Weed Technology 2016 30:888–897

Weed Decision Threshold as a Key Factor for Herbicide Reductions in Site-Specific Weed Management

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The objective of this research was to explore the influence that weed decision threshold (DT; expressed as plants m^{-2}), weed spatial distribution patterns, and spatial resolution of sampling have on potential reduction in herbicide use under site-specific weed management. As a case study, a small plot located in a typical corn field in central Spain was used, constructing very precise distribution maps of the major weeds present. These initial maps were used to generate herbicide prescription maps for each weed species based on different DTs and sampling resolutions. The simulation of herbicide prescription maps consisted of on/off spraying decisions based on information from two different approaches for weed detection: ground-based vs. aerial sensors. In general, simulations based on ground sensors resulted in higher herbicide savings than those based on aerial sensors. The extent of herbicide reductions derived from patch spraying was directly related to the density and the spatial distribution of each weed species. Herbicide savings were potentially high (up to 66%) with relatively sparse patchy weed species (e.g., johnsongrass) but were only moderate (10 to 20%) with abundant and regularly distributed weed species (e.g., velvetleaf). However, DT has proven to be a key factor, with higher DTs resulting in reductions in herbicide use for all the weed species and all sampling procedures and resolutions. Moreover, increasing DT from 6 to 12 plants m^{-2} resulted in additional herbicide savings of up to 50% in the simulations for johnsongrass and up to 28% savings in the simulations for common cocklebur. Nonetheless, since DT determines the accuracy of patch spraying, the consequences of using higher DTs could be leaving areas unsprayed, which could adversely affect crop yields and future weed infestations, including herbicide-resistant weeds. Considering that the relationship between DT and accuracy of herbicide application depends on weed spatial pattern, this work has demonstrated the possibility of using higher DT values in weeds with a clear patchy distribution compared with weeds distributed regularly.

Nomenclature: Common cocklebur, *Xanthium strumarium* L. XANST; johnsongrass, *Sorghum halepense* (L.) Pers. SORHA; velvetleaf, *Abutilon theophrasti* Medik. ABUTH; corn, *Zea mays* L.

Key words: Patch spraying, prescription map errors, weed decision threshold, weed mapping, weed spatial distribution

El objetivo de esta investigación fue explorar la influencia que tienen el umbral de decisión para el control de malezas (DT; expresado como plantas m^{-2}), los patrones de distribución espacial de malezas, y la resolución espacial del muestreo, sobre la reducción potencial en el uso de herbicidas con un manejo de malezas de sitio-específico. Como un caso de estudio, se usó una parcela pequeña localizada en un campo de maíz típico en el centro de España, para construir mapas muy precisos de distribución de las principales malezas presentes. Estos mapas iniciales fueron usados para generar mapas de prescripción de herbicidas para cada especie de maleza con base en diferentes DTs y resoluciones de muestreo. La simulación de mapas de prescripción de herbicidas consistió de decisiones de iniciar/detener la aspersión con base en la información proveniente de dos estrategias diferentes para la detección de malezas: sensores terrestres vs. aéreos. En general, las simulaciones con base en sensores terrestres resultaron en mayores ahorros de herbicidas que aquellas basadas en sensores aéreos. La magnitud de las reducciones en el uso de herbicidas derivadas de las aspersiones localizadas estuvieron directamente relacionadas a la densidad y la distribución espacial de cada especie de malezas. Los ahorros de herbicidas fueron potencialmente altos (hasta 66%) con especies de malezas relativamente esparcidas en patrones agregados (e.g., *Sorghum halepense*), pero fueron solamente moderados (10 a 20%) con especies de malezas abundantes y distribuidas en forma regular (e.g., *Abutilon theophrasti*). Sin embargo, el DT ha probado ser un factor clave, y DTs altos resultan en reducciones en el uso de herbicidas para todas las especies de malezas y todos los procedimientos y resoluciones de muestreo. Además al incrementar el DT de 6 a 12 plantas m^{-2} resultó en ahorros adicionales de herbicidas en hasta 50% en las simulaciones para *S. halepense* y hasta

