Precision Agric (2017) 18:366–382
DOI 10.1007/s11119-017-9520-y

The value of precision for image-based decision support in weed management

Camilo Franco[1] · Søren Marcus Pedersen[1] · Haris Papaharalampos[1] · Jens Erik Ørum[1]

Published online: 28 March 2017

Abstract Decision support methodologies in precision agriculture should integrate the different dimensions composing the added complexity of operational decision problems. Special attention has to be given to the adequate knowledge extraction techniques for making sense of the collected data, processing the information for assessing decision makers and farmers in the efficient and sustainable management of the field. Focusing on weed management, the integration of operational aspects for weed spraying is an open challenge for modeling the farmers' decision problem, identifying satisfactory solutions for the implementation of automatic weed recognition procedures. The objective of this paper is to develop a decision support methodology for detecting the undesired weed from aerial images, building an image-based viewpoint consisting in relevant operational knowledge for applying precision spraying. In this way, it is possible to assess the potential herbicide cost reductions of increased precision at the spraying device, selecting the appropriate weed precision spraying technology. Findings from this study indicate that the potential gains and marginal cost reductions of herbicides decrease significantly with increased precision in spraying.

Keywords Precision value · Precision spraying · Image-based viewpoint · Image analysis · Expert knowledge · Weed recognition

Introduction

It is commonly accepted that in the field of precision agriculture, the use of technologies helps in identifying and managing spatial and temporal attributes within fields to achieve efficiency and sustainability of land resources (Bongiovanni and Lowenberg-Deboer 2004;

✉ Camilo Franco
cf@ifro.ku.dk

[1] Department of Food and Resource Economics, Faculty of Science, University of Copenhagen, Rolighedsvej 25, 1958 Frederiksberg, Denmark

Pedersen et al. 2004). In a study by Jensen et al. (2012), it is assumed that herbicide application can be reduced between 40 and 60% in cereals with site-specific application. Gutjahr and Gerhards (2010) have found potential savings for herbicides in between 60 and 77% for broad leaved and grass weeds, respectively.

In particular, concerning field management tasks such as the control of undesirable weeds among crops, intelligent support is needed for decision making on where and how to treat those weeds site-specifically. Hence, decision support methodologies should integrate timely data collection, data processing and management actions, aiding the efficient and sustainable management of the field (Kitchen 2008).

Unmanned aerial vehicles (UAV) have an attractive potential given their low operational costs and flexible driving (e.g., adjusting height-resolution of the image), offering the means of mowing cameras all over the field without harming the crop (for a recent and detailed overview on the adoption of UAVs in weed research see Rasmussen et al. 2013). The obtained images can be either stitched together into a weed map, showing the position and the distribution of weeds (see e.g. Peña et al. 2013; Rasmussen et al. 2013), or can be *smartly interpreted* for learning the characteristic visual attributes of the weed-objects, saving on the added costs related to map construction tasks, and even allowing treating weeds in situ upon detection.

Images alone hold rich information on the conditions of the field. From a computational perspective, they hold pixel-data which have to be *understood* in an efficient and reliable way for extracting the *desired knowledge*. Based on such knowledge, it is possible to develop sound and useful decision support for farmers and decision makers in information-intensive practices in agriculture (see Fountas et al. 2006; Sorensen et al. 2010).

With this purpose in mind, an efficient weed-recognition algorithm is required for extracting information from aerial images. Here it is acknowledged that the detection and identification of weeds under a wide range of conditions stands as one of the greatest challenges for weed control systems (Slaughter et al. 2008). Hence, we propose a first basic approach to characterize weeds and verify their existence by learning from examples given by expert knowledge.

The relevance of this proposal is also grounded on the lack of attention that in general has been given to the use of *knowledge extraction technologies* in precision agriculture (Bullock et al. 2007). These technologies allow handling the different sources of information, e.g. sensor readings or high precision images, arriving at the recommended decisions (actions) regarding the optimal management of the fields. Therefore, our proposal addresses the integration of data processing techniques together with data collection practices and management actions, examining the increasing value of information in precision agriculture (see again Bullock et al. 2007).

The objective of this paper is to develop an integrated decision support methodology, detecting the undesired weed from aerial images and building an image-based viewpoint, consisting in relevant operational knowledge for applying precision spraying. In this way, it is possible to assess and discuss the potential value—in terms of herbicide cost reduction—from increased precision levels at the spraying device.

Therefore, we suggest an efficient methodology for building an image-based viewpoint from an automatic weed recognition procedure, namely the *WR algorithm*. The whole system facilitates the interaction of the user for incorporating new sample images, thus updating its outcome with the new conditions of the field. The proposed procedure for detection of undesired weeds is based on fuzzy reasoning (Klir and Yuan 1995; Zadeh 1975), a soft computing technique that represents the experts' knowledge under different levels of precision. In this way, the use of fuzzy concepts and decision rules for image analysis (see e.g. Bárdossy and Samaniego 2002; Benz et al. 2004; Lucas et al. 2007) can be coupled with different sources of information, such as spatial or sensor data (see e.g. Tagarakis et al. 2013), for knowledge extraction and decision-making purposes in precision agriculture (see Hemming and Rath 2001; Meyer et al. 2004, for some specific applications to weed image-based fuzzy classification).

The results of the image processing method (here obtained by means of the *WR* algorithm) can then be used by the user for deciding how to treat weeds. In particular, the handling of weeds can be done in correspondence with the *distribution* and size of the detected weeds in the field, determining the type of *technology* that should be used for reducing costs and maximizing efficiency. This technology refers to the use of GPS and injection-based sprinklers for spraying herbicide, but the whole system approach could also be developed towards an autonomous (robot-based) eradication or UAV-spraying mechanisms. This proposal, which extends the initial proposal of Franco et al. 2015, presents an efficient procedure which can be used for developing an autonomous decision support system, where aerial images are in fact the *source of information* for the identification of weeds. The autonomous system would be capable of detecting the undesired weed in the field, offering an *image-based viewpoint* aiding the user (farmer/expert or decision maker) to better understand the conditions of the field and decide on the appropriate *precision* and *technology* for treating weeds. In order to integrate the *value of precision spraying* within the decision support methodology, a simple spray/no-spray site-specific herbicide application case is explored, articulating data collection and processing with operational actions for thistle control in a mature cereal crop. Under this setting, the decision support methodology is formally introduced, followed by some results and discussion regarding the optimal spraying precision. Finally some concluding remarks are given together with suggestions for future research.

