Journal of Physics: Conference Series

PAPER • **OPEN ACCESS**

Use of multispectral and thermal imagery in precision viticulture

To cite this article: G Tanda and V. Chiarabini 2019 *J. Phys.: Conf. Ser.* **1224** 012034

IOP Conf. Series: Journal of Physics: Conf. Series **1224** (2019) 012034 doi:10.1088/1742-6596/1224/1/012034

Use of multispectral and thermal imagery in precision viticulture

G Tanda[1] and V.Chiarabini[2]
[1]DIME, Università degli Studi di Genova, Genova, Italy
[2]KIM-RemoteSensing GmbH, Klagenfurt am Wörthersee, Austria

[1]Corresponding Author. E-mail: giovanni.tanda@unige.it

Abstract. The increasing demand for higher quality and yield of wine production has led to a growing interest in precision viticulture, i.e., practices of monitoring and managing spatial variations in variables related to productivity within a vineyard. This paper presents a few applications of optical measurements, in combination with monitoring systems making use of geolocation and remote/proximal sensing, to calculate vegetation indices related to plant vigour and water stress in vineyards. Measurements were performed on vineyards in Burgenland, Austria, by both aerial and proximal (terrestrial) sensing techniques. A remote-sensing, four-band multispectral sensor, placed on an Unmanned Aerial Vehicle (UAV), has been used to detect the spectral signature of the vineyard and to calculate the NDVI index, useful to selectively address the harvest on the basis of quality and quantity of grapes. Proximal, thermal infrared imaging complemented the investigation providing information about the water status of the vegetation through the CWSI index. Examples of vigour maps are provided, showing, inside a given parcel, the presence of canopies at different level of vegetation characteristics. Results provide a range of information useful to make the optimal choice in management strategies of vineyards.

1. Introduction

Precision viticulture aims at optimizing vineyard performance, in particular by maximizing grape yield and quality while minimizing costs, environmental impacts and risk. This is accomplished by measuring local variation in factors that influence grape yield and quality, and by applying appropriate viticulture management practices (e.g. timing of harvest, irrigation, etc.). Nowadays, remote and proximal sensing sensors efficiently allow to detect the vineyard status, that is, plant health, water and nutrient availability, or soil conditions.

Techniques for investigating the physiological status of vegetation include the detection of reflectance of light (solar radiation) in the visible and near infrared wavelengths and the use of infrared thermography. The spectral signature of vegetation is distinctive and characterized by a low reflectance in the visible spectral region (400–700 nm), especially in blue or red wavelengths, because of strong absorption by chlorophylls, while exhibits a relatively high reflectance in the near-infrared band (700–1300 nm), to which the human eye is insensitive, because of internal leaf scattering and no absorption [1]. The sharp contrast between reflectance in the near-infrared and visible bands has been exploited in the construction of reflectance spectral indices. In particular, the most widely used indicator of plant vigour is the normalized difference vegetation index (NDVI), related to the difference between the light reflected in the near infrared and in the red regions; healthy vegetation is characterized by large NDVI values, whereas low NDVI values correspond to stressed vegetation [2]. In the context of precision viticulture, the alternation of vegetation and soil (with the need to separate the grapevine canopy from other image features) and the spatial variability in terms of canopy characteristics within the vineyard require the monitoring of large areas with relatively high spatial accuracy; unmanned aerial vehicle (UAV) applications in remote sensing combine the requirements of gathering multispectral data at high spatial ground resolution and monitoring vineyards of small to medium size (1 to 10 hectares) in a relatively short time [3].

Infrared thermography is a diagnostic tool useful to record the surface temperature of canopy on the basis of aerial and/or terrestrial monitoring systems. The use of thermal infrared imaging of vegetation dates back to 60s (e.g., [4]). The crop water stress index (CWSI), introduced in [5] and calculated from a combination of the canopy surface temperature and environmental factors (such as net radiation, vapor pressure deficit, wind speed), can be efficiently used to map the spatial variability in water deficits. The recent development of portable thermal imagers and remote sensing technology has greatly extended the opportunities to analyse thermal properties of plant canopies and widened the available information on the growth and condition of plants.

2. Analysis

2.1 Reflectance: definitions and spectral signature of vegetation

The angular reflectance pattern of vegetation canopies is of particular interest for diagnosing plant physiological status. Several definitions of reflectance can be found in the literature (e.g., [6]) based on the feature of incident and reflected radiation. Figure 1 provides some pictorial examples of different reflectance quantities ranging from the bidirectional condition (a single direction for the incident and reflected radiances) to the bihemispherical condition (both illumination and reflection are integrated over the hemisphere). As outlined in [7], in remote sensing the most common measurement condition on field is the hemispherical-conical configuration. This definition assumes the surface incident radiance consisting of a mixture of solar direct and diffuse components creating an illumination field that is hemispherical in angular extent. On the other hand, the field-of-view of the measuring instrument implies a reflected radiance acquired within a finite solid angle.

