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Is the current state of the art of weed monitoring suitable for site-specific weed management in arable crops?

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Summary

Weed monitoring is the first step in any site-specific weed management programme. A relatively large variety of platforms, cameras, sensors and image analysis procedures are available to detect and map weed presence/abundance at various times and spatial scales. Remote sensing from satellites or aircraft can provide accurate weed maps when the images are obtained at late weed phenological stages. Cameras located on unmanned aerial vehicles (UAVs) have been shown to be adequate for early-season weed detection in a variety of wide-row crops, providing images with relatively high spatial resolutions. Alternatively, weed detection/mapping systems from ground-based platforms can achieve even higher resolutions using a variety of non-imaging and imaging technologies. These ground systems are suited, in some cases, for real-time site-specific weed management. Despite this rich arsenal of technologies, their commercial adoption is, apparently, low. In this study, we describe the state of the art of remotely sensed and ground-based weed monitoring in arable crops and the current level of adoption of these technologies, exploring major constraints for adoption and trying to identify research gaps and bottlenecks.

Keywords: weed maps, real-time detection, unmanned aerial vehicle, ground-based platforms, sensors, cameras, image analysis.

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Introduction

Site-specific weed management (SSWM) is a strategy of varying weed management within a crop field to match the variation in location, density and composition of the weed population (Wiles, 2009). This concept is based on three facts: (i) weed populations are often irregularly distributed within crop fields, (ii) new sensors and platforms together with geospatial technologies (e.g. GPS, GIS) have provided the tools required to detect and map weeds and (iii) new smart sprayers, robots and mechanical cultivators have opened the possibility of careful tailoring of weed management to fit the different conditions found in each field (Christensen *et al.*, 2009; González-de-Santos *et al.*, 2016). Site-specific weed management has a real potential to deliver a more productive and sustainable agricultural production based on a more precise and resource-efficient approach.

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In order to apply a SSWM strategy, the first step is weed monitoring. This task can be accomplished in two ways: (i) creation of a weed map, using this information in subsequent control operations, or (ii) real-time weed detection, integrating the sensor, the processing procedures and the actuation system. Weed images or non-imaging records may be acquired from either on-ground or remote sensing platforms. The opportunities and limitations of both detection approaches have been reviewed in the past by various authors (Slaughter *et al.*, 2008; López-Granados, 2011; Mulla, 2013; Peteinatos *et al.*, 2014). These reviews note the potential of ground-based approaches (also called proximal sensing) to capture high-resolution images and, consequently, to allow an early detection of relatively low weed densities and discrimination of the major weed species (Weis & Sökefeld, 2010; Longchamps *et al.*, 2013; Herrera *et al.*, 2014; Peteinatos *et al.*, 2014). Alternatively, conventional remote sensing platforms (i.e. piloted airborne and satellite) allow larger areas to be inspected but with lower image spatial resolution (Lamb & Brown, 2001; Rasmussen *et al.*, 2013). Currently, the better image resolutions provided by unmanned aerial vehicles (UAV), the recent developments in miniaturisation of sensors to be embedded on them, and the latest generation of multispectral and hyperspectral images provided by new satellites also offer an opportunity to create very precise weed maps. Additionally, progress on 2D and 3D sensors and cameras, and more powerful and efficient computers capable of processing a large volume of data in a short time may provide the tools required for real-time SSWM (Van Evert *et al.*, 2017).

Reliable information on current commercial adoption of these technologies is scant. Although there are a few success stories (Griffin *et al.*, 2012; Baille, 2013; Melander *et al.*, 2015; Fennimore *et al.*, 2016; Society of Precision Agriculture Australia, 2016), there are various indications suggesting that the adoption of SSWM systems among farmers has been modest. The purpose of this review was to (i) examine the availability and suitability of current weed monitoring technologies, (ii) identify relevant gaps or bottlenecks in our knowledge that may be limiting farmer adoption and (iii) explore new opportunities for research and practice.

Availability of weed monitoring technologies

Remotely sensed weed detection and mapping

Investigations of remote sensing technology for weed detection and mapping primarily explore three connected issues: (i) spectral differences of weeds and crops (i.e. discrimination) as affected by weed/crop phenology (e.g. early or late), (ii) types of remote images (from several sensors and platforms) and influence of spatial, spectral and temporal resolutions on weed detection and (iii) algorithms and analysis techniques for weed mapping. López-Granados (2011) reviewed the major sensors and platforms available at that time and their main characteristics (altitude, spatial and spectral resolutions). In Table 1, we have summarised information on some relevant studies conducted on remote weed detection.