Site-specific herbicide application in practice

Research into variable application of pesticides has mainly focused on herbicides, although some research is also carried out within the area of fungi detection and variable application (Pedersen 2003). Preventive and site-specific treatment with insecticides is complex since insects are difficult to monitor on the field, whereas some weeds and some fungi have a tendency to concentrate in patches. Nevertheless, weeds can hardly be considered as a stable factor in the field. On the other hand, armers are aware of the potential savings of chemicals from precision farming within the field, although they also have reservations about the potential benefits due to technical difficulties and lack of decision support systems when using site-specific technologies (e.g. Pedersen et al. 2004).

Variable-rate application can be achieved in many ways, from varying turning on/off sprayers and regulation of speed and tank pressure to advanced high precision control of individual sprayer sections and nozzles (see e.g. Grisso et al. 2011). Conventional boom sprayers are usually mounted with a water tank with chemicals that are mixed with water. Usually 2–3 different chemicals are mixed at a time for each treatment. To conduct variable rate application, some sprayers are equipped with devices to regulate the amount of chemicals on the run. A GPS-receiver and a tractor-computer can be installed in order to regulate and carry out variable rate application of pesticides. Conventional boom sprayers can also be divided into different sections to enable site-specific application along the boom. An example for this application is the Sensispray development project, in which a 27 m length boom sprayer with seven sections was equipped with sensors to control spray volume per boom section, having a length of about 3–4.5 m for each section (van de Zande et al. 2009).

Farmers' spraying strategies usually require a previous mixture with the exact amount of water and expected application of active ingredients before spraying. Hence, they need to estimate the precise amount for each ingredient for that particular area to avoid emptying the tank after each operation in the field. This common technique however, which has been used for many years, conflicts with the idea of variable treatment in which the farmer should strive to reduce the amount of herbicides on areas with no weeds (Pedersen 2003). It requires that the farmer knows in advance the exact amount of chemicals that he will apply on the field. As there are some practical difficulties with pre-mixed herbicides for variable rate and patch spraying, it is vital that site-specific spraying systems (1) work with a separate load of ingredients, i.e., water and chemicals and (2) efficiently use the knowledge of weed attributes and distribution for estimating the desired herbicide composition. In the first case (injection) weed distribution could be applied by using cameras and software simultaneously with the spraying. In the second case (no injection, but pre-mixed herbicides) weed monitoring, mapping and dosage calculation is needed in advance.

Injection sprayers stand as an efficient solution, where the various undiluted chemicals are kept in a container, separated from the water tank. Water is then pumped through the nozzles and thereafter injected with the chemicals (Walter and Heisel 2001). Commercial injection systems usually have about five chemical containers for different chemical ingredients. With the injection system there are no leftovers after the spraying job is carried out and there are no additional chemicals in the water tank. An injection system can in principle be mounted on any hydraulic sprayer. Although several systems are commercial available, the injection system sprayers still need further improvement in regard to reaction time, cleaning of containers and relatively high costs (Anglund and Ayers 2003).

The ultimate site-specific weed management strategy is the one that applies one drop of herbicide per weed crop. This strategy was tested by Lund et al. (2006), by using micro-spray tubes that individually open and close with solenoid valves. In a field with 100 weed plants per m^2 and 20 tubes per 100 mm, it was possible to obtain 84% weed control efficacy by using as little as 27 g of glyphosate per ha. Even a slightly reduced precision with traditional herbicides may result in a significant reduction in herbicide use. Lund et al. (2008) has shown that vision-based spraying techniques can treat the surface of the field in small 100 $\times$ 100 mm cells with a dosage requirement that does not differ significantly from the dosage used for conventional boom spraying. This approach could potentially reduce pesticide use by 50–70% compared to conventional boom spraying.

Compared to a full dose of conventional herbicides the micro-spraying system offers a potential saving of 10–20 € per ha and the cell-spraying system offers a saving of 5–14 € per ha. The main question is, however, if the cost reductions can justify the investment for a system with all the required remote controlled micro-tubes, cell-sprayers and image/video devices for real-time detection of weed or high precision weed maps in combination with RTK-GPS technology. On the other hand, the capacity of high precision systems is another challenge for their commercialization. Despite of low capacity, a small 1 m micro-sprayer could, however, be enough if the system was un-manned and RTK-GPS guided. High precision micro-tube systems are not yet available and affordable for farmers, and the video guided cell-spraying systems are only commercially available for crops established in rows.

For conventional broad-sown crops like winter wheat and spring barley, a higher precision and reduced herbicide consumption could, however, be achieved by using traditional boom sprayers equipped with remote control of the individual nozzles or boom sections. In case of a traditional boom sprayer, having between 2 and 4 nozzles per m, the spraying precision with section length with remote control of each and every nozzle would be 250–500 mm. Considering a weed density varying from 25 to 200 plants per m^2, and a precision between 250 and 500 mm, would most likely result in a full spraying of the field. Hence, a precision of 30–100 mm would be needed to significantly reduce the pesticide use. However, in that case, the cost savings of reduced herbicide would not be sufficient to pay for video devices, weed mapping, RTK-GPS equipment, and remote controlled solenoid valves for individual nozzles or boom sections. To make a 250–500 mm precision spraying profitable, a high, patchy variation in the weed density and distribution would be required, as is the case for thistles and couch grass, which tend to grow in colonies, patches, spots, and clusters.

In this way, to estimate the value of a more precise spraying, the collection and processing of image data has to identify not only where to spray, but also offer a general overview of the weed density and distribution of patches and weed free areas. Here, the knowledge on the weed distribution is crucial for estimating the cost associated with different precision technologies, and choosing the optimal precision technique to be adopted.

