# The informative potential of remote and proximal sensing application on vertical- and overhead-trained vineyards in Northeast Italy

**Authors:** Ron SHMULEVIZ*, Marianna FASOLI, Giovanni Battista TORNIELLI
*Department of Biotechnology, University of Verona, 37134 Verona, Italy*

*Corresponding author: ron.shmuleviz@univr.it

## Abstract:

### Context and purpose of the study

The application of remote and proximal sensing in viticulture have been demonstrated as a fast and efficient method to monitor vegetative and physiological parameters of grapevines. The collection of these parameters could be highly valuable to derive information on associated yield and quality traits in the vineyard. However, to leverage the informative potential of the sensing systems, a series of preliminary evaluations should be carried out to standardize working protocols for the specific features of a winegrowing area (e.g., pedoclimate, topography, cultivar, training system). This work aims at evaluating remote and proximal sensing systems for their performance and suitability to provide information on the vegetative, physiological, yield and qualitative aspects of vines and grapes as a function of different training systems in the Valpolicella wine region (Verona, Italy).

### Material and methods

Five vineyards in the Valpolicella wine region were investigated for their intra-parcel variability during 2022 growing season. Three vineyards were trained with cane pruning vertical shoot positioning system (Guyot), while the other two were trained with cane pruning overhead system (Pergola). Blocks presenting intra-parcel variability were selected and monitored in each vineyard. The Normal Difference Vegetation Index (NDVI) was calculated using both the data of remote sensors such as the satellite Sentinel-2 and UAV-mounted multispectral camera, and a proximal handheld NDVI device. Further proximal sensor evaluation was carried out employing a handheld thermal camera, which estimates the Crop Water Stress Index (CWSI). The data collected from the sensors was then compared with that of direct measurements on the vines and the berries (e.g., bud fertility, shoot growth kinetics, leaf area, yield, berry skin thickness and technological berry ripening parameters). Multivariate and correlation analyses were applied to determine the relationship between the sensor data and the direct vine and berry measurements and to further evaluate the nature of these relationships as a function of the vine training system.

### Results

Multivariate analyses on the whole dataset distinguished the Guyot-trained blocks from the Pergola-trained blocks. Positive correlations emerged between the NDVI values obtained from the satellite images, the UAV images and the proximal NDVI sensor, which were ground-truthed by obtaining high positive correlations with a series of direct measurements, among which the bud fertility, the shoot growth kinetic, the leaf area and the crop yield. The vigor data correlated negatively with quality berry parameters such as the sugar and the polyphenolic content. The strength of the detected relationships varied as a function of the training system, suggesting different informative potential of the tested sensor systems for Guyot and Pergola.

