Agriculture and Food

AIMS Agriculture and Food, 10(2): 390–422.
DOI: 10.3934/agrfood.2025020
Received: 09 November 2024
Revised: 30 April 2025
Accepted: 23 May 2025
Published: 13 June 2025

https://www.aimspress.com/journal/agriculture

Review

Precision viticulture in Mediterranean countries: From vegetation vigour and yield maps to spatially and temporally variable vintage

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Abstract: In Mediterranean countries, due to warmer and drier environmental conditions, viticulture faces problems such as drought, short biological cycle, and frequent infestations by pests. Precision Viticulture (PV), through spatially variable rate application of crop inputs, enhances grape yield and quality, while reducing operational costs and environmental impact. PV has been a reality in Mediterranean countries since the end of the last century. Proximal/remote sensors such as LIght Detection And Ranging (LIDAR), soil electrical conductivity proximal sensors, and remote sensing from Unmanned Aerial Vehicles (UAVs) and/or satellites and/or robots can monitor vegetation vigour, thus delineating vineyard Management Zones (MZs), needing specific crop input amounts. MZs enable us to plan either temporally variable vintage in zones having different ripeness periods for producing uniform quality grapes and, therefore, wine, or spatially variable vintage for producing different quality grapes and, therefore, wines. The economic and environmental benefits of PV should be quantified by refining user-friendly data processing software and developing models to better understand and address the within-vineyard spatial variability of crop and soil parameters. Our aim of this review article was to highlight the ways PV can be implemented in Mediterranean countries to face problems such as drought, short biological cycle, and frequent infestations by pests.

Keywords: vineyard; spatial variability; proximal/remote sensing; crop inputs; site-specific application

1. Overview

The agricultural landscape is undergoing significant changes as a result of the digital revolution: State-of-the-art machines, computerised tools, and advances in Information and Communication Technology (ICT). This integration aims at improving decision-making processes and productivity in agriculture [1]. Precision Agriculture (PA) is the targeted application of crop inputs according to the locally determined crop needs: It is the geo-referenced application of crop inputs, whose amounts should be appropriate to the crop needs [2,3]. The International Society of Precision Agriculture (ISPA) adopted a new definition in January 2021: "Precision agriculture is a management strategy that integrates temporal, spatial, and individual data to improve resource efficiency, productivity, quality, profitability, and sustainability in agricultural production". This evolving approach, characterised by the geo-referenced use of crop protection products not only increases agricultural productivity but is also in line with the global imperative of sustainability. The latest ISPA definition emphasises the contribution of PA to increase the resource efficiency and the sustainability of agricultural production, as well as it fitting into current discussions on environmentally conscious practices and climate resilience [4].

Viticulture is very important for Mediterranean countries, accounting for 40% of the global vineyards area in 2018. However, Mediterranean viticulture is expected to be significantly affected by climate change. Due to the warmer and drier environmental conditions, viticulture is facing problems such as drought, shorter biological cycle, and more frequent infestations by pests, causing lower yield [5]. Thus, changes are needed in the viticulture crop operations to mitigate this impact.

Precision Viticulture (PV) can significantly mitigate climate change impact on vineyards. PV is defined as the branch of PA that corresponds to viticulture [6]. PV enhances grape yield and quality, while reducing operational costs and environmental impact and risks [7]. In order to achieve its objectives, PV must manage the spatial and temporal variability found in vineyards through variable rate crop input application and selective vintage [8]. Therefore, PV is highly dependent on the information used for delineating Management Zones (MZs) and performing spatial and temporal analyses, thus enabling us to apply spatially variable rates of crop inputs and perform selective vintage [6].

Remote Sensing (RS), an essential component of PA, is a non-destructive method for collecting information about objects or areas and is fast and cost effective compared to destructive techniques [9]. Several RS sensors are used in viticulture to capture the spatial and temporal variability of key vineyard parameters and, therefore, help vine (*Vitis vinifera* L.) growers make decisions for optimal management [10]. These sensors can be hyperspectral [11], multispectral [12], thermal [13] and RGB cameras [14], spectroradiometers [15], proximal canopy sensors [16], LIght Detection And Ranging (LIDAR) [17], soil electrical conductivity sensors [18], RADAR [19], and others such as Leaf Area Index (LAI) sensors [20]. RS can be classified into satellite, airborne, and ground/proximal, based on sensor platforms. Satellite RS quickly covers large areas but it provides medium spatial resolution (meter level) data. Aerial RS provides high spatial resolution (centimeter level) data but it does not cover as much area as satellite RS. Proximal RS, carried out on foot, by means of manned vehicles or ground robots, provides high spatial resolution data but requires a long time [9,10,12,21].

The use of the above platforms, together with the aforementioned sensors, alone or in combination with each other, can enable non-destructive estimations of key vine parameters that are related with crop vegetation vigour [22], water stress [23], disease severity [24], and soil conditions [25]. After proper analysis (e.g., by using spectral vegetation indices for optical RS sensors), the values of these parameters can enable us to delineate MZs [18] and apply spatially variable rate crop inputs, e.g.

fertilisers, water, and Plant Protection Products (PPPs) [10].

Based on the aforementioned technology, PV can also contribute to mitigate the effects of climate change on Mediterranean viticulture, both now and in the future [26,27]. Therefore, our aim of this review article is to summarise PV technologies.

A schematic diagram illustrating the structure of this review is shown in Figure 1.

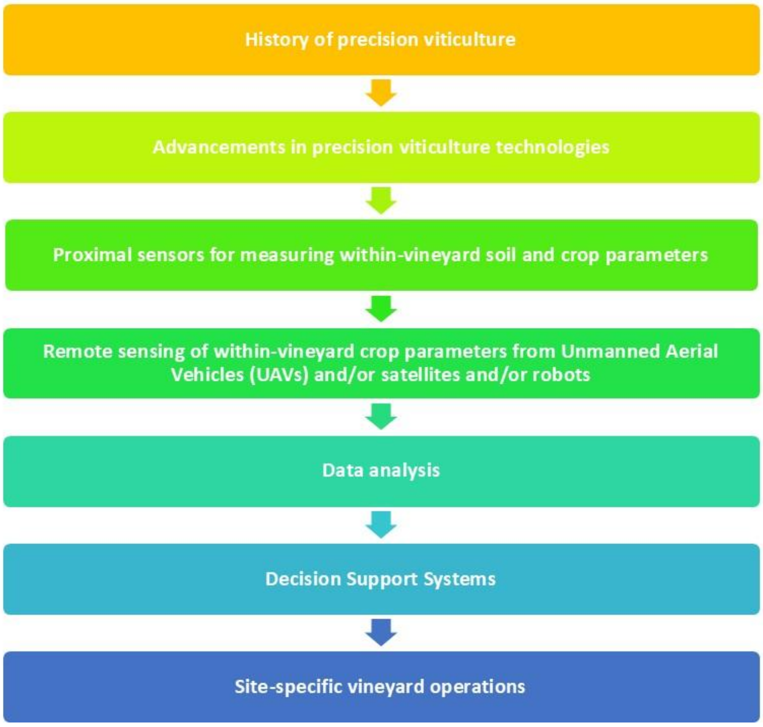

Figure 1. Schematic diagram illustrating the structure of this review.

2. History of precision viticulture

PV is recognised as a relatively new practice in agriculture, initially emerging prominently in the USA and Australia during the late 1990s. The first known implementations of PV were carried out in 1998 in the USA and 1999 in Australia, by introducing spatially variable management techniques that significantly influenced viticulture practices worldwide [28–31]. Shortly thereafter, PV applications began appearing in Mediterranean countries, notably in Italy. By 2001 and 2002, advanced PV practices were adopted in the vineyards of Cantine Giacomo Montresor in Cavalcaselle (Verona) and Riccagioia in Torrazza Coste (Pavia). These implementations used satellite RS to produce detailed vegetation vigour maps, which facilitated targeted management interventions like spatially variable green pruning and harvest [32,33]. Additionally, sensor technologies were employed to monitor grape yield, sugar content, and acidity, thus establishing a foundation for yield and quality optimisation.

In Greece, the PV movement took a different initial focus, by concentrating on the delineation of MZs, based on soil and topographic parameters, by 2011 [34]. This approach highlighted the importance of adapting PV technologies to local environmental conditions and vineyard characteristics. The adoption of PV also extended to other key wine-producing Mediterranean countries. In Spain, efforts centred around the use of UAVs and ground sensors to enhance water management strategies, that are crucial under arid conditions. In France, researchers in the Provence region explored the integration of PV with traditional viticulture practices, aiming to enhance grape quality and environmental sustainability [35,36]. The early 2000s saw significant technological advancements with manufacturers like Pellenc and Gregoire introducing machines specifically designed for precision viticulture. These included wood pruning machines and grape harvesters equipped with dual hoppers for harvesting different quality grapes from designated MZs, thus reflecting spatially variable vegetation vigour levels [37–39]. In Turkey, the initial application of PV included the use of high spatial resolution satellite images to map vineyards in a region, by using object-based image analysis [40]. In Croatia, one of the first applications of PV included the selection of vineyard sites using satellite images, pedometric data, and Geographic Information Systems (GISs) [41]. In Portugal, the applications of PV included the use of satellite vegetation vigour maps together with soil electrical conductivity maps to delineate Management Zones (MZs) [42], as well as to validate these zones and, then, guide smart soil sampling [43]. The implementation of PV in Mediterranean countries has not only improved the efficiency of vineyard management but it also addressed specific regional challenges such as water scarcity and the adaptation to microclimatic variability. This historical overview underscores the progressive adoption and adaptation of PV technologies in Mediterranean countries, thus highlighting their critical role in the evolution of modern viticulture.