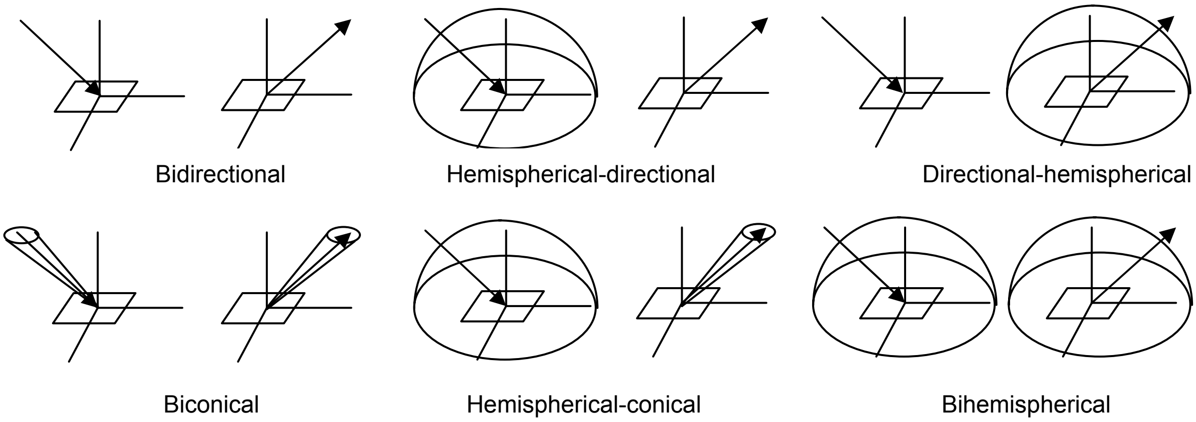

Figure 1. Reflectance definitions.

The reflectance variation with wavelength of vegetation, in the visible and near infrared ranges, can be associated with the plant physiological response to growth conditions and adaptations to the environment. As shown in Fig.2, in the visible spectrum (400−700 nm), plant reflectance is low because of absorption by photosynthetic pigments (mainly chlorophylls and carotenoids). In the near-infrared region (700−1300 nm), the structural discontinuities encountered in the leaf are responsible for high reflectance values both at plant and canopy levels. The red-edge (680−750 nm) is the wavelength of maximum slope in the increase of reflectance from red to near-infrared, while the middle infrared region (1300−3000 nm) presents a reflectance profile affected by the absorption characteristics of water and other compounds.

Of particular relevance is the difference between the high reflectance of near infrared radiation and the low reflectance (high absorption by chlorophyll) of red radiation, since it can be related to the vegetative status, as outlined in the figure.

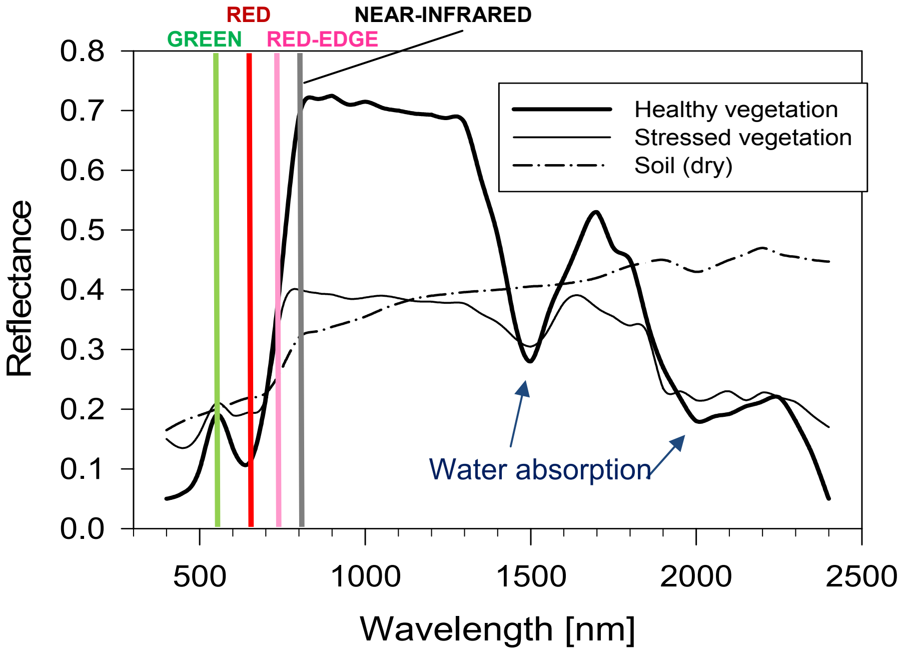

Figure 2. Typical spectral signatures (from visible to middle infrared) of vegetation and soil.

