Evaluation of optical remote sensing models for crop residue cover assessment

D.P. Thoma, S.C. Gupta, and M.E. Bauer

ABSTRACT: Measurement of crop residue cover over large areas is useful for monitoring conservation tillage adoption, assessing carbon sequestration potential and erosion modeling. This study was designed to test the accuracy of crop residue estimates in current Tillage Transect Surveys, and to test the feasibility of predicting crop residue cover based on data recorded by Landsat Enhanced Thematic Mapper Plus (ETM+) satellite scenes. A total of 468 corn and/or soybean fields in 11 Minnesota counties were characterized for residue cover in the course of three sampling campaigns coinciding in time with satellite scene acquisition. Results showed that Tillage Transect Survey estimates were correct for 49 percent to 74 percent of fields when either five or two categories were used in classification respectively. Regression analysis showed a strong positive relationship between percent soybean residue cover and ETM+ bands 1, 3, and 7 (r^2 =0.66) and between percent corn residue and ETM+ bands 4, 5 and 7 (r^2 = 0.44). Three additional indices based on satellite digital numbers, the Soil Tillage Index, Normalized Difference Index, and Normalized Difference Tillage Index had coefficients of determination between 0.02 and 0.56 for corn and soybean residues. The Crop Residue Index Multiband model, a more physically based model, correctly predicted residue cover categories for 30 to 64 percent of fields when five or two categories were used in classification respectively. We conclude that remote-sensing techniques had accuracy as good or better than Tillage Transect Surveys estimates when residue cover classifications were decreased to two categories (0 to 30 percent, and >30 percent). Since residue cover information is primarily needed to assess the extent of two categories, conservation and conventional tillage, remote sensing with Landsat imagery provides a means of sampling every field with an efficient, economical and uniform methodology.

Keywords: Crop residue, Landsat, tillage

A comprehensive and efficient monitoring program for estimating spatially distributed crop residue cover is needed to track trends in adoption of conservation practices, compliance regulation, prioritization of conservation efforts, carbon sequestration and erosion modeling. However, the only broad-scale monitoring effort currently implemented relies on a roadside survey methodology, the Tillage Transect Survey of Hill (1995) that is time consuming, laborious and expensive. The Tillage Transect Survey is conducted annually or every three to five years by most Midwestern states in agricultural counties (CTIC, 2004). Methods of residue cover assessment are needed that can replace or augment information collected by the Tillage Transect Survey over large areas. A remote sensing approach may provide a more efficient method for obtaining this critical information over large areas in a timely manner.

Estimating crop residue cover using remote sensing techniques has been extensively researched but infrequently implemented in monitoring programs. Major obstacles include cost and availability of cloud free optical imagery, and difficulties in developing an effective way to differentiate soil and residue under field conditions. Three general categories including fluorescence, active radar backscatter, and passive optical reflectance have been investigated for crop residue cover assessment.

Fluorescence induced by laser excitation has been shown to unambiguously differentiate crop residues from soil (McMurtrey et al., 1993; Daughtry et al.,1997; and Daughtry et al., 1996b). However, detection of fluorescence signals is hampered by difficulty in generating sufficient laser-induced excitation energy for field-scale work. The weakness of the fluorescence signal relative to ambient daylight conditions is also problematic.

Using radar satellite data, McNairn et al. (1996, 1998a, 1998b) reported that quantitative residue cover estimates were difficult to determine due to interacting effects of surface roughness and soil moisture that affect backscatter intensity. However, type of residue was easily discerned due to roughness characteristics of the residues. They also found it possible to determine whether tillage had occurred between two successive image acquisition dates due to changes in surface roughness that increased backscatter.

Optical imagery is more readily available and affordable than other remote sensing data products, making it an attractive choice for assessing crop residue cover over large areas. The primary complicating factor in a passive optical reflectance approach was the similarity of spectral signatures for soils and residues across a wide range of wavelengths (Daughtry et al., 1996a; Gausman et al., 1975; Nagler et al., 2000). However, Aase and Tanaka (1984) and McMurtrey et al. (1993) recognized that calibrations for unique combinations of soil and residue could be achieved provided the contrast between the soil and residue was great. Because reflectance signatures of crop residues and soils are monotonic over much of the spectrum, even band ratios have not substantially improved discrimination capability. A notable exception is the Cellulose Absorption Index (CAI) (Nagler et al., 2000; Daughtry et al., 1996b) that exploits the weak absorption of short wave infrared wavelengths in senesced plant materials that does not occur in soils. Water is also a strong absorber of energy in the same wavelength region, and thus may obscure differences between soil and plant litter.

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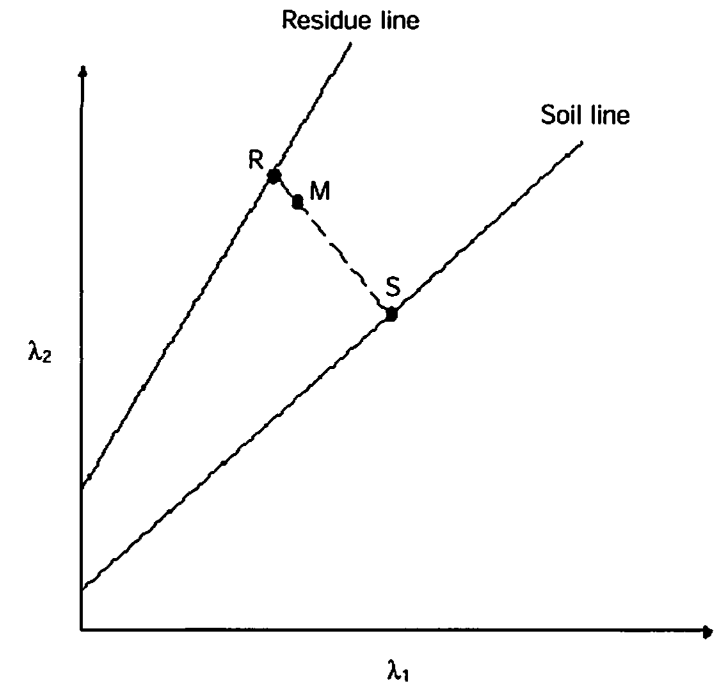
Figure 1

