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Evaluation of proximal sensing techniques and testing of variable-rate kit for sprayers to improve environmental and economic sustainability of crop protection stages

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Abstract

In crop protection science, variable rate application refers to the application of plant protection products at variable rates according to the size of the canopy to be sprayed. This system, therefore, adapts the spray mixture (pesticide + water) to the canopy in real time. As a result, this system enables significant improvements in spray deposition while reducing the environmental footprint simultaneously. In order to perform variable-rate application, a sensing system capable of characterising the canopy in real time is required. In recent years, many sensors have been developed that can detect the canopy, such as laser scanner, ultrasonic sensor, depth cameras and multispectral cameras. In addition, many technologies and techniques have been proposed for the acquisition and management of canopy data. Under these circumstances, the aim of this thesis is to evaluate the most promising sensors for the acquisition of canopy data (height, thickness, volume, density, foliar layers) in order to support the development and testing of a variable-rate implementation kit, based on an innovative ultrasonic sensor, with the aim of reducing the environmental footprint of crop protection operations. The first step of this work is presented in **Paper I**, which describes a LiDAR-based algorithm for the automatic characterisation of the tree canopy. This algorithm has been developed to automate and simplify the canopy volume calculation in order to support future developments of the variable-rate system. The algorithm was tested in different vineyards to evaluate its reliability in canopy characterisation. The results showed a good reliability in canopy volume estimation. In fact, a coefficient of determination of around 0.7 is obtained between manual and LiDAR-based measurements. These findings prove the effectiveness of the proposed algorithm. On this basis, the **Paper II** disclosed an evaluation of different technologies (mobile laser scanner, mobile app, unmanned aerial vehicle) and techniques (structure from motion, 2-3D point clouds) in the assessment of canopy size parameters such as thickness, height and volume. Therefore, the study aimed to evaluate, compare and cross-validate the

potential and limitations of different technologies to characterise the vine canopy and its spatial variability of growth. The highest coefficients of determination were obtained between the height ($R^2 > 0.8$) and volume data ($R^2 > 0.7$) for the mobile app vs. mobile laser scanner ($R^2 = 0.86$) and unmanned aerial vehicle vs. mobile laser scanner ($R^2 = 0.78$) comparisons, respectively. For the thickness data, instead, the correlations were weaker ($R^2 > 0.5$). On the basis of these results, all tools analysed are able to correctly assess different canopy size characteristics. In particular, the mobile laser scanner combines good estimation of canopy size characteristics with good usability, being an embedded solution. The further step was to combine this information with the innovative ultrasonic sensor proposed for the development and implementation of the variable-rate system. Therefore, **Paper III** presented the results of both the reliability of the innovative ultrasonic sensor in terms of canopy characterisation and the relationship between sensor readings, canopy characteristics and spray rates with the aim of future ultrasonic sensor implementation in a variable-rate sprayer. Based on this, the study revealed interesting correlations, particularly between the canopy height and the ultrasonic sensor parameters ($R^2 > 0.7$) and between the canopy volume and the ultrasonic sensor measurements ($R^2 > 0.6$). On the basis of these findings, two actuation ranges, based on normalised deposition and spray coverage parameters, between sensor readings and applied spray volumes were investigated in order to transfer this system to a sprayer. This allowed the spray rates to be refined in relation to the ultrasonic readings, thus enabling the use of this sensor in a variable-rate sprayer. Finally, in **Paper IV**, the variable-rate application kit was integrated into a sprayer and tested to verify the operational functioning of the system and to analyse its economic performance over an entire crop protection season. The study analysed the parameters of spray deposition and spray coverage for evaluating the reliability of quality and quantity distribution of plant protection products. Based on the results obtained, the variable-rate system ensures good deposition rates and coverage of plant protection products. In fact, over the three trials, the variable-rate system provided spray coverage of approximately 28%, compared to approximately 36% for the conventional system (uniform application). Using 30% coverage as the threshold beyond which overspray occurs, the uniform application system over-sprayed the canopy, particularly the part of the canopy that lies near the cordon. Moreover, the economic analysis highlighted the potential of variable-rate system. In fact, it showed significant savings in pesticide, water and fuel consumption. These savings had an impact both on the economic analysis, leading the break-even point to around the 4th year, and on the environmental sustainability of the crop protection stages, reducing above all the pesticides consumption.

List of papers

Paper I

Pagliai, A.; Sarri, D.; Lisci, R.; Lombardo, S.; Vieri, M.; Perna, C.; Cencini, G.; De Pascale, V.; Araùjo E Silva Ferraz, G. Development of an algorithm for assessing canopy volumes with terrestrial LiDAR to implement precision spraying in vineyards. Agronomy Research. 2021, 19.
https://doi.org/10.15159/ar.21.159

Paper II

Pagliai, A.; Ammoniaci, M.; Sarri, D.; Lisci, R.; Perria, R.; Vieri, M.; Eugenio, M.; D'Arcangelo, M.; Storchi, P.; Kartsiotis, S.P. Comparison of Aerial and Ground 3D Point Clouds for Canopy Size Assessment in Precision Viticulture. Remote Sensing. 2022, 14, 1145.
https://doi.org/10.3390/rs14051145

Paper III

Pagliai, A.; Sarri, D.; Perna, C.; Vieri, M. Second-generation ultrasonic sensor in precision spraying: testing and actuation range refinement. *Submitted* to 14th European Conference on Precision Agriculture on January 10th, 2023

Paper IV

Pagliai, A.; Sarri, D.; Perna, C.; Vieri, M. Can a variable-rate sprayer be efficient and economic? Testing and economic analysis in viticulture. *Revised 22 December,2023; Being published* in Lectures Notes in Civil Engineering.

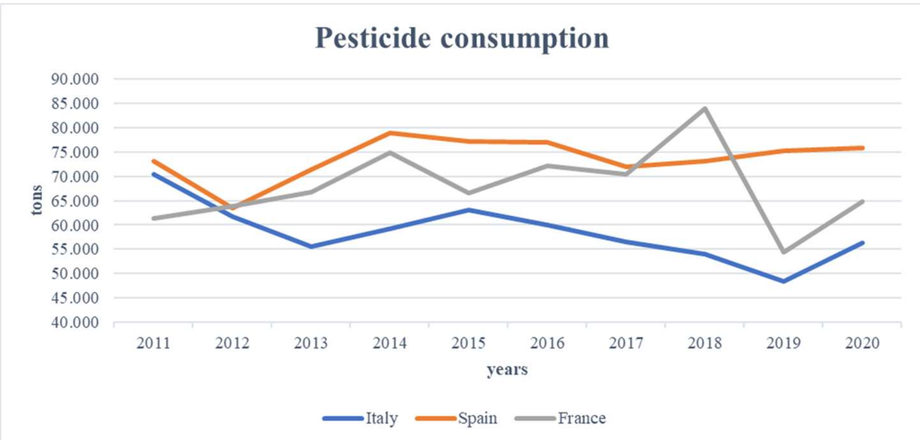
Abbreviations

2D	Two dimensions
3D	Three dimensions
BBCH	Biologische bundesanstalt, bundessortenamt and chemical industry
BEP	Break even point
BS ISO	British standard - international organization for standardization
CSV	Comma-separated value
CV	Coefficient of variations
D-GNSS	Differential - global navigation satellite system
DSM	Digital surface model
DSS	Decision support system
EPSG	European petroleum survey group
GNSS	Global navigation satellite system
GPS	Global positioning system
GSD	Ground sampling distance
H	Height of the canopy
ICPA	International Conference on Precision Agriculture
IDW	Inverse distance weighting
IPM	Integrated pest management
LAI	Leaf area index
LiDAR	Light detection and ranging
LWA	Leaf wall area
MA	Mobile app
MLS	Mobile laser scanner
NDRE	Normalized difference red edge index
NDVI	Normalized difference vegetation index
PA	Precision agriculture

PCD	Plant cell density
PNC	Point net cloud
PPP	Plant protection product
R^2	Coefficient of determination
RGB	Red Green Blue
RMSE	Root mean square error
ROI	Region of interest
ROPS	Roll-over protective structure
RTK	Real-time kinematics
SfM	Structure from Motion
T	Thickness of the canopy
TOF	Time-of-flight
TRV	Tree row volume
TRW	Tree row volume per meter of cordon
UA	Uniform application
UAV	Unmanned aerial vehicle
US	Ultrasonic sensor
V	Volume of the canopy
VRA	Variable rate application
VRT	Variable rate technology
WGS	World geodetic system
WSP	Water sensitive paper

1. Introduction

Nowadays, crop productions are specialised systems, characterised by high planting densities, low genetic diversity and high intensity of external inputs (Di Bene et al. 2022). In this context, crops are highly susceptible to pests and diseases (Rockström et al. 2017), so the use of plant protection products (PPPs) is necessary to protect the crop from pathogens and to achieve high-quality production (Gil et al. 2014). In recent decades, the extensive use of PPPs has contributed to a strong negative environmental footprint (Messéan et al. 2021). Pesticide use also affects the economic sustainability of farms, as PPPs are very expensive, costing farmers hundreds of euros per hectare (Mahmud et al. 2021). According to research by Pimentel, pesticide use in the United States region results in annual environmental and economic losses of approximately $8.2 billion (Pimentel 2005). This is most evident in tree crops, such as vines, where plants need to be sprayed with pesticides several times during the season (Román et al. 2020). In order to understand the scale of pesticide consumption, the trends in pesticide use over the last decade and the ratio of use between different types of pesticide are shown in Figure 1 for the main European wine-growing countries (Eurostat 2022).



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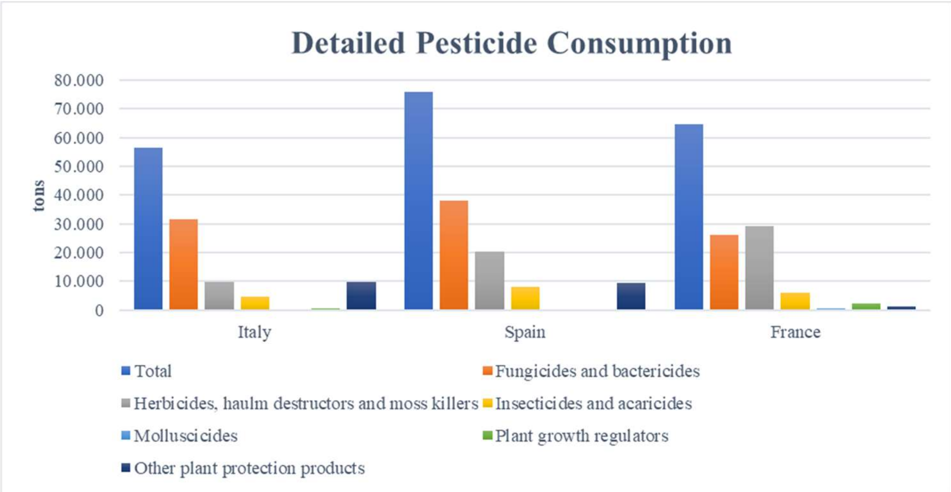


b)

Fig.1a. – Pesticide consumption trends in the main European country for arboreal crops.
Fig.1b. – Detailed pesticide consumption in 2020 in the main European country for tree crops. (Eurostat 2022)

On the basis of Figure 1a, the trend of pesticide consumption in Italy between 2011 and 2020 seems to be decreasing. In fact, in 2011 it was around 70,000.00 tonnes and at the end of this period it was around 55,00.00 tonnes, with a percentage reduction of 20%. In the other countries (France and Spain) the trend is very different from that in Italy. In fact, in France the trend is unpredictable because of the peaks and troughs in the middle part of the period considered. However, pesticide consumption at the beginning of the period is comparable to that at the end. On the contrary, the trend in Spain was a slight increase over the period considered. In fact, it was around 70,000.00 tonnes in 2011 and around 75,00.00 tonnes at the end of the period, with a percentage increase of around 5%.

The data on pesticide consumption shown in Figure 1a include the total amount of pesticides, but cover different types of pesticides, such as fungicides, bactericides, herbicides, molluscicides, plant growth regulators and other products. Figure 1b shows the consumption of different types of pesticides in the main European countries. The categories fungicides, bactericides and herbicides are the most represented in the three countries. In Italy and Spain, only the category fungicides/bactericides accounts for more than half of the total pesticide consumption. In France, this category represents slightly less than half of the total pesticides and the herbicides category is the most represented. This data is consistent with the findings of Pertot et al. (2017), who highlighted that it is common to apply an average of 10-15 treatments per year for fungal pathogens in Mediterranean basin tree crops (Pertot et al. 2017). In addition, the machinery used to spray PPPs does not have high efficiency pesticide deposition (Balsari and Marucco 2009). In fact, according to various studies, the amount of pesticide applied to the target is no more than 55% of the total volume sprayed, and in many cases as little as 20% (Chen et al. 2013; Hong et al. 2018).

On this basis, public authorities have focused their attention in recent years on drastically reducing the use of pesticides and/or improving the efficiency of spraying operations (European Directive 2009/128/EC 2009; MIPAAF 2014). On this path, for instance, the maximum amount of copper that can be used has recently been decreased by the European Commission to 28 kg per hectare over a 7-year period (an average of 4 kg per hectare per year) (EU Regulation 2018/1981 2018). In addition, the European Commission has recently established challenging objectives to achieve a wholesome and sustainable food system in its publication "From Farm to Fork" (European Commission 2020). To fulfil these targets, farmers will need to reduce the number of chemical inputs such as PPPs, fertilisers and antimicrobials by at least 50% by 2030.

Under these circumstances, the Precision Agriculture (PA) became a valuable strategy (Ammoniaci et al. 2021). According to the 14th International Conference on Precision Agriculture (ICPA), PA is “a management strategy that uses a wide range of technologies to gather, process and analyse data for the purpose of guiding targeted actions that improve the efficiency, productivity and sustainability of agricultural operations” (Sulecki 2018).Technologies such as sensors, GNSS receivers, microprocessors and others have paved the way for improvements in spraying techniques and machinery. (Gil et al. 2014). In this context, precision spraying relies on precise application of PPPs based on canopy information such as shape, architecture, size and density. (Tona et al. 2018). Therefore, the precision spraying refers to the application of plant protection products (PPP) at variable rates according to the size of the canopy to be sprayed (A. Miranda-Fuentes et al. 2016). For this reason, it is also called Variable-Rate Application (VRA) (Gil et al. 2007; Román et al. 2020).

Traditionally, crop protection treatments are applied uniformly, but the bottleneck is that crop canopies don't grow uniformly across a field (Wandkar et al. 2018). This aspect causes unavoidable inhomogeneous depositions of PPPs, resulting in underspray or overspray and causing significant environmental impact due to spray drift (Abbas et al. 2020). Instead, the VRA system adapts, in real-time, the spray mixture (PPP + water) to the canopy size or growth stage of trees. Therefore, a sensing system capable of assessing the spatial variability of canopy growth is necessary to perform VRA in tree crops (Gil et al. 2013). This is valid for both sensor-based VRA and map-based VRA. In fact, both when a sensor calculates the canopy characterisation in real time and performs the spray rate adjustment at the same time, and when the canopy characterisation is performed in one period and the VRA is subsequentially performed, a sensing system is essential to perform it (Del-Moral-Martínez et al. 2020; Escolà et al. 2013; Román et al. 2020). For this reason, a variety of sensors, tools and techniques are used to characterise the canopy of tree crops and, depending on the distance between the sensing system and the target, are differentiated in remote sensing and proximal sensing techniques (Ammoniaci et al. 2021; Arnó et al. 2013; López-Granados et al. 2020; Sassu et al. 2021).

1.1. Proximal sensing technologies for canopy characterisation

In crop or forestry science, the remote sensing relies on information gathering about a phenomena or a target without coming into contact with it (Hall et al. 2002). It is thus a set of techniques that enable the detection of the physical or chemical properties of an object from a certain distance (Matese et al. 2015). Sensing technology is therefore fundamental to detecting the characteristics or properties of an object. The distance between the sensor and the target distinguishes remote sensing from proximal sensing (Ammoniaci et al. 2021; Khaliq et al. 2019). In fact, the distance can vary from a few metres to thousands of kilometres, depending on the platform in which the sensors are embedded. If the distance is close, it is proximal sensing, otherwise it is remote sensing.

In recent years, many applications of remote or proximal sensing techniques have been tested to detect the spatial variability of crops, predict crop yield, characterise and quantify canopy size, estimate water stress and predict crop diseases (Anifantis et al. 2019; Chandel et al. 2021; Khaliq et al. 2019; Ouyang et al. 2020; Romero et al. 2018; Rosell Polo et al. 2009; Sun et al. 2017; Terrón et al. 2015; Verma et al. 2016). It is generally accepted that for a specialised crop such as vines, and for some objectives such as canopy characterisation, proximal sensing is more appropriate than remote sensing based on satellite data because of its high spatial resolution, which allows better discrimination of canopy patterns (Khaliq et al. 2019; Matese et al. 2015). Instead, UAV-based remote sensing can provide greater accuracy and spatial resolution, paving the way for canopy characterisation and assessment of intra-field spatial variability in viticulture (Lorenzo Comba et al. 2019; Di Gennaro and Matese 2020; Matese and Di Gennaro 2018). However, a comprehensive comparison between remote and proximal sensing, terrestrial and aerial, real-time and post-processing is lacking to better understand the potential and limitations of different technologies for a strategic objective such as the canopy size quantification.

In arboreal crop protection science, the assessment of canopy size has always been a pivotal aspect for adjusting the rate of PPPs to plants (Pergher and Petris 2008). Originally, the canopy measurements were made using manual techniques, and then, converted into appropriate canopy indicators such as Leaf Area Index (LAI), Tree Row Volume (TRV), Leaf Wall Area (LWA) and others (Antonio Miranda-Fuentes et al. 2015). In general, manual techniques are time-consuming, subject to human error and, in some cases such as the LAI index, destructive measurement (Cohen et al. 2000). For these reasons, a number of instruments have been developed over the years to provide more efficient, accurate and faster measurement methods (De Bei et al. 2016; Grantz et al. 1993). Thanks to technological advances, many sensors have been developed, proposed and field-tested in recent years to measure canopy parameters in tree crops (Escolà et al. 2011; Rinaldi et al. 2013; Rosell et al. 2009). The most promising sensors for canopy characterisation in arboreal crops can be divided into two main categories: passive sensors and active sensors. (Rodríguez-Gonzálvez et al. 2014). This distinction is based on different modes of operation (Stamatiadis et al. 2010). The first category depends on the light available in the environment, as sensors detect the reflectance of natural sunlight reflected from a target (L. Comba et al. 2020; Matese and Di Gennaro 2018; Terrón et al. 2015). Instead, the second category actively uses an artificial signal (laser beam or ultrasonic waves) to detect the target, (Colaço et al. 2018; Escolà et al. 2011; Llorens et al. 2011).

<u>Passive sensor</u>

This category includes multispectral, hyperspectral, red-green-blue (RGB) and stereo cameras. The first two technologies are able to measure the electromagnetic radiation reflected by canopies. This allows the spectral response of plants to be distinguished and their health condition to be assessed using various vegetation indices such as Normalised Difference Vegetation Index (NDVI), Normalised Difference Red Edge Index (NDRE) and others (Mazzia et al. 2020; Sirera et al. 2021). These sensors can be categorised as multispectral if they have a small number of broad or narrow bands (less than 20) or as hyperspectral if they have a large number of narrow bands (Ammoniaci et al. 2021). They do not directly assess canopy dimensions, but focus on plant vigour, which is assessed using various indices and methods such as Plant Cell Density (PCD) (Román et al. 2020). However, many studies have shown promising correlations between vine vigour and the presence of plant diseases or pathogens, such as fungal infections, botrytis (*Botrytis cinerea* Pers.) and the yellow spider mite (*Eotetranychus carpini* Oud.), allowing them to be used for canopy characterisation and subsequently for precision spraying (Bramley et al. 2011; Ferrer et al. 2020, Román and Planas 2018). Typically, these sensors are embedded in satellites or UAVs (Ammoniaci et al. 2021). A UAV-based multispectral camera is shown in Figure 2.

Fig.2. – UAV-based multispectral camera (Micasense Altum Camera, AgEagle Aerial Systems Inc., Wichita, Kansas, USA).

RGB cameras work in a similar way to multispectral cameras, except that they only detect the red, green and blue spectral bands (around 400 - 700 nm) (Matese and Di Gennaro 2018). Thanks to the high resolution of these cameras, it is possible to obtain 2D images with very high spatial resolution. This makes it possible to obtain 3D plant models using Structure from Motion (SfM) algorithms (Lorenzo Comba et al. 2020). Therefore, the combination of the RGB sensor and the appropriate algorithms (SfM) paves the way for the characterisation of the tree canopy (Jay et al. 2015). In fact, Kalisperakis et al. showed relevant correlations between the LAI index and 3D crop surface models based on RGB camera data (R^2 = 0.81) (Kalisperakis et al. 2015). The 3D crop models can be also obtained with multispectral imagery. Comba et al. reported promising correlations (R^2 = 0.82) between manual LAI and 3D crop model-based LAI, enabling the digitalization of LAI measurements (Lorenzo Comba et al. 2019).

Another category of sensors that is interesting for the characterisation of the canopy is known as the depth cameras. With this definition, different operating modes are included based on stereoscopy vision, structured light method, and time-of-flight approach (Luo et al. 2016; Rosell-Polo et al. 2017; Saberioon and Cisar 2016). The basic operating principle of these sensors is to discriminate the depth of an image by combining two images taken simultaneously from different angles (stereoscopic vision), or by combining two cameras, one dedicated to capturing RGB images and the other dedicated to discriminating depth through infrared images (structured light), or by combining an RGB camera with a time-of-flight (TOF) sensor that provides direct measurements (Abbas et al. 2020; Mahmud et al. 2021; Moreno et al. 2022). In terms of canopy characterization, these sensors have some limitations due to the susceptibility to direct sunlight (Abbas et al. 2020). Depth cameras based on stereoscopic vision and structured light are the most susceptible to outdoor sunlight conditions, as noted by (Halmetschlager-Funek et al. 2019). Instead, the TOF-based depth cameras have good enough performance even in strong lighting conditions (Kuan et al. 2019). However, considering these limitations Bao et al. (2019) proposed to acquire data late in the evening (no earlier than 1 h before sunset). This solution provided promising correlations between manual and digital canopy characterization (before flowering: R^2 = 0.96; after flowering: R^2 = 0.83) (Bao et al. 2019).

<u>Active sensor</u>

This category includes multispectral cameras, laser scanners and ultrasonic sensors. Active multispectral cameras work in a similar way to passive sensors. The only difference is that they emit laser beams to illuminate the canopy and measure the reflectance intensity of the plants, reducing the effect of sunlight intensity and time of day (Ammoniaci et al. 2021). Typically, these sensors are embedded in terrestrial platforms such as the OptRx sensor (Ag Leader Technology, Ames, IA, USA) and the CropSpec sensor (Topcon, Livermore, CA, USA) or hand-held such as the GreenSeeker sensor (Trimble Inc., Sunnyvale, USA) (Putra et al. 2018). A active-based multispectral sensor is shown in Figure 3. This type of sensor is a critical element in many canopy characterisation applications due to its versatility and ability to reproduce high-quality information (Ammoniaci et al. 2021; Gatti et al. 2016; Terrón et al. 2015). In addition, by reducing sunlight interferences these sensors provide more reliable vegetation indices, especially in tree crops, by avoiding ground interference (De la Fuente et al. 2020).

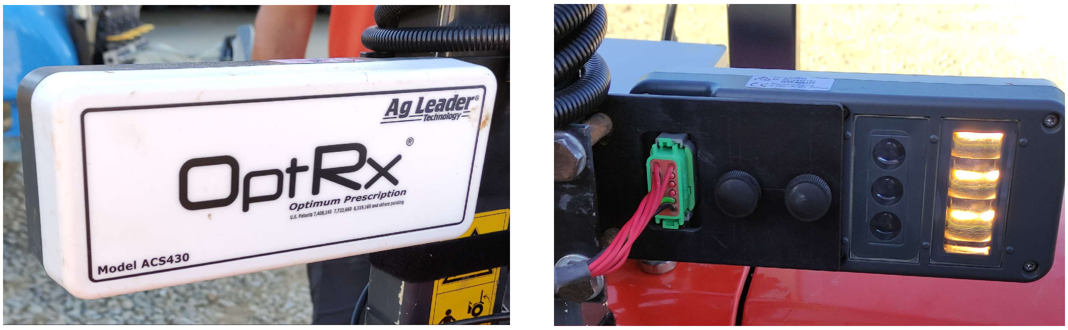
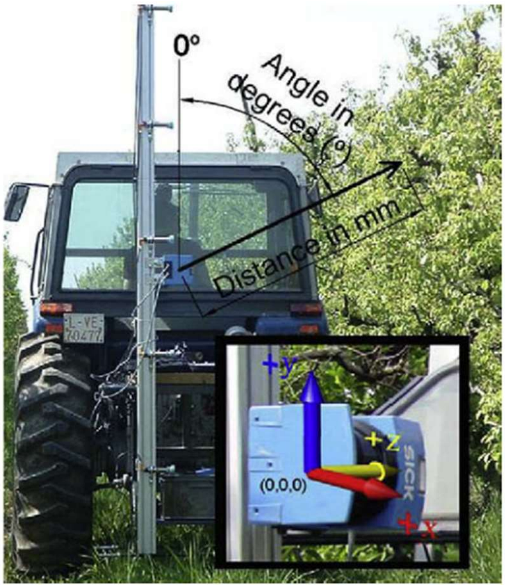


Fig 3. – Terrestrial platform-based multispectral camera (Ag Leader Technology, Ames, IA, USA)

In recent years, the use of laser scanners in agriculture has increased exponentially, particularly in the field of canopy characterisation. (Arnó et al. 2013; Colaço et al. 2017; Paulus et al. 2014; Rosell et al. 2009). Laser scanners are active sensing technologies that calculate the distance from sensor to target based on the time of flight of an artificial laser beam emitted by the sensors. Laser scanners can operate at different wavelengths, such as visible, ultraviolet or near-infrared light, and because they emit their own light source, they can measure day and night as they are independent of changing light conditions. (Rosell and Sanz 2012). As a representative of scanning systems, Light Detection And Ranging (LiDAR) can have horizontal and/or vertical scanning ranges with various aperture angles (most common: 180°, 270°, 360°). Based on scanning ranges, it is to 2D LiDAR if it has only horizontal one, instead, 3D LiDAR has both horizontal and vertical scanning ranges (Rinaldi et al. 2013). Other important LiDAR characteristics are: angular resolution, i.e. the number of points detected within the aperture angle (most common: 1°, 0.5°, 0.33°, 0.25°); working range, i.e. the maximum scanning distance; scanning frequency, i.e. the number of scans per second (Hz). A 2D LiDAR sensor is shown in Figure 4.



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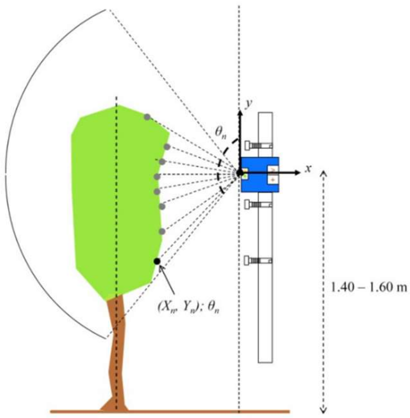


b)

Fig.4a. – A tractor-mounted 2D LiDAR sensor (LMS-200 LiDAR, SICK AG, Waldkirch, Germany) (Rosell Polo et al. 2009).
Fig.4b. – Schematic representation of 2D LiDAR operation (Llorens et al. 2011).

The most common LiDAR sensors used for on-the-go canopy characterisation are 2D LiDAR (x, y axis), which is positioned vertically in such a way as to scan tree rows (Llorens et al. 2011; Rosell Polo et al. 2009). Typically, 2D LiDAR sensors are embedded in terrestrial platforms, such as tractor, allowing the 3D reconstruction of the canopy thanks to the forward movement (z-axis) of the terrestrial platform. (Rinaldi et al. 2013). Data obtained from LiDAR sensors are consistent and reliable for the canopy estimation. Indeed, Rosell Polo et al. (2009) reported very good correlations between manual and LiDAR measurements in pear, apple orchards and vineyards (R^2 = 0.97, R^2 = 0.81 and R^2 = 0.92, respectively) (Rosell Polo et al. 2009). Rinaldi et al (2013) showed very promising correlations between LiDAR impacts and the LAI index (R^2 = 0.82) and between estimated TRV and LWA at different crop stages (R^2 = 0.99 and R^2 = 0.95, respectively) after processing the data with an R package, named PROTOLIDAR (PROcess TO LIdar Data) (Rinaldi et al. 2013). In recent years, thanks to technological advances in GNSS positioning accuracy (RTK, D-GNSS), the LiDAR data are collected with spatial positioning to reconstruct geo-referenced 3D point clouds (Cheraiet et al. 2019; Tsoulias et al. 2019). These approaches are able to detect geometric variables in tree crops and show interesting correlations between manual and LiDAR-based canopy measurements (height, width and volume). However, these results are obtained in post-processing data processing and with expensive instrumentation. Therefore, the application of these approaches in sensor-based VRA is uncertain, as the reliability in real-time data processing has not been tested and the cost of VRA implementation may not be sustainable.

Finally, another type of active technology used to characterise the vine canopy is the ultrasonic sensor (US). The basic principle is similar to the LIDAR sensor because it works with TOF measurements, but US works with ultrasonic waves instead of laser beams (Zhang et al. 2018). In addition, many sensors are needed to characterise the canopy, as the US provides a single measurement point for each ultrasonic emission (Rosell and Sanz 2012). A schematic representation of differences between US and LiDAR sensors is shown in Figure 5. For decades, US have been used in agriculture thanks to their robustness, low price and ease of use (Rosell and Sanz 2012). Many studies have demonstrated the reliability of US measurements in relation to the manual canopy measurements in different crop species (Escolà et al. 2011; Gil et al. 2007; Giles et al. 1988; Llorens et al. 2011;

Schumann and Zaman 2005), paving the way for precision spraying. However, some limitations may affect the canopy characterisation. In fact, Escolà et al. (2011) reported that when USs are located close to each other, errors can occur in the calculation of the TOF due to return ultrasonic waves from different sensors (Escolà et al. 2011). In order to reduce the source of error, Escolà et al. (2011) suggested that the sensors should be separated by more than 0.6 m (Escolà et al. 2011).

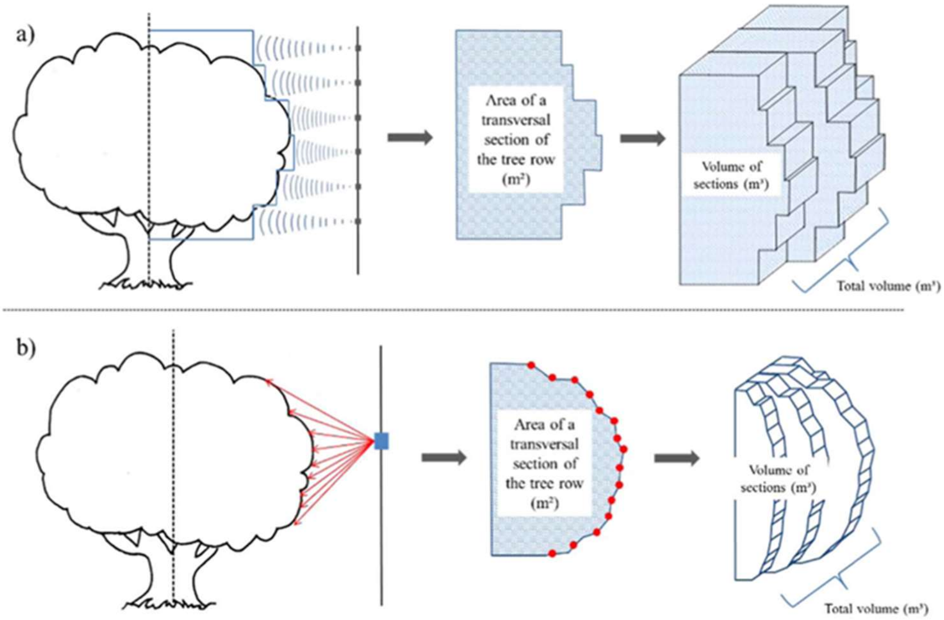


Fig.5. – Schematic representation of differences between US and LiDAR sensors; a) Ultrasonic sensor; b) LiDAR sensor; (Colaço et al. 2018).