2.2 Reflectance-based vegetation indices

The accurate description of the spectral signature of target requires the use of sensors, termed hyperspectral, able to record the reflectance in a large number of wavebands, typically greater than 10. Multispectral instruments gather information in a small number of wavebands (from 2 to 10). Despite this important distinction, it is worth noting that the most widely used indicator of plant vigour, the normalized difference vegetation index (NDVI), utilises only two reflectance values, taken at the same time instant and for the same target area, according to the relation:

$$\mathrm{NDVI} = (\rho_{NIR} - \rho_{R}) / (\rho_{NIR} + \rho_{R}) \tag{1}$$

where ρ is the spectral reflectance of the target and the subscripts *NIR* and *R* denote the near-infrared (typically 790−890 nm) and the red (typically 610−680 nm) wavelengths, respectively (see, for instance, [8], [9]). The NDVI is a number between -1 and +1 and quantifies the relative difference between the near infrared reflectance ‘peak’ and the red reflectance ‘trough’ in the spectral signature [2]. For highly vegetated targets, the vigour level is high and the NDVI value is close to unity, while for non-vegetated target the vigour level is low and the NDVI value is close to zero (negative values rarely occur in natural targets). Information regarding the spatial variations of the vigour level has many applications for improving the management of the vineyards: more vigorous grapevines produce a larger yield than stressed ones but the vine quality is lower. Therefore, NDVI maps within the vineyard can suggest a selective grape harvest, dividing parcels into zones of different grape quality and processing the grapes separately [10], with significant benefits for winegrowers since the assessment of the vineyard productivity with traditional methods (i.e. measuring basic fruit quality and yield parameters) is generally more expensive and time-consuming than remote sensing [2].

2.3 Thermal imaging and water stress indices

An important factor influencing both quality and quantity of wine grapes is water: excessive water leads to increased vegetative growth and yield, but grape quality parameters, such as sugar content, pigment formation, acidity, and wood maturation of the wine are negatively affected. Conversely, severe water stress induces stomatal closure, causing strongly reduced or no assimilative activity and shoot growth with negative effects on grape yield. Maintaining a slight-to-moderate water deficit and thus inducing a certain level of stress can be very beneficial in grapevine cultivation as it stimulates optimal quality parameters without significantly compromising yield. In order to achieve this, crop water status must be measured accurately and reliably with the aim of maintaining a predetermined level of mild stress [11]. Reflectance in the middle infrared region presents a shape mainly linked to the absorption characteristics of water and other compounds and can be indicative of the plant water status. At the same time, indices based on the surface temperature of foliage or canopy are useful to evaluate the accuracy of water stress detection based on aerial and/or terrestrial infrared thermography. The crop water stress index (CWSI) indicator, used to map the spatial variability in water deficits, is deduced from thermal imaging according to the relation:

$$\mathrm{CWSI} = (T_s - T_{wet}) / (T_{dry} - T_{wet}) \tag{2}$$

where T is the surface temperature and subscripts *s*, *dry* and *wet* denote values measured by infrared thermography, upper and lower values, respectively. More precisely, T_{dry} is the surface temperature of a fully-stressed, non-transpiring plant, whereas T_{wet} is the surface temperature of a well-watered, transpiring plant. Upper and lower bounds of T_s can be theoretically calculated by the energy balance for a completely dry leaf and for a well-watered leaf, as follows

$$T_{dry} = T_{air} + (r_{HR}\, R_{ni}) / (\delta_{air}\, C_{p,air}) \tag{3}$$

$$T_{wet} = T_{air} + (r_{HR}\, r_{aW}\, R_{ni}\, \gamma) / [(\delta_{air}\, C_{p,air})\, (r_{aW}\, \gamma + r_{HR}\, \Delta)] - (r_{HR}\, \mathrm{VPD}) / (r_{aW}\, \gamma + r_{HR}\, \Delta) \tag{4}$$

where T_{air}, δ_{air}, and $C_{p,air}$ are the temperature (°C), density (kg m^{-3}) and specific heat (J kg^{-1}K^{-1}) of air, respectively; R_{ni} is the net radiation (W m^{-2}), γ is the psychrometric constant (Pa K^{-1}), VPD is the vapour pressure deficit (Pa), Δ is the slope of the curve relating saturation vapour pressure to temperature (Pa K^{-1}), while r_{HR} (s m^{-1}) and r_{aW} (s m^{-1}) are parameters related to the canopy heat transfer and water vapour resistances, respectively (see, for instance, [5], [11],[12]). Upper and lower bounds of surface temperature can either be evaluated as a function of environmental factors such as net radiation, vapor pressure deficit, and wind speed (affecting both the heat transfer and water vapour resistance) measured on field or be deduced by direct measurements over reference, dry and wet surfaces, either natural or artificial ([13]). For a well-watered crop, CWSI is typically lower than 0.2, while values of 0.8−0.9 indicate water stress conditions.

