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Consumer-grade UAV utilized for detecting and analyzing late-season weed spatial distribution patterns in commercial onion fields

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Abstract

Studying weed spatial distribution patterns and implementing precise herbicide applications requires accurate weed mapping. In this study, a simple unmanned aerial vehicle (UAV) was utilized to survey 11 dry onion (*Allium cepa* L.) commercial fields to examine late-season weed classification and investigate weeds spatial pattern. In addition, orthomosaics were resampled to a coarser spatial resolution to simulate and examine the accuracy of weed mapping at different altitudes. Overall, 176 weed maps were generated and evaluated. Pixel and object-based image analyses were assessed, employing two supervised classification algorithms: Maximum Likelihood (ML) and Support Vector Machine (SVM). Classification processes resulted in highly accurate weed maps across all spatial resolutions tested. Weed maps contributed to three insights regarding the late-season weed spatial pattern in onion fields: 1) weed coverage varied significantly between fields, ranging from 1 to 79%; 2) weed coverage was similar within and between crop rows; and 3) weed pattern was patchy in all fields. The last finding, combined with the ability to map weeds using a low cost, off-the-shelf UAV, constitutes an important step in developing precise weed control management in onion fields.

Keywords Classification · UAV · Weed mapping · Site specific weed management · Spatial pattern

Rafi Kent and Lior Blank have contributed equally to this work.

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Introduction

Weed infestation in agricultural fields is considered a major threat to crop yield (Oerke 2006). Weeds compete with the crop for resources such as light, water and nutrients, inflicting significant losses (van Heemst 1985). Herbicides are an essential means for controlling weeds (Zimdahl 2018). However, herbicide application can cause various negative results to biodiversity (Freemark and Boutin 1995), human health (Jepson et al. 2014; C. Wilson and Tisdell 2001) and underground water (Pretty et al. 2000). In addition, herbicide residuals in the soil can potentially harm future crops (Keeling et al. 1989) and contribute to the development of herbicide-resistant weeds (Bagavathiannan et al. 2019; Pretty et al. 2000). Nevertheless, herbicides are essential for maintaining high yield production; Kudsk and Streibig (2003) state that research should find ways to optimize their use.

One of the reasons for the excessive use of herbicides is that they are applied uniformly throughout the field. One emerging method to reduce the overall use of herbicides is site specific weed management (SSWM) (Alvarez-Fernandez 2012). Weeds tend to cluster and are not uniformly distributed throughout a field (Cardina et al. 1997; Gerhards et al. 2002; Nordmeyer 2006; San-Martín et al. 2015; Jurado-Expósito et al. 2019; Blank et al. 2019). The SSWM approach promotes precise herbicide treatments that is adjusted to the level of infestation in each part of the field, thereby reducing the amount of chemicals applied and thus costs (Timmermann et al. 2003).

One way to implement SSWM would be to use an accurate map of the weed-infested areas in the field (Ribeiro et al. 2005). Generating weed maps can be done by field scouting. However, this can be tedious, time consuming, expensive (Schuster et al. 2007), and often requires additional interpolation to estimate weed infestation in unsampled areas (Rew and Cousens 2001). An alternate method to map weeds derives from relatively recent advanced technological developments in remote sensing in general, and the use of unmanned aerial vehicles (UAVs) in particular (Hunt and Daughtry 2018). Attributes such as low maintenance cost, light weight, user-friendly interface, along with the ability to produce high spatial resolution orthomosaics of large areas on demand, even on cloudy days, make UAVs an attractive tool for field mapping (Huang et al. 2018a, b; Hunt and Daughtry 2018). Furthermore, recent studies found this mapping technique to be more accurate than the traditional practice of mapping by field scouting (Kalischuk et al. 2019; Rasmussen et al. 2018).

For producing an easy-to-use map, the resulting orthomosaic needs to be categorized into several meaningful classes (Abburu and Golla 2015). However, the spectral and textural similarity of weeds and crops complicates the classification process (Huang et al. 2018a, b). Differences in the phenological stages of crops and weeds can be utilized to identify spectral differences between the two, and improve classification accuracy (Lamb and Brown 2001). For example, Castillejo-González et al. (2014) successfully mapped wild oat patches in wheat fields, utilizing spectral differences at the end of the growing season. However, due to the importance of early weed detection, numerous studies have focused on mapping in early-season growth and addressed the crop and weed similarity in various ways e.g. Peña et al. (2013), Pérez-Ortiz et al. (2015), de Castro et al. (2018), and Lambert et al. (2018). By contrast, despite the importance of late-season weed mapping, research about it remains limited (Bagavathiannan and Norsworthy 2012; Rasmussen et al. 2018).