DOI: 10.1614/WT-D-16-00039.1

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28% de ahorros en las simulaciones para *Xanthium strumarium*. Sin embargo, como el DT determina la exactitud de la aspersión del agregado de malezas, las consecuencias de usar DTs altos podría ser el dejar áreas sin asperjar, lo que podría afectar adversamente los rendimientos de los cultivos y las infestaciones futuras de las malezas, incluyendo malezas resistentes a herbicidas. Considerando que la relación entre el DT y la exactitud de la aplicación del herbicida depende del patrón de distribución espacial de la malezas, este trabajo ha demostrado la posibilidad de usar valores más altos de DT en malezas con un patrón claro de distribución agregada al compararse con malezas distribuidas en forma regular.

POST patch spraying (spraying herbicides only in those field areas where weed density or weed cover is above a given threshold) has been proposed as a promising method to reduce the amount of herbicides used in agriculture (Christensen et al. 2009; Gerhards and Oebel 2006; Wiles 2009). The concept of economic weed threshold has been defined as the weed density at which the cost of herbicide application is equal to the annual economic benefit of spraying (Coble and Mortensen 1992). Although this concept has been widely proposed for integrated weed management, it has rarely been incorporated into commercial practice (Swanton et al. 1999; Wilkerson et al. 2002). For practical application of this concept in patch spraying, prediction of yield loss from early estimation of weed infestation is required. The use of leaf cover of weeds, estimated by image analysis, has been suggested for estimation of yield loss (Ngouajio et al. 1998, 1999). However, in order to define weed thresholds that are usable for patch spraying purposes, various factors should be considered: (1) weeds grow in mixed populations, with their leaves overlapping and with overlapping effects on crop yield (Ali et al. 2015); (2) economic thresholds are generally very low (Longchamps et al. 2014); (3) spray decisions are usually taken at an early weed stage; (4) discriminating individual weed populations at low densities and at early growth stages is still a challenge (Ali et al. 2015; Christensen et al. 2009); and (5) the establishment of an economic threshold should take into account the impact of the seed production of residual and resistant weeds (Simard et al. 2009).

Conversely, one of the most important challenges of patch spraying is weed detection. Currently, various imaging technologies are being developed to measure weed cover and weed density and to identify weed species based on their morphological characteristics (Andújar et al. 2011a; Christensen et al. 2009; Weis et al. 2008). This information can be used to generate site-specific herbicide prescription maps.

The accuracy of prescription maps and actual herbicide savings achieved by patch spraying depend on various biological (weed size, density, and spatial distribution) and technological (action thresholds, detection, and actuation equipment) factors (Andújar et al. 2011b; Berge et al. 2007).

Weed scouting and herbicide spraying are usually conducted at early stages of crop and weed development. In order to detect small weeds, appropriate sensing tools and equipment are required. Weed detection can be conducted from either ground or aerial platforms. The ground-based approach typically produces high-resolution images allowing early detection of relatively low weed densities, while cameras placed on aerial platforms allow larger areas to be inspected but image resolution is usually lower (Lamb et al. 1999; Martín et al. 2011; Thorp and Tian 2004). Since increasing weed detection resolution (i.e., the accuracy) is costly (Andújar et al. 2013; Barroso et al. 2004; Wiles 2009), it is necessary to assess the effect that reducing this resolution has on the amount of herbicide used and on spraying errors. Indeed, the spatial distribution of weeds far from regular can be highly variable among species and fields (Christensen et al. 2009; San Martín et al. 2015). In addition, distribution of individual weed species may exhibit different spatial patterns when viewed at different spatial scales (Cousens et al. 2004; Heijting et al. 2007; Wyse-Pester et al. 2002). Consequently, sampling strategies decreasing the sampling intensity (i.e., resolution) can decrease sampling efficiency (Cardina et al. 1997) and consequently affect the accuracy of prescription maps (Berge et al. 2007, 2008).

The main hypothesis of this work was that the herbicide reductions in prescription maps for site-specific weed management depends on the combined effect of weed thresholds, weed distribution patterns, and sampling resolution. This hypothesis was tested with simulated data generated from a real data set obtained in a corn field.