Materials and methods

Chemical control of thistles and coach grass

Thistle (*Cirsium Arvense*) and couch grass (*Elymus Repens*) are common and wide spread perennial root weeds in Danish fields. Unlike most other weed species these weeds cannot be effectively controlled by herbicides in the early growth stages of the cereals, and both species tend to appear in spots and clusters. Chemical control of thistles normally takes place in cereals like winter wheat and spring barley, by using MCPA (4-(2-methyl-4-chlorophenoxy)acetic acid) products at growth stage 39 when flag leaf ligule is just visible (Zadoks et al. 1974) or by using glyphosate products (e.g. Roundup©) either a few weeks before harvest or in the stubble after harvest. The most efficient chemical control of couch grass takes place a few weeks before harvest. Consequently, efficient chemical control of coach grass and thistles can take place, at a growth stage where patches of both weeds are green and easily detectable in the almost mature and yellow cereal. Thistles require a higher dose than the coach grass and the chemical is applied no later than 10 days before harvest (Middeldatabasen 2017). The glyphosat solution holds 450–480 g active ingredients per liter.

Instrumentation

In the experiment used here to illustrate the proposal, images were captured by a hexacopter equipped with a standard RGB camera with a 10 megapixel CCD sensor (further details on the collecting of data can be found in Rasmussen et al. 2013). These images were taken from mature barley (*Hordeum Vulgare*) fields located at Taastrup, Denmark, infested with thistle. The computational procedure for the WR algorithm was developed in Matlab, where images were treated according to their basic pixel-color composition, such that each pixel has associated three dimensions regarding the red, green and blue components.

Expert knowledge on undesirable weed

Experts (such as farmers) introduce their knowledge into the system by identifying, over a representative set of sample images, some examples of undesired weeds. This can be done by drawing directly on the images, so that the system can properly characterize the attributes of pixels belonging (up to a given extent) to the *target weed object*. In this way, experts can be as precise as they want, by drawing a broad area (rather imprecise sampling) or indicating the exact boundary between the undesired and the desired weed (Fig. 1a). Notice then that the more precise the sampling is, the better the outcome of the system (based on the WR algorithm) can be. Nonetheless, it is acknowledged that a completely precise sampling may not be obtained. Take e.g., a given pixel or group of pixels sharing the properties of being both a member of the two classes (1) *desired* and (2) *undesired* weeds (as shown in Fig. 1b). Then, the pixel(s) cannot possibly be assigned to any of the two classes with absolute certainty, because there is some gradual *fuzziness* when trying to crisply define borders in between desirable and undesirable weeds.

The WR algorithm

As mentioned above, the precision in the sampling provided by the experts may vary according to the *exactness* in which they identify the target weed object. Hence, the model for detecting weeds, based on that input knowledge, has to be capable of handling different levels of precision provided by different experts. In this sense, fuzzy logic (Zadeh 1975) is an appropriate tool for designing a general and reliable representation of expert knowledge (see e.g., Franco 2014), in particular when dealing with the different image-data that can be introduced into the model for detecting the pixel-color characteristics of weeds.

First, let us define a fuzzy set, which generalizes the classical notion of a *crisp* set. A fuzzy set W is characterized by its membership function $\mu_W{:}P \rightarrow [0, 1]$, such that $\mu_W(p) \in [0, 1]$ expresses the degree up to which $p \in P$ belongs to W. Here, W is understood as the fuzzy set representation of the actual weed, whose elements are collections of pixels belonging to it under different degrees of intensity.

Now, based on the experts' sampling, the reference sets R, B and G are defined, respectively containing all the different values for the red (r), blue (b) and green (g) components of the pixels that are known to belong to the target weed object. Therefore, given any image M, composed by $n \times m$ pixels, every pixel $x_{ij} = (r, b, g)$, $i = 1,\ldots, n$, $j = 1,\ldots, m$, can be examined to determine if it fulfills the minimum requirements to be considered an element of W. In formal terms, for any pattern $x_{ij} = (r, b, g)$ and given a set C of *reference pixel-values*, such that $C = R \times B \times G$, the minimum requirements for a (pixel) pattern to be considered as part of a weed object are such that $x_{ij} \in C$ holds if and

(a) (b)

Fig. 1 The **a** sampling for *cirsium arvense* and **b** a group of pixels sharing the properties of both classes (1) and (2) only if $r \in R$, $b \in B$, and $g \in G$ hold true. Hence, taking the normalized values for every pattern $x_{ij} = (r, b, g)$, the following function is defined,

$$\mu_C(x_{ij}) : [0,1]^3 \to \{0,1\}, \tag{1}$$

such that $\mu_C(x_{ij}) = 1$ if and only if $x_{ij} \in C$; $\mu_C(x_{ij}) = 0$ otherwise.

Building on this initial characterization of pixels, weed objects can be automatically detected by examining cells of $k \times k$ pixels and identifying the number of pixels that verify the minimum requirement of being in fact elements of C. Thus, the greater the proportion of pixels belonging to C, the greater it will be the membership degree of the entire cell to the fuzzy set W.

In this way, for every cell $p_{k \times k} \in M$, the intensity of membership $\mu_W(p)$ is computed according to the following expression,

$$\mu_W(p) = \sum_{i=1}^{k} \sum_{j=1}^{k} \frac{\mu_C(x_{ij})}{k \times k}. \tag{2}$$

Notice that by defining a *confidence threshold* $\varphi, 0 < \varphi \leq 1$, it is possible to evaluate Eq. (2) such that φ represents the minimum intensity required for classifying the cell as being a weed object. Here, both k and φ are free parameters that have to be calibrated while tuning the WR algorithm, adjusting the error of classification for the effective detection of weed objects.

In summary, the WR algorithm can be formulated as follows:

Input: A set S with sampled images, a set I with the crop aerial images and the parameters k and φ.

(*WR-1*): Based on S, identify the reference set C.

(*WR-2*): For every image $M \in I$, and for every pixel $x_{ij} \in M$, compute the value of $\mu_C(x_{ij})$ according to Eq. (1).

(*WR-3*): For every image $M \in I$, and for every cell $p_{k \times k} \in M$, compute the membership degree $\mu_W(p)$ based on Eq. (2), such that p is classified as a weed object if it is verified that $\mu_W(p) \geq \varphi$.

Output: For every image $M \in I$, the detected weed objects.

The decision support system methodology

The outcome of the WR output can be used in different ways. On the one hand, it can be directly used, e.g. by a conventional field sprayer, an herbicide equipped drone or an autonomous robot, acting upon detection of the undesired weed; on the other hand, it can be used as decision support, aiding the management actions and the treatment of weeds in the field. Then, based on the detected objects, an image-based viewpoint is obtained, generating new knowledge on the weeds needing treatment and the type of actions that should be taken.