The fundamental idea for weed discrimination relies on locating the spectral region or, alternatively, the vegetation indices that maximise the differences between soil, crop residues and vegetation and between weed and crop plants according to the reflectance values captured in the remote images. Spectral measurements at leaf or canopy levels revealed that the greatest differences appear in the infrared region (Zwiggelaar, 1998; Vrindts *et al.*, 2002), although the results varied according to plant species and phenological stages of the plants (Peña-Barragán *et al.*, 2006). For example, Martín *et al.* (2011) explored the potential of hyperspectral measurements to discriminate two grass weeds (*Avena sterilis* L. and *Lolium rigidum* Gaudin) from four cultivars of winter wheat and barley. They found that the far short-wave infrared (SWIR) region (1900–2500 nm) had special importance in the discrimination of *A. sterilis* in the stem elongation and ripening crop stages. However, in the case of *L. rigidum*, the best results were obtained with the early SWIR region (1300–1900 nm) at the late tillering and stem elongation crop stages. These authors also selected the red-edge region (680–780 nm) as sensitive for weed discrimination. This is consistent with the results obtained by Peña-Barragán *et al.* (2006) for *Ridolfia segetum* Moris in sunflower at early and late stages, by Fletcher *et al.* (2016) for *Amaranthus palmerii* S. Watson in cotton and by Shapira *et al.* (2013) for grass and broad-leaved weed detection in wheat and chickpea fields. The SWIR wavelengths were also ranked as most important for discriminating several weed species commonly found in the soyabean fields located in the south-eastern United States (Gray *et al.*, 2009; Fletcher & Reddy, 2016). However, previous work has shown that several wavelengths in the red, green and blue (RGB) visible (400–680 nm) region were optimal for discriminating two *Amaranthus* species in cotton with bronze or yellow leaves (Fletcher *et al.*, 2016). Similarly, when combined with information from the near-infrared (NIR, 780–1300 nm) region, these RGB wavelengths were also found to be useful for classifying cruciferous weeds in winter wheat and broad bean (de Castro *et al.*, 2012a) and *A. sterilis*

Table 1 Information on relevant studies on remotely sensed weed detection and mapping

Crop/Weed	Phenology stage of crop	GSD (m)/ Area (ha)*	Platform/sensor	Weed detection procedure†	Reference
Wheat/*Diplotaxis* spp., *Sinapis* spp.	Vegetative, Mature	2.40/2656	Satellite (QuickBird)/RGB + NIR	BDVI, ML	de Castro *et al.* (2013)
Wheat/*Avena sterilis*	Mature	2.40/3000	Satellite (QuickBird)/RGB + NIR	Several pixel-based classifiers¶, OBIA	Castillejo-González *et al.* (2014)
Soybean/common weeds§	Vegetative, Mature	0.50/30	Airborne/RGB + NIR	Maximum likelihood (ML)	Gray *et al.* (2008)
Sunflower/*Ridolfia segetum*	Flowering	0.50/29	Airborne/RGB + NIR	Spectral angle mapper (SAM)	Peña-Barragán *et al.* (2010)
Wheat, broad beans, pea/*Diplotaxis* spp., *Sinapis* spp.	Vegetative, Flowering	0.25/92	Airborne/RGB + NIR	Boundary digital value intervals (BDVI), ML, SAM	de Castro *et al.* (2012b)
Barley/*Cirsium arvense, Tussilago farfara*	Mature & Seedling	<0.02/0.2	UAV††/RGB	ExG vegetation index (pixel-based)	Rasmussen *et al.* (2013)
Maize/*Amaranthus blitoides, Sorghum halepense*	Seedling	0.02/1.4	UAV††/RGB + NIR	OBIA	Peña *et al.* (2013)
Maize, sunflower/ several weeds‡‡	Seedling	0.014/1.0	UAV††/RGB	OBIA, machine learning	Pérez-Ortiz *et al.* (2015, 2016)

*Ground sampling distance (GSD) is a measure of spatial resolution (i.e. pixel size). Area refers to the total studied crop surface.
†ML, SAM and BDVI are pixel-based image analysis procedures.
‡ND: weed species were not described in the study.
§Studied weeds: *Cassia obtusifolius*, *Sida spinosa*, *Sesbania exaltata*, *Ipomoea lacunosa*, *Jacquemontia tamnifolia*, *Ipomoea wrightii*.
¶Parallelepiped, Mahalanobis distance, ML, SAM, support vector machine, decision tree.
**A commercially available unmanned helicopter was used in this investigation.
††A commercially available rotary-wing unmanned vehicle was used in this investigation.
‡‡The sunflower field was infested by *Amaranthus blitoides*, *Sinapis arvensis* and *Convolvulus arvensis*, whereas the maize field was infested by *Salsola kali*.

and *Phalaris paradoxa* L. in mature wheat fields (Gómez-Casero *et al.*, 2010).

A high spatial resolution of the remote images is required for weed detection. This constrains the types of sensors and remote platforms suitable for this task. Generally, higher spatial resolution is penalised with lower spectral resolution limited to the visible and NIR spectral regions. For example, despite the sensitiveness of SWIR wavelengths observed in the spectral studies described previously, remote images in this region generate pixel sizes in the range of several metres (e.g. Hymap, EnMap, AVIRIS or ASTER satellites), which limits their potential applications to the detection of very large weed patches. Therefore, remote images with visible and NIR spectral information and spatial resolutions in the range of 1–3 m (e.g. QuickBird, WorldView or GeoEye satellites), 0.1–0.5 m (piloted aircraft flying about 1–2 km altitude) and 0.01–0.05 m (UAVs flying below 120 m altitude) have been evaluated in many weed–crop scenarios (Table 1).