3. Advancements in precision viticulture technologies

The following technologies are implemented in PV: Technology for producing vegetation vigour maps, enabling us to perform spatially variable pruning; technology for producing crop yield maps, allowing to perform temporally variable harvest, in the vineyard MZs having different ripeness periods, or spatially variable harvest, in the MZs having different vegetation vigour levels; and spatially variable crop operations, e.g., green pruning, fertilisation, fungicide application, and vintage [44–46].

Since the first implementations of PV at the world level, as well as in Mediterranean countries, much has changed. The fast-pacing advancements of the technological sector enabled the broader and intensive implementation of PV. Specifically, freely available satellite data from Copernicus Sentinel-2 processed with RS methods (e.g., for sensing spectral vegetation indices), enabled us to periodically monitor vines [47]. Internet of Things (IoT) technologies enabled us to continuously monitor weather, soil and vine parameters, as well as insects and diseases [48]. Proximal sensors, e.g., spectroradiometers, canopy sensors, soil Electrical Conductivity (EC) sensors, thermal and multispectral cameras, and proximal/remote sensors, i.e., LIDAR, can contribute to the spatially variability assessment of important soil and vine parameters, either directly or indirectly [49]. UAVs can be used for vine monitoring and crop protection [50]. Additionally, Fountas et al. [51] reviewed the uses of terrestrial robots in agriculture, thus identifying their possible implementation in viticulture, for several operations, including crop monitoring and protection, as well as pruning and tillage.

PV significantly contributes to sustainability by efficiently reducing the waste of resources, minimising the use of chemicals, and increasing the efficiency of vineyards. This fits the wine industry's increasing emphasis on environmentally friendly practices that are key in Mediterranean countries, which are facing challenges such as water scarcity, soil erosion, and biodiversity loss. By using PV technologies, vineyard operators can finely tune the use of water, fertilisers, and pesticides for optimal resource management while improving soil quality and nature conservation [10,52,53]. In addition, PV can significantly contribute to preserving the cultural and natural heritage of the

Mediterranean wine sector, as well as promote the biodiversity and identity of local grapevine varieties and terroirs (vineyard soils) [54].

The aforementioned technologies are analysed below.

4. Proximal sensors for measuring within-vineyard soil and crop parameters

In recent years, researchers and companies proposed proximal real-time sensors to monitor the conditions of a vineyard. These sensors enable us to compute the crop input amounts needed by the crop in each MZ, thus improving the vineyard management and accurately addressing its potential problems.

4.1. Soil sensors

Soil sensors measuring water content play a key role in the micro-vineyard monitoring. As vine roots cannot penetrate in the soil below 0.60–0.90 m depth, its ground water reservoirs are considered as surface ones and the soil water content sensors can be easily set up, in order to provide temporal predictions by means of fuzzy and neural network algorithms [55].

Soil water content sensors can be classified in the following categories:

1. Matric potential sensors;
2. Time Domain Reflectometry (TDR) and Time Domain Transmissometry (TDT) sensors;
3. Capacitance sensors.

Matric potential sensors, i.e. tensiometers, measure the water retention capacity, i.e. the tension between soil and water. These sensors are constituted by a water-filled tube and a ceramic holed tip to directly measure the tube-soil water absorbance (tension or water retention capacity) as pressure (kPa) of the vacuum generated inside the tube. The advantages of tensiometers are their medium cost and high accuracy, while their disadvantage is their need for a significant maintenance. Therefore, tensiometers are suggested for small vineyards having an area smaller than 5000 m^2.

Both TDR and TDT sensors use electromagnetic waves for measuring the variations of soil dielectric constant caused by soil water content [56,57]. TDR sensors measure soil reflectance by sensing the response to pulses, while TDT sensors use wire loops having an oscillating frequency and Phase-Locked Loop (PLL) detectors for measuring phase shifts. These sensors have very low prices, 10–20 times cheaper than that of a tensiometer, and require medium maintenance, including cleaning and replacing defective electrodes. TDR soil sensors also include soil water content resistance sensors that directly measure soil EC through voltage amplifiers. These sensors are the cheapest ones, as their maximum price is € 5, but they require electrode replacement once a month [55]. TDR, TDT, and soil EC sensors can provide accurate multiple soil depth adjustments. Capacitance sensors are similar to TDR sensors unless they indirectly measure the dielectric soil permittivity by directly measuring the charging time of a two-electrode capacitor. The price of capacitance sensors is much higher than TDR and TDT ones, and are 5–10 times more expensive than tensiometers. However, capacitance sensors require less maintenance and are more accurate at different soil depths compared to tensiometers.

Another soil sensor is soil cone penetrometer, which can measure soil cone penetrometer resistance, which is the index of soil compaction. In fact, the measurement of soil cone penetrometer resistance is an easy, quick, and cheap practical method, used at worldwide for sensing and evaluating soil compaction. The soil cone penetrometer resistance measured by this sensor is equal to the pressure encountered by plant roots during their growth. The root growth stops where soil cone penetrometer resistance is between 0.8 and 5 MPa. Therefore, measurements up to 5 MPa indicate compacted soils, where root growth is hindered, thus reducing crop yield. Moreover, maps of within-field soil compaction can be produced by means of an electronic penetrometer. This sensor is constituted by a rod, ending with a cone, pushed into the soil by a hydraulic cylinder, a load cell measuring the applied force (whose absolute value is equal to soil cone penetrometer resistance), and a displacement detector measuring the penetration depth [58,59].

4.2. Solar intensity and radiation sensors

Solar intensity and radiation sensors are used for micro-vineyard monitoring using the following secondary indices: The Heliothermal Index (HI), based on the daily temperature and solar irradiance, can express the mass of leaves' photosynthetic products; and Biologically Effective Degree Days (BEDD), an index equal to the daily temperature difference between maximum and minimum measured by a weather sensor [60,61]. Furthermore, the following statistical climate indices are used for assessing the suitability of a location for viticulture: Growing Degree Days (GDD); Huglin Index (HI); Accumulated Growing Degree Days (AGDD), an index that can predict the time of grapevine growing stages; average Growing Season Temperatures (GST), also measured by a weather sensor [62,63]; and Normal Heat Hours (NHH), which attempt to exceed the limits characterising the other thermal indices [64].

Quantum light Photosynthetically Active Radiation (PAR) sensors (PAR meters) or ceptometers are used to indirectly measure the solar intensity of reflected photosynthetic plant radiation [65]. They directly measure the amount of photons absorbed in 400–700 nm band, so that they provide a voltage index of the Photosynthetic Photon Flux Density (PPFD) gradient or the canopy LAI value [66]. Ceptometers are expensive sensors because they can self-calibrate the monitoring frequency range of reflected radiation, while the sunshine duration time is measured by means of Light Dependent Resistors (LDRs).

Leaf-shaped sensors are commonly used to measure solar radiation luminescence by quantifying the light reflection of flat, diffuse, and uniform surfaces (expressed as cd), and pyranometers measure solar power (W) in the spectral range 500–2800 nm. These sensors carry out measurements once a day or every hour, for Near-Infrared (NIR), Infrared (IR), falling radiation, and optical solar radiation that can be absorbed by a vineyard. Pyranometer sensors can measure the absorbed solar radiation in a wide range of frequencies of either NIR or IR. Appropriate sensors for solar ionising radiation UVA, UVB, and UVC can measure the absorbed radiation in the range 315–400 nm.

These sensors are classified in three categories:

1. CO_2 sensors, placed in the upper area of a cane near the vine trunk, in order to measure vineyard anaerobic respiration;
2. Dendrometers or digital caliper meters, for measuring the swelling and shrinkage, growing, or ripeness as an indication of growth or plant stress;
3. Bipolar electrodes (USA patent), wrapped around the cane near the vine trunk, for measuring the amount of nutrient ions moving from the cane to the vine leaves [67].

4.3. Electromagnetic induction sensors

Soil surveys, above all in gravelly soils, require time and a high work load, meaning they are expensive. This limits the ability to carry out an appropriate sampling aimed at quantifying within-vineyard spatial variability.

The spatial variation of soil parameters, including topography, highly affects within-vineyard spatial variability. The proximal sensing of soil variability requires the use of a wide range of sensors. The apparent soil electrical conductivity (ECa) sensor, mounted on a mobile platform and coupled with a GNSS receiver, is paramount when designing a new vineyard or redeveloping an existing one, as well as for the definition of MZs for spatially variable crop management. Two types of sensors are currently marketed for measuring soil ECa, based on the method of measurement: Contact or non-contact ones.

The former (e.g. Veris sensor) is invasive and includes electrodes, usually shaped as coulters that come into contact with the soil: In the soil, a transmitter electrode generates an electric current, whose potential difference is measured, so that a second receiver electrode measures the electrical resistivity (i.e., the inverse of electrical conductivity).

The latter (e.g., Dualem and EM38 sensors) is non-invasive and is constituted by a transmitter and a receiver coil, usually mounted at the opposite ends of a non-conductive bar. This sensor type is based on the working principle of Electromagnetic Induction (EMI): In the soil, it is possible to generate a magnetic field that induces an electric current, which in turn creates a second magnetic field proportional to its electrical conductivity, which is measured by the sensor. The ECa is correlated to many soil physical and chemical parameters, such as texture, depth, water retention capacity, organic matter content, salinity, Cationic Exchange Capacity (CEC), pH, exchangeable magnesium content, and other soil nutrients contents [43].