**Keywords**: Ground-truthing, Proximal and remote sensing, NDVI, CWSI, training system, Valpolicella.

## 1. Introduction

In recent years several rapid non-destructive *smart* technologies that estimate the grapevine status have been developed. These technologies aim at replacing some of the traditional laborious agricultural monitoring methods, allow to increase the information input from the vineyard, and hence, pave the way to a more efficient and sustainable viticulture. Many of these technologies include optical sensors that capture the light reflected or transmitted by the canopy, individual leaves or berries and attributes it to specific physiological parameters. The visible (VIS) range can be used directly to estimate the canopy volume and yield quantity (Hacking et al., 2019; Di Gennaro and Matese, 2020), the near infrared (NIR) range can be used to identify the organic chemical structure of the canopy or fruit (Power et al., 2019; Ye et al., 2022) and the short-wave infrared (SWIR) can be correlated to the canopy water status (Laroche-Pinel et al., 2021).
By mathematical manipulation of the reflectance values in the VIS, NIR and SWIR ranges, various vegetational indices (VIs) can be calculated (Giovos et al., 2021) . Further, longer thermal infrared (TIR) wavelengths indicate the vegetation temperature, which can be used to estimate the plant water stress, considering the canopy temperature as a manifestation of the canopy energy balance (Jackson et al., 1977).
However, the ability of the sensors to provide accurate vine physiological information is highly dependent in the context and nature of the viticulture in question, such as the climate conditions (Baca-Bocanegra et al., 2019), the vine phenological stage (Kasimati et al., 2021) and the vineyard topography.
For that reason, specific calibrations should be applied in order to develop suitable sensing survey protocols, which can include different sensor types, distinct temporal and spatial sensing resolutions and the choice of certain VIs to elaborate.
The present work aims at validating various proximal and remote sensing systems for their potential to reveal different aspects of the vines and berries in the Valpolicella wine region (north-eastern Italy). In particular, the correspondence between the sensor data and several ground truthing measurement will be confronted among two distinct typical training systems of the wine region; Guyot, in which 1-2 canes of 6-12 buds are placed horizontally at about 70 cm above ground and density of approximately 5000 vines/ha; and Pergola, in which 1-4 canes of 10-15 buds are placed overhead on two inclined wings at about 150-200 cm above ground and density of approximately 2500 vines/ha. In the Guyot training system the canopy management is necessary, the yield is limited and the clusters are well exposed to the sun, whereas in the Pergola training system the canopy management is minimized, the yield is generally higher and clusters are partially shaded by the overhead foliage.

## 2. Material and methods

### 2.1. *Vineyards*

The experiment was undertaken in the classic Valpolicella wine region (Verona, north-east Italy), during the 2022 growing season. Five vineyards, in which the principle Valpolicella varieties are grown, Corvina, Corvinone, Rondinella and Molinera, were monitored. Three vineyards were trained in cane pruning vertical shoot positioning system (Guyot with plant spacing of 2.80 x 0.95 m), while the other two in overhead system (Pergola with plant spacing of 3.7 x 1.1 m). The vineyard's location, altitude, area, training system and cultivated variety details are summarized in Table 1.

### *2.2. Block selection*

A prelaminar evaluation of the intra-parcel variability within each vineyard was done elaborating Sentinel2 satellite images acquired during the previous vegetative season (28$^{th}$ May ;15$^{th}$ June ;20$^{th}$ July of 2021). The 10-m spatial resolution bands 4 (Red) and 8 (NIR) were used to calculate the NDVI index according to the equation: NDVI= (NIR – RED) / (NIR + RED)
Blocks of equal dimension were selected in zones that exhibited different NDVI values in the three dates analyzed. In these blocks the following described proximal and ground truthing measurements were applied. The blocks coordinates were registered on site with a Trimble® R2 Global Navigation Satellite System (GNSS) receiver (Trimble Inc., Westminster, Colorado, USA). Block information is supplied in Table 1.

### *2.3. Measurements*

#### 2.3.1. Proximal sensors

A soil moisture content survey was done on May 17th using a portable FieldScout TDR 350 soil moisture instrument (Spectrum Technologies INC., Aurora, IL, USA).
A handheld NDVI GreenSeeker® sensor (Trimble Inc., Westminster, Colorado, USA) was used on May 31st to evaluate the vines canopy vigor from 1 m distance.
A portable FLIR E6 Thermal Imaging Camera (Teledyne FLIR LLC, Wilsonville, Oregon, USA) was employed to capture canopy images between 13 to 15 pm of July 21st. The canopy temperature was extracted from the images employing FLIR TOOLS software, version 6.4 (Teledyne FLIR LLC © 2022). The CWSI index was calculated according to the equation: CWSI= (Tcanopy – Twet) / (Tdry – Twet).

