Monitoring onion crops using multispectral imagery from unmanned aerial vehicle (UAV)

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Abstract. Precision agriculture (PA) can be considered as management strategy of spatial and temporal variability in fields using information and communications technologies with the aim to optimize profitability, sustainability, and protection of agro-ecological services. In the context of PA and with reference to a specific case study on onion crop, the present paper shows the monitoring of fields, using multispectral imagery acquired by UAVs, through the use of different VIs. Multitemporal surveys were carried out using a fixed-wing UAV, equipped with a multispectral camera Sequoia Parrot (R-G-RedEdge-NIR). UAV MS imagery were calibrated using a panel with known reflectance and verified with a spectroradiometer (Apogee Ps-300) on bare soil and vegetation. The results of the analysis of the three datasets showed a high correlation of GNDVI and NDVI with SAVI. The latter was chosen to analyze the vegetative vigor by applying the VI to onion crop's masks extracted after segmentation and classification of the three images by a geographical object-based image classification (GEOBIA).

Keywords: Precision Agriculture (PA); remote sensing (RS); unmanned aerial vehicle (UAV); vegetation indices (VIs); multispectral surveys; onion crop.

1 Introduction

Remote sensing (RS) can be defined as the acquisition of information about an object by means of sensors without coming into direct contact with it [1]. RS investigations are based on relationship between the reflected, emitted or backscattered electromagnetic energy, in specific bands, and the chemical, biological, and physical characteristics of the subject or phenomenon under investigation [2]. Since the late 1980s, great progress has been made in the RS in precision agriculture (PA) [3]. PA can be considered as management strategy of spatial and temporal variability in fields using information and communications technologies [4] with the aim to optimize sustainability of agro-ecological services. In this regard, an increasing availability of technological solutions are available to remotely collect and transmit environmental parameters.

The agricultural sector is important for the application of geographic information systems and RS data and methods [5]. RS, in this context, is employed to collect and analyze information about crop and soil characteristics using sensors mounted on satellites, aerial platforms and instruments for field measurements [6]. Among these, important technological developments and steep rise have affected unmanned aerial vehicles (UAVs) in the last decade [7]. In a comparison with other RS platforms, UAVs are cheap and more independent of climatic variables, especially during rainy seasons, when clouds are an obstacle for the acquisition of satellite images. UAVs, being able to provide with greater temporal and spatial resolution, today represent a significant source of RS imagery in PA [8]. As highlighted by scholars in PA applications the knowledge of the within-field spatial variation of edaphic factors and the state of crops constitute a prerequisite [9]. Among the sensors mounted on UAVs employed in agriculture, multispectral (MS) cameras are the most common [6]. Thanks to UAVs and high resolution multispectral images, managers and specialists in agriculture can use new tools and have more information to optimize management decisions and formulate precision farming solutions [10]. In fact, MS UAV cameras permit to obtain spectral information in the Red-edge (RE) and Near-infrared (NIR) band for vegetation applications with a very high spatial resolution [11]. On the basis of the combination of these two bands, most of the indices (i.e., vegetation indices, VIs) were developed with the aim to monitor, analyze, and map temporal and spatial variations of vegetation [12] in both field and tree crops [11]. In the framework of PA, the accurate monitoring of crop status is crucial and VIs can be efficiently used for detecting differences in Nitrogen (N) status and yield [13]. The present paper shows the monitoring of onion crop, through the use of different VIs using MS imagery acquired by fixed wing UAV. The work is based on the study of three datasets surveyed on the same field in a three consecutive months.

