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Development of an Image Processing System and a Fuzzy Algorithm for Site-Specific Herbicide Applications

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Abstract. In precision farming, image analysis techniques can aid farmers in the site-specific application of herbicides, and thus lower the risk of soil and water pollution by reducing the amount of chemicals applied. Using weed maps built with image analysis techniques, farmers can learn about the weed distribution within the crop. In this study, a digital camera was used to take a series of grid-based images covering the soil between rows of corn in a field in southwestern Quebec in May of 1999. Weed coverage was determined from each image using a "greenness method" in which the red, green, and blue intensities of each pixel were compared. Weed coverage and weed patchiness were estimated based on the percent of greenness area in the images. This information was used to create a weed map. Using weed coverage and weed patchiness as inputs, a fuzzy logic model was developed for use in determining site-specific herbicide application rates. A herbicide application map was then created for further evaluation of herbicide application strategy. Simulations indicated that significant amounts of herbicide could be saved using this approach.

Keywords: image processing, fuzzy logic, precision farming, herbicide application, weed map

Introduction

In conventional weed management, herbicides are applied uniformly to a field in significant amounts. The over application of agrochemicals, which can damage crops, has become one of the main sources of non-point source pollution (Mannion, 1995). The extra agrochemicals remain in the soil, leach into the ground water and drain into surface water bodies (Smith Jr. et al., 1995). Consequently, it is becoming increasingly important to protect the environment from this pollution, by reducing the application of herbicides.

Since weed density and weed distribution often vary significantly from site to site within an agricultural field, herbicide application can be reduced by considering this inherent variability in weediness (Cardina et al., 1997; Lindquist et al., 1999; Medlin and Shaw, 2000; Zanin et al., 1998).

In contrast with conventional agricultural practices, precision farming involves the collection of site-specific information (such as weed density, weed distribution, soil characteristics, soil fertility, and crop yields) from numerous locations in a field; a site-specific management plan is then formulated based on this information (Ascheman, 1993; Blackmore, 1994; Tyler, 1993). Precision farming is a practice in which many technologies are integrated in order to solve site-specific problems (Blackmore, 1994). The technologies that are chosen for use vary depending on the demands of individual farms.

For weed control and management, the quantities of herbicide applied can be reduced by using a site-specific application approach (Blackmore, 1994; Vangessel et al., 1995; Zanin et al., 1998). In some parts of a field, herbicide may not be required at all, or a lower application rate may be sufficient for weed management (Zanin et al., 1998; Medlin and Shaw, 2000). By taking the variability in weediness into account, less herbicide can be applied by spraying only where it is necessary. However, reduced application rates may contribute to the development of herbicide resistance in weeds, and therefore require careful consideration. The system for herbicide application recommendation, based on domestic weed distribution should be developed before the site-specific herbicide application is carried out (Medlin and Shaw, 2000). Although some computer models have been developed for weed control recommendation, the decision should be generated from in-field weed detection (Shaw et al., 1998).

To guide site-specific herbicide application, a machine vision and image processing system, based on digital camera technology, can be used to detect the presence and variability of weeds in the field (Blackmer and Schepers, 1996; Franz et al., 1991; Hemming and Rath, 2001). Machine vision technology that can be used to detect weeds and distinguish them from crop plants is currently under development (Andreasen et al., 1997; Meyer et al., 1998; Perez et al., 2000; Stafford and Benlloch, 1997; Tian et al., 1999). This allows for the precise, site-specific application of suitable chemicals, instead of their general application to the entire field. The cost of these technologies is, however, relatively high.

Fuzzy logic can help in the site-specific application of herbicides based on outputs from an image processing system, either in the real time or by the image-based weed maps. First introduced in 1965, fuzzy logic has been applied to a wide range of commercial, engineering, and scientific applications (Heske and Heske, 1996; Yen et al., 1995; Zadeh, 1965). Fuzzy logic differs from conventional logic in that it allows the representation of full or partial true values, and also tolerates imprecise data (Kasabov, 1996; MathWorks, 1998a). Fuzzy values for input and output are continuous functions $\{0, 1\}$. A set of fuzzy rules represents the statements used in fuzzy logic in an "if-then" format, such as "if the weed coverage is high and the weed patchiness is thick, then the herbicide application is large." Membership functions represent the degree, or possibility, of truthfulness of a statement. After applying all of the fuzzy rules to obtain the corresponding degrees, finally, defuzzification produces a single crisp output from these degrees for the whole system.