The CRIM concept in 2-D feature space. Points R and S were 100% and zero% residue cover, respectively. Point M represented residue cover between zero and 100% that was proportional to its position between the soil and residue lines. The X and Y axes were reflectance intensities in waveband 1 and waveband 2 (modified from Biard and Baret, 1997).



McNarin and Protz (1993) applied linear regression to Landsat thematic mapper derived indexes and percentage residue cover measured in the field and found TM bands 4 and 5 were most strongly related to percentage residue cover. They correctly classify 65 percent of lighter-colored sandy fields into one of three residue categories and 92 percent of darker silty soils. Using logistic regression, vanDeventer et al. (1997) determined that a ratio of thematic mapper bands 5 and 7 was most strongly correlated with crop residue type. They achieved 93 percent classification accuracy of tillage type into either a conventional or a conservation practice. Gowda et al. (2001) extended this approach and obtained up to 77 percent classification accuracy for two residue cover categories. As noted by others, both vanDeventer et al. (1997) and McNarin and Protz (1993) attribute increased classification accuracy for darker soils to the greater contrast with light-colored residues.

The Crop Residue Index Multiband model developed by Biard and Baret (1997) is a unique semi-physical approach based on a linear mixing model of composite soil and residue reflectance. It requires that bare soil and pure residue reflectance spectra are known (Figure 1). A laboratory test of their linear mixing model showed that the relationship of Crop Residue Index Multiband model predicted vs. measured residue cover was very strong ($R^2 = 0.988$).

The objectives of this study were; 1) to evaluate the accuracy of the currently implemented Tillage Transect Survey; 2) to determine the absolute accuracy of published optical remote sensing models; and 3) to determine the accuracy of new simple empirical models by comparing model predictions to in-field residue cover measurements.

Materials and Methods

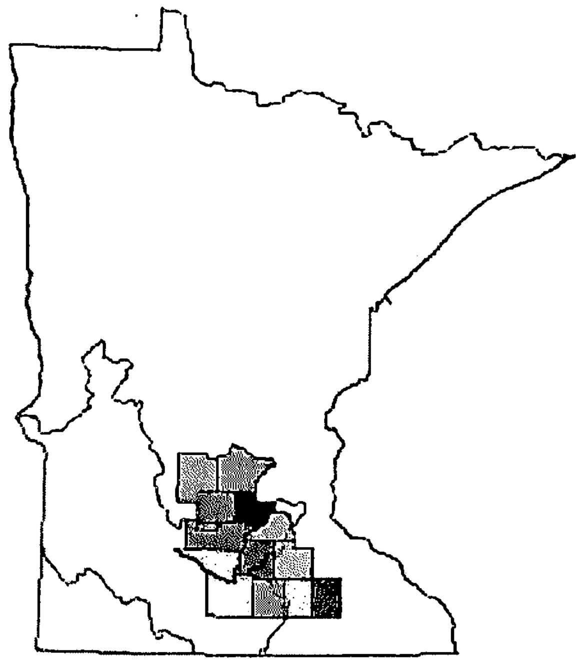
Ground measurements. The ground reference data used in this project were collected with a modification of the line transect method described by Morrison et al. (1993). A 3.05 m (10 ft) length of 2.5 cm (1 in) diameter PVC pipe was marked every 15.2 cm (6 in). The pipe was laid perpendicular to tillage direction at multiple random locations within fields. At each tick mark on the pipe an observer looking vertically straight down on one side of the pipe noted the presence or absence of crop residues. The reliability of this method for obtaining repeatable measures of residue cover was determined by intensively sampling several large fields in December 1999. These data were used to determine appropriate sample sizes needed to obtain a repeatable measure of crop residue cover.

A total of 468 corn and/or soybean fields were sampled in 13 southern Minnesota counties (Figure 2) using the above method in the course of three sampling campaigns coinciding in time with three Landsat 7 ETM+ satellite scene acquisitions. All fields were sampled within five days of scene acquisition to minimize the possibility of changes in surface conditions (i.e. tillage) that would not be represented in the scene. Residue type was also noted for each field. To eliminate mixed pixel effects line transects were chosen to avoid field, topographic, or soil type boundaries. The locations of all fields sampled were recorded with a 'sportsman grade' global positioning system (GPS) that measured positions to within 10 m (32.81 ft) of true location. Fifty percent of the sampled fields were withheld for model validation. Each optical model (McNarin and Protz, 1993; vanDeventer et al. 1997; Biard and Baret, 1997) and the Tillage Transect Survey data was evaluated by comparing computed percentage residue cover vs. residue cover measured in the field using the modified line transect method.

We physically measured residue cover using the modified line transect method in 161 fields that were part of the Tillage Transect Survey. Fields were chosen based on a random start point and sampling of every n^{th} field thereafter along Tillage Transect Survey routes (Congalton and Green, 1999). For these fields, physically measured percentage residue cover values were placed in categories (0 to 15, 16 to 30, 31 to 50, 51 to 75, and 76 to 100 percent) corresponding to those used in the Tillage Transect Survey. This allowed measured percentage residue cover to be compared directly with visually estimated residue cover obtained by Tillage Transect Survey observers. Agreement was tabulated to determine the number of fields correctly classified by observers using the physically measured percentage as the reference standard.

