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Determining the number of measurements required to estimate crop residue cover by different methods

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Abstract: Crop residue left after harvest plays an important role in controlling against soil erosion and in increasing soil organic matter content of agricultural soils. Crop residue management is a practice of great importance in southwestern Ontario, where soil management practices have an effect on Great Lakes water quality. The use of remote sensing data to measure and monitor crop residue can be fast and efficient. However, remote sensing–based studies need calibration and validation using field observations. The objective of this study was to determine the optimal number of ground-truthing field measurements (i.e., digital photographs) required to estimate residue levels. To do so, we compared the residue estimates derived from digital photographs with those derived from the standard line-transect method. Residue was measured from 18 fields located in southern Ontario, and data collected included percentage of crop residue using line-transect and photographic grid methods. Results were analyzed using linear regression, correlation tests, ANOVA, and means tests. Analyses were also conducted to retrospectively determine the minimum number of line transects or digital photos required to estimate crop residue cover at specified levels of power. Results showed that (1) percentage of crop residue estimates derived from using digital photographs were strongly correlated ($r = 0.91$, $p < 0.001$, $R^2 = 0.83$, and $n = 90$) to those derived from using line transects; (2) counting 50 to 100 points per digital photograph was sufficient to accurately estimate the percentage of residue cover; and (3) there was greater variability in the results for soybean (*Glycine max* [L.] Merr.) than for corn (*Zea mays* L.), with the highest variability for medium-level soybean residue. Overall, the digital photograph method to estimate percentage of residue was found to be a suitable alternative to the line-transect method, which is more time consuming and labor intensive. Determining the optimal numbers of measurements to estimate crop residue cover is important to those wishing to use digital photo capture methods to record, archive, and measure residue for remote sensing calibration and validation or for handheld mobile device applications.

Key words: digital photograph method—field crops—Great Lakes—line-transect method—soil cover—validation and calibration

Ontario, Canada's most populous and second largest province, has more than half of the highest quality farmland in Canada, with a total number of about 52,000 farms according to the 2011 Census of Agriculture (AAFC 2013). Crop residue (nonphotosynthetic vegetation) management is an important agricultural component of these farms' activities. To appropriately manage crop residue, Ontario farmers have increasingly implemented conservation tillage practices (i.e., no-till or reduced tillage; Ketcheson and Stonehouse 1983; Lal 2015) from 1991 to 2011 (Smith 2015; Statistics Canada 2011). There is concern, however, that the extent of conservation tillage has peaked and that there is now more tillage and bare soil exposed over winter than in the past (A. Hayes, Ontario Ministry of Agriculture, Food and Rural Affairs [OMAFRA] personal communication; Statistics Canada 2016). Such practices are of even greater importance in southwestern Ontario, an area where agricultural practices, including tillage practices, have an effect on Great Lakes water quality (Joosse and Baker 2011; Molder et al. 2015). The amount of crop residue left in the field after harvest is important for soil and water storage (Daughtry and Hunt Jr. 2008), erosion control (Kumar and Goh 1999; Mailapalli et al. 2013; Enciso et al. 2014), and assessment and modeling of soil carbon (C) sequestration (Aguilar et al. 2012a). For instance, retaining more than 30% of crop residue cover on the surface is considered a conservation tillage practice (Shelton et al. 1990; Huggins and Reganold 2008; Lal 2015) and is an important objective of the Great Lakes Agricultural Sustainability Initiative funded by the Ontario Ministry of Agriculture, Food and Rural Affairs (OMAFRA) and Agriculture and Agri-Food Canada (OMAFRA 2015b). Other studies have found that conservation tillage and crop residue cover are important for reducing time and fuel consumption, improving water and soil quality (Clarke et al. 1990; Patni et al. 1998; Yang et al. 2005), increasing the amount of organic matter (Kochsiek et al. 2013; Congreves et al. 2014; Van Eerd et al. 2014), reducing greenhouse gas emissions (Smith et al. 2008), and reducing soil erosion (Ketcheson and Stonehouse 1983). The latter authors found that soil erosion can be reduced by 75% by maintaining a corn (*Zea mays* L.) crop residue cover of 15%. In this context, deriving quantitative information on the amount of crop residue cover by field, which can then be extrapolated to regions, is essential to understand the state of soil management and the capacity for additional change in an area of interest. In addition, crop residue cover estimation is important for planning field operations by farmers and has been used to determine if a specific field qualifies for federal or provincial conservation programs (e.g., the Land Stewardship I and II Programs offered by OMAFRA from 1987 to 1994).

There are several methods to quantify percentage of residue cover, which can be separated into conventional ground-based measurements (i.e., line transect, windshield surveys, and photograph methods using field observations) and more novel airborne and satellite-based approaches. Systematic con-