The potential use of EMI sensors for measuring apparent EC and improving the measurement accuracy of sparsely sampled major parameters was assessed by Morari et al. [68] in a 5-ha gravelly soil vineyard in Valpolicella (Verona), Northern-Eastern Italy. EC was measured by means of a Geonics EM38DD, operating in both horizontal and vertical modes. Geo-electrical measurements were also carried out in 18 positions through the Electrical Resistivity Tomography (ERT) method, in order to produce high resolution images of the soil profile. The spatial variability of soil parameters and their correlations with EC in both horizontal and vertical modes were estimated through multivariate geostatistical techniques. Spatial dependence between EC and soil texture was explored through Factorial Kriging Analysis (FKA), which could isolate and display sources of variation acting at different spatial scales and represented them as regionalised factors. EC was highly correlated with the measured physical soil parameters: EC was negatively correlated with the coarser textural components (gravel and sand) and positively with the finer ones (clay and silt). EC measurements were also consistent with ERT profiles, highlighting the presence of gravelly parent material, having a low EC, being variably distributed along the three dimensions and affecting vine root depth. FKA enabled to isolate two significant regionalised factors, which describe the variability of soil physical parameters at the different selected spatial scales, with an acceptable loss of information. These factors, used in fuzzy c-means classification, enabled to delineate MZs to be separately treated. The results proved that EM38DD could be effectively used to produce a soil map in gravelly soils, even if soil samples are needed for understanding and interpreting the measured EC values.

Andrenelli et al. [69] developed a procedure for minimising the cost of soil surveys by optimising the Automatic Resistivity Profiling (ARP) method and selecting the best sampling sites for soil profile description and analysis.

Tests were carried out in a 3.5 ha vineyard in Tuscany, Central Italy. ARP enabled close-spaced measurements of 2335 geo-referenced values of apparent Electrical Resistivity (ERa) at 0.5 m ca.

depth. Furthermore, a fast soil surface sampling (0.1–0.3 m depth) was carried out for analysing water content, texture, and EC. Correlations among soil parameters, elevation, and ERa data were analysed, together with a comparative computation of the cost for soil description, analysis, and ARP surveys. Clay was the soil parameter best correlated to ERa, so its predictability was assessed by starting from different combinations of reduced ARP measurements and sampling sites selected through the regression-driven method and ECa Sampling, Assessment, and Prediction (ESAP) software. The reduction of the soil sample number affected clay predictability less than the decrease of ARP survey density. The regression approach provided better clay prediction than ESAP software for the densest ARP survey and widest soil sampling. This method can be used in fields after geoelectrical calibration. As the case study can be considered as representative of many Mediterranean viticulture districts, this procedure can be widely used. These results suggest that ARP on-the-go sensor can fruitfully support conventional soil surveys by reducing the cost for sampling and laboratory analysis.

5. Remote sensing of within-vineyard crop parameters from Unmanned Aerial Vehicles (UAVs) and/or satellites and/or robots

Vineyards can be classified in two categories of macro-level or high-level surveillance and micro-level or dense probing surveillance. Macro-level surveillance is performed by means of RS or infrared and multi/hyper spectral tools. RS can be performed by means of robots, UAVs, autonomous vehicles equipped with Global Navigation Satellite System (GNSS) mobile receivers, or cameras in the visible spectrum. The Proba-1 satellite was launched in 2001 for Earth observations using a compact spectrometer monitoring 18 user-selected visible and near-infrared wavelengths of medium spatial resolution, i.e., 8–12 m pixel, and acquiring more than 20,000 environmental images.

GeoEye is DigitalGlobe's high spatial resolution (1.65 m) imaging satellite, used by Google Maps, while Landsat 7–9 and EO-1 satellites are used by National Aeronautics and Space Administration (NASA).

Copernicus Sentinel-2 from the European Space Agency (ESA) provides a 10 m pixel spatial resolution [70]. In the RS process, data and models acquired from meteorological satellites in the EU, such as Geostationary Operational Environmental Satellite (GOES), for the EU and Africa, METEOSAT, Soil Moisture Active Passive (SMAP) satellites, and National Oceanic and Atmospheric Administration (NOAA) satellites, in accordance with the dense positioning of meteorological and geodesy stations monitoring atmosphere water vapour content [71,72], offer solid grid observations and notifications of severe weather events. Moreover, it is possible to perform the RS of vineyards by means of thermal imaging (aerial and ground-based) and hyperspectral techniques [73–77]. These RS approaches involve the acquisition of spectral data from expensive platforms, such as satellites or aircrafts or Remotely Piloted Aerial Systems (RPAS) or UAVs.

In order to remotely sense the vegetation vigour of grapevine plants, the images acquired in the phenological stages when a variation of the value of a vegetation vigour index, e.g. Normalised Difference Vegetation Index (NDVI), is are used, in Mediterranean countries:

- Before green shoot removal (April);
- After green shoot removal (May);
- Before harvest (August);
- After harvest (September).

Several vegetation indices can be used to assess various vineyard parameters (e.g. vigour, leaf area, grape yield, and quality), in a non-destructive way. Some of them are presented in Table 1.

Table 1. Vegetation indices used in viticulture studies.

Vegetation Index Name	Equation	Reference
Optical		
Difference Vegetation Index (DVI)	$DVI = NIR - RED$	[78]
Normalised Difference Vegetation Index (NDVI)	$NDVI = \frac{NIR - RED}{NIR + RED}$	[78]
Enhanced Normalised Difference Vegetation Index (EVI)	$EVI = \frac{2.5 \times (NIR - RED)}{NIR + 6 \times RED - 7.5 \times BLUE + 1}$	[78]
Green Normalised Difference Vegetation Index (GNDVI)	$GNDVI = \frac{NIR - GREEN}{NIR + GREEN}$	[78]
Renormalised Difference Vegetation Index (RDVI)	$RDVI = \frac{NIR - RED}{\sqrt{NIR + RED}}$	[78]
Normalised Green-Red Difference Index (NGRDI)	$NGRDI = \frac{GREEN - RED}{GREEN + RED}$	[78]
Visible Atmospherically Resistant Index (VARI)	$VARI = \frac{GREEN - RED}{GREEN + RED - BLUE}$	[78]
Soil Adjusted Vegetation Index (SAVI)	$SAVI = \frac{NIR - RED}{NIR + RED + L} \times (1 + L)$	[78]
Optimised Soil Adjusted Vegetation Index (OSAVI)	$OSAVI = \frac{NIR - RED}{NIR + RED + 0.16} \times (1 + 0.16)$	[78]
Green Leaf Index (GLI)	$GLI = \frac{(GREEN - RED) \times (GREEN + BLUE)}{2 \times GREEN + RED + BLUE}$	[78]
Normalised Difference Red Edge (NDRE)	$NDRE = \frac{NIR - REDEDGE}{NIR + REDEDGE}$	[78]
Normalised Difference Water Index (NDWI)	$NDWI = \frac{NIR - SWIR}{NIR + SWIR}$	[78]
Radar		
Sentinel Normalised Index (SNI)	$SNI = 2 \times \frac{VH - VV}{VH + VV}$	[79]

NIR: Near Infrared; L: coefficient; SWIR: Short Wave Infrared; VH: Vertical Transmission—Horizontal Reception Polarisation; VV: Vertical Transmission—Vertical Reception Polarisation.

The major multi/hyper spectral indices used for detecting vine stress are the following ones:

- NDVI [77,80–83], utilising wavelengths to accurately detect greenness, including grasses, bushes, and trees [84,85];
- Chlorophyll Photochemical Reflectance Index (PRI), which can detect plant water stress [86] by using bands at specific wavelengths where photosynthetic pigments are affected by water stress conditions; when PRI, which is related to leaves' xanthophyll, is high, it indicates plant stress [87];
- Leaf Area Index (LAI), that is defined as unilateral leaf area per unit ground area, uses the light near the soil reflected by the plants due to photosynthesis; for vineyards, LAI measurements can distinguish only severe stress events and can be used for indirectly measuring evapotranspiration, even if the results are unreliable, due to the plant orientation (plant distances of 1.2–2.4 m between

rows x 0.3–0.8 m between vines) [88];

- Visible-band Difference Vegetation Index (VDVI), which is similar to LAI and is calculated using the three bands of the visible light spectrum (Red, Green and Blue - RGB) [85];
- Green Normalised Difference Vegetation Index (GNDVI), which uses the green spectrum (540–570 nm), where chlorophyll is active to detect plant senescence and stress during all vine growth phases until grape harvest [89];
- Soil Adjusted Vegetation Index (SAVI), which is an index aggregating canopy and NDVI, and enhances the contrast between soil and vegetation, thereby minimising the effects of illumination conditions [90]; for a specific amount of vegetation, darker soils result in higher SAVI values [91].

Therefore, selecting the vegetation indices to be remotely sensed is needed (e.g. NDVI), and when the weather factors (e.g., wind) are favourable, let the UAV fly over the cultivated fields. Thus, it is possible to remotely sense images and, after processing, produce maps of each vegetation index for each field.

A possible protocol for RS from UAVs is the following. For each species (i.e., grapevine) and for each cultivar (e.g., Syrah), the sampling of plant leaves should be carried out by randomly collecting the leaves of four levels of vegetation activity, in a specific zone (e.g., 1 ha ca.):

1. Maximum;
2. Intermediate higher;
3. Intermediate lower;
4. Minimum.

The sampling points can be identified by means of row numbers and plant numbers, such as in a vineyard having fruit tree form Vertical Shoot Position (VSP) and plant distances 2.5 x 1 m.

The result of the chemical analysis of each collected sample is the nitrogen content of the plant leaves of the surveyed species and cultivar for the considered level of vegetation activity.

