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The potential of thermal imaging to assist winemakers in the detection of downy mildew in Vitis vinifera cv Loureiro

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Abstract

Vineyards represent one of the main crop systems of greatest importance in the world economy, both in terms of the value chain of wine production and in its current expression of generating tradable goods. One of the challenges of grape production is grapevine health, which annually forces the winegrowers to incur fixed costs associated with the prevention and/or treatment of pests and diseases, causing an impact on the environment due to the application of phytosanitary products. Among the various diseases affecting grapevines, downy mildew (*Plasmopara viticola*) stands out, which causes negative impacts throughout the phenological cycle, particularly on leaves by affecting the absorption of photosynthetic pigments and consequent chlorophyll production, ultimately influencing grape yield and quality. Traditional methods for detecting vineyard diseases are often insufficient in crop protection, favoring new forms of a more agile decision support with timely responses. Proximal sensing trough optical sensors can assist in early disease detection. In this context, thermal infrared sensors stand out for their ability to capture changes in thermal response of leaves due to changes in grapevine metabolism and photosynthetic production. This study aims to explore

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the use of thermal infrared imagery to assess the detection of downy mildew by evaluating temperature variations in the surface of grapevine leaves when compared with non-infected leaves in a vineyard plot of the cv. Loureiro. The effects of temporal and spatial variability on the temperature of mildew-infected vine leaves are reported. A temperature variation of 2.71 °C was found within the same leaf when comparing to infected and non-infect areas. As the infection progresses over time, thermal variation tends to increase.

Keywords: proximity sensors; thermography; disease detection; precision viticulture; agricultural mechanization and automation.

1. Introduction

Diseases caused by pathogens are among the main factor of productivity losses in agricultural crops worldwide, leading to economic losses for farmers [1]. The challenges in identifying chemical, physical, and biological changes before its visible manifestation of a disease makes necessary to have early knowledge and diagnosis approaches, not only due to the need to anticipate the action and efficiency of a treatment, but also to reduce potential preventive and curative treatments, which carry environmental and economic impacts [2].

Downy mildew, caused by the fungus *Plasmopara viticola*, has substantial impacts on viticulture, affecting grapevines in various ways. Primary consequences range from reduced grape production to decreased wine quality, along with additional costs associated with disease control [3]. Leaf damage compromise the grapevines' ability to perform photosynthesis, resulting in lower sugar accumulation in grapes and, consequently, wines with low sugar content and unbalanced acidity. Additionally, rapid spread of downy mildew can lead to significant production losses, generating substantial economic impacts for grape growers. Disease control often requires the use of fungicides, which not only implies additional costs for producers but also raises environmental concerns [4].

There are two main methods for disease identification: invasive and non-invasive methods [5]. Invasive methods require sampling in the field, destroying the leaf for later analysis in the laboratory [6]. Non-invasive methods identify diseases through metabolic changes in plants, mainly in the leaves [7]. In this methods, detections through optical sensors [7,8], stand out, which can be classified as proximity sensors [9] or aerial sensors [10,11]. Different sensors that can be used for this task as: multispectral [10,12], hyperspectral [13], thermal infrared (TIR) [14], field spectroradiometers [14], and/or fluorescence sensors [15]. In this variety of sensors, TIR sensors emerged as a tool to help in the early and even pre-early identification of disease outbreaks [9,16].

In viticulture, TIR sensors can help in identifying minimal thermal variations in grapevine leaves, which can be crucial for identifying the onset of infections. These subtle variations can be indicators of diseases, allowing for rapid and effective interventions. With an early detection of these problems, winegrowers can implement targeted control measures, reducing losses and increasing grape and yield quality. Thus, proximity TIR sensors are a valuable tool in attempting to ensure grapevine health and their productivity [9,17].

This study aims to analyze the thermal variations in the grapevine leaves affected by downy mildew, comparing it with an unaffected area. Moreover, the feasibility of detecting the presence of this fungus in leaves through the analysis of thermal variation is also assessed. This can help in the understanding the relationship between the presence of downy mildew, thermal variations in leaves, and the possibility of using TIR sensors as an indicator for fungus detection, providing a helpful tool for winegrowers.

2. Materials and methods

2.1. Study area and experimental design

This study was conducted during 2022 in a plot of *vitis vinifera* cv. Loureiro planted in 2009, with a total area of 5.5 hectares, located in the demarcated Vinho Verde region, Viana do Castelo, northwest Portugal (41°47'34.79"N, -8°31'21.11"W, altitude 52 meters), as shown in Fig. 1a. The choice of this location allowed for a detailed analysis of the thermal responses of *vitis vinifera* cv. Loureiro leaves in a typical environment of the Vinho Verde wine region, contributing to the understanding of plant adaptations to local conditions. The vineyard rows are oriented in a North-South direction, with a plant spacing of 2 × 3 meters, in a single upward cordon training system.

