

# Assessing the potential of images from unmanned aerial vehicles (UAV) to support herbicide patch spraying in maize

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**Abstract** The capability of images acquired from unmanned aerial vehicles (UAVs), with multispectral cameras, to detect weed patches, should be tested in operational situations of site-specific weed management. In this regard, different post-emergence herbicide application strategies were evaluated on a total of four silage maize fields in Central Italy. The treatments compared were uniform blanket application, patch spraying according to the application map and an untreated control (the latter treatment only in the second year). Images were acquired a few weeks after maize emergence and were processed into application (i.e. prescription) maps. The accuracy of prescription maps was evaluated on the basis of ground-truth data. Maize and weed biomass data collected at end of the growing season were used to assess differences among the herbicide application strategies. Results showed no differences between uniform and patch spraying treatments for silage maize biomass in the two fields of the first year. In the second year, maize biomass differences were observed between the untreated control and the other two treatments. In terms of weed biomass there were no differences among treatments, for three out of four fields. The use of UAV image data captured early post-emergence in maize lead to a decrease in the use of herbicide without negative consequences in terms of crop yield and, at the same time, increased the silage biomass production as compared to non-treated area. The saving of herbicide calculated in terms of untreated area ranged between 14 and 39.2 % for patch spraying as compared to a uniform blanket application, and saved between 16 and 45 € ha<sup>-1</sup>.

**Keywords** Weed · Prescription map · Biomass · Site-specific weed management · Multispectral sensor · Corn

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## Introduction

Maize silage yield is reduced by competition with weeds for light, water, and nutrients, and weed control has always been one of the main concerns of agriculture. Yield losses due to weeds are estimated to reach potentially 34 % globally (Oerke 2006). Conventional mainstream agriculture relies heavily on chemical weed control, but the excessive use of herbicides has often led to agronomic and environmental problems (Zanin et al. 1993). In this regard, the Directive 2009/128/EC of the European Union stipulates a more rational use of crop protection products to ensure worker safety, maintain consumer health by reducing herbicide residues in the environment and food chain, and at the same time, provide savings on production costs. One of the main challenges of precision agriculture, in the context of a contribution to reach the aims of the Directive, is to develop efficient weed management systems that reduce the amount of herbicides used. Usually farmers carry out blanket herbicide treatments and do not consider the spatial variability of weeds (Nordmeyer 2009). However, weed species have a heterogeneous spatial distribution, showing patches within the field with different shapes and densities alternated with areas without weeds (Cardina et al. 1997). Knowledge of the spatial distribution of weeds can lead to a targeted use of herbicides. In this regard, site-specific weed management (SSWM) consisting of targeting weed control according to their density, spatial distribution and typology, could allow for a decrease of herbicide usage, lower costs and environmental impact (Gerhards and Christensen 2003; Christensen et al. 2009; López-Granados 2011).

Weed patch detection within the field is the key to applying a patch-spraying system. SSWM requires accurate information on the spatial distribution of weeds (Hamouz et al. 2014). Field scouting coupled with the application of geostatistical techniques could yield accurate weed maps, but this approach is not feasible outside research contexts, being time consuming and expensive. The spatial autocorrelation of the majority of the weeds has been generally observed to span short distances, i.e. the ranges of the semi-variogram are generally small, in the order of 30–50 m (Blanco-Moreno et al. 2006; Nordmeyer 2009). This is mainly due to the patchy distribution of weeds within the field, which is related in turn to the seed dispersal or vegetative propagation mechanisms, as well as to management factors such as tillage direction and soil properties (Gerhards et al. 1997). Hence, in order to obtain a reliable semi-variogram describing the spatial autocorrelation of weed density, it is necessary to collect a consistent number of weed samples (high resolution) over the whole field.

Sensor technologies (spectrometers, fluorescence sensors and digital cameras) and differential global positioning systems (DGPS) can be coupled to obtain information about variation of weed populations within a field (Gerhards 2013), both using proximal (on-the-go sensors mounted on the tractor) and remote sensing instruments. However, to carry out efficient SSWM, in addition to the weed sensing system, it is necessary to implement a weed management decision making process and have a precision weed control device, such as a boom sprayer having independent nozzles, allowing to vary the application of herbicide according to the inputs provided by a map (Christensen et al. 2009).

In order to rapidly obtain information on the spatial distribution of weeds, high spatial resolution remote sensing imagery offers perhaps the only practicable method (Thorp and Tian 2004). A number of studies have demonstrated the feasibility of such an approach. Goel et al. (2003) used hyperspectral data acquired by compact airborne spectrographic imager (CASI) to detect changes in the spectral response of corn induced by stress caused by weed infestation. De Castro et al. (2013) employed multi-spectral aerial images to

evaluate the capability of mapping cruciferous weed patches in winter crops, while Gutiérrez et al. (2008) used aerial images to produce a weed probability map in a sunflower crop by using logistic models approaches. Airborne data are expensive, but data from sensors on board of satellite platforms are often not suitable for the objectives of weed mapping due to their low spatial and temporal resolution (Torres-Sánchez et al. 2014). The use of unmanned aerial vehicles (UAVs) with low altitude flights, provides images with a very high spatial resolution (<50 mm), which are less expensive and have fewer logistic constraints as compared to manned airborne data collection (Zhang and Kovacs 2012). Therefore, UAVs offer the possibility of having more acquisitions during the crop growing season, providing high spatial and temporal resolution data (Rango et al. 2006), and adapting spectral resolution and flight altitude to the detection objectives in the field (López-Granados et al. 2015).

Research on the use of UAVs in the context of precision agriculture has increased considerably in recent years. Torres-Sánchez et al. (2014) employed ultra-high resolution images acquired by UAVs equipped with an Olympus PEN E-PM1 RGB camera (Olympus Corporation, Tokyo, Japan) over a wheat field, calculating from the images six vegetation indices, to test the influence of flight altitude and days after sowing on vegetation fraction mapping. Ballesteros et al. (2014) studied the relationship between green canopy cover and leaf area index values retrieved from images acquired using a RGB camera mounted on a UAV, on maize and onion fields. Peña et al. (2013) used images from UAVs to generate a weed map in a maize field and obtained 86 % overall accuracy. López-Granados et al. (2015) employed a multispectral camera, on board of a UAV, to map the weed coverage in sunflower, evaluating the influence of weed thresholds on the amount of herbicide to be sprayed.