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ventional ground-based methods such as line transects are time consuming, labor intensive, and cannot provide continuous data over large areas since percentage of residue cover can be estimated only at spatially disconnected fields. Roadside surveys, though faster, are still time consuming, with an inherent error between residue estimated from the road (e.g., distance from field, angle of view) and that existing in the field. In contrast, remote sensing techniques using satellites can capture continuous residue cover data over hundreds of square kilometers within minutes. For example, Landsat-8 and Sentinel-2 satellites have a 185 and 290 km swath width, respectively, and they also have regular frequent revisit times of every 16 and 10 days, respectively. Many previous studies have used remote sensing techniques to quantitatively assess residue cover amount (Daughtry et al. 1996, 2006; Bannari et al. 2006, 2015; Pacheco and McNairn 2010; Aguilar et al. 2012; Sakamoto 2012; Zheng et al. 2014). Other studies have used software programs (Booth et al. 2006) to automatically estimate green crop cover using nadir-looking photography, but these methods have been rarely tested for residue estimation. All remote sensing–based studies need calibration and validation as essential components, which can be done by collecting a limited number of ground measurements and relating them to remote sensing observations (Baccini et al. 2007). However, reported attempts to systematically determine the optimal number of ground measurements and the concomitant area sampled on the ground are limited. For example, Laflen et al. (1981) used between 4 and 11 photos for most fields, while Pacheco and McNairn (2010) and Aguilar et al. (2012b) used 5 and 2 photos per plot, respectively. Therefore, an essential challenge in using field data for calibration and validation in remote sensing–based studies for residue cover mapping is ensuring that field measurements provide an appropriate and representative sample in support of mapping purposes. Using an inappropriate number or type of measurement points could under- or overestimate the spatial variability and the accuracy of crop residue estimates. The objective of this study was to determine the number of measurements (i.e., digital photographs) required to optimize the precision and accuracy of crop residue cover estimations from remotely sensed techniques using satellites.

Materials and Methods

Study Area. This study was conducted in Elgin County, located in the Lake Erie basin of southwestern Ontario, Canada (figure 1). This area is primarily agricultural, with corn, soybean (*Glycine max* [L.] Merr.), and winter wheat (*Triticum aestivum* L.) as the dominant crops grown in rotation. Other crops include oats (*Avena sativa* L.), barley (*Hordeum vulgare* L), red clover (*Trifolium pratense* L.), vegetables, and alfalfa (*Medicago sativa* L.). The topography is generally characterized by a combination of flat and rolling terrains, occasionally interspersed with steep ravines, and soils in the sample area range from clay to sand (Schut 1992). Southwestern Ontario has the greatest proportion of tillable land in the province, with a total of 3,026,576 ha (Kludze et al. 2011), and an estimated biomass of residue (from three common crops—corn, soybean and winter wheat) that could be removed annually, ranging between 6,963 and 7,223 kg ha^{-1} (Kludze et al. 2013).

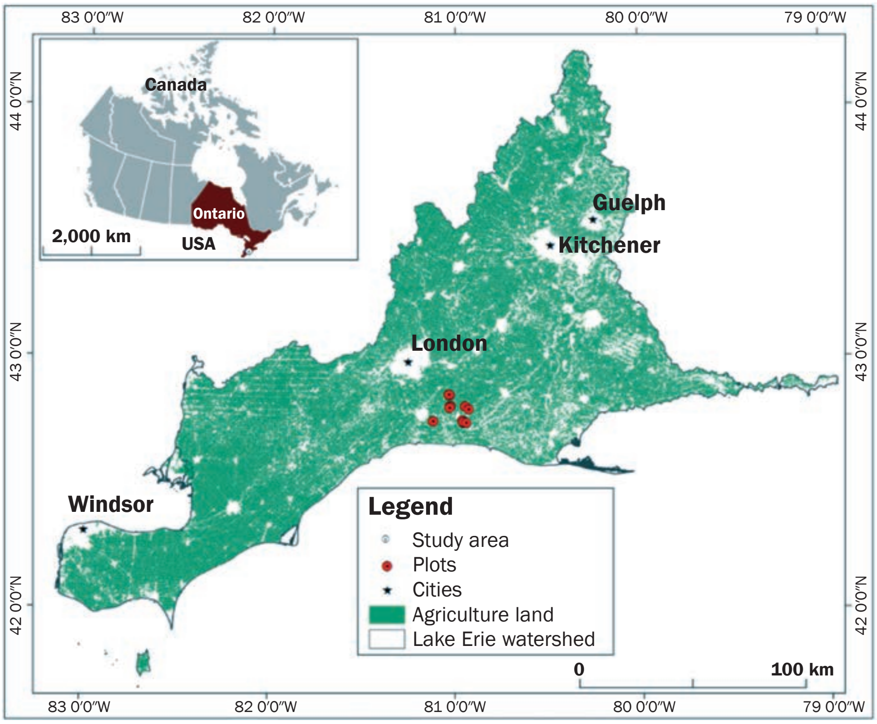
The climate is characterized by long, moderate winters (November through April) and hot, humid summers. Mean annual temperature is 8.7°C: June, July, and August are the warmest months, with a mean temperature of 20.1°C, and December, January, and February are the coldest months, with a mean temperature of −3.2°C. Total annual precipitation is 993 mm, of which about one-third falls during the peak vegetative growth period between early May and August (Environment and Climate Change Canada 2011). The remaining two-thirds of the precipitation falls during the nongrowing season as fall or spring rain or winter snow, which then leaves the landscape after melting during winter thaw periods or as spring runoff. This is of significance as it means that the bulk of the precipitation occurs during the nongrowing season when the landscape is most likely vulnerable to soil erosion and emphasizes why retaining sufficient crop residue cover is an important and effective soil management practice in this region (Molder et al. 2015).

