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Recent progress on grapevine water status assessment through remote and proximal sensing: A review

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ABSTRACT

According to modern precision agriculture principles, remote and proximal sensing can be extraordinarily useful tools for sustainable water resource management in viticulture. More than one hundred papers were read and cataloged to outline the most effective methodology (comprised of platforms, cameras, indices, single bands, and statistical methods) for monitoring water status in different wine grape varieties located in different areas. Satellites and airplanes can monitor areas at the regional or larger scale; however, while satellite images can be free, airplane imagery can be more expensive. The use of satellite platforms is particularly promising, especially due to recent technical progress aimed at improving spatial and temporal resolution. In addition, unmanned aerial vehicles (aka drones) equipped with thermal, multispectral, and hyperspectral cameras have provided excellent results. Proximal thermal and spectral cameras (e.g., handheld or installed in tractors) can be an inexpensive alternative but often present similar problems to traditional methods (e.g., time-consuming). The best results were obtained from thermal indices (e.g., Crop Water Stress Index) and the use of machine learning (ML) algorithms on individual bands and indices obtained with hyperspectral or multispectral cameras carried on drone or satellite platforms.

1. Introduction

From the earliest civilizations, viticulture has been inextricably linked with human history, traditions, and the people's identity from different nations and regions. Today, from an agronomical viewpoint, all this is threatened by climate change. Among the highest likelihood risks of the next ten years are extreme weather events, water scarcity, and environmental damage due to human activities (World Economic Forum, 2021). Many grapevine areas will be increasingly affected by drought, heat waves, and extreme climatic events until at least the mid-century (IPCC, 2022). In addition, more pressure on water resources is expected to increase due to the rapid population and urbanization growth (Caser et al., 2017; Nazemi Rafi et al., 2019). Moreover, the intensive use of wells has led to the progressive saltwater intrusion into coastal aquifers, further reducing the water availability for irrigation (Maggiore et al., 2001; Phogat et al., 2018). Therefore, applying a sustainable irrigation approach (that may reduce viticulture water-footprint) is essential.

Grapevine (*Vitis spp* L.) is one of the most cultivated species in the world (9 percent of the world fruit production in 2020, FAO, 2022), with a cultivated area of 7 million ha according to Bezner Kerr et al. (2022). China, Italy, and France are the largest producing nations (FAOSTAT, 2024). In the Mediterranean area, vineyards have been traditionally cultivated under rainfed conditions. However, the increase in yield and quality as a response to irrigation has promoted installing irrigation systems in newly planted vineyards. Furthermore, in areas with high evaporative demand, irrigation is sometimes necessary not only for economically viable production but also for vine survival.

In agricultural fields, water requirements may be highly variable (Brillante et al., 2016): uniformly irrigating in a vineyard with a specific variability would lead to water stress in some parts and overwatering in others (Brillante et al., 2017; Yu et al., 2020). Irrigation surplus causes a decrease in berry quality due to low tasting scores, loss of color, reduction of sugars, and increase in pH (Bravdo et al., 1985). Therefore, precision irrigation's main objective is rationalizing water consumption, which is possible by determining the within-field spatial variability and

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differentiating water inputs according to it. Given the complex relationships in the Soil-Plant-Atmosphere Continuum (SPAC), grapevine water status at each specific location of the vineyard could be considered related to soil and atmosphere water status but cannot be reliably determined based on either. Furthermore, if we take into consideration that the distribution of water in the soil is quite heterogeneous even within the volume of soil affected by the root system of a single vine and that the agroclimatic parameters of the atmosphere (used to obtain VPD, ETo, etc.) are normally detected with only one onsite agro-meteorological station per vineyard and often for an entire grouping of adjacent vineyards, this result in objective constraints to obtaining the field spatial variability of the water status of the vine based on indirect methods, both soil- and/or atmosphere-based, while they can be reliable in determining vineyard water requirements and its irrigation scheduling. Digital agriculture, especially in the last decade, is addressing the need to determine the within-field spatial variability of the water status of the grapevine in the vineyard by employing thermal and spectral imagery of the canopy derived from remote or proximal sensing, a topic on which this paper will be focused. Remote spectral imagery as well as proximal, in cases where handheld devices are not used but sensor installation platforms such as rovers or operating machines used in the vineyard, cope at the same time with the need to not physically go into the field to collect data and not to leave expensive and sophisticated instrumentation in the field exposed to the elements and to the risk of accidental damage or theft. Techniques involving the application of moderate and mild water stress can be an essential resource if appropriately managed to increase water use efficiency and improve grape composition in red and black varieties (Chaves et al., 2010). Grapevine response to water stress strongly depends on variety (Bota et al., 2016; Levin et al., 2019), intensity (van Leeuwen et al., 2009), cropping systems (Nowack et al., 2024; Mihailescu and Bruno Soares, 2020) and phenological stage (Castellarin et al., 2007). Moreover, it is well documented that a moderate water deficit has the tendency to favorably impact the composition of black grapes, particularly promoting anthocyanin concentration (Castellarin et al., 2007; van Leeuwen et al., 2009; Romero et al., 2013; Gambetta et al., 2020). Basile et al. (2011) demonstrated that different levels of water stress impact the composition of *Cabernet Sauvignon* berries differently depending on the phenological phase. Mild-to-moderate water stress, applied post-fruit-set, and moderate to severe water stress applied post-veraison improved soluble solids concentration (SSC) and increased anthocyanin and polyphenols levels. However, applying water stress, even if mild, during the early stages of berry development, from anthesis to fruit set, had detrimental effects on both yield and berry quality. These results are in agreement with those obtained by Romero et al. (2013) on cv. '*Monastrell*', where mild water stress at the beginning of the season and moderate water stress during pre- and post veraison enhanced berry and wine quality. Moreover, Pérez-Alvarez et al. (2021) found that Vitis vinifera L. cv. *Bobal* grapevines, irrigated at 35% of the crop evapotranspiration (ET_c), exhibited higher total soluble solids accumulation, increased acidity, lower pH, and a greater potential of phenolic compounds compared to grapes under full irrigation, which received 100% of the ET_c. Moreover, no statistically significant differences in anthocyanin extractability were observed between the deficit and full irrigated treatments. However, the water stress response from grapevine is not uniform for all varieties. Some have demonstrated a more or less isohydric trend where a stomatal closure occurs at the first signs of stress (Tardieu, 1998) does not show a large circadian leaf water potential (Ψ_{leaf}) excursion. Other varieties, on the other hand, are characterized by near anisohydric behavior, limiting stomatal aperture only partially and showing considerable circadian variation in leaf water potential (Ψ_{leaf}) (Schultz, 2003).

