Proximal optical sensing for vineyard control and management: a review

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Abstract

Optical proximal sensing is playing an increasingly important role in the development of advanced strategies for monitoring and optimizing vineyard management. Technological advancements are now enabling the creation of smart systems that support growers in data-driven decision-making processes. This review investigates the specific needs and challenges of modern viticulture and then explores the current applications and future perspectives of optical sensing technologies such as spectroscopy, multispectral and hyperspectral imaging, and thermography for assessing grape ripening and monitoring vine water status. Special attention is given to optical technologies that are particularly well-suited for viticultural applications, as they address key demands for high-quality, real-time, and sustainable information. Recent innovations include the integration of optical sensors with spectral platforms, Internet of Things (IoT) systems, and robotics within agricultural machinery technologies that are especially relevant for managing vineyards under increasing climatic stress. Therefore, this review also highlights emerging trends, for the development of autonomous and distributed sensing networks, and their incorporation into next-generation decision-support systems. By synthesizing existing knowledge and outlining future directions, this work aims to provide researchers and practitioners with a forward-looking perspective on how optical proximal sensing can contribute to build a more resilient, efficient, and precision-driven viticulture system.

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Introduction

Challenges of the viticulture sector

The wine sector operates within a complex context where market dynamics, pricing strategies, and financial aspects are paramount (Camillo *et al*., 2023). Vineyard managers are constantly called upon to ensure their operations' profitability and economic sustainability. The guarantee of obtaining (continuously over the years) grapes in adequate quality and quantity reducing the uncertainty linked to the variability of weather phenomena, assumes a crucial aspect to strengthen the enterprises of the sector guaranteeing productive, economic, and employment returns.

Summer stresses, resulting from frequent heat waves (days with particularly high daytime maximum temperatures and night-time minimums) during grape ripening, along with late spring frosts, represent constant pitfalls for the productivity of vineyards and the quality of their grapes. Vineyard areas are in the context of an expected increase in the frequency and intensity of heat waves and, as a result, it is essential to anticipate the development of strategies to reduce the risks involved (Ioriatti *et al*., 2023). In the viticulture sector, the vineyard manager's decisions depend on the probability of different situations occurring. However, it is important to consider that changes in decision processes, as well as deviations from the plan, often entail non-negligible costs.

Therefore, a change in a decision led by an unfulfilled prediction (or incorrect interpretation) can potentially cause higher damages than the ones that may have originated from seasonal variability. The challenge is to provide better knowledge to support the increase of crop systems' yield production at high-quality standards. This implies new integrated approaches able to sustain ecological integrity and biodiversity while seeking long-term resilience and cost-efficient strategies (Bramley, 2022). While the wine market opens up new markets, it also intensifies competition. Producers must navigate complex standardized productions, quality standards, and consumer preferences to establish a foothold in the global market (Morrish *et al*., 2022). This requires keen monitoring of vineyards and a commitment to producing wines that meet consumers' taste-evolving preferences while maintaining the distinctive characteristics of origin production (e.g., DOC and DOCG). Precision viticulture allows for more efficient resource utilization by employing data-driven technologies to monitor and manage vineyards (Abu *et al*., 2022; Bwambale *et al*., 2022). This can enhance decision-making processes related to irrigation, fertilization, and disease control, improving overall crop yield and quality. The use of field sensors can lead to detailed mapping of the quality status of vineyards, for both grape ripening and vine water status. New perspectives about digital innovations and integrated approaches can be of major importance in answering this challenge (Lezoche *et al*., 2020; Santesteban *et al*., 2013; Arnó Satorra *et al*., 2009), by helping to identify the probability thresholds to safely trigger a decision, which is critical for the decision-making process.

Hence, new techniques using sensors, spectral platforms, Internet of Things (IoT), and robotics integrated with agricultural machinery (Fasiolo *et al.,* 2022; Hallik *et al*., 2022; Milella *et al*., 2019) are being used to map two of the most important aspects of modern vineyard management (i.e., grape maturation and plant water status). This is increasingly important in current scenarios of extreme weather events and water shortages, under pressure to optimize plant protection products to be applied in vineyards and other crops, ensuring maximum precision while supporting agronomic processes.

Among the main techniques already used in viticulture, the optical ones seem to be most suitable to face the current viticulture needs in terms of provided information and sustainability (Ferro *et al*., 2023; Moreno *et al*., 2023; Ye *et al*., 2022). Optical sensors in viticulture refer to spectroscopy, hyperspectral/multispectral imaging, and thermography, capable of acquiring optical fingerprints at different spectral regions to collect relevant data to vineyard monitoring and management. Indeed, the optical technology allows for real-time and stand-alone monitoring with low costs, it is non-destructive and chemical-free, capable of drastically reducing the need for manpower, and also providing information with an adequate temporal and spatial resolution (Pampuri *et al*., 2021b, Casson *et al*., 2020) promising for precision applications in viticulture 4.0.

Fundaments of the optical sensing and multivariate data processing

Optical sensing is an analytical method of acquiring, processing, and interpreting data that record interactions between electromagnetic radiation (composed of photons) and a specific target (Borràs *et al*., 2015). These interactions involve the reflection, absorption, and transmission of a flux of photons by the target matter and the emission of radiation (Corti *et al*., 2018) (Figure 1). At research level, the optical techniques, based on IR, UV, and Vis, are widely applied in agriculture and for food fingerprinting (both in pre- and post-harvest) to ensure authenticity, quality, and safety of food product (Cavaco *et al*., 2022; Tugnolo *et al*., 2019).

In the infrared (IR) region, near-infrared (NIR, 4000-14,286 cm^{-1}; 700-2500 nm) and mid-infrared (MIR, 400-4000 cm^{-1}; 2500-5,000 nm) spectroscopy comprises the absorbance of radiation at molecular vibrational frequencies occurring for the O-H, N-H, and C-H groups and the C-C, C-O, C-N, and N-O groups in organic materials, respectively (Malegori *et al*., 2018; Tugnolo *et al*., 2020). Instead, electronic transitions are responsible for radiation absorption in the UV region (25,000-40,000 cm^{-1}; 250-400 nm) and in the visible (Vis) region (14,286-25,000 cm^{-1}; 400-700 nm) (Beghi *et al*., 2017; Gómez-Caravaca *et al*., 2016). Moreover, the region from 750 to 15,000 nm is used to monitor the temperature (thermography) by evaluating the IR radiation emitted by an object. Thermography provides key facts on the dimension, heat distribution as well as structural analysis (Fernández-Cuevas *et al*., 2015). The main factor that influences the amount of radiation is the emissivity (energy ratio emitted from a sample at the surface temperature) (Ali *et al*., 2020; Still *et a*l., 2019). The resulting information derived from the interaction between photons and the target can be handled in terms of punctual information (spectroscopy) or image information (thermal imaging and hyperspectral/multispectral imaging). The advantage of imaging techniques is characterized by the presence of spatial resolution (Sx and Sy), which measures the geometric relationship between the image pixels. In thermography, the information retrieved from the thermal image could be used to describe the thermal distribution without exerting any energy on the sample. The spatial resolution can be used in mutual combination with the spectral resolution (Sλ, which measures the variations in illumination within the image pixels as a function of wavelength) in multispectral (up to 10 wavelengths) and hyperspectral (more than 10 wavelengths) imaging techniques (Khan *et al*., 2018). These data are represented in the form of a 3-Dimensional data cube where each slice of the cube along Sλ, represents a specific band from the electromagnetic spectrum (Amigo, 2020; Stuart *et al*., 2019). However, especially the hyperspectral techniques, they have a limited adoption for some disadvantages like purchase and engineering costs of the plant, more complex data analysis and difficult integration with farming practices (lack of familiarity with the technology) (Vignati *et al*., 2023).