Currently, the spatial resolution offered by UAVs is suitable to allow the discrimination of weed patches, considering to the possibility of setting the flying height. However the spectral resolution of sensors on board UAVs is often still too coarse to allow the discrimination of crops from weeds. Most of the commercial UAVs are equipped with RGB or RGB + NIR cameras, while only recently real multispectral cameras having 6–8 bands can be found in the market of UAV service providers. However, the remarkable technological developments in the context of low weight remote sensors is leading to increasing spectral resolutions on board of UAVs, and better quality data, making these instruments more attractive for precision agriculture applications.

Despite the above mentioned limitations, UAVs were used to detect weed patches within annual crops (e.g. Zhang and Kovacs 2012; Peña et al. 2013; López-Granados et al. 2015), however, these weed maps have been rarely tested in operational situations of SSWM (e.g. Pelosi et al. 2015), i.e. converted into herbicide prescription maps and employed for patch spraying, so that an assessment of their effective economic and environmental benefits could be evaluated.

The goal of the present work is to assess the feasibility of SSWM based on weed maps from images acquired from UAVs, encompassing the whole process leading to variable rate herbicide application, in an operational context. The steps were to acquire images from UAVs early in the silage maize crop to detect weed spatial distribution within four fields in Central Italy. The weed maps derived from UAV data were used to evaluate two (2014) or three (2015) post-emergence herbicide application strategies: (i) untreated control, (ii) uniform blanket application, and (iii) patch spraying according to the prescription map. The specific objectives were to assess the capability images from UAVs to detect weed occurrence early in silage maize crop, to quantify the decrease in herbicide applied and to verify if this reduction has significant silage maize yield impacts.

## Materials and methods

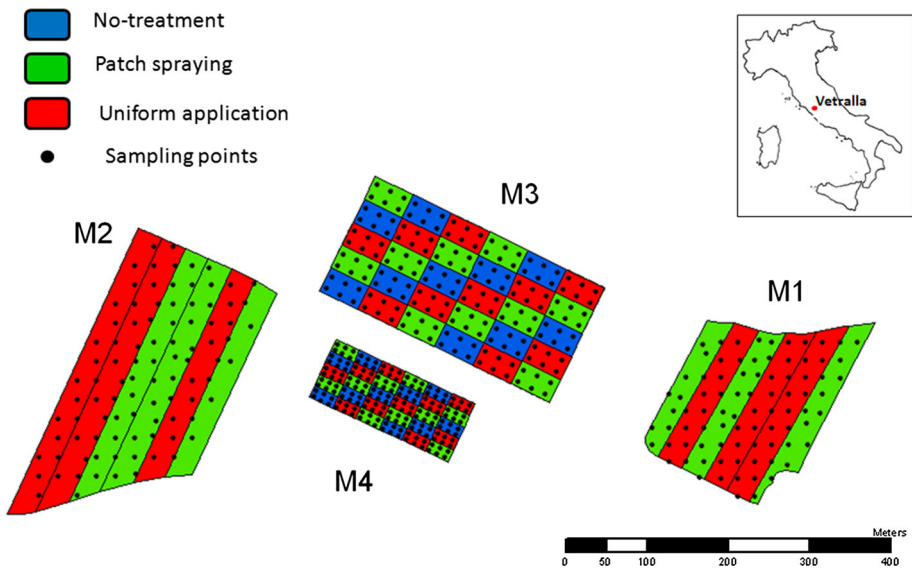
### Study area and experimental design

A total of four fields (Fig. 1) were evaluated across two growing seasons (2014 and 2015), located in Vetralla (lat. 42.54 N, long. 12.00 W, alt 300 m), near Viterbo, Central Italy. Fields were coded as M1 and M2 for the first year and M3 and M4 for the second year (Table 1). Soils of the study area are Epileptic Andosol (IUSS Working Group WRB 2015; Costantini et al. 2012) originated on pyroclastic deposits of the Vicano District (red tuff with black scoria; Late Pleistocene). The plowed soil horizon (Ap) is characterized by acid reaction (pH = 6 in H<sub>2</sub>O), clay or clay loam texture and 1.4 % organic matter content.

Details of the agronomic managements of the fields are reported in Table 1. In 2014, two herbicide application strategies were compared: (i) uniform blanket application and (ii) patch spraying according to the prescription map (Fig. 1). Each field was divided into six 24 m wide strips extending to the whole length of the field, with three randomly assigned strips for each treatment.

In 2015, a different experimental designed was employed, in order to allow the application of an improved methodology for the spatial modelling of the results, i.e. employing model-based statistics (see section on [Post-treatment field survey and biomass estimation](#)). In this case three different herbicide application strategies were compared: (i) untreated control, (ii) uniform blanket application and (iii) patch spraying according to the prescription map (Fig. 1). Each field was divided into 30 plots, with ten replicates for each treatment. The dimension of each plot was 24 × 40 m in M3 and 12 × 24 m in M4.

Images were collected using UAVs early in the silage maize crop, processed and used to generate prescription maps that were applied according to the treatments. At the end of the season, crop and weed biomass were sampled.



**Fig. 1** Overview of the experimental layout of the fields employed in the 2 years of the experiment and of the points used for final maize LAI and biomass sampling

**Table 1** Details of the agronomic management of the maize fields in which the experiments were carried out

Field code	Area (ha)	Soil tillage	Fertilization	Sowing	UAV flight date	Herbicide spraying date	Harvest date
M1	2.21	18 April 2014: ploughed with subsoiler; 22 April 2014: disk harrowed	24 April 2014: 193 kg N ha <sup>-1</sup> ; 66 kg P2O5 ha <sup>-1</sup> ; incorporated with a power harrow	5 May 2014: 6.8 seeds m <sup>-2</sup> with a row spacing of 75 cm. Variety Calcio (FAO Class 720)	5 June 2014	1 July 2014	22 September 2014
M2	3.47	18 April 2014: ploughed with subsoiler; 22 April 2014: disk harrowed	24 April 2014: 193 kg N ha <sup>-1</sup> ; 66 kg P2O5 ha <sup>-1</sup> ; incorporated with a power harrow	5 May 2014: 6.8 seeds m <sup>-2</sup> with a row spacing of 75 cm. Variety Calcio (FAO Class 720)	5 June 2014	1 July 2014	22 September 2014
M3	2.88	9 April 2015: ploughed with subsoiler; 13 April 2015: disk harrowed	16 April 2015: 193 kg N ha <sup>-1</sup> ; 66 kg P2O5 ha <sup>-1</sup> ; incorporated with a power harrow	29 April 2015: 6.8 seeds m <sup>-2</sup> with a row spacing of 75 cm. Variety Calcio (FAO Class 720)	13 June 2015	4 July 2015	5-6 October 2015
M4	0.86	9 April 2015: ploughed with subsoiler; 13 April 2015: disk harrowed	16 April 2015: 193 kg N ha <sup>-1</sup> ; 66 kg P2O5 ha <sup>-1</sup> ; incorporated with a power harrow	29 April 2015: 6.8 seeds m <sup>-2</sup> with a row spacing of 75 cm. Variety Mas 78.T (FAO Class 700)	13 June 2015	4 July 2015	5-6 October 2015