To make irrigation practices efficient and sustainable while avoiding quantitative and qualitative production losses, it is essential to identify some physiological parameters, that provide an early indicator of vine response to drought. Stomatal conductance (g_s) and stem water potential (Ψ_{stem}) are amongst the most important parameters to observe. Stomatal regulation is a crucial issue for vineyard drought response and water use efficiency (Lovisolo et al., 2010; Martorell et al., 2015). It is well known that stomatal closure is one of the first physiological responses of plants to water deficit and it induces a reduction in net photosynthesis rate (Flexas et al., 2002), and leaf chlorophyll content (Romero et al., 2010). Water potential, measured with a pressure chamber (Scholander et al., 1965) assesses the tension of water inside the xylem. Among daily measurements, stem water potential (Ψ_{stem}), is preferred to leaf water potential (Ψ_{leaf}) in viticulture, because it is more stable and reliable (Ψ_{leaf}) (Choné et al., 2001; Patakas et al., 2005), while Ψ_{leaf} is affected by vapor pressure deficit or leaf intercepted radiation (Álvarez et al., 2020; Vivaldi et al., 2021). The pressure chamber is still the most widely used tool for the accurate monitoring of plant water status, because it is relatively cheap and easy to use (Tomasella et al., 2023). The assessment of plant water status by water potential measurements is a useful tool for irrigation management and it is essential in many studies focused on basic and applied plant sciences. However, monitoring water potentials and stomatal conductance is time-consuming, therefore costly, and requires a consistent assortment of equipment, as well as the need for measurements on many leaves to minimize the high spatial variability of plant water status (Petruzzellis et al., 2022). Remote and proximal sensing collect information over large areas at low costs and can detect spatial variability of crop water stress, overcoming the limitations of traditional methods. This provides a significant benefit over traditional data sources because it is possible and cost-effective to cover a wide area routinely (Kasampalis et al., 2018). High-resolution imagery can be obtained from remote or proximal sensors on different platforms. The distance from the surveyed objects can vary from a few centimeters (e.g., hand-held or tractor mounted sensors), in the case of proximal sensing, to a few hundred meters (MAVs and UAVs, respectively, Manned and Unmanned Aerial Vehicles), to hundreds of kilometers (satellite), in the case of remote sensing. UAVs allow for obtaining the highest spatial and temporal resolution imagery over modest-sized areas, can carry custom/modern sensors and are the most expensive option (Matese et al., 2015). Commercial satellite services have moved in recent years toward offering higher spatial and temporal accuracy and allow large coverage with minimal user intervention (Roy et al., 2021). The vegetation indices or the individual spectral bands acquired by these sensors can be related to ground-data acquired with traditional methods to monitor water stress, to delineate irrigation management zones (Bahat et al., 2021), or to build predictive models (Pôças et al., 2020).

This review aims to highlight the best methodologies (comprised of indices, single bands, and statistical methods) for grapevine water stress assessment through remote and proximal sensing on several varieties under different climate and irrigation conditions. First, the traditional methods used to monitor water status in grapevines were defined, highlighting the strengths, weaknesses and possible methods to improve correlations with thermal or spectral data, Section 3. A similar approach was followed for Platforms and Cameras, Section 4. Section 5 presents a comparison of the best correlations between physiological parameters and vegetation indices or single reflectance bands, obtained with thermal, multi- and hyperspectral cameras. Finally, data analysis methods were described, focusing on innovative machine learning techniques, Section 6. The experiences, advice and opinions found in the reviewed articles were presented and discussed in this paper to support future research and improve achievements in the area of remote and proximal sensing in viticulture.

2. Review methodology

Article were found on Scopus and Web of Science data bases. Several keywords were used to include as many items as possible. First, the crop of interest was inserted: ("viticulture" OR "vineyard" OR "vine" OR "grapevine" OR "wine" OR "Vitis" OR "vinifera"). Next, traditional parameters and instruments used in crop water stress assessment were included: ("water" OR "water stress" OR "SWP" OR "LWP" OR "stem" OR "stomatal conductance" OR "gs" OR "pressure chamber" OR "Scholander" OR "porometer" OR "gas exchange" OR "chlorophyll"). Finally, the innovative methods used in Agriculture 4.0 were added to the research: ("remote sensing" OR "proximal sensing" OR "thermal" OR "multispectral" OR "hyperspectral" OR "UAV" OR "drone" OR "satellite" OR "airborne") AND ("index" OR "indices" OR "VI" OR "vegetation index"). Only works from 2012 onward were selected. After removing duplicates and papers unsuitable for this review, more than one hundred papers were collected. Finally, all the documents and 151 indices and bands (from hyperspectral, multispectral, and thermal cameras from satellites, UAVs, aircraft, and proximal sensors) were cataloged. For each paper, the following were highlighted: author, year, DOI, title, location, platform, camera, indices/bands, parameters studied, number of surveys, vines considered, size of the dataset, statistical methodology, cropping system, variety, irrigation treatment, main objective, and highlights. For each index, the following parameters were highlighted: sensor/camera, full name, formula, estimated parameter, and bibliographical references.

3. Physiological indicators to assess water status

Traditionally, spot measurements of physiological parameters, such as Ψ_{leaf} and Ψ_{stem}, or g_s have been used for the assessment of plant water status. The physiological parameters described in this section are those commonly used to monitor the water status of crops (Fig. 1). They are also used to validate new methodologies, in this case, modern remote and proximal sensing, that can overcome traditional techniques' limitations. These paragraphs introduce the techniques, their strengths, and limitations, and especially suggestions for improving the results regarding correlations with spectral and thermal data.

3.1. Stem water potential (Ψ_{stem})

The Ψ_{stem}, was the most common method across all papers in the collection (Fig. 1).

It is considered a solid reference technique for sustainable irrigation management (Levin, 2019), according to several other studies on grapevine and other tree species (Choné et al., 2001; Moriana et al., 2012). As for the best timing, solar noon is the most used time to conduct the evaluations. Best practices to carry-out this measurement were recently assessed by Levin (2019). The advantage of Ψ_{stem} over Ψ_{leaf} is the very low variability across leaves on the same plant (coefficient of variation lower than 5%), which makes possible to assess grapevine water status by collecting only one leaf per vine (López-García et al., 2021). In addition, the leaves must be covered in bags made of a low water vapor transmission material (high-density polyethylene, HDPE, or metalized biaxially-oriented polyethylene terephthalate BoPET) to stop transpiration and stabilize the water status between the leaf and stem. The equilibration time is very low, Levin (2019) showed that 10 min is sufficient for equilibrium, and Hochberg (2020), suggested that even a shorter timeframe may be needed although from a practical stand-point longer time intervals are most common, as often used in the reviewed articles. Finally, the best practice consists in minimizing the time between excision and measurement, although it is possible to transport the leaves to a more convenient location within a limited timeframe if the bags are fully closed (petiole in the bag) and composed of low water vapor transmission material. Levin (2019) reported a maximum timeframe of 240 s using low density polyethylene, while Hochberg (2020) suggested that longer times are theoretically possible when using lower water vapor transmission material, considering that excised leaves would lose 0.1 MPa for every 9mg of water loss, thus about 0.3 MPa after 150 min when fully enclosed in foil laminated bags. The timeframe between excision and measurement remains a critical issue from a practical standpoint, which limits the amount of leaves that could be assessed in a day also considering that measurements should be conducted within a limited time window, to limit any circadian variation in the Ψ_{stem} (Lopez-Garcia et al., 2021). For the development of predictive models linking to achieve better correlations with data obtained by remote and proximal sensing is important to optimize the pressure chamber protocol; this is possible due to larger datasets and a reduction in the effect given by the circadian variation of the Ψ_{stem}.

3.2. Leaf water potential (Ψ_{leaf})

Ψ_{leaf} is one of the most significant metrics of plant water status, providing key information for several physiological processes including the plant response to water deficit (Rodriguez-Dominguez et al., 2022). Ψ_{leaf} can be measured, using a pressure chamber, using the recommendations described in the previous paragraph (Levin, 2019). As previously discussed, Ψ_{leaf} has a higher variability than Ψ_{stem}, as it is more influenced by the environmental conditions at the leaf level, such as Vapor Pressure Deficit (VPD) or leaf intercepted radiation (Álvarez et al., 2023). As a consequence, the relationships with remote sensed data can be more robust when developed on Ψ_{stem} (Bellvert et al., 2014) or pre-dawn Ψ_{leaf} (Pôças et al., 2020; Tosin et al., 2021). The pre-dawn Ψ_{leaf} is widely recognized as a valid indicator for vines water status monitoring (Intrigliolo and Castel 2006). It allows minimizing the influence of transpiration and environmental variables (e.g., VPD) on measurements (Santesteban et al., 2011). In fact, before sunrise, stomata are still closed determining the equilibrium between leaf and plant potential (Santesteban et al., 2011). Additionally, the aforementioned different isohydric and anisohydric behavior of various varieties must also be considered, as it leads to different patterns in the circadian Ψ_{leaf} trends. Blanco-Cipollone et al. (2017) suggested that pre-dawn Ψ_{leaf} would be preferred to Ψ_{stem} in plants with isohydric behavior. Moreover, both Ψ_{leaf} and Ψ_{stem} are sensitive to environmental conditions at the day of the measurement, (Williams and Baeza, 2007; Suter et al., 2019) and