#### 2.3.2. Remote sensors

Crop vigor was assessed on July 2nd employing a MicaSense RedEdge-MX multi spectral camera (MicaSense, Inc., Seattle, Washington, USA) mounted on DJI Matrice 600 Pro UAV (Z DJI Technology Co., Ltd, Shenzhen, Guangdong, China). The flight velocity was 3 m/s at 40 m altitude above ground level, with forward and side overlap settings of 70% and ground sampling distance of 0.03 cm/pixel.
The camera presents an array of sensors with band-path filters whose center-wavelengths were 475 (Blue), 560 (Green), 668 (Red), 717 (Red Edge) and 842 (NIR) nm. The images were stitched into orthomosaics employing Pix4D Mapper software (Pix4D, Switzerland) and a series of VIs was compute and their average value within each block was calculated. The VIs equations are listed in Table 2. A corrected NDVI was additionally elaborated by setting non-canopy pixels to 0 before computing the block average. By this procedure each block contained the index values for canopy pixels and 0 value for non-canopy pixels.
Sentinel2 satellite images acquired on the same day as the UAV flight were downloaded and used to calculate the two VIs indicated in Table 2, and their block averages were extracted as well.
All Raster elaboration was done employing Qgis software v 3.16.16 (QGIS Development Team).

#### 2.3.3. Ground truthing

A serious of direct measurements on the canopy and grapes were applied during the vegetative growing phase and at full maturity, respectively. The measurements included bud fertility, shoot growth kinetics, plant leaf area, berry weight, must parameters (sugars, acids, pH, anthocyanins and polyphenols), vine yield and pruning weight.

### *2.4. Statistics*

Principle component analysis (PCA) was applied on dataset contain the blocks from the five different vineyards and the measured parameters, scaled by variable. To reduce the effect of the intrinsic variability of the different locations a second PCA was applied on dataset in which the parameters were scaled by vineyard.
To better understand the differences between training systems Pearson's correlations were evaluated between the VIs measured and specific ground truthing measurements: shoot growth kinetic, pruning weight and the sugar level (°Brix), for Pergola and Guyot separately.
All statistical analyses were applied using R (R2.13.2, Foundation for Statistical Computing, Vienna, Austria).

## **3. Results and discussion**

The biplot of the PCA applied to the dataset scaled by variable (Figure 1A), showed sample distribution based on vineyard (indicated with different colors) with a clear separation of the Pergola (circles) from the Guyot (squares) trained vines. This indicates that the relationships among the measured parameters are affected by the vineyard condition and the training system. The VIs computed from the proximal and remote sensors were associated with each other, as well as with the vine fertility and yield parameters, and were negatively correlated to PC1. Contrariwise, the berry quality components (sugars, anthocyanins, polyphenols and skin thickness) were associated with the CWSI and positively correlated to PC1. The leaf area to yield ratio, inversely describing the crop load, was found associated with the Guyot trained vineyards and positively correlated with PC1.

A second PCA biplot presents the analysis of the same dataset scaled by vineyard (Figure 1B). The scaling reduced differences caused by the intrinsic characteristics of each vineyard and the biplot presented samples grouped by vigor along PC1. High vigor blocks were associated with the VIs and berry acidity at harvest and were positioned opposite to the sugar level and the CWSI.

To investigate if the relationship between the sensor data and the ground truthing measurements was affected by the training system, correlation analyses between specific parameters have been applied on Pergola and Guyot vineyards separately (Figure 2).

The direct canopy measurements, shoot growth kinetics and pruning weight, had remarkably higher correlations with the VIs calculated for the Pergola training system, rather than for the Guyot. The guyot training system is characterized by low vegetation coverage and the inter-row bare soil might interfere in the computation and accuracy of the VIs. Indeed, the VIs that were most correlated with the canopy measurements in the Guyot training system were the MSAVI, which includes soil correction, and the NDVI calculated from proximity to the canopy, which record the canopy reflectance excluding the soil background. Likewise, the corrected NDVI, which includes index values for canopy pixels and 0 values for non-canopy pixels, improved the non-corrected NDVI for the Guyot training system, while it had no effect on the Pergola.

Notably, high correlations were achieved between the pruning weight and the VIs computed based on satellite data.