Field Measurements. In early December of 2014, a quantitative assessment of annual crop residue cover was conducted after harvest on fields located on privately owned farms using line transect and digital photograph methods. The sampling design consisted of 18 square sample plots (15 × 15 m), and each plot was located within a unique field, for a total of 18 fields (one plot per field). The harvested crops on these plots were corn (nine plots) and soybean (nine plots). The crop residue cover in each plot was considered to be representative of the crop residue cover in the 30 × 30 m area corresponding to the pixel from which crop residue cover is calculated by remotely sensed imagery. Tillage intensity varied from conventional, where most residue was buried, to no-till where no residue had been removed. For each crop type, plots were selected to represent a range in crop residue cover (3 low [≤29%], 3 medium [30% to 59%], and 3 high [≥60%] residue cover plots). This classification scheme (≤29%; 30% to 59%; and ≥60%) corresponds to that used in the Farmland Health Check-Up workbook of the OMAFRA Great Lakes Agricultural Stewardship Initiative program (OMAFRA 2015a). In each plot, five line transects of 15.2 m each were established and five vertical photos were taken.

Line-Transect Method. In each plot, a 15.2 m measuring tape was marked at 15.2 cm intervals (total of 100 marks) and stretched diagonally at a 45-degree angle across harvested field crop rows (figures 2a and 2b). At predetermined, marked intervals, the presence of residue was recorded. The proportion of crop residue cover in the plot was determined by counting the number of marks that intersected or lay directly over a piece of residue along the stretched tape (Laflen et al. 1981; Richards et al. 1984; Morrison et al. 1993). For instance, if 30 marks intersected a piece of residue along the 15.2 m measuring tape with marks at every 15.2 cm, then the estimated percentage of residue cover was equal to 30%. To be counted, a piece of residue had to be ≥0.24 cm in diameter, which was confirmed in the field by comparing residue diameter with the diameter of a 0.24 cm wooden dowel (figure 2c) following the method of Shelton et al. (1990, 1993). Each of the five transects in a plot was measured by up to three separate persons, and the respective measurements were averaged to obtain one residue estimate for each transect.

Digital Photo Method. Five vertical (i.e., taken at a 90° angle to the ground) digital photographs were also taken per plot in such a way that each photo was co-located with a transect line (figure 2a). To do so, a 75 × 100 cm quadrat (figure 2d) was placed on the middle of each transect with its longest side perpendicular to tillage direction, or planting direction if there was no tillage. Once photographs of the quadrat were taken, percentage

Figure 1
Map showing the location of the 18 study sites within the Lake Erie watershed, southern Ontario, Canada.



of residue cover from those photographs was estimated using digital grids. As part of this study, the optimal digital grid size to use was also evaluated by comparing three different digital grids—grids with 25 (figure 2d), 64, and 100 intersections. To estimate percentage of residue cover using a digital grid, the grid was first superimposed on each digital photograph, as in Pacheco and McNairn (2010), and then the number of the intersections that overlay residue was counted. The grid line thicknesses were set to match that of the wooden dowel specifications to ensure that only residue pieces >0.24 cm were counted in the photograph. Percentage of residue cover was calculated as the sum of intersections that overlay residue divided by the total number of intersections of each grid (i.e., 25, 64, and 100) and multiplied by 100.

To determine which digital grid was optimal for estimating residue cover, the respective percentage of residue cover calculated for each grid for every photograph was compared to that derived from the line-transect method. Each digital photograph was analyzed and its percentage of residue cover obtained using a two-phase process carried out by three different human counters (blind process) according to a preestablished set of rules. When the estimates of a minimum of two counters agreed (±5% difference) on the percentage of residue estimate of an individual photograph, the two estimates with smallest difference were averaged and used as the photograph's datum (83% of the data, n = 75). When all of the counters disagreed (i.e., more than ±5% difference; 17% of the data, n = 15), a second phase of interpretation was initiated and the estimate provided by the most accurate counter (considered to be the counter whose estimate was in closest agreement with the line-transect estimate) was retained and averaged together with the estimate of the second counter in closest agreement with the estimate of the most accurate counter. Therefore, for each photo, estimates from only two counters were averaged in order to minimize the human error that might affect the counting process and to increase the accuracy of the estimated percentage of crop residue cover.

Statistical Analyses. Statistical analyses were performed to quantify percentage of crop residue cover and to directly compare the residue estimates derived from digital photographs with those derived using the line-transect method. Three replicate plots of each residue type (e.g., corn and soybean) and crop residue level (i.e., low, medium, high) were measured, for a total of 18 plots. Slope and intercept statistics between the two methods (transects versus photographs) were also calculated to test a 1:1 relationship between the two methods. If confidence limits encompassed 1 for the slope and 0 for the intercept, the two methods were not considered to be significantly different. If the confidence limits overlapped for crop types, the two slopes were not considered to be significantly different. Means of crop residue and standard deviation (SD) were used in this study. A linear regression model was also used to analyze the relationship between photographs and line-transects values. Pearson product moment correlations (r) and coefficient of determination (R^2) were also used to explore the strength of the relationship between crop residue measured by line-transects (considered to be the standard) versus that estimated by the photo-grid method. Root mean square error (RMSE) was calculated to determine the magnitude of error between the different comparisons. An analysis of variance (ANOVA) followed by Tukey honest significant difference (HSD) pairwise comparison tests were used to determine whether the percentage of residue cover statistically differed between crops and among levels of residue within crops. Significance was declared at α = 0.05. The LINEST matrix function in Microsoft Office Excel 2010 was used to generate 1:1 line parameters, and other statistical analyses were conducted in R (R Development Core Team 2011).