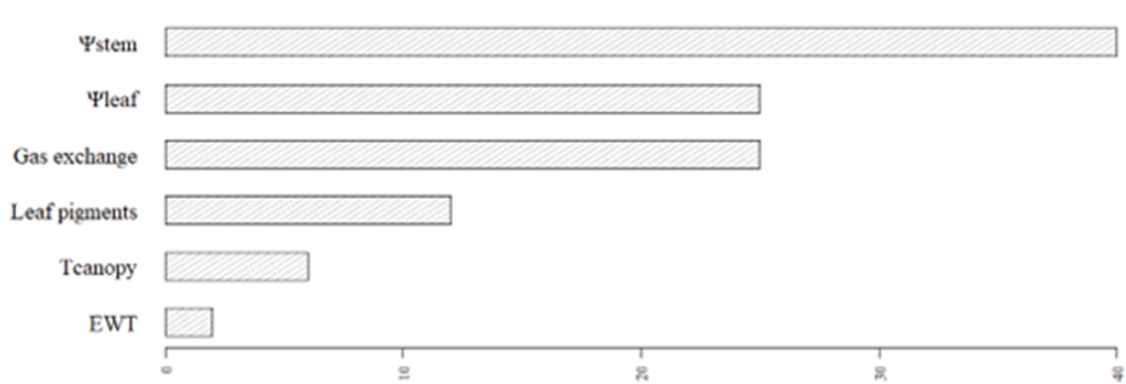

Fig. 1. Physiological measurements (Stem Water Potential, Leaf Water Potential, gas exchange, leaf pigments, canopy temperature, Equivalent Water Thickness) usually correlated with proximal and remote sensed data in the bibliography.

Ψ_{stem} has been modeled from coarse soil and topography information and environmental data alone (Brillante et al., 2016). It should not therefore be surprising to observe, that the inclusion of weather data in association with remotely sensed canopy information can improve the fit of these models (Tang et al., 2022). Furthermore, both phenological stage and variety can influence Ψ_{leaf}, affecting therefore the relationships with remotely or proximally sensed data. Bellvert et al. (2015) attributed the effect of variety in the correlation of Ψ_{leaf} with thermal indices to the different stomata regulation. Moreover, there could be an effect of the seasonal changes in leaf turgor and osmotic potential (Bartlett et al., 2022). This variability makes relationships harder to fit when more comprehensive dataset including multiple varieties and dates are grouped together (Bellvert et al., 2015). Bellvert et al. (2015) suggested to develop different seasonal baselines for different varieties. Finally, leaf senescence can also affect Ψ_{leaf} values by changing gas exchange mechanisms (Zufferey, 2016); therefore, leaves of the same age-group should be analyzed with the pressure chamber, or alternatively relying on the use of Ψ_{stem} data.

3.3. Leaf gas exchange and fluorimetry parameters

It is well known that plants respond to water stress with partial stomatal closure, which induces a decrease in photosynthesis and limits the leaf transpiration rate. This leaf response reduces the evaporative cooling process, resulting in higher leaf surface temperature. Moreover, different varieties have different physiological response to water stress (Dayer et al., 2022), thus they have different reductions in net photosynthesis (P_n), stomatal conductance (g_s) or leaf transpiration rate (E) at different water potential thresholds. Varieties that exhibit a tighter stomatal regulation, may be more problematic to model from remotely sensed data, as their response to environmental conditions is more immediate and not necessarily translated in a whole-canopy modification that can be recorded from coarse satellite imagery. Cogato et al. (2022) reported low correlation coefficients in this scenario between thermal or spectral indices and physiological parameters. These relationships may also be influenced by the time of the day when the physiological parameters are acquired, for example, García-Tejero et al. (2016) obtained good results on two varieties (*Touriga Nacional* and *Aragonez*) for g_s measurements between 11:00 and 14:00 h, without genotype interferences. On the other hand, using the pooled data relative to the time window of 14:00 - 17:00 h, a significant effect of the variety was noticed. To cope with this issue, Fuentes et al. (2012) recommended to use midday g_s, during the period of maximum evapotranspiration. Moreover, chlorophyll fluorescence techniques are also essentials for understanding plant responses to water stress. In drought conditions, plants reduce CO_2 assimilation due to stomatal closure and decreased mesophyll conductance, leading to lower photosynthetic carbon fixation (Salazar-Parra et al., 2012) hence reducing photosynthesis rates and inducing a photo-oxidative damage . The absorbed light energy, which cannot be used for photosynthesis, is then redirected to non-photochemical quenching processes to protect the photosynthetic system (Demmig-Adams et al., 1996). This response can be effectively monitored using chlorophyll fluorescence parameters, which provide insights into energy absorption, utilization, and dissipation in photosystem II (PSII). Matese et al. (2018) monitored leaf gas exchange and chlorophyll fluorescence on plants subjected to different water regimes to compare them with proximal and remote sensed data. Measurements were conducted at midday using the LI-6400XT portable photosynthesis system (LI-COR, Lincoln, NE, USA). Finally, it can be useful to assess the different responses to water stress shown by various cultivars. Hochberg et al. (2013) found that *Cabernet Sauvignon* (isohydric), compared with *Shiraz* (anisohydric), despite showing reduced stomatal conductance, compensated with higher photosynthesis and photorespiration, thereby improving its ability to avoid photosynthetic damage under drought conditions.

3.4. Sap flow measurement

Sap flow measurements allow us to directly verify the functioning of the plant's hydraulic transport system, which is indicative of the water flow from the soil to the leaves where it is released into the atmosphere. The latter is influenced at the same time by the water availability of the soil and by the transpiration flow, i.e. by the conditions at the extremes of the SPAC, it is also determined by the resistances upstream (e.g. roots, grafting point, etc.) and downstream (e.g. branches, leaves, etc.) of the measuring point but it is also an important indicator of the presence of cavitation and/or dead biomass from pruning wounds at the measuring point. Different authors have demonstrated how a sufficiently accurate management of vineyard irrigation at farm level is quite reliable (Eastham and Gray, 1998; Ginestar et al., 1998a, 1998b; Ferreira et al., 2012; Scholasch, 2018; Mancha et al., 2021). From a practical perspective, it should be noted that the probes used in the Thermal dissipation probes method proposed by Granier (1985) are needles that can determine variable observations depending on the point of intrusion into the stem of vines along the circumference and the depth of insertion into the wood, especially when part of the needle probe involves non-conducting tissues that will lead to an underestimation of the sap flow. Differently, the stem heat balance method uses heaters made of flexible sheets that are wrapped around the stem and insulated from the surrounding environment with one or more layers of packaging insulation material and aluminum foil, all held together with elastic bands, thus constituting a sleeve that easily adapts to the variations in diameter of the stem and integrates the sap flow of the entire section taken into consideration including conducting and non-conducting tissue. This last, the stem heat balance method has been used on vines with notable precision results by Lascano et al. since the early 90s (Lascano et al., 1992) and onwards until more recent years in which the same authors have tested new commercially available sensors, detecting an even greater capacity to maintain contact with the stem and an easier connection with the datalogger (Lascano et al., 2016). Pearsall et al. (2014), while noting that the scientific literature clearly shows the ability of sap flow measurements to effectively discriminate irrigated and non-irrigated vines in a large number of grape varieties, based on both their own data and data and observations found in numerous other studies in which sap flow measurements were carried out in the vineyard, indicated some inherent problems of this method related to the translation of sap velocities to absolute volumetric water use compared to determinations carried out based on ETo and weighing lysimeters and observed how the daily patterns of sap flow velocity and water use of the grapevine always differed considerably. In addition, Yunusa et al. (2005) also observed a decoupling between sap flow and leaf water status measured as stomatal resistance using a porometer.

