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Detection of homogeneous wheat areas using multi-temporal UAS images and ground truth data analyzed by cluster analysis

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ABSTRACT

Vegetation indices (VIs) obtained from unmanned aerial system (UAS) are effective for monitoring quantitative and qualitative characteristics of vegetation cover. Nevertheless, the identification of agronomic homogeneous crop areas to be managed in a specific different agronomic way is still to be improved in precision farming.

The aim of the study was to reduce information gap on the detection of homogeneous wheat areas using multi-temporal remote sensing image and agronomic crop traits by cluster analysis. The images were acquired by an eBee UAS on a small plot of 720 m² at three different crop growth stages: High-resolution orthoimages (3.5 cm·pixel⁻¹) were generated by Pix4D and QGIS. At each growth stage, biometric ground-truth data and VIs (NDVI and SAVI) were clustered to detect homogeneous crop areas. At tillering and anthesis stages, three significant homogeneous areas with low (L) medium (M) and high (H) VIs and agronomical values were identified for both indices. Yield-related traits (at harvest) and VIs (at anthesis) confirmed that L and M areas, with agronomic constraints identified at anthesis, showed crop yield losses at harvest. Cluster analysis, using UAS and ground truth data, has proved to be a good strategy to identify the homogeneous wheat crop areas.

Introduction

Assessment of the impact of agriculture decisions could be enhanced through the use of field-scale monitoring to help evaluate the changes that have occurred within fields as a result of applied practices or to help guide the decisions that translate into differential agronomic practices that affect plant growth (Alvino & Marino, 2017; Hatfield & Prueger, 2010). The application of geospatial techniques and sensors to identify variations in the agricultural field due to biotic and abiotic constraints is important for the implementation of precision agriculture (Marino & Alvino, 2015). Furthermore, precision agriculture requires an increasing amount of information in order to be sufficiently managed (Fountas et al., 2015), information produced from unmanned aerial system (UAS) surveys might help farmers in decision-making processes, improving agricultural production and optimizing the resource utilization (Thenkabail, Lyon, & Huete, 2012; Zhang & Kovacs, 2012). UASs can be frequently used during the entire growth period; with simple mission planning, instantaneous operation, near-real-time imagery, low man power and imaging below cloud cover (Floreano & Wood, 2015), it provides ultra-high resolution images of the crop canopy due to the low flight altitude (Schirrmann et al., 2016a).

UASs equipped with multispectral sensors are emerging as an important and affordable component of precision agriculture and crop improvement (Candiago, Remondino, De Giglio, Dubbini, & Gattelli, 2015; Colomina & Molina, 2014; Torres-Sanchez, Pena, De Castro, & Lopez-Granados, 2014). In order to make better use of the spectral data, numerous spectral vegetation indices (VIs) have been developed to characterize vegetation canopies (foliage, biomass, leaf area index (LAI), crop yield, phenology, nitrogen, evapotranspiration and primary productivity), using crop reflectance at differing wavelengths (Basso, Cammarano, Cañiero, Marino, & Alvino, 2011; Cabrera-Bosquet et al., 2011; Marino & Alvino, 2014; Marino, Aria, Basso, Leone, & Alvino, 2014; Marino, Basso, Leone, & Alvino, 2013).

Among VIs, the normalized difference vegetation index (NDVI) and the soil-adjusted vegetation index (SAVI) are generally employed as the typical quantitative data for the detection of important agronomic traits and constraints (Tanaka et al., 2015; Verger et al., 2014), since many relationships have been developed between VIs acquired by UASs and vegetation parameters (Caturegli et al., 2016; Lelong et al., 2008).

Wheat is the most widespread crop grown in the world (FAOSTAT, 2017) and there is a strong interest...
in obtaining spatial and temporal information about the wheat canopy for detecting agronomic constraints and improve production efficiency (Jin et al., 2013; Jin, Liu, Baret, Hemerlé, & Comar, 2017; Thoel & Ehlert, 2010). To develop appropriate prescription maps for variable-rate application, the identification of agronomic homogeneous areas is still considered a crucial point. Quebrajo, Pérez-Ruiz, Rodriguez-Lizana, and Agüera (2015) found a visual similarity of the spatial distributions of the NDVI and wheat yield suggesting that the index can be used for delineating management zones across a field. Schirrmann et al. (2016b) report many different types of segmentation methods used in image processing, such as thresholding, clustering, histogram-based methods, object-based image analysis or neural networks. Segmentation methods were mostly used in early season weed mapping (López-Granados et al., 2016; Peña, Torres-Sánchez, De Castro, Kelly, & López Granados, 2013) or in distinguishing crop from soil background (Schirrmann et al., 2016a).