## UAV acquisitions

In 2014, UAV imagery was acquired 4 weeks after planting with a modified Canon s110 camera with four channels corresponding to red (660 nm), green (520 nm), blue (450 nm), and near infrared (NIR; 850 nm) regions of the optical spectrum, mounted on a fixed-wing eBee Ag UAV (senseFly SA, Cheseaux-Lausanne, Switzerland), with a wingspan of 0.96 m and a weight of 0.71 kg. The flight height was 150 m, obtaining a spatial resolution of 0.05 m. At the time of UAV acquisition, the crop was at the third leaf phenological stage (V3) and the main weed, *Cyperus rotundus* L., was at the end of the leaf development stage, with a height of about 100–150 mm and nine or more true leaves, i.e. at BBHC stage 19 (Hess et al. 1997). *Cynodon dactylon* L., *Malva sylvestris* L., *Artemisia vulgaris* L. and *Polygonum aviculare* L. were also observed within the two fields, but at lower densities than *C. rotundus*.

In 2015 UAV flights were carried out on the 13 June. Since the results of the first year had not been entirely satisfactory in terms of weed classification (see Results section), a different UAV system with a camera having a much better spectral resolution was employed in the second year. Images were acquired using the Agrosensor (AIRINOV, Paris, France) multispectral camera mounted on a VTOL (vertical take-off and landing) SF6 UAV system (Skyrobotic, Narni, Italy), a multicopter with a width of 1.2 m and a weight of 4.8 kg. The Agrosensor camera acquires data in four well resolved spectral bands: green (550 nm), red (660 nm), red edge (735 nm) and NIR (790 nm). Since this camera had a lower spatial resolution as compared to the one used in 2014, a lower flight height than the previous year had to be adopted, in order to have images of comparable spatial resolution. Flight height was about 35 m, obtaining a spatial resolution of 0.09 m for M3 and 0.08 m for M4, comparable to the one of the first year (0.05 m). Maize was at the V3 stage and the main weed, *C. rotundus*, was at the BBHC 19 stage.

In both years, the day following the UAVs image acquisition, ground-truth data were acquired from 15 points in each of the four fields, a number of points that could be achieved in one day given the labour resources available. These sampling points were chosen visually so that low, medium and high weed density categories were equally represented. Ground-truth data consisted of downward looking photographs acquired using the 8 megapixel RGB camera of an iPhone® 4S (Apple, Cupertino, CA). The photographs were taken over rectangular quadrats (1.50 × 0.75 m), freehand from a height of about 1.5 m so that the whole quadrat was included in the photograph. These data were processed using a supervised classification technique based on the Support Vector Machine algorithm as done for UAV images (see following section), obtaining weeds, soil and crop classes. A region of interest (ROI) was chosen for each class in each picture and the accuracy of the results was visually checked. Given the very high resolution of these images (0.6 mm for pixel), they were considered as ground truth and used for the validation of the weed maps obtained from UAV images, as detailed in the following section.

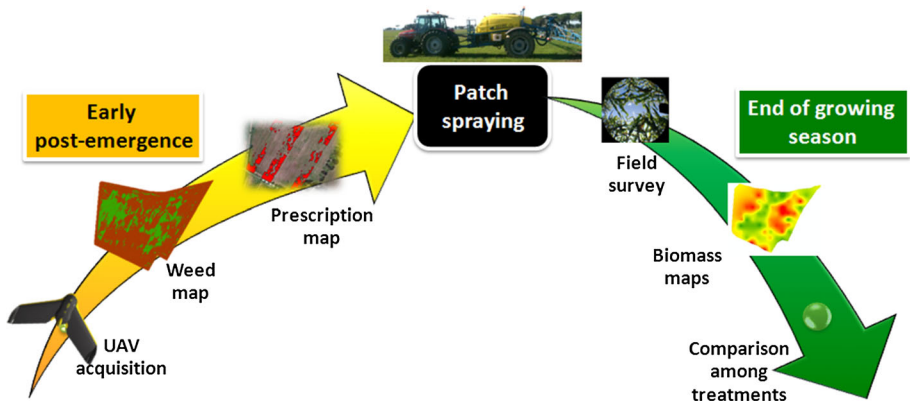
## Prescription maps and herbicide treatments

The UAV imagery was employed to create weed maps of the fields using supervised classification based on the support vector machine algorithm (SVM; Melgani and Bruzzone 2004). This technique allows to separate defined training classes (soil, crop and weeds in our case) using a decision surface, which is called hyperplane, that maximizes the margin between the classes. ROI concerning the training classes were manually selected by means of the ground-truth data. Points closest to the hyperplane are called support vectors, which are the critical elements of the training set (Hsu et al. 2007). This classifier considers geometrical rather than statistical properties of the classes and there is no need to know the mapping function, as SVMs do not require an estimation of the statistical distributions of classes to carry out the classification task, but they define the classification model by exploiting the concept of margin maximization (Melgani and Bruzzone 2004). The SVM parameters used in the ENVI 5.2 software (EXELIS, Rochester, NY, USA) were (i) the radial basis function as kernel type, which works well in most cases, with a gamma in the kernel function of 1.0, (ii) a penalty parameter of 100 that allows a certain degree of misclassification, which is particularly important for non-separable training sets, and (iii) a classification probability threshold of 0.30, which is used to set the probability that is required for the SVM classifier to classify a pixel, so that pixels where all rule probabilities are <0.30 were unclassified.