Modern optical instruments rapidly detect photons interactions across wavelengths, producing large volumes of data that require efficient processing and storage (Cortés *et al*., 2019). Modern optical instruments rapidly detect photon interactions across wavelengths, producing large volumes of data that require efficient processing and storage (Bro and Smilde, 2014).

Chemometrics uses supervised and unsupervised mathematical and statistical approaches employing formal logic to design or select optimal measurement procedures and experiments and, to maximize and isolate relevant chemical information in the data (Wold and Sjöström, 1998). In the chemometrics branch fell all those techniques of artificial intelligence (e.g., data mining, machine learning, and deep learning) applied to natural systems (Amigo *et al*., 2021). Such techniques are normally applied to data structures represented by a bidimensional (second order tensor) or three-dimensional (third-order tensor) matrix (Figure 1). As reported in Figure 2, before carrying out any type of processing on the data matrix, mathematical pre-treatments (e.g., normalization and/or scaling) are needed. Then, the process continues with i) exploratory data analysis (which summarizes the main information contained in the data); ii) model calibration and validation; and ii) model transfer (Cortés *et al*., 2019).

Preprocessing of optical spectral data aims to reduce noise, correct artifacts, and enhance useful signals. Techniques such as smoothing (e.g., Gaussian, moving average, Savitzky-Golay), baseline correction (e.g., SNV, MSC), and derivation are commonly applied to improve spectral quality (Oliveri *et al*., 2019). Finally, different normalizations and/or scaling treatments (like mean centering, autoscaling, range scaling, Pareto scaling, *etc*.) become fundamentals to homogenize the data to perform a correct explorative and modeling phase. Since the variance values depend on the scale of the variables, it becomes difficult to compare and impossible to combine information from variables of different nature (coming from different type of sensors) or from the same nature (e.g., wavelengths) but coming from different devices, unless properly normalized (Boulet and Roger, 2012; Rinnan, 2014; Biancolillo and Marini, 2018).

Then, with the aim of i) extracting useful information, ii) correlating the variables, iii) eliminating anomalous data, and iv) hypothesizing the subsequent work procedures, a valid unsupervised exploratory data analysis is essential to summarize the main features of data in easy-to-understand form (visual graphs). For this purpose, principal component analysis (PCA) can be used conveniently to summarize and explore the data using plots and figures (Bro and Smilde, 2014).

Supervised regression and classification approaches are focused on predicting qualitative properties or belonging classes (*e.g.*, origin, infections, or vine water stress classes). For these purposes, multiple linear regression (MLR), principal component regression (PCR), partial least square (PLS), support vector regression (SVR), artificial neural network (ANN) and convolutional neural network (CNN) are broadly used for regression (Liakos *et al*., 2018), and linear discriminant analysis (LDA), partial least square-discriminant analysis (PLS-DA), K-nearest neighbors (KNN), soft independent modelling by class analogy (SIMCA), support vector machine (SVM), artificial neural network discriminant analysis (ANNDA) are used to define membership of each sample to its appropriate class (classification). To evaluate the model performance different indexes described elsewhere are used for regression (Nicolaï *et al*., 2007) and classification (Ballabio and Consonni, 2013; Oliveri and Downey, 2013; Zhong *et al*., 2018). However, the developed models are usually calibrated on a limited set of training data. The models based on optical data, generating large and complex spectral databases, suffer from robustness over time caused by small variations of influence factors such as temperature, cultivars, and instrumental disturbances (Zeaiter *et al*., 2006). For this reason, calibration models should be regularly checked and corrected to maintain their robustness in the long term or to be used on other cultivars. The implementation of the calibration models in these new domains (i.e., cultivars) poses specific challenges. Therefore, the calibration models should be easily adapted to the sources of variability that new measurements can bring to avoid their prediction performance degradation. For these reasons, Zeaiter *et al*. (2006) and Diaz (2022) proposed two approaches based on the dynamic orthogonal projection capable of maintaining (in a supervised manner) the model robustness or efficiently transferring the calibration without standard samples (i.e., in an unsupervised manner). The models would inform the decision support tool to create better decision models leading the growers through clear decision stages and presenting the likelihood of various outcomes resulting from different options (Navarro-Hellín *et al*., 2016).

Optical technology in viticulture

Within the viticulture sector, the development of optical instruments and applications (especially in the Vis/NIR spectral range) is considerable (dos Santos Costa *et al*., 2019). This is due to a strong need to i) reduce the costs of routine analysis; ii) reduce the environmental impact; iii) improve the management practices (and consequently the quality of the final product); iv) build and hold a historical dataset based on the optical acquisitions aiming at improving the predictive models and therefore refine the decision-making process for the future campaigns (Tardaguila *et al*., 2021; Ghozlen *et al*., 2010).

Optical instruments have been present in winery laboratories for decades but, currently, the trend is to move from the laboratory to the field (Figure 3) (Tardaguila *et al*., 2021). Recent research has demonstrated alternative optical methods and instruments of remote and proximal sensing that allowed a more cost-effective evaluation of the grape quality insight directly in the field (Power *et al*., 2019). Remote sensing (RS) technology is the acquisition of information by space-borne satellites, aircraft, and UAVs without any physical contact with the target, and with different application methods and types of sensors. RS detects and records the sunlight radiation reflected from the surface of objects on the ground. The capability of a sensor to detect these objects is quantified in terms of the sensor's spatial, radiometric, spectral, and temporal resolution. However, despite RS is a landmark for the current agricultural sector, many small companies are not capable of fully embracing this technology. Some reasons behind this include i) a limited understanding of the efficacy of RS, and the techno-economic benefits of such technologies; ii) the limited availability and training

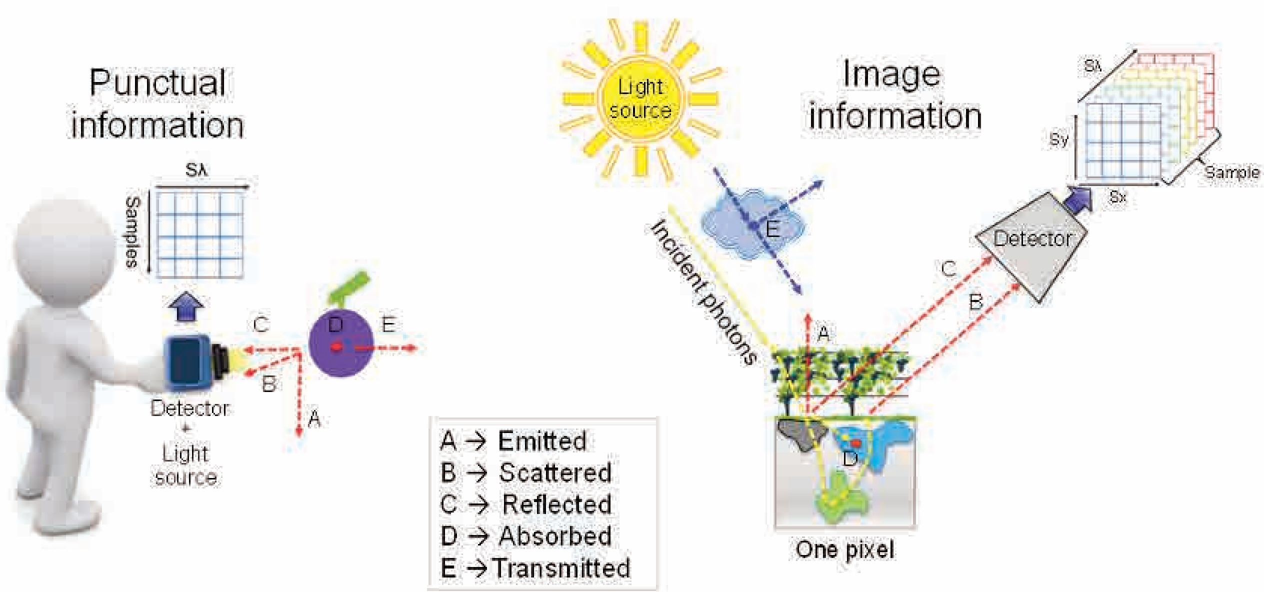

Figure 1. The rationale of the differences between punctual information and image information.