Partitioning clustering has been little adopted for crop image segmentation; fuzzy-c-means has been used by Schirrmann et al. (2016b) in wheat crop to estimate biomass combining imaging with crop height and by Tagarakis, Liakos, Fountas, Koundouras, and Gemtos (2013) on grapevine. Previously, cluster analyses has been adopted in our study on a drip-irrigated tomato (Marino et al., 2014) and by Zarco-Tejada, Ustin, and Whiting (2005) on cotton. As far as our knowledge goes and according to Schirrmann et al. (2016b), cluster analysis has not been used for identifying homogeneous agronomic crop areas by combining UAS images with yield traits such as biomass, LAI, spikes for square meters.

The overall goal of the study was to reduce information gap on the detection of homogeneous agronomic wheat areas using multi-temporal remote sensing image and ground truth data by cluster analysis for delineating homogeneous management zones across the field. The objectives were (1) to identify, at each phenological stage, the significant number of crop areas characterized by statistical agronomic similarity and (2) to evaluate the ability of cluster maps to provide, at anthesis, agronomic and spectral information, related to constraints that can affect crop yield.

**Materials and methods**

**Experimental setup**

**Study area and field measurements**

The on-farm study was conducted in Central Italy in 2015 crop season (411,079.29 E, 4,730,615.48 N; UTM-WGS84 zone 33N Italy). The experimental field was in a flat area at 75 m above sea level on a total surface of about 2 ha, cultivated with different plots of durum and winter wheat. The present study presents results of the durum cv. Odisseo, cultivated on a surface of 720 m² (24 m × 30 m), previously cultivated with soybean. Sowing was performed on 15 December 2014, applying 200 kg of seeds per hectare. Harvest was done on 9 July 2015. Minimum-tillage technique was adopted, using a milling and a disk harrowing.

Basic fertilization was performed in December 2014 with P₂O₅, while N applications were performed during the crop cycle. The weed and pest control was chemically carried out during the crop cycle. Daily maximum and minimum temperatures and rainfall were recorded through a standard agro-meteorological station placed beside the experimental fields (Figure 1).

The phenological stages were periodically recorded according to the Zadoks’ scale (Zadoks, Chang, & Konzak, 1974). Four samplings were carried out at seedling growth (February 23), at tillering (March 30), at anthesis (May 14) and at harvest (July 7). Plants from

![Figure 1. Ten-day averages for rainfall, maximum (T_max) mean (T_mean) and minimum (T_min) temperatures as recorded by a standard meteorological station placed near the experimental fields, during the 2014–2015 growing seasons.](image-url)
0.5 m² (10–12 samplings per date) were georeferenced and hand cut for the calculation of yield-related traits (biomass, green LAI, number of spikes, plant height, yield). Whole plant dry mass was determined after oven drying fresh plant material at 75°C until constant weight.

The sampling points were randomly chosen based on visual spatial crop variability identified by low-resolution orthoimages of flight, processed in real time in the field. Ground truth coordinates of target locations were recorded with GPS Leica Viva GS15 (Leica Geosystems AG, Switzerland) at each sampling and flights.

**UAS system and flight missions**

The flights were carried out at three different dates, in line with the destructive plant samples, with eBee μ using the Pix4D manager tool of the eMotion software and the mission area was saved in the software. The imaged area of experimental field, including the surroundings, is about 15 ha. The time needed for a single flight of the UAS imaging was 15 min. At any acquisition date, two flights were carried out, the first one by a Canon Powershot S110 photo camera (visible spectrum, RGB-red/green/blue) for visible RGB image (orthophoto) to run a rapid analysis for visual crop variability. A second fly with a Canon Powershot S110 NIR camera (near infra-red [NIR], near infra-red/green/blue) that provides the maximum absorption peaks at 550 nm (green), 625 nm (red) and 850 nm (NIR) wavelengths respectively, allowing the computation of VIs. The technical features of the S110 RGB or the S110 NIR involve resolution of 12 million pixels, a weight of 0.7 kg, sensor size of $7.44 \times 5.58$ mm², pixel pitch of 1.33 μm and image format in RAW and JPEG. In fact, the image data consisting of the above four bands were acquired twice by UAS imaging. S110 RGB acquired the true-color image data in single UAS imaging; another UAS imaging with the S110 NIR acquired the false-color image data that consists of the red (570–690 nm), green (510–660 nm) and NIR (780–1000 nm) bands and is therefore able to capture the amount of NIR radiation a surface reflects. This is especially useful to calculate indices like the NDVI as reported by Joseph (2005).