Before the widespread use of the UAVs, piloted aircraft were generally used to map weed patches at the scale of individual or a few farms, reporting good results in mapping weed patches in soyabean (Gray *et al.*, 2008), sunflower (Peña-Barragán *et al.*, 2010), and wheat, broad bean and pea (López-Granados *et al.*, 2006; de Castro *et al.*, 2012b). When the target is to assess weed distribution in large areas including many individual fields, satellite images might be recommended. Castillejo-González *et al.* (2014) used multispectral QuickBird satellite images to map *A. sterilis* weed patches at the field level (15 wheat fields) and at region level (entire satellite scene of 80 km^2) with global accuracies ranking between 80% and 99%. With similar technology, de Castro *et al.* (2013) mapped cruciferous weed patches in 263 winter wheat fields, which covered approximately 2656 ha, obtaining global classification accuracies of 89–91%. These authors reported that herbicide savings above 61% could be potentially obtained by applying site-specific treatment maps on the study area.

The previous results were mostly obtained with airborne and satellite imagery at the late growth stages of the crops (flowering or mature stages). However, herbicide treatments and other control practices cannot be generally applied at these stages. Thus, and due to the fact that weed infestations are frequently consistent in location from year to year (Gerhards, 2010), the solution could be using late-season weed maps to design early SSWM measures the next year. However, this increases the uncertainty and reduces the efficiency of these treatments. This limitation has been traditionally considered as a major bottleneck of conventional remote imagery for practical and timely SSWM. Other limitations of remote sensing are as follows: (i) insufficient imagery resolution for visualising crop and weed seedlings, (ii) early-stage weed and crop plants usually have similar spectra and appearance and (iii) the reflectance of the background soil interferes with detection. In addition, commercial piloted aircraft and satellite systems have difficulties acquiring the data at the most appropriate time for herbicide treatments (usually a few days) due to limitations of the revisit schedules (temporal resolution) and to adverse (cloudy) weather conditions (Christensen *et al*., 2009).

Unmanned aerial vehicle (UAV) platforms are helping to overcome some of the historical limitations to remote sensing of weeds. Their potential lies in their flexibility to work on demand according to the weeding goal and their capacity to collect remote images with the centimetre-scale spatial resolution needed for discriminating small weeds at early crop stages (Torres-Sánchez *et al*., 2013). A quantitative weed map generated by analysing UAV-based images can facilitate the task of planning weed control prior to the operation and helping to choose herbicides and spraying volume (Rasmussen *et al*., 2013). Peña *et al*. (2013) used a six-band multispectral camera to collect UAV images in an early-season maize field to map the position and coverage of the weeds, exporting the results in a customised grid structure adapted to an herbicide sprayer. A map with three categories of weed coverage was produced with 86% of overall accuracy and a root mean square error of 2% in weed percentage estimations.

Castaldi *et al*. (2017) used UAV imagery in the RGB and NIR spectral ranges to evaluate different post-emergence herbicide application strategies in maize fields. They reported a range of herbicide savings between 14% and 39% as compared with a uniform application.

In row crops, weed discrimination can be based on classifying crop rows and, subsequently, detecting weed plants as vegetation existing between the rows. The success of this approach is associated with the development of advanced algorithms for the analysis of the UAV images, such as the object-based image analysis (OBIA) methodology (Blaschke *et al*., 2014). The OBIA identifies spatially and spectrally homogenous objects created by grouping adjacent pixels according to a procedure known as segmentation. This method uses multiple features of location, texture, proximity and hierarchical relationships together with an automatic thresholding of the vegetation fraction. The use of OBIA methodology drastically increased the success of weed discrimination in woody crops such as vineyards and row crops such as sunflower or maize compared with conventional pixel-based analysis (Peña *et al*., 2015; Torres-Sánchez *et al*., 2015a; López-Granados *et al*., 2016a,b; de de Castro *et al*., 2017). This procedure offers the advantage of solving the problem of weed and crop spectral similarity. However, it is less effective at discriminating weeds in crops planted in narrowly spaced rows (e.g. wheat) or weeds growing within crop rows (Torres-Sánchez *et al*., 2014). Nevertheless, recent advances in machine-learning algorithms combined with pattern and feature selection techniques have offered excellent results for between- and within-crop-row weed detection and classification (Hung *et al*., 2014; Pérez-Ortiz *et al*., 2015, 2016).

An additional advantage of the UAVs is their capacity to acquire images with high overlaps at low altitude. As a result, the overlapped images can produce a digital surface model (DSM) of the flight area by applying the structure-from-motion (SfM) technique that allows modelling the three dimensions (3D) of the topography and all the elements (e.g. trees) over the surface (Nex & Remondino, 2014). As a consequence, recent investigations have focused on studying these 3D models to monitor woody crops such as olive trees (Torres-Sánchez *et al*., 2015b), vineyards (Mathews & Jensen, 2013), palm trees (Kattenborn *et al*., 2014) or sparse vegetation (Hung *et al*., 2012).

Ground-based weed detection and discrimination

Current techniques for plant characterisation and weed detection from on-ground platforms use a great variety of non-imaging and imaging technologies (Peteinatos *et al*., 2014). Table 2 summarises information on some major studies conducted on ground-based weed detection. Non-imaging techniques include spectral reflectance, fluorescence, ultrasonic and LiDAR sensors.