Materials and Methods

Area of Study. The experimental data set was obtained from a study conducted on a 41.0-m by 10.5-m plot located approximately in the center of a 4-ha corn field equidistant from the margins, with the longest side in the same direction of field equipment in previous years. The field was located in the La Poveda Experimental Farm in Arganda del Rey, Madrid, Spain (40.31°N, 3.49°W). Corn was planted on April 1 with 0.75-m row spacing and a population of 85,000 plants ha^{-1}. Corn had been grown continuously on this field during the previous 9 yr, using conventional tillage and sprinkler irrigation. Although the field received various herbicide treatments (PRE: *S*-metolachlor + mesotrione; POST: rimsulfuron) in previous years, no herbicides were applied during the study year in order to avoid interference with the potential spatial distribution of weed species. The field was heavily infested with a number of weeds: common cocklebur, johnsongrass, and velvetleaf.

Weed Assessment and Mapping. Weed assessments were conducted on digital images. Densities of the various weed species present in each image were determined visually in the laboratory using digital images previously acquired in the field with a D70 Nikon digital camera located at a 1.5-m height over the ground. Images were obtained on April 27 at the two- to four-leaf stage of corn, the optimal time for POST herbicide application. Weed growth stages at the sampling date for different species ranged from one to four true leaves. A total of 1,148 sampling points ("cells") were defined, each of which correspond to an image covering a 0.75-m by 0.5-m quadrat, with the longest side covering the interrow area and the shorter sides coinciding with respective rows of corn. Thereby, weed density data at each sample point were recorded in the entire image including the interrow and the area along the crop row. This sampling procedure covered the entire area of the plot. Geopositioned data of the quadrats was provided by a differential global positioning system receiver. Weed density data for each species and quadrat were plotted according to their geoposition in the field. These initial maps were then used as the basis for patch-spraying simulations using different spatial resolutions.

Simulations. A number of herbicide prescription maps were generated from these initial maps. Simulations consisted of on/off spraying decisions based on information from different types of sensors. We simulated two basic approaches: (1) ground-based sensors detecting weeds in interrow areas (continuous linear sampling) with several different sampling resolutions (distances between sensors); and (2) aerial sensors flying at various altitudes (continuous square sampling), also with several sampling resolutions (pixel sizes). For simulations based on ground sensors, the sprayer had a 10.5-m boom with 15 individual nozzles spraying 0.75-m strips. However, for simulations based on aerial sensors a 9-m sprayer boom was used with 13 individual nozzles spaced at 0.5 m. Although both sprayer sizes are not representative of the conventional sizes in Spain, these dimensions were used to fit (1) the individual cell size (0.75 m wide), (2) the various spraying resolutions (explained below), and (3) the width of the experimental plot (10.5 m).

For the ground-based sensors, the information captured from a sensor (a 0.75-m sampling strip) was extrapolated to spraying strips of different widths: (1) 1.5 m (50% of the field area sampled), (2) 5.25 m (14% of the field area sampled), and (3) 10.5 m (7% of the field area sampled).

For the aerial sensor, sampling areas were arranged in squares of different sizes simulating different pixel sizes. Three resolutions were assessed: (1) high (1.5 m by 1.5 m $pixel^{-1}$), (2) low (4.5 m by 4.5 m $pixel^{-1}$), and (3) very low (9.0 m by 9.0 m $pixel^{-1}$). In these three cases, the whole experimental plot area was sampled. Since all resolutions were multiples of the individual cell size (0.75 m by 0.5 m), their weed densities were calculated as the average of all the individual cells.

The decision to spray or not (open or close nozzles) was based on the information captured from the sensor and the weed threshold. Due to the considerable degree of uncertainty associated with the use of thresholds, rather than using a single decision threshold (DT), two values were used: 6 and 12 plants m^{-2}. Although these arbitrarily defined values were based on threshold values previously published (Cardina et al. 1995; McDonald and Riha 1999; Swanton et al. 1999; Werner et al. 2004), they were adapted to our specific experimental conditions at the site with some weed species occurring in high densities throughout the plot, and to the real potential of current detection technologies, which have limitations on detecting very low densities of weeds.