of RS-based decision-support tools; iii) crop architecture and size for target identification; iv) costs; v) and interoperability with data and tools from a variety of sources (Khanal *et al*., 2020). Concerning the wine sector, vineyards also represent a real challenge for the application of RS technologies. This is due to the discontinuous nature of grapevine canopies and to the grapevine canopies that don't completely block or cover the underlying terrain causing noisy backgrounds and shadows that influences the measured reflectance signals (Borgogno-Mondino *et al*., 2018). Moreover, grape quality prediction has been attempted by different means (e.g., by correlating the vigor of plants with fruit/wine quality) but remains quite challenging (Bonilla *et al*., 2013; Priori *et al*., 2013). For these reasons, the use of proximal sensing (PS) can be a convenient or complementary option. PS is defined as the use of field-based sensors with a detector placed directly in contact or close (a few meters) to a specific target (e.g., soil, plant, crop). These sensors provide information related to the properties of the objects analyzed through signals coming from physical measures (Rossel *et al*., 2013).

A wide range of proximal sensing tools for vineyard manage-

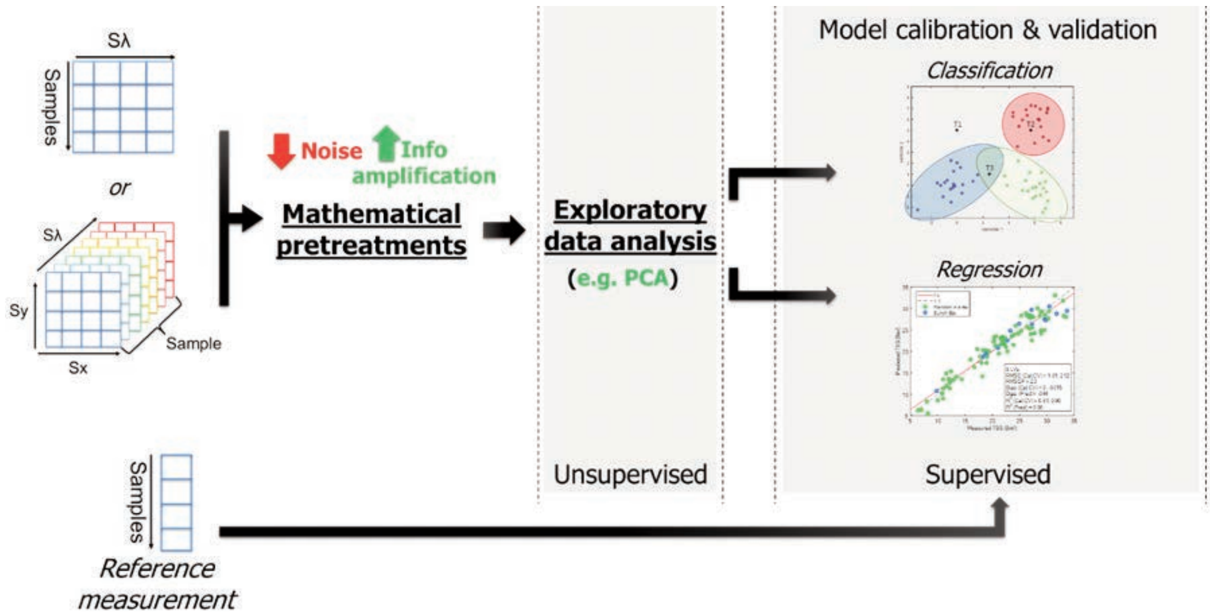

Figure 2. Main chemometrics steps for data exploration and modelling.

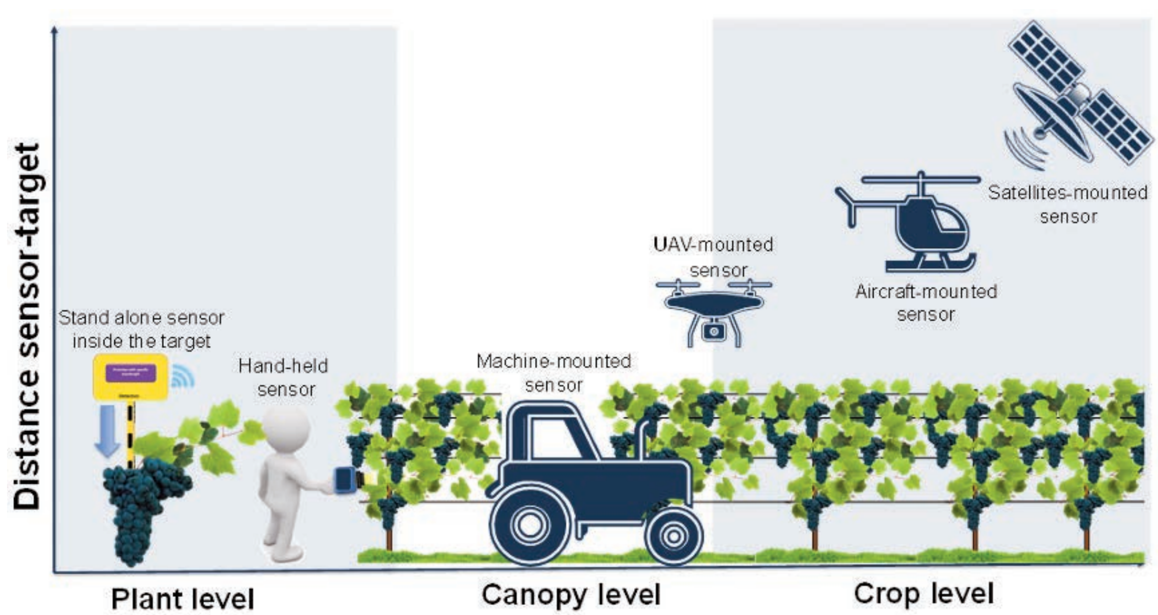

Figure 3. Different optical sensors management based on acquisition levels: plant, canopy, and crop.

ment has been documented in the literature. Predictive models for grape water status and ripeness parameters have been developed using on-the-go, contactless sensing platforms operating in the Vis and NIR regions (Diago *et al.*, 2018; Fernández-Novales *et al.*, 2019). Moreover, studies have employed handheld or operator-driven instruments to build multivariate models and indices for monitoring variables like pH, acidity, water potential, and stomatal conductance (Diago *et al.*, 2016; Urraca *et al.*, 2016; Giovenzana *et al.*, 2015; Rapaport *et al.*, 2015; Giovenzana *et al.*, 2014; Ghozlen *et al.*, 2010).