2 Materials and methods

2.1 Study site

UAV MS surveys were performed in an onion field located in Campora S. Giovanni, in the municipality of Amantea (Cosenza, Italy). The onions produced here are an economically important local crop. This particular pink-red coloured onion type, since 2008 is labeled with the European Protected Geographical Indication label "Cipolla Rossa di Tropea IGP". It is well-known worldwide for its sweet flavor and for its high content of nutraceuticals that make it an upcoming “functional food” [14]. The producing farms are organized in a consortium whose cultivated area is over 500 hectares. The study area covers a surface of 2 hectares (Fig. 1). The surveys were carried out between the middle (November) and the end of the cultivation cycle (January) that began with the transplantation between mid-August (late summer) and mid-September (early autumn). The UAV flights were carried out three times (Fig 1, a and b). The first flight was performed on 23 November 2018, the second on 19 December 2018 and the last on 18 January 2019. Multispectral surveys were carried out at 50 m of flight height using a fixed-wing UAV Parrot Disco-Pro AG equipped with a multispectral camera Parrot Sequoia (Fig 2b). The Parrot Sequoia MS has four different channels, each with 1.2 Mpx of resolution: Green (530–570 nm), Red (640–680 nm), Red edge (730–740 nm) and NIR (770–810 nm). Furthermore, it is also equipped with a RGB composite sensor, and an external irradiance sensor with global navigation satellite system (GNSS) and inertial measurement unit (IMU) modules placed on top of the UAV. The IMU allows to capture sensor angle, sun angle, location, and irradiance for every image taken during the flight.

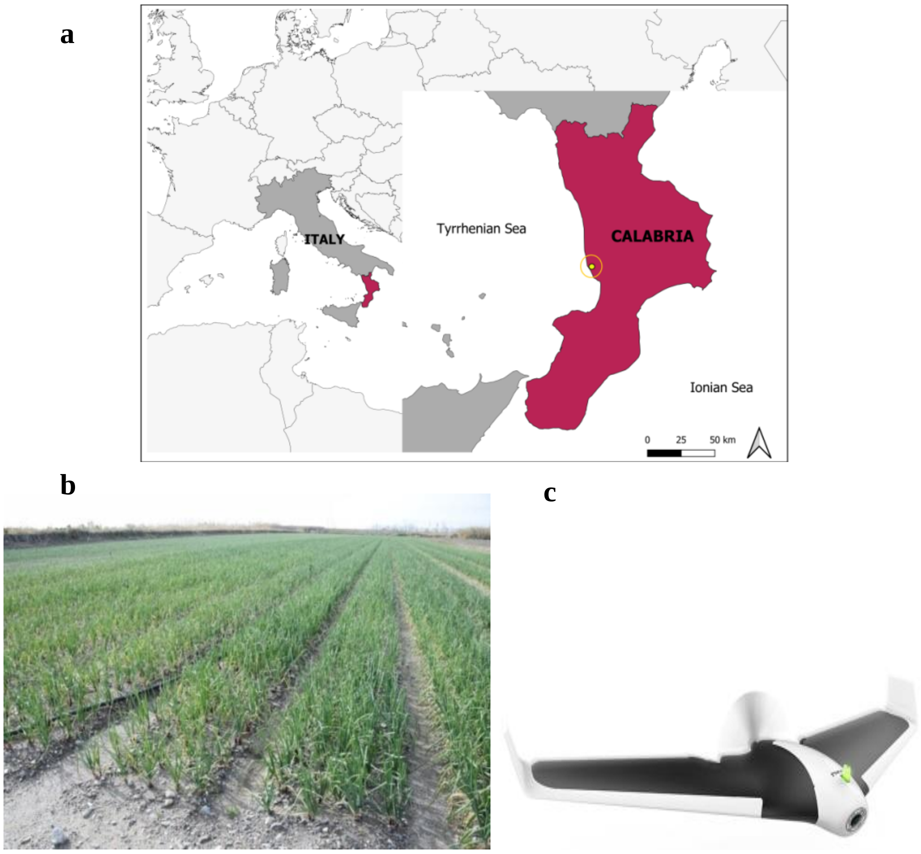

Fig. 1. **a** The location of the study site. **b** The Onion field in which the experiments were performed (Campora S. Giovanni, CS – Italy). **c** Parrot Disco-Pro AG**.**