The image-based viewpoint consists in a collection of WR-processed images. Associated with this viewpoint there is knowledge on relevant matters such as the distribution and size of weeds, supporting a recommended course of action for an optimal treatment of the field. It allows tuning up the instruments used in handling weeds. In particular, it allows determining the rate of herbicide application together with the size of herbicide sprinklers, as it will be explored in the following section.

Here it is noted that choosing a specific technique for treating weeds depends on the specific costs of its implementation and its associated use of resources (see e.g., Thompson et al. 1991; Slaughter et al. 2008). Then, an optimal technology can be identified taking into account the costs of implementing the technology and the gains and/or savings associated with its efficient and sustainable use of herbicide. The usage of herbicide can then be effectively reduced with respect to a homogeneous treatment, by spraying in function of the characteristic attributes and distribution of the detected weed objects, subject to *efficiency* and *sustainability* restrictions.

It can be conjectured that the higher the precision in which technology (sprinklers) can be adjusted, the higher it will be the saving of herbicide, up to the extent that the implementation costs justify the investment that *precision* entails.

Overall, the decision support system automatically processes all the available images of the field (based on the WR procedure), and based on the detected weeds, supports the actions required for the optimal management of the field. Any time that the farmer needs to do so, new knowledge can be introduced into the system, sampling new images for updating the conditions of the field. As a result, technology can be adjusted to properly take care of the detected weeds.

Integrating the value of increased precision

Given the thistle distribution, and based on the image-based viewpoint, thistle clusters are identified with varying location, number and size. Then, in order to explore the (marginal) value of precision for spraying, we consider a boom section spraying technology composed by multiple (management) Remote Control (RC) units.

The number of RC units (z), i.e. nozzles or boom-sections, is represented by a function of the total length of the boom (l) and the length of each unit (w), where $l \geq w$, such that,

$$z = l/w. \tag{3}$$

Notice that the *precision of the spraying* holds an inverse relation with respect to the length of the units, and thus, a positive relation with respect to its number (i.e. the smaller the units, the greater the precision, and hence, the greater the number of units there will be). In this sense, precision can be grasped through the meaning of z.

The relative sprayed area (S) can then be measured by a monotone (e.g. power) function with respect to the precision of spraying (z), such that,

$$S = \gamma + \alpha z^{\beta} = \gamma + \alpha \left(\frac{l}{w} \right)^{\beta} = \gamma + \alpha l^{\beta} w^{-\beta} \tag{4}$$

where the γ agrees with the infested area. I.e., given an *ultimate level of precision*, the sprayed area (S) would eventually match the infested area, being verified that $S = \gamma$

Therefore, the *marginal change* in the sprayed area, measured as a function of the last engaged unit, is given by,

$$\frac{\Delta S}{\Delta z} = \alpha \beta z^{(\beta - 1)} = \alpha \beta \left(\frac{l}{w} \right)^{(\beta - 1)}. \tag{5}$$

Overall, the value of increased precision, under this basic approach, solely depends on the subsequent herbicide cost reductions. For the simulation of the spraying, thistles clusters are treated with 2 L per ha of the herbicide Roundup Flex©, with a content of

480 g of glyphosate per liter and a total cost of around 22 € per ha, including Danish taxation of 9 € on the pesticide load (Middeldatabasen 2017). The value of a more precise application heavily depends on the density and distribution of the thistles, but the herbicide cost reduction will never exceed 22 € per ha.

Following Eq. (3), the precision of the spraying is expressed in terms of the number of remote controlled boom sections. Neither the kind of equipment that is needed to increase the precision, nor its costs are taken into account. Instead, the reduction in herbicide costs per extra remote controlled boom section is taken as the principal objective for the weed spraying actions. The herbicide costs are computed by the multiplication of the sprayed area (S) and the cost of a full herbicide dose (H), and consequently, based on Eq. (4), the marginal value (v) of an extra unit becomes a function of length of the sprayer (l), the length of the units (w) and the cost of a full herbicide dose (H), such that,

$$v(H, l, w) = H\alpha\beta\left(\frac{l}{w}\right)^{(\beta-1)}. \tag{6}$$

Two characteristic cases for precision spraying are simulated. The first one has eight significant patches and many small patches covering 10.9% of the total area. The second case has eight concentrated thistle patches per ha, covering 10.0% of the whole crop area. In both cases the field is sprayed with a 40 m boom having different precision, i.e., containing 40, 20, 8, 4, 2 or 1 spraying unit(s) (in total, six different precision scenarios).

Results

The WR algorithm applied to thistle detection in barley fields

Based on a set of images taken by a UAV on the barley crops, the WR algorithm has been calibrated for determining the acceptable values for the parameters k and φ. First, following the sampling process from experts, the reference set C is defined. Then, images are examined pixel by pixel, computing the pixels' membership to C, and inferring the occurrence of weed objects according to the WR algorithm.

As illustrated in Fig. 2a, pixels are classified one by one in a given image as being candidate members of a weed object (the selected pixels are in fact candidates). Different clusters of pixels configure a weed object, while other scattered pixels are outliers, pointing out coincidences between the color components of thistle and barley weeds. Thus, recognizing that real weeds (such as thistle) cannot be captured by a single pixel, but by a collection of adjacent pixels, weed objects are then properly identified by means of pixel cells, as shown in Fig. 2b.

The calibration for the parameters k and φ, necessary for tuning the algorithm in step (*WR-3*), is developed by optimizing the classification error so it is as close as possible to 0. Here, the error is positive according to the number of pixel-cells that are wrongly classified as weed objects, and it is negative according to the number of weeds missing proper identification, i.e., that are passed over by the detection procedure and are not tagged by any weed object. Table 1 shows some examples of the error arising from the combination of $k = 15$ and $\varphi = 0.3$, where 2 weed objects are wrongly identified, or from $k = 20$ and $\varphi = 0.3$, where 1 weed is missing proper identification.