Based loosely on natural language, a fuzzy logic system is simple to understand and facilitates the representation and processing of human knowledge in a computer. The inputs, outputs, and rules of fuzzy logic are easy to modify. These features of fuzzy logic make it particularly well-suited for use in control systems and non-linear modelling. For example, fuzzy logic has been used in agriculture to control hydraulic motors (Ambuel et al., 1993); in the vacuum control system of a milking machine (Tan and Chang, 1994); in decision support systems in the dairy milk industry (Lacroix et al., 1998); and for the analysis of uncertainty in the design of drainage systems (Perret and Prasher, 1998). Fuzzy logic has been applied to site-specific herbicide application management in this study.

The main objectives of this study were to develop a simple and effective image-processing system and fuzzy logic based herbicide application maps for use in the site-specific application of herbicides. In this system, digital images taken in the field were analysed to determine weed distribution. A fuzzy logic algorithm used the information generated from a weed coverage map, and a weed patchiness map to adjust herbicide application rates accordingly. The localized amount of herbicide application was thus determined according to site-specific weed distribution. This system was verified by the simulation of site-specific herbicide application in a corn field. Using the herbicide application map generated from this study, the herbicide application strategy could be evaluated and improved in future work.

Materials and methods

The digital images used for this study were taken in an experimental corn (*Zea mays*, L) field (field #22) on the Macdonald Campus Farm of McGill University, in Ste-Anne-de-Bellevue, in southwestern Québec. The area of the field was 11.7 ha. The most common weeds found in this field were *Abutilon theophrasti* (velvetleaf), *Agropyron repens* (quack grass), *Ambrosia artemisiifolia* (common ragweed), *Chenopodium album* (lamb's-quarters), *Cyperus esculentus* (yellow nut sedge), *Equisetum arvense* (field horsetail), *Plantago major* (broad-leaved plantain), and *Taraxacum officinale* (dandelion). Other species of weeds that occurred frequently, included *Amaranthus retroflexus* (redroot pigweed), *Asclepias syriaca* (common milkweed), *Echinochloa crusgalli* (barnyard grass), *Malva neglecta* (common mallow), and *Polygonum convolvulus* (wild buckwheat). This weedy field was selected to test the capability of the image processing method for weed detection, and to evaluate the assumption that, with the fuzzy logic algorithm, the herbicide application can be reduced even in such a weedy field. Conventional tillage was used in this field.

In 1999, images were taken on May 17, 18, 20, 21, and 22, the dates between pre-emergence and post-emergence herbicide applications. At this time, the corn plants were in the two- to five-leaf stage. The images were taken under various natural lighting conditions, from bright, noon-day sun to dull, cloudy conditions at dawn. Ten rows from the east side of the field were chosen and the images were taken of the area between the crop rows (row spacing 0.75 m), thus excluding the corn plants themselves. This was done because it was observed that the presence of weeds in a given area between two rows usually indicated the presence of weeds in the rows. By collecting images between rows, it was possible to estimate the distribution of weeds in the field, both between and within corn rows. Such an approach eliminates the need to distinguish corn plants from weeds while determining the presence of weeds from an image, and therefore decreases the computational time and effort that are required (Donald, 2000; Lussier, 1999).

A Kodak DC260 zoom camera (Eastman Kodak, Rochester, NY) was used to capture the digital images. The camera was equipped with a $3\times$ zoom lens (focal length 38–115 mm). The focus range was from 0.3 m to infinity. The aperture range was from f/3.0 to f/14.0, and the shutter speed ranges from 1/4 to 1/400 s. The area covered by each image was 0.7 m^2 ($= 0.7$ m $\times$ 1 m), and the resolution of an image was 512×768 pixels. Empirically, the actual ground-size of the pixel, 1.78 mm^2/pixel, was sufficient to show any green objects in the field, and so this approach was deemed to be suitable for the purposes of this study. The camera had 8 MB and 16 MB of external storage cards, which could store up to 56 and 121 field images in this quality mode. During image collection, the camera was mounted on a tripod at a height of 1.15 m, perpendicular to the ground. There were 242 images taken between each adjacent pair of the 10 rows, and so an area of 1694 m^2 ($= 0.7 \times 242 \times 10$) was imaged.