The classification accuracy was assessed by comparing the results with those obtained from ground data acquired as described in the previous section. The validation of the prescription maps was performed by using the data from all the 60 rectangular plots from the four fields as ground truth, calculating a confusion matrix (Congalton 1991). The latter, also known as error matrix, is obtained by placing in the rows the number of pixels of each class from ground truth data and in the columns the corresponding results from the UAV image classification. It allows to calculate the overall accuracy of the classification (% of the pixels correctly classified) as well as producer and user accuracy. The producer accuracy indicates the probability that the classifier has labeled an image pixel into the weed class given that the ground truth is actually weeds. Conversely, the user accuracy indicates the probability that a pixel is actually weeds given that the classifier has labeled the pixel as weeds. A low producer accuracy would imply a high omission error, i.e. a high proportion of true weedy pixels not identified in the detection method and thus contributes to underestimation of the weed patches. A low user accuracy corresponds to a high commission error, a high proportion of pixels misclassified as weedy, i.e. the classification overestimates the weed patches providing a conservative estimation. As remarked by López-Granados (2011), from the farmers' perspective it is desirable have lower omission errors (high producer accuracy) and higher commission errors (low user accuracy), so that the weed patches are less likely to be missed. All the validation data were bulked to have a more representative sample.

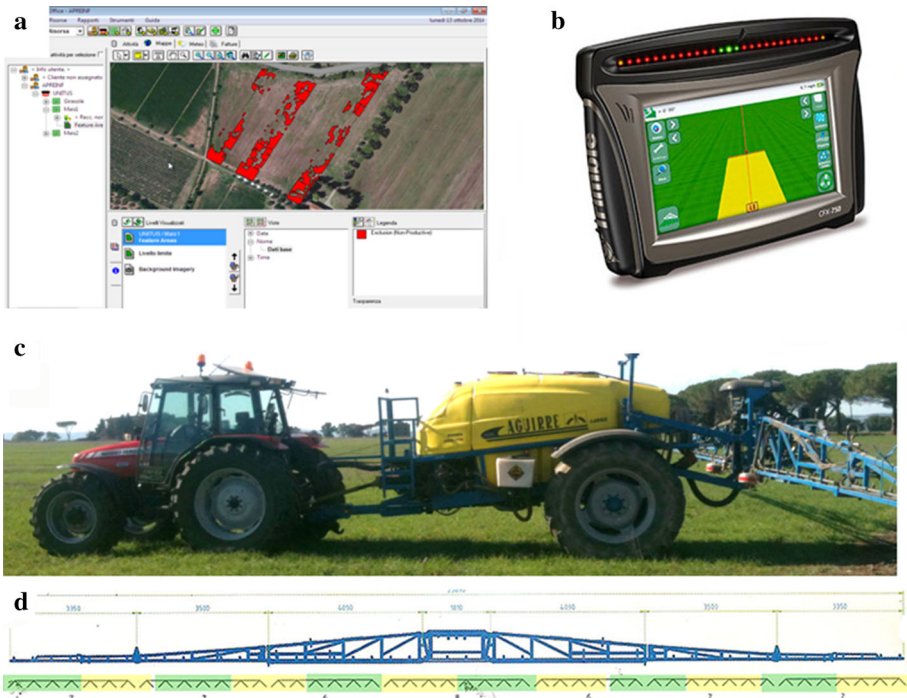
A regular grid of 2 by 2 m was laid over the weed maps retrieved from supervised classification and cells without weeds were selected as exclusion areas not to be sprayed, in order to generate binary (on/off) herbicide prescription maps. The dimension of the grid of the prescription maps was chosen according to the width of the independent sections of the boom sprayer (Fig. 2).

The prescription maps were uploaded onto a Trimble CFX-750 monitor (Sunnyvale, CA, USA) on board a Massey Ferguson 4365 tractor (Massey Ferguson, Duluth, GA, USA), equipped with a Field-IQ Crop Input Control System (Trimble Navigation Ltd, Sunnyval, CA, USA). The system controlled the opening and closing (on/off) of 12 independent boom sections, each of 2 m width with four nozzles, of a 24 m Aguirre Norma 4000-7TR (Aguirre, Tafalla, Spain) boom sprayer (Fig. 3).



**Fig. 2** Work flow of the activities concerning field data collection and processing at an early post-emergence stage and at the end of the growing season





**Fig. 3** Components of the patch spraying system implemented: **a** application map, **b** upload of the prescription map onto the tractor on-board monitor, **c** tractor and sprayer, **d** boom sprayer with twelve independent sections controlled separately

The post-emergence herbicide treatments were carried out on 1 July in 2014 and on 4 July in 2015 using a herbicide rate of  $2 \text{ l ha}^{-1}$  with active ingredient (a.i.) mesotrione ( $150 \text{ g a.i. ha}^{-1}$ ) and nicosulfuron ( $60 \text{ g a.i. ha}^{-1}$ ), in the areas to be treated for both growing seasons. The delay between UAV acquisition and herbicide treatment was due to technical problems concerning the availability of the herbicide to the farmer. However, based on field observations carried out during this lapse of time, the spatial distribution of weeds did not vary much during this period. Maize was about at V6 phenological stage at herbicide treatment time, while *C. rotundus* was at the beginning of the flowering stage (BBHC 5).

### Post-treatment field survey and biomass estimation

At the end of the season, on September 8–10, 2014, maize leaf area index (LAI) was measured in 85 points per field (about  $30 \text{ points ha}^{-1}$ ), according to a 17 by 17 m grid. In 2015, on September 1–2 for field M4 and September 9–10 for field M3, maize LAI measurements were taken on six points per plot, at a density of 62 and 208 points  $\text{ha}^{-1}$  for M3 and M4, respectively (Fig. 1). In the second year, the different spatial analysis approach adopted, required regularly distributed samples with the same number of points for each plot, in this way LMEMs could be compared among treatments.