To avoid geometric distortion due to low altitude, 96 overlapping pictures from each camera and fly were used for mosaicking to produce an ortho-image. An 80% frontal overlap and an 80% side overlap were used as suggested by Gómez-Candón, De Castro, and López-Granados (2014). The flight plans were prepared on the eMotion® software and the mission area was saved in order to repeat the same mission from one campaign to another. In order to orient and relate UAS imagery to the ground, at the beginning of the season, 10 ground control points (GCPs) were distributed across the field, to obtain photogrammetric imagery with uniform horizontal and vertical accuracy. The GCPs were 25 cm × 25 cm square, with a specific albedo for camera calibration, mounted on a 50-cm post. The GCP coordinates were ensured with a Leica Viva GS15 (Leica Geosystems AG) GPS, with a horizontal accuracy of 0.025 m and a vertical accuracy of 0.035 m. To enable more accurate geo-referencing of UAS aerial imagery and overlay of measurements from multiple dates, GCPs for spectral calibration boards with a known albedo were used. GCPs were positioned, during the experimental season, at the same georeferenced points before each flight and removed soon afterwards.

**Data processing**

For each flight, images were georeferenced and elaborated using the Pix4D manager tool of the eMotion software. The eBee's supplied software to build a project using the drone's geotagged images. The project is loaded on a laptop in Pix4D mapper Ag (senseFly) for a real-time visual observation of spatial crop variability (low-resolution image).

To create an accurately georeferenced orthomosaicked image of the entire plot, the multiple overlapped images were stitched together and ortho-rectified. In the laboratory, data processing (orthomosaicking) of acquired images was performed with Pix4D software package, to generate ortho-images. This registered software is supplied with the eBee and is designed specifically for this application. Pix4D incorporates scale-invariant feature transform algorithm to match key points across multiple images (Küng et al., 2011; Lowe, 2004) and processes data in three key steps: (1) initial processing (camera internals and externals, automated aerial triangulation, bundle block adjustment); (2) point cloud densification; and (3) (digital surface map [DSM]) and orthomosaicking generation. The exterior position and orientation parameters of the UAS, referring to the roll, pitch and yaw angles of every overlapped image, were provided by the UAS inertial system. These parameters were used as input data to the Pix4D software for ortho-rectification by aero-triangulation and mosaicking. Aero-triangulation involves the transformation of image coordinates to ground coordinates through a set of GCPs that are clearly visible in the set of images. This step consists of forcing an exact match between image and GCP coordinates implemented in the software. Additional auto tie points were generated automatically to improve the aero-triangulation results. Orthoimages and DSMs were produced from the flights; DSMs were interpolated from the densified point clouds and used to orthorectify the individual images. The final step
combined the orthorectified images to form a seamless orthoimage mosaic. The orthomosaic was georeferenced to UTM-WGS84 zone 33N Italy. The final outputs were an RGB (visible) GeoTIFF with a resolution of 3.5 cm pixel$^{-1}$.

The NDVI and SAVI layers were generated in raster calculator from extracted red (R) and NIR channels. The index calculator function of Pix4D was used for generating VIs maps. To optimize internal parameters, such as focal length, principal points, lens distortions, a calibration file (certified by SensFly on canon S110 NIR camera) was uploaded in the software.

The 10 GCPs with a known albedo for Red, Green and NIR channel (reflectance panel) were used to calibrate the camera to achieve uniform quality of image (exposure and brightness) and for atmospheric correction in the software section processing options, point 3 DSM, Orthomosaic, Index and for creating VIs map. The resolution of reflectance map (NDVI and SAVI) has been set at 3.5 cm pixel$^{-1}$ GeoTIFF. GeoTIFF images and georeferenced sampling data were processed for agronomic purpose with QGIS 2.8.1.

