et al., 2020). A decrease in precipitation by 4% per 1°C of global warming for all seasons is projected (Lionello and Scarascia, 2018; Hertig and Trambly, 2017). The predicted reductions in precipitation, combined with rising temperatures and decreased cloud cover (EEA, 2024; IPCC, 2023; EEA, 2021; MedECC, 2020; EEA, 2012), are expected to increase evapotranspiration rates, leading to significant deficits in soil water balance during the grapevine's vegetative period, with particularly pronounced impacts during grape berry ripening (Gambetta and Kurtural, 2021; Santos et al., 2020b). The widespread increasing of evaporative demand and decreasing precipitation are contributing to increased droughts in the mediterranean in the recent decades (Ali et al., 2022). In the future, droughts are projected to become more severe, more frequent and longer in the Mediterranean (Ali et al., 2022; Lionello and Scarascia, 2020; Hertig and Trambly, 2017). Consequently, groundwater recharge, water level in lakes, and availability of reservoirs are projected to decrease in the future (Ali et al., 2022). The sea level rise combined with heat waves and droughts are impacting freshwater and terrestrial ecosystems, namely agriculture. The growing demand for freshwater and salinization risks associated with sea level rises and strengthening freshwater supplies (Ali et al., 2022). This shift will likely exacerbate water scarcity, intensifying competition for resources between agriculture and other sectors and posing a serious limitation on agricultural water access, especially for crop irrigation (EEA, 2024; FAO, 2023; Dinis et

al., 2022; EEA, 2021; EEA, 2012; Fraiture and Wichelns, 2010). A potential water deficit for agriculture of 28% to 47% is predicted by 2030 (Sebri, 2017).

Climate also plays a crucial role in the terroir of wine regions, as atmospheric conditions directly affect grapevine phenology, growth, development, yield, and grape berry quality parameters, which, in turn, influence wine attributes. The predicted climate changes present notable challenges for grape production and wine quality in affected regions (Prada et al., 2024; Dinis et al., 2022; Guiot et al., 2021; MedECC, 2020; Santos et al., 2020a; Santos et al., 2020b; Poni et al., 2018). Advances in grapevine phenology, are shortening the growing season and shifting the maturation period to higher summer temperatures, thereby increasing evapotranspiration and exacerbating water deficits (Leolini et al., 2018; Ramos et al., 2018; Fraga et al., 2016). Consequently, adaptation strategies are essential for sustaining the sector, with a focus on selecting varietal genotypes better adapted to local conditions, as well as implementing improved management practices for canopy cover, soil health, and water resource management (Dinis et al., 2022). Although irrigation has become more common in arid regions to mitigate climate impacts, prioritizing sustainable water use is critical (Dinis et al., 2022; Costa et al., 2016), as future water reserves may fall short of meeting agricultural demands under projected climate change and socioeconomic scenarios (Claro et al., 2024; EEA, 2024; EEA, 2021; EEA, 2012) and may also contribute to issues like soil salinization and aquifer degradation (Puigdefàbregas and Mendizábal, 1998).

Furthermore, due to its socioeconomic importance, viticulture is instrumental in fostering sustainable regional development, affecting land use, environmental sustainability, and landscape preservation (Yago, 2024). Vineyards contribute to rural ecosystem maintenance, promote biodiversity, and help prevent soil erosion (Paiola et al., 2020). However, vineyard expansion and intensification have raised environmental concerns (Paiola et al., 2020). As consumer awareness of these issues increases, winegrowers are adapting their management practices to prioritize environmental stewardship and sustainability (Giffard et al., 2022).

1.4. Vineyard precision irrigation

In semi-arid to arid climates, such as those found in Mediterranean regions, non-irrigated vineyards are frequently exposed to varying levels of water and thermal stress depending on seasonal and annual climatic variability. Winter rains generally provide enough soil moisture to support early vegetative growth of the grapevine canopy. However, as the canopy expands in spring, the transpiring surface area increases, which gradually depletes soil water reserves as rainfall decreases. As a result, water stress often intensifies during the reproductive and maturation phases, making irrigation essential to sustain both plant and fruit development. Consequently, yield and grape quality often fluctuate from vintage to vintage with yearly climate variations. To mitigate these fluctuations and reduce variability in yield and grape quality, irrigation has become increasingly important in sustaining winegrape production in Mediterranean regions (Costa et al., 2016).

To enhance water sustainability in the Mediterranean and reduce soil evaporation losses, vineyards are increasingly adopting drip irrigation systems. By leveraging the grapevine's natural tolerance to water stress, specific irrigation strategies have been developed to minimize water consumption while maintaining yields and improving water use efficiency (WUE) (Medrano et al., 2015; Costa et al., 2007; Chaves and Oliveira, 2004). These are globally known as deficit irrigation (DI) strategies, as the water applied in each irrigation is below the crop's full requirements, thereby keeping the crop under controlled

water stress. One such strategy is Sustained Deficit Irrigation (SDI), which involves deliberately supplying less water than the crop's full water requirement across the growing season. Instead of meeting the crop's full evapotranspiration (ET) requirements, SDI consistently applies a reduced amount of water, promoting efficient resource use without significantly impacting productivity (Costa et al., 2007). By applying water below the ET rate, the crop initially extracts water from the soil reserves until they are depleted. At that point, the soil reservoir can no longer meet the vine's water demand, water stress begins, and both crop growth and transpiration decrease. Consequently, ET drops below its maximum potential (Ferreira and Soriano, 2007).

Advances in understanding grapevine physiology and metabolic responses to water stress have revealed the crop's sensitivity to water availability at different growth stages (Medrano et al., 2015; Chaves et al., 2010; McCarthy et al., 2000). During critical phases such as flowering and fruit set, when water stress could substantially reduce yield, it is essential to meet the vine's full water needs (Matthews and Anderson, 1989). Conversely, in phases where water stress has a lesser impact on yield—such as post-fruit set or during ripening—water can be supplied at levels slightly below the crop's requirements, inducing mild stress. This targeted approach reduces vegetative growth, reallocating the plant's resources toward fruit production, which often enhances fruit quality through concentration of flavors and beneficial compounds (Baeza et al., 2019; Rienh and Scholasch, 2019; Ojeda and Saurin, 2016; Medrano et al., 2015; Santos et al., 2007; Deloire et al., 2004; Chaves et al., 2002; Ojeda et al., 2001; McCarthy et al., 2000; Dry et al., 1999; Carbonneau, 1998; Matthews et al., 1990; Matthews and Anderson, 1988). This understanding has been pivotal in developing Partial Root Drying (PRD) and Regulated Deficit Irrigation (RDI), two sustainable DI strategies for managing water resources that aim to improve fruit quality while conserving water. The PRD practice requires wetting one half of the rooting zone while leaving the other half dry, thereby reducing the amount of irrigation water applied (Antolín et al., 2006; Dry and Loveys, 1999). In subsequent irrigations, the wetted and dry sides are interchanged, allowing for an alternating irrigation pattern in both space and time, which generates wet-dry cycles in different sections of the root system (Sadras, 2009; Dry and Loveys, 1999). This irrigation strategy aims to promote the release of chemical signals from roots in dry soil, which reduces stomatal conductance (Medrano et al., 2015; Davies et al., 2002; Chaves et al., 2002; Davies and Zhang, 1991; Zhang et al., 1987), transpiration, and shoot growth (Chaves et al., 2002; Dry and Loveys, 1999). The increased concentration of abscisic acid (ABA) in the xylem flow from roots to leaves triggers stomatal closure (Stoll et al., 2000; Loveys, 1984), activating genes for drought tolerance and mechanisms such as hydraulic signaling (Comstock, 2002; Tardieu and Davies, 1993). Meanwhile, water supply from roots in the wet soil fraction is maintained, thereby avoiding severe water deficits (Medrano et al., 2015; Santos et al., 2003; Chaves et al., 2002; Davies et al., 2002).

However, effectively controlling root drying in field conditions is not always feasible. Numerous factors, including variety-rootstock interactions, soil characteristics, and environmental conditions throughout the growing season, can impact PRD outcomes (Romero et al., 2022). For example, due to the wet bulb formed during irrigation, sandy loam and deep porous soils provide optimal conditions for successful partial drying of the root zone (Chaves et al., 2007; Santos et al., 2003). In contrast, shallow sandy soils tend to place crops under chronic stress, while deep clay soils wet slowly and allow excessive lateral spreading of wetted areas (Kriedemann and Goodwin, 2008). Moreover, the benefits of PRD depend heavily on precise irrigation management, as inadequate switching intervals can either overstress plants or fail to induce the desired stress

response. Additionally, PRD systems require a double irrigation line controlled by separate valves, alternating between irrigating one line while keeping the other dry, and shifting sides subsequent irrigations. This setup increases the complexity, cost, installation, maintenance, and management requirements compared to other deficit irrigation systems (Adu et al., 2018; García-García et al., 2012).

In turn, RDI is based on the physiological principle that plant sensitivity to water, particularly in terms of yield and quality, varies across different phenological stages. Therefore, applying irrigation at levels below crop evapotranspiration (ET_c) during specific growth periods can significantly reduce vegetative vigor while enhancing harvest quality and increasing water use efficiency (Feres and Soriano, 2007; McCarthy et al., 2000). This irrigation strategy requires careful management to maintain soil and plant water status within a narrow range, as an excessive water reduction can lead to substantial yield and quality losses, while over-irrigation promotes excessive vigor, suppressing the benefits of this approach (Medrano et al., 2015; McCarthy et al., 2000).

To implement a precision irrigation system, such as RDI, that delivers the exact amount of water to vines precisely when needed, an accurate assessment of vine water status is essential. This approach should rely on simple, non-destructive and precise measurements of weather, soil, and plant variables that influence actual crop transpiration and soil evaporation. Additionally, accounting for the spatial and temporal variability of these factors within the vineyard is crucial for managing vine water stress while optimizing yield and berry composition (Chaves et al., 2016; Costa et al., 2016).

1.5. Assessing grapevine water status

As referred, to mitigate water scarcity while sustaining viticultural activities, vineyard irrigation management should prioritize optimizing yield and fruit quality per unit of water applied (water use efficiency). Water availability significantly influences the vine's vegetative and reproductive growth, as well as grape composition. Excess water, especially during ripening, promotes vegetative growth, which can create poor cluster microclimate, increase disease risk, and negatively affect grape quality (Van Leeuwen et al., 2009; Williams and Matthews, 1990). In contrast, water stress reduces carbon assimilation (Buckley and Mott, 2013; Chaves et al., 2007), curtails vegetative growth and yield, and alters grape composition (Poni et al., 2018; Lopes et al., 2011; Santos et al., 2003). While severe water stress can lead to premature senescence of older leaves, potentially causing perennial issues and hindering proper grape maturation (Chaves et al., 2010; Keller, 2010a). Thus, optimizing yield and fruit quality per unit of water requires efficient, precision irrigation management in vineyards, alongside a comprehensive understanding of intricate climate, soil, and plant interactions. While weather stations and other meteorological instruments accurately measure the variables needed to estimate the atmospheric demand and crop evapotranspiration, several soil-based sensor systems can monitor soil moisture at different depths.

1.5.1. Meteorological-based methods

Currently, the standard method for estimating evapotranspiration (ET) is the Food and Agriculture Organization (FAO) approach, which uses crop evapotranspiration under standard conditions (FAO-56 K_c-ET₀). This meteorological-based method (Figure 1.1a), which is grounded in the Penman–Monteith (PM) equation (Allen et al., 1998; Monteith and Unsworth, 1990), is widely accepted for assessing ET—defined as the combined water loss through soil evaporation and plant transpiration—across various crops (Feres

and Soriano, 2007). However, while the FAO-56 K_c - ET_0 method provides accurate ET estimates for many herbaceous crops that nearly cover the soil and experience minimal water stress, it may not be ideally suited for sparse, row-planted crops that expose a significant area of soil, such as grapevines (Forster et al., 2022; Rallo et al., 2021; Schymanski and Or, 2017; Picón-Toro et al., 2012; Fereres and Soriano, 2007; Paço et al., 2006). Moreover, for crop species with tight stomatal control of water loss and regulation of leaf water potential, such as grapevines, literature has reported major accuracy limitations in using the FAO-56 K_c - ET_0 method (Foster et al., 2022; Schymanski and Or, 2017; Pereira et al., 2015; Campos et al., 2010; Shuttleworth and Wallace, 2009; Paço et al., 2006).

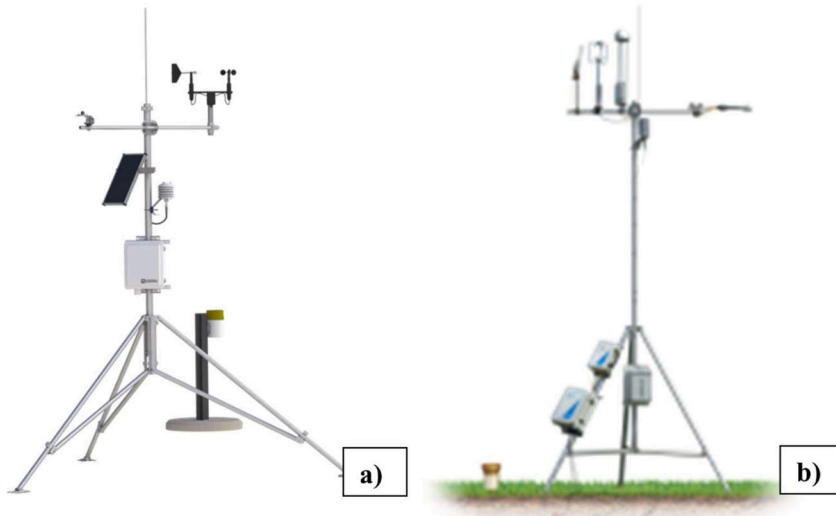


Figure 1.1 – Meteorological-based methods to assess grapevine water status. a) Automatic meteorological station, WxPRO (Campbell Scientific, Logan, UT, USA); Micrometeorological station (eddy covariance / Instantaneous fluxes method), (FLIR Systems Inc., Wilsonville, OR, USA).

The biophysical interactions governing water and energy exchanges between the vineyard and the atmosphere can be precisely measured using micrometeorological methods (Figure 1.1b), such as eddy covariance (EC), which provide accurate estimates of actual evapotranspiration. EC systems monitor three-dimensional wind velocity and vertical flux densities of LE (latent heat flux), and H (sensible heat flux) and scalars including carbon dioxide (CO_2), water vapor and other greenhouse gases. The vertical fluxes are calculated as the covariance between fluctuations in vertical wind velocity and the respective scalar concentration (Skinner and Wagner-Riddle, 2012). The eddy covariance method is considered one of the most widely recognized and reliable reference methods in environmental sciences, particularly for measuring ecosystem fluxes like CO_2 , water vapor, and energy exchange between the Earth's surface and the atmosphere (Baldocchi, 2003). It is commonly used in micrometeorology, climate science, and agriculture to quantify key processes such as evapotranspiration, photosynthesis, and carbon cycling. Moreover, the method is used to model and/or validate other methods such as thermal infrared imagery and vegetation indices (VIs) as indicators of grapevine water status (Costa et al., 2019; Costa et al., 2018; Chaves et al., 2016; Garcia-Tejero et al., 2016; Grant et al., 2007). However, the EC method is not commonly used at the farm level due to its high cost, complexity, and limitations in spatial representativeness.

1.5.2. Soil-based methods

The gravimetric method is the oldest and most accurate soil-based technique for evaluating soil water content. This method determines soil moisture by measuring the weight difference of a soil sample before and after oven drying.

Although the gravimetric method provides precise results, it is labor-intensive and unsuitable for real-time monitoring. However, it remains an ideal reference method, often used to validate sensor measurements that indirectly estimate soil moisture based on signals correlated with moisture levels. Several alternative methods are available today (Jones, 2007; Jones, 2004). Soil moisture sensors—such as tensiometers, neutron probes, time-domain reflectometry (TDR), Frequency-domain reflectometry (FDR), resistance probes and capacitance sensors (Figures 1.2a to 1.2f)—offer more practical, continuous, and scalable monitoring solutions providing precise real-time data. However, due to their limited measurement range, soil moisture sensors require careful installation. Furthermore, the depth at which the soil moisture is measured should correspond to the depth explored by the vine roots, which is not always well-defined. Also, to ensure sufficient spatial resolution, soil moisture monitoring methods must involve strategically placing individual sensors across the vineyard to represent distinct homogeneous plots. Each plot should consist of vines of the same variety, sharing the same irrigation network. Additionally, the soil's physical characteristics—such as depth, texture, and water-holding capacity—should be uniform within each plot. Notwithstanding, in addition to providing metrics on soil water content, soil moisture sensors have been employed to estimate plant water status, such as pre-dawn leaf water potential (Egipto et al., 2023; Groenvelt et al., 2023; Ding et al., 2021; Gaudin et al., 2017; Pellegrino et al., 2005b; Lebon et al., 2003; Lacape et al., 1998). When applicable, this approach is one of the most commonly used strategies for managing deficit irrigation in commercial vineyards.

The main challenge in field measurement of soil water content is its variability across the field and throughout the soil profile (IAEA, 2000). Another difficulty arises from the modification of soil properties during the probe installation process (IAEA, 2000). Additionally, due to the small measurement volume of the soil (IAEA, 2000), a significant limitation of soil-based methods is the difficulty in selecting the optimal location for sensor installation to collect the required data. Furthermore, neutron probes have restrictive use due to the radioactive nature of its components. Capacitance probes exhibit low precision, being highly sensitive to variations in soil type, salinity, and temperature (IAEA, 2000), requiring distinct calibration curves for different soil textures (Tanriverdi et al., 2016).

Nowadays, satellite sensors are increasingly capable of detecting soil moisture over large areas using electromagnetic waves, typically in the microwave range. The reflection of these waves from the soil varies with moisture content, enabling large-scale moisture mapping. Several free satellite-based products are available, such as the NASA-USDA Global Soil Moisture Data, developed by the Hydrological Sciences Laboratory at NASA's Goddard Space Flight Center in collaboration with the USDA Foreign Agricultural Service. This dataset provides both surface and subsurface soil moisture measurements (in millimeters), as well as soil moisture profiles (in percentage), with global coverage and a spatial resolution of $0.25^\circ \times 0.25^\circ$. However, these data have several limitations for precision irrigation. The spatial resolution is too coarse for field-level precision, and the frequency of data availability, along with the depth of soil profile

measurements, may not align with the requirements of detailed precision irrigation management.

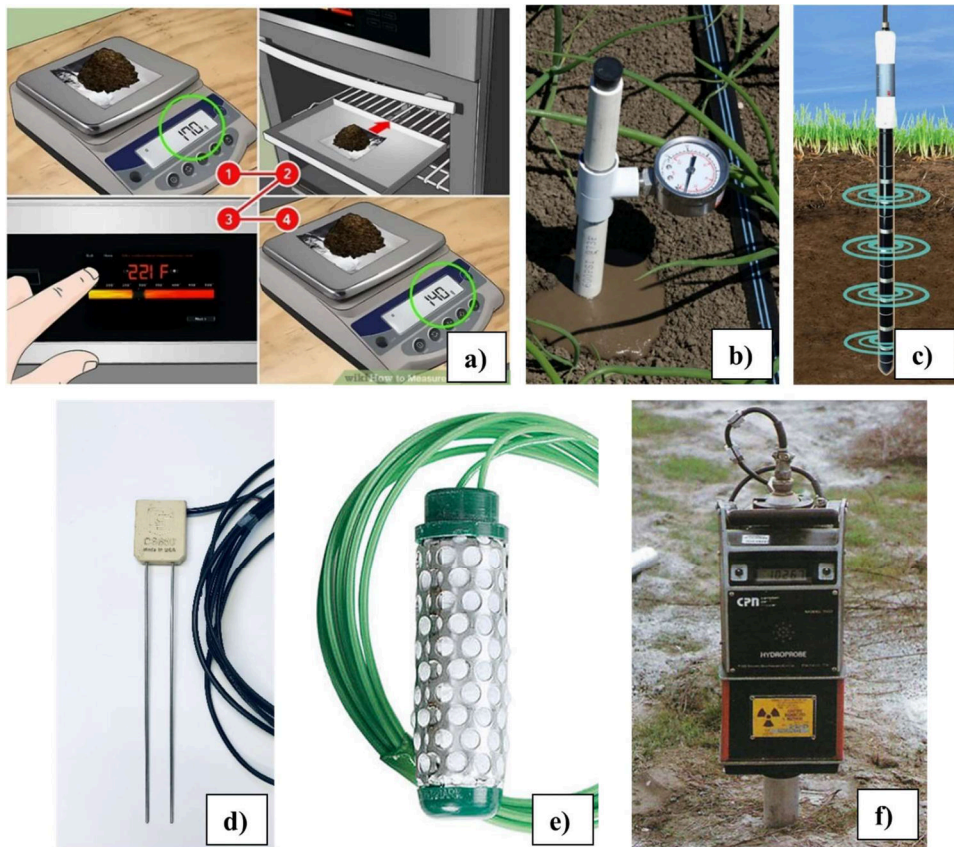


Figure 1.2 – Soil-based sensors to assess grapevine water status. a) gravimetric method (Photo: <https://www.wikihow.com/Measure-Soil-Moisture>); b) Tensiometer. (Photo: <https://ucanr.edu>); c) Capacitance probe. (Photo: <https://extension.umn.edu>); d) TDR probe. (Photo: <https://extension.umn.edu>); e) Watermark (The Irrrometer Company, Inc., CA, USA) - Electric resistance probe (Photo: <https://extension.umn.edu>); f) Neutron probe. (Photo: <https://ucanr.edu>).

1.5.3. Plant-based methods

Due to the limitations of atmospheric and soil-based methods, much of the research has focused on direct or indirect measures of plant water status as indicators for precision irrigation. Plant-based methods offer a direct, accurate, and dynamic approach to estimating plant water status, which is essential for making timely and precise irrigation decisions. These methods are sensitive to variations in environmental factors such as wind, temperature, and radiation, all of which can influence plant transpiration and water uptake. By providing real-time data, they help optimize water use, prevent (or induce adequate) crop stress, and improve water-use efficiency, especially in regions where water is a limited resource. When combined with other soil-based and meteorological data, plant-based methods offer a comprehensive understanding of a crop's water needs, thereby contributing to more sustainable agricultural practices. Furthermore, due to their inherent adaptability, these methods can quickly adjust to changing conditions, ensuring that irrigation is tailored to the plant's immediate needs. Jones (2004), Fernandez (2017) and Velazquez-Chavez et al. (2024) present an extent and critical review on crop water-

status monitoring and irrigation scheduling by plant-based methods. Some of the principal methods are discussed in the next subsections.

1.5.3.1. Visual observation

One of the first responses of plants to water stress is the downregulation of leaf photochemical processes, followed by a reduction in photosynthetic capacity and a slowdown in vegetative growth (Osakabe et al., 2014; Flexas et al., 2009; Chaves et al., 2002), which results in a decrease in the transpiring surface. Shoot growth slackening can be easily observed at the apical meristem (shoot apex) of grapevines. This slowing of leaf expansion and shoot growth becomes evident when the first expanded leaf covers the shoot apex (Rienth and Scholasch, 2019). Additionally, the temperature of exposed leaves tends to be higher compared to shaded leaves. Another symptom of moderate water stress is the wilting of tendrils (Keller, 2010b). MacMillan et al., (2021) observed a direct correlation between the decline in petiole hydraulic conductivity and an increase in water stress in the 'Chardonnay' cultivar, suggesting that this may result from a reduction in the permeability of the water-conducting pathway. This decline in hydraulic function could explain why some varieties, such as Tempranillo and Syrah, exhibit escape behaviors by altering leaf morphology—such as rolling parts of the leaf or changing the angle of insertion with the petiole—to reduce incident radiation and transpiration. Another example can be observed in Touriga Nacional, where persistent drought conditions can lead to the abscission of older basal leaves, thereby reducing canopy transpiration. This phenomenon is further generalized for grapevines by Chaves et al. (2007) and Jones (2014). Under persistent drought stress, the shoot apex may drop, shoot growth will cease, and tendrils will abscise (Rienth and Scholasch, 2019; Keller, 2010b).

The limitations of this method include the requirement for highly trained personnel and its relatively low temporal and spatial resolution. Furthermore, certain observed responses are not consistent across all varieties and can only be detected during specific time periods, which complicates its practical application in the field.

1.5.3.2. Water potential method (pressure chamber method)

Water moves along an inverse potential gradient in the soil-plant-atmosphere continuum (SPAC) (Goldsmith, 2013; Nobel, 1983). The uptake of water by plants from the soil occurs when there is a driving gradient for water loss from the leaf stomata by transpiration, due to a large difference between the low water potential of the dry atmosphere and the relatively higher water potential of the leaves. This gradient is propagated through the plant along a continuous water column that is under tension, ultimately driving water uptake from the soil, which has a less negative water potential compared to the roots (Garcia-Tejera et al., 2021; Rienth and Scholash, 2019; Nobel, 1983). In consequence, as the soil water content decreases, the soil water potential at the root surface becomes more negative, which increases the soil-plant hydraulic resistance (Jones, 2014) and causes a decrease in the vine's water potential (Rienth and Scholash, 2019), resulting in greater water stress.

The pressure chamber method is a widely accepted technique, often used as a reference for measuring leaf and stem water potential in plants (Figure 1.3). This method, typically performed using a Scholander pressure chamber, determines the pressure required to extract water from plant tissues, providing an indication of the plant's water status. Below is a detailed description of the method, including its various applications and limitations.

a. Leaf Water Potential (ψ_l)

Leaf water potential reflects the water status of a plant and can be measured at different times of the day, depending on the objectives.

i. Predawn leaf water potential (ψ_{PD})

Measurement Timing: ψ_{PD} is measured at predawn, before daytime transpiration begins.

Significance: ψ_{PD} is thought to equilibrate closely with soil water potential and is often used as an indicator of soil moisture status. This makes it particularly useful in situations where direct soil measurements may be difficult or unreliable. It avoids some of the complications associated with heterogeneous soil conditions and can provide insights into the plant's access to water in the soil (Zhang et al., 2024; Groenvelde et al., 2023; Gaudin et al., 2017; Taylor et al., 2012; Jones, 2007; Lebon et al., 2003; Williams and Araujo, 2002).

ii. Midday leaf water potential (ψ_{mid})

Measurement Timing: ψ_{mid} is typically measured 1 to 3 hours after solar noon, when leaf water potential generally reaches its lowest point due to the peak of transpiration (Costa et al., 2019; García-Tejero et al., 2016).

Significance: ψ_{mid} is commonly used to assess plant water stress, as it reflects the combined effects of soil moisture availability, transpiration rates, and plant physiological conditions (Williams et al., 2012). It provides important information about a plant's ability to maintain water balance during the hottest part of the day (Girona et al., 2006).

b. Stem Water Potential (ψ_{stem})

Stem water potential is typically measured at midday using the same method as ψ_{mid} , but with a key modification: leaves are wrapped in aluminum foil and enclosed in plastic bags for at least 30 minutes before sampling to prevent transpiration (Tomasella et al., 2023; Myburgh, 2010). This allows the water potential in the leaf to stabilize and become similar to that in the stem's xylem, near the point where the leaf is attached.

Significance: The stem water potential is crucial for understanding the plant's internal water transport system, particularly how water moves through the xylem from the soil to the leaves. Measuring stem water potential in combination with leaf water potential provides a more comprehensive picture of plant hydration status (Suter et al., 2019; Villalobos-González et al., 2019; Fernandez, 2017; Choné et al., 2001).

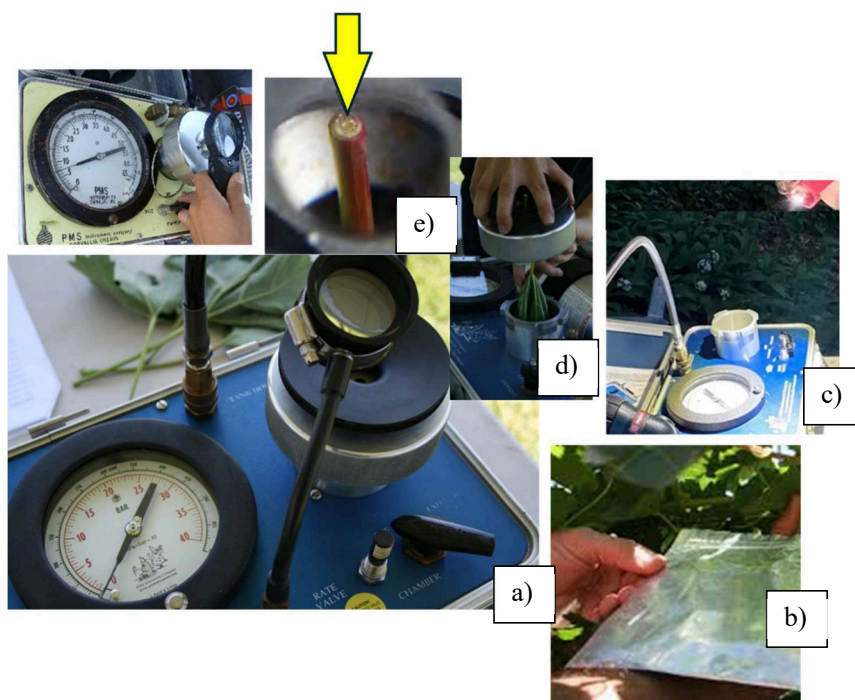


Figure 1.3 – Water potential (pressure chamber) method to assess grapevine water status. a) Scholander-type pressure chamber (PMS 600, PMS Instrument Company, Albany, OR, USA); b) Stem water potential measurement (reflective plastic bag leaf enclosure); c) Predawn leaf water potential measurement (leaves collected before sunrise); d) introducing the leaf into the chamber, ensuring a small portion of the petiole remains exposed outside of the chamber; e) water appears at the cut surface of the petiole, reflecting the tension the leaf is experiencing to retain water.

Several studies have contributed to determining threshold values for ψ_{PD} (Lovisolo et al., 2016; Lovisolo et al., 2010; van Leeuwen et al., 2009; Carbonneau, 1998), ψ_{mid} (Williams and Araújo, 2002) and ψ_{stem} (Lovisolo et al., 2010; Choné et al., 2001), which allow for the evaluation of grapevine water stress in the field (Deloire et al., 2020; Rienth and Scholash, 2019) (Table 1.1).

Table 1.1 – Predawn leaf water potential (ψ_{PD}), stem water potential (ψ_{stem}), midday leaf water potential (ψ_{mid}) thresholds for grapevine water stress. (Adapted from Rienth and Scholash, 2019)

Grapevine water stress	ψ_{PD} (MPa)	ψ_{stem} (MPa)	ψ_{mid} (MPa)
No water stress	> -0.2	> -0.6	> -0.9
Mild to Moderate Water stress	-0.2 to -0.5	-0.6 to -1.1	-0.9 to -1.3
Moderate to severe water stress	-0.5 to -0.8	-1.1 to -1.4	-1.3 to -1.4
Severe water stress	< -0.8	< -1.4	< -1.4

Although the pressure chamber method is reliable, it does have several limitations:

- *Destructive Nature:* Both leaf (predawn and midday) and stem water potential measurements are destructive, meaning they require the removal of plant leaves. This limits the ability to take multiple measurements on the same plant over time.

- *Time-consuming*: The process of preparing and measuring water potential is labor-intensive and requires precise timing. The method must also be repeated across different conditions or variables, which can be logistically challenging.
- *Low Spatial Resolution*: The pressure chamber method provides limited spatial resolution, making it difficult to obtain measurements across large areas or in heterogeneous environments. It is generally best suited for homogeneous plots, where plants are of the same variety, planted in similar soils, and subject to similar environmental conditions.
- *Homogeneity Requirement*: To obtain accurate results, the plants must be relatively uniform in terms of variety, soil type, and root characteristics. This requirement can make field applications of the method challenging, especially in natural or diverse environments.

1.5.3.3. Stomatal and Canopy Conductance

a) Stomatal conductance (g_s)

Stomatal conductance (g_s) measures the rate of gas exchange (i.e., carbon dioxide uptake) and transpiration (i.e., water loss) through leaf stomata, determined by the degree of stomatal aperture and the resulting resistance to gas movement between the leaf interior and the surrounding air under prevailing atmospheric conditions (Velazquez-Chavez et al., 2024). Stomatal conductance rapidly changes in response to several factors, including soil water status, hormonal and hydraulic signals generated in the roots and leaves, the water status in the vicinity of the guard cells, and atmospheric demand (vapor pressure deficit between the leaf stomata and the surrounding air) (Chaves et al., 2016; Buckley, 2005). As one of the most effective short-term indicators of water stress (Cifre et al., 2005; Jones, 2004), g_s is often used to assess plant water stress (Table 1.2), particularly the maximum daily stomatal conductance ($g_{s\ max}$), which refers to the g_s measured at the time of day when stomatal opening is at its peak (Fernández, 2017). However, due to the high sensitivity of g_s to environmental factors and the variation in leaf exposure to these factors within the canopy, there is considerable leaf-to-leaf variability in g_s . As a result, selecting a representative leaf (or leaves) can be challenging, and a large sample size is required for reliable data collection (Velazquez-Chavez et al., 2024). Another significant drawback of using g_s to schedule irrigation is that stomatal conductance is not always directly related to plant water status. In fact, some plants exhibit isohydric behaviour, meaning they can maintain a stable leaf water status across a wide range of atmospheric demands and soil water content (Fernández, 2017). Furthermore, grapevines can show either isohydric or anisohydric behaviour (Table 1.3), depending on water stress conditions (Chaves et al., 2016; Schultz, 2003). Additionally, the inability to automate g_s measurements limits its commercial application (Velazquez-Chavez et al., 2024; Fernández, 2017; Jones, 2004).

Table 1.2 – Leaf stomatal conductance to water vapour (g_s) thresholds for grapevine water stress. (Adapted from Rienth and Scholasch, 2019)

Grapevine water stress	g_s (mmol H ₂ O m ⁻² .s ⁻¹)
No water stress	> 500
Mild to Moderate Water stress	150 to 500
Moderate to severe water stress	50 to 150
Severe water stress	< 50

The iso/anisohydric terminology was initially proposed to differentiate plants based on their ability to decouple leaf water potential from atmospheric demand (Hochberg et al., 2018). Rather than describing an intrinsic property of the plant, the classification depends on the definition employed and the environmental conditions of plant growth, specifically referring to the plant's response to water use during long-term drought (Hochberg et al., 2018). A concise summary of the definitions of iso- and anisohydric plants, as found in the literature, was provided by Hochberg et al. (2018) and is presented in Table 1.3.

Table 1.3 – Terminology used to define Iso and Anisohydric behaviour according to bibliography (Notable Mentions). (Adapted from Hochberg et al., 2018)

Definition	Isohydric	Anisohydric
Daily fluctuation in leaf water content or water potential in response to VPD	'Small' fluctuations	'Large' fluctuations
Ability (or lack) to maintain constant ψ_{mid} when ψ_{soil} declines	Constant ψ_{mid} in response to decreasing ψ_{soil}	Decreasing ψ_{mid} in response to decreasing ψ_{soil}
Daily $\Delta\psi = \psi_{\text{PD}} - \psi_{\text{mid}}$	'Small' $\Delta\psi$	'large' $\Delta\psi$
g_s vs ψ_{min} or ψ_{soil}	Stomatal closure at low $\psi_{\text{min/soil}}$	Stomatal closure at high $\psi_{\text{min/soil}}$
σ (slope of ψ_{mid} vs ψ_{PD})	$\sigma < 1$	$\sigma > 1$
Hydroscape area (area of triangle bounded by the regression line, y axis, and 1:1 line in a plot of ψ_{mid} versus ψ_{PD})	'Small' hydroscape area	'Large' hydroscape area



Figure 1.4 – Stomatal conductance measurement sensors. a) Steady-state leaf porometer model LI-1600 (LI-COR, Lincoln, NE, USA); b) Portable Photosynthesis system model LI-6800, InfraRed Gas Analyzer (IRGA) (LI-COR, Lincoln, NE, USA) c) Leaf porometer/fluorometer model LI-600 (LI-COR, Lincoln, NE, USA).

b) Canopy conductance (g_c)

Stomatal conductance is a leaf-level measurement of water vapor flux through the stomata, focusing on leaf-specific responses. While g_s is useful for understanding how individual leaves regulate transpiration, it may not capture the full water flux behavior of the entire plant or canopy (Jones, 2014; Monteith and Unsworth, 2013). In contrast, canopy conductance (g_c) integrates water vapor flux from all leaves in the canopy and is often a more comprehensive metric for assessing the water status of the whole plant or ecosystem (e.g., a vineyard) (Gowdy et al., 2022b; Zhai et al., 2020). The g_c reflects the combined behavior of the entire canopy, incorporating factors like leaf area, spatial distribution of stomata, and environmental influences, providing a more holistic view of plant water use at the canopy level (Xu et al., 2021; Villalobos et al., 2013; Franks and Farquhar, 2007; Lu et al., 2003). This is also particularly valuable for water management and climate modeling, as it reflects the total water flux across vegetation areas, such as agricultural fields or forests. While g_s is measured directly via gas exchange techniques (e.g., porometers or infrared gas analyzers), canopy conductance is measured by sap-flow techniques combined with eddy-covariance techniques or, more frequently, estimated indirectly using models that combine leaf-level g_s with other variables, such as canopy structure, leaf area index, and environmental conditions (e.g., temperature, humidity, wind) that influence water vapor loss from the entire canopy (Egipto et al., 2024; Irmak et al., 2008; Lu et al., 2003).

In response to environmental changes, plants regulate transpiration through various physiological mechanisms that modify water conductance along the soil-plant-atmosphere continuum (Gowdy, 2022b). The importance of estimating g_c using models is evident in the reliance of general circulation models (GCMs)—which simulate the fluxes of heat, water, and momentum at the land-atmosphere interface—on canopy conductance to model plant transpiration (Lawrence et al., 2007; Cox et al., 1998).

Canopy conductance measurements can be used to understand plant physiology, water relations (Flo et al., 2021; Wei et al., 2018; Lu et al., 2003) and hydraulic architecture (Novick et al., 2009), allowing to gain insights into resistance to water flow, and energy exchanges between vegetation and the atmosphere (Jiao et al., 2018). In fact, canopy conductance to water vapor represents one of the most responsive variables to water stress in grapevines. The value of g_c lies in its ability to elucidate the division of net radiation (R_n) between latent heat and sensible heat fluxes (Monteith, 1995), thereby influencing plant transpiration. As the canopy acts to stabilize the considerable variability in g_s across individual leaves, g_c offers a suitable spatio-temporal measure of stomatal response to soil water and atmospheric conditions within the boundary layer (Wu et al., 2022; Fuentes et al., 2012; Damour et al., 2010; Avissar, 1993). This capability is crucial for identifying temporal and spatial patterns of water stress in vineyards (Zhai et al., 2020). The g_c can be estimated by inverting Penman-Monteith equation (Monteith and Unsworth, 2013). However, the complexity and feasibility constraints of parametrizing the Penman-Monteith equation, have led to the development of alternative methods for estimating g_c in grapevines. Several attempts were made to model g_c from meteorological and plant variables (Du et al., 2023; Gowdy et al., 2022b; Xu et al., 2021; Lu et al., 2003; Granier et al., 2000).

1.5.3.4. Sapflow

Sap flow measurements are used to assess water transport within plants, providing insights into plant physiology, transpiration rates, and responses to environmental

conditions. Sap flow measurements rely on the thermal properties of the xylem, where heat is applied to the stem and temperature changes are monitored to estimate sap flow rate. One of the most widely used methods for measuring sap flow is the heat pulse velocity (HPV) technique (Figure 1.5). This method involves introducing a heat pulse into the xylem and measuring the time it takes for the heat to move through the sapwood. The velocity of the heat pulse is proportional to the rate of sap flow, allowing for the calculation of sap flow rates based on the temperature profile observed around the heated area (Sun et al., 2021; Clearwater et al., 2009). This method has been validated in various studies, confirming its effectiveness in estimating whole-tree transpiration and canopy conductance (Kumagai et al., 2009; Čermák et al., 2004). Among the available techniques, the thermal dissipation method (Figure 1.5a), also known as the Granier method, is widely used. This approach estimates sap flow by measuring the temperature difference between a heated sensor and a reference sensor (Lu et al., 2004; Granier, 1985), providing continuous measurements that can be summed over time to yield total transpiration rates (Förster, 2017; Zhao et al., 2008). The ability to monitor sap flow continuously is crucial for understanding diurnal patterns of transpiration and for assessing the impact of environmental factors such as humidity, temperature, and light on plant water use (Chai et al., 2021; Tokuda et al., 2018). Moreover, sap flow measurements can also be influenced by the radial and circumferential patterns of water movement within the stem. Research shows that sap flow is uneven across the stem, with variations influenced by xylem anatomy and environmental factors (Nadezhdina et al., 2012; Nadezhdina et al., 2002). This variability highlights the need for caution when scaling sensor measurements to represent entire trees or forest stands. Assuming uniform flow ratios across the stem can lead to significant errors (Nadezhdina et al., 2002). The applications of sap flow measurements extend beyond basic physiological studies; they are also essential for practical applications in agriculture and forestry. By understanding plant water use, these measurements can inform irrigation strategies and improve water management practices. Furthermore, sap flow data can provide valuable insights into plant health and stress responses, making it a vital tool in both ecological research and agricultural management (Chai et al., 2021; Tokuda et al., 2018).

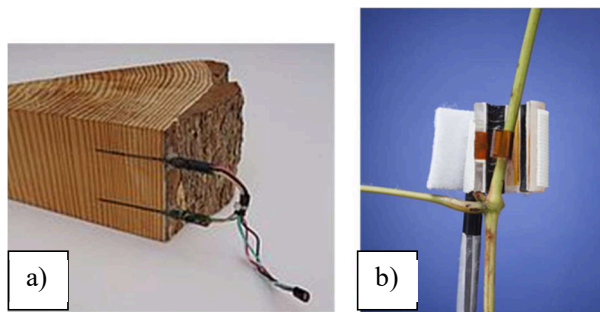


Figure 1.5 – Sapflow sensors. a) Heat dissipation method (Granier method) (<https://bwf.wsl.ch>); b) Stem heat balance (SHB) method (Valancogne and Nasr, 1989; Sakuratani, 1981) – Dynagage sensor(<https://www.dynamax.com>).

Notwithstanding, the low spatial resolution of the method requires the installation of numerous sensors strategically placed on individual plants within representative plots. Each plot must account for vine variety and share the same irrigation network. Furthermore, uniformity in soil physical characteristics—such as depth, texture, and water-holding capacity—is essential for reliable data. These requirements make the

system costly, labor-intensive, and reliant on trained users for data processing. Consequently, these constraints limit the method's feasibility in commercial orchards (Fernandez, 2017).

Given the limitations of the previous methods —specifically their low spatial and temporal resolution, as well as their high labor and expertise requirements—researchers have been exploring alternative approaches for assessing plant water status. Sensor-based methods (e.g., dendrometers, stem psychrometers) have been developed and evaluated to provide rapid, non-destructive measurements with improved spatial and temporal resolution. More recently, remote sensing techniques, such as thermal imaging, have been explored for detecting plant stress without damaging plant tissues. However, these techniques still require validation against traditional methods, such as the pressure chamber, to ensure their accuracy and reliability. Examples of these approaches will be discussed in the following sections.

1.5.3.5. Stem and fruit diameter

After stomatal opening, solar radiation drives the evaporation of water from the surface of leaves. This process generates tension in the water column within plant tissues, including the stem, branches, roots, leaves, and fruits (Fernandez, 2017; Čermák et al., 2007; Sevanto et al., 2002; Ueda and Shibata, 2001), enabling the plant to rapidly respond to changes in atmospheric demand (Fernandez, 2017). However, as this process is faster than water uptake by the roots, water from the phloem, adjacent tissues, and the living cells of the sapwood is lost by transpiration, leading to a reduction in stem diameter (Fernandez, 2017; Zweifel et al., 2000; Čermák and Nadezhdina, 1998; Brough et al., 1986) (Figure 1.6a). With sunset, as solar irradiance decreases, the plants start to rehydrate, reaching equilibrium with available soil water, and causing both stem and fruit diameter to increase. This daily stem diameter variation (SDV) patterns can be integrated into various water stress indicators (Fernandez, 2017). Widely used indicators include maximum daily shrinkage (MDS) and stem growth rate (SGR) (Fernandez, 2017). However, Fernandez (2017) cautions that MDS should be used with care for certain species, as seasonal changes and diurnal hysteresis between MDS and stem water potential (Ψ_{stem}) have been observed. In grapevines, Ortuño et al. (2010) reported that MDS increases as water potential decreases to a certain threshold, after which MDS decreases as water potential continues to decline. Additionally, SGR is not considered a reliable indicator of plant water stress during periods of negligible growth, such as in grapevines after veraison (Intrigliolo and Castel, 2007). Therefore, expert interpretation of SDV records is essential before using them for irrigation scheduling, limiting their potential for automating irrigation dose calculations (Fernandez, 2014). Data interpretation is further complicated by the fact that SDV patterns are influenced not only by environmental water conditions and growth patterns but also by factors such as plant age, size, and crop load (Fernandez, 2017).

Research indicates that variations in fruit diameter (FD), driven primarily by water influx and efflux rather than carbon gain, serve as sensitive indicators of plant water status (Figure 1.6b). Scalisi et al. (2020) demonstrated that probes equipped with linear variable displacement transducers (LVDTs) effectively captured FD dynamics in olive trees under different water regimes, highlighting their potential for continuous water status

monitoring. Similarly, a study on nectarines established a strong correlation between Ψ_{stem} and other water status indicators, further supporting the use of stem diameter variations as a reliable measure of overall plant hydration levels (Scalisi et al., 2020). Furthermore, other studies have indicated that fruit size and quality are significantly affected by water availability, as evidenced by research on apple trees where variations in trunk water potential were linked to fruit diameter and weight (González-Nieto et al., 2023).



Figure 1.6 – Stem and fruit diameter variation sensors. a) Trunk/stem dendrometer; b) Fruit dendrometer (<https://edaphic.com.au>)

Due to their size and the more or less compact arrangement within the bunch, applying this technique to grapevine berries is challenging. Additionally, the positioning of berries within the bunch exerts a major influence on the acquired data (Zarrouk et al., 2016).

1.5.3.6. Infrared Thermal Imaging

The fundamental principle behind thermal imaging for evaluating plant water status is that water stress induces stomatal closure, which reduces transpiration and increases leaf temperature. This phenomenon has been extensively documented, with thermal imaging proving to be a valuable tool in precision agriculture for assessing plant physiological responses to water availability (Elsayed et al., 2021; Li et al., 2014; Costa et al., 2013).

Thermal imaging systems operate by capturing infrared radiation emitted from plant surfaces, enabling non-contact measurement of leaf temperatures (Figure 1.7). This non-invasive method is particularly advantageous as it allows for continuous monitoring of plant water status under diverse environmental conditions (Pineda et al., 2020; Vadivambal and Jayas, 2010). Research has demonstrated that thermal imaging effectively differentiates between irrigated and non-irrigated plants, providing actionable insights into crop stress levels and irrigation requirements (Vieira and Ferrarezi, 2021; Knipper et al., 2019; Costa et al., 2013; Alchanatis et al., 2009). Its capability to monitor plant temperatures in real-time over extensive areas makes thermal imaging especially suitable for agricultural scenarios where timely irrigation decisions are critical. For instance, applications in sweet cherry trees and grapevines have highlighted how variations in canopy temperature can reveal water availability levels (Blaya-Ros et al., 2020; Belfiore et al., 2019).

Thermal imaging data correlates reliably with traditional physiological measurements, establishing its utility in water stress assessment (Hackl et al., 2012; Padhi et al., 2012). Calibration against known reference surfaces, such as wet and dry leaves, further enhances the accuracy of stomatal conductance estimates derived from thermal imaging (Jones, 1999). Recent advancements in image processing techniques have enabled the integration of thermal and visible imagery, improving the precision of water status assessments by distinguishing between sunlit and shaded canopy areas (Raza et al., 2014; Leinonen and Jones, 2004). These methods provide a deeper understanding of plant responses to water stress while also supporting the development of automated systems for real-time monitoring (Sharma et al., 2023; Jiménez-Bello et al., 2011).



Figure 1.7 – Infrared Thermal Imaging sensors. a) Drone DJI Matrice 300 (SZ DJI Technology Co., Ltd., Shenzhen, China) equipped with FLIR Vue TZ20 b) FLIR Vue Pro for UAV; c) FLIR T865 handheld thermal imaging camera (FLIR Systems Inc., Wilsonville, OR, USA).

Beyond water stress evaluation, thermal imaging has proven valuable for detecting plant responses to biotic and abiotic stresses, including early symptoms of diseases, by monitoring changes in transpiration rates (Raza et al., 2015; Chaerle et al., 2004). By linking thermal data with physiological traits, thermal imaging aids in phenotyping plant responses to environmental fluctuations, supporting breeding programs for drought-resistant varieties (Mertens et al., 2023; Pineda et al., 2020; Kwon et al., 2015). Furthermore, the deployment of unmanned aerial vehicles (UAVs) equipped with thermal cameras has expanded the capability to monitor plant water status across large-scale agricultural fields (Noguera et al., 2020; Ludovisi et al., 2017) (Figure 1.7a and 1.7b). This enables precise canopy temperature mapping, optimizing irrigation practices and water use efficiency (Gutiérrez et al., 2018; Espinoza et al., 2017).

Despite its potential, infrared thermal imaging has notable limitations. One key challenge is its sensitivity to environmental factors, particularly wind. Wind can induce rapid fluctuations in stomatal conductance, disrupting canopy microclimates and complicating the interpretation of thermal data (Grant et al., 2016; Fuentes et al., 2012). This variability is particularly problematic in heterogeneous vineyards, where microclimatic differences are pronounced.

Additionally, thermal imaging may capture mixed signals from non-leaf materials, such as fruit clusters or soil, which can obscure the relationship between canopy temperature

and actual leaf water potential (Sepulveda-Reyes et al., 2016; Pou et al., 2014; Fuentes et al., 2012). Shadows within the canopy pose another challenge, as shaded leaves exhibit different thermal characteristics than sunlit leaves, further complicating data interpretation (Poblete et al., 2018; Sepulveda-Reyes et al., 2016).

Another significant limitation is the reliance on accurately determining reference temperatures, such as the dry surface temperature (T_{dry}) and wet surface temperature (T_{wet}), for indices like the Crop Water Stress Index ($CWSI$). Establishing these references in dynamic field conditions is complex and prone to inaccuracies, which can compromise water status assessments (Fernández-Navales et al., 2021; Tardáguila et al., 2017). These challenges highlight the need for careful calibration and skilled interpretation, limiting the automation potential of thermal imaging compared to alternative non-destructive methods like near-infrared spectroscopy, which may provide more straightforward approaches to assessing water status (Tardáguila et al., 2017; De Bei et al., 2010).

1.5.3.7. Spectral and Hyperspectral Imaging

The spectral characteristics of leaves, particularly in the near-infrared (NIR) and shortwave infrared (SWIR) regions, provide valuable insights into plant water content. Notably, key water absorption bands occur around 1450 nm, 1940 nm, and 2500 nm (Kovár et al., 2019; Wang et al., 2008; Carter, 1993; Carter, 1991). Plant tissue reflectance behavior is directly influenced by internal water content, impacting the overall spectral response. As water content diminishes, a general increase in reflectance is observed across a broad spectral range (400–2500 nm), with the most significant changes occurring at the aforementioned absorption bands (Kovár et al., 2019; Wang et al., 2008; Carter, 1991).

The sensitivity of reflectance to water content is particularly pronounced in the 1450 nm and 1940 nm bands, which are strongly associated with water absorption features (Wang et al., 2008; Carter, 1993; Carter, 1991). These wavelengths are critical for remote sensing applications aimed at monitoring plant water stress, as they serve as reliable indicators of variations in hydration levels (Clevers et al., 2010; Govender et al., 2009).

In the NIR region (700–1300 nm), high reflectivity arises from the structural properties of leaf tissues, such as cell walls and air spaces, which scatter light efficiently. Conversely, the SWIR region (1300–2500 nm) exhibits lower reflectivity due to stronger water absorption (Zhao et al., 2020; Liu et al., 2012). This contrasting spectral behavior allows for the differentiation between healthy and water-stressed plants based on their unique spectral signatures. For instance, the NIR plateau is indicative of non-stressed plant tissues, while increased absorption above 1300 nm is directly linked to water stress and dehydration (Zhao et al., 2020; Liu et al., 2012). Spectral methods have been widely applied to capture these spectral characteristics, facilitating the development of spectral indices that correlate strongly with plant water status. Research has shown that specific indices derived from water absorption features can effectively monitor water stress in various crops (Ngie et al., 2017; Govender et al., 2009). Furthermore, spectral indices such as the Normalized Difference Water Index (NDWI) and the Water Index (WI) have been shown to effectively estimate water content in various crops, including wheat and grapevines, by analyzing reflectance in specific NIR and SWIR bands (Gutiérrez et al., 2010). Also the Water Balance Index (WABI), which integrates spectral data from both the visible and near-infrared regions, was demonstrated to effectively predict crop irrigation needs. Rapaport et al. (2017) demonstrated that WABI was highly correlated to

grapevine leaf water content and physiological responses under water deficit conditions, achieving high accuracy in identifying water stress. These indices are particularly valuable as they capture variations in water content that are not easily detectable through traditional methods (Govender et al., 2009).

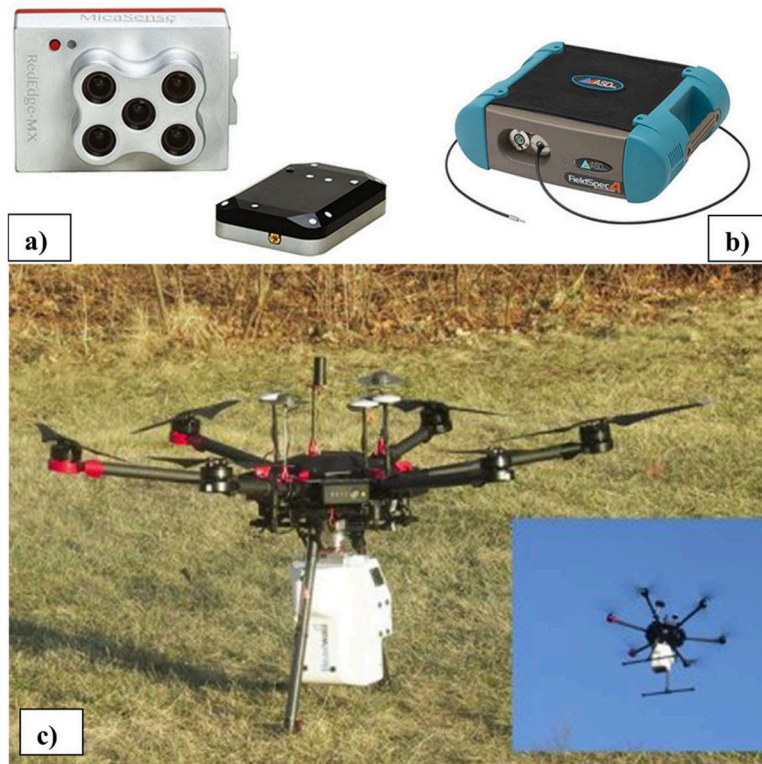


Figure 1.8 – Spectral and Hyperspectral Imaging sensors. a) Micasense RedEdge MX camera (<https://ageagle.com>); b) Portable remote sensing spectroradiometer - ASD Fieldspec4 (<https://www.malvernpanalytical.com>); c) DJI Matrice 600 (SZ DJI Technology Co., Ltd., Shenzhen, China) equipped with a co-aligned Headwall Photonics VNIR/SWIR hyperspectral camera (<https://analytik.co.uk/airborne-hyperspectral-imaging>).

Hyperspectral methods extend this approach by capturing reflectance data across a broader range of wavelengths, allowing for the detection of more subtle changes in plant water status. For instance, Asgari (2023) demonstrated that spectral indices derived from hyperspectral data can effectively assess water status in semi-arid regions, showcasing the potential of these advanced techniques for precise water management. Pôças et al. (2015) emphasized the utility of hyperspectral reflectance vegetation indices derived from SWIR data. According to these authors, VIs derived from SWIR data promise in detecting crop water stress and assessing grapevine water status. Additionally, El-Hendawy et al. (2017) emphasized that hyperspectral reflectance is more sensitive to changes in vegetative water content than traditional spectral indices, making it a powerful tool for assessing plant water status under varying irrigation conditions.

The non-destructive nature and rapid assessment capabilities of spectral and hyperspectral methods have garnered significant attention in agricultural research for evaluating plant water status. The adoption of unmanned aerial vehicles (UAVs) equipped with hyperspectral imaging has further revolutionized large-scale water stress monitoring, enabling assessments with high spatial resolution. This capability is enhanced by integrating hyperspectral data with advanced machine learning algorithms, which

significantly improve the precision and accuracy of water content assessments in plant tissues (Vitrac-Tamam et al., 2020). Gago et al. (2015) demonstrated that combining hyperspectral and thermal sensors on UAVs enables the detection of water stress by analyzing variations in leaf temperature and transpiration rates, both of which are closely tied to water availability.

The use of NIR spectroscopy in conjunction with machine learning algorithms (Gutiérrez et al. 2016) or hyperspectral imaging conjugated with artificial neural networks (ANNs) (Poblete et al., 2017) emerged as powerful tools to estimate relative water content in grapevine leaves, predicting with high accuracy the spatial variability in vine water status.

The integration of these advanced techniques provides a more nuanced understanding of grapevine physiology and water dynamics. This technology enables real-time monitoring, offering actionable data that can optimize irrigation practices and promote more sustainable agricultural practices.

However, spectral and hyperspectral methods for evaluating grapevine water status present several challenges that may impact the accuracy and reliability of the assessments. These challenges can be categorized into limitations associated with spectral data, the physiological complexity of grapevines, and the difficulties of applying these technologies in field conditions.

A significant limitation of spectral and hyperspectral methods is their sensitivity to environmental factors and the inherent variability in grapevine physiology. For instance, spectral indices based on visible and near-infrared wavelengths may not consistently correlate with water status under different environmental conditions. Studies have shown that indices based on wavelengths between 500 and 800 nm may not reliably estimate vine water potential in all field conditions, suggesting that longer wavelengths could provide better correlations (Poblete et al., 2017). Additionally, grapevine physiological responses to water stress can vary significantly among cultivars, complicating the interpretation of spectral data (Medrano et al., 2003). This variability may lead to inaccuracies when using generalized spectral models that fail to account for cultivar-specific responses (Rapaport et al., 2015).

Furthermore, the complexity of grapevine water status regulation also presents challenges for spectral methods. Also, certain grapevine varieties exhibit isohydric behavior, meaning they can maintain water potential above a threshold even under significant water deficit, which may not be adequately captured by spectral measurements (Medrano et al., 2003). This homeostatic regulation can lead to misleading interpretations of water stress based on spectral data alone, as the physiological indicators may not accurately reflect the plant's actual water status (Pellegrino et al., 2005a). Moreover, reliance on specific physiological indicators, such as leaf water potential, can be problematic as they may not respond uniformly to changes in soil water availability or climatic conditions (Intrigliolo and Castel, 2007).

Practical limitations also affect the field application of spectral and hyperspectral technologies. The time-consuming nature of data collection and the requirement for extensive calibration can hinder the efficiency of these methods (Gutiérrez et al., 2016). Furthermore, the representativeness of the sampled areas may be limited, as only a small number of samples are typically measured, which may not accurately reflect the overall vineyard water status (Gutiérrez et al., 2016). The integration of advanced statistical methods, such as partial least squares regression, has been proposed to improve the predictive capabilities of spectral data. However, these methods still face challenges

related to model robustness and generalizability across different vineyard conditions (Wei et al., 2021).

1.5.3.8. Carbon Isotopic Discrimination ($\delta^{13}\text{C}$)

Carbon dioxide (CO_2) in the atmosphere and terrestrial biosphere exists as a mixture of two stable isotopes, ^{13}C and ^{12}C , with a typical ratio of approximately 0.011 (NOAA, 2024). In 1984, Farquhar and Richards demonstrated that variations in carbon-isotope composition among wheat genotypes correlated with differences in water-use efficiency (WUE), highlighting carbon-isotope analysis as a valuable tool for improving WUE in C3 species. In grapevines, carbon isotope discrimination ($\delta^{13}\text{C}$) is primarily influenced by the ratio of intercellular to atmospheric CO_2 concentrations (C_i/C_a), which is closely tied to stomatal conductance (g_s) (Lanari et al., 2015). Higher $\delta^{13}\text{C}$ values are typically observed under water stress due to stomatal closure limiting CO_2 uptake, which enriches ^{13}C in plant tissues (Bchir et al., 2016; Santesteban et al., 2014). For example, grapevines subjected to water deficits show increased $\delta^{13}\text{C}$ compared to well-watered plants (Santesteban et al., 2014). Various tissues—such as leaves, stems, and grape berries—can be analyzed for their carbon isotope composition, providing integrated insights into vineyard water status (Brillante et al., 2017; Gaudillère et al., 2002).

Studies have shown that variations in $\delta^{13}\text{C}$ in grape pulp reflect grapevine water stress levels (Gómez-Alonso and García-Romero, 2009; Gaudillère et al., 2002), highlighting the importance of $\delta^{13}\text{C}$ as an indicator of the integrated effects of water stress on grapevines (Table 1.4). However, several factors complicate its application, including environmental variability, cultivar differences (Tomás et al., 2012), and the timing of measurements (Dinis et al., 2022). For instance, $\delta^{13}\text{C}$ values measured at different stages of berry ripening may reflect metabolic processes in the fruit that do not directly correspond to the vine's overall water status (Gowdy et al., 2022a; Conti et al., 2018). Additionally, while $\delta^{13}\text{C}$ provides indirect information about the ratio of total dry matter yield to water transpired, it does not account for absolute yield, limiting its utility as a standalone metric for WUE (Farquhar and Richards, 1984). Addressing these limitations requires careful experimental design and a nuanced understanding of grapevine physiology and environmental interactions (Taskos et al., 2020; Hernández-Montes et al., 2017).

Table 1.4 – Carbon isotopic discrimination ($\delta^{13}\text{C}$) thresholds for grapevine water stress. (Adapted from Rienth and Scholasch, 2019)

Grapevine water stress	$\delta^{13}\text{C}$
No water stress	< -26.0
Mild to Moderate Water stress	-23.0 to -26.0
Moderate to severe water stress	-21.5 to -23.0
Severe water stress	> -21.5

1.5.3.9. Leaf Thickness

Under drought conditions, plants often exhibit changes in leaf thickness as an adaptive response to conserve water and maintain turgor pressure, highlighting the use of leaf thickness as a sensitive indicator of leaf water content (Afzal et al., 2017). For example, mesophyll tissue may thicken, which enhances the leaf's capacity to store water and preserve cellular turgidity (Zakariyya et al., 2019; Silva et al., 2018). Traditionally, leaf thickness is measured using tactile methods, such as analog thickness gauges or mechanical micrometers. While these techniques are direct, they are invasive and can disturb the leaf's physiological state during measurement (Dupuis et al., 2017).

More advanced approaches, such as using linear variable displacement transducers, provide non-destructive and dynamic measurements of leaf thickness, enabling continuous monitoring over time, including during water stress or growth cycles (Schmitt et al., 2022; Pfeifer et al., 2017; Yumeina and Morimoto, 2017). Additionally, non-invasive techniques such as X-ray computed tomography (CT) and laser scanning have been developed. X-ray CT offers detailed 3D imaging of leaf structures, allowing for assessment of leaf thickness while preserving leaf integrity (Nožková et al., 2018; Pfeifer et al., 2017). Laser scanners are another promising method for measuring leaf thickness, although the small dimension of some leaves presents challenges (Dupuis et al., 2017).

Remote sensing technologies also offer innovative methods for estimating leaf thickness and water content. Reflectance indices derived from remote sensing data can help assess leaf characteristics at a distance, which is especially valuable for large-scale agricultural monitoring (Deng et al., 2019; Sui et al., 2012). For example, leaf equivalent water thickness (EWT), derived from remote sensing, provides insights into leaf water content and overall plant health (Qian et al., 2012).

Despite these advances, several weaknesses affect the accuracy of using leaf thickness as a water status indicator. In fact, some species may show a decrease in leaf thickness when water stress occurs, reflecting a loss of turgor and potential wilting (Seelig et al., 2011). Also, environmental factors like light exposure and temperature can introduce variability in leaf thickness readings, making them unreliable (Williams, 2012). Furthermore, diurnal fluctuations in leaf water potential and stomatal conductance due to changing climatic conditions complicate the interpretation of leaf thickness as a water status measure (Intrigliolo and Castel, 2007; Moutinho-Pereira et al., 2004). These diurnal variations may not reflect the plant's water needs at any given time, leading to potential misinterpretations.

The physiological long-term responses of grapevines to water stress also contribute to changes in leaf morphology, which may not always correlate directly with water availability. For example, prolonged water stress may lead to leaf shedding and alterations in leaf thickness, making it challenging to assess water status based on leaf thickness alone (Degu et al., 2019; Medrano et al., 2003). Additionally, the isohydric behavior of certain grapevine cultivars, which allows them to maintain leaf water status above a threshold even under water deficit conditions, can further complicate assessments (Villalobos-González et al., 2019; Medrano et al., 2003).

Ultimately, relying on leaf thickness as a sole indicator of water status is not sufficient, as it does not account for other critical physiological metrics such as stomatal conductance, stem water potential, and predawn leaf water potential, which are more reliable for assessing grapevine water status (Jež-Krebelj et al., 2022; Suter et al., 2019). To ensure accurate and reliable assessments of grapevine water status, it is imperative to integrate leaf thickness measurements with complementary physiological indicators, such as stomatal conductance and predawn leaf water potential. This multi-dimensional approach not only provides a holistic understanding of plant hydration but also supports more effective irrigation management and sustainable vineyard practices.

1.5.3.10. Leaf Turgor Pressure

The leaf turgor pressure method measures relative changes in turgor pressure within leaf tissues (Zimmermann et al., 2013). Turgor pressure is the hydrostatic pressure exerted by the fluid inside plant cells against the cell wall, which is essential for maintaining cell structure. Studies show that turgor pressure fluctuates diurnally, typically being higher at night than during the day. This variation suggests that turgor pressure may serve as a sensitive indicator of plant water status, reflecting real-time changes in response to water availability (Bunce, 2022; Zimmermann et al., 2013; Zimmermann et al., 2010; Zimmermann et al., 2008). Furthermore, the method can be integrated with other physiological measurements, such as stomatal conductance and transpiration rates, offering a holistic view of the plant's water regulation (Zait et al., 2017; Rodriguez-Dominguez et al., 2016).



Figure 1.9 – Leaf turgor pressure sensor. YARA water sensor (YARA ZIM Plant technology GmbH, Hennigsdorf, Germany). (www.yara.com/water)

One of the most effective tools for measuring leaf turgor pressure is the leaf patch clamp pressure probe. This device applies controlled pressure to a specific area of the leaf, allowing the measurement of the resulting pressure changes, which correlate with turgor pressure (Rüger et al., 2011). Studies have shown that this method can continuously monitor changes in turgor pressure over extended periods, providing real-time data that is particularly useful for assessing plant responses to water stress (Rüger et al., 2011; Ache et al., 2010). The ability to track turgor pressure dynamically makes this method a sensitive indicator of plant hydration.

Nevertheless, several challenges are associated with using turgor pressure as an indicator of plant water status. One such challenge is the variability in turgor loss points (Ψ_{TLP}) among different grapevine cultivars. Grapevines exhibit a range of Ψ_{TLP} values, which influence their ability to maintain turgor under drought conditions. Cultivars with lower Ψ_{TLP} tend to maintain higher stomatal conductance and leaf hydraulic conductance, indicating genetic differences in drought responses (Knipfer et al., 2020; Hochberg et al., 2017a). This variability complicates the use of turgor pressure as a universal measure for assessing water status across different grapevine varieties.

Turgor pressure also fluctuates diurnally due to environmental factors such as transpiration rates and temperature (Bunce, 2022). This variability highlights the importance of timing measurements accurately, as improper timing can yield data that does not reflect the plant's true water status, complicating its interpretation. Furthermore, pressure probes may fail to provide accurate measurements of turgor pressure under conditions of severe dehydration, leading to misinformed irrigation decisions that could exacerbate water stress (Mirás-Avalos and Araujo, 2021). This is especially problematic when managing water stress in grapevines, where accurate data is crucial for preventing crop damage.

The relationship between leaf turgor pressure and stomatal closure is complex. Although reductions in turgor pressure generally led to stomatal closure, other factors—such as root-derived abscisic acid (ABA) signals—also play a significant role in regulating stomatal conductance under drought conditions (Herrera et al., 2021; Rodríguez-Domínguez et al., 2016). Therefore, relying solely on turgor pressure measurements may not provide a comprehensive assessment of the plant's water status and physiological responses to drought stress. Additionally, grapevines exhibit osmotic adjustment mechanisms to maintain turgor pressure under water stress, as the accumulation of solutes in cells. This ability to adjust osmotic potential can mask the effects of turgor loss, potentially leading to an underestimation of water stress in the plant (Sinclair, 2024; Gutiérrez-Gamboa et al., 2021). Such osmotic adjustment complicates the interpretation of turgor pressure data, as the plant may maintain turgor despite experiencing significant water stress.

1.5.3.11. Stem Water Content

The stem water content (θ_{stem}) method is based on the principle that stems function not only as conduits for water transport but also as reservoirs that can store and release water, thereby influencing the plant's overall water status. For instance, during periods of high transpiration, stem water reserves can help maintain xylem water potentials, thereby supporting continuous water flow from roots to leaves (Kumagai et al., 2009; Holbrook and Sinclair, 1992). Stem water content varies significantly through the season, reflecting the dual role of stems in both transpiration and water storage (Hernández-Santana et al., 2008; Hernández-Santana et al., 2007). This dynamic variation is crucial for assessing plant responses to water deficits, as it reflects the balance between root water uptake and leaf water loss. For instance, during periods of drought, the stem can release stored water to maintain leaf turgor and support physiological processes (Salomón et al., 2020; Kumagai et al., 2009). This capacity for water storage is particularly evident in species like *Quercus pyrenaica*, where variations in stem water content are closely linked to soil moisture availability (Salomón et al., 2020; Hernández-Santana et al., 2008).

Several techniques have been developed to measure stem water content, each with its advantages and limitations. Traditional methods, such as gravimetric measurements, provide accurate data but are often labor-intensive and destructive (Gao et al., 2019; Wang and Zhao, 2010). In contrast, non-invasive techniques, such as time-domain reflectometry and frequency domain methods, allow for real-time monitoring of stem water content without damaging the plant (Lv et al., 2022; Zhou et al., 2014). These methods utilize the relationship between the dielectric properties of the stem and its water content, enabling researchers to track changes dynamically (Lyu et al., 2016). Also, as mentioned earlier, stem water potential is a measure of the potential energy of water within the stem, influencing water movement from roots to leaves, while θ_{stem} refers to the actual amount of water stored in the stem tissues. These two parameters are interrelated, as changes in water content can directly influence water potential. For example, an increase in stem water content typically corresponds to an increase in stem water potential, as the additional water in the stem raises the potential energy available for movement (Dzikiti et al., 2009). This relationship suggests that Ψ_{stem} could be a potential indicator of θ_{stem} .

Moreover, advancements in sensor technology, such as ultrasonic and standing wave ratio methods, have enhanced the precision of stem water content measurements (Yang et al., 2021). These sensors can provide continuous data on water dynamics, which is essential for understanding plant responses to environmental stressors (Asgharina et al., 2022).

For example, studies have shown that integrating these technologies can provide better insights into how trees cope with drought conditions by effectively utilizing stored water (Asgharinia et al., 2022).

A significant limitation in evaluating grapevine water status through θ_{stem} is the variability in Ψ_{stem} thresholds that define different stress levels (Gaiotti, 2023). Since these thresholds can vary significantly across different grapevine cultivars and environmental conditions, their miscalibration may lead to the misinterpretation of water status under local conditions (Mirás-Avalos and Araujo, 2021).

Moreover, the relationship between θ_{stem} and physiological processes in grapevines is complex. For instance, while Ψ_{stem} can indicate water availability, it does not directly correlate with the plant's physiological responses, such as stomatal conductance and photosynthesis, which are also influenced by other factors like temperature and humidity (Nguyen et al., 2013; Lovisolo et al., 2010). The same occurs with stem water content dynamics which are also influenced beside available soil moisture by other external factors such as plant size. Larger trees tend to have greater stem water storage capacity, enhancing their resilience to drought conditions (Goldstein et al., 1998). This disconnect can be challenging in using θ_{stem} as a standalone measure for assessing plant water stress, as it may not fully capture the plant's physiological state under varying environmental conditions (Hochberg et al., 2013).

Additionally, the methods used to measure θ_{stem} can introduce inaccuracies. Traditional methods of measuring θ_{stem} , such as gravimetric techniques, can be labor-intensive and may not provide real-time data, which is crucial for timely irrigation decisions (Santesteban et al., 2019). Newer technologies, such as capacitive sensors and ultrasonic detection methods, offer non-destructive alternatives for monitoring θ_{stem} , but their effectiveness can be influenced by environmental factors and require careful calibration (Asgharinia et al., 2022; Zhou et al., 2014). While these technological advancements are promising, challenges remain regarding their widespread adoption and reliability in varying vineyard conditions.

1.5.3.12. Chlorophyll Fluorescence

This method leverages the fluorescence emitted by chlorophyll molecules when they absorb light, providing valuable insights into plant physiology, particularly regarding photosynthetic efficiency and water stress responses. Chlorophyll fluorescence serves as a sensitive indicator of changes in photosystem II (PSII) activity, a key process in plant responses to water stress. Water deficits impair PSII efficiency, leading to a reduction in the quantum yield of photosynthesis. This reduction is measurable through parameters such as the maximum quantum yield (Fv/Fm) and the effective quantum yield (ΦPSII) (Torun, 2023; Radwan and Saleh, 2022; Iqbal et al., 2019). Mitra et al. (2018) highlighted that under severe drought stress, Fv/Fm may drop below critical thresholds, reflecting both the physiological status of plant and the influence of soil moisture levels, thereby enabling the assessment of water status (Zoro-Diama et al., 2017; Ni et al., 2015). Additionally, it can detect early signs of water stress before visible symptoms appear, facilitating timely interventions in agricultural practices (Murchie and Lawson, 2013). For instance, research has shown that combining chlorophyll fluorescence with temperature measurements enhances the detection of water stress, providing a more comprehensive understanding of the plant's physiological responses (Sepúlveda and Johnstone, 2018; Ni et al., 2015). Furthermore, the non-invasive nature of chlorophyll fluorescence makes it an attractive tool for real-time monitoring of plant water status.



Figure 1.10 – Chlorophyll fluorescence sensors. a) Multiplex® 3 (FORCE-A, Centre Universitaire Paris-Sud ORSAY, Orsay, France); b) Walz MINI-PAM-II with Porometer leaf clip. Fluorometry and stomatal conductance (Heinz Walz GmbH, Effeltrich, Germany); c) Leaf porometer/fluorometer model LI-600 (LI-COR, Lincoln, NE, USA)

Recent advances in imaging technologies have enhanced chlorophyll fluorescence measurements. Techniques such as laser-induced fluorescence and imaging fluorimetry enable detailed spatial analysis of chlorophyll fluorescence across leaf surfaces, providing insights into localized stress responses and overall plant health (Zakhidov et al., 2016; Rolfe and Scholes, 2010). These innovations facilitate a deeper understanding of how plants manage water under varying environmental conditions, aiding in the development of more resilient crop varieties and sustainable agricultural practices (Mihaljević et al., 2021).

Despite its advantages, chlorophyll fluorescence measurements have certain limitations, primarily their sensitivity to environmental conditions. Factors such as the physiological state of the grapevine may not always correlate with water status, potentially leading to inaccurate interpretations. For instance, Hailemichael et al. (2016) found that while chlorophyll content and fluorescence parameters can indicate water stress, they may not always provide a comprehensive view of the plant's physiological performance under varying water conditions. This highlights the importance of integrating additional physiological indicators to avoid drawing misleading conclusions about the grapevine's water status.

The timing of measurements is also critical for the accuracy of chlorophyll fluorescence assessments. Parameters such as F_v/F_m and the photochemical quenching (qP) – the ability of photosystem II to transfer electrons to acceptors within the chloroplast – can fluctuate throughout the day due to variations in light intensity and temperature, potentially masking the plant's true water status. Additionally, Ye et al. (2022) noted that water stress affects chlorophyll synthesis and degradation, causing fluorescence readings to vary depending on the time of day the measurements are taken. Therefore, careful consideration of measurement timing is essential to ensure accurate assessments.

Another potential limitation of chlorophyll fluorescence is its ability to detect stress before visible symptoms manifest. While this early detection can be beneficial, it may also lead to premature conclusions regarding the need for irrigation or other interventions.

As noted by Aazami et al. (2021), chlorophyll fluorescence can detect declines in plant health before visible signs of stress, potentially resulting in unnecessary interventions if not corroborated by additional assessments. Therefore, integrating chlorophyll fluorescence with additional physiological metrics is essential for a comprehensive evaluation of grapevine water status.

Lastly, the interpretation of chlorophyll fluorescence data can be complex and require expertise. Parameters such as F_v/F_m and qP can be influenced by various factors, including leaf age, light conditions, and even the specific grapevine cultivar. As highlighted by Benyahia et al. (2023), a thorough understanding of these parameters and their interactions with environmental conditions is essential for accurate assessments of grapevine water status. This complexity can pose challenges for practitioners who may not have the necessary training to interpret fluorescence data accurately. To enhance the reliability of chlorophyll fluorescence for water status assessments, it must be integrated with other physiological indicators, considering the broader environmental context.

1.5.3.13. Xylem Hydraulic Conductivity

The method for assessing xylem hydraulic conductivity involves measuring the hydraulic conductance of xylem vessels, which reflects the efficiency of water transport from the roots to the leaves. Xylem hydraulic conductivity (K_{sx}) is influenced by several factors, including the presence of embolisms, xylem anatomy, and environmental stressors such as drought. Embolisms, defined as air bubbles that form within the xylem vessels, can significantly impair water transport and substantially reduce hydraulic conductance. This phenomenon is particularly pronounced in plants experiencing water stress, where the formation of embolisms can lead to a loss of conductivity, often quantified as the percentage loss of conductivity (PLC) (Li, 2024; Neghliz et al., 2016; Trifil et al., 2011). The vulnerability of xylem to cavitation—where negative pressure causes the disruption of water columns—can be quantified through vulnerability curves that relate PLC to xylem water potential (Pereira et al., 2016; Choat et al., 2010). These curves provide valuable insights into how different plant species cope with water stress and can inform irrigation practices (Li, 2024).

Several techniques are employed to measure xylem hydraulic conductivity, including flushing xylem segments with water to remove embolisms and assess the resultant hydraulic conductance (Dzikiti et al., 2009; Hietz et al., 2008). Modified Sperry apparatuses have been used to precisely measure PLC by connecting stem segments to a water column and monitoring flow rates (Zhang et al., 2018; Cochard, 2002). These methods have been validated across different species and environmental conditions, demonstrating their reliability in assessing plant water status (Melcher et al., 2012; Scheenen et al., 2007).