After acquiring and processing the images, a map of the vegetation index can be produced.

For each species and cultivar, and for any NDVI value from −1 to +1, at intervals of 0.25, the sampling of leaves should be carried out in order to determine the nitrogen content for any value of the vegetation index.

The same value of nitrogen content can be associated with any point of the map characterised by the above value of the vegetation index.

Therefore, the map of the vegetation index can be converted into a map of nitrogen content and, then, based on the nitrogen demand by that species and cultivar, into a nitrogen application map and, finally, based on the nitrogen content of the fertiliser to be used, into a spatially variable rate nitrogen fertiliser application map.

Yet, when the field area is higher than 5 ha, the images acquired by satellites can be cheaper than those taken by UAVs.

Moreover, the use of a UAV, equipped with a multispectral camera and a GNSS (e.g., GPS, GLONASS, and EGNOS) mobile receiver, implies an initial investment and the availability of skilled staff to set up and pilot this device and perform the subsequent processing of the acquired images, while satellite imagery providers offer ready-to-work images, and the possibility of consulting the whole images archive.

The satellite Copernicus Sentinel-2B acquires images with a spatial resolution of 10 m and a temporal resolution of five days, thus providing maps of NDVI and Normalised Difference Water Index (NDWI), i.e., index of leaf water content, every five days.

NDVI is defined generically and accurately for the Sentinel-2 satellite [92].

In fact, it is possible to convert the images remotely sensed by the satellite Copernicus Sentinel-2B (e.g., provided by the Portoguese web-based platform AgroInsider) into maps of within-field crop and soil parameters and spatially variable rate crop input application maps.

Thus, RS from UAVs and/or satellites is useful as DSS for both precision and traditional agriculture, e.g., for deciding if, when, and how spatially variable rate fertiliser application must be performed in a field.

In fact, RS from UAVs and/or satellites can be used to:

- Decide if spatially variable rate fertiliser application must be performed in a field, based on the eventual within-vineyard spatial variability of plant vegetation vigour;
- Identify the optimal fertilisation time (only for RS from satellites), based on the comparison between the graph of NDVI, index of plant vegetation vigour, and that of NDWI, index of plant leaf water content (also for spatially uniform rate fertiliser application, within traditional agriculture);
- Determine the spatially variable fertiliser rate to be applied in each MZ (based on the within-vineyard spatial variability of plant vegetation vigour);
- Delineate two or three zones of different levels of vegetation vigour inside each plot, e.g., high, intermediate and low, so that, for example, the grapes harvested in these zones can be processed for producing different wines having different quality.

However, the two aforementioned image sources, i.e., UAVs and satellites, can be combined in order to validate each other for a better spatially variable vineyard management [92].

Besides UAVs and satellites, terrestrial robots show a high potential for use in viticulture. Moreover, terrestrial robots are able to carry heavier loads, compared to UAVs. Fernández-Novales et al. [93] used a terrestrial robot equipped with an infrared radiometer, a multispectral camera, and a climate sensor (able to measure air temperature, relative humidity, and atmospheric pressure), in order to produce a map of the water status in a commercial vineyard. Vrochidou et al. [94] developed a robot for vintage: They equipped it with RGB-D, thermal, and multispectral cameras, as well as a robotic arm to carry out grape harvest. The robot can be combined with an UAV and a remote-control unit operated by humans. Oberti et al. [95] developed a modular agricultural robot to perform spatially variable rate application on grapevines for disease control. The robot is equipped with a robotic arm that carries a spraying nozzle, while the disease detection is carried out by a multispectral camera, followed by image analysis and use of algorithmic models.

Kasimati et al. [96] thoroughly compared NDVI maps from different proximal and remote sensing platforms and assessed their impact on vineyard variability. The study, which spanned two seasons (2019 and 2020), showed strong similarities among similar sensors but notable differences between proximal and airborne/spaceborne observations. Proximal sensors, especially during early and late growth stages, showed better performance in explaining the variability of grape yield and quality, while UAV-based management units outperformed other sensors in describing yield.

6. Data analysis

6.1. Multivariate geostatistics

PV requires very small-scale spatial and temporal resolutions to accurately assess within-vineyard variability of soil and crop parameters. Many researchers have used proximal sensing technology and spatial/temporal data analysis to characterise the temporal and spatial variability of soil, plant vegetation vigour, and yield. Paoli et al. [97] produced maps of grape yield and sugar content using an online sensor mounted on a grape harvester. They also collected qualitative soil data from farmers who had manually drawn zone boundaries in their vineyards and provided information on soil parameters (e.g., soil depth). These data were analysed by using an innovative geostatistics approach called the semantic based aggregation method in order to delineate MZs. This method provided results similar to the MZs delineated through kriging and fuzzy kriging methods, thus indicating that it can be used with high confidence in MZs delineation. Morari et al. [68] collected soil data from soil sampling and soil sensors, in order to delineate MZs. They used an electro-magnetic induction sensor and an electrical resistivity sensor to map soil EC. Moreover, they applied an electrical resistivity tomograph by using a resistivity meter and collected soil samples from the same vineyard. Afterwards, they applied geostatistics, i.e. factorial cokriking to fuse data. In this way, it was possible to establish a relationship between EC and some soil physical parameters, which were coupled with fuzzy c-means and led to the delineation of MZs. Anastasiou et al. [18] proved the potential of multivariate geostatistical techniques to fuse multi-temporal data measured by a multi-band radiometer and a geophysical sensor, in order to delineate vineyard homogeneous MZs to be differently treated. This study was carried out in a commercial table grape vineyard, located in Southern Greece, and spanned 2016 and 2017. Soil EC was measured by means of an EM38 sensor, while a Crop Circle canopy sensor, located at 1.5 m height from the soil surface and 1.2 m from the vines, was used to scan the side canopy area at different crop stages. The temporal multi-sensor data were analysed through the geostatistical fusion techniques of block cokriging to produce thematic maps, and factorial block cokriging to estimate synthetic scale-dependent regionalised factors. The factor maps at different scales were characterised by random variability showing several microstructures of different soil and crop parameters and, therefore, leading to difficulties in delineating homogeneous management macrozones. In these conditions, high resolution Variable Rate Application (VRA) should be preferred rather than management by homogeneous zones for PV. The results showed the potential of the proposed approach for handling data from multiple sources in PV.

6.2. Machine Learning techniques

The integration of Machine Learning (ML) and computational intelligence into precision viticulture has transformed the capability to analyse and predict viticultural outcomes. Studies such as those by Kasimati et al. [98,99] underscore the power of ML in optimising grape quality parameters through high-resolution multispectral data from various proximal and RS technologies. The researchers used high-resolution multispectral data from various sources, including vehicle-mounted crop reflectance sensors, UAV-captured data, and Sentinel-2 satellite images, in order to estimate the characteristics of grapevine canopies at different growth stages. By using data pre-processing techniques and applying statistical and ML algorithms, the proximal sensors performed better in predicting grape quality parameters at earlier growth stages, while RS performed better at later stages. Moreover, autoML techniques proved to be an innovative approach and showed promising performance in predicting grape sugar content, especially in the mid to late season with full canopy growth. The comparison between manually finely tuned ML and autoML achieved similar results, even if autoML performed slightly better, thus indicating its higher long-term performance potential in efficiently predicting grape quality.

A systematic review by Matese and Di Gennaro [10] outlines the state of the art in the technology used for PV, by emphasising the broad range of data sources and ML applications that enhance vineyard management. These include the deployment of fuzzy inference systems, which have been used to handle the inherent uncertainties in viticulture data [100], offering nuanced insights into complex agronomic variables. Gutiérrez et al. [101] explored data mining and non-invasive proximal sensing to enhance variety discrimination and assess water status in vineyards. Their work demonstrates how ML algorithms, including support vector machines, can leverage sensor data to deliver precise and actionable insights that significantly influence viticulture. The application of image processing techniques in viticulture, reviewed by Whalley and Shanmuganathan [102], has enabled detailed assessments of canopy features and cluster morphology. These techniques facilitate accurate yield estimation and crop health monitoring, which are crucial for effective vineyard management. Further, Liu et al. [103,104] developed methodologies for automatic grape bunch detection using machine vision, directly impacting yield forecasting and operational efficiency. SmartVineyard by De Filippis et al. [105] represents an innovative web-GIS application that integrates geo-referenced data and web services for PV. This tool exemplifies how geoinformatics, combined with ML techniques, can streamline vineyard management and decision-making processes. Incorporating computational intelligence into geo-informatics, as discussed by Shanmuganathan et al. [106], has facilitated advanced resource management and operational planning in viticulture. These technologies not only predict viticulture outcomes but also adaptively manage the spatial and temporal variability of vineyard conditions, thus ensuring optimal grape quality and vine health. The future of ML in PV lies in enhancing the scalability and accuracy of these technologies.

7. Decision Support Systems

Among Decision Support Systems (DSSs), the grapevine health status in a vineyard can be monitored and, then, analysed through the vine architecture (canopy analysis). The continuous evaluation of the tree canopy volume and LAI in vineyards is one of the major objectives of PV. The DSS Vite.net, which is a holistic approach for the sustainable management of vineyards, was tested by Rossi et al. [107]. This user-friendly DSS includes a real-time monitoring system based on IoT and a web-based platform that analyses the data collected through advanced modelling techniques and provides updated information for vineyard management. These scientists used a monitoring software, based on third-party hardware, thus providing promising results in Italian vineyards. Moreover, new DSSs like VINETO, which was developed by Feruzzi and Gavazzeni [108], integrate optical and thermal data from Earth Observation satellites to recommend targeted interventions like grapevine removal, weed management, and application of Plant Protection Products (PPPs), by identifying areas with infected plants. Visconti et al. [109] developed a DSS for selecting the rootstock, irrigation regime, and nitrogen fertilisation in vineyards for winemaking. Additionally, Pilafidis et al. [110] developed a DSS to help farmers assess energy use and Greenhouse Gas (GHG) emissions in vineyards. This can help them adopt more sustainable vineyard practices like avoiding burning pruning residues, replacing mechanical weeding, and reducing tillage. Dias et al. [111] developed a DSS to improve integrated pest management for vineyards, based on multiple criteria relevant to life cycle, environmental risk, and human risk assessment.