In the field were placed 9 ground control points (GCPs) whose position has been geo-referenced using a Leica RTK GNSS with a planimetric accuracy of 0.03 m. In particular, GCPs were made using 50 cm × 50 cm white polypropylene panels and covering two quadrants by means of black cardboard to locate the point. MS imagery was calibrated using a panel with known reflectance, the Parrot Sequoia calibration target, and a spectroradiometer for ground truth measurements (Apogee Ps-300) performed on bare soil and vegetation. All consecutive images were processed via aerial image triangulation with the geo-tagged flight log and the geographic tags by means of the software Pix4D mapper (Pix4D S.A., Switzerland).

Four VIs were obtained to analyze the vegetative vigour of the onion crop: NDVI (Normalized Difference Vegetation Index), SAVI (Soil-Adjusted Vegetation Index), NDRE (Normalized Difference Red Edge Vegetation Index), GNDVI (Green Normalized Difference Vegetation Index) (details can be found in Tab.1).

NDVI is still the most widely used index because of its simplicity of calculation and interpretation [15]. It derived from the multispectral information and is calculated by normalized ratio between the NIR and Red bands [16]. It can assume values between -1 and 1 and measures healthy vegetation exploiting the highest chlorophyll absorption and reflectance regions [17]. NDRE has a range of values and formula similar to that of NDVI but takes advantage of the sensitivity of the vegetation to the Red Edge by replacing the Red band. GNDVI [18] was developed to estimate leaf chlorophyll concentration and uses a Green band rather than a Red band as in the classic NDVI.

Table 1. Formulation of the four vegetation indices (VIs) used in the present research.

Index denomination	Index formula	References
Normalized Difference Vegetation Index (NDVI)	$\frac{(\rho NIR1 - \rho Red)}{(\rho NIR1 + \rho Red)}$	[19]
Soil-Adjusted Vegetation Index (SAVI)	$\frac{(\rho NIR1 - \rho Red)}{(\rho NIR1 + \rho Red + L)}(1+L)$	[20]
Normalized Difference Red Edge Vegetation Index (NDRE)	$\frac{(\rho NIR1 - \rho RedEdge)}{(\rho NIR1 + \rho RedEdge)}$	[21]
Green Normalized Difference Vegetation Index (GNDVI)	$\frac{(\rho NIR1 - \rho Green)}{(\rho NIR1 + \rho Green)}$	[18]

* ρ is the reflectance at the given wavelength.

Since NDVI is very sensitive to back-ground factors, SAVI was developed by Huete (1988) with the aim of minimizing the effects of soil background on the vegetation signal by inserting in the NDVI formula a constant soil adjustment factor L [22], the value of which can assume values between 0 and 1 depending on the level of vegetation cover. To better understand the behavior of each MS band and of the vegetation indices, a correlation analysis between them was implemented by means of Python. For each dataset, a scatter plot correlation matrix was produced and the Pearson's correlation index (r) was provided.

3 Results and discussions

The scatter plot of the November dataset shows a high correlation between Red Edge and NIR (r = 0.96) bands. As regards the correlations between indices, NDVI and SAVI have quite the same behaviour (r = 0.95); analogous consideration can be made for the comparison between NDVI and GNDVI (r = 0.95) and between GNDVI and SAVI (r = 0.94). Also in the case of the December dataset the scatter plot matrix (Fig. 3) shows a high correlation between Red Edge and NIR (r = 0.94). The correlation between indices NDVI and SAVI coincide (r = 0.98). The same can be observed between NDVI and GNDVI (r = 0.99) and between GNDVI and SAVI (r = 0.99). In the January's dataset the scatter plot shows data similar to the previous two.

In particular, there is a high correlation between bands Red Edge and NIR (r = 0.98), NDVI and SAVI (r = 0.98), NDVI and GNDVI (r = 0.99), GNDVI and SAVI (r = 0.98). Therefore, we choose to analyze the vegetative vigor using just the SAVI that takes into account the soil effect. To extract the cover of onion crop, a geographical object-based image classification (GEOBIA) procedure was performed.