The image processing was carried out on a PC with a Pentium II microprocessor, 4 GB of hard disk space, 128 MB of RAM, and the Windows 98 operating system. The image files were downloaded onto the computer in JPEG format, and ranged from 66 KB to 170 KB in size, depending on the color complexity of the images. The images were then pre-processed with the Image Processing Toolbox v2.1 for MATLAB v5.2.1 (MathWorks, 1998b, c) to convert them to numerical matrices. In MATLAB, JPEG files are read directly using the red-green-blue (RGB) color system. In this system, each pixel of an image is associated with three values, ranging from 0 to 255, that define the red, green, and blue color intensities. The combination of these three primary colors makes up the actual color for each pixel. Therefore, each image of 512×768 pixels is represented in MATLAB by a $512 \times 768 \times 3$ matrix. The resolution of an image was thus 1.78 mm^2/pixel. Empirically, this resolution is fine enough to clearly show most of the weeds and corn even when these plants are tiny and young. The appropriate image resolution for weed recognition and herbicide application determination may vary according to local weed situations. The pixel size should be adjusted to be smaller than the size of the plants during the image collection.

Since the images were taken between rows so as to exclude corn plants, it was assumed that any green pixels in the images would represent weeds. Therefore, the greenness method was applied to distinguish green objects in the image. In this method, the intensities of the three base colors (red, green, and blue) were compared with each other on a pixel-by-pixel basis. When the intensity of green was greater than both red and blue, the pixel was considered to represent part of a plant. The ratio of pixels in each image that were green was calculated as the greenness ratio, which was then considered to indicate the weed coverage for the area included in the image. In this study, the built-in algorithm for "loop vectorization" in the MATLAB matrix programming language was used to significantly reduce computational effort and processing time. This is a method in MATLAB to speed up program executions by converting programming loops with equivalent vector or matrix operations.

It was found that, for some images, even in the absence of any weeds, the intensity of green for some shadows was higher than the intensity of each of the other two colors, resulting in false weed coverage values. Since the color intensity of shadows was usually very low, a threshold for the intensity of green was used to alleviate this problem. A pixel was not considered to be green if the intensity of green was less than the threshold, regardless of whether the relative intensity of green was higher than each of the other two colors. However, it was difficult to determine an appropriate value for this threshold. If the threshold is set too low, many shadows may be falsely classified as being covered by weeds. If the threshold is set too high, weeds in shadow may be neglected. Different thresholds were tested on a trial-and-error basis with numerous images that were taken in both good lighting conditions and where parts of the images were in shadow. Preliminary studies indicated that an optimum threshold value could be set at 40, where the intensity ranges from 0 to 255. With an intensity threshold of 40, weeds in shadow were not neglected, while most other pixels in shadow were not classified as green. This threshold did not affect the results for images in which there was little shadow. Figure 1 shows sample images and the areas that were classified as being green using a threshold value of 40. The no-weed areas in the extracted greenness images were identified by white color.

After calculating the greenness ratio for each of the images, a composite weed coverage map was created. The weed coverage for location (x, y), covering an area of 0.7 m^2, was taken to be equal to the greenness ratio of the image taken at that location. To determine the site-specific herbicide application rate for each location in the field, the weed coverage at the location and the weed patchiness around the location should be determined (Cardina et al., 1997; Vangessel et al., 1995; Zanin et al., 1998). The weed