Imagery. Landsat ETM+ satellite images were obtained for 28 March 2000, 3 June 2001, and 10 November 2001. The June

Figure 2
The Minnesota River Basin watershed and location of counties in and near the Minnesota River Basin where fields were sampled for crop residue cover in 1999, 2000 and 2001. The counties sampled were: McLeod, Carver, Sibley, Scott, Wright, Nicollet, Meeker, LeSueur, Rice, Blue Earth, Waseca, Steele, and Dodge.



scene represented spring residue cover conditions after planting while the November scene represented residue cover after fall tillage. In general, the November scene had the driest soil conditions with an average of 18 days having passed since precipitation. The June and March scenes had dry surface crusts, but moist subsurface conditions resulting from up to 1.5 cm (0.6 in) of precipitation in some locations two to four days prior to scene acquisition.

All scenes were georeferenced using road intersections visible on both USGS 7.5' digital orthophoto quadrangles and the satellite image. The accuracy of registration was evaluated by root-mean-square (RMS) error and was maintained < 0.30 pixel (10 m or 32.8 ft) for all three scenes. Each scene was radiometrically and atmospherically corrected using the cosine of sun angle and dark object subtraction method of Chavez (1996), or normalized with the multiple-date empirical radiometric normalization method described by Jensen (1996). In the remainder of this paper cosine of sun angle and dark object subtraction corrected pixels were reflectance corrected, while multiple-date empirical radiometric normalization method pixels were empirically corrected brightness values. Digital number refers to un-corrected pixel brightness values.

Table 1. Average accuracy of the Tillage Transect Survey visual classifications of crop residue cover conducted by agency personnel in three Minnesota counties.

Number of Categories[§]	Corn + Bean n = 161[ξ]	Corn n = 100	Bean n = 53
	% Fields correctly classified		
5[α]	49	50	45
3[β]	74	70	77
2[ε]	74	70	77

[§] The number of categories between 0 and 100% into which residue cover was grouped for classification assessment.

[α] Categories were: 0 to 15, 16 to 30, 31 to 50, 51 to 75, 76 to 100 percent

[β] Categories were: 0 to 30, 31 to 75, 76 to 100 percent

[ε] Categories were: 0 to 30, 31 to 100 percent

[ξ] The Bean + Corn data groupings were not the sum of Bean and Corn groups because additional fields that had both corn and soybean residue mixed in the same field were included in the Bean + Corn group.

An area of interest polygon was drawn on the image around portions of fields where physical measurements of residue cover were made via the modified line transect method. Due to errors inherent in scene registration that induce positional uncertainty of up to one-third pixel we focused our analysis on a cluster of nine pixels that encompassed the area sampled in the field, thus ensuring that the area sampled in the field was included in the area of interest. The pixel values within the area of interest were extracted for the six visible and near-infrared bands and arithmetically averaged for regression analysis. Data were grouped by digital number, multiple-date empirical radiometric normalization, or cosine of sun angle and dark object subtraction method to evaluate the effectiveness of atmospheric correction on predictive capability of the models. Within these groups, data were analyzed by residue type to determine whether corn or soybean residue was more easily discriminated from bare soil backgrounds.

Soil and residue lines for the Crop Residue Index Multiband model were typically determined by regression on Landsat band three versus band five values from completely covered or completely bare fields (Biard and Baret, 1997). In this study, residue predictions using this approach of determining soil and residue lines were poor and for this reason, an alternative method was tested where the soil line was determined as a line drawn through the 'darkest' two pixels that could form a lower bound for the cloud of all points plotted in two-band feature space. Similarly, the residue line was determined as a line drawn through the 'brightest' two pixels that were not bare light colored fields. Percent residue cover was determined computationally as the ratio of two angles, that between the soil and residue line, and that defined by a vector passing through the mixed pixel and the intersection of the soil and residue lines.

Results and Discussion

Evaluation of in-field measurement of residue cover. On December 13, 1999 we intensively sampled corn residue fields that had been moldboard plowed, and chisel plowed. Results indicated that approximately 200 tick-points were sufficient to provide a repeatable measure of residue cover (within five percent of the mean) for both chisel and moldboard plowed fields. This is in agreement with findings of Laflen et al. (1981) for minimizing variance in corn residue cover estimates.

Evaluation of Tillage Transect Survey. The residue cover estimates of the Tillage Transect Survey for the soybean and corn fields ranged from 45 to 77 percent correct, depending on the type of residue and number of categories into which residue cover was grouped (Table 1). For this reason only in-field line-transect measurements of residue cover were used for remote sensing model development and evaluation.

The relatively poor classification accuracy achieved by Tillage Transect Survey observers using five cover categories was likely due in part to making observations at oblique view angles. When viewed obliquely, exposed soil was more difficult to see which generally resulted in overestimation of crop residue for categories less than 25 percent (Table 2). Approximately 15 percent of all fields sampled by the line-transect method in this study fell between 25 and 35 percent residue cover, a cover range important for discriminating between conservation and conventional tillage, which was mis-classified 58 percent of the time by Tillage Transect Survey personnel.

Table 2. Evaluation of Tillage Transect Survey (TTS) observer error. Percentage of TTS visual classifications of crop residue cover that were below, above or equal to the category determined by in-field measures of crop residue.

Cover category[§]	n[α]	% Visual estimates: Below	Above	Equal
0-9.9%	55	0	27	73
10-19.9%	38	8	55	37
20-24.9%	18	39	56	5
25-34.9%	24	46	12	42
35-44.9%	12	25	0	75
45-54.9%	7	86	0	14
55-69.9%	6	50	0	50
70-100%	1	0	0	100

[§] Categories in italics were chosen to represent +/- 5% of the upper boundary used in each of the TTS classification system categories.