New commercial miniaturized modules are available on the market of optoelectronic components, mainly equipped with a set of light sources, photodiodes, filters, or micro-spectrometers on a package. These instruments in combination with digital circuitry, wireless transceivers, micro-electromechanical systems (MEMS), make it possible to integrate sensing, data processing, wireless communication, and power supply into low-cost millimeter-scale devices (Spachos and Gregori, 2019). The resulting miniaturization and cost reduction of electronic components is leaving room for a completely new approach to data acquisition and management, using WSNs based on small battery-powered nodes (Spachos, 2020). The availability of miniaturized optical devices is driving the research to develop IoT sensors that are highly sensitive to the detection of substances in an environment, such as chemicals or biological materials (Misra *et al.*, 2020). In viticulture, the sensors can be directly installed in proximity to the target (vine leaf or grape bunch) to remotely monitor the vineyard during the crop season. This review aims to critically examine the current and emerging applications of proximal optical sensing techniques in vineyard control and management, with an emphasis on the evaluation of grape maturation and vine water status. Beyond presenting the state of the art, the review highlights future trends, opportunities for technological integration, and the role of these sensing tools in the development of next-generation precision viticulture systems.

Grape maturation control

Monitoring the grapevine ripening process is the most crucial aspect for winemakers. It is now well-accepted that the quality of a wine depends on the qualitative features in terms of the chemical characteristics of the grapes used to produce it (Giovenzana *et al.*, 2018b). Therefore, this probably makes the time of harvest one of the factors with the greatest impact on the quality and value of the final product together with the vineyard management prior to the harvest date. The conventional grape maturation assessment methodologies rely on wet-chemistry analysis of the grape composition in the laboratory (Pampuri *et al.*, 2021). These methods are reliable but suffer from the limited number of samples probed, the distance to the field, and the time gap between sample collection and results. Furthermore, they are i) destructive, ii) time-consuming, iii) labor-intensive, and iv) are not sustainable from an environmental impact point of view, which are critical factors in view of more sustainable production (Casson *et al.*, 2019). Zambelli *et al.* (2022) conducted a life cycle assessment (LCA) study on the

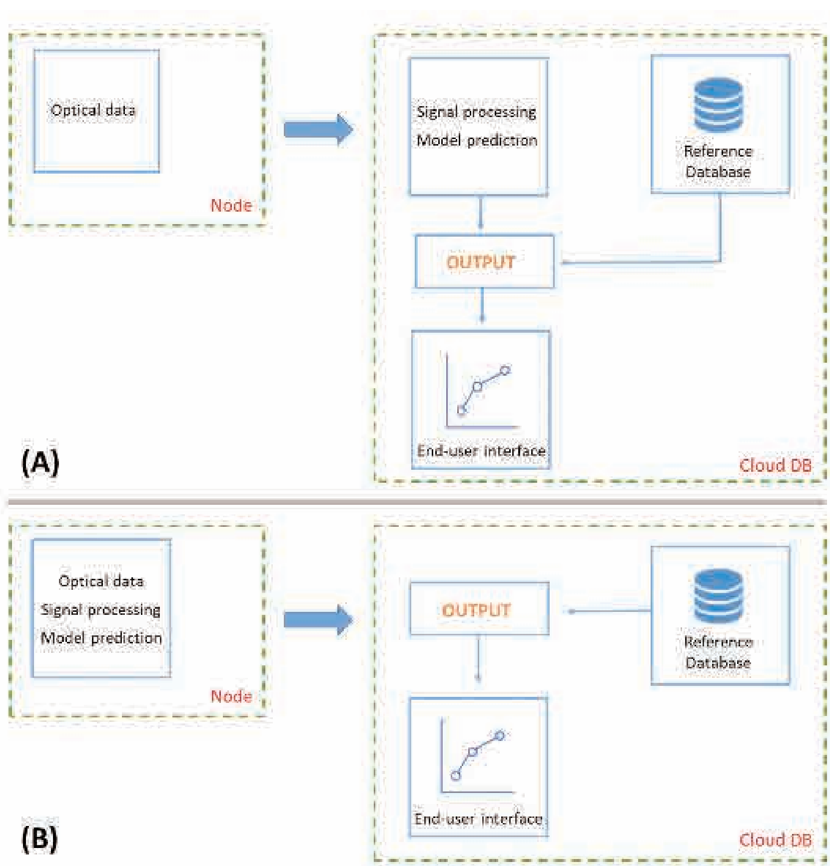

Figure 4. Data pipeline architectures for a sensor network based on (**A**) simplified optical devices (*e.g.*, spectral sensors) and (**B**) portable spectrophotometers.

analyzes conducted to measure total soluble solid (TSS), pH and titratable acidity (TA) and demonstrated how optical analyzes performed with a portable prototype are the greenest solution as this technology proved to be 3.2 times more sustainable than the wet-chem method.

Over the years, many approaches have been followed toward more effective methods which could explore many samples and give a rapid and comprehensive overview of the ripening process. Optical-based measurements are particularly suited to this end, and for this reason sensing techniques based on UV, Vis, NIR, and IR are widely used in agriculture and for food fingerprinting. Indeed, the literature shows many applications where the advantages of optical sensing based on either benchtop or portable instruments are widely explored (Table 1).

The limited adoption of optical technology (especially for devices in the NIR and IR region) by the viticulture sector can be attributed to both costs and technical limitations. To change this scenario, and to improve the support to vine-growers and wine-makers, research activities are privileged by simplified, easy-to-use, cost-effective systems for real-time assessment of fruit ripeness directly in-situ. For this purpose, the use of silicon detectors in the Vis/NIR region can be considered a real cost-effective alternative to acquire optical data. This makes it possible to break down the cost barrier in precision viticulture, allowing reliable monitoring of grape composition within the vineyard at an effective cost.

One step forward has been recently given by Gutiérrez *et al*. (2019), who reported the quantification of TSS and anthocyanins in grape berries under field conditions using on-the-go his system between 400 and 900 nm, acquired from a moving platform. HSI is a very powerful technology able to yield a large amount of relevant information, although the drawbacks in analyzing (extract

Table 1. Optical sensing applied in viticulture for real-time detection of maturation quality parameters of wine grapes.