Fig. 1. Location of the study area within Portugal mainland and the experimental design (a) and a demonstrative example of the location of leaves used for thermal infrared data acquisition (b), in the upper, middle, and lower thirds of the grapevine.

The experimental design consisted of two blocks: one zone with phytosanitary treatments (purple rows in Fig. 1a), hereinafter referred as WT; and another where no phytosanitary treatments were applied (red rows in Fig. 1a), hereinafter referred as NT. Each block comprised six rows. The two rows located in the middle of the NT and WT blocks were used for data acquisition, while the other was used as containment rows on each side. Four plants per block were selected for the data acquisition, with three leaves analyzed on each grapevine, as illustrated in Fig. 1b. This experimental arrangement was designed to provide a significant representation of leaf thermal conditions, allowing for a precise analysis of plant responses throughout the study period.

2.2. Data acquisition

The infrared camera FLIR E75 (Teledyne FLIR LLC, Oregon, USA), was used for TIR imagery acquisition in a study conducted between June 24th and August 31st, 2022. The imagery capture process was conducted in weekly basis, resulting in a total of 11 acquisition periods. Images were obtained during solar noon, between 13:30 and 14:30, when solar radiation reaches its peak, maximizing temperature variations on the leaf surface (Fig. 2). Each pixel of the image has a temperature reading in degrees Celsius.

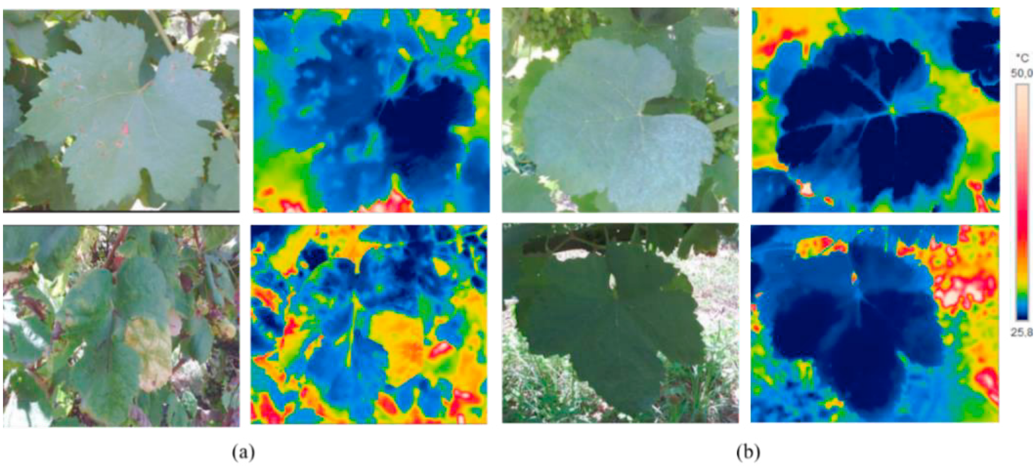

Fig. 2. Example of captured thermal infrared and RGB images of grapevine leaves, infected with downy mildew (a) and not infectd (b).

All images were acquired under clear sky, with minimal wind conditions. The air temperature, relative humidity and reflected temperature at the time of imagery acquisition were collected using a psychrometer. Each TIR image covered an area of one leaf, allowing for a detailed analysis of thermal variations. This approach enabled the identification of specific patterns and the assessment of areas susceptible to stress. The captured images were processed using FLIR Tools software. This software suite offers advanced analysis and visualization functionalities, allowing for the extraction of relevant information about leaf thermal conditions and its environment.

2.3. Data extraction and statistical analysis

The TIR imagery provided data on absolute temperature after being inserted the ambient temperature and relative humidity (acquired through a psychrometer), reflected temperature, thermal emissivity (0.95), and object distance which varied between 0.30 and 0.60 m. Thermal data were analyzed by extracting leaf temperature from sampling areas. From these areas, the maximum, minimum, mean, and median temperatures were extracted. These values were used to calculate other metrics by including air temperature, as presented in Table 1.

Table 1. Variables used for the analysis of leaf temperature with and without downy mildew infection. T_{air}: air temperature; T_{min}, T_{max}, T_{mean}, T_{median}: minimum, maximum, mean, median leaf temperature; T_{inf}, T_{noninf}: leaf temperature in areas infected by downy mildew and in non-infected areas.