3.5. Leaf pigments

Leaf pigments, measured with a spectrophotometer or with a SPAD, are meaningful parameters to assess plants' physiological status (Tosin et al., 2021; Zarco-Tejada et al., 2013). In addition, leaf chlorophyll content can be assessed following extraction with N, N-dimethylformamide (Moran and Porath, 1980) and measured using a spectrophotometer. Subsequently, the concentration of total chlorophyll ($a+b$) (mg/dm^2 of leaf area) can be calculated from the equations provided by Lichtenthaler and Wellburn (1983). Water stress causes a reduction in leaf chlorophyll content (Serrano et al., 2012) and an increase in leaf lutein concentration (Tosin et al., 2021). Furthermore, Caruso et al. (2017) have shown that leaf chlorophyll content is affected by leaf aging; therefore, to obtain good correlations with spectral data, they suggested considering leaf position and phenological stage. Indeed, they also found an increase in apical leaves chlorophyll concentration from June to August and a decrease in basal leaves. In addition, the study of xanthophylls, which are part of the carotene group, can also be useful in assessing the water status of vines (Tosin et al., 2021). The xanthophyll cycle involves pigments like violaxanthin (Vx), antheraxanthin (Ax), and zeaxanthin (Zx), crucial for protecting plants from excess light energy, especially under heating or water stress (Frioni et al., 2020; Féret et al., 2017). When water is scarce, stomata close, reducing transpiration and increasing the risk of photodamage. The cycle shifts Vx to Zx, dissipating excess energy as heat, thus protecting photosynthetic machinery. Tosin et al. (2022) observed increased oxidation of xanthophylls in non-irrigated vines due to intense light, heat and lack of water. Suárez et al. (2008), to detect water stress in grapevines, used the Photochemical Reflectance Index (PRI) (from airborne hyperspectral imagery) because of its sensitivity to the de-epoxidation status of xanthophyll cycle pigments and the effectiveness of photosynthesis (Gamon et al., 1992).

3.6. Equivalent water thickness (EWT)

EWT is the leaf area-weighted moisture content. It is obtained by calculating the difference between fresh (FM) and dry mass (DM) (dehydrated in an oven) per unit leaf area (A):

$$EWT = \frac{(FM - DM)}{(A)} \tag{1}$$

However, it is rarely used compared to the parameters described above. Furthermore, EWT values, and consequently correlations with spectral data, are strongly influenced by the variety. Indeed, high-vigor varieties (like Tempranillo) have the largest leaves, the highest leaf water content and the highest correlation with spectral data (González-Fernández et al., 2015; Rodríguez-Pérez et al., 2018).

4. Platforms & cameras

In the last years, new techniques have emerged as an alternative to the traditional methodologies to assess the crop-water status. In this sense, the use of remote and proximal sensing in agriculture to assess crop water status is being progressively introduced for improving water resource management.

4.1. Ground-based

4.1.1. Thermal

It is well known that plant temperature is associated with plant water status (Tanda and Chiarabini, 2019). Thermal imaging techniques rely on water-stressed crops closing the stomata, limiting leaf transpiration and surface cooling and determining an increase in canopy temperature (Costa et al., 2010).

Proximal measurements of vegetation surface temperature can be carried out using thermal sensors installed close to the canopy. This can provide an early indication of plant water status since the increase in leaf temperature values is one of the first physiological changes associated with water stress (Gómez-Candon et al., 2022). Several authors have worked to identify methodologies based on portable thermal sensors that can support farmers' irrigation scheduling with reduced costs. For example, Amogi et al. (2020) identified a real-time crop image capture tool via smartphone based on low-cost thermal-RGB sensors. Diago et al. (2022) used a radiometer mounted on a mobile platform; and recommended installing the system on tractors or other machines routinely used in viticultural operations. Vehicle-mounted cameras, which move at slow speeds, can monitor several plants instead of handheld sensors that focus only on a few (Gutiérrez et al., 2021). De Oliveira et al. (2021) suggested that the accuracy of canopy temperature measurements using infrared thermography could be improved by proximal detection to reduce the effects of wind, humidity, sunlight and shadow (which affect canopy boundary layer temperature). Gutter et al. (2022) obtained better results with data measured on the north side of the canopy. In addition, several authors recommend using thermal data obtained during the maximum atmospheric demand period (Pou et al., 2014; Sepúlveda-Reyes et al., 2016). Araújo-Paredes et al. (2022) and Sepúlveda-Reyes et al. (2016) used both proximal and Unmanned Aerial Vehicles (UAVs) thermal indices; they found that proximal data were in line with remotely sensed data. Moreover, the ground-based method can be expensive and time-consuming and, since each reading provides only values for each plant in isolation, it does not allow an overall evaluation. Consequently, the limitations of this methodology do not significantly differ from those already indicated for traditional methods such as the Scholander pressure chamber.

4.1.2. Multispectral

Multispectral camera applications are mainly based on spectroscopy techniques; in fact, each surface shows a unique spectral signature (namely, the reflectance as a function of wavelength), that can be used to obtain information about the crop's biophysical and biochemical variables. As expected, correlations with traditionally measured physiological parameters are higher with proximal sensing models than with remote sensing (Bianchi et al., 2021). However, in this study, models based on proximal and remote sensing are both valid in identifying water status variability. Furthermore, as mentioned above, several critical issues are involved when using proximal sensing (Araújo-Paredes et al., 2022).

4.1.3. Hyperspectral

Hyperspectral cameras use hundreds of bands with smaller amplitude (5–10 nm); thus, they can identify specific absorption peaks relative to specific substances. Spectroradiometers (De Bei et al., 2011; García-Estévez et al., 2017; Pôças et al., 2017) or spectrophotometers, by measuring one leaf per vine (Cogato et al., 2021) or contactless from a vehicle (obtaining a larger number of measurements) (Diago et al., 2017), have been used frequently. To the best of our knowledge, 23 authors (24.5% of the total papers reviewed) have conducted studies using hyperspectral proximal cameras to assess water status variability in vineyards. The high spectral resolution allows for capturing specific absorption peaks of specific substances such as leaf pigments directly related to crop water status, i.e., chlorophyll (Tosin et al., 2021; Vaz et al., 2016; Zarco-Tejada et al., 2013). Moreover, Diago et al. (2017) proposed an on-the-go method to successfully take a large number of measurements, thus ensuring high temporal, spatial and spectral resolution. Finally, the availability of a large number of wavelengths is a relevant aspect especially if they are all used within ML models (Loggenberg et al., 2018).

4.2. Unmanned aerial vehicles (UAVs)

4.2.1. Thermal

Thermal cameras are an effective tool for monitoring crop transpiration activity. Several studies showed that thermal data acquired with UAV are as accurate as the Scholander pressure chamber method in Ψ_{stem} estimation (Araújo-Paredes et al., 2022). Furthermore, Matese et al. (2018) obtained similar results using UAV and ground-based thermal cameras.

Moreover, it has been reported that the relationships between thermal and physiological data are stronger during the maximum atmospheric demand period (i.e., midday); lower relationships were obtained during the non-water stress period (Sepúlveda-Reyes et al., 2016) and in the early morning because of the difficulty in separating soil from canopy temperatures (Bellvert et al., 2014).

In addition, better spatial resolution (e.g., 30 cm) can help to reduce soil temperature influence and achieve better correlations (Bellvert et al., 2014). To this end, Gago et al. (2017) used a multicopter that allowed them to fly extremely close to the vine canopy (15 m above the ground), achieving high spatial resolution images ($<$ 2.5 cm/pixel).

4.2.2. Multispectral

Multispectral cameras use a few bands (4–10) with high amplitude

(15–70 nm). Therefore, they cannot distinguish specific details of the reflectance spectrum. However, within the reviewed works, they were used more than hyperspectral cameras because they are less expensive and they have been accessible to more consumers for a longer time.

UAVs enable the obtaining of multispectral images with high spatial (centimetric) and temporal resolution.

Reynolds et al. (2017, 2018) showed that UAV-NDVI (Normalized Difference Vegetation Index) maps are comparable with those obtained by proximal sensing. As in the previous case, it is recommended to do the surveys at midday, to avoid the "shadow effect" on the images (Caruso et al., 2017; López-García et al., 2021; Poblete et al., 2017).