[α] Fields of corn and or soybean residue classified via the TTS survey crew and independently using the in-field line transect method.

Evaluation of published regression models. Other researchers have published models for predicting crop residue cover using Landsat imagery (McNarin and Protz, 1993; vanDeventer et al., 1997). The Soil Tillage Index and Normalized Difference Tillage Index indices of vanDeventer et al. (1997), using bands 5 and 7, generally out performed the Normalized Difference Index of McNarin and Protz (1993), using bands 4 and 5 (Table 3), which may be due to cellulose absorption in band 7. These indices were tested with digital number and atmospherically corrected, and radiometrically normalized pixel values. When data from all three scenes were combined the indices computed from digital number values outperformed those computed from atmospherically corrected and multiple-date empirical radiometric normalization method corrected scenes, indicating the atmospheric correction methods did not improve discrimination of residues from soil backgrounds. This lack of improvement with corrective measures may reflect the atmospherically clear conditions at the time of scene acquisitions.

Given that these indices were empirically derived, there was no physical explanation for their performance ranking based on coefficients of determination. In general, the results showed that the indices suggested by McNarin and Protz (1993) and vanDeventer et al. (1997) were poor predictors of residue cover for the conditions tested in this study.

Evaluation of new regression models. Using the ground reference database of measured residue cover, regression models were developed for digital number, multiple-date empirical radiometric normalization, and atmospherically corrected pixel values (Table 4) by splitting the data set and using half for calibration and half for validation. In all cases a three-band combination (3, 5, and 7) yielded the most efficient model. This was in agreement with vanDeventer et al. (1997) and Gowda et al. (2001). Inclusion of additional bands in regression models did not

Table 3. Coefficients of determination for indexes published in the literature when applied to Minnesota conditions.

Residue[ξ]	Signal[§]	n	r^2: NDI[α]	STI[β]	NDTI[ε]
Bean + Corn	DN	468	0.38	0.47	0.48
Bean + Corn	MERN	468	0.36	0.46	0.47
Bean + Corn	COST	468	0.10	0.40	0.08
Bean	DN	205	0.47	0.38	0.40
Bean	MERN	205	0.46	0.36	0.38
Bean	COST	205	0.06	0.05	0.19
Corn	DN	258	0.31	0.56	0.56
Corn	MERN	258	0.29	0.55	0.55
Corn	COST	258	0.13	0.03*	0.02*

[ξ] The Bean + Corn data groupings were not the sum of Bean and Corn groups because additional fields that had both corn and soybean residue mixed in the same field were included in the Bean + Corn group.

[§] Signal represents type of radiometric correction applied to scene for regression analysis
COST = pixel values were atmospherically corrected reflectance
DN = pixel values were uncorrected digital numbers
MERN = pixel values were empirically corrected digital numbers

[α]NDI = Normalized Difference Index (B4-B5)/(B4+B5) reported by McNairn and Protz (1993)

[β]STI = Soil Tillage Index (B5/B7) by van Deventer et al. (1997)

[ε]NDTI = Normalized Difference Tillage Index (B5-B7)/(B5+B7) by van Deventer et al. (1997)

* All p-values were ≤ 0.05 except those marked which were ≤ 0.10

Table 4. A subset of all fields was used as a calibration data set to determine the best combination of three bands for predicting residue cover from best subsets regression of measured percent residue cover on satellite signal.

				Regression coefficients for ETM+ bands						
Residue[ξ]	Signal[§]	n[α]	r^2	Constant	1	2	3	4	5	7
Bean + Corn	DN	233	0.56	49.20		-2.24	2.96			-0.78
Bean + Corn	MERN	233	0.55	-64.70	1.52			0.83		-0.69
Bean + Corn	COST	233	0.51	11.30			906		-325	85
Bean	DN	101	0.66	78.80	-2.12		2.83			-0.70
Bean	MERN	101	0.60	-36.40		1.49		1.09	-0.69	
Bean	COST	101	0.56	-0.05			1094		-388	137
Corn	DN	128	0.44	33.00				0.42	1.50	-1.95
Corn	MERN	128	0.43	16.90				0.63	0.64	-0.96
Corn	COST	128	0.37	46.60		-695	1148		-241	

[ξ] The Bean + Corn data groupings were not the sum of Bean and Corn groups because additional fields that had both corn and soybean residue mixed in the same field were included in the Bean + Corn group

[§] Signal represents the type of radiometric processing used to account for atmosphere and sun angle
DN = pixel values were uncorrected digital numbers
MERN = pixel values were empirically corrected digital numbers
COST = pixel values were atmospherically corrected reflectance

[α] Half of the data were withheld for model validation.

substantially improve (> 4 percent) the coefficient of determination. An advantage to using linear regression of bands over band indices (such as those used in Table 3) was that in flat and non-shadowed landscapes the relative influence of individual bands in the model results remained independent (Lawrence and Ripple, 1998). Regression models developed with data collected locally were typically superior to models developed elsewhere, thus coefficients of determination in Table 4 were generally greater or equal to those in Table 3.

Regression relationships were stronger for soybean residue than for corn residue or a combination of soybean and corn residue (Table 4). It was unclear why soybean residue induced a more consistent satellite signal response. Based on coefficients of determination the models developed with digital number outperformed models developed with multiple-date empirical radiometric normalization or atmospherically corrected pixels. This again indicates that atmospheric correction did not substantially improve the results, most likely due to the relatively clear atmospheric conditions at times of scene acquisition.