GEOBIA was preferred to a pixel-based approach considering its stronger reliability in classifying UAV imagery [23]. Differently from previous research carried out by the research group, and using Orfeo Toolbox [24] or Erdas Imagine Objective [5], in this case GEOBIA was implemented through eCognition Developer 9.5 (Trimble GeoSpatial, Munich, Germany) (Fig. 2).

The classification was developed using images in the bands Green, NIR, Red and Red Edge exploiting only the spectral response of the vegetation in the different bands. The images were segmented into uniform multi-pixel objects using the multiresolution algorithm [25] and setting the following parameters: 0.3 for scale parameter, 0.1 for shape and 0.5 for compactness. After completing the segmentation phase, the onion crops were classified basing only on a SAVI threshold value ≥ 0.25 because of the high correlation with NDVI and GNDVI.

The data obtained concerning the vegetation coverage of the field was used to create a mask to be applied to the map. SAVI maps were created for the three months of monitoring by applying the VI to the extracted masks. The index for these months is between 0 and 0.9. The values for November are the lowest. This could be due to the fact that the crop is still in the early stages of the cultivation cycle. In addition, during the segmentation phase the software was not always able to correctly separate the vegetation from the background. It is conceivable that the lower values in the map can be traced back to the underlying terrain. Considering the map of December, the values are higher than the previous month. In the portion of the field where the transplant took place in mid-September the index values are lower and are between 0.15 and 0.45.

There are also evident areas where vegetation is difficult to grow as shown in [26]. In the portion of the field in advanced stage of cultivation, the values are higher. In particular, the values are between 0.45 and 0.9. The contrast of colours between the two areas of the field with different transplanting times is evident. The January map shows a reduction in SAVI values where the crop is at a near harvest stage.

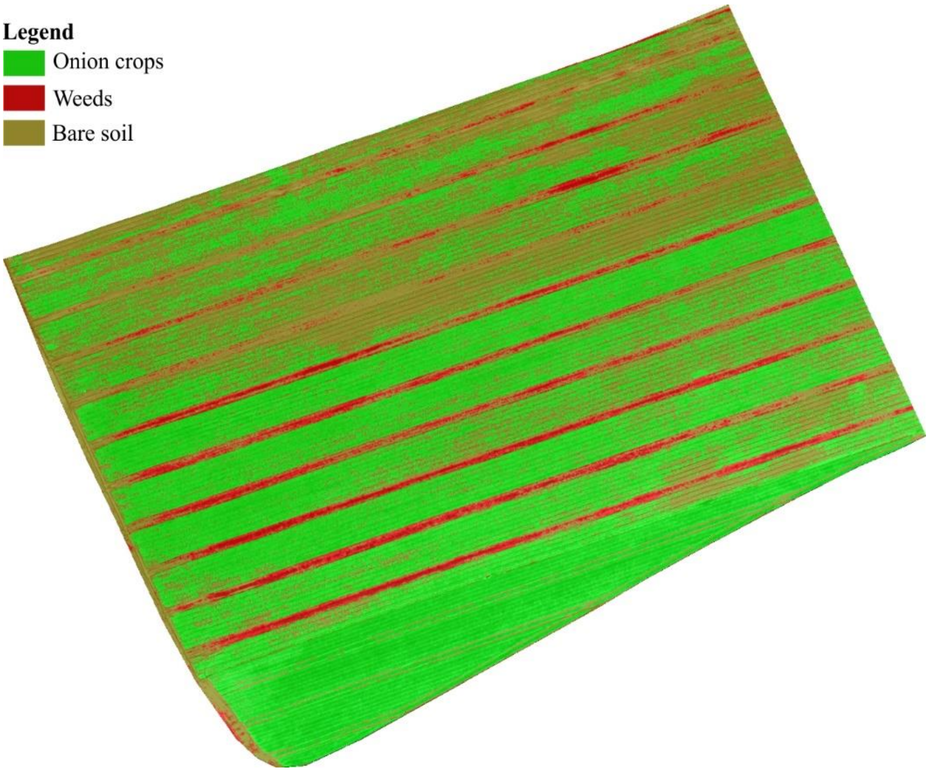

Fig. 2. A map showing the image-object classification of weeds (in red) and onions (in green) performed in the eCogniotion Developer suite. Dataset of 19 December 2018.