Utilizing UAVs for the purpose of weed mapping is yet to achieve its full potential (Krähmer et al. 2020). Expanding research on the efficacy of this method vis-à-vis various crops and scales, to examine its feasibility under various conditions

(Fernández-Quintanilla et al. 2018), is important and valuable. In this study, a low-cost UAV (< 1000 USD) was used to map weeds in dry onion (*Allium cepa* L.) fields. World production of dry onion has grown consistently from 1961 to 2017, the last year for which statistics are available, and is currently estimated to 100 million tons per year (FAO 2020). Weed infestation is a critical problem; onion is considered to be a weak competitor with weeds, due to its slow growth rate, shallow root depth, and foliage structure (Khokhar et al. 2006). In dry onion, as in most crops, the critical period in which to eliminate weed competition so as to allow the crop's growth is in the early stages of the growing season (Dunan et al. 1996; van Heemst 1985). However, owing to the crop's characteristics, many weed species successfully compete with the onion throughout the entire growing season (Sivesind et al. 2012). In addition, some weed species thrive later in the growing season and can enrich the weeds seedbank. Thus, controlling weeds at this stage is significant for long-term weed management (Bagavathiannan and Norsworthy 2012). Furthermore, the presence of weeds interrupts the harvesting process (Ghosheh 2004). However, herbicide treatments performed at this stage might result in crop injury and decreased yields, as reported in other crops (Bagavathiannan and Norsworthy 2012). Therefore, while late-season weed management in this crop is of particular importance, applying herbicides at this stage should be kept to a minimum. During that period in the growing season, the dry onion foliage plummets, dehydrates and changes its color to yellowish-brown (López-Granados et al. 2010), while the growing weeds remain vital and green. Therefore, it is hypothesized that using the spectral differences resulting from the different phenological stages in the crops and the weeds at the same point in time can be used to distinguish between the two fairly easily.

The main objectives of this study were to: (1) examine late-season weed mapping, utilizing a simple off-the-shelf UAV, employing different methods across various spatial resolutions; (2) estimate weed coverage in the fields; and (3) assess the spatial pattern of weeds. In accordance with the research goals, it is hypothesized that: (1) spectral differences between weeds and onions will allow accurate classification of weeds late in the growing season due to the expected spectral contrast between the crop and the weeds at that stage of the season; (2) weed coverage would vary considerably among fields as different farmers employ different weeds management protocol and potentially due to the different climatic conditions persisting throughout the study area; (3) weed communities would exhibit aggregated patterns as shown in other studies on weeds distribution, with tendency to establish in crop rows as irrigation and fertilization are applied there.

Materials and methods

Study area

This study was conducted on 11 commercial onion fields, located in different areas throughout Israel (Fig. 1). All the fields were sown in the winter (December–February) and harvested in the summer (July–August) of 2018 (Table 1). Aerial mapping was conducted at June–July 2018, when the onion's foliage had dried out, shortly before harvest. Conditions were sunny with no strong winds. A subset (2500–5200 m^2) of each field, defined as the core of the field, located at least 20 m from the field boundary, was mapped. These