In recent years, thanks to the technological advances new USs have been proposed (Palleja and Landers 2015). The breaking point of this sensor related to others, is that it has the potentiality to discriminate the foliar layers and the canopy density thanks to its innovative mode of operation. In fact, these innovative sensors are able to measure and discriminate the number of echoes and their intensity in a pre-selected region-of-interest (ROI) (Palleja and Landers 2017). Initial trials have shown promising results for estimating canopy density and thickness during the growing season in both apple orchards and vineyards, with an average error of 4.76%

(Ou et al. 2022; Palleja and Landers 2017). These recent studies proved the ability of new USs to estimate foliar layers, canopy density and thickness, paving the way for future advances in precision spraying (Ou et al. 2022; Zhou et al. 2021). However, to the best of my knowledge, no study has been carried out to develop and test a VRA sprayer fitted with these innovative sensors.

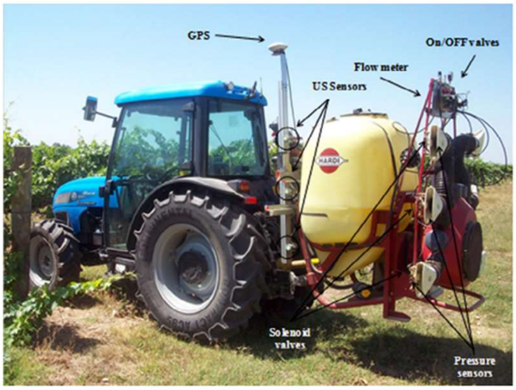
1.2. Variable-rate technologies in viticulture

Proximal sensing technologies pave the way for precision spraying, with the ultimate goal of improving the economic and environmental sustainability of crop protection (Zhang et al. 2018). As clearly stated in the previous sections, precision spraying, also known as variable-rate application, has become necessary to apply an adjusted volume rate of PPP to the target, based on tree size, and it arises in contrast to the uniform application (UA) of pesticides (Wandkar et al. 2018). In fact, since each tree in an orchard varies greatly in size and shape, uniform application results in low efficiency in terms of spray quality and quantity, with unavoidable losses of PPP to the environment (Abbas et al. 2020). Depending on the type of technology used, a distinction is made between sensor-based VRA sprayers, where a sensing system is embedded in the sprayer and directly controls the spray rate, and map-based VRA sprayers, where a PPP prescription map is uploaded to the on-board console to control the spray rate (Rosell and Sanz 2012).

Sensor-based

The first implementations of precision sprayers date back to before the 2000s. Giles et al. (1987) developed a prototype that used ultrasonic sensors to switch spraying on and off in the presence or absence of foliage, reducing pesticide consumption by 28% to 35% for peaches and 36% to 52% for apples (Giles et al. 1987). This sprayer did not perform a variable-rate application but it introduced the first sensing systems to crop protection spraying, reducing pesticide use. Subsequently, thanks to advances in electronics and technology, sensing systems began to become more powerful, paving the way for the differentiation of canopy characteristics (Rosell and Sanz 2012). In the first decades of the 2000s, many VRA sprayers were developed based on different sensing systems (camera-based, ultrasonic-based and laser-based) in order to improve both spraying efficiency and environmental sustainability (Escolà et al. 2013; Gil et al. 2007; Llorens et al. 2010). Moltò et al (2001) developed a prototype VRA sprayer based on two ultrasonic sensors (one per side) and tested it in the field to evaluate both spray quality and savings on globular trees. They found that the VRA sprayer achieved an average saving of 37% of the spray mixture (Moltó et al. 2001). Gil et al (2007) developed a prototype VRA air-blast sprayer based on three ultrasonic sensors per side and reported that the VRA sprayer has been able to reduce spray volume by approximately 41.2% compared to UA without affecting spray deposition (Gil et al. 2007). These results were obtained by comparing two application modes (VRA and UA) on 100 m of vine row. Llorens et al. (2010) extensively tested the previous sprayer in different phenological phases and on different varieties. The results confirmed those obtained by Gil et al. (2007), in fact they obtained savings of more than 40% in all the trials, with the maximum savings being 76.9% (Llorens et al. 2010). Vieri et al. (2011) went a step further by developing a VRA sprayer prototype based on eight ultrasonic sensors (four per side), which can not only vary the application rate according to tree size, but also vary the inclination of the upper and lower outlet diffusers to improve spray deposition (Vieri et al. 2011). They expected PPP savings of 50 to 70% compared to conventional applications. Hočevar et al. (2010) developed a VRA sprayer based on an RGB camera and appropriate image analysis This system achieved an overall pesticide saving of 23% compared to uniform application (Hočevar et al. 2010). In addition, the authors stated that future improvements, such as moving the camera position or changing of sensing technology, are needed to increase the efficiency of the camera-based VRA sprayer (Hočevar et al. 2010). Chen et al. (2013) tested a VRA sprayer based on a laser scanner to evaluate the reduction of spray drift and off-target losses. The results showed significant reductions in spray loss on the ground (68-90%), spray drift (70-100%) and spray volume (47-73%) compared to a uniform rate sprayer (Chen et al. 2013).

a)



b)

c)

d)

Fig.5. – Sensor-based VRA sprayer: a) Ultrasonic-based (Vieri et al. 2011); b) Ultrasonic-based (Gil et al. 2013); c) LiDAR-based (Chen et al. 2013); d) Camera-based (Hočevar et al. 2010).

Li et al. (2018) developed and tested a VRA sprayer based on LiDAR sensor, in contrast to two conventional sprayers (air blast sprayer and air-jet sprayer). According to the results, the VRA sprayer used less spray solution than the conventional sprayer while maintaining the same penetration rates of PPP. In addition, VRA sprayers were more effective than conventional sprayers, as evidenced by the fact that normalised deposition was higher with VRA than with UA (Li et al. 2018). Various sensor-based VRA sprayers are shown in Figure 6.

<u>Map-based</u>

The concept of map-based variable rate application was derived from arable crops (Ess et al. 2001). For this reason, the first implementations were developed for variable-rate application of herbicides according to the presence of weeds or for application of granular fertilisers according to vigour indices or soil characteristics (Ammoniaci et al. 2021). For instance, Vogel et al. (2005) modified a conventional sprayer into a VRA sprayer in order to apply herbicides in a site-specific manner. Results showed that this system was able to control weeds in maize and soybean (Vogel et al. 2005). A crucial aspect of map-based VRA systems is the strategy used to generate a map (Ess et al. 2001). In tree crops, the precision spraying of PPPs is typically based on the canopy size such as height, thickness, volume or density (Mahmud et al. 2021). In map-based sprayers, the spatial variability of canopy needs to be assessed with a dedicated sampling (manual or digital) in order to generate a geo-referenced map (Ammoniaci et al. 2021). In addition, geo-statistical techniques are necessary for the production of accurate and reliable prescription maps (Del-Moral-Martínez et al. 2020). In recent years, advances in remote and proximal sensing have made digital canopy characterisation practical and reliable, allowing precision spraying based on PPP prescription maps and increasing the economic and environmental sustainability of crop protection phases (Campos et al. 2020). Under these circumstances, Román et al. (2020) tested a variable-rate application, based on prescription maps generated from a multispectral airborne camera, in contrast with a uniform application. Results showed a reduction in pesticides use of around 25% without affecting the spray deposition (Román et al. 2020). A schematic representation of the process behind map-based VRA system is shown in Figure 6.

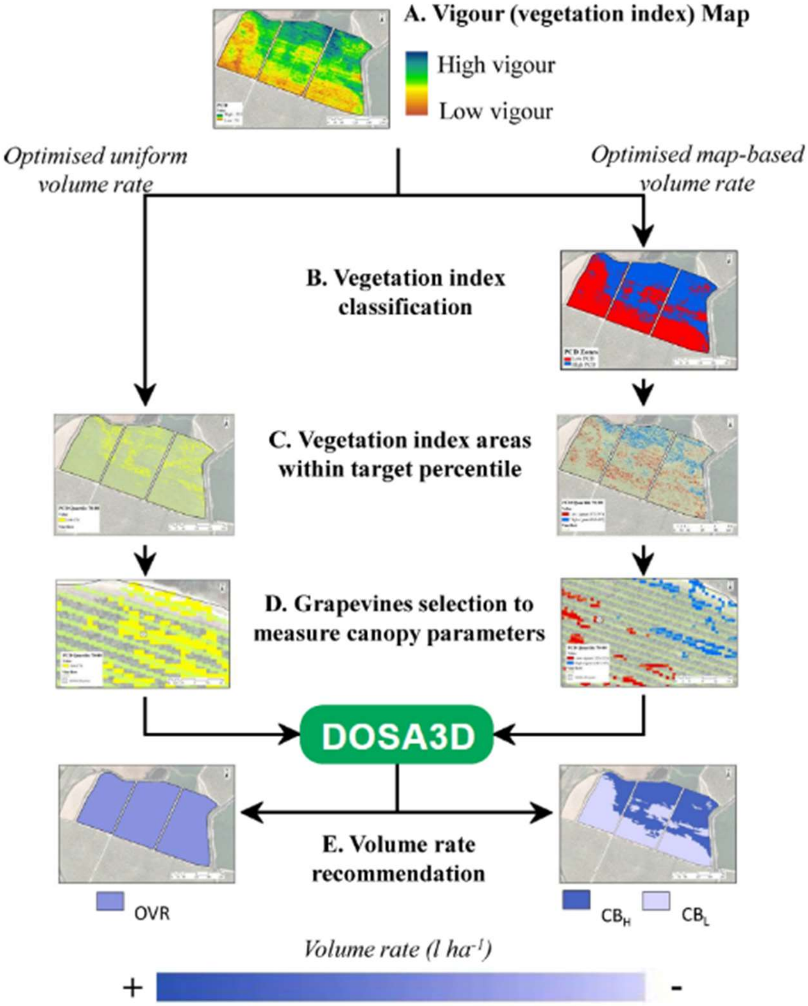


Fig.6. – Schematic representation of the process behind map-based VRA system (Román et al. 2020).

Another interesting study is that of Campos et al. (2020). In this study, a map-based VRA sprayer and a conventional sprayer were extensively tested over an entire growing season to evaluate the quality of spray distribution and the biological efficacy of PPP spraying. The mapping process was very similar to the previously reported study (Román et al. 2020). Results showed an adequate spray coverage of 20 - 40% and same rates of biological efficacy (Campos et al. 2020).

Although numerous studies have noted a relevant decrease in the amount of pesticide used when spraying, the majority of them assessed their savings on a small scale or in relatively controlled area. Only Campos et al. (2020) conducted a study to evaluate a map-based VRA sprayer on a large vineyard and over a full growing season (Campos et al. 2020). Therefore, a comprehensive study of a sensor-based VRA sprayer in a large orchard and over a full season is lacking. Additionally, despite numerous prototypes developed by various research groups for tree crops over the last two decades very few variable-rate sprayers are commercially available for arboreal crops (Mahmud et al. 2021). Moreover, VRA sprayers are more expensive than conventional sprayers due to the use of sensors and more electronic components, and are therefore still out of the economic reach of the majority of wineries (Tona et al. 2018). Furthermore, Tona et al. (2018) identified other reasons for the low adoption of VRA sprayers in tree crops such as the need for specific technical training for operators or the maintenance requirements (Tona et al. 2018). Under these circumstances, a kit for the implementation of VRA systems instead of the purchase of an expensive and new VRA sprayer is missing.

2. Aim and outline of the research

The heavy environmental and economic footprint of crop protection stages and the availability of low-cost sensors and technologies inspired this thesis. This thesis addresses the development and evaluation of different proximal sensing tools for the characterisation of vine canopies with the aim of supporting the development, validation and testing of a variable-rate application kit for sprayers in order to improve the environmental and economic sustainability of crop protection stages.

In detail, the following specific objectives will be conducted through four steps:

1. To develop an algorithm for characterizing the vine canopies in real-time with terrestrial LiDAR through the Tree Row Volume index calculation (Paper I);

2. To assess the reliability of different 3D point clouds sources for vine canopy size assessment based on aerial and ground photogrammetry and terrestrial laser scanner (Paper II);

3. To assess the operative performance of a second-generation ultrasonic sensor in canopy characterization and to fine-tune the actuation range between sensor readings and applied volume of plant protection products (Paper III);

4. To develop and implement a variable-rate application kit in a conventional sprayer and to assess its spraying performance and its economic sustainability in an entire crop protection season (Paper IV).

3. Papers

3.1. Paper I

Development of an algorithm for assessing canopy volumes with terrestrial LiDAR to implement precision spraying in vineyards

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Abstract

Precision spraying is one of the techniques for the reduction of pesticides use and it can help achieve the new European Green Deal standards. The aim of such technique is to apply the right amount of pesticides according to the target characteristics. The precision spraying implementation requires target volume assessment, which can be carried out by LiDAR sensors. Such technique requires complex and time-consuming procedures of canopy characteristics computing through post-processing points cloud reconstruction. The present work aimed to develop and test an algorithm through the use of a tractor-coupled with terrestrial LiDAR and GNSS technology in order to simplify the process. With the aim to evaluate the algorithm the LiDAR-based volume was correlated with two manual measurements of canopy volume (Tree Row Volume and Point Net Cloud). The results showed good correlations between manual and LiDAR measures both for total canopy volumes (R^2 = 0.67 and 0.56) and for partial canopy volume (R^2 = 0.74). In conclusion, although the LiDAR-based algorithm works in automatic mode, the canopy volumes approximation seems acceptable to estimate the canopy volumes, with the advantages of a swifter procedure and less laborious post-processing computations.

Key words: canopy management technique, canopy measurements, site-specific data, variable rate technique, viticulture.

Introduction

In the last few decades, the public authorities focused their attention on reducing pesticide use and/or improving the efficiency of spraying operation (European Parliament, 2009; MIPAAF, 2014). The European Commission has recently declared that it is essential to introduce coherent strategies to halve the use of chemical pesticides by the year 2030 (ECP, 2020). Variable rate applications (VRA), telemetry of crop protection stages, integrated pest management (IPM) and decision support systems (DSS) can be effective strategies to achieve the European goals. VRA consists of variable-rate spraying according to the characteristics of the canopy (height, width, volume, leaf area, leaf density) or vigour index (Miranda-Fuentes et al., 2016; Tsoulias et al., 2019; Cheraïet et al., 2020; Román et al., 2020). A 20–30% reduction in pesticide use has been achieved by detecting tree size and architecture, (EPRS, 2016). Other improvements have been reached by using auxiliary telemetry tools for crop protection phases (Sarri et al., 2020). In addition, the adoption of Integrated Pest Management (IPM) was able to reduce a sprayed area by approximately 50–80% (EPRS, 2017). The variable-rate application technique consists in obtaining similar plant protection products (PPP) deposits according to canopy characteristics (Gil et al., 2013). To fulfil the variable-rate applications, canopy dimensions have to be measured. Originally, canopy measurement was carried out manually and the corresponding canopy indicators were created (Tree Row Volume, Leaf Area Index, Leaf Wall Area, Unit Canopy Row, Ellipsoid Volume Method) (Pergher & Petris, 2008; Miranda-Fuentes et al., 2015). Obtaining these manual indicators was time-consuming. Gradually, thanks to technological development, faster and more efficient measurement methods have been developed (Rosell & Sanz, 2012; Comba et al., 2019). Several studies have used ultrasonic sensors to improve variable-rate application (Llorens et al., 2010; Llorens et al., 2011, Gil et al., 2013). These sensors operate with ultrasonic waves, and provide a precise assessment of canopy width in small portions of vegetation. Improvements of canopy detections were provided by LiDAR (Light Detection and Ranging) sensors. The LiDAR technology works with laser beams, and it provides canopy point cloud, at various angular resolution and various aperture angle (Rosell & Sanz, 2012). Thus, the entire vertical profile of the canopy can be reconstructed. Many studies were carried out for implementing the LiDAR-based canopy measurements (Palacín et al., 2007; Rosell et al., 2009a; Llorens et al., 2011; Sanz et al., 2013; Miranda-Fuentes et al., 2015; Tsoulias et al., 2019). Some works obtained canopy characteristics with complicated and laborious steps that required a great amount of post-processing operations. In other works it was necessary to carry out point cloud reconstruction and data filtering to obtain a correct and precise canopy characterization. Only after these operations it was possible to run the canopy parameters computing. Although they are valid methods for research domains, these procedures do not coincide with the implementation of variable-rate operations during work operations. The data extract must be well suited with the tractor speed during spray operations to implement VRA. Therefore, for data processing, few milliseconds are usable. Moreover, the accuracy of canopy measurements, reached by post-processing operations is often too high for practical purposes. Very few studies were focused on practical and operative tools for assessing canopy volumes in real time (Zhang et al., 2018). It is thus evident that a functional LiDAR-based tool is needed to optimise the variable-rate application of pesticides in viticulture. A procedure for automating the LiDAR-based canopy volume computing in real-time was developed to reach this target.

Therefore, this paper focuses on the development and testing of a LiDAR-based algorithm and software for the automatic calculation of canopy volume using a tractor- coupled with terrestrial 2D LiDAR and GNSS receiver.

In order to check algorithm and software, a number of comparison tests were carried out between two different manual canopy volume measurements and LiDAR canopy volume measurements. The experimental tests were carried out in two vineyards, with different row spacing and plant density parameters. Finally, the canopy volumes of four vine-rows, which were completely travelled, were analysed in two work sessions to check the software functioning during the different growth stages.

Materials and Methods

Instrumentations:

The 2D LiDAR Sick TIM561 was used (Fig. 1, a) to perform the study. The main sensor features were an angular resolution of 0.33°, an aperture angle of 270°, a working range from 0.05 m to 10 m, a laser emission wavelength of 850 nm and a scanning frequency of 15 Hz (TIM561 Sick). Thanks to these characteristics, 12,150 points were captured each second.

Moreover, to obtain geo-referenced data, the 2D LiDAR was coupled with Ag Leader GPS6500 GNSS receiver (Fig. 1, b). This GNSS receiver provides differential correction with a horizontal position accuracy of 0.4 m, a velocity accuracy of 0.03 m s^{-1} and a maximum data rate of 50 Hz (GPS 6500, Ag Leader).

The LiDAR sensor and GNSS receiver were connected together through a Panasonic Tough Pad FG-Z1, where the algorithm and software for calculating the canopy volume were installed (Fig. 1, c).

During field tests, all these instrumentations were mounted on a Kubota B2420 tractor. On the one hand, the Panasonic computer and the GNSS receiver were assembled near the steering station. On the other hand, the 2D LiDAR was positioned in the rear of the tractor in a vertical position to correctly scan the vertical profiles of the canopy, thanks to 270° opening angle.

Figure 1. Instruments assembled during a field test session with details of the individual tools used (a) GNSS receiver; b) LiDAR sensor; c) Panasonic computer.

Algorithm and Software:

The calculation of the canopy volume was made using an algorithm for extracting the canopy contours, integrated into software for real-time visualisation of the canopy volumes and its main characteristics. In addition, the software creates a comma-separated values (CSV) file-data where the volumes of canopies, associated with their global position (EPSG:4326-WGS 84), and working parameters of the tractor (speed, distance between $scan_i$–$scan_{i+1}$) were recorded.

It is worth noting that before starting the data acquisition, the GNSS acquisition frequency can be changed from 0.1 to 15 Hz in the software interface page. Its frequency rate controlled the entire exchange of data. Specifically, each time the GNSS string arrived, it was processed by software that sent a data request to the LiDAR. Instantly, a LiDAR scan was run, processed and recorded (with an angular resolution of 0.33° and a scan range of 270°). This process was reiterated until the data acquisition end. For the transfer of LiDAR data, an ethernet connection was used. Instead, an RS232 serial port was used for GNSS data transfer.

First of all, row data provided by LiDAR sensor were transformed from polar to cartesian coordinates. The transformation was made for all points individuated by LiDAR sensor in a single scan (angular resolution: 0.33°; aperture angle: 270°;

maximum point for single scan: 810) and for all scan frequency (scan frequency: 15 Hz = 15 scan s^{-1}), using the following formula:

$$C\_xy_{ij} = \begin{cases} X = DV_{ij} * \cos\alpha_{ij} \\ Y = H_{Li} + DV_{ij} * \sin\alpha_{ij} \end{cases} \quad (1)$$

where C_xy_{ij} – detected canopy point in cartesian coordinates; DV_{ij} – distance between LiDAR and canopy at determined angular position j and the moment i; α_{ij} – angle subtended by DV_{ij}; H_{Li} – LiDAR average height from ground-level. Graphically representation is shown in Fig.2.

Then, if X coordinates of the canopy points (C_xy_{ij}), that corresponded to the distance between LiDAR and canopy in the cartesian system, were equal or bigger than semi row spacing ($D_{rs}/2$), they were considered in the calculation of canopy volume as values 0, because these points did not belong to the canopies near the tractor. In comparison, laser beams that did not encounter any obstacles were not counted. Moreover, another condition had to be respected. The Y coordinates of the canopy points (C_xy_{ij}) must be bigger than H_{co} (average cordon height). In this way, the points detected in the ground-level or other interferences, as grass or vine trunk, were not considered. Thanks to LiDAR characteristics (TIM561 Sick), particularly the aperture angle of 270°, it was possible to detect two sides of vine-rows for each working route. Therefore, the conversion formula and the conditions previously exposed were viable for both sides of vine-rows (Fig.2_left side).

A subdivision of total canopy volume in three bands according to the height from cordon was carried out. Specifically the low band was between the cordon (H_{co}) up to 0,30 m in vertical height (H_{co+3}), the middle band was between the end of the previous one up to 0.60 m apart the cordon (H_{co+60}) and the high band was between the end of the previous one up to the last canopy detected point ($ymax$) (Fig. 2_right side). The subdivision in three bands was necessary to discriminate how the canopy arranges on the vertical profile. Without these partitions, only the total canopy volume would have been measured and it would not have been possible to show the differences in the vertical profile of the canopy.

Then the algorithm, according to different canopy bands, computed total and partial means of the x-values of canopy points (C_xy_{ij}). To differentiate the three bands, the y-values of canopy points (C_xy_{ij}) were used. These average values ($\overline{X_{tot}}$; $\overline{X_{high}}$; $\overline{X_{mid}}$; $\overline{X_{low}}$) correspond to distance between LiDAR and canopy in a different portion of canopy profile. The subtraction between semi row spacing ($D_{rs}/2$) and average values were done to obtain both total average canopy width and partial average canopy widths (low, mid and high canopy bands). Finally, the entire and partial areas of canopy sections were obtained by the multiplication between their widths and heights. In such a manner, the canopy areas (m^2 $scan^{-1}$) of vertical LiDAR scan were obtained, both for left and right sides. The equations below showed the procedure aforementioned (2) (3) (4) (5).

$$\overline{X_{tot}} = \frac{\sum_{y=H_{co}}^{ymax} x_i}{n_t} \rightarrow A_{tot} = \left(\frac{D_{rs}}{2} - \overline{X_{tot}}\right) * (ymax - H_{co}) \quad (2)$$

$$\overline{X_{high}} = \frac{\sum_{y=H_{co+60}}^{ymax} x_i}{n_h} \rightarrow A_{high} = \left(\frac{D_{rs}}{2} - \overline{X_{high}}\right) * (ymax - H_{co+60}) \quad (3)$$

$$\overline{X_{mid}} = \frac{\sum_{y=H_{co+30}}^{H_{co+60}} x_i}{n_m} \rightarrow A_{mid} = \left(\frac{D_{rs}}{2} - \overline{X_{mid}}\right) * (H_{co+60} - H_{co+30}) \quad (4)$$

$$\overline{X_{low}} = \frac{\sum_{y=H_{co}}^{H_{co+30}} x_i}{n_l} \rightarrow A_{low} = \left(\frac{D_{rs}}{2} - \overline{X_{low}}\right) * (H_{co+30} - H_{co}) \quad (5)$$

where $\overline{X_{tot}}, \overline{X_{high}}, \overline{X_{mid}}, \overline{X_{low}}$ – average values of x coordinates, respectively for total canopy, high canopy band, mid canopy band and low band; H_{co} – cordon height; H_{co+30} – cordon height plus 0.30 m; H_{co+60} – cordon height plus 0.60 m; $ymax$ – the y coordinate of last canopy point detected by LiDAR; x_i – x coordinate in C_xy_{ij}; n_t, n_h, n_m, n_l – number of canopy points included respectively in total, high, mid and low canopy band; $A_{tot}, A_{high}, A_{mid}, A_{low}$ – respectively total section area of the canopy and partial sections area (high, mid, low); ($D_{rs}/2$) – semi row spacing.

The first version of the algorithm had not division into three canopy bands. Nevertheless, during the early tests, it became necessary to highlight how the canopy arranges in the vertical profile. It has been essential for showing how the total canopy volume and the proportion of partial canopy volume, in the vertical profile, changed during the growing season.

The final algorithm step consisted in calculating the canopy volumes through the multiplication between the canopy area and travelled distance by tractor during a detection session. The travelled distance was obtained by GNSS receiver. The final output was a CSV file with canopy volumes (total and partial) linked with their global positions, provided by GNSS receiver. The volumes of canopy can be obtained referring to the distance travelled (Eqs 6, 7, 8, 9) or to the linear meter of row (Eqs 10, 11, 12, 13).

$$V_{tot} = A_{tot} * D_t \quad m^3 {D_t}^{-1} \quad (6) \qquad V_{tot} = (A_{tot} * D_t) * \frac{1}{D_t} \quad m^3 m^{-1} \quad (10)$$

$$V_{high} = A_{high} * D_t \quad m^3 {D_t}^{-1} \quad (7) \qquad V_{high} = (A_{high} * D_t) * \frac{1}{D_t} \quad m^3 m^{-1} \quad (11)$$

$$V_{mid} = A_{mid} * D_t \quad m^3 {D_t}^{-1} \quad (8) \qquad V_{mid} = (A_{mid} * D_t) * \frac{1}{D_t} \quad m^3 m^{-1} \quad (12)$$

$$V_{low} = A_{low} * D_t \quad m^3 {D_t}^{-1} \quad (9) \qquad V_{low} = (A_{low} * D_t) * \frac{1}{D_t} \quad m^3 m^{-1} \quad (13)$$

where V_{tot} – total canopy volume; V_{high} – high band canopy volume; V_{mid} – mid band canopy volume; V_{low} – low band canopy volume; D_t – distance travelled.

The algorithm carried out all calculations, both for left and right side of vine-rows, during a working session.

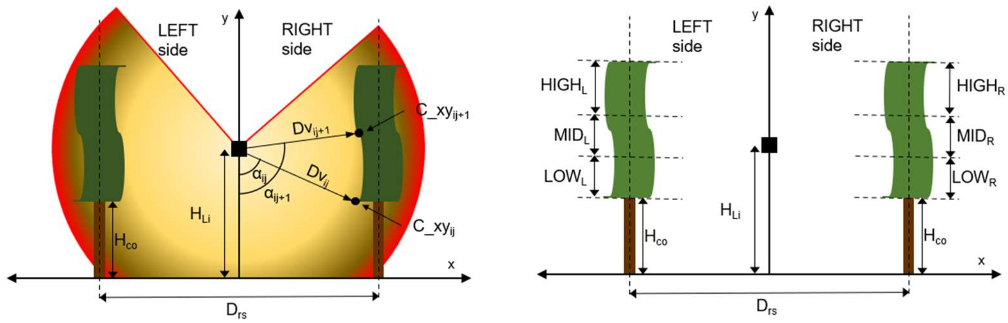

Figure 2. In the left side of the figure, the LiDAR and algorithm working principles were represented. In the other side, the subdivisions in three bands were shown.

The algorithm was integrated into a software, designed to process LiDAR data automatically and in real-time. This software was implemented in Visual Studio with C# programming language. The software has an interface page, where parameters can be changed according to vineyards characteristics, and a working page, where canopy volumes and heights, positions and errors codes (about LiDAR) can be seen. On the first page, it was possible to change parameters such as row spacing, LiDAR height and cordon height from ground level. This allowed the setting into other vineyards (with different characteristics) or potentially into other crops for instance orchards. In the second window, the recording of the work session can be activated and, at the end of it, a CSV file is created. This output contains the main working parameters such as time, GNSS position and tractor speed, and canopy characteristics such as total canopy volumes, high band, mid band and low band canopy volumes for both the right and left side.

Figure 3. Software interface for computing, in real-time, canopy volumes. On the left, the interface window, that allows to set parameters about LiDAR position and vineyard characteristics was shown. On the right, there is the working window, where canopy volumes (right and left side) and canopy heights were shown in real-time.

Field tests:

The field tests were carried out in two different vineyards in Chianti Classico region. The first one was located in Gretole (43°27'23.0" N; 11°13'51.9" E), Castellina in Chianti, Siena, Italy and the other located in San Felice (43° 23' 24.8" N; 11° 27' 26.5" E), Castelnuovo Berardenga, Siena, Italy.

At the moment of tests, the vineyard in Gretole was 11 years old, was cordon trained, with a row spacing of 2.5 m and an average distance between vines of 0.8

m. With a plant density of ~5,000 vine ha^{-1}. San Felice's vineyard was cordon trained, it was 15 years old, and the plant density was higher than the first one (~9,000 vine ha^{-1}). It is due to a smaller row spacing (~1.4 m). Both vineyards were mainly composed of *Vitis vinifera* L. cv. 'Sangiovese'. During the 2020 vegetative season (May-July), three test sessions were carried out in three different phenological phases (BBCH 57, BBCH 71, BBCH 81), for a total of 26 vines sampled for each measurement technique. This was done to test whether the algorithm could work at very different inter-row distances, distinguish canopy growth during sprout's development, and differentiate canopy volume according to different vigour zones.

To check the algorithm two different types of manual non-destructive canopy measurements were carried out. The first manual measurements was the Tree Row Volume (TRV) which was measured for each single vines involved in the experiments. The TRV technique involved in this experiment was partially revised from conventional TRV to provide the volume of the canopy of each vine (m^3 plant^{-1}) (Scapin et al., 2015). This was achieved by computing the average canopy height (m), the average canopy width (m) and the average canopy length (m) of a single vine with the following Eq. (14).

$$TRV = \overline{H} * \overline{W} * \overline{L} \qquad (m^3\ pl^{-1}) \qquad (14)$$

where $\overline{H}$ – was the average canopy height; $\overline{W}$ – was the average canopy width; $\overline{L}$ – was the average canopy length; m^3 pl^{-1} – unit of measure;

The other manual measurements adopted was the Point Net Canopy (PNC). It consisted in measuring the canopy width for each mesh of the net, positioned in parallel to vineyard row and in front of the canopy surface (Fig. 4). The PNC provides more detailed canopy volume than TRV because several canopy width for each vine sampled were measured. To calculate the PNC, a net, with a mesh of 0.15 m × 0.15 m, was located to a distance of 0.5 m from vertical canopy axis. Then, the distance (d_i) between canopy external surface and net was manually measured for each mesh of the net. In addition, the value di was subtracted by the distance between the net and vertical canopy axis (0.5 m) in order to obtain canopy widths for each mesh of the net. This value was multiplied by the area of the mesh (Ai = 0.0225 m^2) to obtain the volumes of the canopy subtended by single meshes. Finally, they were added up to obtain the total volume of the canopy of a single vine, as follows in the Eq. (15).

$$PNC = \sum_{i=1}^{n}[A_i * (0.5\,m - d_i)] \qquad (m^3\ pl^{-1}) \qquad (15)$$

where d_i – distance between canopy external surface and net; A_i – mesh area; $0.5\ m$ – the distance between net and canopy vertical axis; i – number of meshes contained the sampled vine canopy.

PNC provides detailed information on the spatial distribution of canopy volume. In particular, canopy volumes for different vegetation bands (0–0.3 m; 0.30–0.60 m; and > 0.60 m; distance from cordon) can be extracted from this manual measurements. This was essential to correlate with the canopy volume bands provided by LiDAR algorithm.

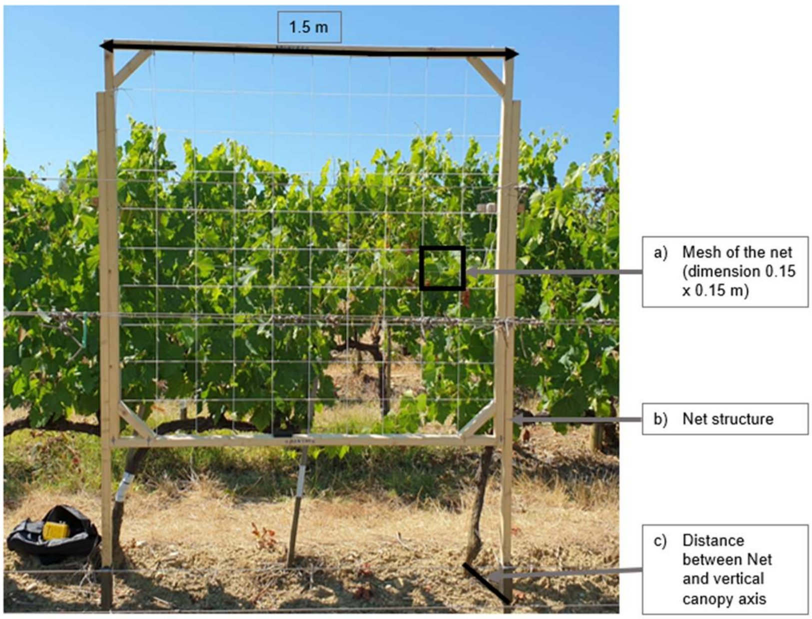

Figure 4. Net positioned for a manual measurement session. (a) Net mesh dimension; b) Net structure; c) Distance Net structure–Vertical canopy axis.