The best regression equations from Table 4 were used to classify the test fields into five residue cover categories matching those used by Tillage Transect Survey personnel (Table 5). The choice of atmospheric correction had little effect on classification accuracy, except that classification accuracy for two categories was better for corn by 6 percent

Table 5. A subset of all fields not used in Table 4 was used to validate relationships. Coefficient of determination and accuracy of classification for best subsets regression models of Table 4 validated against measured residue cover.

				Number of residue categories*		
				5	3	2
Residue[ξ]	Signal[§]	n[α]	r^2	% Fields correctly classified		
Bean + Corn	DN	235	0.55	39	60	71
Bean + Corn	MERN	235	0.52	38	60	71
Bean + Corn	COST	235	0.46	34	55	67
Bean	DN	101	0.68	34	54	71
Bean	MERN	101	0.68	29	52	69
Bean	COST	101	0.62	40	57	73
Corn	DN	130	0.16	22	43	59
Corn	MERN	130	0.14	18	43	59
Corn	COST	130	0.2	19	45	65

[ξ] The Bean + Corn data groupings were not the sum of Bean and Corn groups because additional fields that had both corn and soybean residue mixed in the same field were included in the Bean + Corn group

[§] Signal represents the type of radiometric processing used to account for atmosphere and sun angle
DN = pixel values were uncorrected digital numbers
MERN = pixel values were empirically corrected digital numbers
COST = pixel values were atmospherically corrected reflectance

[α] Half of the data were withheld for model calibration

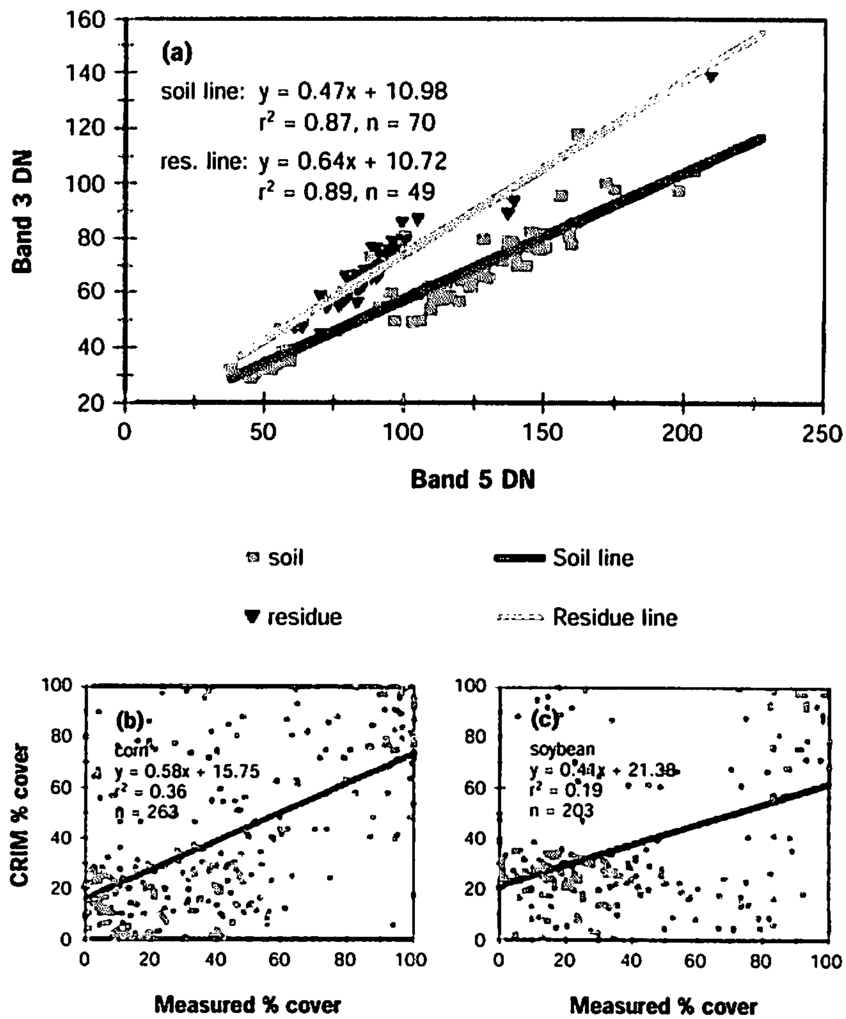
[*] Categories were same as those used in Table 1.

using the atmospherically corrected model. The accuracy of cover classification dramatically improved when fewer cover categories were used. Comparison of classification accuracy of the Tillage Transect Survey and atmospherically corrected empirical equations for two cover categories (Tables 1 and 5) indicated that the empirical approach was 7, 4 and 5 percent less accurate than Tillage Transect Survey accuracy for bean + corn, bean and corn residues respectively. This result indicated that a remote sensing approach to residue cover classification may be nearly as good as the imperfect Tillage Transect Survey, with the advantage of being able to sample every field.

Evaluation of the Crop Residue Index Multiband model using digital number values. Generally, soil and residue lines determined by linear regression on bare or no-till fields were clearly defined and the residue line was consistently brighter in feature space than the soil line. Good separation is highly desirable for accurate and consistent cover estimates. It is important to note that variability around the soil line was typically greater than the variability around the residue line (Figure 3a). The variability in the soil line was likely due to subtle differences in soil color, and soil roughness. The variability in the residue line was likely due to residue distribution in the field i.e. whether they were standing up or lying down, chopped or whole. Variance in either of these lines diminished the accuracy of Crop Residue Index Multiband model predictions. Outliers (ie. bright soils, and dark residues) had a strong influence and pulled the lines closer together in feature space. These factors partially explained why cover estimates developed using regression-based bounding lines were poor (r^2 = 0.31) when digital number values for three scenes and all crop residues were combined. Crop Residue Index Multiband accuracy improved when analysis was performed on corn fields only (r^2 = 0.36) (Figure 3b), but unexpectedly decreased (r^2 = 0.19) when performed on only soybean fields (Figure 3c).