Once the values for the parameters have been adequately determined (here they have been set up to $k = 15$ and $\varphi = 0.4$), the model can be validated on another set of images in

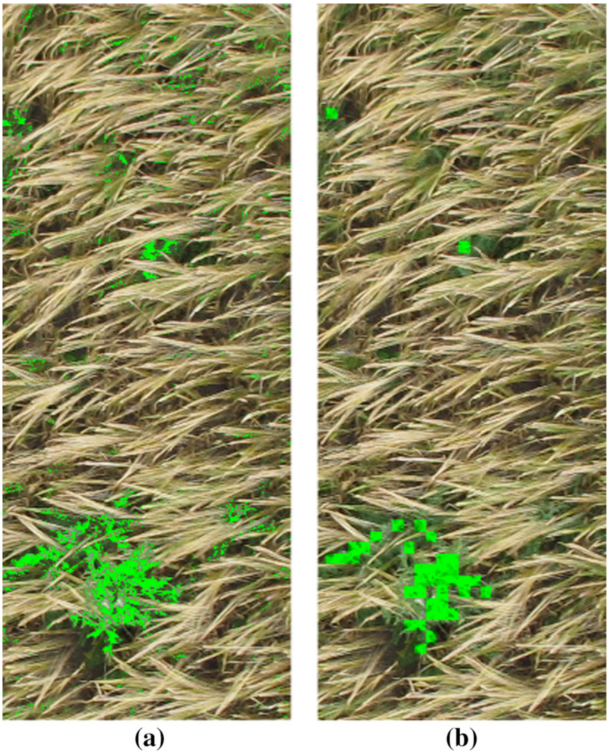


Fig. 2 Detecting the weed objects by algorithm WR, **a** identifying candidate pixels and **b** grouping them into weed objects by means of pixel cells

Table 1 Different combinations for k and φ, with their associated classification error

[k, φ]	Classification error
[15,0.3]	2
[20,0.3]	−1
[15,0.4]	0

the same field. The validation results show no misclassification error, i.e., the weed objects are properly identified when examining a different set of images from the ones used before.

The value of spraying with increased precision

The results for the two cases on precision spraying are shown in Table 2, having the estimated parameters for Eq. (4) and the respective results for the sprayed area (S), as well as the marginal value of an extra Remote Control (RC) spraying unit. As stated in Eq. (6), the marginal value of an extra RC spraying unit (v) depends on herbicide cost (H) and length of both the sprayer (l) and the RC spraying unit (w), whereas the sprayed area (S) solely depends on the precision of the spraying (z).

Figures 3, 4 and 5 present the general overview for the simulated spraying of the weed. In this way, Fig. 3 presents the results from estimating the sprayed area as a function of the number of the RC spraying units per 40 m, while Fig. 4 refers to the estimation of the sprayed area as a function of the length of the RC spraying units. In consequence, the

Table 2 Estimated values for γ, α and β, and derived functions (Eqs. 4, 6) for sprayed area and marginal value of extra RC spraying units

Cases	γ	α	β	R^2	Sprayed area (S) Eq. (4)	Marginal value of extra RC spraying units (v) Eq. (6) [€ per unit per ha]
1. Many, scattered patches	10.9%	0.56	−0.73	99.6%	$10.9\% + 3.8\%w^{0,73}$	$0.405\left(\frac{w}{l}\right)^{1,73}H$
2. Few, significant patches	10.0%	0.29	−1.01	99.7%	$10.0\% + 0.68\%w^{1,01}$	$0.289\left(\frac{w}{l}\right)^{2,01}H$

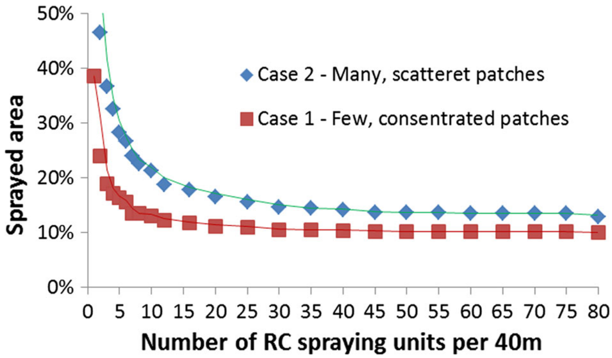


Fig. 3 Results from estimating the sprayed area as a function of the number of the RC spraying units per 40 m (*points* are simulated values, and *lines* are calculated by using Eq. (4))

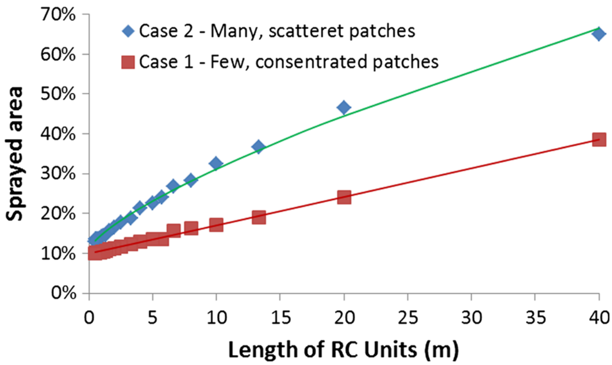


Fig. 4 Results from estimating the sprayed area as a function of the length of the RC spraying units (*points* are simulated values, and *lines* are calculated by using Eq. (4))

marginal reduction in the herbicide costs seems to be significantly decreasing with respect to the number of RC units (see Fig. 5).

The key figures for spraying, herbicide costs, and marginal cost reductions are shown in Tables 3 and 4, respectively for each case and six precision scenarios. It can be seen that the simplest and most profitable increase in precision comes from turning the full meter

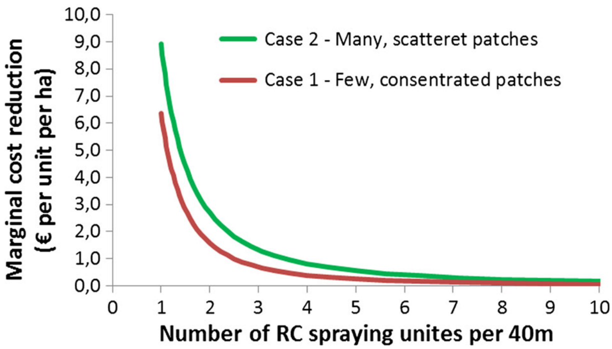


Fig. 5 Results from estimating the marginal cost reduction [€ per ha] per additional RC spraying unit as a function of the number of RC spraying units Eq. (6)

boom sprayer on (and later off) every time it passes a weed patch. Such an increase in precision reduces the herbicide cost by 35–60%, respectively equivalent to a 7.36–13.51 € per ha reduction, compared to a uniform spraying of the whole area (see again Tables 3, 4).