Finally, TRV and PNC measurements were compared with LiDAR measurements to validate the performance of the algorithm. The LiDAR measurements were carried out throughout vine-rows, containing the sampled vines, at an average speed of 1 m s-1. The acquisition frequency was set up at 10 Hz, to obtain a scan each about 0.1 m. From these data, the LiDAR canopy volumes, corresponding to sampled vines manually, were extracted thanks to GNSS receiver and a digital marker that highlights sampled vines in the file output. The vine-rows, including the sampled vines, were travelled in their entirety in order to get the full characterisation of the canopy.

Results and Discussion

Manually and LiDAR measurements on single vines:

As far as the canopy volumes of sampled vines, the minimum, average and maximum values for the three measurement techniques (TRV, PNC and LiDAR) were summarised in Table 1. In this table, canopy volume values, in different work sessions (May and July), were simultaneously shown to highlight how LiDAR measurements have detected the increase of canopy volumes during the growing phase (from BBCH 57 to BBCH 81). The increase in canopy volumes was also identified by the other manual measurements. This suggest that the algorithm and software work well enough.

Table 1. Minimum, mean and maximum values of manuals and LiDAR measurements in the same plants at different growth stages (BBCH 57–BBCH 81).

	TRV		**PNC**		**LIDAR**	
	BBCH 57	BBCH 81	BBCH 57	BBCH 81	BBCH 57	BBCH 81
Min.	0.118	0.326	0.086	0.115	0.096	0.219
Mean	0.229	0.368	0.150	0.253	0.193	0.288
Max.	0.307	0.472	0.210	0.360	0.290	0.403

Two comparisons of total canopy volumes between instrumental and manually measurements to validate the LiDAR measurements were analysed. Linear regressions provide more evidence of the algorithm good functioning. This analysis highlights good correlations between TRV and LiDAR measurements ($R^2 = 0.67$) and PNC and LiDAR measurements ($R^2 = 0.56$), how it is shown in Fig. 5. The obtained linear regression (TRV *vs* LiDAR) has slightly lower coefficients of determination than other similar comparisons presented in some papers (Rosell et al., 2009b; Tsoulias et al., 2019). Indeed, Tsoulias et al. (2019) found a better coefficient of determination ($R^2 = 0.77$), under similar conditions and with the same experimental parameters, but this result was obtained with a significantly lower tractor speed. Instead, Rosell et al. (2009b) reported a better coefficient of determination ($R^2 = 0.97$), but this was obtained with a small sample size and in an apple orchard.

This study wanted to test the automated assessment algorithm of canopy volume in operational working conditions, hence this could be the reason for obtaining smaller coefficients of determination. However, this approximation is justified because the tractor speed was set to the average speed for future software implementation in canopy management operations and variable-rate spraying applications.

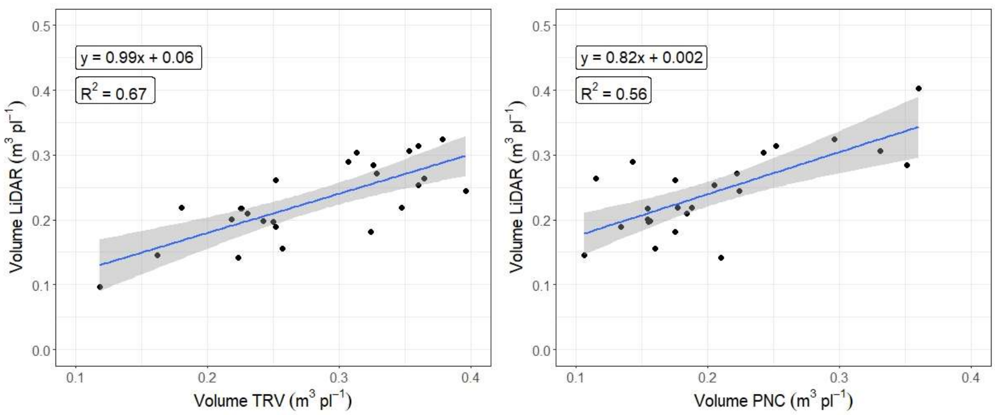

Figure 5. The linear regression of TRV (x) versus LiDAR (y) volume measurements is shown on the left graph. The linear regression of PNC (x) versus LiDAR (y) volume measurements is represented on the right chart.

With regard to canopy volumes divided into three bands, linear regressions between LiDAR and PNC measurements were obtained. The TRV measurements were not considered because the TRV method does not provide specific canopy information as vertical distribution of canopy volumes. LiDAR and PNC correlations for low and mid bands reported similar determination coefficients, respectively 0.498 and 0.491 (Fig. 6). Instead, the coefficient of determination for the high band, i.e. the portion of the canopy between a distance of 0.60 m from cordon height and the last canopy point detected by LiDAR, is 0.736, as shown in Fig. 6. The differences in coefficient of determination between the canopy bands are probably due to the dimension of bands. In fact, the high band includes a portion of canopy bigger than other bands. So, this brings about the values of the canopy of high band (m^3 pl^{-1}) being bigger than those of the mid and low band. Therefore, slight deviations between PNC and LIDAR measurements in the high band cause a minor deterioration of the coefficient of determination compared to what happens in low and mid bands, where the values of the canopy are smaller.

However, this value highlights a good approximation provided by the algorithm for automated canopy volumes computing. This information is essential in future developments of precision spraying. In fact, the total canopy volume based on LiDAR is an excellent index to assess the spatial variability in terms of canopy quantity in vineyards. Thanks to the total canopy volume, the pesticides spray volume can vary according to site-specific information. Moreover, the spray volume can be targeted according to the vertical canopy variability, due to the division of the canopy into bands.

The significant correlation obtained in the high canopy bands is another interesting aspect to be evaluated more carefully. Indeed, the computation of canopy high bands could potentially be affected by less accuracy due to slight lateral inclinations of vineyards or tractor roll motion. Nevertheless, they do not seem to be problematic in the canopy volume approximation. Therefore, the algorithm gives a good approximation of the total canopy volume and provides helpful information about the vertical distribution of canopy volumes.

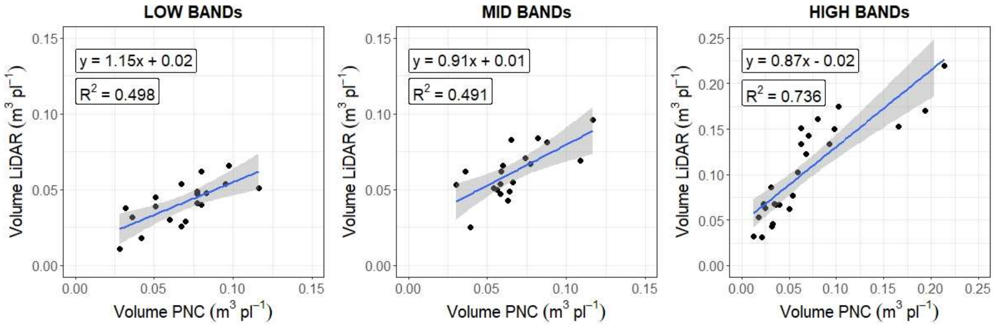

Figure 6. The linear regressions of PNC (x) *versus* LiDAR (y) volume measurements are shown with the detail of the three canopy bands (on the left: Low Band; in the middle: Mid Band; on the right: High Band).

LiDAR measurements of entire vineyards

The canopy volumes detected by LiDAR software during two working sessions (May and July) were showed. The data represent the canopy volumes (m^3 m^{-1}) of four vine-rows completely travelled at a constant tractor speed of 1 m s^{-1}. This situation simulated the usual working conditions of canopy management.

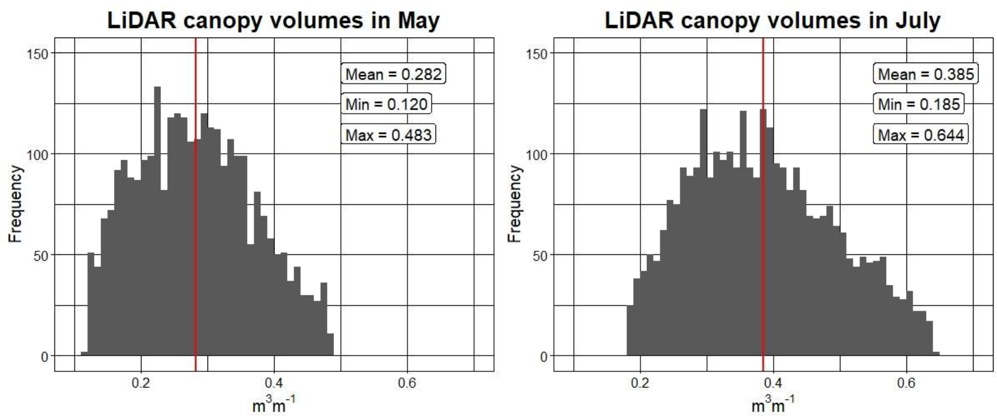

Figure 7. Absolut frequencies of LiDAR measurements with a interval of 0.01 (m^3 m^{-1}). Such measurements were part of the software output (CSV file) where tractor, coupled with LiDAR, travelled completely four vine-rows. The red line corresponds to the mean value.

The absolute frequency of total canopy volumes partitioned in breaks of 0.01 m^3 m^{-1} during the evolution of total canopy volumes from BBCH 57 stage to BBCH

81 was showed in Figure 7.

In BBCH 57 stage, an average canopy volume of 0.282 m^3 per linear meter of vine-row was detected, with a minimum value of 0.120 m^3 m^{-1} and a maximum of 0.483 m^3 m^{-1}. Instead, in BBCH 81 stage, an average canopy volume of 0.385 m^3 m^{-1} was measured, with a minimum of 0.185 m^3 m^{-1} and a maximum of 0.644 m^3 m^{-1}.

The increase in canopy volume (from 0.282 to 0.385 m^3 m^{-1}) between the two phases was 37% reflecting the natural growth phase of the vineyard, as shown in table 2. This increase was also detected by the two manual canopy measurements (Table 1). Therefore, the algorithm for the automatic calculation of canopy volumes was able to detect the different canopy volumes during the growth phase of the vineyard.

Table 2. Means of canopy volumes of LiDAR measurements, percentage of canopy distribution between bands and rate of volume increase between different growth stages (BBCH 57 – BBCH 81)

	BBCH 57		**BBCH 81**		**BBCH 57 - 81**
	Mean	**%**	**Mean**	**%**	**%**
Tot	0.282		0.385		37%
High	0.1565	61%	0.205	60%	31%
Mid	0.0598	23%	0.0834	24%	39%
Low	0.0417	16%	0.0549	16%	32%

In addition, the canopy volumes data were analysed according to the differentiation of the three bands (low, mid and high band). In this case, the absolute frequency of partial canopy volumes was partitioned in intervals of 0.001 m^3 m^{-1} because of the lower canopy volume detected for single bands. Fig. 8 showed the data obtained in two different work sessions, corresponding to the BBCH 57 and BBCH 81 growth stage, and differentiated for single bands. The lower band is situated on the bottom of Fig. 8, and the others are above according to an increasing levels layout.

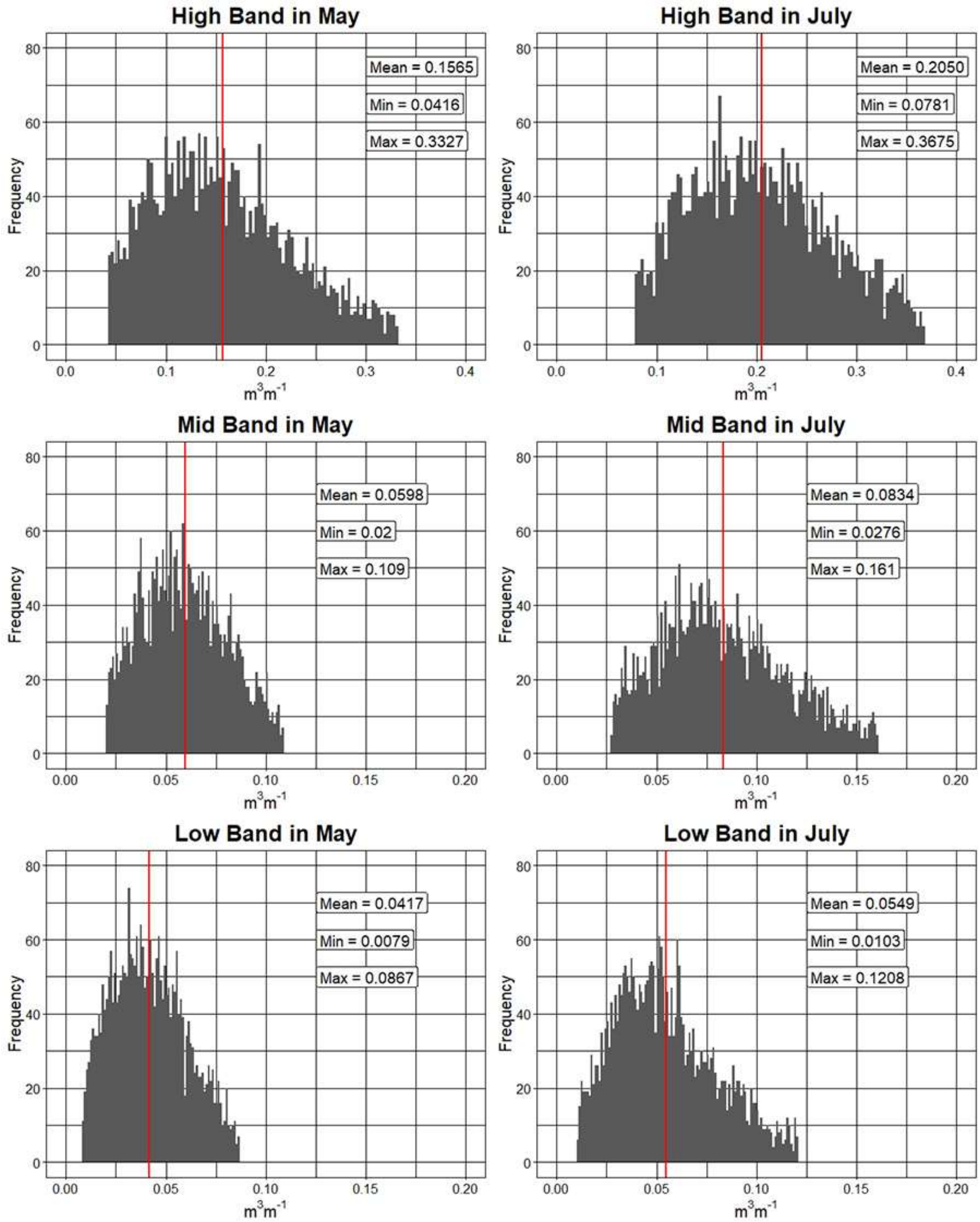

Figure 8. Absolut frequencies of LiDAR measurements of the three bands (Low, Mid, High) with an interval of 0.01 (m^3 m^{-1}). These measurements are part of software output (CSV file) where tractor, coupled with LiDAR, travelled completely four vine-rows. The red line corresponds to the mean value.

The graphs of low band canopy volumes showed that the average value of canopy volumes ranges from 0.042 m^3 m^{-1} to 0.055 m^3 m^{-1} during the growth stage (May–July), increasing 32%. A similar trend was highlighted for the other bands.

The mid band ranges from 0.059 $m^3 m^{-1}$ to 0.083 $m^3 m^{-1}$, with a volume increase of 39%, and the high band goes from 0.156 $m^3 m^{-1}$ to 0.205 $m^3 m^{-1}$, with a rise of 31% (Table 2) These increases prove that the software could also detect the growth of canopy volumes into the three bands between different moments of detections. The proportion of canopy distribution between bands seems not to change in the two different data collections.

Conclusions

The LiDAR-based algorithm and software for automated canopy volume calculation described in this work, can be a valid alternative to the complex and laborious procedures of canopy characteristics computing through post-processing points cloud reconstruction. The good correlations obtained between manual and LiDAR-based measurements (R^2= 0.67, R^2= 0.74) suggest that the simplified computing system can be a valuable tool for measuring canopy characteristics, such as tree row volume, and distinguishing the spatial canopy distribution. The LiDAR-based algorithm showed good working adaptability on different vineyards vertical training systems, such as cordon training or Guyot, with different plant density. With inputs that can be set (row spacing, cordon height and LiDAR height) according to crop characteristics, the software for automatic canopy volume calculation can potentially be used in orchards. The working conditions under which the software was tested are an indication that the LiDAR-based system can work at speeds similar to the on-farm management and spraying operations. Further tests will need to be carried out to fully investigate the best scanning frequency to achieve more accurate canopy volumes without compromising tractor working speed and efficiency. In addition, another interesting suggestion to evaluate further is the relation between canopy evaluation shown in this paper and canopy extraction in post-processing. The results achieved in correlations between manual and LiDAR measurements take the work to the next stage of development. Firstly, it is necessary to check for bugs or other instrumental problems through a large number and lengthy field tests. Moreover, it will be about understanding how to best interact the data obtained from this system with the spraying equipment and spray volume. In conclusion, the system (LiDAR, GNNS receiver, algorithm and software) has the potential to be implemented in precision viticulture both in on the go variable-rate equipment and in on-board terminals based on prescription maps.

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References

Cheraïet, A., Naud, O., Carra, M., Codis, S., Lebeau, F. & Taylor, J. 2020. An algorithm to automate the filtering and classifying of 2D LiDAR data for site-specific estimations of canopy height and width in vineyards. Biosystems Engineering, 200: 450–465. doi: 10.1016/j.biosystemseng.2020.10.016.

Comba, L., Biglia, A., Aimonino, D. R., Barge, P., Tortia, C. & Gay, P. 2019. 2D and 3D data fusion for crop monitoring in precision agriculture. In: Proceedings of 2019 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor). Portici, Italy, pp. 62–67. doi: 10.1109/MetroAgriFor.2019.8909219.

Communication from the commission to the European Parliament, the Council, the European Economics and Social Committee and the Committee of the Regions. A Farm to Fork Strategy for a fair, healthy and environmentally-friendly food system. 2020. COM/2020/381 final, pp 19.

Directive 2009/128/EC of the European Parliament and the Council of 21 October 2009 establishing a framework for Community action to achieve the sustainable use of pesticides. 2009. Official Journal of the European Union, L309, 71–86.

EPRS (European Parliamentary Research Service). 2016. Precision agriculture and the future of farming in Europe. European Parliamentary Research Service, PE 581.892, pp40.

https://ec.europa.eu/knowledge4policy/publication /precision-agriculture-future-farming-europe_en%0Ahttps://euagenda.eu/upload/publications/untitled-63196-ea.pdf

EPRS (European Parliamentary Research Service). 2017. Precision agriculture in Europe: Legal, social and ethical considerations. European Parliamentary Research Service, PE 603.207, pp 80. http://www.europarl.europa.eu/RegData/etudes/STUD/2017/603207/EPRSSTU(2017)603207_EN.pdf

Gil, E., Llorens, J., Llop, J., Fàbregas, X. Escolà, A., & Rosell, J. R. 2013. Variable rate sprayer. Part 2 - Vineyard prototype: Design, implementation, and validation. Computers and Electronics in Agriculture, 95, 136–150. doi: 10.1016/j.compag.2013.02.010.

Llorens, J., Gil, E., Llop, J. & Escolà, A. 2010. Variable rate dosing in precision viticulture: Use of electronic devices to improve application efficiency. Crop Protection, 29(3), 239–248. doi: 10.1016/j.cropro.2009.12.022

Llorens, Jordi, Gil, E., Llop, J. & Escolà, A. 2011. Ultrasonic and LIDAR sensors for electronic canopy characterization in vineyards: Advances to improve pesticide application methods. Sensors, 11(2), 2177–2194. doi: 10.3390/s110202177

MIPAAF (Ministry of Agricultural, Food and Forestry Policies). 2014. National action plan for sustainable use of plant protection products. pp 83 (in Italian). https://www.mite.gov.it/sites/default/files/archivio/normativa/dim_22_01_2014.pdf

Miranda-Fuentes, A., Llorens, J., Rodríguez-Lizana, A., Cuenca, A., Gil, E., Blanco-Roldán, G. L. & Gil-Ribes, J. A. 2016. Assessing the optimal liquid volume to be sprayed on isolated olive trees according to their canopy volumes. Science of the Total Environment, 568, 296–305. doi: 10.1016/j.scitotenv.2016.06.013

Miranda-Fuentes, Antonio, Llorens, J., Gamarra-Diezma, J. L., Gil-Ribes, J. A. & Gil, E. 2015. Towards an optimized method of olive tree crown volume measurement. Sensors, 15(2), 3672–3687. doi: 10.3390/s150203671

Palacín, J., Pallejà, T., Tresanchez, M., Sanz, R., Llorens, J., Ribes-Dasi, M., Masip, J., Arnó, J., Escolà, A. & Rosell, J. R. 2007. Real-time tree-foliage surface estimation using a ground laser scanner. IEEE Transactions on Instrumentation

and Measurement, 56(4), 1377–1383.
doi: 10.1109/TIM.2007.900126

Pergher, G. & Petris, R. 2008. Pesticide dose adjustment to the canopy parameters for treatments to the tree crops. In: Proceedings of Phytophatology Days, pp. 317–322 (in Italian).

Román, C., Llorens, J., Uribeetxebarria, A., Sanz, R., Planas, S. & Arnó, J. 2020. Spatially variable pesticide application in vineyards: Part II, field comparison of uniform and map-based variable dose treatments. Biosystems Engineering, 195, 42–53.
doi: 10.1016/j.biosystemseng.2020.04.013

Rosell, J. R. & Sanz, R. 2012. A review of methods and applications of the geometric characterization of tree crops in agricultural activities. Computers and Electronics in Agriculture, 81, 124–141.
doi: 10.1016/j.compag.2011.09.007

Rosell, J. R., Llorens, J., Sanz, R., Arnó, J., Ribes-Dasi, M., Masip, J., Escolà, A., Camp, F., Solanelles, F., Gràcia, F., Gil, E., Val, L., Planas, S. & Palacín, J. 2009a. Obtaining the three-dimensional structure of tree orchards from remote 2D terrestrial LIDAR scanning. Agricultural and Forest Meteorology, 149(9), 1505–1515.
doi: 10.1016/j.agrformet.2009.04.008

Rosell, J. R., Sanz, R., Llorens, J., Arnó, J., Escolà, A., Ribes-Dasi, M., Masip, J., Camp, F., Gràcia, F., Solanelles, F., Pallejà, T., Val, L., Planas, S., Gil, E. & Palacín, J. 2009b. A tractor-mounted scanning LIDAR for the non-destructive measurement of vegetative volume and surface area of tree-row plantations: A comparison with conventional destructive measurements. Biosystems Engineering, 102(2), 128–134.
doi: 10.1016/j.biosystemseng.2008.10.009

Sanz, R., Rosell, J. R., Llorens, J., Gil, E. & Planas, S. 2013. Relationship between

tree row LIDAR-volume and leaf area density for fruit orchards and vineyards obtained with a LIDAR 3D Dynamic Measurement System. Agricultural and Forest Meteorology, 171–172, 153–162.
doi: 10.1016/j.agrformet.2012.11.013

Sarri, D., Lombardo, S., Pagliai, A., Zammarchi, L., Lisci, R. & Vieri, M. 2020. A technical-economic analysis of telemetry as a monitoring tool for crop protection in viticulture. Journal of Agricultural Engineering, 51(2), 91–99. doi: 10.4081/jae.2020.1029

Scapin, M. D. S., Behlau, F., Scandelai, L. H. M., Fernandes, R. S., Silva Junior, G. J. & Ramos, H. H. 2015. Tree-row-volume-based sprays of copper bactericide for control of citrus canker. Crop Protection, 77, 119–126.
doi: 10.1016/j.cropro.2015.07.007

Tsoulias, N., Paraforos, D. S., Fountas, S. & Zude-Sasse, M. 2019. Estimating canopy parameters based on the stem position in apple trees using a 2D lidar. Agronomy, 9(11).
doi:10.3390/agronomy9110740

Zhang, Z., Wang, X., Lai, Q. & Zhang, Z. 2018. Review of Variable-Rate Sprayer Applications Based on Real-Time Sensor Technologies. In (book) Automation in Agriculture - Securing Food Supplies for Future Generations, i(4), 53-7.
doi: 10.5772/intechopen.73622

3.2. Paper II

Comparison of Aerial and Ground 3D Point Clouds for Canopy Size Assessment in Precision Viticulture

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Abstract

In precision viticulture, the intra-field spatial variability characterization is a crucial step to efficiently use natural resources by lowering the environmental impact. In recent years, technologies such as Unmanned Aerial Vehicles (UAVs), Mobile Laser Scanners (MLS), multispectral sensors, Mobile Apps (MA) and Structure from Motion (SfM) techniques enabled the possibility to characterize this variability with low efforts. The study aims to evaluate, compare and cross-validate the potentiality and the limits of several tools (UAV, MA, MLS) to assess the vine canopy size parameters (thickness, height, volume) by processing 3D point clouds. Three trials were carried out to test the different tools in a vineyard located in the Chianti Classico area (Tuscany, Italy). Each test was made of a UAV flight, an MLS scanning over the vineyard and a MA acquisition over 48 geo-referenced vines. The Leaf Area Index (LAI) were also assessed and taken as reference value. The results showed that the analysed tools were able to correctly discriminate between zones with different canopy size characteristics. In particular, the R^2 between the canopy volumes acquired with the different tools was higher than 0.7, being the highest value of R^2= 0.78 with a RMSE = 0.057 m^3 for the UAV vs. MLS comparison. The highest correlations were found between the height data, being the highest value of R^2 = 0.86 with a RMSE = 0.105 m for the MA vs. MLS comparison. For the thickness data, the correlations were weaker, being the lowest value of R^2 = 0.48 with a RMSE = 0.052 m for the UAV vs. MLS comparison. The correlation between the LAI and the canopy volumes was moderately strong for all the tools with the highest value of R^2 = 0.74 for the LAI vs. V_MLS data and the lowest value of R^2 = 0.69 for the LAI vs. V_UAV data.

Keywords: precision farming; vegetation index; remote sensing; sensor; vineyard; spatial variability; mobile app; UAV; LAI; LiDAR

Introduction

Site-specific crops management represents an essential improvement in efficiency and efficacy of the different labours, and its implementation has experienced significant development in the last decades, especially for field crops [1, 2]. In particular, precision viticulture techniques are becoming necessary in a production context focused on achieving the best possible operating efficiency and reducing costs by paying attention to environmental sustainability [3].

Precision Agriculture (PA) is defined as an agricultural, forestry and livestock management based on the observation, measurement and response of the set of inter and intra-field quantitative and qualitative variables that act in agricultural productions [4]. Data collection by proximal or remote sensors is the first step for acting a precision agriculture approach [5]. Then, collected data are interpreted and evaluated by an agronomical point of view (e.g., canopy vigour) to traduce them into manual implementations or into inputs for variable rate technology (VRT) machines, which can perform the prescribed actions in a semi-automatic or fully automatic way [6, 7]. Many studies stated that the canopy size of Vitis vinifera L. is closely correlated with the amount of sunlight intercepted, i.e., the amount of carbon assimilated [8–10]. It is also an essential characteristic in assessing crop management and plant health and water use [11]. The vineyard spatial variability is mainly due to exposure, soil composition, soil tillage, micro-climate, and water availability [12–14]. All these characteristics directly affect morphological, physiological and productive responses. Among the primary affected vegetative and productive responses there are canopy vigour, leaf area index (LAI), canopy volume, yield, grape quality, which can be further influenced by the type of rootstock used [15]. In specialty crops, the canopy size measurement is the main practice to fulfil the variable-rate applications that can be performed with manual techniques or by digital sensing tools. Usually, the measurements are then converted into corresponding canopy indicators (e.g., Tree Row Volume, Leaf Area Index, Leaf Wall Area, Unit

Canopy Row, Ellipsoid Volume Method) [16, 17].

In assessing the canopy size, the most used traditional methodologies and tools are listed as following: empirical and non-destructive methods [18–20], direct and destructive methods [21], point quadrat [22], optical and radiation sensors methods [21, 23, 24]. However, these methods can be very time-consuming and can have several uncertainties.

Thanks to technological advancements, more efficient, more precise and quicker measuring methods have emerged in the last decade [25, 26]. Ultrasonic sensors were employed in several researches to enhance variable-rate applications [27–30]. Some researchers used them in orchards and vineyards in a continuous way (non-discrete), others used image processing from RGB cameras or laser scanners that measured the canopy shape or volume for selective real-time spraying [28, 31–33]. The ultrasonic sensors enable an accurate measurement of canopy width in spot areas of canopy plants using ultrasonic waves. With the 2D LiDAR (Light Detection And Ranging) sensors, significant advancements in canopy recognition were made. LiDAR technology uses laser beams to create a point cloud of the canopy at varying angular resolutions and aperture angles [25]. As a result, the canopy complete vertical profile may be rebuilt. Recently, Mendez highlighted the potential of 3D LiDAR technology for canopy reconstruction in citrus and stated the critical issues for information extraction due to the lack of commercial software which allows quick processing [34].

Recently, thanks to open-source satellites imaging (e.g., ESA Sentinel-2, NASA Landsat-8), a considerable quantity of geo-referenced datasets are available for free. However, the resolution of satellites images is not often sufficient to highlight vineyard spatial variability because of different types of soil tillage and canopy management that can invalidate the canopy vigour data [35–37]. Therefore, other technologies are necessary to point out the vineyard spatial variability. Among them, the most recent tools that can be used in viticulture for measuring the canopy size in a precise and fast way are: Unmanned Aerial Vehicles (UAVs) [26, 38], Mobile Laser Scanners (MLS) [39], multispectral sensors [40], Mobile Apps (MA) (e.g., Viticanopy) [41] and Structure from Motion (SfM) photogrammetry techniques [42]. These tools, also used in combination with each other, permit the reconstruction of a 3D model of the vine that can be processed to assess the canopy size in terms of volume, LAI and vigour [26, 38, 39]. Several studies proved the advantages and the potential in viticulture of the canopy 3D reconstruction to evaluate the spatial variability of the vineyard, to estimate the yields, to optimize pesticide treatments, fertilizers and water use [43–48].

In light of the mentioned framework, this article aims to evaluate, compare, and cross validate the potentials and limits of MA, MLS and UAV to assess the canopy size parameters and their variability within the vineyard by processing 3D point clouds. Moreover, it is emphasized that this study is not meant to validate the quantitative volume assessment but to compare different tools used to calculate volumes and understand their limitations and advantages.

Materials and Methods

Three surveys were carried out for data collection, namely:

1. Ground data acquisition with a smartphone and mobile apps (MA);
2. Ground data acquisition with a mobile laser scanner (MLS);
3. Aerial data acquisition with an unmanned aerial vehicle (UAV).

The MA data were first processed to generate a LAI map of the test vineyard and then to reconstruct 3D point clouds of the tested vines. The MLS data were directly processed to create a NDVI (Normalized Difference Vegetation Index) map, a NDRE (Normalized Difference Red Edge) map and a 3D point cloud of the scanned vineyard rows. The UAV data were preliminary processed to generate an RGB orthomosaic of the vineyard and then reconstruct its 3D point cloud using the same MA algorithm and processing workflow.

The point clouds were processed to assess the canopy size (i.e., height, thickness, volume) of the sampled vines and then to compare the results of the different tools.

The complete workflow for the different tools is shown in Figure 1.