Data Analyses. Spraying errors were determined to assess the accuracy of the different herbicide prescription maps. To estimate spraying decision errors, a distinction between two types of errors was performed using a classification system similar to that proposed by Berge et al. (2008): type I, where cells with weed density below DT were sprayed; and type II, where cells with weed density above DT were not sprayed. Spraying errors were calculated independently for each weed species using the DT cited in the previous section. We also calculated total errors as the sum of both error types. Errors were quantified at per-cell level, comparing the initial map with the simulated maps by means of contingency tables. For the ground-based sensors, it was assumed that high resolution (i.e., each sensor controlling a nozzle) provided the most reliable spraying information and was therefore used as a benchmark against which to compare the other resolutions. In the case of the aerial sensors, we compared all resolutions with the information from each data cell in initial map.

Herbicide savings were calculated by comparing the number of treated cells in each simulation with the total number of cells (which would all be sprayed in conventional treatment).

Statistical analysis was performed with the package SPSS® 22.0 (IBM SPSS Statistics for Windows, Armonk, NY, USA).

Results and Discussion

Weed Infestation. Although the small size of the study area and the high weed densities present may have included a bias in the analysis, our experimental data can be considered as representative of the conditions prevailing in the Jarama River Valley corn-producing area. According to a study conducted in 16 commercial corn fields located in the same geographic area, weed infestations were quite similar to those of this study (San Martín et al. 2015). Weed species were grouped according to their biological propagation mechanism, differentiating between perennials propagated by underground organs (johnsongrass) and annuals propagated by seeds (common cocklebur and velvetleaf). The distribution of johnsongrass, with relatively low density, was patchy (Table 1; Figure 1). Velvetleaf, in contrast, which was very dense throughout nearly the entire plot, did not exhibit any clear aggregation pattern. Although numerous annual weed species have aggregated distribution patterns (Cardina et al. 1997; Heijting et al. 2007; Johnson et al. 1996), perennial species such as johnsongrass have been specifically noted for their patchy spatial distribution (Andújar et al. 2012).

Table 1. Mean density (seedling m^{-2}) and frequency (percentage of cells with a density above a detection threshold of 6 and 12 plants m^{-2}) of major weed species present in the experimental plot.

		Frequency of cells above:	
	Mean density ± SD	6 plants m^{-2}	12 plants m^{-2}
Annuals			
Common cocklebur	23.8 ± 18.1	81.4	64.8
Velvetleaf	35.0 ± 2	86.3	79.5
Perennial			
Johnsongrass	12.9 ± 15.7	52.4	31.6

Errors in Herbicide Prescription Maps. In general, an inverse relationship was observed between sampling resolution and errors in prescription maps. In other words, the lower the resolution (i.e., 10.5 m by 0.5 m for ground sensors or 9.0 m by 9.0 m for aerial sensors) the more errors were committed regardless of the detection system (ground or aerial) or weed species (Tables 2 and 3). This inverse relationship was evident in the case of johnsongrass, especially when simulations were done using aerial sensors. In this case, high pixel sizes (i.e., 9 m by 9 m) resulted in spraying zones larger than the actual patch size, thus increasing the errors in prescription maps. This increase was associated with a higher percentage of type I errors (i.e., spraying cells with densities below DT). These results coincide with those obtained by Berge et al. (2007, 2008). These authors also found that spraying errors increased as boom section increased.