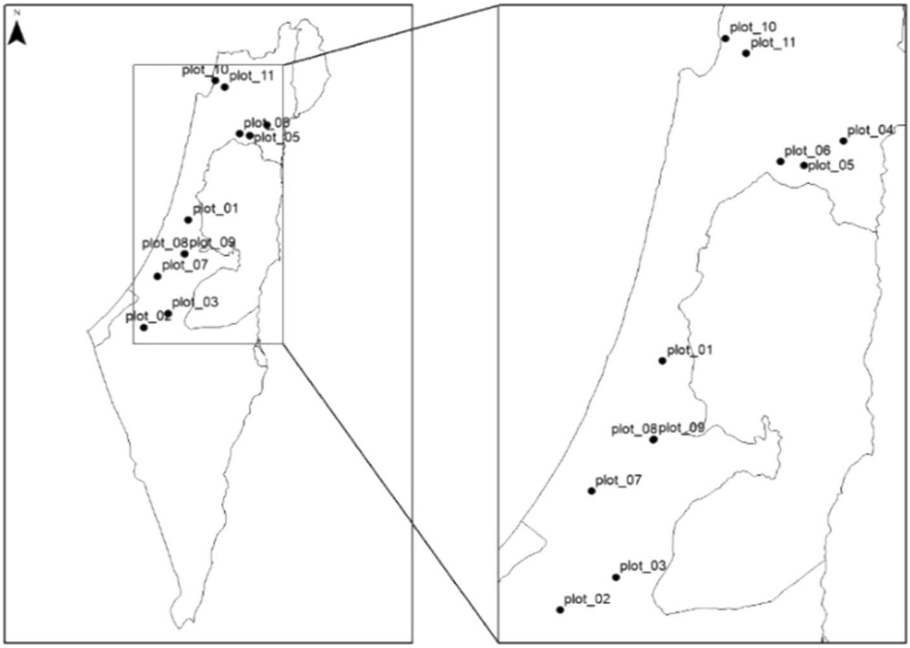

Fig. 1 The 11 commercial fields that were mapped in the study

Table 1 The 11 commercial fields surveyed. na—information unavailable

Plot ID	Field size (m^2)	Sowing date	Harvest date	Field survey date	Area surveyed (m^2)
Plot 01	220,000	21/12/2017	15/7/18	7/6/18	3,120
Plot 02	226,000	1/1/2018	25/7/18	20/6/18	3,804
Plot 03	130,000	28/12/2017	n/a	20/6/18	2,646
Plot 04	30,000	n/a	n/a	27/6/18	2,548
Plot 05	120,000	11/1/18	5/7/18	27/6/18	2,692
Plot 06	100,000	n/a	n/a	27/6/18	3,607
Plot 07	300,000	11/2/18	30/7/18	9/7/18	4,016
Plot 08	50,000	13/2/18	30/7/18	9/7/18	2,926
Plot 09	38,000	13/2/18	30/7/18	9/7/18	2,820
Plot 10	100,000	7/2/18	n/a	18/7/18	3,927
Plot 11	200,000	15/1/18	n/a	18/7/18	5,270

plots were subjected to the same farming practices as the rest of the fields. Among the weeds frequently found in the study fields were the *Cyperus rotundus*, *Sorghum halepense*, *Chenopodium album*, *Xanthium strumarium* along with various species belonging to Amaranth, Conyza and Solanum genus (Table 1S).

Data acquisition

A simple off-the-shelf DJI Mavic pro drone was utilized to acquire images of each field. The UAV's camera is a 1/2.3-inch CMOS sensor with 12.71 megapixels, which captures photos in the visible light spectrum i.e. red, green and blue (RGB). Coordinates were marked to set the survey's perimeter, and autonomous flight was planned at 15 m altitude, with 85% and 70% frontal and side image overlap, respectively. High overlap results in a larger number of images taken and a longer flight duration over a given area; thus, the battery's life and area covered are limited. Nevertheless, the Pix4D instructions (Pix4D 2019) recommend this method in homogeneous landscapes such as agricultural fields, and in low-altitude flights. The GPS coordinates, along with the camera settings automatically acquired for each picture taken, were utilized in the Pix4D Mapper software (Pix4D, Switzerland) to construct a georeferenced orthomosaic. the Pix4D algorithm included all three standard steps: 1) initial processing, 2) point cloud and mesh and 3) DSM and orthomosaic generation. The low altitude flight resulted in very high-resolution orthomosaics (0.5 cm/pixel).

Image resampling

Low flight altitudes entail several drawbacks and limitations, as mentioned above. For a simple UAV to be considered a practical tool for weed mapping of whole fields, it should be tested at various altitudes. That means getting varying spatial resolutions but gaining in scope of area covered. To cover whole fields, lower spatial resolution must be accepted as a compromise; spatial resolution decreases as the area covered increases. Therefore, orthomosaics were resampled with the use of the Nearest Neighbor (NN) algorithm, following Borra-Serrano et al. (2015), using ArcGIS 10.5 (ESRI, The Redlands, CA) to simulate higher altitudes. In this method, new pixels are created from the neighboring pixels, with each new pixel encompassing several of the original ones. The value of each new pixel cell is set according to the original pixel situated at its center. Three new spatial resolutions of 1, 2 and 3 cm/pixel, corresponding to altitudes of 30, 60 and 90 m, respectively, were generated.