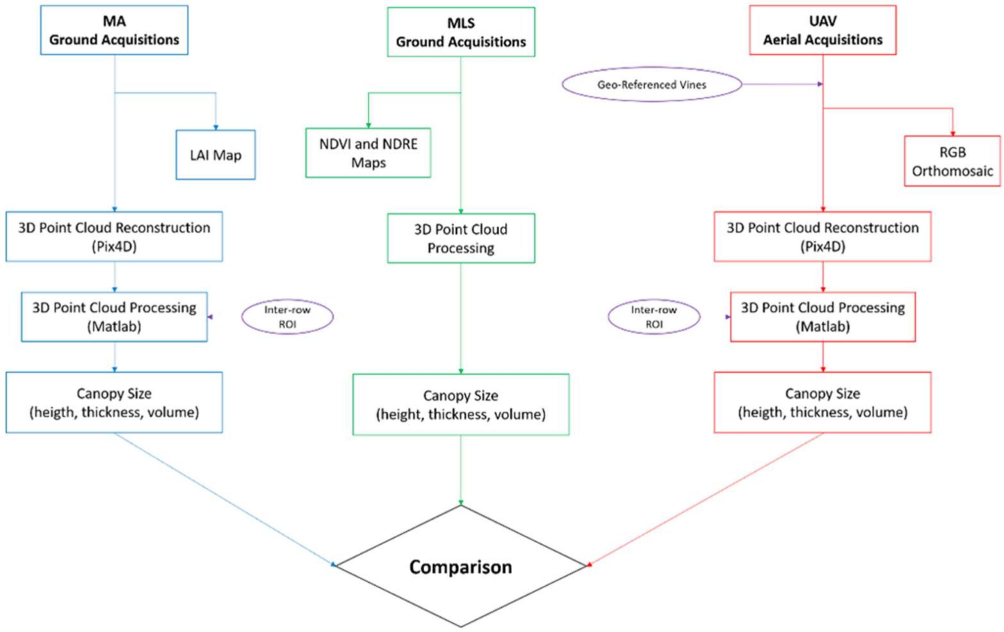


Figure 1. Overview of the methodology and general workflow. In blue, green and red, the steps for MA, MLS and UAV data processing, respectively. In purple, the input data necessary for processing: the GNSS position of the test vines was used to correctly geo-reference the orthomosaic, the inter-row and the Region of Interest (ROI) were used to select and process each test vine point cloud.

Experimental Site:

Field tests were carried out in a vineyard in the Chianti Classico area, located in Gretole (43°27’23.0’’ N; 11°13’51.9’’ E), Castellina in Chianti, Siena, Italy (Figure 2). The experimental site was focused on 2 ha, where 48 test vines were sampled at three different phenological stages (BBCH 55, BBCH 65, BBCH 73) [49]. In each phenological stage, three types of measurements technologies, namely MA, MLS and UAV, were performed in the same day. The vineyard was located on a hillside, had a density of 5000 vines ha^{-1} and the cultivar was the *Vitis vinifera* L. cv. ‘Sangiovese’. The vines were 15-years old, trained with a horizontal spur-cordon

(4–6 buds per spur), at 0.80 m mean height from the ground with a planting distance of 2.50 x 0.80 m. The vine rows orientation was East-West.

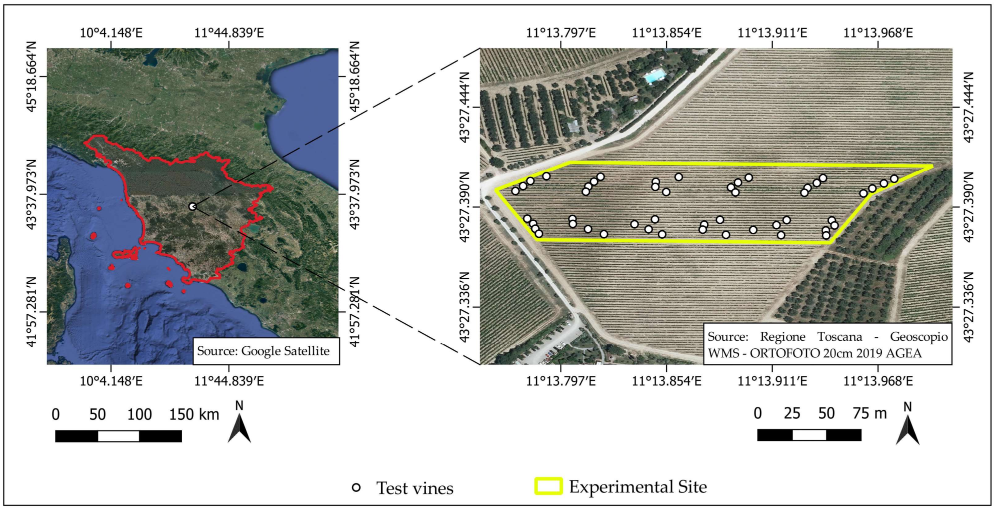


Figure 2: The geographical border of Tuscany is shown in red line, whereas the yellow line highlights the experimental site and the white points are the test vines locations.

Data Acquisition:

Ground Measurements

- Leaf Area Index

To characterize the spatial variability of the vineyard, the LAI was acquired over the 48 geo-referenced test vines using VitiCanopy, a free app for iOS and Android devices that has been developed by a team of researchers of the University of Adelaide and the University of Melbourne [41]. The working scheme of the app is reported in Figure 3.

VitiCanopy allowed to quickly and easily monitor the vine growth and the vigour of a vineyard and was used in place of traditional manual measures, which are time consuming (e.g., point quadrat method), not accurate and often require the destruction of the samples (e.g., defoliation of the vine to scan all the leaves and estimate the total leaf area).

The images were acquired using the frontal camera of an Apple iPad mini 2, placing it on the ground under the row line and at the middle of the vine cordon, following the indication provided by the app developer. Specifically, images were taken at 0.70 to 0.80 m from the cordon with a number of subdivisions of 5 (25 sub-images), a gap fraction threshold equal to 0.75 and a standard light extinction coefficient (k) = 0.7 [41].

Figure 3: Example of LAI measurement procedure using the VitiCanopy app. From left to right, the app user interface, the shot image of the vine canopy, the segmented binary image of the canopy and the results in terms of LAI and canopy porosity.

- Mobile App (MA)

Ground images of the 48 geo-referenced test vines were collected in each survey date using a MA called Pix4Dcatch (Pix4D SA, Prilly, Switzerland), available for Android and iOS devices.

This app allowed ground-based 3D point clouds to be created using a smartphone or tablet camera. While the user scans a scene or an object, the app automatically records geo-referenced images with a very high overlap (i.e., 95%). Each vine was scanned on both sides by hand with approximately 150–200 images, as schematically shown in Figure 4.

The scans were performed by positioning the tablet perpendicular to the vine canopy at a distance of approximately 2 m. The acquisitions of the images were made by scanning from 0.30 m under the vine cordon and continuing in height on further two levels to reach the maximum height of 2.50 m above ground level in order to guarantee a good overlap between the photos. Half of the adjacent vines in the same row were also scanned to collect enough data for the sampled vine under study. The sampled vine was then extracted in the pre-processing phase and the borders cleaned.

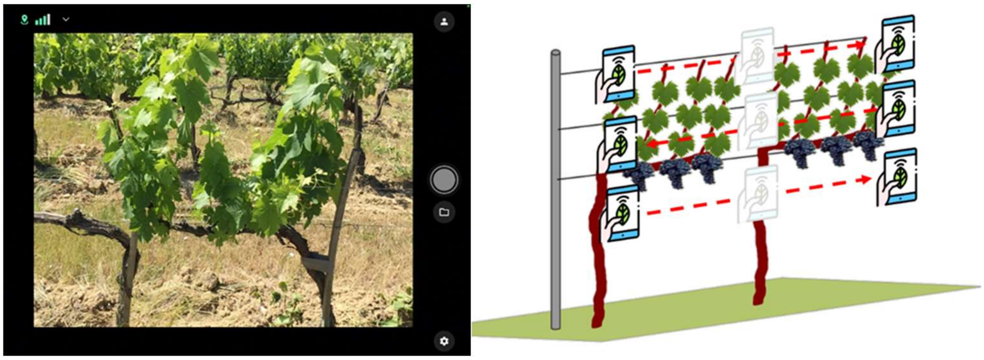


Figure 4: MA ground data acquisition: (a) Pix4Dcatch window app; (b) scanning pattern followed during the surveys.

- Mobile Laser Scanner (MLS) and Vigour Index

The MLS was carried out through a 2D LiDAR TIM 561 (Sick,Waldkirch, Germany) and a D-GNSS receiver (Differential-Global Navigation Satellite System) mounted on the rear part of a tractor (Figure 5a), where, on the right side of the Roll-Over Protective Structure (ROPS) the OptRx sensor (AgLeader Technology, Ames, IO, USA) is placed and coupled with the hardware and the rough book for data collection and storing, on the top of the front ROPS the D-GNSS receiver is placed and in the centre of the rear ROPS the LiDAR is oriented to the ground. In Figure 5b, the algorithm geometry scheme and the sensor are shown. In particular, LiDAR has an angular resolution of 0.33°, a working range from 0.05 m to 10 m, a scanning angle of 270° and a scanning frequency of 15 Hz.

Along with the LiDAR sensor, the OptRx sensor was used to collect canopy vigour information. This proximal sensing tool was mounted in the central part of the tractor and arranged parallel to the vertical canopy axis, in order to avoid any noises of soil and grass. It measures the reflectance in the 630–685 nm (red), 695–

750 nm (red edge) and 760–850 nm (NIR—Near InfraRed) wavebands, which were used to process the NDVI and NDRE indices. Reflectance data were collected simultaneously and at the same acquisition frequency of LiDAR data.

The average speed of MLS was 1.4 m s^{-1} with an acquisition frequency of 5 Hz, in order to obtain a scan every 0.30 m.

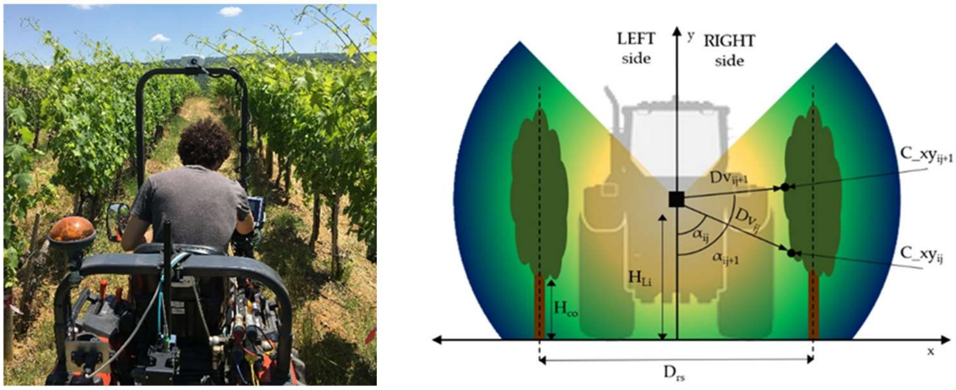


Figure 5. MLS ground data acquisition: (a) Main devices installed on the MLS for the canopy volume and vigour data acquisition. On the right side of the Roll-Over Protective Structure (ROPS), the OptRx sensor is placed and coupled with the hardware and the rough book for data collection and storing. On the top of the front ROPS, the D-GNSS receiver is placed and in the centre of the rear ROPS the LiDAR is oriented to the ground. (b) LiDAR and algorithm working geometry. Model orientation and main geometries and measurements considered for the calculation of the volumes i.e., H_{Li} – LiDAR height from ground-level; H_{co} – cordon height from ground-level; D_{rs} – row-spacing; Dv_{ij} – distance between LiDAR and canopy at specified angular position *j* and at moment *i*, α_{ij} – angle subtended by DV_{ij}, C_xy_{ij} – pinpointed canopy data in cartesian coordinates.

<u>Aerial Measurements</u>

- Unmanned Aerial Vehicle (UAV)

The DJI Phantom 3 Professional UAV (DJI, Shenzhen, China) (Figure 6a) was used as aerial platform. This UAV is equipped with a 12.4-megapixel CMOS sensor, has a diagonal size of 350 mm, a maximum take-off weight of 1280 g, a full flight time of 23 min, a top horizontal flight speed of 16 m s^{-1} and maximum ascent and descent speeds of 5 and 3 m s^{-1}, respectively. The pitch angle range of the camera is approximately – 90° to +30°.

(a) (b)

Figure 6: UAV aerial data acquisition: (a) DJI Phantom 3 Professional UAV in the vineyard; (b) UAV photogrammetry mission over the vineyard (Map Pilot app) with the overview of the interface for the flight mission and parameters. The yellow lines indicate the borders of the survey area, the green and red placemarks indicate the mission start and end points respectively and the purple placemark indicate the UAV take-off/landing point (i.e., the UAV pilot position).

On every survey date, the UAV imagery acquisition was made using the mobile app Map Pilot (Drones Made Easy, San Diego, CA, USA) (Figure 6b) to reconstruct the orthomosaic and the 3D point cloud of the vineyard in different phenological stages. UAV nadir, i.e., perpendicular to the terrain, photogrammetry images were acquired at a flight height of 30 m above ground level and a maximum cruise speed of 1.8 m s^{-1}. The overlap between two consecutive acquired images as well as the side lap, i.e., the overlap between images in adjacent parallel flight lines, was 85%. The image resolution was 4000 pixels x 3000 pixels and the GSD (Ground Sampling Distance) was 1.3 cm/pixel. In order to guarantee a high quality of the post-processed orthomosaic, the "terrain following" feature was considered, i.e., the autopilot automatically adjusted the UAV altitude to keep the same relative height above the vineyard during the mission.

3D Point Cloud Reconstruction:

The 3D point cloud reconstruction was carried out by the software Pix4Dmapper Pro (Pix4D SA, Prilly, Switzerland). Pix4Dmapper Pro is a photogrammetric software that can quickly and automatically merge thousands of geo-referenced images to produce accurate orthomosaic, DSM (Digital Surface Model), point clouds and 3D models. It has been widely used in the fields of aerial photogrammetry and remote sensing applied to agriculture [50–52].

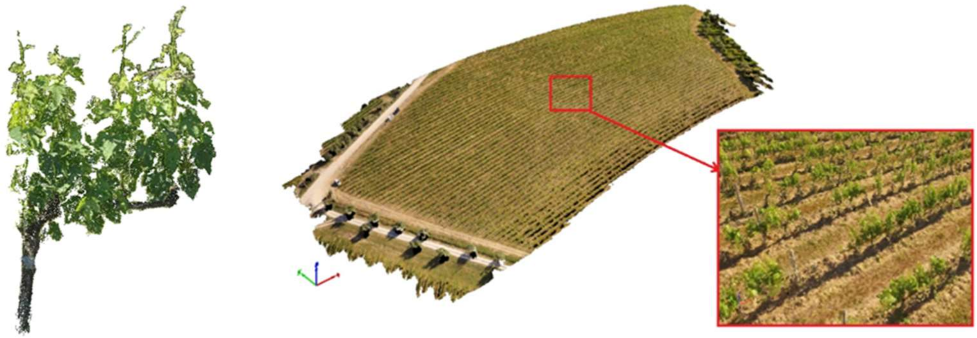
The software firstly evaluates the quality of the photogrammetric survey (e.g., good overlap between images), then marks key points between the images and automatically generates a densified point cloud and an orthomosaic of the test site or subject. Pix4Dmapper Pro was used to:

(1) Generate three 3D point clouds of the test vineyard from the aerial RGB images, i.e., about 600 images for each UAV flight;
(2) Generate 144 3D point clouds of the test vines from the ground RGB images, i.e., about 200 images for each MA acquisition;

To geo-reference the aerial 3D point clouds in the WGS84 (World Geodetic System 1984) reference system, the position of 4 header poles located at the vertices of the test vineyard were measured with a GNSS RTK system. The CloudCompare v. 2.10.2 open- source software (http://www.cloudcompare.org/ (accessed on 3 February 2022) was used to remove the noise and separate the vines from the soil for the point clouds generated by the MA. In particular, the “segment” feature was used to manually select the points, or point cloud portions, that had to be removed.

The average density of the processed aerial 3D point clouds was about 1800 points m^{-3}, while the ground 3D point clouds had a density ranging between 50,000 points m^{-3} and 500,000 points m^{-3}.

The point clouds generated by the MA and the UAV are reported in Figure 7, whereas it was not possible to represent graphically the MLS point clouds due to the different processing procedure.



(a) (b)

Figure 7: 3D Point Cloud Reconstruction: (a) MA vine point cloud processed with Pix4DMapper and cleaned with CloudCompare; (b) UAV vineyard point cloud processed with Pix4DMapper. In the detail, the vineyard rows and vines are shown.

3D Point Cloud Processing Algorithm

The UAV and MA 3D point clouds were processed by an algorithm that was coded in Matlab (The MathWorks Inc., Natick, MA, USA). The algorithm was built following the approach defined in Comba et al. [26]. In particular, the 3D point cloud of a vineyard row portion, where the x, y and z axes were aligned with the vineyard row, the canopy width and the vertical axis, respectively, was processed through a series of spatial manipulation, also taking into account for the local soil slope. Then, the canopy density, height and thickness were calculated. For the canopy height and thickness assessment, respectively, the 80th percentile of the point cloud distribution projected in the xz plane and the difference between the 98th and the 2nd percentile of the point cloud distribution projected in the yz plane were found to be the best numerical descriptors with respect to the measured ones. For these reasons, the same descriptors were used in the present code.

Substantially, the code reads the processed UAV and MA 3D point clouds and gives as results the main canopy size parameters (i.e., thickness, height and volume). The working schemes of the algorithm for the UAV and MA 3D point clouds are reported in Figure 8.

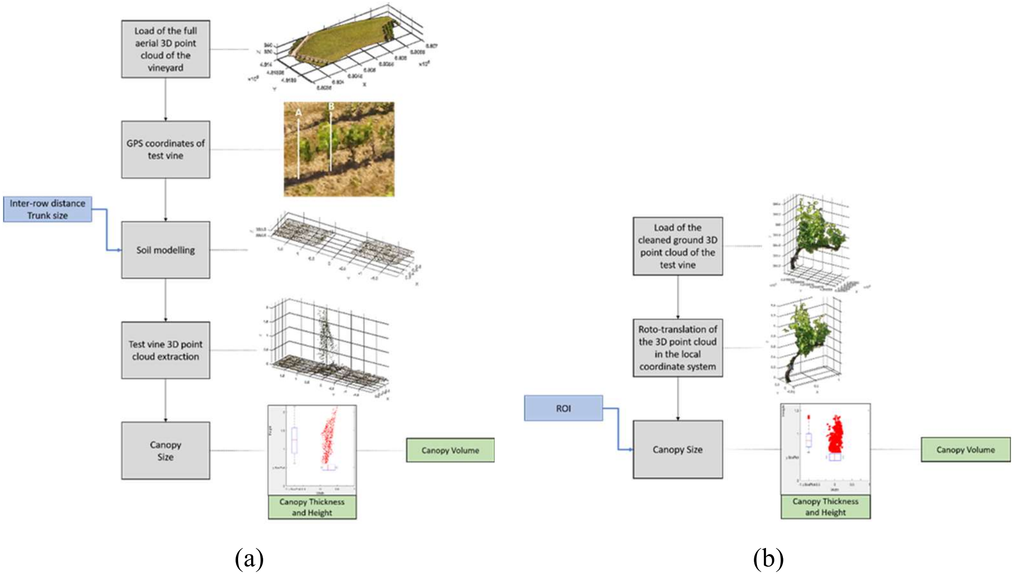


Figure 8. Matlab algorithm processing scheme: (a) processing workflow for the aerial 3D point cloud; (b) processing workflow for the ground 3D point cloud.

For the UAV aerial survey (Figure 8a), the 3D point cloud was firstly loaded in its original coordinate system (WGS84), and the GNSS coordinates of the start (A) and end (B) of the trunk of the test vine were given as input to isolate it from the rest of the vineyard. Then, the algorithm took into account the soil slope in the proximity of the test vine, which is, in turn, roto-translated to achieve the local coordinate system origin in A and the x, y and z axes aligned with the vineyard row, the canopy width and the vertical axis, respectively. Finally, the canopy size was assessed in terms of thickness, height and volume.

For the MA ground survey (Figure 8b), the process was analogous, but in this case, the input 3D point cloud of the test vine was previously cleaned from noise and the soil was deleted thanks to Cloud Compare. The roto-translation of the 3D point cloud of the test vine to match the x, y and z axes was carried out manually as well as the definition of the Region of Interest (ROI), i.e., the parallelepiped containing the selected test vine which was necessary to detect the processing canopy volume.

The MLS point clouds were processed separately by an integrated software. In particular, MLS data were processed, in real-time, by an algorithm that provided the canopy size parameters (volume, width, height) using canopy contours extraction operations, that consisted in converting the MLS raw data from polar to cartesian coordinates. Then, the contours widths (right and left) of the vertical canopy profiles were extracted for each MLS laser beam. After this step, the mean value of the widths was calculated and multiplied by the height of the canopy, extracted from the MLS data, for both sides, resulting in the total area of the canopy. These steps were repeated for each scan provided by the MLS during the work sessions. Lastly, the distance from one scan to another was calculated through the D-GNSS positioning and multiplied by the canopy areas previously calculated to achieve the total canopy volumes. The MLS-based algorithm was implemented in the software to automatically calculate the canopy volume. Such a process was repeated continuously throughout the survey stage. The software provided an output file (.csv—comma-separated values) with the data of the canopy volumes and their spatial position. Further information can be found in Pagliai et al. [53].

The canopy volume calculation for the three tools was carried out using the following equation:

$$V = T \cdot H \cdot L \tag{1}$$

where T and H are the canopy thickness and height, respectively, as calculated by processing the point clouds of the different tools, and L was the cordon length that was considered equal to 1 m on average.

Data Analysis and Correlation

The LAI, NDVI, NDRE and the canopy size parameters, extracted by MLS, UAV and MA technologies, were analysed using the open-source software R (R Core Team, 2021) [54]. The statistical analysis adopted to check the reliability and goodness of variables was the linear correlation between all measured and calculated parameters. The coefficient of determination (R^2) and the Root Mean Square Error (RMSE) were used to assess the model goodness and reliability. All the variables were checked to ensure a normal distribution of errors with the Shapiro-Wilk test (p > 0.05), by visual inspections (frequencies histogram, normal Q-Q plots and box plots) and by the verification of homoscedasticity using the Levene's test.

The "corrplot" package was used to visualize the R^2 data matrix and the "ggplot2" package was chosen to show the linear correlations and canopy parameters trends with scatters- and box-plots, respectively [55, 56].

After the statistical analysis, the LAI and the canopy parameters were processed and transformed from punctual data into spatialized maps using the open-source software QGIS (https://www.qgis.org (accessed on 3 February 2022). The raster maps were generated using the IDW (Inverse Distance Weighting) interpolation algorithm [57] with the distance coefficient P equal to 5. Then, the maps were smoothed by the application of a Gaussian filter with a square grid of 9 × 9 pixels.

Results

Vineyard Spatial Variability Assessment:

The spatial variability results in terms of LAI, NDVI and NDRE for each phenological stage are reported in Table 1. The LAI, NDVI and NDRE ranged in 0.34–3.11, 0.40–0.85 and 0.11–0.28, respectively.

Table 1. LAI, NDVI and NDRE values and percent coefficient of variation (C.V.%) over the three phenological stages.

BBCH	Canopy Parameter	Max	Min	Mean	C.V.%
55	LAI	0.99	0.34	0.60	23%
	NDVI	0.65	0.40	0.57	9%
	NDRE	0.18	0.11	0.15	13%
65	LAI	2.02	0.47	1.10	21%
	NDVI	0.78	0.55	0.70	7%
	NDRE	0.23	0.15	0.20	10%
73	LAI	3.11	0.89	1.93	25%
	NDVI	0.85	0.64	0.78	6%
	NDRE	0.28	0.18	0.24	13%

In Figure 9, the LAI, NDVI and NDRE box-plots and the LAI zonation map in three classes are reported for each phenological stage, highlighting the trend of canopy growth in time and the intra-field spatial variability of the vineyard. The classes in the LAI maps were determined using the 25% quantile for the LOW class and the 75% for the HIGH class, being the MEDIUM class related to the 25–75% quantile interval.

The LAI, NDVI and NDRE data were used as reference values to validate the canopy size parameters reported in par. 4.2, since they are directly related to the amount of biomass [58], i.e., higher values of LAI, NDVI and NDRE represent denser vegetation areas and higher canopy volumes.

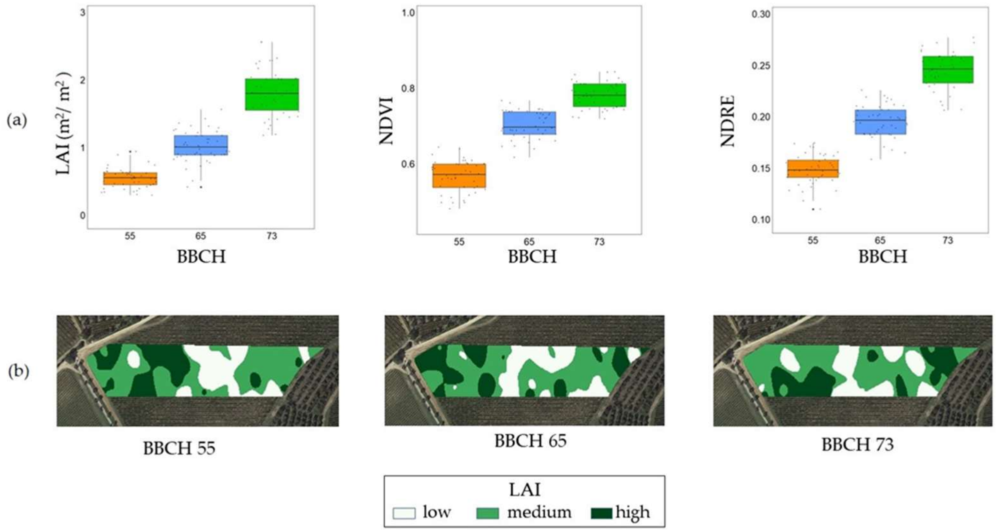


Figure 9: (a) LAI, NDVI and NDRE box-plots for the three phenological stages; (b) LAI zonation maps in three classes of the test vineyard for each phenological stage, where the classes were determined using the 25% quantile for the LOW class and the 75% for the HIGH class, being the MEDIUM class related to the 25%-75% quantile interval.

Canopy Size Assessment

The canopy size results in terms of thickness, height and volume of the 48 test vines for each phenological stage are summarized in Table 2, where the maximum, minimum and mean values are reported along with the percent coefficient of variations (C.V.%).

For the UAV, the thickness, height and volume ranged in 0.18–0.84 m, 0.13–1.36 m and 0.02–0.87 m^3, respectively. For the MA, the thickness, height and volume ranged in 0.13–0.50 m, 0.14–1.23 m and 0.02–0.49 m^3, respectively.

For the MLS, the thickness, height and volume ranged in 0.14–0.48 m, 0.15–1.34 m and 0.01–0.52 m^3, respectively. The UAV thickness estimation was higher than the other tools over the three phenological stages since the point cloud had more noise due to the inter-row (grass and soil) and to neighbour vines. In fact, the UAV point cloud is less precise in detecting a single vine than the other tools. On the other hand, the MA and MLS thickness estimations are very close one to each other. The height values are closer for the UAV-MLS comparison than for the UAV-MA and MLS-MA in all the phenological stages because of the more detailed point cloud generated from the MA processing with respect to the other ones. As results, the canopy volumes estimations are greater for the UAV due to a less precise detection of the single vine and a noisier point cloud, whereas the MA volumes estimations are the lowest among all the tools because of a more detailed and cleaner point cloud with respect to the UAV and MLS ones, being the latter coarser and with lower resolution.

Table 2. Main canopy size results and percent coefficient of variation (C.V.%) in terms of thickness, height and volume for the different tools over the three phenological stages.

BBCH	Value	Thickness			Height			Volume		
		UAV	MA	MLS	UAV	MA	MLS	UAV	MA	MLS
55	Max	0.50	0.34	0.29	0.61	0.36	0.66	0.23	0.09	0.15
	Min	0.18	0.13	0.14	0.13	0.14	0.15	0.02	0.02	0.01
	Mean	0.29	0.21	0.21	0.40	0.24	0.42	0.12	0.05	0.09
	C.V.%	24%	24%	19%	30%	17%	24%	42%	40%	33%
65	Max	0.61	0.45	0.35	1.05	0.70	0.97	0.48	0.20	0.34
	Min	0.28	0.21	0.20	0.28	0.29	0.40	0.12	0.04	0.08
	Mean	0.41	0.32	0.29	0.68	0.52	0.75	0.28	0.10	0.22
	C.V.%	20%	19%	10%	24%	19%	16%	29%	40%	23%
73	Max	0.84	0.50	0.48	1.36	1.23	1.34	0.87	0.49	0.52
	Min	0.38	0.29	0.22	0.73	0.68	0.71	0.36	0.26	0.26
	Mean	0.58	0.40	0.36	1.07	0.94	1.04	0.59	0.38	0.40
	C.V.%	22%	13%	17%	12%	14%	13%	22%	16%	15%

The canopy thickness, height and volume data were processed and transformed into raster maps for each phenological stage using the same procedure that was described in par. 3.5. In Figures 10–12, the maps are reported along with the box-plots for each phenological stage and for each tool.

Linear regression models between each tool were analysed to verify whether the different point clouds results were able to represent the canopy structure correctly. The results are shown in Figure 13, where H, T and V are, respectively, the canopy height, thickness and volume. As main result, it can be noted that the R^2 between the canopy volumes acquired with the different tools was higher than 0.7, being the highest value of $R^2 = 0.78$ with a RMSE = 0.057 m^3 for the UAV vs. MLS comparison, which indicates a strong correlation between them [59]. Such regressions indicate that all the tools have the same trends in representing the variability of the canopy volumes during the three phenological stages. The highest correlations were found between the height data for all the tools, being the R^2 values higher than 0.8 with the highest value of $R^2 = 0.86$ with a RMSE = 0.105 m for the MA vs. MLS comparison. For the thickness data, the correlations were weaker, being the R^2 between 0.5 and 0.6 with the lowest value of $R^2 = 0.48$ with a RMSE = 0.052 m for the UAV vs. MLS comparison.

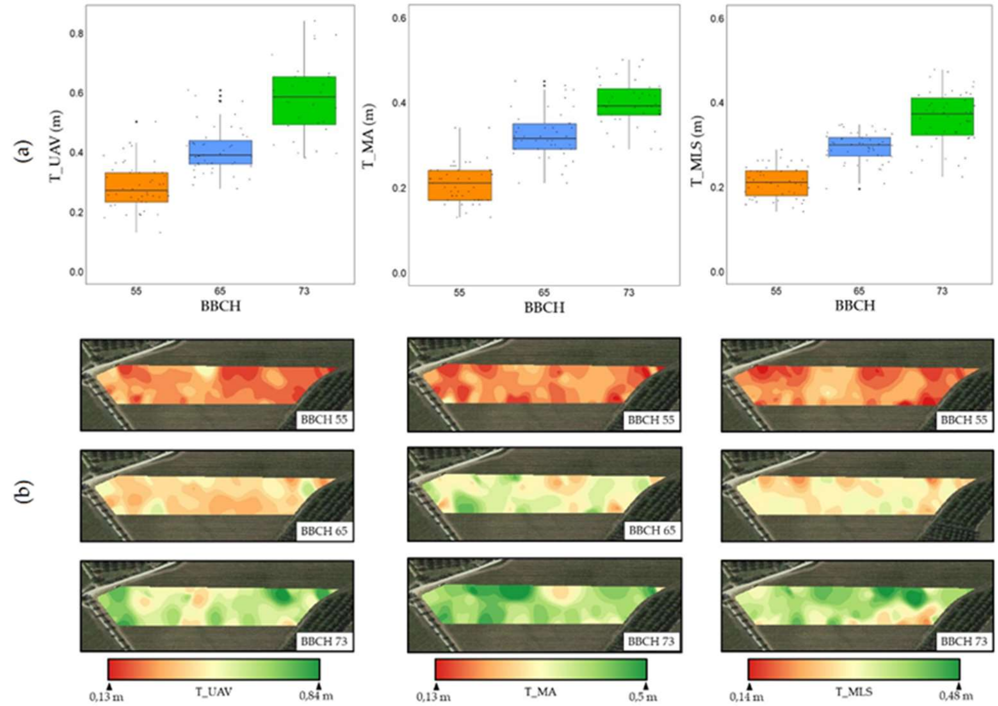


Figure 10. UAV, MA and MLS thickness results: (a) box-plots for the three phenological stages; (b) thickness zonation maps of the test vineyard for each phenological stage, where a single colour scale was used starting from the minimum value (red) to reach the maximum value (green).