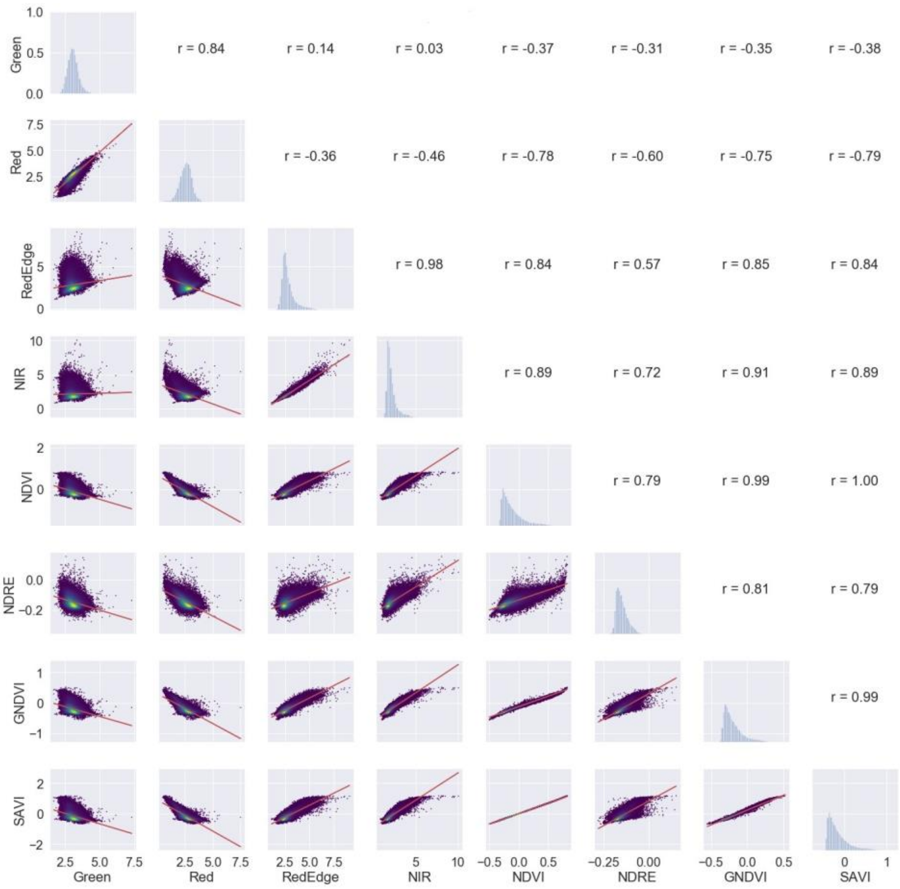

Fig. 3. Scatter plots matrix showing the correlation between the four bands (Green, Red, Red Edge, NIR) and the four vegetation indices (VIs) analysed (NDVI, NDRE, GNDVI and SAVI). Dataset of 19 December 2018.

4 Conclusions

The proposed method for the identification of onions in the field is fast and effective, in line with the needs of the PA to provide in a short time, compared to the time of execution of the surveys in the field, answers and useful information to companies. Certainly the type of sensor used, the accuracy of the surveys and the cultivation phase play an important role on the quality of the final result. As can be seen by looking at the maps, despite the use of the SAVI index, portions of soil between plants were not completely excluded from the classification and not all plants, due to the small size, were identified. The use of a higher resolution sensor might probably have partly solved these problems. The possibility to prepare in short time vigour maps, highlighting areas of the field where there are problems related to plant growth, are the strengths of the method and make it suitable for use in a PA context.