Image classification and validation

The classification process involved two major steps. In the first step, in order to perform an object-based images analyses (OBIA), a segmentation method was applied; this concept was suggested to improve classification accuracy in cases where the resolution is such that the pixels represent only a miniscule part of the objects under examination (Blaschke 2010). In this process, segments are generated based on adjacent pixels that contain similar spectral values. Classification is then preformed based on objects, e.g. weeds and crop, constructing the orthomosaic to mimic a more realistic identification process as opposed to pixel-based classification. This study employed a method of clustering contiguous spectrally related pixels into segments containing their average values (for details see: Comaniciu and Meer 2002). The ArcGIS 10.5 program (ESRI, Redlands, CA, USA) does this via a simple command- "Segment mean shift". Selected parameters, spectral detail, spatial detail and minimum segment size in pixels, were set to 15.5, 15 and 20, respectively, with no band indexes. The process results in a smoother and homogenous mosaic segmented to objects.

In the second step, pixel- and object-based classifications were performed using Maximum Likelihood (ML) and Support Vector Machine (SVM) algorithms. The two classification algorithms were employed in ArcGIS 10.5 where no additional parameters are required. Both algorithms perform supervised classification, i.e., use training samples, set by the user, to define meaningful classes. Information regarding both algorithms is elaborated in Otukei and Blaschke (2010). Training samples were constructed using polygons uniformly dispreads across each orthomosaic. The number of polygons varied according to weed patches layout. Initially, the categories chosen were "soil", "onion", and "weed". Later, the first two categories were merged, to create two main classes: "non-weed" and "weed", respectively. Each classification process used the training set produced for the plot. Finally, single pixel values were altered according to their neighbors' values, using the common majority filter to reduce the "salt-and-pepper" effect that often occurs in classification procedures (Lu and Weng 2007).

The original 11 orthomosaics, along with the 33 resampled ones, were subjected to pixel- and object-based classifications using the two common algorithms, ML and SVM, as noted above. Thus, a total of 176 classification processes were performed. In order to examine the differences between the four modes of classification, a Kruskal–Wallis Test was used, followed by a multiple comparison test, using the "pgirmess" package (Giraudoux et al. 2018) implemented in R studio 1.1.456 (R Development Core Team, Vienna, Austria).

The very high resolution orthomosaics enabled the visual identification of land cover i.e. a distinction between weed, crop and soil. A total of 300 points were generated by randomly using the "create accuracy assessment points" tool in ArcGIS 10.5, and manually identified as "weed" and "non-weed". To avoid bias, identification was made before the classification processes took place. A confusion matrix was then used to calculate overall accuracy (OA) and kappa coefficient (Congalton 1991). The first calculates the percentage of cases classified correctly and ranges from 0–100% whereas the second provides information on classification results as opposed to random classification and ranges from 0–1. In both cases, a higher number indicates a more accurate classification product. The two indices are commonly used, as reflected in classification literature; values higher than 85% and 0.75 for the OA and kappa coefficient, respectively, are considered satisfactory (de Castro et al. 2012; Castillejo-González et al. 2014). In addition, a stratified random sampling was performed on the highest ranked weed map, according to OA and kappa coefficients. This process can handle the uneven spatial distribution of weeds. Thirty quadrates (0.25 m^2) were equally divided into three infestation categories by the extent of weed coverage: 0–33%, 34–67%, and 67–100%. The weed coverage was determined by calculating the percentage of pixels classified as "weed" out of the total pixels in each cell. Weed coverage in each quadrate was visually evaluated and tested for correlation to the calculated coverage using R studio 1.1.456 (R Development Core Team, Vienna, Austria) to perform a Pearson correlation.

Weed coverage and spatial pattern

Weed maps produced from the original orthomosaics were used for further examination of weed dispersion in the plots. The highest ranked classification maps, as determined by OA and kappa coefficients, were used to evaluate weed coverage and spatial pattern. When two (or more) methods produced equal OA and kappa coefficients, the method of classification was randomly chosen. Weed coverage in percentage was calculated for the whole plot, as well as for the areas between and within crop rows, after the crop rows were manually plotted based on the orthomosaics.

Considering the high spatial resolution of the orthomosaic, single pixels could not serve as the basis for evaluating the weeds' spatial distribution pattern, because the image of each individual weed was composed of many pixels and thus a single weed might be misidentified as a patch. Another problem might result when weed patches intersect and thus are grouped and classified as a single patch. By using those patches as the bases of the spatial pattern analysis, the information regarding individual weeds that compose these patch aggregations will be lost.

To overcome both challenges, a grid of 0.25 square meters (0.5 × 0.5 m), which was recently used for generating treatment maps according to machinery specifications (López-Granados et al. 2016a, b) and herbicide treatment units (Castillejo-González et al. 2019), was overlaid on the highest-ranked weed maps. In each cell, the percentage of weed coverage was calculated, and Moran's I, a common spatial autocorrelation test (Moran 1950; Krähmer et al. 2020), was used to describe the spatial pattern of the grid cells comprised of weeds (weed coverage > 0%) using the "Spatial Autocorrelation Global Moran's I" in ArcMap 10.5.