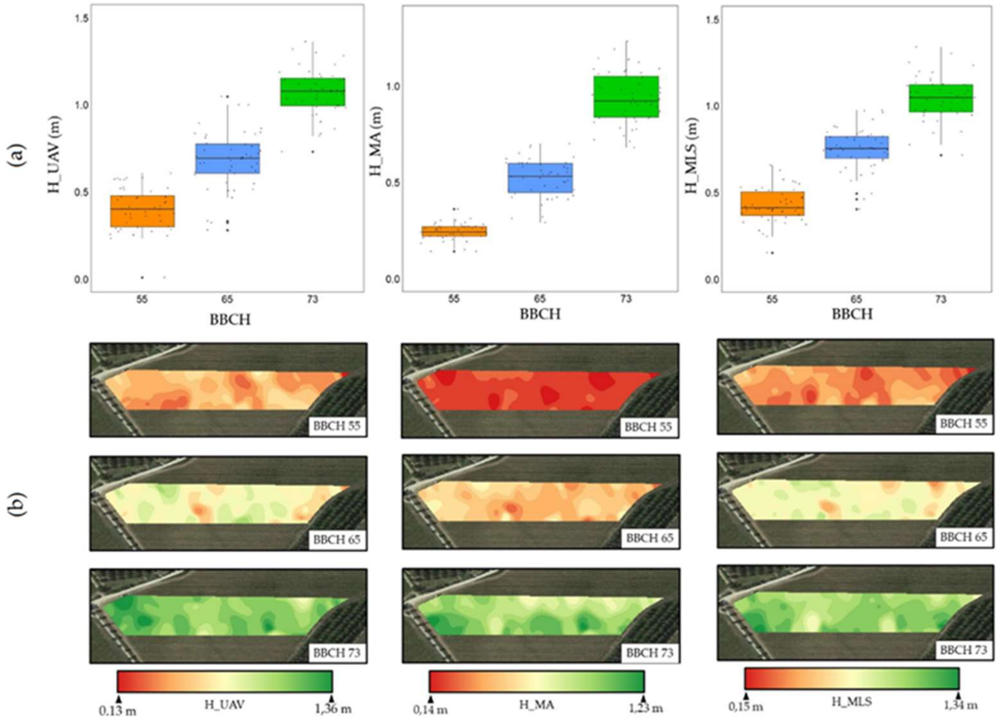


Figure 11. UAV, MA and MLS height results: (a) height box-plots for the three phenological stages; (b) height zonation maps of the test vineyard for each phenological stage, where a single colour scale was used starting from the minimum value (red) to reach the maximum value (green).

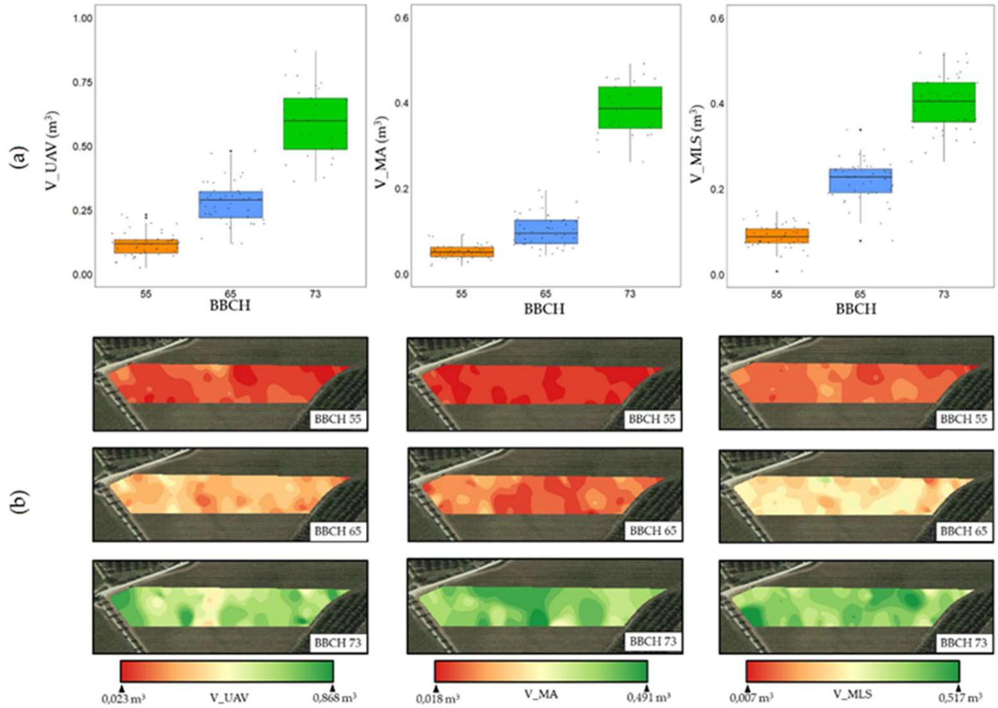


Figure 12. UAV, MA and MLS volume results: (a volume box-plots for the three phenological stages; (b) volume zonation maps of the test vineyard for each phenological stage, where a single colous scale was used starting from the minimum value (red) to reach the maximum value (green).

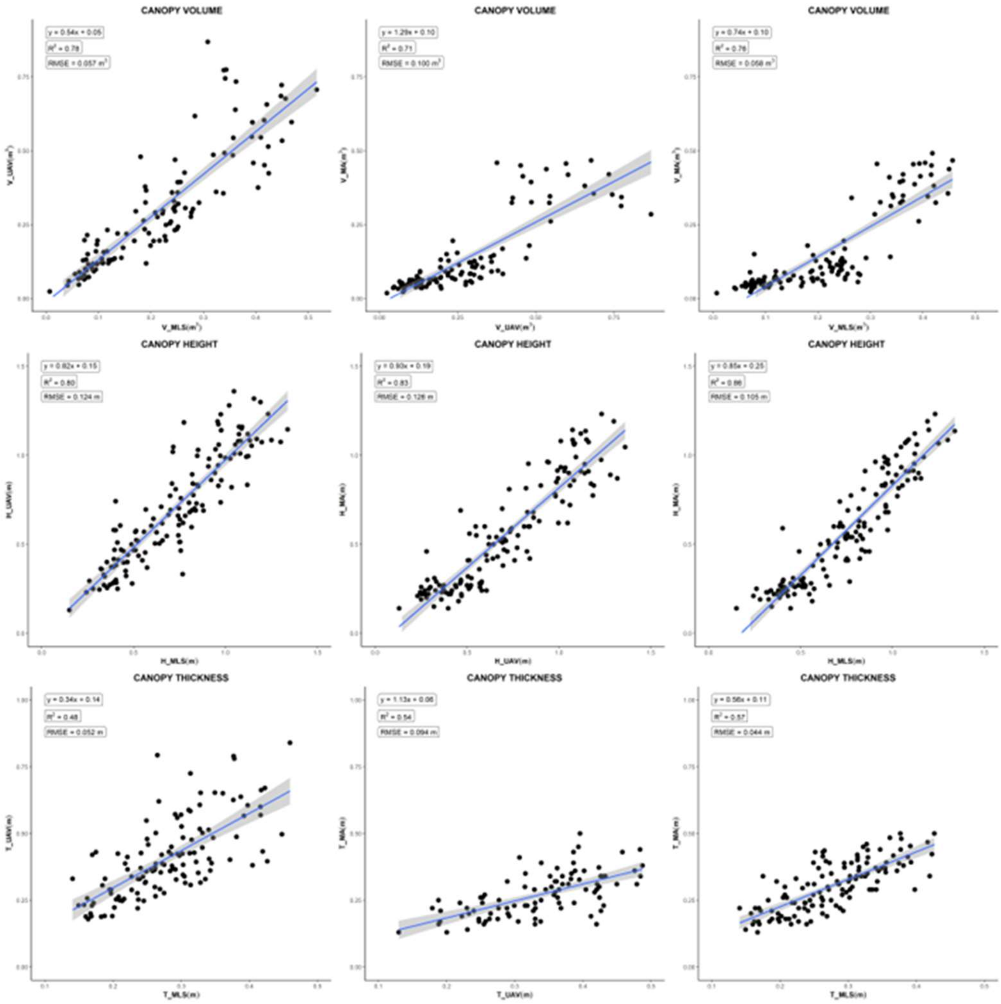


Figure 13. Scatter plots of the 48 sampled vines in the three phenological stages for all the tools.

The full R^2 matrix is reported in Figure 14, where it is shown that the correlation between the LAI values and the canopy volumes was moderately strong (> 0.65) for all the tools. Being the measured LAI values taken as reference data to represent the test vineyard spatial variability, this indicates that all the point clouds were able to correctly represent the spatial variability of the canopy size in all the analysed phenological stages, with the highest value of R^2 = 0.74 for the LAI vs. V_MLS data and the lowest value of R^2 = 0.69 for the LAI vs. V_UAV data. Furthermore, good correlations were found for the NDVI and NDRE variables with respect to the measured LAI (R^2 = 0.67 and R^2 = 0.74, respectively) and with respect to the canopy volumes, being the best value of $R^2 = 0.79$ for the NDRE vs. V_MLS comparison. Interesting correlations were also found between H_MA and H_UAV with respect to V_MLS ($R^2 = 0.87$ and $R^2 = 0.8$, respectively) and between H_MA and H_MLS with respect to V_UAV ($R^2 = 0.78$ and $R^2 = 0.7$, respectively).

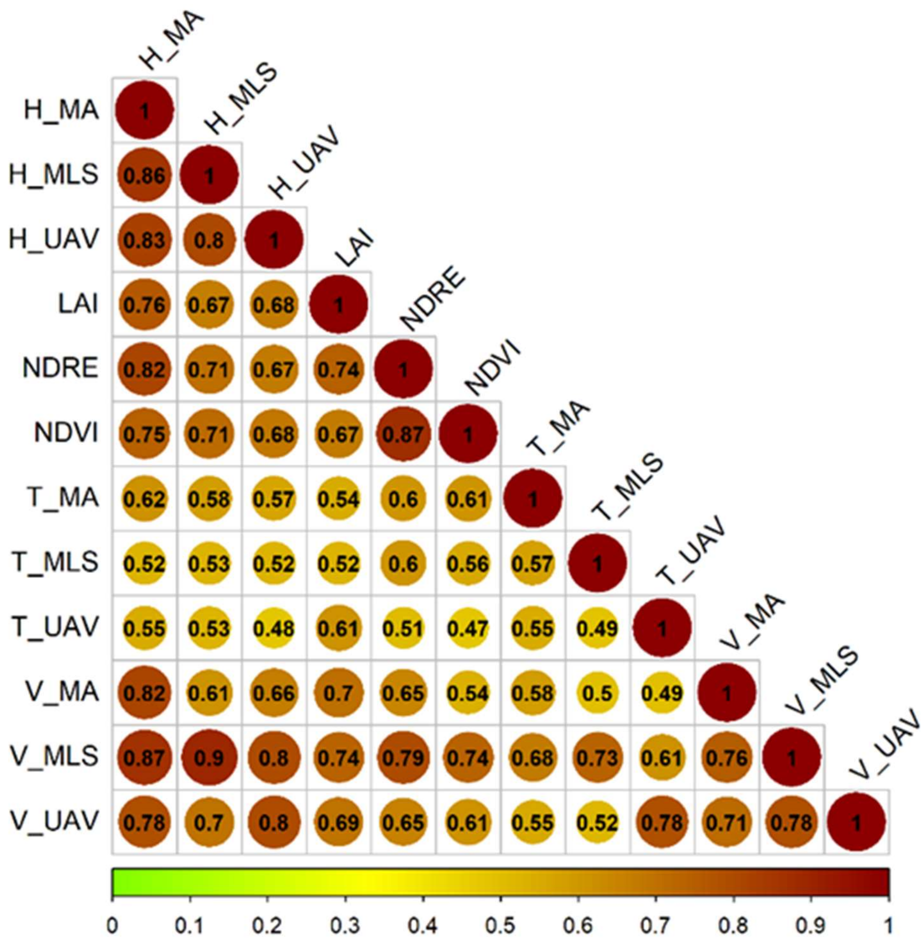


Figure 14. R^2 matrix for all the involved parameters and tools. H, T and V represents respectively the canopy height, thickness and volume.

Discussion

In this research, UAV, MA and MLS point clouds were compared to assess the canopy size parameters of vertical trained vines (*Vitis vinifera* L.). Manual measurements of the canopy volumes were not taken due to several uncertainties, such as the identification of the vine canopy boundary and being subjective and dependent on the person taking the measure itself as well as on the tool or strategy used to assess the canopy height and thickness [60, 61]. Moreover, some researchers have found that manual measurements over-estimate the canopy thickness of about 30% with respect to LiDAR ones [62].

This study aims to give all the stakeholders an overview of the available tools and procedures used to assess the canopy size parameters of the vines in order to provide a reference for the vineyard precision management. The spatial variability detection is crucial in precision farming to automatize the VRT operations and to optimize the chemical inputs. Therefore, more than the precise quantitative estimations of the canopy volumes, it is essential to assess whether an area in the vineyard is more vigorous than another to differentiate the operations such as pruning, harvest, fertilization and crop protection stages, being the agronomist responsible to determine the quantitative applications based on the spatial variability maps.

Since LAI is directly related to the canopy volume in vineyards [28, 29, 63], LAI measurements computed with the app VitiCanopy were taken as an objective reference value to assess whether the different tools correctly characterize the canopy volume intra-field variability.

The results indicate that it is feasible to use 3D point clouds from the investigated tools to automatically compute the canopy height, thickness and volume of the vines and that the canopy size parameters variability in the test vineyard is detected correctly by all the tools in the analysed phenological stages. The results highlight the possibility to use different tools to determine the vines canopy growth trend, thanks to a good correlation that was found between them for the same variable.

UAV technology was widely used to assess canopy volumes and it was shown to be a quick and low-cost solution compared to ground measurements of canopy size parameters [50, 60, 64–69]. The UAV point cloud processing led to similar results in canopy volume values concerning other research, but they used a voxel method [70] and an alpha- shape approach [38, 71]. Therefore, direct comparison is not possible. Among different UAV-based measurements, canopy volume was found to be more sensitive to changes in canopy structure, compared to NDVI and projected canopy area, and demonstrated a more significant potential to assess the outcomes of a range of canopy management practices [72]. In addition, the MLS technology has also been widely used to assess canopy characteristics (canopy height, thickness and volume) but the goodness of canopy characterization was, mainly, compared to manual estimation. [28, 61, 62, 64, 73, 74]. Rosell et al. [74] and Llorens et al. [28] stated that LiDAR is a valuable tool to characterize the canopy parameters and provides very precise canopy characterization. Instead, the MA technology based on the Pix4DCatch app is very recent (2020) and no research was found on its use in assessing vines canopy volumes. However, it is possible to affirm that this technology is a high-resolution photogrammetry solution to reconstruct high-detailed point clouds that is based on the same principle followed by the UAV technology. Even though the cost for the photogrammetric software to process the photos can be a bottleneck, an advantage of this method is the fact that it is not necessary to buy any expensive tool to take the photos nor an expensive hardware to process them (common smartphones and PC are enough), which makes it the most cost-effective and versatile approach for wineries with small vineyards scattered in distant areas. Moreover, the use of open-source photogrammetric software such as Open Drone Map (https://www.opendronemap.org/ (accessed on 3 February 2022) could overcome the economic limitation due to the software cost.

Confirmed that all the analysed tools can assess the intra-field variability of the canopy size parameters, their advantages and limitations can be assessed. The UAV technology allows to quickly map lots of hectares, taking about 20 min of acquisition time for 2 ha of vineyard at an altitude of 30 m and 2 h of processing time with a standard laptop. For this reason, this solution can be more practical and economically relevant in medium- to-big wineries (> 20 ha) and hilly environments. However, it requires trained staff and specific requirements to respond to national and international laws. The MA technology generates the more detailed point clouds but its measurement is punctual. It can be helpful for research purposes or in small wineries (< 5 ha) because, at this time, the processing procedure requires a lot of work. However, if all the processing parts are automatized, it can become a powerful tool to directly assess the canopy volumes by the agronomists or farmers in order to support their vineyard management decisions more rationally. The MLS technology has the advantage to be an on-the-go system that can be installed directly on farm tractors so that the data are collected automatically during field operations. On the other hand, this technology is more time consuming than the UAV one, being 1.5 h the acquisition time for 2 ha, and the LiDAR sensor requires maintenance since it is very sensitive and susceptible to dust and its use can be complex in high-slope vineyards [75].

For all the tools, the processing procedures were time consuming and required enough computational resources to be performed in an efficient way. Some limitations and issues were experienced during the trials. In particular, the use of VitiCanopy to measure the LAI experienced difficulties in early stage (BBCH 55) and in vines with a low canopy volume, because the cordon was detected as a part of the canopy volume itself, making an overestimation of the LAI. On the other hand, the Matlab algorithm used for the UAV and MA data overestimates the canopy thickness when the canopy is very well developed (i.e., BBCH 73). The overestimation is due to some very long branches that deflected inside the vineyard inter-rows so that the generated vines point clouds were much thicker than they actually were. For the MLS processing, the limitations are due to the data verification that has to be carried out manually and that the point cloud cannot be graphically visualized for further investigations. Another critical issue is the post-processing data analysis, how highlighted by Rosell et al., 2009 and Cheraiet et al., 2020. Despite these issues, in the last years many improvements regarding automated MLS data processing were developed and one of them was used in this study [53, 75–77].

Conclusion

In this study, different digital tools, namely MA, MLS and UAV, were used to create 3D point clouds of test vines (*Vitis vinifera* L.) in order to assess the canopy size parameters such as thickness, height and volume in three different phenological stages. The tools were compared in terms of ability to detect and characterize the spatial variability of the vineyard in order to generate zonation maps useful for a precision farming management and VRT applications. Along with these measurements, the LAI, the NDVI and the NDRE indices were also assessed, being the LAI values taken as reference data to represent the vineyard spatial variability. The results indicated a good correlation between all the tools in terms of detecting the intra-field variability and the canopy size parameters. In particular, the R^2 between the canopy volumes acquired with the different tools is higher than 0.7, being the highest value of $R^2 = 0.78$ with a RMSE = 0.057 m^3 for the UAV vs. MLS comparison. The highest correlations were found between the height data for all the tools, being the R^2 values higher than 0.8 with the highest value of $R^2 = 0.86$ with a RMSE = 0.105 m for the MA vs. MLS comparison. For the thickness data, the correlations were weaker, being the R^2 between 0.5 and 0.6 with the lowest value of $R^2 = 0.48$ with a RMSE = 0.052 m for the UAV vs. MLS comparison. The correlation between the LAI values and the canopy volumes was moderately strong (> 0.65) for all the tools with the highest value of $R^2 = 0.74$ for the LAI vs. V_MLS data and the lowest value of R^2 = 0.69 for the LAI vs. V_UAV data. All the tested tools demonstrated to have some advantages and limitations: the UAV technology allows to quickly map lots of hectares but it requires trained staff and specific requirements to respond to national and international laws, the MA is a more punctual measurement but cheaper than the other tools so more affordable by small farms, the MLS can be installed directly on farm tractors so that the data can be collected automatically during field operations. The major limitations for all the tools are related to the data processing step which is time consuming and requires proper computational power. Further developments of this study can be the use of UAV-based multispectral imagery, the automatization of the algorithms and the processing steps as well as the creation of prescription maps for pesticide treatments, based on the canopy volume maps.

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References

1. Bhakta, I.; Phadikar, S.; Majumder, K. State-of-the-art technologies in precision agriculture: A systematic review. J. Sci. Food Agric. 2019, 99, 4878–4888. [CrossRef] [PubMed]
2. Verma, N.K.; Lamb, D.W.; Reid, N.; Wilson, B. Comparison of canopy volume measurements of scattered eucalypt farm trees derived from high spatial resolution imagery and LiDAR. Remote Sens. 2016, 8, 388. [CrossRef]
3. Sassu, A.; Gambella, F.; Ghiani, L.; Mercenaro, L.; Caria, M.; Pazzona, A.L. Advances in Unmanned Aerial System Remote Sensing for Precision Viticulture. Sensors 2021, 21, 956. [CrossRef] [PubMed]
4. Franzen, D.; Mulla, D. A History of Precision Agriculture. In Precision Agriculture Technology for Crop Farming; Zhang, Q., Ed.; Taylor & Franics: Abingdon, UK, 2016; Volume 1, pp. 1–20. [CrossRef]
5. Sarri, D.; Lombardo, S.; Pagliai, A.; Perna, C.; Lisci, R.; De Pascale, V.; Rimediotti, M.; Cencini, G.; Vieri, M. Smart farming introduction in wine farms: A systematic review and a new proposal. Sustainability 2020, 12, 7191. [CrossRef]
6. Ammoniaci, M.; Kartsiotis, S.P.; Perria, R.; Storchi, P. State of the art of monitoring technologies and data processing for precision viticulture. Agriculture 2021, 11, 201. [CrossRef]
7. Vieri, M.; Sarri, D.; Rimediotti, M.; Perria, R.; Storchi, P. The new architecture in the vineyard system management for variable rate technologies and traceability. Acta Hortic. 2013, 978, 47–53. [CrossRef]
8. Sommer, K.J.; Islam, M.T.; Clingeleffer, P.R. Light and temperature effects on shoot fruitfulness in Vitis vinifera L. cv. Sultana: Influence of trellis type and grafting. Aust. J. Grape Wine Res. 2000, 6, 99–108. [CrossRef]
9. Petrie, P.R.; Trought, M.C.T.; Howell, G.S.; Buchan, G.D.; Palmer, J.W. Whole-canopy gas exchange and light interception of vertically trained Vitis

vinifera L. under direct and diffuse light. Am. J. Enol. Vitic. 2009, 60, 173–182.
10. Haselgrove, L.; Botting, D.; Van Heeswijck, R.; Høj, P.B.; Dry, P.R.; Ford, C.; Iland, P.G. Canopy microclimate and berry composition: The effect of bunch exposure on the phenolic composition of Vitis vinifera L. cv. Shiraz grape berries. Aust. J. Grape Wine Res. 2000, 6, 141–149. [CrossRef]
11. Schultz, H. Grape canopy structure, light microclimate and photosynthesis. I: A two-dimensional model of the spatial distribution of surface area densities and leaf ages in two canopy systems. Vitis 1995, 34, 211–215.
12. Brillante, L.; Bois, B.; Lévêque, J.; Mathieu, O. Variations in soil-water use by grapevine according to plant water status and soil physical-chemical characteristics—A 3D spatio-temporal analysis. Eur. J. Agron. 2016, 77, 122–135. [CrossRef]
13. Costantini, E.A.C.; Castaldini, M.; Diago, M.P.; Giffard, B.; Lagomarsino, A.; Schroers, H.J.; Priori, S.; Valboa, G.; Agnelli, A.E.; Akça, E.; et al. Effects of soil erosion on agro-ecosystem services and soil functions: A multidisciplinary study in nineteen organically farmed European and Turkish vineyards. J. Environ. Manag. 2018, 223, 614–624. [CrossRef] [PubMed]
14. Sirera, À.P.; Antichi, D.; Raffa, D.W.; Rallo, G. Application of remote sensing techniques to discriminate the effect of different soil management treatments over rainfed vineyards in chianti terroir. Remote Sens. 2021, 13, 716. [CrossRef]
15. Zombardo, A.; Crosatti, C.; Bagnaresi, P.; Bassolino, L.; Reshef, N.; Puccioni, S.; Faccioli, P.; Tafuri, A.; Delledonne, M.; Fait, A.; et al. Transcriptomic and biochemical investigations support the role of rootstock-scion interaction in grapevine berry quality. BMC Genom. 2020, 21, 468. [CrossRef] [PubMed]
16. Pergher, G.; Petris, R. Pesticide dose adjustment to the canopy parameters for treatments to the tree crops. In Proceedings of the Giornate Fitopatologiche; ATTI Giornate Fitopatologiche (University of Bologna, Department of Agri-Food Sciences and Technologies, Bologna): Bologna, Italy, 2008; pp. 317–322.

17. Miranda-Fuentes, A.; Llorens, J.; Gamarra-Diezma, J.L.; Gil-Ribes, J.A.; Gil, E. Towards an optimized method of olive tree crown volume measurement. Sensors 2015, 15, 3671–3687. [CrossRef]
18. Grantz, D.A.; Zhang, X.J.; Metheney, P.D.; Grimes, D.W. Indirect measurement of leaf area index in Pima cotton (Gossypium barbadense L.) using a commercial gap inversion method. Agric. For. Meteorol. 1993, 67, 1–12. [CrossRef]
19. Montero, F.J.; De Juan, J.A.; Cuesta, A.; Brasa, A. Non-destructive methods to estimate leaf area in Vitis vinifera L. HortScience 2000, 35, 696–698. [CrossRef]
20. Lopes, C.; Pinto, P.A. Easy and accurate estimation of grapevine leaf area with simple mathematical models. Vitis—J. Grapevine Res. 2005, 44, 55–61.
21. Cohen, S.; Striem, M.J.; Bruner, M.; Klein, I. Grapevine leaf area index evaluation by Gap Fraction Inversion. Acta Hortic. 2000, 537, 87–94. [CrossRef]
22. Smart, R.E.; Smith, S.M. Canopy management: Identifying the problems and practical solutions. Second Int. Cool Clim. Vitic. Oenology Symp. 1988, 109–115.
23. Poblete-Echeverría, C.; Fuentes, S.; Ortega-Farias, S.; Gonzalez-Talice, J.; Yuri, J.A. Digital cover photography for estimating Leaf area index (LAI) in apple trees using a variable light extinction coefficient. Sensors 2015, 15, 2860–2872. [CrossRef] [PubMed]
24. Johnson, L.F.; Pierce, L.L. Indirect measurement of leaf area index in California North Coast vineyards. HortScience 2004, 39, 236–238. [CrossRef]
25. Rosell, J.R.; Sanz, R. A review of methods and applications of the geometric characterization of tree crops in agricultural activities. Comput. Electron. Agric. 2012, 81, 124–141. [CrossRef]
26. Comba, L.; Biglia, A.; Aimonino, D.R.; Barge, P.; Tortia, C.; Gay, P. 2D and 3D data fusion for crop monitoring in precision agriculture. In Proceedings of the

2019 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor), Portici, Italy, 24–26 October 2019; pp. 62–67. [CrossRef]
27. Llorens, J.; Gil, E.; Llop, J.; Escolà, A. Variable rate dosing in precision viticulture: Use of electronic devices to improve application efficiency. Crop Prot. 2010, 29, 239–248. [CrossRef]
28. Llorens, J.; Gil, E.; Llop, J.; Escolà, A. Ultrasonic and LIDAR sensors for electronic canopy characterization in vineyards: Advances to improve pesticide application methods. Sensors 2011, 11, 2177–2194. [CrossRef]
29. Sanz, R.; Rosell, J.R.; Llorens, J.; Gil, E.; Planas, S. Relationship between tree row LIDAR-volume and leaf area density for fruit orchards and vineyards obtained with a LIDAR 3D Dynamic Measurement System. Agric. For. Meteorol. 2013, 171–172, 153–162. [CrossRef]
30. Vieri, M.; Lisci, R.; Rimediotti, M.; Sarri, D. The RHEA-project robot for tree crops pesticide application. J. Agric. Eng. 2013, 44, 359–362. [CrossRef]
31. Gil, E.; Escolà, A.; Rosell, J.R.; Planas, S.; Val, L. Variable rate application of plant protection products in vineyard using ultrasonic sensors. Crop Prot. 2007, 26, 1287–1297. [CrossRef]
32. Hočevar, M.; Širok, B.; Jejčič, V.; Godeša, T.; Lešnika, M.; Stajnko, D. Design and testing of an automated system for targeted spraying in orchards. J. Plant Dis. Prot. 2010, 117, 71–79. [CrossRef]
33. Jejčič, V.; Godeša, T.; Hočevar, M.; Širok, B.; Malneršic, A.; Štancar, A.; Lešnik, M.; Stajnko, D. Design and testing of an ultrasound system for targeted spraying in orchards. J. Mech. Eng. 2011, 57, 587–598. [CrossRef]
34. Méndez, V.; Pérez-Romero, A.; Sola-Guirado, R.; Miranda-Fuentes, A.; Manzano-Agugliaro, F.; Zapata-Sierra, A.; Rodríguez- Lizana, A. In-field estimation of orange number and size by 3D laser scanning. Agronomy 2019, 9, 885. [CrossRef]
35. Khaliq, A.; Comba, L.; Biglia, A.; Ricauda Aimonino, D.; Chiaberge, M.; Gay,

P. Comparison of satellite and UAV-based multispectral imagery for vineyard variability assessment. Remote Sens. 2019, 11, 436. [CrossRef]

36. Matese, A.; Toscano, P.; Di Gennaro, S.F.; Genesio, L.; Vaccari, F.P.; Primicerio, J.; Belli, C.; Zaldei, A.; Bianconi, R.; Gioli, B. Intercomparison of UAV, aircraft and satellite remote sensing platforms for precision viticulture. Remote Sens. 2015, 7, 2971–2990. [CrossRef]
37. Pastonchi, L.; Di Gennaro, S.F.; Toscano, P.; Matese, A. Comparison between satellite and ground data with UAV-based information to analyse vineyard spatio-temporal variability. Oeno One 2020, 54, 919–934. [CrossRef]
38. Di Gennaro, S.F.; Matese, A. Evaluation of novel precision viticulture tool for canopy biomass estimation and missing plant detection based on 2.5D and 3D approaches using RGB images acquired by UAV platform. Plant Methods 2020, 16, 91. [CrossRef] [PubMed]
39. Del-Moral-Martínez, I.; Rosell-Polo, J.R.; Company, J.; Sanz, R.; Escolà, A.; Masip, J.; Martínez-Casasnovas, J.A.; Arnó, J. Mapping vineyard leaf area using mobile terrestrial laser scanners: Should rows be scanned on-the-go or discontinuously sampled? Sensors 2016, 16, 119. [CrossRef] [PubMed]
40. Chandel, A.K.; Khot, L.R.; Molaei, B.; Peters, R.T.; Stöckle, C.O.; Jacoby, P.W. High-resolution spatiotemporal water use mapping of surface and direct-root-zone drip-irrigated grapevines using uas-based thermal and multispectral remote sensing. Remote Sens. 2021, 13, 954. [CrossRef]
41. De Bei, R.; Fuentes, S.; Gilliham, M.; Tyerman, S.; Edwards, E.; Bianchini, N.; Smith, J.; Collins, C. Viticanopy: A free computer app to estimate canopy vigor and porosity for grapevine. Sensors 2016, 16, 585. [CrossRef]
42. Fareed, N.; Rehman, K. Integration of remote sensing and GIS to extract plantation rows from a drone-based image point cloud digital surface model. ISPRS Int. J. Geo-Inf. 2020, 9, 151. [CrossRef]
43. Herrero-Huerta, M.; González-Aguilera, D.; Rodriguez-Gonzalvez, P.;

Hernández-López, D. Vineyard yield estimation by automatic 3D bunch modelling in field conditions. Comput. Electron. Agric. 2015, 110, 17–26. [CrossRef]

44. Font, D.; Tresanchez, M.; Martínez, D.; Moreno, J.; Clotet, E.; Palacín, J. Vineyard yield estimation based on the analysis of high resolution images obtained with artificial illumination at night. Sensors 2015, 15, 8284–8301. [CrossRef]
45. Terrón, J.M.; Blanco, J.; Moral, F.J.; Mancha, L.A.; Uriarte, D.; Marques Da Silva, J.R. Evaluation of vineyard growth under four irrigation regimes using vegetation and soil on-the-go sensors. Soil 2015, 1, 459–473. [CrossRef]
46. Matese, A.; Di Gennaro, S.F. Practical applications of a multisensor UAV platform based on multispectral, thermal and RGB high resolution images in precision viticulture. Agriculture 2018, 8, 116. [CrossRef]
47. De la Fuente, C.P.; Valdés-Gómez, H.; Roudet, J.; Verdugo-Vásquez, N.; Mirabal, Y.; Laurie, V.F.; Goutouly, J.P.; Acevedo-Opazo, C.; Fermaud, M. Vigor thresholded NDVI is a key early risk indicator of botrytis bunch rot in vineyards. Oeno One 2020, 54, 279–297. [CrossRef]
48. Campos, J.; Llop, J.; Gallart, M.; García-Ruiz, F.; Gras, A.; Salcedo, R.; Gil, E. Development of canopy vigour maps using UAV for site-specific management during vineyard spraying process. Precis. Agric. 2019, 20, 1136–1156. [CrossRef]
49. Lorenz, D.; Eichhorn, K.; Bleiholder, H.; Klose, R.; Meier, U.; Weber, E. Growth Stages of the Grapevine: Phenological growth stages of the grapevine (*Vitis vinifera* L. ssp. *vinifera*)—Codes and descriptions according to the extended BBCH scale. Aust. J. Grape Wine Res. 1995, 1, 100–103. [CrossRef]
50. Jurado, J.M.; Pádua, L.; Feito, F.R.; Sousa, J.J. Automatic grapevine trunk detection on UAV-based point cloud. Remote Sens. 2020, 12, 3043. [CrossRef]
51. Pádua, L.; Marques, P.; Hruška, J.; Adão, T.; Peres, E.; Morais, R.; Sousa, J.J.