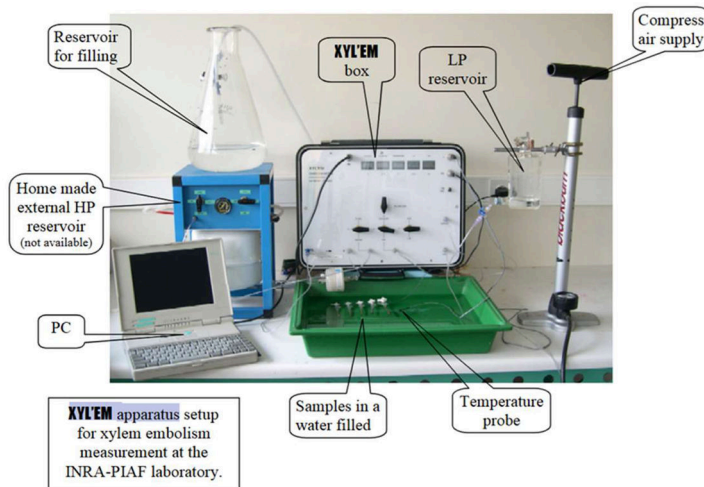


Figure 1.11 – Xylem hydraulic conductivity monitoring apparatus. The XYL'EM (INRA, Clermont-Ferrand, Auvergne France) (<https://eng-piaf.clermont.hub.inrae.fr/methods-and-models/xyl-em>)

Moreover, the relationship between xylem hydraulic conductivity and various plant physiological processes is of considerable importance. For instance, a plant's ability to maintain high hydraulic conductance is closely linked to photosynthetic efficiency and overall growth (Melcher et al., 2003). Changes in xylem anatomy, such as variations in vessel diameter and density, can also affect hydraulic properties, influencing how plants cope with environmental stresses, such as drought (Pramsohler et al., 2022; Liu et al., 2019). Understanding these relationships is essential for predicting plant responses to climate change and for optimizing agricultural practices. Measuring hydraulic conductance and understanding its underlying factors can provide valuable insights into plant stress responses and broader ecosystem dynamics.

Grapevines, in particular, are highly susceptible to cavitation, where embolisms induced by water stress lead to significant reductions in K_{sx} . Studies have shown that even small declines in water potential can trigger substantial decreases in K_{sx} , highlighting the sensitivity of grapevine xylem to water deficits (Albuquerque et al., 2020; Shelden et al., 2017; Jacobsen and Pratt, 2012). This vulnerability is particularly evident in certain grapevine organs, such as petioles and roots, which are more susceptible to cavitation than stems (Hochberg et al., 2016; Tramontini and Lovisolo, 2015). In such situations, embolism formation can lead to substantial losses in hydraulic conductance, complicating the interpretation of K_{sx} values as indicators of plant water status (Hochberg et al., 2017b; Hochberg et al., 2016). Consequently, measurements of hydraulic conductivity may not always accurately reflect the plant's actual water status, especially during periods of water stress.

Moreover, the method's reliance on specific environmental conditions can further limit its effectiveness. The hydraulic conductance of grapevines is influenced by various factors, including soil moisture levels and atmospheric conditions, which can vary considerably over time (Pagay et al., 2016; Brodersen et al., 2010). This variability can lead to inconsistent measurements of xylem hydraulic conductivity, making it difficult to establish a reliable baseline for assessing water status across different growing conditions or grapevine cultivars (Melcher et al., 2012). Additionally, the dynamic nature of xylem function, including the potential for embolism repair, adds another layer of complexity

that can affect the accuracy of hydraulic measurements (Brodersen et al., 2013; Zufferey et al., 2011).

Measurement errors associated with techniques used to assess xylem hydraulic conductivity also merit consideration. For instance, centrifuge-based methods may not fully account for the physiological state of the plant or the presence of embolisms, potentially leading to underestimations or overestimations of hydraulic conductance (Sorek et al., 2020; Jacobsen and Pratt, 2012). Also, the structural characteristics of xylem vessels also significantly influence hydraulic conductivity. Studies have demonstrated that vessel diameter and arrangement play pivotal roles in determining plant's water transport efficiency. For instance, the primary xylem to secondary xylem ratio is a key determinant of vulnerability to cavitation, with petioles, which have sparse secondary thickening, being more prone to hydraulic rupture (Zufferey et al., 2011). Moreover, the presence of immature or living vessel elements in developing xylem can obstruct water flow, further affecting the accuracy of hydraulic conductivity assessments (Sorek et al., 2020; Halis et al., 2011). Also, the dynamics of embolism formation and repair are critical to understanding xylem hydraulic conductivity in grapevines. Under drought conditions, embolism formation can lead to a substantial loss of hydraulic conductivity, with reported losses ranging from 5% to 20% at low ψ_{stem} (Brodersen et al., 2013; Brodersen et al., 2010). This loss is exacerbated by the grapevine's limited ability to refill embolized vessels under tension, which represents a significant constraint during prolonged droughts (Hochberg et al., 2017b ; Charrier et al., 2016).

Additionally, the interpretation of xylem hydraulic conductivity data can be confounded by the interactions between hydraulic and non-hydraulic signals in the plant. Grapevines, for example, utilize both hydraulic and chemical signals—such as those mediated by abscisic acid—to regulate stomatal conductance and manage water loss (Jež-Krebelj et al., 2022; Tramontini and Lovisolo, 2015; Lovisolo et al., 2010). This dual signaling pathway can complicate the relationship between measured hydraulic conductivity and plant's actual physiological state, potentially leading to erroneous conclusions about water status when based solely on hydraulic conductivity data (Jež-Krebelj et al., 2022; Tramontini and Lovisolo, 2015).

1.5.3.14. Electrical Potential

The electrical potential (EP) method relies on changes in electrical signals within plant tissues as indicators of water availability and stress. It is based on the principle that plants generate electrical signals in response to environmental *stimuli*, including water stress (Ríos-Riojas et al., 2014; Oyarce and Gurovich, 2011; Gurovich and Hermosilla, 2009; Gil et al., 2009; Fromm and Eschrich, 1993). The electrical potential variations can be quantitatively measured and correlated with physiological parameters (Yan et al., 2009). For instance, evidence has shown that real-time electrical sensors can measure plant water status through variations in electrical potentials, suggesting that these signals may serve as early indicators of plant water stress (Ríos-Riojas et al., 2015) as they change before observable physiological or morphological alterations (Zhang et al., 2012). Similarly, Zhou et al. (2022) established that the relationship between electrical signals and physiological parameters, such as chlorophyll fluorescence and root vitality, can effectively indicate drought stress in strawberry seedlings. Changes in electrical signals, particularly in membrane potential, are closely linked to water availability (Saraiva et al., 2017).

Moreover, studies have shown that the electrophysiological responses of plants can vary significantly under different water availability conditions. Toledo (2024) research indicated that distinct electrical activity patterns emerge in plants subjected to varying levels of water stress, which can be classified and used to assess plant water status. This is further supported by the work of Oyarce and Gurovich (2010), who proposed that daily variations in electric potential in tree trunks could be utilized to assess evapotranspiration and enhance water use efficiency in woody plants.

The integration of machine learning techniques with electrophysiological data has also been explored to improve the accuracy of water stress assessments. Supervised machine learning algorithms, as support vector machines (SVM), further enhanced the ability to classify and predict plant water stress states based on electrical signal patterns (Tian, 2023; Tran et al., 2019), providing a robust framework for real-time monitoring (Tran et al., 2019). This approach aligns with the findings of Ríos-Rojas et al. (2014), who developed a real-time sensor for monitoring water stress in fruit-bearing woody plants, correlating electrical potential measurements with soil water content and evaporative demand.

However, the electrical potential method has its limitations. One primary challenge is the inherent variability and sensitivity of electrical signals to environmental factors, which can complicate data interpretation. For instance, factors such as temperature, light, and humidity can influence electrical responses, potentially leading to misleading conclusions about a plant's water status (Wang et al., 2009). Additionally, the electrical signals generated by plants are typically weak, often in the range of tens to hundreds of millivolts, making them susceptible to noise and interference from external sources (Cai and Qi, 2017). This requires sophisticated amplification and processing techniques, which can introduce additional errors and complicate the measurement process (Cai and Qi, 2017). Moreover, the method's reliance on surface electrodes may limit its effectiveness, as the electrical potential can vary significantly across different plant tissues and under different stress conditions (Cooper et al., 2022). The need for precise electrode placement and the potential for damage to plant tissues during measurement can also pose practical challenges (Senavirathna and Muhetaer, 2020). Furthermore, while electrical signals can provide valuable insights into plant water status, they may not fully capture the complexity of physiological responses to water stress, as they represent only one aspect of a multifaceted system (Sukhova et al., 2021).

1.5.4. The Energy Balance Method: An Integrative Approach to the Soil-Plant-Atmosphere System

The energy balance method integrates various components of energy exchange to assess how plants regulate water under different environmental conditions, analyzing the interactions between energy inputs and outputs within the soil-plant-atmosphere system. The method is grounded in thermodynamic principles, with the energy balance equation accounting for energy fluxes associated with key components, including net radiation, sensible heat, latent heat (evapotranspiration), and soil heat flux. Quantifying these components enables the inference of plant water status, which is essential for understanding physiological responses to water stress and for designing effective deficit irrigation strategies.

Jackson et al. (1981) introduced the use of canopy temperature, measured via infrared thermometry, as an indicator of crop water stress, highlighting the application of energy balance principles to directly assess crop water status. Building on these principles, they

developed the Crop Water Stress Index (CWSI), which relates canopy temperature to the air vapor pressure deficit. By integrating these variables, the CWSI offers a robust quantitative framework for assessing water stress and optimizing irrigation scheduling (Jackson et al., 1981). The CWSI is calculated using Equation 1, establishing a direct link between energy balance and plant water availability:

$$CWSI = 1 - \left(\frac{ET_{act}}{ET_0} \right), \quad (1)$$

where ET_{act} represents the actual evapotranspiration, or the rate of water loss under current conditions, and ET_0 denotes the potential evapotranspiration, or the rate of water loss under optimal water availability.

Additionally, Wang and Dickinson (2012) examined global terrestrial evapotranspiration and highlighted the critical role of accurate modeling in understanding regional water balances. They observed that discrepancies in transpiration estimates could significantly impact the assessment of plant water status, highlighting the need for robust energy balance models that account for local climatic and vegetative conditions. Similarly, Boulet et al. (2018) emphasized the value of dual-source energy balance models in partitioning evaporation and transpiration, thereby improving insights into plant water uptake and overall ecosystem health. Such insights are essential for accurately determining plant water requirements under varying climate conditions.

In practical applications, several techniques have been developed to measure the components of the energy balance. Studies by multiple authors have explored the use of thermography to examine plant-environment interactions, revealing critical insights into stomatal conductance and transpiration rates under varying water conditions (Santesteban et al., 2017; Costa et al., 2013; Jiménez-Bello et al., 2011; Jones, 1999). Further emphasis on the significance of physiological indicators, such as stomatal conductance and leaf water potential, in assessing plant water status has concluded that these metrics can be directly correlated with energy balance components, providing a comprehensive understanding of how plants respond to water deficits (Jones, 2004). This non-invasive method has proven effective in mapping plant water status in real-time, enabling more precise irrigation management.

The work of Ohta and Kimura (2009) further advanced the integration of energy balance models with climate-physiological models, enhancing our understanding of plant-environment interactions. These integrated models provide valuable predictions regarding the potential impacts of future climate changes on water dynamics within agricultural systems. Such a framework is essential for anticipating plant responses to water stress and for optimizing irrigation strategies in response to evolving environmental conditions.

1.6. Challenges and future perspectives

Several challenges arise from the current technologies and methods used to manage plant water stress in vineyards, aiming to avoid significant yield reduction while preserving or enhancing grape and wine quality. As climate change exacerbates water scarcity issues, precision irrigation is becoming an essential practice for maintaining vineyard health and ensuring fruit and wine quality.

A major challenge is the need for real-time, accurate data with appropriate spatial resolution. To date, various approaches have been studied, ranging from meteorological-based to soil and plant-based methods for measuring or estimating plant water status and

managing deficit irrigation. However, no single method has been universally accepted as the standard for vineyard. These methods have been previously summarized, with the major drawbacks of each identified.

Currently, the challenge for researchers is to develop complementary, non-destructive techniques that enable rapid, accurate, and high-resolution measurements of plant water status across a variety of environments and conditions. To address this, non-intrusive remote and/or proximal sensing methods based on the plant's physiological response to water stress, soil water availability, and meteorological data are required. This data should be integrated into decision support systems (DSS) that can be easily applied to estimate water status at an appropriate spatiotemporal resolution, ensuring optimal growth conditions and enhanced grape quality.

Electronic and communication advances are enabling the broader adoption of telematics in agriculture by providing more affordable sensors, related systems, and more efficient communication networks. With automated systems, irrigation schedules can be controlled remotely or set to respond to real-time data. These systems will enable precise timing and volume adjustments, aligning irrigation closely with vine requirements at each phenological stage. Also, the variable rate irrigation (VRI) technology will allow irrigation systems to apply different amounts of water to different vineyard sections based on specific needs, avoiding over- or under-watering in areas that may vary in soil composition or slope.

Additionally, the use of unmanned autonomous systems (namely, aerial—UAVs—and ground—UGVs vehicles), such as satellites, drones, and robots equipped with proximal and/or remote sensors, can help capture data on vine canopy water status, growth patterns, and stress areas with high spatial resolution and appropriate temporal resolution. By mapping the vineyard, these tools facilitate the identification of sections that may require variable water application, thereby enabling more targeted vineyard management aimed at sustainability.

1.7. Motivation of the thesis

Given the context outlined above, this thesis presents as a collection of four high impact published articles, encompassing research conducted over the past five years. The primary goal of this research was to advance the state of the art in precision irrigation techniques, specifically deficit irrigation methods, within the viticulture sector. As discussed, significant scientific efforts have been made to improve the economic and environmental sustainability of irrigation scheduling in viticulture. However, the methodologies developed to date are not yet adequate to serve as universal solutions. Precision irrigation in viticulture involves the use of advanced technologies and data-driven methods to optimize water application, ensuring optimal growth conditions and enhancing grape quality. Several limitations of the current methods—spanning meteorological, soil-based, and plant-based approaches—have been addressed in the preceding sections. Notably, a key distinction exists between contact and intrusive methods and non-intrusive proximal and remote sensing techniques. Key considerations include the spatial and temporal resolution of each method, as well as their ability to incorporate data in real-time into DSS algorithms, delivering accessible and comprehensive data to winegrowers. An ideal reference method must account for these factors and enable the acquisition of data through non-intrusive proximal (or remote) sensor platforms with adequate spatiotemporal resolution, capable of real-time operation to feed DSSs.

Therefore, this thesis addresses key challenges related to precision irrigation, with a particular focus on grapevine stress detection as a proxy for optimizing vineyard deficit irrigation scheduling. The proposed methodologies are intended to be a contribution to the state of the art, taking directly or indirectly into account the needs listed above.

For these reasons, this thesis aims to leverage advances in vineyard deficit irrigation, focusing on managing grapevine water status through appropriate sensing and data-driven approaches. The developed methods generate data that can be incorporated into DSSs to support vineyard deficit irrigation management, with particular emphasis on both economic and environmental sustainability.

1.8. Scientific contributions of the thesis

This thesis is presented as a compilation of four articles published in high-impact, peer-reviewed journals, along with two presentations at international conferences. The manuscripts serve as the central focus of the dissertation and represent the key milestones achieved throughout the research, in alignment with the established lines of argument. The works developed throughout the research period are listed below, providing details of their publication, and offering a concise overview, including their significant novel contributions to the state of the art.

Article 1. Predicting Crop Evapotranspiration under Non-Standard Conditions Using Machine Learning Algorithms, a Case Study for *Vitis vinifera* L. cv Tempranillo

Authors: Ricardo Egipto, Arturo Aquino, Joaquim Miguel Costa and José Manuel Andújar

Journal: Agronomy (EISSN 2073-4395)

Editorial: MDPI

Reference: Agronomy. 2023, 13 (10), 2463

DOI: 10.3390/agronomy13102463

Year: 2023

Quality index (Journal Citation Reports®, 2023): 65/265 (Q1) in the category "Plant Sciences", 20/126 (Q1) in the category "Agronomy". Impact Factor of 3.3.

This work aimed to deliver a contribution to the reference meteorological-based method to estimate vineyard actual water use. The traditional method of estimating actual crop evapotranspiration using the FAO-56 K_c - ET_0 approach faces limitations in row-based, drip-irrigated crops due to data requirements and difficulties in accurately estimating the basal crop coefficient. This study aimed to assess the accuracy of supervised machine learning regression algorithms in predicting actual crop evapotranspiration for a deficit-irrigated *Vitis vinifera* cv. Tempranillo vineyard in a Mediterranean climate. The study highlighted the potential of supervised machine learning regression algorithms to estimate the actual crop evapotranspiration with high accuracy, improving water management practices in vineyards, and promoting more sustainable and resource-efficient irrigation strategies, particularly in Mediterranean climates.

Article 2. Predicting the canopy conductance to water vapor of grapevines using a biophysical model in a hot and arid climate

Authors: Ricardo Egipto, Arturo Aquino and José Manuel Andújar

Journal: Frontiers in Plant Science (EISSN 1664-462X)

Editorial: Frontiers Media SA

Reference: Frontiers in Plant Science. 2024, 15, 1334215

DOI: 10.3389/fpls.2024.1334215

Year: 2024

Quality index (Journal Citation Reports®, 2023): 44/265 (Q1) in the category "Plant Sciences". Impact Factor of 4.1.

Canopy conductance is a key factor in modelling plant transpiration and is highly responsive to water stress. This study aimed to develop a straightforward method for estimating this variable in grapevines. The method combines stomatal conductance to water vapor measurements, scaled by the leaf area index, with atmospheric variables such as net solar radiation and air vapor pressure deficit. The model was validated by comparing its predictions with reference canopy conductance values calculated using the inverse of the Penman-Monteith equation. The results demonstrate the model estimation effectiveness, with a residual error as compared to the canopy conductance observed in the field. The study highlights the significant influence of both air vapor pressure deficit and stomatal conductance to water vapor on grapevine canopy conductance, and consequently on grapevine water exchange with the atmosphere.

Article 3. The role of soil temperature in mediterranean vineyards in a climate change context

Authors: Joaquim Miguel Costa, Ricardo Egipto, Francisca Aguiar, Paulo Marques, Amaia Nogales and Manuel Madeira

Journal: Frontiers in Plant Science (EISSN 1664-462X)

Editorial: Frontiers Media SA

Reference: Frontiers in Plant Science. 2023, 14, 1145137

DOI: 10.3389/fpls.2023.1145137

Year: 2023

Quality index (Journal Citation Reports®, 2023): 44/265 (Q1) in the category "Plant Sciences". Impact Factor of 4.1.

This manuscript addresses the challenges faced by the wine sector, particularly concerning sustainability and the impacts of climate change, such as increased frequency of extreme climate events in Mediterranean regions. Soil, a crucial natural resource, plays a significant role in sustaining ecosystems, economic growth, and prosperity, and has a major influence on crop performance in viticulture, including growth, yield, berry composition, and wine quality. Soil temperature affects various physical, chemical, and biological processes in both the soil and plants. Its impact is particularly strong in row crops like grapevine, as it enhances soil exposure to radiation and increases

evapotranspiration. Despite its importance, its role in crop performance, especially under extreme climatic conditions, is not well understood. This study emphasizes the need for a better understanding of soil temperature's effects on vineyards, including plant growth, soil health, and the soil microbiome. The article reviews its effects on ecophysiological and agronomical performance in Mediterranean vineyards and discusses the potential of imaging techniques, such as thermography, to assess it and vertical canopy temperature profiles. Finally, it proposes soil management strategies to mitigate the impacts of climate change, optimize soil temperature variation, and improve the thermal microclimate of crops, with a focus on Mediterranean systems.

Article 4. Dynamics of Energy Fluxes in a Mediterranean Vineyard: Influence of Soil Moisture

Authors: Ricardo Egipto, Arturo Aquino and José Manuel Andújar

Journal: Agriculture (EISSN 2077-0472)

Editorial: MDPI

Reference: Agriculture. 2024, 14, 1845

DOI: 10.3390/agriculture14101845

Year: 2024

Quality index (Journal Citation Reports®, 2023): 20/126 (Q1) in the category "Agronomy". Impact Factor of 3.3.

This study focused on the evaluation of sensible and latent energy fluxes at various locations within a vineyard—specifically, the canopy, soil beneath the canopy, and interrow areas—during grapevine berry maturation. The primary objective was to develop a model framework for accurately estimating these energy fluxes, improving understanding of their behavior during berry ripening. The results demonstrated a high level of agreement between observed and estimated fluxes, confirming the model's reliability. The study provides valuable insights into the energy flux dynamics of vineyards, contributing to optimized irrigation strategies, improved grape quality, sustainable water use, and enhanced vineyard productivity in arid and water-scarce regions.

2. Objectives

This thesis addresses key challenges in precision irrigation, with a particular focus on grapevine stress detection as a means of optimizing deficit irrigation scheduling. The overarching goal of the research is to develop methodologies for evaluating grapevine water status using non-intrusive proximal sensing techniques and data-driven approaches. These methodologies aim to support the management of grapevine deficit irrigation, optimizing water use while enhancing both the economic and environmental sustainability of the winegrape sector. The specific objectives established for this thesis are outlined below:

Objective 1. Development and evaluation of a machine learning algorithm to estimate actual crop evapotranspiration adapted to vineyards grown under arid conditions.

This work aimed to deliver a contribution to the reference meteorological-based method to estimate vineyard actual water use. The traditional method of estimating actual crop evapotranspiration (ET_c) using the FAO-56 K_c - ET_0 approach faces limitations in row-based, drip-irrigated crops due to data requirements and difficulties in accurately estimating the basal crop coefficient (K_{cb}). This study aimed to assess the accuracy of supervised machine learning regression algorithms (MLAs) in predicting actual ET_c for a deficit-irrigated *Vitis vinifera* cv. Tempranillo vineyard in a Mediterranean climate.

Objective 2. Development and evaluation of a biophysical model to predict the canopy conductance to water vapor of grapevines under arid conditions.

The canopy conductance (g_c), which describes grapevine transpiration, is highly responsive to water stress. This study aimed to develop a straightforward method for estimating g_c in grapevines by combining plant-based measurements—specifically the leaf stomatal conductance to water vapor (g_{sw}), scaled to the whole canopy by the leaf area index (LAI)—with atmospheric measurements, including net solar radiation (R_n) and air vapor pressure deficit (VPD). The method integrates the plant leaf conductance to water vapor flux (leaf transpiration scaled to the canopy surface) with atmospheric demand for water vapor flux (solar radiation and air vapor pressure deficit) to estimate canopy conductance to water vapor. The developed model was expected to accurately simulate the grapevine's response to water scarcity, increased solar irradiance, and high atmospheric water demand.

Objective 3. Review of soil temperature effect on ecophysiological and agronomical performance in Mediterranean vineyards. Discuss the potential of imaging techniques to assess ST and vertical canopy temperature profiles.

Soil temperature (ST) influences various physical, chemical, and biological processes in both soil and plants. Its impact is particularly pronounced in row crops such as grapevine, where it enhances soil exposure to radiation and increases evapotranspiration. However, the effect of ST on crop performance is still not well understood. This study aims to review the effects of ST on the ecophysiological and agronomic performance of Mediterranean vineyards, while also discussing the potential of imaging techniques, such as thermography, to assess ST and vertical canopy temperature profiles.

Objective 4. Development and evaluation of a modeling framework to estimate the dynamics of energy fluxes at the soil and plant levels under arid conditions.

This study focused on the evaluation of sensible and latent energy fluxes at various locations within a vineyard—specifically, the canopy, soil beneath the canopy, and interrow areas—during grapevine berry maturation. The primary objective was to develop a model framework for accurately estimating these energy fluxes, improving understanding of their behavior during berry ripening. The model's reliability was tested against the fluxes measured with an eddy-covariance system installed within the experimental plot.

3. Experimental layout

This thesis explores the development of non-intrusive proximal sensing methods for collecting data to integrate into models and algorithms aimed at predicting real-time grapevine water status, thereby supporting water stress management. The research contributes to precision irrigation management, focusing on improving both the economic and environmental sustainability of irrigation scheduling in viticulture. Current methods, including meteorological, soil-based, and plant-based approaches, present several limitations, particularly in terms of spatial and temporal resolution and their capacity to integrate real-time data into decision support system (DSS) algorithms. These constraints often hinder the delivery of accessible and comprehensive information to winegrowers. In this context, an ideal reference method would address these limitations by enabling data acquisition via non-intrusive proximal (or remote) sensing platforms with sufficient spatiotemporal resolution for real-time operation, thereby enhancing the effectiveness of DSSs.

The objectives of this thesis necessitated the establishment of an experimental framework conducted annually from 2019 to 2021, during the berry development to grape ripening phases. This period, characterized by the greatest soil and atmospheric water deficits, corresponds to critical phenological stages that significantly influence berry composition at harvest, including parameters related to quality and yield.

The research was conducted in a commercial vineyard, Herdade do Esporão, located in Reguengos de Monsaraz in the Alentejo wine region of southern Portugal (38°23'55" N, 7°32'46" W). The study focused on a 17-year-old vineyard of the red *Vitis vinifera* cv. Tempranillo (syn. Aragonez), grafted onto 1103 Paulsen rootstock, due to the variety's sensitivity to water stress during maturation and its impact on grape quality. The vines are spaced 1.5 m within rows and 3.0 m between rows, resulting in a planting density of 2220 vines per hectare. Oriented north-south, the vines are trained using vertical shoot positioning and spur-pruned on a bilateral Royat cordon system, with uniform winter pruning to retain 15–16 buds per vine.

The experimental plot is located on Eutric Cambisol soil with a depth of 1.0 m and a silty-clay texture. The soil has a pH ranging from 7.0 to 7.6, low organic matter content, and high levels of phosphorus and potassium. The vineyard is equipped with a drip irrigation system delivering water at a flow rate of 2.4 L h⁻¹ through emitters spaced 1.0 m apart, enabling precise irrigation scheduling for the 5.25 ha block containing the experimental plot. All management practices within the experimental plot adhered to the standard procedures implemented by the vineyard owner.

For the study, 20 adult healthy vines were randomly selected from two adjacent rows, with 10 vines per row. This targeted sampling approach was designed to enhance the reliability of measurements by minimizing temporal and spatial variability within each measurement while preserving natural field variability. Measurements of the variables required to adjust and validate the models developed in this thesis, were taken during daylight hours to capture field temporal variability, focusing on daily fluctuations in solar radiation, air temperature, relative humidity, vapor pressure deficit, and soil water content. The experimental design also facilitated the evaluation of solar radiation effects on the vines by comparing the east and west sides of the canopy, which were exposed to contrasting incident radiation conditions throughout the day. This approach ensured a comprehensive assessment of microclimatic influences on vine physiology and water status.

The climate of the study site is Mediterranean, characterized by hot, dry summers and mild, rainy winters. Between 2019 and 2021, rainfall accumulated from winter to flowering ranged from 338 to 535 mm, compared to a historical mean of 360 mm recorded between 1981 and 2010. During the critical berry set to ripening period (June to August), the maximum recorded precipitation was 13.4 mm, occurring between June 17 and 20 in 2021. Throughout the three years, no additional rainfall events occurred during the research period, and all measurements were conducted under clear skies. Air temperature data collected at the experimental plot between June and August, detailing diurnal and seasonal variations, is summarized in Table 3.. This data provides essential context for interpreting vine physiological responses under the prevailing environmental conditions.

Table 3.1 – The characterization of air temperature patterns, the number of days with air temperatures exceeding 35 °C, and the number of days with precipitation during berry development to grape ripening (June to August) is presented. Air temperature data are expressed as the mean $\pm$ standard deviation, with the following variables: T_{avg} (daily mean air temperature), T_{min} (daily minimum air temperature), and T_{max} (daily maximum air temperature).

Year	Air Temperature (°C)			Nr Days	
	T _{avg}	T _{min}	T _{max}	T _{max} > 35°C	with rainfall
2019	23.3 $\pm$ 1.15	14.3 $\pm$ 1.17	33.2 $\pm$ 1.36	31	5
2020	24.7 $\pm$ 1.83	15.2 $\pm$ 1.32	34.6 $\pm$ 2.33	49	3
2021	23.7 $\pm$ 0.98	15.2 $\pm$ 0.80	31.9 $\pm$ 1.35	22	4
1981-2010 ^a	22.8 $\pm$ 0.85	16.1 $\pm$ 0.66	29.5 $\pm$ 1.05	23	5

^a Mean values over 30 years for the presented elements (considered representative of the prevailing values of these elements) were used (IPMA, 2024)

To achieve the goals outlined in Objective 2, the experimental framework was designed specifically to support the development of a biophysical model predicting canopy conductance to water vapor in grapevines under arid conditions. This required ensuring that all water evaporated from the vineyard originated exclusively from the grapevine canopies. This scenario reflects the typical conditions of wine-growing soils in arid and dry climates during much of the grape ripening period. To minimize soil evaporation, the soil water availability within the top 10 cm layer was reduced to negligible levels. Soil water content was measured in this layer to confirm dry conditions, and data collection was restricted to days preceding irrigation, with a minimum interval of five days since the last irrigation event. This approach ensured that variations in soil water availability within the top 10 cm remained minimal throughout the day, meeting the conditions necessary for accurate model development.

4. Materials

The development and validation of the methodologies proposed in this thesis required intense sensor-based data acquisition in the field. The key parameters registered, along with the equipment used, are described below. Additionally, the software used for data processing and analysis is also specified.

For all the objectives except Objective 3 (note that it is a review), actual crop evapotranspiration, along with its components—soil evaporation and canopy transpiration—was assessed as the target parameter in at least one aspect of the research. The eddy covariance (EC) method was employed as the reference technique over a three-year measurement period. The EC system included a fast-response (0.1 Hz) open-path CO₂/H₂O analyzer (LI-7500 DS, LI-COR Inc., Lincoln, NE, USA) and a 3D sonic anemometer (Gill Windmaster Pro, Gill Instruments Limited, Hampshire, UK), connected to a Smartflux 3 system (LI-COR Inc., Lincoln, NE, USA) (Figure 4.1). The recorded data were processed and quality-checked using EddyPro software v7.0.6 (LI-COR Inc., Lincoln, NE, USA). The EC method's high temporal resolution and comprehensive coverage of fluxes made it a robust reference for modeling and analysis throughout the research.

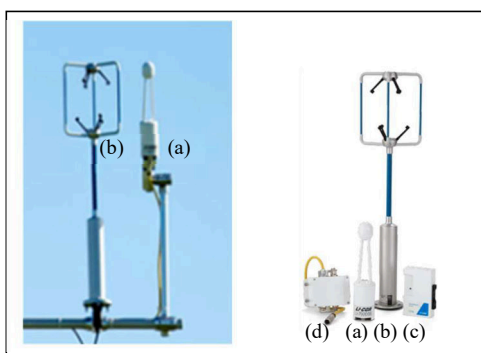


Figure 4.1 – Open path eddy covariance system. (a) LI-7500DS Open Path CO₂/H₂O Gas Analyzer (LI-COR Inc., Lincoln, NE, USA), (b) Gill WindMaster/Pro sonic anemometer (Gill Instruments Limited, Hampshire, UK), (c) SmartFlux® 3 System (LI-COR Inc., Lincoln, NE, USA), and (d) network switch (LI-COR Inc., Lincoln, NE, USA).

Atmospheric variables, including air temperature and relative humidity, were measured at the canopy, under the canopy, and in the interrow using thermohygrometers (CS215-PWS, Campbell Scientific, Logan, UT, USA) (Figure 4.2). Soil temperatures at the canopy and interrow were measured using two-junction, fine-wire copper-constantan T-type thermocouples. Soil water content was continuously monitored beneath the grapevine canopy with two ML3 Thetaprobe sensors (Delta-T devices, Cambridge, UK) (Figure 4.3). To measure the energy inputs in the vineyard, four net radiometers (NR2, Delta-T Devices, Cambridge, UK) (Figure 4.4) were strategically placed to measure radiation at the canopy, beneath the canopy, and at the middle of the interrow. Soil heat flux was determined using six heat flux plates (HFP01, Hukseflux Thermal Sensors, Delft, The Netherlands) (Figure 4.5), and taking the average of all six measurements. To assess the aerodynamic resistances to heat flux, wind speed was measured with a 3D sonic anemometer (Gill Windmaster Pro, Gill Instruments Limited, Hampshire, UK) at a height of 2 m above the canopy, and beneath the canopy and above the bare soil between vine rows using two additional 2D sonic anemometers (Gill Ultrasonic ANE 5M, Gill Instruments Limited, Hampshire, UK) (Figure 4.6). All soil and meteorological sensors

were connected to a CR1000 datalogger (Campbell Scientific, Logan, UT, USA) (Figure 4.7) which recorded data every minute and provided averages every five minutes.



Figure 4.2 – Solar radiation shield and Thermohygrometer CS215-PWS (Campbell Scientific, Logan, UT, USA).



Figure 4.3 – Soil moisture ML3 Thetaprobe sensor (Delta-T devices, Cambridge, UK).



Figure 4.4 – Net radiometer NR2 (Delta-T devices, Cambridge, UK).



Figure 4.5 – HFP01 heat flux plate (Hukseflux Thermal Sensors, Delft, The Netherlands).



Figure 4.6 – Gill 2D Ultrasonic anemometer ANE 5M (Gill Instruments Limited, Hampshire, UK).



Figure 4.7 – CR1000 Datalogger (Campbell Scientific, Logan, UT, USA).

Canopy temperature was recorded using an infrared (IR) thermal camera FLIR model C5 (FLIR Systems Inc., Wilsonville, OR, USA) (Figure 4.8), equipped with a 160×120 (19,200 pixels) IR sensor and operating in the 8 to 14 μm spectral range. Thermal images were analyzed using 'Flir Thermal Studio' software (version 2.0.21, FLIR Systems, Inc.,

Wilsonville, OR, USA), converted into CSV files, and subsequently exported to Matlab R2023a (The MathWorks, Inc., Natick, MA, USA) to create a temperature data matrix.



Figure 4.8 – Infrared thermal camera FLIR model C5 (FLIR Systems Inc., Wilsonville, OR, USA).

To assess grapevine water status, pre-dawn leaf water potential was measured on each sampling date using a Scholander-type pressure chamber (PMS 600, PMS Instrument Company, Albany, OR, USA) (Figure 4.9). Stomatal conductance was measured using a steady-state leaf porometer model LI-1600 (LI-COR, Lincoln, NE, USA) (Figure 4.10).



Figure 4.9 – Scholander-type pressure chamber (PMS 600, PMS Instrument Company, Albany, OR, USA).



Figure 4.10 – Steady-state leaf porometer model LI-1600 (LI-COR, Lincoln, NE, USA).

Table 4.1 summarizes the equipment used along with the registered variables.

Other software used for model development, analysis and validation, include MATLAB Statistics and Machine Learning Toolbox, release 2021b, and 2023a, and Microsoft Excel (Microsoft Corp., Redmond, Washington, USA) release 2410.

Table 4.1 – Equipment utilized and variables recorded

Variable	Equipment
Actual crop evapotranspiration and Canopy transpiration	LICOR model LI-7500 DS open path CO ₂ /H ₂ O analyzer (LI-COR Inc., Nebraska USA), connected to a Smartflux 3 system (LI-COR Inc., Nebraska USA). (Part of the eddy covariance system)
Wind speed–Eddy covariance system	3D sonic anemometer, model GillWindmaster Pro (Gill Instruments Limited, Hampshire, UK), connected to a Smartflux 3 system (LI-COR Inc., Nebraska USA). (Part of the eddy covariance system)
Net radiation	Net radiometer, model NR2 (Delta-T Devices, Cambridge, UK), connected to a datalogger (CR1000, Campbell Scientific, Inc., Logan, UT, USA)
Air Temperature and Relative Humidity	Thermohygrometer, model CS215-PWS (Campbell Scientific, Inc., Logan, UT, USA), connected to a datalogger (CR1000, Campbell Scientific, Inc., Logan, UT, USA)
Soil heat fluxes	Heat flux plates HFP01, Hukseflux Thermal Sensors, Delft, The Netherlands) connected to a datalogger (CR1000, Campbell Scientific, Inc., Logan, UT, USA)
Soil temperature	Two-junction, fine wire copper-constantan T-type thermocouples, connected to a datalogger (CR1000, Campbell Scientific, Inc., Logan, UT, USA)
Soil water content	ML3 Thetaprobe sensor (Delta-T devices, Cambridge, UK), connected to a datalogger (CR1000, Campbell Scientific, Inc., Logan, UT, USA)
Wind speed	2D sonic anemometer, model Gill Ultrasonic ANE 5M (Gill Instruments Limited, Hampshire, UK), connected to a datalogger (CR1000, Campbell Scientific, Inc., Logan, UT, USA)
Stomatal conductance to water vapour	Steady state porometer (Model LI-1600, LI-COR Lincoln, NE, USA)
Predawn leaf water potential	Scholander-type pressure chamber (PMS 600, PMS Instrument Company, Albany, OR, USA)
Canopy temperature	Infrared Thermal camera, FLIR model C5 (FLIR systems Inc., Wilsonville, OR, USA).

5. Methodology

The methodologies employed in this research, designed to achieve the objectives outlined above, are presented. A brief description of the specific procedures and techniques used throughout the experimentation is provided. The corresponding published documents, compiled in Section 4, offer a more detailed exposition of the methods employed.

5.1. Methodology for Objective 1. Development and evaluation of a machine learning algorithm to estimate actual crop evapotranspiration (ET_c) adapted to vineyards grown under arid conditions.

Actual crop evapotranspiration, ET_c , is an important measure of crop water use and provides key information for designing optimal deficit irrigation management systems in vineyards. Therefore, the first step of this study was to propose an alternative to the FAO-56 K_c - ET_0 approach that, by addressing the limitations of the reference method, could accurately estimate the actual ET_c of the vineyard, a crop managed under non-standard conditions.

This research assesses the performance of eight state-of-the-art supervised machine learning regression algorithms (MLA), using three main atmospheric variables (net radiation— R_n , wind speed— u , and vapor pressure deficit— VPD) and a plant variable (stomatal conductance to water vapor— g_{sw}), to predict actual ET_c . The selected variables encompass all parameters that govern energy exchange and the corresponding latent heat flux (evapotranspiration) process, as described by the Penman-Monteith equation (Allen et al., 1998).

Data pre-processing included outlier analysis and data structuring. Outliers were identified by the interquartile range (IQR) method with a cut-off of $1.5 \times IQR$, and the data were randomly split into three datasets: A training and testing dataset containing 40% of the 2019 and 2020 data, and two validation datasets, one containing the remaining 2019 data, and the other containing the remaining 2020 data (Figure 5.1). The three datasets were configured to maintain similar data patterns.

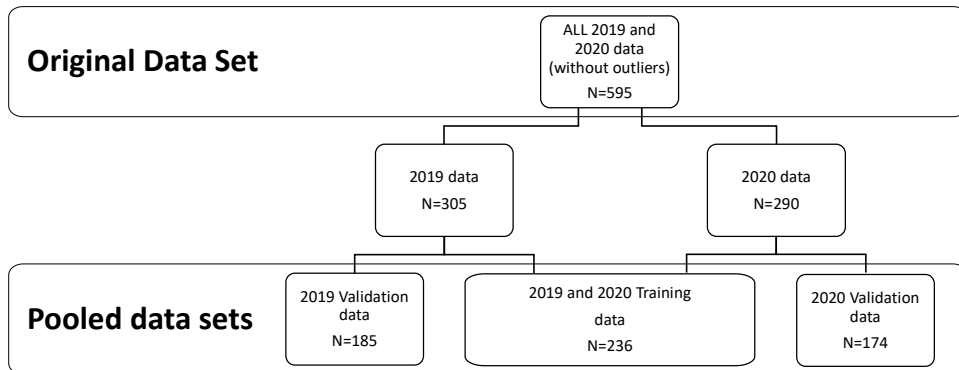


Figure 5.1 – Data structure. The original data was divided into three final datasets: a training and testing dataset containing 40% of all data from the years 2019 and 2020, and two external validation datasets containing the remaining data from the years 2019 and 2020.

The pooled training dataset was used to train and fit a set of supervised machine learning regression models to predict the actual ET_c , employing a five-fold cross-validation scheme to protect against overfitting. After reviewing the state of the art, the following

supervised machine learning models were developed, tested and compared using Matlab R2021b (The Mathworks Inc., USA):

- (a) a non-parametric kernel-based probabilistic model (Gaussian process regression model – GPR), using either an exponential kernel function, or a squared exponential kernel function,
- (b) a support vector machine (SVM) regression model using either a linear kernel function, a quadratic kernel function, a cubic kernel function, or a medium Gaussian kernel function,
- (c) an ensemble of regression trees (ERT), either using least-squares boosting regression trees learners or using bootstrap-aggregating (bagging) regression trees learners.

Actual ET_c was also predicted using the FAO-56 K_c - ET_0 standard method. First, ET_0 was calculated following the method proposed by (Allen et al., 1998), using data from the farm's meteorological station. The crop coefficient (K_c) was divided into two components: soil evaporation (K_e) and grapevine transpiration, defined by the basal crop coefficient (K_{cb}). The K_{cb} was estimated using the Normalized Differential Vegetation Index (NDVI) derived from Sentinel-2 imagery time-series with a spatial resolution of 10 m, for the experimental plot. As the grapevines in the study were subjected to some stress, a stress coefficient (K_s) was applied to K_{cb} , according to the FAO-56 K_c - ET_0 methodology. K_s was calculated according to Ferreira (2017), by Equation (1):

$$K_s = 1.217 \times e^{(1.444 \times \psi_{PD})} \quad (1)$$

The predictive accuracy of actual ET_c estimated by the FAO-56 K_c - ET_0 method was compared with the actual ET_c recorded in the field using the Eddy Covariance (EC) method. To assess the predictive accuracy of the MLA models, the actual ET_c predicted by the MLA models was compared to actual ET_c recorded in the field by the EC method (using the same dataset used to test the accuracy of actual ET_c estimated by the FAO-56 K_c - ET_0 method), and to that estimated by the FAO-56 K_c - ET_0 method.

The study demonstrates the effectiveness of MLA in accurately estimating actual ET_c in vineyards. The five best-performing algorithms account for over 89% of the variability in the measured actual ET_c in the experimental plot, with a maximum root mean squared error (RMSE) of less than $0.03 \text{ mm} \cdot \text{h}^{-1}$, which is below the minimum actual ET_c observed in the field. The standard FAO-56 K_c - ET_0 method was found to be 2.2 to 2.8 times less accurate, in 2019 and 2020, respectively, when compared to the best MLA models, explaining only 74% of the measured variability in actual ET_c and results in an RMSE that is approximately twice as large.

5.2. Methodology for Objective 2. Development and evaluation of a biophysical model to predict the canopy conductance to water vapor of grapevines under arid conditions.

Canopy conductance to water vapor plays a pivotal role in regulating water and heat exchange within the soil-plant-atmosphere continuum. It is one of the most responsive variables to water stress in grapevine and it is a key factor in modeling plant transpiration. Therefore, this study aimed to develop a comprehensive model to estimate canopy conductance based on the parameters governing energy exchange at the canopy level and the associated latent heat flux (i.e., transpiration).

After reviewing the state of the art, a biophysical model was developed to estimate canopy conductance using key plant variables (leaf stomatal conductance to water vapor— g_{sw} , and

leaf area index– LAI) and environmental factors (net solar radiation– R_n , and air vapor pressure deficit– VPD) (Equation 2).

$$g_{c\ est} = f(LAI, g_{sw}, R_n, VPD) = LAI \cdot \left(g_{sw} \cdot \frac{R_n}{VPD} \right)^{0.5} \quad (m.s^{-1}) \quad (2)$$

The measured data for the selected variables were incorporated into a structured database. Data pre-processing included outlier detection using the interquartile range (IQR) method, with a cutoff set at 1.5 times the IQR.

Taking advantage of the negligible soil evaporation, the Penman-Monteith (PM) bulk surface conductance was assumed to be solely determined by the canopy conductance (Allen et al., 1998). Consequently, the observed canopy conductance was also calculated from the inverted Penman-Monteith equation, following the formulation proposed by Lhomme et al. (2012). This calculation used data from the farm's meteorological station and Eddy Covariance measurements of vine transpiration (E_c). The observed canopy conductance, calculated using this method, served as the gold-standard reference to assess the accuracy of the proposed biophysical model. Subsequently, the predictive accuracy of the model was compared with the observed canopy conductance values, derived from the inverse Penman-Monteith equation.

The study highlights the role of grapevine water status in regulating leaf stomatal conductance. It also demonstrates that, in addition to leaf stomatal conductance, factors such as air vapor pressure deficit and net solar radiation significantly influence vine transpiration. Despite the simplicity of the proposed biophysical model, the study shows that it accurately predicts canopy conductance under both soil and atmospheric water stress conditions. The proposed model explains over 91% of the variability in canopy conductance as calculated by the gold standard method—the Penman-Monteith method—with a root mean squared error three times lower than the minimum canopy conductance predicted by the reference method.

5.3. Methodology for Objective 3. Review of soil temperature effect on ecophysiological and agronomical performance in Mediterranean vineyards. Discuss the potential of imaging techniques to assess ST and vertical canopy temperature profiles.

This research focuses on reviewing the state of the art regarding the influence of soil temperature on vineyard ecosystems, including grapevines, weeds, and microbiota. Soils are a key component of terroir, significantly influencing vine growth, yield, and berry composition. Soil temperature influences the physical, chemical, and biological processes in the soil, as well as crop growth. Its impact is particularly pronounced in row crops, such as grapevine, due to their increased exposure to radiation. Despite its importance, the impact of soil temperature on crop performance remains underexplored, particularly under extreme climatic conditions. The goal of this study was to enhance the management and prediction of vineyard performance, plant-soil interactions, and the soil microbiome in the context of more extreme climate conditions.

This study reviews the role of soil temperature in Mediterranean vineyards, focusing on its impact on vine ecophysiological and agronomic performance, as well as its relationship with soil properties and management strategies. It provided an overview of the factors influencing soil temperature in vineyards, followed by a discussion on the effects of soil temperature on grapevines, spontaneous vegetation, soil macro- and microorganisms, microbiota, and fauna. The study also reviews available techniques for measuring soil temperature, including the potential use of imaging approaches such as

thermography, which could serve as an alternative or complementary tool for assessing soil and vertical canopy temperature profiles in vineyards. Finally, soil management strategies are proposed to mitigate the negative impacts of climate change, optimize soil temperature variation, and improve crop thermal microclimates (leaf and berry temperatures), with a particular focus on Mediterranean systems.

5.4. Methodology for Objective 4. Development and evaluation of a modeling framework to estimate the dynamics of energy fluxes at the soil and plant levels under arid conditions.

Water evaporation requires a substantial amount of energy, either in the form of sensible heat or radiant energy. Consequently, the evapotranspiration process is governed by energy exchange at the vegetation and soil surface and is constrained by the available energy. Due to this limitation, the rate of evapotranspiration can be predicted by applying the principle of energy conservation. Specifically, the energy entering the surface must balance the energy leaving the surface over the same time period (Allen et al., 1998).

The energy balance equation is composed of four main components: net radiation (R_n), latent heat flux (λET), sensible heat flux (H) and soil heat flux (G). Other energy terms, such as heat stored or released by the plant, or the energy used in metabolic activities, represent a small fraction of the daily net radiation and can be considered negligible compared to the other components.

This study aims to investigate the dynamics of water and heat flux in a vineyard during grapevine berry maturation. To achieve this, a model framework was developed to accurately estimate these energy fluxes, thereby enhancing the understanding of their behavior during berry ripening (Figure 5.2). The framework facilitated the independent measurement of heat fluxes from each vineyard component, including the vine canopy, bare soil between rows, and bare soil beneath the vines. Additionally, latent energy fluxes from each component were estimated as unknown variables in their respective energy balance equations. This approach enabled the estimation of vine canopy transpiration and soil evaporation.

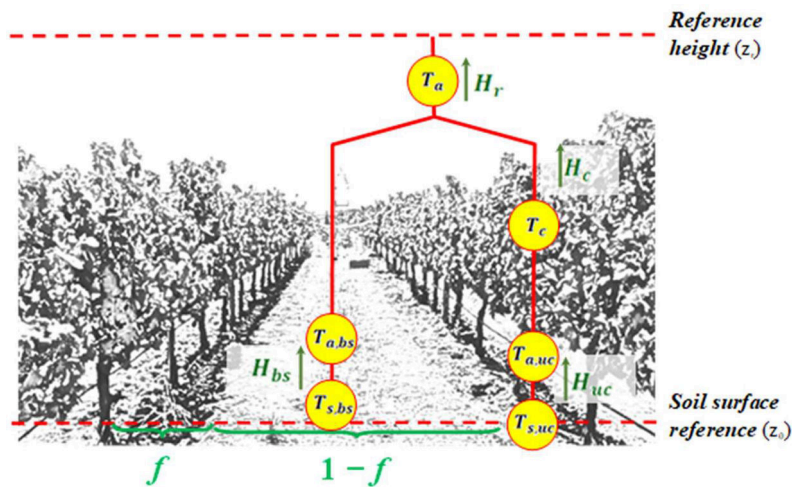


Figure 5.2 – Schematic representation of the three-source clumped model for convective fluxes (specifically sensible heat, H) partitioning in a sparse canopy, illustrating the associated air and surface temperatures. This system enabled the measurement of the vertical profile of energy fluxes, including the observed latent heat flux and sensible heat flux at the reference height, over the experimental vineyard.

The sensible heat fluxes under the canopy (H_{uc}), from the canopy (H_c), and from bare soil between rows (H_{bs}) were calculated using the canopy, soil, and meteorological variables measured within the proposed model framework. The estimates of sensible and latent energy fluxes, calculated for each position within the model framework, were then used as inputs for a three-source clumped model (Lhomme et al., 2012; Brenner and Incoll, 1997) to estimate the aggregated energy fluxes at a reference height (z_r) above the vineyard (Figure 5.2). Simultaneously, the energy fluxes were measured using an eddy covariance system installed in the experimental field to obtain the reference sensible and latent heat fluxes.

To test and validate the model's accuracy, the aggregated fluxes estimated from the three-source clumped model were compared with the reference energy flux measurements obtained from the eddy covariance system.

The study reveals the influence of soil water content, not only in regulating the temperature of the soil beneath the canopy but also in affecting the temperature and energy balance of the grapevine canopy. Additionally, it demonstrates the feasibility of separately evaluating energy fluxes from three distinct components: the canopy, the area beneath the canopy, and the bare soil between the rows. This approach allows for accurate measurement of energy fluxes within each compartment. When compared to the turbulent fluxes measured by the eddy covariance system installed in the experimental field, the aggregated fluxes estimated using the three-source clumped model—derived from energy fluxes measured within each compartment—accounted for 98% of the variability observed in the turbulent fluxes recorded by the eddy covariance system. The average error magnitude between the observed and estimated sensible heat fluxes remained consistently below 3 W.m^{-2} during daylight hours. However, a slight tendency to underestimate latent heat fluxes was noted, particularly when irrigation was in progress, a finding also reported by other researchers. This study enhances the understanding of energy dynamics in vineyard ecosystems under regulated deficit irrigation practices.

6. Results

The following section compiles the four articles published in high-impact, peer-reviewed journals that constitute this thesis, as well as two additional presentations delivered at international conferences.

6.1. Article 1

Predicting Crop Evapotranspiration under Non-Standard Conditions Using Machine Learning Algorithms, a Case Study for *Vitis vinifera* L. cv Tempranillo

Ricardo Egipto, Arturo Aquino, Joaquim Miguel Costa and José Manuel Andújar.

Journal: Agronomy (eISSN 2073-4395).

Editorial: MDPI.

Reference: Agronomy. 2023, 13 (10), 2463.

DOI: 10.3390/agronomy13102463

Year: 2023

Quality index (Journal Citation Reports®, 2023): 65/265 (Q1) in the category "Plant Sciences", 20/126 (Q1) in the category "Agronomy". Impact Factor of 3.3.

Article

Predicting Crop Evapotranspiration under Non-Standard Conditions Using Machine Learning Algorithms, a Case Study for *Vitis vinifera* L. cv Tempranillo

Ricardo Egipto ^{1,*}, Arturo Aquino ², Joaquim Costa ³ and José Manuel Andújar ²

¹ INIAV, I.P. — Instituto Nacional de Investigação Agrária e Veterinária, Pólo de Inovação de Dois Portos, Quinta da Almoinha, 2565-191 Dois Portos, Portugal

² CITES, Centro de Investigación en Tecnología, Energía y Sostenibilidad, Universidad de Huelva, La Rábida, Palos de la Frontera, 21819 Huelva, Spain; arturo.aquino@desia.uhu.es (A.A.); andujar@desia.uhu.es (J.M.A.)

³ LEAF, Linking Landscape, Environment, Agriculture and Food, Instituto Superior de Agronomia, Universidade de Lisboa, 1349-017 Lisboa, Portugal; miguelcosta@isa.ulisboa.pt

* Correspondence: ricardo.egipto@iniav.pt

Abstract: This study focuses on assessing the accuracy of supervised machine learning regression algorithms (MLAs) in predicting actual crop evapotranspiration (ET_c act) for a deficit irrigated vineyard of *Vitis vinifera* cv. Tempranillo, influenced by a typical Mediterranean climate. The standard approach of using the Food and Agriculture Organization (FAO) crop evapotranspiration under standard conditions (FAO-56 Kc-ET₀) to estimate ET_c act for irrigation purposes faces limitations in row-based, sparse, and drip irrigated crops with large, exposed soil areas, due to data requirements and potential shortcomings. One significant challenge is the accurate estimation of the basal crop coefficient (K_{cb}), which can be influenced by incorrect estimations of the effective transpiring leaf area and surface resistance. The research results demonstrate that the tested MLAs can accurately estimate ET_c act for the vineyard with minimal errors. The Root-Mean-Square Error (RMSE) values were found to be in the range of 0.019 to 0.030 mm·h^{−1}. Additionally, the obtained MLAs reduced data requirements, which suggests their feasibility to be used to optimize sustainable irrigation management in vineyards and other row crops. The positive outcomes of the study highlight the potential advantages of employing MLAs for precise and efficient estimation of crop evapotranspiration, leading to improved water management practices in vineyards. This could promote the adoption of more sustainable and resource-efficient irrigation strategies, particularly in regions with Mediterranean climates.

Keywords: grapevine; vineyard irrigation; actual crop evapotranspiration; machine learning algorithms; decision support systems

Citation: Egipto, R.; Aquino, A.; Costa, J.; Andújar, J.M. Predicting Crop Evapotranspiration under Non-Standard Conditions Using Machine Learning Algorithms, a Case Study for *Vitis vinifera* L. cv Tempranillo. *Agronomy* **2023**, *13*, 2463. <https://doi.org/10.3390/agronomy13102463>

Academic Editor(s): Junliang Fan

Received: 1 August 2023

Revised: 12 September 2023

Accepted: 19 September 2023

Published: 23 September 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Viticulture is a vital socio-economic activity for Mediterranean countries, but it faces significant challenges due to climate change and extreme weather conditions. More severe droughts and higher temperatures are expected [1], leading to increased evaporative demand and reduced water availability for irrigation. In this context, efficient irrigation management is crucial for optimizing yield and berry composition in vineyards. Such a scenario brings new challenges to Mediterranean viticulture, as irrigation emerges as an adaptation strategy aimed at optimizing yield while improving ripening and berry composition [2,3].

Grape ripening is a critical phenological phase that greatly influences berry composition at harvest time. Moderate water stress during this period benefits grapevine

water-use efficiency and grape quality [2]. Accurate quantification of this condition requires monitoring actual crop evapotranspiration (ET_c act), which allows for the implementation of efficient irrigation management schemes. To ensure optimal plant water status, irrigation protocols must be based on accurate knowledge of weather, soil, and plant variables. Nevertheless, there is some debate among plant physiologists and micrometeorologists regarding the factors contributing to plant water loss through transpiration. Plant physiologists emphasize the role of stomata in this process [4–6], while micrometeorologists focus on the high energy required for water evaporation [7].

Several methods to estimate evapotranspiration (ET), incorporating various factors from soil to vegetation and based on weather variables, have been developed [8]. Some are derived from the Penman–Monteith equation, which describes the ET process considering the soil and air moisture, mass transfer, and the energy required for the process [7]. The Food and Agriculture Organization (FAO) recommends crop evapotranspiration under standard conditions (FAO-56 K_c - ET_0) as the standard approach for defining and calculating reference ET (ET_0). Since ET_0 reflects the weather-related effects on water use by a reference crop [9,10], in order to be applicable to different crops, the method needs to scale ET_0 by a crop coefficient (K_c), which accounts for the physical and physiological differences from the reference crop, their impact on ET_0 , and their variability during the growing season [9]. Several simplifications were incorporated into the K_c coefficients, including plant transpiration and soil evaporation [11]. To avoid incorrect estimation of crop ET (ET_c) in orchards and sparse crops with drip irrigation and large exposed soil areas, the FAO-56 K_c - ET_0 method was adapted to separate plant and soil components of K_c , the basal crop (K_{cb}) and the soil evaporation coefficient (K_e) [9]. However, for crop species with tight stomatal control of water loss and regulation of leaf water potential, such as grapevine, literature has reported major accuracy limitations in using the FAO-56 K_c - ET_0 method [11–15]. These inaccuracies are mainly related to the surface resistance and incorrect estimation of K_{cb} [16–18]. In fact, the procedure for the practical estimation of the ET_c act, must take into account the effective transpiring leaf area, and additionally include auxiliary sub-models for aerodynamics and surface conductance, which must be parameterized for each new measurement, location, and condition [15,19–22].

To overcome the limitations of the FAO-56 K_c - ET_0 method, alternative approaches, such as employing machine learning regression algorithms (MLA) can be considered [23,24]. Indeed, MLAs have the capacity to map input-dependent variables to output-independent ones by learning patterns from training datasets with known pairs of input-output data [25]. Previous studies in the literature describe the use of MLA approaches to estimate ET_0 , but to the best of our knowledge, none of them relates to farm scale calculation of the ET_c act for grapevines [24,26–29].

This research assesses the performance of eight state-of-the-art supervised machine learning regression algorithms (MLA), using three main atmospheric variables (net radiation— R_n , wind speed— U , and vapor pressure deficit— VPD) and a plant variable (stomatal conductance to water vapor— g_{sw}), to predict ET_c act as key information for designing optimal irrigation management systems in vineyards. To assess the accuracy of the algorithms, ET_c act estimates by MLA are compared to the accuracy of the ET_c act computed by the FAO-56 K_c - ET_0 method, using the actual crop ET recorded by the Eddy covariance tower flux installed in the field as an external validation variable.

The findings suggest that MLA models can be effective in estimating the ET_c act and optimizing irrigation management in vineyards. These models can continuously improve and expand their knowledge by incorporating new data from agronomic campaigns. The application of MLA in arid climates can significantly benefit viticulture in Mediterranean regions.

2. Materials and Methods

2.1. Experimental Layout

The trials were carried out in a commercial vineyard (Herdade do Esporão) in Reguengos de Monsaraz, Alentejo wine region, southern Portugal (lat. 38°23'55.00" N; long. 7°32'46.00" W). Specifically, a 17-year-old commercial vineyard of the red *Vitis vinifera* cv Tempranillo (syn. Aragonez), grafted on 1103 Paulsen rootstock, was chosen for the study. The vines are 1.5 m within and 3.0 m between rows (2220 vines/ha), north-south oriented, trained to vertical shoot positioning, and spur-pruned on a bilateral Royat cordon system. All vines were pruned evenly, with 15–16 buds per vine. A Eutric Cambisol (CM) with a depth of 1.0 m and a silty-clay texture was found, with a pH ranging from 7.0 to 7.6, a low organic matter content, and a high content of phosphorus and potassium. Standard cultural practices in the region were followed, and the vines were irrigated weekly with drip irrigation, using 2.4 L·h⁻¹, 1.0 m spaced emitters, in accordance with owners' practices.

For the study, 20 adult and healthy vines were randomly selected from two adjacent rows, with 10 vines per row. This criterion of narrow sample selection increases confidence in the coherence of the measurements, as it ensures an optimal data acquisition procedure under conditions of low temporal and spatial variability within each measurement, without compromising the variability observed in the field. This experimental design also allowed for the assessment of solar radiation effects, as both sides of the canopy (east and west) were studied under contrasting incident radiation.

The field trial, detailed in Section 2.2.1, was carried out during the ripening period in 2019 (20 and 22 July) and 2020 (24, 29 and 31 August), from 8 a.m. to 7 p.m.

2.2. Field and Reference Measurements

2.2.1. Field Measurements

Wind speed (U) was measured with a 3D sonic anemometer (Gill Windmaster Pro, Gill Instruments Limited, Hampshire, UK). To avoid gust peaks, the wind speed was recalculated using a 300-s running average over the incoming wind signal [30] and corrected by applying Equation (1) to wind speed measured 3 m above the ground surface [9]:

$$U = U_z \cdot \frac{4.87}{\ln(67.8z - 5.42)} \quad (1)$$

where U is the wind speed (m·s⁻¹) measured at 2 m above the ground surface, U_z is the wind speed (m·s⁻¹) measured in z m above the ground surface, and z is the height above the ground surface (m) at which the wind speed is measured. Air temperature (T_{air}) and relative humidity (RH) were recorded using a thermohygrometer (CS215-PWS Campbell Scientific, Logan, UT, USA) placed 2 m above the soil surface. Net radiation (R_n) was measured with a net radiometer (NR2, Delta-T Devices, Cambridge, UK), installed above the top of the canopy. Soil heat flux (G) was measured with six heat flux plates (Hukseflux HFP01, Hukseflux Thermal Sensors, Delft, The Netherlands), placed at 5 mm depth, one under the canopy, and the others 0.5 m apart, perpendicular to the vine row and covering all the inter-row. Soil heat flux data are presented as the average of all six measurements. Soil and meteorological sensors were connected to a datalogger (CR1000, Campbell Scientific, Logan, UT, USA) and data was collected every minute and averaged every five minutes. Plant water status was assessed by pre-dawn leaf water potential (Ψ_{PD}) measurements on each sampling date using a Scholander-type pressure chamber. Water vapor gas exchange was also monitored by measuring stomatal conductance to water vapor (g_{sw}) on adult leaves from each side of the canopy, from 8 a.m. to 7 p.m., using a steady state porometer (LI-1600, LI-COR, Lincoln, NE, USA). A summary of the field measurements is shown in Table 1.

2.2.2. Characterization of the Climate and Grapevine Water Status

The study zone's climate is Mediterranean, with hot and dry summers and mild rainy winters. Accumulated rainfall from October to August ranged from 341 to 466 mm in 2019 and 2020, respectively (Table 2).

Table 1. Summary of field measurements and instrumentation.

Measurement	Periodicity and Data Integration	Units	Source
Stomatal conductance to water vapor (g_{sw})	Hourly from 8 a.m. to 7 p.m.	$m \cdot s^{-1}$	Steady-state porometer (Model LI-1600, LI-COR, Lincoln, NE, USA)
Air temperature (T_{air})	Every minute and averaged every 5 min	$^{\circ}C$	Temperature and relative humidity probe, model CS215-PWS (Campbell Scientific, Logan, UT, USA) connected to a datalogger (CR1000, Campbell Scientific, Inc.)
Air relative humidity (RH)		%	
Wind speed (U)	Every 1/10 s and averaged every minute	$m \cdot s^{-1}$	3D sonic anemometer (model Gill Windmaster Pro, Gill Instruments Limited, Hampshire, UK)
Net radiation (Rn)	Every minute and averaged every 5 min	$W \cdot m^{-2}$	Net radiometer, model NR2, (Delta-T Devices, Cambridge, UK) connected to a datalogger (CR1000, Campbell Scientific, Inc., Logan, UT, USA)
Soil heat flux (G)	Every minute and averaged every 5 min	$W \cdot m^{-2}$	Hukseflux heat flux plate, model HFP01 (Hukseflux Thermal Sensors, Delft, The Netherlands) connected to a datalogger (CR1000, Campbell Scientific, Inc., Logan, UT, USA)
Vapor pressure deficit (VPD)	Every minute and averaged every 5 min	kPa	$VPD = e_s - e_a$ (2)
			$e_a = e^0(T) \cdot \frac{RH}{100}$ (3)
			$e^0(T) = 0.6108 \cdot \exp\left(\frac{17.27 \times T}{T + 237.3}\right)$ (4)
			$e_s = \frac{e^0(T_{min}) + e^0(T_{max})}{2}$ (5)
			where (e_s) is the saturation and (e_a) is the actual vapor pressure, for a given period [9]

Table 2. Characterization of rainfall patterns. Accumulated rainfall during grapevine dormancy, from October (Oct) to December (Dec) of the previous year's vintage (year (i – 1)), dormancy to flowering (January–May), and berry development to grape ripening (June (Jun) to August (Aug)) of the harvest year (year (i)) and the cumulative rainfall from October of the previous year to August.

Rainfall (mm)				
Year (i – 1)		Year (i)		Accum
Year (i)	Oct–Dec	Jan–May	Jun–Aug	Oct–Aug
2019	204.4	133.6	3.4	341.4
2020	226.0	239.0	1.2	466.2

Hourly averaged net solar radiation above the canopy (R_n , $W \cdot m^{-2}$), soil heat flux (G , $W \cdot m^{-2}$), air temperature (T_{air} , $^{\circ}C$), wind speed (U , $m \cdot s^{-1}$), and air vapor pressure deficit (VPD, kPa), during the experimental period and measured on the experimental plot, are shown in Figure 1. All measurements were taken under clear-sky conditions. T_{air} and VPD followed a similar daily pattern. In the afternoon, the VPD was always above 3 kPa and reached 4.5 to 5 kPa between 5 p.m. and 6 p.m. The wind speed, U , was moderate, with a maximum of $4.4 m \cdot s^{-1}$. The vineyard row orientation and the apparent daily course of the sun influenced the soil heat flux. The G increased from the early hours of the day until 2 p.m., when it almost reached its maximum value, and decreased after 3 p.m. when R_n decreased. R_n , soil G , T_{air} , and VPD showed a similar diurnal pattern during all measurement periods.

Predawn leaf water potential (Ψ_{PD}) varied between -0.4 and -0.6 MPa, corresponding to a condition of moderate to severe stress in grapevine, considered adequate to produce high-standard wines [2,31] (Table 3). A moderate recovery in Ψ_{PD} was observed after each irrigation event, with an increase of more than 0.1 MPa, (e.g., on 22 August 2019, and on 24 and 29 July 2020).

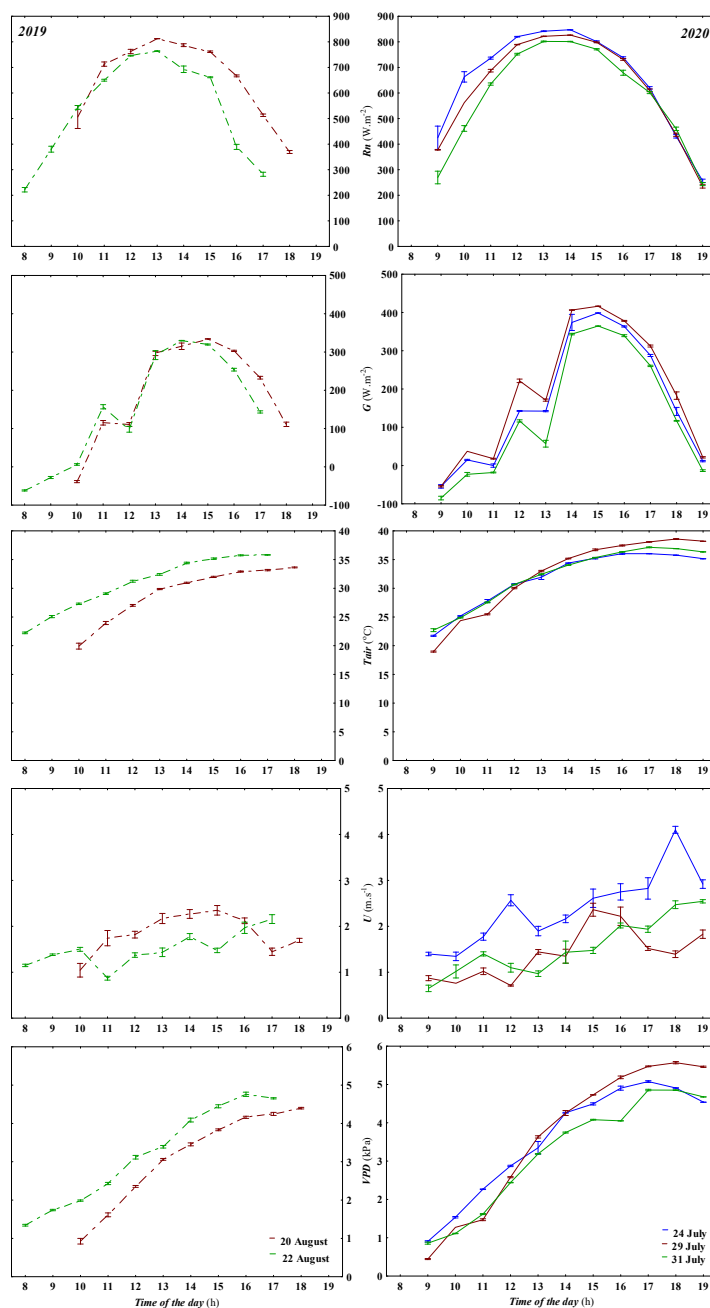


Figure 1. Atmospheric and Soil Variable Patterns on the Measurement Days. The figure illustrates the measurements of net solar radiation above the canopy (R_n , $W \cdot m^{-2}$), Soil heat flux (G , $W \cdot m^{-2}$), air temperature (T_{air} , $^{\circ}C$), wind speed (U , $m \cdot s^{-1}$), and air vapor pressure deficit (VPD , kPa) measured on 20 and 22 August 2019 and 24, 29 and 31 July 2020 on the experimental plot is presented. The values represent means, and the vertical bars indicate the standard error of the mean plots ($n = 12$).

Table 3. Predawn leaf water potential (Ψ_{PD}) of grapevines on the measurement days. The table displays measurements of predawn leaf water potential (Ψ_{PD}) of grapevines on specific measurement days. Measurements were conducted on 20 August (before irrigation) and 22 August 2019 (after irrigation) at 4–5 a.m., as well as on the 24 July (after irrigation), 29 July 29 (before irrigation), and 31 July 2020 (after irrigation). The data is presented as the mean (Avg) and standard error of the mean (SE) of five replicates per day.

DAY	Ψ_{PD} (MPa)	
	Avg	SE
20 August 2019 (before irrigation)	−0.60	0.012
22 August 2019 (after irrigation)	−0.52	0.021
24 July 2020 (after irrigation)	−0.42	0.020
29 July 2020 (before irrigation)	−0.55	0.017
31 July 2020 (after irrigation)	−0.47	0.017

2.2.3. Reference Actual Crop Evapotranspiration Measurements

An EC system installed on the experimental plot was used to record actual crop evapotranspiration ($ET_{c \text{ act meas}}$) simultaneously with U. A part of the collected data was used as a target variable in the model training phase and a part as an external validation dataset. The EC system consisted of a fast response, 0.1 Hz, open path CO_2/H_2O analyzer (LI-6500 DS, LI-COR Inc., Lincoln, NE, USA) and a 3D sonic anemometer (Gill Windmaster Pro, Gill Instruments Limited, Hampshire, UK) connected to a Smartflux 3 system (LI-COR Inc., Lincoln, NE, USA). The sonic anemometer and the open path CO_2/H_2O analyzer were installed at a height of 3.0 m above the ground surface, over the top of the canopy. A fetch of at least 300 m, facing the prevailing north winds and covering the experimental field ensured that all fluxes within the area of interest were measured. The quality of the recorded data was tested and analyzed with the EddyPro software v7.0.6 (LI-COR Inc., Lincoln, NE, USA). The measurements enabled us to record the registered actual evapotranspiration ($ET_{c \text{ act meas}}$) at a high temporal resolution, every 1/10 s.

More than 90% of the daily data flux of the dataset analyzed here had an energy balance closure greater than 0.95. Consequently, the uncertainty of the measured $ET_{c \text{ act meas}}$ values was less than 5%, which corresponded to an $ET_{c \text{ act meas}}$ measurement uncertainty of less than 0.002 mm h^{-1} on the hourly flux determination of 90% of the data.

Despite the significant differences between the $ET_{c \text{ act meas}}$ recorded before and after irrigation days, similar patterns were found in the $ET_{c \text{ act meas}}$ recorded before irrigation and in the $ET_{c \text{ act meas}}$ recorded after irrigation (Figure 2). Irrespective of the irrigation difference, the $ET_{c \text{ act meas}}$ increased exponentially from the early morning hours, reaching its peak between 11 a.m. and 12 p.m. In 2020, when the grapevines were less stressed after irrigation (Table 3), the maximum $ET_{c \text{ act meas}}$ reading was recorded at 1 p.m., when the air VPD reached 3.5 MPa, and decreased towards the end of the day, regardless of the energy available for water evaporation. In both years, prior to irrigation, and under more severe water stress conditions, the maximum $ET_{c \text{ act meas}}$ reading was registered at 11 a.m. and was maintained at a similar level for an extended period, only decreasing after 5 p.m. to 6 p.m. (Figure 2). These results are consistent with the strong regulation of g_{sw} on grapevine transpiration [4], and the large contribution of plant transpiration compared to soil evaporation to total evapotranspiration in vineyards. While before irrigation, $ET_{c \text{ act meas}}$ ranged from 0.06 to less than $0.2 \text{ mm} \cdot \text{h}^{-1}$, the recorded $ET_{c \text{ act meas}}$ after irrigation was on average 1.3 to 1.4 times higher, thus suggesting larger stomata opening and greater water loss through transpiration.

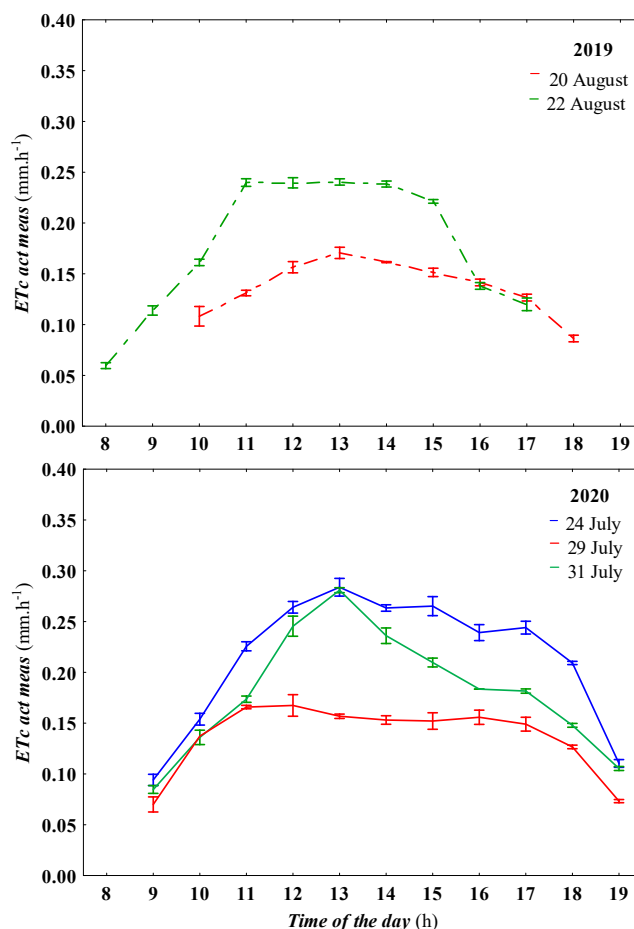


Figure 2. Actual crop evapotranspiration (ET_c act meas) measured in the experimental plot. The figure displays the actual crop evapotranspiration (ET_c act meas) measured in the experimental plot using an Eddy covariance flux tower. Measurements were taken on the 20 and 22 August 2019, before and after irrigation, respectively, as well as on the 24 July, after irrigation, 29 July, before irrigation, and after irrigation on 31 July 2020. The values represent means, and the vertical bars indicate the standard error of the mean plots.

2.3. Developed Methodology

2.3.1. Data Processing and Analysis

In order to estimate actual crop evapotranspiration, under non-standard conditions (ET_c act est), from weather and plant variables using machine learning techniques, the initial field measurement data underwent a transformation to create a suitable data structure for processing and analysis. The original data were structured into a nine-dimensional vector composed of the seven measured variables (g_{sw} , ET_c act meas, T_{air} , RH , U , R_n , and G) and two derived variables ($R_n - G$ and VPD), with 600 measurements per variable. VPD was calculated using T_{air} and RH as described in Equations (2)–(5) (Table 1). To train the machine learning models (MLA) to estimate actual crop evapotranspiration, ET_c act est, the ET_c act meas recorded in the experimental plot was used as the label/dependent variable (target), and the variables g_{sw} , VPD , R_n , G , U , and T_{air} were initially considered as predictors, subject to the results of the pre-processing analysis. The predictor variables were selected from the crop and meteorological variables with the greatest influence on ET_c act according to the literature.

Data pre-processing included outlier analysis, variable correlation analysis, and data structuring into an internal training and testing set, and an external validation dataset. Outliers were identified by the interquartile range (IQR) method with a cut-off of $1.5 \times \text{IQR}$. Scores that fell below $1.5 \times \text{IQR} - Q1$ (the 1st or 25% quartile) or above $1.5 \times \text{IQR} + Q3$ (the 3rd or 75% quartile) were considered as outliers and removed from the dataset. To avoid multicollinearity of the model, the correlation of the variables was analyzed by a Pearson product-moment correlation test. Variables not correlating below -0.6 or above a threshold of 0.6 were selected as good candidates for ET_c act predictors. Consequently, the variable Tair was removed based on this criterion. After removing the outliers and discarding the variable, the data were randomly split into three datasets: A training and testing dataset containing 40% of the 2019 and 2020 data, and two validation datasets, one containing the remaining 2019 data, and the other containing the remaining 2020 data (Figure 3). The three datasets were configured to maintain similar data patterns (Table 4).

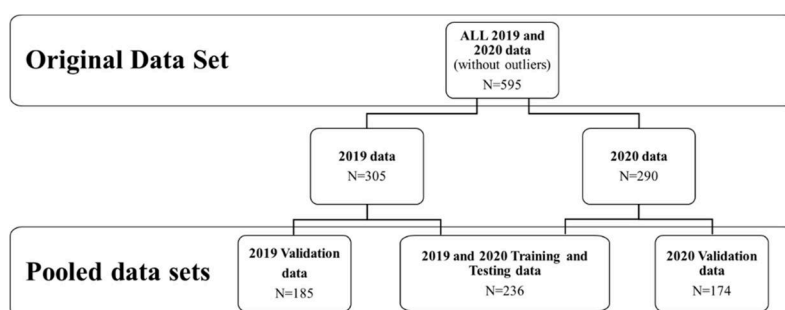


Figure 3. Data structure. The original data was divided into three final datasets: a training and testing dataset containing 40% of all data from the years 2019 and 2020, and two external validation datasets containing the remaining data from the years 2019 and 2020.