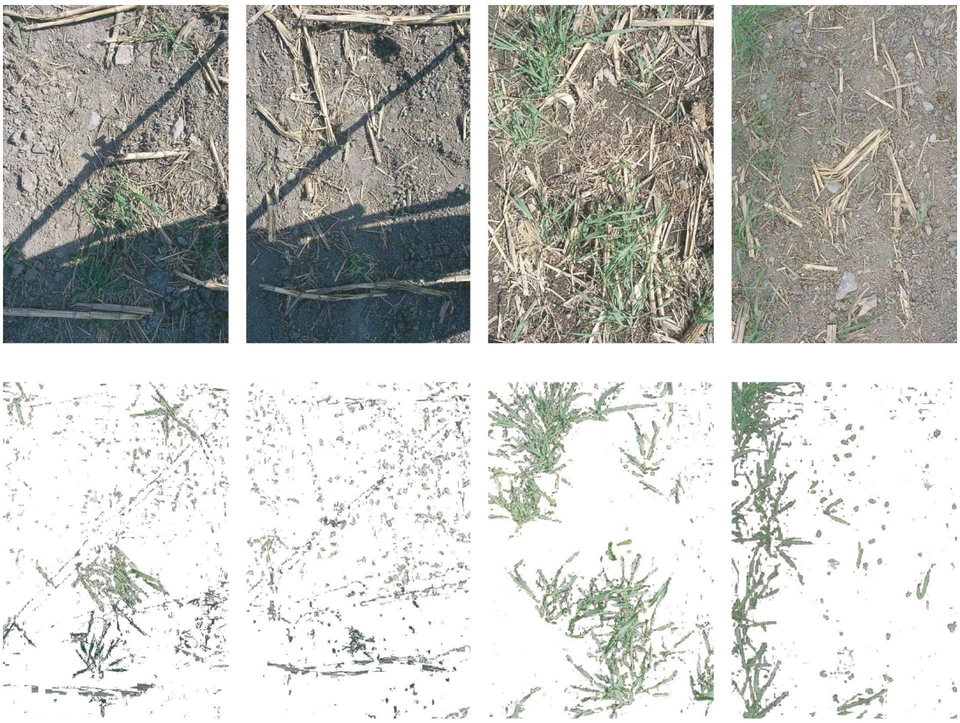


Figure 1. Some sample images and extracted greenness images (greenness threshold of 40).

patchiness for location (x, y) was represented by the average greenness ratio of nine images covering 6.3 m^2: the one at (x, y), and its eight nearest neighbors. To calculate the weed patchiness at locations at the boundary of the experimental area, the weed coverage for the nearest neighbor locations outside the boundary was set to the highest value (100%), since no herbicide would be applied outside the boundary and empirically the weed coverage would have been very high. The weed patchiness map, thus created, represented the weed distribution in the experimental area.

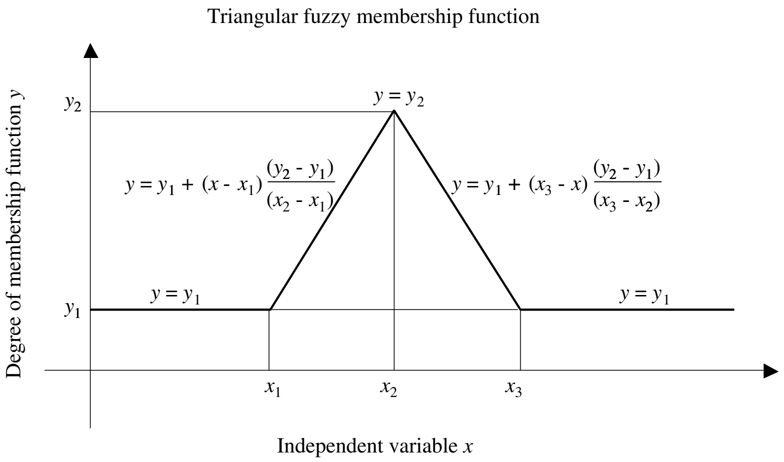
The images were taken on a grid basis. No image was taken between locations (x, y) and $(x+1, y)$, or between locations (x, y) and $(x, y+1)$. Thus, the effort for image storage and management was significantly reduced. Also, it was easier to create a weed map in real time without the need to identify and remove the overlapping images. However, for grid-based image collection, it is necessary to precisely determine the location for taking an image to eliminate overlap and missing space between two adjacent images.

Both weed coverage and weed patchiness values were then used as inputs to a fuzzy logic algorithm, which calculated the herbicide application rate for each location (Vangessel et al., 1995; Zanin et al., 1998). The output ranged from 0.0 (representing no application) to 1.0 (representing the full application). When weed coverage and weed patchiness were each higher than a pre-set threshold, the full application rate would be used. Otherwise, the application would be less than the full rate. After the simulation for the site-specific herbicide application, the difference between the site-specific herbicide application and the full application was calculated to determine the simulated savings that were achieved. Furthermore, a herbicide application map could be created. This map illustrates a herbicide application amount for each location (x, y).

The Fuzzy Logic Toolbox v2.0 for MATLAB was used to develop the fuzzy logic algorithm (MathWorks, 1998a, c). The triangular and the trapezoidal membership functions were applied to transfer an input (x) into the corresponding degree of membership function for an output (y). These two types of fuzzy membership functions were selected because they are simpler than other types of membership functions to build, and are considered to be sufficient for most applications (Heske and Heske, 1996). Figure 2 shows the definitions for these membership functions. The main difference between these two functions was that, for the triangular function, $y = y_2$ when $x = x_2$, but for the trapezoidal function, $y = y_2$ when x was between x_2 and x_4.