Multi-temporal vineyard monitoring through UAV-based RGB imagery. Remote Sens. 2018, 10, 1907. [CrossRef]

52. Anifantis, A.S.; Camposeo, S.; Vivaldi, G.A.; Santoro, F.; Pascuzzi, S. Comparison of UAV photogrammetry and 3D modelling techniques with other currently used methods for estimation of the tree row volume of a super-high-density olive orchard. Agriculture 2019, 9, 233. [CrossRef]
53. Pagliai, A.; Sarri, D.; Lisci, R.; Lombardo, S.; Vieri, M.; Perna, C.; Cencini, G.; De Pascale, V.; Araùjo E Silva Ferraz, G. Development of an algorithm for assessing canopy volumes with terrestrial LiDAR to implement precision spraying in vineyards. Agron. Res. 2021, 19. [CrossRef]
54. R Core Team. R: A Language and Environment for Statistical Computing; R Foundation for Statistical Computing: Vienna, Austria, 2021.
55. Wei, T.; Simko, V. R Package "Corrplot": Visualization of a Correlation Matrix. 2021. Available online: https://github.com/ taiyun/corrplot (accessed on 3 February 2022).
56. Wickham, H. Ggplot2: Elegant Graphics for Data Analysis. 2016. Available online: https://ggplot2.tidyverse.org/ (accessed on 3 February 2022).
57. Bartier, P.M.; Keller, C.P. Multivariate interpolation to incorporate thematic surface data using inverse distance weighting (IDW). Comput. Geosci. 1996, 22, 795–799. [CrossRef]
58. Orlando, F.; Movedi, E.; Coduto, D.; Parisi, S.; Brancadoro, L.; Pagani, V.; Guarneri, T.; Confalonieri, R. Estimating leaf area index (LAI) in vineyards using the pocket LAI smart-app. Sensors 2016, 16, 2004. [CrossRef] [PubMed]
59. Moore, D.S. The Basic Practice of Statistics, 4th ed.; Baruth, R., Ed.; Craig Bleyer: New York, NY, USA, 2006; ISBN 9780716774785. 60. Qi, Y.; Dong, X.; Chen, P.; Lee, K.-H.; Lan, Y.; Lu, X.; Jia, R.; Deng, J.; Zhang, Y. Canopy Volume Extraction of Citrus reticulate Blanco cv. Shatangju Trees Using UAV Image-Based Point Cloud Deep Learning. Remote Sens. 2021, 13, 3437.

[CrossRef]
61. Colaço, A.F.; Trevisan, R.G.; Molin, J.P.; Rosell-Polo, J.R.; Escolà, A. A method to obtain orange crop geometry information using a mobile terrestrial laser scanner and 3D modelling. Remote Sens. 2017, 9, 763. [CrossRef]
62. Gil, E.; Arnó, J.; Llorens, J.; Sanz, R.; Llop, J.; Rosell-Polo, J.R.; Gallart, M.; Escolà, A. Advanced technologies for the improvement of spray application techniques in Spanish viticulture: An overview. Sensors 2014, 14, 691–708. [CrossRef] [PubMed]
63. Arnó, J.; Escolà, A.; Vallès, J.M.; Llorens, J.; Sanz, R.; Masip, J.; Palacín, J.; Rosell-Polo, J.R. Leaf area index estimation in vineyards using a ground-based LiDAR scanner. Precis. Agric. 2013, 14, 290–306. [CrossRef]
64. Parmehr, E.G.; Amati, M. Individual Tree Canopy Parameters Estimation Using UAV-Based Photogrammetric and LiDAR Point Clouds in an Urban Park. Remote Sens. 2021, 13, 2062. [CrossRef]
65. Krause, S.; Sanders, T.G.M.; Mund, J.P.; Greve, K. UAV-based photogrammetric tree height measurement for intensive forest monitoring. Remote Sens. 2019, 11, 758. [CrossRef]
66. Karl, J.W.; Yelich, J.V.; Ellison, M.J.; Lauritzen, D. Estimates of Willow (Salix Spp.) Canopy Volume using Unmanned Aerial Systems. Rangel. Ecol. Manag. 2020, 73, 531–537. [CrossRef]
67. Tian, J.; Dai, T.; Li, H.; Liao, C.; Teng, W.; Hu, Q.; Ma, W.; Xu, Y. A novel tree height extraction approach for individual trees by combining TLS and UAV image-based point cloud integration. Forests 2019, 10, 537. [CrossRef]
68. Comba, L.; Biglia, A.; Ricauda Aimonino, D.; Gay, P. Unsupervised detection of vineyards by 3D point-cloud UAV photogrammetry for precision agriculture. Comput. Electron. Agric. 2018, 155, 84–95. [CrossRef]
69. De Castro, A.I.; Jiménez-Brenes, F.M.; Torres-Sánchez, J.; Peña, J.M.; Borra-Serrano, I.; López-Granados, F. 3-D characterization of vineyards using a novel

UAV imagery-based OBIA procedure for precision viticulture applications. Remote Sens. 2018, 10, 584. [CrossRef]
70. López-Granados, F.; Torres-Sánchez, J.; Jiménez-Brenes, F.M.; Oneka, O.; Marín, D.; Loidi, M.; Castro, A.I.D.; Santesteban, L.G. Monitoring vineyard canopy management operations using UAV-acquired photogrammetric point clouds. Remote Sens. 2020, 12, 2331. [CrossRef]
71. Ouyang, J.; De Bei, R.; Collins, C. Assessment of canopy size using UAV-based point cloud analysis to detect the severity and spatial distribution of canopy decline. Oeno One 2021, 55, 253–256. [CrossRef]
72. Ouyang, J.; de Bei, R.; Fuentes, S.; Collins, C. UAV and ground-based imagery analysis detects canopy structure changes after canopy management. Oeno One 2020, 54, 1093–1103. [CrossRef]
73. Moreno, H.; Valero, C.; Bengochea-Guevara, J.M.; Ribeiro, Á.; Garrido-Izard, M.; Andújar, D. On-ground vineyard reconstruction using a LiDAR-based automated system. Sensors 2020, 20, 1102. [CrossRef] [PubMed]
74. Rosell, J.R.; Llorens, J.; Sanz, R.; Arnó, J.; Ribes-Dasi, M.; Masip, J.; Escolà, A.; Camp, F.; Solanelles, F.; Gràcia, F.; et al. Obtaining the three-dimensional structure of tree orchards from remote 2D terrestrial LIDAR scanning. Agric. For. Meteorol. 2009, 149, 1505–1515. [CrossRef]
75. Palleja, T.; Tresanchez, M.; Teixido, M.; Sanz, R.; Rosell, J.R.; Palacin, J. Sensitivity of tree volume measurement to trajectory errors from a terrestrial LIDAR scanner. Agric. For. Meteorol. 2010, 150, 1420–1427. [CrossRef]
76. Rinaldi, M.; Llorens, J.; Gil, E. Electronic characterization of the phenological stages of grapevine using a LIDAR sensor. In Proceedings ofthe Precision Agriculture ’13; Stafford, J.V., Ed.; Wageningen Academic Publishers: Wageningen, The Netherlands, 2013; pp. 603–609. [CrossRef]
77. Cheraïet, A.; Naud, O.; Carra, M.; Codis, S.; Lebeau, F.; Taylor, J. An algorithm to automate the filtering and classifying of 2D LiDAR data for site-specific

estimations of canopy height and width in vineyards. Biosyst. Eng. 2020, 200, 450–465. [CrossRef]

3.3. Paper III

Second-generation ultrasonic sensor in precision spraying: testing and actuation range refinement

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Abstract

The reduction of pesticide use in agriculture is one of the main goals of the European Union and it can be achieved with new technologies. This work aimed to test in the field a 2nd generation ultrasonic sensor (US), able to directly distinguish foliar layers and density, and to verify its working performance. Field trials were carried out in a vineyard and in different phenological phases. The best correlations were found between the canopy volume and the US Envelope parameter, and between the canopy height and the US Density parameter, R^2 of 0.67 and 0.73 respectively. Therefore, US parameters can estimate canopy characteristics with good reliability and thanks to the actuation-range refinement, this system can be implemented in conventional sprayers, improving their environmental sustainability.

Keywords: proximal sensing, sustainable pesticide management, spray coverage, deposit, viticulture

Introduction

One of the most environmentally impacting factors in crop production is plant-protection product management and distribution. The reduction of pesticides is considered a fundamental process by the European Union, as stated in the “Farm to Fork” strategy. The European Union addresses, as a viable solution, the application of precision agriculture (PA) techniques. In viticulture, and generally in perennial crops, various planting layouts, different canopy management and shapes can be considered sources of variability. All these aspects must be carefully considered in the management of operations like crop protection (Miranda-Fuentes et al. 2018).

Variable Rate Application (VRA) is a technique capable of taking into account these aspects and, at the same time, reducing the environmental impacts by adjusting, in real-time, the amount of spray distributed based on the volume of canopy that has to be treated (Gil et al. 2013). A sensing system able to detect the canopy is necessary to carry out VRA management. In general, sensors such as ultrasonic sensors (US) or laser scanners (LS), which provide direct measurements of the canopy, are more reliable than sensors that measure the reflectance of visible and infrared light for obtaining three-dimensional characteristics of canopies and therefore for performing real-time VRA (Abbas et al. 2020). In addition, LS performance is significantly weakened in high-light intensity and dusty environments (Rosell and Sanz 2012). Instead, US's robustness and low price make it more suitable for agriculture purposes (Rosell and Sanz 2012). In last decades, many authors have used US to assess canopy characteristics, using various sensors to characterise the whole canopy and the time of flight (TOF) as a sensing parameter (1st generation) (Gil et al. 2014; Llorens et al. 2010). However, in recent years new integrated US capable of managing TOF of different echoes and wavelengths, have been developed (2nd generation). Those sensors can distinguish foliar layer and

canopy density. Some studies have shown promising results for real-time canopy characterisation with these new sensors, but linking these results to spray quality and quantity parameters to improve VRA is lacking (Palleja and Landers 2017).
The present work aimed to test in-field a second-generation ultrasonic sensor, able to directly determine foliar layers and density, to verify the canopy detection reliability performances of the sensor and to fine-tune the spray actuation range.

Materials and Methods

Experimental site and design

Field trials were carried out in a cordon spur vineyard, located in Castellina in Chianti, Siena, Italy (43°27'39.27"N; 11°13'22.51"E), in the middle of Chianti Classico. The vineyard had a density of 5000 pl ha^{-1} and followed the traditional Tuscan planting layout, with a planting distance of 2.5 x 0.8 m and a cordon mean height from the ground of 0.8 m. The cultivar was *Vitis vinifera* L. cv. "Sangiovese". The experimental site covered around 0.5 ha, where 20 vines were sampled and data were collected at three phenological phases (BBCH 61, BBCH 73, BBCH 81), both for canopy characterisation and for refining the spraying range (Lorenz et al. 1995). Since the vineyard was located on a hillside and showed important vigour variability along the vine row, a completely randomized design was performed with three repetitions. The main characteristics of the trials were reported in Table 1.

Table 1. Main characteristics of trials and spray volumes applied.

Trials	Phenological phase (BBCH)	Tree row volume (m^3 m^{-1}) ± sd	Sampled vines	n° artificial target	Levels	Application volume (l ha^{-1}) ± sd
1°	61	0.258 ± 0.08	20	3	L_1	150 ± 0.5
					L_2	200 ± 0.8
					L_3	175 ± 0.7
2°	73	0.311 ± 0.10	20	4	L_1	200 ± 0.8
					L_2	225 ± 0.8
					L_3	250 ± 0.9
3°	81	0.334 ± 0.10	20	5	L_1	275 ± 1.1
					L_2	250 ± 0.8
					L_3	225 ± 0.4

Data acquisition for canopy characterisation

For canopy manual measurements, a revised Tree Row Volume (TRW) was adopted: the canopy height (H) and thickness (T) were measured for each sampled vine, and the volume of the canopy (V) was calculated as meter cubic of vegetation per meter of vine row (m^3 m^{-1}). To ensure good reliability of measurements three repetitions were taken. A second-generation ultrasonic sensor was used for canopy instrumental measurement assessment. The instrumentation (Fig. 1) used was a NORAC Ultrasonic sensor (Topcon Positioning Group, Tokyo, Japan). The sensor features a 1 mm resolution, a measurement range of 0.15 m to 10 m, a maximum acquisition frequency of 30 Hz, and it generated 50 kHz ultrasound waves. The sensor was integrated with a microprocessor capable of performing all computations onboard, i.e. selecting the range of interest (ROI) and outputting the final values in a .csv file (comma-separated values). This sensor was able to measure the number of echoes and their intensity in a pre-selected ROI and it provided three simplified values of readings (Edges, Envelope and Density). Considering the canopy layout in the involved vineyard, the ROI was set at 1 m and the relative ultrasonic cone diameter was around 0.50 m.

a)


b)

Figure 1. a) Schematic representation of NORAC ultrasonic sensors (NORAC – Datasheet); b) Sensors used in the experimentation.

Data acquisition for spray quality and quantity

To perform the calibration of the actuation range, a study of spray distribution for each phenological stages was conducted on the same day of the canopy data acquisition. The profile sampling strategy of the British Standard ISO 22522/2007 was followed. Particularly, both plastic sheets (50 x 90 mm, SEFAR NITEX) and water-sensitive papers (WSPs, 26 x 76 mm, Syngenta, Switzerland) were arranged on the canopy on both sides and in various positions, following the plant growth in the three trials (Tab 1.). To verify the right amount of spray volume in relation to the canopy dimensions, the sampled vines were sprayed at three different application levels in each phenological phase, with an 8 g l^{-1} concentrated solution of water and yellow Tartrazine (Andrea Gallo S.r.l., Genova, Italy). To analyse spray distribution reliability, normalized deposit and spray coverage have been taken into account. A well-known spectrophotometer methodology was used to quantify the Tartrazine concentration in plastic sheets (Gil et al. 2007). In particular, the Eq. (1) was applied to obtain the normalized deposits.

$$d_n = \frac{\left[\frac{\frac{(A_r - A_b)}{\alpha} \times V_{dil}}{S_{ps}}\right] \times 100}{A_{vol} \times c_{tar}} \tag{1}$$

where: d_n is the normalized deposit expressed in μg cm^{-2}; A_r is the absorbance value of the sample; A_b is the absorbance of the blank sample; α is the calibration curve coefficient; V_{dil} is the amount of washing solution; S_{ps} is the area of plastic sheet; A_{vol} is the applied spray volume expressed in l ha^{-1}; c_{tar} is the concentration of tartrazine.

Instead, an image analysis technique was used to measure the spray coverage from the WSPs. First of all, the collected WSPs were digitized with a professional scanner at a resolution of 600 dpi. Finally, the WSP images were analysed by the Deposit Scan software to extract the spray coverage values.

Instrumentation

Both the canopy characterisation studies and the spray tests were conducted with the same equipment. A Lamborghini RF90 tractor coupled with a drawn pneumatic sprayer (Martignani M612 Whirlwind, Ravenna, Italy) was used. The main characteristics of the sprayer were: a 1000 l tank, a centrifugal fan capable of generating a homogeneous air flow of about 26,000 m^3 h^{-1}, a centrifugal pump, and 6 nozzles per side (4 mm) located inside two radial fans. In addition, two US sensors were mounted in the front part of the sprayer and the maximum acquisition frequency (30 Hz) was set in all the canopy characterisation sessions. Both for the instrumental characterisation and the spray tests the tractor speed was set at 1.4 m s^{-1} and the sprayer or the sensors sprayed/measured both sides of the vine rows. Before each spray test, the sprayer was accurately calibrated to ensure homogeneous depositions and coverages. During the tests, a weather station was placed inside the vineyard to record the main meteorological parameters (air temperature, air humidity, wind speed and direction).

Data analysis

The statistical analysis and the graphical representation were undertaken with the open-source statistical software R under an RStudio environment. All the variables were analysed to ensure the reliability and robustness of the linear model assumption. The normal distribution of errors and the respect of homoscedasticity were inspected using the Shapiro-Wilk test ($p < 0.05$) and Levene's test, respectively.

The coefficient of determination (R^2) was used to evaluate the model's goodness and reliability. R-software native functions, the "corrplot" package and the "ggplot" package were used to check the assumptions of the linear model, to visualize the R^2 matrix and to show the linear correlations with scatters-plots, respectively (Wickham 2016).

Results and discussion

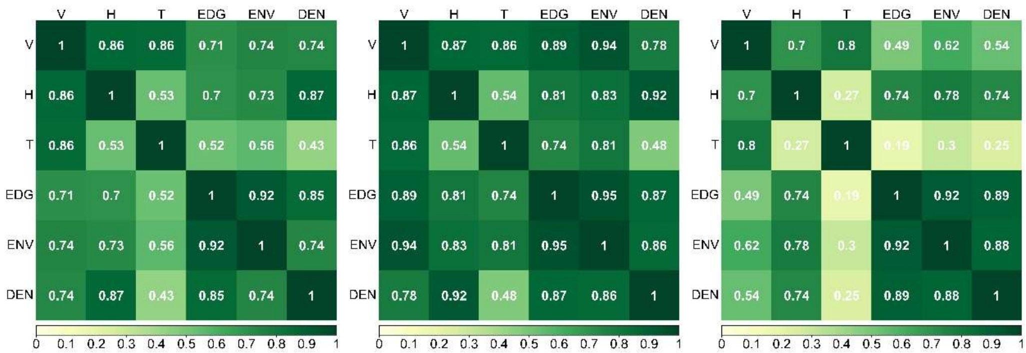


Figure 2. R^2 matrix for all the involved canopy measurements. V, H and T represent canopy volume, height and thickness. EDG, ENV and DEN represent edges, envelope and density of US variables.

In Figure 2, the three correlation matrices for each phenological phase are shown. The matrices concern the canopy manual measurements (V, H, T) and the canopy instrumental characterizations (Edges - EDG, Envelope - ENV, Density - DEN). The second trial showed the highest values of R^2 between different combinations. Instead, the R^2 values of the third trial revealed the lowest performance in terms of correlation. Between the second and the third trial, a vertical and horizontal topping was carried out by the wine farm. Palleja and Landers (2017) highlighted that there is a correlation between manual measurements and envelope signal of the US but it is not constant and it could differ for many reasons, for instance the canopy management. On the basis of the BBCH 81 matrix, the canopy management (topping) could have affected the canopy measurements in the last trial. A common trend showed in the matrices was that the lowest R^2 values are shown between the canopy thickness and the US readings (EDG, ENV and DEN). Instead, the highest R^2 values are disclosed between canopy volume and the instrumental measurements, except for the last trial where the canopy height highlighted the highest values. However, the highest R^2 was observed between the canopy height and the US Density in the first trial ($R^2 = 0.87$), between the canopy volume and the US Envelope in the second trial ($R^2 = 0.94$), and between the canopy height and the US Envelope in the last trial ($R^2 = 0.78$).

In Table 2, the linear relation of aggregated data (BBCH 61, BBCH 73, BBCH 81) were reported for all the involved measurements. Generally, a common decrease in the goodness of R^2 is shown in Table 2. The maximum achieved R^2 is 0.75, while in the previous matrices was 0.94. In particular, a significant decrease in goodness was disclosed between the canopy thickness and the US measurements, in which the maximum value of R^2 was 0.57 (T *vs* DEN). This is due to the values recorded in the last trial (BBCH 81). In fact, they showed the worst R^2 and they impacted on the correlation coefficients showed in table 2. The maximum values of R^2 were shown between the canopy height and all the involved US measurements. In particular, the R^2 were 0.74, 0.75 and 0.73 between the H variable and EDG, ENV, and DEN respectively. Llorens et al (2010) showed the best R^2 between US parameters and canopy height (around 0.55) than the other manual canopy measurements. This trend is reported also in the present work, as shown in Table 2.

Table 2. Linear relation between all the involved canopy measurements for aggregated data.

Sources	DF	p>(F)	Significance[a]	R^2	Equation
EDG ~ V	59	4.7E-13	***	0.59	y = 5.37x + 2.02
ENV ~ V	59	7.6E-16	***	0.67	y = 809.37x + 92.41
DEN ~ V	59	1.5E-11	***	0.54	y = 4355.1x + 3306.3
EDG ~ H	59	2.2E-16	***	0.74	y = 3.54x + 0.66
ENV ~ H	59	2.2E-16	***	0.75	y = 505.07x - 87.06
DEN ~ H	59	2.2E-12	***	0.73	y = 2994.1x + 2094.6
EDG ~ T	59	2.3E-09	***	0.46	y = 7.36x + 1.18
ENV ~ T	59	6.4E-09	***	0.44	y = 1020.87x - 3.14
DEN ~ T	59	2.7E-12	***	0.57	y = 6953.6x + 2268.9

Statistical significance level: NS $p > 0.05$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

In Figure 3, the scatter plots between canopy volume (TRW) and spray parameters (spray coverage and normalized deposits) are shown. In particular, the points are represented in different shapes and colours depending on trials and applied volume levels. The horizontal lines represent the thresholds for filtering spray data in order to maximize the efficacy and minimize the over and under-spraying and the over and under-dosing of application (Grella et al. 2022; Miranda-Fuentes et al. 2016). In general, the spray coverage data exceeded significantly the thresholds related to the normalized deposits, especially for the highest applied volume (black triangle and black circle). In fact, the spray deposits are more concentrated in the region of interest. This is probably due to the type of analysis. Spray coverage values were extracted by WSPs. They are artificial targets very susceptible to external interference, such as the dislocation of collectors in the spraying moment or in general weather conditions (wind direction and intensity) (Grella et al. 2022). Instead, the deposit values are more stable to external interferences and this is the reason many authors used this parameter than the spray coverage (Gil et al. 2007; Llorens et al. 2010; Miranda-Fuentes et al. 2016). However, in the present work, both methods were presented and disclosed in order to provide a deeper analysis.

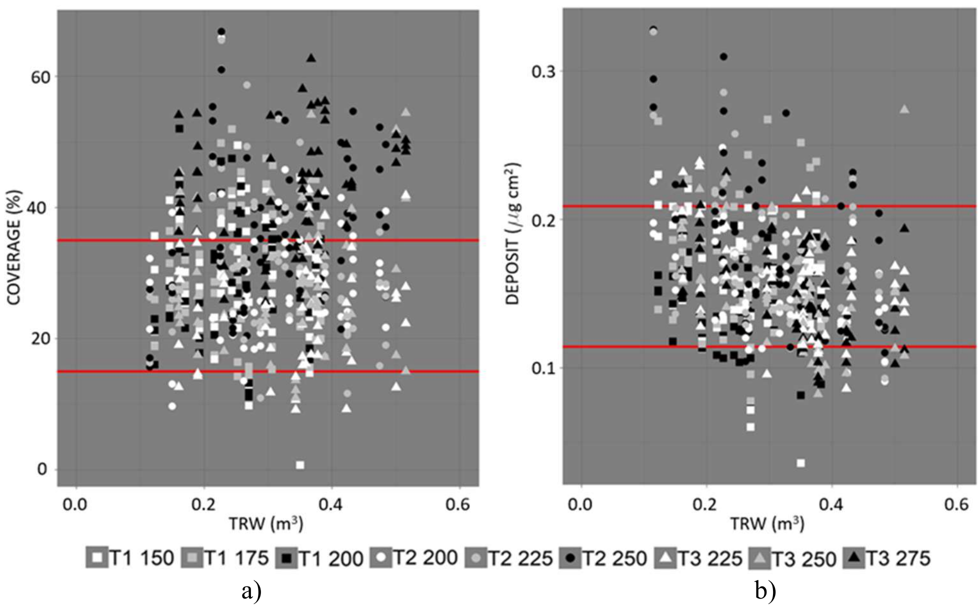
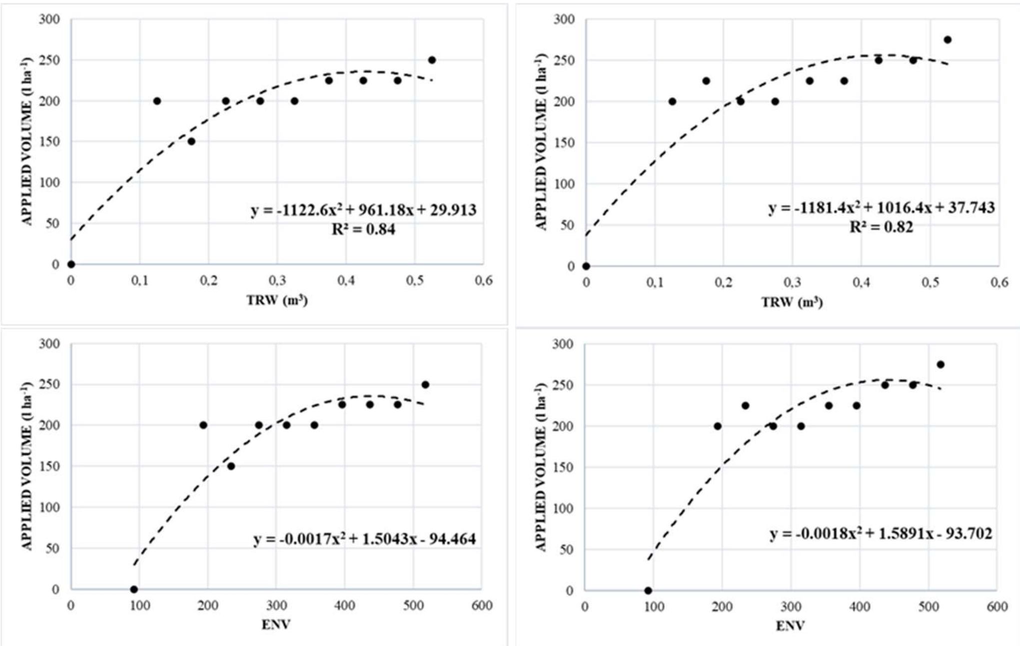
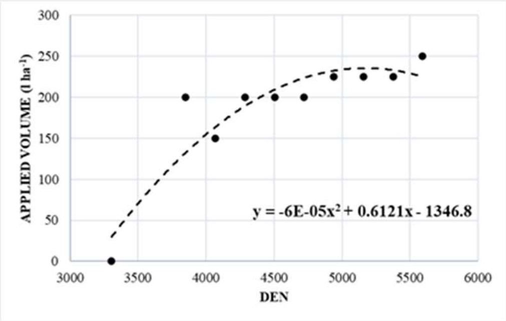


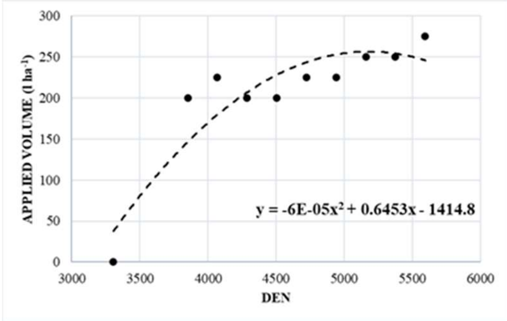
Figure 3. a) Scatter plot between spray coverage and canopy volume; b) Scatter plot between

normalized deposit and canopy volume. Different shape of points represent different trials and different colour represent different applied volumes.

The data showed in Figure 3 were used to refine the actuation range after filtering them according to the set thresholds. The filtered data was then portioned into ten subsets according to the canopy volume. This portioning has been necessary to create small datasets of homogeneous and representative vines regarding the canopy volume. Subsequently, the modal values of applied volume for each dataset were collected and plotted to build the actuation range. Finally, the equations of regression between the canopy volume and all the US parameters (EDG, ENV, DEN) were used to create and refine the actuation range for the US sensor. The actuation ranges, build according to spray coverage and normalized deposits, for the TRW and for the more reliable US measurements are shown in Figure 4.







a) b)

Figure 4. Actuation ranges for the TRW and for the US measurements. a) on the left, according to spray coverage; b) on the right, according to normalized deposits

Conclusion

The second-generation US sensor tested in this study opens new frontiers in precision spraying in terms of increasing environmental sustainability. In particular, concerning canopy detection reliability, the ultrasonic sensor showed good reliability in estimating canopy characteristics. Indeed, interesting correlations were found, especially between the canopy height and the US Envelope and Density parameters (R^2 = 0.94 and 0,92). On the basis of these results, two actuation ranges were reported according to the normalized deposit and spray coverage parameters. Thanks to them, it was possible to refine the spray volume application in compliance with good spraying thresholds. Moreover, thanks to these actuation ranges, this US sensor can be mounted in a sprayer, enabling the variable-rate application so as to improve the environmental footprint and meet European goals.

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References

Abbas, I., Liu, J., Faheem, M., Noor, R. S., Shaikh, S. A., Solangi, K. A., et al. (2020). Different sensor based intelligent spraying systems in Agriculture. *Sensors and Actuators, A: Physical*, *316*, 112265. https://doi.org/10.1016/j.sna.2020.112265

Gil, E., Arnó, J., Llorens, J., Sanz, R., Llop, J., Rosell-Polo, J. R., et al. (2014). Advanced technologies for the improvement of spray application techniques in Spanish viticulture: An overview. *Sensors (Switzerland)*, *14*(1), 691–708. https://doi.org/10.3390/s140100691

Gil, E., Escolà, A., Rosell, J. R., Planas, S., & Val, L. (2007). Variable rate application of plant protection products in vineyard using ultrasonic sensors. *Crop Protection*, *26*(8), 1287–1297. https://doi.org/10.1016/j.cropro.2006.11.003

Gil, E., Llorens, J., Llop, J., Fàbregas, X., Escolà, A., & Rosell-Polo, J. R. (2013). Variable rate sprayer. Part 2 - Vineyard prototype: Design, implementation, and validation. *Computers and Electronics in Agriculture*, *95*, 136–150. https://doi.org/10.1016/j.compag.2013.02.010

Grella, M., Gioelli, F., Marucco, P., Zwertvaegher, I., Mozzanini, E., Mylonas, N., et al. (2022). Field assessment of a pulse width modulation (PWM) spray system applying different spray volumes: duty cycle and forward speed effects on vines spray coverage. *Precision Agriculture*, 23 219 - 252. https://doi.org/10.1007/s11119-021-09835-6

Llorens, J., Gil, E., Llop, J., & Escolà, A. (2010). Variable rate dosing in precision viticulture: Use of electronic devices to improve application efficiency. *Crop Protection*, *29*(3), 239–248. https://doi.org/10.1016/j.cropro.2009.12.022

Llorens, J., Gil, E., Llop, J., & Escolà, A. (2011). Ultrasonic and LIDAR sensors for electronic canopy characterization in vineyards: Advances to improve pesticide application methods. *Sensors*, *11*(2), 2177–2194. https://doi.org/10.3390/s110202177

Lorenz, D., Eichhorn, K., Bleiholder, H., Klose, R., Meier, U., & Weber, E. (1995). Growth Stages of the Grapevine: Phenological growth stages of the grapevine (*Vitis vinifera* L. ssp. *vinifera*)—Codes and descriptions according to the extended BBCH scale. *Australian Journal of Grape and Wine Research*, *1*, 100–103. https://doi.org/https://doi.org/10.1111/j.1755-0238.1995.tb00085.x

Miranda-Fuentes, A., Llorens, J., Rodríguez-Lizana, A., Cuenca, A., Gil, E., Blanco-Roldán, G. L., et al. (2016). Assessing the optimal liquid volume to be sprayed on isolated olive trees according to their canopy volumes. *Science of the Total Environment*, *568*, 296–305. https://doi.org/10.1016/j.scitotenv.2016.06.013

Miranda-Fuentes, A., Marucco, P., González-Sánchez, E. J., Gil, E., Grella, M., & Balsari, P. (2018). Developing strategies to reduce spray drift in pneumatic spraying in vineyards: Assessment of the parameters affecting droplet size in pneumatic spraying. *Science of the Total Environment*, *616–617*, 805–815. https://doi.org/10.1016/j.scitotenv.2017.10.242

Palleja, T., & Landers, A. J. (2017). Real time canopy density validation using ultrasonic envelope signals and point quadrat analysis. *Computers and Electronics in Agriculture*, *134*, 43–50. https://doi.org/10.1016/j.compag.2017.01.012

Rosell, J. R., & Sanz, R. (2012). A review of methods and applications of the geometric characterization of tree crops in agricultural activities. *Computers and Electronics in Agriculture*, *81*, 124–141. https://doi.org/10.1016/j.compag.2011.09.007

Wickham, H. (2016). ggplot2: Elegant Graphics for Data Analysis. New York, USA: Springer-Verlag.

https://ggplot2.tidyverse.org/

3.4.Paper IV

Can a variable-rate sprayer be efficient and economic? Testing and economic analysis in viticulture

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Abstract

The European Union has set ambitious goals in terms of reducing pesticides in agriculture. These goals could be achieved in different ways e.g. by Variable-Rate Application (VRA) technologies. This work aims to assess the spraying performance of a VRA sprayer and its economic sustainability. To evaluate operational performance, three trials (BBCH 65, BBCH 73, BBCH 83) were performed in a vineyard following a profile sampling strategy (BS ISO 22522:2007). A randomized complete block design was performed with three replications for each application mode (Uniform and Variable - UA and VRA). Variables (normalized deposition and spray coverage) were extracted from artificial targets using spectrophotometry and image analysis techniques, respectively. Moreover, the economic performance of the VRA sprayer compared to the UA sprayer was performed for an entire vegetative season in two plots. Normalized deposit results showed differences between detection heights (H1, H2, H3, H4) rather than between modes (VRA vs UA). Therefore, VRA and UA efficacy was confirmed, given the similar values of deposit. The same trend was evident in the spray coverage results, even though the UA spray coverages were higher than VRA, usually exceeding the overspray threshold. The economic performance highlighted an average volume saving of 35% for VRA, ranging from 76% in the first session to 10% in the last. The resulting economic saving was €2,599.50, consisting of: €2,502.5 in pesticides, €52.14 in water and €44.86 in fuel. Overall, the VRA system showed good spray performances reducing the spray volume significantly and enhancing economic sustainability.

