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Could Weed Sensing in Corn Interrows Result in Efficient Weed Control?

Louis Longchamps, Bernard Panneton, Marie-Josée Simard, and Gilles D. Leroux*

At the field scale, weeds generally appear aggregated rather than randomly distributed, and this aggregation is linked to the spatial heterogeneity of biotic and abiotic factors. Crop management practices shape the spatial pattern of weed infestations by modifying certain factors having an impact on weed emergence and growth. Although crop seeding is often the last in-field disturbance before crop and weed emergence, its effect on the distribution of weeds has received little attention in the literature. The purpose of this study was to assess the influence of the planting operation on weed cover and presence in corn fields using digital images to investigate the possibility of sensing the interrow to infer the presence or absence of weeds on the corn row. A total of 18 site-years under conventional tillage treated with a single POST application of herbicide were selected across seven locations. Image analysis, at the V2 to V4 growth stage of corn, was used to compare the weed cover in three zones: the undisturbed interrows, the corn rows, and the interrows compacted by tractor wheel traffic. For 61% of site-years, there was no significant difference among the zones. When there was a significant difference compared with the other two zones, the undisturbed interrow was usually less infested. Point-to-point comparisons of weed presence or absence (based on a threshold of five pixels) between the interrow and the corn row revealed 70 or 73% correspondence, depending on the type of interrow (undisturbed or tracked). However the error of inference of the corn row weed cover generated by sensing only adjacent interrows may be too high for efficient commercial weed control.
Nomenclature: Corn, *Zea mays* L.
Key words: Imagery, tractor tracks, site-specific weed management, weed cover, wheel compaction, weed sensing.

A una escala de campo, las malezas generalmente aparecen distribuidas en forma agregada y no aleatoriamente, y este agregado está relacionado a la heterogeneidad espacial de los factores bióticos y abióticos. Las prácticas de manejo del cultivo dan forma a los patrones espaciales de las infestaciones de malezas, al modificar ciertos factores que impactan la emergencia y crecimiento de malezas. Aunque la siembra del cultivo es a menudo la última perturbación dentro del campo antes de que se de la emergencia del cultivo y de las malezas, su efecto sobre la distribución de las malezas ha recibido poca atención en la literatura. El objetivo de este estudio fue evaluar la influencia de la operación de siembra sobre la presencia y cobertura de malezas dentro de campos de maíz usando imágenes digitales para investigar la posibilidad de inferir la presencia o ausencia de malezas sobre la hilera de siembra, a partir de datos de los espacios entre-hileras del maíz. Un total de 18 sitios-años bajo labranza convencional tratados con una sola aplicación de herbicida fueron seleccionados a lo largo de siete localidades. Se usó análisis de imágenes, en los estados de crecimiento del maíz de V2 a V4, para comparar la cobertura de malezas en tres zonas: entre-hileras sin perturbación, en la hilera del maíz, y entre-hileras compactadas por el tráfico de las llantas del tractor Para el 61% de los sitios-años, no hubo diferencias significativas entre zonas. Cuando hubo una diferencia significativa en comparación con las otras dos zonas, las entre-hileras sin perturbación estuvieron usualmente menos infestadas. Comparaciones de punto-a-punto de la presencia o ausencia de malezas (con base en un umbral de cinco pixeles) entre la hilera del maíz y entre-hileras revelaron 70 ó 73% de correspondencia, dependiendo del tipo de entre-hilera (sin perturbación o con compactación por las llantas). Sin embargo, el error de la inferencia de la cobertura de malezas en la hilera del maíz, generada solamente con los datos de las entre-hileras adyacentes puede ser muy alto para un control de malezas eficiente a nivel comercial.

The spatial distribution of weeds in crop fields is often aggregated rather than random or regular (Woolcock and Cousens 2000). In this context, spraying whole fields uniformly leads to the overuse of herbicides because areas with no or few weeds are still sprayed (Dent et al. 1989). Performing weed control only where necessary (spot treatment) would be a more optimal solution. To achieve spot spraying in real time, many studies are underway to develop sensors capable of discriminating weeds from crop plants, using different strategies; notably, machine vision (Wang et al. 2007), visible spectrum analysis (Mao et al. 2008), reflectance (Paap et al. 2008), or fluorescence (Longchamps et al. 2010). The diversity of weed phenotypes, shapes, colors, and textures, but also their taxonomic proximity with some crops, makes real-time discrimination unprofitable because of signal processing time or classification inaccuracy. As suggested in certain studies, the difficulties with weed–crop discrimination could possibly be avoided by scouting only the interrow (where there are no crop plants) and extrapolating the level of weed infestation to surrounding areas, including the crop rows (Andújar et al. 2011; Biller 1998; Sui et al. 2008; Tian 2002). Vegetation sensors that discriminate the soil from green plants, such as the WeedSeeker® (NTech Industries, Ukiah, CA), already exist on a commercial basis. However, this approach could only work if the weed infestation level in the row can be inferred from that of neighboring interrows. Multiple factors could potentially modify the distribution of