Spectral reflectance sensors are relatively inexpensive devices that can separate bare ground from green vegetation. They are based on the fact that the reflectance curve of plants differs significantly from the reflectance of soil (Felton & McCloy, 1992). As plant species cannot be discriminated with these sensors, this principle can only be used to locate weeds before crop emergence, in the inter-row area or in the tramlines of the crops. This principle has been widely used in the past for real-time patch spraying of herbicides (Felton & McCloy, 1992; Dammer & Wartenberg, 2007; Dammer, 2016). The integration of hyperspectral images with a machine-learning procedure can achieve high recognition levels for crop vs. weed discrimination (Zhang & Slaughter, 2011; Zhang *et al*., 2012a). This

Table 2 Information on relevant studies on ground-based weed detection and discrimination

Crop/Weed	Phenology stage of crop	Sampling area	Classes	Technique	Sensor	Sensor specifications	Reference
Wheat, triticale, rye barley, pea/various weeds*	Early stage	518 × 2.5 cm	Bare ground/weeds	Spectral imagining	Optoelectronic	Self-developed	Dammer and Wartenberg (2007)
Maize/various weeds†	Early stage	0.042 cm^2	Crop/grasses/broad leaves	Fluorescence imaging‡	Spectrometer	LS-1-CAL	Longchamps *et al.* (2010)
Maize/various weeds§	Early stage	30 cm	Crop/grasses/broad leaves	Ultrasound	Ultrasonic	Pepperl + Fuchs UC2000-30GM-IUR2-V15	Andújar *et al.* (2011a, b)
Maize/various weeds¶	Vegetative	300 cm long	Crop/grasses/broad leaves	Laser imaging	LiDAR-TLS	Hokuyo URG-04LX	Andújar *et al.* (2013)
Wheat/various weeds**	Seedling	55 × 42 cm	Grasses/broad leaves	Red/Infrared imaging	Bispectral camera	Red + NIR Camera	Peteinatos *et al.* (2014)
Maize/various weeds††	Vegetative	10 000 cm^2	Crop/grasses/broad leaves	3D imaging	RGB-D	Kinect One	Andújar *et al.* (2016)
Barley/*Avena sterilis*, *Papaver rhoeas*	Seedling	60 × 85 cm	Crop/weed/Bare soil	Automatic row crop detection	RGB camera	Nikon Coolpix 5700/ Sony DCR PC110E	Burgos-Artizzu *et al.* (2009)
Wheat/*Lamium purpureum*, *Stellaria media*, *Galium aparine*	Seedling	60 × 45 cm	Crop/grasses/broad leaves	Automatic detection of broad-leaved	RGB camera	Nikon Coolpix 5400	Berge *et al.* (2008)
Barley	Seedling	48 × 36 cm	Crop/weed species	Skeleton-based features	Bispectral camera	IR + VIS camera	Weis and Gerhards (2007)

**Agropyron repens*, *Chenopodium album*, *Lamium* spp., *Viola arvensis*.

†*Digitaria ischaemum*, *Echinochloa crus-galli*, *Panicum capillare*, *Setaria glauca*, *Ambrosia artemisiifolia*, *Amaranthus retroflexus*, *Chenopodium album*, *Capsella bursa-pastoris*.

‡Laboratory study.

§*Sorghum halepense*, *Datura* spp., *Xanthium strumarium*.

¶*Sorghum halepense*, *Cyperus rotundus*, *Datura* spp., *Xanthium strumarium*.

***Alopecurus myosuroides*, *Veronica persica*, *Matricaria chamomilla*.

††*Sorghum halepense*, *Datura ferox*, *Salsola kali*, *Polygonum aviculare*, *Xanthium strumarium*.

principle has been used in various horticultural crops for automated weed control (Zhang *et al.*, 2012b). Another approach is to combine plant detection (from soil) by colour or infrared to red light reflectance ratios, and crop recognition (from weeds) by apparent plant size and spatial planting pattern (Tillet *et al.*, 2008). This technique has been shown to be fairly effective in transplanted crops where the crop plants are larger and more easily distinguished from weeds.

UV-induced fluorescence sensors measure the emitted fluorescent radiation of leaves after exposing plants with a specific radiation of visible or UV light. As several intrinsic leaf properties determine plant fluorescence, the characteristics of its emission spectrum can be considered as a distinct and meaningful signature that can be used for plant discrimination. Longchamps *et al.* (2010), working under laboratory conditions, were able to discriminate three plant types (maize, and grass and broad-leaved weeds) using UV-induced fluorescence. Although this is a first step for a new weed detection technique, no further testing has been conducted under field conditions.