Maize LAI values at each point were obtained by acquiring upward looking hemispherical photographs from beneath the maize canopy using a smartphone digital camera



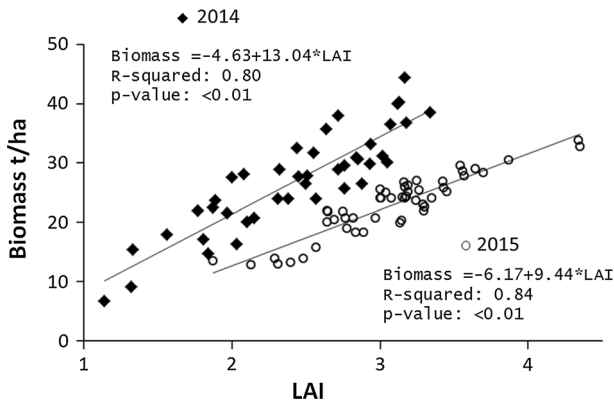
equipped with a fish-eye lens (iPhone 4S with Rollei Fisheye). The photographs were acquired at a height of about 200 mm from the soil, above the weed canopy, in order to capture only maize LAI. The processing of the hemispherical photographs was carried out using the CAN-EYE software (Demarez et al. 2008), which calculates the effective LAI from the gap fraction estimated from the classification of the hemispherical photographs. Concurrently with the LAI data acquisition, the above-ground maize biomass was collected from 1 m<sup>2</sup> area at 42 different locations in the fields in 2014 and at 60 locations in 2015. The maize samples were weighted in the field and then dried in an oven for 48 h to obtain dry biomass. The relationship between LAI and dry maize biomass was used to estimate maize biomass at the points in which only LAI and not biomass had been measured, according to the equations shown in Fig. 4. Two different equations were used for the 2 years, since the harvest was carried out much later in the second year as compared to the first, thus the maize growth stage was different. It should be noted that the use of these regression equations entails a root mean square error of 2.80 t ha<sup>-1</sup>, but it was not feasible to collect maize biomass data in 65–82 points per field in a reasonable amount of time to avoid the introduction of perhaps even higher experimental error.

Weed biomass was harvested from all sampling points where maize LAI was measured at the end of growing season. Weeds were collected from two 0.5 by 0.5 m squares for each sampling point and dried for 48 h to obtain dry biomass.

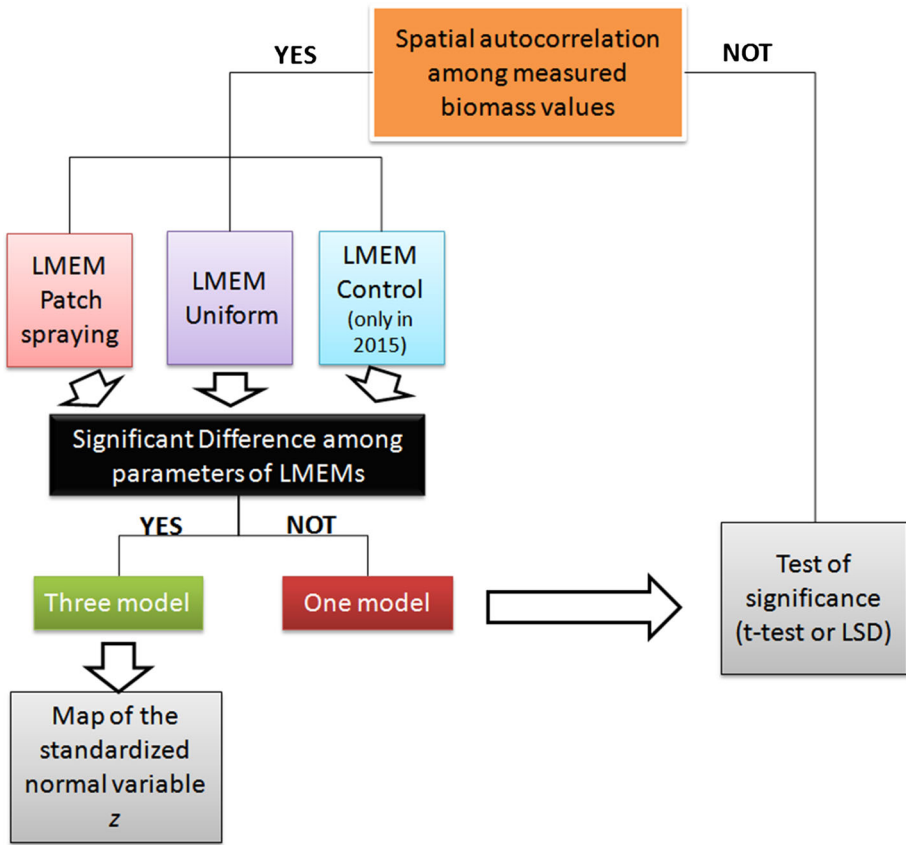
The maize silage and weed biomass values for each plot at the end of growing season were analysed across the fields to detect differences among post-emergence herbicide application strategies (Fig. 5). The existence of spatial autocorrelation among biomass values within each field was checked by the Moran I test (Moran 1950) in order to include it into the comparison among herbicide strategies. Where spatial autocorrelation was verified, a linear mixed effect model (LMEM) was used to estimate maize silage biomass at unsampled locations, according to the spatial resolution of the image acquired by UAV. In this case, the normalized difference vegetation index (NDVI) map obtained by UAV's image was used as auxiliary variable in the LMEM. The formula of a LMEM is given by

$$Y_i = x_i\beta + s_i + \varepsilon_i, \quad (1)$$

where  $Y_i$  represents the response at the location  $i$ ,  $x_i$  is a vector containing spatially-referenced non-random predictors, i.e. NDVI values obtained from UAVs' images, and  $\beta$  is a vector of the fixed effect parameters,  $s_i$  is a spatially correlated random effect and  $\varepsilon_i$  is the



**Fig. 4** Relationships between maize LAI and biomass measured at harvest time in 2014 and 2015



**Fig. 5** Work flow of the methods employed to assess differences among post-emergence herbicide application strategies in terms of maize and weed biomass at the end of growing season

random measurement error (Pollice and Bilancia 2002). The simultaneous estimation of model parameters (correlation and fixed effect coefficients) were obtained by the restricted maximum likelihood (REML) method. Separate LMEMs were tested for samples belonging to each herbicide treatment, then if the differences between the model parameters were not significant, only one model was applied for the whole field.

The differences of crop biomass response among herbicide treatments were evaluated in three different ways depending on the presence/absence of spatial autocorrelation among biomass values and the difference between the parameters of the LMEMs (Fig. 5). When the spatial autocorrelation was detected, the biomass values obtained by the implementation of the LMEMs were used. If the parameters of the LMEMs were not different among herbicide treatments, the biomass values were compared using a Student’s *t* test. Conversely, maize and weed biomass maps were obtained for each treatment and consequently the differences across the fields was estimated. In the latter case, the contrast between treatments was expressed both as difference of estimated biomass value ( $t \text{ ha}^{-1}$ ) and standardized normal variable *z*. The computation of variable *z* for each cell of the grid allowed to obtain maps showing field areas having significant differences between

treatments at the 1 % of confidence ( $|z| > 2.58$ ), 5 % (if  $|z| > 1.96$  and  $< 2.58$ ), 10 % (if  $|z| > 1.645$  and  $< 1.96$ ).