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* First and fourth authors: Graduate Student and Professor, Department de Phytologie, Université Laval, Québec, Canada; second author: Researcher, Agriculture and Agri-Food Canada, Horticulture Research and Development Centre, Saint-Jean-sur-Richelieu, Canada; third author: Researcher, Agriculture and Agri-Food Canada, Soils and Crops Research and Development Center, Québec, Canada. Corresponding author's E-mail: louis.longchamps@gmail.com

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weed cover between corn rows and interrows when weed control is required. These include the disturbance generated by the seeding unit, the presence of corn plants in the row, starter fertilizer added in band, and compaction by tractor wheels in interrows.

When a conventionally tilled corn crop is planted, the soil is disturbed by the different components of the seeding row unit. The coulter (Figure 1a) digs a trench in the soil that exposes buried seeds to light and oxygen and releases gases trapped in the soil. Exposure to light is an important trigger of weed germination (Buhler 1997; Hartmann et al. 2003), oxygen promotes seed respiration (Roberts and Smith 1977), and exposure to the surface boosts the aerobic metabolism of seeds by lowering or eliminating the volatile anaerobic metabolites (acetaldehyde, acetone, and ethanol) that inhibit seed germination (Holm 1972). During the same planting operation, the covering disks (Figure 1b), the gauge wheel (Figure 1c), or the press wheel (Figure 1d) will compact the soil. Soil compaction by wheels can also affect seed germination. Increasing the density of soil particles lowers soil water evaporation by reducing porosity, thus increasing soil moisture content in the microenvironment of the seed (Brown et al. 1996). In addition, water transport to the seed is enhanced where there is a good seed–soil contact due to the capillarity water located between soil aggregates and seed embryos (Benech-Arnold and Sanchez 2004). Compacted soil above and around the seed will also dry out more slowly than loose soil (Thompson et al. 1995). On the other hand, if the soil is over-compacted, germination and emergence will be hindered due to lack of oxygen and mechanical constraints (Dexter 1988).

Starter fertilizers are often added in band near the seeds, modifying the soil chemical properties. Usually, this fertilizer contains mostly phosphorus (P) and nitrogen (N), and may contain other macro-, secondary, and micro-elements (Jensen 2007). The chemical environment of the seed can also modify germination. However, inorganic ions do not alter seed germination, with the exception of nitrate (NO_3^-) ions and ammonium nitrate [$NH_4(NO_3^-)$] ions (Egley and Duke 1985; Karssen and Hilhorst 1992). The growth of weed seedlings, however, can be enhanced by the addition of fertilizer (Blackshaw et al. 2004).

The presence of corn plants in the rows can generate competition and modify surrounding light quality. Competition for water, nutrients, and light will be minimal if weed control is done at the right stage (Hall et al. 1992). Light quality has an effect on the germination of certain seeds through the influence of the red to far-red ratio (R : FR) on seed phytochrome (Casal and Sánchez 1998). A lower R : FR ratio (under corn plants) could reduce weed germination (Sattin et al. 1994). Twelve-centimeter-tall corn plants may influence seed germination up to 37 cm from the plant (Morgan et al. 1981; Sattin et al. 1994). Since average interrows are 75 cm wide, most of the light reaching the ground area would be influenced by the corn plants from the V3 to V4 growth stage of corn. However, it is possible that as they grow, corn plants modify the light environment in the rows before they affect the center of the interrows, and this may potentially result in higher weed cover in the interrow than in the row.