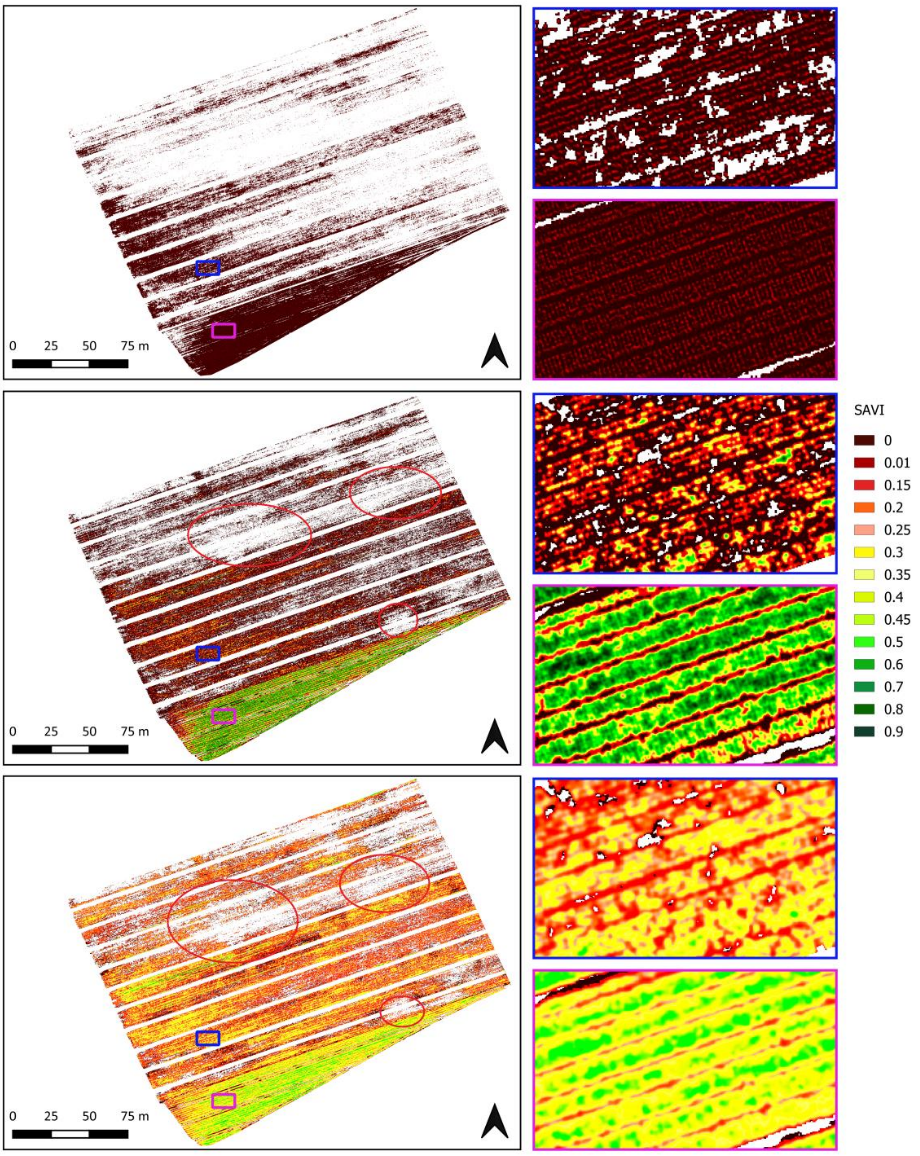

Fig. 4. Analysis of the vegetation vigour of onion crops according to the SAVI maps from November 2018 (top) to January 2019 (bottom). Next to the image of each dataset, blue and magenta rectangles magnify the details of the vegetative vigour of onion crop in two different parts of the field and where the transplanting took place with a month apart. Ellipses in red highlight areas of the field where the onion crop shows a low vegetative vigour.

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