DSSs that cover large areas can contribute to better management and planning. These can use publically available data and private data to provide better decisions. For example, Tsirogiannis et al. [112] developed a DSS that uses publically available weather data from Greece. They found that it can significantly contribute to the irrigation management of grapevines by saving water and improving water use efficiency, although spatial variability and network density could affect the accuracy of the results. Additionally, Terribile et al. [113] developed GeoVit, which is a DSS that not only focuses on vine management but also on the characterisation of the terroir. This is very helpful for planning plantations of varieties that are optimal to the terroir, as well as for adopting more sustainable cultivation practices (e.g., organic viticulture). Bregaglio et al. [114] presented the MISFITS-DSS, which is a public DSS that provides decision support on pesticide use for Italian farmers of nine regions and, therefore, contributes to their economic sustainability.

8. Site-specific vineyard operations

8.1. Spatially variable rate fertilisation

Spatially variable rate fertilisation is the application of different fertiliser rates across a vineyard, based on the specific needs of different cells of the application map. This technique may improve the efficiency of fertiliser use and reduce the environmental impact of viticulture. The implementation of spatially variable rate fertilisation can help reduce the amount of fertiliser applied to cells that do not require it, while ensuring that cells having nutrient deficiencies receive the appropriate amount of this crop input. This can contribute to reduce the risk of over-fertilisation and minimise the negative impacts of fertiliser on soil and water quality [115].

In precision viticulture (but also in traditional viticulture), a criterion for deciding the optimal fertilisation time can be based on the comparison between NDVI and NDWI graphs for the considered vineyard. For instance, in the graphs of average NDVI and NDWI for Syrah and Nero d'Avola cv. plots, it is possible to observe that vegetation vigour suddenly increased from 12 May 2021, while the leaf water content suddenly increased until 12 April 2021 (Figure 2). Thus, as fertilisation is aimed at supporting vegetation activity and must be carried out when the soil water content and, consequently, the plant leaf water content is high, the optimal time for this crop operation should have been 12 April 2021, also because neither plot was irrigated. In fact, in this case study, a low soil water content would cause root burning and emissions of Greenhouse Gases (GHGs), i.e., nitrous oxides from nitrate, if fertilisation was carried out after 12 April 2021. Thus, plotting the curves of NDVI and NDWI for both cultivars (Figure 2) enables us to define the optimal fertilisation time, which is before the date when the plant growth peak is achieved, as fertilisation is essential for providing the plants with enough nutrients to be adsorbed by their roots [92].

Several researchers stated that climate change effects are quickly arising in Mediterranean countries: Increasing temperature and droughty summers are, above all, threatening the grape quality of sparkling wines. Zanchin et al. [116] investigated nitrogen nutrition in order to increase acidity and preserve the aromatic compounds in vine (*Vitis vinifera*), cv. Glera, to produce white sparkling wine. Half of the 1-ha vineyard, located in Northern-Eastern Italy, was fertigated with nitrogen during summer, while the control half received only mineral fertiliser during spring as usual in the district. It was possible to monitor and compare the grape quality at harvest during three testing years. The statistical analysis proved a common trend among treatments: The fertigated grapes showed, on average, higher amounts of aminoacids (+32%), yeast assimilable nitrogen (+71%), acidity (+21%) and lower total Soluble Solids (SS) concentration (−3% ca.) than the control grapes. Energy storage, grape yield, and wood biomass were also measured. The study proved that the nitrogen supply affected neither grape yield nor vegetation vigour. Therefore, nitrogen fertigation was confirmed as a reasonable growing practice that can preserve wine aroma and acidity against climate change.

Thus, the great challenge will be to reduce the nitrogen rate by optimising fertilisation towards more sustainability without changing the must quality.

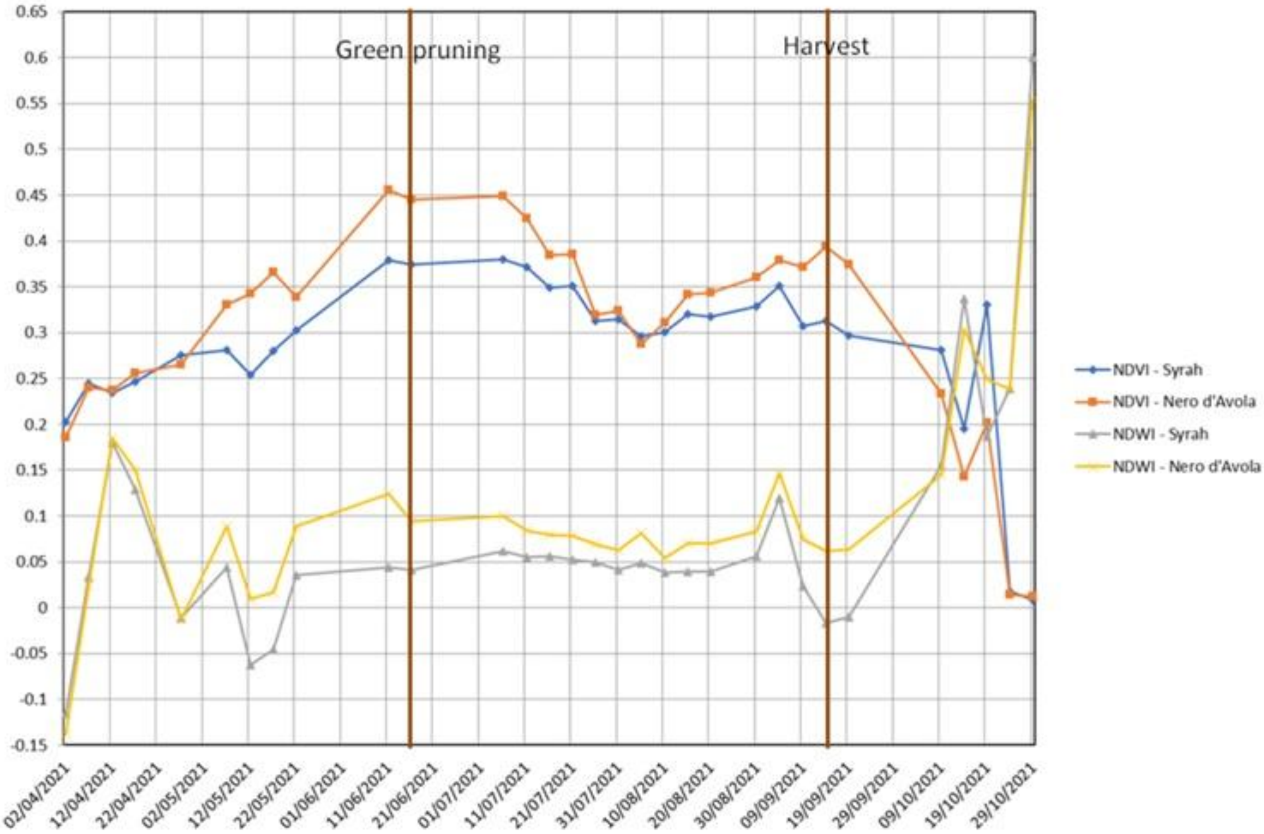

Figure 2. Graph of average NDVI and NDWI of vine plants (the values of either index can range from −1 to +1) for Syrah cv. and Nero d'Avola cv. plots, located in Naro (Agrigento, Sicily, Italy), from the beginning of April to the end of October 2021 [92].

Two optional approaches are possible, i.e., application of a different fertiliser rate in each of the above MZs and spatially variable rate fertiliser application.

In the former approach, these MZs could also be used for soil sampling, in order to determine the soil parameters, both chemical (e.g., water and nutrients contents) and physical (e.g., texture) in each zone.

In the latter approach, a fertiliser rate can be associated with each range of the average NDVI shown in the map related to the optimal fertilisation time, in order to produce a spatially variable rate fertiliser application map [92].

Soil fertilisation cannot be based only on vegetation parameters (such as NDVI and NDWI) but also on soil monitoring (e.g., of apparent electrical conductivity). Moreover, validation of MZs through smart soil sampling is essential.

8.2. Spatially variable rate irrigation

As viticulture is gradually shifting to more environmentally friendly production, it is needed to assess the environmental impact of different crop operations and technologies implemented for wine production through Life Cycle Assessment (LCA). It was possible to identify the major environmental issues, i.e. water, soil and energy use, management of organic and inorganic solid waste streams, GHG emissions, and chemical use. Precision viticulture can play a key role in the sustainable use of water and fertilisers for grape production through the spatially variable rate application of these crop inputs, thus improving grape yield and quality while minimising the environmental impact. However, PV often implies investments and additional management costs. Casson et al. [117] compared different strategies for the management of water and fertilisers in vineyards, i.e., from the conventional ones to the most technologically advanced, in order to assess their economic and environmental sustainability. Six scenarios were surveyed, by considering different irrigation and fertiliser management strategies. A multidisciplinary approach, including LCA, economic assessment and multivariate analysis, was used to assess the sustainability of the different vineyard management strategies. The results showed the highest economic and environmental sustainability for the scenario, implying water supply from an irrigation consortium, as well as spatially variable rate drip irrigation and fertigation. Finally, the implementation of PV technologies enabled to reduce the environmental impact and increase the farmer's profit.