2.3.2. Modeling Vineyard Actual Evapotranspiration under Non-Standard Conditions

The pooled training dataset (Figure 3) was used to train and fit a set of supervised machine learning regression models to predict ET_c act pred, employing a five-fold cross-validation scheme to protect against overfitting. The selected model predictors, as detailed above, were the daily course of net radiation (R_n , $W \cdot m^{-2}$), soil heat flux (G , $W \cdot m^{-2}$), air vapor pressure deficit (VPD, kPa), wind speed (U , $m \cdot s^{-1}$) measured above the canopy, as well as the stomatal conductance to water vapor (g_{sw} , $m \cdot s^{-1}$). The pooled training dataset, ET_c act meas data, recorded in the field (Figure 3), was used as the target variable. For modeling purposes, the units of g_{sw} were converted to $m \cdot s^{-1}$ using the molar density of the air ($mol \cdot m^{-3}$), and R_n after subtracting G to determine the energy available for crop ET processes.

Accordingly, a set of supervised machine learning models was developed, using Matlab R2021b (The Mathworks Inc., Natick, MA, USA), which included:

- A non-parametric kernel-based probabilistic model (Gaussian process regression model—GPR), using either an exponential kernel function or a squared exponential kernel function;
- A support vector machine (SVM) regression model using either a linear kernel function, a quadratic kernel function, a cubic kernel function, or a medium Gaussian kernel function;
- An ensemble of regression trees (ERT), either using least-squares boosting regression trees learners or using bootstrap-aggregating (bagging) regression trees learners.

Table 4. Model predictors and characterization of response variables. The table provides variable characterization for each pooled dataset (training, testing, and validation). It includes stomatal conductance to water vapor (g_{sw}), net radiation above the canopy minus soil heat flux ($Rn - G$), wind speed (U), air vapor pressure deficit above the canopy (VPD), and crop evapotranspiration measured by the Eddy covariance method under non-standard conditions (ET_c act meas). The data are characterized by the total number of cases (N), the mean of the variable (Mean), the minimum (Min) and maximum (Max) values, the standard deviation (SD), and the respective coefficient of variation (CV, %).

Variable	Training and Testing Data Set					
	Valid N	Mean	Min	Max	SD	CV
g_{sw} (mol·H ₂ O m ⁻² ·s ⁻¹)	236	0.081	0.004	0.254	0.041	50.5
$Rn - G$ (W·m ⁻²)	236	425.0	56.3	779.7	159.0	37.4
U (m·s ⁻¹)	236	1.69	0.57	4.16	0.72	42.2
VPD (kPa)	236	3.36	0.46	5.62	1.43	42.4
ET_c act meas (mm·h ⁻¹)	236	0.167	0.020	0.388	0.066	39.5
Variable	2019 Validation Dataset					
	Valid N	Mean	Min	Max	SD	CV
g_{sw} (mol·H ₂ O m ⁻² ·s ⁻¹)	174	0.085	0.014	0.249	0.050	58.6
$Rn - G$ (W·m ⁻²)	174	455.5	189.1	767.5	159.1	34.9
U (m·s ⁻¹)	174	1.81	0.52	4.45	0.83	45.6
VPD (kPa)	174	3.47	0.41	5.70	1.58	45.6
ET_c act meas (mm·h ⁻¹)	174	0.176	0.025	0.369	0.072	41.0
Variable	2020 Validation Dataset					
	Valid N	Mean	Min	Max	SD	CV
g_{sw} (mol·H ₂ O m ⁻² ·s ⁻¹)	185	0.079	0.004	0.149	0.030	38.0
$Rn - G$ (W·m ⁻²)	185	403.7	82.0	665.4	145.1	35.9
U (m·s ⁻¹)	185	1.59	0.73	3.05	0.49	31.2
VPD (kPa)	185	3.17	0.76	5.22	1.26	39.6
ET_c act meas (mm·h ⁻¹)	185	0.157	0.043	0.280	0.058	37.3

2.4. Methodology to Evaluate the Predictive Accuracy of MLA Models in Estimating Actual Crop Evapotranspiration

To assess the predictive accuracy of the proposed MLA models, the actual crop evapotranspiration predicted by the models, ET_c act pred, was compared to the ET_c act meas measurements recorded in the field by the Eddy covariance method. To better examine the performance of the proposed models, we also compared the predictive accuracy of ET_c act estimated by the FAO-56 Kc- ET_0 method with the values from the same dataset of ET_c act meas recorded in the field using the Eddy covariance method. Finally, the accuracy of MLA models for predicting ET_c act was verified by comparison with the accuracy of the recommended standard method FAO-56 Kc- ET_0 for estimating ET_c act.

2.4.1. Predictive Accuracy of MLA Models to Estimate Actual Crop Evapotranspiration

The accuracy of the MLA proposals for predicting ET_c act was verified by comparing the fitted values of all models with the ET_c act meas measures recorded in the field by the Eddy covariance method. The predictive accuracy of the MLA models was evaluated according to the method described in Section 2.4.3.

2.4.2. Predictive Accuracy of the FAO-56 Kc- ET_0 Model to Estimate Actual Crop Evapotranspiration

The accuracy of the predicted ET_c act using the recommended standard method FAO-56 Kc- ET_0 was compared to the ET_c act meas measurements recorded in the field by the Eddy covariance method.

To predict ET_c act using the FAO-56 K_c-ET₀ standard method, ET₀ was first calculated according to the method proposed by [9] using data from the farm's meteorological station. A detailed description of the FAO-56 K_c-ET₀ method can be found in the work by [9]. In this study, the dual crop coefficient K_c approach was employed to assess crop evapotranspiration (ET_c). This approach involves splitting K_c into two factors that separately describe the components soil evaporation (K_e) and grapevine transpiration (K_{cb}). The basal crop coefficient (K_{cb}) was estimated by the Normalized Differential Vegetation Index (NDVI) obtained from Sentinel 2 imagery time-series with a spatial resolution of 10 m, following the model presented in [32] (Equation (6)).

$$K_{cb} = 1.44 \times NDVI - 0.10 \quad (6)$$

The model presented in [32] was developed for a vineyard with the same cultivar and rootstock, and a similar climate and crop management, showing a high coefficient of determination ($R^2 = 0.96$). Thus, Equation (6) was selected to estimate K_{cb} from the NDVI measured in the experimental plot.

As the grapevines in the study were subjected to some stress, a stress coefficient (K_s) was applied to K_{cb} to assess ET_c act according to the FAO-56 K_c-ET₀ methodology, following Equation (7):

$$ET_c \text{ act} = (K_e + K_s \times K_{cb}) \times ET_0 \quad (7)$$

The calculation of K_s was based on Equation (8), as described in [32]:

$$K_s = 1.217 \times e^{(1.444 \times \Psi_{PD})} \quad (8)$$

The predictive accuracy of the FAO-56 K_c-ET₀ standard method was evaluated according to the method described in Section 2.4.3.

2.4.3. Comparative Analysis of the Predictive Accuracy of MLA Models and the FAO-56 K_c-ET₀ Method for Estimating Actual Crop Evapotranspiration

The models' predictive accuracy was assessed for the pairs model—dataset by examining the coefficient of determination (R^2) of the trained models and comparing the goodness of fit measures of the simulated vs observed ET_c act. For this purpose, we used the Root-Mean-Square-Error (RMSE), which is defined as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}} \quad (9)$$

where $\hat{y}_i$ and y_i are the predicted and measured actual crop ET, respectively, for the i -th segment of the dataset and n is the number of ET_c act measurements used in each dataset.

To avoid the differences in ET_c act between different datasets, the relative error ($|E|$) was calculated and expressed as a percentage, from the expression:

$$|E| = \frac{|\sum_{i=1}^n (\hat{y}_i - y_i)|}{\sum_{i=1}^n y_i} \times 100 \quad (10)$$

3. Results and Discussion

3.1. Characterization and Correlations of Actual Crop Evapotranspiration Predictors

Figure 4 shows the correlation between all variables trained as predictors of actual crop evapotranspiration (ET_c act) before data was split into datasets. Since air temperature (T_{air}) showed a positive and significant correlation with air VPD ($R = 0.97$, $p < 0.001$), T_{air} was not used as a predictor of ET_c act to avoid multicollinearity. All variables correlated positively and significantly ($p < 0.001$) with the target variable (ET_c act meas). With the exception of R_n-G, the energy available for the ET process, which showed a correlation coefficient (R) value with ET_c act meas twice that of the other predictors, all others correlate

in a similar order of magnitude. None of the predictors per se explained more than 40% of the variability of the ET_{c act meas}, thus suggesting that non-linear relationships between predictors and the ET_{c act meas} may be involved, and/or the interaction between the variables are the main contributors to the observed variability.

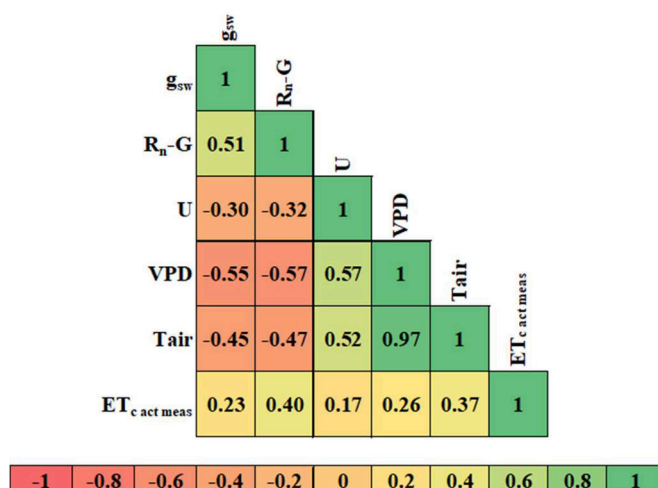


Figure 4. Correlogram Showing Pearson Product-Moment Correlation Coefficients. The figure displays the Pearson product-moment correlation coefficients between pairs of variables selected as predictor candidates for actual crop evapotranspiration (ET_{c act}). The variables include meteorological variables such as R_n-G (the energy available for crop evapotranspiration processes, calculated as the net solar radiation above the canopy (R_n) minus the soil heat flux (G)), U (the wind speed above the canopy), VPD (the air vapor pressure deficit), and T_{air} (the air temperature). Additionally, the grapevine variable g_{sw} (stomatal conductance to water vapor) and field-measured actual crop evapotranspiration (ET_{c act meas}) are included in the correlation analysis. All correlation coefficients are significantly different from zero ($p < 0.001$). Correlations of similar magnitude are depicted with the same color, according to the color code shown below.

Table 4 shows the characterization of the datasets used for training and testing, as well as for external validation of the MLA approach and FAO-56 Kc-ET₀ models. The table shows considerable variability within each variable across all datasets, as indicated by the coefficient of variation (CV). This variability can be attributed to how the different variables changed throughout the day. Despite the variability, the mean and the amplitude of data variability, represented by the maximum (Max) and minimum (Min) values, as well as the standard deviation (SD) of each variable (both predictor and target variables), were found to be similar between datasets (Table 4).

3.2. Evaluation of MLA Models in Estimating Actual Crop Evapotranspiration

Table 5 shows the fitted supervised machine learning (MLA) models that were trained and tested to estimate ET_{c act} using the variables R_n, G, U, VPD, and g_{sw} as predictors. In the testing phase, all trained models achieved a high and significant coefficient of determination (R^2), thus indicating high efficiency in predicting the ET_{c act}. The poorer model was the SVM approach, using a linear kernel function, which yielded an R^2 score of 0.746. The two ERT approaches, the SVM model, using a medium Gaussian kernel function, and the GPR, using an exponential kernel function, showed the best performance in predicting the ET_{c act}, with R^2 values between 0.910 and 0.992. The high and significant R^2 of all MLA regression models (Table 5) indicates that the selected variables (g_{sw} , R_n-G, U, and VPD) account for a very high proportion of the observed ET_{c act} variability, suggesting that they are robust explanatory variables of the ET_{c act}.

Table 5. Fitted Machine Learning Algorithms for actual vineyard evapotranspiration under non-standard conditions (ETc act). The table presents the results of fitted Machine Learning Algorithms for actual vineyard evapotranspiration under non-standard conditions (ETc act) using the pooled dataset for training and testing. The data was obtained from the years 2019 and 2020, based on actual vineyard evapotranspiration measured by the Eddy covariance method in the field ($n = 236$). The values of the coefficient of determination (R^2) for all the algorithms are significant ($p < 0.001$).

Machine Learning Algorithms	R^2
GPR Exponential kernel function	0.992
GPR Squared Exponential kernel function	0.899
SVM Linear kernel function	0.746
SVM Quadratic kernel function	0.819
SVM Cubic kernel function	0.878
SVM Medium Gaussian kernel function	0.925
Ensemble Boosted Trees	0.934
Ensemble Bagged Trees	0.910

Table 6 presents the goodness-of-fit measures for the MLA approaches used to estimate the ETc act using the validation dataset with the variables Rn, G, U, VPD, and g_{sw} . The results of the validation phase were consistent with those of training and testing. Except for the SVM implementing a linear kernel function, the model validation process demonstrated the high accuracy of the remaining MLA models for predicting the ETc act. The results showed a correlation (R) between observed and fitted values greater than 0.880 and a maximum root mean square error (RMSE) of $0.032 \text{ mm}\cdot\text{h}^{-1}$, which is below the minimum ETc act value recorded in both years (as shown in Table 6 and Figure 5).

Table 6. Statistical indicators of goodness-of-fit measures of the supervised machine learning regression algorithms. The table presents statistical indicators of goodness-of-fit measures for estimating vineyard evapotranspiration under non-standard conditions (ETc act) using supervised machine learning regression algorithms. The data validation was performed with two independent datasets: observed (field recorded) vineyard evapotranspiration under non-standard conditions (ETc act meas) and model-estimated vineyard evapotranspiration under non-standard conditions (ETc act est). The datasets are from the years 2019 ($n = 185$) and 2020 ($n = 174$). The goodness-of-fit measures included are root mean square error (RMSE) and relative error (|E|).

Machine Learning Algorithms	Year Dataset	RMSE ($\text{mm}\cdot\text{h}^{-1}$)	E (%)
GPR Exponential kernel function	2019	0.019	4.6
	2020	0.026	1.8
GPR Squared Exponential kernel function	2019	0.020	6.3
	2020	0.027	0.9
SVM Linear kernel function	2019	0.026	0.9
	2020	0.042	1.1
SVM Quadratic kernel function	2019	0.022	1.9
	2020	0.032	3.5
SVM Cubic kernel function	2019	0.022	4.9
	2020	0.031	1.5
SVM Medium Gaussian kernel function	2019	0.019	5.4
	2020	0.029	0.7
Ensemble Boosted Trees	2019	0.020	0.2
	2020	0.030	5.1
Ensemble Bagged Trees	2019	0.020	4.5
	2020	0.030	1.3

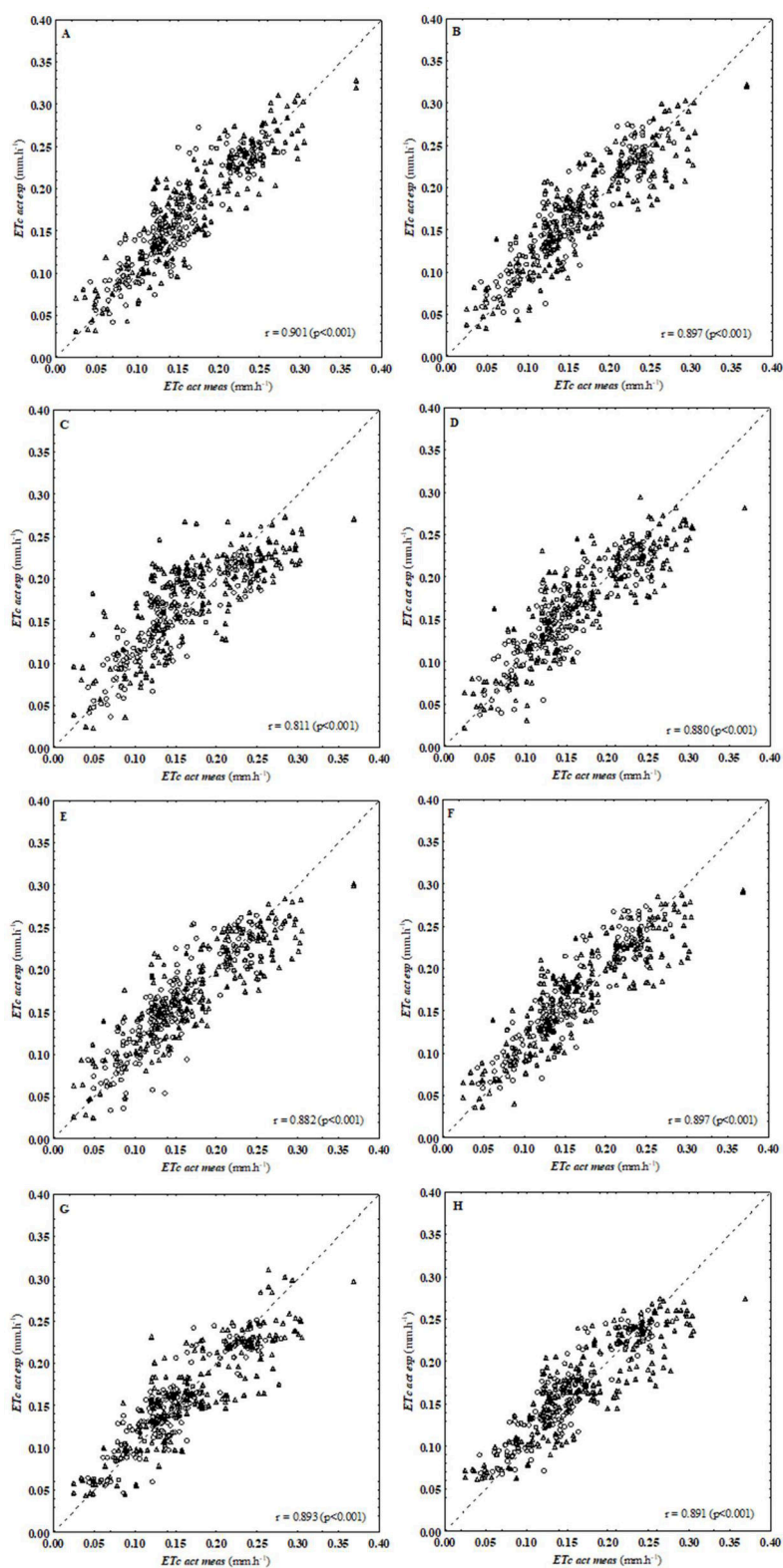


Figure 5. Relationship between observed and estimated crop evapotranspiration. This figure illustrates the relationship between the observed crop evapotranspiration (ET_c act meas, $mm \cdot h^{-1}$), recorded with an Eddy covariance flux tower, and the actual crop evapotranspiration (ET_c act est, $mm \cdot h^{-1}$) estimated by different supervised machine learning algorithms. Each subfigure shows a specific algorithm used for estimation. Figure (A) recorded ET_c act meas value versus ET_c act est value estimated by a GPR using an exponential kernel function. Figure (B) relationship estimated by a GPR algorithm using a squared exponential kernel function. Figure (C) relationship estimated by an SVM algorithm with a linear kernel function. Figure (D) relationship estimated by an SVM algorithm with a quadratic kernel function, while Figure (E) relationship estimated by an SVM algorithm with a cubic kernel function. Figure (F) relationship estimated by an SVM algorithm with a medium Gaussian kernel function. Figure (G) relationship estimated by an Ensemble boost tree algorithm, and Figure (H) relationship estimated by an Ensemble bagged tree algorithm. The data validation samples from 2019 are represented with circles ($n = 185$), and data from 2020 are represented with triangles ($n = 174$). The dotted line in each subfigure represents the 1:1 line, indicating perfect alignment between the observed and estimated values.

The analysis of the goodness-of-fit measures of the models in Table 6 confirmed that the MLA with a linear transformation had the poorest performance in estimating the ET_c act. However, the MLA models tested with the year 2019 and 2020 independent validation datasets demonstrated high accuracy potential in predicting the ET_c act, with R^2 values ranging between 0.629 (SVM using a linear kernel function, and the 2020 validation dataset) and 0.915 (SVM using a medium Gaussian kernel function, and the 2019 validation dataset). The relative error ($|E|$) of the predictions made with the 2019 validation dataset was in the $[0.2, 6.3]$ interval, while with the 2020 dataset, the range was $[0.7, 5.1]$, both expressed in percentage. Overall, the MLA models exhibited strong predictive capabilities for estimating ET_c act, as evidenced by their high R^2 values and relatively low errors.

All algorithms explained more than 80% of the ET_c act variability present in the validation dataset. The GPR using an exponential and a squared exponential kernel function, both ERT, using either least squares boosting or bootstrap aggregation methods and the SVM with a medium Gaussian kernel function, showed the best accuracy in estimating the ET_c act. These algorithms explain between 80 and 90% of the variability of the ET_c act measured in the field while exhibiting an RMSE in the range of 0.019 to 0.030 $mm \cdot h^{-1}$. Excluding the SVM using a linear transformation, the MLA algorithms, using plant and weather variables, showed a remarkable ability to learn the inner relations between ET_c act meas, R_n , G , U , and VPD , by predicting the actual vineyard ET variability with high accuracy. Similar results were obtained by other authors [24,26,27,33–35] for other crops.

3.3. Evaluation of FAO-56 Kc- ET_0 Method to Estimate Actual Crop Evapotranspiration

Figure 6 depicts the scatter plot representing the relationship between the observed actual crop evapotranspiration (ET_c act meas) recorded with the Eddy covariance method and the estimated actual crop evapotranspiration (ET_c act est) obtained through the application of the FAO 56 Kc- ET_0 method (fitted values). The results reveal a noteworthy and statistically significant correlation ($R = 0.858$, $p < 0.001$) between the observed and fitted data. However, it is evident that the variability increases as the magnitude of the observed values rises, as illustrated in Figure 6. Moreover, the FAO 56 Kc- ET_0 method exhibits a tendency to overestimate the actual crop evapotranspiration values, which is consistent with findings in other studies concerning olive orchards [36] and peach orchards [16]. Consequently, the goodness-of-fit measures indicate an RMSE of 0.059 $mm \cdot h^{-1}$, a value 1.3 to 2.9 times higher than the minimum ET_c act recorded in the field using the Eddy covariance method. Furthermore, the relative error ($|E| = 26.5\%$) is relatively high, indicating certain weaknesses of the FAO-56 Kc- ET_0 method in accurately predicting ET_c act in sparse vegetation crops like vineyards. This observation underscores the method's limitations in simulating soil resistance and vine stomatal conductance under more stressful conditions, as investigated in this study. The observed limitations of the FAO-56

Kc-ET₀ method in accurately estimating ETc act in vineyards are consistent with previous literature, including studies by [15,16,19,22,36,37].

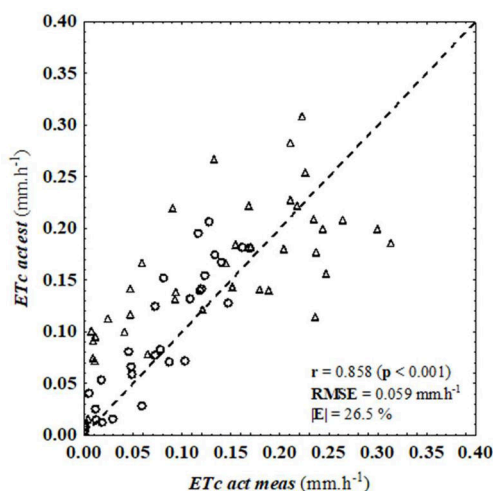


Figure 6. Relationship between observed and estimated actual crop evapotranspiration. The figure illustrates the relationship between the observed actual crop evapotranspiration (ETc act meas) recorded using the Eddy covariance flux tower, and the actual crop evapotranspiration estimated (ETc act est) with the FAO-56 Kc-ET₀ method. The coefficient of determination (R^2) and goodness-of-fit measures from data validation with two independent datasets of observed vineyard evapotranspiration under non-standard conditions (ETc act meas) and estimated actual crop evapotranspiration (ETc act est) with FAO 56 Kc-ET₀ method from the year 2019 ($n = 48$, circles) and 2020 ($n = 72$, triangles) are presented in the figure. The Goodness-of-fit measures include root mean square error (RMSE) and relative error ($|E|$). The dotted line in the figure represents the 1:1 line, indicating perfect agreement between the observed and estimated values.

3.4. Comparison of the Prediction Accuracy of MLA and FAO-56 Kc-ET₀ Method to Estimate Actual Crop Evapotranspiration

With the exception of SVM implementing a linear kernel, all MLA proposals demonstrated superior performance in predicting ETc act compared to the FAO-56 Kc-ET₀ method. The scatterplots depicting the relationship between the observed ETc act values (recorded with the EC method) and the estimated ETc act est values (obtained through MLA) showed a close alignment with the 1:1 line, indicating a good fit of all MLA models (see Figure 5). During the validation process, the MLA models exhibited a very high and statistically significant coefficient of determination (R^2) between the simulated and observed values. Moreover, the intercept and slope of the MLA fitted values were very close to 0 and 1, respectively, further confirming the accuracy of the predictions. In contrast, when compared to the FAO-56 Kc-ET₀ method, only the SVM with a linear kernel exhibited a lower R^2 and a less satisfactory fit to the observed data. This outcome suggests that the SVM with a linear kernel might not be as effective as the other MLA models in accurately estimating ETc act under the conditions considered in this study.

The comparison of accuracy between models, using the external validation dataset, clearly indicates that the MLA models outperform the FAO-56 Kc-ET₀ method. The MLA models' fitted values demonstrated significantly smaller errors (as measured by RMSE and $|E|$) compared to the FAO-56 Kc-ET₀ method. Specifically, the scatterplots between the observed and the FAO-56 Kc-ET₀ fitted values showed an RMSE that was 1.65 to 1.98 times less accurate, in 2019 and 2020, respectively, when compared to the worst MLA proposal (SVM with a linear kernel function). Moreover, the FAO-56 Kc-ET₀ method was found to be 2.2 to 2.8 times less accurate, in 2019 and 2020, respectively, when compared to the best

MLA models, namely the GPR with an exponential kernel function, and the SVM with a medium Gaussian kernel function. In terms of prediction capacity, all MLA models exhibited higher accuracy compared to the FAO-56 Kc-ET₀ model. The absolute value of the error ($|E|$) in the MLA predictions was more than 6.8 times lower than the values predicted by the FAO-56 Kc-ET₀ model, as shown in Table 7.

Table 7. Comparison of prediction accuracy to estimate actual crop evapotranspiration recorded in the field. The table provides a comparison of prediction accuracy to estimate actual crop evapotranspiration recorded in the field using the Eddy covariance method. It includes results from the FAO-56 Kc-ET₀ and the two best machine learning algorithms: GPR (Gaussian process regression) using an exponential kernel function, and SVM (Support vector machine) using a medium Gaussian kernel function. Prediction accuracy measures include The coefficient of determination (R^2) of the trained models, and the goodness-of-fit measures from the data validation process (root mean square error—RMSE and relative error— $|E|$).

	R^2	RMSE (mm·h ⁻¹)		$ E $ (%)	
		2019	2020	2019	2020
FAO-56 Kc-ET ₀	0.736	0.043	0.083	37.0	22.6
GPR Exponential kernel function	0.805	0.019	0.026	4.6	1.8
SVM Medium Gaussian kernel function	0.812	0.019	0.030	5.4	0.7

These findings further strengthen the superiority of MLA models in accurately estimating actual crop evapotranspiration compared to the traditional FAO-56 Kc-ET₀ method. The significant reduction in errors, as indicated by RMSE and $|E|$ values, highlights the enhanced predictive capabilities of MLA models in this study.

4. Conclusions

The present work demonstrates that machine learning regression algorithms, when provided with g_{sw} , G , and three meteorological variables (R_n , U , and VPD), can accurately predict the ET_c act. The five best-performing algorithms explain more than 89% of the measured variability in ET_c act recorded in the field, with RMSE values below 0.03 mm·h⁻¹. The results showcase the MLA's capacity to estimate the ET_c act with a simple parameterization and lower computational requirements compared to the traditional FAO-56 Kc-ET₀ method while retaining robustness in calculations.

Furthermore, the findings highlight the limitations of the FAO-56 Kc-ET₀ method in accurately predicting ET_c act for grapevines under deficit irrigation, where vine stomatal significantly impacts water usage and soil surface water evaporation is limited. In contrast, the presented MLA models, which incorporate g_{sw} as input knowledge, proved to be accurate in predicting ET_c act under such conditions.

The study shows that the MLA models are well suited for application in semi-automated or automated field data analysis for predicting vineyard ET_c act. Their ability to continuously process new data in near real time, retrain the algorithm, and adapt to new data patterns and associations can enhance prediction accuracy and support more efficient irrigation practices.

Additionally, the use of machine learning algorithms for monitoring the ET_c act based on grapevine and atmospheric parameters can provide valuable insights for decision support systems aimed at optimizing vineyard irrigation management. However, further optimization is required concerning the amount of available data and consideration of climatic conditions.

In conclusion, the study demonstrates the efficacy of MLA algorithms in accurately estimating vineyard ET_c act, making them a promising approach for water management in grapevine cultivation. Nonetheless, future research should focus on refining the models with respect to data availability and varying climatic conditions.

Author Contributions: Conceptualization, R.E.; methodology, R.E.; formal analysis, R.E.; investigation, R.E.; resources, A.A. and J.M.A.; data curation, R.E.; writing—original draft preparation, R.E.; writing—review and editing, R.E., A.A., J.C. and J.M.A.; supervision, A.A. and J.M.A.. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by Fundação para a Ciência e a Tecnologia (Portugal) through the R&D Unit "GREEN-IT - Bioresources for Sustainability" (UIDB/04551/2020 and UIDP/04551/2020)

Data Availability Statement: Data available on request. The data presented in this study are available on request from the corresponding author.

Acknowledgments: We acknowledge FCT Research Unit "GREEN-IT—Bioresources for Sustainability" (UIDB/04551/2020 and UIDP/04551/2020) for financial support. We also thank the support of the research units CITES, Centro de Investigación en Tecnología, Energía y Sostenibilidad, Universidad de Huelva, and LEAF (UID/AGR/04129/2019). We also address our acknowledgements to Herdade do Esporão (Reguengos de Monsaraz, Alentejo, PT) and Rui Flores for their contribution to field management of the experimental vineyard.

Conflicts of Interest: The authors declare no conflicts of interest.

References

- Intergovernmental Panel on Climate Change (IPCC). AR6 Synthesis Report: Climate Change. 2022. Available online: https://www.ipcc.ch/site/assets/uploads/2018/02/WGIIAR5-Chap3_FINAL.pdf (accessed on 30 May 2023).
- Chaves, M.M.; Zarrouk, O.; Francisco, R.; Costa, J.M.; Santos, T.; Regalado, A.P.; Rodrigues, M.L.; Lopes, C.M. Grapevine under deficit irrigation: Hints from physiological and molecular data. *Ann. Bot.* **2010**, *105*, 661–676. [\[CrossRef\]](#) [\[PubMed\]](#)
- Costa, J.M.; Vaz, M.; Escalona, J.M.; Egipto, R.; Lopes, C.M.; Medrano, H.; Chaves, M.M. Modern viticulture in Southern Europe: Vulnerabilities and strategies for adaptation to water scarcity. *Agr. Water Manag.* **2016**, *164*, 5–18. [\[CrossRef\]](#)
- Chaves, M.M.; Costa, J.M.; Zarrouk, O.; Pinheiro, C.; Lopes, C.M.; Pereira, J.S. Controlling stomatal aperture in semi-arid regions—The dilemma of saving water or being cool? *Plant Sci.* **2016**, *251*, 54–64. [\[CrossRef\]](#) [\[PubMed\]](#)
- Simonneau, T.; Lebon, E.; Coupel-Ledru, A.; Marguerit, E.; Rossdeutsch, L.; Ollat, N. Adapting plant material to face water stress in vineyards: Which physiological targets for an optimal control of plant water status? *OENO One* **2017**, *51*, 167–179. [\[CrossRef\]](#)
- Levin, A.D.; Williams, L.E.; Mathews, M.A. A continuum of stomatal responses to water deficits among 17 wine grape cultivars (*Vitis vinifera*). *Funct. Plant Biol.* **2019**, *47*, 11–25. [\[CrossRef\]](#)
- Monteith, J.L.; Unsworth, M. *Principles of Environmental Physics*, 4th ed.; Academic Press: Cambridge, MA, USA; Elsevier: Oxford, UK, 2013; ISBN: 978-0-12-386910-4.
- Priestley, C.H.B.; Taylor, R.J. On the assessment of surface heat flux and evaporation using large-scale parameters. *Mon. Weather Rev.* **1972**, *100*, 81–92. [\[CrossRef\]](#)
- Allen, R.G.; Pereira, L.S.; Raes, D.; Smith, M. *Crop Evapotranspiration Guidelines for Computing Crop Water Requirements—FAO Irrigation and Drainage Paper 56*, 1st ed.; FAO: Rome, Italy, 1998. Available online: <http://www.fao.org/3/X0490E/X0490E00.htm> (accessed on 4 May 2023).
- Pereira, A.R. The Priestley–Taylor parameter and the decoupling factor for estimating reference evapotranspiration. *Agr. For. Meteorol.* **2004**, *125*, 305–313. [\[CrossRef\]](#)
- Pereira, L.S.; Allen, R.G.; Smith, M.; Raes, D. Crop evapotranspiration estimation with FAO56: Past and future. *Agr. Water Manag.* **2015**, *147*, 4–20. [\[CrossRef\]](#)
- Shuttleworth, W.J.; Wallace, J.S. Calculating the water requirements of irrigated crops in Australia using the Matt-Shuttleworth approach. *Trans. ASABE* **2009**, *52*, 1895–1906. [\[CrossRef\]](#)
- Campos, I.; Neale, C.M.U.; Calera, A.; Balbontina, C.; González-Piqueras, J. Assessing satellite-based basal crop coefficients for irrigated grapes (*Vitis vinifera* L.). *Agr. Water Manag.* **2010**, *98*, 45–54. [\[CrossRef\]](#)
- Schymanski, S.J.; Or, D. Leaf-scale experiments reveal an important omission in the Penman–Monteith equation. *Hydrol. Earth Syst. Sci.* **2017**, *21*, 685–706. [\[CrossRef\]](#)
- Forster, M.A.; Kim, T.D.H.; Kunz, S.; Abuseif, M.; Chulliparambil, V.R.; Srichandra, J.; Michael, R.N. Phenology and canopy conductance limit the accuracy of 20 evapotranspiration models in predicting transpiration. *Agr. For. Meteorol.* **2022**, *315*, 108824. [\[CrossRef\]](#)
- Paço, T.A.; Ferreira, I.; Conceição, N. Peach orchard evapotranspiration in a sandy soil: Comparison between eddy covariance measurements and estimates by the FAO 56 approach. *Agr. Water Manag.* **2006**, *85*, 305–313. [\[CrossRef\]](#)
- Picón-Toro, J.; González-Dugo, V.; Uriarte, D.; Mancha, L.A.; Testi, L. Effects of canopy size and water stress over the crop coefficient of a “Tempranillo” vineyard in south-western Spain. *Irrig. Sci.* **2012**, *30*, 419–432. [\[CrossRef\]](#)
- Rallo, G.; Paço, T.A.; Paredes, P.; Puig-Sirera, À.; Massai, R.; Provenzano, G.; Pereira, L.S. Updated single and dual crop coefficients for tree and vine fruit crops. *Agr. Water Manag.* **2021**, *250*, 106645. [\[CrossRef\]](#)
- Villalobos, F.J.; Orgaz, F.; Testi, L.; Fereres, E. Measurement and modeling of evapotranspiration of olive (*Olea europaea* L.) orchards. *Eur. J. Agron.* **2000**, *13*, 155–163. [\[CrossRef\]](#)

20. Ortega-Farias, S.; Irmak, S.; Cuenca, R.H. Special issue on evapotranspiration measurement and modeling. *Irrig. Sci.* **2009**, *28*, 1–3. [\[CrossRef\]](#)
21. Rana, G.; Katerji, N.; Lorenzi, F. Measurement and modelling of evapotranspiration of irrigated citrus orchard under Mediterranean conditions. *Agr. For. Meteorol.* **2021**, *128*, 199–209. [\[CrossRef\]](#)
22. Nyolei, D.; Diels, J.; Mbilinyi, B.; Mbungu, W.; van Griensven, A. Evapotranspiration simulation from a sparsely vegetated agricultural field in a semi-arid agro-ecosystem using Penman-Monteith models. *Agr. For. Meteorol.* **2021**, *303*, 108370. [\[CrossRef\]](#)
23. Sarker, I.H. Machine Learning: Algorithms, Real-World Applications and Research Directions. *Sn Comput. Sci.* **2021**, *2*, 160. [\[CrossRef\]](#)
24. Yong, S.L.S.; Ng, J.L.; Huang, Y.F.; Ang, C.K. Estimation of evapotranspiration with three different machine learning models and limited meteorological variables. *Agronomy* **2023**, *13*, 1048. [\[CrossRef\]](#)
25. Mahesh, B. Machine learning algorithms—A review. *Int. J. Sci. Res.* **2020**, *9*, 381–386. [\[CrossRef\]](#)
26. Dou, X.; Yang, Y. Evapotranspiration estimation using four different machine learning approaches in different terrestrial ecosystems. *Comput. Electron. Agr.* **2018**, *148*, 95–106. [\[CrossRef\]](#)
27. Granata, F. Evapotranspiration evaluation models based on machine learning algorithms—A comparative study. *Agr. Water Manag.* **2019**, *217*, 303–315. [\[CrossRef\]](#)
28. Chen, Z.; Zhu, Z.; Jiang, H.; Sun, S. Estimating daily reference evapotranspiration based on limited meteorological data using deep learning and classical machine learning methods. *J. Hydrol.* **2020**, *591*, 125286. [\[CrossRef\]](#)
29. Yamaç, S.S.; Todorovic, M. Estimation of daily potato crop evapotranspiration using three different machine learning algorithms and four scenarios of available meteorological data. *Agr. Water Manag.* **2020**, *228*, 105875. [\[CrossRef\]](#)
30. WMO Guide to Instruments and Methods of Observation. *Measurement of Meteorological Variables*; World Meteorological Organization: Geneva, Switzerland, 2018. Available online: https://library.wmo.int/doc_num.php?explnum_id=10179 (accessed on 10 May 2023).
31. van Leeuwen, C.; Trégoat, O.; Choné, X.; Bois, B.; Pernet, D.; Gaudillère, J.-P. Vine water status is a key factor in grape ripening and vintage quality for red Bordeaux wine. How can it be assessed for vineyard management purposes? *OENO One* **2009**, *43*, 121–134. [\[CrossRef\]](#)
32. Ferreira, M.I. Stress Coefficients for Soil Water Balance Combined with Water Stress Indicators for Irrigation Scheduling of Woody Crops. *Horticulturae* **2017**, *3*, 38. [\[CrossRef\]](#)
33. Torres, A.F.; Walker, W.R.; McKee, M. Forecasting daily potential evapotranspiration using machine learning and limited climatic data. *Agr. Water Manag.* **2011**, *98*, 553–562. [\[CrossRef\]](#)
34. Zhang, Z.; Gong, Y.; Wang, Z. Accessible remote sensing data based reference evapotranspiration estimation modelling. *Agr. Water Manag.* **2018**, *210*, 59–69. [\[CrossRef\]](#)
35. Fernández-López, A.; Marín-Sánchez, D.; García-Mateos, G.; Ruiz-Canales, A.; Ferrández-Villena-García, M.; Molina-Martínez, J.M. A Machine Learning Method to Estimate Reference Evapotranspiration Using Soil Moisture Sensors. *Appl. Sci.* **2020**, *10*, 1912. [\[CrossRef\]](#)
36. Er-Raki, S.; Chehbouni, G.; Hoedjes, J.; Ezzahar, J.; Duchemin, B.; Jacob, F. Improvement of FAO-56 method for olive orchards through sequential assimilation of thermal infrared-based estimates of ET. *Agr. Water Manag.* **2008**, *95*, 309–321. [\[CrossRef\]](#)
37. Ramos, T.B.; Darouich, H.; Oliveira, A.R.; Farzadian, M.; Monteiro, T.; Nadia Castanheira, N.; Paz, A.; Gonçalves, M.C.; Pereira, L.S. Water use and soil water balance of Mediterranean tree crops assessed with the SIMDualKc model in orchards of southern Portugal. *Agr. Water Manag.* **2023**, *279*, 108209. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.

6.2. Article 2

Predicting the canopy conductance to water vapor of grapevines using a biophysical model in a hot and arid climate

Ricardo Egipto, Arturo Aquino and José Manuel Andújar

Journal: Frontiers in Plant Science (eISSN 1664-462X)

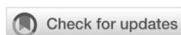
Editorial: Frontiers Media SA

Reference: Frontiers in Plant Science. 2024, 15, 1334215

DOI: 10.3389/fpls.2024.1334215

Year: 2024

Quality index (Journal Citation Reports®, 2023): 44/265 (Q1) in the category "Plant Sciences". Impact Factor of 4.1.



OPEN ACCESS

EDITED BY

Gastón Gutiérrez Gamboa,
Instituto de Investigaciones Agropecuarias,
Chile

REVIEWED BY

Luca Vitale,
National Research Council (CNR), Italy
Iván Francisco García-Tejero, IFAPA
Centro Las Torres Tomejil, Spain

*CORRESPONDENCE

Ricardo Jorge Lopes Egipto

✉ ricardo.egipto@iniav.pt

RECEIVED 06 November 2023

ACCEPTED 17 January 2024

PUBLISHED 06 February 2024

CITATION

Egipto RJL, Aquino A and Andújar JM (2024)
Predicting the canopy conductance to water vapor
of grapevines using a biophysical model in a hot
and arid climate. *Front. Plant Sci.* 15:1334215.
doi: 10.3389/fpls.2024.1334215

COPYRIGHT © 2024 Egipto, Aquino and Andújar.
This is an open-access article distributed under the
terms of the [Creative Commons Attribution License](#)
(CC BY). The use, distribution or reproduction
in other forums is permitted, provided the
original author(s) and the copyright owner(s)
are credited and that the original publication
in this journal is cited, in accordance with
accepted academic practice. No use,
distribution or reproduction is permitted which
does not comply with these terms.

Predicting the canopy conductance to water vapor of grapevines using a biophysical model in a hot and arid climate

Ricardo Jorge Lopes Egipto^{1*}, Arturo Aquino²
and José Manuel Andújar²

¹INIAV, I.P.—Instituto Nacional de Investigação Agrária e Veterinária, Pólo de Inovação de Dois Portos, Dois Portos, Portugal, ²CITES, Centro de Investigación en Tecnología, Energía y Sostenibilidad, Universidad de Huelva, Huelva, Spain

Canopy conductance is a crucial factor in modelling plant transpiration and is highly responsive to water stress. The objective of this study is to develop a straightforward method for estimating canopy conductance (g_c) in grapevines. To predict g_c , this study combines stomatal conductance to water vapor (g_{sw}) measurements from grapevine leaves, scaled to represent the canopy size by the leaf area index (LAI), with atmospheric variables, such as net solar radiation (R_n) and air vapor pressure deficit (VPD). The developed model was then validated by comparing its predictions with g_c values calculated using the inverse of the Penman Monteith equation. The proposed model demonstrates its effectiveness in estimating the g_c , with the highest root-mean-squared-error (RMSE = $1.45 \times 10^{-4} \text{ m.s}^{-1}$) being lower than the minimum g_c measured in the field ($g_{c \text{ obs}} = 0.0005 \text{ m.s}^{-1}$). The results of this study reveal the significant influence of both VPD and g_{sw} on grapevine canopy conductance.

KEYWORDS

grapevine, canopy conductance modeling, water stress in grapevines, vineyard water management, sustainable irrigation

1. Introduction

Mediterranean viticulture faces numerous constraints, notably those associated with climate changes and less favorable meteorological conditions. The increasing frequency and severity of extreme climate events, such as warmer and drier climate conditions, and intense heat waves coupled with severe droughts, are exerting significant pressure on the available water resources. Projections for future climate scenarios anticipate a continued increase in the occurrence and magnitude of such extreme weather events. These changes are expected to have a profound impact on irrigation water supply systems, which are already under strain (IPCC, 2019). This scenario introduces new challenges to Mediterranean viticulture, where irrigation has emerged as a pivotal short-term

adaptation measure. The effective implementation of grapevine irrigation requires a comprehensive understanding of the climate, soil, and water conditions specific to the vines. Additionally, accounting for their variability within the vineyard is essential, to manage the vine water stress while optimizing yield and berry composition (Chaves et al., 2016; Costa et al., 2016).

The Penman–Monteith method, describing evapotranspiration, considers soil and air humidity, mass transport and the energy required for the process (Monteith and Unsworth, 2013), and reflects the weather-related effects on crop water use (Allen et al., 1998; Pereira, 2004). However, this method has limitations related to soil and canopy conductance measurement (Paço et al., 2006; Picón-Toro et al., 2012; Rallo et al., 2021). Indeed, some of these limitations have been reported in the literature for sparsely planted, drip-irrigated crops, with significant exposed soil and a stringent stomatal control mechanism for water loss, such as grapevines (Shuttleworth and Wallace, 1985; Campos et al., 2010; Pereira et al., 2015; Schymanski and Or, 2017; Forster et al., 2022).

A simplified method for estimating evapotranspiration under conditions of minimal advection was formulated by Priestley and Taylor (1972). This model assumes the proportionality between the evaporation rate and available energy through a coefficient α , known as the Priestley–Taylor factor (Priestley and Taylor, 1972). This factor mitigates the uncertainties associated with the canopy resistance (Xu et al., 2021) and omits the aerodynamic term featured in the Penman–Monteith method (Pereira, 2004). Empirical findings suggest that the Priestley–Taylor parameter (α) is intricately linked to various physical factors influencing evapotranspiration (Pereira, 2004). Nevertheless, in addition to the requisite for local parameterization of α (Priestley and Taylor, 1972; Pereira, 2004), the model's efficacy in semiarid regions remains variable (Xiaoying and Erda, 2005; Shahidian et al., 2012; Kustas et al., 2022).

In 1985, Shuttleworth and Wallace developed a physical process-based model to address the evapotranspiration of sparse crops. This model presupposes that total evapotranspiration encompasses the evapotranspiration from both the soil surface and vegetation canopy, considering the coupled effects of vapor and energy exchanges between the soil surface and vegetation canopy (Shuttleworth and Wallace, 1985). Treating sparse crops using the same conceptual framework as the Penman–Monteith method — a two-component system governed by energy balance and aerodynamic principles (Stannard, 1993) — the model shares analogous limitations with the Penman–Monteith method, particularly significant uncertainties in the computation of canopy and soil surface resistances (Chen et al., 2022).

The development of remote sensing methodologies, facilitated by the aerial or satellite imaging and advancements in image processing, has facilitated the computation of evapotranspiration as a residual of the surface energy balance (McShane et al., 2017). These methodologies employ an analytical approach to estimate evapotranspiration based on physically derived models that combine ground-based and remote sensing data (Courault et al., 2005).

Surface energy balance (SEB) models can be categorized into two categories:

1. Single-source energy balance models analyze vegetation and soil within a unified energy budget, exemplified by the Surface Energy Balance Algorithm for Land (SEBAL) (Bastiaanssen et al., 1998) or the Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC) (Allen et al., 2007). Within this context, Mallick et al. (2014) proposed an alternative big-leaf method, that eliminates the necessity for the parametrization of surface and aerodynamic conductances, achieved by integrating the radiometric surface temperature into the Penman–Monteith equation. The Mallick et al. (2014) surface temperature-initiated closure (STIC) method, driven by surface temperature, air temperature, relative humidity, net radiation, and ground heat flux, facilitates the decomposition of evapotranspiration into its constituent components (Mallick et al., 2014).

2. Dual-source energy balance models analyze vegetation and soil energy budgets independently, encompassing models such as Two-Source Energy Balance (TSEB) model (Norman et al., 1995; Kustas and Norman, 1999), Atmosphere–Land Exchange Inverse (ALEXI) (Anderson et al., 1997), and clumped models accounting with the clumping of vegetation to estimate evaporation from soil and sparse crops (Brenner and Incoll, 1997).

Two-source energy balance models provide more accurate estimations of evaporation from crops with more or less extensive bare surfaces, e.g. orchards, whereas single-source energy balance models are most suited for estimating transpiration from vegetated surfaces (Tang et al., 2013). The use of the TSEB model under the advection of hot dry air masses from surrounding non-irrigated areas necessitates modifications to accurately estimate ET under such conditions, as well as to ascertain the partitioning between evaporation and transpiration (Kustas et al., 2022).

Although, the inclusion of resistance terms remains imperative in the Penman–Monteith equation to elucidate the conjoined impacts of water stress and stomatal resistance on the transfer of heat and water flux (Alves and Pereira, 2000; Schymanski and Or, 2017; Zhao et al., 2020). This necessity is observed not only in other micrometeorological methodologies such as those articulated by Shuttleworth and Wallace (1985) but also in residual methods embedded within the energy-balance equation, exemplified by models like TSEB (two-source energy balance model) introduced by Norman et al. (1995).

Noteworthy, to devise accurate irrigation strategies, the use of simple and non-destructive plant-based methods is essential. In this context, vineyard evapotranspiration is chiefly governed by factors such as stomatal conductance to water vapor (g_{sw}), net solar radiation (R_n), air vapor pressure deficit (VPD), air temperature (T_{air}) and wind speed (U) (Jarvis and McNaughton, 1986). Grapevine water status is significantly affected by soil moisture content, which

governs plant water supply, and by leaf transpiration, which controls plant water loss (Dry and Loveys, 1999; Buckley, 2017; Levin et al., 2019). Both these factors influence the regulation of g_{sw} (Chaves et al., 2010; Costa et al., 2012; Buckley and Mott, 2013; Buckley, 2017; Levin and Nackley, 2021). Several studies aiming to identify water stress thresholds in grapevines have focused on using g_{sw} as a key indicator, especially for deficit irrigation strategies (Jones, 2004). However, factors such as genotype, leaf distribution within the canopy, exposure to sunlight, and high spatio-temporal variability within the vineyard have constrained the direct use of g_{sw} (Fernández and Cuevas, 2010; Bota et al., 2016).

Canopy conductance to water vapor (g_c) plays a pivotal role in regulating water and heat exchange within the soil-plant-atmosphere continuum. It represents one of the most responsive variables to water stress in grapevines. The value of g_c lies in its ability to elucidate the division of R_n between latent heat and sensible heat fluxes (Monteith, 1995), thereby influencing plant transpiration. As the canopy acts to stabilize the considerable variability in g_{sw} across individual leaves, g_c offers a suitable spatio-temporal measure of stomatal response to soil water and atmospheric conditions within the boundary layer (Avisar, 1993; Damour et al., 2010; Fuentes et al., 2012; Wu et al., 2022). Consequently, it allows the identification of temporal and spatial patterns of water stress in the vineyard (Zhai et al., 2020).

While g_c can be estimated by inverting the Penman-Monteith equation (Monteith and Unsworth, 2013), the complexity and feasibility constraints of its parameterization have led to the proposal of alternative methods for estimating g_c in grapevines. These models are categorized based on how they aggregate canopy properties and account for atmospheric properties that influence the canopy. The simplest, big-leaf (BL) models, scale the leaf g_{sw} to the entire canopy, treating it as a single leaf (Baldocchi et al., 1967; Todorovic, 1999; Zhang et al., 2008). On the other hand, the two leaf models consider the contributions of the sunlit and shaded leaf fractions, scaling them using the associated g_{sw} weighted by their respective fractions of the leaf area index (LAI) (Leuning et al., 1995; Wang and Leuning, 1998; Ding et al., 2014). Lastly, the multilayer models, assume spatial independence of leaf gas exchange properties and consider atmospheric properties' variation across canopy layers (Baldocchi and Meyers, 1998; Chen et al., 1999).

This article evaluates the accuracy of a biophysical model based on a BL approach that utilizes g_{sw} from leaves with contrasting sun exposure, scaled to the canopy size by the LAI, along with variables such as R_n and air VPD, to estimate g_c . The model's validity is established through comparison with g_c measurements derived from the gold-standard inverse Penman-Monteith method (Monteith and Unsworth, 2013). The outcomes reveal that the proposed model, grounded in both plant and atmospheric variables, proficiently predicts g_c , thus positioning it as a promising indicator for assessing grapevine stress.

2. Material and methods

2.1. Location and experimental layout

Field experimentation was carried out in an experimental vineyard known as Herdade do Esporão, located in Reguengos de Monsaraz, within the Alentejo wine growing region in southern Portugal (latitude 38° 23' 55.00" N; longitude 7° 32' 46.00" W). For this study, the red *Vitis vinifera* cv. Tempranillo variety, grafted onto 1103 Paulsen rootstock, was selected. The vineyard encompasses a density of 2220 vines per hectare, with a spacing of 1.5 meters within rows and three meters between rows, all north-south oriented. The vines are trained on a vertical shoot positioning system and are uniformly pruned, maintaining 15 to 16 buds per vine in a bilateral Royat cordon system. The soil, identified as an Eutric Cambisol (CM), has a depth of approximately one meter and features a silty-clay-loam texture. Standard cultural practices prevalent in the region were employed. Irrigation followed the vineyard owners' practices, with an average application of 140 mm of water from the berry set to harvest (approx. 30% crop evapotranspiration, ET_c).

Data collection was carried out on the 20th of August 2019, the 29th of July 2020, the 8th and 15th of July 2021, and the 12th of August 2021, from 9:00 am to 7:00 pm, as detailed in section 2.3. For this purpose, 20 vines evenly distributed were selected along two adjacent rows, with 10 vines in each row. This arrangement allowed for a thorough examination of the impact of solar radiation, as it enabled the study of both sides of the canopy (east and west) under varying incident radiation conditions.

To ensure the measurements' accuracy, and to mitigate any potential influence from soil water evaporation, measurements were carried out at least five days after the most recent irrigation, thus ensuring that fluctuations in the soil surface's water content did not confound the readings. This precaution was crucial to guarantee that, under these controlled conditions, no soil evaporation was observed. To confirm the negligible impact of soil evaporation, the soil water content was continuously monitored beneath the grapevine canopy in the top 10 cm of the irrigated soil portion. To this effect, the readings of two ML3 Thetaprobe sensors (Delta-T devices, Cambridge, UK) were collected every 15 minutes and registered into a datalogger (CR1000, Campbell Scientific, Inc., Logan, UT, USA) for convenient analysis. In addition to soil measurements, the vines water condition was evaluated by measuring the pre-dawn leaf water potential (ψ_{PD}), by using a Scholander type pressure chamber on each measurement day. This measure provides valuable insights into the water status of the grapevines.

2.2 Biophysical model proposal to predict canopy conductance to water vapor. Theoretical development

The central objective of this study is to develop an effective grapevine canopy conductance model capable of accurately representing the grapevine's response to water scarcity, increased solar irradiance, and high atmospheric water demand. The modelling approach encompasses the considerations and assumptions described below.

In the context of the Mediterranean climate, the summer season is characterized by reduced precipitation levels,

abundant solar radiation, high air temperatures, and elevated atmospheric evaporative demand. Consequently, grapevines experience pronounced water and heat stress during this period (Chaves et al., 2016). To optimize the utilization of available solar radiation and facilitate vineyard management, grapevines are typically arranged in rows. This configuration results in a low canopy profile, which significantly increases the portion of soil directly exposed to evaporation (Costa et al., 2019; Costa et al., 2023). As the grapevines reach their maximum vegetative growth during the veraison stage, soil water availability rapidly diminishes, thus requiring irrigation intervention. Drip irrigation systems are typically positioned beneath the grapevine canopy to meet the plants' water requirements. Moreover, irrigation often falls short of meeting the actual crop needs, particularly with deficit irrigation strategies, which limit soil water evaporation. Accurately partitioning evapotranspiration into its constituent elements, plant transpiration and soil water evaporation, becomes especially relevant in arid environments, making it a crucial source of information for water management decisions (Kool et al., 2014).

The primary regulation of vine transpiration is through stomata, which responds to changes in atmospheric demand and soil water availability, as explained by Chaves et al. (2010); Chaves et al. (2016). Consequently, a simplification of the Penman-Monteith approach has been employed, assuming a similarity between canopy resistance and the integration of leaf stomatal resistances under dry conditions (Shuttleworth and Wallace, 1985). Analogous to Ohm's law, this model considers the proportional relationship between canopy conductance and the available energy for evaporation (R_n), as well as the inverse relationship with stomatal resistance (Lhomme, 1991; Alfieri et al., 2008). Additionally, the model accounts for changes in canopy conductance induced by air vapor pressure deficit (VPD) (Wang and Leuning, 1998; Lu et al., 2003; Chaves and Oliveira, 2004; Buckley, 2005; Rogiers et al., 2012; Buckley and Mott, 2013; Klein, 2014; Sperry et al., 2017; Luo et al., 2018; Zhu et al., 2022; Zhong et al., 2023). VPD is closely linked to climatic conditions, and variations in stomatal conductance (g_{sw}) responses to VPD may be associated with varying levels of atmospheric dryness (Rogiers et al., 2012; Grossiord et al., 2020; Liu et al., 2020; Zhong et al., 2023). Furthermore, VPD accounts for the difference between the actual moisture content in the air and the moisture it could hold at saturation (Allen et al., 1998), thereby affecting soil and canopy evaporation. As a result, a comprehensive model that considers all parameters governing energy exchange and the corresponding latent heat flux has been developed. This model estimates canopy conductance, $g_{c\ est}$, based on factors such as energy inputs, R_n , atmospheric demand, VPD, leaf stomatal conductance, g_{sw} , and leaf area index, LAI. This approach accounts for the spatial independence of leaf gas exchange characteristics within sunlit and shaded leaves, while also considers the distinct atmospheric conditions present in these various canopy layers.

Thus, the proposed model to estimate canopy conductance, $g_{c\ est}$, is calculated as follows:

$$g_{c\ est} = f(LAI, g_{sw}, R_n, VPD) = LAI \cdot \left(g_{sw} \cdot \frac{R_n}{VPD} \right)^{0.5} \quad (m.s^{-1}) \quad (1)$$

where LAI is the dimensionless leaf area index, g_{sw} is the leaf stomatal conductance measured in $m.s^{-1}$ for both sunlit and shaded leaves, R_n stands for the net solar radiation at the canopy level, measured in $MJ.m^{-2}.h^{-1}$, and VPD represents the air vapor deficit, measured in Pa. Air VPD is calculated from relative humidity, RH, and air temperature, T_{air} , by applying the following Equations (2-5) defined by Allen et al. (1998):

$$VPD = e_s - e_a \quad (Pa) \quad (2)$$

where

$$e_a = e_0(T_{air}) \cdot \frac{RH}{100} \quad (3)$$

$$e_0(T_{air}) = 0.6108 \times e^{\left[\frac{(17.27 \cdot T_{air})}{(T_{air} + 237.3)} \right]} \quad (4)$$

and

$$e_s = \frac{[e_0(T_{min}) + e_0(T_{max})]}{2} \quad (5)$$

being T_{min} and T_{max} the minimum and maximum air temperature ($^{\circ}C$) registered for a given period, respectively.

The proposed model is designed to maintain the dimensions of the dependent variable $g_{c\ est}$ [$L.T^{-1}$], where L represents length, and T represents time. This modelling process accounts for the influence of environmental factors and the regulation of stomata on grapevine leaves, thus contributing to the overall behavior of the canopy surface conductance.

2.3. The reference method, the inverted Penman-Monteith equation

The Penman-Monteith method (Monteith and Unsworth, 2013) is a widely recognized tool to estimate canopy conductance (g_c), so it is used as gold-standard reference to assess goodness of the biophysical model proposed in this paper.

Motivated by the absence of significant soil evaporation, as explained in section 2.1, the bulk surface conductance (g_s) was assumed to be solely determined by the canopy conductance (g_c) (Allen et al., 1998). As a result, the observed canopy conductance ($g_{c\ obs}$), used to validate the proposed model, was calculated from the inverted Penman - Monteith equation, according to the formulation proposed by Lhomme et al. (2012), as follows:

$$g_{c\ obs} = \frac{\gamma \lambda E_c g_a}{\Delta R_n + k_t \rho C_p VPD g_a - \lambda (\Delta + \gamma) E_c} \quad (m.s^{-1}) \quad (6)$$

where:

- R_n is net radiation ($MJ.m^{-2}.h^{-1}$).
- k_t is a time unit conversion ($3600\ s.h^{-1}$).
- λ is the latent heat of water vaporization ($2.45\ MJ.kg^{-1}$).
- C_p is the dry air specific heat at constant pressure ($0.001013\ MJ.kg^{-1}.^{\circ}C^{-1}$).
- VPD is air vapor pressure deficit as defined in Equation 2.
- E_c is canopy transpiration in $mm.h^{-1}$ units.
- γ is the psychrometric constant, calculated according to Allen et al. (1998) by the Equation 7:

$$\gamma = \frac{c_p \cdot P}{\varepsilon \cdot \lambda} \quad (kPa \cdot ^\circ C^{-1}) \quad (7)$$

where ε is the ratio of the molecular weight of water vapor/dry air (dimensionless and equal to 0.622), P is the atmospheric pressure, depending only on the local elevation above sea level (220 m in this study), and equal to 98.726 kPa, and λ and C_p are the previously mentioned latent heat of vaporization and dry air specific heat at constant pressure, respectively.

• g_a is the aerodynamic conductance, as defined by Equation 8 (Granier et al., 2000):

$$g_a = \frac{k^2 U_z}{\ln[(z_m - d)/z_{om}] \ln[(z_m - d)/z_{ov}]} \quad (m \cdot s^{-1}) \quad (8)$$

where k is the von Karman's constant (0.41), U_z is wind speed at height z_m ($m \cdot s^{-1}$) (Monteith and Unsworth, 2013), z_m is the height of wind speed and humidity measurements (3 m in this study), d is the zero-plane displacement height (m), and z_{om} and z_{ov} are the roughness lengths governing transfer of momentum and water vapor (m). The quantities d , z_{om} and z_{ov} were estimated using $d = 2h/3$, $z_{om} = 0.123 \cdot h$ and $z_{ov} = 0.1 \cdot z_{om}$, where h is canopy height (averaged as 1.7 m in this study) (Allen et al., 1998).

• Δ is the vapor pressure curve's slope, as defined by Equation 9 Allen et al. (1998):

$$\Delta = \frac{4098 \times e_0(T_{air})}{(T_{air} + 237.3)^2} \quad (9)$$

where $e_0(T_{air})$ is the saturation vapor pressure at air temperature T_{air} , computed in kPa according to the Equation 4.

• ρ is air density, calculated according to Equation 10:

$$\rho = \frac{P}{[1.01 \times (T_{air} + 237.3) \times R]} \quad (10)$$

where P and T_{air} are the previously mentioned atmospheric pressure and air temperature, and R is the specific gas constant ($287 J \cdot kg^{-1} \cdot K^{-1}$).

2.4. Field and reference measurements

2.4.1. Climate and grapevine water status

The climate is of Mediterranean type, with hot and dry summers and mild rainy winters. Rainfall accumulated from winter to flowering ranged from 338 to 535 mm between 2019 and 2021. The maximum precipitation recorded in the three years from berry set to full ripening (June to August) was 13.4 mm in 2021 (Table 1). There were no recorded instances of rain events during the analyzed period, and none of the measurements were taken under cloudy conditions.

Overall, the predawn leaf water potential (Ψ_{PD}) measurements consistently indicated moderate to severe water stress, which is considered adequate for producing high-quality vintages (Deloire et al., 2005; van Leeuwen et al., 2009). Moreover, the readings showed a contained maximum variation of 0.1 Mpa between the minimum and maximum observed values (Table 2).

2.4.2. Field measurement of key variables

This section describes the in-the-field measurement of key variables involved in the calculation of the proposed biophysical model (section 2.2, Equation 1), and of the reference inverted Penman-Monteith equation (section 2.3, Equation 6).

Under the experimental conditions described in section 2.1, where soil evaporation was found to be negligible, actual crop evapotranspiration ($ET_{c \text{ act}}$) served as a suitable proxy for vine transpiration (E_c). The measurements of E_c were conducted concurrently with those of wind speed, U , at a high temporal resolution (every 1/10 s), this to capture fine-scale variations in transpiration dynamics. The equipment employed to this end, was composed of an eddy covariance system comprising a fast-response, 0.1 Hz, open-path CO₂/H₂O analyzer (LI-6500 DS, LI-COR Inc., Lincoln, NE, USA), along with a 3D sonic anemometer (Gill Windmaster Pro, Gill Instruments Limited, Hampshire, UK). For experimental requirements, the eddy covariance system was installed over the top of the canopy, concretely at a height of 3.0 m above the ground surface. The acquired data underwent processing using EddyPro software v7.0.6

TABLE 1 Rainfall figures within the experimentation window: rainfall registered during the grapevine dormancy period, which spans from October (Oct) to December (Dec) of the previous vintage year [Year (i-1)]; rainfall registered during the period from dormancy to flowering (January (Jan) to May); rainfall registered during the period from berry development to grape ripening [June (Jun) to August (Aug)] of the current vintage year [Year (i)]; and accumulated rainfall from October of the vintage previous year to August (Aug).

Year (i)	Rainfall (mm)			
	Year (i-1)	Year (i)		Accum
	Oct-Dec	Jan-May	Jun-Aug	Oct-Aug
2019	204.4	133.6	3.4	341.4
2020	226.0	239.0	1.2	466.2
2021	249.8	285.4	13.4	548.6

TABLE 2 Predawn leaf water potential (ψ_{PD}) figures measured at the predawn on the 20th of august 2019, the 29th of July 2020, the 8th and 15th of July 2021, and the 12th of August 2021

DAY	ψ_{PD} (MPa)	
	Mean	SE
20-08-2019	-0.60	0.012
29-07-2020	-0.55	0.017
8-7-2021	-0.50	0.010
15-7-2021	-0.50	0.010
12-8-2021	-0.60	0.015

Data are presented by the means (Mean) and standard error of the mean (SE) of 5 repetitions by day.

(LI-COR Inc., Lincoln, NE, USA) for the purpose of quality testing and analysis. The data collection setup was designed to cover a fetch distance of at least 300 m, aligned with the prevailing northerly winds, thereby ensuring comprehensive measurement of fluxes within the designated area of interest. The utilization of EddyPro software played a crucial role in quality assessment and analysis, revealing that over 90% of the daily data flux within the analyzed dataset exhibited an energy balance closure greater than 0.95.

Air temperature (T_{air}) and relative humidity (RH) were recorded using a thermohygrometer (CS215-PWS, Campbell Scientific, Inc., Logan, UT, USA), which was positioned at a height of 2.0 m above the ground, and thus over the canopy. Additionally, net radiation (R_n) over the canopy was quantified using a net radiometer (NR2, Delta-T Devices, Cambridge, UK), also positioned above the canopy. All these soil and meteorological sensors were integrated into a datalogger (CR1000, Campbell Scientific, Inc., Logan, UT, USA), which addressed data saving at every minute.

The Leaf area Index (LAI) of grapevines was determined using a non-destructive allometric method applied to the 20 grapevines selected for the research. The method by [Lopes and Pinto \(2005\)](#) was utilized to compute the entire area of grapevine leaves. Thus, LAI was estimated from the overall leaf area divided by the area occupied by each individual vine, being measured on four occasions: the 21st of August 2019, the 24th of July 2020, the 14th of July 2021, and the 16th of August 2021. Water vapor gas exchange was assessed by hourly measurements of stomatal conductance (g_{sw}) on mature leaves from both sides of the canopy, using a steady-state porometer (LI-1600, LI-COR, Lincoln, NE, USA).

[Table 3](#) summarizes key information related to the described variables measured in the field.

2.5. Implementation and evaluation

2.5.1. Implementation of the proposed biophysical model. Data processing and analysis

In order to assess the accuracy of the proposed biophysical model ([Equation 1](#)), a dataset was built including the implied

TABLE 3 Summary of field measurements.

Variable measurements	
Canopy transpiration (E_c)	
Source	LICOR Model LI-6500 DS, (LI-COR Inc., Nebraska USA) eddy covariance system. Measured when soil evaporation was found to be negligible.
Periodicity	Every 1/10 seconds
Units	mm.h ⁻¹
Net radiation (R_n)	
Source	Net radiometer, model NR2, (Delta-T Devices, Cambridge, UK) connected to a datalogger (CR1000, Campbell Scientific, Inc., Logan, UT, USA)
Periodicity	Every minute
Units	MJ.m ⁻² .h ⁻¹
Air Temperature (T_{air})	
Source	Thermohygrometer Model CS215-PWS (Campbell Scientific, Inc., Logan, UT, USA), connected to a datalogger (CR1000, Campbell Scientific, Inc., Logan, UT, USA)
Periodicity	Every minute
Units	°C
Relative Humidity (RH)	
Source	Thermohygrometer Model CS215-PWS (Campbell Scientific, Inc., Logan, UT, USA), connected to a datalogger (CR1000, Campbell Scientific, Inc., Logan, UT, USA)
Periodicity	Every minute
Units	%
Wind speed (U)	
Source	3D sonic anemometer (model GillWindmaster Pro, Gill Instruments Limited, Hampshire, UK)
Periodicity	Every 1/10 seconds
Units	m.s ⁻¹
Stomatal conductance to water vapor (g_{sw})	
Source	Steady state porometer (Model LI-1600, LI-COR Lincoln, NE, USA)
Periodicity	Hourly from 9 am to 7 pm
Units	m.s ⁻¹
Leaf area index (LAI)	
Source	Non-destructive allometric method applied to compute the entire area of grapevine leaves (Lopes and Pinto, 2005). The LAI was estimated from the overall leaf area divided by the area occupied by each individual vine.
Periodicity	On the 21 st of August 2019, the 24 th of July 2020, the 14 th of July 2021, and the 16 th of August 2021
Units	m ² .m ⁻²

This table provides a comprehensive summary of the field measurements used in the study, including the measurement name, data collection periodicity, units of measurement, and the source equipment for each measurement.

Variables measured in the field and included in Table 3. Namely:

- Leaf area index (LAI, $m^2.m^{-2}$).
- Net solar radiation (R_n , $MJ.m^{-2}.h^{-1}$).
- Air vapor pressure deficit (VPD, Pa), calculated according to Equation 2 from the measured variables RH and T_{air} ($^{\circ}C$).
- Stomatal conductance to water vapor (g_{sw} , $mol.m^{-2}.s^{-1}$).

To make the proposed method suitable for scaling to canopy dimensions, note that LAI was considered as a factor in Equation 1. Notwithstanding, LAI measured values of the selected vines throughout the three seasons covered during the experimentation, was always in the range 1.91 to 2.0 $m^2.m^{-2}$, so a mean value of 1.96 $m^2.m^{-2}$ was used in practice. To ensure consistency in modelling and facilitate unit compatibility, the units of g_{sw} were converted to $m.s^{-1}$ by using the molar density of air ($mol.m^{-3}$). On the other hand, to mitigate the influence of very low net solar radiation (R_n) on stomatal opening, data collected before 10 am and after 6 pm, when R_n was below 0.60 $MJ.m^{-2}.h^{-1}$, were excluded. This exclusion respects the principles established by Granier et al. (2000). No outliers were identified using the interquartile range (IQR) method with a cut-off of 1.5 times the IQR. Consequently, the final dataset included 550 measurements of g_{sw} , R_n , and air VPD, along with the mean value of LAI.

2.5.2. Methodology for model evaluation

The evaluation of the model involved fitting the estimated canopy conductance values, $g_{c\ est}$, given by the model proposed in this study (Equation 1), to the observed canopy conductance values, $g_{c\ obs}$, obtained by using the inverse Penman-Monteith equation (Equation 6). Thus, the predictive potential of the model is firstly quantified by using the Pearson's coefficient of correlation (R). Additionally, the following accuracy measures were used:

1. The Root-Mean-Square Error (RMSE), measuring the overall deviation between predicted and observed canopy conductance values, defined by Equation 11 as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (g_{c\ est}^i - g_{c\ obs}^i)^2}{n}} \quad (11)$$

2. The Mean Absolute Error (MAE), measuring the absolute error between estimated and observed g_c , was determined using Equation 12:

$$MAE = \frac{\sum_{i=1}^n |g_{c\ est}^i - g_{c\ obs}^i|}{n} \quad (12)$$

3. The Relative Error ($|E|$), quantifying the estimation error as a percentage of the observed value, was determined by Equation 13:

$$|E| = \frac{|\sum_{i=1}^n (g_{c\ est}^i - g_{c\ obs}^i)|}{\sum_{i=1}^n g_{c\ obs}^i} \times 100 \quad (13)$$

In the presented formulas, $g_{c\ est}^i$ is the i -th g_c value estimated by the proposed model formulated in Equation 1, from the dataset of $n=550$ elements, and $g_{c\ obs}^i$ is the i -th observed g_c value given by the Penman-Monteith equation, calculated on the same dataset.

Model Evaluation processes were implemented using Matlab R2021b (The Mathworks Inc.).

3. Results and discussion

3.1. Characterization and variance of canopy conductance predictors

Figure 1 represents the hourly variation of canopy conductance to water vapor, $g_{c\ obs}$, calculated with the Penman Monteith's method (Equation 6). As it can be observed, it exponentially increased from sunrise to a peak of approximately 0.0028 $m.s^{-1}$ at 10 am, and then gradually decreased until the end of the day to a minimum of 0.0005 $m.s^{-1}$ at 7 pm. Hourly variation of the biophysical variables used in the proposed model formulated in Equation 1, measured at the experimental plot during defined period, are presented in Figure 2; namely: stomatal conductance to water vapor (g_{sw} , $m.s^{-1}$), net solar radiation above the canopy (R_n , $MJ.m^{-2}.h^{-1}$), and air vapor pressure deficit (VPD, Pa). The plot shows an inverted trend of g_{sw} to the daily variation of air VPD. Since no highly severe water stress was imposed to the vines, the maximum g_{sw} value was attained between 10:00 and 12:00 hours, when stomata were not limited either by the available R_n (Jones et al., 2002) neither air VPD (Rogiers et al., 2012; Zhong et al., 2023).

Figure 3 provides box and whisker plots of the biophysical variables used in the proposed model. The statistical characterization of $g_{c\ obs}$, is also shown, which revealed a tight clustering of the data around the mean. A subsequent analysis of $g_{c\ obs}$, also showed a strong and significant correlation with the biophysical variables used in the proposed model (see Table 4). Similar results were referred by Monteith (1995); Wang and Leuning (1998); Irmak et al. (2008); Lhomme et al. (2012); Ding et al. (2014) or Wu et al. (2022). As indicated in Table 4, when considering all the variables used to calculate $g_{c\ obs}$, it is worth noting that only measured wind speed, U , exhibited a weak correlation with the observed changes in canopy conductance ($g_{c\ obs}$). This observation is consistent with findings previously reported by Lhomme (1991). Consequently, wind speed was not included as a predictor in the proposed model.

Since no precipitation fell during the measurement periods, no evaporation was registered from the soil between the vine rows. Furthermore, no fluctuations were found in terms of water content in the soil surface under the vines either, thus corroborating the absence of evaporation on the measurement days. Under these conditions, actual crop evapotranspiration, $ET_{c\ act}$, was strongly

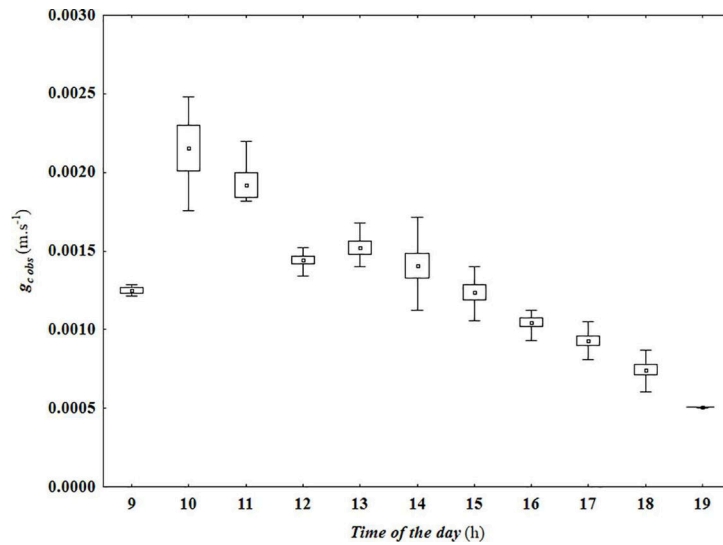


FIGURE 1

Hourly variation of canopy conductance to water vapor ($g_{c,obs}$, $m.s^{-1}$), calculated using the inverted Penman-Monteith equation (Equation 6), using the variables measured at the experimental plot. Data are represented by their mean ($\bullet$), 95% confidence interval ($\square$), and respective non-outlier range ($\times$).

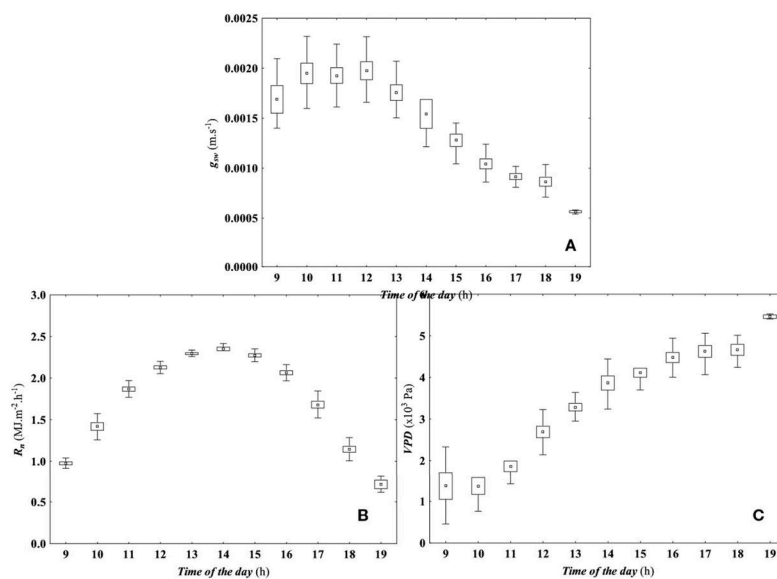


FIGURE 2

Hourly variation of canopy conductance predictors. The figure shows the hourly variation of key canopy conductance predictors, including (A) stomatal conductance to water vapor (g_{sw} , $m.s^{-1}$), (B) net solar radiation above the canopy (R_n , $MJ.m^{-2}.h^{-1}$), and (C) air vapor pressure deficit (VPD, Pa). The figure illustrates the diurnal patterns of these predictors during the experimental period. Data are represented by their mean ($\bullet$), 95% confidence interval ($\square$), and respective non-outlier range ($\times$).