Three fuzzy membership functions were defined for each input and output: low, normal, and high functions for weed coverage (w_c); thin, average, and thick functions for weed patchiness (w_p); and small, medium, and large functions for herbicide application (a_h). The names of the fuzzy membership functions were arbitrarily selected to identify these functions. When the input value was determined from image processing, the corresponding degrees of three membership functions for this input were obtained. The fuzzy rules, constructed as shown in Table 1, were used to combine the fuzzy degree (d_c) for weed coverage and the fuzzy degree (d_p) for weed patchiness. From each rule, the minimum method was selected to determine the fuzzy degree (d_a) for herbicide application. The centroid method was used for defuzzification which combines the outputs of the fuzzy degrees (d_a) from all of the rules to determine the amount of herbicide application (a_h) (Heske and Heske, 1996; Kasabov, 1996; MathWorks, 1998a).

Initially, triangular membership functions were used to represent normal and low coverage, as well as average and thin patchiness inputs, because of their simplicity. However,



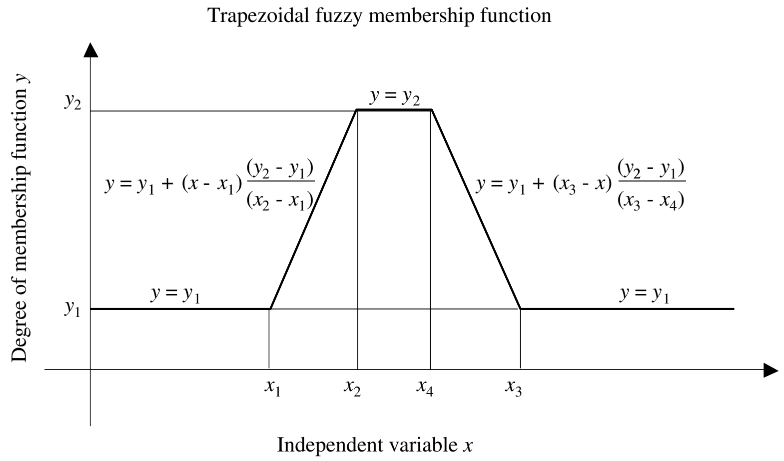


Figure 2. Typical triangular and trapezoidal fuzzy membership functions.

the functions for high coverage and thick patchiness were always trapezoidal to ensure the highest output when the input value was greater than the aforementioned threshold values. As shown in Figure 3, when the greenness ratio was higher than the threshold, the coverage and patchiness inputs were always evaluated as high or thick with a value

Table 1. The fuzzy rules used for herbicide application control

		Weed coverage		
Herbicide application		High	Normal	Low
	Thick	Large[1]	Large	Medium
Weed patchiness	Average	Large	Medium	Small
	Thin	Medium	Small	Small

[1]The rule: (if weed coverage is high) and (if weed patchiness is thick) then (herbicide application is large).