Ultrasonic sensors measure the distance from the sensor to the plant. A short bust of sound in a unique direction is produced into the emitter, and sound waves are reflected after impacting the target. The estimation of the distance is based on the principle of time-of-flight. This device measures the travel time of the acoustic signal and transforms it into a voltage signal. These sensors are fast, inexpensive and robust, allowing a relatively simple characterisation of plant structures under rough conditions. This principle was used by Andújar *et al.* (2011a) to automatically detect and discriminate *Sorghum halepense* (L.) Pers. and various broad-leaved weeds in a maize field. An ultrasonic sensor located in the inter-row area and pointing directly to the ground was able to detect and discriminate both types of weeds due to their differential height. As ultrasonic sensors can also be used to estimate plant biomass (Reusch, 2009), it is even possible to use these sensors to estimate weed pressure. Andújar *et al.* (2012), working in a wheat field infested with various grasses and broad-leaved weeds, found that ultrasonic readings were well correlated with weed density, coverage and biomass. However, these results, obtained at an early tillering stage of the crop, were not reproduced at a later stage. Apparently, when crop coverage increases and the crop canopy covers the ground, ultrasonic readings reflect the echo from the canopy, ignoring the weeds growing under the crop. Thus, measurement must be taken when weeds are emerging and crop does not cover the soil. This coincides with the time usually recommended for weed control (herbicide application or weed harrowing). The low cost and fast response of ultrasonic sensors make them a promising tool for real-time actuation of weed control, either chemical or physical (Rueda-Ayala *et al.*, 2015).

Discriminating plants based on their height can be improved using light detection and ranging (LiDAR) sensors. These sensors have higher accuracy and measurement frequencies than ultrasonic sensors. In addition, their wider field of view (footprint) allows detecting both the crop row and the weeds present in the inter-row area. The LiDAR sensor estimates the distance to the target by measuring the phase difference between the emitted laser beam and the reflected one within a plane. This principle has been widely used in agriculture for crop monitoring and tree characterisation. Andújar *et al.* (2013) explored this principle in maize crops creating 3D vegetation models combining the information obtained from a LiDAR sensor and a differential GPS located in a vehicle in movement. The profiles obtained allow the identification of the positions of crop rows, vegetation-free areas and weed-infested areas. As weed height was generally lower than maize height, this method resulted in good discrimination of both vegetation types. The major weed present, *S. halepense*, was identified in almost 80% of the cases, showing a high specificity for recognition of this species. Although this sensor was not able to discriminate between broad-leaved species, this fact does not represent a major problem in practice, as these species are generally controlled by the same herbicide active ingredients.

The use of imaging sensors in weed detection has been studied extensively (Peteinatos *et al.*, 2014). Relatively low-cost bispectral or RGB cameras can acquire images with proper spatial resolution to allow the identification of plant species based on their location, shape, colour and texture features. The procedure used to discriminate weed plants from other elements in the image generally involves three processes: (i) the segmentation of the original image, obtaining an image with white pixels representing plant cover and black pixels depicting soil, (ii) the identification of zones corresponding to crop rows, quantifying crop cover and eliminating these pixels and (iii) the estimation of weed cover after the improvement of image by filtering noise and errors from previous steps. Several techniques have been used to efficiently segment plants from a soil background (Tellaeche *et al.*, 2008; Burgos-Artizzu *et al.*, 2009; Panneton & Brouillard, 2009; Guijarro *et al.*, 2011; Longchamps *et al.*, 2013). In addition, diverse approaches have been proposed for crop row detection and removal from the image (Hague *et al.*, 2006; Tellaeche *et al.*, 2008, 2011; Bossu *et al.*, 2009; Sainz-Costa *et al.*, 2011; Longchamps *et al.*, 2013).

Due to the relatively long processing time of all these procedures, they cannot be used for real-time actuation. In this regard, Burgos-Artizzu *et al.* (2011) achieved good weed/crop discrimination over a wide variety of conditions by the combination of a fast processing system (delivering results in real-time) with a more exhaustive and slower processing system.

To discriminate plant species, various numerical shape features can be calculated. Gerhards and Oebel (2006) and Weis and Gerhards (2007) used image analysis software to identify characteristic shape features (region-based, contour-based and skeleton-based) of various crops, grass weeds and two to three groups of broad-leaved weed species, creating an image database for all those species. An automatic classification process based on those features resulted in 90% to 98% correct identification. Various other classification algorithms have been devised more recently. Berge *et al.* (2008) used an object-oriented algorithm based on size and roundness for the automatic detection of broad-leaved weeds in cereals. The ability of the algorithm to predict 'spray'/'no spray' decisions according to a previously suggested spray decision model for spring cereals was tested, resulting in correct spray decisions in 65–85% of the test images. In a later study, Kaspersen *et al.* (2010) further developed this image analysis algorithm (Weeder) to discriminate very small weeds in very narrow-row cereals. Berge *et al.* (2012) used Weeder to estimate cereal cover, total broad-leaved weed cover and the cover of *Tripleurospermum inodorum* (L.) Schultz Bip. and *Matricaria chamomila* L. and, based on those data, estimate their threshold values as decision rules for herbicide spraying. Herrera *et al.* (2014) proposed a strategy for discriminating between grass and broad-leaved weeds using a set of shape descriptors (the seven Hu moments and six geometric shape descriptors). This combined strategy worked properly when the weeds were at an early growth stage, before leaves start overlapping. However, leaf overlap may represent a serious problem at later stages. Overlapped leaves tend to be segmented as one object, as they are connected regions belonging to different plants. This problem is especially important in long-leaved plants such as cereals or grass weeds. Laursen *et al.* (2016) used a monocotyledon and dicotyledon coverage ratio vision (MoDiCoVi) algorithm to estimate leaf cover of broad-leaved weeds in a grass crop (maize). The proposed approach was based on a close analysis of the contours of vegetation regions. By observing vegetation contours instead of individual plants, the problem of overlapping leaves was mitigated to some extent. Plant contours were located, using a subset of edge segments along the contours for further analysis. The results obtained with this algorithm showed that weed cover in undisturbed inter-row areas was generally lower than or equivalent to weed cover in rows (previous methods only performed analysis between the crop rows). A major weakness of MoDiCoVi is that it is not able to handle grass weeds.