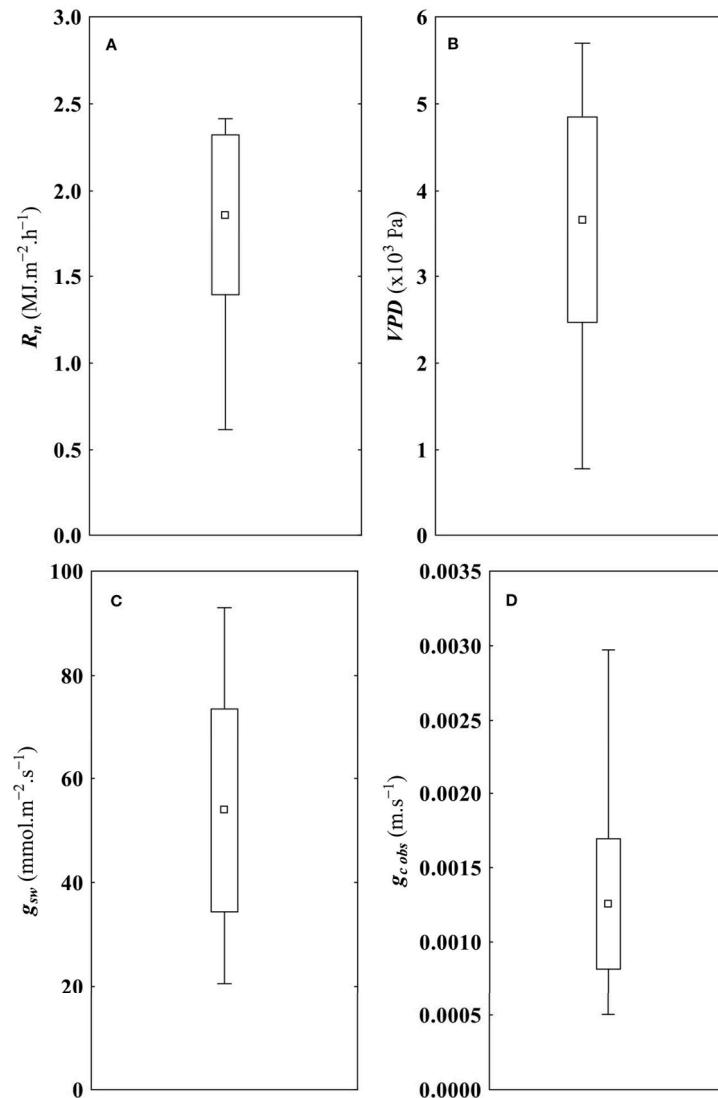


FIGURE 3

Characterization of model predictors and response variables. (A) Net solar radiation above the canopy (R_n), (B) air vapor pressure deficit above the canopy (VPD), (C) leaf stomatal conductance to water vapor (g_{sw}), and (D) canopy conductance calculated by Penman Monteith method using canopy transpiration (E_c) registered on an eddy covariance flux tower as input ($g_{c\text{ obs}}$). The data are characterized by the mean ($\square$), the standard deviation range ($\square$) and the respective minimum and maximum value ($\top$) of each variable. (N = 550).

related to vine transpiration, E_c , and strongly controlled by canopy conductance, g_c (Table 5). Similar results were presented by Lu et al. (2003).

On a Typical Mediterranean summer day, there is an abundance of solar radiation and high temperatures, along with low relative humidity, resulting in elevated air VPD. Under these circumstances, grapevines undergo significant water and heat stress from midday until the day's end (Chaves et al., 2016). Figure 4 depicts how $g_{c\text{ obs}}$ fluctuates during a typical Mediterranean day in response to g_{sw} , R_n ,

and air VPD. Following the available solar radiation, $g_{c\text{ obs}}$ increased rapidly after sunrise, reaching a maximum of approximately 0.003 m.s^{-1} at 10 a.m (Figure 4B). As also mentioned by Rogiers et al. (2012), it is noteworthy that air VPD did not appear to limit g_{sw} during this period (Figures 2A, C and 4A). Subsequently, g_{sw} began to decrease as air VPD increased (Figures 2A, C, 4A). In addition, $g_{c\text{ obs}}$ started a progressive decrease until reaching 0.0005 m.s^{-1} at 6 pm (Figures 1, 4A–C).

TABLE 4 Correlation matrix between the reference canopy conductance ($g_{c\text{ obs}}$) calculated with the inverted Penman-Monteith equation, and field data measured at the experimental plot: net solar radiation above the canopy (R_n), air vapor pressure deficit (VPD), stomatal conductance to water vapor (g_{sw}), and wind speed (U).

	$g_{c\text{ obs}}\text{ (m.s}^{-1}\text{)}$			
	R_n ($MJ.m^{-2}.h^{-1}$)	VPD (Pa)	g_{sw} ($m.s^{-1}$)	U ($m.s^{-1}$)
20 Aug 2019 sig.	0.833 ***	−0.962 ***	0.773 ***	−0.282 n.s.
29 Jul 2020 sig.	0.858 ***	−0.832 ***	0.994 ***	−0.221 n.s.
8 Jul 202 sig.	0.866 ***	−0.811 ***	0.849 ***	−0.298 n.s.
15 Jul 2021 sig.	0.831 ***	−0.871 ***	0.963 ***	−0.354 n.s.
12 Aug 2021 sig.	0.893 ***	−0.866 ***	0.969 ***	−0.265 n.s.

Significance levels: n.s. (not significant); * (significant differences at a 90% confidence level); ** (significant differences at a 95% confidence level); *** (significant differences at a 99% confidence level).

3.2. Model performance evaluation results

Table 6 presents the accuracy measures of the proposed biophysical model (Equation 1) used to estimate canopy conductance ($g_{c\text{ est}}$). These quantitative accuracy metrics allows to assess the extent to which the model’s predictions align with those given by the reference method, i.e., the observed canopy conductance ($g_{c\text{ obs}}$) given by the inverted Penman-Monteith equation (Equation 6).

The model’s estimations demonstrate a high degree of agreement with the reference dataset obtained by calculating the inverted Penman-Monteith equation. Furthermore, the model’s metrics for residuals deviation, which evidence the discrepancies between the observed and estimated values of $g_{c\text{ est}}$, are notably lower than the minimum $g_{c\text{ obs}}$, in the context of the statistical profile represented in Figure 3D. It is important to emphasize that all goodness-of-fit metrics underscore the model’s robustness within the specific conditions of the study.

TABLE 5 Correlation matrix between the reference canopy conductance ($g_{c\text{ obs}}$) calculated with the inverted Penman-Monteith equation, and the field data vine transpiration (E_c) measured at the experimental plot.

	VPD ≤ 3 kPa	VPD > 3 kPa
20 Aug 2019 sig.	−0.962 ***	0.895 ***
29 Jul 2020 sig.	−0.832 ***	0.985 ***
8 Jul 2021 sig.	−0.811 ***	0.972 ***
15 Jul 2021 sig.	−0.871 ***	0.930 ***
12 Aug 2021 sig.	−0.866 ***	0.988 ***

Significance levels: n.s. (not significant); * (significant differences at a 90% confidence level); ** (significant differences at a 95% confidence level); *** (significant differences at a 99% confidence level).

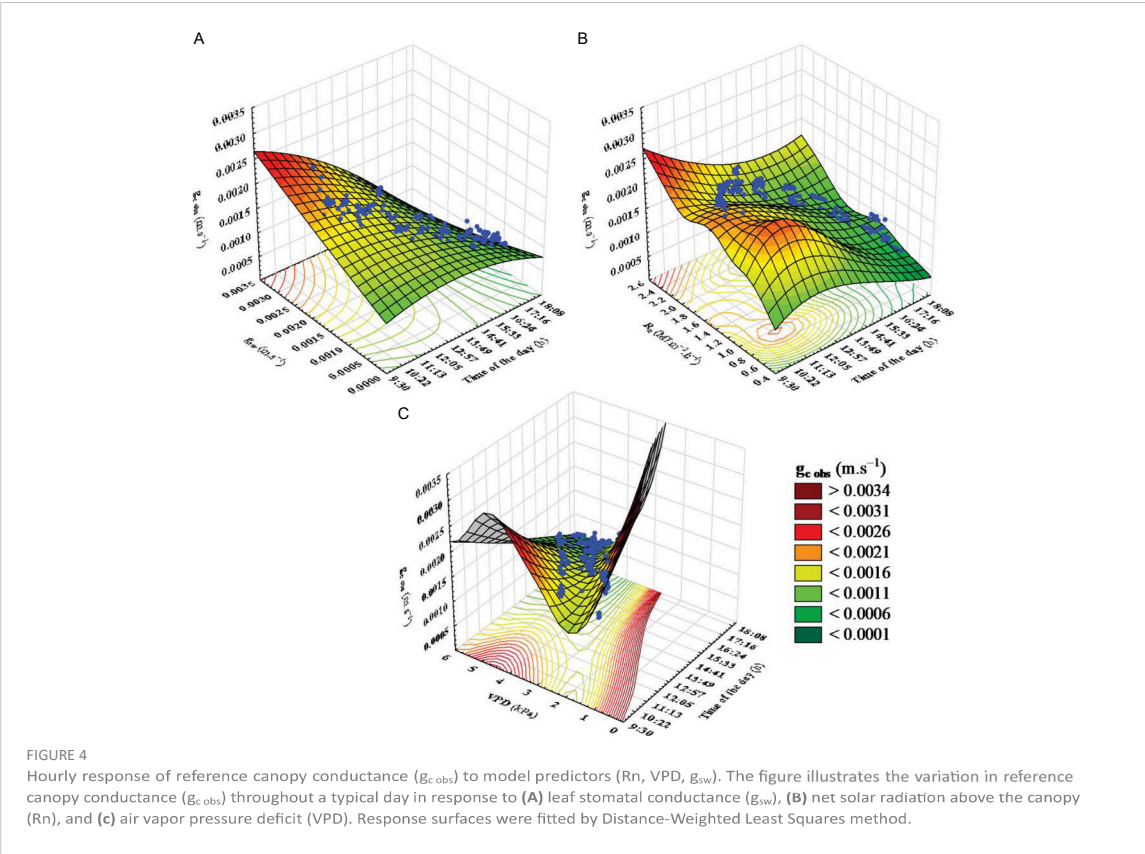
The data is categorized into two groups based on the vapor pressure deficit (VPD) conditions: VPD ≤ 3 kPa (morning) and VPD > 3 kPa (afternoon).

Figure 5 shows the scatterplot depicting the linear relationship between $g_{c\text{ obs}}$ values and $g_{c\text{ est}}$ values. As it can be checked, the obtained linear regression closely aligns with the 1:1 line, which indicates proper model fitting. Indeed, the estimated data exhibits a very high and statistically significant coefficient of correlation ($r = 0.956$, $p < 0.0001$) with the observed values. Notably, at a 95% confidence level, most of the plotted data falls within the prediction interval. However, a tendency to overestimate the reference canopy conductance, particularly for smaller $g_{c\text{ obs}}$ values near the intercept point, can be noticed. To access the significance of the model’s overestimation near the intercept point (β_0), a hypothesis test was conducted to determine whether the intercept of the least-squares regression between $g_{c\text{ obs}}$ and $g_{c\text{ est}}$, could be considered null ($\beta_0 = 0$). This null hypothesis (H_0 : $\beta_0 = 0$) was tested using a t-Student’s statistic (Eisenhauer, 2003). The simple linear regression between the observed and estimated canopy conductance was defined by Equation 14 as:

$$g_{c\text{ est}} = \beta_0 + \beta_1 \cdot g_{c\text{ obs}} + e_i \tag{14}$$

where β_0 is the intercept, β_1 is the slope, and e_i denotes the i th residual.

The results showed that the null hypothesis (H_0) cannot be rejected ($p = 0.124$), leading to the use of a regression through the origin, considering $\beta_0 = 0$, to compare the model estimates with the reference values. This least square regression between $g_{c\text{ obs}}$ and $g_{c\text{ est}}$ ($g_{c\text{ est}} = 1.051 \cdot g_{c\text{ obs}}$) also exhibited a very high and statistically significant coefficient of correlation ($r = 0.995$, $p < 0.0001$) between the observed and estimated $g_{c\text{ est}}$ values (Figure 5). The model’s ability to make accurate predictions is highlighted when we compare the estimated and observed canopy conductance. The biophysical model’s estimation of $g_{c\text{ est}}$ was, at most, approximately 10% lower than the minimum observed value (minimum $g_{c\text{ obs}} = 0.0005\text{ m.s}^{-1}$)



(see Figure 6). Conversely, the model slightly overestimated the maximum observed canopy conductance by 4%. It's worth noting that the overestimation for both the average and standard deviation remained within the 10% range, with observed values at 0.00126 and $\pm 0.00044\text{ m.s}^{-1}$, respectively (Figure 6). The two datasets achieved comparable coefficients of variation, specifically 34.36% and 34.37% for the observed and estimated canopy conductance data, respectively. A Cohen's measure for effects size (d) was applied to the mean differences between the observed and estimated canopy conductance. Cohen's d measure was defined according to Cohen (1988), as:

$$d = \frac{\overline{g_{c\text{ obs}}} - \overline{g_{c\text{ est}}}}{S_p} \tag{15}$$

TABLE 6 Goodness-of-fit measures between the reference canopy conductance ($g_{c\text{ obs}}$), calculated with the inverted Penman-Monteith equation (Equation 6), and the estimated canopy conductance ($g_{c\text{ est}}$) given by the proposed biophysical model (Equation 1).

	RMSE	MAE	E
g_c	1.45×10^{-4}	9.45×10^{-1}	7.5

These metrics encompass: root mean square error (RMSE), mean absolute error (MAE), and relative error (|E|). The metrics were calculated on the dataset of 550 samples ($n = 550$).

where $\overline{g_{c\text{ obs}}}$ is the mean value of $g_{c\text{ obs}}$ measures, $\overline{g_{c\text{ est}}}$ is the mean value of the $g_{c\text{ est}}$ measures, and S_p is the pooled standard deviation, defined by:

$$S_p = \sqrt{\frac{(N_{\text{obs}} - 1)S_{\text{obs}}^2 + (N_{\text{est}} - 1)S_{\text{est}}^2}{N_{\text{obs}} + N_{\text{est}} - 2}} \tag{16}$$

where N_{obs} , N_{est} , S_{obs}^2 and S_{est}^2 are in Equation 16 the number of samples and the variance of the $g_{c\text{ obs}}$ and $g_{c\text{ est}}$ datasets, respectively.

The calculated Cohen's measure (Equation 15) was compared to Cohen's standards for very small ($d < 0.2$), small ($0.2 \leq d < 0.5$), medium ($0.5 \leq d < 0.8$), and large ($d \geq 0.8$) effect sizes (Cohen, 1988; Sawilowsky, 2009). Results revealed a small difference between the mean of $g_{c\text{ obs}}$ and $g_{c\text{ est}}$, equal to 21.7% of the standard deviation of the reference $g_{c\text{ obs}}$ (Lakens, 2013). Additionally, according to Cohen's criteria, only 15.8% of the $g_{c\text{ est}}$ exhibited no overlap with the reference $g_{c\text{ obs}}$ data (Cohen, 1988).

These results emphasize the proposed biophysical model's capability to estimate vine canopy conductance under the stressful conditions of this study. Indeed, they highlight the model's effectiveness in capturing the impact of climatic factors such as net solar radiation, vapor pressure deficit, and leaf stomatal conductance on canopy conductance. This finding aligns with the conclusions of other researchers, who have emphasized the significant impact of

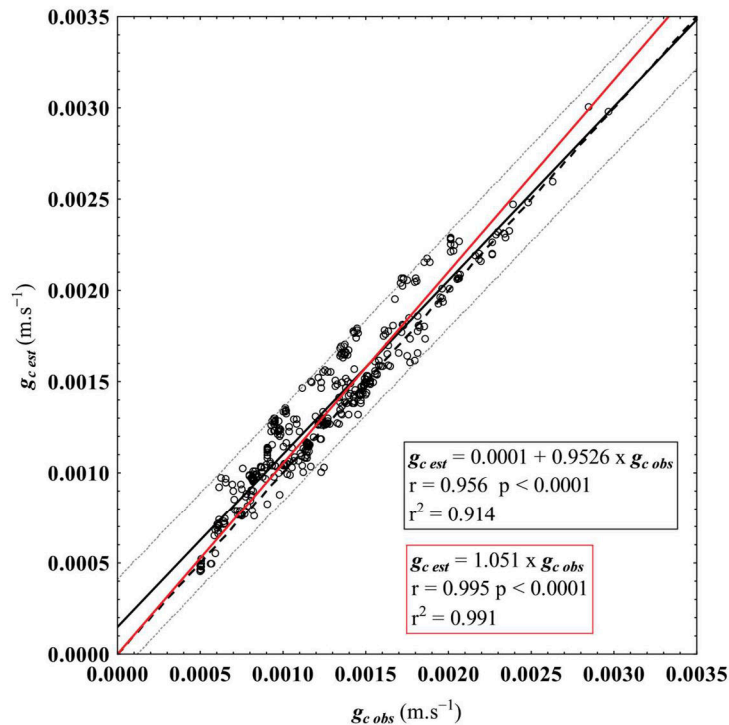


FIGURE 5

Least square regression (solid black line) between the reference $g_{c\text{ obs}}$ (observed), calculated from the inverted Penman-Monteith equation (Equation 6), and the estimated canopy conductance $g_{c\text{ est}}$, given by the proposed model (Equation 1). Confidence prediction interval at 95% is represented by the dotted lines. Additionally, a regression through the origin is shown in a solid red line, and the dashed line represents the 1:1 relationship, which indicates a perfect matching between the observed and estimated values.

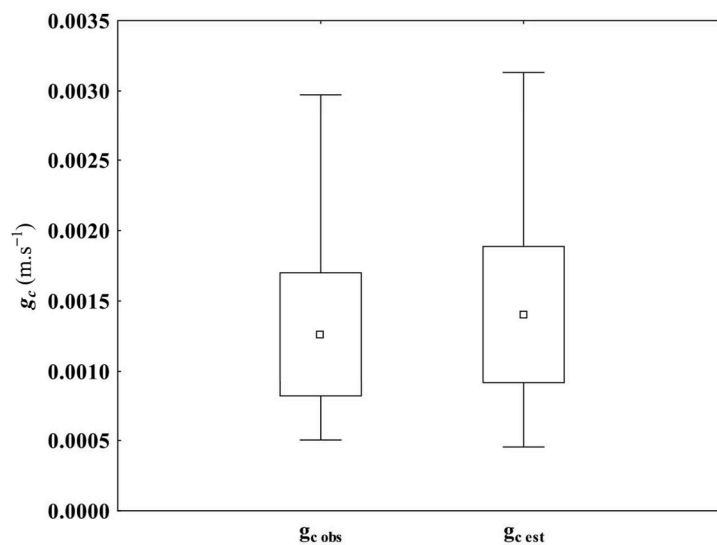


FIGURE 6

Comparison of observed ($g_{c\text{ obs}}$) and estimated ($g_{c\text{ est}}$) canopy conductance datasets. The datasets are characterized by their respective mean (α), the standard deviation range ($\square$) and the minimum and maximum value (τ). (N = 550).

stomata on gas exchange, affecting both leaf-level transpiration (Chaves et al., 2016) and canopy-level transpiration (Irmak et al., 2008; Ding et al., 2014; Wehr et al., 2017; Wehr and Saleska, 2021; Wu et al., 2022).

Moreover, in comparison to the method introduced by Lhomme et al., 2012, the model's simplicity eliminates the need for intricate techniques to monitor vine transpiration. Instead, it replaces this process with a representative value of the leaf's stomatal conductance at the canopy surface.

It is noteworthy that the presented model was intentionally designed to address vine water stress, addressing the challenges posed by water and heat stress in Mediterranean climates. The utilization of drip irrigation, implemented in a deficit strategy, aims to optimize water usage and enhance berry quality, while meticulously controlling water stress levels. Although the primary focus remains on water-stressed conditions, it is crucial to emphasize that the model has not undergone testing under nonwater-stressed conditions.

4. Conclusions

Grapevine leaf stomatal conductance to water vapor is highly influenced by climate and water availability. Under stressful conditions, grapevines tightly regulate canopy transpiration through leaf stomatal conductance.

The developed model for predicting canopy conductance from leaf stomatal conductance (g_{sw}), and the meteorological variables net solar radiation and air vapor pressure deficit, scaled by leaf area index, showed good accuracy under stressful conditions.

Several authors have documented a strong correlation between leaf stomatal conductance and soil water content (Dry and Loveys, 1999; Tuzet et al., 2003; Prieto et al., 2010; Costa et al., 2012; Lavoie-Lamoureux et al., 2017), and between soil water content and predawn leaf water potential (Williams and Araujo, 2002; Groenvelde et al., 2023). This article emphasizes the role of grapevine water status, in controlling leaf stomatal conductance, and demonstrates a strong correlation between canopy conductance and vine transpiration. The results reveal that, in addition to leaf stomatal conductance, net solar radiation, and air vapor pressure deficit, significantly influence canopy conductance and vine transpiration.

Model validation addressed on a dataset built throughout three data-acquisition campaigns carried out in a commercial vineyard, demonstrated that the proposed biophysical model was an effective predictor of canopy conductance and, consequently, of vine transpiration, under the conditions of this study, as it was previously reported by Lu et al. (2003).

One notable advantage of the presented model, compared to the Penman-Monteith method, is its enhanced simplicity. Importantly, the presented model eliminates the need for intricate methods to monitor vine transpiration and replaces them with a representative value of stomatal conductance of the leaves at the surface of the canopy.

According to the results, monitoring canopy conductance with the presented and simpler biophysical model, can provide valuable information on plant transpiration for efficient vineyard irrigation management in stressful environments. Future work, will rely in validating the model

under less stressful environments and on different grape varieties.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

RE: Conceptualization, Formal Analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. AA: Supervision, Validation, Visualization, Writing – review & editing. JA: Supervision, Writing – review & editing.

Funding

The author(s) declare financial support was received for the research, authorship, and/or publication of this article. This work was supported by Fundação para a Ciência e a Tecnologia (Portugal) through the R&D Unit “GREEN-IT-Bioresources for Sustainability” (UIDB/04551/2020 -DOI 10.54499/UIDB/04551/2020, and UIDP/04551/2020 -DOI 10.54499/UIDP/04551/2020).

Acknowledgments

We acknowledge FCT Research Unit “GREEN-IT-Bioresources for Sustainability” (UIDB/04551/2020 - DOI 10.54499/UIDB/04551/2020, and UIDP/04551/2020 - DOI 10.54499/UIDP/04551/2020) for financial support. We thank the support of the research units CITES, Centro de Investigación en Tecnología, Energía y Sostenibilidad, Universidad de Huelva, and

LEAF (UID/AGR/04129/2019). We also address our acknowledgements to Herdade do Esporão (Reguengos de Monsaraz, Alentejo, PT) and Rui Flores for their contribution on field management of the experimental vineyard.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

- Alfieri, J. G., Niyogi, D., Blanken, P. D., Chen, F., LeMone, M. A., Mitchell, K. E., et al. (2008). Estimation of the minimum canopy resistance for croplands and grasslands using data from the 2002 international H2O project. *Mon. Weather Rev.* 136, 4452–4469. doi: 10.1175/2008MWR2524.1
- Allen, R. G., Pereira, L. S., Raes, D., and Smith, M. (1998). Crop evapotranspiration guidelines for computing crop water requirements – FAO irrigation and drainage paper 56. 133 (4): 380–394 1st ed. (Rome, Italy: FAO). Available at: <http://www.fao.org/3/X0490E/X0490E00.htm>.
- Allen, R. G., Tasumi, M., and Trezza, R. (2007). Satellite-based energy balance for mapping evapotranspiration with internalized calibration (METRIC)-model. *J. Irrig. Drain. Eng.*, 133(4):380–394. doi: 10.1061/(ASCE)0733-9437(2007)133:4(380)
- Alves, I., and Pereira, L. S. (2000). Modelling surface resistance from climatic variables? *Agr. Water Manage.* 42, 371–385. doi: 10.1016/S0378-3774(99)00041-4
- Anderson, M. C., Norman, J. M., Diak, G. R., Kustas, W. P., and Mecikalski, J. R. (1997). A two-source time-integrated model for estimating surface fluxes using thermal infrared remote sensing. *Remote Sens. Environ.* 60 (2), 195–216. doi: 10.1016/S0034-4257(96)00215-5
- Avissar, R. (1993). Observations of leaf stomatal conductance at the canopy scale: An atmospheric modeling perspective. *Bound.-Lay. Meteorol.* 64, 127–148. doi: 10.1007/BF00705665
- Baldocchi, D., Hicks, B., and Camara, P. (1967). A canopy stomatal resistance model for gaseous deposition to vegetated surfaces. *Atmos. Environ.* 21 (1), 91–101. doi: 10.1016/0004-6981(87)90274-5
- Baldocchi, D., and Meyers, T. (1998). On using eco-physiological, micrometeorological and biogeochemical theory to evaluate carbon dioxide, water vapor and trace gas fluxes over vegetation: a perspective. *Agric. For. Meteorol.* 90, 1–25. doi: 10.1016/S0168-1923(97)00072-5
- Bastiaansen, W. G. M., Menenti, M., Feddes, R. A., and Holtslag, A. A. M. (1998). A remote sensing surface energy balance algorithm for land (SEBAL). 1. Formulation. *J. Hydrol.* 212–213, 198–212. doi: 10.1016/S0022-1694(98)00253-4
- Bota, J., Tomás, M., Flexas, J., Medrano, H., and Escalona, J. M. (2016). Differences among grapevine cultivars in their stomatal behavior and water use efficiency under progressive water stress. *Agr. Water Manage.* 164, 91–99. doi: 10.1016/j.agwat.2015.07.016
- Brenner, A. J., and Incoll, L. D. (1997). The effect of clumping and stomatal response on evaporation from sparsely vegetated shrublands. *Agric. For. Meteorol.* 84, 187–205. doi: 10.1016/S0168-1923(96)02368-4
- Buckley, T. N. (2005). The control of stomata by water balance. *New Phytol.* 168 (2), 275–292. doi: 10.1111/j.1469-8137.2005.01543.x
- Buckley, T. N. (2017). Modelling stomatal conductance. *Plant Physiol.* 174, 572–582. doi: 10.1104/pp.16.01772
- Buckley, T. N., and Mott, K. A. (2013). Modelling stomatal conductance in response to environmental factors. *Plant Cell Environ.* 36 (9), 1691–1699. doi: 10.1111/pce.12140
- Campos, I., Neale, C. M. U., Calera, A., Balbontina, C., and González-Piqueras, J. (2010). Assessing satellite-based basal crop coefficients for irrigated grapes (*Vitis vinifera* L.). *Agr. Water Manage.* 98, 45–54. doi: 10.1016/j.agwat.2010.07.011
- Chaves, M. M., Costa, J. M., Zarrouk, O., Pinheiro, C., Lopes, C. M., and Pereira, J. S. (2016). Controlling stomatal aperture in semi-arid regions—The dilemma of saving water or being cool? *Plant Sci.* 251 (10), 54–64. doi: 10.1016/j.plantsci.2016.06.015
- Chaves, M. M., and Oliveira, M. M. (2004). Mechanisms underlying plant resilience to water deficits: prospects for water-saving Agriculture. *J. Exp. Bot.* 55 (407), 2365–2384. doi: 10.1093/jxb/erh269
- Chaves, M. M., Zarrouk, O., Francisco, R., Costa, J. M., Santos, T., Regalado, A. P., et al. (2010). Grapevine under deficit irrigation: Hints from physiological and molecular data. *Ann. Bot.* 105, 661–676. doi: 10.1093/aob/mcq030
- Chen, H., Jiang, A. Z., Huang, J. J., Li, H., McBean, E., Singh, V. P., et al. (2022). An enhanced shuttleworth-wallace model for simulation of evapotranspiration and its components. *Agric. For. Meteorol.* 313, 108769. doi: 10.1016/j.agrformet.2021.108769
- Chen, J. M., Liu, J., Cihlar, J., and Goulden, M. (1999). Daily canopy photosynthesis model through temporal and spatial scaling for remote sensing applications. *Ecol. Model.* 124 (2–3), 99–119. doi: 10.1016/S0304-3800(99)00156-8
- Cohen, J. (1988). Statistical power analysis for the behavioral sciences. 2nd Edition (Routledge). doi: 10.4324/9780203771587
- Costa, J. M., Egipto, R., Aguiar, F. C., Marques, P., Nogales, A., and Madeira, M. (2023). The role of soil temperature in mediterranean vineyards in a climate change context. *Front. Plant Sci.* 14. doi: 10.3389/fpls.2023.1145137
- Costa, J. M., Egipto, R., Sá nchez-Virosta, A., Lopes, C. M., and Chaves, M. M. (2019). Canopy and soil thermal patterns to support water and heat stress management in vineyards. *Agric. Water Manage.* 216, 444–496. doi: 10.1016/j.agwat.2018.06.001
- Costa, J. M., Ortuño, M. F., Lopes, C. M., and Chaves, M. M. (2012). Grapevine varieties exhibiting differences in stomatal response to water deficit. *Funct. Plant Biol.* 39 (3), 179–189. doi: 10.1071/FP11156
- Costa, J. M., Vaz, M., Escalona, J. M., Egipto, R., Lopes, C. M., Medrano, H., et al. (2016). Modern viticulture in Southern Europe: Vulnerabilities and strategies for adaptation to water scarcity. *Agr. Water Manage.* 164, 5–18. doi: 10.1016/j.agwat.2015.08.021
- Courault, D., Seguin, B., and Olioso, A. (2005). Review on estimation of evapotranspiration from remote sensing data: From empirical to numerical modeling approaches. *Irrig. Drainage Syst.* 19, 223–249. doi: 10.1007/s10795-005-5186-0
- Damour, G., Simonneau, T., Cochard, H., and Urban, L. (2010). An overview of models of stomatal conductance at the leaf level. *Plant Cell Environ.* 33, 1419–1438. doi: 10.1111/j.1365-3040.2010.02181.x
- Deloire, A., Vaudour, E., Carey, V., Bonnardot, V., and van Leeuwen, C. (2005). Grapevine responses to terroir: A global approach. *J. Int. Sci. Vigne Vin* 39 (4), 149–162. doi: 10.20870/oeno-one.2005.39.4.888
- Ding, R., Kang, S., Du, T., Hao, X., and Zhang, Y. (2014). Scaling up stomatal conductance from leaf to canopy using a dual-leaf model for estimating crop evapotranspiration. *PLoS One* 9 (4), e95584. doi: 10.1371/journal.pone.0095584
- Dry, P. R., and Loveys, B. R. (1999). Grapevine shoot growth and stomatal conductance are reduced when part of the root system is dried. *Vitis* 38 (4), 151–156. doi: 10.5073/vitis.1999.38.151-156
- Eisenhauer, J. G. (2003). Regression through the origin. *Teach. Stat* 25 (3), 76–80. doi: 10.1111/1467-9639.00136
- Fernández, J. E., and Cuevas, M. V. (2010). Irrigation scheduling from stem diameter variations: a review. *Agric. For. Meteorol.* 150 (2), 135–151. doi: 10.1016/j.agrformet.2009.11.006
- Forster, M. A., Kim, T. D. H., Kunz, S., Abuseif, M., Chulliparambil, V. R., Srichandra, J., et al. (2022). Phenology and canopy conductance limit the accuracy of 20 evapotranspiration models in predicting transpiration. *Agr. For. Meteorol.* 315, 108824. doi: 10.1016/j.agrformet.2022.108824
- Fuentes, S., De Bei, R., Pech, J., and Tyerman, S. (2012). Computational water stress indices obtained from thermal image analysis of grapevine canopies. *Irrig. Sci.* 30, 523–536. doi: 10.1007/s00271-012-0375-8
- Granier, A., Biron, P., and Lemoine, D. (2000). Water balance, transpiration and canopy conductance in two beech stands. *Agric. For. Meteorol.* 100 (4), 291–308. doi: 10.1016/S0168-1923(99)00151-3
- Groenveld, T., Obiero, C., Yu, Y., Flury, M., and Keller, M. (2023). Predawn leaf water potential of grapevines is not necessarily a good proxy for soil moisture. *BMC Plant Biol.* 23 (1), 369. doi: 10.1186/s12870-023-04378-6
- Grossiord, C., Buckley, T. N., Cernusak, L. A., Novick, K. A., Poulter, B., Siegwolf, R. T. W., et al. (2020). Plant responses to rising vapor pressure deficit. *New Phytol.* 226, 1550–1566. doi: 10.1111/nph.16485
- IPCC (2019) AR6 synthesis report: climate change 2022. Available at: https://www.ipcc.ch/site/assets/uploads/2018/02/WGIIAR5-Chap3_FINAL.pdf (Accessed Sep. 30, 2023).
- Irmaak, S., Mutibwa, D., Irmaak, A., Arkebauer, T. J., Weiss, A., Martin, D. L., et al. (2008). On the scaling up leaf stomatal resistance to canopy resistance using photosynthetic photon flux density. *Agric. For. Meteorol.* 148, 1034–1044. doi: 10.1016/j.agrformet.2008.02.001
- Jarvis, P. G., and McNaughton, K. G. (1986). Stomatal control of transpiration: scaling up from leaf to region. *Adv. Ecol. Res.* 15, 1–49. doi: 10.1016/S0065-2504(08)60119-1
- Jones, H. G. (2004). Irrigation scheduling: Advantages and pitfalls of plant-based methods. *J. Exp. Bot.* 55, 2427–2436. doi: 10.1093/jxb/erh213
- Jones, H. G., Stoll, M., Santos, T., Sousa, C., Chaves, M. M., and Grant, O. M. (2002). Use of infrared thermography for monitoring stomatal closure in the field: application to grapevine. *J. Exp. Bot.* 53 (378), 2249–2260. doi: 10.1093/jxb/erf083
- Klein, T. (2014). The variability of stomatal sensitivity to leaf water potential across tree species indicates a continuum between isohydric and anisohydric behaviours. *Funct. Ecol.* 28 (6), 1313–1320. doi: 10.1111/1365-2435.12289
- Kool, D., Agam, N., Lazarovitch, N., Heitman, J. L., Sauer, T. J., and Ben-Gal, A. (2014). A review of approaches for evapotranspiration partitioning. *Agric. For. Meteorol.* 184, 56–70. doi: 10.1016/j.agrformet.2013.09.003
- Kustas, W. P., Nieto, H., Garcia-Tejera, O., Bambach, N., McElrone, A. J., Gao, F., et al. (2022). Impact of advection on two-source energy balance (TSEB) canopy transpiration parameterization for vineyards in the California Central Valley. *Irrig. Sci.* 40, 575–591. doi: 10.1007/s00271-022-00778-y
- Kustas, W. P., and Norman, J. M. (1999). Evaluation of soil and vegetation heat flux predictions using a simple two-source model with radiometric temperatures for partial canopy cover. *Agric. For. Meteorol.* 94, 13–29. doi: 10.1016/S0168-1923(99)00005-2
- Lakens, D. (2013). Calculating and reporting effect sizes to facilitate cumulative science: a practical primer for t-tests and ANOVAs. *Front. Psychol.* 4. doi: 10.3389/fpsyg.2013.00863
- Lavoie-Lamoureux, A., Sacco, D., Risse, P.-A., and Lovisolo, C. (2017). Factors influencing stomatal conductance in response to water availability in grapevine: a metaanalysis. *Physiol. Plantarum* 159 (4), 468–482. doi: 10.1111/ppl.12530

- Leuning, R., Kelliher, F. M., De Pury, D. G. G., and Schulze, E. D. (1995). Leaf nitrogen, photosynthesis, conductance and transpiration: scaling from leaves to canopies. *Plant Cell Environ.* 18, 1183–1200. doi: 10.1111/j.1365-3040.1995.tb00628.x
- Levin, A. D., and Nackley, L. (2021). Principles and practices of plant-based irrigation management. *HortTechnology* 31, 1–11. doi: 10.1021/HORTTECH04862-21
- Levin, A. D., Williams, L. E., and Mathews, M. A. (2019). A continuum of stomatal responses to water deficits among 17 wine grape cultivars (*Vitis vinifera*). *Funct. Plant Biol.* 47, 11–25. doi: 10.1071/FP19073
- Lhomme, J.-P. (1991). The concept of canopy resistance: historical survey and comparison of different approaches. *Agric. For Meteorol.* 54 (2–4), 227–240. doi: 10.1016/0168-1923(91)90007-D
- Lhomme, J.-P., Montes, C., Jacob, F., and Prévot, L. (2012). Evaporation from heterogeneous and sparse canopies: on the formulations related to multi-source representations. *Bound.-Lay. Meteorol.* 144, 243–262. doi: 10.1007/s10546-012-9713-x
- Liu, Y., Kumar, M., Katul, G. G., Feng, X., and Konings, A. G. (2020). Plant hydraulics accentuates the effect of atmospheric moisture stress on transpiration. *Nat. Clim. Change* 10, 691–695. doi: 10.1038/s41558-020-0781-5
- Lopes, C., and Pinto, P. A. (2005). Easy and accurate estimation of grapevine leaf area with simple mathematical models. *Vitis - J. Grapevine Res.* 44 (2), 55–61. doi: 10.5073/vitis.2005.44.55-61
- Lu, P., Yunusa, I. S. A., Walker, R. R., and Müller, W. J. (2003). Regulation of canopy conductance and transpiration and their modelling in irrigated grapevines. *Funct. Plant Biol.* 30 (6), 689–698. doi: 10.1071/FP02181
- Luo, X., Chen, J. M., Liu, J., Black, T. A., Croft, H., Staebler, R., et al. (2018). Comparison of big-leaf, two-big-leaf, and two-leaf upscaling schemes for evapotranspiration estimation using coupled carbon-water modeling. *J. Geophys. Res.-Biogeod.* 123, 207–225. doi: 10.1002/2017JG003978
- Mallick, K., Jarvis, A. J., Boegh, E., Fisher, J. B., Drewry, D. T., Tu, K. P., et al. (2014). A Surface Temperature Initiated Closure (STIC) for surface energy balance fluxes. *Remote Sens. Environ.* 141, 243–261. doi: 10.1016/j.rse.2013.10.022
- McShane, R. R., Driscoll, K. P., and Sando, R. (2017). A review of surface energy balance models for estimating actual evapotranspiration with remote sensing at high spatiotemporal resolution over large extents. *U.S. Geological Survey Scientific Investigations Report 2017-5087*, 19. doi: 10.3133/sir20175087
- Monteith, J. L. (1995). Accommodation between transpiring vegetation and the convective boundary layer. *J. Hydrol.* 166 (3–4), 251–263. doi: 10.1016/0022-1694(94)05086-D
- Monteith, J. L., and Unsworth, M. H. (2013). “Principles of environmental physics,” in *Plants, animals, and the atmosphere*, 4th ed. (Elsevier: Academic Press), ISBN: .
- Norman, J. M., Kustas, W. P., and Humes, K. S. (1995). A two-source approach for estimating soil and vegetation energy fluxes from observations of directional radiometric surface temperature. *Agric. For. Meteorol.* 77, 263–293. doi: 10.1016/0168-1923(95)02265-Y
- Paco, T. A., Ferreira, I., and Conceição, N. (2006). Peach orchard evapotranspiration in a sandy soil: Comparison between eddy covariance measurements and estimates by the FAO 56 approach. *Agr. Water Manage.* 85, 305–313. doi: 10.1016/j.agwat.2006.05.014
- Pereira, A. R. (2004). The Priestley–Taylor parameter and the decoupling factor for estimating reference evapotranspiration. *Agric. For. Meteorol.* 125 (3–4), 305–313. doi: 10.1016/j.agrformet.2004.04.002
- Pereira, L. S., Allen, R. G., Smith, M., and Raes, D. (2015). Crop evapotranspiration estimation with FAO56: Past and future. *Agr. Water Manage.* 147, 4–20. doi: 10.1016/j.agwat.2014.07.031
- Picón-Toro, J., González-Dugo, V., Uriarte, D., Mancha, L. A., and Testi, L. (2012). Effects of canopy size and water stress over the crop coefficient of a “Tempranillo” Vineyard South Western Spain. *Irrig. Sci.* 30, 419–432. doi: 10.1007/s00271-012-0351-3
- Priestley, C. H. B., and Taylor, R. J. (1972). On the assessment of surface heat flux and evaporation using large-scale parameters. *Mon. Weather Rev.* 100 (2), 81–92. doi: 10.1175/1520-0493(1972)100<0081:OTAOSH>2.3.CO;2
- Prieto, J. A., Lebon, E., and Ojeda, H. (2010). Stomatal behavior of different grapevine cultivars in response to soil water status and air water vapor pressure deficit. *J. Int. Sci. Vigne Vin* 44 (1), 9–20. doi: 10.20870/oeno-one.2010.44.1.1459
- Rallo, G., Paço, T. A., Paredes, P., Puig-Sirera, À., Massai, R., Provenzano, G., et al. (2021). Updated single and dual crop coefficients for tree and vine fruit crops. *Agr. Water Manage.* 250, 106645. doi: 10.1016/j.agwat.2020.106645
- Rogiers, S. Y., Greer, D. H., Hatfield, J. M., Hutton, R. J., Clarke, S. J., Hutchinson, P. A., et al. (2012). Stomatal response of an anisohydric grapevine cultivar to evaporative demand, available soil moisture and abscisic acid. *Tree Physiol.* 32 (3), 249–261. doi: 10.1093/treephys/tp131
- Sawilowsky, S. S. (2009). New effect size rules of thumb. *J. Modern Appl. Stat. Methods* 8 (2), 597–599. doi: 10.22237/jmasm/1257035100
- Schymanski, S. J., and Or, D. (2017). Leaf-scale experiments reveal an important omission in the Penman–Monteith equation. *Hydrol. Earth Syst. Sci.* 21, 685–706. doi: 10.5194/hess-21-685-2017
- Shahidian, S., Serralheiro, R., Serrano, J., Teixeira, J., Haie, N., and Santos, F. (2012). “Hargreaves and other reduced-set methods for calculating evapotranspiration,” in *Evapotranspiration - remote sensing and modeling*. Ed. A. Imrak (IntechOpen), 528. doi: 10.5772/18059
- Shuttleworth, W. J., and Wallace, J. S. (1985). Evaporation from sparse crops—an energy combination theory. *QJR Meteorol. Soc.* 111, 839–855. doi: 10.1002/qj.49711146910
- Sperry, J. S., Venturas, M. D., Anderegg, W. R. L., Mencuccini, M., Mackay, D. S., Wang, Y., et al. (2017). Predicting stomatal responses to the environment from the optimization of photosynthetic gain and hydraulic cost. *Plant Cell Environ.* 40 (6), 816–830. doi: 10.1111/pce.12852
- Stannard, D. I. (1993). Comparison of Penman–Monteith, Shuttleworth–Wallace, and modified Priestley–Taylor evapotranspiration models for woodland vegetation in semiarid rangeland. *Water Resour. Res.* 29 (5), 1379–1392. doi: 10.1029/93WR00333
- Tang, R., Li, Z.-L., Jia, Y., Li, C., Chen, K.-S., Sun, X., et al. (2013). Evaluating oneand two-source energy balance models in estimating surface evapotranspiration from Landsat-derived surface temperature and field measurements. *Int. J. Remote Sens.* 34 (9–10), 3299–3313. doi: 10.1080/01431161.2012.716529
- Todorovic, M. (1999). Single-layer evapotranspiration model with variable canopy resistance. *J. Irrig. Drain. Eng.* 125 (5), 235–245. doi: 10.1061/(ASCE)0733-9437(1999)125:5(235)
- Tuzet, A., Perrier, A., and Leuning, R. (2003). A coupled model of stomatal conductance, photosynthesis and transpiration. *Plant Cell Environ.* 26 (7), 1097–1116. doi: 10.1046/j.1365-3040.2003.01035.x
- van Leeuwen, C., Trégoat, O., Choné, X., Bois, B., Pernet, D., and Gaudillière, J.-P. (2009). Vine water status is a key factor in grape ripening and vintage quality for red Bordeaux wine. How can it be assessed for vineyard management purposes? *OENO One* 43, 121–134. doi: 10.20870/oeno-one.2009.43.3.798
- Wang, Y.-P., and Leuning, R. (1998). A two-leaf model for canopy conductance, photosynthesis and partitioning of available energy I: Model description and comparison with a multi-layered model. *Agric. For. Meteorol.* 91, 89–111. doi: 10.1016/S0168-1923(98)00061-6
- Wehr, R., Commare, R., Munger, J. W., McManus, J. B., Nelson, D. D., Zahniser, M. S., et al. (2017). Dynamics of canopy stomatal conductance, transpiration, and evaporation in a temperate deciduous forest, validated by carbonyl sulfide uptake. *Biogeosciences* 14, 389–401. doi: 10.5194/bg-14-389-2017
- Wehr, R., and Saleska, S. R. (2021). Calculating canopy stomatal conductance from eddy covariance measurements, in light of the energy budget closure problem. *Biogeosciences* 18 (1), 13–24. doi: 10.5194/bg-18-13-2021
- Williams, L. E., and Araujo, F. J. (2002). Correlations among predawn leaf, midday leaf, and midday stem water potential and their correlations with other measures of soil and plant water status in *Vitis vinifera*. *J. Amer. Soc. Hortic. Sci.* 127 (3), 448–454. doi: 10.21273/JASHS.127.3.448
- Wu, R.-Q., Jia, J.-B., Yan, W.-D., Hu, L., Wang, Y.-F., and Chen, Y. (2022). Characteristics of canopy conductance and environmental driving mechanism in three monsoon climate regions of China. *Front. Environ. Sci.* 10. doi: 10.3389/fenvs.2022.935926
- Xiaoying, L., and Erda, L. (2005). Performance of the Priestley–Taylor equation in the semiarid climate of North China. *Agric. Water Manage.* 71, 1–17. doi: 10.1016/j.agwat.2004.07.007
- Xu, J., Wu, B., Ryu, D., Yan, N., Zhu, W., and Ma, Z. (2021). Quantifying the contribution of biophysical and environmental factors in uncertainty of modeling canopy conductance. *J. Hydrol.* 592, 125612. doi: 10.1016/j.jhydrol.2020.125612
- Zhai, Z., Martinez, J. F., Beltran, V., and Martí nez, N. L. (2020). Decision support systems for agriculture 4.0: Survey and challenges. *Comput. Electron. Agr.* 170, 105256. doi: 10.1016/j.compag.2020.105256
- Zhang, B., Kang, S., Li, F., and Zhang, L. (2008). Comparison of three evapotranspiration models to Bowen ratio–energy balance method for a vineyard in an arid desert region of northwest China. *Agric. For. Meteorol.* 148, 1629–1640. doi: 10.1016/j.agrformet.2008.05.016
- Zhao, W. L., Qiu, G. Y., Xiong, Y. J., U, K. T. P., Gentine, P., and Chen, B. Y. (2020). Uncertainties caused by resistances in evapotranspiration estimation using highdensity eddy covariance measurements. *J. Hydrometeorol.* 21 (6), 1349–1365. doi: 10.1175/JHM-D-19-0191.1
- Zhong, Z., He, B., Wang, Y.-P., Chen, H. W., Chen, D., Fu, Y. H., et al. (2023). Disentangling the effects of vapor pressure deficit on northern terrestrial vegetation productivity. *Sci. Adv.* 9, 32. doi: 10.1126/sciadv.adf3166
- Zhu, Y., Cheng, Z., Feng, K., Chen, Z., Cao, C., Huang, J., et al. (2022). Influencing factors for transpiration rate: a numerical simulation of an individual leaf system. *Thermal Sci. Eng. Prog.* 27, 101110. doi: 10.1016/j.tsep.2021.101110

Glossary

BL	Big-leaf model
E_c	Vine canopy transpiration
ET_c	Crop evapotranspiration
$ET_{c_{act}}$	Actual crop evapotranspiration
g_c	Canopy conductance to water vapor
$g_{c_{est}}$	Canopy conductance to water vapor estimated by the proposed biophysical model
$g_{c_{obs}}$	Observed/Reference field measured canopy conductance to water vapor
g_s	Bulk surface conductance
g_{sw}	Leaf stomatal conductance to water vapor
LAI	Leaf area index
RH	Relative humidity
R_n	Net solar radiation
SWC	Soil water content
T_{air}	Air temperature
T_{min}	Minimum air temperature
T_{max}	Maximum air temperature
U	Wind speed
VPD	Vapor pressure deficit
Ψ_{PD}	Pre-dawn leaf water potential
C_p	Dry air specific heat at constant pressure
d	Zero-plane displacement height
E_c	Vine canopy transpiration
e_a	Actual Vapor pressure
e_s	Saturation Vapor pressure
$e_0(T_{air})$	Saturation Vapor pressure as function of temperature
g_a	Aerodynamic conductance
h	Canopy height
k	Von Karman's constant
K_t	Time unit conversion factor
P	Atmospheric pressure
R_n	Net solar radiation
R	Specific gas constant
VPD	Vapor pressure deficit
z_m	Wind speed and Humidity measurement height
z_{om}	Roughness length governing transfer of momentum
z_{ov}	Roughness length governing transfer of water vapor
Δ	Vapor pressure curve's slope

Continued

ϵ	Ratio of molecular weight of water Vapor/dry air
λ	Latent heat of water vaporization
γ	Psychrometric constant
ρ	Air density
d	Cohen's measure for effect size
$ E $	Relative error
$g_{c_{est}}^i$	The i -th g_c value estimated by the proposed model
$g_{c_{obs}}^i$	The i -th observed g_c value given by the Penman-Monteith equation
$\overline{g_{c_{obs}}}$	Mean value of the $g_{c_{obs}}$ measures
$\overline{g_{c_{est}}}$	Mean value of the $g_{c_{est}}$ measures
MAE	Mean absolute error
N_{obs}	Number of samples of the $g_{c_{obs}}$ dataset
N_{est}	Number of samples of the $g_{c_{est}}$ dataset
RMSE	Root mean squared error
s_{obs}^2	Variance of the $g_{c_{obs}}$ dataset
s_{est}^2	Variance of the $g_{c_{est}}$ dataset
s_p	Pooled standard deviation

(Continued)

6.3. Article 3

The role of soil temperature in mediterranean vineyards in a climate change context

Joaquim Miguel Costa, Ricardo Egipto, Francisca Aguiar, Paulo Marques, Amaia Nogales and Manuel Madeira

Journal: Frontiers in Plant Science (eISSN 1664-462X)

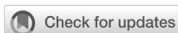
Editorial: Frontiers Media SA

Reference: Frontiers in Plant Science. 2023, 14, 1145137

DOI: 10.3389/fpls.2023.1145137

Year: 2023

Quality index (Journal Citation Reports®, 2023): 44/265 (Q1) in the category "Plant Sciences". Impact Factor of 4.1.



OPEN ACCESS

EDITED BY

Tommaso Frioni,

Catholic University of the Sacred Heart,
Piacenza, Italy

REVIEWED BY

Suzy Rogiers,

NSW Government, Australia

Elena Brunori,
University of Tuscia, Italy

*CORRESPONDENCE

J. Miguel Costa

✉ miguelcosta@isa.ulisboa.pt

RECEIVED 15 January 2023

ACCEPTED 20 March 2023

PUBLISHED 09 May 2023

CITATION

Costa JM, Egipto R, Aguiar FC, Marques P, Nogueiras A and Madeira M (2023) The role of soil temperature in mediterranean vineyards in a climate change context. *Front. Plant Sci.* 14:1145137. doi: 10.3389/fpls.2023.1145137

COPYRIGHT

© 2023 Costa, Egipto, Aguiar, Marques, Nogueiras and Madeira. This is an open-access article distributed under the terms of the [Creative Commons Attribution License \(CC BY\)](https://creativecommons.org/licenses/by/4.0/). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

The role of soil temperature in mediterranean vineyards in a climate change context

J. Miguel Costa^{1,2*}, Ricardo Egipto³, Francisca C. Aguiar^{2,4}, Paulo Marques⁵, Amaia Nogueiras^{1,2} and Manuel Madeira^{2,4}

¹Linking Landscape, Environment, Agriculture and Food, LEAF Research Center, Instituto Superior de Agronomia, Universidade de Lisboa, Lisboa, Portugal, ²Laboratório Associado TERRA, Instituto Superior de Agronomia, Lisboa, Portugal, ³INIAV, Instituto Nacional de Investigação Agrária e Veterinária, Polo de Inovação de Dois Portos, Dois Portos, Portugal, ⁴CEF, Centro de Estudos Florestais, Instituto Superior de Agronomia, Universidade de Lisboa, Lisboa, Portugal, ⁵Instituto Superior de Agronomia, Universidade de Lisboa, Lisboa, Portugal

The wine sector faces important challenges related to sustainability issues and the impact of climate change. More frequent extreme climate conditions (high temperatures coupled with severe drought periods) have become a matter of concern for the wine sector of typically dry and warm regions, such as the Mediterranean European countries. Soil is a natural resource crucial to sustaining the equilibrium of ecosystems, economic growth and people's prosperity worldwide. In viticulture, soils have a great influence on crop performance (growth, yield and berry composition) and wine quality, as the soil is a central component of the terroir. Soil temperature (ST) affects multiple physical, chemical and biological processes occurring in the soil as well as in plants growing on it. Moreover, the impact of ST is stronger in row crops such as grapevine, since it favors soil exposition to radiation and favors evapotranspiration. The role of ST on crop performance remains poorly described, especially under more extreme climatic conditions. Therefore, a better understanding of the impact of ST in vineyards (vine plants, weeds, microbiota) can help to better manage and predict vineyards' performance, plant-soil relations and soil microbiome under more extreme climate conditions. In addition, soil and plant thermal data can be integrated into Decision Support Systems (DSS) to support vineyard management. In this paper, the role of ST in Mediterranean vineyards is reviewed namely in terms of its effect on vines' ecophysiological and agronomical performance and its relation with soil properties and soil management strategies. The potential use of imaging approaches, e.g. thermography, is discussed as an alternative or complementary tool to assess ST and vertical canopy temperature profiles/ gradients in vineyards. Soil management strategies to mitigate the negative impact of climate change, optimize ST variation and crop thermal microclimate (leaf and berry) are proposed and discussed, with emphasis on Mediterranean systems.

KEYWORDS

radiation, row-crops, sustainable soil management, thermal data, water, soil temperature sensing, cover crops

1. Introduction

1.1. European viticulture and climate change

Agriculture is a nature-based, climate-dependent sector and is strongly affected by climate change. A recent report from the European Environment Agency indicates that the overall impacts of climate change can decrease significantly the EU's agricultural sector production (up to 16% loss in income by 2050), with large regional variations (EEA, 2019). Even in regions not experiencing a decrease in rainfall, air temperature rise will result in higher evapotranspiration (Seneviratne et al., 2010; Abad et al., 2021). For this reason, the agricultural sector must build up the capacity to adapt to increasing dry and warm conditions induced by climate change. Soil characteristics and soil management have a major role in this adaptation (EEA, 2019), but a better understanding is needed for Mediterranean viticultural systems.

The EU protects high-quality wines by linking them to legally defined geographic areas, specific sustainable production practices, traditional varieties and soil characteristics (Candiago et al., 2022; Onofre, 2022). The contribution of Mediterranean viticulture (e.g. Spain, Italy, France, Portugal and Greece) to the global wine industry is large, accounting for more than 50% of the world production and about 55% of world exports (OIV, 2022). However, Mediterranean viticulture is highly vulnerable to climate change (Costa et al., 2016; Fraga et al., 2016; Santos et al., 2020; Xyrafis et al., 2022), especially to the combination of longer warmer and drier periods. The same occurs for other Mediterranean perennial crops, such as olive groves and almond orchards (Andrade et al., 2014; Garcia-Tejero et al., 2018; Fraga et al., 2021).

Higher air temperature promotes earlier bud break, flowering, maturation and harvest, which can be negative for berry composition (e.g. higher sugar concentration and decreasing acidity) and can result in unbalanced wines (Bonada et al., 2015; Droulia and Charalampopoulos, 2022). Drier conditions exacerbate the effects of heat stress because dry soils cannot provide latent heat cooling by evapotranspiration, resulting in higher and more stressful temperatures at the plant level (Seneviratne et al., 2010; Stéfanon et al., 2014; Guion et al., 2022). This not only affects vine's phenology but also yields and vines longevity and, ultimately the overall sustainability of the sector (economical, environmental and social) (Santos et al., 2020; Costa et al., 2022; Droulia and Charalampopoulos, 2022). In addition, these climatic scenarios may limit the expansion of the cultivated area in some regions of Mediterranean countries and may force the relocation of vineyards at higher altitudes (Jones, 2012).

1.2. Soil, climate change and surface energy balance

Soils are critical to sustain the equilibrium of ecosystems, economic growth and people's prosperity worldwide (Brady and Weil, 2017). Soils provide multiple ecosystem services and socioeconomic activities and in viticulture, they are an important component of the terroir, since they are one of the major factors influencing berry traits, wine characteristics and styles (White, 2015; Van Leeuwen et al., 2018; Sremac et al., 2021). Soils have a relevant function in the adaptation

of the agricultural sector to adverse climatic conditions and more sustainable soil management is needed to ensure food security but also to improve adaptation to climate crises (EEA, 2019; Cataldo et al., 2021). Soil characteristics govern vegetation growth and influence heat, water and carbon fluxes between soil and the atmosphere (Evelt, 2000; Lorenz et al., 2010; Liu et al., 2022).

Soil-atmosphere temperature relations are particularly important in the context of climate change (Hirschi et al., 2011). They involve partitioning of the surface energy into sensible (H) and latent heat (LE) fluxes (Figure 1), which depend on soil moisture content (Wang and Yang, 2018). Under dry conditions, the available net radiation (R_n) energy is converted into H fluxes, which increases air temperature. The relationship (coupling) between ST and soil moisture regimes explains the use of both variables in natural resource management, to better quantify and predict climate change impacts (Houle et al., 2012; Bradford et al., 2019). The energy balance equation for soil is commonly expressed as: $R_n = LE + H + G$, in which R_n is the net flux density of radiation (W/m^2), and G is the soil heat flux,

Soil characteristics and soil management influence the energy balance at the soil's surface and on the plant's energy balance due to the reflection of shortwave irradiation that becomes a source of longwave radiation for plants (Nobel, 2005) (Figure 1). Furthermore, ST influences physical, chemical and biological processes taking place in the soil and regulates energy and matter exchange with the atmosphere (Baver, 1965; Hillel, 2004; Brady and Weil, 2017). Soil temperature influences evaporation, aeration and the type and rates of chemical reactions occurring in soils (Hillel, 2004).

Predictions for air temperature increase due to climate change are well described in the literature (IPCC, 2021). However, less information is available for ST. In a recent study, Schultz (2022) reports a progressive increase of ST for Northern European countries (e.g. Germany) in the last decades. Nonetheless, this trend observed for ST is expected to be more marked in Southern Europe. The Mediterranean region has a warm season transitional climate, in which evapotranspiration is limited by low soil moisture rather than by solar radiation (Feng et al., 2022). In this context, low soil moisture will amplify heat anomalies and extremes in the region (Seneviratne et al., 2010; Vogel et al., 2021; Feng et al., 2022) with a potential major impact on growth and yield of both crop and weed species.

In Mediterranean areas, ST and soil moisture regimes are classified as xeric, as precipitation concentrates in the winter and summers are dry, and the mean annual ST can range between 15 and 22°C (Soil Survey Staff, 2014). Soil temperature is one of the major drivers of grapevine physiology, growth and productivity. Soil temperature affects physical and biological processes at soil's surface (e.g. weed and crop phenology, growth, respiration, etc.) (Bullied et al., 2003; Howell et al., 2020). At deeper soil layers ST influences root metabolism and growth, soil respiration, water and nutrient uptake, microbial diversity and activity, organic matter (OM) dynamics, soil biochemistry (Akter et al., 2015; Onwuka and Mang, 2018; Mehdizadeh et al., 2020a; Mehdizadeh et al., 2020b; Shah et al., 2022).

Mean temperatures of air and soil, and in particular their extremes, influence weeds and crop physiology (seeds,

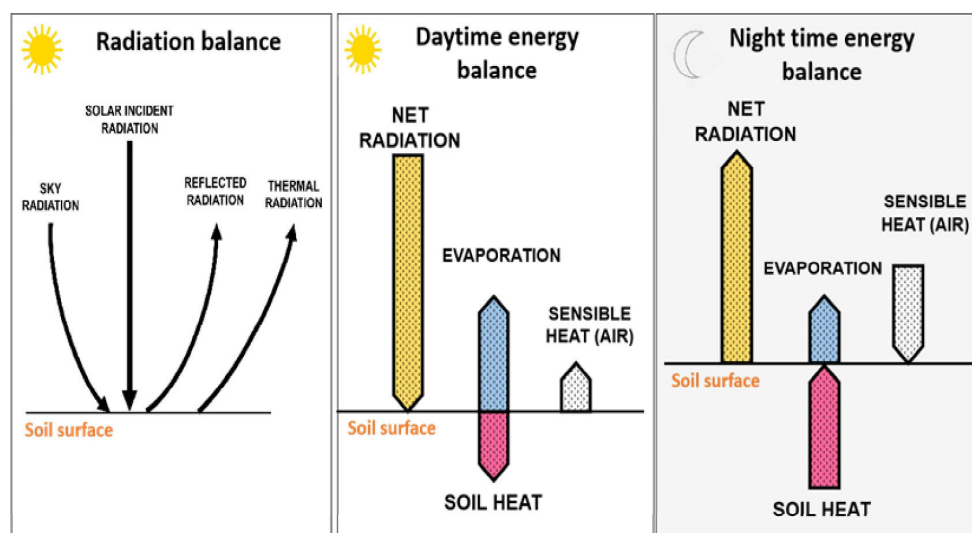


FIGURE 1

Schematic representation of the radiation balance, the daytime energy balance, and the night time energy balance. Net radiation at soil surface represents the sum “solar radiation plus sky radiation” minus the sum of “reflected radiation plus thermal radiation”. Most of the radiation that reaches earth’s surface in the daytime is used for evapotranspiration or reflected and emitted to the atmosphere. Evaporation translates the latent heat. The arrows indicate the direction of the exchange and arrow lengths tentatively indicate the magnitude of the different fluxes (Adapted from [Evvett, 2000](#); [Hillel, 2004](#) and [Brady and Weil, 2017](#)).

fruits, leaves, and roots) ([Bullied et al., 2003](#); [Chaves et al., 2016](#); [Field et al., 2020](#); [Gambetta et al., 2021](#); [Sremac et al., 2021](#)). In vineyards, the proximity of leaves and clusters to soil surface enhances the warming effect of ST and soil sensible heat fluxes on berries, clusters and leaves. This is observed for the worldwide used Vertical Shoot Positioning (VSP) system in which the cluster zone and basal leaves often get warmer than the upper part of the canopy due to soil sensible fluxes, under warm and dry conditions ([Costa et al., 2019](#)).

A deeper understanding of vineyard soils, including their properties, functions, ecological roles, and management is required to increase the resilience of Mediterranean viticulture systems to more extreme climate conditions. There is a need to integrate the components of the terroir related to ST and the solutions for adaptation to climate change. This must be done at local level and should consider the trade-offs between adaptation strategies ([Naulleau et al., 2021](#)). In the following section, some of the major determinants of ST are presented.

2. Determinants of soil temperature in vineyards

Soil properties (e.g. color, texture, structure, moisture content) together with dominant atmospheric conditions (e.g. air temperature, solar radiation and wind) ([Baver, 1965](#); [Evvett, 2000](#)) influence soil heat and water fluxes and ultimately ST variables (thermal conductivity, thermal regime, maximum and minimum temperatures) ([Brady and Weil, 2017](#)). On the other hand, anthropological conditions, including agricultural soil management strategies ([Table 1](#)),

can modify heat and water fluxes between soil, plant and atmosphere influencing ST variation ([Nielsen et al., 1986](#); [Rességuier et al., 2023](#)).

The impact of climatic conditions on surface energy balance and consequently on ST is expressed by daily and seasonal variations in surface ST. In summer months (June–July in the northern hemisphere) maximum incident global radiation is closely related to maximum ST at midday ([Figure 2](#)) ([Costa et al., 2019](#); [Sremac et al., 2021](#)). The stronger seasonal warming response of soils in summer as compared to autumn period mainly relates to decreased soil moisture content at the top layers of soil during summer ([Schultz, 2022](#)). Together with the effect of climate conditions, various soil properties and soil management (e.g. irrigation, mulching) can influence ST to a different extent ([Table 1](#)).

2.1. Topography and soil temperature

Soil temperature is related to the amount of incident radiation ([Figure 1](#)). Topographic components (e.g. slope and exposition to sunlight) influence ST and soil moisture regimes ([Baver, 1965](#); [Griffiths et al., 2009](#); [Brady and Weil, 2017](#)). Slopes with a southern aspect have higher levels of insolation, and consequently, higher heat accumulation and are usually considered ideal ([Yau et al., 2014](#)). Usually, the temperature of corrugated fields is higher than that of flattened ones due to different degrees of incident and reflected radiation ([Brady and Weil, 2017](#)). [Radke \(1982\)](#) in turn, reported that inclined ridge surfaces absorbed about 10% more solar radiation than flat surfaces contributing to higher ST.

TABLE 1 Non-exhaustive list of major determinants influencing soil temperature (ST), and general individual effect on the increase (↑), decrease (↓), reliable with other factors, such as climate (↓↑).

FACTORS	GENERAL EFFECT ON ST	SOURCE
Topographic		
Slope	flat↑ large sloping ↓	Baver (1965)
Exposition	North↓ South↑	Brady and Weil (2017)
Soil properties		
Color and albedo	dark ↑ light ↓	Meinhold et al. (2010)
Soil texture	silty ↑ sandy ↓	Sremac et al. (2021)
Organic matter content	OM and darker color↓ poor/lighter color↑	Brady and Weil (2017)
Soil structure	stable large round aggregates↓ unstable or platy, prismatic, blocky aggregates↑	Sremac et al. (2021)
Soil moisture	dry ↑ wet ↓	Brady and Weil (2017); Wang and Yang (2018); Krapez et al. (2012)
Soil and canopy management		
Tillage	↑	Radke (1982); Pradel and Pieri, (2008)
Plant density	high ↓ low ↑	White (2015)
Canopy size/shedding	large ↓ small ↑	White (2015)
Irrigation	↓	Costa et al. (2019); Costa et al. (2020); Krapez et al. (2012)
Row orientation	↑↓	Hunter et al. (2021); White (2015); Pisciotta et al. (2021)
Soil cover ¹	↓	Baver (1965); Lazcano et al. (2020); Akter et al. (2015); Brady and Weil (2017)
Soil and canopy cover ²	↓	Marigliano et al. (2022); Tadayon and Hossein (2022); Pradel and Pieri, (2008)

¹mulching, natural vegetation, cover crops; ²nets and other covering structures.

Extremes of the scale, when pertinent, are given as indicators of the general effect on ST.

2.2. Soil properties and soil temperature

2.2.1. Soil albedo and color

The surface albedo represents the reflectivity of the Earth's surface for incident solar radiation (Evet, 2000). The amount and type of reflected radiation depend on the characteristics of the surface and of the vegetation cover or mulch beneath crops, and soil properties (Meinhold et al., 2010). Soil vegetation controls the amount of sunlight that hits the ground surface, and bare soils cool down and warm up faster than soils covered with vegetation (Akter et al., 2015; Brady and Weil, 2017). Regarding soil color, dark-colored soils can warm more than light-colored soils, since they absorb more radiation (Baver, 1965). Nevertheless, large amounts of OM in dark soils can increase their water retention, which can offset the increased heat absorption due to the dark color (Brady and Weil, 2017). Soil's albedo can be manipulated by different management strategies such as soil conservation tillage (Brady and Weil, 2017) or the use of certain products such as biochar (Verheijen et al., 2013), or the use of other organic (Burg et al., 2022) and inorganic mulches (Marshall et al., 1996; Aragüés et al., 2014).

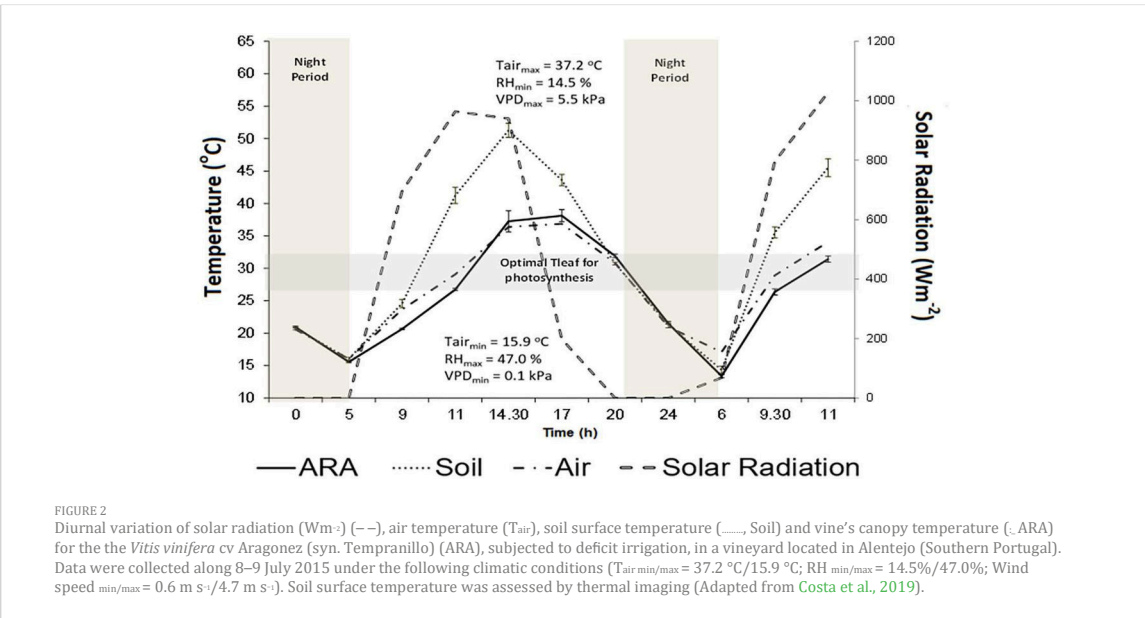
2.2.2. Soil texture and structure

Soil texture refers to the proportion of sand, silt and clay sized particles that make up the mineral fraction of the soil, while soil structure refers to the organization of soil particles and the tendency of individual soil particles

to combine into aggregates (Marshall et al., 1996; Hillel, 2004). The degree of aggregation influences water and air transport in the soil, solutes movement and soil's biological activity (Brady and Weil, 2017). The texture influences soil thermal behaviour and soil surface temperature. Sandy soils tend to warm up faster than clay soils due to their lower heat capacity, lower thermal conductivity, and lower evaporative cooling (Hillel, 2004). On the other hand, the amplitude of the daily ST variation decreases in the order sand > loam > clay. Soil moisture at the surface and in the subsurface moderates the daily range of ST (Krapez et al., 2012) (Figure 3). In orchards, sandy soils usually have a higher night time cooling rate than clay soils, due to a faster energy loss and lower minimum air temperature (Sremac et al., 2021). Soil structure also influences ST. Soil structure controls pore spaces due to different arrangements of soil particles and soils with a more spherical structure warm up faster due to higher aeration and reduced waterlogging conditions (Brady and Weil, 2017). Soil structure is negatively affected by compaction which increases soil density and thermal conductivity which also enables faster changes in ST and affects root growth and morphology (Brady and Weil, 2017; Gürsoy, 2021).

2.2.3. Soil water content

Soil water and heat fluxes are coupled (Wang and Yang, 2018) and their study is highly relevant for climate research (e.g. climate models) (Lanyon et al., 2004; Seneviratne et al., 2010) and agronomical and remote sensing



research (Krapez et al., 2012; Kustas et al., 2022). The specific heat of water is higher than that of soil, and consequently, soils with high moisture have higher specific heat than dry soils, resulting in lower ST (Baver, 1965). Therefore, higher soil water content makes the variation (increase/ decrease) in ST occur more slowly than in dry soils (Brady and Weil, 2017). Lower moisture content results in a higher conversion of solar radiation into sensible heat (measurable as temperature) (Figure 1), in opposite to high soil moisture conditions, in which the incident solar energy is used to evaporate water (Heilman et al., 1994). Soil water evaporation reduces ST, and the temperature difference

between soil and the atmosphere is proportional to the evaporation rate (Zeng et al., 2021) and as a consequence soil surface temperature inversely correlates with soil water content (Krapez et al., 2012). As a result, the typical wet-dry irrigation cycles occurring in irrigated crops often result in spikes in ST (See Figure 3).

Severe precipitation events and flooding can greatly affect soil characteristics, leading in general to soil erosion, compaction and nutrient runoff, with detrimental effects on crops (root growth, yield) and soil fauna, and influencing soil temperature (Mancuso and Shabala, 2010; Ruperti et al., 2019).

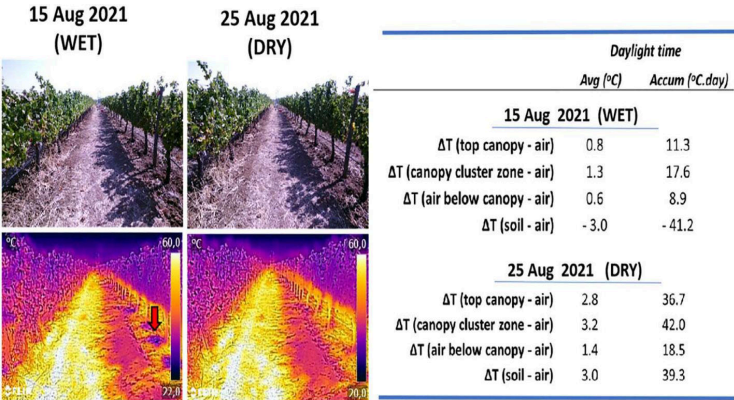


FIGURE 3
RGB and thermal images taken with a medium cost thermal camera (Flir C5, 160 x 120 pixels, 8-14mm, Emissivity = 0.96) from the inter row and rows with *Vitis vinifera* cv Tempranillo, taken at 16:00 hours, on 15 and 25 August 2021, showing the marked effect of shadow and sunlit soil sides as well as effect of irrigation on soil temperature (arrow) as part of a typical wet-drying cycle in irrigated vineyards. (Adapted from Egipto et al., 2022).

2.2.4. Soil organic carbon content

Soil organic carbon (OC) content depends on the balance between carbon inputs and outputs. Carbon inputs relate to plant productivity, while carbon outputs relate to microbial decomposition of OM. Soil OM decomposition is controlled by ST during wet periods and by the combined effect of soil water and ST during dry periods (Yuste et al., 2007). On the other hand, high ST promotes OM mineralization rates and drives several physical, chemical and biological changes, which accelerates microbial decomposition of soil OM and, decreases soil fertility (Guoju et al., 2020). Soil microbial respiration uses soil OC and releases CO₂, and higher ST promotes soil respiration and higher CO₂ release to the atmosphere (Karhu et al., 2014).

Soil management practices (tillage, the use of cover crops, mulching) combined with changes in soil water content due to precipitation or irrigation, influence C dynamics in soils and soil biodiversity (Haddaway et al., 2017; Crystal-Ornelas et al., 2021). Soil tillage promotes CO₂ release and disrupts protected OM in soil aggregates, increasing its availability for microorganisms (Haddaway et al., 2017). Precipitation and irrigation modify CO₂ fluxes in soil, and the wet-dry cycles due to precipitation or irrigation events result in marked fluctuations in soil CO₂ efflux and in dynamic responses in soil C pools (Yu et al., 2022).

3. The impact of soil temperature in vineyards

3.1. Grapevine responses

Vitis vinifera is a crop species well adapted to dry and warm conditions. However, more variable and extreme climatic conditions (heat and drought) pose risks to the wine sector. Temperature is a primary environmental factor influencing grapevine development, growth and physiological processes occurring in roots, shoots/leaves and berries, including growth and phenology, respiration and photosynthesis, flowering and fruit set, yield and berry composition (Chaves et al., 2016; Pagay and Collins, 2017; Field et al., 2020; Bernardo et al., 2021; Gambetta et al., 2021; Keller et al., 2022). Warmer conditions lead to earlier bud break and earlier harvests, resulting in wines with lower organic acids, higher pH levels, higher ethanol levels and altered sensory characteristics (Van Leeuwen and Destrac-Irvine, 2017; Venios et al., 2020). Heat stress due to air temperatures above 35°C decreases the synthesis of secondary metabolites, reduces photosynthesis rates and vegetative growth (Moutinho-Pereira et al., 2004; Chaves et al., 2010) and may affect plant water transport (Galat Giorgi et al., 2020). Excessively high temperatures (air and soil) in wine-growing regions can reduce berry color due to inhibition of anthocyanin biosynthesis or their degradation and promote the synthesis of reactive oxygen species (ROS) (Carvalho et al., 2014; Venios et al., 2020). Higher average air temperatures in the growing season can negatively impact yield and quality (Bonada et al., 2015) and brief episodes of extreme temperatures are detrimental when occurring at specific phenological stages, e.g. flowering and fruit set (Pagay and Collins, 2017; Gambetta et al., 2021; Keller et al., 2022).

High air temperatures and drought stress can influence leaf morphology and structure resulting in larger but thinner leaves, with smaller cells, and higher stomatal density (Pierce et al., 2022). High diurnal air temperatures and low night air temperatures ensure a low pH in berries which is highly relevant for wine production in warm areas (e.g. Mediterranean), which are increasingly experiencing an increase in night time temperatures (Venios et al., 2020).

The response of grapevine to heat and drought stress depends on several factors that include the atmospheric climatic conditions, the genotype (variety/rootstock), soil characteristics and soil and crop management (Lopes et al., 2011; Bota et al., 2016; Simonneau et al., 2017). Leaf gas exchange traits (e.g. photosynthesis, transpiration or stomatal conductance) respond fast to abiotic stresses, namely to drought and high temperatures (Chaves et al., 2010; Simonneau et al., 2017). Optimal leaf temperatures for photosynthesis range between 25 and 30°C (Greer and Weedon, 2012), but stomatal response to the environment depends on the genotype and their strategy (isohydric or anisohydric) to cope with water stress while optimizing thermal regulation (Chaves et al., 2010; Chaves et al., 2016; Simonneau et al., 2017).

Current studies on crop response to high-temperature stress are mainly focused on the effects of air temperatures on the aerial part of plants/crops (shoots, leaves) and its immediate environment, while the potential adverse effects of high ST are less examined (Dong et al., 2016; Costa et al., 2019). This applies to the effects of day time and night time temperatures under scenarios of warmer nocturnal air temperatures that tend to increase root-zone ST (Dong et al., 2016).

Metabolic processes such as respiration, photosynthesis and transpiration are sensitive to short-term temperature fluctuations and air and ST influence carbohydrate relations in grapevine (Chaves et al., 2016; Venios et al., 2020; Gambetta et al., 2021). Carbohydrate reserves are most abundant in grapevine roots, and ST regulates their mobilization to shoot and trunk (Rogiers et al., 2011). Soil warming up to 24°C promote shoot growth by increasing the use of starch reserves, while soil cooling (13°C) result in starch accumulation in both roots and stem and shift the overall biomass partitioning to the root system (Field et al., 2020). High night air temperature reduces carbohydrates exportation from leaves, but promotes respiration resulting in lower leaf carbohydrate contents (Tombesi et al., 2019). Moreover, higher air temperatures coupled with higher surface ST during early evening may promote excessive carbon loss due to maintenance of higher respiration (Escalona et al., 2012). Therefore, carbon losses and modified carbohydrate dynamics due to increased respiration must be better quantified for vines growing under dry and warm conditions (Medrano et al., 2016).

In grapevine, pot-based experiments showed that the highest biomass production and shoot growth rates were achieved under warmer treatment regimens (24°C compared to 13°C) (Field et al., 2020). However, above certain critical temperatures, growth is often hindered due to lower net assimilation rates, and in more extreme cases leaf overheating and death (Chaves et al., 2016). Supraoptimal ST may also affect the root system. Root survival can be negatively affected by ST above 35°C, which can lead to root

death (Huang et al., 2005). Fluctuations in air temperature and ST modulate grapevine's morphology. ST can affect root characteristics (size, architecture, and function) (Luo et al., 2020; Gavelienė et al., 2022). Exposure of plant roots to temperatures above their optimum often decreases primary root length and lateral root density, reducing the volume of soil explored by roots and consequently, reducing water and nutrient uptake (Koevoets et al., 2016). Meanwhile, the root architecture may dynamically adapt to spatial and temporal temperature changes by acclimation of root structure and geometry (Nagel et al., 2009; Fonseca de Lima et al., 2021; Fichtl et al., 2023). Nevertheless, it is difficult to quantify the effect of root temperature in real conditions, as the distribution of roots changes according to soil characteristics and conditions of the soil surface (Pradel and Pieri, 2008). Temperature influences grapevine hormonal relations at root and shoot level (Walker and Winter, 2006; Chaves et al., 2016; Field et al., 2020; Bernardo et al., 2021). Soil temperature was found to regulate hormone content such as cytokinins (CKs) in grapevine xylem sap (Field et al., 2020) and also of abscisic acid (ABA) (Bernardo et al., 2021). The effects of ST on vine performance still need to be better quantified and the interaction between air and ST and soil moisture on vines must be evaluated for their physiology and agronomical performance under extreme dry and high temperature conditions.