When the spatial autocorrelation among measured biomass values was not detected, a one-way analysis of variance (ANOVA) and Fisher's Least Significant Difference (LSD) multiple-comparison test were used to evaluate the statistical difference among the measured biomass values of the treatments (at  $p < 0.01$ ).

## Results

### Maize/weed classification and prescription maps

The maize/weed classification procedure indicated a high weed infestation within the M2 field (60.7 % of the field covered by weeds), while the area affected by weeds in the other fields ranged from 27.9 % (M4) to 35.6 % (M3). Consequently, the percentages of treated and untreated areas within plots assigned to the patch spraying treatment were different across the four fields (Table 2; Fig. 6). The area sprayed with herbicide was 61 % in both M1 (0.78 ha) and M4 (0.19 ha), whereas it was 77 % in M3 (0.74 ha) and 86 % in M2 (1.49 ha).

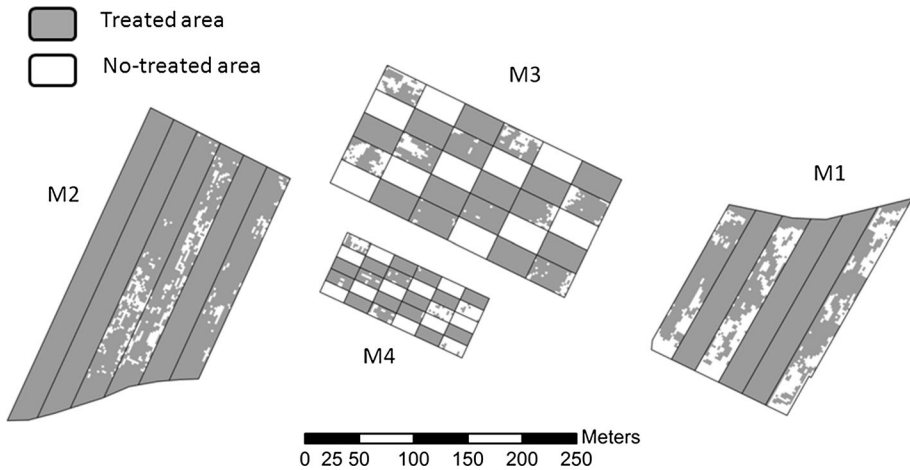
The overall classification accuracy of the prescription maps was of 61 %, as revealed by the confusion matrix (Table 3). In particular, all the areas without weeds were correctly identified by the UAV image classification procedure described in the Methods section on Prescription maps and herbicide treatments. On the other hand, only 57 % of the area to be sprayed, i.e. where weeds occurred, were correctly identified (Table 3). Therefore, spraying was not carried out on 43 % of the areas actually affected by weeds, however in these areas the mean weed ground cover was rather low, i.e. about 10 %. The overall classification accuracy was higher in the 2015 season (69 %) as compared to the 2014 (53 %), probably because of the better spectral resolution of the camera used in 2015, despite a slightly lower spatial resolution. The differences between growing seasons were particularly evident for the producer's accuracy of the weeding area (Table 3).

### Biomass sampling at the end of growing season

The correlation between maize LAI and biomass values obtained by destructive sampling was significant ( $R^2 \geq 0.80$ ;  $p < 0.01$ ) in both growing seasons (Fig. 6). Consequently, the equations shown in Fig. 6 were used to estimate maize biomass at each sampling point.

**Table 2** Summary of weed occurrence across the entire area of four fields (M1 and M2 in 2014; M3 and M4 in 2015) and total and % of sprayed and non-sprayed areas within the plots assigned to the patch spraying treatment

	2014		2015	
	M1	M2	M3	M4
<i>Whole fields</i>				
Total area (ha)	2.21	3.47	2.88	0.86
Weed area (ha)	0.70	2.11	1.03	0.24
(%)	31.6	60.7	35.6	27.9
<i>Patch spraying plots</i>				
Total area (ha)	1.29	1.73	0.96	0.29
Not sprayed (ha)	0.50	0.24	0.22	0.11
(%)	39.2	14.0	23.2	38.9



**Fig. 6** Treated (i.e. sprayed with herbicide) and untreated areas within the four fields (M1, M2, M3 and M4)

**Table 3** Results from the confusion matrix of the validation of the herbicide weeding prescription map against ground truth data

Class	Producer accuracy (%)	User accuracy (%)	Overall accuracy (%)
Mean of both years			
Weeding	57	100	61
No-weeding	100	18	
2014			
Weeding	48	100	53
No-weeding	100	18	
2015			
Weeding	67	100	69
No-weeding	100	18	

The maize biomass sampling at the end of growing season revealed greater silage maize yields in 2014 as compared to 2015. In particular, the highest yield was obtained in field M1, where dry maize biomass ranged between 15.6 and 54.7 t ha<sup>-1</sup> (Table 4). Samples showing very low biomass values were observed in M2. In this field the mean silage yield was 26.5 t ha<sup>-1</sup>. The difference in maize biomass between treatments of uniform blanket herbicide application and patch spraying according to the prescription map were more evident in M1 as compared to M2, but in both fields these differences were not statistically significant (Table 5). In the second growing season, the difference between the two experimental fields (M3 and M4) was less marked than in the first season: the mean maize biomass values across all treatments was 20.3 (t ha<sup>-1</sup>) in M3 (Fig. 7) and 23.9 (t ha<sup>-1</sup>) in M4.