Reference parameter	Variety	Optical sensing/region of the spectra (nm)	Spectral index or chemometric model	Model coefficients	Reference
TSS	Chardonnay	Benchtop spectrometer	PLS	R^2 = 0.70, SECV=1.27	Arana *et al.*, 2005
Origin		800-2500	PLS-DA	Acc = 97.2%	
TSS Firmness	Corvina	Portable spectrometer 400-1000	PLS	R^2 =0.62, RPD = 1.87 R^2 =0.56, RPD = 1.79	Beghi *et al.*, 2015
EPC EFC EAC	Tempranillo + Syrah	Portable spectrometer 908-1676	PLS-DA	Acc=69.6 Acc=87.0 Acc=78.3	Baca-Bocanegra *et al.*,2019
TSS Total anthocyanins Yellow flavonoids	Syrah	Benchtop spectrometer 450-1800	PLS, PCR	R^2 = 0.95 – 0.92 R^2 = 0.94 – 0.92 R^2 = 0.75 – 0.75	Dos Santos Costa *et al.*, 2019
TSS Total anthocyanins Yellow flavonoids	Cabernet Sauvignon	Benchtop spectrometer 450-1800	PLS-PCR	R^2 = 0.96 – 0.94 R^2 = 0.98 – 0.97 R^2 = 0.74 – 0.74	Dos Santos Costa *et al.*, 2019
TSS Titratable acidity	Chardonnay	Portable spectrometer 400-1000	PLS	R^2 = 0.71, SEP=1.8 ºBrix, RPD=1.94 R^2 = 0.81, SEP=2.2 gdm-2, RPD=2.32	Giovenzana *et al.*, 2015
Amino acids	Grenache	Benchtop spectrometer	PLS	R^2 $\geq$ 0.60	Fernández-Novales *et al.*,
2019					
TSS		570-1000 and 1100-2100		R^2 = 0.90, SEP=1.6 ºBrix, RPD=3.79	
pH TSS Pedicel detach force	Syrah	600-1000	Ordinary Least Square	R^2 = 0.99 R^2 = 0.99 R^2 = 0.87	Vallone *et al.*, 2019
pH TSS Pedicel detach force	Chardonnay	600-1000	Ordinary Least Square	R2 = 0.99 R^2 = 0.99 R^2 = 0.85	Vallone *et al.*, 2019
TSS Titratable acidity	Chardonnay	Selected bands 630, 690, 750, 850	MLR	R^2 = 0.66, SEP = 1.9 ºBrix, RPD = 1.74 R^2 = 0.85, SEP = 1.8 gdm-2, RPD = 2.50	Giovenzana *et al.*, 2015
Anthocyanin	Shiraz	470 nm, 516 nm, 635 nm	Nonlinear Least Squares	R^2 =0.87, RMSE=0.22	Bramley *et al.*, 2011
TSS titratable acidity firmness anthocyanins	Sangiovese	Cherry meter 560,64	Nonlinear Least Squares	R^2 = 0.92 R^2 = 0.87 R^2 = 0.89 R^2 = from 0.68 to 0.97	Ribera-Fonseca *et al.*, 2016
TSS titratable acidity pH Anthocyanins	Nebbiolo	Selected bands 450, 500, 550, 570, 600, 650, 610, 680, 730, 760, 810 and 860	Multiple linear regression	R^2 = 0.86, SECV=1.51 ºBrix, RPD=2.65 R^2 = 0.47, SECV = 0.83 gdm-2, RPD =1.44 R^2 = 0.45, SECV = 0.09, RPD = 1.33 R^2 = 0.50, SECV = 5.21 %, RPD = 1.46	Pampuri *et al.*, 2021
TSS	Tempranillo	Portable spectrometer 1595.7-2396.3	PLS	RMSEP = 1.42 ºBrix, R^2 = 0.91 RMSEP = 1.48 ºBrix, R^2 = 0.47 RMSEP = 1.68 ºBrix, R^2 = 0.38	Urreca *et al.*, 2016

TSS, total soluble content; RPD, ratio performance deviation; R^2, determination coefficient in validation; Acc, classification accuracy in validation; SECV, standard error in cross-validation; SEP, standard error in prediction; PLS-DA, partial least squares discriminant analysis; EPC, extractable phenolic content; EFC, extractable flavanol content; EAC, extractable anthocyanin content.

useful information) and compute this large amount of information are still a limiting factor for the large-scale application of this technique. For this reason, the same authors (Fernández-Novales *et al.*, 2019) proposed a proximal (0.30 m) optical on-the-go spectroscopic system operating in the 570–990 nm spectral range mounted on a motorized moving platform for measurements on the canopy. The authors proved that this technology is a real alternative to appraise and map the vineyard grape composition variability (in terms of TSS, anthocyanin, and total polyphenols concentrations) with a high spatial and temporal resolution and in a fast and non-destructive way. Moreover, Vallone *et al* (2019), over the traditional prediction of the technological maturation parameters (TSS and pH), proposed an ordinary least squares model using a Vis/NIR device (600-1000 nm) for the prediction of the pedicel detachment force on cv. Syrah and Chardonnay, due to their enormous importance in grapes' mechanical harvest. The results showed a R^2 = 0.85, Standard Error in cross-validation (SECV) = 1.008, and Bias = -0.83 for Chardonnay grapes, and R^2 = 0.87; SECV = 0.362, and Bias = -0.11 for Syrah grapes. All these innovative approaches are becoming crucial in view of an industry (grape and wine) more efficient and completely interconnected. For winemakers, the development of inexpensive optical sensing instrumentation equipped that can be placed in proximity to the fruits for continuous monitoring during the ripening period for several weeks without an operator (thanks to its stand-alone features) could be an interesting opportunity for future development. In the context of precision agriculture, the development of new sensors, especially based on spectroscopy, enables high-resolution data acquisition that could be used to track crop development and ripening. The capability to assess ripening in a fast, non-destructive way, would substantially and positively impact the processes of harvesting (operating procedures, scheduling, and classification) and could change the habits of winegrowers proposing new monitoring solutions.

Vine water status monitoring

Proximal optical sensing of vine water status can be performed by detecting different regions of the spectra. Table 2 summarizes the different indexes and the chemometric models reported in the literature to predict the grapevine water status.

The region of thermal infrared has been widely explored in literature and it founds its major application in thermal imaging (Gutiérrez *et al.*, 2021; Tardaguila *et al.*, 2021). Several studies measured the temperature of leaves and the relative indexes using thermal imaging to estimate the early response of vines to water stress. Leaf temperature (T_c) can be used as an indicator of water status, but an enhanced performance is reported when it is normalized to the environmental conditions through thermal indexes (García-Tejero *et al.*, 2016). The most common thermal indexes are the stomatal conductance index (I_g) (Jones *et al.*, 2002) and the

Table 2. Spectral indexes or chemometric models are used as a proxy for the water status of the grapevine. Best relations to the water stress parameters are reported for each work.

Reference parameter	Region of the spectra – wavelengths (nm)	Spectral index or chemometric model	Model coefficients	Reference
g_{as}	Thermal infrared	Tc	$R^2 = 0.48$	García-tejero *et al.*, 2016
g_s	Thermal infrared	CWSI	$R^2 = 0.61$	García-tejero *et al.*, 2016
gs	Thermal infrared	Ig	$R^2 = 0.76$	García-tejero *et al.*, 2016
g_s	Thermal infrared	Ig	$R^2 = 0.78$	Pou *et al.*, 2014
Ψ_S	1000–1850	PLS	r = 0.84; R^2p = 0.71	De Bei *et al.*, 2011
Ψ_L	1000–1850	PLS	r = 0.74	De Bei *et al.*, 2011
g_s	1000–1850	PLS	r = 0.58	De Bei *et al.*, 2011
Ψ_S	1600–2400	MPLS	$r_c = 0.82$; rcv = 0.77	Tardaguila *et al.*, 2017
RWC	1600–2400	MPLS	$r_c = 0.83$; rcv = 0.77	Tardaguila *et al.*, 2017
Ψ_S	1100–2100	PLS	$R^2_c = 0.74$; R^2cv = 0.71; R^2p = 0.69	Diago *et al.*, 2018
g_s	900; 970	WI	$R^2 = 0.95$	Serrano *et al.*, 2010
Ψ_{PD}	900; 970	WI	$R^2 = 0.41$	González-Flor *et al.*, 2019
Ψ_S		Dark green	$R^2 = 0.71$	Briglia *et al.*, 2019
Ψ_{PD}	520; 539; 586	$VARI_{opt}$	$R^2 = 0.80$	Pôças *et al.*, 2015
Ψ_{PD}	531; 587	$NDGI_{opt}$	$R^2 = 0.79$	Pôças *et al.*, 2015
Ψ_{PD}	561; 554	NRI	ρ = 0.86	Pôcas *et al.*, 2017
Ψ_{PD} and Ψ_L	400–1000	PLS	$R^2_c = 0.70$; R^2p = 0.69	Giovenzana *et al.*, 2018
Ψ_{PD}	900; 680	NDVI	$R^2 = 0.57$	Serrano *et al.*, 2010
N_{PQ}	1490; 531	WABI-1	$R^2 = 0.86$	Rapaport *et al.*, 2015
Ψ_{PD}	1500; 538	WABI-2	$R^2 = 0.89$	Rapaport *et al.*, 2015
g_s	1485; 550	WABI-3	$R^2 = 0.80$	Rapaport *et al.*, 2015
T_c	Thermography	ANOVA	R = 0.94	Costa *et al.*, 2019
g_s	Infrared Thermography	ANOVA	$R^2 = 0.94$	Leinonen *et al.*, 2006