3.2. Vineyard weeds and spontaneous vegetation

Soils of vineyards in the Mediterranean region are often subjected to intensive labor to reduce or eliminate competition by light, water, and nutrients, between vines and the weedy flora. Therefore, vineyard landscapes depend on a great investment in tillage, mowing, or herbicide application (Winter et al., 2018). Intensive soil management practices result in increasing ST with feedback loops on soil seed bank, altered seed dormancy, seed longevity and germination patterns, along with general plant composition changes towards resilient species to heat and water stress (Kathiresan and Gualbert, 2016). ST and soil moisture are key determinants for seed dormancy breaking and a trigger for germination, along with exposure to flashes of light on non-deep buried seeds caused by soil disturbance (Sauer and Struik, 1964). Higher ST due to bare soils and warmer climate conditions can promote synchronized mass seed germination of certain species, resulting in homogeneous and well-adapted weedy plant communities, which can be more damaging if agrochemicals (fertilizers and pesticides) are used, stimulating growth and weed resistance to herbicides. However, the mechanisms and traits of weed species can differ, and for some summer annual species, dormancy breaking occurs under low ST conditions, whereas optimal germination is triggered by higher ST (Forcella, 1998). Soil growing degree days (GDD) has been used with success for weeds, estimated from ST to predict emergence rates of weed seedlings. Following germination, higher air temperature and ST usually favoured rapid development of weed seedlings and plant growth, and GDD based on air temperatures can be used to estimate postemergence seedling height growth (Forcella, 1998).

The proportion of bare soil was tested as a predictor of the taxonomic diversity of plant communities and vine yield, and results pointed to slightly lower berry productivity for higher plant diversity, corresponding to lower bare soil area, and lower ST (Guerra et al., 2022). Nevertheless, soil management decisions made by winegrowers involve cost-effectiveness of weed control that needs to be addressed locally and over the long term. These factors include, for instance, the weed resistance to herbicides, the role of weeds as a refuge for pests and diseases, or as resources for pollinators and pest predators, amongst other goods and services that spontaneous flora can provide to the well-being and society (Paola et al., 2020). Higher ST promotes the dominance of exotic weedy species from tropical climates, such as *Conyza* spp. or native Mediterranean species that have clear positive photoblastic germination mechanisms, such as *Dittrichia viscosa* (Parolin et al., 2014). Evolutionary mechanisms of exotic annuals or seed-dispersed perennials out of the native range are likely to take place as an environmental adaptation, which increases the risk of unbalanced agroecosystems (Clements and Ditommaso, 2011; Garcia et al., 2018).

Effects of extreme ST on plants ecophysiology were studied for a few species and mostly on crops or grasslands but in general, extreme high ST affected photosynthesis by reducing carboxylation efficiency, with differences between C3 and C4 plants (Nóia Júnior et al., 2018). A reduction in leaf stomatal conductance, relative water content and increased concentration in intercellular CO₂ occurred and C4 plants are likely to be more affected than C3, given the differences in photosynthetic pathways. In turn, extreme low ST on C4 plants resulted in higher leaf stomatal resistance and reduced photosynthetic rates.

Weeds and spontaneous vegetation present diverse seasonal dynamics that, together with the vine's phenology, produce a dynamic ecosystem across time and space, on the rhizosphere and above ground. Relations with ST and vineyard management must be addressed by looking at the seasonality of the complex of crop-spontaneous vegetation and weedy flora, and the constraints and objectives of wine producers (Garcia et al., 2018).

3.3. Soil organisms

The biological component of the soil is a vital part of agricultural ecosystems, including vineyards, and is composed of a diverse set of macro- and micro-organisms like insects, myriapods, worms, nematodes, bacteria, archaea, fungi, actinomycetes, protozoa, algae (Pritchard, 2011; Sassenrath et al., 2018). They compose the soil food web and can be divided into four groups according to their body size and functional roles: micro-organisms and macro-, meso- and microfauna (Giffard et al., 2022). Those organisms have important ecological functions and lead crucial processes in the soil that determine soil and plant health, such as OM decomposition, nutrient cycling, soil structure improvement, including soil aeration and increased water and nutrient retention, as well as pest, disease and weed control (Giffard et al., 2022). Climate change and increased ST are likely to affect their diversity

and community dynamics, which may have a strong influence on the overall food soil web and on the ecosystem services they provide, which may ultimately affect grapevine performance.

3.3.1. Soil microbiota

In the particular case of soil microbiota, a rich and diverse community of soil microorganisms can ensure productive soils, because they largely influence nutrient cycling and soil fertility, promote pathogen suppression, enhance CO₂ sequestration and increase soil OM mineralization rates. Due to those crucial roles for agro-ecosystem functioning, microbial biodiversity is considered as an important determinant of the *terroir* (Gobbi et al., 2022).

In vineyards, soils are the main reservoir of microorganisms for the grapevine phyllosphere and endosphere, since every growing season, aboveground plant organs, including leaves and berries, obtain their microbes mainly from the soil (Compant et al., 2011; Zarraonaindia et al., 2015). Nowadays, it is well accepted that balanced grapevine-associated microbial communities are essential not only for plant growth and biotic and abiotic stress tolerance (Pinto et al., 2014), but affect the organoleptic properties of the must (Zarraonaindia et al., 2015). It can also influence the fermentation dynamics at the winery and ultimately wine quality (Belda et al., 2017). Hence, any changes in soil microbial community composition and structure may influence plant performance and berry composition, given their direct and indirect influence on grapevine growth, health, stress tolerance and berry development (Di Giacinto et al., 2020).

Temperature is one of the most important determinants of microbial growth and metabolic rates. However, the assessment of the overall soil microbial community response as a function of temperature is still challenging (Jansson and Hofmockel, 2020) and an acclimatization of microbial communities to soil warming cannot be excluded (Pritchard, 2011; Snyder and Callaham, 2019). The increase of ST may have two contrasting consequences on soil organisms and microbiota. Since there is a linear relationship between temperature and respiration, it could be expected that in response to temperature rises, soil microbial respiration will also increase, releasing CO₂ to the atmosphere (Bond-Lamberty et al., 2018), which contributes to the greenhouse effect, and further temperature increase. On the other hand, at higher temperatures, the metabolism of OM decomposers (mainly fungi) is expected to be more active (Schindlbacher et al., 2011) and, therefore, microbial OM mineralization rates could be faster. Under such circumstances, nutrient release is accelerated (e.g. nitrogen), which can be translated into faster plant growth, contributing to carbon sequestration. This issue is even more complex, with several other interacting factors in the local soil environment (e.g. high temperatures also affect the nitrification process or soil oxygen concentration) that ultimately affect microbial growth and metabolism (Bai et al., 2013; Hu et al., 2016; Jansson and Hofmockel, 2020).

Some studies demonstrate that as temperature increases, population shifts, and variations in microbial community structure and changes in functional genes occur (Zhang et al., 2005;

Schindlbacher et al., 2011; Melillo et al., 2017; RomeroOlivares et al., 2017). In the case of vineyards, in a recent study across the world, Gobbi et al. (2022) found a positive correlation between temperature and fungal alpha diversity, but not between prokaryotic alpha diversity and temperature, indicating that fungal communities might be more sensitive to temperature than soil bacteria and archaea. Větrovský et al. (2019) also found that among the different environmental factors (climatic, soil and vegetation parameters), temperature and precipitation were the key factors regulating fungal diversity and community composition in soils. Nevertheless, to our knowledge, no studies have been conducted yet in vineyards to assess the direct effect of an increase in ST in key microbial soil processes as well as in the community composition/structure of soil micro-organisms. In particular, due to the major roles of fungal communities in vineyard soils as OM decomposers, as plant mutualists (and therefore promoting plant tolerance to stress factors) and also as pathogens, more knowledge is needed on the specific ways in which ST affects these communities. This will allow to develop better strategies to manage vineyard soils to buffer the negative effects of climate change on particular soil microbial functional groups.

3.3.2. Soil fauna

Soil macro, meso and micro-fauna have important roles in the soil. They are involved in OM decomposition, attract microbial communities that mineralize nutrients, and contribute to improve soil structure by creating aggregates and soil pores and mixing the soil (Culliney, 2013). For instance, macroinvertebrates like earthworms, ants and termites can move large portions of soil, creating new microhabitats for other soil organisms, and can assimilate plant materials, integrating them into the soil as OM (Snyder and Callaham, 2019). On the other hand, isopods and myriapods promote OM decomposition by feeding on carbonbased compounds and by excreting enzymes and feces into the soil, thereby enhancing the proliferation of microbial decomposer communities, that release nutrients into the soil (Hendrix, 2000; Zagatto et al., 2021).

The study of how soil warming affects soil fauna is challenging, since depending on the methodological approach (air, soil or air and soil warming), the outcome can be substantially different (Snyder and Callaham, 2019). Therefore, artificial/experimental temperature manipulation may not lead to a real response of soil fauna under natural conditions (Snyder and Callaham, 2019), which makes drawing conclusions somewhat challenging. Moreover, ST and moisture are directly linked, and therefore, differentiating the independent effects of each factor on soil fauna is often difficult. In addition, distinct taxonomical or functional groups may react differently to ST increases and to the indirect effects that this entails in the soil ecosystem.

In a model described by Snyder and Callaham (2019), the increase in ST leads first to changes in animal behavior, such as up- or downward movements in the soil profile. It can also lead to physiological changes that have consequences on their fitness and reproduction, with a subsequent effect on soil animal taxa abundance, community structure and diversity. This can ultimately lead to changes

in their functions, including nutrient cycling, OM decomposition and soil respiration. In their review, [Snyder and Callaham \(2019\)](#) also present a conceptual model generalizing how soil warming may affect the soil environment and summarize the direct and indirect interactions that may occur between vegetation, microorganisms, soil macro-, meso- and microfauna and OM under a global warming context.

Although some studies already describe the diversity and ecosystem functions of soil fauna in vineyards ([Ghiglieno et al., 2020](#); [Gonçalves et al., 2021](#); [Andrés et al., 2022](#); [Giffard et al., 2022](#)), much less information is available on the effects of soil warming on soil fauna ([Snyder and Callaham, 2019](#)). It is known that agricultural soils, and thus vineyards, tend to have low soil invertebrate diversity, which are often characterized by species that are well-adapted to environmental disturbances ([Callaham et al., 2006](#)). However, the management regime can strongly influence their populations, with a generally beneficial effect observed in arthropod abundance and diversity in organic vineyards ([Caprio et al., 2015](#); [Gagnarli et al., 2015](#); [Ghiglieno et al., 2019](#); [Ghiglieno et al., 2020](#); [Bosco et al., 2022](#)). According to [Blankinship et al. \(2011\)](#), soil fauna may be more sensitive to soil moisture content, and therefore to changes in precipitation, than to mild increases in temperature.

In a study conducted by [Ghiglieno et al. \(2020\)](#) in Italian vineyards, Collembola and Acari were the most frequent taxa observed in vineyard soils. While taxa of the first group showed a variety of responses related to ST, Acari, as well as Thysanoptera, Diplopoda and Hymenoptera were more related to lower ST. Contrastingly, Diptera, Isopoda, Hemiptera, as well as Coleoptera and Diptera larvae taxa abundance, was related to higher ST. This may lead to the hypothesis that the latter taxa may be more negatively affected by soil warming in the context of climate change than the former group, which could be benefited, since they appear to be thermophilic ([Eisenbeis and Wichard, 1987](#); [Reddy and Venkataiah, 1990](#); [Zhu et al., 2018](#)). This would be the case of ants, as some studies showed that they increase their activity at higher temperatures ([Dunn et al., 2009](#); [Snyder and Callaham, 2019](#)).

More knowledge is needed on how soil fauna, in particular invertebrates, will react to soil warming and the associated changes in the above-ground vegetation and soil moisture. Understanding how those animal communities will respond to increased ST may help to decide on the most appropriate vineyard soil management strategies that can buffer ST changes and foster the proliferation of taxa that benefit both soil and crops.

4. Soil temperature measurements

Ecological patterns and processes are often more related to below-canopy soil temperature rather than to well-ventilated air temperatures ([Lembrechts et al., 2022](#)). Moreover, near-surface, rather than air temperature can work as better predictors of ecosystem functions and processes such as OM decomposition, soil respiration and other components of the global carbon balance ([Lembrechts et al., 2022](#)). Therefore, ST measurements are highly relevant and needed to achieve good reference data for specific ecological conditions as well

as to use ST as a major variable to support modelling of ecosystem processes. However, due to the complexity and large labour costs of ST measurements, in situ observations of ST are less commonly described in literature than those of precipitation and air temperature ([Li et al., 2020](#)).

Soil surface temperature measurements are usually carried out with thermocouples and radiometers, but these devices have limitations concerning logistics, access, and technician costs ([Frodella et al., 2020](#)). In turn, measuring ST at different depths can be done with different types of thermometers and sensors installed at various depths ([Abdel-Ghany et al., 2022](#)), which do requires knowledge and significant manpower.

Consequently, there is a general consensus about the need to achieve soil spatial information (e.g. temperature, moisture) faster and with fewer human resources. The use of remote sensing technologies can offer an alternative or a complementary solution for localized and punctual measurements as it allows to retrieve a larger set of spatial data to study vegetation or soil properties at different resolution scales (temporal and spatial) ([Jones and Vaughan, 2010](#); [Wulf et al., 2014](#)). In the last decades, it has increased the interest in developing methodologies for remotely measuring soil surface and vegetation temperature and to assess soil moisture conditions by using spaceborne, airborne or ground-based sensors ([Jones and Vaughan, 2010](#); [Krapez et al., 2012](#); [Frodella et al., 2020](#); [Xu et al., 2020](#); [Diago et al., 2022](#)).

Thermal imaging emerged as a highly flexible and non-contact measurement technique that enables small to large scale, surface temperature sensing and it can be used as an alternative or as a complementary tool for conventional soil surface temperature and moisture monitoring technologies, in a wide variety of geoenvironmental and agricultural applications ([Jones and Vaughan, 2010](#); [Frodella et al., 2020](#); [Zeng et al., 2021](#); [Diago et al., 2022](#)). Ground-based thermal imaging sensors, such as thermal cameras, experienced a fast technological development (e.g. focal plane array uncooled microbolometer sensors) that increased detectors' accuracy, spatial resolution, and decreased costs ([Jones and Vaughan, 2010](#)).

Thermal imaging was successfully used in viticulture to monitor canopy and ST variation at different time scales and different irrigation conditions ([Jones et al., 2002](#); [Gutiérrez et al., 2018](#); [Costa et al., 2019](#); [Gago et al., 2020](#); [Diago et al., 2022](#); [Kustas et al., 2022](#)) (Figure 3). Thermography has been used to monitor the effects of soil, irrigation and different soil covering materials on ST in vineyards ([Frodella et al., 2020](#)). Other studies using thermography helped to characterize the mechanisms behind soil desiccation cracking ([Zeng et al., 2021](#)), or to study heat transfer processes in vineyards ([Kustas et al., 2022](#)). Thermography has been also used as an alternative method to monitor and detect soil microbial activity ([Schwarz et al., 2021](#)).

Satellite remote sensing has been developed for thermal applications, but data calibration and validation remain complex and costly ([Frodella et al., 2020](#)). Indeed, there are still limitations concerning image resolution because satellite measurements still have limited spatial and temporal resolution ([Basurto-Lozada et al., 2020](#)), when considering their practical application to field crops.

Atypical vineyard canopy architecture and row disposition, characterizes by a large amount of bare soil/cover crop separating rows of trellised vines, which demands higher imaging spatial resolution (of one meter or less) for high robustness (BasurtoLozada et al., 2020). Nevertheless, a combination of ground-based in-situ measurements with aerial and satellite imaging may be a solution to monitor ST more effectively (Xu et al., 2020). The same applies to methodological approaches based on the fusion of information retrieved from thermal and multispectral sensors to generate estimates of ST by using computational intelligence models (Basurto-Lozada et al., 2020).

Other techniques such as soil resistivity measurements can be used as a proxy for ST: soils with high resistivity have generally coarse-textured and are warm in contrast to low resistivity soils that are richer in clay and are cooler (Van Leeuwen et al., 2020). Soil electrical conductivity (or its reciprocal soil electric resistivity) reflects a combination of soil mineralogy, salts, moisture and texture, which makes it a robust parameter to characterize soil properties. The advantage of this proximal sensing methodology gives high-resolution maps of the soil resistivity, which can be further related to ST. Furthermore, regression equations have been developed to predict and map moisture content, topsoil thickness, and clay content (Samouëlian et al., 2005). The development of digital soil science, that is the study of soil using the tools of the digital convergence (Wadoux and McBratney, 2021), also opens new possibilities for imaging studies applied to ST and their effects on plants and soil. In addition, the existing cooperative works and data sources on

ST (Lembrechts et al., 2022) can open new opportunities to use ST data in agriculture.

5. Strategies to manage soil temperature in vineyards

Sustainable water and soil management are the core of several sustainability programs in the wine sector (Costa et al., 2022) and other perennial woody crops, such as olive groves and almond orchards (Andrade et al., 2014; Garcia-Tejero et al., 2018; Fraga et al., 2021). More sustainable practices related to soil management can help to alleviate the harmful effects of more extreme drought and heat events due to climate change. This is an increasingly important issue for Mediterranean viticulture and must combine effective soil and canopy management strategies (Figure 4), together with more efficient use of irrigation water and better-adapted varieties/rootstock combinations (Andrade et al., 2014; Costa et al., 2016; Cataldo et al., 2021; Naulleau et al., 2021).

Irrigation is probably the most important and effective short-term adaptation strategy to face the impacts of climate change in Mediterranean vineyards, attending to its high effectiveness in moderating thermal microclimatic extremes at both soil, plant and atmosphere levels (Andrade et al., 2014; Costa et al., 2016) (see Figures 3, 5). Watering and higher soil moisture promote transpiration and the related evaporative cooling in plants, and also favor soil water evaporation (Figures 1, 3). As a result, irrigation in

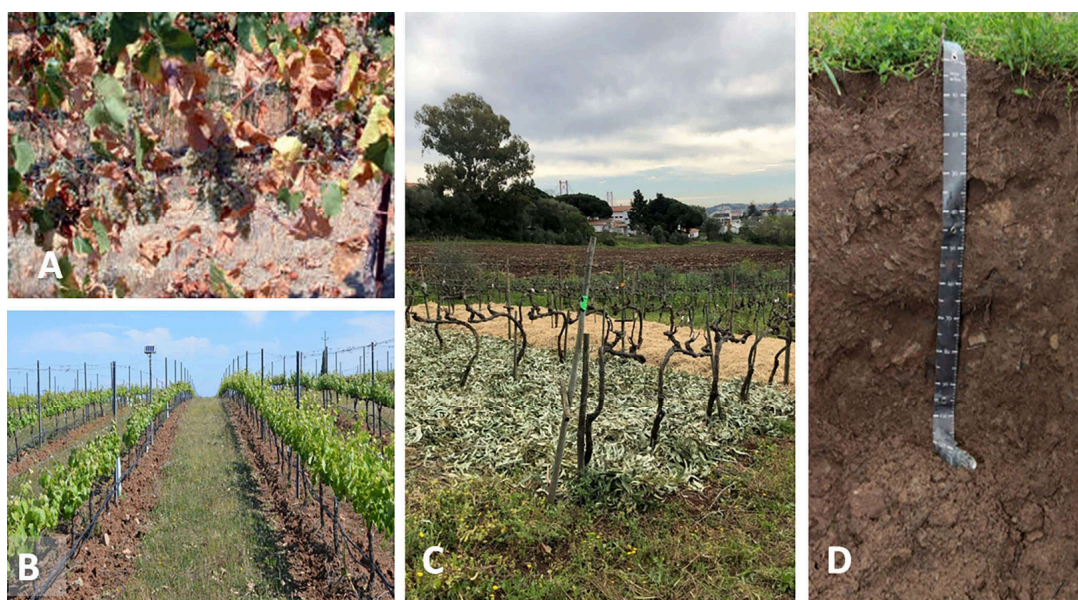


FIGURE 4
(A) The impact of dry and extreme heat in the basal leaves of a Mediterranean vineyard (South Portugal) and sustainable management practices in Mediterranean vineyards, (B) Soil grass cover in the inter row combined with row tillage in a vineyard in Alentejo's wine region (South Portugal), (C) Mulching with different organic materials (rice straw and Eucalyptus foliage) and (D) Soil profile characterization as a tool to support best practices in soil management (ISA campus U. Lisboa).

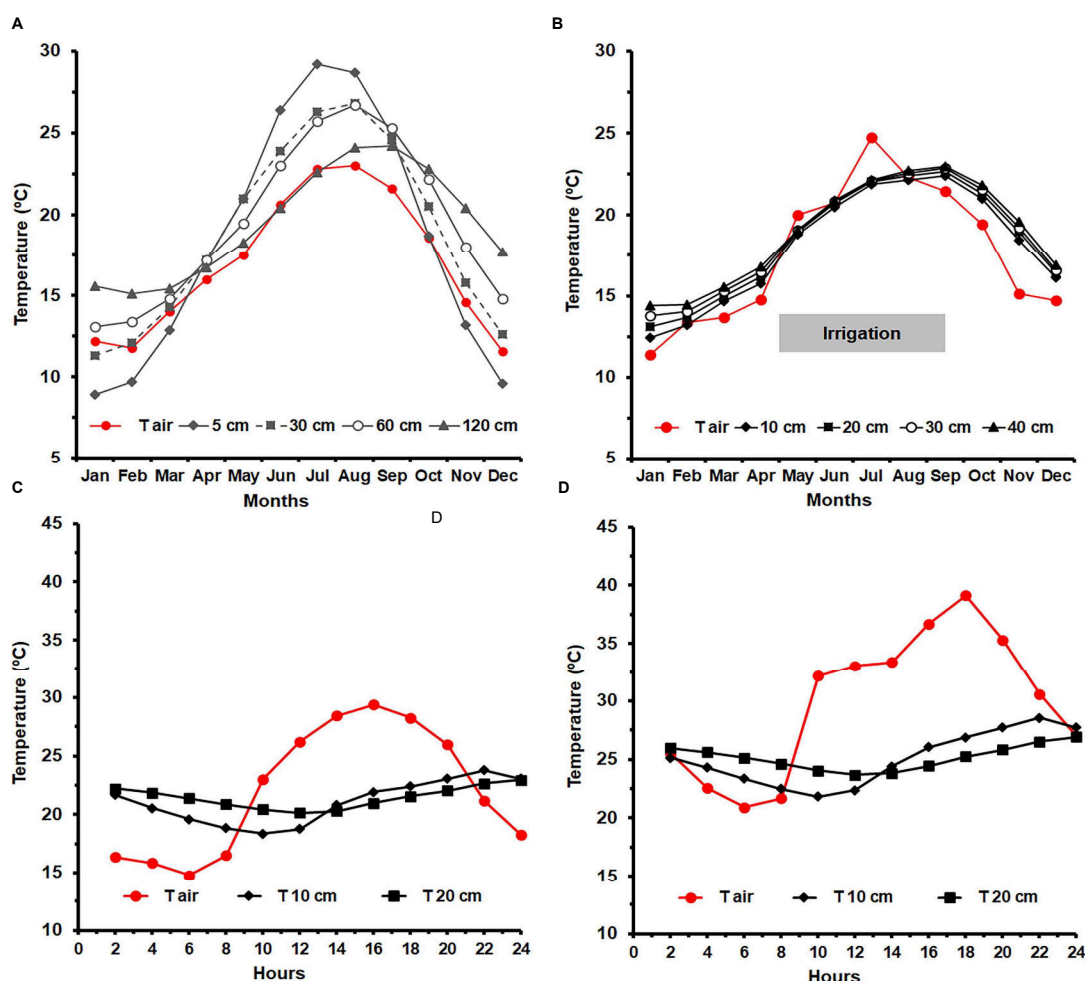


FIGURE 5

(A) Annual variation of soil monthly mean temperature (ST) at 5, 10, 30, 60 and 120 cm depth, for a 30-yr period (1931-1960), measured at the campus of the Instituto Superior de Agronomia (ISA), Lisbon (38°42'27.5"N; 9°10'56.3"W), under rainfed conditions (Botelho da Costa, 1995). (B) Monthly variation ST during the year of 2022, at 10, 20, 30 and 40 cm, in an irrigated vineyard, at ISA (data provided by Hidrosoph, Oeiras, Portugal). The red line indicates variation in the monthly mean air temperature, and the peak in July relates to a heat wave event; Daily ST variation during 1st July 2022 (C) and 9th July 2022 (D), respectively before and at the end of a heat wave, measured every two hours at 10 and 20 cm depth, in the irrigated vineyard; the red line indicates the air temperature.

vineyards expanded fast in southern Europe (Costa et al., 2016; Fraga et al., 2018; Gambetta et al., 2021), but water resources are increasingly scarce and demand more precise irrigation management in Mediterranean vineyards (Mirás-Avalos and Araújo, 2021).

A detailed soil characterization (soil profile, soil properties, fertility) (Figure 4) in new vineyards and in the already installed ones is crucial to support more efficient irrigation and fertilization programs. Soil characterization is also essential for an effective distribution of soil water sensors across the vineyard. In addition, thermal measurements of soil, air and plants (punctual and imagebased) coupled with computer-based information systems can support Decision Support Systems (DSS) (Figure 6) for more efficient

vineyard management (Costa et al., 2020; Naulleau et al., 2021). DSS systems using these multi-parameter thermal data besides supporting precise irrigation strategies are potential indicators of water and heat stress in vineyards that can help to predict and mitigate climate risks.

In addition to irrigation, ST (and plant temperature) can be regulated in vineyards under warmer and dryer conditions, by promoting the use of spontaneous soil cover vegetation, selected cover crops, or mulching. Soil cover protects against soil erosion, increases infiltration and water retention, reduces evaporation, and in the case of living mulches or maintenance of adequate spontaneous vegetation, they act as a source of nutrients and OM, and can improve physical, chemical and biological conditions

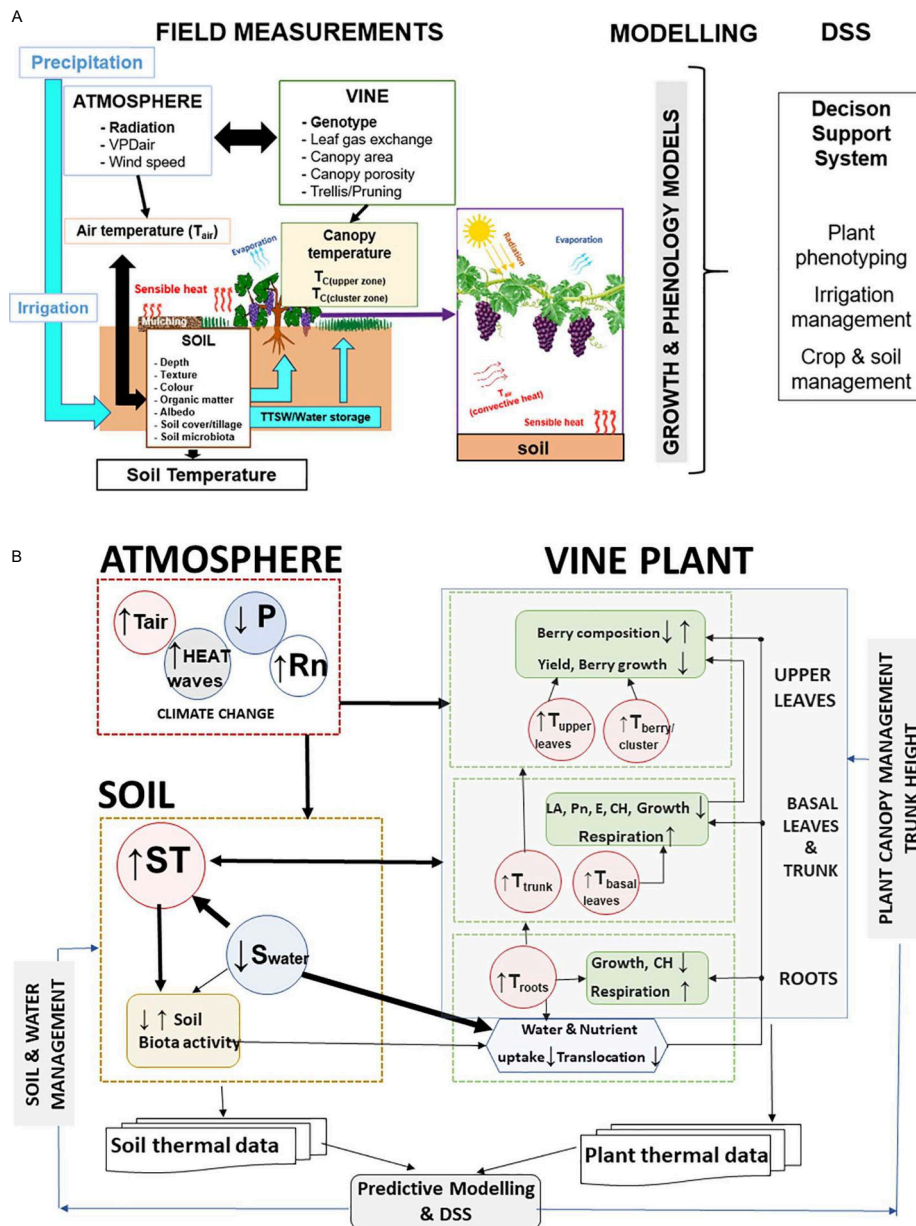


FIGURE 6

(A) Diagram illustrating the potential interactions between soil, canopy and berries in terms of heat exchange and temperature regulation and the use of air temperature (T_{air}), soil temperature (TS), canopy temperature (T_c), and cluster or berry temperature as parameters to feed models to support decision on plant phenotyping, and vineyard management (irrigation, canopy and soil). TTSW – total transpirable soil water; VPDair – Air Vapour-Pressure Deficit (Adapted from Costa et al., 2020). (B) Conceptual framework showing the interaction between soil temperature (ST) and soil water (S_{water}) on vines temperature (roots, trunk, basal and upper leaves, berry/cluster) in a context of climate change (higher radiation - R_n , air temperature - T_{air} , less precipitation - P). Atmospheric conditions and ST influence vine plants T and morpho-physiological and biophysical processes (Leaf area - LA, Net photosynthesis - Pn, Transpiration - E, Carbohydrates - CH, Soil temperature - ST) depends on atmospheric climate conditions (R_n , T_{air} , P). Higher R_n and T_{air} and lower P , promote soil warming and increase evapotranspiration. Soil and plant management influence the thermal regulation of both soil and plants and can be optimized by thermal data (atmosphere, plant and soil) and Decision Support Systems - DSS.

(Marshall et al., 1996; Lazcano et al., 2020). Specifically, natural or spontaneous vegetation cover can also stimulate deeper vine root distribution and promote the use of resources in deeper soil layers (Pradel and Pieri, 2000). The replacement of mineral fertilizers and herbicides with cover crops or vegetation will take years to have a proper impact on soil nutrients and microbial activity, apart from the need to monitor and maintain soil cover (Döring et al., 2019).

Mulching can help to control pests and weeds and maintain yield levels under adverse climatic conditions. Fraga and Santos (2018) investigated the effects of mulching in a typical Mediterranean climate region in Southern Portugal, under future climate change scenarios. Although ST was not directly addressed, their results suggest that mulch can mitigate the adverse effects of hotter and drier weather and extreme events, expressed by an estimated increase of yield by 10 to 25% as compared to bare soil vineyards. The use of soil covering material (mulches) influences maximum summer ST, minimum winter ST, as well as the daily ST fluctuations. In apple orchards, for example, plastic mulching promoted more extreme maximum and minimum ST, but the effect on weed control and water losses was positive and resulted in no major negative effects on plants' performance (Neilsen et al., 1986).

A more sustainable soil management involving no-tillage or improved tillage strategies is key to minimize soil erosion, decrease soil compaction and avoid the formation of impermeable layers which influence soil thermal and water regimes, nutrient cycles and crop performance. Tillage strategies must be based on a good spatial characterization of the soil profile and properties, avoiding the numerous drawbacks of its use and at larger spatial scales, as it hampers surface water run-off, increases greenhouse gas emissions, difficult the groundwater recharge and promote biodiversity losses (Gürsoy, 2021) (Figure 4).

Adaptation to increasing ST may encompass larger rooting depth and involve the use of rootstocks with a wider root-zone temperature optimum to enhance the future performance of woody perennial crops (Koevoets et al., 2016; Darriaut et al., 2022). Therefore, selecting new rootstocks to specific environments should be a challenge to face cultivation problems associated with global climate change.

Other strategies to minimize soil and canopy insulation, control ST and protect crops from light stress and high temperatures may be envisaged. However, they are costly and/or may have negative environmental impacts (e.g. visual pollution; recycling issues). This is the case of the use of shading nets in VSP trellis systems as a strategy to mitigate the negative impact of heat waves and sun exposure of berries. Indeed, partial shading (less than 60% of solar radiation) at the cluster zone reduced by about 4 °C the cluster temperature as compared to sunlit clusters (Marigliano et al., 2022). Shadowing in combination with water availability can avoid berry dehydration during the last phases of ripening with positive effects on anthocyanins and flavonols, as compared to sun exposed clusters (Martinez-Lüscher et al., 2020; Marigliano et al., 2022). Nowadays, the installation of photovoltaic panels over crops ("agrivoltaic" farming) is being advertised as a win-win solution for

climate change adaptation of vineyards and to produce energy (Fraunhofer, 2022). Nevertheless, vine's morphophysiological responses must be taken into account and the respective cost-benefits analysis must be carried out, along with the quantification of the damaging effects on the landscape (e.g. loss of the aesthetics of the natural rural landscapes). Furthermore, row orientation has a dramatic effect on the vine's exposition to sunlight and consequently on ST and canopy temperature (White, 2015; Hunter et al., 2020; Pisciotta et al., 2021). In addition, row spacing, and trellis design influence ST by varying the percentage of shading of solar radiation on the soil. For example, the soil layers of east – west oriented rows reach their highest temperature in the afternoon, and ST generally increases in the two top layers and decreases in the lower layers from mid-morning to late afternoon (Hunter et al., 2020). A combination of higher planting density with shading can also be considered, which favors both natural and artificial shading in vineyards and minimizes the impacts of extreme radiation and heat conditions on both crops and soil cover crops and benefit the activity of the relevant soil microorganisms (microbiota).

6. Conclusions

More sustainable agricultural, hydrological, and environmental management in the context of climate change demands a better understanding of soil resources variability, at increasingly higher resolutions (Wulf et al., 2014). Though soil temperature maps are already available for many regions of the world (Lembrechts et al., 2022), high resolution data on ST that can be representative of microhabitat conditions for below-ground organisms is still needed, and especially for deeper soil layers.

The effects of spatiotemporal variation of temperature on ecological processes and functioning of agroecosystems has been investigated but the predictive capacity remains low, and more studies focused on the interaction of soil-organisms-crop productivity and quality are still required (Pipan et al., 2021). This knowledge at fine scales would help to better understand the roles of soil and soil management on climate change adaptation and will help to cope with current and future challenges of climate change by supporting predictive modelling and decision-making applied to perennial crops systems, such as grapevine or other typical Mediterranean crops.

Long-term field measurements using sensors of both ST and soil moisture are being developed and tested in vineyards and other perennial crops (García-Tejero et al., 2018; Costa et al., 2019; Wild et al., 2019). Thermal sensors have become less expensive and offer larger robustness and energy autonomy though limitations such the low contact of the logger in certain soil types (e.g. drying clay soils) were reported (Wild et al., 2019).

Climate warming may have diverse effects on ST according to the diverse types of heat stress (heat shocks, heat waves, or increasing warming conditions), leading to diverse physiological and molecular responses at leaf and fruit levels, and on root morphology as well as on reproductive traits. There is evidence that the phenological

stage of crops influences crops vulnerability to increase temperature, either by pulses or in a continuous trend (Jagadish et al., 2021). This applies to grapevines. Future research should encompass a better understanding of the mechanism(s) by which ST affects leaf and berry traits across different grapevine varieties, clones and/or rootstocks.

Soil remains sidelined in viticulture research, suggesting a lack of attention to non-new but highly relevant issues such as the detailed spatial distribution and characterization of soil types before designing and planting new vineyards. As consequence there is an urgent need to improve monitoring and better evaluate the roles of soil properties and ST in Mediterranean vineyards, which are increasingly exposed to more adverse climatic conditions and increasing irrigation limitations (Costa et al., 2016). A better understanding of the roles of soil properties on soil microbiota, weed and vine morpho-physiology, and on heat and water fluxes, is crucial to achieve a more efficient soil and crop management, and to ensure a more sustainable Mediterranean viticulture under extreme stress conditions. This achievement will certainly contribute to the Sustainable Development Goals, namely in terms of soil and biodiversity protection and more sustainable water management. Ultimately, we must consider the feasibility and economic implications of the proposed management strategies that vary with the wine regions and the fact that improved soil and canopy management solutions will be only achieved with multidisciplinary knowledge and more trained professionals.

Author contributions

JMC: idea, writing, editing, reviewing and funding. MM, FA, AN and RE writing, editing, and reviewing. JMC, FA, PM: illustrations and editing. All authors contributed to the article and approved the submitted version.

References

- Abad, J., Hermoso de Mendoza, I., Marin, D., Orcaray, L., and Santesteban, L. G. (2021). Cover crops in viticulture. a systematic review (1): Implications on soil characteristics and biodiversity in vineyard. *OENO One* 55 (1), 295–312. doi: 10.20870/oeno-one.2021.55.1.3599
- Abdel-Ghany, A. M., Al-Helal, I. M., Alsadon, A., Ibrahim, A., and Shady, M. (2022). Measuring and predicting the in-ground temperature profile for geothermal energy systems in the desert of arid regions. *Energies* 15, 7268. doi: 10.3390/en15197268
- Akter, M., Miah, A. H., Hassan, M. M., Mobin, M. N., and Baten, M. A. (2015). Textural influence on surface and subsurface soil temperature under various conditions. *J. Env. Sci. Nat. Resour.* 8 (2), 149–154. doi: 10.3329/jesnr.v8i2.26882
- Andrade, J. A., Santos, F. L., Correia, M., and Paço, T. A. (2014). Effects of irrigation and tree spacing on soil and air temperature profiles of olive orchards. *Acta Hortic.* 1057, 443–450. doi: 10.17660/ActaHortic.2014.1057.56
- Andrés, P., Doblas-Miranda, E., Silva-Sánchez, A., Mattana, S., and Font, F. (2022). Physical, chemical, and biological indicators of soil quality in Mediterranean vineyards under contrasting farming schemes. *Agronomy* 12, 2643. doi: 10.3390/agronomy12112643
- Aragüés, R., Medina, E. T., and Claveria, I. (2014). Effectiveness of inorganic and organic mulching for soil salinity and sodicity control in a grapevine orchard drip-irrigated with moderately saline waters. *instituto nacional de investigación y tecnología agraria y alimentaria (INIA). Spanish J. Agric. Res.* 12 (2), 501–508. doi: 10.5424/sjar/2014122-5466
- Bai, E., Li, S., Xu, W., Li, W., and Dai, W. (2013). A meta-analysis of experimental warming effects on terrestrial nitrogen pools and dynamics. *New Phytol.* 199, 441–451. doi: 10.1111/nph.12252

Funding

JMC and AN were funded by national funds through FCT – Fundação para a Ciência e a Tecnologia, I.P., under the project UIDB/04129/2020 of LEAF-Linking Landscape, Environment, Agriculture and Food, Research Unit. MM and FCA acknowledge the support by the Centro de Estudos Florestais, a research unit funded by Fundação para a Ciência e a Tecnologia I.P. (FCT) Portugal, through the project UIDB/00239/2020 and FCA is supported by national funds via FCT under the contracts Norma Transitória - DL57/2016/CP1382/CT0028.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

- Basurto-Lozada, D., Hillier, A., Medina, D., Pulido, D., and Karaman, S. (2020). Dynamics of soil surface temperature with unmanned aerial systems. *Pattern Recognit. Lett.* 138, 68–74. doi: 10.1016/j.patrec.2020.07.003
- Baver, L. D. (1965). *Soil physics*. 3rd ed. (New York: John Wiley & Sons), 489 pp. Fifth Printing.
- Belda, I., Ruiz, J., Esteban-Fernández, A., Navascués, E., and Marquina, D. (2017). Microbial contribution to wine aroma and its intended use for wine quality improvement. *Molecules* 22 (2), 189. doi: 10.3390/molecules22020189
- Bernardo, S., Dinis, L.-T., Luzio, A., Machado, N., and Gonçalves, A. (2021). Optimising grapevine summer stress responses and hormonal balance by applying kaolin in two Portuguese demarcated regions. *OENO One* 55 (1), 207–222. doi: 10.20870/oeno-one.2021.55.1.4502
- Blankinship, J. C., Niklaus, P. A., and Hungate, B. A. (2011). A meta-analysis of responses of soil biota to global change. *Oecologia* 165 (3), 553. doi: 10.1007/s00442011-1909-0
- Bonada, M., Jeffery, D. W., Petrie, P. R., Moran, M. A., and Sadras, V. O. (2015). Impact of elevated temperature and water deficit on the chemical and sensory profiles of barossa Shiraz grapes and wines. *Aust. J. Grape Wine Res.* 21, 240–253. doi: 10.1111/ajgw.12142
- Bond-Lamberty, B., Bailey, V., Chen, M., Gough, C., and Vargas, R. (2018). Globally rising soil heterotrophic respiration over recent decades. *Nature* 560, 80–83. doi: 10.1038/s41586-018-0358-x
- Bosco, L., Siegenthaler, D., Ruzzante, L., Jacot, A., and Arlettaz, R. (2022). Varying responses of invertebrates to biodynamic, organic and conventional viticulture. *Front. Conserv. Sci.* 3. doi: 10.3389/fcsc.2022.837551
- Bota, J., Tomas, M., Flexas, J., Medrano, H., and Escalona, J. M. (2016). Differences among grapevine cultivars in their stomatal behavior and water use efficiency under progressive water stress. *Agric. Water Manage.* 164, 91–99. doi: 10.1016/j.agwat.2015.07.016
- Botelho da Costa, J. V. (1995). *Caracterização e constituição do solo*, 5ª Edição. 527 pp, com revisão e aditamentos de Ario L. Azevedo e R. Pinto Ricardo. Serviço de

Educação, Fundação Calouste Gulbenkian, Lisboa, Portugal. Depósito legal N.º 88 996/95, ISBN 972-31-0073-8.

Bradford, J. B., Schaefer, D. R., Laurenroth, W. K., Palmquist, K. A., Chambers, J. C., et al. (2019). Climate-driven shifts in soil temperature and moisture regimes suggest opportunities to enhance assessments of dryland resilience and resistance. *Front. Ecol. Evol.* 7. doi: 10.3389/fevo.2019.00358

Brady, N. C., and Weil, R. R. (2017). The nature and properties of soils. Fifteenth Edition (New Jersey, USA: Pearson International Edition, Upper Saddle River), 975 pp.

Bullied, W. J., Marginet, A. M., and Van Acker, R. C. (2003). Conventional- and conservation-tillage systems influence emergence periodicity of annual weed species in canola. *Weed Sci.* 51, 886–897. doi: 10.1614/P2002-117

Burg, P., Čížková, A., Masán, V., Sedlar, A., Matwijczuk, A., and Souček, J. (2022). The effect of mulch materials on selected soil properties, yield and grape quality in vineyards under central European conditions. *Agronomy* 12, 1862. doi: 10.3390/agronomy12081862

Callahan, M. A. R., Richter, D. D., Coleman, D. C., and Hofmoeckel, M. (2006). Long-term land use effects on soil invertebrate communities in southern piedmont soils. *Eur. J. Soil Biol.* 42, S150–S156. doi: 10.1016/j.ejsobi.2006.06.001

Candiago, S., Tscholl, S., Bassani, L., Fraga, H., and Vigl, L. E. (2022). A geospatial inventory of regulatory information for wine protected designations of origin in Europe. *Sci. Data* 9, 394. doi: 10.1038/s41597-022-01513-0

Caprio, E., Nervo, B., Isaia, M., Allegro, G., and Rolando, A. (2015). Organic versus conventional systems in viticulture: Comparative effects on spiders and carabids in vineyards and adjacent forests. *Agric. Syst.* 136, 61–69. doi: 10.1016/j.agsy.2015.02.009

Carvalho, L. C., Coito, J. L., Colaço, S., Sangiorgio, M., and Amâncio, S. (2014). Heat stress in grapevine: the pros and cons of acclimation. *Plant Cell. Environ.* 38 (4), 778–789. doi: 10.1111/pce.12445

Cataldo, E., Fucile, M., and Mattii, G. B. (2021). A review: soil management, sustainable strategies and approaches to improve the quality of modern viticulture. *Agronomy* 11 (11), 2359. doi: 10.3390/agronomy11112359

Chaves, M. M., Costa, J. M., Zarrouk, O., Pinheiro, C., Lopes, C. M., and Pereira, J. S. (2016). Controlling stomatal aperture in semi-arid regions - the dilemma of saving water or being cool? *Plant Sci.* 251, 54–64. doi: 10.1016/j.plantsci.2016.06.015

Chaves, M. M., Zarrouk, O., Francisco, R., Costa, J. M., Santos, T., and Regalado, A. P. (2010). Grapevine under deficit irrigation: hints from physiological and molecular data. *Ann. Bot.* 105, 661–676. doi: 10.1093/aob/mcq030

Clements, D. R., and Ditommaso, A. (2011). Climate change and weed adaptation: can evolution of invasive plants lead to greater range expansion than forecasted? *Weed Res.* 51, 227–240. doi: 10.1111/j.1365-3180.2011.00850.x

Compant, S., Mitter, B., Colli-Mull, J. G., Gangl, H., and Sessitsch, A. (2011). Endophytes of grapevine flowers, berries, and seeds: identification of cultivable bacteria, comparison with other plant parts, and visualization of niches of colonization. *Microb. Ecol.* 62, 188–197. doi: 10.1007/s00248-011-9883-y

Costa, J. M., Catarino, S., Escalona, J. M., and Comuzzo, P. (2022). “Achieving a more sustainable wine supply chain – environmental and socioeconomic issues of the industry,” Eds. J. M. Costa, S. Catarino, J. M. Escalona and P. Comuzzo (Academic Press, Elsevier), 1–24, ISBN: . doi: 10.1016/B978-0-323-85150-3.00009-8

Costa, J. M., Egipto, R., Lopes, C., and Silvestre, J. (2020). “Using soil and canopy temperature to support efficient management of irrigated vineyards,” in 15th Quantitative InfraRed Thermography (QIRT) conference, Oporto. doi: 10.21611/qirt.2020.120

Costa, J. M., Egipto, R., Sánchez-Virosta, A., Lopes, C. M., and Chaves, M. M. (2019). Canopy and soil thermal patterns to support water and heat stress management in vineyards. *Agric. Water Manage.* 216, 484–496. doi: 10.1016/j.agwat.2018.06.001

Costa, J. M., Vaz, M., Escalona, J., Egipto, R., Lopes, C., and Medrano, H. (2016). Modern viticulture in southern Europe: Vulnerabilities and strategies for adaptation to water scarcity. *Agric. Water Manage.* 164, 5–18. doi: 10.1016/j.agwat.2015.08.021

Crystal-Ornelas, R., Thapa, R., and Tully, K. L. (2021). Soil organic carbon is affected by organic amendments, conservation tillage, and cover cropping in organic farming systems: A meta-analysis. *Agric. Ecos. Env.* 312, 107356. doi: 10.1016/j.agee.2021.107356

Culliney, T. W. (2013). Role of arthropods in maintaining soil fertility. *Agriculture* 3, 629–659. doi: 10.3390/agriculture3040629

Darriaut, R., Lailheugue, V., Masneuf-Pomarède, I., Marguerit, E., Martins, G., et al. (2022). Grapevine rootstock and soil microbiome interactions: Keys for a resilient viticulture. *Hortic. Res.* 9, uhac019. doi: 10.1093/hr/uhac019

Diago, M. P., Tardaguila, J., Barrio, I., and Fernández-Novales, J. (2022). Combination of multispectral imagery, environmental data and thermography for on-the-go monitoring of the grapevine water status in commercial vineyards. *Eur. J. Agron.* 140, 126586. doi: 10.1016/j.eja.2022.126586

Di Giacinto, S., Friedel, M., Poll, C., Döring, J., Kunz, R., and Kauer, R. (2020). Vineyard management system affects soil microbiological properties. *OENO One* 54 (1), 131–143. doi: 10.20870/oenoone.2020.54.1.2578

Dong, X., Xu, W., Zhang, Y., Daniel, I., and Leskovar, D. I. (2016). Effect of irrigation timing on root zone soil temperature, root growth and grain yield and chemical composition in corn. *Agronomy* 6, 34. doi: 10.3390/agronomy6020034

Döring, J., Collins, C., Frisch, M., and Kauer, M. (2019). Organic and biodynamic viticulture affect biodiversity and properties of vine and wine: a systematic quantitative review. *Am. J. Enol. Vitic.* 70 (3), 221–242. doi: 10.5344/ajev.2019.18047

Droulia, F., and Charalampopoulos, I. (2022). A review on the observed climate change in Europe and its impacts on viticulture. *Atmosphere* 13, 837. doi: 10.3390/atmos13050837

Dunn, R. R., Agosti, D., Andersen, A. N., Arnan, X., Bruhl, C. A., and Cerdá, X. (2009). Climatic drivers of hemispheric asymmetry in global patterns of ant species richness. *Ecol. Lett.* 12, 324–333. doi: 10.1111/j.1461-0248.2009.01291.x

EEA (2019) Soil, land and climate change. Available at: <https://www.eea.europa.eu/signals/signals-2019-content-list/articles/soil-land-and-climate-change>.

Egipto, R., Neves, M., Mota, M., Lopes, C., Silvestre, J., and Costa, J. M. (2022) Low-cost sensors as a support tool to monitor soil-plant heat exchanges in a Mediterranean vineyard | TERCLIM, IVES conferences series. Available at: <https://ives-openscience.eu/13109/>.

Eisenbeis, G., and Wichard, W. (1987). Atlas on the biology of soil arthropods (Berlin/Heidelberg, Germany: Springer). doi: 10.1007/978-3-642-72634-7

Escalona, J. M., Tomás, M., Martorell, S., Medrano, H., Ribas-Carbo, M., et al. (2012). Carbon balance in grapevines under different soil water supply: importance of whole plant respiration. *Aust. J. Grape Wine Res.* 18, 308–318. doi: 10.1111/j.1755-0238.2012.00193.x

Evetts, S. R. (2000). “Soil physics. 5. energy and water balances at soil-plant-atmosphere interfaces,” in Handbook of soil science. Eds. M. E. Sumner (CRC press), 129–182.

Feng, X., Qian, C., and Materia, S. (2022). Amplification of the temperature seasonality in the Mediterranean region under anthropogenic climate. *Geoph. Lett.* 49 (20), 1–10. doi: 10.1029/2022GL099658

Fichtl, L., Hofmann, M., Kahlen, K., Voss-Fels, K. P., Cast, C. S., Ollat, N., et al. (2023). Towards grapevine root architectural models to adapt viticulture to drought. *Front. Plant Sci.* 14. doi: 10.3389/fpls.2023.1162506

Field, S. K., Smith, J. P., Morrison, E. N., Neil Emery, R. J., and Holzapfel, B. P. (2020). Soil temperature prior to veraison alters grapevine carbon partitioning, xylem sap hormones, and fruit set. *Am. J. Enol. Vitic.* 71, 52–61. doi: 10.5344/ajev.2019.19038

Fonseca de Lima, C. F., Kleine-Vehn, J., De Smet, I., and Feraru, E. (2021). Getting to the root of belowground high temperature responses in plants. *J. Exp. Bot.* 72 (21), 7404–7413. doi: 10.1093/jxb/erab202

Forcella, F. (1998). Real-time assessment of seed dormancy and seedling growth for weed management. *Seed Sci. Res.* 8, 201–210. doi: 10.1017/S0960258500004116

Fraga, H., Cortázar-Atauri, I. G., Malheiro, A. C., and Santos, J. A. (2016). Modelling climate change impacts on viticultural yield, phenology and stress conditions in Europe. *Glob. Change. Biol.* 22, 3774–3788. doi: 10.1111/gcb.13382

Fraga, H., Garcia de Cortázar Atauri, I., and Santos, J. A. (2018). Viticultural irrigation demands under climate change scenarios in Portugal. *Agric. Water Manage.* 196, 66–74. doi: 10.1016/j.agwat.2017.10.023

Fraga, H., Morondo, M., Leolini, L., and Santos, J. A. (2021). Mediterranean Olive orchards under climate change: A review of future impacts and adaptation strategies. *Agronomy* 11, 56. doi: 10.3390/agronomy11010056

Fraga, H., and Santos, J. A. (2018). Vineyard mulching as a climate change adaptation measure: Future simulations for Alentejo, Portugal. *Agric. Syst.* 164, 107–115. doi: 10.1016/j.agsy.2018.04.006

Fraunhofer (2022) Agrivoltaics: Opportunities for agriculture and the energy transition a guideline for Germany. Available at: <https://www.ise.fraunhofer.de/content/dam/ise/en/documents/publications/studies/APV-Guideline.pdf>.

Frodella, W., Lazzeri, G., Moretti, S., Keizer, J., and Verheijen, F. G. A. (2020). Applying infrared thermography to soil surface temperature monitoring: Case study of a high-resolution 48 h survey in a vineyard (Anadia, Portugal). *Sensors* 20, 2444. doi: 10.3390/s20092444

Gagnarri, E., Goggioli, D., Tarchi, F., Guidi, S., Nannelli, R., Vignozzi, N., et al. (2015). Case study of microarthropod communities to assess soil quality in managed vineyards. *Soil* 1, 527–536. doi: 10.5194/soil-1-527-2015

Gago, J., Estrany, J., Estes, L., Fernie, A. R., Alorda, B., Brotman, Y., et al. (2020). Nano and micro unmanned aerial vehicles (UAVs): A new grand challenge for precision agriculture? *Curr. Prot. Plant Biol.* 5 (1), e20103. doi: 10.1002/cppb.20103

Galat Giorgi, E., Keller, M., Sadras, V., Alejandro-Roig, F., and Perez-Peña, J. (2020). High temperature during the budwell phase of grapevines increases shoot water transport capacity. *Agric. For. Met.* 295, 108173. doi: 10.1016/j.agrformet.2020.108173

Gambetta, J. M., Holzapfel, B. P., Stoll, M., and Friedel, M. (2021). Sunburn in grapes: A review. *Front. Plant Sci.* 11. doi: 10.3389/fpls.2020.604691

Garcia, L., Cellet, F., Gary, C., Ripoché, A., Valdés-Gómez, H., and Metay, (2018). Management of service crops for the provision of ecosystem services in vineyards: A review. *Agric. Eco. Env.* 251, 158–170. doi: 10.1016/j.agee.2017.09.030

Garcia-Tejero, I. F., Ortega-Arévalo, C. J., Iglesias-Contreras, M., Moreno, J. M., Souza, L., et al. (2018). Assessing the crop-water status in almond (*Prunus dulcis* mill.) trees via thermal imaging camera connected to smartphone. *Sensors* 18 (4), 1050. doi: 10.3390/s18041050

Gavelini, V., Jurkonienė, S., Jankovska-Bortkevič, E., and Sveždienė, D. (2022). Effects of elevated temperature on root system development of two lupine species. *Plants* 11 (2), 192. doi: 10.3390/plants11020192

- Ghiglieno, I., Simonetto, A., Donna, P., Tonni, M., Valenti, L., Bedussi, F., et al. (2019). Soil biological quality assessment to improve decision support in the wine sector. *Agronomy* 9, 593. doi: 10.3390/agronomy9100593
- Ghiglieno, I., Simonetto, A., Orlando, F., Donna, P., Tonni, M., et al. (2020). The response of the arthropod community to soil characteristics and management in the Franciacorta viticultural area (Lombardy, Italy). *Agronomy* 10 (5), 740. doi: 10.3390/agronomy10050740
- Giffard, B., Winter, S., Guidoni, S., Nicolai, A., Castaldini, M., Cluzeau, D., et al. (2022). Vineyard management and its impacts on soil biodiversity, functions, and ecosystem services. *Front. Ecol. Evol.* 10. doi: 10.3389/fevo.2022.850272
- Gobbi, A., Acedo, A., Imam, N., Santini, R. G., Ortiz-álvarez, R., Ellegaard-Jensen, L., et al. (2022). A global microbiome survey of vineyard soils highlights the microbial dimension of viticultural terroirs. *Commun. Biol.* 5, 241. doi: 10.1038/s42003-02203202-5
- Gonçalves, F., Carlos, C., Crespo, L., Zina, V., Oliveira, A., Salvação, S., et al. (2021). Soil arthropods in the douro demarcated region vineyards: General characteristics and ecosystem services provided. *Sustainability* 13, 7837. doi: 10.3390/su13147837
- Greer, D. H., and Weedon, M. M. (2012). Modelling photosynthetic responses to temperature of grapevine (*Vitis vinifera* cv. semillon) leaves on vines grown in a hot climate. *Plant Cell Env.* 35 (6), 1050–1064. doi: 10.1111/j.1365-3040.2011.02471.x
- Griffiths, R. P., Madritch, M. D., and Swanson, A. K. (2009). The effects of topography on forest soil characteristics in the Oregon cascade mountains (USA): Implications for the effects of climate change on soil properties. *For. Ecol. Manage.* 257, 1–7. doi: 10.1016/j.foreco.2008.08.010
- Guerra, J. G., Cabello, F., Fernández-Quintanilla, C., Peña, J. M., and Dorado, J. (2022). How weed management influence plant community composition, taxonomic diversity and crop yield: A long-term study in a Mediterranean vineyard. *Agric. Eco. Env.* 326, 107816. doi: 10.1016/j.agee.2021.107816
- Guion, A., Turquet, S., Polcher, J., Pennel, R., Bastin, S., and Arsouze, T. (2022). Droughts and heatwaves in the Western Mediterranean: impact on vegetation and wildfires using the coupled WRF-ORCHIDEE regional model (RegIPSL). *Clim. Dyn.* 58, 2881–2903. doi: 10.1007/s00382-021-05938-y
- Guoju, X., Qiang, Z., Jiangtao, B., Fengju, Z., and Chengke, L. (2020). The relationship between winter temperature rise and soil fertility properties. *Air Soil Water Res.* 5. doi: 10.1177/ASWR.S8599
- Gürsoy, S. (2021). "Soil compaction due to increased machinery intensity in agricultural production: its main causes, effects and management," in *Technology in agriculture*. Eds. F. Ahmad and M. Sultan (IntechOpen). doi: 10.5772/intechopen.98564
- Gutiérrez, S., Diago, M. P., Fernández-Navales, J., and Tardaguila, J. (2018). Vineyard water status assessment using on-the-go thermal imaging and machine learning. *PLoS One* 13 (2), e0192037. doi: 10.1371/journal.pone.0192037
- Haddaway, N. R., Hedlund, K., Jackson, L. E., Katterer, T., Lugato, E., et al. (2017). How does tillage intensity affect soil organic carbon? a systematic review. *Environ. Evidence* 6, 30. doi: 10.1186/s13750-017-0108-9
- Heilman, J. L., McInnes, K. J., Savage, M. J., Gesh, R. W., and Lascano, R. J. (1994). Soil and canopy energy balances in a west Texas vineyard. *Agric. For. Met.* 71, 99–114. doi: 10.1016/0168-1923(94)90102-3
- Hendrix, P. F. (2003). "Soil fauna," in *Handbook of soil science*. Ed. M. E. Sumner (Boca Raton, FL, USA: CRC Press).
- Hillel, D. (2004). *Introduction to environmental soil physics* (Amsterdam: Elsevier, Academic Press), 494 pp.
- Hirschi, M., Seneviratne, S., Alexandrov, V., Boberg, F., and Boroneant, C. (2011). Observational evidence for soil-moisture impact on hot extremes in south-eastern Europe. *Nat. Geosci.* 4, 17–21. doi: 10.1038/ngeo1032
- Houle, D., Bouffard, A., Duchesne, L., Logan, T., and Harvey, R. (2012). Projections of future soil temperature and water content for three southern Quebec forested sites. *J. Climate* 25 (21), 7690–7701. doi: 10.1175/JCLI-D-11-00440.1
- Howell, A., Winkler, D. E., Phillips, M. L., McNellis, B., and Reed, S. C. (2020). Experimental warming changes phenology and shortens growing season of the dominant invasive plant *bromus tectorum* (cheatgrass). *Front. Plant Sci.* 11. doi: 10.3389/fpls.2020.570001
- Hu, H. W., Macdonald, C. A., Trivedi, P., Anderson, I. C., Zheng, Y., et al. (2016). Effects of climate warming and elevated CO₂ on autotrophic nitrification and nitrifiers in dryland ecosystems. *Soil Biol. Biochem.* 92, 1–5. doi: 10.1016/j.soilbio.2015.09.008
- Huang, X., Lakso, A. N., and Eissenstat, D. M. (2005). Interactive effects of soil temperature and moisture on concord grape root respiration. *J. Exp. Bot.* 56, 2561–2660. doi: 10.1093/jxb/eri258
- Hunter, J. J. K., Tarricone, L., Volschenk, C., Giacalone, C., and Melo, M. S. (2020). Grapevine physiological response to row orientation-induced spatial radiation and microclimate changes. *OENO One* 54 (2), 411–433. doi: 10.20870/oeno-one.2020.54.2.3100
- Hunter, J. J., Volschenk, C. G., Mania, E., Vicente-Castro, A., Booysse, M., et al. (2021). Grapevine row orientation mediated temporal and cumulative microclimatic effects on grape berry temperature and composition. *Agric. For. Met.* 310, 108660. doi: 10.1016/j.agrformet.2021.108660
- IPCC. (2021). "Climate change 2021: The physical science basis," in *Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change*. Eds. V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors and C. Péan (New York, NY: Cambridge University Press).
- Jagadeish, S. V. K., Way, D. A., and Sharkey, T. D. (2021). Plant heat stress: Concepts directing future research. *Plant Cell Environ.* 44, 1992–2005. doi: 10.1111/pce.14050
- Jansson, J. K., and Hofmockel, K. S. (2020). Soil microbiomes and climate change. *Nat. Rev. Microbiol.* 18, 35–46. doi: 10.1038/s41579-019-0265-7
- Jones, G. (2012). "A climate assessment for the douro wine region: An examination of the past, present and future climate conditions for wine production," in *ADVID – associação para o desenvolvimento da viticultura duriense* (Régua: Godim).
- Jones, H. G., Stoll, M., Santos, T., Sousa, C., Chaves, M. M., and Grant, O. M. (2002). Use of infrared thermography for monitoring stomatal closure in the field: Application to grapevine. *J. Exp. Bot.* 53 (378), 2249–2260. doi: 10.1093/jxb/erf083
- Jones, H. G., and Vaughan, A. R. (2010). *Remote sensing of vegetation: principles, techniques, and applications*. Oxford University Press, New York. 353.
- Karhu, K., Auffret, M., Dungait, J., Hopkins, D., Prosser, J., Singh, B. K., et al. (2014). Temperature sensitivity of soil respiration rates enhanced by microbial community response. *Nature* 513, 81–84. doi: 10.1038/nature13604
- Kathiresan, R., and Gualbert, G. (2016). Impact of climate change on the invasive traits of weeds. *Weed Biol. Manage.* 16, 59–66. doi: 10.1111/wbm.12096
- Keller, M., Scheele-Baldinger, R., Ferguson, J. C., Tarara, J. M., and Mills, L. J. (2022). Inflorescence temperature influences fruit set, phenology, and sink strength of Cabernet sauvignon grape berries. *Front. Plant Sci.* 13. doi: 10.3389/fpls.2022.864892
- Koevoets, I. T., Venema, J. H., Elzenga, J. T. M., and Testerink, C. (2016). Roots withstanding their environment: exploiting root system architecture responses to abiotic stress to improve crop tolerance. *Front. Plant Sci.* 7. doi: 10.3389/fpls.2016.01335
- Krapez, J. C., Chatelard, C., Nouvel, J. F., and Déliot, Ph. (2012). "Combined airborne thermography and visible-to-near infrared reflectance measurement for soil moisture mapping," in *Proceedings of the 11th International Conference on Quantitative Infrared Thermography (QIRT 2012)*, Naples, Italy, Vol. 17. 11–14, June. e-J. Nondest. Testing. doi: 10.21611/qirt.2012.231
- Kustas, W. P., Nieto, H., Garcia-Tejera, O., Bambach, N., and McElrone, A. J. (2022). Impact of advection on two-source energy balance (TSEB) canopy transpiration parameterization for vineyards in the California central valley. *Irrig. Sci.* 40, 575–591. doi: 10.1007/s00271-022-00778-y
- Lanyon, D. M., Cass, A., and Hansen, D. (2004). The effect of soil properties on vine performance. *CSIRO Land Water. Technical Report No. 34/04*. doi: 10.4225/08/586bc7e218029
- Lazcano, C., Decock, C., and Wilson, S. G. (2020). Defining and managing for healthy vineyard soils intersection, with the concept of terroir. *Front. Environ. Sci.* 8. doi: 10.3389/fenvs.2020.00068
- Lembrechts, J. J., van den Hoogen, J., Aalto, J., Ashcroft, M. B., and De Frenne, P. (2022). Global maps of soil temperature. *Global Change Biol.* 28, 3110–3144. doi: 10.1111/gcb.16060
- Li, M., Wu, P., and Ma, Z. (2020). A comprehensive evaluation of soil moisture and soil temperature from third-generation atmospheric and land reanalysis data sets. *Int. J. Climat.* 40 (13), 5744–5766. doi: 10.1002/joc.6549
- Liu, S., Li, J., and Zhang, X. (2022). Simulations of soil water and heat processes for no tillage and conventional tillage systems in mollisols of China. *Land* 11, 417. doi: 10.3390/land11030417
- Lopes, C. M., Santos, T. P., Rodrigues, M. L., Monteiro, A., and Costa, J. M. (2011). Combining cover cropping with deficit irrigation in a Mediterranean low vigor vineyard. *Sci. Hortic.* 129, 603–612. doi: 10.1016/j.scienta.2011.04.033
- Lorenz, R., Jaeger, E. B., and Seneviratne, S. I. (2010). Persistence of heat waves and its link to soil moisture memory. *Geophys. Res. Lett.* 37, L09703. doi: 10.1029/2010GL042764
- Luo, H., Xu, H., Chu, C., He, F., and Fang, S. (2020). High temperature can change root system architecture and intensify root interactions of plant seedlings. *Front. Plant Sci.* 11. doi: 10.3389/fpls.2020.00160
- Mancuso, S., and Shabala, S. (Eds.) (2010). *Waterlogging signalling and tolerance in plants* (Heidelberg: Springer). doi: 10.1007/978-3-642-10305-6
- Marigliano, L. E., Yu, R., Torres, N., Tanner, J. D., and Battany, M. (2022). Photosensitive shade films mitigate heat wave damage by reducing anthocyanin and flavonol degradation in grapevine (*Vitis vinifera* L.) berries. *Front. Agron.* 4. doi: 10.3389/fagro.2022.898870
- Marshall, T. J., Holmes, J. W., and Rose, C. W. (1996). *Soil physics*. 3rd ed. (Cambridge University Press), 453 pp.
- Martinez-Lüscher, J., Chen, C. C. L., Brillante, L., and Kurtural, S. K. (2020). Mitigating heat wave and exposure damage to "Cabernet sauvignon" wine grape with partial shading under two irrigation amounts. *Front. Plant Sci.* 11 (November). doi: 10.3389/fpls.2020.579192
- Medrano, H., Perez-Peña, J., Prieto, J., Tomás, M., Franck, N., and Escalona, J. M. (2016). "Carbon balance in grapevine under a changing climate," in *Grapevine in a changing environment: A molecular and ecophysiological Perspective*. Eds. H. Varanda Gerós, M. M. Chaves, H. Medrano and S. Delrot (John Wiley & Sons, Ltd.), pp. 110–pp. 134. doi: 10.1002/9781118735985.ch5
- Mehdizadeh, S., Ahmadi, F., and Sales, A. K. (2020a). Modelling daily soil temperature at different depths via the classical and hybrid models. *Met. Appl.* 1–15. doi: 10.1002/met.1941

- Mehdizadeh, S., Fathian, F., Safari, M. J. S., and Khosravi, A. (2020b). Developing novel hybrid models for estimation of daily soil temperature at various depths. *Soil Till. Res.* 197, 104513. doi: 10.1016/j.still.2019.104513
- Meinhold, T., Richters, J.-P., Damerow, L., and Blanke, M. M. (2010). 'Optical properties of reflection ground covers with potential for enhancing fruit colouration'. *Biosystem Eng.* 107 (2), 155–160. doi: 10.1016/j.biosystemseng.2010.07.006
- Melillo, J. M., Frey, S. D., Deangelis, K. M., Werner, W. J., Bernard, M. J., Bowles, F. P., et al. (2017). Long-term pattern and magnitude of soil carbon feedback to the climate system in a warming world. *Science* 358, 101–104. doi: 10.1126/science.aan2874
- Mirás-Avalos, J., and Araujo, E. S. (2021). Optimization of vineyard water management: Challenges, strategies, and perspectives. *Water* 13, 746. doi: 10.3390/w13060746
- Moutinho-Pereira, J. M., Correia, C. M., Gonçalves, B. M., Bacelar, E. A., and TorresPereira, J. M. (2004). Leaf gas exchange and water relations of grapevines grown in three different conditions. *Photosynthetica* 42 (1), 81–86. doi: 10.1023/B:PHOT.0000040573.09614.1d
- Nagel, K. A., Kastenholz, B., Jahnke, S., van Dusschoten, D., Aach, T., Mühlich, M., et al. (2009). Temperature responses of roots: impact on growth, root system architecture and implications for phenotyping. *Funct. Plant Biol.* 36 (11), 947–959. doi: 10.1071/FP09184
- Naulleau, A., Gary, C., Prévot, L., and Hossard, L. (2021). Evaluating strategies for adaptation to climate change in grapevine production—a systematic review. *Front. Plant Sci.* 11. doi: 10.3389/fpls.2020.607859
- Neilsen, G. H., Hogue, E. J., and Drought, B. G. (1986). The effect of orchard soil management on soil temperature and apple tree nutrition. *Can. J. Soil Sci.* 66, 701–711. doi: 10.4141/cjss86-069
- Nobel, P. S. (2005). *Physicochemical and environmental plant physiology* (San Diego: Elsevier/ Academic Press).
- Nóia Júnior, R. S., do Amaral, G. C., Pezzopane, J. E. M., Toledo, J. V., and Xavier, T. M. T. (2018). Ecophysiology of C3 and C4 plants in terms of responses to extreme soil temperatures. *Theor. Exp. Plant Physiol.* 30, 261–274. doi: 10.1007/s40626-018-0120-7
- OIV (2022) State of the world vine and wine sector 2021. Available at: https://www.oiv.int/sites/default/files/documents/eng-state-of-the-world-vine-and-wine-sectorapril-2022-v6_0.pdf.
- Onofre, J. (2022). "European Wine policy framework - the path toward sustainability," in *Improving sustainable viticulture and winemaking practices*. Eds. J. M. Costa, S. Catarino, J. Escalona and P. Commuzzo (Academic Press, Elsevier), 485–499.
- Onwuka, B., and Mang, B. (2018). Effects of soil temperature on some soil properties and plant growth. review article. *Adv. Plants Agric. Res.* 8 (1), 34–37. doi: 10.15406/apar.2018.08.00288
- Pagay, V., and Collins, C. (2017). Effects of timing and intensity of elevated temperatures on reproductive development of field-grown Shiraz grapevines. *OENO One* 51 (4), 409–421. doi: 10.20870/oeno-one.2017.51.4.1066
- Paola, A., Assandri, G., Brambilla, M., Zottini, M., Pedrini, P., et al. (2020). Exploring the potential of vineyards for biodiversity conservation and delivery of biodiversity-mediated ecosystem services: A global-scale systematic review. *Sci. Total Env.* 706, 135839. doi: 10.1016/j.scitotenv.2019.135839
- Parolin, P., Scotta, M., and Bresch, C. (2014). Biology of *dittrichia viscosa*, a Mediterranean ruderal plant: a review. *Intern. J. Exp. Bot.* 83, 251–262. doi: 10.1016/j.journal.pone.0085622
- Pierce, S., Maffi, D., Faoro, F., Cerabolini, B. E. L., and Spada, A. (2022). The leaf anatomical trade-offs associated with plant ecological strategy variation. *Plant Ecol.* 223, 1233–1246. doi: 10.1007/s11258-022-01270-5
- Pinto, C., Pinho, D., Sousa, S., Pinheiro, M., and Egas, C. (2014). Unravelling the diversity of grapevine microbiome. *PLoS One* 9 (1), e85622. doi: 10.1371/journal.pone.0085622
- Pipán, P., Hall, A., Rogiers, S. Y., and Holzapfel, B. P. (2021). Accuracy of interpolated versus in-vineyard sensor climate data for heat accumulation modelling of phenology. *Front. Plant Sci.* 12. doi: 10.3389/fpls.2021.635299
- Pisciotta, A., Catania, P., Orlando, S., and Vallone, M. (2021). Influence of row orientation on the canopy temperature of Sicilian vineyards. *Acta Hort.* 1314, 367–374. doi: 10.17660/ActaHort.2021.1314.46
- Pradel, E., and Pieri, P. (2000). Influence of a grass layer on vineyard soil temperature. *Aust. J. Grape Wine Res.* 6 (1), 59–67. doi: 10.1111/j.1755-0238.2000.tb00163.x
- Pritchard, S. G. (2011). Soil organisms and global climate change. *Plant Pathol.* 60, 82–99. doi: 10.1111/j.1365-3059.2010.02405.x
- Radke, J. K. (1982). Managing early season soil temperatures in the northern corn belt using configured soil surfaces and mulches. *Soil Sci. Soc. J. Am.* 46, 1067–1071. doi: 10.2136/sssaj1982.03615995004600050036x
- Reddy, M. V., and Venkataiah, B. (1990). Seasonal abundance of soil-surface arthropods in relation to some meteorological and edaphic variables of the grassland and tree-planted areas in a tropical semi-arid savanna. *Int. J. Biometeorol.* 34, 49–59. doi: 10.1007/BF01045820
- Rességuier, L., Pieri, P., Mary, S., Pons, R., Petitjean, T., et al. (2023). Characterisation of the vertical temperature gradient in the canopy reveals increased trunk height to be a potential adaptation to climate change. *OENO One* 57 (1), 41–53. doi: 10.20870/oenoone.2023.57.1.5365
- Rogiers, S. Y., Smith, J. P., Holzapfel, B. P., and Hardie, W. J. (2011). Soil temperature moderates grapevine carbohydrate reserves after bud break and conditions fruit set responses to photoassimilatory stress. *Funct. Plant Biol.* 38 (11), 899–909. doi: 10.1071/FP10240
- Romero-Olivares, A. L., Allison, S. D., and Treseder, K. K. (2017). Soil microbes and their response to experimental warming over time: a meta-analysis of field studies. *Soil Biol. Biochem.* 107, 32–40. doi: 10.1016/j.soilbio.2016.12.026
- Ruperti, B., Botton, A., Populin, F., Eecher, G., Brilli, M., et al. (2019). Flooding responses on grapevine: A physiological, transcriptional, and metabolic perspective. *Front. Plant Sci.* 10. doi: 10.3389/fpls.2019.00339
- Samouëlian, A., Cousin, I., Tabbagh, A., Bruand, A., and Richarde, G. (2005). Electrical resistivity survey in soil science: a review. *Soil Till. Res.* 83 (2), 173–193. doi: 10.1016/j.still.2004.10.004
- Santos, J. A., Fraga, H., Malheiro, A. C., Moutinho-Pereira, J., Dinis, L.-T., et al. (2020). A review of the potential climate change impacts and adaptation options for European viticulture. *Appl. Sci.* 10, 3092. doi: 10.3390/app10093092
- Sassenrath, G. F., Davis, K., Sassenrath-Cole, A., and Riding, N. (2018). Exploring the physical, chemical and biological components of soil: Improving soil health for better productive capacity. *Kansas Agric. Experiment Station Res. Rep.* 4 (3), 1–8. doi: 10.4148/2378-5977.7577
- Sauer, J., and Struik, G. (1964). A possible ecological relation between soil disturbance, light-flash, and seed germination source. *Ecology* 45, 884–886. doi: 10.2307/1934942
- Schindlbacher, A., Rodler, A., Kuffner, M., Kitzler, B., Sessitsch, A., et al. (2011). Experimental warming effects on the microbial community of a temperate mountain forest soil. *Soil Biol. Biochem.* 43 (7), 1417–1425. doi: 10.1016/j.soilbio.2011.03.005
- Schultz, H. (2022). Soil, vine, climate change: the challenge of predicting soil carbon changes and greenhouse gas emissions in vineyards and is the 4 per 1000 goal realistic? *OENO One* 56 (2), 251–263. doi: 10.20870/oeno-one.2022.56.2.5447
- Schwarz, K., Heil, J., Marschner, B., and Stumpe, B. (2021). Hot movements on soil surfaces – innovative insights into microbial dynamics using passive infrared thermography. *Geoderma* 385, 114879. doi: 10.1016/j.geoderma.2020.114879
- Seneviratne, S. I., Corti, T., Davin, E. L., Hirschi, M., Jaeger, E. B., Lehner, I., et al. (2010). Investigating soil moisture–climate interactions in a changing climate: A review. *Earth Sci. Rev.* 99 (3–4), 125–161. doi: 10.1016/j.earscirev.2010.02.004
- Shah, A. M., Khan, I. M., Shah, T. I., Bangroo, S. A., Kirmani, N. A., Nazir, S., et al. (2022). Soil microbiome: a treasure trove for soil health sustainability under changing climate. *Land* 11 (11), 1887. doi: 10.3390/land11111887
- Simonneau, T., Lebon, E., Coupel-Ledru, A., Marguerit, E., Rosse Deutsch, L., Ollat, N., et al. (2017). Adapting plant material to face water stress in vineyards: which physiological targets for an optimal control of plant water status? *OENO One* 51 (2), 167–179. doi: 10.20870/oeno-one.2017.51.2.1870
- Snyder, B. A., and Callahan, M. A. (2019). "Soil fauna and their potential responses to warmer soils," in *Ecosystem consequences of soil warming: Microbes, vegetation, fauna and soil biogeochemistry*. Ed. J. E. Mohan (Elsevier), 279–296.
- Soil Survey Staff (2014). *Keys to soil taxonomy*. 13th edn (Washington, DC: NRCS, USDA).
- Sremac, A. F., Lalic, B., Cuxart, J., and Marcic, M. (2021). Maximum, minimum, and daily air temperature range in orchards: what do observations reveal? *Atmosphere* 12, 10. 1279. doi: 10.3390/atmos12101279
- Stéfanon, M., Drobinski, P., D'Andrea, F., Lebeauupin-Brossier, C., and Bastin, S. (2014). Soil moisture-temperature feedbacks at meso-scale during summer heat waves over western Europe. *Clim. Dyn.* 42 (5–6), 1309–1324. doi: 10.1007/s00382-013-1794-9
- Tadayon, M. S., and Hossein, S. M. (2022). Shade net and mulching measures for improving soil and plant water status of fig trees under rainfed conditions. *Agric. Water Manage.* 271, 107796. doi: 10.1016/j.agwat.2022.107796
- Tombesi, S., Cincera, I., Frioni, T., Ughini, V., Gatti, M., Palliotti, A., et al. (2019). Relationship among night temperature, carbohydrate translocation and inhibition of grapevine leaf photosynthesis. *Environ. Exp. Bot.* 157, 293–298. doi: 10.1016/j.jenvexphot.2018.10.023
- Van Leeuwen, C., and Destrac-Irvine, A. (2017). Modified grape composition under climate change conditions requires adaptations in the vineyard. *OENO One* 51, 2. doi: 10.20870/oeno-one.2017.51.2.1647
- Van Leeuwen, C., Roby, J.-P., and Ressaiguier, L. (2018). Soil related terroir factors, a review. *OENO One* 52, 2. 173–2. 188. doi: 10.20870/oeno-one.2018.52.2.2208
- Van Leeuwen, C., Roby, J.-P., and Ressaiguier, L. (2020). "How to measure and manage the soil effect in terroir expression," in *IVES technical reviews (vine & wine)*. doi: 10.20870/IVES-TR.2020.4484
- Venios, X., Korkas, E., Nisioutou, A., and Banilas, G. (2020). Grapevine responses to heat stress and global warming. *Plants* 9 (12), 1754. doi: 10.3390/plants9121754
- Verheijen, F. G. A., Jeffery, S., Velde, M. V., Peniz ek, V., Beland, M., et al. (2013). Reductions in soil surface albedo as a function of biochar application rate: Implications for global radiative forcing. *Environ. Res. Lett.* 8, 44008. doi: 10.1088/1748-9326/8/4/044008
- Větrovský, T., Kohout, P., Kopecký, M., Machac, A., Man, M., Bahnmann, B. D., et al. (2019). A meta-analysis of global fungal distribution reveals climate-driven patterns. *Nat. Commun.* 10, 1–9. doi: 10.1038/s41467-019-13164-8

- Vogel, J., Paton, E., and Aich, V. (2021). Seasonal ecosystem vulnerability to climatic anomalies in the Mediterranean. *Biogeosciences* 18, 5903–5927. doi: 10.5194/bg-18-5903-2021
- Wadoux, A., and McBratney, A. (2021). Digital soil science and beyond. *Soil Sci. Am. Soil Soc* 85 (5), 1313–1331. doi: 10.1002/saj2.20296
- Walker, R., and Winter, E. (2006). "Vine carbohydrate dynamics and source sink relationships," in Report to grape and wine research and development corporation (CSIRO). Available at: <https://www.wineaustralia.com/getmedia/2315d7a1-47e3-4e07af36-2164883097ff/Final-Reportgwr0202h>.
- Wang, C., and Yang, K. (2018). A new scheme for considering soil water-heat transport coupling based on community land model: Model description and preliminary validation. *J. Adv. Model. Earth Syst.* 10, 927–950. doi: 10.1002/2017MS001148
- White, R. (2015). *Understanding vineyard soils* (Oxford University Press), 263 pp.
- Wild, J., Kopecký, M., Macek, M., Sanda, M., Jankovec, J., and Haase, T. (2019). Climate at ecologically relevant scales: A new temperature and soil moisture logger for long-term microclimate measurement. *Agric. For. Met.* 268, 40–47. doi: 10.1016/j.agrformet.2018.12.018
- Winter, S., Bauer, T., Strauss, P., Kratschmer, S., Paredes, D., Popescu, D., et al. (2018). Effects of vegetation management intensity on biodiversity and ecosystem services in vineyards: A meta-analysis. *J. Appl. Ecol.* 55, 2484–2495. doi: 10.1111/1365-2664.13124
- Wulf, H., Mulder, V. L., Schaepman, M., Keller, A., and Joerg, P. C. (2014). "Remote sensing of soils," in Technical report (University of Zurich, INRA). doi: 10.13140/2.1.1098.0649
- Xu, C., Qu, J. J., Hao, X., Zhu, Z., and Gutenberg, L. (2020). Surface soil temperature seasonal variation estimation in a forested area using combined satellite observations and in-situ measurements. *Int. J. Appl. Earth Observ. Geoinf.* Volume 91, 102156. doi: 10.1016/j.jag.2020.102156
- Xyrafis, E. G., Fraga, H., Nakas, C. T., and Koundouras, S. (2022). A study on the effects of climate change on viticulture on santorini island. *OENO One* 56, 1. doi: 10.20870/oeno-one.2022.56.1.4843
- Yau, I.-H., Davenport, J. R., and Moyer, M. M. (2014). Developing a wine grape site evaluation decision support system for the inland pacific northwestern united states. *Hortecology* 24 (1), 88–98. doi: 10.21273/HORTTECH
- Yu, O. T., Greenhut, R. F., O'Geen, A. T., Mackey, B., Horwath, W. R., Steenwerth, K. L., et al. (2022). Precipitation events, soil type, and vineyard management practices influence soil carbon dynamics in a mediterranean climate (Lodi, California). *Soil Sci. Soc. Am. J.* 83, 772–779. doi: 10.2136/sssaj2018.09.0345
- Yuste, J. C., Baldocchi, D. D., Gershenson, A., Goldstein, A., Misson, L., Wong, S., et al. (2007). Microbial soil respiration and its dependency on carbon inputs, soil temperature and moisture. *Glob. Change Biol.* 13, 2018–2035. doi: 10.1111/j.13652486.2007.01415
- Zagatto, M. R. G., Zanão Júnior, L. A., Pereira, A. P. A., Estrada-Bonilla, G., and Nogueira Cardoso, E. J. B. (2021). Soil mesofauna in consolidated land use systems: how management affects soil and litter invertebrates. *Sci. Agric.* 76 (2), 165–171. doi: 10.1590/1678-992X-2017-0139
- Zarraonaindia, I., Owens, S. M., Weisenhorn, P., West, K., Hampton-Marcell, J., et al. (2015). The soil microbiome influences grapevine-associated microbiota. *mBio* 246 (2), e02527–e02514. doi: 10.1128/mBio.02527-14
- Zeng, H., Tang, C.-S., Zhu, C., Cheng, Q., Lin, Z.-Z., Shi, B., et al. (2021). Investigating soil desiccation cracking using an infrared thermal imaging technique. *Water Resour. Res.* 58, e2021WR030916. doi: 10.1029/2021WR030916
- Zhang, W., Parker, K. M., Luo, Y., Wan, S., Wallace, L. L., Hu, S., et al. (2005). Soil microbial responses to experimental warming and clipping in a tallgrass prairie. *Glob. Change Biol.* 11, 266–277. doi: 10.1111/j.1365-2486.2005.00902.x
- Zhu, G., Luo, Y., Xue, M., Zhao, H., Xia, N., Wang, X., et al. (2018). Effects of hightemperature stress and heat shock on two root maggots, *Bradysia odoriphaga* and *Bradysia difformis* (Diptera: Sciaridae). *J. Asia-Pac. Entomol.* 21, 106–114. doi: 10.1016/j.aspen.2017.11.001

6.4. Article 4

Dynamics of Energy Fluxes in a Mediterranean Vineyard: Influence of Soil Moisture

Ricardo Egipto, Arturo Aquino and José Manuel Andújar

Journal: Agriculture (eISSN 2077-0472)

Editorial: MDPI

Reference: Agriculture. 2024, 14, 1845

DOI: 10.3390/agriculture14101845

Year: 2024

Quality index (Journal Citation Reports®, 2023): 20/126 (Q1) in the category "Agronomy". Impact Factor of 3.3.