Mean weed biomass values confirmed the high weed infestation in field M2, with 0.72 t ha<sup>-1</sup> across both treatments and the maximum value of 2.81 t ha<sup>-1</sup>. In M1 the dry weed biomass was lower than for M2. The experimental fields of the second year had similar level of weed infestation, both in terms of mean (about 0.35 t ha<sup>-1</sup>) and maximum biomass

**Table 4** Maize and weeds above ground biomass ( $\text{t ha}^{-1}$ ) determined at harvest in four field (M1, M2, M3, M4) in the 2 years of the experiment

Year	Field	Maize					Weeds				
		N°	Min	Max	Mean	$\sigma$	N°	Min	Max	Mean	$\sigma$
2014	M1	84	15.6	54.7	34	8.5	84	0	0.97	0.2	0.2
	M2	87	3.3	47.5	26.5	8.1	87	0	2.81	0.72	0.6
2015	M3	180	11.4	33.9	20.3	3.3	180	0	1.52	0.35	0.2
	M4	180	13	37.2	23.9	3.3	180	0	1.73	0.37	0.4

Number of sampling points (N), minimum (Min), maximum (Max) and mean biomass values and standard deviation ( $\sigma$ )

**Table 5** Average maize and weeds above ground biomass ( $\text{t ha}^{-1}$ ) determined at harvest in four fields (M1, M2, M3, M4) for the different herbicide spraying treatments tested: uniform blanket; patch spraying and untreated control

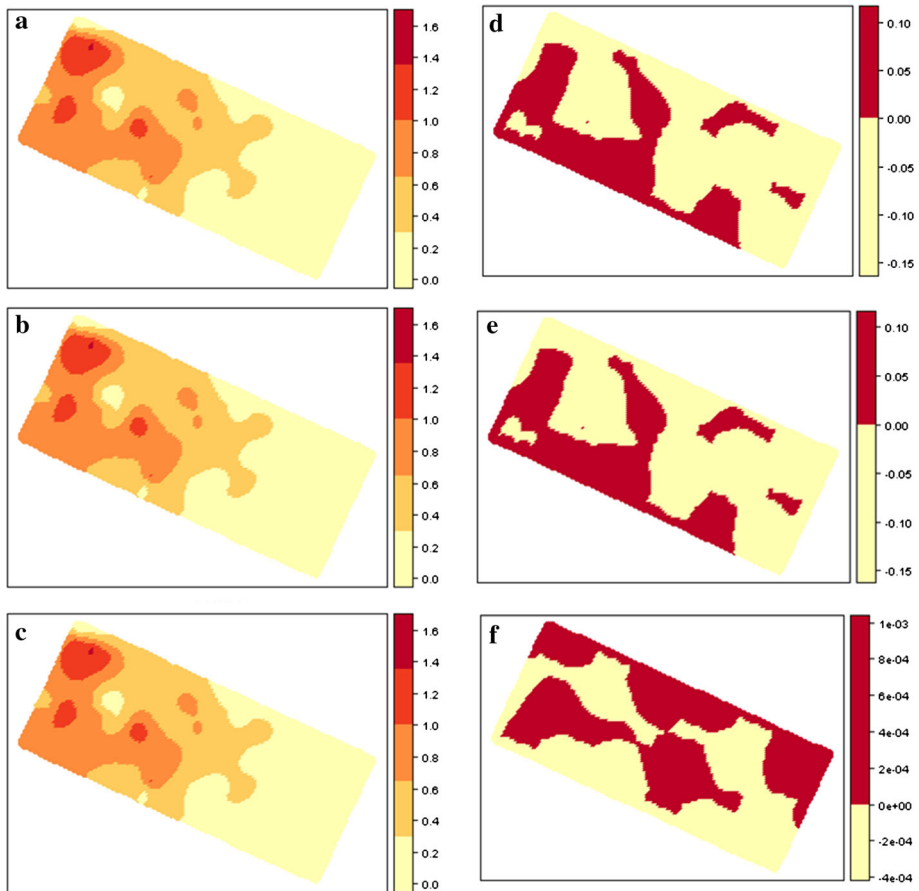
	Field	Treatment		
		Uniform blanket application	Patch spraying	Untreated control
Maize	M1	33.44a	33.1a	–
	M2	27.15a	24.95a	–
	M3	20.7a	20.9a	19.4b
	M4	24.6a	24.9a	22.1b
Weeds	M1	0.22b	0.24a	–
	M2	0.78a	0.74a	–
	M3	0.32a	0.34a	0.39a
	M4	0.33a	0.39a	0.4a

Means with different letters correspond to statistically significant differences ( $p < 0.05$ ). Statistical differences were evaluated using Student's  $t$  test for maize and weed biomass in M1 and M2, ANOVA and Fisher's Least Significant Difference (LSD) for maize biomass in M3 and M4 and weed in M4, map of standardized normal variable  $z$  for weeds in M3

values. The differences of weed biomass among treatments within each field were not significant except for M1.

### Statistical differences among herbicide treatments

The presence of spatial autocorrelation among maize and weed biomass values at sampling points was detected both in M1 and M2 and only for weed biomass in M3. The LMEM method was applied to these cases to compare biomass values among treatments. Concerning M1 and M2, the parameters of LMEMs obtained using the samples collected in uniform blanket area were not different from those estimated using the samples within patch spraying area, both for maize and weed biomass. For this reason, a singular LMEM was applied to estimate biomass in each field, and the difference between herbicide treatments in M1 and M2 were evaluated by means of the Student's  $t$ -test. The parameters of LMEMs for weed estimation in M3 field were different among areas affected by different herbicide treatments, thus three different LMEMs were applied and the difference



**Fig. 7** Weed biomass ( $\text{t ha}^{-1}$ ) maps for the M3 field, corresponding to different herbicide treatment effects: **a** patch spraying, **b** uniform spraying and **c** untreated control. The maps were obtained using the different LMEMs parameters for each treatment. Weed biomass differences ( $\text{t ha}^{-1}$ ) between **d** patch spraying and control, **e** uniform and control and **f** patch spraying and uniform are shown, highlighting positive (dark red) and negative (yellow) differences (Color figure online)

among biomass values was evaluated using the maps of standardized normal variable  $z$ . Since NDVI values in images had a significant correlation with the biomass values at the end of growing season ( $p < 0.001$ ), a NDVI map was used as covariate in all LMEMs.

Where the spatial autocorrelation among biomass samples was not detected, i.e. for maize and weed biomass in M4 and maize biomass in M3, the differences among herbicide treatments were assessed by ANOVA and Fisher's LSD test.

No differences between uniform and patch spraying treatment were found for maize biomass in M1 and M2 in 2014 (Table 5). In 2015 maize biomass differences were observed only between the untreated control and the other two treatments (Table 5). No differences in weed biomass among treatments were observed across fields except for M1 (Table 5).



## Discussion

The main objective of this work was to compare uniform blanket herbicide spraying to a patch spraying treatment derived from UAV image data, in terms of impact on maize silage yield.