Combination of various sensing principles could improve weed detection and discrimination. When several sensors are joined in a single device, the total cost and total errors could be reduced. Depth cameras combine three types of cameras. Infrared and RGB cameras provide spectral information covering different bandwidths. RGB-D cameras capture RGB colour images augmented with depth data at each pixel. A variety of techniques can be used for producing the depth estimates, such as time-of-flight imaging, structured light stereo, dense passive stereo and laser range scanning. Specific software can fuse the raw data coming from the three cameras and create a point cloud by detecting the overlapping areas in sequential frames showing a 3D model. This principle has already been used for weed–crop discrimination in weed-infested maize crops (Andújar *et al.*, 2016). These authors used algorithms to reconstruct 3D point clouds and a dual methodology, using height selection and RGB segmentation, to separate weeds from crops. The colour 3D models allowed separating maize from the connected structures in the model. Then, after the selection and removal from the model, RGB filters could select the remaining green parts, corresponding with weeds. As the predominant grass weed (*S. halepense*) was considerably taller than the neighbour broad-leaved weeds, a new height selection was made to separate them.

The combination of data from different sensors represents a major challenge for sensor fusion. Weis *et al.* (2013) used four commercial sensors (e.g. LiDAR, ultrasonic sensor, RGB camera and spectral reflectance device) located on a ground platform to characterise plants of spring barley and oil seed rape under different conditions (planting density and herbicide stress). They compared two data fusion concepts: (i) a software approach for parallel measurements with multiple sensors (raw data fusion), and (ii) a fusion of data from the set of sensors made in a post-processing step at the feature level. Similar patterns were obtained with both approaches. In both cases, the analysis of the fused data allowed the exploitation of synergies from different measurement principles. However, each approach has different advantages and disadvantages. When data fusion is performed at software level, a synchronisation of sensor measurement is needed. Although this approach allows real-time operations, a higher computational capacity is needed. If fusion is performed in a post-processing step, a differential GPS and an inertial navigation system are required to correct vehicle movements. Also, additional steps are required in data fusion for following field operations.

Adoption of SSWM technologies

Although precision agriculture technologies have been available for several decades, adoption of these technologies has been less than expected (Fountas *et al.*, 2005; Griffin, 2016). According to surveys carried out between farmers who had used precision agriculture practices, yield mapping was used in 92% and 67% of the cases in Denmark and the Eastern Corn Belt respectively. In contrast, weed mapping was only used in 28% and 5% and variable pesticide application in 32% and 4% of the cases in these two countries (Fountas *et al.*, 2005). Other surveys of precision agriculture practices used by Kansas, USA farmers′ (Griffin, 2016) and by cotton producers in the southern states of USA (Lambert *et al.*, 2015) did not include weed mapping between the technologies used. However, they considered some closely related technologies such as aerial imagery and variable rate application of inputs.

Although the adoption of weed mapping and site-specific weed control systems among farmers seems to be, in general, modest, there are some success stories. Various patch spraying systems based on real-time information from spectral reflectance sensors have been in the market for many years. Some examples are Weedseeker® (Trimble Inc., Sunnyvale CA, USA), AmaSpot® (Amazonen-WerkeH. Dreyer GmbH & Co, Hasbergen, Germany) and Weed-it® (Rometron BV, Steenderen, the Netherlands). As these sensors only discriminate plants from soil, they can only be used for broad spectrum weed control. This technology has been used extensively in Australia for weed control in vineyards, tree crops and fallows, as well as for inter-row spraying of various row crops using protective shields (Griffin *et al.*, 2012; Baille, 2013; Society of Precision Agriculture Australia, 2016). In order to discriminate the crop from the weeds (and different weed species) and to apply herbicides selectively, more sophisticated sensor systems are required. H-Sensor (Agricon GmbH, Ostrau, Germany), introduced to the German market some years ago, is able to discriminate online crop plants from various weed species. However, its level of adoption has been, apparently, very low. See and Spray (Blue River Technology, Sunnyvale, CA, USA), a recently developed smart sprayer, is expected to be commercialised in the near future by John Deere (Moline, IL, USA) (Chostner, 2017).