Article

Dynamics of Energy Fluxes in a Mediterranean Vineyard: Influence of Soil Moisture

Ricardo Egipto ^{1,*}, Arturo Aquino ² and José Manuel Andújar ²

¹ INIAV, I.P.—Instituto Nacional de Investigação Agrária e Veterinária, Pólo de Inovação de Dois Portos, Quinta da Almoínha, 2565-191 Dois Portos, Portugal

² CITES, Centro de Investigación en Tecnología, Energía y Sostenibilidad, Universidad de Huelva, La Rábida, Palos de la Frontera, 21819 Huelva, Spain; arturo.aquino@dieia.uhu.es (A.A.); andujar@uhu.es (J.M.A.)

* Correspondence: ricardo.egipto@iniav.pt

Abstract: Accurate evaluation of grapevine water use is essential for optimizing water management and maximizing grapevine yield and berry quality in Mediterranean climates. Understanding the water and heat flux dynamics in a vineyard during grapevine berry maturation is of utmost importance. This study focuses on evaluating sensible and latent energy fluxes at the canopy, the soil beneath the canopy, and the interrow areas. The primary objective is to develop a model framework for accurately estimating these energy fluxes, contributing to a better understanding of their behavior during berry ripening. The model's accuracy was assessed by comparing the estimated fluxes with those measured by an eddy-covariance system installed at a reference height of three meters in the experimental vineyard. This validation step was essential to confirm the model's ability to capture the intricate energy flux dynamics of the vineyard, especially during grape maturation. The results revealed a high level of agreement between the observed and estimated fluxes, confirming the model's reliability. This comprehensive evaluation of energy fluxes provides valuable insights for optimizing irrigation strategies. By doing so, this study contributes to improving grape quality, ensuring sustainable water resource use, and ultimately enhancing vineyard productivity in arid and water-scarce regions.

Keywords: vineyard; grapevine water use; radiative fluxes; turbulent fluxes

Citation: Egipto, R.; Aquino, A.; Andújar, J.M. Dynamics of Energy Fluxes in a Mediterranean Vineyard: Influence of Soil Moisture. *Agriculture* **2024**, *14*, 1845. <https://doi.org/10.3390/agriculture14101845>

Academic Editor: Tommaso Frioni

Received: 11 September 2024

Revised: 14 October 2024

Accepted: 16 October 2024

Published: 19 October 2024



Copyright: © 2024 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Mediterranean climates, characterized by mild winters, autumn-spring rainfall with erratic distribution, and recurrent drought in late spring and summer, are particularly favorable for viticulture [1,2]. These climatic conditions contribute significantly to global wine production, with some of the oldest and most prestigious wine-producing regions, such as Southern France, Italy, Spain, Portugal, and parts of Greece, located within the Mediterranean zone. Furthermore, regions like California, Chile, South Africa, and the southern coastal zone of Australia, which also experience Mediterranean climates, have gained recognition for producing high-quality wines that often rival those from traditional Mediterranean areas.

Mediterranean vineyards benefit from abundant sunlight, essential for grape ripening and flavor development [3]. However, excessive solar radiation can pose challenges, including heat and water stress [4–7]. Future climate projections indicate an increase in extreme weather events [8], with more frequent and intense occurrences of warmer, drier conditions and severe heatwaves with accompanying droughts expected in the near future [8–11]. Additionally, vineyards are typically planted in sparsely spaced rows and utilize drip irrigation, minimizing the wetted area to reduce soil water

evaporation and optimize plant water use. Consequently, the exposed soil between vine rows (interrow) can act as a significant sink and/or source of energy [12–16]. Furthermore, in Mediterranean conditions, the absence of rain during grape ripening renders interrow soil evaporation negligible compared to row soil evaporation and grapevine transpiration (T) in drip-irrigated vineyards. Under these circumstances, with a fully developed canopy, grapevine transpiration dominates the evapotranspiration (ET) process [17]. The partitioning between T and ET is strongly influenced by factors such as the grapevine leaf area index (LAI) and the area of soil covered by the projected canopy shade at midday (the fractional cover of the canopy, f) [12,18].

Convective energy fluxes (comprising sensible heat and latent heat fluxes) within the vineyard are directly influenced by the distribution of available radiative energy fluxes, which partition between the canopy and the soil surface [17,18]. A thorough understanding of energy partitioning and respective energy fluxes within the vineyard is crucial for adapting vineyard management to environmental conditions. To this end, several models have been developed to assess the energy balance in agricultural systems (see Table 1).

Table 1. Models for assessing energy balance in agricultural systems.

Model	General Description	References
Penman–Monteith (PM)	A big-leaf model conceptualizing the vegetation as a large, homogeneous, and uniformly saturated surface subjected to resistance to latent heat transfer. Furthermore, it postulates the equality between the aerodynamic resistances for sensible and latent heat transfer to the atmosphere.	[19]
Shuttleworth and Wallace (S-W)	A one-dimensional model describing the energy partition in sparse crops. The analytical approach utilizes two Penman–Monteith equations: one applied to the crop and another to the soil surface.	[20]
Two-source energy balance (TSEB)	A two-source model of energy fluxes incorporating the view geometry associated with directional radiometric surface temperature measurement.	[21]
Clumped model	A two-source model adapted to a semi-arid shrubland incorporating vegetation clumping as defined by the fractional vegetative cover to estimate energy fluxes from both soil (beneath vegetation and bare soil) and shrubs.	[16]
Three-source energy balance (3SEB)	An adaptation of the TSEB model to enhance the partitioning of latent energy fluxes from heterogeneous and sparse canopies.	[12,15]

Vineyards, characterized by widely spaced rows, 2 to 3 m apart, and vertical shoot positioning systems, result in a unique energy balance system. The concentration of foliage in the upper two-thirds of the vine canopy leaves significant soil surface area exposed, making energy fluxes at both interrow and under-vine soil crucial to the vineyard’s overall energy dynamics [17,18,22]. This exposed soil experiences increased radiation and evaporative demand, influencing vertical temperature profiles within the canopy [4,13,18]. Additionally, the small-wetted area characteristic of drip irrigation systems promotes thermal convection while minimizing evaporation [23,24], resulting in a greater proportion of sensible heat directed towards both the canopy and soil [4,13,23,24].

These factors necessitate tailoring energy balance models to accurately capture the complexities of vineyard systems, including turbulent energy fluxes from the soil between rows, the soil beneath the canopy, and the vine canopy itself. The three-source clumped model is particularly suited to systems, like vineyards, with significant spatial variability due to row structure and vertical development of the canopy. This model must comprehensively account for energy fluxes and resistances from all components: vegetation, bare or cover-cropped soil between rows, and bare soil under the vines. As

radiation transmission to the surface through interrow spaces, canopy gaps, and canopy leaves, fluctuate throughout the day, the model must also reliably describe radiation divergence through the canopy [18].

This article investigates the dynamics of energy fluxes in a drip-irrigated vineyard under regulated deficit irrigation in an arid climate during the 2021 grape maturation period. A novel framework, based on the three-source clumped model initially developed by Brenner and Incoll [16] and further developed by Lhomme et al. [15], is introduced to provide insights into the distribution of available energy and to calculate energy fluxes within the vineyard. The framework allows for the independent measurement of heat fluxes from each vineyard component—the vine canopy, bare soil between rows, and bare soil beneath the vines. Additionally, latent energy fluxes from each component are estimated as the unknowns to their respective energy balance equations.

This research aims to enhance our understanding of energy dynamics in vineyards under regulated deficit irrigation, providing valuable insights for optimizing irrigation management and grape production in arid climates.

2. Materials and Methods

2.1. Location and Experimental Layout

This experiment was carried out during the 2021 growing season at Herdade do Esporão, a commercial vineyard located in Reguengos de Monsaraz, in the Alentejo wine region of southern Portugal (lat. 38°23'55" N; long. 7°32'46" W). This study focused on a 17-year-old vineyard of the red *Vitis vinifera* cv. Tempranillo (syn. Aragonez), grafted onto 1103 Paulsen rootstock. The vines were planted in north-south rows, 3.0 m apart, with 1.5 m between vines within each row (resulting in a density of 2220 vines/ha). The vines were spur-pruned on a bilateral Royat cordon system, with each vine evenly pruned to 15–16 buds and trained to vertical shoot positioning. The soil, classified as a eutric cambisol with a silty-clay texture, had an average bulk density of 1.35 g.cm⁻³, low organic matter content, an effective root depth of 1.0 m, and a pH range of 7.0 to 7.6. The average volumetric soil water content at field capacity (θ_f) and wilting point (θ_{wp}) were 0.37 and 0.23 m³.m⁻³, respectively. Standard regional viticultural practices were followed, including maintaining bare soil under the vines and cultivating a native cover crop between rows. To minimize competition with the vines, the cover crop was sustained until mid-June and then allowed to dry out, leaving bare soil between the rows. Drip irrigation, using 2.4 L.h⁻¹ emitters spaced 1.0 m apart, was applied weekly, in line with the vineyard owner's practices.

The field trial for studying vineyard energy fluxes, detailed in Section 2.4, was conducted during the ripening period of 2021, from 8 July to 31 August. Four days of intensive measurements—15 July, as well as August 10th, 18th, and 26th—are detailed in this work. For this purpose, ten healthy adult vines were randomly selected from two adjacent rows (five vines per row). This narrow selection criterion aimed to enhance measurement coherence and optimize data acquisition under conditions of low temporal and spatial variability. The experimental design also allowed for the assessment of solar radiation effects, as both sides of the canopy (east and west) were studied under contrasting incident radiation levels.

2.2. Climate Characterization

The study area experiences a Mediterranean climate, characterized by hot, dry summers and mild, rainy winters. From October 2020 to August 2021, the total rainfall recorded was 548.6 mm. Notably, no rainfall events occurred during the measurement days detailed in this study. The last rain event took place from June 17th to June 20th, resulting in an accumulated rainfall of 13.4 mm, which was also the total rainfall for June 2021 (Figure S1). Hourly averaged air temperature (T_{air} , °C) and air vapor pressure deficit (VPD, kPa), measured at the experimental plot during the experimental period, are shown in Figure 1. All measurements were taken under clear-sky conditions. Air temperature

anged from a minimum of 15.5 °C at sunrise to a maximum of 37.5 °C at 4 pm. *VPD* increased from a minimum of 0.15 kPa at sunrise to a maximum of 5.6 kPa at 4 pm. In the afternoon, air temperature consistently exceeded 33.5 °C, and the *VPD* remained above 4 kPa, before both gradually declined later in the day. During the measurement period, the vineyard was irrigated on 11th, 16th, 23rd, and 29th of July, as well as on August 1st, 5th, 8th, 13th, 22nd, and 26th (Figure S1).

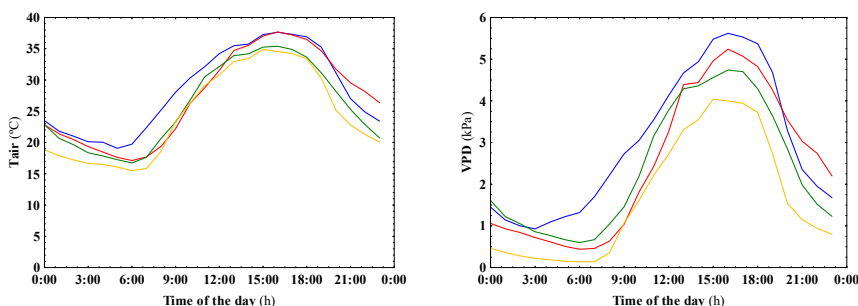


Figure 1. Atmospheric patterns on the measurement days. The figure illustrates the measurements of air temperature (T_{air} , °C) and air vapor pressure deficit (VPD , kPa) measured on 15 July (blue) and 10 (red), 18 (green), and 26 August 2021 (yellow) at the experimental plot.

2.3. Theoretical Background and Implemented Model Framework

Energy balance models are valuable tools for understanding how available radiative energy is partitioned into sensible and latent heat fluxes within a system. The Shuttleworth and Wallace model is considered suitable for assessing the crop energy balance in dense, homogeneous crops with horizontal canopies that completely cover the soil [24]. The model's general expression for partitioning the available radiation ($R_n - G$, where R_n is the net solar radiation and G is the soil heat flux) into latent heat flux (LE) and sensible heat flux (H) can be written as proposed by Shuttleworth and Wallace [20] in the following form (Equation (1)):

$$R_n - G = H + LE \quad (1)$$

However, it is crucial to assess the energy partitioning between canopy and soil in sparse crops planted in rows, where a significant fraction of the soil remains exposed under and between the crop rows [12,14,15,18,24].

Net radiation fluctuations are influenced by factors such as vine row orientation, row spacing, canopy height, the Earth's daily and seasonal rotational and orbital movements, and cloud cover intensity and duration [25]. These fluctuations impact net radiation at the vine canopy top, the soil beneath the vine canopy, and the soil between rows, varying throughout the day and season. Therefore, to better understand the divergence of available energy and derive the energy fluxes within the vineyard, this study proposes assessing the energy flux from each component—the vine canopy, bare soil between rows, and bare soil under the vines—separately. The resulting modeling framework partitions the energy balance of each soil component and the canopy, enabling the estimation of vine canopy transpiration and soil evaporation, described by Equations (2)–(4) as:

- i. energy balance of vine canopy [21,24,26]:

$$R_{n,c} = H_c + LE_c \quad (2)$$

Note that, since the energy balance at the canopy level only accounts for the fluxes measured just above the canopy, the contribution of soil heat flux is negligible and can be disregarded in this calculation.

- ii. energy balance under vine canopy:

$$R_{n,uc} - G_{uc} = H_{uc} + LE_{uc} \quad (3)$$

iii. energy balance between vine rows:

$$R_{n,bs} - G_{bs} = H_{bs} + LE_{bs} \quad (4)$$

For all equations, R_n is the net solar radiation (W.m^{-2}), G is the soil heat flux (W.m^{-2}), H is the sensible heat flux (W.m^{-2}), LE is the latent heat flux (W.m^{-2}). The subscripts c , uc , and bs represent the fluxes measured from the canopy, under the canopy, and above bare soil between rows, respectively.

Individual assessments of sensible and latent energy fluxes, calculated within our model framework, were used as inputs for the three-source clumped model described in Section 2.4.5. This model, initially developed by Brenner and Incoll [16] and further refined by Lhomme et al. [15], was applied to estimate the aggregated energy fluxes at a reference level above the vineyard. The aggregated fluxes derived from the three-source clumped model were then compared with energy flux measurements obtained from an eddy covariance (EC) tower installed in the experimental field.

2.4. Field and Reference Measurements

The measurement setup for calculating the turbulent energy fluxes within the proposed model framework involved the deployment of various sensors to capture key meteorological variables at different heights and locations (reference (r), canopy (c), under the canopy (uc), and bare soil between rows (bs)) within the vineyard. This section briefly describes the field measurements used to estimate the turbulent energy fluxes within the model framework and to measure the energy fluxes at the reference heights. It outlines the methods and instrumentation employed to capture the data necessary for calculating the energy fluxes within the vineyard.

All soil and meteorological sensors used were connected to a datalogger (CR1000, Campbell Scientific, Logan, UT, USA), with data collected every minute and averaged every 15 min.

2.4.1. Net Solar Radiation (R_n)

To account for energy inputs in the vineyard, net solar radiation measurements were conducted using four net radiometers (NR2, Delta-T Devices, Cambridge, UK) placed at specific locations and heights. These measurements provided the net solar radiation over the vineyard at the reference level ($R_{n,r}$), the net solar radiation above the canopy ($R_{n,c}$), the net solar radiation beneath the canopy ($R_{n,uc}$), and the net solar radiation between the vine rows ($R_{n,bs}$) data as follows:

Net Solar Radiation above the Canopy ($R_{n,c}$)

To measure the available energy above the canopy, a net radiometer was positioned at the top of the canopy, 2 m above the soil surface, and aligned with the vine canopy.

Net Solar Radiation Beneath the Canopy ($R_{n,uc}$)

To measure the available energy beneath the canopy, a net radiometer was positioned 0.3 m above soil surface, directly under the vine canopy.

Net Solar Radiation between Vine Rows ($R_{n,bs}$)

To measure the available energy between vine rows, a net radiometer was positioned in the middle of the interrow, 0.3 m above the soil surface.

2.4.2. Soil Heat Fluxes (G)

The measurements of energy to/from the soil were conducted using two heat flux plates (HFP01, Hukseflux Thermal Sensors, Delft, The Netherlands) placed at specific locations. These measurements provided the soil heat flux beneath the canopy (G_{uc}), and the soil heat flux between vine rows (G_{bs}) data.

Soil Heat Flux Beneath the Canopy (G_{uc})

To measure the soil heat flux beneath the canopy, a heat flux plate was installed 0.05 m below the soil surface, positioned beneath the vine canopy.

Soil Heat Flux between Vine Rows (G_{bs})

To measure the soil heat flux between vine rows, a heat flux plate was installed in the middle of the interrow, 0.05 m below the soil surface.

2.4.3. Sensible Heat Fluxes (H)

The sensible heat fluxes under the canopy (H_{uc}), from the canopy (H_c), and from bare soil between rows (H_{bs}) were calculated using the soil and meteorological variables measured within the proposed model framework. The equations used to calculate the sensible heat fluxes are presented in the following sections.

Sensible Heat Fluxes under the Canopy (H_{uc})

The below-canopy sensible heat flux (H_{uc}) was computed according to Kool et al. [17] by Equation (5):

$$H_{uc} = \rho c_p \frac{T_{s,uc} - T_{a,uc}}{r_{a,uc}} \quad (5)$$

where H_{uc} is the sensible heat flux under the canopy, ρ is the air density, c_p is the air specific heat capacity at constant pressure ($1013 \text{ J.kg}^{-1}.\text{°C}^{-1}$), $T_{s,uc}$ is the soil temperature measured beneath the canopy, $T_{a,uc}$ is the air temperature measured beneath the canopy, and $r_{a,uc}$ is the aerodynamic resistance beneath the canopy (Equation (6)).

$T_{s,uc}$ was measured using a two-junction, fine-wire copper-constantan T-type thermocouple placed approximately 0.01 m above the top surface of the G_{uc} soil heat flux sensor. In addition, $T_{a,uc}$ was recorded simultaneously with the relative humidity using a thermohygrometer (CS215-PWS Campbell Scientific, Logan, UT, USA) placed beneath the vine canopy (0.3 m above soil surface).

The aerodynamic resistance between the soil surface and the sink of the momentum below the canopy ($r_{a,uc}$) was calculated accordingly to Lhomme et al. [15] by Equation (6):

$$r_{a,uc} = \frac{h \exp(n)}{n k_h} [\exp(-n z'_0/h) - \exp(-n(z_0 + d_p)/h)] \quad (6)$$

where h is the vine canopy height (m), n is the eddy diffusivity decay coefficient (following Shuttleworth and Wallace [20], $n = 2.5$, dimensionless), k_h is the eddy diffusivity at the top of the canopy ($\text{m}^2.\text{s}^{-1}$), z'_0 is the bare soil roughness length (m), equal to 0.01 m [15], z_0 is the canopy roughness length ($z_0 = 0.13 h$, m), and d_p is the zero-plane displacement height ($d_p = 0.6 h$, m).

Sensible Heat Fluxes from the Canopy (H_c)

The sensible heat fluxes from the canopy (H_c) were computed according to Kool et al. [17] by Equation (7):

$$H_c = \rho c_p \frac{T_c - T_{a,c}}{r_{a,c}} \quad (7)$$

where H_c is the sensible heat flux from the canopy, ρ is the air density, c_p is the air specific heat capacity at constant pressure ($1013 \text{ J.kg}^{-1}.\text{°C}^{-1}$), T_c is the canopy temperature, $T_{a,c}$ is the air temperature measured above the canopy, and $r_{a,c}$ is the aerodynamic resistance above the canopy (Equation (8)).

To measure T_c , a thermal image was taken from the vine canopies using an infrared (IR) thermal camera (FLIR model C5, FLIR Systems Inc., Wilsonville, OR, USA), equipped with a 160×120 (19,200 pixels) IR sensor and operating in the 8 to 14 μm spectral range.

The thermal images were captured perpendicularly to the canopy at approximately 2 m, with an emissivity (ϵ) set at 0.96. Images were taken from both the sunlit and shadow

canopy sides, with one image per vine and five plants per canopy exposure ($n = 10$). The background temperature was determined by measuring the temperature of a crumpled sheet of aluminum foil placed near the canopy using an emissivity (ϵ) value of 1 [27]. Thermal images were analyzed using the 'Flir Thermal Studio' software version 2.0.21 (Flir Systems, Inc., Wilsonville, OR, USA), converted into csv files, and exported to Matlab R2023a (The Mathworks, Inc., Natick, MA, USA) to generate a temperature data matrix, where each cell corresponded to a pixel temperature value. The pixels were counted and recorded in an absolute frequency table based on their temperature range. To isolate canopy surface data and minimize interferences, pixels representing the background and vine trellising materials were excluded. The process of canopy surface data validation involved excluding all pixels with temperatures falling below the 10th percentile or above the 90th percentile. To facilitate calculations while integrating all the T_c values measured in each thermal image, a mean of all the validated pixel temperature values was assumed as representative of T_c .

$T_{a,c}$ was measured using a thermohygrometer (CS215-PWS Campbell Scientific, Logan, UT, USA) placed above the vine canopy (2 m above the soil surface). $r_{a,c}$ was then calculated according to Lhomme et al. [15] by the Equation (8):

$$r_{a,c} = \frac{\left[\left(\frac{n}{0.01} \right) \left(\frac{w}{u_h} \right)^{0.5} \left(1 - \exp\left(-\frac{n}{2}\right) \right)^{-1} \right]}{LAI} \quad (8)$$

where the wind speed at the top of the canopy (u_h , m.s^{-1}) was calculated from the wind speed measured at the reference height (z_r) by Equation (9) [15], as follows:

$$u_h = \left(\frac{u_*}{k} \right) \ln \left(\frac{h - d_p}{z_0} \right) \quad (9)$$

the wind friction velocity (u_* , m.s^{-1}) is given by Equation (10):

$$u_* = \frac{(ku_r)}{\ln \left[\frac{(z_r - d_p)}{z_0} \right]} \quad (10)$$

the canopy roughness length (z_0 , m) is given by Equation (11) [15]:

$$z_0 = 0.13 h \quad (11)$$

and the zero-plane displacement height (d_p , m) is given by Equation (12) [15]:

$$d_p = 0.63 h \quad (12)$$

In the previous equations, LAI is the leaf area index ($\text{m}^2.\text{m}^{-2}$), z'_0 is the bare soil roughness length (m), z_r is the reference height (3 m in the present study), k is the von Karman's constant ($k = 0.41$, dimensionless), u_r represents the wind speed at the reference height, measured with a 3D sonic anemometer (Gill Windmaster Pro, Gill Instruments Limited, Hampshire, UK) (m.s^{-1}), h is the vine canopy height (m), n is the eddy diffusivity decay coefficient (following Shuttleworth and Wallace [20], $n = 2.5$, dimensionless), and w is the average width of a representative leaf (m).

The average leaf width, w , was measured from 20 leaves (two median-sized leaves from each of the 10 grapevines selected for the research), resulting in an estimated mean of 0.18 m. The leaf area index (LAI) of the grapevines was determined using a non-destructive allometric method applied to the same 10 selected grapevines. The total leaf area was computed using the method described by Lopes and Pinto [28]. Subsequently, LAI was estimated by dividing the total leaf area by the area occupied by each individual vine. The surface area of each vine was calculated by considering the space between vines and the projection of the canopy shadow at midday. Since the distance between vines is fixed and the canopy maintains a consistent shape, the surface area is estimated by

multiplying the fixed distance between the vines by the horizontal distance of the canopy shadow projected at midday. This procedure ensures an accurate representation of the spatial area occupied by each vine within the row, with minimal overlap between adjacent vines. Measurements were conducted on four separate occasions: 14 July 2021, 16 August 2021, 17 August 2021, and 24 August 2021. The measured LAI values for the selected vines consistently fell within the range of 1.8 to 2.1 $\text{m}^2\cdot\text{m}^{-2}$ throughout the experimental period; therefore, a mean value of 2.0 $\text{m}^2\cdot\text{m}^{-2}$ was employed in the analysis.

Sensible Heat Fluxes from Bare Soil between Rows (H_{bs})

Variations in the sensible heat fluxes between rows (H_{bs}), were accounted for as a difference in temperatures across the bare soil and air resistances [29], as described by Equation (13):

$$H_{bs} = \rho c_p \frac{T_{s,bs} - T_{a,bs}}{r_{a,bs}} \quad (13)$$

Equation (13) represents the computation of the bare soil heat flux (H_{bs}) using the soil surface temperature ($T_{s,bs}$), air temperature ($T_{a,bs}$), and the aerodynamic resistance above bare soil between rows ($r_{a,bs}$). Additionally, ρ represents the air density, and c_p represents the specific heat capacity of air at constant pressure (1013 $\text{J}\cdot\text{kg}^{-1}\cdot^\circ\text{C}^{-1}$).

The $T_{s,bs}$ was measured using a two-junction, fine-wire copper-constantan T-type thermocouple placed approximately 0.01 m above the top surface of the G_{bs} soil heat flux sensor. The $T_{a,bs}$ was measured simultaneously with the relative humidity using a thermohygrometer (CS215-PWS Campbell Scientific, Logan, UT, USA) placed in the middle of the interrow (0.3 m above soil surface).

The $r_{a,bs}$ was calculated according to Brenner and Incoll [16] by the Equation (14):

$$r_{a,bs} = \frac{\ln\left(\frac{z_m}{z_0}\right)^2}{(k^2 u_m)} \quad (14)$$

where z_m represents the mean surface flow height [16]. In the present study, the mean surface flow height between vine rows was assumed to be 0.30 m. The z_0 represents the bare soil roughness length (m), equal to 0.01 m [15], k denotes the von Karman's constant ($k = 0.41$, dimensionless), and u_m stands for the wind speed at the mean surface flow height ($\text{m}\cdot\text{s}^{-1}$).

Wind speed measurements were obtained using a 2D sonic anemometer (Gill Ultrasonic ANE 5M, Gill Instruments Limited, Hampshire, UK) positioned 0.3 m above the soil surface, between vine rows, and facing the predominant north winds.

2.4.4. Latent Heat Fluxes Estimation

In the present model framework, the latent heat fluxes were calculated as the unknowns of Equations (2)–(4) by:

- i. The latent heat above the canopy (LE_c) [21,24,26]:

$$LE_c = R_{n,c} - H_c \quad (15)$$

- ii. The latent heat from soil beneath the canopy (LE_{uc}):

$$LE_{uc} = R_{n,uc} - G_{uc} - H_{uc} \quad (16)$$

- iii. The latent heat from bare soil between vine rows (LE_{bs}):

$$LE_{bs} = R_{n,bs} - G_{bs} - H_{bs} \quad (17)$$

2.4.5. Estimation of Energy Fluxes at the Reference Level

To validate the accuracy of the fluxes calculated from each component (soil and canopy) within the proposed model framework (using Equations (5), (7), (13), (15), (16), and (17)), these turbulent fluxes were aggregated at a reference height above the vineyard. The calculated fluxes for each component within the proposed model framework were used as inputs for a three-source clumped model, originally formulated by Brenner and Incoll [16] and further developed by Lhomme et al. [15], to calculate the energy fluxes at the reference height. The formalism concerning the calculation of total resistances and fluxes over heterogeneous and sparse canopies used in this work is explained in detail in Lhomme et al. [15].

Estimated Sensible Heat Flux at the Reference Level

Figure 2 illustrates a visual representation of the modeling framework for sensible heat fluxes (H) and the depiction of air and surface temperatures originating from a sparse canopy. Within this model framework, the aggregation of sensible heat fluxes at the reference height (z_r) is given by Equation (18) [16]:

$$H_r = f(H_{uc} + H_c) + (1 - f)H_{bs} \quad (18)$$

where H represents the sensible heat flux ($\text{W}\cdot\text{m}^{-2}$), and f is the fractional cover of the canopy (0.3 under present conditions), representing the area of soil covered by the projected canopy shade at midday. The subscripts r , uc , c , and bs represent the fluxes estimated at specific locations relative to the canopy and soil surfaces: at the reference height (at the EC system height), under the canopy (from bare soil surface to the base of the canopy), immediately above the canopy, and above bare soil surface between rows, respectively.

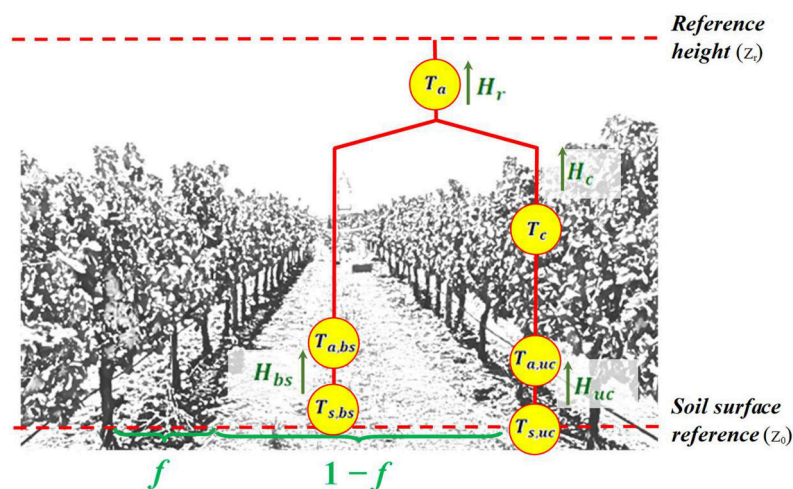


Figure 2. Schematic representation of the three-source clumped model for convective fluxes (specifically sensible heat, H) partitioning in a sparse canopy, illustrating the associated air and surface temperatures.

Estimated Latent Heat Flux at the Reference Level

Similarly, within the presented modeling framework, the aggregated latent heat fluxes (LE) at the reference height (z_r) are given by Equation (19) [16]:

$$LE_r = f(LE_{uc} + LE_c) + (1 - f)LE_{bs} \quad (19)$$

This equation describes the estimated latent heat flux (LE_r) at the reference height, where LE_{uc} , LE_c , and LE_{bs} represent latent heat fluxes calculated from Equations (15) to (17) for the regions under the canopy, from the canopy, and above the bare soil between rows, respectively. As with the sensible heat fluxes, f represents the fractional cover of the canopy.

2.4.6. Energy Fluxes Measured at the Reference Level

To validate the estimated fluxes aggregated at the reference heights, LE_r and H_r , an eddy-covariance (EC) system was installed on the experimental plot. This system enabled the measurement of the vertical profile of energy fluxes, including the observed latent heat flux (LE_{obs}) and sensible heat flux (H_{obs}) at the reference level (z_r), over the experimental vineyard.

The EC system comprised a 3D sonic anemometer (Gill Windmaster Pro, Gill Instruments Limited, Hampshire, UK) oriented to a fast-response, 0.1 Hz, open-path CO₂/H₂O analyzer (LI-6500 DS, LI-COR Inc., Lincoln, NE, USA) and connected to a Smartflux 3 system (LI-COR Inc., Lincoln, NE, USA). Both the sonic anemometer and the open-path CO₂/H₂O analyzer were positioned at a height of 3.0 m above the ground surface, directly over the canopy top, and oriented towards the predominant north winds. The EC system facilitated high-temporal-resolution recording of monitored reference latent heat (LE_{obs}) and sensible heat (H_{obs}) fluxes at intervals of every 1/10 s.

Net Solar Radiation over the Vineyard, at the Reference Level

To measure the available energy above the vineyard, at the reference level (R_{nobs}), a net radiometer was positioned at a height of 3 m.

Reference Soil Heat Flux

The reference soil heat flux was assessed using six heat flux plates (Hukseflux HFP01, Hukseflux Thermal Sensors, Delft, The Netherlands) placed at a depth of 0.05 m. One plate was positioned beneath the vine canopy within the row (also used to measure G_{uc}), while the remaining plates were evenly spaced at 0.5 m intervals perpendicular to the vine rows, covering the entire interrow area. To calculate the reference soil heat flux (G_{obs}) between vine rows, it was necessary to account for the coexisting differences between shaded and exposed soil areas. Therefore, the G_{obs} value was calculated as the average of the measured heat flux at each point along the interrow cross-section.

Overall Assessment of the Balance Fluxes at the Reference Level

Data quality assessment and analysis were conducted using EddyPro software v7.0.6 (LI-COR Inc., Lincoln, NE, USA). The measurement site was situated within a larger vineyard of the same variety and subjected to identical viticultural practices, ensuring a homogenous fetch. A minimum fetch of 300 m, encompassing the experimental field, was maintained to ensure that all fluxes within the area of interest were captured, thereby minimizing the influence of advective fluxes from surrounding areas. A linear regression analysis was performed between the turbulent energy fluxes ($LE_{obs} + H_{obs}$) and the available energy (solar radiation, R_{nobs} , and soil heat flux, G_{obs}), using 15-min averaged measurements throughout the study period. This analysis revealed that more than 90% of the analyzed fluxes achieved an energy balance closure of approximately 0.95 (Figure 3). Similar energy balance closure results have been reported in previous studies [17, 30–33]. Table 2 provides a summary of the reference field measurements and the instrumentation employed.

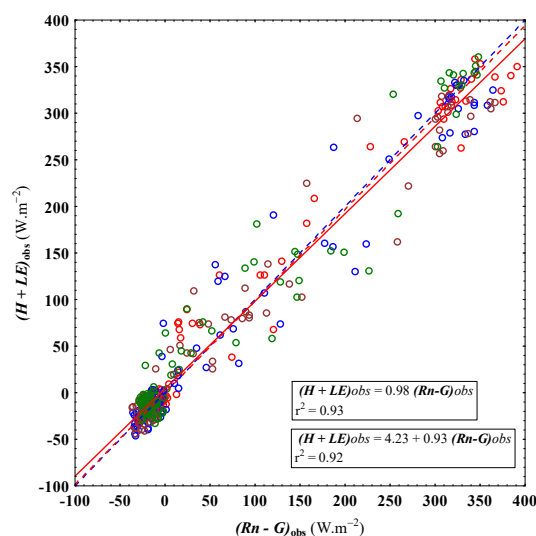


Figure 3. Least squares linear regression (solid red line) between the observed turbulent energy fluxes $(H + LE)_{obs}$ and the available energy $(Rn - G)_{obs}$, both measured at the reference level. The colored circles represent data collected on specific dates: July 15th (red), August 10th (blue), August 18th (brown), and August 26th (green). The dashed red line represents the least squares linear regression forced through the origin ($y = ax$), where a is the slope indicating the proportionality between turbulent energy fluxes and available energy. The dashed blue line corresponds to the 1:1 relationship ($y = x$), signifying a perfect match between the turbulent energy fluxes and available energy.

Table 2. Summary of variables used for measuring the validation set of energy fluxes: field measurements and instrumentation.

Variable	Periodicity and Data Integration	Units	Source
Net radiation (Rn_{obs})	Every minute and averaged every 15 min	$W.m^{-2}$	Net radiometer, model NR2, (Delta-T Devices, Cambridge, UK)
Soil heat flux (G_{obs})			Hukseflux sensor (model HFP01, Hukseflux Thermal Sensors, Delft, The Netherlands)
Wind speed (u_{obs})	Every 1/10 s and averaged every 15 min	$m.s^{-1}$	3D sonic anemometer (model Gill Windmaster Pro, Gill Instruments Limited, Hampshire, UK)
Latent heat (LE_{obs})		$W.m^{-2}$	EC system comprised by a fast-response, 0.1 Hz, open-path CO ₂ /H ₂ O analyzer (LI-6500 DS, LI-COR Inc., Lincoln, NE, USA)
Sensible heat (H_{obs})			

2.5. Evaluation of the Estimated Energy Fluxes at the Reference Height

The energy fluxes estimated at the reference height, H_r , and LE_r , were validated by comparison with the energy fluxes measured by the EC system at the same reference height. The validation process involved fitting the estimated energy flux values (e_{Φ}^i) calculated by Equations (18) and (19) to the observed energy fluxes (o_{Φ}^i) measured by the EC system. This evaluation included both convective energy fluxes (Φ), which encompassed the latent energy flux (LE), and sensible energy fluxes (H).

The model's performance was assessed using several statistical parameters, including Pearson's coefficient of correlation (R), root-mean-square error ($RMSE$), mean bias error (MBE), and relative error ($|E|$). These parameters are defined as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (e_{\Phi}^i - o_{\Phi}^i)^2}{n}} \quad (20)$$

$$MBE = \frac{\sum_{i=1}^n (e_{\Phi}^i - o_{\Phi}^i)}{n} \quad (21)$$

$$|E| = \frac{|\sum_{i=1}^n (e_{\Phi}^i - o_{\Phi}^i)|}{\sum_{i=1}^n o_{\Phi}^i} \times 100 \quad (22)$$

In these formulas, e_{Φ}^i represents the i -th value of the energy flux estimated by the three-source clumped model formulated in Equations (18) and (19) from a dataset of $n = 320$ elements. Similarly, o_{Φ}^i denotes the i -th observed value of energy flux measured by the EC system during the same period. Here, the subscript Φ stands for the convective energy fluxes, encompassing both latent energy flux (LE) and sensible heat flux (H).

Model evaluation processes were implemented using Matlab R2023a (The Mathworks Inc, Natick, MA, USA).

3. Results and Discussion

3.1. Characterization of the Available Energy and Turbulent Energy Fluxes within the Proposed Model Framework

The daily and seasonal variation of the sun's apparent movement, combined with the orientation of vine rows and the structure and dimensions of the canopy, differentially affected the shadow cast by the vine canopy. This variation influenced the extension of exposed canopy and soil areas, as well as the intensity of incident radiation within the vineyard. Consequently, the available energy at various points in the vineyard fluctuated throughout the day and season.

In this section, we analyze and discuss the variability of the available energy and how it was partitioned into sensible and latent heat fluxes throughout our experiment. Conventionally, the net radiation energy flux terms (R_n and G) used here are considered positive when directed towards the surface and into the soil, while the turbulent fluxes (H and LE) are positive when directed away from the surface.

3.1.1. Available Energy within the Model Framework

In the present experiment, the available energy at the top of the canopy ($R_{n,c}$) followed a consistent pattern across all measurement days, increasing from sunrise to a peak at 2 pm and decreasing thereafter (Figure 4a). The daily variation patterns of available energy beneath the canopy ($(R_n - G)_{uc}$) also remained consistent across the measurement days (Figure 4b), as was the energy available between the vine rows ($R_n - G)_{bs}$ (Figure 4c).

At the beginning and end of the day, the available energy between vine rows was minimal, reaching its maximum when the space between rows was fully or almost fully exposed to sunlight (Figure 4c). In contrast, the available energy beneath the canopy was highest at the beginning and end of the day, peaking at approximately 350 to 380 W.m⁻² around 12 am and 4 pm, when the shadow projected by the vine canopy over the row was minimal. Between 12 am and 4 pm, the shadow projected by the canopy reduced the net radiation at the soil beneath the canopy to zero, thus resulting in negative available energy beneath the canopy (Figure 4b); similar results were described by Kool et al. [17]. A rapid transition occurs between the maximum values of $(R_n - G)_{uc}$ and $(R_n - G)_{bs}$ at noon and 4 pm. Additionally, the available energy beneath the canopy was influenced by irrigation, which impacted the soil's heat flux (G) and the distribution of energy under the canopy. The results indicate that G_{uc} on August 10th and 26th was slightly lower than that observed on the days before irrigation, leading to a slight decrease in the available energy beneath the canopy when topsoil water content was higher (Figure 4b and Figure S2); comparable results were found by Heitman et al. [34].

Throughout the clear measurement days, the available energy at the canopy level was predominantly influenced by the optical properties of the leaves, particularly their albedo, accounting for approximately 72% of the available energy. This aligns with findings reported by Pieri and Gaudillière [35], who observed similar values in their studies.

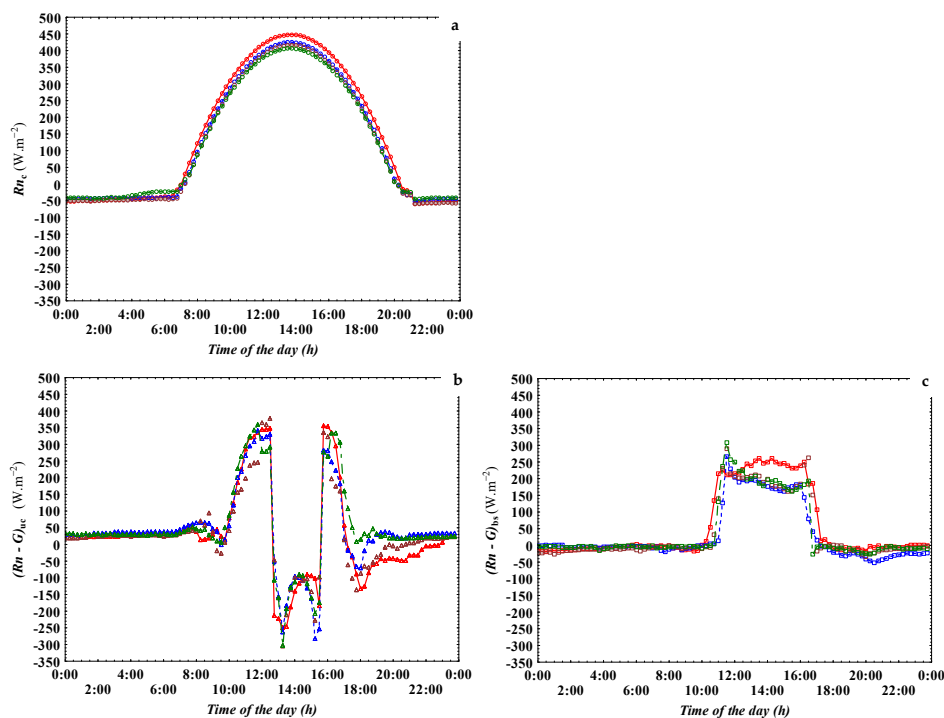


Figure 4. Energy available to each component within the proposed model framework. (a) Shows the net radiation measured above the canopy ($R_{n,c}$), (b) shows the available energy measured under the canopy ($R_{n,uc} - G_{uc}$), and (c) shows the available energy measured between vine rows ($R_{n,bs} - G_{bs}$), where $R_{n,i}$ and G_i are the net solar radiation and the soil heat flux measured in the i -th compartment, respectively. The solid red line represents the data measured on 15th July, the blue dashed line the data measured on 10th August, the brown dotted line the data measured on 18th August, and the green dash-dotted line the data measured on 26th August.

3.1.2. Turbulent Fluxes within the Model Framework

Available radiation at the soil surface and soil water content significantly influenced the partition of turbulent fluxes (H and LE) throughout the experiment. As the time since the last irrigation increased, the soil under the vine canopy dried out, reducing the evaporative cooling effect and leading to an increase in measured soil temperature. The measured canopy temperature followed a similar pattern. As soil water content diminished (Figure S2), vine canopy resistance increased, causing a rise in canopy temperatures due to reduced heat dissipation through transpiration. Indeed, a higher H_c was measured on July 15th and August 18th (four and five days after last irrigation, respectively) compared to August 10th and 26th (two days after irrigation or during ongoing irrigation) (Figure 5a).

As time elapsed since the last irrigation, H_c progressively increased. This resulted from the lower vine transpiration rates and consequent reduction in evaporative cooling (with latent heat representing approximately 20% of the total available energy). Consequently, H_c reached 70% and 72% of the available energy at the canopy surface on July 15th and August 18th, respectively (Figures 4a and 5a). Additionally, on those same days, the available energy beneath the canopy was entirely converted into sensible energy fluxes (H_{uc}) (Figures 4b and 5b). On August 26th, with irrigation ongoing, H_c decreased throughout the day, accounting for approximately 50% of the energy available at the canopy level. On August 10th, just two days after irrigation, H_c accounted for an average of 65% of the total available energy at the canopy surface, remaining consistent throughout both the morning (from 9 am to 12 pm) and the afternoon (from 4 pm to 7 pm) (Figures 4a

and 5a). Meanwhile, beneath the canopy, H_{uc} accounted for an average of 60% and 50% of the total available energy beneath the canopy on the 10th and 26th of August, respectively (Figures 4b and 5b).

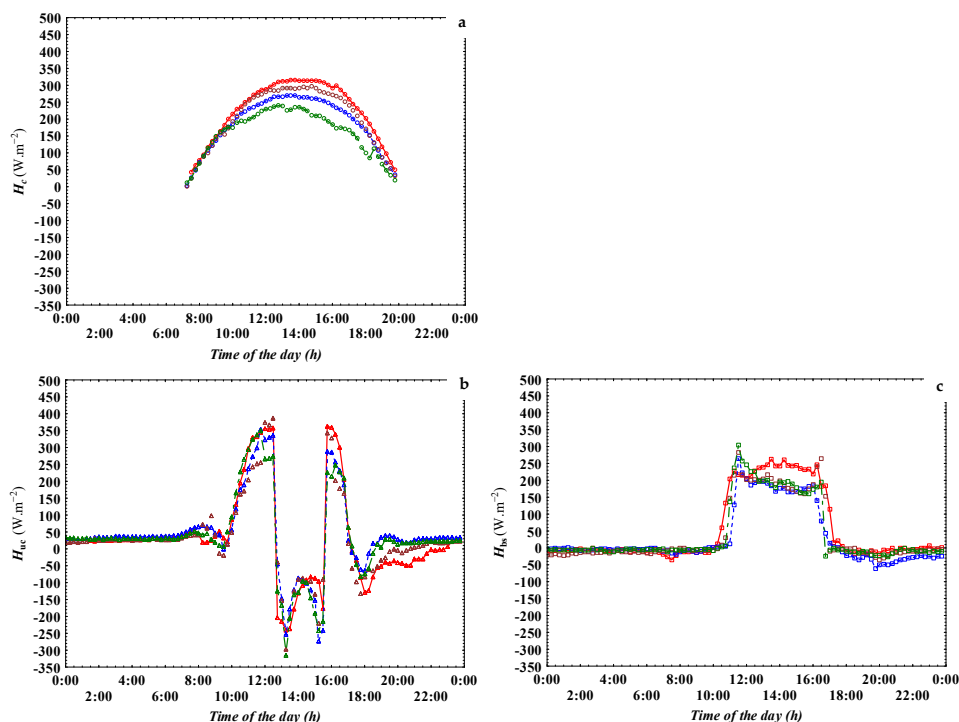


Figure 5. Estimated sensible heat fluxes from each component within the proposed model framework. (a) Shows the sensible heat above the canopy (H_c) calculated by Equation (7), (b) shows the sensible heat under the canopy (H_{uc}) calculated by Equation (5), and (c) shows the sensible heat between vines row (H_{bs}) calculated by Equation (13). The solid red line represents the data measured on 15th July, the blue dashed line the data measured on 10th August, the brown dotted line the data measured on 18th August, and the green dash-dotted line the data measured on 26th August.

Low soil water content, particularly surface dryness, significantly influenced the estimated sensible heat fluxes from both the soil beneath the canopy (H_{uc}) (Figure 5b) and from the canopy itself (H_c) (Figure 5a). With low soil water content, the available energy was primarily allocated to surface heating processes, as minimal evaporative cooling occurred due to the lack of soil moisture (Figure S2). In contrast, during the days following irrigation, such as August 10th and 26th, the energy was diverted towards soil water evaporation (Figure 6b), resulting in lower sensible heat fluxes from both H_{uc} and H_c (Figure 5a,b). Maximum values of 316 and 298 W.m^{-2} were calculated for H_c on July 15th (four days after irrigation) and August 18th (five days after irrigation), respectively. In contrast, maximum values of 270 and 240 W.m^{-2} were calculated for H_c on August 10th (two days after irrigation) and August 26th (irrigation ongoing), respectively (Figure 5a). Furthermore, a higher amplitude between the maximum and minimum estimated values of H_c was observed when soil water content was lower. This indicates a diminished ability of the canopy to dissipate heat through transpiration, which in turn led to greater fluctuations in sensible heat flux. As observed by Hsu and Dirmeyer [36], the present data also suggest that the higher soil moisture content, both in the topsoil layer and in the deeper soil profile where the roots extract water, can contribute to moderating soil and vine canopy temperatures. This results in lower sensible heat fluxes calculated from both the soil under the canopy and the canopy itself.

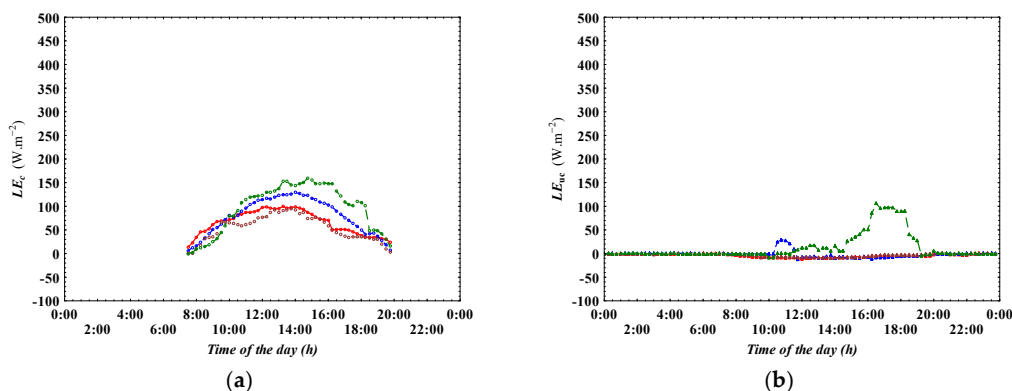


Figure 6. Estimated latent heat fluxes from each component within the proposed model framework. (a) Shows the latent heat calculated above the canopy (LE_c), and (b) shows the latent heat calculated under the canopy (LE_{uc}). The solid red line represents the data measured on 15th July, the blue dashed line the data measured on 10th August, the brown dotted line the data measured on 18th August, and the green dash-dotted line the data measured on 26th August.

Due to the characteristics of vine drip irrigation and the absence of precipitation, the soil between vine rows remained dry throughout the experimental period. Consequently, all the energy available at the soil surface between vine rows was converted into sensible heat fluxes (H_{bs}). The fluctuations of H_{bs} during the day were solely influenced by the canopy's shadow projection on the soil between vine rows (Figure 5c).

Maximum values of 29 and 107 $W.m^{-2}$ were estimated for LE_{uc} on August 10th (two days after irrigation) and August 26th (with irrigation ongoing), respectively (Figure 6b). On August 26th, the estimated LE_{uc} values represented approximately 40% of the estimated turbulent fluxes beneath the canopy ($H+LE$)_{uc} (Figure 6a, b). In contrast, the contribution of LE_{uc} to the total fluxes on August 10th was almost negligible (Figure 6b). Near-zero values for LE_{uc} were estimated on days when the topsoil was dry, such as July 15th and August 18th (Figure 6b). Similarly, the latent heat fluxes from the canopy (LE_c) were significantly influenced by irrigation. Increased soil moisture reduced canopy resistance, leading to higher LE_c values on August 10th and particularly on August 26th (Figure 6a). On these days, LE_c accounted for approximately 30 to 40% of the estimated turbulent fluxes from the canopy ($H+LE$)_c (Figure 6a,b).

3.2. Model Performance Evaluation

3.2.1. Turbulent Energy Fluxes at Reference Level

To accommodate the dynamics of vineyard systems and capture all turbulent energy fluxes—encompassing those from the bare soil between rows, the bare soil beneath the canopy, and the vine canopy—a tailored energy balance model framework was proposed. This section presents a characterization of the turbulent energy fluxes estimated using a three-source clumped model at the reference level, as described by Equations (18) and (19).

It is worth noting that, during the measurement period, H_{est} accounted for approximately 65% of the available energy at the reference level on July 15th and August 18th. In contrast, on irrigation days or close to irrigation, H_{est} accounted for an average of 58% of the available energy at reference level (Table 3). This pattern, which mirrors observations at the vine canopy level, highlights the influence of soil water content, particularly due to irrigation, on the partitioning of available energy into sensible and latent heat fluxes. This is consistent with findings reported by Kool et al. [14] and Choudbury and Monteith [37].

Table 3. Proportion of the radiative energy partition between the sensible (H_{est}) and latent (LE_{est}) energy fluxes estimated at reference level. On July 15th and August 18th, data were measured under dry topsoil conditions. On August 10th data were measured two days post-irrigation and on August 26th data were measured while irrigation was ongoing.

DAY	$H_{est}/(Rn - G)_{obs}$	$LE_{est}/(Rn - G)_{obs}$
15/07/2021	0.67	0.28
10/08/2021	0.56	0.38
18/08/2021	0.66	0.26
26/08/2021	0.58	0.48

Throughout the experimental period, the estimated sensible heat flux (H_{est}) closely resembled the observed heat flux (H_{obs}), which was measured by the EC system. Although H_{est} slightly underestimated H_{obs} , the variability of H_{est} closely aligned with the observed variability in H_{obs} . Similarly, the latent heat flux (LE_{est}) estimated by the proposed model framework also showed a slight underestimation of approximately 4 W.m^{-2} compared to the observed latent heat flux (LE_{obs}) during daylight hours (Table 4). Consequently, the combined energy fluxes ($H+LE$) estimated by the model slightly underestimated the observed fluxes by about 5 W.m^{-2} during the same period (Table 4).

Table 4. Goodness-of-fit measures between the observed convective energy fluxes (Φ_{obs}), encompassing the latent (LE), sensible (H), and the combined ($H+LE$) energy fluxes, and the corresponding model-estimated fluxes (Φ_{est}) calculated using equations (18) and (19). Observed fluxes were measured by the eddy-covariance system at the reference height (3 m). Data presented are for daylight hours only.

DAY	Energy Flux	RMSE (W.m^{-2})	MBE (W.m^{-2})	E (Dimensionless)	N
15/07/2021	H	2.99	−0.37	0.26	50
	LE	4.46	−1.68	2.80	
	H + LE	10.90	−1.50	0.74	
10/08/2021	H	2.08	−0.03	0.03	50
	LE	5.33	−0.88	1.23	
	H + LE	11.10	−2.44	1.37	
18/08/2021	H	2.69	0.70	0.58	50
	LE	8.34	−5.76	10.77	
	H + LE	11.42	−5.68	3.25	
26/08/2021	H	2.16	−0.40	0.37	50
	LE	11.41	−8.51	8.76	
	H + LE	15.87	−10.94	5.31	
ALL DAYS	H	2.51	−0.03	0.02	200
	LE	7.87	−4.21	5.96	
	H + LE	12.49	−5.14	2.70	

3.2.2. Model Validation

To evaluate the ability of the proposed model framework to capture the dynamics of turbulent energy fluxes, the model-estimated fluxes at a reference level (the same height as the EC system) were validated against the fluxes observed by the EC system.

This section presents the results of the validation of the estimated sensible heat flux (by Equation (18)) and the estimated latent heat fluxes (by Equation (19)) against the respective fluxes measured by the EC system.

The validation of the energy fluxes estimated at the reference height involved fitting the estimated energy fluxes values (e_{Φ}^i) to the observed energy fluxes (o_{Φ}^i), measured by the EC system (Figure 7 and Table 4). This evaluation included both convective energy fluxes (Φ), encompassing the latent energy flux (LE), and sensible energy fluxes (H).

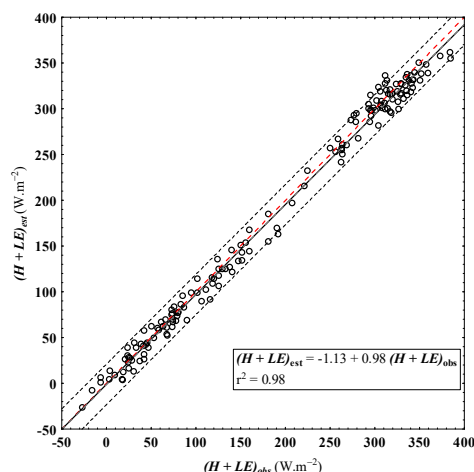


Figure 7. Least square linear regression (solid black line) between observed turbulent fluxes $(H+LE)_{obs}$, measured by the eddy-covariance system at the reference height (3 m), and the estimated turbulent fluxes $(H+LE)_{est}$, calculated using equations (18) and (19). The black dotted lines represent the 95% confidence prediction interval, and the red dashed line indicates the 1:1 relationship (perfect agreement between observed and estimated turbulent fluxes).

Table 4 presents the accuracy measures of the proposed model framework to estimate the turbulent energy fluxes at the reference height, calculated by Equations (18) and (19). These accuracy metrics allow the assessment of the extent to which the estimated fluxes align with those measured by the EC system.

The model's estimated fluxes demonstrate a high degree of agreement with the reference fluxes measured by the EC system, as illustrated in Figure 7. The model's performance is further supported by the metrics for the deviation of the residuals, which reveal a minimal discrepancy between the observed and estimated values of the turbulent fluxes, including sensible heat flux (H), latent heat flux (LE), and the combined fluxes ($H+LE$). Notably, the average error magnitude between the observed and estimated sensible heat fluxes was consistently lower than 3 W.m^{-2} (Table 4). While the model slightly underestimated the sensible heat fluxes at the reference level, the deviation was minimal, indicating strong model performance. Similarly, latent energy fluxes were underestimated during the experimental period, with a particularly noticeable deviation on August 26th, when irrigation was ongoing. On this date, the mean bias between the estimated and observed LE was -8.5 W.m^{-2} , suggesting that while the model performed well overall, it tended to underpredict latent heat flux under conditions of increasing soil moisture due to irrigation (Table 4). Similar findings were reported by Poblete-Echeverria and Ortega-Farias [32]. It is important to emphasize that all goodness-of-fit metrics underscore the model's robustness within the specific conditions of this study. These metrics indicate that the model reliably estimated the energy fluxes in vineyard systems, despite slight underestimations that occurred under certain irrigation conditions. The high degree of agreement between the observed and estimated fluxes reaffirms the model's accuracy in capturing the complex dynamics of energy fluxes in viticultural environments. This validation of the energy fluxes estimated from each component—both soil and canopy—within the proposed model framework underscores the model's effectiveness in accurately reflecting the intricate energy dynamics at play in vineyard systems.

4. Conclusions

The water content in the soil plays a crucial role not only in regulating the temperature of the soil beneath the canopy but also in influencing the temperature and

energy balance of the canopy itself. This study reveals that, even when vines are maintained under moderate water stress, the application of controlled volumes of water can significantly alter the energy fluxes in both the canopy and the soil beneath it, particularly under conditions of intense heat stress. Given that grape clusters are typically located in the lower part of the canopy, these findings underscore the potential of irrigation management to mitigate heat stress at the level of the vine bunches.

By treating the under-canopy fluxes separately, the three-source model enables the estimation of soil evaporation under the canopy—affected by shading—and vine transpiration. This distinction is important for water resource management, particularly in vineyards employing regulated deficit irrigation, where water use efficiency is a primary concern. The three-source model separately estimates the sensible heat fluxes from both the soil beneath the canopy (H_{uc}) and the canopy (H_c) itself. This separation is important because these fluxes can differ in magnitude and behavior due to the effects of canopy shading and microclimatic variations. In vineyard systems, characterized by spatially discontinuous canopies and distinct rows, the three-source model provides a more realistic description of the energy dynamics by addressing the fluxes from both the vine canopy and the underlying soil.

This research demonstrates the feasibility of evaluating the energy fluxes within a model framework that accounts for variations in energy fluxes beneath the vine canopy, from the canopy itself, and from the bare soil between vine rows. Furthermore, it underscores the importance of accurately estimating the energy fluxes at different key vineyard locations. By enhancing our understanding of energy dynamics in vineyard ecosystems under regulated deficit irrigation, this study emphasizes the critical role of thermal and water stresses in controlling these fluxes. These insights are crucial for optimizing irrigation management practices, ultimately improving grape production in arid climates. Effective irrigation strategies can enhance both grape quality and yield while ensuring sustainability in challenging environments.

To further refine and optimize the control of heat stress in vineyards, additional research is warranted. Future studies should investigate a range of factors at both the plant and soil levels, including different planting row distances, vine row orientations, pruning techniques, and trellis systems. Additionally, exploring various soil coverings, such as cover crops or mulching, and irrigation management and applied water volumes, will provide a more comprehensive understanding of the dynamics associated with energy fluxes in vineyard systems. This holistic approach will help develop improved practices for protecting grape quality and vineyard health under varying environmental conditions.

Supplementary Materials: Figure S1: Rainfall and irrigation events recorded from June 15th to September 15th, 2021, in the experimental vineyard. The figure displays periods of irrigation (marked by vertical lines) and the last recorded rain event (June 17th to June 20th), highlighting the dry conditions leading up to the measurements.; Figure S2: Soil water content (SWC): (a) measured at the soil surface layer (0.1 m) using an ML3 Thetaprobe sensor (Delta-T Devices, Cambridge, UK), and (b) measured at 0.2 m, 0.6 m, and 0.8 m depths, with daily maximum values recorded during the measurement events on July 15th (red line), and August 10th (blue line), 18th (brown line), and 26th (green line) using an Enviroscan probe (Sentek Sensor Technologies, SA, Australia). Table S1: Adapted and measured parameters, and measured and calculated variables.; Table S2: Characterization of the Canopy temperature (T_c) and Air temperature beneath the canopy ($T_{a,uc}$) on the measurement days, 15th July, 10th, 18th and 26th of August 2021.

Author Contributions: Conceptualization, R.E.; methodology, R.E.; formal analysis, R.E.; investigation, R.E.; resources, A.A. and J.M.A.; data curation, R.E.; writing—original draft preparation, R.E.; writing—review and editing, R.E., A.A., and J.M.A.; supervision, A.A. and J.M.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: Data is available on request. The data presented in this study are available on request from the corresponding author.

Acknowledgments: We acknowledge the support of the CITES research unit, Centro de Investigación en Tecnología, Energía y Sostenibilidad, Universidad de Huelva and the FCT Research Unit “GREEN-IT -Bioresources for Sustainability” (UIDB/04551/2020 – DOI 10.54499/UIDB/04551/2020, and UIDP/04551/2020 – DOI 10.54499/UIDP/04551/2020). We also address our acknowledgements to Herdade do Esporão (Reguengos de Monsaraz, Alentejo, PT) and Rui Flores for their contribution to field management of the experimental vineyard.

Conflicts of Interest: The authors declare no conflicts of interest.

List of Symbols

Energy flux variables

$R_{n,c}$	Net solar radiation at the top of vine canopy ($W \cdot m^{-2}$)
$R_{n,uc}$	Net solar radiation under vine canopy ($W \cdot m^{-2}$)
$R_{n,bs}$	Net solar radiation between vine rows ($W \cdot m^{-2}$)
$R_{n,obs}$	Net solar radiation measured at the reference height ($W \cdot m^{-2}$)
G_{uc}	Soil heat flux under vine canopy ($W \cdot m^{-2}$)
G_{bs}	Soil heat flux between vine rows ($W \cdot m^{-2}$)
G_{obs}	Soil heat flux measured at the reference height ($W \cdot m^{-2}$)
H	Sensible heat flux ($W \cdot m^{-2}$)
H_c	Sensible heat flux from vine canopy ($W \cdot m^{-2}$)
H_{uc}	Sensible heat flux under vine canopy ($W \cdot m^{-2}$)
H_{bs}	Sensible heat flux between vine rows ($W \cdot m^{-2}$)
H_{obs}	Sensible heat flux measured at the reference height ($W \cdot m^{-2}$)
H_r	Sensible heat fluxes aggregated at the reference height ($W \cdot m^{-2}$)
LE	Latent heat flux ($W \cdot m^{-2}$)
LE_c	Latent heat flux from vine canopy ($W \cdot m^{-2}$)
LE_{uc}	Latent heat flux under vine canopy ($W \cdot m^{-2}$)
LE_{bs}	Latent heat flux between vine rows ($W \cdot m^{-2}$)
LE_{obs}	Latent heat flux measured at the reference height ($W \cdot m^{-2}$)
LE_r	Latent heat fluxes aggregated at the reference height ($W \cdot m^{-2}$)

Surface and meteorological scalar constants and variables

C_p	Air specific heat capacity at constant pressure ($1013 J \cdot kg^{-1} \cdot ^\circ C^{-1}$)
d_p	Zero-plane displacement height (m)
f	Fractional cover of the canopy (dimensionless)
h	Canopy height (m)
k	Von Karman’s constant (0.41 dimensionless)
k_h	Diffusivity at the top of the canopy ($m^2 \cdot s^{-1}$)
n	Eddy diffusivity decay coefficient (2.5 dimensionless) [20]
R_n	Net solar radiation ($W \cdot m^{-2}$)
G	Soil heat flux ($W \cdot m^{-2}$)
RH	Relative humidity (%)
T_{air}	Air temperature ($^\circ C$)
T_c	Canopy temperature ($^\circ C$)
$T_{a,bs}$	Air temperature between vine rows ($^\circ C$)
$T_{a,c}$	Air temperature above the canopy ($^\circ C$)
$T_{a,uc}$	Air temperature under vine canopy ($^\circ C$)
$T_{s,uc}$	Soil temperature under vine canopy ($^\circ C$)
$T_{s,bs}$	Soil temperature between rows ($^\circ C$)
u	Wind speed ($m \cdot s^{-1}$)
u_m	Wind speed at the mean surface flow height ($m \cdot s^{-1}$)
u_h	Wind speed at the top of the canopy ($m \cdot s^{-1}$)
u_r	Wind speed measured at the reference height ($m \cdot s^{-1}$)
u_*	Wind friction velocity ($m \cdot s^{-1}$)
VPD	Vapor pressure deficit (kPa)
w	Average width of a representative leaf (m)

z_0	Canopy roughness length (m)
z_0'	Bare soil roughness length (m)
z_m	Mean surface flow height (m)
z_r	Reference height (m)
ρ	Air density ($\text{kg}\cdot\text{m}^{-3}$)
LAI	Leaf area index ($\text{m}^2\cdot\text{m}^{-2}$)
Aerodynamic resistance network	
$r_{a,bs}$	Aerodynamic resistance of bare soil unaffected by the canopy ($\text{s}\cdot\text{m}^{-1}$)
$r_{a,c}$	Aerodynamic resistance above the canopy ($\text{s}\cdot\text{m}^{-1}$)
$r_{a,uc}$	Aerodynamic resistance between bare soil under the vines canopy and z_m ($\text{s}\cdot\text{m}^{-1}$)

References

- Deitch, M.J.; Sapundjieff, M.J.; Feirer, S.T. Characterizing Precipitation Variability and Trends in the World's Mediterranean-Climate Areas. *Water* **2017**, *9*, 259. <https://doi.org/10.3390/w9040259>.
- Lionello, P.; Malanotte-Rizzoli, P.; Boscolo, R.; Alpert, P.; Artale, V.; Li, L.; Luterbacher, J.; May, W.; Trigo, R.; Tsimplis, M.; et al. The Mediterranean climate: An overview of the main characteristics and issues. *Dev. Earth Environ. Sci.* **2006**, *4*, 1–26. [https://doi.org/10.1016/S1571-9197\(06\)80003-0](https://doi.org/10.1016/S1571-9197(06)80003-0).
- Smart, R.; Robinson, M. *Sunlight into Wine: A Handbook for Wine Grape Canopy Arrangement*. Winetitles Media: Broadview, Australia, 1991; ISBN 978-1875130108.
- Costa, J.M.; Egipto, R.; Aguiar, F.C.; Marques, P.; Nogales, A.; Madeira, M. The role of soil temperature in mediterranean vineyards in a climate change context. *Front. Plant Sci.* **2023**, *14*, 2023. <https://doi.org/10.3389/fpls.2023.1145137>.
- Venios, X.; Korkas, E.; Nisiotou, A.; Banilas, G. Grapevine Responses to Heat Stress and Global Warming. *Plants* **2020**, *9*, 1754. <https://doi.org/10.3390/plants9121754>.
- Del-Castillo-Alonso, M.-A.; Diago, M.P.; Tomas-Las-Heras, R.; Monforte, L.; Soriano, G.; Martínez-Abaigar, J.; Núñez-Olivera, E. Effects of ambient solar UV radiation on grapevine leaf physiology and berry phenolic composition along one entire season under Mediterranean field conditions. *Plant Physiol. Biochem.* **2016**, *104*, 379–386. <https://doi.org/10.1016/j.plaphy.2016.10.018>.
- Zarrouk, O.; Brunetti, C.; Egipto, R.; Pinheiro, C.; Genebra, T.; Gori, A.; Lopes, C.M.; Tattini, M.; Chaves, M.M. Grape Ripening Is Regulated by Deficit Irrigation/Elevated Temperatures According to Cluster Position in the Canopy. *Front. Plant Sci.* **2016**, *7*, 1640. <https://doi.org/10.3389/fpls.2016.01640>.
- IPCC (2019) AR6 Synthesis Report: Climate Change 2022. Available online: https://www.ipcc.ch/site/assets/uploads/2018/02/WGIIAR5-Chap3_FINAL.pdf (accessed on 30 September 2023).
- Santillán, D.; Garrote, L.; Iglesias, A.; Sotes, V. Climate change risks and adaptation: New indicators for Mediterranean viticulture. *Mitig. Adapt. Strat. Glob. Change* **2020**, *25*, 881–899. <https://doi.org/10.1007/s11027-019-09899-w>.
- Santos, J.A.; Fraga, H.; Malheiro, A.C.; Moutinho-Pereira, J.; Dinis, L.-T.; Correia, C.; Moriondo, M.; Leolini, L.; Dibari, C.; Costafreda-Aumedes, S.; et al. A Review of the Potential Climate Change Impacts and Adaptation Options for European Viticulture. *Appl. Sci.* **2020**, *10*, 3092. <https://doi.org/10.3390/app10093092>.
- Malheiro, A.C.; Santos, J.A.; Fraga, H.; Pinto, J.G. Climate change scenarios applied to viticultural zoning in Europe. *Clim. Res.* **2010**, *43*, 163–177. <https://doi.org/10.3354/cr00918>.
- Burchard-Levine, V.; Nieto, H.; Kustas, W.P.; Gao, F.; Alfieri, J.G.; Prueger, J.H.; Hipps, L.E.; Bambach-Ortiz, N.; McElrone, A.J.; Castro, S.J.; et al. Application of a remote-sensing three-source energy balance model to improve evapotranspiration partitioning in vineyards. *Irrig. Sci.* **2022**, *40*, 593–608. <https://doi.org/10.1007/s00271-022-00787-x>.
- Costa, J.M.; Egipto, R.; Sánchez-Virosta, A.; Lopes, C.M.; Chaves, M.M. Canopy and soil thermal patterns to support water and heat stress management in vineyards. *Agric. Water Manag.* **2019**, *216*, 484–496. <https://doi.org/10.1016/j.agwat.2018.06.001>.
- Kool, D.; Ben-Gal, A.; Agam, N.; Šimunek, J.; Heitman, J.L.; Sauer, T.J.; Lazarovitch, N. Spatial and diurnal below canopy evaporation in a desert vineyard: Measurements and modeling. *Water Resour. Res.* **2014**, *50*, 7035–7049. <https://doi.org/10.1002/2014WR015409>.
- Lhomme, J.P.; Montes, C.; Jacob, F.; Prévot, L. Evaporation from Heterogeneous and Sparse Canopies: On the Formulations Related to Multi-Source Representations. *Bound. Layer Meteorol.* **2012**, *144*, 243–262. <https://doi.org/10.1007/s10546-012-9713-x>.
- Brenner, A.J.; Incoll, L.D. The effect of clumping and stomatal response on evaporation from sparsely vegetated shrublands. *Agric. For. Meteorol.* **1997**, *84*, 187–205. [https://doi.org/10.1016/S0168-1923\(96\)02368-4](https://doi.org/10.1016/S0168-1923(96)02368-4).
- Kool, D.; Kustas, W.P.; Ben-Gal, A.; Lazarovitch, N.; Heitman, J.L.; Sauer, T.J. Energy and evapotranspiration partitioning in a desert vineyard. *Agric. For. Meteorol.* **2016**, *218*–219, 277–287. <https://doi.org/10.1016/j.agrformet.2016.01.002>.
- Kustas, W.P.; Alfieri, J.G.; Nieto, H.; Wilson, T.G.; Gao, F.; Anderson, M.C. Utility of the two-source energy balance (TSEB) model in vine and interrow flux partitioning over the growing season. *Irrig. Sci.* **2019**, *37*, 375–388. <https://doi.org/10.1007/s00271-018-0586-8>.
- Monteith, J.L.; Unsworth, M.H. *Principles of Environmental Physics in Plants, Animals, and the Atmosphere*, 4th ed.; Academic Press: Cambridge, MA, USA, **2013**; ISBN: 978-0-12-386910-4.