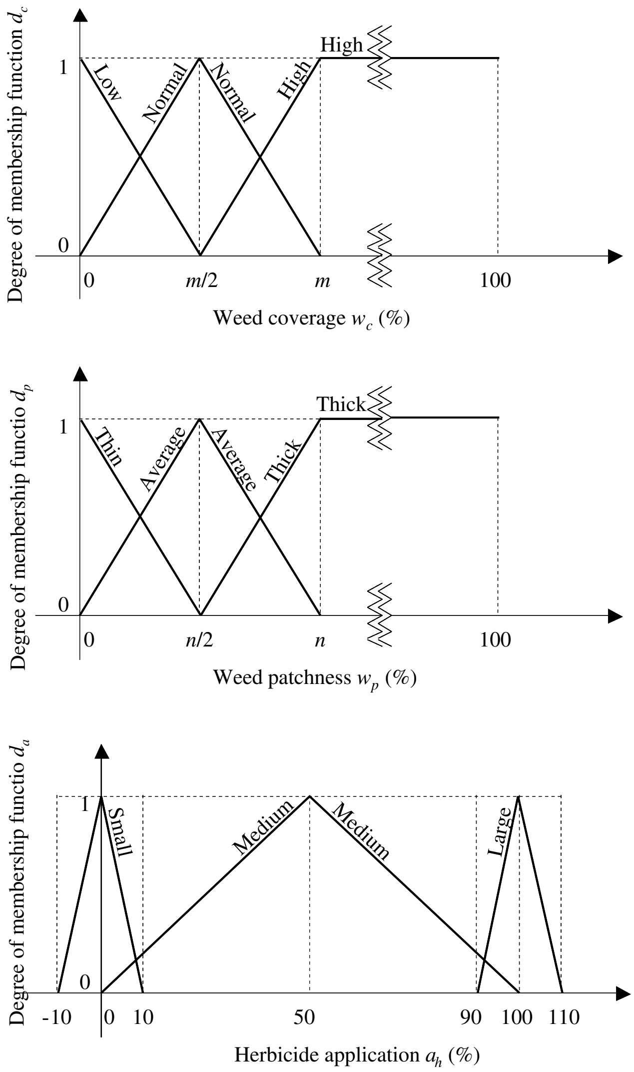


Figure 3. Triangular fuzzy logic herbicide application model.

of 1.0 (the highest value). The coverage and patchiness threshold values (m and n) were used to define the peaks of the triangular functions: $(m/2)$ for normal coverage, 0.0 for low coverage, $(n/2)$ for the average patchiness, and 0.0 for the thin patchiness. The degree of the membership functions (d_c) for low, normal and high coverage and the degree of the membership functions (d_p) for the thin, average and thick patchiness are also shown in Figure 3.

In addition, Figure 3 shows the definitions of the triangular membership functions for the output, i.e., the rate of herbicide application (a_h). Three triangular output membership functions were built for small, medium, and large application amounts. The range for the actual application amount is from 0 to 100%. In Figure 3, to ensure that the final value for the lowest application rate would be 0%, the negative value for the left bottom of the small application amount function was considered in the calculation only when all of the inputs were the lowest values. Also, the value greater than 100% for the right bottom of the large application amount function was considered in the calculation only when all of the inputs were the highest values to ensure that the final output value for the highest application rate would be 100%.

To further investigate the fuzzy logic model, a set of trapezoidal membership functions were applied. As shown in Figure 4, besides the thresholds (m) for the weed coverage

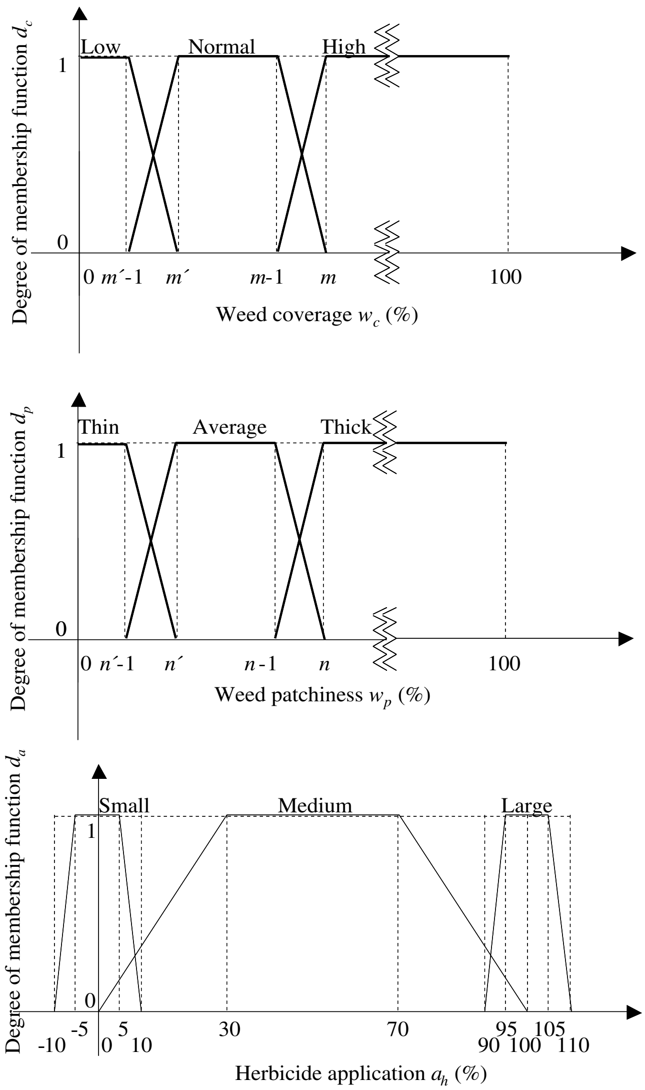


Figure 4. Trapezoidal fuzzy logic herbicide application model.