On the other hand, by using an extra switch, the 40 m boom will act as two individual RC units, each with a length of 20 m. Whereas the first switch reduces the herbicide cost by 7.36 and 13.51 € per ha, respectively for cases 1 and 2, the second switch only reduces the cost by 4.85 and 3.17 € per ha (again, with respect to both cases). With two more remote controlled units, the length of each remote controlled unit is decreased to 10 m, and the herbicide costs are reduced, respectively, from 9.78 to 5.32 € per ha to 6.86 and 3.75 € per ha, equivalent to an average of 1.46 and 0.79 € per ha per unit. Hence, the marginal herbicide cost reduction of the last (extra) unit is estimated to be 0.81 and 0.39 € per ha per (10 m) unit. In the same way, there is a marginal herbicide cost reduction of 0.25 and 0.10 € per ha per (5 m) unit. Overall, the higher the precision, the more units are needed, and at the same time, the marginal reduction in the herbicide costs seems to be significantly decreasing (see again Fig. 5).

Discussion

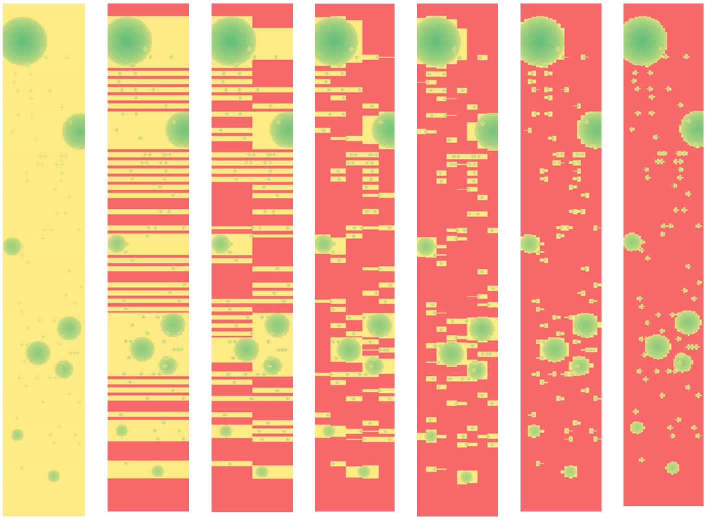
One of the main advantages of the WR automatic recognition procedure is the saving of resources (time and effort in identifying weeds from aerial images), as farmers only have to focus on a small amount of representative samples which can then be used by the system to learn the visual attributes of the target weed object. Therefore, the system can handle a very large amount of images without extra costs, while replicating the human (farmer/expert) knowledge on weed detection.

The inclusion of an interactive phase between the system and the user/expert allows handling well known difficulties in developing a sound image-based system. The difficulties usually refer to the obscuration of weed by the crop, the required resolution of the images and the lack of consistency in discriminating weed from crop characteristics (Thompson et al. 1991). The preliminary results obtained here show that at the mature stage, barley and thistle can be efficiently distinguished under a standard image resolution based only on the 3-color decomposition of the weed objects.

Regarding the management actions and the implementation of selective herbicide application, the relevance of the image-based viewpoint in the whole decision system is

Table 3 Simulated herbicide application for case 1 (field infested with many scattered thistle patches), together with reduced costs for different precision scenarios, with RC units of different length

Image-based viewpoint and weed distribution[a]



RC units per 40 m	0	1	2	4	8	20	40
RC unit length (m)	40	40	20	10	5	2	1
Sprayed area (%)	100%	65.0%	46.5%	32.6%	22.7%	16.5%	14.1%
	Herbicide costs per ha (€ per ha)						
Herbicide costs	22.0	14.64	9.78	6.86	5.09	3.78	3.23
Total reduction[b]		7.36	12.22	15.14	16.91	18.22	18.77
Marginal reduction		7.36	4.85	2.93	1.77	1.31	0.55
	Marginal herbicide cost reduction per RC unit (€ per ha per unit)						
Average		7.36	4.85	1.46	0.44	0.11	0.03
Last RC unit[c]		8.91	2.69	0.81	0.25	0.05	0.02

[a] Green = thistles, all sprayed, yellow = no thistles, but sprayed, red = no thistles and not sprayed)

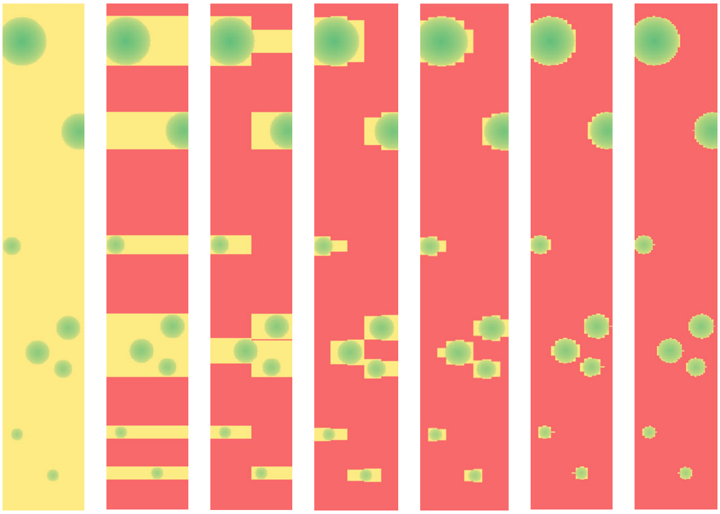
[b] Herbicide cost reduction relative to 100% sprayed area with zero RC units

[c] Calculated by using Eq (6) and estimated values (Table 2)

critical; as it allows detecting the presence and concentration of weeds for its efficient and sustainable treatment (see e.g. Stafford and Miller 1993, for the importance of weed detection in selective herbicide application). Going beyond the weed detection mechanism, and integrating the three areas dealing with recollection of data, data processing and management actions, the complete decision system can be examined under a unified framework for understanding its complexity and evaluating its overall performance.