Results

A total of 16 weed maps were produced for each of the 11 plots: four were the original orthomosaic maps and 12 were of the resampled plots. Overall, the four classification methods produced very similar outputs (Fig. 2 and Figs. 1S–11S). All the OA percentages derived for the original orthomosaics were above the threshold value of 85%; the majority of the kappa coefficients values were also above 0.75, the standard threshold value (Table 2). In most cases, the ML algorithm resulted in higher scores compared to the SVM. Pixel and object-based classifications resulted in very similar scores. Validations with stratified sampling of the highest-ranked weed classification maps attained correlation scores equal to or greater than 0.94 ($P < 0.001$).

Similar procedures were employed for analyses of the resampled classifications (Tables 2s—5S). In most cases, OA and kappa values were higher than 85% and 0.75, respectively. While the mean OA of all the classification methods met the standard of 85% threshold (See Tables 2S, 3S), focusing solely on the kappa coefficients, some variation can be found (Fig. 3 and Tables 4S, 5S). Pixel-based ML algorithm consistently produced slightly higher kappa coefficients. At the lowest spatial resolution, pixel-based classification performed substantially better than object-based processes. However, the differences were not statistically significant ($p > 0.05$ in Kruskal–Wallis Test). The only significant difference was found in the lowest spatial resolutions, between the ML pixel-based classification and the SVM object-based classification.

Weed coverage quantification and spatial pattern analyses

Mean weed coverage in the study plots was 28% ± 8.5% (Table 3). The study plots exhibited a wide range of weed infestation levels, with a minimum of 1% in plot 06 and a maximum of 79% in plot 04. Out of the 11 plots, five can be characterized as having relatively