Tc, leaf temperature; CWS, crop water stress index; Ig, stomal conductance index; PLS, partial least square; MPLS, modified partial least square; WI, water index; VARIopt, visible atmospherically resistant index (optimized wavelength); NDGIopt, normalized difference greenness index (optimized wavelength); NRI, normalized reflectance index; NDVI, normalized difference vegetation index; WABI-1, WABI-2, WABI-3, water absorption indexes; ANOVA, analysis of variance; R^2, coefficient of determination; r, correlation coefficient of Pearson; ρ, correlation coefficient of Spearman; c, calibration; cv, cross-validation; p, prediction; opt, optimized wavelength.

crop water stress index (CWSI) (Idso *et al*., 1981). These indexes are strongly related to g_s when measured during the middle of the day (García-tejero *et al*., 2016; Pou *et al*., 2014). Matese *et al*. (2018) calculated CWSI to evaluate the water status of three vine cultivars (Vermentino, Cabernet Sauvignon, and Cagnulari) under different irrigation regimes. In the study, the analyzed water managements were discriminated by CWSI, and the obtained results were consistent with gas exchange measured in leaves.

Besides thermal IR, also the NIR spectral band can be detected and applied to proximal sensing of grapevine water status. In a pot experiment under controlled conditions, Rapaport *et al*. (2015) found a change in the reflectance of this region of the spectra between well-watered and water-stressed plants. Reflectance from leaves of plants under water deficit was higher than the control in the range 1380-1590 nm, corresponding to a peak of water absorbance. Under field conditions, De Bei *et al*. (2011) reported lower absorbance in the NIR region for stressed vines than for well-watered ones. Using a chemometric approach, the authors were able to fix models for the prediction of stem water potential (Ψ_S), leaf water potential (Ψ_L), and g_s on three different varieties: Cabernet Sauvignon, Shiraz, and Chardonnay. The same approach was performed by Tardaguila *et al*. (2017) using several *Vitis* varieties: Albariño, Pedro Ximenez, Verdejo, White Grenache, Grenache, Cabernet Sauvignon, Marselan, and Tempranillo. Selecting the NIR region the authors were able to predict Ψ_S and the relative leaf water content (RWC). In both studies (De Bei *et al*., 2011; Tardaguila *et al*., 2017), better models were obtained by absorbance from the abaxial leaf surface than the adaxial, although both surfaces provided consistent models. Diago et al (2018) predicted Ψ_S of Tempranillo by on-the-go spectral measurements in the NIR region. Specific wavelengths in the NIR regions have been selected to define the water index (WI) (Peñuelas *et al*., 1993). A close relation between WI and g_s was reported by Serrano *et al*. (2010) on Chardonnay in both pot and field experiments, whereas González-Flor *et al*. (2019) found a significant regression between WI and Ψ_{PD}.

The Vis region was also used to monitor the vine plant water status. For example, Rapaport *et al*. (2015) identified two spectral ranges that were affected by water stress, both included in the Vis region: 530-550 nm and 700-750 nm. Another pot experiment was described by Briglia *et al*. (2019) to assess the effectiveness of Vis and NIR imaging to be a proxy for water stress phenotyping. The authors identified the dark green region as the most promising for proximal sensing, showing the strongest relation to Ψ_S. Pôças *et al*. (2015) compared several optical indexes available in the literature and selected the visible atmospherically resistant index (VARI) and the normalized difference greenness index (NDGI) to predict the predawn water potential (Ψ_{PD}) after optimization of the wavelengths. Both indexes are calculated using wavelengths in the Vis region. In Pôças *et al*. (2017) a normalized reflectance index (NRI) reported a higher correlation to predawn water potential than WI. In the study, the two indexes were used along with the index D1 (the ratio between the first derivatives of the hyperspectral curve for the reflectance values at 730 nm and 706 nm) and the day of the year (DOY) in models to predict predawn water potential, calibrated on Touriga National and validated on other cultivars. Tosin *et al.* (2020) selected two optical indexes in the range of Vis (ARI and NRI) and two structural variables (irrigation treatment and test site) to fix logistic selection models to predict the Ψ_{PD} of three varieties (Touriga Nacional, Touriga Franca, and Tinta Barroca) under field conditions. A similar approach to predict Ψ_{PD} is reported by Tosin *et al*. (2021): four optical indexes were calculated in the Vis region ($SPVI_{opt1}$, $SPVI_{opt2}$; PRI_CI2 and NPCI) and used in regression models along with the previous value of predawn water potential (Ψ_0) measured using the reference method based on a Scholander chamber.

Information from the Vis/NIR region has been used to develop some optical indexes. A chemometric model was fixed by Giovenzana *et al*. (2018a) on the variety Biancolella to predict Ψ_{PD} by the Vis/NIR spectra. In Vis/NIR chemometric models, González-Fernández *et al*. (2019) obtained the best results at around 1450 nm using raw data, whereas at 826 nm and 1520 nm with derivative pre-processing. Serrano *et al*. (2010) found a relation between the normalized difference vegetation index (NDVI) and Ψ_{PD} on Chardonnay in ten commercial vineyards. Involving the water absorption peak in the NIR and the Vis range around 550 nm, Rapaport *et al*. (2015) developed three indexes (WABI-1; WABI-2; WABI-3) which reported high relation to g_s, Ψ_{PD}, and non-photochemical quenching (NPQ). Finally, a recent study

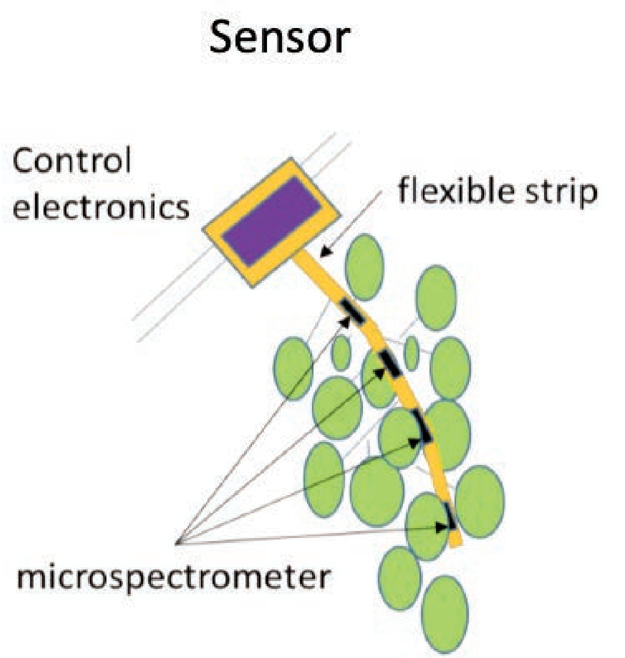

Figure 5. Maturation control stand-alone sensor.

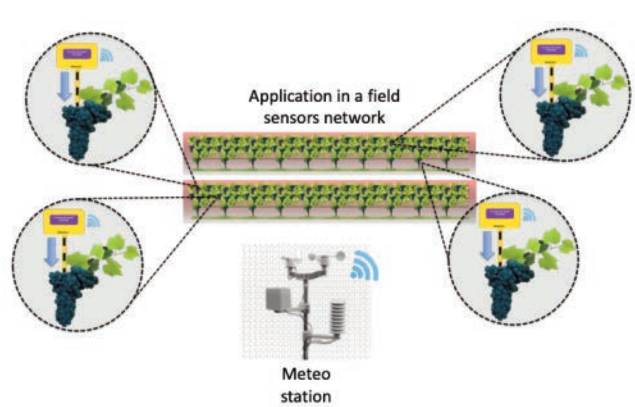

Figure 6. Field sensors network for a data fusion approach.