20. Shuttleworth, J.; Wallace, J.S. Evaporation from sparse crops—an energy combination theory. *Q. J. R. Meteorol. Soc.* **1985**, *111*, 839–855. <https://doi.org/10.1002/qj.49711146910>.
21. Norman, J.M.; Kustas, W.P.; Humes, K.S. Source approach for estimating soil and vegetation energy fluxes in observations of directional radiometric surface temperature. *Agric. For. Meteorol.* **1995**, *77*, 263–293. [https://doi.org/10.1016/0168-1923\(95\)02265-Y](https://doi.org/10.1016/0168-1923(95)02265-Y).
22. Ortega-Farías, S.; Poblete-Echeverría, C.; Brisson, N. Parameterization of a two-layer model for estimating vineyard evapotranspiration using meteorological measurements. *Agric. For. Meteorol.* **2010**, *150*, 276–286. <https://doi.org/10.1016/j.agrformet.2009.11.012>.
23. Qin, S.; Fan, Y.; Li, S.; Cheng, L.; Zhang, L.; Xi, H.; Qiu, R.; Liu, P. Partitioning of available energy in canopy and soil surface in croplands with different irrigation methods. *Agric. Water Manag.* **2023**, *288*, 108475. <https://doi.org/10.1016/j.agwat.2023.108475>.
24. Zhao, P.; Zhang, X.; Li, S.; Kang, S. Vineyard Energy Partitioning Between Canopy and Soil Surface: Dynamics and Biophysical Controls. *J. Hydrometeorol.* **2017**, *18*, 1809–1829. <https://doi.org/10.1175/JHM-D-16-0122.1>.
25. Hunter, J.K.; Tarricone, L.; Volschenk, C.; Giacalone, C.; Melo, M.S.; Zorer, R. Grapevine physiological response to row orientation-induced spatial radiation and microclimate changes. *OENO One* **2020**, *54*, 411–433. <https://doi.org/10.20870/oenone.2020.54.2.3100>.
26. Ham, J.M.; Heilman, J.L. Aerodynamic and surface resistances affecting energy transport in a sparse crop. *Agric. For. Meteorol.* **1991**, *53*, 267–284. [https://doi.org/10.1016/0168-1923\(91\)90047-T](https://doi.org/10.1016/0168-1923(91)90047-T).
27. Jones, H.G.; Stoll, M.; Santos, T.; de Sousa, C.; Chaves, M.M.; Grant, O.M. Use of infra-red thermography for monitoring stomatal closure in the field: Application to the grapevine. *J. Exp. Bot.* **2002**, *53*, 2249–2260. <https://doi.org/10.1093/jxb/erf083>.
28. Lopes, C.; and Pinto, P.A. Easy and accurate estimation of grapevine leaf area with simple mathematical models. *Vitis J. Grapevine Res.* **2005**, *44*, 55–61. <https://doi.org/10.5073/vitis.2005.44.55-61>.
29. Shuttleworth, J.; Gurney, R.J. The theoretical relationship between foliage temperature and canopy resistance in sparse crops. *Q. J. R. Meteorol. Soc.* **1990**, *116*, 497–519. <https://doi.org/10.1002/qj.49711649213>.
30. Fuentes, S.; Ortega-Farías, S.; Carrasco-Benevides, M.; Tongson, E.; Viejo, C.G. Actual evapotranspiration and energy balance estimation from vineyards using micro-meteorological data and machine learning modeling. *Agric. Water Manag.* **2024**, *297*, 108834. <https://doi.org/10.1016/j.agwat.2024.108834>.
31. Kool, D.; Kustas, W.P.; Ben-Gal, A.; Agam, N. Energy partitioning between plant canopy and soil, performance of the two-source energy balance model in a vineyard. *Agric. For. Meteorol.* **2021**, *300*, 108328. <https://doi.org/10.1016/j.agrformet.2021.108328>.
32. Poblete-Echeverría, C.; Ortega-Farías, S. Estimation of actual evapotranspiration for a drip-irrigated Merlot vineyard using a three-source model. *Irrig. Sci.* **2009**, *28*, 65–78. <https://doi.org/10.1007/s00271-009-0183-y>.
33. Ortega-Farías, S.; Carrasco, M.; Olioso, A.; Acevedo, C.; Poblete, C. Latent heat flux over Cabernet Sauvignon vineyard using the Shuttleworth and Wallace model. *Irrig. Sci.* **2007**, *25*, 161–170. <https://doi.org/10.1007/s00271-006-0047-7>.
34. Heitman, J.L.; Horton, R.; Sauer, T.J.; Ren, T.S.; Xiao, X. Latent heat in soil heat flux measurements. *Agric. For. Meteorol.* **2010**, *150*, 1147–1153. <https://doi.org/10.1016/j.agrformet.2010.04.017>.
35. Pieri, P.; Gaudillère, J. Sensitivity to training system parameters and soil surface albedo of solar radiation intercepted by vine rows. *Vitis* **2003**, *42*, 77–82. <https://doi.org/10.5073/vitis.2003.42.77-82>.
36. Hsu, H.; Dirmeyer, P.A. Soil moisture-evaporation coupling shifts into new gears under increasing CO₂. *Nat. Commun.* **2023**, *14*, 1162. <https://doi.org/10.1038/s41467-023-36794-5>.
37. Choudhury, B.J.; Monteith, J.L. A four-layer model for the heat budget of homogeneous land surfaces. *Q. J. R. Meteorol. Soc.* **1988**, *114*, 373–398. <https://doi.org/10.1002/qj.49711448006>.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.

7. Discussion

This section summarizes the key findings from the investigation conducted during this thesis. For a detailed discussion of the results, readers should refer to the corresponding documents provided in Section 6.

As previously discussed, deficit irrigation strategies are increasingly adopted by winegrowers to improve water sustainability and minimize soil evaporation losses. These strategies aim to maintain crop yields and enhance water use efficiency, offering a valuable approach for sustainable viticulture. A critical aspect of implementing these strategies is the accurate evaluation of actual vineyard water use to optimize grapevine water stress. To address this, advanced supervised machine learning algorithms (MLAs) were trained and tested to predict the actual crop evapotranspiration ($ET_{c\ act}$) of the Tempranillo variety. The predictive models used key variables, including net solar radiation (R_n), soil heat flux (G), wind speed (u), air vapor pressure deficit (VPD), and leaf stomatal conductance to water vapor (g_{sw}). Evaluation against a validation dataset revealed that these variables explained a significant proportion of the variability in field-measured $ET_{c\ act}$, confirming their suitability as predictors. These findings align with previous studies (Velazquez-Chavez et al., 2024; Fernández, 2017; Chaves et al., 2016; Rogiers et al., 2012; Buckley, 2005; Cifre et al., 2005; Jarvis and McNaughton, 1986). The validation phase produced results consistent with the training and testing phases. All MLA models, except for the support vector machine (SVM) implementing a linear kernel function, demonstrated high accuracy in predicting $ET_{c\ act}$. The correlation coefficient (r) between observed and predicted values exceeded 0.88, while the maximum root mean square error (RMSE) was 0.032 mm.h^{-1} , which is below the minimum $ET_{c\ act}$ value recorded during the experimental period. Similar findings have been reported for other crops (Granata, 2019; Dou and Yang, 2018; Zhang et al., 2018). In addition, an external validation dataset, consisting of $ET_{c\ act}$ measurements obtained from an eddy covariance (EC) system, was used to test the accuracy of the MLAs. The results confirmed that all models, except the SVM with a linear kernel, outperformed the FAO-56 K_c - ET_0 method in estimating $ET_{c\ act}$.

The obtained MLAs reduced data requirements for estimating $ET_{c\ act}$ while also learning from acquired data. This combination of efficiency and adaptability enhances their predictive capacity, demonstrating their feasibility for optimizing sustainable irrigation management in vineyards and other row crops. These findings further strengthen the ability of MLA models in accurately estimating actual crop evapotranspiration compared to the traditional FAO-56 K_c - ET_0 method. These findings align with previous studies (Granata, 2019; Dou and Yang, 2018; Zhang et al., 2018).

Despite its advantages, the model developed in the first objective has limited ability to separately estimate the transpiration component of the vine and soil water evaporation. This limitation motivated Objective 2 of this thesis, which aimed to develop a model capable of estimating canopy resistance to transpiration under controlled water stress conditions in grapevines.

Accordingly, the second research task enabled the development of a biophysical model capable of accurately estimating the canopy resistance of grapevines under stressful environmental conditions using a limited number of plant and atmospheric variables. The study highlighted the significant impact of R_n , VPD , and g_{sw} , on canopy conductance (g_c), demonstrating their critical roles in regulating grapevine water use. These findings are consistent with previous studies (Wu et al., 2022; Wehr and Saleska, 2021; Wehr et al., 2017; Chaves et al., 2016; Ding et al., 2014; Irmak et al., 2008). Furthermore, the model

emphasized the influence of canopy boundary layer conditions on g_c and vine transpiration, highlighting their importance in understanding grapevine water dynamics. Notably, the model was specifically designed to address vine water stress and the challenges posed by water and heat stress in Mediterranean climates. Under these stressful conditions, it demonstrated high accuracy in estimating g_c compared to values calculated from the inverted Penman-Monteith equation, using the vine transpiration data recorded by the EC system installed in the experimental plot.

While the primary focus was on water-stressed conditions, it is important to note that the model has yet to be tested under non-water-stressed conditions. Future research is required to test and validate the model under these conditions and, if necessary, adapt it for more universal applications.

Preceding the realization of the third objective, a short-term scientific mission was conducted at the Instituto Superior de Agronomia, Universidade de Lisboa, from May 1st to September 30th, 2021. This mission focused on utilizing remote sensing technology to estimate grapevine water status and developing algorithms to improve the estimation of grapevine transpiration, contributing to more precise water management in vineyards. The findings were presented in 2022 at the TERCLIM / 2nd ClimeWine Symposium / XIVth International Terroir Congress, in Bordeaux, France, through a poster titled “Low cost sensors as a support tool to monitor soil-plant heat exchanges in Mediterranean vineyards”. This work contributed to the development of the fourth objective of this thesis by emphasizing the vertical temperature gradients between soil and canopy and highlighting the influence of surface soil water content on soil and canopy cooling.

The third objective of the thesis did not involve experimental field research. Instead, this study focused on reviewing the effects of soil temperature (ST) on the ecophysiological and agronomical performance of Mediterranean vineyards. The work began during a short-term scientific mission at the Instituto Superior de Agronomia, Universidade de Lisboa, in 2022, and culminated in a published review article. The manuscript reviewed available techniques for measuring soil temperature, including imaging approaches such as thermography, as an alternative or complementary tool for assessing ST and vertical canopy temperature profiles in vineyards. A better understanding of soil and vine heat and water fluxes was identified as crucial for improving soil and crop management, ensuring more sustainable Mediterranean viticulture under extreme stress conditions, such as drought and high temperatures.

Simultaneously, from June 1st to September 30th, 2022, another short-term scientific mission was conducted at the Instituto Superior de Agronomia, Universidade de Lisboa. Building on the previous short-term scientific mission, this research focused on studying the biophysical interactions of water and energy within the soil-vineyard-atmosphere system. This scientific mission, build the foundation for the forth objective of this thesis, the development evaluation of a modeling framework to estimate the dynamics of energy fluxes at the soil and plant levels under arid conditions.

Previous models, developed in this research, have typically relied on contact sensing methods to measure g_{sw} , enabling the estimation of vineyard evapotranspiration and canopy transpiration. The present study addresses this gap by demonstrating the potential of remote sensing data for estimating transpiration. Building on our understanding of water and heat flux dynamics during grapevine berry maturation, this research focuses on evaluating sensible and latent heat fluxes at the canopy, the soil beneath the canopy, and the interrow areas. The accuracy of the proposed framework was validated through comparisons with flux measurements obtained from an eddy covariance system, which

was installed at a reference height of three meters in the experimental plot. This comparison was essential for confirming the framework's ability to capture the complex energy flux dynamics within the vineyard, particularly during grape maturation. The research further confirms the feasibility of estimating heat and sensible fluxes (canopy transpiration and soil evaporation) by measuring temperature and wind speed at strategic vineyard locations. It also highlights the significant role of irrigation in influencing soil and canopy temperatures.

One of the main objectives of this thesis was to estimate grapevine water status using remote sensing data. This research facilitated the development of algorithms that estimate vineyard water status by integrating energy balance models. The comprehensive evaluation of energy fluxes offers valuable insights for optimizing irrigation strategies, improving grape quality, ensuring sustainable water use, and enhancing vineyard productivity in arid and water-scarce regions.

8. Conclusions

This thesis demonstrated the potential of non-destructive remote sensing techniques to evaluate grapevine water status. By estimating parameters such as actual crop evapotranspiration, canopy conductance (or its inverse, canopy resistance), and energy flux balances measured at various locations within the vineyard, the models and methods developed in this research provide valuable tools for assessing grapevine water status. These tools can also support the implementation of deficit irrigation strategies. The main conclusions of the study are summarized below.

8.1. Objective 1. Development and evaluation of a machine learning algorithm to estimate actual crop evapotranspiration adapted to vineyards grown under arid conditions.

- The findings demonstrate the potential advantages of employing supervised machine learning regression algorithms (MLAs) for precise and efficient estimation of actual crop evapotranspiration ($ET_{c\ act}$), which could significantly improve water management practices in vineyards.
- This study demonstrated that MLAs, when given specific parameters such as stomatal conductance to water vapor (g_{sw}), soil heat flux (G), and three meteorological variables (net solar radiation, R_n ; wind speed, u ; and air vapor pressure deficit, VPD), can effectively predict $ET_{c\ act}$.
- Results highlight the capability of supervised machine learning regression algorithms (MLAs) to estimate actual crop evapotranspiration ($ET_{c\ act}$) with a simplified parameterization and reduced computational requirements, offering an efficient alternative to the traditional FAO-56 K_c - ET_0 method while maintaining robustness and accuracy.

8.2. Objective 2. Development and evaluation of a biophysical model to predict the canopy conductance to water vapor of grapevines under arid conditions.

- The developed model, which predicts canopy conductance using stomatal conductance (g_{sw}) and meteorological variables such as net solar radiation (R_n) and air vapor pressure deficit (VPD), scaled by leaf area index (LAI), demonstrated strong predictive accuracy under stressful conditions.
- The findings reveal that, alongside leaf stomatal conductance to water vapor (g_{sw}), net solar radiation (R_n) and air vapor pressure deficit (VPD) significantly impact canopy conductance (g_c) and vine transpiration.
- Model validation confirmed that the proposed biophysical model is an effective predictor of canopy conductance (g_c) and, consequently, vine transpiration, under the conditions examined in this study.
- The results emphasize that monitoring canopy conductance (g_c) through a simplified biophysical model provides valuable insights into plant transpiration, supporting efficient vineyard irrigation management in stressful arid environments.

8.3. Objective 3. Review of soil temperature effect on ecophysiological and agronomical performance in Mediterranean vineyards. Discuss the potential of imaging techniques to assess soil temperature and vertical canopy temperature profiles.

- This review underscores the need for future research to elucidate the mechanisms through which soil temperature (ST) influences leaf and berry traits across various grapevine varieties, clones, and rootstocks.
- The potential impacts of climate warming on soil temperature (ST) vary depending on the type of heat stress (e.g., heat shocks, heat waves, or gradually increasing warming conditions). These variations result in distinct physiological and molecular responses at the leaf and fruit levels, affect root morphology, and influence reproductive traits.
- A deeper understanding of the role of soil properties in regulating heat and water fluxes is essential for developing more efficient soil and crop management practices, ensuring sustainable Mediterranean viticulture under extreme stress conditions.
- Imaging techniques show promise for assessing soil temperature and vertical canopy temperature profiles, providing valuable insights into plant responses to environmental stressors and informing adaptive management strategies.

8.4. Objective 4. Development and evaluation of a modeling framework to estimate the dynamics of energy fluxes at the soil and plant levels under arid conditions.

- Soil water content (*SWC*) is a key factor in regulating soil temperature beneath the canopy and significantly influences the temperature and energy balance of the canopy itself.
- The study revealed that controlled water applications, even under moderate water stress, can markedly alter energy fluxes in both the canopy and the underlying soil, particularly during periods of intense heat stress.
- By advancing our understanding of energy dynamics in vineyard ecosystems under regulated deficit irrigation, this study highlights the pivotal role of thermal and water stresses in governing these fluxes.
- The findings demonstrate the potential of precision irrigation management strategies to mitigate heat stress at the level of vine bunches, contributing to improved vineyard performance under arid conditions.

8.5. Global conclusion

This thesis demonstrated the feasibility of evaluating the grapevine water status using non-intrusive measurement methods. Under the study conditions, a set of metrics was identified that could be directly measured or calculated to determine grapevine water status through contact or proximal sensors. Numerous studies indicate that stomatal conductance to water vapor (g_{sw}), the ratio between actual crop evapotranspiration ($ET_{c_{act}}$) and reference evapotranspiration (ET_0), are directly related to grapevine water status. These metrics have also been linked to wine profiles, facilitating their application in deficit irrigation strategies.

Despite the abundance of studies, a universal equation for assessing vine water status has not yet been developed. A key challenge lies in the absence of methods capable of accurately measuring vine water status at appropriate temporal and spatial scales. This

thesis aimed to address these gaps and contribute to advance precision irrigation in vineyards.

The research highlighted the efficacy of machine learning algorithms (MLAs) for accurately estimating actual crop evapotranspiration ($ET_{c\ act}$), positioning them as a promising alternative to the standard FAO-56 K_c - ET_0 method. This approach is particularly advantageous for row-based, sparse, and drip-irrigated crops with extensive exposed soil areas.

Additionally, a biophysical model was developed to estimate canopy conductance (g_c) by integrating leaf stomatal conductance to water vapor (g_{sw}) from leaves with varying environmental exposures and accounting for the effects of the leaf boundary layer. While acknowledging the challenge of the proposed model's limited spatial resolution, this thesis highlights alternative methods for estimating leaf stomatal conductance to water vapor (g_{sw}). Beyond direct measurements using porometers or infra-red gas analyzers (IRGAs), leaf stomatal conductance to water vapor (g_{sw}) can be reliably estimated through thermal infrared imaging. Supported by findings from studies such as Costa et al. (2019, 2018, 2013), Jones (2018, 2004), Garcia-Tejero et al. (2016), Stoll and Jones (2007), Grant et al. (2007, 2006), and Jones and Leinonen (2003) this approach offers a practical solution to address spatial resolution limitations. The thesis further proposed a method to estimate energy flux dynamics at the soil and canopy levels using the energy balance equation within an adapted framework. By utilizing canopy temperature (from thermal imaging), air temperature, and wind speed (measured above the canopy), the study estimated sensible and latent heat fluxes, including canopy transpiration and soil evaporation. The results showed that deficit irrigation strategies influence soil and canopy temperatures, with reduced canopy transpiration under limited soil water content. Controlled water applications under moderate water stress conditions significantly altered energy fluxes, especially under intense heat stress.

Effective irrigation strategies enhance grape quality and yield while ensuring sustainability in challenging environments. This thesis provides valuable insights for optimizing irrigation management, with a particular focus on improving grape production in arid climates.

Future research should further refine water stress assessment methods by exploring factors at both the plant and soil levels. These include variations in row spacing, vine orientation, pruning techniques, and trellis systems. Investigating the effects of soil coverings (e.g., cover crops and mulching), irrigation strategies, and applied water volumes will deepen our understanding of energy flux dynamics in vineyard systems. A holistic approach will support the development of sustainable practices to maintain grape quality and vineyard health under diverse environmental conditions.

9. Conclusiones

Esta tesis demuestra el potencial de las técnicas basadas en datos de sensores remotos para la evaluación del estado hídrico de la vid. Al estimar parámetros como la evapotranspiración real del cultivo, la conductancia del dosel (o su inversa, la resistencia del dosel), y los balances de flujos de energía medidos en diversas ubicaciones dentro del viñedo, los modelos y métodos desarrollados en esta investigación proporcionan herramientas valiosas para evaluar el estado hídrico de la vid. Estas herramientas también pueden apoyar la implementación de estrategias de riego deficitario. Las principales conclusiones del estudio se resumen a continuación.

9.1. Objetivo 1. Desarrollo y evaluación de un algoritmo de aprendizaje automático para estimar la evapotranspiración real del cultivo adaptado a viñedos cultivados en condiciones áridas.

- Los hallazgos demuestran las ventajas potenciales de emplear algoritmos de regresión supervisada de aprendizaje automático (MLA) para estimar con precisión y eficiencia la evapotranspiración real del cultivo ($ET_{c\ act}$), lo que podría mejorar significativamente las prácticas de gestión del agua en los viñedos.
- Este estudio demostró que los MLA, al incorporar parámetros específicos tales como la conductancia estomática al vapor de agua (g_{sw}), el flujo de calor del suelo (G), y tres variables meteorológicas (radiación solar neta, R_n ; velocidad del viento, u ; y déficit de presión de vapor del aire, VPD), pueden predecir eficazmente la evapotranspiración real del cultivo, $ET_{c\ act}$.
- Los resultados resaltan la capacidad de los MLA para estimar la evapotranspiración real del cultivo, $ET_{c\ act}$, con una parametrización simplificada y requisitos computacionales reducidos, ofreciendo una alternativa eficiente al método tradicional FAO-56 K_c - ET_0 , sin perder precisión ni robustez.

9.2. Objetivo 2. Desarrollo y evaluación de un modelo biofísico para predecir la conductancia del dosel al vapor de agua de la vid bajo condiciones áridas.

- El modelo desarrollado, que predice la conductancia del dosel utilizando la conductancia estomática (g_{sw}), y variables meteorológicas tales como la radiación solar neta (R_n) y el déficit de presión de vapor del aire (VPD), escalado por el índice de área foliar (LAI), demostró una alta precisión predictiva bajo condiciones de estrés.
- Los hallazgos revelan que, junto con la conductancia estomática al vapor de agua (g_{sw}), la radiación solar neta (R_n), y el déficit de presión de vapor del aire (VPD), tienen un impacto significativo en la conductancia del dosel (g_c) y en la transpiración de la vid.
- La validación del modelo confirmó que, el modelo biofísico propuesto, es un predictor eficaz de la conductancia de la canopia (g_c) y, en consecuencia, de la transpiración de la vid, bajo las condiciones estudiadas.
- Los resultados enfatizan que la monitorización de la conductancia del dosel (g_c) a través de un modelo biofísico simplificado, proporciona información valiosa sobre la

transpiración de la planta, apoyando una gestión eficiente del riego en viñedos situados en ambientes áridos estresantes.

9.3. Objetivo 3. Revisión de los efectos de la temperatura del suelo sobre el rendimiento ecofisiológico y agronómico en viñedos mediterráneos. Discusión sobre el potencial de las técnicas basadas en imagen para evaluar la temperatura del suelo y los perfiles de temperatura vertical de la canopia.

- Esta revisión subraya la necesidad de futuras investigaciones para dilucidar los mecanismos a través de los cuales la temperatura del suelo (ST), influye en las características de las hojas y las bayas en diversas variedades de vid, clones y portainjertos.
- Los posibles impactos del calentamiento climático sobre la temperatura del suelo (ST), varían según el tipo de estrés térmico (por ejemplo, golpes de calor, olas de calor o condiciones de calentamiento gradual). Estas variaciones dan lugar a respuestas fisiológicas y moleculares distintas a nivel de la hoja y del fruto, afectan a la morfología de las raíces, e influyen en las características reproductivas.
- Una comprensión más profunda del papel de las propiedades del suelo en la regulación de los flujos de calor y del agua, es esencial para desarrollar prácticas más eficientes de manejo del suelo y los cultivos, garantizando una viticultura mediterránea sostenible bajo condiciones de estrés extremo.
- Las técnicas basadas en imagen muestran un gran potencial para evaluar la temperatura del suelo y los perfiles de temperatura vertical del dosel, proporcionando valiosos conocimientos sobre las respuestas de las plantas a los factores estresantes ambientales, e informando sobre las estrategias de gestión adaptativas.

9.4. Objetivo 4. Desarrollo y evaluación de un marco de modelado para estimar la dinámica de los flujos de energía a nivel del suelo y de la planta bajo condiciones áridas.

- El contenido de agua en el suelo (*SWC*) es un factor clave en la regulación de la temperatura del suelo bajo el dosel, y tiene una influencia significativa sobre el balance térmico y de energía del propio dosel.
- El estudio reveló que las aplicaciones controladas de agua, incluso bajo estrés hídrico moderado, pueden alterar notablemente los flujos de energía tanto en el dosel como en el suelo subyacente, especialmente durante períodos de estrés térmico intenso.
- Al avanzar en la comprensión de la dinámica energética en los ecosistemas de viñedos bajo riego deficitario regulado, este estudio resalta el papel crucial del estrés térmico y hídrico en la regulación de estos flujos.
- Los hallazgos demuestran el potencial de las estrategias de gestión del riego de precisión para mitigar el estrés térmico a nivel de los racimos de uvas, contribuyendo a mejorar el rendimiento de los viñedos en condiciones áridas.

9.5. Conclusión global

Esta tesis demuestra la viabilidad de evaluar el estado hídrico de la vid mediante métodos de medición no invasivos. Bajo las condiciones del estudio, se identificó un conjunto de métricas que pueden medirse directamente o calcularse para determinar el estado hídrico de la vid mediante sensores de contacto o proximales. Diversos estudios indican que la conductancia estomática al vapor de agua (g_{sw}), y la relación entre la evapotranspiración real del cultivo ($ET_{c\ act}$) y la evapotranspiración de referencia (ET_0), están directamente implicadas en la determinación del estado hídrico de la vid. Estas métricas también se han vinculado con los perfiles del vino, lo que facilita su aplicación en estrategias de riego deficitario.

A pesar de la abundancia de estudios existentes, aún no se ha desarrollado una ecuación universal para evaluar el estado hídrico de la vid. Un desafío clave radica en la falta de métodos capaces de medir con precisión el estado hídrico de la vid a escalas temporales y espaciales apropiadas. Esta tesis tiene como objetivo abordar estas brechas y contribuir al avance del riego de precisión en los viñedos.

La investigación destaca la eficacia de los algoritmos de aprendizaje automático (MLA) para estimar con precisión la evapotranspiración real del cultivo ($ET_{c\ act}$), posicionándolos como una alternativa prometedora al método estándar FAO-56 K_c - ET_0 . Este enfoque es particularmente ventajoso para cultivos en hileras, dispersos y con riego por goteo, con amplias áreas de suelo expuesto.

Además, se desarrolló un modelo biofísico para estimar la conductancia del dosel (g_c), integrando la conductancia estomática al vapor de agua (g_{sw}) de las hojas con diversas exposiciones ambientales, y teniendo en cuenta los efectos de la capa límite de la hoja. Si bien se reconoce el desafío de la resolución espacial limitada del modelo propuesto, esta tesis resalta métodos alternativos para estimar la conductancia estomática al vapor de agua (g_{sw}). Más allá de las mediciones directas mediante porómetros o analizadores de gases infrarrojos (IRGA), la conductancia estomática de la hoja (g_{sw}) puede ser estimada de manera confiable mediante imágenes térmicas infrarrojas. Respaldado por estudios como los de Costa et al. (2019, 2018, 2013), Jones (2018, 2004), García-Tejero et al. (2016), Stoll y Jones (2007), Grant et al. (2007, 2006) y Jones y Leinonen (2003), este enfoque ofrece una solución práctica para abordar las limitaciones de resolución espacial. La tesis también propone un método para estimar la dinámica de los flujos de energía en el suelo y el dosel utilizando la ecuación del balance de energía dentro de un marco adaptado. Al utilizar la temperatura del dosel (determinada a partir de imágenes térmicas), la temperatura del aire y la velocidad del viento (medidas sobre el dosel), el estudio logró estimar los flujos de calor sensible y latente, incluyendo la transpiración del dosel y la evaporación del suelo. Los resultados mostraron que las estrategias de riego deficitario influyen en las temperaturas del suelo y del dosel, con una transpiración reducida del dosel bajo condiciones de contenido limitado de agua en el suelo. Las aplicaciones controladas de agua bajo condiciones de estrés hídrico moderado alteraron significativamente los flujos de energía, especialmente bajo estrés térmico intenso.

Las estrategias de riego efectivas mejoran la calidad de la uva y el rendimiento, garantizando la sostenibilidad en entornos desafiantes. Esta tesis proporciona valiosos

conocimientos para optimizar la gestión del riego, con un enfoque particular en mejorar la producción de uvas en climas áridos.

Investigaciones futuras deberían de centrarse en refinar aún más los métodos de evaluación del estrés hídrico, explorando factores tanto a nivel de la planta como del suelo. Estos incluyen variaciones en el espaciado de las hileras, la orientación de las vides, las técnicas de poda, y los sistemas de emparrado. Investigar sobre los efectos de las coberturas del suelo (por ejemplo, cultivos de cobertura y mulching), las estrategias de riego, y los volúmenes de agua aplicados, permitirá profundizar nuestra comprensión sobre la dinámica de los flujos de energía en los sistemas de viñedos. Un enfoque integral logrará apoyar el desarrollo de prácticas sostenibles para mantener la calidad de la uva y la salud del viñedo, bajo diversas condiciones ambientales.

10. References

- Aazami M., Asghari-Aruq M., Hassanpouraghdam M., Erçişli S., Baroň M., Sochor J. (2021). Low temperature stress mediates the antioxidants pool and chlorophyll fluorescence in *Vitis vinifera* L. cultivars. *Plants*, 10(9): 1877. <https://doi.org/10.3390/plants10091877>
- Acevedo E., Silva P., Silva H.R., Solar B.R., Satorre E., Slafer G. (1999). Wheat production in Mediterranean environments. In: Satorre E.H, Slafer G.A. (eds) *Wheat: ecology and physiology of yield determination*. Haworth Press Inc., New York, USA. p. 295-331.
- Ache P., Bauer H., Kollist H., Al-Rasheid K., Lautner S., Hartung W, Hedrich R. (2010). Stomatal action directly feeds back on leaf turgor: new insights into the regulation of the plant water status from non-invasive pressure probe measurements. *The Plant Journal*, 62(6): 1072-1082. <https://doi.org/10.1111/j.1365-3113x.2010.04213.x>
- Adu M.O., Yawson D.O., Armah F.A., Asare P.A., Frimpong K.A. (2018). Meta-analysis of crop yields of full, deficit, and partial root-zone drying irrigation. *Agricultural Water Management*, 197: 79-90. <https://doi.org/10.1016/j.agwat.2017.11.019>
- Afzal A., Duiker S.W., Watson J.E. (2017). Leaf thickness to predict plant water status. *Biosystems Engineering*, 156: 148-156. <https://doi.org/10.1016/j.biosystemseng.2017.01.011>
- Albuquerque C., Scoffoni C., Brodersen C., Buckley T., Sack L., McElrone A. (2020). Coordinated decline of leaf hydraulic and stomatal conductances under drought is not linked to leaf xylem embolism for different grapevine cultivars. *Journal of Experimental Botany*, 71(22): 7286-7300. <https://doi.org/10.1093/jxb/eraa392>
- Alchanatis V., Cohen Y., Cohen S., Möller M., Sprinstin M., Meron M., Tsipris J., Saranga Y., Sela E. (2009). Evaluation of different approaches for estimating and mapping crop water status in cotton with thermal imaging. *Precision Agriculture*, 11(1): 27-41. <https://doi.org/10.1007/s11119-009-9111-7>
- Ali E., Cramer W., Carnicer J., Georgopoulou E., Hilmi N.J.M., Le Cozannet G., Lionello P. (2022). Cross-Chapter Paper 4: Mediterranean Region. In: *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 2233–2272. <https://doi.org/10.1017/9781009325844.021>
- Allen, R.G.; Pereira, L.S.; Raes, D.; Smith, M. *Crop Evapotranspiration Guidelines for Computing Crop Water Requirements—FAO Irrigation and Drainage Paper 56*, 1st ed.; FAO: Rome, Italy, 1998; Available online: <http://www.fao.org/3/X0490E/X0490E00.htm> (accessed on 4 May 2023).
- Antolín M.C., Ayari M., Sánchez-Díaz M. (2006). Effects of partial rootzone drying on yield, ripening and berry ABA in potted Tempranillo grapevines with split roots. *Australian Journal of Grape and Wine Research*, 12: 13-20. <https://doi.org/10.1111/j.1755-0238.2006.tb00039.x>
- Asgari A. (2023). Potential application of spectral indices for olive water status assessment in (semi-)arid regions: a case study in Khuzestan province, Iran. *Plant Direct*, 7(6). <https://doi.org/10.1002/pld3.494>

- Asgharinia S., Leberecht M., Marchesini L., Friess N., Gianelle D., Nauss T., Opgenoorth L., Yates J., Valentini P. (2022). Towards continuous stem water content and sap flux density monitoring: IoT-based solution for detecting changes in stem water dynamics. *Forests*, 13(7): 1040. <https://doi.org/10.3390/f13071040>
- Avisar R. (1993). Observations of leaf stomatal conductance at the canopy scale: An atmospheric modeling perspective. *Bound.-Lay. Meteorol.*, 64: 127–148. <https://doi.org/10.1007/BF00705665>
- Baeza P., Junquera P., Peiro E., Ramón Lissarrague J., Uriarte, D., & Vilanova, M. (2019). Effects of Vine Water Status on Yield Components, Vegetative Response and Must and Wine Composition. *IntechOpen*. <https://doi.org/10.5772/intechopen.87042>
- Baldocchi D. (2003). Assessing the eddy covariance technique for evaluating carbon dioxide exchange rates of ecosystems: past, present and future. *Global Change Biology*, 9 (4): 479–492. <https://doi.org/10.1046/j.1365-2486.2003.00629.x>
- Ballantyne D., Terblanche, N.S., Lecat B., Chapuis C. (2019). Old world and new world wine concepts of terroir and wine: perspectives of three renowned non-French wine makers. *Journal of Wine Research*, 30 (2): 122–143. <https://doi.org/10.1080/09571264.2019.1602031>
- Barham E. (2003). Translating terroir: the global challenge of French AOC labeling. *Journal of Rural Studies*, 19 (1): 127–138. [https://doi.org/10.1016/S0743-0167\(02\)00052-9](https://doi.org/10.1016/S0743-0167(02)00052-9)
- Barrio-Galán R., Bueno-Herrera M., Cuesta P., Pérez-Magariño S. (2020). Stepwise linear discriminant analysis to differentiate spanish red wines by their protected designation of origin or category using physico-chemical parameters. *Oeno One*, 54(1): 86–99. <https://doi.org/10.20870/oeno-one.2020.54.1.2588>
- Barrio-Galán R., Valle-Herrero H., Bueno-Herrera M., López-de-la-Cuesta P., Pérez-Magariño S. (2021). Volatile and non-volatile characterization of white and rosé wines from different spanish protected designations of origin. *Beverages*, 7(3): 49. <https://doi.org/10.3390/beverages7030049>
- Bchir A., Escalona J., Gallé A., Hernández-Montes E., Tortosa I., Braham M., Medrano H. (2016). Carbon isotope discrimination ($\delta^{13}C$) as an indicator of vine water status and water use efficiency (WUE): looking for the most representative sample and sampling time. *Agricultural Water Management*, 167: 11–20. <https://doi.org/10.1016/j.agwat.2015.12.018>
- Belfiore N., Vinti R., Lovat L., Chitarra W., Tomasi D., Bei R., Meggio F., Gaiotti F. (2019). Infrared thermography to estimate vine water status: optimizing canopy measurements and thermal indices for the varieties merlot and moscato in northern Italy. *Agronomy*, 9(12): 821. <https://doi.org/10.3390/agronomy9120821>
- Belletti G., Marescotti A., Touzard J. (2017). Geographical indications, public goods, and sustainable development: the roles of actors' strategies and public policies. *World Development*, 98: 45–57. <https://doi.org/10.1016/j.worlddev.2015.05.004>
- Bentley, J.H. (1999). Sea and Ocean Basins as Frameworks for Historical Analysis. *Geographical Review*. 89 (2): 215–219. <https://doi.org/10.1111/j.1931-0846.1999.tb00214.x>
- Benyahia F., Campos F., Abdelkader A., Basile B., Tagliavini M., Andreotti C., Zanotelli D. (2023). Assessing grapevine water status by integrating vine transpiration, leaf gas exchanges, chlorophyll fluorescence and sap flow measurements. *Agronomy*, 13(2), 464. <https://doi.org/10.3390/agronomy13020464>

- Berg H., Boulton R., Webb A. (1980). A century of wine and grape research. *Hilgardia* 34 (7): 4-5. <https://doi.org/10.3733/ca.v034n07p4>
- Blaya-Ros P., Blanco V., Miguel R., Vallés F., Torres-Sánchez R. (2020). Feasibility of low-cost thermal imaging for monitoring water stress in young and mature sweet cherry trees. *Applied Sciences*, 10(16): 5461. <https://doi.org/10.3390/app10165461>
- Bouby L., Figueiral I., Bouchette A., Rovira N., Ivorra S., Lacombe T., Pastor T., Picq S., Marinval P., Terral J.-F. (2013). Bioarchaeological Insights into the Process of Domestication of Grapevine (*Vitis vinifera* L.) during Roman Times in Southern France. *PLoS ONE*, 8 (5): e63195. <https://doi.org/10.1371/journal.pone.0063195>
- Boulet G., Delogu E., Saadi S., Chebbi W., Olioso A., Mougenot B., Fanise P., Lili-Chabaane Z., Lagouarde J. (2018). Evapotranspiration and evaporation/transpiration partitioning with dual source energy balance models in agricultural lands. *Proceedings of the International Association of Hydrological Sciences*, 380: 17-22. <https://doi.org/10.5194/piahs-380-17-2018>
- Bramley R., Ouzman J. (2021). Underpinning terroir with data: on what grounds might subregionalisation of the barossa zone geographical indication be justified? *Australian Journal of Grape and Wine Research*, 28(2): 196-207. <https://doi.org/10.1111/ajgw.12513>
- Brenner A.J., Incoll L.D. (1997). The effect of clumping and stomatal response on evaporation from sparsely vegetated shrublands. *Agric. For. Meteorol.*, 84: 187–205. [https://doi.org/10.1016/S0168-1923\(96\)02368-4](https://doi.org/10.1016/S0168-1923(96)02368-4)
- Brillante L., Mathieu O., Lévêque J., van Leeuwen C., Bois B. (2017). Water status and must composition in grapevine cv. Chardonnay with different soils and topography and a mini meta-analysis of the $\delta^{13}\text{C}$ /water potentials correlation. *Journal of the Science of Food and Agriculture*, 98 (2): 691-697. <https://doi.org/10.1002/jsfa.8516>
- Brodersen C., McElrone A., Choat B., Lee E., Shackel K., Matthews M. (2013). In vivo visualizations of drought-induced embolism spread in *Vitis vinifera*. *Plant Physiology*, 161(4): 1820-1829. <https://doi.org/10.1104/pp.112.212712>
- Brodersen C., McElrone A., Choat B., Matthews M., Shackel K. (2010). The dynamics of embolism repair in xylem: in vivo visualizations using high-resolution computed tomography. *Plant Physiology*, 154(3): 1088-1095. <https://doi.org/10.1104/pp.110.162396>
- Brough D.W., Jones H.G., Grace J. (1986). Diurnal changes in water content of the stems of apple trees, as influenced by irrigation. *Plant Cell Environ.*, 9: 1–7. <https://doi.org/10.1111/j.1365-3040.1986.tb01716.x>
- Buckley T.N. (2005). The control of stomata by water balance. *New Phytol.*, 168: 275-292. <https://doi.org/10.1111/j.1469-8137.2005.01543.x>
- Buckley T.N., Mott K.A. (2013). Modelling stomatal conductance in response to environmental factors. *Plant, Cell and Environment*, 36: 1691-1699. <https://doi.org/10.1111/pce.12140>
- Bunce J. (2022). Unexpected responses of bean leaf size to elevated CO₂. *Plants*, 11(7): 908. <https://doi.org/10.3390/plants11070908>
- Cai W., Qi Q. (2017). Study on electrophysiological signal monitoring of plant under stress based on integrated Op-Amps and patch electrode. *Journal of Electrical and Computer Engineering*, 2017: 1-7. <https://doi.org/10.1155/2017/4182546>

- Campbell G., Guibert N. (2007). Introduction: The History and Culture of Wine. In: Campbell, G., Guibert, N. (eds). *Wine, Society, and Globalization*. Palgrave Macmillan, New York. https://doi.org/10.1057/9780230609907_1
- Campos I., Neale C.M.U., Calera A., Balbontina C., González-Piqueras J. (2010). Assessing satellite-based basal crop coefficients for irrigated grapes (*Vitis vinifera* L.). *Agr. Water Manag.*, 98: 45–54. <https://doi.org/10.1016/j.agwat.2010.07.011>
- Candiago S., Tscholl S., Bassani L., Fraga H., Vigl L. (2022). A geospatial inventory of regulatory information for wine protected designations of origin in europe. *Scientific Data*, 9 (1): 394. <https://doi.org/10.1038/s41597-022-01513-0>
- Carbonneau A. (1998). Irrigation, vignoble et produit de la vigne. Aspects qualitatifs. In: Tec et Doc Lavoisier (ed.), *Traité d'irrigation*, pp. 258–276. Tiercelin JR.
- Carter G. (1991). Primary and secondary effects of water content on the spectral reflectance of leaves. *American Journal of Botany*, 78(7): 916-924. <https://doi.org/10.1002/j.1537-2197.1991.tb14495.x>
- Carter G. (1993). Responses of leaf spectral reflectance to plant stress. *American Journal of Botany*, 80(3): 239. <https://doi.org/10.2307/2445346>
- Čermák J., Kučera J., Baurerle W.L., Phillip N., Hinckley M. (2007). Tree water storage and its diurnal dynamics related to sap flow and changes in stem volume in old-growth Douglas-fir trees. *Tree Physiol.*, 27: 181–198. <https://doi.org/10.1093/treephys/27.2.181>
- Čermák J., Kučera J., Nadezhdina N. (2004). Sap flow measurements with some thermodynamic methods, flow integration within trees and scaling up from sample trees to entire forest stands. *Trees*, 18(5): 529-546. <https://doi.org/10.1007/s00468-004-0339-6>
- Čermák J., Nadezhdina N. (1998). Sapwood as the scaling parameter—Defining according to xylem water content or radial pattern of sap flow? *Ann. Sci. Forest.*, 55: 509–521. <https://doi.org/10.1051/forest:19980501>
- Chaerle L., Hagenbeek D., Bruyne E., Valcke R., Straeten D. (2004). Thermal and chlorophyll-fluorescence imaging distinguish plant-pathogen interactions at an early stage. *Plant and Cell Physiology*, 45(7): 887-896. <https://doi.org/10.1093/pcp/pch097>
- Chai Y., Chen C., Luo X., Zhan S., Kim J., Luo J., Wang X., Hu Z., Ying Y., Liu X. (2021). Cohabiting plant-wearable sensor in situ monitors water transport in plant. *Advanced Science*, 8(10). <https://doi.org/10.1002/advs.202003642>
- Charrier G., Torres-Ruiz J., Badel É., Burlett R., Choat B., Cochard H., Delmas C.E.L., Domec J.-C., Jansen S., King A., Lenoir N., Martin-StPaul N., Gambetta G.A., Delzon S. (2016). Evidence for hydraulic vulnerability segmentation and lack of xylem refilling under tension. *Plant Physiology*, 172(3): 1657-1668. <https://doi.org/10.1104/pp.16.01079>
- Chaves M.M., Costa J.M., Zarrouk O., Pinheiro C., Lopes C.M., Pereira J.S. (2016). Controlling stomatal aperture in semi-arid regions - The dilemma of saving water or being cool? *Plant Science*, 251: 54-64. <https://doi.org/10.1016/j.plantsci.2016.06.015>
- Chaves M.M., Oliveira M.M. (2004). Mechanisms underlying plant resilience to water deficits: prospects for water-saving agriculture. *Journal of Experimental Botany*, 55 (407): 2365–2384. <https://doi.org/10.1093/jxb/erh269>
- Chaves M.M., Pereira J.S., Maroco J., Rodrigues M.L., Ricardo C.P.P., Osório M.L., Carvalho I., Faria T., Pinheiro C. (2002). How plants cope with water stress in the field. Photosynthesis and growth. *Ann. Bot.*, 89 (7): 907–916. <https://doi.org/10.1093/aob/mcf105>

- Chaves M.M., Santos T.P., Souza C.R., Ortuño M.F., Rodrigues M.L., Lopes C.M., Maroco J.P., Pereira J.S. (2007). Deficit irrigation in grapevine improves water-use efficiency while controlling vigour and production quality. *Annals of Applied Biology*, 150: 237-252. <https://doi.org/10.1111/j.1744-7348.2006.00123.x>
- Chaves M.M., Zarrouk O., Francisco R., Costa J.M., Santos T., Regalado A.P., Rodrigues M.L., Lopes, C.M. (2010). Grapevine under deficit irrigation: hints from physiological and molecular data. *Annals of Botany*, 105 (5): 661-676. <https://doi.org/10.1093/aob/mcq030>
- Cherif S., Doblas-Miranda E., Lionello P.; Borrego C.; Giorgi C., Iglesias A., Jebari S., Mahmoudi E., Moriondo M., Pringault O., Rilov G., Somot S., Tsikliras A., Vilà M., Zittis G. (2020). Drivers of change. In: Climate and Environmental Change in the Mediterranean Basin – Current Situation and Risks for the Future. First Mediterranean Assessment Report [Cramer, W., J. Guiot and K. Marini (eds.)]. Union for the Mediterranean, Plan Bleu, UNEP/MAP, Marseille, France, pp. 59–180. <https://doi.org/10.5281/zenodo.7100601>
- Choat B., Drayton W., Brodersen C., Matthews M., Shackel K., Wada H., McElrone A. (2010). Measurement of vulnerability to water stress-induced cavitation in grapevine: a comparison of four techniques applied to a long-vesseled species. *Plant Cell & Environment*, 33(9): 1502-1512. <https://doi.org/10.1111/j.1365-3040.2010.02160.x>
- Choné X., Van Leeuwen C., Dubourdieu D., Gaudillère J.P. (2001). Stem Water Potential is a Sensitive Indicator of Grapevine Water Status, *Annals of Botany*, 87 (4): 477-483. <https://doi.org/10.1006/anbo.2000.1361>
- Cifre J., Bota J., Escalona J.M., Medrano H., Flexas J. (2005). Physiological tools for irrigation scheduling in grapevine (*Vitis vinifera* L.). An open gate to improve water-use efficiency? *Agric. Ecosyst. Environ.*, 106: 159–170. <https://doi.org/10.1016/j.agee.2004.10.005>
- Claro A.M., Fonseca A., Fraga H., Santos J.A. (2024). Future Agricultural Water Availability in Mediterranean Countries under Climate Change: A Systematic Review. *Water*, 16 (17): 2484 <https://doi.org/10.3390/w16172484>
- Clearwater M., Luo Z., Mazzeo M., Dichio B. (2009). An external heat pulse method for measurement of sap flow through fruit pedicels, leaf petioles and other small-diameter stems. *Plant Cell & Environment*, 32(12), 1652-1663. <https://doi.org/10.1111/j.1365-3040.2009.02026.x>
- Clevers J., Kooistra L., Schaepman M. (2010). Estimating canopy water content using hyperspectral remote sensing data. *International Journal of Applied Earth Observation and Geoinformation*, 12(2): 119-125. <https://doi.org/10.1016/j.jag.2010.01.007>
- Cochard H. (2002). A technique for measuring xylem hydraulic conductance under high negative pressures. *Plant Cell & Environment*, 25(6): 815-819. <https://doi.org/10.1046/j.1365-3040.2002.00863.x>
- Comstock J.P. (2002). Hydraulic and chemical signalling in the control of stomatal conductance and transpiration, *Journal of Experimental Botany*, 53 (367): 195–200. <https://doi.org/10.1093/jexbot/53.367.195>
- Conti L., Melo G., Ceretta C., Tarouco C., Marques A., Nicoloso F., Tassinari A., Tiecher T.L., Cesco S., Mimmo T., Brunetto G. (2018). Photosynthesis and growth of young grapevines intercropped with native grasses in soils contaminated with copper. *Acta Horticulturae*, 1217: 179-184. <https://doi.org/10.17660/actahortic.2018.1217.23>

- Cooper R., Thomas M., McLetchie D. (2022). Impedance measures for detecting electrical responses during acute injury and exposure of compounds to roots of plants. *Methods and Protocols*, 5(4): 56. <https://doi.org/10.3390/mps5040056>
- Costa J.M., Egipto R., Sánchez-Virosta A., Lopes C.M., Chaves M.M. (2019). Canopy and soil thermal patterns to support water and heat stress management in vineyards. *Agr. Water Manag.*, 216: 484-496. <https://doi.org/10.1016/j.agwat.2018.06.001>
- Costa J.M., Egipto R., Silvestre J., Lopes C.M., Chaves, M.M. (2018). Water and heat fluxes in Mediterranean vineyards: indicators and relevance for management. In: I.F. Garcia-Tejero and V.H. Durán-Zuazo (eds.). *Water Scarcity and Sustainable Agriculture in Semiarid Environment. Tools, Strategies, and Challenges for Woody Crops*. Academic Press, p. 219-245. <https://doi.org/10.1016/B978-0-12-813164-0.00010-7>
- Costa J.M., Grant O., Chaves M.M. (2013). Thermography to explore plant–environment interactions. *Journal of Experimental Botany*, 64 (13): 3937-3949. <https://doi.org/10.1093/jxb/ert029>
- Costa J.M., Ortuño M.F., Chaves M.M. (2007) Deficit irrigation as strategy to save water: physiology and potential application to horticulture. *J Integr Plant Biol*, 49:1421–1434. <https://doi.org/10.1111/j.1672-9072.2007.00556.x>
- Costa J.M., Vaz M., Escalona J.M., Egipto R., Lopes C.M., Medrano H., Chaves M.M. (2016). Modern viticulture in Southern Europe: Vulnerabilities and strategies for adaptation to water scarcity. *Agr. Water Manage.*, 164: 5–18. <https://doi.org/10.1016/j.agwat.2015.08.021>
- Cox P.M., Huntingford C., Harding R.J. (1998). A canopy conductance and photosynthesis model for use in a GCM land surface scheme. *Journal of Hydrology*, 212–213: 79-94. [https://doi.org/10.1016/S0022-1694\(98\)00203-0](https://doi.org/10.1016/S0022-1694(98)00203-0)
- Dallman P. (1998). *Plant Life in the World's Mediterranean Climates: California, Chile, South Africa, Australia, and the Mediterranean Basin*. University of California Press, California, USA. 257 p. <https://doi.org/10.5860/choice.36-3322>
- Damour G., Simonneau T., Cochard H., Urban L. (2010). An overview of models of stomatal conductance at the leaf level. *Plant Cell Environ.*, 33: 1419–1438. <https://doi.org/10.1111/j.1365-3040.2010.02181.x>
- Davies W.J., Wilkinson S., Loveys B. (2002) Stomatal control by chemical signalling and the exploitation of this mechanism to increase water use efficiency in agriculture. *New Phytologist*, 153 (3): 449–460. <https://doi.org/10.1046/j.0028-646X.2001.00345.x>
- Davies W.J., Zhang J. (1991). Root signals and the regulation of growth and development of plants in drying soil. *Annu. Rev. Plant Physiol. Plant Mol. Biol.*, 42: 55-76. <https://doi.org/10.1146/annurev.pp.42.060191.000415>
- De Bei R., Cozzolino D., Sullivan W., Cynkar W., Fuentes S., Dambergers R., Pech J., Tyerman S. (2010). Non-destructive measurement of grapevine water potential using near infrared spectroscopy. *Australian Journal of Grape and Wine Research*, 17(1): 62-71. <https://doi.org/10.1111/j.1755-0238.2010.00117.x>
- Degu A., Hochberg U., Wong D., Alberti G., Lazarovitch N., Peterlunger E., Castellarin S.D., Herrera J.C., Fait A. (2019). Swift metabolite changes and leaf shedding are milestones in the acclimation process of grapevine under prolonged water stress. *BMC Plant Biology*, 19(1): 69. <https://doi.org/10.1186/s12870-019-1652-y>
- Delmastro M. (2005). An investigation into the quality of wine: Evidence from piedmont. *Journal of Wine Research*, 16(1): 1–17. <https://doi.org/10.1080/09571260500236799>

- Deloire A., Carbonneau A., Wang Z., Ojeda H. (2004). Vine and water: a short review. *OENO One*, 38 (1): 1–13. <https://doi.org/10.20870/oeno-one.2004.38.1.932>
- Deloire A., Pellegrino A., Rogiers S. (2020). A few words on grapevine leaf water potential. IVES Technical Reviews, June 2020. <https://doi.org/10.20870/IVES-TR.2020.3620>
- Deng Y., Yu K., Yao X., Xie Q., YiTa H., Liu J. (2019). Estimation of *Pinus massoniana* leaf area using terrestrial laser scanning. *Forests*, 10(8): 660. <https://doi.org/10.3390/f10080660>
- DGADR (2025). Portuguese traditional products. Agricultural products, foodstuffs and prepared dishes. Available online: Wines PDO. <https://tradicional.dgadr.gov.pt/en/quality-products/pdo-protected-designation-of-origin-wine> (accessed on 8 January 2025)
- Disinis L., Bernardo S., Yang C., Fraga H., Malheiro A.C., Moutinho-Pereira J., Santos J.A. (2022). Mediterranean viticulture in the context of climate change. *Ciência Téc. Vitiv.*, 37 (2): 139-158. <https://doi.org/10.1051/ctv/ctv20223702139>
- Ding R., Kang S., Du T., Hao X., Zhang Y. (2014). Scaling up stomatal conductance from leaf to canopy using a dual-leaf model for estimating crop evapotranspiration. *PloS One*, 9 (4): e95584. <https://doi.org/10.1371/journal.pone.0095584>
- Ding Y., Nie Y., Chen H., Wang K., Querejeta J.I. (2021). Water uptake depth is coordinated with leaf water potential, water-use efficiency and drought vulnerability in karst vegetation. *New Phytologist*, 229 (3): 1339-1353. <https://doi.org/10.1111/nph.16971>
- Dodd E. (2022) The archaeology of wine production in Roman and pre-Roman Italy. *American Journal of Archaeology*, 126 (3): 443-480. <https://doi.org/10.1086/719697>
- Dong, Y. et al. (2023). Dual domestications and origin of traits in grapevine evolution. *Science*, 379: 892–901. <https://doi.org/10.1126/science.add8655>
- Dou X., Yang Y. (2018). Evapotranspiration estimation using four different machine learning approaches in different terrestrial ecosystems. *Comput. Electron. Agr.*, 148: 95–106. <https://doi.org/10.1016/j.compag.2018.03.010>
- Dry P.R., Loveys B.R. (1999). Grapevine shoot growth and stomatal conductance are reduced when part of the root system is dried. *Vitis*, 38 (4): 151-156. <https://doi.org/10.5073/vitis.1999.38.151-156>
- Dry P.R., Stoll M., McCarthy M.G., Loveys B.R. (1999). Using plant physiology to improve the water use efficiency of horticultural crops. In III International Symposium on Irrigation of Horticultural Crops 537: 187-197.
- Du J., Dai X., Huo Z., Wang X., Wang S., Wang C., Zhang C., Huang G. (2023). Stand transpiration and canopy conductance dynamics of *Populus popularis* under varying water availability in an arid area. *Sci Total Environ.*, 892: 164397. <https://doi.org/10.1016/j.scitotenv.2023.164397>
- Dupuis J., Holst C., Kuhlmann H. (2017). Measuring leaf thickness with 3d close-up laser scanners: possible or not? *Journal of Imaging*, 3(2): 22. <https://doi.org/10.3390/jimaging3020022>
- Dzikiti S., Verreyne S., Strever A., Stuckens J., Verstraeten W., Swennen R., Coppin P. (2009). Detecting citrus tree water status by integrating hyperspectral remote sensing and physiological data in a water flow-storage model. *Proceedings of the 2009 IEEE International Geoscience and Remote Sensing Symposium*, 12-17 July 2009, Cape Town, South Africa. pp. V-348-V-350. <https://doi.org/10.1109/igarss.2009.5417659>

- EC – European Commission (2023). Geographical indications and quality schemes explained. Available online: https://agriculture.ec.europa.eu/farming/geographical-indications-and-quality-schemes/geographical-indications-and-quality-schemes-explained_en#documents (accessed on 15 January 2025).
- EC – European Commission (2020). Geographical Indications – a European treasure worth €75 billion. Press Release, April 20, 2020. Available online: https://ec.europa.eu/commission/presscorner/detail/en/ip_20_683 (accessed on 15 January 2025).
- EC – European Commission (2024). Monitoring EU agri-food trade. European Commission (EC), DG Agriculture and Rural Development, Brussels. Available online: https://agriculture.ec.europa.eu/document/download/b2e5ee02-4a25-4a6b-9663-92dbec9eb211_en?filename=monitoring-agri-food-trade_dec2023_en.pdf (accessed on 29 October 2024)
- EEA – European Environment Agency (2024). Europe's state of water 2024: the need for improved water resilience. European Environment Agency (EEA) Report No 07/2024. Publications Office of the European Union. Available online: <https://doi.org/10.2800/02236> (accessed on 30 October 2024)
- EEA – European Environment Agency (2021). Water resources across Europe — confronting water stress: an updated assessment. European Environment Agency (EEA) Report No 12/2021. Publications Office of the European Union. Available online: <https://data.europa.eu/doi/10.2800/320975> (accessed on 31 October 2024)
- EEA – European Environment Agency (2012). Water resources in Europe in the context of vulnerability. EEA 2012 state of water assessment. Publications Office, 2012. Available online: <https://data.europa.eu/doi/10.2800/65298> (accessed on 15 October 2020)
- Egipto R., Costa J.M.; Silvestre J., Lopes C.M. (2023). Using the fraction of transpirable soil water to estimate grapevine leaf water potential: Comparing the classical statistical regression approach to machine learning algorithms. 22nd GIESCO International Meeting, Cornell University, Ithaca, USA, 2023. *IVES Conference Series*, GIESCO 2023.
- Egipto R.J.L., Aquino A., Andújar J.M. (2024). Predicting the canopy conductance to water vapor of grapevines using a biophysical model in a hot and arid climate. *Front. Plant Sci.* 15:1334215. <https://doi.org/10.3389/fpls.2024.1334215>
- El-Hendawy S., Al-Suhaibani N., Hassan W., Tahir M., Schmidhalter U. (2017). Hyperspectral reflectance sensing to assess the growth and photosynthetic properties of wheat cultivars exposed to different irrigation rates in an irrigated arid region. *Plos One*, 12(8): e0183262. <https://doi.org/10.1371/journal.pone.0183262>
- Elsayed S., El-Hendawy S., Khadr M., Elsherbiny O., Al-Suhaibani N., Alotaibi M., Tahir M.U., Darwish W. (2021). Combining thermal and RGB imaging indices with multivariate and data-driven modeling to estimate the growth, water status, and yield of potato under different drip irrigation regimes. *Remote Sensing*, 13(9): 1679. <https://doi.org/10.3390/rs13091679>
- Espinoza C., Khot L., Sankaran S., Jacoby P. (2017). High resolution multispectral and thermal remote sensing-based water stress assessment in subsurface irrigated grapevines. *Remote Sensing*, 9(9): 961. <https://doi.org/10.3390/rs9090961>
- Estreicher S.K. (2017). The beginning of wine and viticulture. *Physica Status Solidi (C) Current Topics in Solid State Physics*, 14 (7) <https://doi.org/10.1002/pssc.201700008>
- Estreicher S.K. (2019). Wine. The Encyclopedia of Ancient History. Edited. <https://doi.org/10.1002/9781444338386.wbeah25009.pub2>

- FAO. (2023). The Impact of Disasters on Agriculture and Food Security: Avoiding and reducing losses through investment in resilience. FAO, Rome, Italy, 2023; ISBN 978-92-5-138194-6.
- Farquhar G.D., Richards R.A. (1984). Isotopic composition of plant carbon correlates with water-use efficiency of wheat genotypes. *Aust. J. Plant Physiol.* 11: 539–552. <https://doi.org/10.1071/PP9840539>
- Fereres E., Soriano M.A. (2007). Deficit irrigation for reducing agricultural water use. *Journal of Experimental Botany*, 58 (2): 147–159. <https://doi.org/10.1093/jxb/erl165>
- Fernández J.E. (2014). Plant-based sensing to monitor water stress: Applicability to commercial orchards. *Agric. Water Manag.*, 142, 99–109. <https://doi.org/10.1016/j.agwat.2014.04.017>
- Fernández J.E. (2017). Plant-Based Methods for Irrigation Scheduling of Woody Crops. *Horticulturae*, 3(2): 35 <https://doi.org/10.3390/horticulturae3020035>
- Fernández-Navales J., Sáiz-Rubio V., Barrio I., Rovira-Más F., Cuenca-Cuenca A., Alves F., Valente J., Tardaguila J., Diago M. (2021). Monitoring and mapping vineyard water status using non-invasive technologies by a ground robot. *Remote Sensing*, 13(14): 2830. <https://doi.org/10.3390/rs13142830>
- Ferreira, M.I. (2017). Stress Coefficients for Soil Water Balance Combined with Water Stress Indicators for Irrigation Scheduling of Woody Crops. *Horticulturae*, 3: 38. <https://doi.org/10.3390/horticulturae3020038>
- Flexas J., Barón M., Bota J., Ducruet J.-M., Gallé A., Galmés J., Jiménez M., Pou A., Ribas-Carbó M., Sajnani C., Tomàs M., Medrano H. (2009). Photosynthesis limitations during water stress acclimation and recovery in the drought-adapted *Vitis* hybrid Richter-110 (*V. berlandieri* × *V. rupestris*). *Journal of Experimental Botany*, 60 (8): 2361–2377. <https://doi.org/10.1093/jxb/erp069>
- Flo V., Martínez-Vilalta J., Mencuccini M., Granda V., Anderegg W.R.L., Poyatos R. (2021). Climate and functional traits jointly mediate tree water-use strategies. *New Phytologist*, 231 (2): 617–630. <https://doi.org/10.1111/nph.17404>
- Förster M. (2017). How reliable are heat pulse velocity methods for estimating tree transpiration? *Forests*, 8(9), 350. <https://doi.org/10.3390/f8090350>
- Forster M.A., Kim T.D.H., Kunz S., Abuseif M., Chulliparambil V.R., Srichandra J., Michael R.N. (2022). Phenology and canopy conductance limit the accuracy of 20 evapotranspiration models in predicting transpiration. *Agr. For. Meteorol.*, 315: 108824. <https://doi.org/10.1016/j.agrformet.2022.108824>
- Fourcade M. (2012). The Vile and the Noble: On the Relation between Natural and Social Classifications in the French Wine World. *Sociological Quarterly*, 53 (4): 524 - 545. <https://doi.org/10.1111/j.1533-8525.2012.01248.x>
- Fraga H., García de Cortázar Atauri I., Malheiro A.C., Santos J.A. (2016). Modelling climate change impacts on viticultural yield, phenology and stress conditions in Europe. *Global Change Biol*, 22: 3774–3788. <https://doi.org/10.1111/gcb.13382>
- Fraiture C., Wichelns, D. (2010). Satisfying Future Water Demands for Agriculture. *Agric. Water Manag.*, 97: 502–511. <https://doi.org/10.1016/j.agwat.2009.08.008>
- Franks P.J., Farquhar G.D. (2007). The mechanical diversity of stomata and its significance in gas-exchange control. *Plant Physiol.*, 143 (1): 78–87. <https://doi.org/10.1104/pp.106.089367>

- Fromm J., Eschrich, W. (1993). Electric signals released from roots of willow (*Salix viminalis* L.) change transpiration and photosynthesis. *J. Plant Physiol.*, 141: 673–680. [https://doi.org/10.1016/S0176-1617\(11\)81573-7](https://doi.org/10.1016/S0176-1617(11)81573-7)
- Fuentes S., De Bei R., Pech J., Tyerman S. (2012). Computational water stress indices obtained from thermal image analysis of grapevine canopies. *Irrig. Sci.*, 30: 523–536. <https://doi.org/10.1007/s00271-012-0375-8>
- Gago J., Douthe C., Coopman R., Gallego P., Ribas-Carbó M., Flexas J., Escalona J., Medrano H. (2015). UAVs challenge to assess water stress for sustainable agriculture. *Agricultural Water Management*, 153: 9-19. <https://doi.org/10.1016/j.agwat.2015.01.020>
- Gaiotti F. (2023). Comparative effects of drought stress on leaf gas exchange, foliar aba and leaf orientation in four grapevine cultivars grown in northern Italy. *Physiologia Plantarum*, 175(6). <https://doi.org/10.1111/ppl.14063>
- Gambetta G.A., Kurtural S.K. (2021). Global warming and wine quality: are we close to the tipping point? *OENO One*, 3: 353-361. <https://doi.org/10.20870/oeno-one.2021.55.3.4774>
- Gao C., Zhao Y., Zhao Y. (2019). A novel sensor for noninvasive detection of in situ stem water content based on standing wave ratio. *Journal of Sensors*, 2019, 1-10. <https://doi.org/10.1155/2019/3594964>
- García-García J., Martínez-Cutillas A., Romero P. (2012). Financial analysis of wine grape production using regulated deficit irrigation and partial root zone drying strategies. *Irrig. Sci.*, 30: 179–188. <http://dx.doi.org/10.1007/s00271-011-0274-4>
- García-Tejera O., López-Bernal A., Orgaz F., Testi L., Villalobos F.J. (2021). The pitfalls of water potential for irrigation scheduling. *Agric. Water Manag.*, 243: 106522. <https://doi.org/10.1016/j.agwat.2020.106522>
- García-Tejero I.F., Costa J.M., Egipto R., Durán-Zuazo V.H., Lima R.S.N., Lopes C.M., Chaves M.M. (2016). Thermal data to monitor crop-water status in irrigated Mediterranean viticulture. *Agric. Water Manag.*, 176: 80-90. <https://doi.org/10.1016/j.agwat.2016.05.008>
- Gaudin R., Roux S., Tisseyre B. (2017). Linking the transpirable soil water content of a vineyard to predawn leaf water potential measurements, *Agric. Water Manag.*, 182: 13-23. <https://doi.org/10.1016/j.agwat.2016.12.006>
- Gaudillère J., van Leeuwen C., Ollat N. (2002). Carbon isotope composition of sugars in grapevine, an integrated indicator of vineyard water status. *Journal of Experimental Botany*, 53(369): 757-763. <https://doi.org/10.1093/jexbot/53.369.757>
- Giacomarra M., Galati A., Crescimanno M., Vrontis D. (2020). Geographical cues: evidences from new and old world countries' wine consumers. *British Food Journal*, 122(4): 1252-1267. <https://doi.org/10.1108/bfj-08-2019-0580>
- Giffard B., Winter S., Guidoni S., Nicolai A., Castaldini M., Cluzeau D., Coll P., Cortet J., Le Cadre E., d'Errico G., Forneck A., Gagnarli E., Griesser M., Guernion M., Lagomarsino A., Landi S., Bissonnais Y., Mania E., Mocali S., Preda C., Priori S., Reineke A., Rusch A., Schroers H.-J., Simoni S., Steiner M., Temneanu E., Bacher S., Costantini Edoardo A.C., Zaller J., Leyer Ilona L. (2022). Vineyard Management and Its Impacts on Soil Biodiversity, Functions, and Ecosystem Services. *Frontiers in Ecology and Evolution*, 10: 850272. <https://doi.org/10.3389/fevo.2022.850272>

- Gil P., Gurovich L., Schaffer B., Garcia N., Iturriaga R. (2009). Electrical signaling, stomata conductance, ABA and ethylene content in avocado trees in response to root hypoxia. *Plant Signal Behav.*, 4: 100-108. <https://doi.org/10.4161/psb.6786>
- Girona J., Mata M., del Campo J., Arbonés A., Bartra E., Marsal J. (2006). The use of midday leaf water potential for scheduling deficit irrigation in vineyards. *Irrig Sci*, 24: 115–127. <https://doi.org/10.1007/s00271-005-0015-7>
- Goldsmith (2013). Changing directions: the atmosphere–plant–soil continuum. *New Phytologist*, 199 (1): 4-6. <https://doi.org/10.1111/nph.12332>
- Goldstein G., Andrade J., Meinzer F., Holbrook N., Cavelier J., Jackson P., Celis A. (1998). Stem water storage and diurnal patterns of water use in tropical forest canopy trees. *Plant Cell & Environment*, 21(4): 397-406. <https://doi.org/10.1046/j.1365-3040.1998.00273.x>
- Gómez-Alonso S., García-Romero E. (2009). Effect of irrigation and variety on oxygen ($\delta^{18}\text{O}$) and carbon ($\delta^{13}\text{C}$) stable isotope composition of grapes cultivated in a warm climate. *Australian Journal of Grape and Wine Research*, 16(2): 283-289. <https://doi.org/10.1111/j.1755-0238.2009.00089.x>
- Gomis-Bellmunt A., Claret A., Puig-Pujol A., Pérez-Elortondo F., Guerrero L. (2022). Development of a descriptive profile and references for the assessment of taste and mouthfeel descriptors of protected designation of origin wines. *Foods*, 11(19): 2970. <https://doi.org/10.3390/foods11192970>
- González-Nieto L., Huber A., Gao R., Biasuz E., Cheng L., Stroock A., Lakso A.N., Robinson T. (2023). Trunk water potential measured with microtensiometers for managing water stress in “gala” apple trees. *Plants*, 12(9): 1912. <https://doi.org/10.3390/plants12091912>
- Goodman S. (2009). An international comparison of retail consumer wine choice. *International Journal of Wine Business Research*, 21 (1): 41-49. <https://doi.org/10.1108/17511060910948026>
- Govender M., Dye P., Weiersbye I., Witkowski E., Ahmed F. (2009). Review of commonly used remote sensing and ground-based technologies to measure plant water stress. *Water SA*, 35(5). <https://doi.org/10.4314/wsa.v35i5.49201>
- Gowdy M., Julliard S., Frouin M., Poitou X., Destrac-Irvine A., Leeuwen C. (2022a). Carbon isotope discrimination as an indicator of vine water status is comparable in grape must, wine, and distilled wine spirits. *Frontiers in Food Science and Technology*, 2. <https://doi.org/10.3389/frfst.2022.936745>
- Gowdy M., Pieri P., Suter B., Marguerit E., Destrac-Irvine A., Gambetta G., van Leeuwen C. (2022b). Estimating Bulk Stomatal Conductance in Grapevine Canopies. *Front Plant Sci.*, 13: 839378. <https://doi.org/10.3389/fpls.2022.839378>
- Granata F. (2019). Evapotranspiration evaluation models based on machine learning algorithms—A comparative study. *Agr. Water Manag.*, 217: 303–315. <https://doi.org/10.1016/j.agwat.2019.03.015>
- Granier A. (1985). A new method of sap flow measurement in tree stems. *Annales des Sciences Forestières*, 42(2): 193-200.
- Granier A., Loustau D., Bréda N. (2000). A generic model of forest canopy conductance dependent on climate, soil water availability and leaf area index. *Annals of Forest Science*, 57 (8): 755-765. <https://doi.org/10.1051/forest:2000158>

- Grant O., Ochagavía H., Baluja J., Diago M., Tardáguila J. (2016). Thermal imaging to detect spatial and temporal variation in the water status of grapevine (*Vitis vinifera* L.). *The Journal of Horticultural Science and Biotechnology*, 91(1): 43-54. <https://doi.org/10.1080/14620316.2015.1110991>
- Grant O.M., Chaves M.M., Jones H.G. (2006). Optimizing thermal imaging as a technique for detecting stomatal closure induced by drought stress under greenhouse conditions. *Physiologia Plantarum*, 127 (3): 507-518. <https://doi.org/10.1111/j.1399-3054.2006.00686.x>
- Grant O., Tronina L., Jones H., Chaves M.M. (2007). Exploring thermal imaging variables for the detection of stress responses in grapevine under different irrigation regimes. *J. Exp. Bot.*, 58 (4): 815-825. <https://doi.org/10.1093/jxb/erl153>
- Groenveld T., Obiero C., Yu Y., Flury M., Keller M. (2023). Predawn leaf water potential of grapevines is not necessarily a good proxy for soil moisture. *BMC Plant Biol*, 23: 369. <https://doi.org/10.1186/s12870-023-04378-6>
- Guiot J., Bernigaud N., Bondeau A., Bouby L. (2021). The Mediterranean viticulture in response to global climate change drivers, the lesson of the past. EGU General Assembly 2021, online, 19–30 Apr 2021, EGU21-725. <https://doi.org/10.5194/EGUSPHERE-EGU21-725>
- Gurovich, L.; Hermosilla, P. (2009) Electric signaling in fruit trees in response to water applications and light–darkness conditions. *J. Plant Physiol.*, 166: 290–300. <https://doi.org/10.1016/j.jplph.2008.06.004>
- Gutiérrez S., Diago M., Fernández-Navales J., Tardáguila J. (2018). Vineyard water status assessment using on-the-go thermal imaging and machine learning. *Plos One*, 13(2): e0192037. <https://doi.org/10.1371/journal.pone.0192037>
- Gutiérrez S., Tardáguila J., Fernández-Navales J., Diago M. (2016). Data mining and NIR spectroscopy in viticulture: applications for plant phenotyping under field conditions. *Sensors*, 16(2): 236. <https://doi.org/10.3390/s16020236>
- Gutiérrez-Gamboa G., Wu Z., Toda F. (2021). Current viticultural techniques to mitigate the effects of global warming on grape and wine quality: a comprehensive review. *Food Research International*, 139: 109946. <https://doi.org/10.1016/j.foodres.2020.109946>
- Gutiérrez M., Reynolds M., Raun W., Stone M., Klatt A. (2010). Spectral water indices for assessing yield in elite bread wheat genotypes under well-irrigated, water-stressed, and high-temperature conditions. *Crop Science*, 50(1): 197-214. <https://doi.org/10.2135/cropsci2009.07.0381>
- Gutiérrez S., Tardáguila J., Fernández-Navales J., Diago M. (2016). Data mining and NIR spectroscopy in viticulture: applications for plant phenotyping under field conditions. *Sensors*, 16(2): 236. <https://doi.org/10.3390/s16020236>
- Hackl H., Baresel J., Mistele B., Hu Y., Schmidhalter U. (2012). A comparison of plant temperatures as measured by thermal imaging and infrared thermometry. *Journal of Agronomy and Crop Science*, 198(6): 415-429. <https://doi.org/10.1111/j.1439-037x.2012.00512.x>
- Hailemichael G., Catalina A., Rebollo M., Martín P. (2016). Relationships between water status, leaf chlorophyll content and photosynthetic performance in tempranillo vineyards. *South African Journal of Enology and Viticulture*, 37(2): 149-156. <https://doi.org/10.21548/37-2-1004>

- Halis Y., Djehichi S., Senoussi M. (2011). Vessel development and the importance of lateral flow in water transport within developing bundles of current-year shoots of grapevine (*Vitis vinifera* L.). *Trees*, 26(3): 705-714. <https://doi.org/10.1007/s00468-011-0637-8>
- Hammer B.A. (2011). Terroir and cultural identity. *DIVERSIPEDE: Journal of the University of Alberta Anthropology Student Associations*, 1 (1): 22-34. <https://doi.org/10.29173/COMP34>
- Harutyunyan M., Malfeito-Ferreira M. (2022). The Rise of Wine among Ancient Civilizations across the Mediterranean Basin. *Heritage*, 5: 788-812. <https://doi.org/10.3390/heritage5020043>
- Harvey M., White L., Frost W. (2014). Exploring wine and identity. In: Harvey M., White L., Frost W. (eds). *Wine and identity: branding, heritage, terroir*. Routledge, London. <https://doi.org/10.4324/9780203067604>
- Hernández-Montes E., Escalona J., Tomás M., Medrano H. (2017). Influence of water availability and grapevine phenological stage on the spatial variation in soil respiration. *Australian Journal of Grape and Wine Research*, 23(2): 273-279. <https://doi.org/10.1111/ajgw.12279>
- Hernández-Santana V., Martínez-Fernández J., Morán C. (2007). Estimation of tree water stress from stem and soil water monitoring with time-domain reflectometry in two small forested basins in Spain. *Hydrological Processes*, 22(14): 2493-2501. <https://doi.org/10.1002/hyp.6845>
- Hernández-Santana V., Martínez-Fernández J., Morán C., Cano A. (2008). Response of *Quercus pyrenaica* (melojo oak) to soil water deficit: a case study in Spain. *European Journal of Forest Research*, 127(5), 369-378. <https://doi.org/10.1007/s10342-008-0214-x>
- Herrera J., Calderan A., Gambetta G., Peterlunger E., Forneck A., Sivilotti P., Cochard H., Hochberg U. (2021). Stomatal responses in grapevine become increasingly more tolerant to low water potentials throughout the growing season. *The Plant Journal*, 109(4): 804-815. <https://doi.org/10.1111/tpj.15591>
- Hertig E., Trambly Y. (2017). Regional downscaling of Mediterranean droughts under past and future climatic conditions. *Glob. Planet. Change*, 151, 36-48. <https://doi.org/10.1016/j.gloplacha.2016.10.015>
- Hietz P., Rosner S., Sorz J., Mayr S. (2008). Comparaison de méthodes de quantification des pertes de conductivité hydraulique chez l'érable. *Annals of Forest Science*, 65(5): 502-502. <https://doi.org/10.1051/forest:2008023>
- Hochberg U., Albuquerque C., Rachmilevitch S., Cochard H., David-Schwartz R., Brodersen C., McElrone A., Windt C. (2016). Grapevine petioles are more sensitive to drought induced embolism than stems: evidence from *in vivo* MRI and microcomputed tomography observations of hydraulic vulnerability segmentation. *Plant Cell & Environment*, 39(9): 1886-1894. <https://doi.org/10.1111/pce.12688>
- Hochberg U., Bonel A., David-Schwartz R., Degu A., Fait A., Cochard H., Peterlunger E., Herrera J. (2017a). Grapevine acclimation to water deficit: the adjustment of stomatal and hydraulic conductance differs from petiole embolism vulnerability. *Planta*, 245(6), 1091-1104. <https://doi.org/10.1007/s00425-017-2662-3>
- Hochberg U., Degu A., Toubiana D., Gendler T., Nikoloski Z., Rachmilevitch S., Fait A. (2013). Metabolite profiling and network analysis reveal coordinated changes in grapevine water stress response. *BMC Plant Biology*, 13: 184. <https://doi.org/10.1186/1471-2229-13-184>