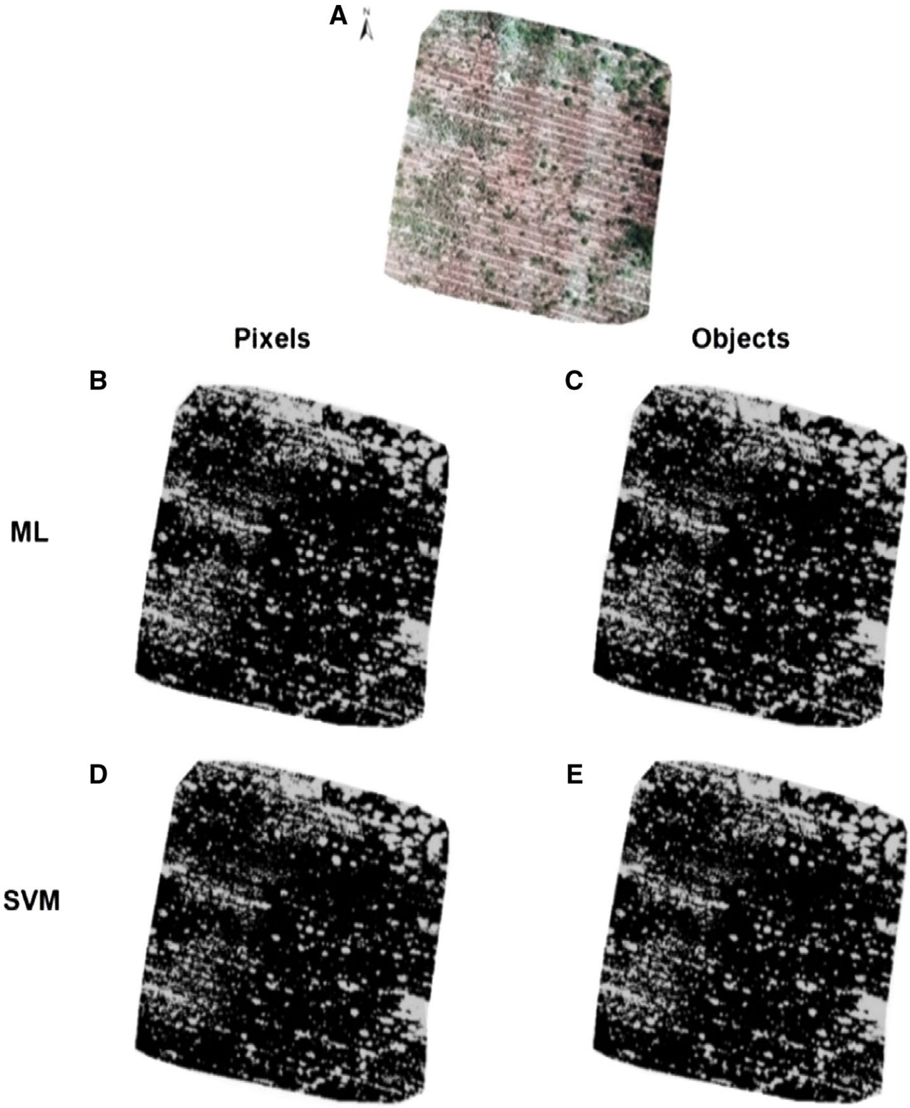

Fig. 2 Example of the four classifications derived from the original orthomosaic of plot 02 (**a**). ML algorithm applied on pixels (**b**) and objects (**c**). SVM algorithm applied on pixels (**d**) and objects (**e**). Black represents weed-free areas and light gray represents weeds

low weed coverage, ranging from 1 to 7% (plots 01, 06, 08, 09 and 11) three with an intermediate weed cover, ranging between 25 and 27% (plots 02, 03 and plot 10) and three with high infestation levels, where weed coverage was greater than 50% (plots 04, 05 and plot 07). In most cases, weed coverage was found to be similar both between and within crop rows. Nevertheless, some exceptions can be found in plots 02, 05 and 10, where weed cover between rows was at least 10% higher than it was within rows. Despite the variation in weed coverage, global Moran's I index was positive in all 11 plots, along with a p

Table 2 OA and kappa indices for each of the plots for the two algorithms ML and SVM, divided by pixel orthomosaic (Pixels) and following a segmentation process (Objects)

	ML				SVM				
	Pixels		Objects		Pixels		Objects		
Plot ID	OA %	kappa	OA %	Kappa	OA %	kappa	OA %	kappa	R
Plot 01	92	0.6	96.3	0.77	93.3	0.65	**98**	**0.87**	0.95***
Plot 02	**96**	**0.9**	95	0.88	93.3	0.83	92.3	0.81	0.94***
Plot 03	97.3	0.92	**97.3**	**0.93**	96.3	0.89	97.3	0.93	0.99***
Plot 04	92.3	0.77	**94.7**	**0.83**	89.7	0.71	92.3	0.78	0.94***
Plot 05	**95.7**	**0.9**	91.7	0.8	94	0.87	91.3	0.8	0.98***
Plot 06	98.7	0.74	98.7	0.7	96.7	0.52	**99**	**0.76**	0.95***
Plot 07	91.7	0.82	**93**	**0.85**	87	0.73	85	0.7	0.97***
Plot 08	**98.3**	**0.88**	97	0.76	98.3	0.87	98	0.85	0.99***
Plot 09	**98.6**	**0.88**	98	0.84	98	0.83	98.3	0.86	0.98***
Plot 10	**92.7**	**0.82**	90	0.74	92.3	0.81	90.1	0.76	0.94***
Plot 11	98.3	0.81	**99.3**	**0.88**	96.7	0.7	**99.3**	**0.88**	0.97***

For each plot, the highest OA and kappa values are marked in bold. R is the Pearson's correlation coefficient of the observed vs. calculated weed coverage, for the highest ranked weed classification map

*** $p < 0.001$

Table 3 Weed coverage and spatial pattern in the 11 study plots

Plot ID	Weed coverage (%)	Crop row weed coverage (%)	Inter row weed coverage (%)	Moran's I	Spatial pattern
Plot 01	7	5	10	0.3	Clustered
Plot 02	25	22	32	0.3	Clustered
Plot 03	26	25	28	0.5	Clustered
Plot 04	79	80	77	0.6	Clustered
Plot 05	69	65	75	0.6	Clustered
Plot 06	1	1	1	0.5	Clustered
Plot 07	58	59	56	0.4	Clustered
Plot 08	7	6	8	0.4	Clustered
Plot 09	6	6	7	0.3	Clustered
Plot 10	27	19	42	0.4	Clustered
Plot 11	3	1	5	0.1	Clustered
Mean	28	26.3	31	0.4	