Keywords: VRA, spraying optimization, pesticide, ultrasonic sensor, vineyard, environmental sustainability.

Introduction

The economic sustainability of farms has always been the main aspect to consider in order to maintain a stable business. In recent years, environmental sustainability has been complemented by economic sustainability [1]. Particularly in viticulture, some field activities such as crop protection have a heavy environmental and economic footprint [2]. Recently, the war between Russia and Ukraine , the post-pandemic situation and ongoing inflation are hitting all sectors hard. The price of raw materials as fertilizers, fuel, pesticides and energy is increasing, pushing farms in a difficult position [3]. At the same time, the attention of public decision-makers is focused on green policies. Recently, the European Commission, through the documents «From Farm to Fork», has set ambitious goals to reach a healthy and sustainable food system [4]. To achieve these targets, farmers must reduce the number of chemical inputs as PPP (plant protection products), fertilizers and antimicrobials products.

In particular, many techniques and tools exist in viticulture to achieve these goals for example decision support systems, development of less dangerous PPP, low volume applications, anti-drift nozzles and variable-rate applications [5].

The latter is one of the most interesting tools for adapting plant protection products to the canopy characteristics, thus reducing their consumption [6]. In general, the new VRA sprayers are very expensive compared to conventional ones. This fact leads farmers not to buy them, even if VRA sprayers can improve spray performance, reduce the consumption of pesticides and, in general, enhance economic and environmental sustainability [7].

Within this context, the present work aims to develop a low-cost modification kit to convert the existent sprayer into an innovative VRA in order to reduce pesticides consumption and enhance environmental and economic sustainability without affecting operational performance. Therefore, the purpose of this research is to test and assess the spraying and economic performance of this kit, for conventional sprayers, able to perform variable rate spraying according to canopy size. The study can be split in two different parts. In the first part, three trials were conducted at different phenological stages to evaluate the spraying performance of the sprayer in VRA compared to UA mode. In the second, the same sprayer was used to perform an entire season of spraying in VRA mode, with the aim of assessing its economic performance in relation to UA one.

Materials and Methods

A vineyard in the Chianti Classico area has been the place of experimentation. In particular, the vineyard was located in Gretole (4813930.984 N; 680511.290 E), Castellina in Chianti, Siena, Italy (Fig. 1). The vineyard had a density of 5000 vines ha^{-1}, with a planting distance of 2.50 x 0.80 m, and the cultivar was the *Vitis vinifera* L. cv. 'Sangiovese'. The vines were 16-years old and trained with a horizontal spur- cordon. This vineyard was used for both operational and economic performance tests.

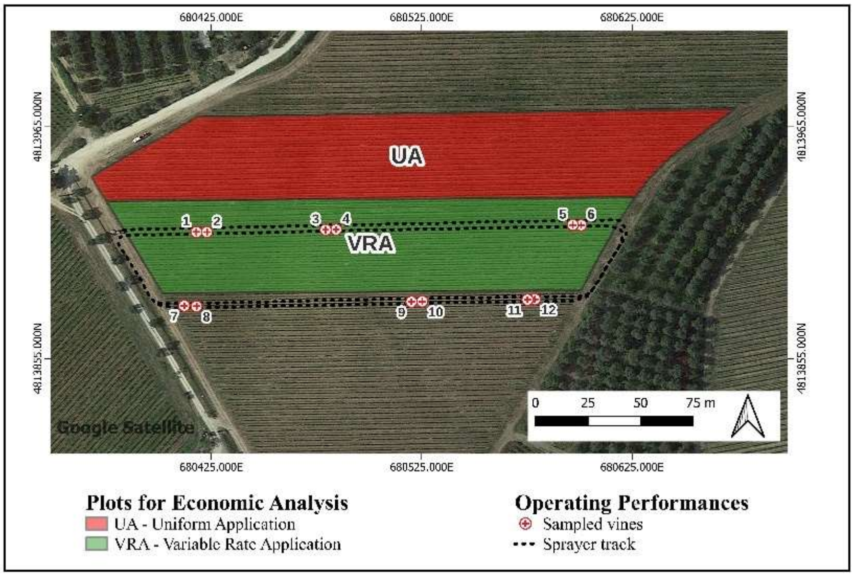


Figure 1. Experimental site for operating and economic performances of VRA sprayer.

During the trials, a tractor-drawn, PTO-powered, pneumatic sprayer (Martignani M612 Whirlwind, Ravenna, Italy) was used. The sprayer was equipped with a 1000 L polyethylene tank, a centrifugal fan, a centrifugal pump (120 l/min, 150kPa), and 6 nozzles per side (Ø 4 mm). Air was expelled by two radial air conveyors at 90° to the direction of the travel, with a homogeneous air flow around 26,000 m^3 h^{-1}. The sprayer was customized to be able to applicate pesticides at variable rate (VRA) according to the canopy size. A new generation of ultrasonic sensors has been installed at the forepart of the sprayer to perform the VRA (NORAC Topcon, Tokyo, Japan). These sensors can analyse the canopy in terms of thickness, foliar layers and density. These data were used to adjust the spray volumes to the size of the canopy. The spraying components were also customised. In fact, the original valves have been replaced by electronic ones. In particular, in the rear of the sprayer, there were eight electro-valves, four for the left side and four for the right side. These valves control the flow rate of spray volume, thanks to their switching on/off. The combination of opening and closing of electro-valves and the variation of pressure from 1 bar to 2 bars permits to applicate pesticides at variable rate. The flow rates for each electro-valves are shown in table 1, at 1.5 bar of pressure.

Table 1. Flow rates for each electro-valves (EV – Electro-Valve; $_L$ or $_R$ – Left or Right; $_{A, B, C, D}$ – correspond to different electro-valves)

1.5 bar	EV_{LA}	EV_{LB}	EV_{LC}	EV_{LD}	EV_{RD}	EV_{RC}	EV_{RB}	EV_{RA}
Flow rate (l m^{-1})	0.56	0.86	1.46	2.26	2.26	1.46	0.86	0.56

All the instrumentations were controlled by X25 Topcon console, mounted on the cabin of the tractor and connected with a D-GNSS antenna (Differential - Global Navigation Satellite Systems). From this monitor, all working parameters can be controlled, managed and recorded.

Operating performances

The operating performances of VRA consist of evaluating the quality and quantity of the application against the uniform application (UA). Both of them followed the British Standard ISO 22522/2007. In particular, the profile sampling strategy was used. During the growing season, three trials were carried out in three different phenological phases (BBCH 65, BBCH 73, BBCH 83) and, in each one, twelve vines were sampled [8]. Before each trial, the sprayer was calibrated correctly. During each test, air temperature, air humidity, wind speed and direction were monitored at a height of 2 m, using a 2900ET Watchdog Weather Station (Spectrum Technologies Inc., Illinois, USA). Fig. 2 shows the sampling strategy within the vines and in the different tests. To guarantee a good sampling strategy, following the BS ISO, a randomized complete block design was performed with three repetitions for each application mode (UA vs. VRA) and both sides of the canopy were sampled.

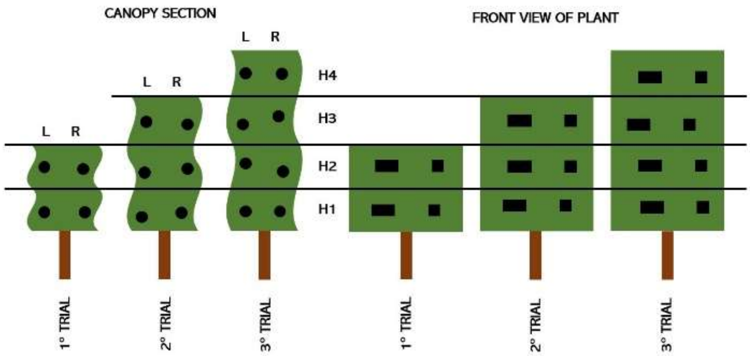


Figure 2. Sampling strategy in different phases (L or R – Left or Right; H1, H2, H3, H4 – Different heights of sampling; ● – collectors; ■ – plastic collector; ▬ – water sensitive paper).

Concerning the spray volume applied in the trials, the farm protocol for the UA mode was followed. Instead, a calibration curve between the canopy size, spray volumes and sensor readings was developed and applied for the VRA mode. During trials, the forward speed of tractor was of 5 km h-1. Table 2 shows the whole spray settings in the three trials.

Table 2. Application parameters during the field trials

Trials	Phenological stage	UA mode	*sd*	VRA mode	*sd*	
1° trial	BBCH 65	200	±0.5	0 (48 - 198)	±4.5	l ha^{-1}
2° trial	BBCH 73	250	±1.9	0 (109 - 299)	±1.6	l ha^{-1}
3° trial	BBCH 83	300	±0.5	0 (131 - 344)	±0.8	l ha^{-1}

Regarding the samples, water-sensitive papers (WSP, 26 x 76 mm, Syngenta, Switzerland) and plastic collectors (50 x 90 mm, SEFAR NITEX) were arranged to evaluate the quality and the quantity of spraying, respectively [9, 10]. In laboratory, the WSPs were scanned at a resolution of 600 dpi using a Kyocera TASKalfa 3554ci KX scanner-printer and then, were analysed by the software ImageJ (v. 1.38x) to extract the spray coverage parameter (%).The amount of application was instead evaluated through the use of tartrazine, plastic collectors and spectrophotometry methodology. In particular, E-102 yellow Tartrazine (Andrea Gallo S.r.l., Genova, Italy) were added to the sprayer's tank at a concentration of 8 g l^{-1} [11]. The tartrazine concentration on plastic collectors was quantified by using a spectrophotometer UV-1200 (ChromTech, Bad Camberg, Germany), after having washed collectors with 20 ml of distilled water. Before obtaining the absorbance values of the samples, the blank values were subtracted from the samples to obtain the real absorbance. Then, the absorbance values were converted to deposits (d_i) using a calibration curve, obtained by dilutions of the tank liquid, and the below formula:

$$d_i = \frac{\frac{(A_r - A_b)}{\alpha} \times V_{dil}}{S_{ps}} \qquad \mu\text{g cm}^{-2} \quad (1)$$

where: d_i is the spray deposit expressed in mg cm^{-2}; A_r is the absorbance value of the sample; A_b is the absorbance of the blank sample; α is the calibration curve coefficient; V_{dil} is the washing solution of collectors; S_{ps} is the area of plastic collectors.

In order to avoid influences of different rate of application and tracer concentration, values of deposit (d_i) were converted to normalized deposits (d_n)

values through the below formula (Eq. 2).

$$d_n = \frac{d_i \times 100}{A_{vol} \times c_{tar}} \qquad \mu g\ cm^{-2} \qquad (2)$$

where: d_n is the spray normalized deposit expressed in mg cm^{-2}; d_i is the spray deposit expressed in mg cm^{-2}; A_{vol} is the application volume of sprayer expressed in l ha^{-1}; c_{tar} is the concentration of tartrazine (8 g l^{-1}).

Economic performances

The economic performance analysis was conducted on an entire season of crop protection in two neighbouring plots of around 1 ha each (Fig. 1). In the first plot, the sprayer was used in UA mode, *i.d.* the same spray volume was applied within the plot for each individual crop protection phase .In the other plot, the sprayer was operated in VRA mode, *i.d.* the ultrasonic sensor varied the spray volume according to the size of the canopy.

Concerning the crop protection protocol (spray volumes, pesticides and schedule), the farm protocol was followed for the UA mode while, only the spray volumes were modified for the VRA mode. In particular, a calibration curve between the canopy size, application volume and sensor readings was developed and applied at every crop protection phase. Table 3 shows the spray settings during the entire crop protection season.

To perform a costs/benefits analysis, spraying volumes, pesticides, equipment and raw materials were monitored. Specifically, the reports for each phase of crop protection were downloaded from the monitor's storage memory and analysed to extract the values of spraying volumes for both modes (UA, VRA). Finally, the accounting of pesticides, equipment and raw materials (water, fuel) was evaluated in terms of quantity and costs using the farm's fields-book and the national/regional quotation.

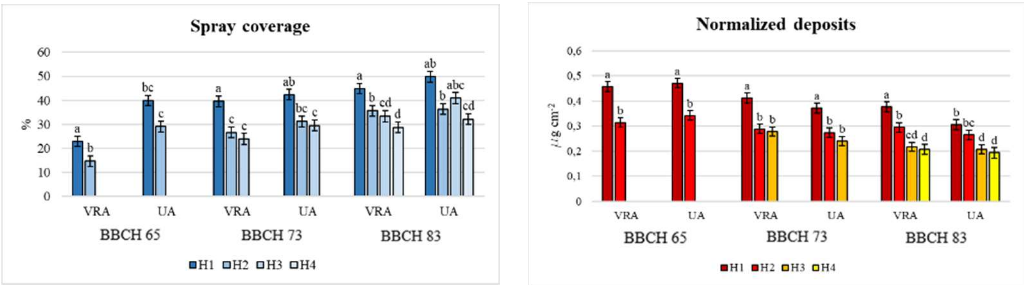
Results and Discussion

Operative performances

The results of the spraying performance were shown in Figure 3a and 3b. The three phenological phases, were reported In each graph. According to the plant growth, the sampling heights increase in the different trials (BBCH 65, BBCH 73, BBCH 83).

Considering the spraying coverage graph (Fig. 5a), it was found that statistically significant differences were found between heights and application mode (VRA, UA) in all theses and trials, with the exception of H3 in BBCH 73 and H2 in BBCH 83 among the application mode, and for H2 and H3 within VRA in BBCH 73 phase. However, the overall spraying coverage trend highlighted quite constant rates of coverage between phenological phases, with the first stage in VRA mode, which was significantly lower than the other theses. In relation to the UA mode, it could mean that the farm protocol was correct because it ensured the same rate of coverage in different canopy volumes. However, the values of coverage are too high in relation to the overspray threshold widely agreed upon by other authors [12]. Regarding the graph in figure 5b, it was found that statistically significant differences were only found between different sampling heights and in the BBCH 83 phase between the application modes in H1, H2 and H3. In all these cases, deposits were higher in VRA in VRA than UA. Generally, the common trend between analysed variables (%, d_n) is the decreasing of values between the H1 detection height and subsequent ones. This aspect was highlighted in both the VRA and UA and was probably due to the construction characteristics of the sprayer. In fact, the sprayer had two air conveyors located below the cordon and they sprayed the entire canopy with a radial spraying. Therefore, the vertical profile of canopy was not at the same distance as the air conveyors, causing scalar values in both deposits and coverage. This aspect was also highlighted by Matthews et al. (2014) [13].

Reading the overall values of the three trials, , the minimum values for good pesticide efficacy were respected in all cases [11, 14, 15]. In general, uniform application provides higher values in the coverage parameter, especially for the sampling zone near the cordon., these values often exceed the maximum value for good coverage.



a b

Figure 3. Results of the two-way ANOVA for the spray coverage (%) and the normalized deposits (mg cm^{-2}). Statistical significance: $p < 0.05$ (Tukey's HSD post-hoc test)

Economic performances

The results of economic performance were shown in table 3. In particular, two main aspects were shown in the table. The first one is called technical analysis, where important parameters such as the number of crop protection phases, volumes of mixture applied in UA and VRA modes, the number of tank refills and the number of days to complete a work activity were reported. These values were recorded or calculated from reports provided by the tractor console and the spatial layout of the farm's vineyards, which affected the downtime of refills. The second aspect concerns the costs of pesticides, water and fuel. Here, the economic performance of the UA and VRA modes were reported for each phase.

Regarding the technical analysis, the wine farm protected the vineyards with nine phytosanitary treatments during the season for both spraying modes. During this period, there was a saving in spray volume ranging from 76% in the first stage to 10% in the last. This decreasing trend in spray volume savings between the first and the last stage is a normal consequence of modern training systems. This is due to the closing and compactness of the canopy during the growing season [16]. The average saving was 35%. Similar savings were found in other studies as reported by Gil et al. (2007), Jejčič et al. (2011) and Tona et al. (2018) [12, 17, 18]. As far as work performance is concerned, an increase in efficiency in VRA mode compared to UA one can be shown. This is due to fewer refills of the sprayer tank because of less spray volume consumption. This increased the work performance of VRA in terms of days to complete a crop protection stage in a 22 ha field . The wine farm size was set at around 22 ha because Tona et al. (2018) stated this value is the limit to perform crop protection with a single sprayer ("sharp cost edges" effect) [18].

With regard to the costs analysis, the type and quantity of pesticides and their costs were monitored at each stage using the field book of the wine farm. Then, the unit cost per litre was calculated and multiplied by the volume sprayed in both application modes for each stage thus obtaining the cost of each treatment. The same was done for water costs. In this case, the local water cost per cubic metre was used. the increase in the fuel cost in UA mode, on the other hand, is due to the need for more refills due to the higher consumption of spray volume. This leads to the farmer going to the farm centre several times to refill the sprayer tank, especially in the early stages, causing considerable fuel consumption. The accounting of cost fuel was carried out following the methodology of Sarri et al. (2020) and analysing the wine farm arrangement of vineyards [2].

In terms of pesticide cost savings , the farm was able to save € 113.75 per year, and € 2,502.50 for a 22 ha farm by using VRA. The savings in terms of water use was smaller. In fact, the farm was able to save € 52.14 per a 22 ha-farm . This is due to the cheaper price for water use. In terms of fuel cost, the farmer was able to save € 44.86 over an entire season and for 22 ha thanks to VRA mode. Overall, the cost saving in VRA mode was € 2,599.50. Regarding savings on raw materials, the farm can reduce its consumption of pesticides by around 262.67 kg, water by around 18.00 m^3 and fuel by around 35.00 l.

Table 3. Summary table of main parameters and their costs in a whole crop protection season both in UA and VRA mode.

Technical parameters								Pesticides cost				Water cost			Fuel cost		
Crop protection stages	UA	VRA	Diff. %	Refill UA	Refill VRA	n° days to end UA	n° days to end VRA	Unit price	UA price	VRA price	Price diff. UA_VRA	UA price	VRA price	Price diff. UA_VRA	UA price	VRA price	Price diff. UA_VRA
n°	l ha^{-1}	l ha^{-1}	%	n°day^{-1}	n°day^{-1}	n° days 22ha^{-1}	n° days 22ha^{-1}	€ l^{-1}	€ ha^{-1}	€ ha^{-1}	€ ha^{-1}	€ ha^{-1}	€ ha^{-1}	€ ha^{-1}	€ 22ha^{-1}	€ 22ha^{-1}	€ 22ha^{-1}
1	200	49	76	2	1	2.62	2.29	0.10	20.00	4.90	15.10	0.60	0.15	0.45	13.20	5.78	7.42
2	200	56	72	2	1	2.62	2.29	0.22	44.00	12.32	31.68	0.60	0.17	0.43	13.20	5.78	7.42
3	200	69	66	2	1	2.62	2.29	0.11	22.00	7.59	14.41	0.60	0.21	0.39	13.20	5.78	7.42
4	200	80	60	2	1	2.62	2.29	0.14	28.00	11.20	16.80	0.60	0.24	0.36	13.20	5.78	7.42
5	250	155	38	3	2	2.75	2.62	0.23	57.50	35.65	21.85	0.75	0.47	0.28	20.79	13.20	7.59
6	250	212	15	3	2	2.75	2.62	0.15	37.50	31.80	5.70	0.75	0.64	0.11	20.79	13.20	7.59
7	330	285	14	3	3	2.82	2.82	0.09	29.70	25.65	4.05	0.99	0.86	0.13	21.32	21.32	-
8	330	289	12	3	3	2.82	2.82	0.06	19.80	17.34	2.46	0.99	0.87	0.12	21.32	21.32	-
9	330	296	10	3	3	2.82	2.82	0.05	16.50	14.80	1.70	0.99	0.89	0.10	21.32	21.32	-
							Values referred to year	€	275.00	161.25	113.75	6.87	4.50	2.37			
							Values referred to 22 ha	€	6,050.00	3,547.50	2,502.50	151.14	99.00	52.14	158.34	113.48	44.86

The costs for customising the sprayer amounted to approximately € 20,000.00. These costs mainly regarded sensors, electro-valves, console, cables and working customisation time. Taking this and the VRA savings into account, it was possible to perform a break-even analysis, as shown in figure 4. This analysis highlighted that the profitability of this technology will be within the 8th year of customization. However, customisation costs were considered as actual costs and therefore overestimated due to prototyping actions. Considering that, it is estimated that customization costs can be reduced by around 50%. For this reason, the break-even point was set at year 4th.

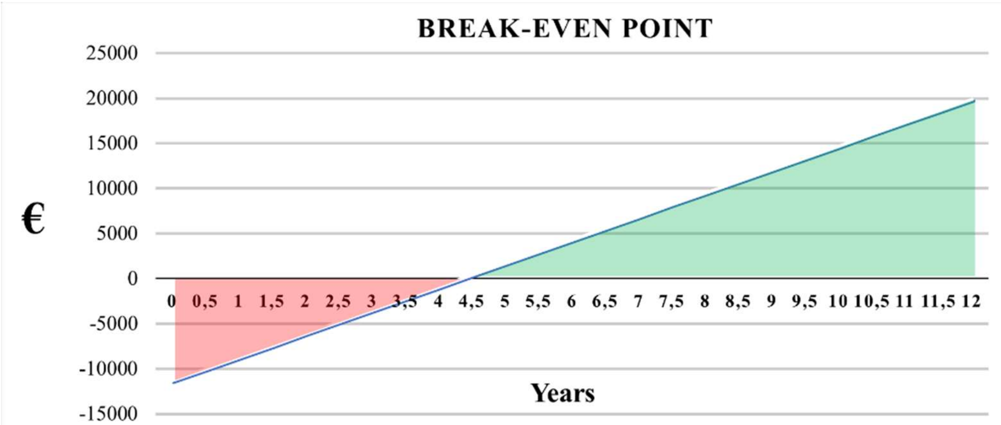


Figure 4. Results of costs/benefits analysis in terms of break-even point.

Conclusion

In order to achieve the EU goals in terms of reducing pesticide use and effectively introducing new technologies on farms, the technological innovation must be both environmentally and economically sustainable . In particular, spatial variability in vineyards is one of the most important aspects to take into account to reduce the environmental footprint of crop protection. This variability can be managed with new variable rate sprayers that can adapt the spray volume to the size of the canopy. However, to keep costs under control, an economic modification kit was presented in this paper. This kit is able to convert conventional sprayers into innovative VRA sprayers to reduce pesticide consumption and enhance environmental and economic sustainability without affecting operational performance. The results obtained are promising. In fact, the differences reported in the results section mainly reflect the architectural design of the sprayer rather than the mode of application (UA & VRA). However, all parameters examined (normalized deposit and spray coverage) in the trials ensure good quality and quantity distribution of pesticides. Moreover, the variable-rate application reduces application volumes while ensuring excellent performance in terms of normalized deposit and spray coverage. Nonetheless, economic analysis has demonstrated that variable-rate technology enhances the economic and environmental sustainability of crop protection.

References

1. Recchia L, Sarri D, Rimediotti M, Boncinelli P, Cini E, Vieri M (2018)Towards the environmental sustainability assessment for the viticulture. J Agric Eng 49:19–28. https://doi.org/10.4081/jae.2018.586
2. Sarri D, Lombardo S, Pagliai A, Zammarchi L, Lisci R, Vieri M (2020) A technical-economic analysis of telemetry as a monitoring tool for crop protection in viticulture. J Agric Eng 51:91–99. https://doi.org/10.4081/jae.2020.1029
3. Nayak J, Mishra M, Naik B, Swapnarekha H, Cengiz K, Shanmuganathan V (2022) An impact study of COVID-19 on six different industries: Automobile, energy and power, agriculture, education, travel and tourism and consumer electronics
4. European Commission (2020) A Farm to Fork Strategy for a fair, healthy and environmentally-friendly food system
5. Pagliai A, Ammoniaci M, Sarri D, Lisci R, Perria R, Vieri M, D'arcangelo E, Storchi P, Kartsiotis SP (2022) Comparison of Aerial and Ground 3D Point Clouds for Canopy Size Assessment in Precision Viticulture. Remote Sens 14. https://doi.org/10.3390/rs14051145
6. Gil E, Llorens J, Llop J, Fàbregas X, Escolà A, Rosell-Polo JR (2013) Variable rate sprayer. Part 2 - Vineyard prototype: Design, implementation, and validation. Comput Electron Agric 95:136–150. https://doi.org/10.1016/j.compag.2013.02.010
7. Sarri D, Lombardo S, Pagliai A, Perna C, Lisci R, De Pascale V, Rimediotti M, Cencini G, Vieri M (2020) Smart farming introduction in wine farms: A systematic review and a new proposal. Sustain 12. https://doi.org/10.3390/su12177191
8. Lorenz D, Eichhorn K, Bleiholder H, Klose R, Meier U, Weber E (1995) Growth

Stages of the Grapevine: Phenological growth stages of the grapevine (Vitis vinifera L. ssp. vinifera)—Codes and descriptions according to the extended BBCH scale. Aust J Grape Wine Res 1:100–103. https://doi.org/https://doi.org/10.1111/j.1755-0238.1995.tb00085.x
9. Salyani M (2000) Methodologies for assessment of spray deposition in orchard applications. In: 2000 ASAE Annual International Meeting. American Society of Agricultural Engineers, Milwaukee, Wisconsin, USA, p 11
10. BS ISO (2007) BS ISO 22522-2007 - Crop protection equipment-Field measurement of spray distribution in tree and bush crops
11. Miranda-Fuentes A, Rodríguez-Lizana A, Gil E, Agüera-Vega J, Gil-Ribes JA (2015) Influence of liquid-volume and airflow rates on spray application quality and homogeneity in super-intensive olive tree canopies. Sci Total Environ 537:250–259. https://doi.org/10.1016/j.scitotenv.2015.08.012
12. Gil E, Escolà A, Rosell JR, Planas S, Val L (2007) Variable rate application of plant protection products in vineyard using ultrasonic sensors. Crop Prot 26:1287–1297. https://doi.org/10.1016/j.cropro.2006.11.003
13. Matthews GA (2014) Air-assisted sprayers. In: Pesticide Application Methods, 4th ed. John Wiley & Sons, Ltd., pp 215–244
14. Salcedo R, Zhu H, Zhang Z, Wei Z, Chen L, Ozkan E, Falchieri D (2020) Foliar deposition and coverage on young apple trees with PWM-controlled spray systems. Comput Electron Agric 178:105794. https://doi.org/10.1016/j.compag.2020.105794
15. Grella M, Gioelli F, Marucco P, Zwertvaegher I, Mozzanini E, Mylonas N, Nuyttens D, Balsari P (2022) Field assessment of a pulse width modulation (PWM) spray system applying different spray volumes: duty cycle and forward speed effects on vines spray coverage. Precision Agric 23, 219–252.

https://doi.org/10.1007/s11119-021-09835-6

16. Zhang Z, Wang X, Lai Q, Zhang Z (2018) Review of Variable-Rate Sprayer Applications Based on Real-Time Sensor Technologies. In: Automation in Agriculture - Securing Food Supplies for Future Generations. p 13. https://doi.org/10.5772/intechopen.73622
17. Jejcic V, Godeša T, Hocevar M, Širok B, Malneršic A, Štancar A, Lešnik M, Stajnko D (2011) Design and testing of an ultrasound system for targeted spraying in orchards. J Mech Eng 57:587–598. https://doi.org/10.5545/sv-jme.2011.015
18. Tona E, Calcante A, Oberti R (2018) The profitability of precision spraying on specialty crops: a technical–economic analysis of protection equipment at increasing technological levels. Precis Agric 19:606–629. https://doi.org/10.1007/s11119-017-9543-4

4. General conclusions

Environmental sustainability is fast becoming a critical aspect of modern crop production. New technologies and digitalisation are paving the way for reducing the environmental footprint without compromising the economic sustainability of farms. In viticulture, for example, one of the largest footprint operations is the crop protection phase. Many phytosanitary treatments need to be applied throughout the growing season to protect the vines from pathogens. This scenario is the basis of my Ph.D. path, in which the main objectives of my studies have been addressed in four scientific manuscripts. In each paper, I have focused on specific preliminary questions and actions, attempting to fulfil them, contribute to the scientific community's knowledge and achieve a concrete result in reducing the environmental footprint of crop protection. Specifically, the objectives of my PhD were to understand the strengths and weaknesses of new sensors (LiDAR, US), technologies (UAV, MA) and techniques (SfM, 2-3D pint clouds) in canopy characterisation. These preliminary studies were fundamental for the development and calibration of a VRA kit, based on a new US sensor, to be implemented in existing sprayers. Finally, the modified sprayer was tested to verify that its operating parameters ensured good crop protection reliability and to determine its economic and environmental sustainability.

Specifically, **Paper I** proved that the proposed automatic algorithm, based on LiDAR sensor and D-GNSS, was able to assess the canopy volumes in vineyards with a good reliability in relation to the TRV index. This solution provided a simplified method to automatically manage the 3D point clouds, avoiding the complex and laborious procedures of canopy characteristics computing through post-processing point clouds reconstruction. Moreover, the proposed solution, thanks to its flexibility, can be used in different contexts (planting distance, training systems) and in different ways (in real-time or in post-processing). In fact, thanks to its high computational speed, the software is able to process data in real time, opening the way to the on the go solutions. It can also record data in a .csv file, giving the opportunity to process data and to create prescription maps thanks to the geo-referenced data. Based on this, an interesting point of investigation not explored in this study is to further evaluate the relationship between canopy assessment shown in this paper and canopy extraction in post-processing with other technologies and techniques.

Under these circumstances, an evaluation of different technologies (MLS, MA, UAV) and techniques (SfM, 2-3D point clouds) in the assessment of canopy size parameters such as thickness, height and volume (TRV) was disclosed in **Paper II**. This comparison was necessary to answer two questions. Firstly, it was a further validation of the functioning of the LiDAR-based algorithm. Secondly, the tools were compared in terms of their ability to detect and characterise the spatial variability of the vineyard in order to generate zonation maps useful for precision spraying management and the implementation of VRA systems. In general, the results showed a good correlation between all the tools in terms of detection of the intra-field variability and the canopy size parameters. Specifically, the highest coefficient of determination were obtained between the height data for all the tools, with the highest value of $R^2 = 0.86$ for the MA vs. MLS comparison. Instead, the lowest correlations were found between the thickness data, ranging from 0.5 to 0.6. In detail, the weaker correlation was between UAV and MLS ($R^2 = 0.48$). Finally, the R^2 between the canopy volumes acquired with the different tools showed moderately strong correlations. In fact, the highest value of $R^2 = 0.78$ was found between the UAV and MLS tools. On the basis of these results, all tools and techniques ensured a good reliability in terms of canopy characterisation. In terms of usability, the UAV technology allows to quickly map lots of hectares but it requires trained staff and specific data collection sessions. The MA shares the specific data collection sessions with the UAV, but it provides more punctual measurements and is cheaper than the other tools, making it more affordable for small farms. Instead, the MLS can be installed directly on farm tractors so that the data can be collected automatically during field operations. The main limitations of the UAV and MA tools are related to the data processing step which is time-consuming and requires adequate computing power. However, as the MLS tool is an embedded solution, the above weaknesses are not a problem.

These studies were critical to the development and the validation of the sensing system in the VRA implementation kit. In fact, the reliability of a new US sensor in terms of canopy characterisation was demonstrated in **Paper III**. In addition, the relationship between sensor readings, canopy characteristics and spray rates was investigated for future implementation of the US sensor in a VRA sprayer. The sensor tested in this study is able to discriminate the foliar layers and the canopy density thanks to its innovative mode of operation. In fact, unlike the most common US, this new sensor works on the wave intensity of different ultrasonic echoes. The study revealed interesting correlations, particularly between the canopy height and the US parameters ($R^2 > 0.7$). However, the correlations between the canopy volume (TRW) and the US measurements also showed moderately strong correlations ($R^2 > 0.6$). Furthermore, the lowest correlations were between the canopy thickness and the US parameters. These findings are consistent with the those of Paper II. On the basis of Paper III's results, a good reliability in the estimation of canopy characteristics was demonstrated for the innovative US sensor. Therefore, in order to transfer this technology to a sprayer, two actuation ranges were reported according to the normalised deposition and spray coverage parameters. This allowed the spray rates to be refined in relation to the US readings, thus enabling the use of this sensor in a VRA sprayer.