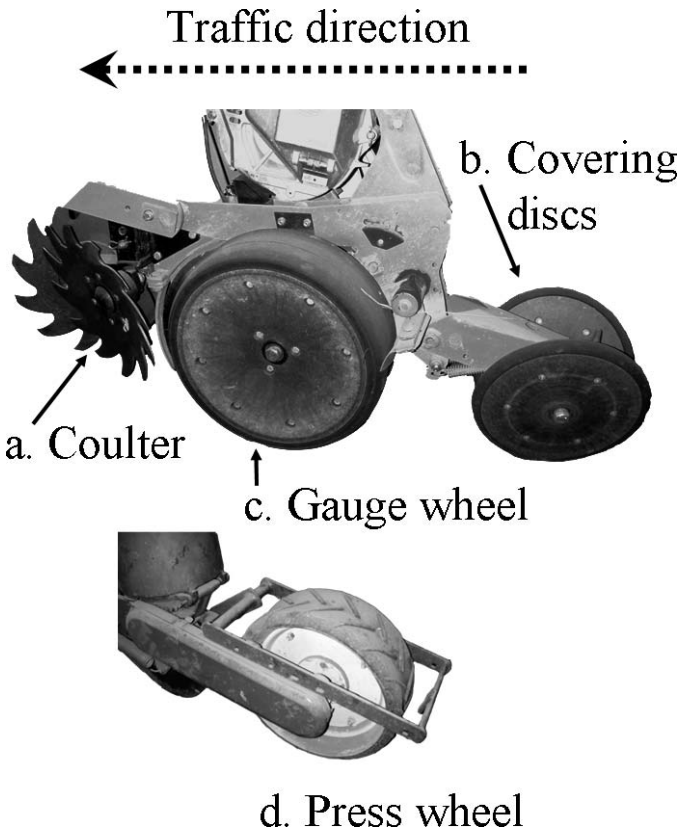


Figure 1. Components of a row unit on a seeder.

Under normal conditions, there is no disturbance induced by the seeding process between crop rows except in some interrows (according to the number of row units on the seeders), where the soil is compacted and potentially over-compacted (leading to asphyxia and mechanical constraint) by the tractor and planter wheels. As already mentioned, soil compaction can promote or hinder plant establishment and growth. Indeed, with double-wheel tractors and seeding done in good conditions (when the soil is sufficiently dry), soil compaction might be adequate to promote germination, at least in some areas of the tracks (i.e., wheel edges) as soil–tire interface pressure varies across lug pattern (Jurik and Zhang 1999; Way and Kishimoto 2004). Compaction effects on weed emergence and growth will also depend on soil texture (Benvenuti 2003; Leblanc et al. 1998).

The overall goal of this study was to investigate the possibility of sensing the interrow to infer the presence or absence of weeds in the corn row. To date, few studies have investigated differences in weed infestation between rows and interrows. Infestations can be evaluated using weed density, leaf cover (leaf area), or biomass data. As pointed out in Simard et al. (2009), leaf cover measurement using imagery is representative of the leaf area index and outperforms crop–weed competitiveness models based on weed density. Therefore, weed pressure was based on the projected green area covered by weeds on digital images. Our specific

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objectives were (1) to assess the weed cover variability that exists among three different zones, the undisturbed interrow (UIR), the corn row (CR), and the interrow compacted by tractor and/or planter wheels (WIR), and (2) to measure the error associated with the inference of the infestation of the crop rows by sensing interrows.

Materials and Methods

Fourteen corn fields located in seven different farms across the corn production area of the province of Québec (Canada) were selected. Selected fields had to be in conventional tillage, treated with a single postemergence application of herbicide, not cultivated (no mechanical weed control), and planted in corn with 75-cm interrow spacing. A 1-ha plot was delineated in each field. One of the 14 fields was sampled during 3 yr (2004, 2005, and 2007) as part of another study (Simard et al. 2009), seven fields were sampled in 2008 only, four fields were sampled in 2009 only, and two fields were sampled in both 2008 and 2009, for a total of 18 site-years spread in time and space. All fields were planted in corn at a density of about 60,000 plants ha^{-1}. The corn growth stage at the time of data collection was V2 to V4 (two to four leaves fully expanded).

Ground Imaging. All 18 site-years were exhaustively photographed using a camera mounted on a capturing/carrying custom mobile platform (see Panneton and Brouillard 2009). About 1,100 pictures were taken in each site-year. The self-propelled platform consisted of a pyramid-shaped aluminum chassis covered with opaque shading material and equipped with two high-power flashlights combined to a custom reflector to ensure uniform illumination and minimum shadow for all pictures. An operator steered the unit and monitored its speed. The camera was linked to a distance sensor located on one wheel so that it took a picture every 3 m. The device was built to hold the camera at its apex (about 2.5 m above the ground), covering an area of 3 m by 2 m with each picture (four rows of corn at 75-cm spacing). The camera was pointing straight down. A Nikon D100 (Nikon, Melville, New York, USA) RGB digital camera was used. Around 6 million pixels (3,034 × 2,024) covered the 3 m by 2 m area giving a resolution of approximately 1 pixel mm^{-2} (Figure 2). The JPEG format files were stored on a 4 GB heavy-duty CF (CompactFlash) memory card and were transferred to a hard drive in the laboratory. Ten percent of the images were systematically selected (1 of every 10 images) for each site-year, giving about 110 images per plot. The images were selected to uniformly cover the whole plot area.