Variable name	Description	Equation
Min. Temperature	Minimum temperature on the leaf subtracted to the air temperature	T_{min}-T_{air}
Max. Temperature	Maximum temperature on the leaf subtracted to the air temperature	T_{max}- T_{air}
Mean Temperature	Mean leaf temperature values subtracted to the air temperature	T_{mean}- T_{air}
Median Temperature	Median leaf temperature values subtracted to the air temperature	T_{median}- T_{air}
Temperature range	Difference between the maximum and minimum temperature on the leaf	T_{max}-T_{min}
Thermal variation	Variation between the average temperature of infected and the non-infected leaf areas	$T_{inf.}$-$T_{nontinf}$

Statistical analysis was conducted using SPSS Statistics 22 (IBM Corp., NY, USA). The focus of the analysis was to evaluate possible temperature differences between downy mildew-infected and non-infected zones on individual leaves, as well as between leaves showing absence of disease compared to infected leaves. The variables described in Table 1 were subjected to standard Analysis of Variance (ANOVA) to determine the effect of *P*, maintaining a minimum significance level of 0.001. Additionally, Pearson correlation (*r*) was performed to examine linear relationships between variables.

3. Results and Discussion

3.1. Data characterization

The data acquired provides a meticulous overview of climatic fluctuations over a three-month period (Fig. 3). During June, the air temperature remained around 21 °C, with relative humidity varying between 62% and 66%. The reflected temperature varied between 25 °C and 28 °C. In July, the average air temperature during data acquisition was 32.75 °C, while relative humidity was 47% and reflected temperature was 34.5 °C. In August, an average air temperature of 30.6 °C was observerd, with relative humidity being 48.8% and the average reflected temperature decreased to 32.4 °C. From the analysis of Fig. 3 it is demonstrated that lower humidity values result in higher reflected temperatures, while higher humidity levels lead to lower reflected temperatures. Temporal analysis reveals specific variations, as evidenced by the data on 13 July, which showed an increase in air temperature (36 °C) with a proportional reduction in relative humidity (38%). The overall average values for the period indicate an air temperature of approximately 29.64 °C and a relative humidity of 50.91% (Fig. 3).

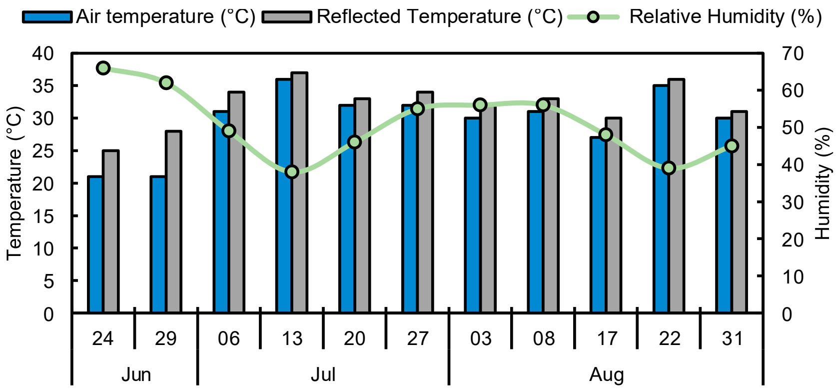

Fig. 3. Air temperature, reflected temperature, and relative humidity of the study area in each thermal infrared imagery collection period.

Upon analysing the statistical data (Table 1), two distinct trends emerge as presented in Table 2. In areas not infected with mildew, temperatures exhibited considerable variation, with significant lower and heigh temperatures throughout the period. The difference between the average leaf temperature and the air temperature remained below zero in the majority of observations, with the lowest values observed in mid-August.. This is a grapevine physiological response to high temperatures and low relative humidity. In contrast, the maximum values observed at the beginning of the study period, in June, reaching an average of 0.39 °C and a maximum of 0.53 °C on 24 June. However, even with these fluctuations, the temperature range was not excessive, with the greatest variation being 0.82 °C on 22 August.

Table 2. Basic statistics according to the temperature for leaf areas infected with downy mildew and non-infected. Values in degrees Celsius subtracted to the air temperature.