(w_c) and (n) for the weed patchiness (w_p), additional parameters were required to define the trapezoidal functions. These parameters were ($m-1$) and (m′) for the normal coverage function, (m′ − 1) and 0.0 for the low coverage function, ($n-1$) and (n′) for the average patchiness function, as well as (n′ − 1) and 0.0 for the thin patchiness function. In this study, the thresholds (m) and (n) were set at 5% only, and two cases were investigated for (m') and (n'). In one case, the values of (m') and (n') were set at 2%. In another case, the values of (m') and (n') were set at 1%. Both cases were compared with the outputs obtained using the triangular membership functions when both thresholds were set at 5%. Figure 4 also illustrates the settings of the parameters to define the trapezoidal membership function for the output value, i.e., the herbicide application rate (a_h).

It should be noted that the weed coverage and weed patchiness thresholds are difficult to determine for a given site without experimentation (Hartzler, 1997). The threshold values are dependent on factors such as local climate and management practices (Lindquist et al., 1999; Scholes et al., 1995; Stoller et al., 1979). Even if threshold values have been previously determined and published, they can be applied only to certain weed species (Lindquist et al., 1999; Scholes et al., 1995). Moreover, such published values are generally based on the number of weed plants per unit area, and therefore, are not directly applicable to the algorithms developed here since weed coverage in this study was described as the area covered by the plant canopy. The threshold values (m) for the weed coverage (w_c) and (n) for the weed patchiness (w_p) were set arbitrarily at 1%, 2%, 3%, 4%, and 5%, and the simulation was repeated using these different values to investigate the functions of the fuzzy logic algorithm. The values were used for simulation purposes only. When the application is carried out in a real field, threshold values should be varied depending on the local weed population and distribution.

Results and discussion

In Table 2, the results show that the weed coverage was very high in the experimental field. Fifty-nine percent of the area where the digital images were collected was covered at the highest rate (>5%). Only 9% of the area was covered at the lowest rate ($\leq$1%). Figure 5 shows the resulting weed coverage map, the weed patchiness map, and the simulated herbicide application map when the thresholds of both inputs were set at 5% using the triangular membership function.

Table 2. Weed coverage classification in field #22 of the Macdonald Campus Experimental Farm

Weed coverage (w) level	Number of images	% of the area
w > 5%	1433	59
5% ≥ w > 4%	166	7
4% ≥ w > 3%	193	8
3% ≥ w > 2%	199	8
2% ≥ w > 1%	207	9
1% ≥ w	222	9
Total	2420	100

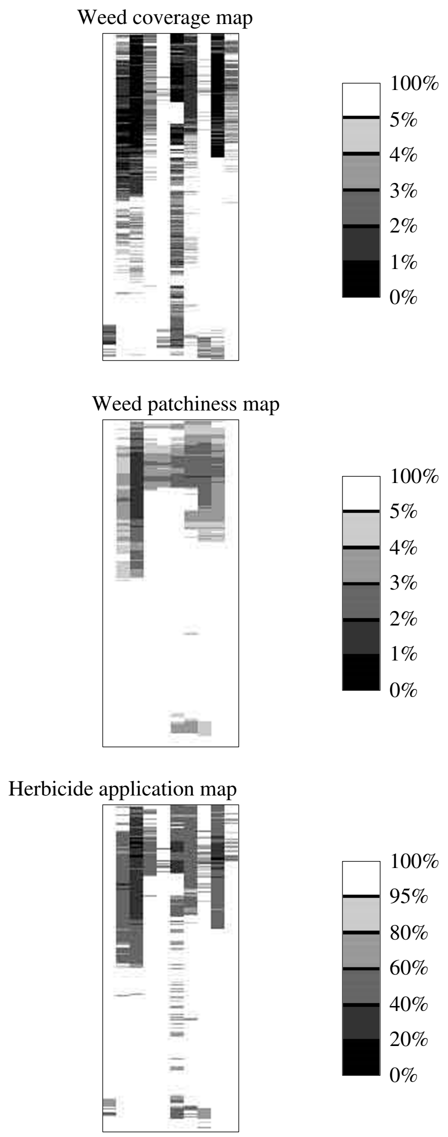


Figure 5. Weed map and a simulated herbicide application map in the field #22 (5% for input thresholds under the triangular fuzzy membership functions).