Interestingly, a combined effect of these two factors (DT and sampling resolution) on errors in herbicide prescription maps was observed, irrespective of the detection system used in the simulations. Indeed, Tables 2 and 3 show a progressive increase in errors as DT rises and sampling resolution declines in both annual species, while in the case of the perennial species, errors increased when both DT and sampling resolution decreased. According

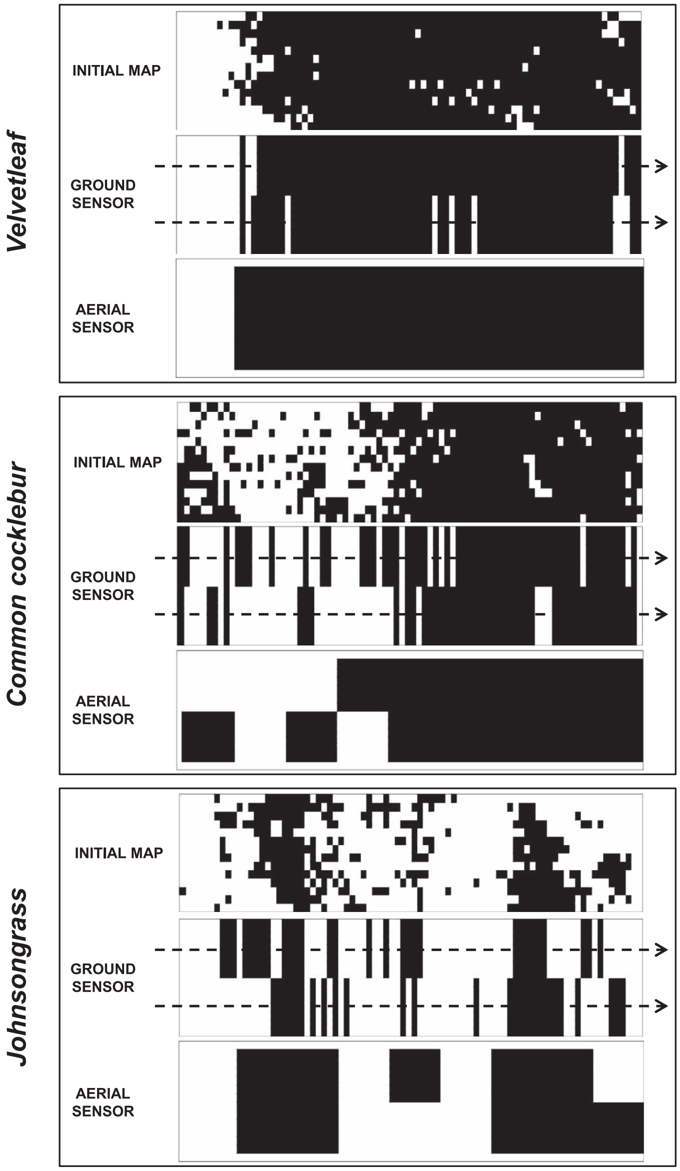

Figure 1. Detailed initial maps (0.75-m by 0.5-m sampling cells) and herbicide prescription maps using a ground-based approach simulating a 5.25-m by 0.50-m sampling resolution (i.e., two ground-based sensors detecting weeds along the corn interrow in the middle of 5.25-m sprayer boom sections [dashed lines]) and an aerial approach simulating a 4.5-m by 4.5-m sampling resolution and operating the nozzles with a detection threshhold of 12 plants m^{-2} for velvetleaf and common cocklebur (two annual species usually evenly distributed) and for johnsongrass (a perennial species generally distributed in patches).

to these results, it is apparently more appropriate to use higher DT values when weed distribution is clearly patchy (e.g., johnsongrass) than when weeds are more regularly distributed.

In general, in both scenarios (aerial and ground sampling) johnsongrass exhibited an increase in total errors with decreasing DT values (Tables 2 and 3). In contrast, velvetleaf exhibited a rise in total errors with increasing DT values. These findings were independent of the type of sensor or the sampling resolution used. In the case of common cocklebur the response was less consistent, with a slight reduction in total errors as DT increased. Typically type I errors (i.e., spraying cells with weed densities below DT) were more prevalent than their type II counterpart (i.e., not spraying cells with weed densities above DT). This was especially true in simulations based on aerial sensors (Tables 2 and 3).