The CWSI exhibited distinct correlation trends with the canopy measurements, for each training system. High vigor resulted positively correlated with the CWSI in the Pergola training system while negative correlations were observed in the Guyot. This can be explained by the fact that the Pergola training system supports unrestrained vegetation growth, which is highly exposed to the sun. As a result high vigor vines with extended leaf surface are more prone to water transpiration and may suffers more from eventual water stress. The situation is different for the Guyot training system, in which the canopy management is stricter, the leaf area per vine is much lower and water deficit can be the cause for differences in vigor.

The level of sugars, which preferably accumulate in berries of low vigor vines, as expected had negative correlations with all the VIs in both training systems. Interestingly, stronger negative correlations of the sugars with most of the VIs computed were assigned for the Guyot training system. This might be related to differences of the vegetative-to-productive vine balance between the training systems which cause higher response of grape composition to vigor variance in the Guyot training system.

## 3. Conclusions

These preliminary results show that the vine training system influences remarkably the relationships between data retrieved from sensors and data taken by direct canopy and fruit measurements. In particular, the remote sensing methods showed high potential in revealing the Pergola canopy size and vigor and can be suggested as a reliable alternative to the traditional canopy assessment practices. Results will need to be replicated to enhance significance.

## 4. Acknowledgments

We wish to thank SMACT Competence Center, Bolla and Montresor wineries, Andrea Piccino and Marco Orso for their support.

## 6. Literature cited

**Baca-Bocanegra B.**, Hernández-Hierro J. M., Nogales-Bueno J., and Heredia F. J., 2019. Feasibility study on the use of a portable micro near infrared spectroscopy device for the “in vineyard” screening of extractable polyphenols in red grape skins. *Talanta* 192, 353–359. doi: 10.1016/j.talanta.2018.09.057.

**Di Gennaro S. F.**, and 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. doi: 10.1186/s13007-020-00632-2.

**Giovos R.,** Tassopoulos D., Kalivas D., Lougkos N., and Priovolou A., 2021. Remote sensing vegetation indices in viticulture: A critical review. *Agriculture (Switzerland)* 11. doi: 10.3390/agriculture11050457.

**Hacking C.,** Poona N., Manzan N., and Poblete-Echeverría C., 2019. Investigating 2-D and 3-D proximal remote sensing techniques for vineyard yield estimation. *Sensors (Switzerland)* 19. doi: 10.3390/s19173652.

**Jackson R. D.** Reginato R. J., and Idso S. B., 1977. Wheat canopy temperature: A practical tool for evaluating water requirements. *Water Resour Res* 13. doi: 10.1029/WR013i003p00651.

**Laroche-Pinel E.**, Albughdadi M., Duthoit S., Chéret V., Rousseau J., and Clenet H., 2021. Understanding vine hyperspectral signature through different irrigation plans: A first step to monitor vineyard water status. *Remote Sens (Basel)* 13. doi: 10.3390/rs13030536.

**Nicolaï B. M.,** Beullens K., Bobelyn E., Peirs A., Saeys W., Theron K. I., et al., 2007. Nondestructive measurement of fruit and vegetable quality by means of NIR spectroscopy: A review. *Postharvest Biol Technol* 46. doi: 10.1016/j.postharvbio.2007.06.024.

**Power A.,** Truong V. K., Chapman J., and Cozzolino D., 2019. From the laboratory to the vineyard-evolution of the measurement of grape composition using NIR spectroscopy towards high-throughput analysis. *High Throughput* 8. doi: 10.3390/ht8040021.

***Table 1***

The vineyard's location, altitude, area, training system, cultivated variety details and block information.

| Vineyard ID | Location | Altitude (m.a.s.l.) | Area (ha) | Vine training method | Grapevine Cultivars | Block information |
|---|---|---|---|---|---|---|
| **Vineyard 1** | 45°33'N;10°56'E | 385 | 0.3 | Guyot | Corvina | 6 blocks |
| **Vineyard 2** | 45°48'N;10°90'E | 84 | 3.65 | Guyot | Corvina; Corvinone | 10 blocks for Corvina, 4 blocks for Corvinone |
| **Vineyard 3** | 45°50'N;10°88'E | 128 | 10.2 | Guyot | Corvina | 11 zones with 3 blocks each |
| **Vineyard 4** | 45°30'N;10°55'E | 141 | 1.3 | Pergola | Corvina; Corvinone; Rondinella | 4 blocks for each cv |
| **Vineyard 5** | 45°48'N;10°90'E | 84 | 0.9 | Pergola | Corvina; Corvinone; Rondinella; Molinara | 2 blocks for each cv |