4.2.3. Hyperspectral

A small number of research studies have been conducted with hyperspectral cameras placed on UAVs (Hurley et al., 2019; Zarco-Tejada et al., 2013; Vasquez et al., 2023).

Zarco-Tejada et al. (2013) obtained better results of leaf carotenoid content estimation with hyperspectral imagery (yielding errors below 1 $\mu g/cm^2$) rather than multispectral imagery. The authors attributed this to the fact that pixel mismatches between bands, inherent to the miniaturized multi-lens camera technology used in most UAVs, affected the indices calculated.

Furthermore, the canopy zone-weighting (CZW) method, employed by Maimaitiyiming et al. (2017), which consists in dividing the canopies into sunlit, nadir, and shaded zones, provided better relationships with vine physiological parameters; indeed, this method can minimize the effects of within-canopy shadows caused by the illumination condition and canopy heterogeneity (Maimaitiyiming et al., 2017).

4.3. Manned aerial vehicles (MAVs)

Of the reviewed studies, nine of them used remote data obtained from aircraft equipped with thermal and multispectral cameras. Multispectral images were mainly used to delineate irrigation management zones. Bellvert et al. (2021) obtained multispectral images with a resolution of 50 cm by flying over 1500 m above ground level. The aforementioned study allowed them to delineate irrigation sectors as a function of vigor level in a 100-ha vineyard. However, the authors acknowledged that the largest contribution to irrigation management costs came from the aircraft flight itself. Moreover, Ledderhof et al. (2016) suggested resampling the images into a 3 × 3-pixel area of interest (≈1.15 × 1.15 m) to obtain stronger correlations with vine performance and grape composition. Furthermore, Bellvert et al. (2016) showed that weekly remotely sensed Ψleaf via a thermal camera placed on an airplane was successfully used to monitor water status during regulated deficit irrigation.

Pagay & Kidman (2019) showed that using indices obtained from a thermal camera placed on a fixed-wing aircraft can be a promising strategy for irrigation management. In that work, the study was conducted in an extended area (approximately 100 ha) and the experimental sites were up to 20 km apart. Indeed, unlike other aerial platforms such as UAVs, the use of an airplane can provide wide spatial coverage in a short period for regional-scale irrigation management.

4.4. Satellite (Landsat 8, sentinel 2, planet)

Satellite platforms have some weaknesses regarding spatial and temporal resolution compared to UAVs. This can represent a problem for irrigation management: large pixels may also include soil or weeds. Laroche-Pinel et al. (2021) obtained better results in plots without grass in the inter-row. Additionally, the revisit periods are fixed, based on the different satellite's orbits, and it's uncommon for them to coincide with ground surveys. This mismatch introduces an initial error that can impact the correlations. In addition, the presence of clouds concurrent with satellite overflight may reduce image reliability (Helman et al., 2018), reducing usable images for prompt irrigation management. However, they have remarkable advantages: the image acquisition is recurrent in time and often free of charge (e.g., Sentinel 2 and Landsat).

Furthermore, they do not require going to the field. Several studies highlighted the feasibility of using satellite platforms in irrigation management in large-scale vineyards or for regional-scale evaluations (Bellvert et al., 2021; Cohen et al., 2019; Helman et al., 2018). Indeed, monitoring vast vineyards by UAVs or traditional methods, would be economically disadvantageous and would be very challenging to collect enough data to represent the whole area. In addition, satellite sensors can capture a very large surface in one single moment, reducing the impact of time change on plant physiology. Indeed, to better reflect vine water conditions across the vineyard, many midday Ψ_{stem} measurements are necessary (Brillante et al., 2017; Yu et al., 2020). Bellvert et al. (2021) suggested using remote sensing data to map the spatial variability of vineyards, identify regions and irrigation sectors with similar characteristics, and geolocate representative vines to be monitored within each region. Helman et al. (2018) used Planet Near Infrared and Visible (NIR-VIS) and seasonal Ψ_{stem} data from several vineyards to derive a general model for in-season monitoring of Ψ_{stem} at the vineyard level. The model achieved a correlation coefficient of $r = 0.78$, a root mean square error (RMSE) of 18.5%. This constellation of small nanosatellites provides high spatial resolution (3m) data and a daily global revisit time. However, Planet delivers only four spectral bands (three in the VIS region and one in the NIR region), although new sensors from the same vendors are planned that will provide higher accuracy and more spectral bands. The multispectral camera on Sentinel-2 can measure reflected solar radiation from VIS into 13 spectral bands with a repetition time of 5 days and a spatial resolution of 10–60 m (Drusch et al., 2012) (Fig. 2).

Using single bands from Sentinel-2 combined with ML algorithms gave promising results to predict Ψ_{stem} on a large scale in the work of Laroche-Pinel et al. (2021). Cohen et al. (2019) in a regional scale research, taking weekly or biweekly measurements on 82 vineyards, obtained good correlations using Sentinel-2 data; moreover, they attributed this especially to the short-wave infrared (SWIR) bands, where water has well defined absorption regions (Caruso and Palai, 2023). In addition, Cohen et al. (2019) showed that satellites such as Sentinel-2 are preferable to others with a better spatial resolution (Planet) but do not have these specific bands related to water status.

5. Indices and single bands

As part of this review, 114 indexes used in the different papers were cataloged. The NDVI (from multi or hyperspectral camera) and Crop Water Stress Index (CWSI) (from thermal camera) are the most widely used indices (Fig. 3). In addition, 19 individual bands were identified (among more than 200 used) that were found to be most correlated with vine water status. Moreover, some authors used more than 30 indexes (Thapa et al., 2022), others more than 60 (Hurley et al., 2019), and still others preferred to use all the available VIs (e.g., from the HSDAR package) (Tosin et al., 2021).

5.1. From thermal cameras

The CWSI is one of the most accurate indices in water status monitoring (Caruso et al., 2021). CWSI values tend to be higher in response to increased water stress. Several works have used thermal indices to generate maps to realize different irrigation management zones (MZs) (Bahat et al., 2021; Baluja et al., 2012). In addition, Ψ_{stem} (coefficient of determination, $R^2 = 0.89$) (Belfiore et al., 2019) and Ψ_{leaf} ($R^2 = 0.83$) (Bellvert et al., 2014) have often been used to validate the method and it is often judged accurate. However, it can be affected by variety, phenological stage, exposure of the measured canopy area, and the measurement time. Furthermore, different varieties may have different control over stomatal closure under water shortage. Indeed, Fuentes et al. (2012) obtained slightly better results correlating CWSI and g_s

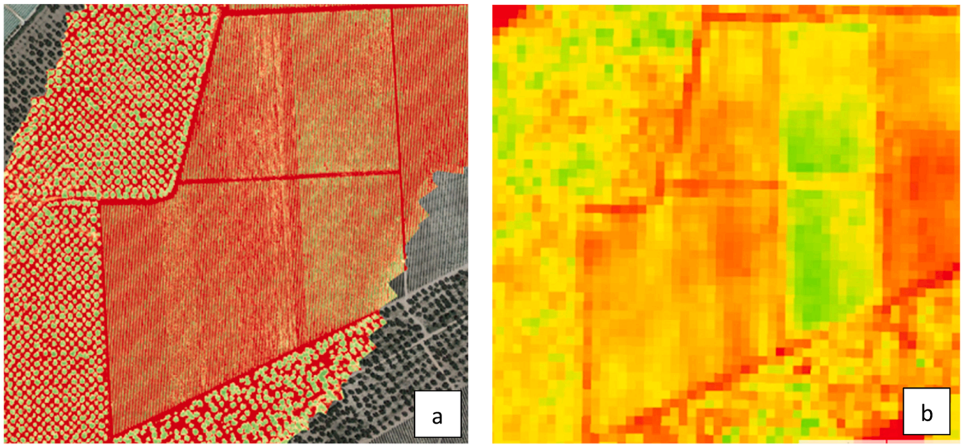

Fig. 2. NDVI maps from different resolution imagery, with (a) UAV imagery and (b) Sentinel-2 imagery, from a study site, a commercial vineyard in Andria (BT), Italy.