Although previous studies had already pointed out that sampling resolution for weed detection is a key factor in patch spraying (Barroso et al. 2004; Berge et al. 2007, 2008), in this work we stress the importance of the DT applied. This parameter determines the accuracy of patch spraying (e.g., herbicide prescription map errors), which is in agreement with the results of Berge et al. (2007). Our simulations showed that the effect of DT depends on the distribution pattern of the weed species. Backes et al. (2005) pointed out that the effectiveness of patch spraying depends on the area occupied by a species (with densities above a given threshold). In weed species characterized by patchy distribution, higher DT values result in a more precise delimitation of weed patches and consequently in fewer decision errors. According to literature, this is because data are spatially correlated such that sampling points with high density are adjacent to sampling points where density is also high, and vice versa. Indeed, Backes et al. (2005) stated that in well-defined patches measuring over 15 m^2 there was a strong correlation between weeds found in the quadrats measured and weeds in the surrounding area.

In contrast, in more regularly distributed species (i.e., common cocklebur and velvetleaf), an increase in the DT value affects a relatively high proportion of cells, thus increasing the error rate in spraying decisions because the densities of adjacent cells may be different. Berge et al. (2007) also found fewer spraying errors in fields with clearly defined patches compared to those with randomly scattered “spray” and “no spray” cells.

Table 2. Simulations for ground-based sensors. Percentage of spraying decision errors for different decision thresholds (DTs) and different sampling resolutions (distances between sensors). Error type I: areas with weed density below DT were sprayed; error type II: areas with weed density above DT were not sprayed.[a]

	Sampling resolution								
	1.5 m by 0.5 m			5.25 m by 0.5 m			10.5 m by 0.5 m		
	Error type		Total	Error type		Total	Error type		Total
DT (plants m^{-2})	I	II	error	I	II	error	I	II	error
	—% —								
Annuals									
Common cocklebur									
6	7.1	2.9	10.0	9.2	10.7	19.9	14.0	6.4	20.4
12	7.8	3.7	11.5	9.4	15.0	24.4	16.3	7.8	24.1
Velvetleaf									
6	0.9	2.0	2.9	4.1	0.8	4.9	3.2	1.7	4.9
12	3.4	2.5	5.9	5.6	5.1	10.7	7.1	2.4	9.5
Perennial									
Johnsongrass									
6	10.9	4.4	15.3	14.5	11.9	26.4	23.5	11.2	34.7
12	8.8	3.0	11.8	13.0	10.4	23.4	16.0	9.8	25.8

[a] The standard map used to calculate spraying decision errors consisted of 1,148 cells covering the entire area of the plot, each cell corresponding to an image covering a 0.75-m by 0.5-m quadrat.

Herbicide Savings. The extent to which herbicide use is reduced was dictated by the degree of infestation and the spatial distribution of each weed species. The highest savings (41 to 66% with ground sensors and 0 to 62% with aerial sensors) were obtained for the most sparse and patchy weed (johnsongrass) and the least savings (10 to 41% with ground sensors and 0 to 30% with aerial

Table 3. Simulations for aerial sensors. Percentage of spraying decision errors for different decision thresholds (DTs) and different sampling resolutions (pixel size). Error type I: areas with weed density below DT were sprayed; error type II: areas with weed density above DT were not sprayed.[a]

	Sampling resolution								
	1.5 m by 1.5 m			4.5 m by 4.5 m			9.0 m by 9.0 m		
	Error type		Total	Error type		Total	Error type		Total
DT (plants m^{-2})	I	II	error	I	II	error	I	II	error
	—% —								
Annuals									
Common cocklebur									
6	12.6	1.5	14.1	19.1	—[b]	19.1	20.3	—	20.3
12	10.8	5.2	16.0	13.2	5.5	18.6	16.9	5.7	22.6
Velvetleaf									
6	2.6	1.1	3.6	2.3	1.5	3.8	7.8	—	7.8
12	6.1	0.8	6.9	8.0	0.5	8.5	14.6	—	14.6
Perennial									
Johnsongrass									
6	16.8	5.0	21.8	27.8	3.8	31.6	41.9	0.0	41.9
12	11.7	5.5	17.2	28.2	5.2	33.4	24.9	10.2	35.1

[a] The standard map used to calculate spraying decision errors consisted of 1,148 cells covering the entire area of the plot, each cell corresponding to an image covering a 0.75-m by 0.5-m quadrat.