For physical weed control, various manufacturers of agricultural machinery have developed advanced vision guidance system and marketed precision camera-guided hoes that remove weeds from between rows and/or in-row in vegetable crops. Some examples are Robocrop (Garford Farm Machinery Ltd, Peterborough, UK), Steketee IC Weeder (Sutton Agricultural Enterprises Inc., Salinas, CA, USA), Robovator (F Poulsen Engineering ApS, Hvalsø, Denmark) and CultiCam (CLAAS, Sommerkämpen, Germany). These smart cultivators are reported to be a viable commercial alternative to hand weeding for vegetable production in Denmark and in the United States (Melander *et al.*, 2015; Fennimore *et al.*, 2016). Recently, two weeding robots, Bonirob (Deepfield Robotics, Renningen, Germany) and OZ Weeding Robot (Naïo Technologies, Escalquens, France), have been developed and commercialised to conduct smart mechanical weed control (Fennimore *et al.*, 2016).

Constraints limiting adoption of weed monitoring systems

Technological constraints

Site-specific weed management can be conducted at three spatial resolution levels: (i) treatment of subfields or large weed patches, (ii) treatment of a grid adapted to the resolution of the weed control actuation unit (nozzle or hoe) and (iii) treatment of individual plants (Christensen *et al.*, 2009). Each approach has different strengths and weaknesses and requires different weed detection methods.

The first approach (zone resolution) is particularly well suited for some troublesome species forming stable and well-defined patches. Typically, it has been used for weed species that can be clearly discriminated from the crop at late phenological stages due to their colour and/or size. The images can be obtained from ground vehicles (e.g. sprayers, combines) or from various remote sensing platforms. In the case of using ground vehicles, this system has generally relied on visual assessments (Rew *et al.*, 1997; Ruiz *et al.*, 2006; Andújar *et al.*, 2011b). The lack of an automatic procedure for this operation is a serious drawback for a wider adoption. In the case of using images obtained from satellites or piloted aircrafts (Lamb & Brown, 2001; López-Granados, 2011; Castillejo-González *et al.*, 2014), a major limitation is sky cloudiness. Due to the relatively short time window available for weed detection and subsequent control actions, the opportunities for these technologies are probably low in climates with a high number of cloudy days. Images obtained from UAVs flying at lower altitudes are likely to be a good alternative. The major weakness of this map-based approach is the possible lack of consistency in the location of weed patches (Castillejo-González *et al.*, 2014). New predictive models are required to describe patch dynamics and create reliable weed infestation maps for subsequent years.

For the second approach (spot resolution), the images (or data) can be obtained from UAVs flying at low altitudes or from ground vehicles. Cameras located on small UAVs have been used for early-season weed detection in a variety of wide-row crops (Peña *et al.*, 2013, 2015; López-Granados *et al.*, 2016a,b). However, UAV images did not allow weed detection in narrow-row cereals (Torres-Sánchez *et al.*, 2014). As far as we know, discrimination between weed species or even weed types (e.g. grass vs. broad-leaved weeds) using UAV images has not been achieved yet. The discrimination of vegetation at early growth stages has been commonly undertaken by analysing images captured with cameras or sensors mounted in ground-based platforms (Berge *et al.*, 2012; Peteinatos *et al.*, 2014; Laursen *et al.*, 2016; Kunz *et al.*, 2017). As we have already mentioned, several commercial machines have used cameras located ahead of the mechanical weed control tools to guide their selective actuation (Melander *et al.*, 2015; Fennimore *et al.*, 2016).

Treatment of individual plants requires the use of images with ultra-high spatial resolution. Although several ground sensors are able to detect the presence of individual seedlings and some of them are even able to discriminate weed species or weed types, various challenges still exist for accurate species classification under variable illumination and overlapping of plants and for definition of multispecies short and long-term thresholds (Ali *et al.*, 2015). In addition, further improvements in processing times are crucial before they can be applied for real-time selective herbicide application. Apparently, the See and Spray system has solved some of these constrains using 'deep learning' algorithms to identify accurately a variety of plants, improved software for a faster and more agile operation and custom nozzle designs that provide spray accuracy down to 2.5 cm (Chostner, 2017). The suitability of a given ground-based sensor for SSWM depends on various operative factors. Ultrasonic devices and spectral reflectance sensors are low cost and can operate at normal tractor speeds (6–10 km h^{-1}). Those two features are interesting for real-time actuation. However, they have small footprints and they are not able to discriminate weeds and crops. These limitations could possibly overcome by scouting only the inter-row areas (where there are no crop plants) and extrapolating the level of weed infestation to surrounding areas (Andújar *et al.*, 2011a,b; Longchamps *et al.*, 2012). Due to the relatively low cost of these sensors, a large number of them could be integrated in the sprayer boom. Some of the limitations of these simple sensors can also be mitigated using LiDAR. The scanned area of this sensor is considerably higher, its plant discrimination power is better, and it is able to operate at high speed. However, the complex processing of the large volume of data generated may represent a problem for real-time actuation. Imaging systems based on machine vision have high spatial discrimination power, but due to their large processing times, they can be used for real-time actuation only when vehicles are moved at ultra-low speeds (e.g. <2 km h^{-1}).