Although water and iron deficiency (iron chlorosis) are common environmental stresses in Mediterranean countries, some data are available in the literature regarding their effects on vineyards, when working simultaneously. González et al. [118] studied the combined effects of iron deficiency and water status on vegetation vigour, yield, and berry chemical composition in rainfed vineyards. Moreover, the aim was to evaluate the feasibility of using leaf chlorophyll content (Chl) and predawn Leaf Water Potential (LWP), measured at veraison, in order to assess the potential grape quality, within PV. For this purpose, 24 non-irrigated Tempranillo cv. vineyard subzones were monitored in Ribera del Duero, Northern-Central Spain, in 2011, 2012, and 2013. The variance analysis (ANOVA) and Principal Component Analysis (PCA) showed that the malic acid concentration of the must was affected only by Chl, while Total Soluble Solids (TSS) and total acidity were mainly modified by LWP. Both water deficiency and iron chlorosis reduced grape yield and berry weight and affected extractable anthocyanin content in grapes, as well as total polyphenol index and colour density of the must. In all years, the ratio Chl/LWP had a better predicting value for grape quality parameters than LAI or Chl or LWP individually. Therefore, these scientists proved the potential interest in physiological indices combining water status and leaf chlorosis as indicators of grape phenolic potential in rainfed vineyards affected by iron deficiency.

Sánchez et al. [119] studied the combined effects of the aforementioned environmental stresses, i.e., water deficiency and iron chlorosis, on the aromatic profile of Tempranillo cv. grapes and evaluated the viability of leaf chlorophyll content (Chl) at veraison to early assess the aromatic quality potential of grapes. A total of 20 non-irrigated vineyard subzones (10×10 m each), affected and non-affected by iron chlorosis, were monitored in Ribera del Duero Appellation of Origin, in Northern-Central Spain, during two consecutive seasons. Factorial ANOVA was implemented to study the effects of predawn LWP and Chl measured at veraison on the chemical composition parameters of the must and, specifically, on the concentrations of free and bound aromatic compounds. Water deficiency tended to increase colour intensity and extractable anthocyanin content of the grapes, while iron deficiency increased total phenolic compound content within subzones having a better water status. More water or iron stressed subzones restricted C6-alcohol contents, compared to less stressed subzones. Iron chlorosis increased the concentrations of some terpenes, C13-norisoprenoids, volatile acids, and volatile phenols. These results proved that low to moderate iron stress can enhance the grape aromatic quality, while Chl can be a useful parameter in PV for producing maps of the aromatic potential within rainfed vineyards affected by iron chlorosis.

Canopy temperature (TC) can be a reliable indicator of grapevine water status. However, the assessment of TC by thermography in a vineyard requires optimisation, especially under temporally variable environmental conditions (daily and seasonal) occurring in Mediterranean countries. Moreover, termography should be user-friendly, in order to be widely used in vineyard conditions.

The major objectives of the test carried out by Garcia-Tejero et al. in Southern Portugal in summer 2013 [120] were:

1. To assess the performance of four common thermal indicators (canopy temperature − TC, Crop Water Stress Index − CWSI, index of relative stomatal conductance − IG, and the difference between TC and the surrounding air − ΔTcanopy-air) in planning irrigation;
2. To optimise the time of thermal measurements for different varieties;
3. To obtain mathematical functions, in order to estimate leaf gas exchange parameters based on the thermal data.

Vines of two *Vitis vinifera* red varieties, Touriga Nacional and Aragonez (or Tempranillo), were subjected to two irrigation strategies:

1. Sustained-deficiency irrigation (based on the farm schedule - control);
2. Regulated-deficiency irrigation (50% ca. of the control).

The measurements performed between 11 and 17 hours provided the most significant correlations between TC, CWSI, and net photosynthesis for both varieties. Different linear mathematical functions were obtained to estimate leaf gas exchange, based on the best performing thermal indicators under vineyard conditions. The results highlight the value of TC as a paramount explanatory variable of vine physiological status, for modelling and phenotyping, even if it is a simpler thermal indicator.

Climate change significantly affects viticulture by reducing grape yield and the quality characteristics of its final product. In some observed cases, the consequences of climate outages such as droughts, hail, and floods are devastating for the farmers and the sustained local economies. Hence, it is essential to develop and implement monitoring solutions that offer remote real-time surveillance, minimum maintenance, and automated generation of alerts. Kontogiannis and Asiminidis [121] proposed a new framework for vine stress monitoring called Vity-stress, which combines field measurements with PV suggestions and stress avoidance planning. This framework can be easily developed and maintained, as well as cheaply implemented. By focusing on the Mediterranean cultivated table grape varieties that are strongly affected by climate change, these scientists proposed a new framework based on monitoring stress conditions, including sensors distributed in the vineyard and a novel camera, and implementing deep neural network algorithms to detect stress indicators. Moreover, a new Wireless Sensor Network (WSN), supported by the iBeacon protocol, was developed. The results of the sensor measurements and image detection evaluation showed that the proposed framework can successfully detect different stress levels in vineyards, thus enabling farmers to identify specific areas for spatially variable rate irrigation and, therefore, save water, energy, and time.

Ortuani et al. [122] studied the efficiency of spatially variable rate drip irrigation on water use efficiency in a vineyard in Northern Italy. Initially, they delineated two MZs after carrying out a soil survey by means of electro-magnetic induction and electrical resistivity sensors. They performed spatially variable rate drip irrigation in each MZ and, then, compared the results to a reference plot, where they performed spatially uniform rate irrigation. They also used weather and satellite data to calculate the vine water needs, together with soil sampling to analyse its water content. They found that spatially variable rate drip irrigation could save 18% of water, compared to spatially uniform rate irrigation, while maintaining similar grape yield and quality.

8.3. Spatially variable pruning

Vine vegetation vigour assessment has been a major concern of precision viticulture in order to delineate zones of uniform vine performance within vineyards. Vine vigour is affected by crop operations (e.g., pruning, fertilisation, and irrigation), topography, soil and weather parameters. Moreover, the counting and weighing of one-year old wood (dormant canes) at winter pruning is considered the most informative measurement to indicate vine balance and is commonly and manually performed by grapevine growers. An improper pruning can lead to increased yield and quality variability, and, therefore, can significantly affect the winemaking process [123]. Yet, this measurement requires time and a high work load, which is expensive and cannot provide a detailed sampling density. Therefore, Tagarakis et al. [124] investigated the potential of using laser scanner technology as an automated, easy, and rapid method for producing maps of the winter pruning wood across the vineyard. Their study was carried out in a 1-ha commercial vineyard, transplanted with Agiorgitiko cv., a traditional Greek grapevine variety for the production of red wine, in Thessaly, Central Greece, and spanned 2010 and 2011. The vines were grafted onto 1103 Paulsen rootstock, trained to a bilateral cordon and spaced 1.0 x 2.6 m. Maps of topography, soil depth, and texture, as well as NDVI, grape yield, and quality were produced and analysed. Furthermore, the weighing of the dormant canes was carried out just before pruning and this wood was scanned by means of a 2D laser scanner, i.e., LIDAR sensor (Figure 3), in order to produce the related maps.

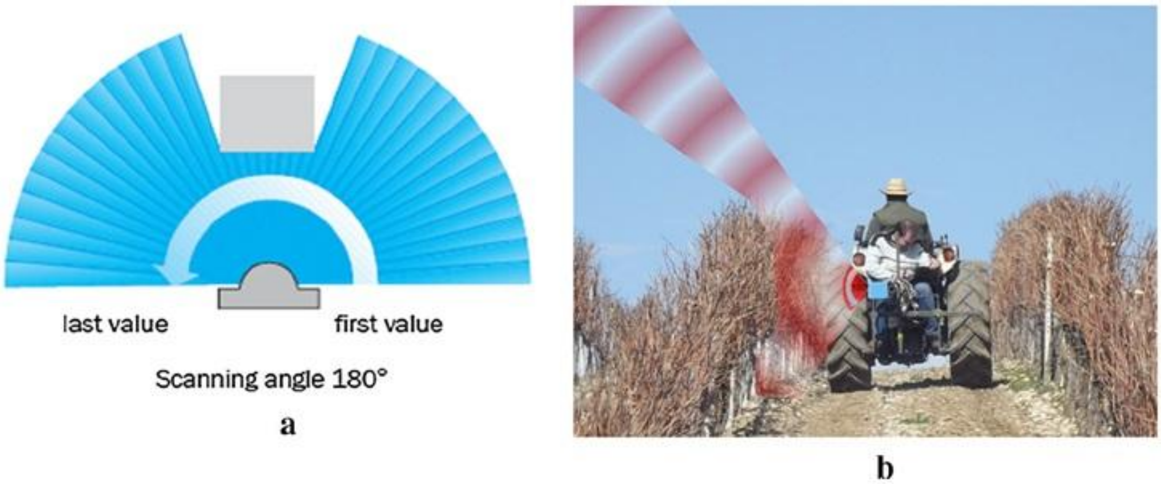

Figure 3. Transmission direction on the top view of the Sick LMS200 2D laser scanner, i.e., LIDAR sensor: (a) Sick LMS200 technical description manual; and (b) scanning of dormant canes throughout the vineyard [124].