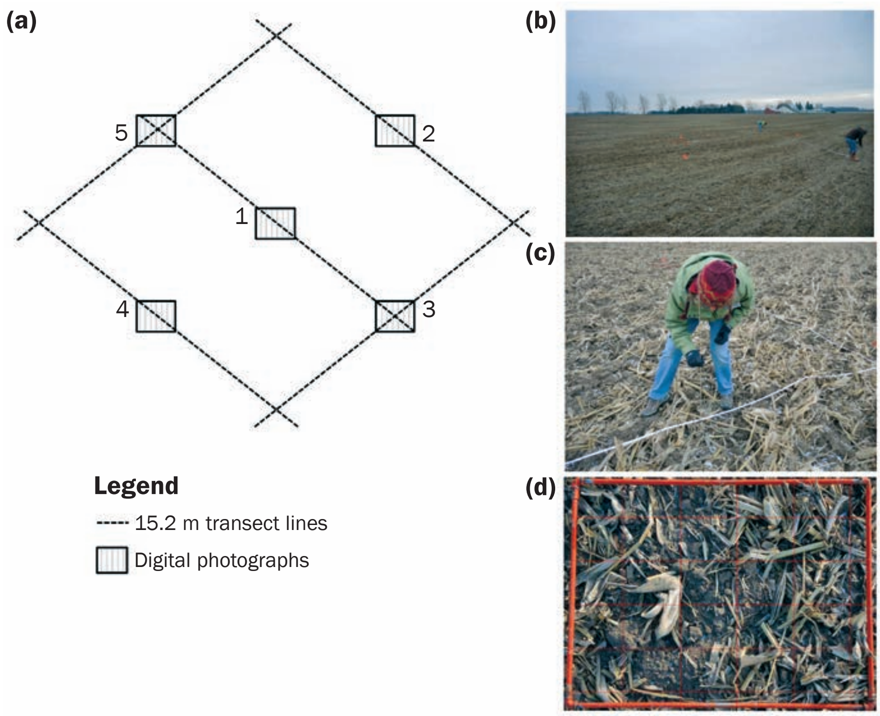
To retrospectively compare the minimum number of line transects or digital photographs required to estimate crop residue cover per residue level with varying levels of power, a power analysis for a two-tailed one-sample t test was conducted using the following equations (Howell 2013):

$$\delta = d\sqrt{n}\ , \qquad (1)$$

where δ (delta) represents the combination of the effect size (d) with the sample size (n). Depending on α (the probability of a type 1 error) and power level desired, δ can be found from the Appendix in Howell (2013). For instance, for a power = 0.85 and α = 0.05, δ = 3.00. The variable d is the difference to be detected in residue cover divided by the standard deviation:

Figure 2

(a) Schematic presentation of the five measured transects (1 to 5), as well as the location of the five digital photographs (dashed squares) along the five transects. (b) and (c) show photographs from field sites. (d) shows a photo of the quadrat (orange frame) with a 25-grid superimposed on it.



$$d = \frac{\mu_1 - \mu_0}{\sigma}, \quad (2)$$

where μ_1 and μ_0 represent what the mean of control population and the studied population would be. In this study, we are interested in detecting a difference of at least 10% between μ_1 and μ_0; 10% is often used as the minimum range to define different residue classes and is a difference that will most likely result in a change in residue class for a variety of classification schemes. Therefore, here we give the value of $\mu_1 - \mu_0$ directly ($\mu_1 - \mu_0$ = 10%). Thus, we have δ and d and can simply solve for n using equation 3:

$$n = \left(\frac{\delta}{d}\right)^2 . \quad (3)$$

Results and Discussions

Residue Cover Estimation Using Line Transects. Results of the crop residue cover estimation using line-transect method are illustrated in table 1. The amount of corn residue cover varied from 5.2% ± 4.4% (mean ± SD) to 94.4% ± 3.9%, while soybean residue cover ranged between 8.4% ± 2.2% and 57.6% ± 2.7% (table 1). Compared to other studies (Aguilar et al. 2012a), there was a significant difference between the residue levels sampled as low, medium, and high for both crop types (Tukey HSD test, $p < 0.05$; figure 3). Sampled plots had residue cover estimates smaller than 30% (seven plots), between 30% and 60% (six plots), and greater than 60% (five plots).

Comparing Line Transect and Photograph Grid Estimations of Crop Residue Cover. Estimates of residue cover from each of the 18 plots were obtained using both line-transect and photograph methods. The five photographs taken at each plot were counted by three counters; then, the average of the two most accurate estimates values was used as the percentage of residue cover estimate for the plot. Table 2 shows that the first counter (#1) had the most accurate estimation of percentage of crop residue from photographs since the regression line was not significantly different from a 1:1 correlation line (slope 0.93 to 0.94, n = 90; table 2). Indeed, the slope 95% confidence limits encompass 1 (0.83 to 1.04) for all grid density levels and the intercept 95% confidence limits encompass 0 (–3.89 to 7.42). Other counters slightly underestimated the residue cover determined by line transect but still with high correlation (table 2). The percentage of crop residue cover estimated using the line-transect method and digital photo method was strongly correlated (r = 0.91, R^2 = 0.83, $p < 0.001$, n = 90; figure 4a), with a RMSE of 12.8%. This correlation was even stronger when the average plot residue cover estimates (five photos and five line-transects per plot) were regressed (r = 0.98, R^2 = 0.95, $p < 0.001$, n = 18; figure 4b and table 3), with a RMSE of 7.6%. When data were analyzed according to residue type (corn versus soybean), R^2 of corn was higher than that of soybean (0.88 versus 0.73, n= 45) while RMSEs were slightly different (13% versus 12.7%). A one-way ANOVA also found that estimates of corn and soybean residue cover are statistically different ($p < 0.001$). Overall, corn and soybean RMSEs found in this study using digital photo and line-transect methods are relatively lower than those found by Pacheco and McNairn (2010), who used satellite imagery based unmixing methodology to produce crop residue estimates with RMSE between 17.3% and 20.7%.