The usefulness of CWSI to assess the relative water stress is still debated. CWSI requires the input of several parameters and is strongly related to the quality of thermal images; moreover, CWSI typically exhibits diurnal changes (even without irrigation or rain) and its use in irrigation scheduling schemes should be based on daily measurements taken always at the same time of the day (for, instance, at noon, as indicated in [14]). Practical aspects of thermal imaging of vegetation are discussed in [15] and include the view angle (side view, as occurs in terrestrial inspections or top view, as occurs in aerial applications) and the sun light conditions (direct radiation, especially in the central hours of the day, increases the sensitivity whereas diffuse radiation reduces the spread of temperature between shaded and sunlit leaves). Moreover, thermal images can be taken at leaf level (or groups of leaves), as occurs in the proximal view at short distance or at canopy level, as occurs in the aerial view from large distance. The sensor quality affects accuracy and resolution of measured data; a given type of camera may provide accurate data over the foliage of a single plant or for rows of a vineyard during a proximal inspection and coarse or misleading information in remote sensing application if the resolution of the sensor is not adequate (with the single pixel incorporating fraction of soil and canopy).

2.4 Monitoring technologies
Precision viticulture has received a significant boost from remote sensing technological development. Satellite, aircrafts and more recently UAV systems have been used to record, at a distance with different scales of resolution, data over a large area in a relatively short time [3]. In particular, UAVs, remotely controlled from the ground, permit to gather synchronized and georeferenced visible, multispectral and thermal infrared images, with reduced planning time and an adequate ground spatial resolution (typically 8-10 cm/pixel for reflectance and 15-20 cm/pixel for thermal measurements at a distance of 100m). Proximal sensing is the most widely used monitoring technique for thermal imaging to inspect grapevines at leaf level; at the same time proximal monitoring is not suitable to infer the spatial variability of the vegetative status unless a very large number of measurements are taken.

3. Applications
Multispectral and thermal measurements were performed on vineyards (total monitored area about 50 hectares) in Burgenland, Austria, during two consecutive days of August 2017, a couple of weeks before the harvest, making use of both aerial and proximal (terrestrial) sensing techniques. Experiments have been performed from 10 a.m. to 4 p.m., in the presence of a clear sky. Air temperature and relative humidity were continuously recorded on ground by a portable weather station, while further meteorological data (hourly values of barometric pressure, solar irradiation and wind velocity) were obtained from a nearby automatic meteorological station. No events of rain or irrigation occurred on the last four days before and during the present investigation. The two-day period of investigation was sufficient to infer significant information concerning the plant vigour due to the long term response of multispectral measurements; conversely, water stress data based on thermal images can show daily or even hourly variations and thus are more useful in the short term.

3.1 Multispectral measurements
A remote-sensing, four-band multispectral sensor, placed on an Unmanned Aerial Vehicle (UAV), has been used to detect the spectral signature of the vineyard, at a distance of 70 m from ground. UAV (shown in Fig.3) was equipped with a multispectral sensor (Parrot Sequoia) collecting data of reflected and incident light in four spectral bands (green 550 nm, red 660 nm, red-edge 735nm, and near-infrared 790nm) at a ground spatial resolution of 9 cm/pixel. Multispectral inspection was integrated with a Zenmuse X5S digital camera to capture visible imagery. An in-built geographic positioning system (GPS) and a photogrammetric software were used to create digital orthophotographs and spatial maps of reflectance data within the target area.

Figure 3. UAV equipped with multispectral sensor, GPS device and digital camera.

Spectral reflectance ρ_λ of the target surface area has been reconstructed by the ratio of reflected and incident radiances ($R_{r,\lambda}$ and $R_{i,\lambda}$, respectively) measured at the same time instant and corrected to take into account the different solid angles subtended by the two sensors, i.e., $\rho_\lambda = k \cdot R_{r,\lambda} / R_{i,\lambda}$. The

IOP Conf. Series: Journal of Physics: Conf. Series **1224** (2019) 012034 doi:10.1088/1742-6596/1224/1/012034

correction factor *k* has been determined by using a calibration sample (a 25cm x 25cm Teflon plate placed on field) of known (and high) reflectance. An example of spectral reflectance over isolated spots (two canopy surface regions at different vigour and the soil) is provided in Fig.4 (left-hand side). The right-hand side of the figure, where the selected spots are indicated, is a visible, aerial image clearly showing the typical heterogeneity of a vineyard, with sequences of narrow vine rows and poorly vegetated background soil between them. For this reason, aerial inspection requires the best spatial resolution to differentiate the canopy from the soil (whose spectral signature is completely different) and to correctly identify the response of each canopy and the great variability in the vegetative status that typically characterizes the vineyards.