Eventually, the improvement that precision agriculture has over conventional management must be evaluated in terms of profitability and environmental impact, both in the short and the long term (Whelan and McBratney 2001). The potential of site-specific management lies in reducing the cost of inputs and environmental impact, while keeping risk at an acceptable level (Heermann et al. 2002). The results of the image-based decision

Table 4 Simulated herbicide application for case 2 (field infested with a few significant thistle patches), together with reduced costs for different precision scenarios, with RC units of different length

Image-based viewpoint and weed distribution[a]							
RC units per 40 m	0	1	2	4	8	20	40
RC unit length (m)	40	40	20	10	5	2	1
Sprayed area (%)	100	38.6%	24.0%	17.2%	13.6%	11.2%	10.4%
	Herbicide costs per ha (€ per ha)						
Herbicide costs	22.0	8.49	5.32	3.75	2.97	2.50	2.35
Total reduction[b]		13.51	16.68	18.25	19.03	19.50	19.65
Marginal reduction		13.51	3.17	1.57	0.78	0.46	0.15
	Marginal herbicide cost reduction per RC unit (€ per ha per unit)						
Average		13.51	3.17	0.79	0.19	0.04	0.01
Last RC unit[c]		6.36	1.58	0.39	0.10	0.02	0.00

[a] Green = thistles, all sprayed, yellow = no thistles, but sprayed, red = no thistles and not sprayed)

[b] Herbicide cost reduction relative to 100% sprayed area with zero RC units

[c] Calculated by using Eq (6) and estimated values (Table 2)

system could be properly tested regarding the optimal risk strategy for uniform or variable/specialized management of the field.

The analyzed thistle and spring barley example is an exceptional case. The marginal gains are relatively small with a high accuracy of the equipment – and the question is to what extent the cost savings from this high degree of accuracy can cover the additional cost of site-specific precision in terms of small controlled sections on the boom sprayer. The results from Tables 3, 4 indicate that the potential gains and marginal cost reductions of herbicides decrease significantly when shifting from uniform application, to *on/off* application and further on to small 1 m length sections.

In practice, weed grows in patches, and is controlled by using herbicides with a broad application (e.g. glyphosate). Most herbicides are, however, normally applied at an early development stage of the crop. Besides, herbicides can't harm cereals that are almost mature. Even though some problematic weed species grow in patches, some weed types may grow almost anywhere implying that detection and identification of individual, overlapping green weed species is complicated. Here, precision spraying with selective herbicides and software with ultra-precise weed detection, such as a future commercial and tested version of the WR algorithm, could be the best option for precision spraying in cereals.

For crops established in rows (like beets and potatoes), band spraying and mechanical weed control might be a competitive low-tech alternative to site-specific spraying. When applying glyphosate, precision spraying will indeed be less harmful to the growing crop, and with selective herbicides, precision spraying will reduce the unnecessary spraying with expensive herbicides. In fact, precision spraying saves on herbicides, having a direct impact on the financial viability of the precision farming technology. Nonetheless, as in the example with micro-spraying with glyphosate (Lund et al. 2008), potential herbicide savings are somewhat limited, and can hardly pay for the individual investment on high precision micro-cell spraying, leaving aside the costs of having a *robust* software for high precision weed recognition. However, high value crops, that require expensive and harmful herbicides, could serve as an example where high precision spraying is profitable.

In summary, the knowledge generated by the image-based viewpoint or by common high precision weed maps is indeed a useful and profitable tool for the farmer, but its added value is conditional to the effective integration of the relevant information with the specific operational tasks. Even though it requires advanced technology to produce the updated knowledge of the field, treating aerial images for crop and weed recognition, it would be expected that costs could be shared under cooperative behavior, and the specific knowledge could be used for sound decision making at the individual farm level. Even though high precision spraying may be too costly and can't reduce herbicide use that much at the present state, high precision images and/or maps could lead to a reduced herbicide use, leading to different herbicide solutions for each field.

Conclusions

The WR algorithm-based viewpoint for site-specific weed management and decision support has been proposed for identifying the distribution of weeds. The algorithm extracts information by processing the collection of aerial images, and offers reliable and relevant knowledge for identifying the necessary and recommendable management actions. In addition, a number of simulated site specific herbicide applications and related cost savings have been estimated, finding that the potential gains and marginal cost reductions of herbicides decrease significantly with higher accuracy. Nevertheless, it is pointed out that high precision weed detection is still required to estimate the optimal spraying precision.

Lastly, it is noted that the weed recognition methodology proposed in this study works well enough for the detection of thistle on mature barley fields in close range aerial images. It still remains to be tested on images captured from higher altitudes, and on different types of crops under different growth stages, infested with different weed species. This future research is necessary to address the *robustness* of the WR method, comparing its performance with other well-established statistical and computational techniques for image analysis.

Acknowledgements This research has been partially supported by the Innovation Fund Denmark (InnovationsFonden), under the Future Cropping partnership. Authors would also like to thank Prof. Jesper Rasmussen, from University of Copenhagen, for making available the images used in this study.

References

Anglund, E. A., & Ayers, P. D. (2003). Field evaluation of response times for a variable rate (pressure-based and injection) liquid chemical applicator. *Applied Engineering in Agriculture, 19,* 273–282.

Bárdossy, A., & Samaniego, L. (2002). Fuzzy rule-based classification of remotely sensed imagery. *IEEE Transactions on Geoscience and Remote Sensing, 40,* 362–374.

Benz, U. C., Hofmann, P., Willhauck, G., Lingenfelder, I., & Heynen, M. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *Photogrammetry & Remote Sensing, 58,* 239–258.

Bongiovanni, R., & Lowenberg-Deboer, J. (2004). Precision agriculture and sustainability. *Precision Agriculture, 5,* 359–387.

Bullock, D. S., Kitchen, N., & Bullock, D. G. (2007). Multidisciplinary teams: A necessity for research in precision agriculture systems. *Crop Science, 47,* 1765–1769.

Fountas, S., Wulfsohn, D., Blackmore, B. S., Jacobsen, H. L., & Pedersen, S. M. (2006). A model of decision-making and information flows for information-intensive agriculture. *Agricultural Systems, 87,* 192–210.