[b] Dashes indicate no errors.

Table 4. Simulations for ground-based sensors. Herbicide savings (%) for different sampling resolutions (distance between sensors) and different decision thresholds (DTs).

	Sampling resolution		
DT (plants m^{-2})	1.5 m by 0.5 m	5.25 m by 0.5 m	10.5 m by 0.5 m
	%[a]		
Annuals			
Common cocklebur			
6	14.5	20.1	11.0
12	31.2	40.9	26.8
Velvetleaf			
6	14.8	10.4	12.2
12	19.7	20.1	15.9
Perennial			
Johnsongrass			
6	41.1	45.1	35.4
12	62.7	65.9	62.2

[a] Percentage was calculated by comparing the number of treated cells in each simulation with the total number of cells in the plot (i.e., a conventional treatment).

Table 5. Simulations for aerial sensors. Herbicide savings (%) for different sampling resolutions (pixel size) and different decision thresholds (DTs).

	Sampling resolution		
DT (plants m^{-2})	1.5 m by 1.5 m	4.5 m by 4.5 m	9.0 m by 9.0 m
	%[a]		
Annuals			
Common cocklebur			
6	7.4	0.0	0.0
12	29.6	27.8	25.0
Velvetleaf			
6	11.1	11.1	0.0
12	14.3	11.1	0.0
Perennial			
Johnsongrass			
6	35.4	22.2	0.0
12	61.9	44.4	50

[a] Percentage was calculated by comparing the number of treated cells in each simulation with the total number of cells in the plot (i.e., a conventional treatment).

sensors) were obtained for the two most abundant and widespread species (velvetleaf and common cocklebur) (Tables 4 and 5). Similarly Williams et al. (2000), in studies on two corn fields in Germany, reported higher herbicide savings for grass weeds present at relatively low densities and with patchy distribution than for more abundant and regularly established broadleaf weeds. Since the results are presented for each species separately, the question that arises is how this information can be used for a practical recommendation to the farmer. For example, in a context of European agriculture in which genetically modified crops are not allowed and therefore different grass and broadleaf herbicides can be applied, the same broadleaf herbicide could be used for both cocklebur and velvetleaf and as a result nearly the entire field would be sprayed; consequently site-specific weed management would not make sense. In contrast, the simulation results clearly show that under the conditions of this study, patch spraying is justified only in johnsongrass using specific grass herbicides.

No relationship was found between sampling resolution and herbicide savings in any of the simulations based on ground sensors (Table 4). In contrast, aerial sensor simulations showed clear reductions in herbicide use with finer sampling resolution (Table 5). A previous study (Berge et al. 2007) based on ground sampling reported no significant differences in herbicide savings as a function of sampling resolution.

Higher DTs resulted in a reduction in herbicide use regardless of weed species, sampling procedure, or resolution (Tables 4 and 5). The largest effect was observed with johnsongrass and common cocklebur. In the case of johnsongrass, increasing DT from 6 to 12 plants m^{-2} resulted in additional herbicide savings ranging from 22 to 50% (depending on the sampling resolution used) in the simulations for aerial sensors and 21 to 27% savings in the simulations using ground-based sensors. In the case of common cocklebur, doubling the DT resulted in additional herbicide savings of between 22 and 28% in the aerial simulations and between 16 and 21% in ground-based simulations.

In general, simulations based on ground sensors resulted in higher herbicide savings than their aerial counterparts. This came as no surprise. While ground sensor resolution ranged from 0.75 m^2 (1.5 m by 0.5 m) to 5.25 m^2 (10.5 m by 0.5 m), resolution from aerial sensors ranged from 2.3 m^2 (1.5 m by 1.5 m) to 81 m^2 (9 m by 9 m). Consequently, simulations from aerial sensors were less accurate than those obtained from ground-based ones. Lamb et al. (1999) and Martín et al. (2011) already reported on the difficulties of detecting low weed densities using aerial sensors.