***Table 2***

The equations of the VIs calculated from data obtained from remote and proximal sensors.

| Index name | Raster sours | Equation |
|---|---|---|
| NDVI | Handheld /UAV/ Sentinel 2 | (NIR-Red)/(NIR+Red); (B08-B04)/(B08+B04) |
| GNDVI | UAV/ Sentinel 2 | (NIR-GREEN) /(NIR+GREEN); (B08-B03)/(B08+B03) |
| MSR | UAV | $(NIR/Red - 1)/((NIR/Red)^{1/2} + 1)$ |
| MSAVI | UAV | $1/2 * ((2*NIR+1) - ((2*NIR+1)^2 - 8*(NIR-Red))^{1/2})$ |
| NDVE | UAV | (NIR-RedEdge)/(NIR+RedEdge) |
| $NDWI_{1640}$ | Sentinel 2 | (B08-B11)/(B08+B11) |

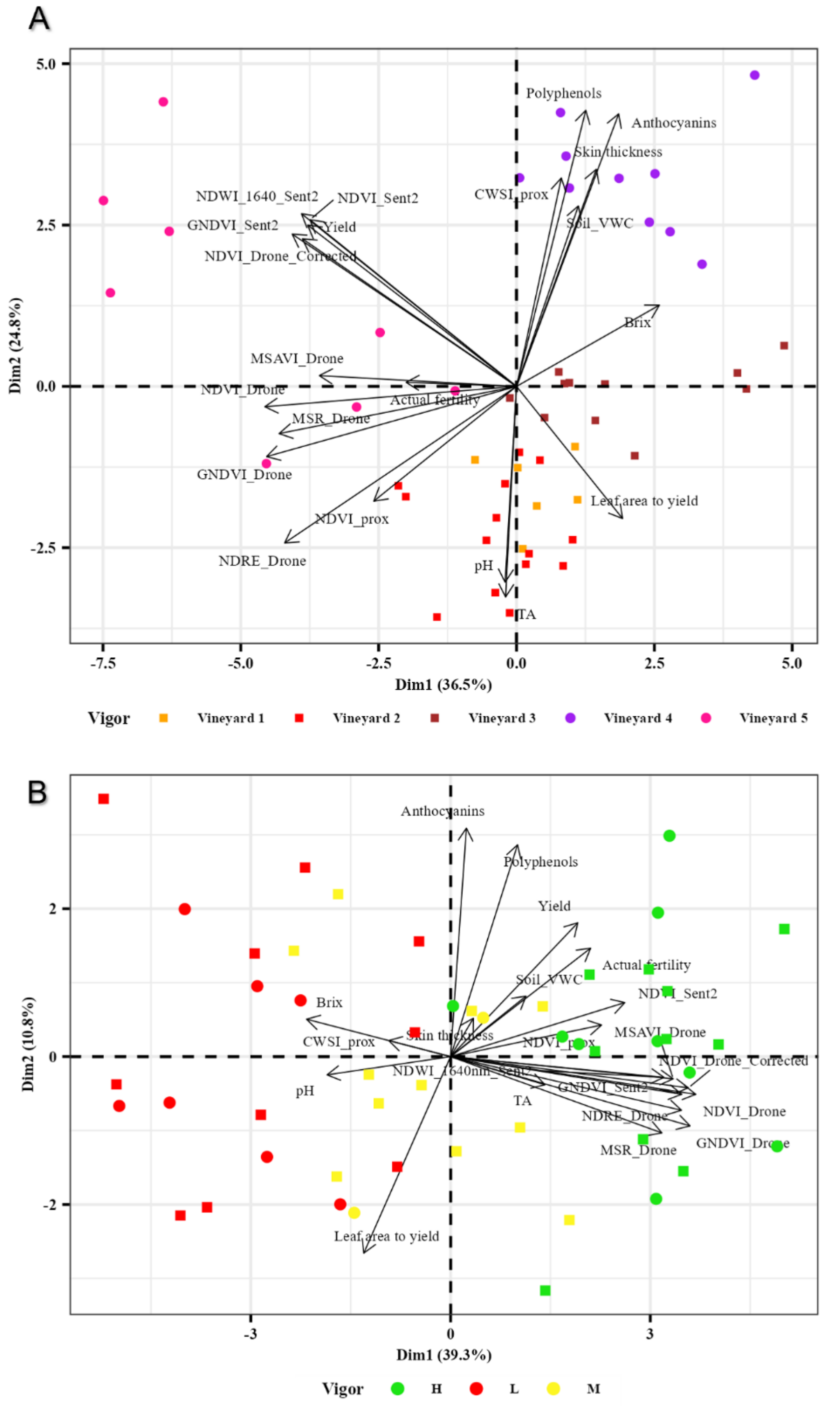