Franco, C. (2014). On the analytic hierarchy process and decision support based on fuzzy-linguistic preference structures. *Knowledge-Based Systems, 70,* 203–211.

Franco, C., Pedersen, S. M., Papaharalampos, H., & Ørum, J. E. (2015). An image-based decision support methodology for weed management. In J. V. Stafford (Ed.), *Precision agriculture'15* (pp. 595–601). Netherlands: Wageningen.

Grisso, R., Alley, M., Thomason, W., Holshouser, D. & Roberson, G.T. (2011). Precision Farming Tools: Variable-Rate Application. Resource document: Virginia Cooperative Extention. https://pubs.ext.vt.edu/442/442-505/442-505_PDF.pdf.

Gutjahr, C., & Gerhards, R. (2010). Decision rules for site-specific weed management. In E. C. Oerke, R. Gerhards, G. Menz, & R. A. Sikora (Eds.), *Precision crop protection—the challenge and use of heterogeneity* (pp. 223–239). Netherlands: Springer.

Heermann, D. F., Hoeting, J., Thompson, S. E., Duke, H. R., Westfall, D. G., Buchleiter, G. W., et al. (2002). Interdisciplinary irrigated precision farming research. *Precision Agriculture, 3,* 47–61.

Hemming, J., & Rath, T. (2001). Computer-vision-based weed identification under field conditions using controlled lighting. *Journal of Agricultural Engineering Research, 78,* 233–243.

Jensen, H. G., Jacobsen, L. B., Pedersen, S. M., & Tavella, E. (2012). Socioeconomic impact of widespread adoption of precision farming and controlled traffic systems in Denmark. *Precision Agriculture, 13,* 661–677.

Kitchen, N. R. (2008). Emerging technologies for real-time and integrated agriculture decisions. *Computers and Electronics in Agriculture, 61,* 1–3.

Klir, G., & Yuan, B. (1995). *Fuzzy sets and fuzzy logic: theory and applications*. New Jersey: Prentice Hall.

Lucas, R., Rowlands, A., Brown, A., Keyworth, S., & Bunting, P. (2007). Rule-based classification of multi-temporal satellite imagery for habitat and agricultural land cover mapping. *ISPRS Journal of Photogrammetry & Remote Sensing, 62,* 165–185.

Lund, I., Christensen, S., Jensen, L. A., Jensen, P. K., Olsen, H. J., Søgaard, H. T. et al. (2008) Cellesprøjtning af ukrudt i majs. Pesticide research document. Resource document: Ministry of Environment of Denmark. http://www2.mst.dk/udgiv/publikationer/2008/978-87-7052-851-1/978-87-7052-851-1/pdf/978-87-7052-852-8.pdf.

Lund, I., Søgaard, H. T. & Graglia, E. (2006) Micro-spraying with one drop per weed plant. Proceedings of Plantekongres 2006, Arhus, Denmark, January 10–11, 2006.

Meyer, G. E., Neto, J. C., Jones, D. D., & Hindman, T. W. (2004). Intensified fuzzy clusters for classifying plant, soil, and residue regions of interest from color images. *Computers and Electronics in Agriculture, 42,* 161–180.

Middeldatabasen (2017) SEGES—Knowledge centre for agriculture. Resource document: www.middeldatabasen.dk.

Pedersen, S. M. (2003). *Precision farming—technology assessment of site-specific input application in cereals*. DTU: IPL.

Pedersen, S. M., Fountas, S., Blackmore, S., Gylling, M., & Pedersen, J. L. (2004). Adoption and perspectives of precision farming in Denmark. *Acta Agriculturæ Scandinavica Section B, Soil and Plant Science, 54,* 2–6.

Peña, J. M., Torres-Sánchez, J., Castro, A. I., Kelly, M., & López-Granados, F. (2013). Weed mapping in early season maize fields using object-based analysis of unmanned aerial vehicle (UAV) images. *PLoS ONE, 8,* 1–11.

Rasmussen, J., Nielsen, J., Garcia-Ruiz, F., Christensen, S., & Streibig, J. C. (2013). Potential uses of small unmanned aircraft systems (UAS) in weed research. *Weed Research, 53,* 242–248.

Slaughter, D. C., Giles, D. K., & Downey, D. (2008). Autonomous robotic weed control systems: A review. *Computers and Electronics in Agriculture, 61,* 63–78.

Sorensen, C. G., Pesonen, L., Fountas, S., Suomi, P., Bochtis, D., Bildsøe, P., et al. (2010). A user-centric approach for information modelling in arable farming. *Computers and Electronics in Agriculture, 73,* 44–55.

Stafford, J. V., & Miller, P. C. H. (1993). Spatially selective application of herbicide to cereal crops. *Computers and Engineering in Agriculture, 9,* 217–229.

Tagarakis, A., Liakos, V., Fountas, S., Koundouras, S., & Gemtos, T. A. (2013). Management zones delineation using fuzzy clustering techniques in grapevines. *Precision Agriculture, 14,* 18–39.

Thompson, J. F., Stafford, J. V., & Miller, P. C. H. (1991). Potential for automatic weed detection and selective herbicide application. *Crop Protection, 10,* 254–259.

van de Zande, J. C., Achten, V. T., Kempenaar, C., Michielsen, J. M., van der Schans, D., de Boer, J., et al. (2009). SensiSpray: site-specific precise dosing of pesticides by on-line sensing. In E. J. van Henten, D. Goense, & C. Lokhorst (Eds.), *Precision agriculture'09* (pp. 785–792). Netherlands: Wageningen.

Walter, A. M. & Heisel, T. (2001) Precision application of herbicides using injection sprayer systems. In G. Grenier, S. Blackmore (Eds.), Proceedings of the 3rd European Conference on Precision Agriculture (pp. 611–616). France: agro Montpellier.

Whelan, B. M., & McBratney, A. B. (2001). The "null hypothesis" of precision agriculture management. *Precision Agriculture, 2,* 265–279.

Zadeh, L. A. (1975). Fuzzy logic and approximate reasoning. *Synthese, 30,* 407–428.

Zadoks, J. C., Chang, T. T., & Konzak, C. F. (1974). A decimal code for the growth stages of cereals. *Weed Research, 14,* 415–421.