Figure 3

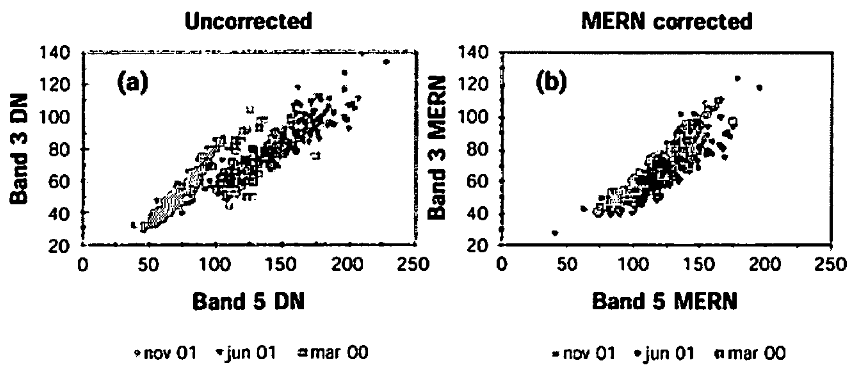
(a) Feature-space plot of fields representing either bare or no-till conditions in three different satellite scenes that have not been radiometrically or atmospherically corrected. The residue line consists of both corn and soybean residues. Fields used to make the residue line had greater than 90% cover and fields used to make the soil line had less than 10% cover. The CRIM model applied to these data explained 31% of the variance in residue cover for all fields. (b) Relationship between measured residue cover and CRIM computed residue cover for corn fields only. (c) Relationship between measured residue cover and CRIM computed residue cover for soybean fields only.



Evaluation of the Crop Residue Index Multiband model using multi-date radiometric correction. Results of the multiple-date empirical radiometric normalization correction presented in Figure 4 indicated that, in general, field pixels in the November scene were brighter than those in the June scene after correction. This was expected because the residues in November were less weathered than those in June. As residues weathered they began to decay and darken. This darkening was compounded as soil particles adhered to residue surfaces after precipitation and wind events.

After multiple-date empirical radiometric normalization correction soil and residue bounding lines were developed as a linear fit through three to five points that by visual inspection best represented the outer limit for bare soil and residue covered surfaces. The purpose of this technique for choosing bounding lines was to minimize the influence of outliers in placement of the lines and to maintain a more physical basis for the Crop Residue Index Multiband model where only bare fields and completely covered fields could be chosen to form the bounding line. Additionally, in this analysis the soil line was constructed from sampled bare fields that had less than five percent residue cover while the residue line was constructed from fields with greater than 95 percent residue cover. The bounding lines for all fields from all three

Figure 4
Results of the MERN correction for three satellite scenes. (a) Uncorrected pixels were more scattered than corrected pixels (b). The March 28, 2000 scene was used as the reference for the empirical correction.



satellite scenes in Figure 5a illustrated that this choice of bounding line excluded some points from the region between the lines. To overcome this limitation, points above the residue line were assigned 100 percent cover and points below the soil line were assigned 0 percent residue cover during Crop Residue Index Multiband estimation of residue cover.

The coefficients of determination for the Crop Residue Index Multiband model computed cover vs. measured residue cover were r^2 = 0.18, 0.25 and 0.16 for corn + bean, bean, and corn residues respectively (Figure 5b). Multiple-date empirical radiometric normalization correction of Crop Residue Index Multiband classification improved as the number of residue categories decreased, and was slightly better at classifying corn residues than the Tillage Transect Survey, but not as good as the Tillage Transect Survey for soybean residues in the two-category system (Tables 1and 6).

The imperfect performance of the Crop Residue Index Multiband model was in part attributed to variability in soil background reflectance as evidenced by scatter of bare fields around an idealized soil line. Ancillary information about soil color such as that available in digital soil surveys may improve Crop Residue Index Multiband model classifications by eliminating the positional uncertainty of a bare soil relative to the soil line.

Evaluation of the Crop Residue Index Multiband model using reflectance values. The Crop Residue Index Multiband model was also tested against crop residue cover after applying radiometric and atmospheric correction (Figure 6). Bounding lines were determined by creating vectors using the brightest and darkest pixel pairs. Although the coefficient of determination for the Crop Residue Index Multiband estimate of corn + soybean cover versus measured cover was very low for the November scene (r^2 = 0.06), it is interesting to note that the classification accuracy was greatest (80 percent) for this scene in the two-category classification scheme after an atmospheric correction (Table 7). The better classification accuracy in the November scene was likely due to un-weathered residues having the greatest contrast with background soils. Even though the soil and residue lines were further apart in feature space, giving a sense of greater contrast, the true vector for an individual field soil could not be known, thus error was introduced into Crop Residue Index Multiband model estimates of cover.

If the Crop Residue Index Multiband model predicted residue cover in an unbiased manner then the linear fit of Crop Residue Index Multiband estimates vs. measured cover would follow the 1:1 line with an equal number of observations on either side of the line. However, in both cases (Figure 7) the Crop Residue Index Multiband model overestimated residue cover in the low range, and underestimated residue cover in the high range. Even when different methods of choosing the residue lines were employed (i.e. using fields with > 90 percent cover vs. using only no-till fields), there was no substantial improvement in the accuracy of the Crop Residue Index Multiband model estimates. This coupled with the fact that residue line coefficients of determination were generally higher than soil line coefficients indicated that variability in the soil lines for individual fields may have been the dominant source of error in the Crop Residue Index Multiband estimates of residue cover.