(Virnodkar *et al*., 2020) identified grapevine as the crop where more spectral indexes were reported in the literature for water stress detection. According to the authors, the most frequent indicator of water stress based on spectral proximal sensing is CWSI, followed by WI, and the Ψ_S is the most used reference parameter.

Perspectives of the proximal optical sensing technology

The multiple aspects of technological evolution are accelerating the development of new sensors and devices based on optical technology in different fields but with a very significant impact on agriculture (including viticulture). Conceptually, two possible architectures for Sensor Network applications as shown in Figure 4, can have a direct influence on how the hardware and software solutions are developed nowadays. On one hand (Figure 4A), there are sensor nodes with high processing capabilities, able to collect data from sensors and run local signal processing with data model prediction (known as Edge IoT sensor nodes). A result (parameter) is then transmitted to a cloud database with the purpose to directly show this data in a simple user interface (it is also possible to observe immediately the result in the display of the instrument). Conversely to this architecture, it is possible to simply collect optical (raw) data and immediately transmit it to a cloud database which will be able to run faster and more complex signal processing and model prediction algorithms (Figure 4B). There is an obvious advantage of this latter architecture that allows for much less complex hardware sensor nodes with lower power consumption and lower costs than the former architecture, contributing to the deployment of larger networks of sensors (with higher density) reinforcing the possibility of expanding the size of the datasets to be acquired. Such networks rely on energy-efficient wireless technologies (Sadowski and Spachos, 2020) to be used in remote areas that include WiFi, Bluetooth, ZigBee, GPRS/3G/4G, LoRa, and SigFox protocols within the radio-frequency bands of 868/915MHz and 2.4GHz, or depending on the operation context, a combination of those wireless communications, to bring real-time data and processing through the IoT to the Cloud as in LoRaWan and NB-IoT. A large number of sensors that address physical and chemical parameters in the soil, water, and air (e.g.,

Table 3. Characteristics of the major optical technologies applicable to the development of optical sensors for proximal sensing in viticulture.

Optical technology	Optical range (nm)	Optical resolution (nm)	Integration potential /size range (nm)	Fabrication process	Power requirements	Stand-alone operation	Cost (USD)	Reference
Mini spectrometers	350-810	2.2-13.1	+cm^2	MEMS + CMOS	500mA@5V	Yes	~1500	Ocean ST Vis micro spectrometer
Grating-based spectrometers	340-850	12-15	++ cm^2	MEMS + CMOS	20mA@5V	No	~200	Hamamatsu C12880ma
Tunable Fabry-Perrot	1350-2150	20	++ mm^2	III-V material + MEMS	FPI 1mA@10-50V	No	~100	Hamamatsu C14272/73
Spectral sensors	750-1100	FWHM ~10 Peak separation 5	+++mm^2	CMOS	2.5mA@3.3V	No	~4-7@100 units	AS7421
	380-1000	20-50			210µA@3.3V			AS7343
	410-940	20			5mA@3.3V			AS7265x

FWHM, full width at half maximum; MEMS, micro-electromechanical systems; MOEMS, micro-opto-electromechanical systems; CMOS, complementary metal-oxide semiconductor; +, low; ++, medium; +++, high.

Table 4. Strengths, weaknesses, opportunities, and threats from review outputs in a view of the application of proximal optical sensing for control and management inside the wine sector.

	Helpful	Harmful
Internal	Strengths Automation with remote control • Reduced manpower • Lower risk of human error • Low-cost analysis • Real-time measurement • Extensive technical support and network • High product quality, scalability, reliability, and flexibility • High sustainable solution (Zambelli *et al.,* 2020) • Higher wine value	Weaknesses • Uncontrolled environmental conditions could affect sensors' performances (Ghiani *et al.,* 2021) • High number of sensors for wide areas to get representative measures (Pampuri *et al.*, 2021a)
External	Opportunities • Patentable devices (Guidetti *et al.,* 2022; Freitas and Piteira, 2018) • Viticulture and enological sector undergoing technological modernization, addressing the Industry 4.0 approach (Sà *et al.,* 2021) • Strong attention to environmental sustainability issues (https://sdgs.un.org/goals, SDGs 9 and 12)	Threats • Strong link with traditional production methods • Reduced orientation to innovation in SMEs managed by the old generation • No established use

humidity, temperature, soil moisture, pH, nitrates, *etc*.) have been used and are commercially available.

A potential limitation of this architecture is the size of the data payload, which should be kept to a minimum to be compatible with the standard IoT communications protocol. Moreover, nodes with capabilities to run edge processing (Figure 4B) are usually more power-hungry, with higher hardware/software complexity and bulkier dimensions (large boxes or systems that require an operator to run them).

For the development of a new generation of stand-alone and on-the-field grape analytical methods as in the architecture concept of Figure 4A, the sensor node hardware has to meet three fundamental criteria: to have highly integrated photonics components and modules (wafer and wafer/package level micro-spectrometers), to have low power consumption, and to be cost-effective, helping to bring the process control of grape maturation into the hands of the growers/winemaker. The parameters of the vine and grape control to the home base station in the farm, without human intervention, can only be achieved by developing modular systems that allow for future integration of cost-effective multi-mode sensors.

Semiconductor fabrication trends in recent years have pushed the boundaries for photonics technologies allowing for increased miniaturization of optical sensors as a key feature for the implementation of disrupting analytical strategies. Table 3 shows how different operation principles and fabrication technologies contributed to the miniaturization process despite evident trade-offs with performance, cost, and power consumption. The silicon CMOS (complementary metal-oxide semiconductor) fabrication processes intrinsically set the operation range of photodetectors into Vis/NIR wavelengths between 350nm and 850nm. Other fabrication processes based on III-V materials allow to address the fabrication of photodetectors in the pure NIR range between 1000 nm and 2000 nm, but those materials are not compatible with CMOS requiring heterogeneous integration (multi-die or multi-module assemblies). Optical wavelength discrimination can be achieved by using optical pass-band filters or gratings. Grating technologies are those with the highest detection efficiency (Hillmer *et al*., 2021). Optical resolutions of 2 nm to 15 nm within the visible range are common and can be seen in some commercial compact spectrometers such as the ones commercialized by Hamamatsu (Hamamatsu Photonics K.K., Hamamatsu, Japan) and Ocean Insight (Ocean Insight, Orlando, FL, USA). The hardware complexity of these devices, which include a mixture of MEMS, complementary metal-oxide-semiconductor (CMOS), and other elements in their assembly not only increases the costs but also its footprint making them less suitable for miniaturized sensor nodes.

An alternative to the gratings technology is another MEMS-based fabrication process, the Fabry-Perrot interferometer (FPI) used as a programmable optical filter. MEMS and micro-opto-electromechanical systems (MOEMS) are microscopic devices with electrical functionality and moving parts (Rai-Choudhury, 2000). The mechanical motion is actuated using electrical driving principles, which can be electrostatic, magnetic, or piezoelectric (Tortschanoff *et al*., 2013). Their application requires its integration (assembly) with a single photodetector and consequently has lower footprints, but also a high voltage to drive the FPI MEMS structure which makes this more complex to use. Commercial offers are mostly available for NIR applications (e.g., Hamamatsu C14272) and only research-based developments can be found for Vis range applications. The interest in the use of these systems, especially for NIR applications, is based on the possibilities of real-time field measurements of organic matter (e.g., vines and grapes for the parameters reported in Tabled 1 and 2) in combination with the availability of other sources of data of different nature thanks to mobile Internet services. NIR offers a good balance of effort of measurement and quality of the results combining chemometrics and access to a database service with reference data that has been obtained using standard laboratory methods (the reference database mentioned in Figure 4).