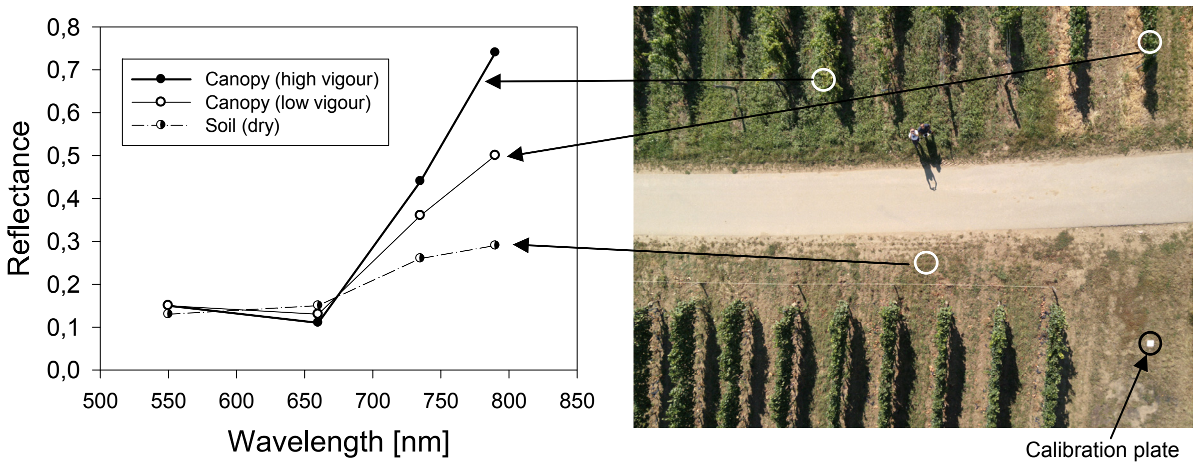

Figure 4. Reflectance measurements over isolated spots encompassing vegetation at different vigour level and soil.

A conventional representation of multispectral data condensed in a single image is the CIR (Colour Infrared Imaging) imagery, where false colours are used to highlight, for each pixel, the dominant reflection wavelength. According to the conventional code colours, the red colour indicates a strong near-infrared reflection and the red variation (from bright to light) indicates the vegetative status (from vigourously growing or healthy to mature or stressed). CIR imaging conventionally uses the green colour for the reflected red wavelength and the blue colour for the reflected green wavelength. As a consequence, regions encompassing soil, sand, dead vegetation and building or manmade materials will appear as white, blue, green or black. Figure 5 shows the standard and the CIR images of a parcel (3.5 hectares) within the vineyard: the corresponding orthophotograph (the inspected field as it would appear to human eyes) is shown of the left, while the false colour image on the right (CIR image) displays the different levels of vegetation health based on the variations in red.

A detail of Fig.5 is extracted and shown in Fig.6 (left-hand side), where the canopies of adjacent grape rows are clearly distinguishable from each other. The processing of spectral reflectance data allows the reconstruction of the vigour maps, according to the definition of NDVI provided by Eq.(1). The right-hand side of Fig.6 reports the NDVI map (according to a colour scale) of the target surface shown in the left-hand side of the same figure. In order to convey a useful indication of grapevine rows, the values for the inter-row space (which would otherwise confound grapevine measurement) have been eliminated. To improve the readability of NDVI maps, the final processing step consists in applying algorithms to produce maps of the area-averaged NDVI value (with different levels of resolution) based only on individual values recorded for the grapevine rows. Figure 7 shows the area-averaged vigour maps for a portion of the vineyard parcel of Fig.5 displayed according to different levels of resolution; grapes included in the red area (at relatively low level of vigour) appear to be mature and likely to produce a wine with an overall higher quality than that potentially achieved from zones at greater vigour (yellow and green areas).

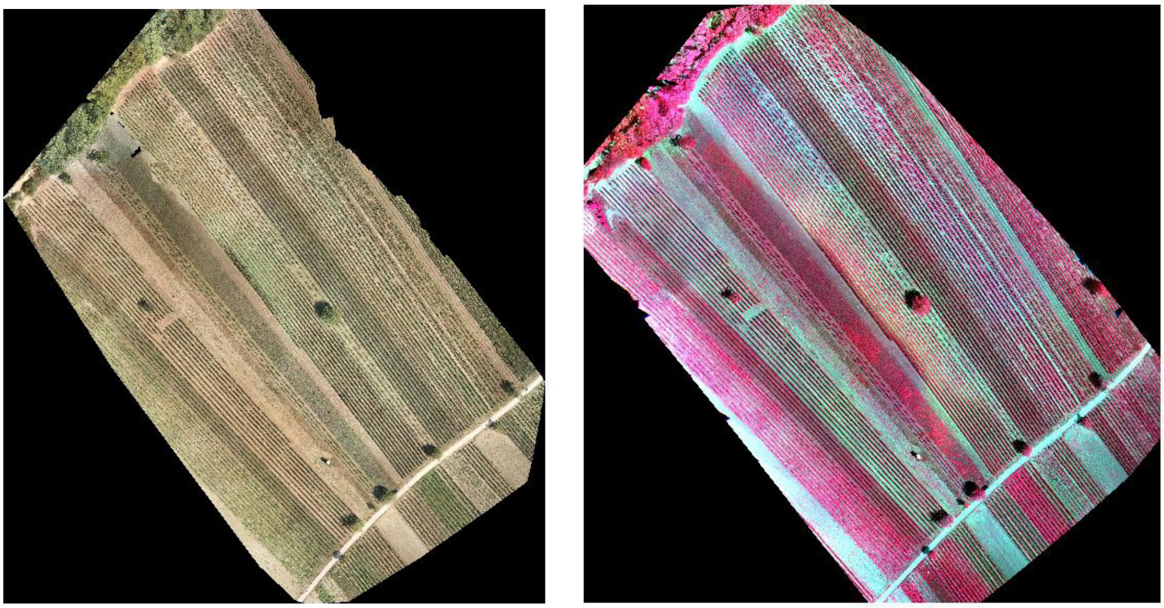

Figure 5. Orthophotograph (left-hand side) and false colour, CIR image (right-hand side) of a vineyard parcel.