Implications for Weed Management. Site-specific patch spraying may result in significant savings in herbicides. In order to maximize these savings with minimum risks to crop yields (current or future), it is required to improve the accuracy of herbicide application. One major step toward this goal is to optimize the use of DTs. Our simulation results confirmed the expected fact that increasing the DTs results in parallel reductions in the proportion of area to be treated with herbicides and, consequently, in higher herbicide savings. However, in order to define the optimum DT, it is necessary to take into account that using higher DTs and reducing the sprayed area may have undesirable consequences on current crop yields and on future weed infestations. Simard et al. (2009) have shown that using relatively high weed thresholds and a coarse spraying resolution resulted in a replenishment of the seed bank that would increase weed infestations during the subsequent years, which would be extremely troublesome for herbicide-resistant weeds. In general, growers have a relatively low tolerance toward weeds for practical reasons such as crop competition, harvesting problems, and seed bank replenishment or less practical reasons such as field appearance (Czapar et al. 1997). This is the main reason why growers are reluctant to assume the risks of using large DTs and skipping spraying large field sections. Unraveling the complex trade-offs between herbicide savings, risks of yield losses, and increasing weed infestations have various biological and technological elements.

Biological features of weeds such as fecundity, competitiveness, population growth rate, seedbank life, and tendency to evolve resistance primarily determine the threshold level (Bagavathiannan and Norsworthy 2012). For weed species characterized by a prolific seed production, high competitiveness with the crop, and rapid dispersal, and wherein further herbicide resistance has evolved, then a zero-tolerance threshold should be considered as the most appropriate. This was the case described by Norsworthy et al. (2014) for the herbicide-resistant species Palmer amaranth (*Amaranthus palmeri* S.Wats.) growing in a glyphosate-resistant cotton crop. Under such conditions, these authors conclude that the threshold for this species is zero, since a single escape is too risky. In contrast, the DT approach could certainly be useful for some weed species, especially those that are naturalized and tend to exhibit an aggregated or patchy distribution, which is generally most stable over time for perennial species (e.g., johnsongrass; Andújar et al. 2012), and for those displaying localized seed dispersal prior to crop harvest (e.g., velvetleaf; Dieleman and Mortensen 1999).

Conversely, current weed detection technologies (both ground and airborne) are not able to accurately estimate very low weed densities at early growth stages (Peteinatos et al. 2014). This fact precludes the use of low DTs. Moreover, and in spite of the huge amount of research on this area, estimation of yield losses based on early assessments of weed abundance is still unreliable (Wilkerson et al. 2002). In addition, there are conflicting reports on the consequences of using patch spraying on weed population dynamics (Ritter 2008; Simard et al. 2009). All these facts, coupled to the effects of the variable spatial structure of weed infestations in different fields and the additional management costs associated to patch spraying, represent the major hurdles to overcome in the development of this technology (Wiles 2009).

According to the approaches simulated in this study, the amount of herbicide savings using site-specific weed management depends on the density and the spatial distribution of each weed species. In patchily distributed species such as johnsongrass, which requires a specific herbicide, the savings would be high. The potential reduction of herbicide also depends on DT, with the highest DT values involving the greatest herbicide savings regardless of weed species, type of sensor, or spatial resolution used in sampling. Nevertheless, it is not advisable to increase DT above a certain value since this parameter determines the accuracy of patch spraying and thus could result in errors; for example leaving areas unsprayed (i.e., type II errors), which could lead to weed problems in the current crop growth cycle and in subsequent years. Moreover, the relationship between DT and accuracy of herbicide application depends on weed spatial pattern: in weed species with regular distribution an increase of DT value involves increasing spraying errors, while in weed species with patchy distribution an increase of DT value results in a decrease in spraying errors. Therefore, this work has demonstrated the possibility of using higher DT values in weeds clearly distributed in patches with respect to those weeds showing more regular distribution.

Acknowledgments

This research was funded by the Spanish Ministry of Economy and Competitiveness (MINECO) under Project AGL2014-52465-C4-1-R.

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Received March 18, 2016, and approved August 4, 2016.

Associate Editor for this paper: Andrew Kniss, University of Wyoming.