The pictures were processed using a color image segmentation algorithm to discriminate vegetation from soil. Physics-based reflection modeling was used to segment pixel clusters in the three-dimensional red, green, and blue color space according to the method developed by Onyango and Marchant (2001). This method transforms green pixels into white and other pixels (i.e., soil, crop residues, or white tarp) into black. The resulting images are black and white (Figure 2). More information about the imaging hardware and segmentation software was reported in Panneton and Brouillard (2009).

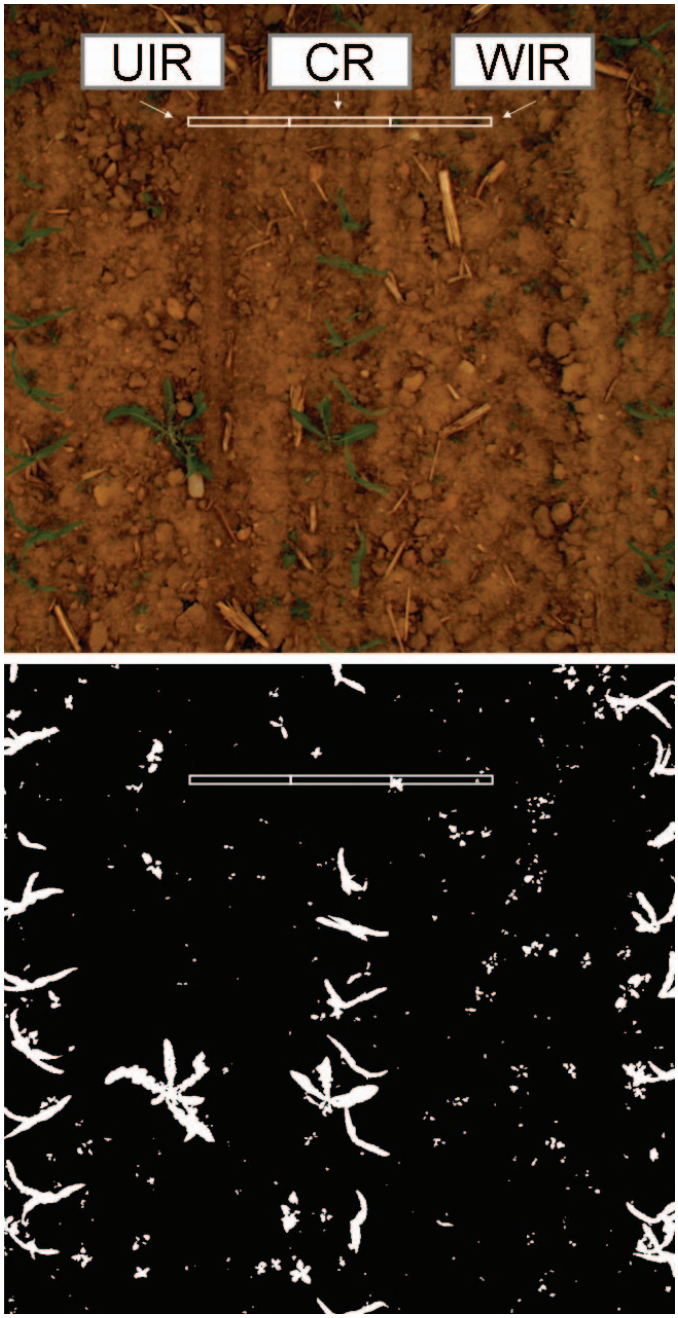


Figure 2. Example of a ground picture section. The upper section shows the original digital image, while the bottom section shows the black and white image resulting from the segmentation of the same image. Tractor wheels are printed on the ground in the wheel-compacted interrow (WIR). In white is an example of sampling strip (23 pixels high by 750 pixels wide) divided in three equal parts to cover the undisturbed interrow (UIR), the corn row (CR), and the WIR. The proportion of the strip in comparison to the picture is dimensionally exact.

Data Extraction from Digital Images. In order to compare the weed cover of the three zones, data were extracted from the black and white images using a custom built Matlab (2007, Mathworks, Natick, MA) program. Horizontal strips (23 pixels high by 750 pixels wide), centered exactly on a CR bordered by a UIR on one side and WIR on the other side,

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were randomly located (Figure 2). An operator selected the largest space between two corn plants on the same row by pointing an upper limit (x_1, y_1) and a lower limit (x_2, y_2) of the band on the image. The horizontal position of the center of the band was the average between x_1 and x_2. This was done in order to outline a zone without any corn pixels that would cover all three zones (UIR, CR, and WIR). The height of the selected area varied from 23 to 112 pixels. From each of these bands, a 23 pixels by 750 pixels strip was randomly located (vertically) within the selected area. Each strip was divided into three 5,750 pixel (23 × 250) sections, each covering the CR, the UIR, or the WIR. White pixel sums where computed in each section. The data used for the analysis consisted of pixel counts for each section (3) of each strip (1,984 strips in total).