- Hochberg U., Rockwell F.E., Holbrook N.M., Cochard H. (2018). Iso/Anisohydry: A plant–environment interaction rather than a simple hydraulic trait, *Trends in Plant Science*, 23 (2): 112-120. <https://doi.org/10.1016/j.tplants.2017.11.002>
- Hochberg U., Windt C., Ponomarenko A., Zhang Y., Gersony J., Rockwell F., Holbrook N. (2017b). Stomatal closure, basal leaf embolism, and shedding protect the hydraulic integrity of grape stems. *Plant Physiology*, 174(2): 764-775. <https://doi.org/10.1104/pp.16.01816>
- Holbrook N., Sinclair T. (1992). Water balance in the arborescent palm, sabal palmetto. ii. transpiration and stem water storage. *Plant Cell & Environment*, 15(4), 401-409. <https://doi.org/10.1111/j.1365-3040.1992.tb00990.x>
- IAEA (2000). Comparison of soil water measurement using the neutron scattering, time domain reflectometry and capacitance methods. Results of a consultants meeting organized by the joint FAO/IAEA Division of Nuclear Techniques in Food and Agriculture, Vienna 23-25 November 1998. International Atomic Energy Agency, Vienna, Austria.
- INAO – Institut Nationale de l’Origine et de la Qualité (2019). Produits viticoles bénéficient d’une AOC. Services territoires et délimitation. Available online: <https://www.inao.gouv.fr/eng/content/download/442/3340/version/4/file/2019-12-%20carte%20des%20AOP%20vins.pdf> (accessed on 8 January 2025)
- INAO – Institut Nationale de l’Origine et de la Qualité (2017). IGP viticoles. Services territoires et délimitation. Available online: https://www.inao.gouv.fr/eng/content/download/445/3358/version/2/file/IGP_Vins_2017_10SansCalvados.pdf (accessed on 8 January 2025)
- Inglis D. (2015). On oenological authenticity: making wine real and making real wine. *M/C Journal*, 18(1). <https://doi.org/10.5204/mcj.948>
- Intrigliolo D.S., Castel J.R. (2007). Evaluation of grapevine water status from trunk diameter variations. *Irrig. Sci.*, 26: 49–59. <https://doi.org/10.1007/s00271-007-0071-2>
- IPCC (2023). Summary for Policymakers. In: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland, pp. 1-34. <https://doi.org/10.59327/IPCC/AR6-9789291691647.001>
- Iqbal N., Hussain S., Raza M., Yang C., Safdar M., Brestič M., Aziz A., Hayyat M.S., Asghar M.A., Wang X.C., Zhang J., Yang W., Liu J. (2019). Drought tolerance of soybean (*Glycine max* L. Merr.) by improved photosynthetic characteristics and an efficient antioxidant enzyme activities under a split-root system. *Frontiers in Physiology*, 10: 786. <https://doi.org/10.3389/fphys.2019.00786>
- Irmak S., Mutiibwa D., Irmak A., Arkebauer T.J., Weiss A., Martin D.L., Eisenhauer D.E. (2008). On the scaling up leaf stomatal resistance to canopy resistance using photosynthetic photon flux density. *Agric. For. Meteorol.*, 148: 1034–1044. <https://doi.org/10.1016/j.agrformet.2008.02.001>
- IVV (2025). Mapa das regiões vitivinícolas de Portugal. Available online: [https://www.ivv.gov.pt/np4/785/%7B\\$clientServletPath%7D/?newsId=10171&fileName=Regi_es_Vitvinicolas_09_12_2024.pdf](https://www.ivv.gov.pt/np4/785/%7B$clientServletPath%7D/?newsId=10171&fileName=Regi_es_Vitvinicolas_09_12_2024.pdf) (accessed on 8 January 2025)

- Jacobsen A., Pratt R. (2012). No evidence for an open vessel effect in centrifuge-based vulnerability curves of a long-vesselled liana (*Vitis vinifera*). *New Phytologist*, 194(4): 982-990. <https://doi.org/10.1111/j.1469-8137.2012.04118.x>
- Jackson R., Idso S., Reginato R., Pinter P. (1981). Canopy temperature as a crop water stress indicator. *Water Resources Research*, 17(4): 1133-1138. <https://doi.org/10.1029/wr017i004p01133>
- Jarvis P.G., McNaughton, K.G. (1986). Stomatal control of transpiration: scaling up from leaf to region. *Adv. Ecol. Res.*, 15: 1-49. [https://doi.org/10.1016/S0065-2504\(08\)60119-1](https://doi.org/10.1016/S0065-2504(08)60119-1)
- Jež-Krebelj A., Rupnik-Cigoj M., Stele M., Chersicola M., Pompe-Novak M., Sivilotti P. (2022). The physiological impact of GFLV virus infection on grapevine water status: first observations. *Plants*, 11(2): 161. <https://doi.org/10.3390/plants11020161>
- Jiao L.J., Ding R.S., Kang S.Z., Du T.S., Tong L., Li S.E. (2018). A comparison of energy partitioning and evapotranspiration over closed maize and sparse grapevine canopies in northwest China. *Agriculture Water Management*, 203: 251-260. <https://doi.org/10.1016/j.agwat.2018.03.019>
- Jiménez-Bello M., Ballester C., Castel J., Intrigliolo D. (2011). Development and validation of an automatic thermal imaging process for assessing plant water status. *Agricultural Water Management*, 98(10): 1497-1504. <https://doi.org/10.1016/j.agwat.2011.05.002>
- Jones H.G. (1999). Use of thermography for quantitative studies of spatial and temporal variation of stomatal conductance over leaf surfaces. *Plant Cell & Environment*, 22(9): 1043-1055. <https://doi.org/10.1046/j.1365-3040.1999.00468.x>
- Jones H.G. (2004a). Irrigation scheduling: advantages and pitfalls of plant-based methods. *Journal of Experimental Botany*, 55 (407): 2427-2436. <https://doi.org/10.1093/jxb/erh213>
- Jones H.G. (2004b). Application of Thermal Imaging and Infrared Sensing in Plant Physiology and Ecophysiology. *Advances in Botanical Research*, 41: 107-163. [https://doi.org/10.1016/S0065-2296\(04\)41003-9](https://doi.org/10.1016/S0065-2296(04)41003-9)
- Jones H.G. (2007). Monitoring plant and soil water status: established and novel methods revisited and their relevance to studies of drought tolerance. *Journal of Experimental Botany*, 58 (2): 119-130. <https://doi.org/10.1093/jxb/erl118>
- Jones H.G. (2014). *Plants and Microclimate: A Quantitative Approach to Environmental Plant Physiology*. 3rd Edition. Cambridge University Press. <https://doi.org/10.1017/CBO9780511845727>
- Jones H.G. (2018). Thermal Imaging and Infrared Sensing in Plant Ecophysiology. In: Sánchez-Moreiras A., Reigosa M. (eds) *Advances in Plant Ecophysiology Techniques*. Springer, Cham. https://doi.org/10.1007/978-3-319-93233-0_8
- Jones H.G., Leinonen I. (2003). Thermal Imaging for the Study of Plant Water Relations. *Journal of Agricultural Meteorology*, 59 (3): 205-217. <https://doi.org/10.2480/agrmet.59.205>
- Joy A., Charters S., Wang J.J., Grohmann B. (2020). A multi-sensory and embodied understanding of wine consumption. *Journal of Wine Research*, 31 (4): 247-264. <https://doi.org/10.1080/09571264.2020.1854700>

- Joy A., LaTour K., Charters S., Grohmann B., Peña-Moreno C. (2021). The artification of wine: lessons from the fine wines of Bordeaux and Burgundy. *Arts and the Market*, 11 (1): 24-39. <https://doi.org/10.1108/AAM-11-2020-0048>
- Keller M. (2010a). Managing grapevines to optimise fruit development in a challenging environment: a climate change primer for viticulturists. *Australian Journal of Grape and Wine Research*, 16: 56-69. <https://doi.org/10.1111/j.1755-0238.2009.00077.x>
- Keller M. (2010b). *The Science of Grapevines. Anatomy and Physiology*. Elsevier Inc.
- Knipfer T., Bambach N., Hernandez M., Bartlett M., Sinclair G., Duong F., Kluepfel D.A., McElrone A. (2020). Predicting stomatal closure and turgor loss in woody plants using predawn and midday water potential. *Plant Physiology*, 184(2): 881-894. <https://doi.org/10.1104/pp.20.00500>
- Knipper K.R., Kustas W.P., Anderson M.C., Alsina M.M., Hain C.R., Alfieri J.G., Prueger J.H., Gao F., McKee L.G., Sanchez L.A. (2019). Using High-Spatiotemporal Thermal Satellite ET Retrievals for Operational Water Use and Stress Monitoring in a California Vineyard. *Remote Sens.*, 11: 2124. <https://doi.org/10.3390/rs11182124>
- Kovář M., Brestič M., Sytar O., Bárek V., Hauptvogel P., Živčák M. (2019). Evaluation of hyperspectral reflectance parameters to assess the leaf water content in soybean. *Water*, 11(3): 443. <https://doi.org/10.3390/w11030443>
- Kriedemann P., Goodwin I. (2008). Irrigation Insights – Regulated deficit irrigation and partial rootzone drying. In: Anne Currey (ed), Land and Water Australia, Irrigation Insights No. 4., Canberra. <http://npsi.gov.au/files/products/national-program-sustainable-irrigation/pr020382/pr020382.pdf>
- Kumagai T., Aoki S., Otsuki K., Utsumi Y. (2009). Impact of stem water storage on diurnal estimates of whole-tree transpiration and canopy conductance from sap flow measurements in japanese cedar and japanese cypress trees. *Hydrological Processes*, 23(16): 2335-2344. <https://doi.org/10.1002/hyp.7338>
- Kwon T., Kim K., Yoon H., Lee S., Kim B., Siddiqui Z. (2015). Phenotyping of plants for drought and salt tolerance using infra-red thermography. *Plant Breeding and Biotechnology*, 3(4): 299-307. <https://doi.org/10.9787/pbb.2015.3.4.299>
- Lacape M.J., Wery J., Annerose D.J.M. (1998). Relationships between plant and soil water status in five field-grown cotton (*Gossypium hirsutum* L.) cultivars. *Field Crops Research*, 57 (1): 29-43. [https://doi.org/10.1016/S0378-4290\(97\)00111-1](https://doi.org/10.1016/S0378-4290(97)00111-1)
- Lanari V., Silvestroni O., Palliotti A., Green A., Sabbatini P. (2015). Plant and leaf physiological responses to water stress in potted ‘vignoles’ grapevine. *Hortscience*, 50(10): 1492-1497. <https://doi.org/10.21273/hortsci.50.10.1492>
- Lantos S., Bar-Oz G., Gambash G. (2020). Wine from the Desert. *Near Eastern Archaeology*, 83 (1): 56-64. <https://doi.org/10.1086/707483>
- Lawrence D.M., Thornton P.E., Oleson K.W., Bonan G.B. (2007). The partitioning of evapotranspiration into transpiration, soil evaporation, and canopy evaporation in a GCM: Impacts on land-atmosphere interaction. *Journal of Hydrometeorology*, 8 (4): 862-880. <https://doi.org/10.1175/JHM596.1>
- Lebon E., Dumas V., Pieri P., Schultz H.R. (2003). Modelling the seasonal dynamics of the soil water balance of vineyards. *Functional Plant Biology*, 30: 699–710. <https://doi.org/10.1071/fp02222>

- Lee H., Sumner D.A. (2013). The Economic Value of Wine Names That Reference Place in the US Market: Analysis of ‘Champagne’ and Sparkling Wine. In: Giraud-Héraud E., Pichery MC. (eds) Wine Economics. Applied Econometrics Association Series. Palgrave Macmillan, London. https://doi.org/10.1057/9781137289520_5
- Leinonen I., Jones H. (2004). Combining thermal and visible imagery for estimating canopy temperature and identifying plant stress. *Journal of Experimental Botany*, 55(401): 1423–1431. <https://doi.org/10.1093/jxb/erh146>
- Leolini L., Moriondo M., Fila G., Costafreda-Aumedes S., Ferrise R., Bindi M. (2018). Late spring frost impacts on future grapevine distribution in Europe. *Field Crops Res.*, 222: 197–208. <https://doi.org/10.1016/j.fcr.2017.11.018>
- Lhomme J.P., Montes C., Jacob F., Prévot L. (2012). Evaporation from Heterogeneous and Sparse Canopies: On the Formulations Related to Multi-Source Representations. *Bound. Layer Meteorol.*, 144: 243–262. <https://doi.org/10.1007/s10546-012-9713-x>
- Li L., Zhang Q., Huang D. (2014). A review of imaging techniques for plant phenotyping. *Sensors*, 14(11): 20078–20111. <https://doi.org/10.3390/s141120078>
- Li Y. (2024). Vulnerability of xylem embolism in maize cultivars with different drought tolerance under water and salt stress. *Agronomy*, 14(3): 438. <https://doi.org/10.3390/agronomy14030438>
- Lionello P., Scarascia L. (2018). The relation between climate change in the Mediterranean region and global warming. *Reg. Environ. Change*, 18 (5): 1481–1493. <https://doi.org/10.1007/s10113-018-1290-1>
- Lionello P., Scarascia L. (2020). The relation of climate extremes with global warming in the Mediterranean region and its north versus south contrast. *Reg. Environ. Change*, 20 (1): 31. <https://doi.org/10.1007/s10113-020-01610-z>
- Liu Z., Jian C., Huang W., Li C., Xu X., Ding X., Shi J., Zhou B. (2012). Hyperspectral discrimination and response characteristics of stressed rice leaves caused by rice leaf folder. In: Li, D., Chen, Y. (eds) Computer and Computing Technologies in Agriculture V. CCTA 2011. IFIP Advances in Information and Communication Technology, vol 369, pp 528–537. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-27278-3_54
- Liu J., Kang S., Davies W., Ding R. (2019). Elevated [CO₂] alleviates the impacts of water deficit on xylem anatomy and hydraulic properties of maize stems. *Plant Cell & Environment*, 43(3): 563–578. <https://doi.org/10.1111/pce.13677>
- Lopes C.M., Santos T., Monteiro A., Rodrigues M.L., Costa J.M., Chaves, M.M. (2011). Combining cover cropping with deficit irrigation in a Mediterranean low vigor vineyard. *Scientia Horticulturae*, 129: 603–612. <https://doi.org/10.1016/j.scienta.2011.04.033>
- Loveys B.R. (1984). Diurnal changes in water relations and abscisic acid in field grown *Vitis vinifera* cultivars III. The influence of xylem-derived abscisic acid on leaf gas exchange. *New Phytologist*, 98: 563–573.
- Lovisolo C., Perrone I., Carra A., Ferrandino A., Flexas J., Medrano H., Schubert A. (2010). Drought-induced changes in development and function of grapevine (*Vitis* spp.) organs and in their hydraulic and non-hydraulic interactions at the whole-plant level: a physiological and molecular update. *Functional Plant Biology*, 37 (2): 98–116. <https://doi.org/10.1071/FP09191>

- Lovisol C., Lavoie-Lamoureux A., Tramontini S., Ferrandino A. (2016). Grapevine adaptations to water stress: new perspectives about soil/plant interactions. *Theor. Exp. Plant Physiol.*, 28: 53–66. <https://doi.org/10.1007/s40626-016-0057-7>
- Lu P., Urban L., Zhao P. (2004). Granier's thermal dissipation probe (TDP) method for measuring sap flow in trees: Theory and practice. *Acta Botanica Sinica*, 46(6): 631-646.
- Lu P., Yunusa I., Walker R., Müller W. (2003). Regulation of canopy conductance and transpiration and their modeling in irrigated grapevines. *Functional Plant Biology*, 30 (6): 689 - 698. <https://doi.org/10.1071/FP02181>
- Ludovisi R., Tauro F., Salvati R., Khoury S., Scarascia G., Harfouche A. (2017). UAV-based thermal imaging for high-throughput field phenotyping of black poplar response to drought. *Frontiers in Plant Science*, 8: 1681. <https://doi.org/10.3389/fpls.2017.01681>
- Lv D., Zi J., Gao M., Xi R., Huang X. (2022). Detection of water changes in plant stems in situ by the primary echo of ultrasound rf with an improved aic algorithm. *Sensors*, 23(1): 20. <https://doi.org/10.3390/s23010020>
- Lyu D., Shi X., Wang X., Dong Y. (2016). Study on dynamic and non-destructive ultrasonic echo detection method of plant stem water content. *Proceedings of the 2016 International Conference on Engineering and Technology Innovations*, Atlantis Press, March 2016. <https://doi.org/10.2991/iceti-16.2016.38>
- MacMillan P., Teixeira G., Lopes C.M., Monteiro A. (2021). The role of grapevine leaf morphoanatomical traits in determining capacity for coping with abiotic stresses: A review. *Ciência Téc. Vitiv.*, 36 (1): 75-88. <https://doi.org/10.1051/ctv/ctv2021360175>
- Matthews M.A., Anderson M.M. (1988). Fruit ripening in grapes (*Vitis vinifera* L.): responses to seasonal water deficits. *American Journal of Enology and Viticulture*, 39: 313–320. <https://doi.org/10.5344/ajev.1988.39.4.313>
- Matthews M.A., Anderson M.M. (1989). Reproductive development in grape (*Vitis vinifera* L.): responses to seasonal water deficits. *American Journal of Enology and Viticulture*, 40: 52–60. <https://doi.org/10.5344/ajev.1989.40.1.52>
- Matthews M.A., Ishii R., Anderson M.M., O'Mahomy M. (1990). Dependence of wine sensory attributes on vine water status. *Journal of Science of Food and Agriculture*, 51: 321–335. <https://doi.org/10.1002/jsfa.2740510305>
- McBurney T. (1992). The Relationship Between Leaf Thickness and Plant Water Potential, *Journal of Experimental Botany*, 43 (3): 327–335. <https://doi.org/10.1093/jxb/43.3.327>
- McCarthy M.G., Loveys B.R., Dry P.R., Stoll M. (2000). Regulated Deficit Irrigation and Partial Rootzone Drying as Irrigation Management Techniques for Grapevines. *FAO Water Reports*, 22, 79-87. Available online: <https://www.fao.org/4/Y3655E/y3655e11.htm> (accessed on 26 October 2020)
- McGonigle I. (2019). In vino veritas? Indigenous wine and indigenization in Israeli settlements. *Anthropology Today*, 35 (4): 7-12. <https://doi.org/10.1111/1467-8322.12515>
- McGovern P. (2019). Ancient Wine: The Search for the Origins of Viniculture. Princeton University Press, New Jersey, USA <https://doi.org/10.1515/9781400849536>
- McGovern P. (2003a). The search for the origins of viniculture. In: McGovern P.E., Fleming S.J., Katz S.H. (eds). *The Origins and Ancient History of Wine*. Taylor and Francis. London, UK. <https://doi.org/10.4324/9780203392836>

- McGovern, P. (2003b). *Ancient Wine: The Search for the Origins of Viniculture*. Princeton University Press. <https://doi.org/10.1515/9781400849536.1>
- McGovern P., Armen M., Hall G.R. (2009). Ancient Egyptian herbal wines. *Proceedings of the National Academy of Sciences*, 106 (18): 7361-7366. <https://doi.org/10.1073/pnas.0811578106>
- McGovern P., Jalabadze M., Batiuk S., Callahan M.P., Smith K.E., Hall G.R., Kvavadze E., Maghradze D., Rusishvili N., Bouby L., Failla O., Cola G., Mariani L., Boaretto E., Bacilieri R., This P., Wales N., Lordkipanidze D. (2017). Early Neolithic wine of Georgia in the South Caucasus. *PNAS*, 114 (48) E10309-E10318. <https://www.pnas.org/content/pnas/114/48/E10309.full>
- MedECC (2020). Climate and environmental change in the Mediterranean Basin – Current situation and risks for the future. In: Cramer W., Guiot J., Marini K. (eds.). *First Mediterranean Assessment Report Union for the Mediterranean*. 632 p., Plan Bleu, UNEP/MAP, Marseille.
- Medrano H., Escalona J., Cifre J., Bota J., Flexas J. (2003). A ten-year study on the physiology of two spanish grapevine cultivars under field conditions: effects of water availability from leaf photosynthesis to grape yield and quality. *Functional Plant Biology*, 30(6): 607. <https://doi.org/10.1071/fp02110>
- Medrano H., Tomás M., Martorell S., Escalona J.-M., Pou A., Fuentes S., Flexas J., Bota J. (2015). Improving water use efficiency of vineyards in semi-arid regions. A review. *Agron. Sustain. Dev.*, 35: 499–517. <https://doi.org/10.1007/s13593-014-0280-z>
- Melcher P., Holbrook N., Burns M., Zwieniecki M., Cobb A., Brodribb T., Choat B., Sack L. (2012). Measurements of stem xylem hydraulic conductivity in the laboratory and field. *Methods in Ecology and Evolution*, 3(4): 685-694. <https://doi.org/10.1111/j.2041-210x.2012.00204.x>
- Melcher P., Zwieniecki M., Holbrook N. (2003). Vulnerability of xylem vessels to cavitation in sugar maple. scaling from individual vessels to whole branches. *Plant Physiology*, 131(4): 1775-1780. <https://doi.org/10.1104/pp.102.012856>
- Meloni G., Anderson K., Deconinck K., Swinnen J. (2019). Wine regulations. *Applied Economic Perspectives and Policy*, 41(4): 620-649. <https://doi.org/10.1093/aep/pz025>
- Mertens S., Verbracken L., Sprenger H., Meyer S., Demuyne K., Cannoot B., Merchie J., Block J., Vogel J., Bruce W., Nelissen H., Maere S., Inzé D., Wuyts N. (2023). Monitoring of drought stress and transpiration rate using proximal thermal and hyperspectral imaging in an indoor automated plant phenotyping platform. *Plant Methods*, 19: 132. <https://doi.org/10.1186/s13007-023-01102-1>
- Mihaljević I., Vuletić M., Šimić D., Tomaš V., Horvat D., Josipović M., Zdunić Z., Dugalić K., Vuković D. (2021). Comparative study of drought stress effects on traditional and modern apple cultivars. *Plants*, 10(3): 561. <https://doi.org/10.3390/plants10030561>
- Mirás-Avalos J., Araujo E. (2021). Optimization of vineyard water management: challenges, strategies, and perspectives. *Water*, 13(6): 746. <https://doi.org/10.3390/w13060746>
- Mitra S., Irshad M., Debnath B., Lu X., Li M., Dash C., Rizwan H.M., Qiu D. (2018). Effect of vineyard soil variability on chlorophyll fluorescence, yield and quality of table grape as influenced by soil moisture, grown under double cropping system in protected condition. *PeerJ*, 6: e5592. <https://doi.org/10.7717/peerj.5592>

- Monteith, J. L. (1995). Accommodation between transpiring vegetation and the convective boundary layer. *J. Hydrol.*, 166 (3-4): 251–263. [https://doi.org/10.1016/0022-1694\(94\)05086-D](https://doi.org/10.1016/0022-1694(94)05086-D)
- Monteith J.L., Unsworth M.H. (2013). Principles of Environmental Physics (4th ed.). Academic Press.
- Mooney H., Arroyo M., Bond W., Canadell J., Hobbs R., Lavorel S., Neilson R. (2001). Mediterranean-Climate Ecosystems. In: Chapin F.S., Sala O.E., Huber-Sannwald E. (eds) Global Biodiversity in a Changing Environment. Ecological Studies, vol 152. Springer, New York, NY. https://doi.org/10.1007/978-1-4613-0157-8_9
- Moutinho-Pereira J., Correia C., Gonçalves B., Bacelar E., Torres-Pereira J. (2004). Leaf gas exchange and water relations of grapevines grown in three different conditions. *Photosynthetica*, 42(1): 81-86. <https://doi.org/10.1023/b:phot.0000040573.09614.1d>
- Murchie E., Lawson T. (2013). Chlorophyll fluorescence analysis: a guide to good practice and understanding some new applications. *Journal of Experimental Botany*, 64(13): 3983-3998. <https://doi.org/10.1093/jxb/ert208>
- Myburgh P.A. (2010). Practical guidelines for the measurement of water potential in grapevine leaves. Wynboer Technical Yearbook 2010, 11-13.
- Nadezhkina N., Čermák J., Ceulemans R. (2002). Radial patterns of sap flow in woody stems of dominant and understory species: scaling errors associated with positioning of sensors. *Tree Physiology*, 22(13): 907-918. <https://doi.org/10.1093/treephys/22.13.907>
- Nadezhkina N., Vandegehuchte M., Steppe K. (2012). Sap flux density measurements based on the heat field deformation method. *Trees*, 26(5): 1439-1448. <https://doi.org/10.1007/s00468-012-0718-3>
- Neghliz H., Cochard H., Brunel N., Martre P. (2016). Ear rachis xylem occlusion and associated loss in hydraulic conductance coincide with the end of grain filling for wheat. *Frontiers in Plant Science*, 7: 920. <https://doi.org/10.3389/fpls.2016.00920>
- Ngie A., Ahmed F., Abutaleb K. (2017). Assessing maize foliar water stress levels under field conditions using in-situ spectroscopy. *Rwanda Journal*, 1(1S). <https://doi.org/10.4314/rj.v1i2s.1d>
- Nguyen T., Fuentes S., Marschner P. (2013). Effect of incorporated or mulched compost on leaf nutrient concentrations and performance of *Vitis vinifera* cv. merlot. *Journal of Soil Science and Plant Nutrition*, 13(2): 485-497. <https://doi.org/10.4067/s0718-95162013005000038>
- Ni Z., Liu Z., Huo H., Li Z., Nerry F., Wang Q., Li X. (2015). Early water stress detection using leaf-level measurements of chlorophyll fluorescence and temperature data. *Remote Sensing*, 7(3): 3232-3249. <https://doi.org/10.3390/rs70303232>
- NOAA (2024). Global monitoring laboratory. The Technical Details: Determining Delta Values. Stable Isotopes. Available online: <https://gml.noaa.gov/education/isotopes/deltavalues.html> (accessed on 18 November 2024).
- Nobel P.S. (1983). Biophysical Plant Physiology and Ecology. W.H. Freeman and Company, San Francisco, California, USA. ISBN 0-7167-1447-7.
- Noguera M., Millán B., Pérez-Paredes J., Ponce J., Aquino A., Andújar J. (2020). A new low-cost device based on thermal infrared sensors for olive tree canopy temperature measurement and water status monitoring. *Remote Sensing*, 12(4): 723. <https://doi.org/10.3390/rs12040723>

- Novick K., Oren R., Stoy P., Juang J.Y., Siqueira M., Katul G. (2009). The relationship between reference canopy conductance and simplified hydraulic architecture. *Advances in Water Resources*, 32 (6): 809-819. <https://doi.org/10.1016/j.advwatres.2009.02.004>
- Nožková V., Šmíd P., Horvath P., Hrabovsky M., Ilík P. (2018). Non-invasive monitoring of hydraulic surge propagation in a wounded tobacco plant. *Plant Methods*, 14(1): 38. <https://doi.org/10.1186/s13007-018-0307-6>
- Ohta S., Kimura A. (2009). The effects of plant growth on the temperature of paddy waters. *Journal of Agricultural Meteorology*, 65(2): 167-178. <https://doi.org/10.2480/agrmet.65.2.9>
- OIV (2024). State of the World Vine and Wine Sector in 2023. Available online: https://www.oiv.int/sites/default/files/2024-04/OIV_STATE_OF_THE_WORLD_VINE_AND_WINE_SECTOR_IN_2023.pdf (accessed on 29 October 2024)
- Ojeda H., Deloire, A., Carbonneau A. (2001). Influence of water deficits on grape berry growth. *Vitis*, 40 (3): 141–145. <https://doi.org/10.5073/vitis.2001.40.141-145>
- Ojeda H., Saurin N. (2014). L'irrigation de précision de la vigne : méthodes, outils et stratégies pour maximiser la qualité et les rendements de la vendange en économisant de l'eau. *Innovations Agronomiques*, 38: 97-108. <https://doi.org/10.17180/n4p2-pr93>
- Ortuño M.F., Conejero W., Moreno F., Moriana A., Intrigliolo D.S., Biel C.A., Mellisho C.A.D., Pérez-Pastor A., Domingo R., Ruiz-Sánchez M.C.A., Casadesus J., Bonany J., Torrecillas A. (2010). Could trunk diameter sensors be used in woody crops for irrigation scheduling? A review of current knowledge and future perspectives. *Agric. Water Manag.*, 97: 1–11. <https://doi.org/10.1016/j.agwat.2009.09.008>
- Osakabe Y, Osakabe K., Shinozaki K., Tran L.-S.P. (2014). Response of plants to water stress. *Front. Plant Sci.*, 5: 86. <https://doi.org/10.3389/fpls.2014.00086>
- Osborne, R. (2014). Intoxication and Sociality: The Symposium in the Ancient Greek World. *Past & Present*, 222 (9): 34-60. <https://doi.org/10.1093/pastj/gtt028>
- Oyarce P., Gurovich L. (2010). Electrical signals in avocado trees. *Plant Signaling & Behavior*, 5(1): 34-41. <https://doi.org/10.4161/psb.5.1.10157>
- Oyarce, P.; Gurovich, L. (2011). Evidence for the transmission of information through electric potentials in injured avocado trees. *J. Plant Physiol.*, 168: 103–108. <https://doi.org/10.1016/j.jplph.2010.06.003>
- Paço T.A., Ferreira I., Conceição N. (2006). Peach orchard evapotranspiration in a sandy soil: Comparison between eddy covariance measurements and estimates by the FAO 56 approach. *Agr. Water Manag.*, 85: 305–313. <https://doi.org/10.1016/j.agwat.2006.05.014>
- Padhi J., Misra R., Payero J. (2012). Estimation of soil water deficit in an irrigated cotton field with infrared thermography. *Field Crops Research*, 126: 45-55. <https://doi.org/10.1016/j.fcr.2011.09.015>
- Payag V., Zufferey V., Lakso A. (2016). The influence of water stress on grapevine (*Vitis vinifera* L.) shoots in a cool, humid climate: growth, gas exchange and hydraulics. *Functional Plant Biology*, 43(9): 827. <https://doi.org/10.1071/fp16017>
- Paiola A., Assandri G., Brambilla M., Zottini M., Pedrini P., Nascimbene J. (2020). Exploring the potential of vineyards for biodiversity conservation and delivery of biodiversity-mediated ecosystem services: A global-scale systematic review. *Science of The Total Environment*, 706: 135839 <https://doi.org/10.1016/j.scitotenv.2019.135839>

- Pappalardo S., Gislimberti L., Ferrarese F., Marchi M., Mozzi P. (2019). Estimation of potential soil erosion in the prosecco DOCG area (NE Italy), toward a soil footprint of bottled sparkling wine production in different land-management scenarios. *Plos One*, 14(5): e0210922. <https://doi.org/10.1371/journal.pone.0210922>
- Parker T. (2015). Tasting French Terroir: The History of an Idea. University of California Press, Oakland, CA, 248 p. <https://doi.org/10.1525/california/9780520277502.001.0001>
- Pellechia T. (2006). Wine: The 8,000 Year-Old Story of the Wine Trade. Thunder's Mouth Press, New York, 272 p. ISBN 13: 9781560258711.
- Pellegrino A., Lebon E., Simonneau T., Wery J. (2005a). Towards a simple indicator of water stress in grapevine (*Vitis vinifera* L.) based on the differential sensitivities of vegetative growth components. *Australian Journal of Grape and Wine Research*, 11(3): 306-315. <https://doi.org/10.1111/j.1755-0238.2005.tb00030.x>
- Pellegrino A., Lebon E., Voltz M., Wery J. (2005b). Relationships between plant and soil water status in vine (*Vitis vinifera* L.). *Plant and Soil*, 266 :129-142. <https://doi.org/10.1007/s11104-005-0874-y>
- Pereira, L.S.; Allen, R.G.; Smith, M.; Raes, D. (2015). Crop evapotranspiration estimation with FAO56: Past and future. *Agr. Water Manag.* 147, 4–20. <https://doi.org/10.1016/j.agwat.2014.07.031>
- Pereira L., Bittencourt P., Oliveira R., Mauro B., Barros F., Ribeiro R., Mazzafera P. (2016). Plant pneumatics: stem air flow is related to embolism – new perspectives on methods in plant hydraulics. *New Phytologist*, 211(1): 357-370. <https://doi.org/10.1111/nph.13905>
- Pfeifer J., Mielewczik M., Friedli M., Kirchgessner N., Walter, A. (2017). Non-destructive measurement of soybean leaf thickness via x-ray computed tomography allows the study of diel leaf growth rhythms in the third dimension. *Journal of Plant Research*, 131(1): 111-124. <https://doi.org/10.1007/s10265-017-0967-8>
- Picón-Toro J., González-Dugo V., Uriarte D., Mancha L.A., Testi L. (2012). Effects of canopy size and water stress over the crop coefficient of a “Tempranillo” vineyard in south-western Spain. *Irrig. Sci.*, 30: 419–432. <https://doi.org/10.1007/s00271-012-0351-3>
- Pineda M., Barón M., Pérez-Bueno M. (2020). Thermal imaging for plant stress detection and phenotyping. *Remote Sensing*, 13(1): 68. <https://doi.org/10.3390/rs13010068>
- Poblete T., Ortega-Farías S., Moreno M., Bardeen M. (2017). Artificial neural network to predict vine water status spatial variability using multispectral information obtained from an unmanned aerial vehicle (UAV). *Sensors*, 17(11): 2488. <https://doi.org/10.3390/s17112488>
- Poblete T., Ortega-Farías S., Ryu D. (2018). Automatic coregistration algorithm to remove canopy shaded pixels in UAV-borne thermal images to improve the estimation of crop water stress index of a drip-irrigated cabernet sauvignon vineyard. *Sensors*, 18(2): 397. <https://doi.org/10.3390/s18020397>
- Pôças I., Rodrigues A., Gonçalves S., Costa P., Gonçalves I., Pereira L., Cunha M. (2015). Predicting grapevine water status based on hyperspectral reflectance vegetation indices. *Remote Sensing*, 7(12): 16460-16479. <https://doi.org/10.3390/rs71215835>
- Poni S., Gatti M., Palliotti A., Dai Z., Duchêne E., Truong T.-T., Ferrara G., Matarrese A.M.S., Gallotta A., Bellincontro A., Mencarelli F., Tombesi S. (2018). Grapevine quality: A multiple choice issue. *Scientia Horticulturae*, 234: 445-462. <https://doi.org/10.1016/j.scienta.2017.12.035>

- Porter S. (2022). A Comprehensive Analysis of the Pennsylvania Wine Industry with Actionable Recommendations for Industry Improvement and Growth. West Chester University Doctoral Projects. 139. https://digitalcommons.wcupa.edu/all_doctoral/139
- Porter S. (2024). Decoding the italian wine market: a quantitative macro-economic examination of price and expert rating influences. *Wine Business Journal*. <https://doi.org/10.26813/001c.94078>
- Pou A., Diago M., Medrano H., Baluja J., Tardáguila J. (2014). Validation of thermal indices for water status identification in grapevine. *Agricultural Water Management*, 134: 60-72. <https://doi.org/10.1016/j.agwat.2013.11.010>
- Prada J., Dinis L.T., Soriato E., Vandelle E., Soletkin O., Uysal S., Dihazi A., Santos C., Santos J.A. (2024). Climate change impact on Mediterranean viticultural regions and site-specific climate risk-reduction strategies. *Mitig Adapt Strateg Glob Change*, 29: 52. <https://doi.org/10.1007/s11027-024-10146-0>
- Pramsohler M., Lichtenberger E., Neuner G. (2022). Seasonal xylem sap acidification is governed by tree phenology, temperature and elevation of growing site. *Plants*, 11(15): 2058. <https://doi.org/10.3390/plants11152058>
- Puigdefabregas J., Mendizábal T. (1998). Perspectives on desertification: western Mediterranean. *Journal of Arid Environments*, 39 (2): 209-224. <https://doi.org/10.1006/JARE.1998.0401>
- Qian Y., Bao A., Luo Y., Zhao J. (2012). Measuring cotton water status using water-related vegetation indices at leaf and canopy levels. *Journal of Arid Land*, 4(3): 310-319. <https://doi.org/10.3724/sp.j.1227.2012.00310>
- Radwan U., Saleh M. (2022). Gas exchange and chlorophyll fluorescence's characteristics of *Hyoscyamus muticus* L. at different phenological stages under extreme arid environmental conditions, south-western desert, Egypt. *Egyptian Journal of Botany*, 62(2): 415-430. <https://doi.org/10.21608/ejbo.2022.87177.1746>
- Raimondo M., Nazzaro C., Nifo A., Marotta G. (2020). Does the institutional quality affect labor productivity in italian vineyard farms? *Wine Economics and Policy*, 9(2): 113-126. <https://doi.org/10.36253/wep-7833>
- Rallo G., Paço T.A., Paredes P., Puig-Sirera À., Massai R., Provenzano G., Pereira L.S. (2021). Updated single and dual crop coefficients for tree and vine fruit crops. *Agr. Water Manag.*, 250: 106645. <https://doi.org/10.1016/j.agwat.2020.106645>
- Ramos M., Jones G., Yuste, J. (2018). Phenology of Tempranillo and Cabernet-Sauvignon varieties cultivated in the Ribera del Duero DO: observed variability and predictions under climate change scenarios. *OENO One*, 52(1). <https://doi.org/10.20870/oeno-one.2018.52.1.2119>
- Rapaport T., Hochberg U., Cochavi A., Karnieli A., Rachmilevitch S. (2017). The potential of the spectral 'water balance index' (WABI) for crop irrigation scheduling. *New Phytologist*, 216(3): 741-757. <https://doi.org/10.1111/nph.14718>
- Rapaport T., Hochberg U., Shoshany M., Karnieli A., Rachmilevitch S. (2015). Combining leaf physiology, hyperspectral imaging and partial least squares-regression (PLS-R) for grapevine water status assessment. *ISPRS Journal of Photogrammetry and Remote Sensing*, 109: 88-97. <https://doi.org/10.1016/j.isprsjprs.2015.09.003>
- Raza S., Prince G., Clarkson J., Rajpoot N. (2015). Automatic detection of diseased tomato plants using thermal and stereo visible light images. *Plos One*, 10(4): e0123262. <https://doi.org/10.1371/journal.pone.0123262>

- Raza S., Smith H., Clarkson G., Taylor G., Thompson A., Clarkson J., Rajpoot N. (2014). Automatic detection of regions in spinach canopies responding to soil moisture deficit using combined visible and thermal imagery. *Plos One*, 9(6): e97612. <https://doi.org/10.1371/journal.pone.0097612>
- Renfrew J. (2002). Archaeology and the origins of wine production. In: Sandler M., Pinder R. (eds). *Wine: A Scientific Exploration*. Taylor & Francis, London, p. 56-69. <https://doi.org/10.1201/9780203361382-8>
- Rienth M., Scholasch T. (2019). State-of-the-art of tools and methods to assess vine water status. *OENO One*, 53 (4). <https://doi.org/10.20870/oeno-one.2019.53.4.2403>
- Ríos-Rojas L., Morales-Moraga D., Alcalde J., Gurovich L.A. (2015). Use of plant woody species electrical potential for irrigation scheduling. *Plant Signal Behav.*, 10: e976487. <https://doi.org/10.4161/15592324.2014.976487>
- Ríos-Rojas L., Tapia F., Gurovich L. (2014). Electrophysiological assessment of water stress in fruit-bearing woody plants. *Journal of Plant Physiology*, 171(10): 799-806. <https://doi.org/10.1016/j.jplph.2014.02.005>
- Rodriguez-Dominguez C., Buckley T., Egea G., Cires A., Hernández-Santana V., Martorell S., Díaz-Espejo A. (2016). Most stomatal closure in woody species under moderate drought can be explained by stomatal responses to leaf turgor. *Plant Cell & Environment*, 39(9): 2014-2026. <https://doi.org/10.1111/pce.12774>
- Rogiers S.Y., Greer D.H., Hatfield J.M., Hutton R.J., Clarke S.J., Hutchinson P.A., Somers A. (2012). Stomatal response of an anisohydric grapevine cultivar to evaporative demand, available soil moisture and abscisic acid. *Tree Physiol.*, 32 (3): 249–261. <https://doi.org/10.1093/treephys/tpr131>
- Rolfe S., Scholes J. (2010). Chlorophyll fluorescence imaging of plant–pathogen interactions. *Protoplasma*, 247(3-4): 163-175. <https://doi.org/10.1007/s00709-010-0203-z>
- Romero P., Navarro J.M., Ordaz P.B. (2022). Towards a sustainable viticulture: The combination of deficit irrigation strategies and agroecological practices in Mediterranean vineyards. A review and update. *Agr. Water Manag.*, 259: 107216. <https://doi.org/10.1016/j.agwat.2021.107216>
- Rüger S., Ehrenberger W., Zimmermann U., Ben-Gal A., Agam N., Kool D. (2011). The leaf patch clamp pressure probe: a new tool for irrigation scheduling and deeper insight into olive drought stress physiology. *Acta Horticulturae*, (888): 223-230. <https://doi.org/10.17660/actahortic.2011.888.25>
- Sadras V.O. (2009). Does partial root-zone drying improve irrigation water productivity in the field? A meta-analysis. *Irrig Sci*, 27: 183–190 <https://doi.org/10.1007/s00271-008-0141-0>
- Sakuratani T. (1981). A heat balance method for measuring water flux in the stem of intact plants. *J Agric Meteorol*, 37 (1) :9-17. <https://doi.org/10.2480/agrmet.37.9>
- Salomón R., Steppe K., Ourcival J., Villers S., Rodríguez-Calcerrada J., Schapman R., Limousin J. (2020). Hydraulic acclimation in a mediterranean oak subjected to permanent throughfall exclusion results in increased stem hydraulic capacitance. *Plant Cell & Environment*, 43(6), 1528-1544. <https://doi.org/10.1111/pce.13751>
- Santesteban L., Di Gennaro S.F., Herrero-Langreo A., Miranda C., Royo J.B., Matese A. (2017). High-resolution UAV-based thermal imaging to estimate the instantaneous and

- seasonal variability of plant water status within a vineyard. *Agricultural Water Management*, 183: 49-59. <https://doi.org/10.1016/j.agwat.2016.08.026>
- Santesteban L., Jiménez C., Barbarin I., Royo J. (2014). Application of the measurement of the natural abundance of stable isotopes in viticulture: a review. *Australian Journal of Grape and Wine Research*, 21(2): 157-167. <https://doi.org/10.1111/ajgw.12124>
- Santesteban L., Miranda C., Marín D., Sesma B., Intrigliolo D., Mirás-Avalos J., Escalona J., Montoro A., de Herralde F., Baeza P., Romero P., Yuste J., Uriarte D., Martínez-Gascueña J., Cancela J.J., Pinillos V., Loidi M., Urrestarazu J., Royo J.B. (2019). Discrimination ability of leaf and stem water potential at different times of the day through a meta-analysis in grapevine (*Vitis vinifera* L.). *Agr. Water Manag.*, 221: 202–210. <https://doi.org/10.1016/j.agwat.2019.04.020>
- Santos M., Fonseca A., Fraga H., Jones G. V., Santos, J.A. (2020a). Bioclimatic conditions of the Portuguese wine denominations of origin under changing climates. *Int. J. Climatol.*, 40: 927–941. <https://doi.org/10.1002/joc.6248>
- Santos J.A., Fraga H., Malheiro A.C., Moutinho-Pereira J., Dinis L.-T., Correia C., Moriondo M., Leolini L., Dibari C., Costafreda-Aumedes S., Kartschall T., Menz C., Molitor D., Junk J., Beyer M., Schultz H.R. (2020b). A Review of the Potential Climate Change Impacts and Adaptation Options for European Viticulture. *Appl. Sci.*, 10: 3092. <https://doi.org/10.3390/app10093092>
- Santos T.P., Lopes C.M., Rodrigues M.L., Souza C.R., Ricardo-da-Silva J.M., Maroco J.P., Pereira J.S., Chaves M.M. (2007). Effects of deficit irrigation strategies on cluster microclimate for improving fruit composition of Moscatel field-grown grapevines. *Scientia Horticulturae*, 112 (3): 321-330. <https://doi.org/10.1016/j.scienta.2007.01.006>
- Santos T.P., Souza C.R., Lopes C.M., Rodrigues, M.L., Maroco, J., Pereira, J.S., Silva J.R., Chaves, M.M. (2003). Partial rootzone drying: Effects on growth and fruit quality of field-grown grapevines (*Vitis vinifera*). *Functional Plant Biology*, 30 :663-671. <https://doi.org/10.1071/fp02180>
- Saraiva G., Ferreira A., Souza G. (2017). Osmotic stress decreases complexity underlying the electrophysiological dynamic in soybean. *Plant Biology*, 19(5): 702-708. <https://doi.org/10.1111/plb.12576>
- Scalisi A., Marino G., Marra F., Caruso T., Bianco, R. (2020). A cultivar-sensitive approach for the continuous monitoring of olive (*Olea europaea* L.) tree water status by fruit and leaf sensing. *Frontiers in Plant Science*, 11. <https://doi.org/10.3389/fpls.2020.00340>
- Scheenen T., Vergeldt F., Heemskerk A., As H. (2007). Intact plant magnetic resonance imaging to study dynamics in long-distance sap flow and flow-conducting surface area. *Plant Physiology*, 144(2): 1157-1165. <https://doi.org/10.1104/pp.106.089250>
- Schmitt S., Trueba S., Coste S., Ducouret É., Tysklind N., Heuertz M., Bonal D., Burban B., Hérault B., Derroire G. (2022). Seasonal variation of leaf thickness: an overlooked component of functional trait variability. *Plant Biology*, 24(3): 458-463. <https://doi.org/10.1111/plb.13395>
- Schultz H.R. (2003). Differences in hydraulic architecture account for near- isohydric and anisohydric behaviour of two field-grown *Vitis vinifera* L. cultivars during drought. *Plant, Cell and Environment*, 26: 1393-1405. <https://doi.org/10.1046/j.1365-3040.2003.01064.x>
- Schymanski S.J., Or D. (2017). Leaf-scale experiments reveal an important omission in the Penman–Monteith equation. *Hydrol. Earth Syst. Sci.*, 21: 685–706. <https://doi.org/10.5194/hess-21-685-2017>

- Seager R., Osborn T., Kushnir Y., Simpson I., Nakamura J., Liu H. (2019). Climate Variability and Change of Mediterranean-Type Climates. *Journal of Climate*, 32 (10): 2887–2915. <https://doi.org/10.1175/JCLI-D-18-0472.1>
- Sebri M. (2017). Bridging the Maghreb's water gap: from rationalizing the virtual water trade to enhancing the renewable energy desalination. *Environ. Dev. Sustain.*, 19 (5): 1673–1684. <https://doi.org/10.1007/s10668-016-9820-9>
- Seelig H., Stoner R., Linden J. (2011). Irrigation control of cowpea plants using the measurement of leaf thickness under greenhouse conditions. *Irrigation Science*, 30(4): 247–257. <https://doi.org/10.1007/s00271-011-0268-2>
- Senavirathna M., Muhetaer G. (2020). Electrode insertion generates slow propagating electric potentials in myriophyllum aquaticum plants. *Plant Signaling & Behavior*, 15(3): 1734332. <https://doi.org/10.1080/15592324.2020.1734332>
- Sepúlveda P., Johnstone D. (2018). A novel way of assessing plant vitality in urban trees. *Forests*, 10(1): 2. <https://doi.org/10.3390/f10010002>
- Sepulveda-Reyes D., Ingram B., Bardeen M., Zúñiga M., Ortega-Farías S., Poblete-Echeverría C. (2016). Selecting canopy zones and thresholding approaches to assess grapevine water status by using aerial and ground-based thermal imaging. *Remote Sensing*, 8(10): 822. <https://doi.org/10.3390/rs8100822>
- Sevanto S., Vesala T., Perämäki M., Nikinmaa E. (2002). Time lags for xylem and stem diameter variations in a Scots pine tree. *Plant Cell Environ.*, 25: 1071–1077. <https://doi.org/10.1046/j.1365-3040.2002.00884.x>
- Sharma N., Banerjee B., Hayden M., Kant S. (2023). An open-source package for thermal and multispectral image analysis for plants in glasshouse. *Plants*, 12(2): 317. <https://doi.org/10.3390/plants12020317>
- Shelden M., Vandeleur R., Kaiser B., Tyerman S. (2017). A comparison of petiole hydraulics and aquaporin expression in an anisohydric and isohydric cultivar of grapevine in response to water-stress induced cavitation. *Frontiers in Plant Science*, 8: 1893. <https://doi.org/10.3389/fpls.2017.01893>
- Shuttleworth J., Wallace J.S. (2009). Calculating the water requirements of irrigated crops in Australia using the Matt-Shuttleworth approach. *Trans. ASABE*, 52: 1895–1906. <https://doi.org/10.13031/2013.29217>
- Silva D., Cabral C., Ferreira E., Carvalho F., Santos J., Dombroski J. (2018). Anatomical adaptations to different soil moisture contents in palisade grass and smooth pigweed. *Revista Ceres*, 65(4): 306–313. <https://doi.org/10.1590/0034-737x201865040002>
- Sinclair G. (2024). Grape cultivars adapted to hotter, drier growing regions exhibit greater photosynthesis in hot conditions despite less drought-resistant leaves. *Annals of Botany*, 134(2): 205–218. <https://doi.org/10.1093/aob/mcae032>
- Sinisterra-Solís N., Sanjuán N., Estruch V., Clemente G. (2020). Assessing the environmental impact of spanish vineyards in Utiel-Requena PDO: the influence of farm management and on-field emission modelling. *Journal of Environmental Management*, 262: 110325. <https://doi.org/10.1016/j.jenvman.2020.110325>
- Skinner R.H., Wagner-Riddle C. (2012). Micrometeorological Methods for Assessing Greenhouse Gas Flux. In: Liebig M.A., Franzluebbers A.J., Follett R.F., Managing Agricultural Greenhouse Gases. Academic Press, 2012, p. 367–383. <https://doi.org/10.1016/B978-0-12-386897-8.00021-8>

- Slaghenaufl D., Luzzini G., Solis J., Forte F., Ugliano M. (2021). Two sides to one story—aroma chemical and sensory signature of Lugana and Verdicchio wines. *Molecules*, 26(8): 2127. <https://doi.org/10.3390/molecules26082127>
- Sorek Y., Greenstein S., Netzer Y., Shtein I., Jansen S., Hochberg U. (2020). An increase in xylem embolism resistance of grapevine leaves during the growing season is coordinated with stomatal regulation, turgor loss point and intervessel pit membranes. *New Phytologist*, 229(4): 1955-1969. <https://doi.org/10.1111/nph.17025>
- Stoll M., Loveys B., Dry P. (2000). Hormonal changes induced by partial rootzone drying of irrigated grapevine. *J. Exp. Bot.*, 51 (350): 1627-1634. <https://doi.org/10.1093/jexbot/51.350.1627>
- Stoll M., Jones H.G. (2007). Thermal imaging as a viable tool for monitoring plant stress. *OENO One*, 41(2): 77–84. <https://doi.org/10.20870/oeno-one.2007.41.2.851>
- Sui X., Zhang X., Wang Y., Li S. (2012). Estimation of leaf thickness with remote sensing. *Applied Mechanics and Materials*, 263-266: 339-345. <https://doi.org/10.4028/www.scientific.net/amm.263-266.339>
- Sukhova E., Ratnitsyna D., Sukhov V. (2021). Stochastic spatial heterogeneity in activities of H⁺-ATP-Aases in electrically connected plant cells decreases threshold for cooling-induced electrical responses. *International Journal of Molecular Sciences*, 22(15): 8254. <https://doi.org/10.3390/ijms22158254>
- Sun X., Li J., Cameron D., Moore G. (2021). On the use of sap flow measurements to assess the water requirements of three australian native tree species. *Agronomy*, 12(1): 52. <https://doi.org/10.3390/agronomy12010052>
- Suter B., Triolo R., Pernet D., Dai Z., van Leeuwen C. (2019). Modeling Stem Water Potential by Separating the Effects of Soil Water Availability and Climatic Conditions on Water Status in Grapevine (*Vitis vinifera* L.). *Front. Plant Sci.*, 10: 1485. <https://doi.org/10.3389/fpls.2019.01485>
- Tanriverdi C., Degirmenci H., Gonen E., Boyaci S. (2016). A comparison of the gravimetric and TDR methods in terms of determining the soil water content of the corn plant. Scientific Papers. Series A. Agronomy, Vol. LIX. ISSN ONLINE 2285-5807.
- Tardáguila J., Fernández-Navales J., Gutiérrez S., Diago M. (2017). Non-destructive assessment of grapevine water status in the field using a portable NIR spectrophotometer. *Journal of the Science of Food and Agriculture*, 97(11): 3772-3780. <https://doi.org/10.1002/jsfa.8241>
- Tardieu F., Davies W.J. (1993). Integration of hydraulic and chemical signaling in the control of stomatal conductance and water status of droughted plants. *Plant, Cell and Environment*, 16: 341–349. <https://doi.org/10.1111/j.1365-3040.1993.tb00880.x>
- Taskos D., Zioziou E., Nikolaou N., Doupis G., Koundouras S. (2020). Carbon isotope natural abundance ($\delta^{13}\text{C}$) in grapevine organs is modulated by both water and nitrogen supply. *Oeno One*, 54(4), 1183-1199. <https://doi.org/10.20870/oeno-one.2020.54.4.3600>
- Taylor J.A., Acevedo-Opazo C., Pellegrino A., Ojeda H., Tisseyre B. (2012). Can within-season grapevine predawn leaf water potentials be predicted from meteorological data in non-irrigated Mediterranean vineyards? *Journal International des Sciences de la Vigne et du Vin*, 46 (3): 221-232. <https://doi.org/10.20870/oeno-one.2012.46.3.1521>

- Tian L. (2023). Research on classification of water stress state of plant electrical signals based on PSO-SVM. *IEEE Access*, 11: 125021-125032. <https://doi.org/10.1109/access.2023.3330651>
- Tokuda A., Kitaya Y., Hirai H. (2018). Development of a simple thermal method for measuring sap flow in plants for space experiments. *Biological Sciences in Space*, 32(0), 17-21. <https://doi.org/10.2187/bss.32.17>
- Toledo G. (2024). Common bean under different water availability reveals classifiable stimuli-specific signatures in plant electrome. *Plant Signaling & Behavior*, 19(1). <https://doi.org/10.1080/15592324.2024.2333144>
- Tomás M., Medrano H., Pou A., Escalona J., Martorell S., Ribas-Carbó M., Flexas J. (2012). Water-use efficiency in grapevine cultivars grown under controlled conditions: effects of water stress at the leaf and whole-plant level. *Australian Journal of Grape and Wine Research*, 18(2): 164-172. <https://doi.org/10.1111/j.1755-0238.2012.00184.x>
- Tomasella M., Calderan A., Mihelcic A., Petruzzellis F., Braidotti R., Natale S., Lisjak K., Sivilotti P., Nardini A. (2023). Best Procedures for Leaf and Stem Water Potential Measurements in Grapevine: Cultivar and Water Status Matter. *Plants*, 12: 2412. <https://doi.org/10.3390/plants12132412>
- Torun, H. (2023). Antioxidant defense system and physiological insights to drought stress in *Urtica dioica* L. *Düzce University Journal of Forestry*, 19(2): 84-96. <https://doi.org/10.58816/duzceod.1405714>
- Tramontini S., Lovisolo C. (2015). Embolism formation and removal in grapevines: a phenomenon affecting hydraulics and transpiration upon water stress. In: Gerós H., Chaves M.M., Medrano H., Delrot S. *Grapevine in a Changing Environment: A Molecular and Ecophysiological Perspective*. Wiley Blackwell, pp. 135-147. <https://doi.org/10.1002/9781118735985.ch6>
- Tran D., Dutoit F., Najdenovska E., Wallbridge N., Plummer C., Mazza M., Raileanu L.E., Camps C. (2019). Electrophysiological assessment of plant status outside a faraday cage using supervised machine learning. *Scientific Reports*, 9(1): 17073. <https://doi.org/10.1038/s41598-019-53675-4>
- Trifil P., Nardini A., Raimondo F., Gullo M., Salleo S. (2011). Ion-mediated compensation for drought-induced loss of xylem hydraulic conductivity in field-growing plants of *Laurus nobilis*. *Functional Plant Biology*, 38(7): 606. <https://doi.org/10.1071/fp10233>
- TTB, Alcohol and Tobacco Tax and Trade Bureau, U.S. Department of the Treasury (2025). AVA Map Explorer. Available online: <https://www.ttb.gov/regulated-commodities/beverage-alcohol/wine/ava-map-explorer> (Accessed on 15 january 2025).
- Ueda M., Shibata E. (2001). Diurnal changes in branch diameter as indicator of water status of Hinoki cypress, *Chamaecyparis obtuse*. *Trees*, 15: 315–318. <https://doi.org/10.1007/s004680100113>
- Ulin R.C. (2021). Terroir and Tourism in the Age of Mass Production. *Tourism Analysis*, 26 (2-3): 109-119. <https://doi.org/10.3727/108354221X16079789765298>
- Ulin R.C. (2009). Invention and Representation as Cultural Capital. *American Anthropologist*, 97 (3): 519 – 527. <https://doi.org/10.1525/aa.1995.97.3.02a00100>
- Vadivambal R., Jayas D. (2010). Applications of thermal imaging in agriculture and food industry—a review. *Food and Bioprocess Technology*, 4(2): 186-199. <https://doi.org/10.1007/s11947-010-0333-5>

- Valamoti S. (2018). Grapes and Viticulture. In: Varela S. (ed). The Encyclopedia of Archaeological Sciences. Wiley Blackwell. <https://doi.org/10.1002/9781119188230.saseas0270>
- Valancogne C., Nasr Z. (1989). Measuring sap flow in the stem of small trees by a heat balance method. *HortSci*, 24 (2): 383-385. <https://doi.org/10.21273/HORTSCI.24.2.383>
- Van Leeuwen C., Trégoat O., Choné X., Bois B., Pernet D., Gaudillère J.P. (2009). Vine water status is a key factor in grape ripening and vintage quality for red Bordeaux wine. How can it be assessed for vineyard management purposes?. *Oeno One*, 43 (3): 121-134. <https://doi.org/10.20870/oeno-one.2009.43.3.798>
- Varriano J. (2022). Wine: A Cultural History. Reaktion Books, London. ISBN 1789146453
- Velazquez-Chavez L.J., Daccache A., Mohamed A.Z., Centritto M. (2024). Plant-based and remote sensing for water status monitoring of orchard crops: Systematic review and meta-analysis. *Agricultural Water Management*, 303: 109051. <https://doi.org/10.1016/j.agwat.2024.109051>
- Vieira G., Ferrarezi R. (2021). Use of thermal imaging to assess water status in citrus plants in greenhouses. *Horticulturae*, 7(8): 249. <https://doi.org/10.3390/horticulturae7080249>
- Villalobos F.J., Testi L., Orgaz F., García-Tejera O., Lopez-Bernal A., González-Dugo M.V., Ballester-Lurbe C., Castel J.R., Alarcón-Cabañero J.J., Nicolás-Nicolás E., Girona J., Marsal J., Fereres E. (2013). Modelling canopy conductance and transpiration of fruit trees in Mediterranean areas: A simplified approach. *Agricultural and Forest Meteorology*, 171–172: 93-103. <https://doi.org/10.1016/j.agrformet.2012.11.010>
- Villalobos-González L., Muñoz-Araya M., Franck N., Pastenes C. (2019). Controversies in Midday Water Potential Regulation and Stomatal Behavior Might Result From the Environment, Genotype, and/or Rootstock: Evidence From Carménère and Syrah Grapevine Varieties. *Front. Plant Sci.*, 10: 1522. <https://doi.org/10.3389/fpls.2019.01522>
- Vitrack-Tamam S., Holtzman L., Dagan R., Levi S., Tadmor Y., Azizi T., Rabinovitz O., Naor A., Liran O. (2020). Random forest algorithm improves detection of physiological activity embedded within reflectance spectra using stomatal conductance as a test case. *Remote Sensing*, 12(14): 2213. <https://doi.org/10.3390/rs12142213>
- Wang K., Dickinson R. (2012). A review of global terrestrial evapotranspiration: observation, modeling, climatology, and climatic variability. *Reviews of Geophysics*, 50: RG2005. <https://doi.org/10.1029/2011rg000373>
- Wang Z., Leng Q., Huang, L., Zhao L., Xu Z., Hou R., Wang C. (2009). Monitoring system for electrical signals in plants in the greenhouse and its applications. *Biosyst. Eng.*, 3: 1–11. <https://doi.org/10.1016/j.biosystemseng.2009.01.013>
- Wang J., Xu R., Yang S. (2008). Estimation of plant water content by spectral absorption features centered at 1,450 nm and 1,940 nm regions. *Environmental Monitoring and Assessment*, 157(1-4): 459-469. <https://doi.org/10.1007/s10661-008-0548-3>
- Wang H., Zhao Y. (2010). Measuring water content variations in stems by standing wave ratio principle. *Proceedings of the 2010 IEEE International Conference on Mechatronics and Automation*, Xi'an, China, 2010, pp. 124-128. <https://doi.org/10.1109/icma.2010.5588432>
- Wei H., Grafton M., Bretherton M., Irwin M., Sandoval E. (2021). Evaluation of point hyperspectral reflectance and multivariate regression models for grapevine water status estimation. *Remote Sensing*, 13(16): 3198. <https://doi.org/10.3390/rs13163198>

- Wei Z.W., Lee X.H., Wen X.F., Xiao W. (2018). Evapotranspiration partitioning for three agro-ecosystems with contrasting moisture conditions: a comparison of an isotope method and a two-source model calculation. *Agricultural and Forest Meteorology*, 252: 296–310. <https://doi.org/10.1016/j.agrformet.2018.01.019>
- Wehr R., Commane R., Munger J.W., McManus J.B., Nelson D.D., Zahniser M.S., Saleska S.R., Wofsy S.C. (2017). Dynamics of canopy stomatal conductance, transpiration, and evaporation in a temperate deciduous forest, validated by carbonyl sulfide uptake. *Biogeosciences*, 14: 389–401. <https://doi.org/10.5194/bg-14-389-2017>
- Wehr R., Saleska S.R. (2021). Calculating canopy stomatal conductance from eddy covariance measurements, in light of the energy budget closure problem. *Biogeosciences*, 18 (1): 13–24. <https://doi.org/10.5194/bg-18-13-2021>
- Williams L. (2012). Leaf water potentials of sunlit and/or shaded grapevine leaves are sensitive alternatives to stem water potential. *Oeno One*, 46(3): 207. <https://doi.org/10.20870/oeno-one.2012.46.3.1522>
- Williams L.E., Araujo F.J. (2002). Correlations among predawn leaf, midday leaf, and midday stem water potential and their correlations with other measures of soil and plant water status in *Vitis vinifera*. *J. Amer. Soc. Hort. Sci.*, 127 (3): 448–454. <https://doi.org/10.21273/JASHS.127.3.448>
- Williams L.E., Baeza P., Vaughn P. (2012). Midday measurements of leaf water potential and stomatal conductance are highly correlated with daily water use of Thompson Seedless grapevines. *Irrig Sci*, 30: 201–212. <https://doi.org/10.1007/s00271-011-0276-2>
- Williams L.E., Matthews M.A. (1990). Grapevine. In: Stewart, B.A., Nielsen, D.R. (eds.), *Irrigation of Agricultural Crops. Series of Agronomy*, vol. 30. American Society of Agronomy, Madison, Wisconsin, USA, pp. 1019–1055.
- Wilson J.E. (2001). Geology and Wine 4. The Origin and Odyssey of Terroir. *Geoscience Canada*, 28 (3): 139–141.
- Wine Australia (2025). Australian Wine Geographical Indications (GIs). Available online: <https://www.wineaustralia.com/labelling/register-of-protected-gis-and-other-terms/australian-wine-geographical-indications> (Accessed on: 15 January 2025).
- Wu R.-Q., Jia J.-B., Yan W.-D., Hu L., Wang Y.-F., Chen Y. (2022). Characteristics of canopy conductance and environmental driving mechanism in three monsoon climate regions of China. *Front. Environ. Sci.*, 10: 935926. <https://doi.org/10.3389/fenvs.2022.935926>
- Xu J., Wu B., Ryu D., Yan N., Zhu W., Ma Z. (2021). Quantifying the contribution of biophysical and environmental factors in uncertainty of modeling canopy conductance. *J. Hydrol.*, 592: 125612. <https://doi.org/10.1016/j.jhydrol.2020.125612>
- Yago F.J.M. (2024). Viticulture in Jumilla (Spain). Contributions to sustainable territorial development. *Perspectiva Geográfica*, 29 (3): 1–23. <https://doi.org/10.19053/upsc.01233769.16625>
- Yan X., Wang Z., Huang L., Wang C., Hou R., Xu Z., Qiao X. (2009). Review Research progress on electrical signals in higher plants. *Prog. Nat. Sci.*, 19: 531–541. <https://doi.org/10.1016/j.pnsc.2008.08.009>
- Yang Y., Kim J., Song H., Lee E., Choi Y., Jo J., Jeon H.J., Kim H.H., Kim K.J., Kim H.J. (2021). Methodology: non-invasive monitoring system based on standing wave ratio for detecting water content variations in plants. *Plant Methods*, 17(1): 56. <https://doi.org/10.1186/s13007-021-00757-y>

- Ye Q., Wang H., Li H. (2022). Arbuscular mycorrhizal fungi improve growth, photosynthetic activity, and chlorophyll fluorescence of *Vitis vinifera* L. cv. *Ecolly* under drought stress. *Agronomy*, 12(7): 1563. <https://doi.org/10.3390/agronomy12071563>
- Yumeina D., Morimoto T. (2017). Identifying and modelling the dynamic response of leaf water content to water temperature in hydroponic tomato plant. *Environment Control in Biology*, 55(1): 13-20. <https://doi.org/10.2525/ecb.55.13>
- Zait Y., Shapira O., Schwartz A. (2017). The effect of blue light on stomatal oscillations and leaf turgor pressure in banana leaves. *Plant Cell & Environment*, 40(7): 1143-1152. <https://doi.org/10.1111/pce.12907>
- Zakariyya F., Indradewa D., Santoso T. (2019). Changes of leaf anatomical profile of cocoa clones seedlings in response to drought. *Pelita Perkebunan* (A Coffee and Cocoa Research Journal), 35(3): 177-185. <https://doi.org/10.22302/iccricri.jur.pelita.perkebunan.v35i3.390>
- Zakhidov E., Nematov S., Kuvondikov V. (2016). Monitoring of the drought tolerance of various cotton genotypes using chlorophyll fluorescence. In: Najafpour M.M. (ed.). *Applied Photosynthesis - New Progress*. InTech. <https://doi.org/10.5772/62232>
- Zambon I., Colantoni A., Cecchini M., Mosconi E. (2018). Rethinking sustainability within the viticulture realities integrating economy, landscape and energy. *Sustainability*, 10(2): 320. <https://doi.org/10.3390/su10020320>
- Zarrouk O., Brunetti C., Egipto R., Pinheiro C., Genebra T., Gori A., Lopes C.M., Tattini M., Chaves M.M. (2016) Grape Ripening is Regulated by Deficit Irrigation/Elevated Temperatures According to Cluster Position in the Canopy. *Front. PlantSci.*, 7: 1640. <https://doi.org/10.3389/fpls.2016.01640>
- Zhai Z., Martínez J.F., Beltran V., Martínez N.L. (2020). Decision support systems for agriculture 4.0: Survey and challenges. *Comput. Electron. Agr.*, 170: 105256. <https://doi.org/10.1016/j.compag.2020.105256>
- Zhang J., Schurr U., Davies W.J. (1987). Control of Stomatal Behaviour by Abscissic Acid which Apparently Originates in the Roots. *Journal of Experimental Botany*, 38 (7): 1174–1181. <https://doi.org/10.1093/jxb/38.7.1174>
- Zhang Y., Lamarque L., Torres-Ruiz J., Schuldt B., Karimi Z., Li, S., Qin D.-W., Bittencourt P., Burlett R., Cao K.-F., Delzon S., Oliveira R., Pereira L., Jansen S. (2018a). Testing the plant pneumatic method to estimate xylem embolism resistance in stems of temperate trees. *Tree Physiology*, 38(7): 1016-1025. <https://doi.org/10.1093/treephys/tpy015>
- Zhang Y., Pichon L., Pellegrino A., Roux S., Péruzzaro S., Tisseyre B. (2024). Predicting predawn leaf water potential while accounting for uncertainty using vine shoot growth and weather data in Mediterranean rainfed vineyards. *Agricultural Water Management*, 302: 108998. <https://doi.org/10.1016/j.agwat.2024.108998>
- Zhang X., Yu N., Xi G., Meng X. (2012). Changes in the power spectrum of electrical signals in maize leaf induced by osmotic stress. *Chinese Science Bulletin*, 57(4): 413-420. <https://doi.org/10.1007/s11434-011-4820-5>
- Zhang Z., Gong Y., Wang Z. (2018b). Accessible remote sensing data based reference evapotranspiration estimation modelling. *Agr. Water Manag.*, 210: 59–69. <https://doi.org/10.1016/j.agwat.2018.07.039>
- Zhao P., Liu X., Rao X., Chen X. (2008). Response of canopy stomatal conductance of acacia mangium forest to environmental driving factors. *Frontiers of Forestry in China*, 3(1), 64-71. <https://doi.org/10.1007/s11461-008-0001-3>

- Zhao T., Nakano A., Iwaski Y., Umeda H. (2020). Application of hyperspectral imaging for assessment of tomato leaf water status in plant factories. *Applied Sciences*, 10(13): 4665. <https://doi.org/10.3390/app10134665>
- Zhou H., Sun Y., Tyree M., Sheng W., Cheng Q., Xue X., Schumann H., Lammers P. (2014). An improved sensor for precision detection of *in situ* stem water content using a frequency domain fringing capacitor. *New Phytologist*, 206(1): 471-481. <https://doi.org/10.1111/nph.13157>
- Zhou J., Yuan W., Di B., Zhang G., Zhu J., Zhou P., Ding T., Qian J. (2022). Relationship among electrical signals, chlorophyll fluorescence, and root vitality of strawberry seedlings under drought stress. *Agronomy*, 12(6): 1428. <https://doi.org/10.3390/agronomy12061428>
- Zimmermann D., Reuss R., Westhoff M., Geßner P., Bauer W., Bamberg E., Bentrup F-W., Zimmermann U. (2008). A novel, non-invasive, online-monitoring, versatile and easy plant-based probe for measuring leaf water status. *Journal of Experimental Botany*, 59(11): 3157-3167. <https://doi.org/10.1093/jxb/ern171>
- Zimmermann U., Bitter R., Marchiori P., Rüger S., Ehrenberger W., Sukhorukov V., Schüttler A., Ribeiro R. (2013). A non-invasive plant-based probe for continuous monitoring of water stress in real time: a new tool for irrigation scheduling and deeper insight into drought and salinity stress physiology. *Theoretical and Experimental Plant Physiology*, 25(1): 2-11. <https://doi.org/10.1590/s2197-00252013000100002>
- Zimmermann U., Rüger S., Shapira O., Westhoff M., Wegner L., Reuss R., Gessner P., Zimmermann G., Israeli Y., Zhou A., Schwartz A., Bamberg E., Zimmermann D. (2010). Effects of environmental parameters and irrigation on the turgor pressure of banana plants measured using the non-invasive, online monitoring leaf patch clamp pressure probe. *Plant Biology*, 12(3): 424-436. <https://doi.org/10.1111/j.1438-8677.2009.00235.x>
- Zoro-Diana E., Soro P., Diomande K., Dian K., Kamate A., Adohi-Krou A. (2017). Water deficiency detection of *Hevea brasiliensis* clones by laser induced fluorescence. *Applied Physics Research*, 9(5): 36-41. <https://doi.org/10.5539/apr.v9n5p36>
- Zufferey V., Cochard H., Améglio T., Spring J., Viret O. (2011). Diurnal cycles of embolism formation and repair in petioles of grapevine (*Vitis vinifera* cv. Chasselas). *Journal of Experimental Botany*, 62(11): 3885-3894. <https://doi.org/10.1093/jxb/err081>
- Zweifel R., Item H., Häslér R. (2000). Stem radius changes and their relation to stored water in stems of young Norway spruce trees. *Trees*, 15: 50-75. <https://doi.org/10.1007/s004680000072>

List of Tables

Section 1. Introduction

Table 1.1 - Predawn leaf water potential (ψ_{PD}), stem water potential (ψ_{stem}), midday leaf water potential (ψ_{mid}) thresholds for grapevine water stress. (Adapted from Rienth and Scholasch, 2019) 24

Table 1.2 - Leaf stomatal conductance to water vapour (g_s) thresholds for grapevine water stress. (Adapted from Rienth and Scholasch, 2019) 25

Table 1.3 - Terminology used to define Iso and Anisohydric behaviour according to bibliography (Notable Mentions). (Adapted from Hochberg et al., 2018) 26

Table 1.4 - Carbon isotopic discrimination ($\delta^{13}C$) thresholds for grapevine water stress. (Adapted from Rienth and Scholasch, 2019) 35

Section 3. Experimental layout

Table 3.1 - The characterization of air temperature patterns, the number of days with air temperatures exceeding 35 °C, and the number of days with precipitation during berry development to grape ripening (June to August) is presented. Air temperature data are expressed as the mean $\pm$ standard deviation, with the following variables: Tavg (daily mean air temperature), Tmin (daily minimum air temperature), and Tmax (daily maximum air temperature)..... 53

Section 4. Materials

Table 4.1 - Equipment utilized and variables recorded 57

List of Figures

Section 1. Introduction

Figure 1.1 – Meteorological-based methods to assess grapevine water status. a) Automatic meteorological station, WxPRO (Campbell Scientific, Logan, UT, USA); Micrometeorological station (eddy covariance / Instantaneous fluxes method), (FLIR Systems Inc., Wilsonville, OR, USA).	19
Figure 1.2 – Soil-based sensors to assess grapevine water status. a) gravimetric method (Photo: https://www.wikihow.com/Measure-Soil-Moisture); b) Tensiometer. (Photo: https://ucanr.edu); c) Capacitance probe. (Photo: https://extension.umn.edu); d) TDR probe. (Photo: https://extension.umn.edu); e) Watermark (The Irrrometer Company, Inc., CA, USA) - Electric resistance probe (Photo: https://extension.umn.edu); f) Neutron probe. (Photo: https://ucanr.edu).	21
Figure 1.3 – Water potential (pressure chamber) method to assess grapevine water status. a) Scholander-type pressure chamber (PMS 600, PMS Instrument Company, Albany, OR, USA); b) Stem water potential measurement (reflective plastic bag leaf enclosure); c) Predawn leaf water potential measurement (leaves collected before sunrise); d) introducing the leaf into the chamber, ensuring a small portion of the petiole remains exposed outside of the chamber; e) water appears at the cut surface of the petiole, reflecting the tension the leaf is experiencing to retain water.	24
Figure 1.4 – Stomatal conductance measurement sensors. a) Steady-state leaf porometer model LI-1600 (LI-COR, Lincoln, NE, USA); b) Portable Photosynthesis system model LI-6800, InfraRed Gas Analyzer (IRGA) (LI-COR, Lincoln, NE, USA) c) Leaf porometer/fluorometer model LI-600 (LI-COR, Lincoln, NE, USA).	26
Figure 1.5 – Sapflow sensors. a) Heat dissipation method (Granier method) (https://lwf.wsl.ch); b) Stem heat balance (SHB) method (Valancogne and Nasr, 1989; Sakuratani, 1981) – Dynagage sensor(https://www.dynamax.com).	28
Figure 1.6 – Stem and fruit diameter variation sensors. a) Trunk/stem dendrometer; b) Fruit dendrometer (https://edaphic.com.au)	30
Figure 1.7 – Infrared Thermal Imaging sensors. a) Drone DJI Matrice 300 (SZ DJI Technology Co., Ltd., Shenzhen, China) equipped with FLIR Vue TZ20 b) FLIR Vue Pro for UAV; c) FLIR T865 handheld thermal imaging camera (FLIR Systems Inc., Wilsonville, OR, USA).	31
Figure 1.8 – Spectral and Hyperspectral Imaging sensors. a) Micasense RedEdge MX camera (https://ageagle.com); b) Portable remote sensing spectroradiometer - ASD Fieldspec4 (https://www.malvernpanalytical.com); c) DJI Matrice 600 (SZ DJI Technology Co., Ltd., Shenzhen, , China) equiped with a co-aligned Headwall Photonics VNIR/SWIR hyperspectral camera (https://analytik.co.uk/airborne-hyperspectral-imaging).	33
Figure 1.9 – Leaf turgor pressure sensor. YARA water sensor (YARA ZIM Plant technology GmbH, Hennigsdorf, Germany). (www.yara.com/water)	37
Figure 1.10 – Chlorophyll fluorescence sensors. a) Multiplex® 3 (FORCE-A, Centre Universitaire Paris-Sud ORSAY, Orsay, France); b) Walz MINI-PAM-II with Porometer leaf clip. Fluorometry and stomatal conductance (Heinz Walz GmbH, Effeltrich, Germany); c) Leaf porometer/fluorometer model LI-600 (LI-COR, Lincoln, NE, USA)	40
Figure 1.11 – Xylem hydraulic conductivity monitoring apparatus. The XYL'EM (INRA, Clermont-Ferrand, Auvergne France) (https://eng-piaf.clermont.hub.inrae.fr/methods-and-models/xyl-em)	42

Section 4. Materials

Figure 4.1 – Open path eddy covariance system. (a) LI-7500DS Open Path CO ₂ /H ₂ O Gas Analyzer (LI-COR Inc., Lincoln, NE, USA), (b) Gill WindMaster/Pro sonic anemometer (Gill Instruments Limited, Hampshire, UK), (c) SmartFlux® 3 System (LI-COR Inc., Lincoln, NE, USA), and (d) network switch (LI-COR Inc., Lincoln, NE, USA).	54
Figure 4.2 – Solar radiation shield and Thermohygrometer CS215-PWS (Campbell Scientific, Logan, UT, USA).....	55
Figure 4.3 – Soil moisture ML3 Thetaprobe sensor (Delta-T devices, Cambridge, UK).	55
Figure 4.4 – Net radiometer NR2 (Delta-T devices, Cambridge, UK).	55
Figure 4.5 – HFP01 heat flux plate (Hukseflux Thermal Sensors, Delft, The Netherlands).	55
Figure 4.6 – Gill 2D Ultrasonic anemometer ANE 5M (Gill Instruments Limited, Hampshire, UK).	55
Figure 4.7 – CR1000 Datalogger (Campbell Scientific, Logan, UT, USA).....	55
Figure 4.8 – Infrared thermal camera FLIR model C5 (FLIR Systems Inc., Wilsonville, OR, USA).	56
Figure 4.9 – Scholander-type pressure chamber (PMS 600, PMS Instrument Company, Albany, OR, USA).	56
Figure 4.10 – Steady-state leaf porometer model LI-1600 (LI-COR, Lincoln, NE, USA).	56

Section 5. Methodology

Figure 5.1 - Data structure. The original data was divided into three final datasets: a training and testing dataset containing 40% of all data from the years 2019 and 2020, and two external validation datasets containing the remaining data from the years 2019 and 2020.	58
Figure 5.2 – Schematic representation of the three-source clumped model for convective fluxes (specifically sensible heat, H) partitioning in a sparse canopy, illustrating the associated air and surface temperatures. This system enabled the measurement of the vertical profile of energy fluxes, including the observed latent heat flux and sensible heat flux at the reference height, over the experimental vineyard.	61