Leaf area	Not infected				Infected with downy mildew			
Date (Day/Month)	Mean	Max.	Min.	Range	Mean	Max.	Min.	Range
24/06	0.39	0.53	0.17	0.40	2.89	3.21	1.87	1.63
29/06	–0.84	–0.53	–1.12	0.59	1.95	2.52	1.26	1.26
06/07	–3.83	–3.44	–4.07	0.63	–0.44	0.07	–1.30	1.37
13/07	–6.11	–5.63	–6.22	0.71	–1.35	–0.85	–2.44	1.59
20/07	–5.52	–5.06	–5.82	0.76	–1.94	–0.97	–2.96	1.99
27/07	–5.84	–5.54	–6.07	0.53	–1.72	–1.36	–2.32	0.96
03/08	–5.49	–5.24	–5.66	0.42	–1.87	–0.98	–2.69	1.71
08/08	–7.33	–7.01	–7.52	0.51	–4.89	–3.99	–5.61	1.62
17/08	–6.18	–5.87	–6.40	0.53	–3.75	–3.31	–4.33	1.02
22/08	–5.01	–4.51	–5.33	0.82	–0.53	0.88	–2.08	2.96
31/08	–6.28	–5.97	–6.53	0.55	–2.08	–1.38	–3.40	2.02

The leaf temperature differences in parts with downy mildew symptoms showed considerable temperature variations over the period analysed. The average temperatures in the infected zones were higher than in the uninfected area of the leaves, but they showed more pronounced fluctuations. The lowest values were observed on 8 August, with an average of –4.89 °C, while the highest values occurred on 24 June, reaching an average of 2.89 °C. It is noteworthy that the temperature variations were more pronounced in leaf parts infected with downy mildew, with the highest temperature amplitude recorded on 22 August (2.96 °C).

When comparing infected leaf parts with parts not infected with mildew, there are considerable temperature variations throughout the observation period. Parts with downy mildew exhibited higher average temperatures but were also more prone to extreme fluctuations in its temperature when compared to not infected parts, resulting in an higher temperature range within leaves. In contrast, non-infected areas maintained lower temperatures, with fewer significant variations over time, following the same trend as Zia-Khan et al. [18].

3.2. Leaf temperature variations between strategies

A comparative analysis of the thermal variation between leaves from NT and WT areas of the vineyard plot (Fig. 1a) from June to August revealed significant fluctuations, as presented in Fig. 4. Leaves in NT area exhibited the greatest variation (4.71 °C) in 13th of July. Similarly, on the 22nd of August, a high temperature variation was also observed, reaching 4.48 °C. Furthermore, the overall average temperature variation on all dates was 2.71°C, which is consistent with the findings of Zia-Khan, et al. [18], providing a consolidated measure of thermal instability during the period analyzed. In the case of leaves from WT part of the vineyard, the tempearture differences within the leaves is consistently lower along the dates when comparing with NT results, with a slight approximation in this variation on 22 August. The minimum variation was observed on 8 August, with a variation of 1.03 °C.

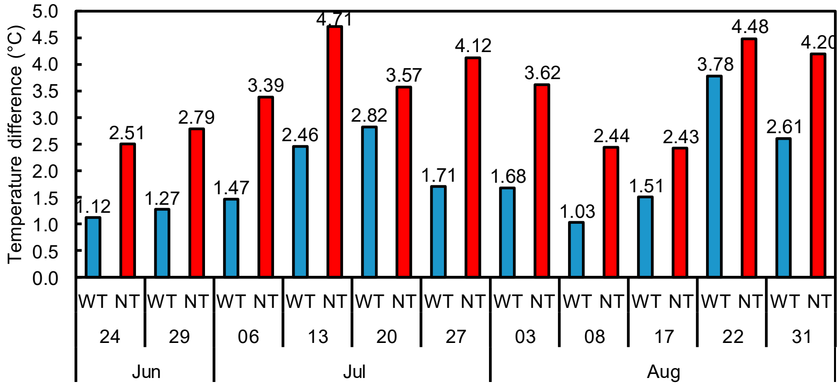

Fig. 4. Differences of the average temperature within the same leaves from plants with phytosanitary treatment (WT) and in leaves with no phytosanitary treatments (NT).

In terms of thermal variation, there are periods that indicate peaks in temperature differences, highlight the amplitude of thermal changes over the period. The maximum variation of 4.71 °C on 13 July (NT) contrasts with the minimum of 1.74 °C on 8 August (WT), emphasizing the wide range of thermal variation in the leaves. This substantial variation serves to highlight the thermal dynamics of the leaves over the weeks analyzed, and thus reinforces the importance of considering not only average values but also amplitude (temperature range) when interpreting leaf thermal patterns in response to infection (Fig. 4).