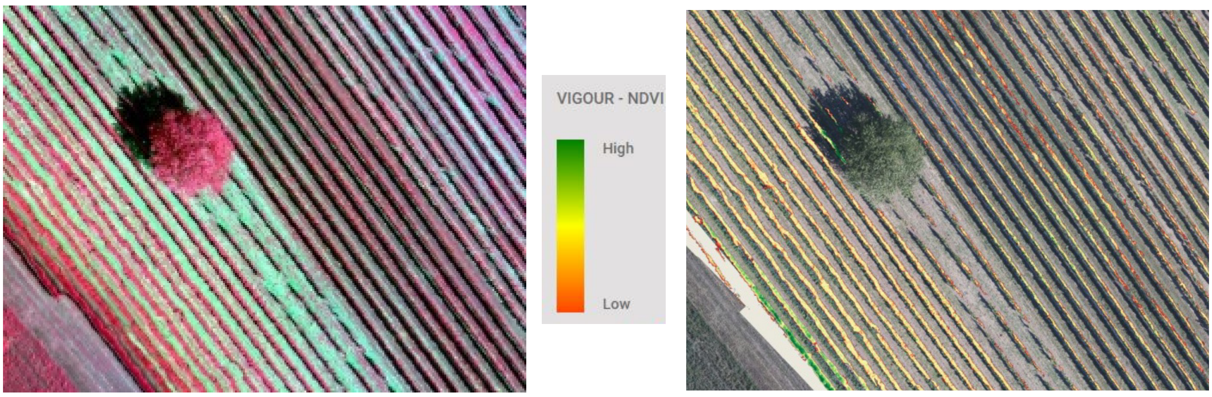

Figure 6. High-resolution CIR image of a reduced target area (left-hand side) and the corresponding NDVI map limited to the grape canopies (right-hand side).

3.2 Thermal measurements

To assess canopy temperature of the grapevine and derive the water stress status, lateral infrared thermal images (proximal or terrestrial view) were obtained using a handheld infrared camera (Model FLIR T335, Flir Systems Inc., 320 x 240 pixels, thermal sensitivity/NETD < 0.05°C), with the emissivity of vegetation fixed at 0.98.

The first example of thermal image is reported in Fig.8 for a grapevine row monitored at leaf level (at about 2m-distance). The figure shows, on the left-hand side, a mosaic image giving the standard visible view with the thermal map overlapped. The thermal map is displayed as CWSI map on the right-hand side. The picture was taken at 9:30 a.m., with T_{air}=23°C and calculated T_{dry} and T_{wet} equal to 24.7 and 19.8°C, respectively. CWSI values over the foliage are mainly in the 0.2−0.4 range,