The relationship was tested to see if fewer photographs (e.g., three) could be used with confidence. When residue estimates from three randomly selected photographs of the five were averaged and plotted against line-transect data, the coefficient of determination slightly decreased but was still very high (r = 0.97, R^2 = 0.94, $p < 0.001$, n = 18; figure 4b and table 3), whereas a similar RMSE of 7.4% was found. Neither the five photographs' nor three photographs' plot averages were significantly different from the line-transect estimates according to comparison to a 1:1 line (table 3).

Overall, analyses showed that percentage of residue cover estimates using the line-transect method were strongly correlated to those estimated from photographs, both when individual estimates were compared and when average plot estimates were compared. In addition, estimates with photographs were found to not overestimate the percentage of residue compared to the line-transect method, except for three plots (one corn and two soybean plots). The results of this study demonstrated that the digital photograph method is a suitable alternative to the line-transect method for the collection of calibration and validation data for remotely

Table 1

Summary of crop residue levels estimated using the line-transect and digital photo methods from the 18 sampling plots. Five line-transect and five photo (grid density = 100) measurements per field were averaged to obtain a residue estimate of each plot.

		Residue cover (%)							
		Transect-derived				Photo-derived			
Plot ID	Type	Mean	Min	Max	SD	Mean	Min	Max	SD
1	CR	5.2	0	10	4.4	10	4	18	5.9
2	CR	7.4	6	9	1.1	3	1	5	1.9
3	CR	10.8	4	15	4.4	6	4	10	2.2
	LCR	*7.8*	*0*	*15*	*4.2*	*6*	*1*	*18*	*4.5*
4	CR	42.4	32	51	6.9	47	35	62	11.2
5	CR	63.0	56	70	5.5	49	39	68	11.7
6	CR	63.0	56	69	5.9	59	41	80	16.5
	MCR	*56.1*	*32*	*70*	*11.5*	*52*	*35*	*80*	*13.6*
7	CR	87.0	85	91	2.3	74	66	85	7.5
8	CR	91.0	90	92	1.0	88	74	97	10.1
9	CR	94.4	89	99	3.9	84	77	92	5.9
	HCR	*90.8*	*85*	*99*	*4.0*	*82*	*66*	*97*	*9.6*
10	SR	8.4	5	11	2.2	12	4	21	8.0
11	SR	10.6	9	13	1.8	6	4	8	1.7
12	SR	16.8	11	21	4.1	10	5	16	4.1
	LSR	*11.9*	*5*	*21*	*4.6*	*9*	*4*	*21*	*5.5*
13	SR	19.6	18	22	1.8	10	6	14	3.2
14	SR	44.8	41	50	3.4	40	29	49	8.8
15	SR	44.0	30	58	11.6	44	15	73	22.3
	MSR	*36.1*	*18*	*58*	*13.8*	*31*	*6*	*73*	*20.3*
16	SR	52.4	43	59	7.1	49	37	65	10.7
17	SR	53.4	46	60	6.1	68	54	83	11.8
18	SR	57.6	55	61	2.7	58	47	70	9.3
	HSR	*54.5*	*43*	*61*	*5.7*	*59*	*37*	*83*	*12.7*

Notes: CR = corn residue. SR = soybean residue. SD = standard deviation. LCR = low corn residue. MCR = medium corn residue. HCR = high corn residue. LSR = low soybean residue. MSR = medium soybean residue. HSR = high soybean residue. Italicized values are level values for the 15 line-transects or photos in each level.

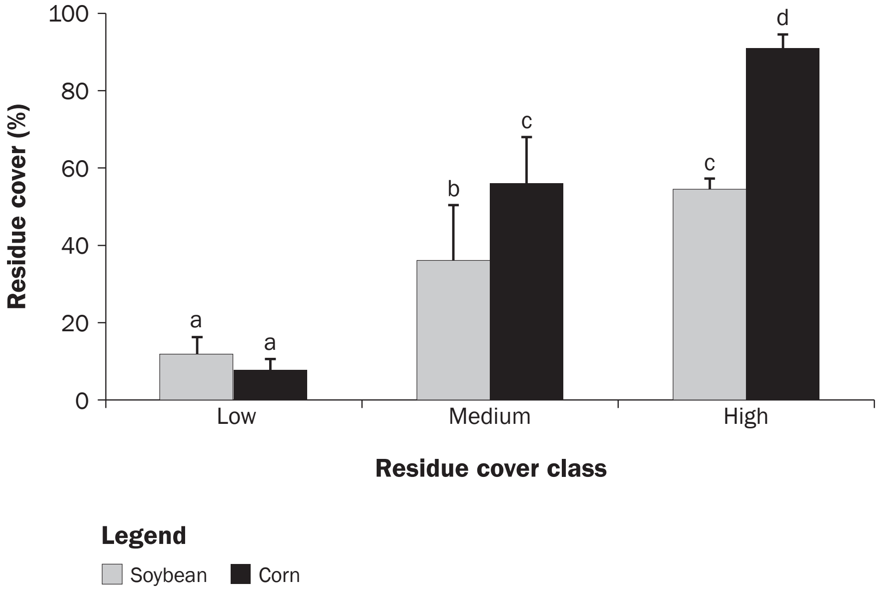
sensed data. This provides the authors with confidence to use the photograph method to ground truth remotely sensed imagery in a subsequent study to map crop residue cover using 30 × 30 m Landsat raster imagery in the Canadian Lake Erie basin.