Crop silage yield varies as function of several factors, such as soil conditions (soil texture, organic matter, nitrogen, topography, etc.), management and only one of these is the herbicide treatment. The yield variation can therefore be attributed to the herbicide treatment as well as to all other factors. Usually the statistical comparison among different agronomic treatments is obtained by design-based statistics, which allows to estimate the change in yield (effect) ascribable to a specific treatment (Pringle et al. 2010). Replication of treatments permits to carry out the analysis of variance (ANOVA). Design-based statistics implies the randomisation of treatment blocks over the field, but the observed values at sampling points are treated as fixed. A different way to take into account the effect of random factors in the experiment is offered by model-based statistics. In this case the values at sampling points are considered as the results of a modelled random function, that takes into account the spatial variation (Brus and de Gruijter 1997). In order to apply model-based statistics the response variable must be spatially correlated. For these reasons, before applying design or model-based statistics, the presence of spatial autocorrelation among biomass values at sampling points was verified in this work. The experimental design employed in the second year in our study, probably led to a decrease of spatial autocorrelation of the biomass values. The small and replicated plots assigned to each herbicide treatments (especially in M4) could have emphasized the differences between plots, masking the underlying spatial structure of the variability. In these cases the comparison among treatments was carried out using designed-based statistics.

The application of patch spraying systems always involves herbicides saving, but the amount and significance of this aspect depends on weed distribution within the field. The herbicide saving in the four fields of our study varied between 14 and 39.2 %, showing the highest percentages in area with low level of weed infestation (M1 and M4). The cost of the post-emergence herbicide used in the four maize crops was  $57 \text{ € l}^{-1}$  (i.e.  $114 \text{ € ha}^{-1}$ ), thus patch spraying allowed to save something in the range from 16 to  $45 \text{ € ha}^{-1}$ , depending on the field. Perry et al. (2001) also observed, in cereals crops, an inverse relationship between herbicide savings and percentage of infested area, with savings ranging between 9 and 42 % using patch spraying instead of uniform application. Gerhards and Christensen (2003) observed 11 % herbicide savings for patch spraying in maize in presence of broad-leaved weeds and 78 % savings in the field affected by grass weeds. The experiment conducted by Wiles (2009) saved between 30 and 34 % herbicide in 16 maize fields using patch spraying and different herbicides. Very few reports have tested the differences between patch- and uniform blanket-spraying treatments in terms of crop yield (Wiles 2009; Hamouz et al. 2013).

The efficiency of a SSWM system strongly depends on the accuracy of the weed map and, consequently, of the prescription map. The failure of the weed detection within fields can entail an overestimation or an underestimation of weed infestation, causing an overuse of the herbicide in the former case and a loss of the crop yield in the latter. Some researchers achieved very good results, in terms of herbicide savings, using weed distribution maps obtained by field surveys (Williams et al. 2000; Wiles 2009; Hamouz et al. 2013). Interesting results were also obtained using on-the-go weed detection systems by means of digital image analysis (Gerhards and Christensen 2003; Gerhards and Oebel

2006). Although both methods (field survey and digital image analysis) have shown good results in terms of weed detection and the application of SSWM, they are time consuming, while the use of remote sensors allows to delineate weed distribution in a much faster way.

In this work the overall classification accuracy obtained by UAV image data was partially satisfactory, especially in the second growing season. Although the SVM image classification method allowed to correctly classify all the areas not to be treated, allowing to save the herbicide quantity, only 57 % of the areas to be treated were detected, leading to a high omission error. Obviously, the spatial resolution of the images acquired from the UAVs did not allow to identify weed patches smaller than 50 mm (i.e. sparse weeds). This error involved an excessive reduction of herbicide rates, that could have resulted into a decrease of crop yield. However, the plots in which the weed coverage was underestimated showed low mean weed coverage (10 %). In fact, the herbicides were applied also on areas having very small weed coverage, i.e. without the use of a threshold of weed density above which spraying should be carried out. Despite the underestimation of the area to be treated, the comparison between patch spraying and blanket application did not show significant differences in terms of maize biomass, which is the main factor that would affect the acceptability of this technique to the farmers.

The best classification accuracy was obtained using the AIRNOV multispectral sensor at the beginning of the second year (Table 3), in spite of the fact that this sensor provided a lower spatial resolution than that supplied by the Canon camera in the first year. This difference could be ascribable to the different spectral resolution and response of the two sensors. The AIRNOV camera has much better defined and narrow bands as compared to the Canon camera. Moreover the spectral sensitivity of the NIR band is much higher for the AIRNOV sensor.

The efficiency of the patch spraying is influenced by the spatial resolution of the prescription map, i.e. it depends on the spatial resolution of the patch sprayer. In this work, the Field-IQ Crop Input Control System regulated the opening and closing of twelve independent sections of 2 m, obtaining a saving of herbicide between 14 and 39 %. A resolution of the patch sprayer greater than 2 m could probably further increase the efficiency of patch spraying. Wallinga et al. (1998) observed a reduction in herbicide use of 41 % using a patch sprayer with a resolution of 1 m and an herbicide saving up to 73 % with a spatial resolution of 0.5 m. The efficiency of patch spraying can be further improved using species-specific spraying, obviously where not only one weed species affects the crop (Gerhards 2013). The application of this type of treatment has a considerable obstacle, i.e. the objective difficulty that sensors, currently on board of most commercial UAVs, have of providing an accurate classification of different weed species. Although this aim is rather difficult, perhaps it could be reached with a much higher spectral and spatial resolution of UAV data. For example, hyperspectral sensors, i.e. sensors having hundreds of bands, would allow to improve significantly the accuracy of the classification and allow to distinguish between weed types (Gray et al. 2009; Younan et al. 2004). Unfortunately, the number of hyperspectral sensors on UAV is still insufficient to verify this hypothesis.

## Conclusions

UAV images acquired 4–5 weeks after maize planting were processed into prescription maps for the patch spraying treatment, which was carried out about 3 weeks after the acquisition. The accuracy of prescription maps was evaluated as satisfactory as compared

to ground data. The prescription maps were used with the Field-IQ Crop Input Control System and a resolution of independent sections of boom sprayer of 2 m.

The results obtained in the experiments carried out showed that image data acquired from a UAV could be used operationally in early post-emergence on maize, under conditions similar to those in which our study was carried out, and would lead to a decrease in the use of herbicide without negative consequences in terms of crop yield. At the same time they allowed to increase the biomass production as compared to no-treated area. The saving of herbicide amounted between 14 and 39.2 % for patch spraying as compared to a blanket application, allowing to save from 16 to 45 € ha<sup>-1</sup>. The saving of herbicide is function of weed coverage and thus of the level of infestation over the field.

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