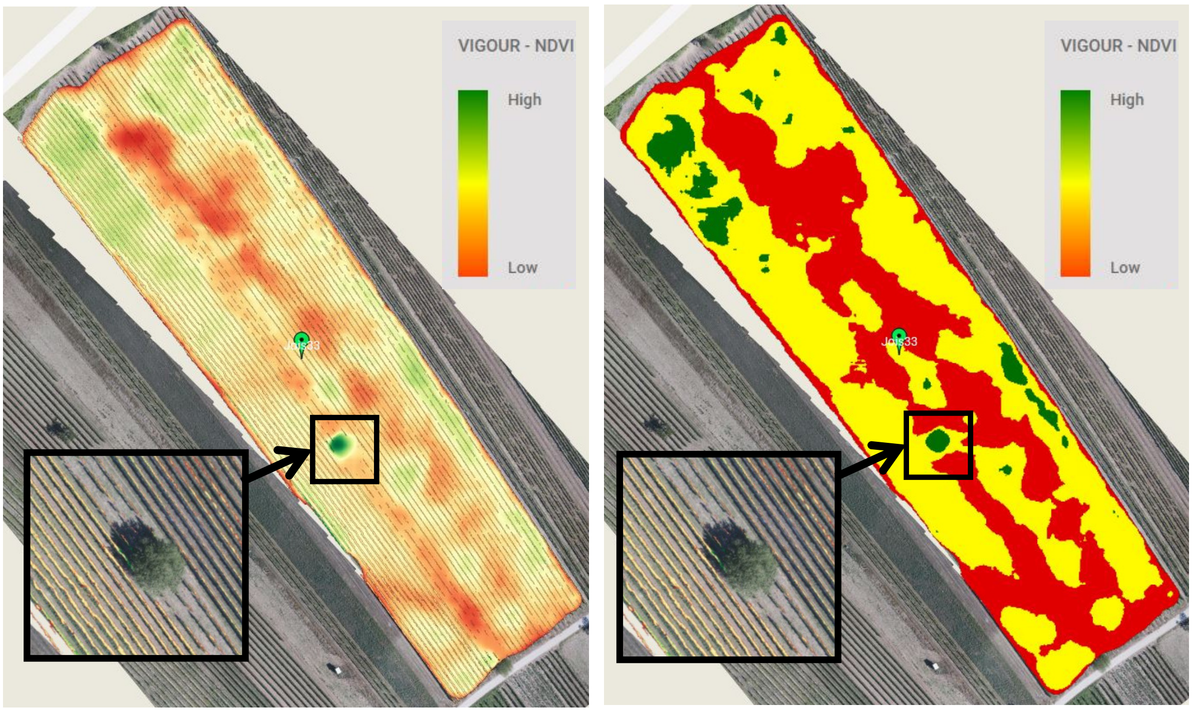

Figure 7. Maps of area-averaged NDVI values for the same vineyard parcel, processed according to different resolutions.

indicating a low to moderate degree of water stress. A different scenario is shown in Fig.9, which refers to an adjacent parcel of vineyard encompassing a larger target area. The thermal image, processed to obtain the CWSI map and overlapped to the visible image, was taken at 2:30 p.m., with T_{air}=30.5°C and calculated T_{dry} and T_{wet} equal to 35.3 and 24.9°C, respectively. The foliage of grapevine rows appears to be water stressed as CWSI is systematically higher than 0.7. This result was not surprising since the month of August 2017 was exceptionally dry and hot (with harvest anticipated by several weeks) and the vineyard was not equipped with irrigation system. Data presented in Figs. 8 and 9 show typical variations of CWSI over time during the day, with peak values during the warmer hours of the day and lower values in the first hours of the morning, when reduced sunlight allows a larger stomatal aperture and transpiration rate of foliage [14].

A final example of thermal imagery is provided in Fig.10, where a visible/thermal mosaic image is shown on the left, with the corresponding CWSI map reported on the right. This image, taken at 11:30 a.m., with T_{air}=25.5°C, T_{dry} =27.7 °C, and T_{wet} = 21.3°C, includes the lateral view of two adjacent grapevine rows and a cluster of rows displaced on a hill at about 100 m of distance (thus simulating an aerial thermal view). Again, CWSI values are relatively high but heterogeneously distributed over the two facing grapevine rows. This is due to the fact that upper and lower values of surface temperature were calculated for sunlit conditions; thus they correctly apply to the right-hand grapevine row (predominately in the sun) and not to the left-hand row (predominately in the shade). CWSI values obtained for the grapevine rows on the background are affected by the limited resolution of infrared camera unable to discriminate canopy values from inter-row values.

Figures 8−10 are not directly comparable since they refer to different hours of the day, to different scale levels (leaves, rows, rows and far canopy, respectively) and different vineyard parcels; even though they are deemed to be poorly correlated to the vigour maps previously shown, they provide some interesting and complementary indications about the water status of vegetation.

Figure 8. Mosaic image (visible + thermal) of a grapevine row at leaf level (left-hand side) and the corresponding CWSI map (right-hand side).

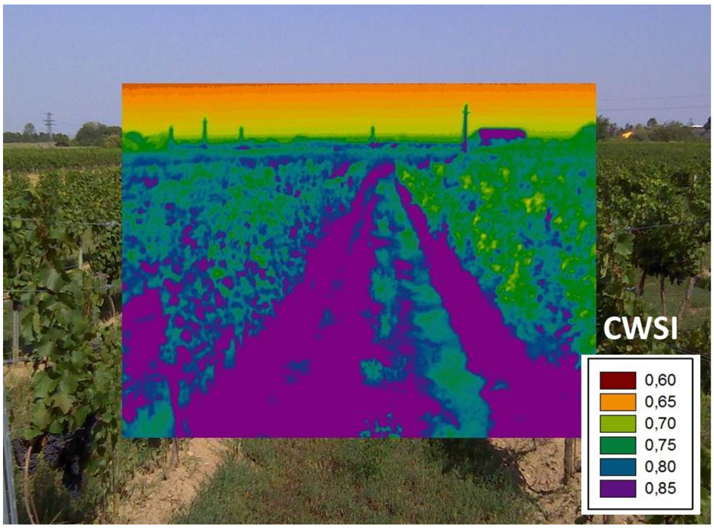

Figure 9. CWSI calculated for grape rows at medium-high water stress level.