The grid intersection density did not have a significant effect on residue cover estimation (Tukey HSD test, $p > 0.05$, $n = 18$; table 2). However, both 64 and 100 grids had the highest R^2 of 0.95 and lower RMSE (7% and 7.6%) compared to the 25-grid size (figure 5). It is important to mention that even though the 25-grid size has a slightly lower R^2 of 0.94 and higher RMSE of 8.7%, it was not significantly different than a 1:1 line (table 3). When a 50-grid size (50 randomly selected intersections from a 64 grid per photograph) was used (not shown here), similar results (R^2 = 0.95) were obtained, suggesting that 50 to 100 points per photograph are sufficient to accurately estimate the percentage of residue cover. This was consistent with other studies in which a 100-grid size was used (Pacheco and McNairn 2010).

Retrospective Comparison of the Number of Line Transects and Digital Photos Required to Estimate Crop Residue. When designing a study, a good estimate of the necessary sample size is key to its success. However, often there is little or no prior information about the population variability, though sometimes information can be obtained from the existing literature or from pilot studies. Since this study has generated data on the population variability of residue estimates using both the line-transect and digital photo method, the sample size (n) for each residue level per crop type was calculated using power analysis for each method using different levels of power. In other words, the number of line transects and digital photographs needed were retrospectively calculated by setting the power at different levels (i.e., 0.85, 0.90, and 0.95; table 4) and holding the type I and type II error rates equal at each level of power. The calculated number of line transects or digital photographs for different residue cover levels (i.e., low, medium, and high residue levels for both corn and soybean) are shown in table 4. Overall, the minimum number of line transect and digital photographs for each residue cover level increases when specified power increases (table 4). For example, the number of line transects for low residue increases from 2 to 3 (corn) and 13 to 19 (soybean) when power increases from 0.85 to 0.95 (table 4). The number of required digital photographs was greater than the number of line transects (except for low levels of soybean residue cover), and the number of both line transects and digital photographs required for all soybean levels (low, medium, and high) was greater than those of corn residue (table 4). The latter finding is consistent with Pacheco and McNairn (2010) who found that residue variability was higher in soybean fields when compared to corn fields. When the power was set at 0.85, the minimum number of line transects and digital photographs calculated was between 2 and 17 for plots with low, medium, and high percentage of corn residue cover, whereas 3 to 54 line transects or digital photographs would be required to estimate low, medium, and high percentage of soybean residue cover. The number of samples at 0.85 power is close to the ones used in this study (i.e., 15 line transects or photographs per residue level). The number of measurements of line transects and photographs (for both crop types) required to reliably estimate residue cover in fields is lower for fields with less than 30% residue cover, except for low soybean measured by transect (table 4). As expected, the greatest minimum number of photographs and line transects is needed for residue levels and crop types with the largest variability (i.e., medium residue levels for corn and soybean). For example, the largest number of line transects or digital photographs required among all line transects and photograph data at test power of 0.85 are 18 and 38, respectively. Overall, the required number of digital photographs was greater than that of line transects. Given that, it would be practical in future studies to collect a greater number of photographs that could

Figure 3

Variation within corn and soybean crop residue covers (low, medium, and high classes). The *y*-axis refers to line-transect residue cover percentage. Error bars refer to the standard deviation of the mean within a crop; different letters designate statistically significant ($p < 0.05$) differences according to pairwise Tukey HSD tests.



be taken more easily than a greater number of line transects in plots where the crop residue cover is expected to be highly variable.

Summary and Conclusions

Determining the optimal type and number of measurements to estimate crop residue cover is an important step in estimating and mapping crop residue cover that can be derived from remotely sensed data across landscapes. The study described in this paper demonstrated that (1) the digital photograph method is a suitable alternative to the line-transect method, even though they have different spatial scale coverages; and (2) counting 50 to 100 points in each photograph is enough to derive crop residue cover estimates. This study found that a 25-intersection grid for counting residue in photos was less accurate for representing residue cover measured by the line-transect method. This study also demonstrated that when trained persons processed and analysed data from transects and photographs, a precise estimation of crop residue cover can be achieved. There are significant logistical advantages to using the digital photograph method versus the line-transect method since it requires less time and labor, with the added advantage that digital photographs can be archived for future reference. Following a retrospective power analysis, the minimum number of line transects needed is generally comparable to the minimum number of digital photographs. Understanding the optimal numbers of photograph measurements to estimate crop residue cover is also of importance to farmers and land managers since mobile device applications are being developed based on image processing techniques to measure crop residue on the field. For instance, a crop residue cover assessment application has been developed with support from OMAFRA to monitor crop residue conditions on farmer's mobile devices (WRAMI 2015). Results from this study could provide a strong validation data set for this mobile device application. Future work will compare the results from this study with those obtained using this appli-