3.3. Statistical analysis

The results indicate that the differences between leaf areas with downy mildew and not infected areas and between leaves with downy mildew (NT) and leaves without the presence of the fungus (WT) are statistically significant in all analyses, as evidenced by the p-values (<0.001), demonstrating the potential of TIR imagery in fungal disease detection [9,14,17]. Additionally, a high correlation values is achieved ($r = 0.966$ and 0.925) presented in Fig. 5. Suggesting that the models used are effective in explaining the variability in temperature data, with the first model being particularly robust (Fig. 5a), explaining almost all observed variability as demonstrated by Khan, et al.[18]. These results are consistent with a statistically significant association between the temperatures analyzed in the NT and WT groups, indicating that temperature variations are related to statistically significant differences in these conditions.

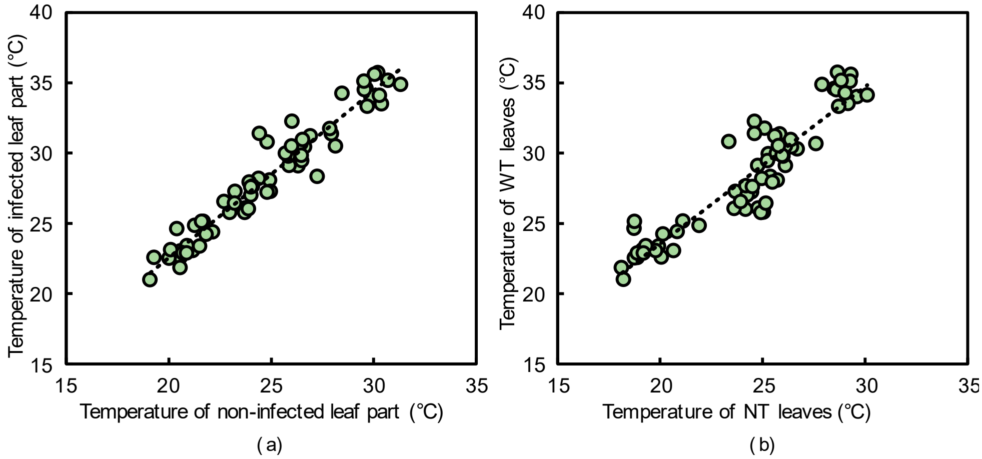

Fig. 5. Correlation between the temperature of infected areas and not-infected areas in the same leaf (a) and (b) between leaves infected with downy mildew (NT) and leaves subjected to downy mildew treatment (WT).

Additionally, it is important to note that no significant differences were observed among healthy leaves or parts in all analyses, regardless of the strategy. This result suggests that for healthy leaves, temperature variations did not play a significant role in the observed differences between groups, indicating thermal normality. Ultimately, a direct relationship was observed between the temperature of the infected leaf parts and healthy leaf parts. This discrepancy increases as the infection progresses over time. In the early stage, the variation is below the average, whereas in the final stage, and even during necrosis, the variation is higher than this average, as demonstrated in Fig. 5.

4. Conclusions

The analysis of the TIR data presented in this study suggests the possibility to monitor the presence downy mildew infection in grapevine leaves. There is a relationship between the temperature in non-infected and infected areas of leaves, with an average temperature difference of 2.71°C, which indicates a direct influence of local temperature on mildew spread. Furthermore, the absence of significant differences between the non-infected leaves and non-mildew zone in the infected leaves suggests that temperature may be a determining factor in the spread or containment of the infection. This equipment could become an important tool for assisting winegrowers in the detection of fungal diseases throughout the whole cycle.

The use of TIR imaging to detect fungal pathogens in grapevines offers significant advantages over traditional laboratory methods. This type of data enables the early identification of infections by capturing and analysing subtle variations in the temperature of grapevine leaves, which can indicate that a fungal infection caused by pathogens is taking place even before symptoms are visible through field observation techniques. This non-invasive, real-time method could enable continuous monitoring of large areas, saving time and resources compared to laboratory analyses, which are more time-consuming and require destructive leaf samples. Although laboratory methods offer greater precision in identifying the specific type of fungus, the agility and practicality of TIR images make them a valuable tool for better management by the winemakers.

As future work, analyzing temperature variations from early infections to leaf senescence, along with weekly readings, offers a temporal and systematic approach to understanding the development of this type of infections and its effects on leaf temperature. This procedure can also be replicated to monitor the incidence of this fungus in grape bunches. Another approach to be evaluated is the comparison of infected and non-infected grapevine canopies and the potential use of other sensors to assess the spatiotemporal influence of downy mildew spread. These sensors can be installed in agriculture machinery, onboard unmanned aerial vehicles or can be permanently installed in wireless sensors networks placed throughout the vineyard plot. Moreover, the findings presented in this study should be corroborated with data from other wine regions with different environmental conditions and grapevine varieties.

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