Comparing the Three Zones. Although one site was sampled during 3 yr and two sites were sampled during 2 yr, the pictures were not taken at the exact same locations and therefore could not be considered as repeated measures in time. Consequently, the analysis was done over what was considered to be 18 site-years. Because of the large number of zeros in the dataset, data were skewed towards zero and the normality assumption was not satisfied according to Kolmogorov-Smirnov's test ($\alpha = 0.05$), despite log and logit data transformation (Hollander and Wolfe 1973). Nonparametric statistics were thus used for the analysis. It was assumed that spatial autocorrelation prevailed in weed distribution and for this reason, the three strip sections were considered as three related samples of the same "individual." Therefore, Friedman's nonparametric test was performed across the 18 site-years (pooled together) to compare the weed cover among each zones (UIR, CR, and WIR) (Hollander and Wolfe 1973). To further investigate the differences among the three zones, a pairwise comparison (Wilcoxon signed ranks test) was also computed. To limit the Type I error, the level of significance of statistical tests was adjusted for three comparisons (0.05/3) and was set to 0.0167. The same analyses were run for each site-year separately. The statistical analyses were run with SPSS for Windows (Rel. 16.0.2, 2008, SPSS Inc., Chicago, IL).

Inferring One Zone Using Data from Other Zones. In order to extract information about the correlation of the weed infestation among zones, integer data (pixel count per strip) were transformed into binary data indicating presence or absence of weeds, using a threshold value. This threshold was based on the average area (in pixels) of the smallest weeds that could be seen by an operator in a random sample of 50 images. For example, if the threshold was set to five pixels and there were more than five white pixels out of 5,750 in a single strip section, this section was considered as infested. Otherwise, the strip section was considered as not infested. This way, it was possible to quantify how often weeds were present or absent from a zone. The aggregation of the pixels was not taken into account when applying the threshold. The choice of a threshold value was determinant on the interpretation of the results, and this method was considered objective because it was not based on the correspondence among the zones, but rather on an operator's capacity to detect weeds.

Using the binary (presence/absence) data, a 2 × 2 contingency table was built. The contingency table consists of four cells: the first (top left) accounting for all cases where weeds were absent in the row and on the interrow simultaneously, the second (top right) accounting for all cases where weeds were present in the row but not on the interrow, the third (bottom left) accounting for all cases where weeds were absent in the row but present on the interrow, and the fourth (bottom right) accounting for all cases where weeds were present in the row and on the interrow simultaneously. Two contingency tables were built this way; the first comparing WIR to CR and the second comparing UIR to CR. The significance of the association between the weed presence or absence in different zones was tested using Pearson's phi-coefficient (Bonett and Price 2007). A Sign test was used to verify if the interrow (WIR or UIR) over- or underestimated the presence of weeds on the corn row (Dixon and Mood 1946).

Two other analyses were also undertaken to measure the variability of the correspondence between the zones across different infestation levels. The first analysis consisted of separating the pixel count data into five classes, one class being the zeros and four classes being pixel counts separated into quartiles. A 5 × 5 contingency table was created. The function "mosaic" from the R package "vcd" (Meyer et al. 2002) was used to create a mosaic plot of the contingency table and to measure the magnitude of standardized Pearson's chi-square residuals indicating the departure from independence of each cell of the mosaic plot (Agresti 2002; Zeileis et al. 2007). The second analysis consisted of using the binary data previously described (i.e., presence or absence) and grouping them into deciles. The deciles were measured over the average pixel count for each of the 1,984 strips (i.e., sets of three adjacent zones). In order to avoid having several deciles at zero, the strips for which the average was zero were excluded to calculate the deciles. As a result, the first decile included over 10% of the data set. Ten 2 × 2 contingency tables were then created and the overall accuracy (i.e., sum of the top-left to bottom-right diagonal divided by the total number of pairs) of each decile was calculated.