Table 2

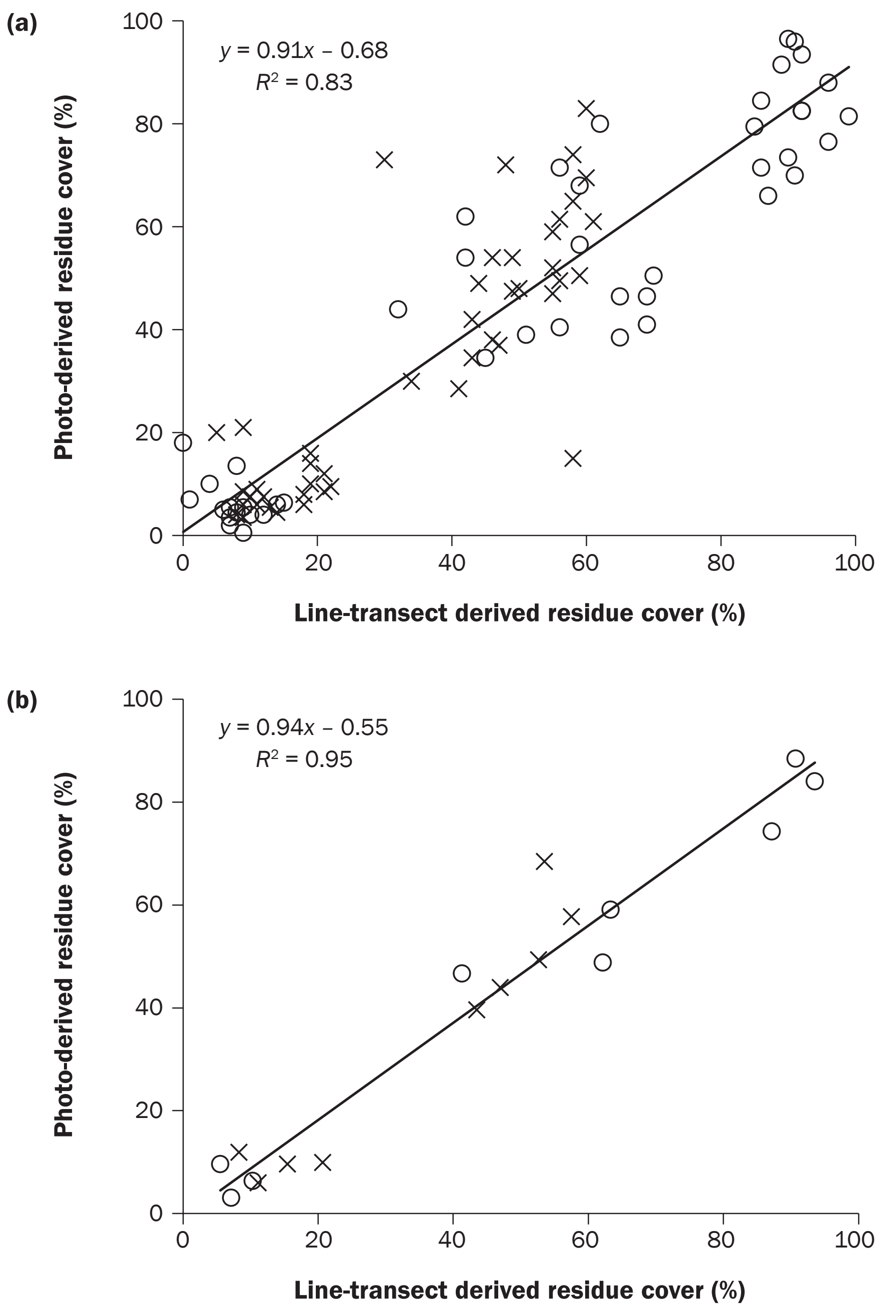
Summary statistics of linear regression of percentage of residue estimates between line-transect (*x*-axis) and digital photograph methods (*y*-axis) as determined by three independent counters (1, 2, and 3; blind process) using three different grid intersection densities (25, 64, and 100). Data from five line transect and five digital photographs per plot were regressed.

	#1			#2			#3		
Statistics	**25**	**64**	**100**	**25**	**64**	**100**	**25**	**64**	**100**
Slope	0.94	0.94	0.94	0.83	0.89	0.87	0.87	0.90	0.88
$SE_{[slope]}$	0.052	0.05	0.05	0.05	0.05	0.05	0.052	0.045	0.05
$Slope_{[UCL]}$	1.04	1.037	1.03	0.94	0.99	0.96	0.98	0.99	0.97
$Slope_{[LCL]}$	0.83	0.84	0.85	0.73	0.80	0.78	0.76	0.81	0.78
Intercept	2.02	1.70	0.99	2.32	0.56	0.75	4.26	2.47	2.61
$SE_{[Intercept]}$	2.72	2.63	2.45	2.77	2.36	2.42	2.87	2.37	2.51
$Intercept_{[UCL]}$	7.42	6.92	5.87	7.83	5.26	5.55	9.96	7.19	7.60
$Intercept_{[LCL]}$	−3.38	−3.53	−3.89	−3.18	−4.14	−4.05	−1.45	−2.24	−2.37
R^2	0.79	0.80	0.82	0.74	0.82	0.80	0.74	0.82	0.79
Df	88	88	88	88	88	88	88	88	88
F	324	347	402	249	389	355	324	391	334

Notes: UCL = upper confidence limit ($p = 0.075$). LCL = lower confidence limit ($p = 0.025$). SE = Standard error. Df = Degree of freedom. $n = 90$. R^2 = Coefficient of determination. F = F statistic value.

Figure 4

Relationship between percentage of residue cover as determined from line transects and digital photos. (a) Each point represents individual transects and photos (r = 0.91, p < 0.001, root mean square error = 12.8%, grid density = 100, and n = 90). (b) Each point represents the average photo-derived and line-transect-derived percentage of residue for each plot using five measurements (transects and photos) per plot (r = 0.98, p < 0.001, root mean square error = 7.4%, grid density = 100, and n = 18).



cation so we can examine whether or not this technology provides an opportunity for crop residue cover assessment using a mobile technology approach.