Then, a second scanning was performed just after pruning, in order to record the trunks or perennial parts of the vines and remove them from the measurements. The pruning weight per each 10 x 20 m cell of a grid (totally 48 cells) was manually measured by weighting and geo-referencing the pruned wood immediately after pruning. The dormant canes sensed by means of laser scanner was significantly correlated with the pruning weight ($r = 0.809$ and $r = 0.829$, respectively, $p < 0.001$), yield, and early season NDVI, in both 2010 and 2011 (Figure 4).

These results proved that laser scanners have the potential to estimate pruning wood. Consequently, this technology can be used for delineating MZs, to adjust spatially variable rate application of crop inputs (water and fertiliser) and, accordingly, adapt pruning in order to improve vine vigour balance and grape quality.

8.4. Spatially variable rate fungicide spraying

Spatially uniform rate fungicide application in vineyards can have significant environmental and human health impacts. Fungicides are used to protect grapevines from fungal diseases but their overuse can lead to the development of resistance in fungi, which can result in the need for higher rates of fungicides. This, in turn, can lead to the accumulation of fungicides in soil and water, which can have negative impacts on soil microorganisms, aquatic organisms, and other non-target organisms [125,126]. Additionally, exposure to fungicides can have negative health effects on humans, including respiratory problems, skin irritation, and cancer [127]. Therefore, it is important to judiciously use fungicides and adopt sustainable practices to minimise their negative impacts on the environment and human health. PV technologies can significantly decrease the used amounts of fungicides in vineyards and their impact on the environment and human health [128].

Pérez-Expósito et al. [129] tested VineSens, a DSS constituted by a hardware and software platform and based on a Wireless Sensor Network (WSN), comprising autonomous and self-powered nodes that are used in a vineyard. These nodes include sensors that enable to obtain detailed knowledge of different viticulture processes. By using epidemiological models, VineSens can propose a customised control plan to prevent diseases such as downy mildew. This DSS generates alerts, warning farmers about the actions to be undertaken, and stores the historical weather data collected in different positions of the vineyard. These data can be accessed through a user-friendly web-based platform by means of a desktop computer or a mobile. VineSens was used in a vineyard in Ribeira Sacra district, in Galicia (Spain) at the beginning of 2016 and, since then, it has been tested to prevent the development of downy mildew. During the first season, this DSS proved to significantly save the used pesticide amounts, thus obtaining a more environmentally friendly and healthy wine.

Compared to other WSNs, VineSens provides five major advantages:

1. It is a complete system, both hardware and software, thus minimising compatibility issues and avoiding the collection of data from or through third-party (and usually expensive) cloud-based platforms;
2. It uses a non-proprietary communication technology (Wi-Fi) that facilitates the integration of VineSens nodes and third-party sensing solutions;
3. By using standard Wi-Fi transceivers, its employment is cheap while providing a good coverage area;
4. It provides an Application Programming Interface (API) for developers in order to further upgrade the system, being really user-friendly to create plugins or mobile apps based on the data collected by this DSS;
5. It has been designed in a modular way, thus enabling an easy addition of new epidemiological models, alarms, sensors, and actuators to it.

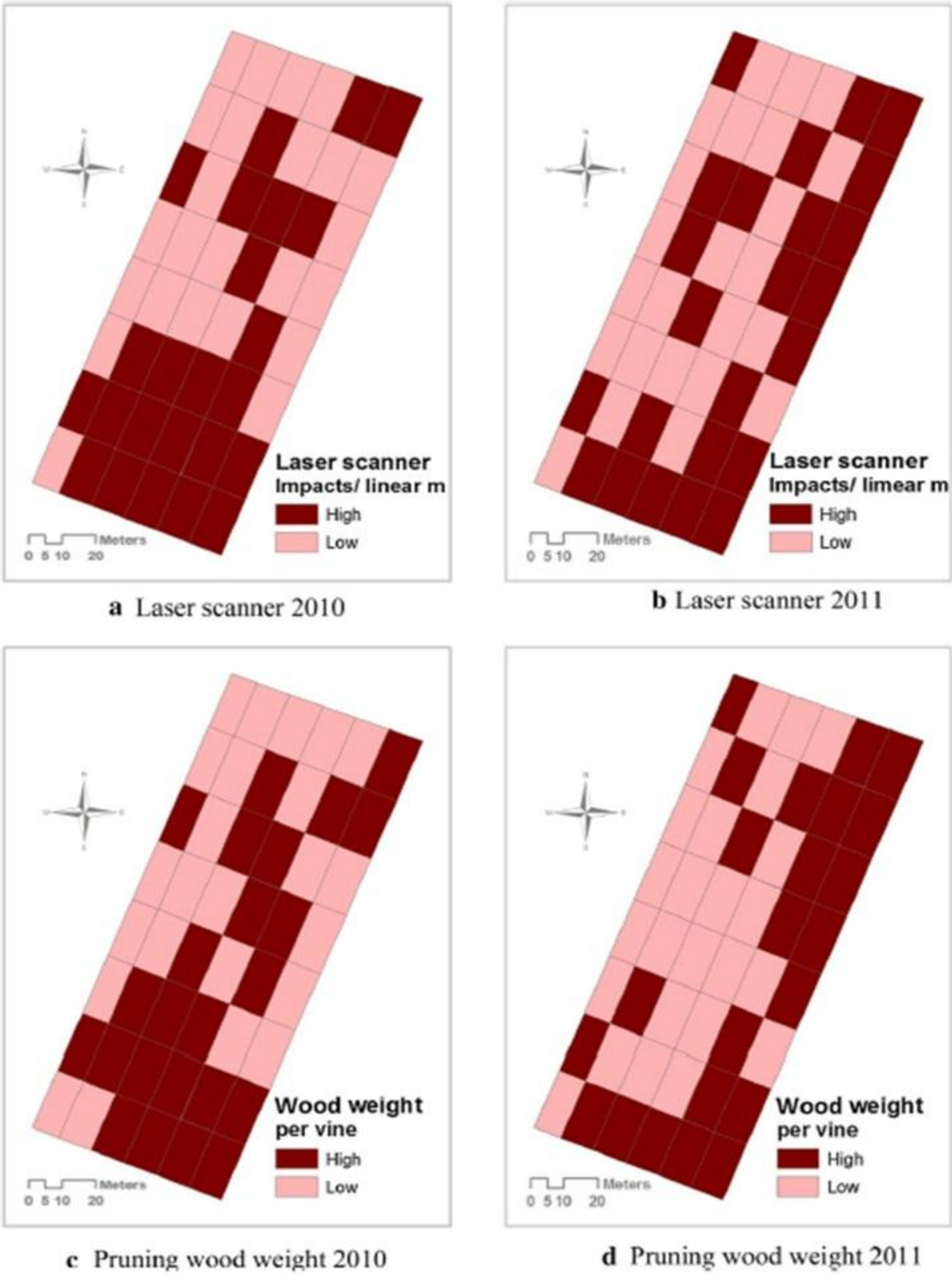

Figure 4. Maps divided into two Management Zones – MZs (high and low) of laser scanner measurements used as reference maps for the agreement analysis in 2010 (a) and 2011 (b); maps divided into two MZs of pruning wood weight for 2010 (c) and 2011 (d) [124].

As far as spatially variable rate fungicide application, the ISO 22866:2005 standard defines the procedure to quantify drift during field tests. However, this method is complex, time-consuming, and expensiveand it highly depends on external conditions, i.e., wind speed and direction, which makes these tests difficult and may cause poor repeatability of results. Another interesting option for measuring fungicide drift is the use of 2D laser scanner (LIDAR) sensors. The spraying in orchards is one of the riskiest crop operations from the environmental point of view [130]. Gil et al. [131] used a LIDAR sensor for measuring the concentration of small droplets in the air above a citrus (orange) orchard canopy during and after spraying. They developed a research project, aimed at testing a LIDAR sensor (low-cost general-purpose Sick LMS-200, adjusted to have an angular resolution of 1° and a scanning angle of 180°) in measuring the drift cloud during pesticide application in a vineyard. They also studied the effect of different operational parameters (nozzle type, sprayer characteristics, and air settings) on the total amount of liquid exceeding the target canopy. Drift was measured by means of the LIDAR sensor, located 4 m from the last sprayed canopy row, and oriented in order to measure the cloud drift on a plane perpendicular to the canopy row. The spray drift cloud exceeding the canopy was scanned for an average of 40 s (the total time of LIDAR scanning in a single test) during the spraying along the row, for 20 s before the sprayer passed in front of LIDAR, and for 20 s afterwards, representing a total measurement distance of 50 m. In order to compare LIDAR measurements, droplets deposit over 20 m far from the last row (perpendicular track) was also collected and quantified using tartrazine as a tracer. The obtained results suggested that the LIDAR sensor can be easily used for measuring the potential drift of a sprayer in specific environmental conditions and during spatially variable rate fungicide application. In fact, the drift cloud measured by means of the LIDAR was significantly correlated with the droplets distribution obtained by means of the artificial collectors placed on the test bench.

Garcia-Ruiz et al. [132] studied the benefits of spatially variable rate copper application in vineyards for fungi control. They used application maps produced from UAV multispectral images for delineating MZs, so that these maps were logged in the on-board computer of a tractor connected to a variable rate sprayer. They found that 40% of copper could be saved without affecting disease control. They concluded that spatially variable rate fungicide application could reduce environmental impact and increase crop input efficiency, as well as enhance grape yield and quality, thus maximising farmer's profit.