**Vegetation indices**

The NDVI was calculated according to Equation (1), based on the difference of the reflectance at NIR and the Red (RED) spectral bands normalized by the sum of the reflectance at these spectral bands.

$$NDVI = (NIR - RED)/(NIR + RED)$$  \(1\)

The NDVI has wide applications providing information about vegetation (biomass and LAI) and chlorophyll content in leaves. The NDVI has good potential to extract useful information regarding dynamic changes in different vegetation types, making it a good indicator for investigating such changes temporally (Geerken, Zaitchik, & Evans, 2005). The NDVI ranges from $-1.0$ to $1.0$, where positive values indicate increasing greenness and negative values indicate non-vegetated features.

The SAVI was calculated according to Equation (2). The SAVI was proposed by Huete (1988) to account for the optical soil properties in the plant canopy reflectance. SAVI involves a constant $L$ to the NDVI (Equation (1)).

$$SAVI = (1 + L)*(NIR - RED)/(NIR + RED + L)$$  \(2\)

The constant $L$ was introduced in order to minimize soil brightness.

Huete (1986), Huete (1988) and (Jiang, Huete, Li, & Qi, 2007) (with Huete as coauthor) defined the soil-adjustment factor $L$ in the SAVI equation varying from 0 to 1 according to the canopy density. $L$ decreases with increases in vegetation amount. For $L = 0$, SAVI is equal to NDVI. According to above cited papers, we have set the $L$ value at 0.5 for the seedling stage and at 0.20 for the tillering and the anthesis stages.

**Statistical analysis**

The yield-related traits and VIs data were analyzed by a clustering method, using hierarchical clustering Ward’s minimum variance approach (Ward, 1963) as reported in a previous paper by Marino et al. (2014). The purpose of cluster analysis is to discover a system that can classify observations into groups, in which the group members have properties in common. Agglomerative clustering begins by finding the most similar two groups, based on the distance matrix, and subsequently merging them into a single group. This procedure is repeated, step-by-step, until all the samples have been added to a single large cluster. The final partition is identified by a distance criterion (Fernández & Gómez, 2008). Starting from the bottom part of the dendrogram, the researcher decides to stop the agglomeration process when successive clusters are too far apart to be merged. In this paper, we used the scree plot to choose the significant number of clusters (Zhu & Ghodsi, 2006). The clusters were created on the VIs (NDVI and SAVI separately) basis and statistical tests were used to verify (a posteriori) dependence conditioning of the different variables.

Statistical procedures were computed using STATISTICA (StatSoft, Inc., Tulsa, OK, USA). To check the normality assumption, Shapiro–Wilk method (Shapiro & Wilk, 1965), Lilliefors method (Lilliefors, 1967) and D’Agostino, Belanger, and D’Agostino (1990) methods were used. The rejection of one or more of this test is a symptom of non-normal distribution. Like most nonparametric tests, the Kruskal–Wallis test (Kruskal & Wallis, 1952) is performed on ranked data in order to verify whether three or more independent groups have the same distribution. Statistical procedures were computed using OriginPRO 8 (Origin Lab Corporation, Northampton, MA, USA). Regression analysis, coefficients of determination, significance levels and root mean square error were computed on the georeferred data (LAI, Biomass and NDVI), using the statistical package Origin PRO 8 (Origin Lab Corporation).

**Results**

**Meteorological conditions**

Decadal minimum and maximum air temperatures and rainfall during the study period are presented in Figure 1. In the cropping season (December–July), the mean temperature was 15.4°C, the winter temperature ranged from a minimum value of $-1^\circ$C (December) to a maximum value of 20.5°C (February and March). During spring, a minimum value was recorded in April ($5.1^\circ$C) and maximum
value in May (31.2°C). The maximum temperature value in July with 36.2°C. Total precipitation amounted to 680.2 mm (December–July). Through the whole cropping season, half of the total precipitation was recorded in 6 weeks, from the third decade of January to the first decade of March. In this last period, 120 mm of rainfall were recorded on the 5th of March, soon after seedling growth. From tillering to anthesis rainfall was scarce, while from anthesis to ripening rainfall was appreciable. Air temperatures were mild from emergence to anthesis. From this stage on, maximum air temperatures were around 30°C, as expected. Therefore, the weather season has not adversely affected the crop growth.