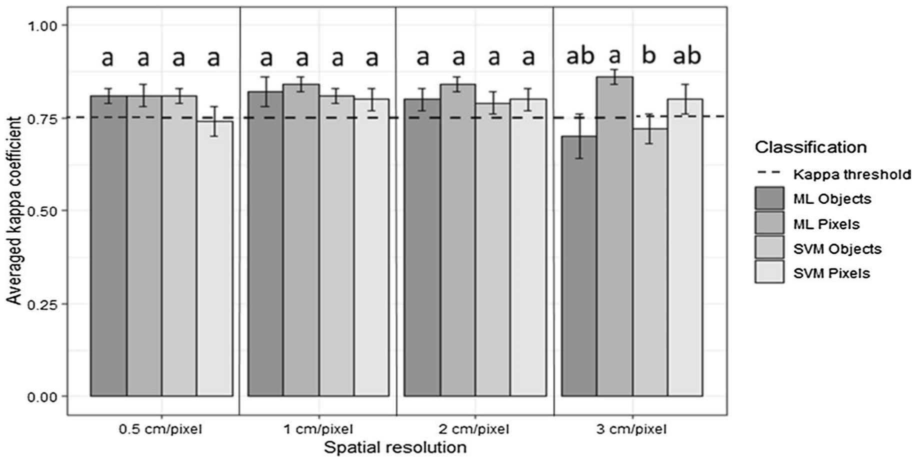

Fig. 3 The post-hoc multiple comparison tests performed separately for each resolution is marked in letters. The average kappa coefficients were compared across the four resolutions (0.5–3 cm / pixel), using the ML and SVM algorithms based on pixels and segmentation, with a threshold of 0.75. Error bars represent ± SE. Bars with the same letter codes do not differ significantly

value < 0.0001 and a positive z score, thus indicating a clustered pattern rather than the null hypothesis of a random spatial pattern.

Discussion

Weeds cause significant yield loss in crops in general, and in dry onion (*Allium cepa*) in particular (van Heemst 1985). As a key component in weed control, herbicides were once described as a “two-edged sword”, meaning that while they are an effective tool for weed control and essential for maintaining high crop yield, their widespread use had various environmental impacts, e.g. water and air pollution, and agricultural ramifications, e.g. herbicide-resistant weeds (Kudsk and Streibig 2003). Numerous studies have identified site-specific weed management as a way of substantially reducing herbicide use, and emphasize both the economic and environmental advantages of this approach (Gerhards et al. 2002; Timmermann et al. 2003; Gerhards and Oebel 2006; Christensen et al. 2009). An accurate weed map is a vital requisite for applying precise weed control practices. Therefore, utilizing UAVs to produce high spatial resolution orthomosaics of large areas, rapidly and with relatively low costs, is of high priority.

To the best of the authors’ knowledge, this is the first study on late-season weed mapping in onion fields. In this work, it was demonstrated that farmers can use a low-cost UAV (< 1000 USD) and a simple RGB camera to produce accurate weeds maps. Operating in several commercial fields in a number of regions shows that a simple UAV can produce accurate weeds maps under various conditions. The high accuracy of weed mapping shown in this study, coupled with previous studies that harnessed spectral differences between crop and weeds resulting from distinct phenological stages (de Castro et al. 2012; Castillejo-González et al. 2014; Rasmussen et al. 2018), highlight the importance of considering the vegetation’s life cycle in weed mapping.

Overall, all four classification processes across the range of spatial resolutions produced accurate weed maps. Both pixel and object-based ML and SVM classifications produced highly accurate outputs. High accuracy was acquired for both low and high weed infestation levels, and the classification process was able to map both large patches and individual weeds. Identifying the best method for classification was not one of the objectives of the study. Nonetheless, it should be noted that the ML algorithm was found to be the most accurate across the various spatial resolutions. ML is a widely used classification algorithm in remote sensing (Lu and Weng 2007) and has been shown to be very accurate in similar studies (de Castro et al. 2013; Castillejo-González et al. 2014). In addition, OBIA was not found to contribute to the weed mapping accuracy (Fig. 3). The segmentation process was found to be vital in early season weed mapping (Peña et al. 2013; López-Granados et al. 2016a, b; López-Granados et al. 2016a, b; de Castro et al. 2018). However, in early stages, crops and weeds share similar spectral signatures; additional attributes, such as the differing shapes and textures might help to distinguish between the two. In addition, the formation of objects from pixels may be influenced by the initial parameters set by the user. A single set of parameters was employed in this study, while the size and shape of the weed patches varied. Due to the marked spectral differences at the phenological stage the data were collected, the use of differential parameters was redundant.