Table 6. Classification accuracy of fields using digital number (DN), empirically corrected (MERN), or atmospherically corrected (COST) corrected pixels in the CRIM model for three ETM + scenes.

Signal§	Number of categories¶	Corn + Beans n = 484	Corn n = 263	Beans n = 203
		— % Fields correctly classified by CRIM —		
DN	5$^{\alpha}$	32	34	29
DN	3$^{\beta}$	55	56	45
DN	2$^{\epsilon}$	69	69	55
MERN	5$^{\alpha}$	31	30	34
MERN	3$^{\beta}$	49	42	55
MERN	2$^{\epsilon}$	66	64	72
COST	5$^{\alpha}$	23	28	33
COST	3$^{\beta}$	49	52	53
COST	2$^{\epsilon}$	61	69	71

§ Signal represents the type of radiometric processing used to account for atmosphere and sun angle
DN = pixel values were uncorrected digital numbers
MERN = pixel values were empirically corrected digital numbers
COST = pixel values were atmospherically corrected reflectance

¶ The number of categories between 0 and 100% into which residue cover was grouped for classification assessment.

$^{\alpha}$ Categories were: 0-15, 16-30, 31-50-51-75, 76-100%

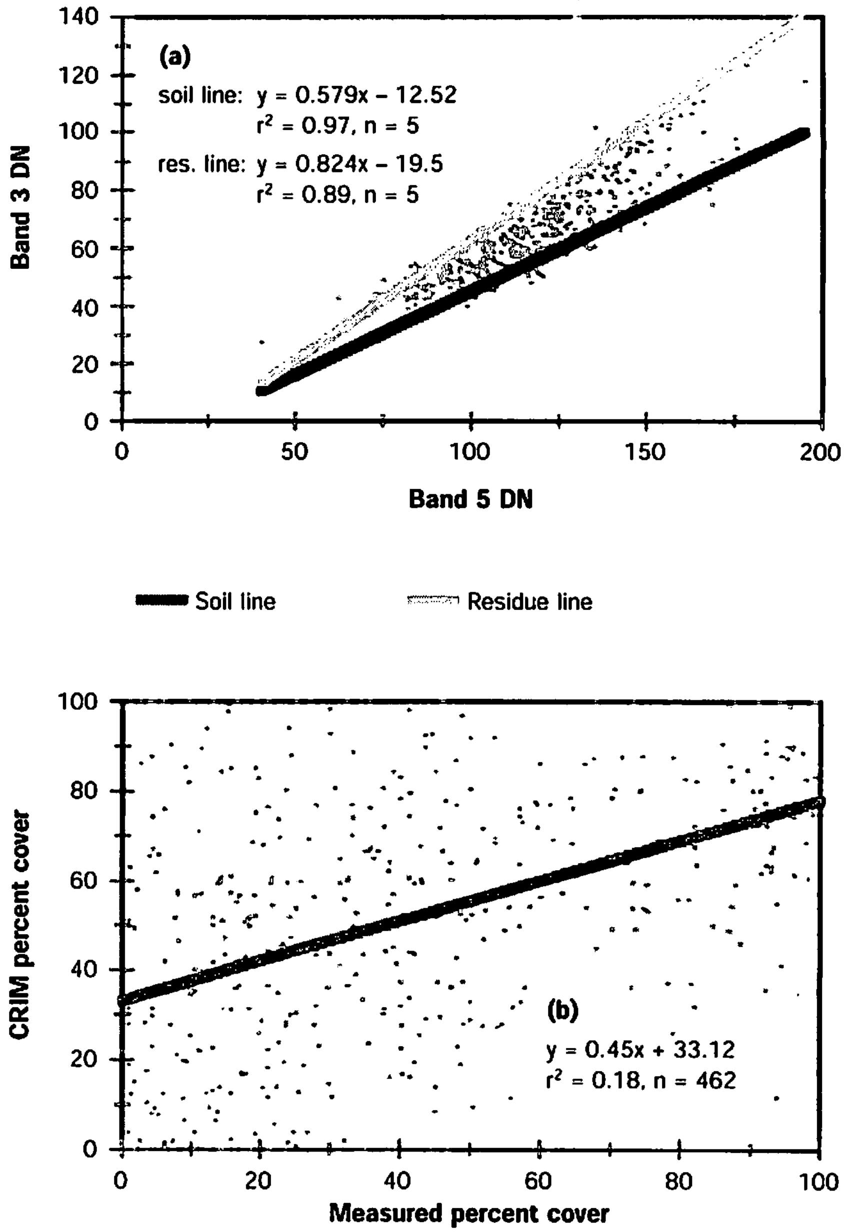
$^{\beta}$ Categories were: 0-30, 31-75, 76-100%

$^{\epsilon}$ Categories were: 0-30, 31-100%

In order to make a direct comparison between the Crop Residue Index Multiband model and the Tillage Transect Survey, Crop Residue Index Multiband residue cover estimates were grouped into the residue cover categories used in the Tillage Transect Survey (Table 7). Atmospherically corrected pixels were used because they would provide a physically based input to a physically based model. In most classification schemes, the Crop Residue Index Multiband estimates were better for the November scene when the residues were least weathered. As expected, classification accuracy improved as number of categories decreased. Comparison of Crop Residue Index Multiband classification accuracy with Tillage Transect Survey accuracy (Tables 1 and 7) showed that Tillage Transect Survey accuracy was better than Crop Residue Index Multiband for classification schemes with greater than two classes. However, when two-category Crop Residue Index Multiband estimates were averaged for the three months sampled in this study they approached the classification accuracy of the Tillage Transect Survey. The average classification accuracy of Crop Residue Index Multiband was 61, 69, and 71 percent compared to Tillage Transect Survey accuracy of 74, 70, and 77 percent for bean + corn, corn and bean residues respectively. The atmospherically corrected Crop Residue Index Multiband model had better classification accuracy than the Tillage Transect Survey for the two-category scheme in the month of November for all groupings of residue. This result was likely due to the un-weathered nature of residue in the fall (Wanjura and Bilbro, 1986).