Homogeneous wheat areas at different crop growth

Crop stage: seedling

Figure 2 shows the RGB, NDVI and SAVI images during seedling growth stage (numbers 13 and 14 of the Zadoks scale). The RGB orthophoto shows a partial surface covered by the crops and, consequently, a significant presence of bare soil. The edges of the field seem to have a greater amount of green biomass than the central area as detected by SAVI image values. The SAVI showed higher values than the NDVI with a range from 0.39 to 0.89 for SAVI and from 0.23 to 0.55 for NDVI. The cluster analysis and the scree plot, based on LAI, biomass, and NDVI, split the NDVI maps into three clusters. The nonparametric ANOVA by Kruskal–Wallis showed no significant differences for the georeferenced NDVI and LAI clustered data, while significant cluster differences in biomass were recorded for the three areas with high (H), medium (M) and low (L) VIs (Table 1). Clustering analysis on SAVI, LAI and biomass showed a similar trend at seedling stage with no differences among SAVI and LAI data and three different classes for the biomass data.

Crop stage: tillering

At tillering stage (numbers 22 and 23 of the Zadoks scale), the RGB, NDVI and SAVI images showed a central area and a left strip with lower greenness (Figure 3). The NDVI values ranged from 0.36 to 0.78 and the SAVI varied from 0.39 to 1.01. The cluster analysis at tillering and the scree plot were based on LAI, biomass and VIs (NDVI and SAVI). Based on the results of the discriminant function analysis, the maximum difference between the groups was observed in three clusters after the third eigenvalue (scree plot) for both NDVI and SAVI groups (Table 1 and Figure 4). Within the NDVI groups, the homogeneous areas showed the following mean values for NDVI, LAI and biomass: 0.67, 1.22 and 329 g m$^{-2}$ for H area; 0.61, 0.96 and 156 g m$^{-2}$ for M area and 0.48, 0.68 and 0.80 g m$^{-2}$ for L area.

Within the SAVI groups, the homogeneous areas showed the following mean values for SAVI, biomass and LAI: 0.83, 1.18 and 327 g m$^{-2}$ for H area; 0.72, 0.94 and 150 g m$^{-2}$ for M area; 0.59, 0.61 and 76 g m$^{-2}$ for L area.

Figure 4 reports the identified agronomic homogeneous areas. In both indices images, was detected a central area and two side strips with lower values of agronomic traits and VIs data. The NDVI cluster images showed a 50% of surface with H area, 16.7% with M area and 33.4% with L area instead the SAVI cluster images identified 55.3% of surface with H area, 21.8% with M area and 22.9% with L area.

Crop stage: anthesis

The RGB image at anthesis (number 65 of the Zadoks scale) showed two strips in the center and two areas in the upper part of the plot (corner) with a lower greenness; at anthesis both the NDVI and the SAVI images showed areas with different greenness (Figure 5). The NDVI values ranged from 0.4 in the upper part of the plot to 0.82 in the lower center area; SAVI values ranged from 0.45 in the same upper part of the plot to 1.06 in the lower center area. The cluster analysis at anthesis and the scree plot were used to compute LAI, biomass and number of spikes per square meter and VIs. Three homogeneous areas (Table 1 and Figure 6) were identified in both indices groups, at this phenological stage. Within the NDVI groups, the H areas covered 46.5% of total surface, with an average cluster value of 0.80 for NDVI, 2.38 for LAI, 1088 g m$^{-2}$ for biomass and 527 spikes m$^{-2}$. The M areas (38% of total surface) showed a mean cluster value of 0.77 for NDVI, 1.62 for LAI, 732 g m$^{-2}$ for biomass and 403 spikes m$^{-2}$. The L areas (15% of total surface) showed a mean value...
Table 1. Homogenous areas (H – high, M – medium and L – low), assessed by cluster analysis using Ward’s method of linkage (and scree plot) and Kruskal–Wallis (KW) one-way analysis of variance, at different crop stages. Vegetation indices: NDVI and SAVI, leaf area index (LAI), total biomass (g m$^{-2}$), spikes for square meter ($n°$ m$^{-2}$) and yield (kg m$^{-2}$) were clustered within each vegetation index.