Socio-economic constraints

Many of the constraints for adoption of SSWM practices are similar to those of other precision agriculture practices. Paustian and Theuvsen (2016) have considered a wide range of farm characteristics and farmer demographics in order to identify the most relevant aspects regarding the adoption of precision agriculture in Germany. Their results show that well-educated, experienced farmers and young farmers were more likely to adopt these practices. Lindblom *et al.* (2017) have reviewed the development of strategies for promoting a sustainable intensification of agriculture in Sweden in the context of site-specific adoption. They identified the 'problem of implementation' as the separation between the decision support systems based on scientific criteria and the tacit knowledge and practical needs of farmers. In addition, they discussed other reasons for the low adoption of precision agriculture, for example the high complexity of procedures and the low knowledge of users, the poor user interface design and low adaption to the farm situation, the lack of incentives to learn new practices and the fear of replacing advisors. They suggest reducing barriers to adoption through co-learning and participatory approaches (e.g. through a consortium in a research project) between the users and the stakeholders in the decision support system development process.

In a recent survey, farmers in Kansas, USA, indicated that they were more likely to adopt technologies that did not require that they acquire additional skills in order to receive value from the technology (e.g. automated guidance, yield monitoring) (Griffin, 2016). Unlike 'embodied' technologies, 'information intensive' technologies provide extra information that can be useful in decision making (e.g. weed mapping and subsequent herbicide application). However, in order to fully capitalise on these technologies, they require specialised skills and additional time investment by the farmer. In this regard, Lutman and Miller (2007) concluded that real-time patch spraying using smart machines seemed to be the preferred approach among British farmers.

In most cases, farmers are reluctant to use SSWM systems due to economic reasons (Pedersen *et al*., 2001). Although various studies have proved substantial reductions in herbicide use and subsequent treatment costs associated with the use of these systems (Gerhards & Christensen, 2003; Gerhards & Oebel, 2006; Castaldi *et al*., 2017), researchers have generally ignored costs for scouting, making treatment maps and patch spraying (Swinton, 2005). In the case of early-season weed mapping from small UAVs, land coverage of a single flight (between 15 and 25 min) ranges between 1 and 20 hectares (Torres-Sánchez *et al*., 2013), depending on the operational conditions (e.g. flight altitude, percentage of image overlapping, wind speed) and the UAV and sensor specifications (e.g. sensor resolution and field of view, UAV battery duration). In addition, it is necessary to consider the subsequent processing time for image analysis (López-Granados *et al*., 2016b).

In the case of detection from ground-based platforms, the estimated costs for camera-guided weed sampling, generation of georeferenced application maps and site-specific weed control could be offset by the savings obtained from these practices (Oebel & Gerhards, 2006). Although the direct economic benefit from SSWM systems seems to be modest, the adoption of these technologies may provide a welfare benefit and a net surplus to the society due to an overall reduction of herbicide contamination of the environment and energy use for mechanical weeding. Therefore, the socio-economic impact of widespread adoption of SSWM practices may be significant (Jensen *et al*., 2012).

New opportunities for practice and research

Aerial monitoring of weed populations at both field and landscape scales may allow new approaches for weed management. Images obtained at late phenological stages may allow mapping fields and field zones with consistently high-weed pressure and areas where weeds have escaped control due to management errors or herbicide resistance. As these high-risk zones are usually stable (Gerhards, 2010), their management should receive a high priority. In addition, the annual surveillance of weed infestations present in different fields could provide a valuable historic data set. The large volume of data gathered in this way has many potential uses, besides the immediate use of weed control. However, these potential uses are currently not implemented because data are often not stored and because farmers and their advisors lack the tools to handle this amount of data. In this regard, Big Data systems provide a powerful tool. Furthermore, the connection of sensors to the Internet of Things (IoT) and the transmission of their measurements to permanent storage should become standard practice (Van Evert *et al*., 2017).

Up to now, only two types of images (conventional-colour from RGB cameras and colour-infrared from NIR-modified or multispectral cameras) have been used for weed mapping from UAV platforms. The recent developments in miniaturisation of LiDAR and hyperspectral sensors offer new opportunities by providing 3D information and images with higher spectral resolutions respectively (Wallace *et al*., 2012).

The current constraints for ground-based real-time detection can be overcome partly by further technical improvements of the systems, for example with active illumination and adapted processing algorithms (Keller *et al*., 2014). In addition, machine vision needs to be improved with faster classification algorithms and more powerful computational hardware.

Regarding the problem of implementation, it can be overcome by new research approaches, with individual farmers and cooperatives playing a major role in the search of technical solutions (co-innovation) (Lindblom *et al*., 2017).

The availability of very precise tools to detect and discriminate weeds may allow new approaches for the study of weed ecology and management. Weed researchers could move from traditional plot studies in experimental stations to farm scale studies. On-farm research has various potential advantages (Luschei *et al*., 2001): (i) this approach is capable of producing results that closely approximate the conditions under which predictions are actually needed, (ii) constraints involved with real production situations are represented in this type of studies, (iii) participatory on-farm research fosters an exchange of ideas between researchers and producers, (iv) by collecting spatially referenced information on weed populations in conjunction with information on cropping and weed management practices, the cause–effect of these practices can be investigated and (v) the inclusion of additional spatial data layers, for example soil or environment data, may also improve response modelling.

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