Moreover, ultrasound technologies can significantly contribute to fungicide savings. In fact, Marques da Silva et al. [133] developed and tested a variable rate sprayer using ultrasonic sensors, and they achieved up to 55% of pesticide savings compared to uniform rate spraying. Gil et al. [134] developed a variable rate sprayer consisting of ultrasonic sensors, so that they achieved 22% savings of Plant Protection Products (PPPs), while having equivalent deposition on vine leaves compared to a conventional sprayer. Finally, according to Román et al. [135], app-based variable rate spraying can contribute to up to 25% savings in PPPs by using aerial images of very high resolution (0.50 m) to delineate MZs.

8.5. Spatially and temporally variable vintage

Martinez-Casasnovas et al. [136] analysed the potential of NDVI maps from satellite images, yield maps, grapevine fertility, and grape parameters to delineate MZs having different wine grape parameters for selective harvest. In two vineyard blocks (cv. Cabernet Sauvignon and cv. Syrah), located in Northern-Eastern Spain, NDVI was computed from a Quickbird-2 multi-spectral image at veraison, in July 2005. Yield data were measured by means of a grape yield sensor in September 2005.

Other parameters, i.e., number of buds, number of shoots, number of wine grape bunches, and weight of 100 berries, were sampled in a 10 rows × 5 vines pattern and used as input variables, in combination with NDVI, in order to define clusters as alternative to yield maps. Two days before harvest, grape samples were taken, and the probable alcoholic degree, juice pH, total acidity, total phenolics, colour, anthocyanins, and tannins were analysed. The input variables, alone or in combination, were clustered (two and three clusters) by means of the ISODATA algorithm, as well as an analysis of variance and a multiple rang test were performed. The MZs derived from NDVI maps resulted more effective in differentiating grape ripeness and quality parameters than the zones derived from yield maps.

A deeper analysis of the frequency data per group of grapevine and grape parameters indicated that, in the case of two MZs, the grape ripeness and quality were much better differentiated than grapevine fertility and production parameters. This occurred in both vineyard blocks, with better results in Syrah block, compared to the Cabernet Sauvignon one, due to the moderate grapevine fertility and grape parameters (50.0% and 12.5% of the cases, respectively). In the case of two MZs, NDVI was the parameter that performed better: 72.7 and 81.8% of the grapevine fertility and grape parameters were differentiated in Cabernet Sauvignon and Syrah blocks, respectively. Therefore, the differentiation of the analysed parameters in two MZs produced better results than in three zones. Moreover, the MZs were delineated, based on the NDVI map, before the harvest, thus enabling to decide the optimum time for selective vintage.

In rainfed vineyards, water deficiency plays a key role in determining grape yield and chemical composition. Therefore, reliable indicators of vine water status might be highly useful for the optimisation of grape yield and quality. Serrano et al. [137] assessed the feasibility of using hyperspectral reflectance indices related to plant bio-physical parameters for predicting grape yield and quality parameters in rainfed vineyards. This study was carried out on *Vitis vinifera*, Chardonnay cv., in commercial vineyards in the Denomination of Origin Penedès region, in Catalonia (Spain), and spanned 2007 and 2008. Field measurements of fractional Intercepted Photosynthetic Active Radiation (fIPAR), canopy reflectance, predawn water potential (Ψp), and the canopy to air temperature difference at midday (ΔTmidday) were carried out at veraison stage. Yield, TSS, Titratable Acidity (TA), and the ratio TSS/TA (ripeness index, i.e., IMAD) were determined at harvest. Contrasting water availability among vineyards caused a significant variation in grape yield and quality. Across years, higher yield was accompanied by higher TA ($r = 0.59$, $p < 0.01$) and lower IMAD ($r = -0.63$, $p < 0.01$). Yield was correlated with vegetation vigour (i.e., fIPAR): In 2007, yield was positively correlated with fIPAR ($r = 0.71$, $p < 0.05$), while yield decreased with increasing fIPAR in 2008 ($r = -0.62$, $p < 0.05$). On the contrary, NDVI provided consistent estimates of yield across years ($r = 0.57$, $p < 0.05$). These results suggested that NDVI can be more appropriate to express the effects of variable water availability on yield than fIPAR. Moreover, grape yield was correlated with ΔTmidday ($r = -0.63$ and $r = -0.66$, in 2007 and 2008, respectively). Accordingly, the Water Index (WI), which is an indicator of vine water status, provided reliable estimates of yield across years ($r = 0.61$, $p < 0.01$). The high correlation between NDVI and WI vs. yield suggests that yield was influenced by changes in both leaf area (intercepted light) and photosynthesis (stomatal aperture), according to the time and severity of water deficiency in the surveyed years. Grape quality was correlated with ΔTmidday. Accordingly, WI was highly correlated with TA ($r = 0.70$, $p < 0.01$) and IMAD ($r = -0.71$, $p < 0.01$) across years. The obtained results suggest that WI can provide reliable estimates of grape quality parameters in vineyards experiencing moderate to severe water deficiency, thus, it can be used in PV, for ripeness assessment and, temporally variable vintage, or spatially variable vintage, according to grape quality. In fact, the above vineyard MZs could allow to plan one of two harvest strategies, i.e. temporally variable vintage in the zones having different ripeness periods, for producing uniform quality grapes and, thus, wine, or spatially variable vintage (by means of a grape harvester equipped with two hoppers) to produce different quality grapes (expressed by grape juice pH, anthocyanins, polyphenols contents, etc.) and, thus, wines [44,92,138,139].

An example of spatially variable vintage was implemented by Priori et al. [140]. Successful adoption of PV depends on the assessment of within-vineyard spatial variability of soil and crop parameters. Yet, knowing the spatial variability of soil parameters is time consuming, labour intensive, and very expensive. An alternative approach could be the combined use of proximal sensors and RS. In fact, the above scientists combined proximal (Geonics EM38-MK2) and Remote Sensing (of NDVI) in order to produce, for two 3.5-ha vineyards in Chianti wine district, in Tuscany (Italy), maps where homogeneous MZs were delineated.

It was possible to delineate two MZs in each vineyard, through a k-means clustering of the first two factors of the Principal Component Analysis (PCA) performed for four maps:

1. Apparent EC, measured by means of EM38-MK2 at 0-75 cm depth (ECa1);
2. Apparent EC, measured by means of EM38-MK2 at 0-150 cm depth (ECa2);
3. Topographic Wetness Index (TWI), calculated from a Digital Elevation Model (DEM);
4. NDVI derived from multispectral airborne images.

Only ECa1 and ECa2 were correlated with some physical (silt and gravel contents) and hydrological (available water capacity) soil parameters. These two variables could also better discriminate the two MZs with respect to NDVI and TWI. The grapes of the selected MZs were separately harvested and vinified to test the differences in the wine quality. Significant differences emerged between the wines produced from the two MZs, especially in terms of colour intensity, dry extract, and anthocyanin content. A wine tasting after 6-month aging of the wines confirmed the differences between the wines produced from the two MZs, especially in terms of colour, structure, and total score.

9. Conclusions

From their historical inception to contemporary applications, PV technologies such as soil sensors and tools for measuring solar intensity and radiation have provided vineyard managers with unprecedented data and insights. These technologies, complemented by the advent of Electromagnetic Induction and multivariate geostatistics, have empowered vineyard operations to be more precise, efficient, and responsive to the microclimatic variables within the vineyard ecosystem.

Proximal and remote sensing technologies, particularly through UAVs, satellites, and robots, offer a comprehensive understanding of within-vineyard crop and soil parameters. DSSs have integrated this wealth of data to inform decision-making in real time or post-processing, leading to tailored approaches in spatially variable rate fertilisation, irrigation, pruning, and fungicide spraying. Therefore, vineyards can be better equipped to enhance yield and quality while reducing environmental impact, aligning with the pressing imperatives of sustainability and climate resilience.

The implementation of spatially and temporally variable vintage strategies underscores the potential for a dynamic and responsive approach to viticulture. However, continuous innovation, research, and development are essential for harnessing the full potential of PV. Collaborative efforts among scientists, technologists, and vineyard managers are paramount to optimise these technologies in order to enhance viticulture excellence.

Additionally, advancing sensor technologies, particularly in the realm of weed detection, where the integration of Machine Vision systems is capable of distinguishing and identifying various weed species, holds promise for a more efficient and targeted weed management. There is also a growing need for sophisticated soil-crop simulation models that can enhance the understanding of within-vineyard spatial variability by informing precise and optimal crop input applications [28,141,142]. The integration and compatibility of electronic devices and user-friendly software are fundamental to achieve the full potential of these innovations [44]. Looking ahead, the role of robotic fleets in viticultural operations is anticipated to be significant, by warranting a detailed exploration into their capabilities, efficiency, and impacts on the product quality and the environmental footprint of vineyard operations [128].

In the unique context of Mediterranean vineyards, PV is proving to be a crucial strategy for adapting to climate change. The development of precision viticulture technologies, including UAVs, robots, and Wireless Sensor Networks, by providing accurate and real-time data on crop and soil within-vineyard parameters, enable a more precise and efficient vineyard management. Particularly promising is the implementation of spatially and temporally variable grape harvest strategies, which offer a dynamic approach to viticulture. PV is not only a technological advancement but also a beacon for sustainability in the winemaking sector and fits the commitment of this processing industry to environmentally friendly practices. By curbing the waste of resources, minimising the use of chemicals and water, and improving the overall efficiency of vineyards, precision viticulture directly addresses pressing issues such as water scarcity, soil erosion, and biodiversity loss in Mediterranean countries. Therefore, PV is not only a technological strategy but also a key force that harmonises economic, environmental, and social dimensions and leads the Mediterranean wine sector towards a sustainable and resilient future.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflict of interest.

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