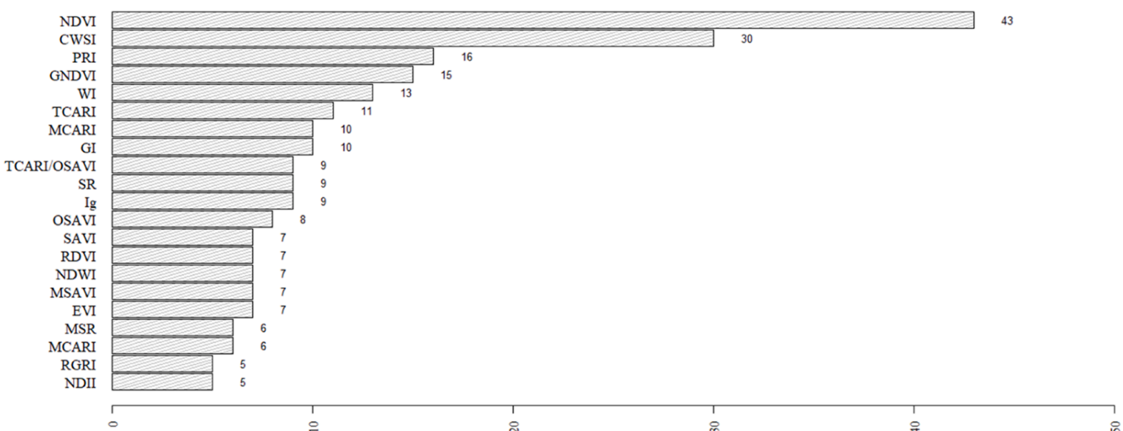

Fig. 3. Frequency of use of Vegetation indices with 5 or more references.

when they used only one variety data (i.e., *Chardonnay*) ($R^2 = 0.87$). Belfiore et al. (2019) obtained better correlations on *Moscato* than on *Merlot* due to a more pronounced response to the irrigation treatments by the former. However, Matese et al. (2018) in an experiment on *Vermentino, Cabernet sauvignon* and *Cagnulari*, consider CWSI a reliable indicator of crop water status, independently of cultivars, collecting good negative correlation with P_n (coefficient of correlation, R = -0.80). Furthermore, changes in osmotic potential and leaf turgor at different phenological stages may result in changes in the correlations obtained (Bellvert et al., 2015). Some authors suggest, when using a proximal thermal camera, that the shaded side should be preferred (Pou et al., 2014; Sepúlveda-Reyes et al., 2016; Zhou et al., 2022). Furthermore, intuitively, early morning is not a good time to conduct surveys because of the minimal changes due to low stress levels. Instead, midday values, obtained during the maximum atmospheric demand, are more stable. Finally, the other indices, Stomatal conductance index (Ig) and the second version of the stomatal conductance index (I3), were correlated with *gs* obtaining good results. *gs* has a positive relationship with Ig (R^2 = 0.92) (Fuentes et al., 2012) and, a negative with I3 (R^2 = - 0.72) (Baluja et al., 2012). The thermal indices used in the reviewed papers are shown in Table 1.

Thermography provided excellent results in numerous studies, obtained by both proximal and remote sensing (both UAVs and aircraft) (in the former (Araújo-Paredes et al. (2022) highlighted the higher costs). However, a potentially critical point is measuring reference temperatures (unlike spectroscopy techniques) (Diago et al., 2017).

Table 1
Overview of the Thermal VIs used to assess vine water status, the physiological parameters found to correlate with them and the related reference.

THERMAL					
ID	INDEX	FULL NAME	FORMULA	PARAMETERS	REFERENCE
1	CWSI	Crop Water Stress Index	$(T_{canopy} - T_{wet})/(T_{dry} - T_{wet})$	SWP, gas exchange	Finco et al. (2022)
3	Ig	Stomatal conductance index	$(T_{dry} - T_{canopy})/(T_{canopy} - T_{wet})$	gas exchange	Baluja et al. (2012)
2	I3	2nd version of the stomatal conductance index	$(T_{canopy} - T_{wet})/(T_{dry} - T_{canopy})$	gas exchange	Baluja et al. (2012)

5.2. From multispectral cameras

NDVI is one of the most widely used indices. However, it has rarely proved accurate enough to discriminate low or medium stress levels (Espinoza et al., 2017; Ferrer et al., 2020) and often showed poor performances (Vaz et al., 2016). Espinoza et al. (2017) found that it can discriminate moderate or severe stresses, exhibiting more significant differences in g_s values. The authors obtained better correlations with g_s using the Green Normalized Difference Vegetation Index (GNDVI) index ($r = 0.65$; $p < 0.01$). NDVI is more sensitive to plant biomass than water status (Oldoni et al., 2020). Larger canopies have a higher water demand, and that is precisely why NDVI may not be a good indicator under water stress (Bellvert et al., 2021). However, Caruso et al. (2017) obtained good correlations between NDVI from UAV and leaf chlorophyll (using a Minolta SPAD 502 portable greenness meter (Konica Minolta, Inc., Osaka, Japan)) but not in all dates ($R^2 = 0.66^{**}$ at fruit set completed, 0.66** at the beginning of bunch closure, and 0.37* at veraison). In addition, Reynolds et al. (2017) found that areas with low NDVI from UAV images corresponded to those with low NDVI from ground-based sensors. These areas also exhibited higher canopy temperatures and more negative Ψ leaf values, all of which are indicators of increased plant stress.

Moreover, in the case of low spatial resolution imagery (e.g., satellite imagery), pixels may not be limited only to canopies but also include parts of soil; however, some indices can reduce the soil background effect such as Soil-adjusted vegetation index (SAVI), Optimized SAVI (OSAVI), and the ratio between Transformed CARI (Chlorophyll Absorption Ratio Index) and OSAVI (TCARI/OSAVI). Helman et al. (2018) achieved better performance using this index with weekly satellite-collected data (Planet) on 82 commercial vineyards (*Cabernet Sauvignon*). Indeed, numerous publications have identified excellent correlations between these indices and parameters such as g_s (Baluja et al., 2012), midday Ψ_{stem} (M. Romero et al., 2018; Tang et al., 2022) and leaf chlorophyll (extracted with acetone and measured with spectrophotometer) (Zarco-Tejada et al., 2013). Baluja et al. (2012) obtained good correlations between UAV TCARI/OSAVI and *gs* ($R^2 = 0.84$, $p<$-0.05) using a watershed algorithm on GRASS GIS (r.watershed) to extract rows and obtain pure vine pixels. Moreover, (Zarco-Tejada et al., 2013) combined the TCARI/OSAVI index with R515/R570 (obtained from a customized PlantPen for carotene estimation) to estimate foliar carotene content on *Tempranillo* obtaining an $R^2 = 0.93$; RMSE = 0.73 g/cm^2. The aforementioned and most used indices in reviewed papers are shown below (Table 2).

Tang et al., 2022 have estimated Ψ_{leaf} on different varieties by utilizing a ML (Random Forest) model trained with meteorological parameters (noontime mean air temperature, vapor pressure deficit) and data obtained through UAVs (especially red-edge band-based indices, like Normalized Difference Red Edge, NDRE) on *Petite Sirah, Cabernet Sauvignon* and *Merlot*. In addition, the ability to utilize individual bands in combination with ML models, and artificial neural networks (ANN) often ensured the most satisfactory results, more accurate than conventional indices (López-García et al., 2022). Poblete et al. (2017) using ANN models with information between 550–800 nm improved the Ψ_{stem} prediction showing values of R^2 (Coefficient of Determination), MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), RE (Relative Error) equal to 0.87, 0.1 MPa, 0.12 MPa, and -9.107%, respectively. Laroche-Pinel et al. (2021), using a regression model with the Red, NIR, Red-edge, and Short-wave infrared (SWIR) bands from Sentinel-2, obtained, indifferently from the variety (isohydric and anisohydric), promising results. In conclusion, papers using single bands and ML models represent only a small percentage of the articles reviewed. However, the results are encouraging and satisfactory, especially when individual band data can be freely (or at a moderate cost) acquired from satellite platforms such as Sentinel-2 or PlanetScope.