The results in Tables 3 and 4 show that the weed coverage map seems to have had a more significant effect on the determination of the herbicide application rate than did the weed patchiness map. The herbicide application rate varied more significantly with changes in the weed coverage threshold than with changes in the weed patchiness threshold. As shown in Table 3, the herbicide savings always increased when the weed coverage threshold was increased and the weed patchiness threshold was kept constant.

Table 3. Saving on herbicide usage (%) in field #22 by the triangular membership function set

		Weed coverage threshold				
		1%	2%	3%	4%	5%
Weed patchiness threshold	1%	1.65	3.54	5.48	7.11	8.76
	2%	1.93	3.69	5.61	7.24	8.89
	3%	2.64	4.74	6.40	7.94	9.69
	4%	3.49	6.10	7.77	9.26	11.04
	5%	4.37	7.56	9.36	10.28	12.54

Although the herbicide savings also increased when the weed patchiness threshold was increased and the weed coverage threshold was kept constant, these latter increases were not as large.

Table 4 shows that the shape of the output membership functions may not have as significant an effect on the herbicide application rate as does the shape of the input membership functions. The optimum shape of the membership function can be judged only when these functions are used in a real application, and the results for herbicide savings and weed elimination are compared. Trial-and-error is the only reliable method to determine the optimum shape of the membership functions. The processing time for the two shapes of membership functions are very similar. If the outputs do not vary significantly with the shape of membership functions, the triangular membership shape would be the optimum choice because it is the easiest to build and modify.

When the weed species found in a field do not pose a significant threat to the crop, the threshold value for weed coverage can be set as high as 5%. In such cases, the simulations indicate that the herbicide sprayer could apply approximately 11% to 16% less herbicide, than the full herbicide application (Table 4). Even when dealing with highly competitive weed species, for which the thresholds of both weed coverage and weed patchiness were set as low as 1%, conventional (full) application might have resulted in over application of about 2%. Such savings may not be significant in terms of cost, but the results indicate that, even in a field with very high weed density, like field #22 (Figure 5), it is possible to save herbicide and reduce the possibility of pollution and waste.

From the simulation, illustrated by the herbicide application map in Figure 5, it can be seen that herbicide may not need to be fully applied in many locations even in a very weedy field. Because the field is known to have a very high weed density, locations where

Table 4. Saving on herbicide usage (%) for different shapes of fuzzy membership functions

		Input function set		
	Shape	Triangular	Trapezoidal[1]	Trapezoidal[2]
Output function set	Triangular	12.54	10.68	15.44
	Trapezoidal	12.46	10.67	15.46

[1]: The values of (m') and (n') were 2%.
[2]: The values of (m') and (n') were 1%.

herbicide should be applied at a lower rate occur less frequently than in other fields. This indicates that, in general, large amounts of herbicide may be unnecessarily applied to fields, possibly resulting in pollution. Therefore, a site-specific herbicide application system may have potential benefits from both environmental and economic standpoints.

In future work, the herbicide application map could be compared to soil, yield, and weed maps for more efficient applications and reductions of herbicide. Based on such a comparison, site-specific herbicide application strategy can also be verified and improved. Furthermore, the image recognition system should be developed to differentiate different weed species from each other, and from the crop. Such an image recognition algorithm could further increase the efficiency of herbicide application strategy by applying different herbicides to certain weed species.

Conclusions

The algorithms developed for precision farming in this study integrate image processing and fuzzy logic for weed coverage determination and site-specific herbicide application. The proposed system can easily obtain the weed coverage for each location in a field by determining the greenness ratio in each image, and determine the weed patchiness using the weed coverage values for neighboring locations. Using the maps that are generated of weed population and distribution, the fuzzy logic algorithm could be used to assist in the localized application of herbicides. These maps could also be generated before herbicide application, during the planting season, and after the harvest season to characterize the temporal weed variations. The thresholds for weed coverage and weed patchiness should be determined by the real weed distribution in the field, and would therefore, vary from field to field. The map of herbicide application should be investigated for a more efficient site-specific herbicide application strategy.

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