**Figure 1**. Principal component analysis biplots applied on the measured parameters (arrows) and the blocks from the different training systems (circle= Pergola: square= Guyot). **(A)** the measured parameters were scaled by variable. **(B)** the measured parameters were scaled by vineyard. H: high; L: low; M: medium.

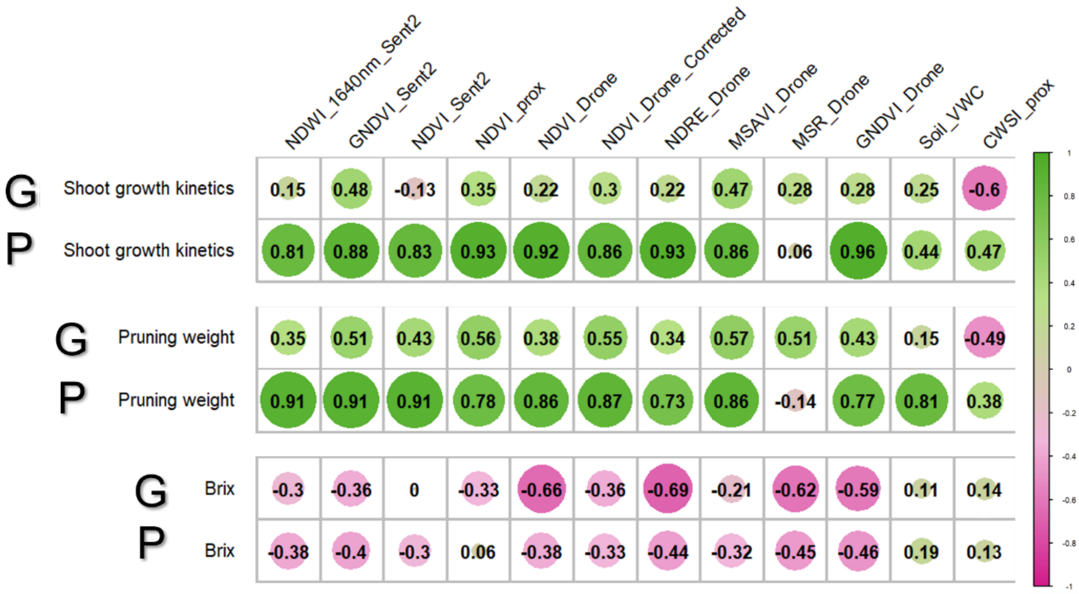


**Figure 2.** Pearson's correlation coefficients assigned for relationships between the VIs computed (horizontally listed) and specific ground truthing measurements: shoot growth kinetic, pruning weight and the sugar level (Brix) (vertically listed), for Pergola (P) and Guyot (G) separately.