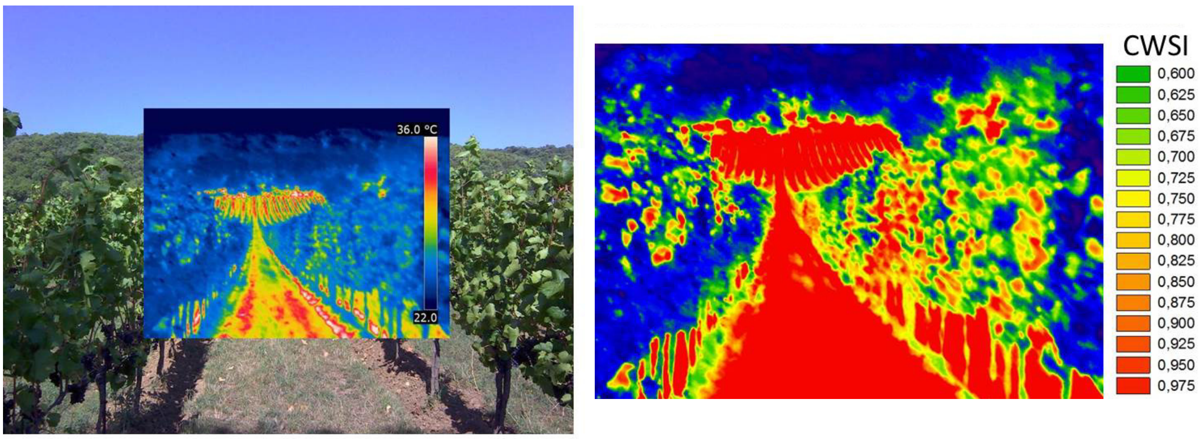

Figure 10. Mosaic image (visible + thermal) of a vineyard parcel (left-hand side) and calculated CWSI (right-hand side).

4. Conclusions

Optical measurements and derived indices used in precision viticulture have been described and commented, together with monitoring (remote and proximal sensing) technologies. Among the wide range of techniques and data processing under investigation worldwide, attention was paid to multispectral (in the visible and near-infrared bands) and thermal imagery. Results obtained for a vineyard in Burgenland, Austria, two weeks before harvest, have been presented and discussed. Multispectral images taken from an unmanned aerial vehicle and the derived maps of vine vigour (NDVI) were capable to discriminate grape yield/quality within single vineyard blocks; for this purpose, high-resolution optical data have to be processed in order to accurately differentiate between individual grapevine rows and adjacent or inter-row soil and vegetation. At the same time, thermal imagery provided complementary information for diagnosis and quantification of plant water stress.

References

[1] Knipling EB 1970 Physical and physiological basis for the reflectance of visible and near-infrared radiation from vegetation *Remote Sensing of Environment* **1** 155−159
[2] Hall A, Lamb DW, Holzapfel B and Louis J 2002 Optical remote sensing applications in viticulture – a review *Australian Journal of Grape and Wine Research* **8** 36−47
[3] Matese A and Di Gennaro SF 2015 Technology in precision viticulture: a state of the art review *International Journal of Wine Research* **7** 69−81
[4] Fuchs M and Tanner CB 1966 Infrared thermometry of vegetation *Agronomy Journal* **58** 597−601
[5] Jackson RD, Idso SB, Reginato RJ and Pinter Jr PJ 1981 Canopy temperature as a crop water stress indicator *Water Resources Research* **17** 1133−1138
[6] Siegel R and Howell JR 1972 *Thermal Radiation Heat Transfer* (McGraw-Hill)
[7] Schaepman-Strub G, Schaepman ME, Painter TH, Dangel S and Martonchik JV 2006 Reflectance quantities in optical remote sensing – definitions and case studies *Remote Sensing of Environment* **103** 27−42
[8] Rodríguez-Pérez JR, Riaño D, Carlisle E, Ustin S and Smart DR 2007 Evaluation of hyperspectral reflectance indexes to detect grapevine water status in vineyards *American Journal for Enology and Viticulture* **58** 302−317
[9] Jones HG 2014 *Plants and Microclimate – A Quantitative Approach to Environmental Plant Physiology, 3rd Edition* (Cambridge University Press)
[10] Arnó J, Martínez-Casasnovas JA, Ribes-Dasi M and Rosell JR 2009 Review. Precision Viticulture. Research topics, challenges and opportunities in site-specific vineyard management *Spanish Journal of Agricultural Research* **7** 779−790
[11] Möller M, Alchanatis V, Cohen Y, Meron M, Tsipris J, Naor A, Ostrovsky V, Sprintsin M and Cohen S 2007 Use of thermal and visible imagery for estimating crop water status of irrigated grapevine *Journal of Experimental Botany* **58** 827−838
[12] Jones HG 1999 Use of infrared thermometry for estimation of stomatal conductance as a possible aid to irrigation scheduling *Agricultural and Forest Meteorology* **95** 139−149
[13] Testi L, Goldhamer DA, Iniesta F and Salinas M 2008 Crop water stress index is a sensitive water stress indicator in pistacchio trees *Irrigation Science* **26** 395–405
[14] Bellvert J, Zarco-Tejada PJ, Girona J and Fereres E 2014 Mapping crop water stress index in a 'Pinot-noir' vineyard: comparing ground measurements with thermal remote sensing imagery from an unmanned aerial vehicle *Precision Agriculture* **15** 361−376
[15] Jones HG and Leinonen I 2003 Thermal imaging for the study of plant water relations *Journal of Agricultural Meteorology* **3** 205−217