A final alternative shown in Table 3, is the spectral sensors. These devices hold a combination of the photodetector (matrix of 6 to 20) and optical filters assembled on top of the CMOS sensor die. A selection of specific optical bandpass filters is chosen according to the application requirements, by reducing the silicon size, power consumption, and complexity of signal processing which has a direct impact on the production costs. These characteristics make the spectral sensors an interesting alternative for the simultaneous detection of multiple optical bands.

Currently, these devices (after proper customization) offer sufficient computation power, and both access to online data ("the cloud") or storage on the device itself, as illustrated in Figure 4. Moreover, they can be improved by using predictive models based on artificial intelligence methods and the possibility to include feedback and statistics from many other measurements performed in the field. This can pave the ground for the future of reference data in several fields (Grüger, 2021).

A potential example of this new trend is the possibility of using an optical stand-alone sensor that can be placed in proximity of the target (e.g., vine leaf and grape) for field data acquisitions. Such an approach (although the number of sensors to be installed to have a meaningful representation of vineyard conditions is an issue yet to be resolved) can maximize the capability to acquire information on both a temporal and spatial basis. The latter aspects are critical for viticultural areas where the implementation of other monitoring techniques cannot reach an adequate level of accuracy, due to their complexity (e.g., areas with complex orography). These simplified devices can be considered as integrated micro spectrometers, where their components/modules could be assembled into an optical detection head (e.g., flexible strip) installed directly in the grape bunch or on the grapevine, including power, signal pre-processing, and communications for "on-line" process monitor (Figure 5). An example of this approach is a concept patented by the authors (Freitas and Piteira, 2018) that proposes a fully integrated, small, low-cost, standalone monitoring device used to monitor fruit status to help the growers to support the decision-making process (Oliveira *et al*., 2024; Jenne *et al*., 2024).

The micro spectrometer should cover the UV-Vis-NIR range using an integration of LED light sources, photodiode/interference filter arrays, and processing electronics at the wafer level or wafer package level. The modular architecture of the concept makes it feasible to perform different optical measurement modes (e.g., reflectance and fluorescence) by customizing the optical components of the sensor (e.g., integrating optical filters for fluorescence and different LEDs for illumination) according to the objectives of the optical measurement.

Another key aspect of the new generations of miniaturized optical sensors is their potential for integrating wireless sensor networks (WSNs) into agriculture (Ojha *et al*., 2015). WSNs are essential tools to monitor multiple parameters of interest in large areas with an adequate degree of resolution that can then be integrated into decision support systems. For example, this concept was applied to the irrigation management of a vineyard (Maraš *et al*., 2020), which is one of the most challenging and complex topics of the viticulture of the 21st century (Mirás-Avalos and Araujo, 2021). Hence, it is expectable that optical sensors will have a pivotal role in the next generation of WSNs. WSNs are nowadays, widely used in agriculture monitoring helping farmers' decision-making towards higher quality and productivity crops (Popescu *et al*., 2020). The extension of WSN to crop proximal sensing requires that their design addresses specific challenges (Jawad *et al*., 2017): to have a versatile, low-power, and low-cost IoT device able to connect multiple sensors for in-field data collection (Morais *et al*., 2021), to optimize IoT device power consumption and battery lifetime (Jawad *et al*., 2017), to optimize communication range within the operation and climate conditions, to provide real-time data, and to be reliable, fault-tolerant and secure (Prodanović *et al*., 2020). Moreover, the vineyard sensors distribution should cover the spatial variability at best. Some approaches can be followed, for example, the sensor can be placed in areas with different vegetative expressions (canopy porosity) and soil physical properties as proposed by Fuentes-Peñailillo *et al*. (2021).

WSNs can also significantly improve the quality and the development timeline of information fusion (Figure 6) which is still in its early stage (Zecha *et al*., 2018). The fusion of such different sources of information would be the first step toward a completely new monitoring method using a complex combination of sensors as a new concept of process analytical technology (PAT) applied in viticulture. The conventional approaches based on wet chemical analysis or optical methods combined with a supervised predictive models could pave the ground for a new monitoring approach that qualitatively follows the entire crop season. The grape and vine optical data can be integrated into decisional support software creating decision models with closed-loop structures that adapt to weather conditions (e.g. temperature, relative humidity, precipitation, wind speed, atmospheric pressure, *etc*.) to prevent possible diseases, stress conditions and identify the best harvest moment (Navarro-Hellín *et al*., 2016; Rose *et al*., 2016; Pérez-Expósito *et al*., 2017).

By moving from a univariate measuring approach (wet-chemical analysis performed every week) to a multivariate one, monitoring of the quality should move from traditional statistical quality control (SQC) to multivariate statistical process control (MSPC) contextualized in agriculture (Kourti, 2019). A multivariate measuring system provides for each sampling point several highly correlated variables (optical and not) that can be handled by multivariate projection methods (e.g., PCA) enabling the reduction in the data dimensionality by taking advantage of its correlated structure (Kourti, 2006) The principal components needed for the description of the process variability could then be used for MSPC chart construction by representing these components against each other or against process time. Such an approach can be able to direct visualize changes occurring along the process or trends which can be potentially related to specific conditions of the grapevines like the occurrence of water stress or to detect infections.

The integration of such innovative PAT tools has the potential to be widely used in the viticulture field (and with proper adaptations in a broad range of optical monitoring applications e.g., other fruit ripening monitoring), and will help vine growers to monitor the crop season autonomously (with minimum external intervention). The PAT tools will certainly result in higher quality of the grapes being supplied to the winery, also allowing irrigation optimization (when allowed to avoid severe water stress) and predicting the harvest time. This will allow the farmer to inform the winery about the ongoing grape ripening status before harvesting. It can be an extra added value in regions where climate change effects are present (e.g., high aridity), and in vineyards where extreme conditions (combination of high temperature and low soil humidity) lead to untimely or severe stress in the vine/grape.

To summarize the strengths, weaknesses, opportunities, and threats from review outputs given the application of proximal optical sensing for control and management inside the wine sector, a SWOT table was created (Table 4), based on published literature and through interviews involving winegrowers and other stakeholders of the sector.

Conclusions

This review has examined the current landscape and emerging perspectives of proximal optical sensing technologies for vineyard control and management. The literature reveals that these non-invasive techniques provide timely, precise, and sustainable means of assessing critical parameters such as grape ripening and vine water status. Their integration into vineyard workflows enables the collection of high-resolution data, offering growers valuable insights that support informed, data-driven decisions.

Relevant is the synergy between proximal optical sensing and advanced data analytics. They have led to the development of decision support systems that enhance vineyard performance and resource efficiency. These systems are increasingly vital in the face of climate-related challenges, which demand adaptable and resilient agricultural practices.

However, to ensure broader adoption and end-user accessibility, key challenges must still be addressed. These include the standardization of sensor calibration, data interpretation protocols, and the development of affordable, easy-to-use sensing platforms suitable for real-world vineyard conditions.

Looking ahead, proximal optical sensing stands as a cornerstone technology in the transition toward precision viticulture and digital farming. With continued progress in sensor miniaturization, wireless communication, and AI-driven modeling, these tools are poised to become integral components of next-generation, autonomous vineyard monitoring systems. In a sector increasingly shaped by climate variability and sustainability demands, proximal sensing technologies will play a crucial role in securing grape quality, optimizing inputs, and supporting decision-making ultimately shaping the viticulture of the 21st century (Ammoniaci *et al*., 2021).

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