Results and Discussion

Differences between Interrows and Rows. According to Friedman's test, when all site-years were pooled together, there was a significant difference among the three zones. Wilcoxon's test for contrasts indicated a significantly lower weed cover in the UIR compared to the CR and the WIR, while there was no significant difference between CR and WIR. However, when looking at each site-year independently, in 61% of the site-years assessed in this study, there was no significant difference in weed cover among the different zones. Among the 39% site-years for which a significantly different weed cover was detected, 72% showed a lower weed cover in the UIR than either the CR or the WIR, or both zones. More specifically, Friedman's test detected a significant difference among the zones for seven site-years (Site1_04, Site1_05,

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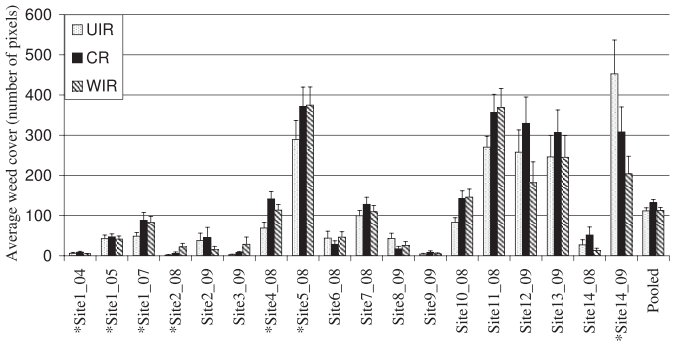


Figure 3. Bar plot of the mean of pixel counts in undisturbed interrow (UIR), corn row (CR), and wheel-compacted interrow (WIR) across the 18 site-years and all site-years pooled together (Pooled). The last two digits after the site number correspond to the year (04 for 2004, 05 for 2005, 07 for 2007, 08 for 2008, and 09 for 2009). Error bars represent standard error. *Significant difference among the zones ($\alpha = 0.05$).

Site1_07, Site2_08, Site4_08, Site5_08, and Site14_09; Figure 3) out of 18. From these seven site-years, one (Site14_09; Figure 3) had a higher weed cover in the UIR and one (Site2_08; Figure 3) had a higher weed cover in the WIR compared to both the CR and the UIR. The remaining five site-years (Site1_04, Site1_05, Site1_07, Site4_08 and Site5_08) had either a significantly lower weed cover in the UIR than in the CR or significantly lower weed cover in the UIR than both WIR and CR. For these five site-years, WIR and CR were not significantly different. Among the site-years for which there was a significant difference among the zones (39% of all sites-years), 43% showed a higher frequency of weed presence in the WIR than in the UIR and 29% showed a higher frequency of weed presence in the CR than in the UIR. Jurik and Zhang (1999) have also observed a higher level of infestation in the wheel-compacted interrows, but only for certain weed species such as giant foxtail (*Setaria faberi* Herrm.) and yellow foxtail [*Setaria pumila* (Poir.) Roem. and Schult.]. Accordingly, the composition of the weed population may influence the discrepancy of weed cover existing across the zones.

Threshold Used to Convert Weed Cover into Weed Presence or Absence. The smallest weed detected by human eye had 5 pixels, corresponding to about 5 mm^2. In comparison, average pixel counts by strip section ranged from 2 (UIR of Site2_08) to 452 pixels (UIR of Site14_09), corresponding to 0.03 and 7.86% weed cover respectively. It was considered that between 1 and 5 pixels, the green particles detected could be due to noise in the segmentation or to partitioning of weed polygons by the strip delineation. Pixel counts above the threshold defined the presence of weeds within the strip zone.

The five pixel threshold corresponds to a weed cover of 0.09%. This threshold was considered conservative based on the observations of Lemieux et al. (2003) who reported that a relative weed cover (weed cover divided by the sum of both crop and weed covers) of 0.2 or less would have no impact on the yield of the current year. Since the corn was about 200 mm long by 20 mm wide (about 4,000 mm^2), the threshold would have to be increased by a factor of 160 (800 pixels) to reach 0.2 in relative weed cover in the images. However, Lemieux et al. (2003) determined their threshold from images of 2 m by 3 m (6 million pixels) while the sampling strips covered 5,750 pixels. Because the sampling strips were relatively small, it was considered that one weed detected was enough to consider the strip section as infested, even though on an area proportion basis it seemed relatively low.

Using Interrow Information to Infer Weeds in the Row. Based on our previous analyses, when weed cover in CR was not similar to that in interrows, it was more similar to WIR than UIR. This was an incentive to choose WIR over UIR for the inference of the presence of weeds on the corn row. Before choosing WIR over UIR, it was important to verify if the same trend would be observed when analyzing presence–absence data. In general, there was a significant positive and relatively high correlation between CR and both UIR and WIR (Table 1). Accordingly, the percentage of inference error with CR was lower than the mutual association for both UIR and WIR zones. The sign test demonstrated that the overestimation was not significantly different from the underestimation for WIR, meaning that inference error was evenly distributed between over- and underestimation (Table 1). In the case of UIR, there were more chances to underestimate CR weed presence. From the CR infested with weeds, 70.4% had a neighboring WIR also infested with weeds and 29.6% had a neighboring WIR not infested with weeds. This implies that infested CR had about 2.38 times higher odds to have an infested WIR neighbor than a weed-free one. In comparison, UIR had about 1.66 times higher

Table 1. Results of the correspondence analysis between the corn row (CR) and the wheel-compacted interrow (WIR) and the correspondence analysis between the CR and the undisturbed interrow (UIR).