| Stage   | Parameter | NDVI clusters H | NDVI clusters M | NDVI clusters L | KW | SAVI clusters H | SAVI clusters M | SAVI clusters L | KW |
|---------|-----------|-----------------|-----------------|-----------------|----|-----------------|-----------------|-----------------|----|
|         |           | 0.38            | 0.36            | 0.29            | n.s. | 0.59            | 0.55            | 0.54            | n.s.  |
| Seedling| NDVI      |                 |                 |                 |      |                 |                 |                 |      |
|         | LAI       | 0.13            | 0.11            | 0.05            | n.s. | 0.14            | 0.12            | 0.05            | n.s.  |
|         | Biomass   | 23              | 15.1            | 13.3            |      | 22.9            | 15.4            | 13.2            |      |
|         |           |                 |                 |                 |      |                 |                 |                 |      |
| Tillering| NDVI    | 0.67            | 0.61            | 0.48            | **  | 0.83            | 0.72            | 0.59            | **  |
|         | LAI       | 1.22            | 0.96            | 0.68            | *   | 1.18            | 0.94            | 0.61            | *   |
|         | Biomass   | 329             | 156             | 80              | *   | 327             | 150             | 76              | *   |
|         |           |                 |                 |                 |      |                 |                 |                 |      |
| Anthesis| NDVI      | 0.8             | 0.77            | 0.57            | **  | 1.01            | 0.91            | 0.65            | *   |
|         | LAI       | 2.38            | 1.62            | 0.85            | **  | 2.38            | 1.62            | 0.85            | *   |
|         | Biomass   | 1088            | 722             | 322             | *   | 1079            | 749             | 322             | *   |
|         | Spikes m$^{-2}$ | 527          | 403             | 310             | *   | 506             | 407             | 310             | *   |
| Harvest | NDVI*     | 0.79            | 0.76            | 0.57            | **  | 1.03            | 1               | 0.86            | *   |
|         | LAI       |                |                 |                 |      |                |                 |                 |      |
|         | Biomass   | 2072            | 1800            | 1416            |      | 2071            | 1802            | 1408            |      |
|         | Spikes m$^{-2}$ | 476          | 423             | 326             | **  | 476             | 420             | 325             | **  |
|         | Yield     | 0.68            | 0.56            | 0.46            | **  | 0.68            | 0.58            | 0.46            | **  |

*P < 0.05; **P < 0.01; n.s. = not significant.

*VI data taken at anthesis, and clustered a posteriori with yield and yield components.

**Figure 3.** RGB, NDVI and SAVI images processed by UAV imagery at tillering stage (numbers 22 and 23 of the Zadoks scale, March 30).

**Figure 4.** NDVI and SAVI images of homogeneous areas elaborated by ground truth data cluster analysis at tillering stage (numbers 22 and 23 of the Zadoks scale). Bar on the left: Area classes H: high, M: medium, L: low, Bar on the right: surface cover (%) of the homogeneous areas.

**Figure 5.** RGB, NDVI and SAVI images processed by UAV imagery at anthesis stage (number 65 of the Zadoks scale, May 14).
of 0.57 for NDVI, 0.85 for LAI, 322 g m\(^{-2}\) for biomass and 310 spikes m\(^{-2}\). Within the SAVI group, the H areas showed a total surface of 51.2% and a mean value of 1.01 for the VI, 2.38 for LAI, 1079 g m\(^{-2}\) for biomass, and 506 spikes m\(^{-2}\). The mean value of the M homogeneous area (39.4% of total surface) recorded a value of 0.91 for SAVI, 1.62 for LAI, 749 g m\(^{-2}\) for biomass and 407 spikes m\(^{-2}\) with 9.4% of total surface.

**Harvest data and VIs at anthesis**

Starting from reflectance measurements, the NDVI and the SAVI at anthesis stage were clustered to the equivalent ground sampling data of LAI, biomass, spikes m\(^{-2}\), and yield at harvest (numbers 87–89 of the Zadoks scale) to evaluate the early detection of the significant different agronomic crop areas. Based on the results of the discriminant function analysis on various sections of the cut, the maximum difference between the groups was observed in three clusters after the third eigenvalue (scree plot). Three homogeneous areas (Table 1) were identified in both indices groups.

Within the NDVI groups (Table 1), the H areas showed an average cluster value of 0.79 for NDVI, 0.68 kg m\(^{-2}\) for crop yield. The M areas showed a mean cluster value of 0.76 for NDVI, 0.56 kg m\(^{-2}\) for crop yield. The L areas showed a mean cluster value of 0.57 for NDVI, 0.46 kg m\(^{-2}\) for crop yield.