Finally, **Paper IV** presents the studies on the operational functioning and economic analysis of the VRA implementation Kit. The previously disclosed sensor system was embedded into a conventional sprayer in order to keep costs under control and make the innovation more profitable. Thanks to that, it was possible to convert it into an innovative VRA sprayer, in order to reduce pesticide consumption and enhance environmental and economic sustainability without affecting operational performance. In terms of operational performance, all the parameters studied in the trials (normalised deposition and spray coverage) ensure good quality and quantity distribution of the pesticides. In fact, the differences observed are mainly due to the sprayer's architectural design rather than to the application method (UA & VRA). In addition, the variable rate application reduces spray volumes while maintaining excellent performance in terms of normalised deposition and spray coverage. These aspects were clearly supported by the economic analysis, which showed significant savings in pesticide, water and fuel consumption. These savings had an impact both on the economic analysis, leading the BEP to around the 4th year, and on the environmental sustainability of the crop protection stages, reducing above all the pesticides consumption.

In summary, during these three years of intensive work, many activities have been carried out to characterise the canopy using different sensors, technologies and techniques, and to develop and implement a VRA kit. These activities have had one main focus, *i.e.* to reduce the environmental footprint in the crop protection phases without compromising economic sustainability. Therefore, this research aims both to increase the scientific community's knowledge of the use of innovative technologies applied to canopy characterisation in viticulture and to implement a practical tool for farmers to convert a conventional sprayer into an innovative VRA one. However, future efforts should focus on solving the homogeneity issue of spray deposition and coverage over the vertical profile of the canopy highlighted in Paper IV. This problem could be solved by replacing the factory radial air conveyor with a tower-shaped one. Another significant improvement in minimising the environmental footprint of crop protection stages could be the implementation of the current VRA kit in a tunnel sprayer. In this way, the spray can be adjusted according to the VRA system, and the spray not retained by the canopy (spray drift) can be recovered by the tunnel system, filtered and re-injected in the sprayer. In addition, full electrification of the sprayer would allow all components, particularly the air fan, to be controlled at variable rates to further improve the application of PPP. Of course, these improvements would change the original concept of this research, which was to find a practical, economic and innovative solution for farmers to minimise the environmental impact of crop protection phases without compromising economic sustainability.

References

Abbas, I., Liu, J., Faheem, M., Noor, R. S., Shaikh, S. A., Solangi, K. A., & Raza, S. M. (2020). Different sensor based intelligent spraying systems in Agriculture. *Sensors and Actuators, A: Physical*, *316*, 112265. https://doi.org/10.1016/j.sna.2020.112265

Ammoniaci, M., Kartsiotis, S. P., Perria, R., & Storchi, P. (2021). State of the art of monitoring technologies and data processing for precision viticulture. *Agriculture (Switzerland)*, *11*(3), 1–21. https://doi.org/10.3390/agriculture11030201

Anifantis, A. S., Camposeo, S., Vivaldi, G. A., Santoro, F., & Pascuzzi, S. (2019). Comparison of UAV photogrammetry and 3D modeling techniques with other currently used methods for estimation of the tree row volume of a super-high-density olive orchard. *Agriculture (Switzerland)*, *9*(11). https://doi.org/10.3390/agriculture9110233

Arnó, J., Escolà, A., Vallès, J. M., Llorens, J., Sanz, R., Masip, J., et al. (2013). Leaf area index estimation in vineyards using a ground-based LiDAR scanner. *Precision Agriculture*, *14*(3), 290–306. https://doi.org/10.1007/s11119-012-9295-0

Balsari, P., & Marucco, P. (2009). Making the most efficient use of pesticide application in vineyards–Experiences from Europe. *Crop Protection in Vineyards Plumpton College*, *38*(1), 10095.

Bao, Y., Tang, L., Srinivasan, S., & Schnable, P. S. (2019). Field-based architectural traits characterisation of maize plant using time-of-flight 3D imaging. *Biosystems Engineering*, *178*, 86–101. https://doi.org/10.1016/j.biosystemseng.2018.11.005

Bramley, R. G. V., Evans, K. J., Dunne, K. J., & Gobbett, D. L. (2011). Spatial variation in response to "reduced input" spray programs for powdery mildew and botrytis identified through whole-of-block experimentation. *Australian Journal of Grape and Wine Research*, *17*(3), 341–350. https://doi.org/10.1111/j.1755-0238.2011.00153.x

Campos, J., Gallart, M., Llop, J., Ortega, P., Salcedo, R., & Gil, E. (2020). On-Farm Evaluation of Prescription Map-Based Variable Rate Application of Pesticides in Vineyards. *Agronomy*, *10*(1), 102. https://doi.org/10.3390/agronomy10010102

Chandel, A. K., Khot, L. R., Molaei, B., Peters, R. T., Stöckle, C. O., & Jacoby, P. W. (2021). High-resolution spatiotemporal water use mapping of surface and direct-root-zone drip-irrigated grapevines using uas-based thermal and multispectral remote sensing. *Remote Sensing*, *13*(5), 1–17. https://doi.org/10.3390/rs13050954

Chen, Y., Zhu, H., Ozkan, H. E., Derksen, R. C., & Krause, C. R. (2013). Spray drift and off-target loss reductions with a precision air-assisted sprayer. *Transactions of the ASABE*, *56*(6), 1273–1281. https://doi.org/10.13031/trans.56.10173

Cheraiet, A., Carra, M., Lienard, A., Codis, S., Vergès, A., Delpuech, X., & Naud, O. (2019). Investigation on LiDAR based indicators for predicting agrochemical deposition within a vine field. In J. V. Stafford (Ed.), *Precision agriculture '19* (pp. 157–164). https://doi.org/https://doi.org/10.3920/978-90-8686-888-9_18

Cohen, S., Striem, M. J., Bruner, M., & Klein, I. (2000). Grapevine leaf area index evaluation by Gap Fraction Inversion. *Acta Horticulturae*, *537*, 87–94. https://doi.org/10.17660/ActaHortic.2000.537.7

Colaço, A. F., Molin, J. P., Rosell-Polo, J. R., & Escolà, A. (2018). Application of light detection and ranging and ultrasonic sensors to high-throughput phenotyping and precision horticulture: Current status and challenges. *Horticulture Research*, *5*(1).

https://doi.org/10.1038/s41438-018-0043-0

Colaço, A. F., Trevisan, R. G., Molin, J. P., Rosell-Polo, J. R., & Escolà, A. (2017). A method to obtain orange crop geometry information using a mobile terrestrial laser scanner and 3D modeling. *Remote Sensing*, *9*(8), 10–13. https://doi.org/10.3390/rs9080763

Comba, L., Biglia, A., Ricauda Aimonino, D., Tortia, C., Mania, E., Guidoni, S., & Gay, P. (2020). Leaf Area Index evaluation in vineyards using 3D point clouds from UAV imagery. *Precision Agriculture*, *21*(4), 881–896. https://doi.org/10.1007/s11119-019-09699-x

Comba, Lorenzo, Biglia, A., Aimonino, D. R., Barge, P., Tortia, C., & Gay, P. (2019). 2D and 3D data fusion for crop monitoring in precision agriculture. *2019 IEEE International Workshop on Metrology for Agriculture and Forestry, MetroAgriFor 2019 - Proceedings*, 62–67. https://doi.org/10.1109/MetroAgriFor.2019.8909219

Comba, Lorenzo, Zaman, S., Biglia, A., Davide Ricauda, A., Dabbene, F., & Gay, P. (2020). Semantic interpretation and complexity reduction of 3D point clouds of vineyards. *Biosystems Engineering*, *197*(July), 216–230. https://doi.org/10.1016/j.biosystemseng.2020.05.013

De Bei, R., Fuentes, S., Gilliham, M., Tyerman, S., Edwards, E., Bianchini, N., et al. (2016). Viticanopy: A free computer app to estimate canopy vigor and porosity for grapevine. *Sensors*, *16*(4), 585. https://doi.org/10.3390/s16040585

De la Fuente, C. P., Valdés-Gómez, H., Roudet, J., Verdugo-Vásquez, N., Mirabal, Y., Laurie, V. F., et al. (2020). Vigor thresholded NDVI is a key early risk indicator of botrytis bunch rot in vineyards. *Oeno One*, *54*(2), 279–297. https://doi.org/10.20870/oeno-one.2020.54.2.2954

Del-Moral-Martínez, I., Rosell-Polo, J. R., Uribeetxebarria, A., & Arnó, J. (2020). Spatially variable pesticide application in vineyards: Part I, developing a geostatistical approach. *Biosystems Engineering*, *195*, 17–26. https://doi.org/10.1016/j.biosystemseng.2020.04.014

Di Bene, C., Dolores Gómez-López, M., Francaviglia, R., Farina, R., Blasi, E., Martínez-Granados, D., & Calatrava, J. (2022). Barriers and Opportunities for Sustainable Farming Practices and Crop Diversification Strategies in Mediterranean Cereal-Based Systems. *Frontiers in Environmental Science*, *10*(July), 1–16. https://doi.org/10.3389/fenvs.2022.861225

Di Gennaro, S. F., & Matese, A. (2020). Evaluation of novel precision viticulture tool for canopy biomass estimation and missing plant detection based on 2.5D and 3D approaches using RGB images acquired by UAV platform. *Plant Methods*, *16*(1), 1–13. https://doi.org/10.1186/s13007-020-00632-2

Escolà, A., Planas, S., Rosell, J. R., Pomar, J., Camp, F., Solanelles, F., et al. (2011). Performance of an ultrasonic ranging sensor in apple tree canopies. *Sensors*, *11*(3), 2459–2477. https://doi.org/10.3390/s110302459

Escolà, A., Rosell-Polo, J. R., Planas, S., Gil, E., Pomar, J., Camp, F., et al. (2013). Variable rate sprayer. Part 1 - Orchard prototype: Design, implementation and validation. *Computers and Electronics in Agriculture*, *95*, 122–135. https://doi.org/10.1016/j.compag.2013.02.004

Ess, D. R., Morgan, M. T., & Parsons, S. D. (2001). Implementing Site-Specific Management : Variable Rate Application. *Precision Agriculture*, *SSM-2-W*, 1–9.

EU Regulation 2018/1981. (2018). *Commission Implementing Regulation (EU) 2018/1981 of 13 December 2018 renewing the approval of the active substances copper compounds, as candidates for substitution, in accordance with Regulation (EC) No 1107/2009 of the European Parliament and of the Co*.

Official Journal of the European Union (Vol. l317).

European Commission. (2020). *A Farm to Fork Strategy for a fair, healthy and environmentally-friendly food system* (Vol. 21). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0381

European Directive 2009/128/EC. (2009). *Directive 2009/128/EC of the European Parliament and the Council of 21 October 2009 establishing a framework for Community action to achieve the sustainable use of pesticides*. *Official Journal of the European Union* (Vol. 309).

Eurostat (ed.) (2022) Pesticide sales by categorisation of active substances. Eurostat. Available at: https://ec.europa.eu/eurostat/databrowser/view/aei_fm_salpest09/default/table?lang=en (Accessed: December 16, 2022).

Ferrer, M., Echeverría, G., Pereyra, G., Gonzalez-Neves, G., Pan, D., & Mirás-Avalos, J. M. (2020). Mapping vineyard vigor using airborne remote sensing: relations with yield, berry composition and sanitary status under humid climate conditions. *Precision Agriculture*, *21*(1), 178–197. https://doi.org/10.1007/s11119-019-09663-9

Gatti, M., Dosso, P., Maurino, M., Merli, M. C., Bernizzoni, F., Pirez, F. J., et al. (2016). MECS-VINE®: A new proximal sensor for segmented mapping of vigor and yield parameters on vineyard rows. *Sensors (Switzerland)*, *16*(12). https://doi.org/10.3390/s16122009

Gil, E., Arnó, J., Llorens, J., Sanz, R., Llop, J., Rosell-Polo, J. R., et al. (2014). Advanced technologies for the improvement of spray application techniques in Spanish viticulture: An overview. *Sensors (Switzerland)*, *14*(1), 691–708. https://doi.org/10.3390/s140100691

Gil, E., Escolà, A., Rosell-Polo, J. R., Planas, S., & Val, L. (2007). Variable rate application of plant protection products in vineyard using ultrasonic sensors. *Crop Protection*, *26*(8), 1287–1297. https://doi.org/10.1016/j.cropro.2006.11.003

Gil, E., Llorens, J., Llop, J., Fàbregas, X., Escolà, A., & Rosell-Polo, J. R. (2013). Variable rate sprayer. Part 2 - Vineyard prototype: Design, implementation, and validation. *Computers and Electronics in Agriculture*, *95*, 136–150. https://doi.org/10.1016/j.compag.2013.02.010

Giles, D. K., Delwiche, M. J., & Dodd, R. B. (1987). Control of Orchard Spraying Based on Electronic Sensing of Target Characteristics. *Transactions of the American Society of Agricultural Engineers*, *30*(6), 1624–1630, 1636. https://doi.org/10.13031/2013.30614

Giles, D. K., Delwiche, M. J., & Dodd, R. B. (1988). Electronic Measurement of Tree Canopy Volume. *Transactions of the American Society of Agricultural Engineers*, *31*(1), 264–272. https://doi.org/10.13031/2013.30698

Grantz, D. A., Zhang, X. J., Metheney, P. D., & Grimes, D. W. (1993). Indirect measurement of leaf area index in Pima cotton (Gossypium barbadense L.) using a commercial gap inversion method. *Agricultural and Forest Meteorology*, *67*(1–2), 1–12. https://doi.org/10.1016/0168-1923(93)90046-K

Hall, A., Lamb, D. W., Holzapfel, B., & Louis, J. (2002). Optical remote sensing applications in viticulture - A review. *Australian Journal of Grape and Wine Research*, *8*(1), 36–47. https://doi.org/10.1111/j.1755-0238.2002.tb00209.x

Halmetschlager-Funek, G., Suchi, M., Kampel, M., & Vincze, M. (2019). An empirical evaluation of ten depth cameras: Bias, precision, lateral noise, different lighting conditions and materials, and multiple sensor setups in indoor environments. *IEEE Robotics and Automation Magazine*, *26*(1), 67–77. https://doi.org/10.1109/MRA.2018.2852795

Hočevar, M., Širok, B., Jejčič, V., Godeša, T., Lešnika, M., & Stajnko, D. (2010). Design and testing of an automated system for targeted spraying in orchards.

Journal of Plant Diseases and Protection, *117*(2), 71–79. https://doi.org/10.1007/bf03356338

Hong, S. W., Zhao, L., & Zhu, H. (2018). SAAS, a computer program for estimating pesticide spray efficiency and drift of air-assisted pesticide applications. *Computers and Electronics in Agriculture*, *155*(September), 58–68. https://doi.org/10.1016/j.compag.2018.09.031

Jay, S., Rabatel, G., Hadoux, X., Moura, D., & Gorretta, N. (2015). In-field crop row phenotyping from 3D modeling performed using Structure from Motion. *Computers and Electronics in Agriculture*, *110*, 70–77. https://doi.org/10.1016/j.compag.2014.09.021

Kalisperakis, I., Stentoumis, C., Grammatikopoulos, L., & Karantzalos, K. (2015). Leaf area index estimation in vineyards from UAV hyperspectral data, 2D image mosaics and 3D canopy surface models. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, *40*(1W4), 299–303. https://doi.org/10.5194/isprsarchives-XL-1-W4-299-2015

Khaliq, A., Comba, L., Biglia, A., Ricauda Aimonino, D., Chiaberge, M., & Gay, P. (2019). Comparison of satellite and UAV-based multispectral imagery for vineyard variability assessment. *Remote Sensing*, *11*(4), 436. https://doi.org/10.3390/rs11040436

Kuan, Y. W., Ee, N. O., & Wei, L. S. (2019). Comparative study of intel R200, Kinect v2, and primesense RGB-D sensors performance outdoors. *IEEE Sensors Journal*, *19*(19), 8741–8750. https://doi.org/10.1109/JSEN.2019.2920976

Li, L., He, X., Song, J., Liu, Y., Zeng, A., Yang, L., et al. (2018). Design and experiment of variable rate orchard sprayer based on laser scanning sensor. *International Journal of Agricultural and Biological Engineering*, *11*(1), 101–108.

https://doi.org/10.25165/j.ijabe.20181101.3183

Llorens, J., Gil, E., Llop, J., & Escolà, A. (2010). Variable rate dosing in precision viticulture: Use of electronic devices to improve application efficiency. *Crop Protection*, *29*(3), 239–248. https://doi.org/10.1016/j.cropro.2009.12.022

Llorens, J., Gil, E., Llop, J., & Escolà, A. (2011). Ultrasonic and LIDAR sensors for electronic canopy characterization in vineyards: Advances to improve pesticide application methods. *Sensors*, *11*(2), 2177–2194. https://doi.org/10.3390/s110202177

López-Granados, F., Torres-Sánchez, J., Jiménez-Brenes, F. M., Oneka, O., Marín, D., Loidi, M., et al. (2020). Monitoring vineyard canopy management operations using UAV-acquired photogrammetric point clouds. *Remote Sensing*, *12*(14). https://doi.org/10.3390/rs12142331

Luo, L., Tang, Y., Zou, X., Ye, M., Feng, W., & Li, G. (2016). Vision-based extraction of spatial information in grape clusters for harvesting robots. *Biosystems Engineering*, *151*, 90–104. https://doi.org/10.1016/j.biosystemseng.2016.08.026

Mahmud, M. S., Zahid, A., He, L., & Martin, P. (2021). Opportunities and possibilities of developing an advanced precision spraying system for tree fruits. *Sensors*, *21*(9). https://doi.org/10.3390/s21093262

Matese, A., & Di Gennaro, S. F. (2018). Practical applications of a multisensor UAV platform based on multispectral, thermal and RGB high resolution images in precision viticulture. *Agriculture*, *8*, 116. https://doi.org/10.3390/agriculture8070116

Matese, A., Toscano, P., Di Gennaro, S. F., Genesio, L., Vaccari, F. P., Primicerio, J., et al. (2015). Intercomparison of UAV, aircraft and satellite remote sensing platforms for precision viticulture. *Remote Sensing*, *7*(3), 2971–2990. https://doi.org/10.3390/rs70302971

Mazzia, V., Comba, L., Khaliq, A., Chiaberge, M., & Gay, P. (2020). UAV and machine learning based refinement of a satellite-driven vegetation index for precision agriculture. *Sensors (Switzerland)*, *20*(9). https://doi.org/10.3390/s20092530

Messéan, A., Viguier, L., Paresys, L., Aubertot, J. N., Canali, S., Iannetta, P., et al. (2021). Enabling Crop Diversification To Support Transitions Toward More Sustainable European Agrifood Systems. *Frontiers of Agricultural Science and Engineering*, *8*(3), 474–480. https://doi.org/10.15302/J-FASE-2021406

MIPAAF. (2014). National action plan for sustainable use of plant protection products, 59–105.

Miranda-Fuentes, A., Llorens, J., Rodríguez-Lizana, A., Cuenca, A., Gil, E., Blanco-Roldán, G. L., & Gil-Ribes, J. A. (2016). Assessing the optimal liquid volume to be sprayed on isolated olive trees according to their canopy volumes. *Science of the Total Environment*, *568*, 296–305. https://doi.org/10.1016/j.scitotenv.2016.06.013

Miranda-Fuentes, Antonio, Llorens, J., Gamarra-Diezma, J. L., Gil-Ribes, J. A., & Gil, E. (2015). Towards an optimized method of olive tree crown volume measurement. *Sensors*, *15*(2), 3672–3687. https://doi.org/10.3390/s150203671

Moltó, E., Martín, B., & Gutiérrez, A. (2001). Pesticide loss reduction by automatic adaptation of spraying on globular trees. *Journal of Agricultural and Engineering Research*, *78*(1), 35–41. https://doi.org/10.1006/jaer.2000.0622

Moreno, H., Bengochea-Guevara, J., Ribeiro, A., & Andújar, D. (2022). 3D Assessment of Vine Training Systems Derived from Ground-Based RGB-D

Imagery. *Agriculture (Switzerland)*, *12*(6). https://doi.org/10.3390/agriculture12060798

Ou, M., Hu, T., Hu, M., Yang, S., Jia, W., Wang, M., et al. (2022). Experiment of Canopy Leaf Area Density Estimation Method Based on Ultrasonic Echo Signal. *Agriculture*, *12*(10), 1569. https://doi.org/10.3390/agriculture12101569

Ouyang, J., de Bei, R., Fuentes, S., & Collins, C. (2020). UAV and ground-based imagery analysis detects canopy structure changes after canopy management. *Oeno One*, *54*(4), 1093–1103. https://doi.org/10.20870/OENO-ONE.2020.54.4.3647

Palleja, T., & Landers, A. J. (2015). Real time canopy density estimation using ultrasonic envelope signals in the orchard and vineyard. *Computers and Electronics in Agriculture*, *115*, 108–117. https://doi.org/10.1016/j.compag.2015.05.014

Palleja, T., & Landers, A. J. (2017). Real time canopy density validation using ultrasonic envelope signals and point quadrat analysis. *Computers and Electronics in Agriculture*, *134*, 43–50. https://doi.org/10.1016/j.compag.2017.01.012

Paulus, S., Schumann, H., Kuhlmann, H., & Léon, J. (2014). High-precision laser scanning system for capturing 3D plant architecture and analysing growth ofcereal plants. *Biosystems Engineering*, *121*, 1–11. https://doi.org/10.1016/j.biosystemseng.2014.01.010

Pergher, G., & Petris, R. (2008). Pesticide dose adjustment to the canopy parameters for treatments to the tree crops. In *Giornate Fitopatologiche* (pp. 317–322). ATTI Giornate Fitopatologiche.

Pertot, I., Caffi, T., Rossi, V., Mugnai, L., Hoffmann, C., Grando, M. S., et al. (2017). A critical review of plant protection tools for reducing pesticide use on grapevine and new perspectives for the implementation of IPM in viticulture.

Crop Protection, *97*, 70–84.
https://doi.org/10.1016/j.cropro.2016.11.025

Pimentel, D. (2005). Environmental and economic costs of the application of pesticides primarily in the United States. *Environment, Development and Sustainability*, *7*(2), 229–252.
https://doi.org/10.1007/s10668-005-7314-2

Putra, B. T. W., Soni, P., Morimoto, E., & Pujiyanto, P. (2018). Estimating biophysical properties of coffee (Coffea canephora) plants with above-canopy field measurements, using CropSpec. *International Agrophysics*, *32*(2), 183–191.
https://doi.org/10.1515/intag-2017-0009

Rinaldi, M., Llorens, J., & Gil, E. (2013). Electronic characterization of the phenological stages of grapevine using a LIDAR sensor. In J. V. Stafford (Ed.), *Precision agriculture '13* (pp. 603–609). Wageningen Academic Publishers.
https://doi.org/https://doi.org/10.3920/978-90-8686-778-3_74

Rockström, J., Williams, J., Daily, G., Noble, A., Matthews, N., Gordon, L., et al. (2017). Sustainable intensification of agriculture for human prosperity and global sustainability. *Ambio*, *46*(1), 4–17.
https://doi.org/10.1007/s13280-016-0793-6

Rodríguez-Gonzálvez, P., Garcia-Gago, J., Gomez-Lahoz, J., & González-Aguilera, D. (2014). Confronting passive and active sensors with non-gaussian statistics. *Sensors (Switzerland)*, *14*(8), 13759–13777.
https://doi.org/10.3390/s140813759

Román, C., Llorens, J., Uribeetxebarria, A., Sanz, R., Planas, S., & Arnó, J. (2020). Spatially variable pesticide application in vineyards: Part II, field comparison of uniform and map-based variable dose treatments. *Biosystems Engineering*, *195*, 42–53.
https://doi.org/10.1016/j.biosystemseng.2020.04.013

Román, C., & Planas, S. (2018). Adjusted dose treatments through PCD vigour maps in vineyards. *Aspects of Applied Biology. International Advances in Pesticide Applications*, 137(265e1491), 385e392

Romero, M., Luo, Y., Su, B., & Fuentes, S. (2018). Vineyard water status estimation using multispectral imagery from an UAV platform and machine learning algorithms for irrigation scheduling management. *Computers and Electronics in Agriculture*, *147*(January), 109–117. https://doi.org/10.1016/j.compag.2018.02.013

Rosell-Polo, J. R., Gregorio, E., Gene, J., Llorens, J., Torrent, X., Arno, J., & Escola, A. (2017). Kinect v2 sensor-based mobile terrestrial laser scanner for agricultural outdoor applications. *IEEE/ASME Transactions on Mechatronics*, *22*(6), 2420–2427. https://doi.org/10.1109/TMECH.2017.2663436

Rosell, J. R., Llorens, J., Sanz, R., Arnó, J., Ribes-Dasi, M., Masip, J., et al. (2009). Obtaining the three-dimensional structure of tree orchards from remote 2D terrestrial LIDAR scanning. *Agricultural and Forest Meteorology*, *149*(9), 1505–1515. https://doi.org/10.1016/j.agrformet.2009.04.008

Rosell, J. R., & Sanz, R. (2012). A review of methods and applications of the geometric characterization of tree crops in agricultural activities. *Computers and Electronics in Agriculture*, *81*, 124–141. https://doi.org/10.1016/j.compag.2011.09.007

Rosell Polo, J. R., Sanz, R., Llorens, J., Arnó, J., Escolà, A., Ribes-Dasi, M., et al. (2009). A tractor-mounted scanning LIDAR for the non-destructive measurement of vegetative volume and surface area of tree-row plantations: A comparison with conventional destructive measurements. *Biosystems Engineering*, *102*(2), 128–134. https://doi.org/10.1016/j.biosystemseng.2008.10.009

Saberioon, M. M., & Cisar, P. (2016). Automated multiple fish tracking in three-Dimension using a Structured Light Sensor. *Computers and Electronics in Agriculture*, *121*, 215–221. https://doi.org/10.1016/j.compag.2015.12.014

Sassu, A., Gambella, F., Ghiani, L., Mercenaro, L., Caria, M., & Pazzona, A. L. (2021). Advances in Unmanned Aerial System Remote Sensing for Precision Viticulture. *Sensors*, *21*, 956.

Schumann, A. W., & Zaman, Q. U. (2005). Software development for real-time ultrasonic mapping of tree canopy size. *Computers and Electronics in Agriculture*, *47*(1), 25–40. https://doi.org/10.1016/j.compag.2004.10.002

Sirera, À. P., Antichi, D., Raffa, D. W., & Rallo, G. (2021). Application of remote sensing techniques to discriminate the effect of different soil management treatments over rainfed vineyards in chianti terroir. *Remote Sensing*, *13*(4), 1–25. https://doi.org/10.3390/rs13040716

Stamatiadis, S., Taskos, D., Tsadila, E., Christofides, C., Tsadilas, C., & Schepers, J. S. (2010). Comparison of passive and active canopy sensors for the estimation of vine biomass production. *Precision Agriculture*, *11*(3), 306–315. https://doi.org/10.1007/s11119-009-9131-3

Sulecki, J. (2018). Association seeks definitive definition of “precision agriculture” What’s your vote?. Available at: https://www. precisionag.com/events/association-seeks-definitive-definition-of-precision-agriculture-whats-your-vote/ (Accessed: November 15, 2022).

Sun, L., Gao, F., Anderson, M. C., Kustas, W. P., Alsina, M. M., Sanchez, L., et al. (2017). Daily mapping of 30 m LAI and NDVI for grape yield prediction in California vineyards. *Remote Sensing*, *9*(4). https://doi.org/10.3390/rs9040317

Terrón, J. M., Blanco, J., Moral, F. J., Mancha, L. A., Uriarte, D., & Marques Da Silva, J. R. (2015). Evaluation of vineyard growth under four irrigation regimes using vegetation and soil on-the-go sensors. *Soil*, *1*(1), 459–473. https://doi.org/10.5194/soil-1-459-2015

Tona, E., Calcante, A., & Oberti, R. (2018). The profitability of precision spraying on specialty crops: a technical–economic analysis of protection equipment at increasing technological levels. *Precision Agriculture*, *19*(4), 606–629. https://doi.org/10.1007/s11119-017-9543-4

Tsoulias, N., Paraforos, D. S., Fountas, S., & Zude-Sasse, M. (2019). Estimating canopy parameters based on the stem position in apple trees using a 2D lidar. *Agronomy*, *9*(11). https://doi.org/10.3390/agronomy9110740

Verma, N. K., Lamb, D. W., Reid, N., & Wilson, B. (2016). Comparison of canopy volume measurements of scattered eucalypt farm trees derived from high spatial resolution imagery and LiDAR. *Remote Sensing*, *8*(5), 388. https://doi.org/10.3390/rs8050388

Vieri, M., Sarri, D., Rimediotti, M., Lisci, R., Peruzzi, A., Raffaelli, M., et al. (2011). Rhea Project Achievement : an Innovative Spray Concept for Pesticide Application To Tree Crops Equipping a Fleet of Autonomous Robots .

Vogel, J. W., Wolf, R. E., & Anita Dille, J. (2005). Evaluation of a variable rate application system for site-specific weed management. *2005 ASAE Annual International Meeting*, *0300*(05). https://doi.org/10.13031/2013.18863

Wandkar, S. V., Bhatt, Y. C., Jain, H. K., Nalawade, S. M., & Pawar, S. G. (2018). Real-Time Variable Rate Spraying in Orchards and Vineyards: A Review. *Journal of The Institution of Engineers (India): Series A*, *99*(2), 385–390. https://doi.org/10.1007/s40030-018-0289-4

Zhang, Z., Wang, X., Lai, Q., & Zhang, Z. (2018). Review of Variable-Rate Sprayer

Applications Based on Real-Time Sensor Technologies. In *Automation in Agriculture - Securing Food Supplies for Future Generations* (Vol. i, p. 13). http://dx.doi.org/10.5772/intechopen.73622

Zhou, H., Jia, W., Li, Y., & Ou, M. (2021). Method for estimating canopy thickness using ultrasonic sensor technology. *Agriculture (Switzerland)*, *11*(10). https://doi.org/10.3390/agriculture11101011

Other publications and contributions

1. Paper

- Sarri, D.; Lombardo, S.; **Pagliai, A.**; Zammarchi, L.; Lisci, R. and Vieri, M. (2020). A technical-economic analysis of telemetry as a monitoring tool for crop protection in viticulture. Journal of Agricultural Engineering, 51(2), pp. 91–99. https://doi.org/10.4081/jae.2020.1029

- Sarri, D.; Lombardo, S.; **Pagliai, A.**; Perna, C.; Lisci, R.; De Pascale, V.; Rimediotti, M.; Cencini, G.; Vieri, M. (2020). Smart Farming Introduction in Wine Farms: A Systematic Review and a New Proposal. Sustainability, 12, 7191. https://doi.org/10.3390/su12177191

- Sarri, D.; Cencini, G.; Lisci, R.; **Pagliai, A.**; Perna, C.; Lombardo, S.; Vieri, M.; Pencelli, M.; Niccolini, M.; Argiolas, A.; Cappalunga, A.; Bartoli, L.; Doveri, N.; Tognetti, F.; (2021). RoboSpray SMASH: proof of concept modular robot platform for crop protection in viticulture. Precision Agriculture ’21, Wageningen Academic Publishers, pp. 727-733. https://doi.org/10.3920/978-90-8686-916-9_87

- Lombardo, S.; Sarri, D.; Perna, C.; **Pagliai, A.**; De Pascale, V.; Cencini, G.; Lisci, R.; Rimediotti, M.; Vieri, M.; (2021). Reliability of new technologies: local ecosystem readiness level, a composite index. Precision Agriculture ’21, Wageningen Academic Publishers, pp. 753-759. https://doi.org/10.3920/978-90-8686-916-9_90

2. Conference talks and seminars

- **Pagliai, A.**; Sarri, D.; Lisci, R.; Lombardo, S.; Vieri, M.; Perna, C.; Cencini, G.; De Pascale, V. and Araújo E Silva Ferraz, G. Development of an algorithm for canopy measurements with terrestrial LiDAR to implement precision spraying in vineyards (2021). 12th International Biosystems Engineering Conference. 5-7 May 2021, Tartu, Estonia

- **Pagliai, A.**; Sarri, D.; Perna, C. and Vieri, M.; Can a variable-rate sprayer be efficient and economic? Testing and economic analysis in viticulture (2022).12th International AIIA Conference: "Biosystems Engineering towards the Green Deal - Improving the resilience of agriculture, forestry and food systems in the post-Covid era". 19-22 September 2022, Palermo, Italy.

- Perna, C.; Sarri, D.; **Pagliai, A.** and Vieri, M.; Assessment of soil and vegetation index variability in a traditional olive grove: a case study (2022). 12th International AIIA Conference: "Biosystems Engineering towards the Green Deal - Improving the resilience of agriculture, forestry and food systems in the post-Covid era". 19-22 September 2022, Palermo, Italy.

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