5.3. From hyperspectral cameras

By recording the full spectrum of solar irradiance with high-resolution instruments, it becomes possible to identify the spectral bands and regions most sensitive to changes in plant water status. Wei et al. (2021) reported low performance by traditional indices, whose application is abundantly found in the bibliography, (i.e. Normalized Difference Vegetation Index (NDVI), Moisture Stress Index (MSI) or Photochemical Reflectance Index (PRI)) in an experiment on *Pinot Noir*; in contrast, a PLSR-trained model with Simple Ratio indices calculated over the entire spectrum ensured the best Ψ_{stem} predictions ($R^2 = 0.85$; RMSE = 110 kPa). Furthermore, Cogato et al. (2022) showed that PRI was the best index to estimate leaf gas exchange, P_n (R^2=0.62 on *Grenache*; R^2=0.68 on *Shiraz*) and g_s (R^2=0.65; on *Grenache*; R^2=0.72 on *Shiraz*). The most closely correlated bands with crop water status are SWIR, NIR, Red, Red-edge, and Green (Table 3 shows some particularly sensitive wavelengths to changes in the vine's water status). Cogato et al. (2021) identified the wavelength ranges 604 (green-red transition), 720 (red-edge), and 1333–1340 nm (NIR) as particularly sensitive to heat wave stress. The red-edge zone has often been selected to distinguish water stress zones in grapevine (Tosin et al., 2020). Vaz et al. (2016) highlighted that the best indicators for chlorophyll content estimation in *Trincadeira* and *Aragonez* leaves were narrow-band hyperspectral indices calculated in the 700–750 nm spectral region ($R^2 = 0.78$ and 0.79). However, Loggenberg et al. (2018) assert that better results on *Shiraz* were obtained using a subset of bands (from the initial 176, only 9 were chosen for Random Forest, mainly in the green region) that did not include red-edge wavelenghts. In addition, Pôças et al. (2020) pointed out the importance of the green region on *Touriga Nacional* and *Touriga Franca*. This can be explained because the green region (i.e., 500–600 nm) is particularly sensitive to changes in chlorophyll and xanthophyll concentration, which correlates with water stress.

Hyperspectral cameras have been used in most of the work concerning chlorophyll and other leaf pigments. This reveals the importance of high spectral resolution in this field. In addition, the possibility of having many individual bands for inclusion in ML models is also attractive. However, higher costs, larger camera sizes, and a considerable amount of data more difficult to handle must be considered.

6. Statistical methods

6.1. Regression methods

Sepúlveda-Reyes et al. (2016) used a linear regression analysis

Table 2
Overview of some main Multispectral VIs used to assess grapevine water, the physiological parameters found to correlate with them and the related reference.

MULTISPECTRAL					
ID	INDEX	FULL NAME	FORMULA	PARAMETERS	REFERENCE
1	GNDVI	Green normalized difference vegetation index	(*R790*−*R510*)/ (*R790*+*R510*)	gas exchange	Espinoza et al. (2017)
2	NDRE	Normalized Difference Red Edge Index	(*R840-R717*)/ (*R840*+*R717*)	leaf pigments, LWP	Tang et al. (2022)
3	NDVI	Normalized difference vegetation index	(*R850*−*R625*)/ (*R850*+*R625*)	SWP, LWP, gas exchange	Oldoni et al. (2020)
4	OSAVI	Optimized soil-adjusted vegetation index	(1 + 0.25)(*R840*−*R668*)/ (*R840*+*R668*+0.25)	SWP	Tang et al. (2022)
5	SAVI	Soil-adjusted vegetation index	1.5*(*R840*−*R668*)/ (*R840*+*R668*+0.5)	SWP	Tang et al. (2022)
6	TCARI	Transformed CARI (Chlorophyll Absorption Ratio Index)	3[(*R700*–*R760*)–0.2(*R700*−*R550*) (*R700*/ *R670*)]	leaf pigments	Zarco-Tejada et al. (2013)
7	TCARI/ OSAVI	TCARI/OSAVI	*TCARI/OSAVI*	leaf pigments	Zarco-Tejada et al. (2013)

Table 3
Overview of the main bands captured with Hyperspectral cameras, correlated to vine water status, the physiological parameters found to correlate with them and the related reference.

SINGLE BANDS					
ID	CAMERA	NAME	WAVELENGTH	PARAMETER	REFERENCE
1	multispectral	GREEN	530 nm	SWP	Poblete et al. (2017)
2	multispectral	GREEN	550 nm	SWP	Poblete et al. (2017)
3	hyperspectral	GREEN	520–610 nm	SWP, gs, E, Pn, WUE	Cogato et al. (2021)
4	multispectral	GREEN	560 nm	chlorophyll	Diago et al. (2022)
5	multispectral	GREEN-YELLOW	570 nm	SWP	Poblete et al. (2017)
6	multispectral	RED	670 nm	SWP	Poblete et al. (2017)
7	hyperspectral	RED	620–640 nm	SWP, gs, E, Pn, WUE	Cogato et al. (2021)
8	multispectral	RED EDGE	700 nm	SWP	Poblete et al. (2017)
9	hyperspectral	RED EDGE	680–720 nm	SWP, gs, E, Pn, WUE	Cogato et al. (2021)
10	multispectral	NIR	800 nm	SWP	Poblete et al. (2017)
11	hyperspectral	NIR	770–1340 nm	SWP, gs, E, Pn, WUE	Cogato et al. (2021)
12	multispectral	NIR	840 nm	LWP, SWP	Diago et al. (2022)
13	hyperspectral	NIR-SWIR	1100–2100 nm	gs	Diago et al. (2017)
14	hyperspectral	SWIR	1400–1450 nm	LWP	Rapaport et al. (2015)
15	hyperspectral	SWIR	1421–1550 nm	SWP, gs, E, Pn, WUE	Cogato et al. (2021)
16	hyperspectral	range 1941–2200 nm	1941–2200 nm	SWP, gs, E, Pn, WUE	Cogato et al. (2021)
17	hyperspectral	range 350 - 2500 nm	350 -2500 nm	LWP	González-Fernández et al. (2019)
18	hyperspectral	range 473–708 nm	range 473–708 nm	SWP	Loggenberg et al. (2018)
19	hyperspectral	HSDAR package for R	HSDAR package for R	LWP, LWC, Car, Lut, Ca, Cb, Cab	Tosin et al. (2021)

between plant physiological variables and CWSI calculated from different points in the canopy. Also, Helman et al., 2018 highlighted significant results for a single linear regression model for four VIs (SAVI, GNDVI, NDVI and Enhanced Vegetation Index (EVI)) ($r = 0.80$–0.82; $p < 0.01$). Laroche-Pinel et al. (2021) obtained the best Ψstem estimation using Bayesian Ridge and Linear Regression ($R^2 = 0.40$ and RMSE = 0.26) and all Sentinel-2 bands, with a database composed by 349 observations.

Moreover, Cogato et al., 2022 used the Statgraphics "comparison of alternative models" tool to choose the best model. The Exponential Type and PRI hyperspectral index seem to be the best regression model for estimating Pn (R^2=0.62 on *Grenache*; R^2=0.68 on *Shiraz*) and gs (R^2=0.65; on *Grenache*; R^2=0.72 on *Shiraz*). Reciprocal-X and the Water Index performed best in Ψ_{stem} estimation (R^2=0.63 on *Grenache*; R^2=0.73 on *Shiraz*).