	Phi[a]	P value	IE[b]	Sign test direction[c]	Sign test (P value)	CR 1 Zone 0	CR 1 Zone 1	Odds[d]
			%			%	%	
WIR	0.461	< 0.001	26.6	NS	1	29.6	70.4	2.38
UIR	0.397	< 0.001	29.7	CR > UIR	0.001	37.6	62.4	1.66

[a] Pearson's phi statistic.

[b] Abbreviation: IE = inference error; i.e., the percentage of all cases in which both zones had different values (presence in the CR and absence in the WIR and vice versa).

[c] Direction accompanies the result of the sign test. In this case, NS means not significant ($P < 0.05$) and CR > UIR means that there was a significant difference ($P > 0.05$); i.e., more cases where weeds were present in the CR and absent in the UIR.

[d] Odds were calculated by dividing the percentage of cases where weeds were present in the neighboring zone (Zone 1) by the percentage of cases where weeds were absent in the neighboring zone (Zone 0), when weeds were present in the CR zone (CR 1).

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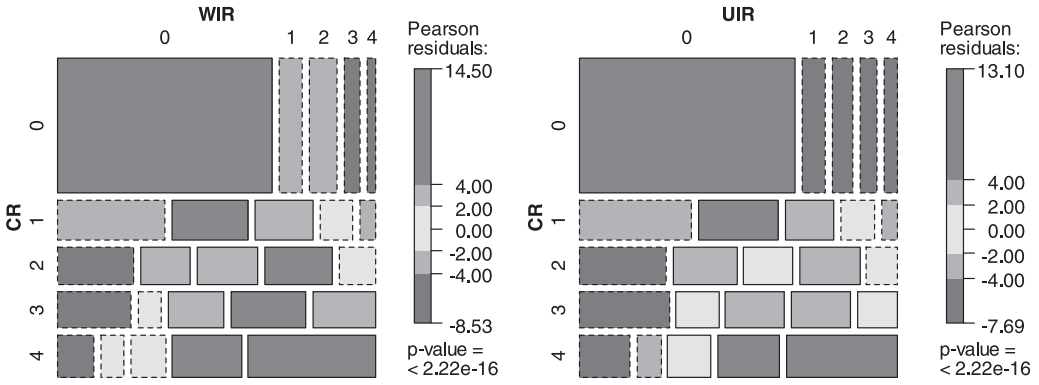


Figure 4. Mosaic plot of a 5 × 5 contingency table between corn row (CR) and wheel-compacted interrow (WIR) quartile counts (left) and between CR and undisturbed interrow (UIR) quartile counts (right) of weed cover based on pixel count. Dark and light shades of gray indicate significant departure from independence at $\alpha = 0.0001$ and $\alpha = 0.05$ levels, respectively. Solid and dashed boxes indicate higher and lower than expected from random association, respectively. The width of the cells is proportional to within class count, while cell height is proportional to the sum of count in the CR classes. Classes 0 to 4 represent zeros and subsequent quartiles. The P value indicates the significance level of the overall correspondence between classes of CR and the interrow (WIR or CR).

odds to have an infested WIR neighbor than a weed-free one. All these results strengthen the idea that WIR has a better potential than UIR for inferring weed presence in the CR. However, it also confirms that there is always a risk of underestimation error if sensing the interrow to infer weed presence in the row.

Accuracy of Inference across Weed Cover Levels. A mosaic plot was used to measure the correspondence between the zones (CR and WIR or UIR) across infestation levels (Figure 4). Correspondence was significantly positive for both mosaic plots (low P values) and more important for the lowest (zero) and highest strata (no. 4) than the intermediate ones (Figure 4). Correspondence was also generally higher when CR was compared to WIR (four solid cells are dark gray and one is pale gray along the diagonal, which indicates higher occurrence than expected for a random association) then to UIR (three solid dark gray cells, one pale gray, and one nonsignificant white cell along the same diagonal). This indicates that WIR was a better indicator of CR infestation levels than UIR. The second analysis also showed that the overall accuracy of inference is higher at lower and higher deciles than at intermediate deciles and that WIR performed better as an indicator of CR than UIR (Figure 5).