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Table 3
Summary statistics of linear regression of average percentage of residue estimates per plot between line-transect and digital photograph methods (three vs. five photos) using three grid densities (25, 64, and 100).

	25		64		100	
Statistics	**3**	**5**	**3**	**5**	**3**	**5**
Slope	0.94	0.95	0.96	0.96	0.96	0.96
$SE_{[slope]}$	0.06	0.06	0.05	0.06	0.05	0.05
$Slope_{[UCL]}$	1.07	1.08	1.07	1.08	1.07	1.07
$Slope_{[LCL]}$	0.82	0.82	0.84	0.84	0.84	0.84
Intercept	1.36	0.45	−0.12	−0.69	−0.49	−0.76
$SE_{[Intercept]}$	3.13	3.19	6.61	2.89	2.80	2.73
$Intercept_{[UCL]}$	8.00	7.21	5.76	5.43	5.45	5.03
$Intercept_{[LCL]}$	−5.28	−6.31	−6.00	−6.81	−6.43	−6.54
R^2	0.94	0.94	0.95	0.95	0.95	0.95
F	244	238	319	296	313	329

Notes: UCL = upper confidence limit (p = 0.075). LCL = lower confidence limit (p = 0.025). SE = standard error. R^2 = coefficient of determination. F = F statistic value.

Figure 5
Relationship between crop residue cover estimates as determined from line transects and digital photos for each of the three digital grid sizes. Each point represents the average of five measurements (transects and photos) per plot (18 plots). $Grid_{(25)}$: $y = 0.951x + 0.45$, $R^2 = 0.94$, root mean square error = 8.7%; $grid_{(64)}$: $y = 0.96x - 0.69$, $R^2 = 0.95$, root mean square error = 7%; and $grid_{(100)}$: $y = 0.96x - 0.76$, $R^2 = 0.95$, root mean square error = 7.6%.

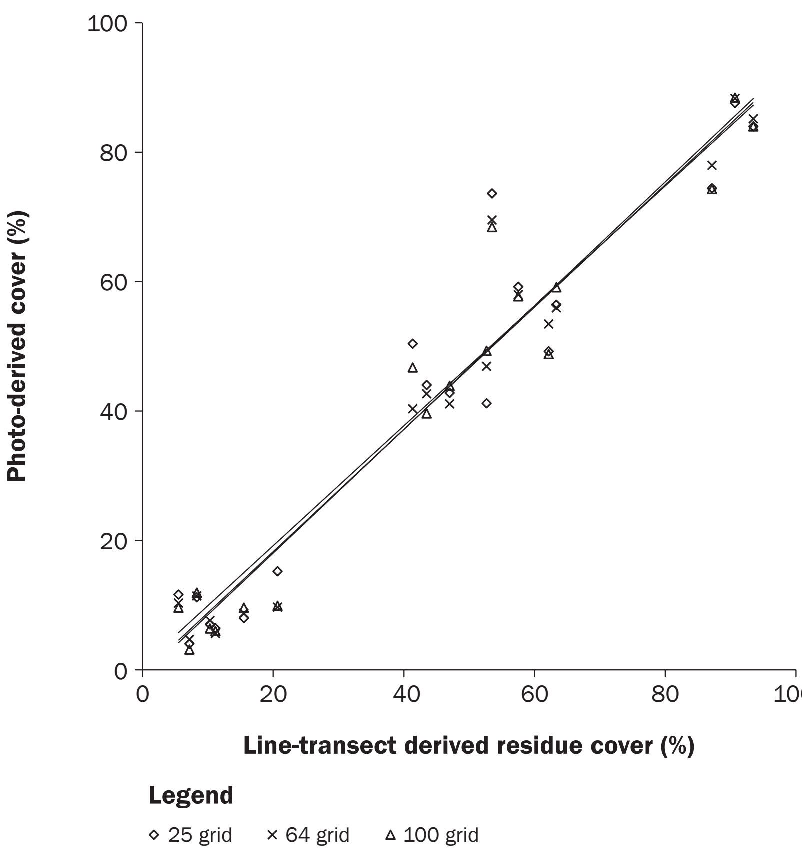

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Table 4

Minimum number of line transects and digital photographs required to detect a difference of 10% with Type I error (α = 0.05) at different levels of test power (0.85, 0.9, and 0.95) among each residue level within a crop type.

Residue level	Line transects			Digital photographs			
	$N_{(p = 0.85)}$	$N_{(p = 0.90)}$	$N_{(p = 0.95)}$	$N_{(p = 0.85)}$	$N_{(p = 0.90)}$	$N_{(p = 0.95)}$	$N_{(\text{sampled this study})}$
LCR	2	2	3	2	3	3	15
MCR	12	14	18	17	20	24	15
HCR	2	2	3	9	10	12	15
LSR	13	15	19	3	4	4	15
MSR	18	21	25	38	44	54	15
HSR	3	4	5	15	18	21	15

Notes: $N_{(p = 085;\ p = 090;\ p = 095)}$ = the required number of line transects and digital photos calculated using power analysis for the two-tailed, one-sample *t* test and by setting the power at different levels (i.e., 0.85, 0.90, and 0.95) using equations in Howell (2013). $N_{(\text{sampled this study})}$ = number of subsamples taken in this study (both for line transect and digital photographs) at each level. LCR = low corn residue. MCR = medium corn residue. HCR = high corn residue. LSR = low soybean residue. MSR = medium soybean residue. HSR = high soybean residue. Residue level means and standard deviations are listed in table 1.

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