Furthermore, the partial least squares-regression (PLS-R) as often been applied with discrete results especially combined with the use of hyperspectral cameras. Indeed, it is a method judged to be performant in building models based on the entire spectrum (Mirzaie et al., 2014), by combining the most important information from hundreds of bands (Huang et al., 2004). Diago et al. (2022) obtained good results in Ψ_{stem} estimation by including atmospheric (canopy and air temperature, relative humidity, atmospheric pressure, VPD) and spectral variables in their models (R^2_{cv} of ~ 0.63, and Root Mean Square Error of Cross Validation between 0.124 MPa and 0.206 MPa). Finally, González-Fernández et al., 2015, demonstrated the utility of PLSR and continuum removal analysis estimating *Tempranillo* EWT obtaining an R^2= 0.675 and RMSE = 0.014% using the range 1265 nm to 1668 nm. In conclusion, however, plant spectral response to physiological changes cannot always be described by linear relationships, making traditional statistical models not robust enough to achieve accurate plant water status estimations (M. Romero et al., 2018).

6.2. Machine learning (ML)

Recently, an increasing number of papers in the bibliography have

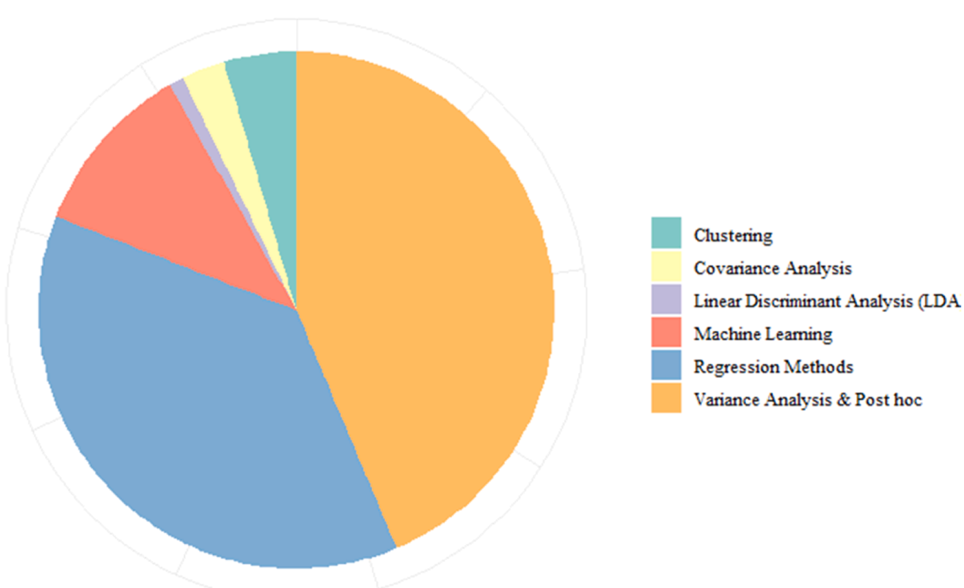

Fig. 4. Statistical Methods for Data Analysis used in the reviewed articles.

applied ML, although they are still a few if compared to other data analysis methods (Fig. 4).

They allow to find the underlying rules and hidden connections between the given information (Gutiérrez et al., 2021). ML techniques can describe linear and non-linear systems by learning from the input-output relationship in the training phase (López-García et al., 2022). Indeed, the algorithms gradually adapt to improve their performance as the number of available training samples increases.

Furthermore, the combination of Artificial Neural Network (ANN) and singular bands usually resulted in more accurate than the traditional indices. ANNs are robust tools for agricultural predictions, handling complex and nonlinear relationships. The learning process in a network is automatic and is based on the selection of appropriate weight values (Samborska et al., 2014); this allows for improved predictive ability over time. ANNs have proven effective in various agricultural applications, including predicting plant water uptake (Qiao et al., 2010) and crop yield (Khairunniza-Bejo et al., 2014). Their ability to integrate with remote sensing data, such as multispectral imagery, allows for more accurate and scalable assessments of plant health and water status. Poblete et al., 2017 obtained good results in Ψ_{stem} prediction using ANN models including 550–800 nm bands (R^2=0.87, MAE=0.1 MPa, RMSE=0.12 MPa, RE=-9.107%). However, the authors also pointed out some critical issues of ANN-based models; i.e., the difficulty in clearly identifying which variables contribute most to the output ('black-box') or the possibility of causing training data overfitting due to the model interaction and nonlinearity.

Finally, some authors underlined the importance of including meteorological variables in the models to improve the prediction accuracy (Thapa et al., 2022); thus, Tang et al. (2022), including in a Random Forest (RF) model T_{air} and VPD, and multispectral UAV-VIs, obtained good results in Ψ_{leaf} prediction (R^2= 0.778, RMSE of 0.123 (±0.03) MPa and a MAE of 0.100 (±0.026) MPa). They also found that RF performed better than extreme gradient boosting (XGB) model according to other studies (Loggenberg et al., 2018). Indeed, RF may ensure greater accuracy when used to classify high-dimensional data such as hyperspectral imagery. Indeed, in the case of hyperspectral imagery, where the dataset is very large due to the large amount of bands, the Hughes effect (Hughes, 1968) may result in a reduction in model accuracy. RF helps mitigate the Hughes effect through two main mechanisms: bagging, which creates multiple decision trees from random subsets of data to reduce overfitting, and aggregating the trees' predictions to improve accuracy by balancing out errors from less relevant variables. This approach enables RF to effectively handle high-dimensional data and improve classification accuracy (Loggenberg et al., 2018). In conclusion, ML methods can detect relationships between spectral data and physiological parameters when traditional methods have not yielded satisfactory results. As evidence of this, M. Romero et al., 2018 showed how a simple regression failed to find relationships between VIs and Ψ_{stem} as opposed to an ANN model (where the coefficients of determination for training, validation and testing were obtained are R = 0.8, 0.72 and 0.62, respectively).

7. Conclusions and future perspectives

Traditional parameters (i.e., Ψ_{stem}, Ψ_{leaf}, g_s) have many critical issues detrimental to the successful monitoring to manage the water resource sustainably. Indeed, they are time-consuming, thus, in the context of an entire vineyard, the data can be significantly affected by time differences between measurements; in fact, it is important to have a congruous number of measurements without, nevertheless, excessively exceeding the midday window. In addition, it is not possible to know the water status of all plants; rather, only some leaves of some vines are measured. The operator's skills and knowledge can greatly influence the reliability of the parameters. On the other hand, about correlations, to obtain more robust models, it is important to choose the most reliable parameter (e.g., especially Ψ_{stem}) and to make more efficient the data collection method (i.e., having more measurements, at different phenological stages with larger datasets). In the reviewed papers, the results from UAVs-thermal, multispectral, and hyperspectral data do not often differ much from traditional results and those obtained from proximal thermal and spectral sensors (moreover, the costs are lower, and they can cover large areas in reduced time). Furthermore, the use of satellites and aircraft appears necessary at regional or district scales. In the former case, the data can often be downloaded for free (Sentinel-2, Landsat); in the latter, however, the costs are considerably high. As technology advances, the use of satellites may even become preferable in some cases to UAVs due to lower costs and data obtained regularly over time without the need to travel to the field.

Finally, within the cataloged papers, the best results were obtained:

a. using indices obtained from thermal cameras, such as CWSI (which, however, require the acquisition of reference temperatures)
b. applying ML techniques and single bands obtained from multispectral or hyperspectral cameras; in contrast, traditional indices (especially NDVI) provided inferior performance.

In addition, bands particularly sensitive to water stress are red-edge, NIR, Green, SWIR, and Red.

In conclusion, the large amount of data acquired from proximal and remote sensors makes it necessary to process them through equally innovative techniques (i.e., artificial intelligence). All this is to integrate Decision Support Systems and be truly beneficial to the final user.

CRediT authorship contribution statement

Francesco Abbatantuono: Writing – review & editing, Writing – original draft. **Giuseppe Lopriore:** Writing – review & editing, Supervision. **Anas Tallou:** Writing – review & editing. **Luca Brillante:** Writing – review & editing. **Salem Alhajj Ali:** Writing – review & editing. **Salvatore Camposeo:** Writing – review & editing. **Gaetano Alessandro Vivaldi:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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