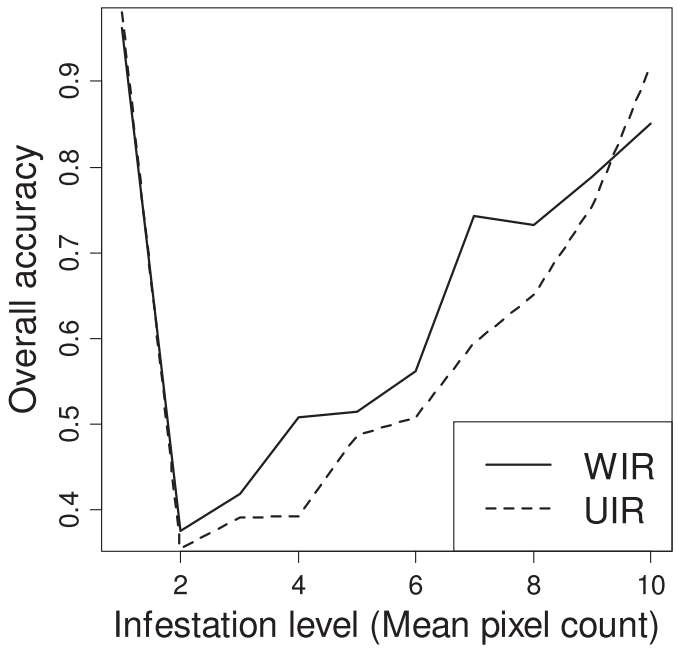


Figure 5. Relationship between weed cover level (in average pixel count) per strip and the overall accuracy of the inference between the corn row (CR) and either the wheel-compacted interrow (WIR) or the undisturbed interrow (UIR).

Better correspondence at low and high weed cover can potentially be explained by the spatial structure of weeds in a field. High weed densities are often observed in patches, which could explain the high correspondence of the high weed covers. Moreover, at the time of herbicide application in corn, weed cover in a field is generally low but spread into many small patches. Therefore, at small scale the odds of seeing no weeds are high, which could explain the high correspondence between zeros.

The results of this study are in line with the idea that weed emergence does not always occur randomly in crop fields (Hughes 1996). In certain site-years, the infestation in compacted zones was higher than in the undisturbed zones, and this was consistent with the observations of Jurik and Zhang (1999) in which the weed emergence (seedling removed after each count) of three species out of four was higher in tractor wheel–compacted zones than in undisturbed zones in mid-June. They did not report differences in emergence between the zones later in the season. This suggests that compaction can trigger top soil seeds to germinate earlier by setting optimal germination conditions (e.g., increasing seed–soil contact). This phenomenon may impact yield as earlier emerging weeds are more competitive with the crop (Knezevic et al. 1994).

This study demonstrated that seeding operations can increase weed infestation, not only in the interrows by compaction from tractor wheels, but also on CR by disturbance from the seeding implements themselves. We attribute this trend to soil compaction increasing conditions

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favorable for seed germination and establishment (Boyd and Van Acker 2004; Voorhees and Hendrick 1977).

If the infestation level is low and weeds are sufficiently aggregated in a field, weed detection followed by localized weed control would reduce weeding costs. Weed–crop discrimination is a significant hurdle to real-time weed detection (Aitkenhead et al. 2003; Berge et al. 2008) while soil–plant discrimination is simple and makes weed detection and spraying possible with currently available technology (e.g., WeedSeeker®). According to general belief, the spatial range of weed patches is larger than the width of the interrow and thus, weed sensing can be done in the interrow and extrapolated to the row (Andújar et al. 2011; Biller 1998; Sui et al. 2008; Tian 2002). Our results demonstrated that weed cover in the interrows is generally equivalent to weed cover in the corn row. Despite the fact that the range of the spatial autocorrelation of most weed species is indeed larger than the width of the interrows (75 cm), other factors may significantly affect weed spatial autocorrelation within that range (Jurado-Expósito et al. 2003; Wiles and Brodahl 2004). Our results indicate that in more than one quarter of the site-years sampled, weed infestation was more important on the corn row than in the undisturbed interrows. For these site-years, sensing the undisturbed interrow to infer the presence of weeds in the row would most likely result in underestimation of weed presence in the row. Moreover, even if there was no significant difference in weed cover between the wheel-compacted interrow and the corn row, there was an inference error of 26.6% (Table 1). The use of optical sensors in the interrows to infer the presence of weeds in the corn rows is thus considered unsafe to achieve adequate weed control on the corn rows.

In conclusion, weed cover was generally similar among zones, and when it was not similar, weed cover was higher in the corn row and in the compacted interrow than in the undisturbed interrow. Therefore, in certain circumstances, wheel-compacted interrows would be more reliable than undisturbed interrows to detect and spot spray weeds in corn fields under conventional tillage. However, point-to-point comparisons of weed presence revealed 26.6% inference error between wheel-compacted interrows and corn rows. Such inference error could be detrimental to efficient weed control due to weed escapes growing in corn rows.

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