Within the SAVI group, the H areas showed a mean value of 1.03 for SAVI, 0.68 kg m\(^{-2}\) for crop yield. The mean value of M homogeneous area recorded a value of 1 for SAVI, 0.58 kg m\(^{-2}\) for crop yield. The cluster’s mean value of the L areas was 0.65 for SAVI, 0.46 kg m\(^{-2}\) for crop yield. The total grain yield at harvest (small plot mean value) was 0.60 kg m\(^{-2}\).

**Discussion**

Remote sensing of crops has been widely used as an excellent high-density data source to assess changes in crop growth environments. The potential of remote sensing in agriculture is very high, because reflectance data can be converted into estimates of canopy area or plant biomass by calculating different spectral VIs (Rodriguez, Fitzgerald, Belford, & Christensen, 2006). VIs are unable to measure the yield components (such as spikes for square meters), which are mandatory information to apply the Variable Rate Application (De Benedetto et al., 2013). Integrating different layers of information is required for the delineation of homogeneous agronomic zones. The approach of this research study was to combine multitemporal data from UASs with crop traits ground data in cluster analysis with the target of delineating spatially contiguous homogeneous subfield areas. This approach provides statistical information for identifying groups of samples that behave similarly.

Ortho-images (RGB) at seedling growth stage revealed few visual different zones. Cluster analysis found one homogeneous area, although lower biomass values for M zone in respect to H (about −33%) and L respect to H (about −42%) for both VIs. LAI and the VIs showed no significant differences among clusters. A possible reason is the low vegetation cover and in the soil background variations as reported by several studies concerning the effects of soil background on VIs (Huete, 1986; Huete, Jackson, & Post, 1985). It is known that some of the soil-induced effects on VIs have been attributed to additional NIR irradiance underneath and in-between canopies due to NIR scattering and transmission properties of the canopy, with intermediate canopies displaying the largest effect (Ward, 1963). Canopy scattering is small with low vegetation cover while the soil signal is small with high vegetation cover. Soil reflects some of the scattered and transmitted NIR flux back toward the sensor, depending upon the soil’s reflectance properties. The results in our experiments are in agreement with those found by Rasmussen et al. (2016). They found that in spring wheat correlations between VIs derived from ground measurements were much lower in the early growth stage than in Figure 6. NDVI and SAVI images of homogeneous areas elaborated by ground truth data cluster analysis at tillering stage (number 65 of the Zadoks scale). Bar on the left: Area classes H: high, M: medium, L: low, Bar on the right: surface cover (%) of the homogeneous areas.
At harvest, the yield and biometric traits were related to VIs measured at anthesis, to assess, in retrospect, the detection of the homogeneous areas. There was a significant correlation between all the parameters measured at harvest with both indices at anthesis. Yield losses at harvest, due to constraints, were identified by cluster analysis performed on the yield-related traits at harvest and the VIs at anthesis. The homogeneous area H sets the upper yield limit of the field for the year 2015 and the cultivar Odiseo; for both NDVI and SAVI homogeneous area, H yield was identified as 0.68 kg m$^{-2}$ for a surface of 220 m$^2$. The M and L areas were identified as the areas in the field affected by constraints which reduced total yield at harvest by 16% and 32% respectively. The procedure led to a yield estimation of 0.61 kg m$^{-2}$ in retrospect, very close to the whole harvest yield data, namely 0.60 kg m$^{-2}$.

**Conclusion**

Our study revealed that cluster analysis, applied on small wheat plots, using UAS and ground truth data has proved to be a good strategy to identify the homogeneous crop areas at different crop stages. At early stage (seedling), cluster analysis returned only homogeneous area due to low vegetation cover although a field visual variability was detectable by SAVI. At tillering and anthesis stages, three significant homogeneous areas L, M and H were identified for both indices (NDVI and SAVI). Furthermore, cluster analysis performed a posteriori on yield-related traits (at harvest) and VIs (at anthesis), confirmed that areas with agronomic constraints were identified at anthesis and showed crop yield losses at harvest. As a matter of fact, crop yield of M and L areas was respectively 16% and 32% lower than the most productive areas (H). These results provided agronomically useful information that can be applied at farm level for a variable rate management of wheat fields. In the case at hand, variable rate N application at tillering might level off constraints, whereas, variable rate N application at anthesis would be based on the potential productivity of each area. In the near future, it will be mandatory to integrate, in short time, clustered groups, georeferenced ground truth data and data from crop and soil sensors to improve the precision in detecting homogeneous areas.

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**Disclosure statement**

No potential conflict of interest was reported by the authors.

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