Degraded spatial resolution did not adversely affect the quality of the classification suggesting weeds may be correctly classified from various altitudes. Previous studies reported similar results when conducting additional flights (Rasmussen et al. 2018) or alternatively resampled image to simulate various altitudes (Tamouridou et al. 2017). While, the results of using low spatial resolution orthomosaics generated using a computer algorithm rather than performing additional flight campaigns may raise some concerns, (Borra-Serrano et al. 2015) found resampling to be comparable to actual flights, despite some limitations and comprise of valuable information. The ability to produce accurate weed maps from higher altitudes will enable the user to survey larger areas and to reduce the time required to process the images for higher resolutions (López-Granados et al. 2016a, b; Rasmussen et al. 2018).

The simple UAV utilized was able to generate accurate weed cover maps, despite the fact that the weed coverage varied substantially among the 11 fields surveyed. The highest infestation level was recorded in plot 04, the only plot in this study under organic management. This may explain the high infestation level, because no herbicides were applied throughout the season. However, extensive weed coverage was also found in fields under conventional management (Table 3). The great variation found in conventionally managed fields could be attributed to various factors, such as herbicide application or fertilization protocols, in addition to other attributes that might affect weed infestation, e.g. landscape heterogeneity and geographical location (Medeiros et al. 2016). Weed cover maps could also be used to extract additional valuable data in an economical and fairly easy way, for example, before-and-after comparisons of weed infestation in a field, following various weed treatments.

The areas within and between crop rows are largely characterized by different conditions. Although irrigation and fertilization take place within crop rows, the established crop casts shade and covers most of the ground, thus competing with the weeds. In contrast, between crop rows, competition with the onion diminishes, but the introduction of external resources e.g. water and fertilizers is limited (Haynes 1985). Moreover, weed coverage between crop rows could be affected by soil compaction due to machinery wheels, thus affecting the emergence of specific weed species (Tardif-Paradis et al. 2015; San Martín et al. 2018). Nonetheless, in this study, weed coverage was found to be similar both within and between crop rows (Table 3). A potential explanation to this result might be due to the onion being a weak competitor with weeds, and thus allowing weeds to flourish within rows. These results are consistent with a previous study conducted on maize (Longchamps et al. 2012), although maize and onion are distinct crops, and the mapping was done at a different stage in the growing season. This finding is important; several studies that successfully mapped weeds in early stages of the growing season were based on weed location outside crop rows (Borra-Serrano et al. 2015; López-Granados et al. 2016a, b).

Understanding weeds spatial pattern is valuable information. However, collecting this information by scouting each field is tedious, time-consuming, and thus costly. Here, it was demonstrated that the information is obtainable using fairly simple and inexpensive means. Weed populations in all of the study plots exhibited a patchy spatial pattern. This is a critical finding, because weed clustering is a key component for SSWM and herbicide reduction (Barroso et al. 2004). Aggregation of weeds is a known phenomenon that has been reported in various studies (Johnson et al. 1995; Cardina et al. 1997; Nordmeyer 2006). However, in most cases, the spatial pattern of weeds was studied either on individual species (Gonzalez-Andujar and Saavedra 2003; Andújar et al. 2011; Blank et al. 2019) or in weed groups, like broadleaves and cereals (Johnson et al. 1995; Nordmeyer 2006). In this study, the spatial pattern of the entire weed community was assessed. Nonetheless, the identification of weed species could further contribute to the understanding of weeds' spatial patterns and weeds management might be accomplished by coupling hyper- or multispectral cameras with novel advanced algorithms.

Obtaining reliable weed maps is beneficial for both farmers and research. Attaining this goal by utilizing inexpensive methods makes it economically feasible and therefore practical to use. Because the location of some species of weeds tends to be stable between seasons (Wilson and Brain 1991; Castillejo-González et al. 2019; Blank et al. 2019), weed mapping may also be used in subsequent seasons to direct pre-emergence herbicide treatments (Koller and Lanini 2005; Castillejo-González et al. 2019). Furthermore, since weeds disturb the harvesting process (Ghosheh 2004), farmers are often forced to apply herbicides when using heavy machinery very late in the season. Accurate extraction or spraying of weeds would reduce use of chemicals (Castaldi et al. 2017) and minimize possible effects on the crop.

Conclusions

This study demonstrates the potential of using low-cost UAVs for late-season weed mapping in dry onion fields, and constitutes an important step in developing precise weed control management. Meaningful data i.e. weed maps, coverage and spatial pattern was generated, utilizing orthomosaics produced from a low-cost device. The high classification accuracy scores across the flights and various altitudes, along with the patchy distribution pattern of weed population, can be harnessed in the future to create accurate treatment maps and thereby reduce the quantity of herbicides applied in onion fields.

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Conflict of interest The authors declare that they have no conflict of interest.

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