Figure 5

(a) MERN corrected feature space plot of corn and soybean residue fields for three scenes with bounding lines determined via regression. Fields used to make the residue line had greater than 95% cover while fields used to make the soil line had less than 5% cover. (b) Relationship between measured residue cover and CRIM computed residue cover.

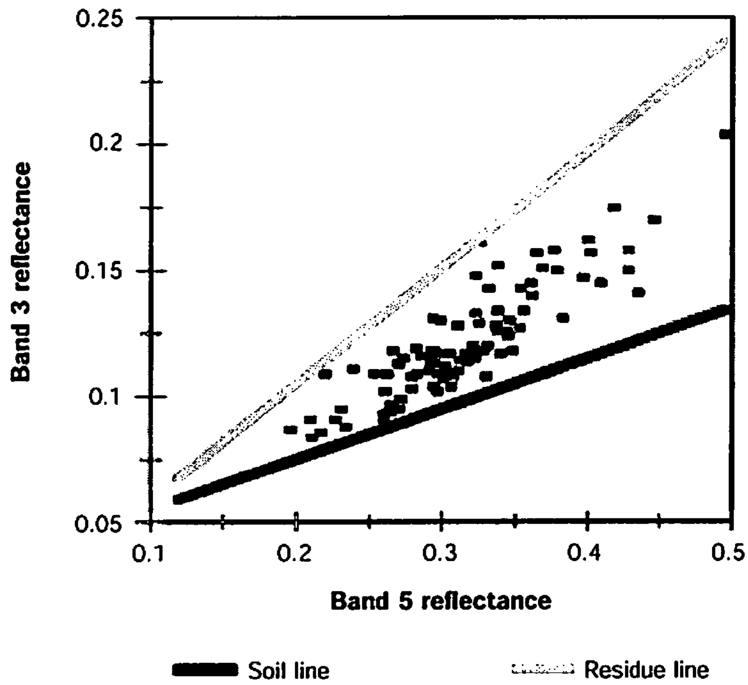


Summary and Conclusion

The Tillage Transect Survey currently used for estimating crop residue cover over large geographic areas is plagued by numerous problems. Different personnel in each county conduct the survey; observers are inherently biased; and it represents only a small sample of fields in each county. For these and other reasons the Tillage Transect Survey has been shown to classify percentage residue cover correctly only 45 to 50 percent of the time as it is currently implemented. This study showed that classification accuracy would improve if fewer residue cover categories were used. This study also showed it was difficult to discriminate small differences in residue cover near the 30 percent category boundary used to differentiate conservation tillage from non-conservation tillage practices. Human observers may not achieve two category classification accuracy much above 58 percent because fields near the category boundary combined with oblique viewing angles obscure bare soil.

Various methods of predicting residue cover using reflectance measurements from Landsat ETM+ satellite scenes had accuracies as good as or better than the Tillage Transect Survey estimates when fields were grouped into only two cover categories. Since many applications require knowing the extent of conservation and conventional tillage (two categories, < 30 percent or > 30 percent cover), it is likely that remote sensing

Figure 6
All corn and soybean residue fields from June and November campaigns plotted in atmospherically corrected (COST) feature space with bounding lines determined by the brightest and darkest pixel pairs.



techniques using Landsat imagery have the potential for being more efficient and economical than the Tillage Transect Survey. Furthermore, remote sensing techniques have the advantage of providing a uniform methodology that has less operative bias than the Tillage Transect Survey technique and covers large areas completely rather than small sub-samples of fields along transects.

Simple linear regression of digital number on percentage residue cover provided a good method of discriminating crop residues in varied landscapes of south-central Minnesota. Although the ease of operability was appealing for using this approach, there were pitfalls. These relationships must be made by time-consuming ground verification and may only be valid for an individual scene. Converting digital number values to reflectance allows the relationship to be extended in time, but not in space.

The Crop Residue Index Multiband model had good potential for residue cover classification, and could be used with either digital number or reflectance pixel values. There are advantages and disadvantages to each. Digital number values or empirically corrected values are easily obtained from satellite imagery with minimal processing. However, because digital number values are not atmospherically corrected, Crop Residue Index Multiband results may only be valid for an individual scene meaning new soil and residue lines for Crop Residue Index Multiband calculations would be required for each new satellite scene. While not difficult, this would require field verification of no-till and completely bare fields. Digital number values for these locations could serve as a means to construct soil and residue lines that are unique to the atmospheric and radiometric conditions of that particular scene. The advantage of using reflectance values in the Crop Residue Index Multiband model is that once soil and residue lines for a given geographic region were defined, they could be used with any scene obtained in the future without the necessity of carrying out more field work. The disadvantage is that radiometric and atmospheric corrections are more difficult and require a higher level of processing. Results from this study indicated that the method for selecting the residue line, regression analysis or the 'brightest pixel pair' may not be important due to the consistent reflectance response of completely residue covered fields. However, the best method for selecting the soil line is the 'darkest pixel pair' because this method eliminated variance in the soil reflectance due to inherent variability in soil properties across the landscape.

In this study, there was no significant improvement in classification accuracy resulting from choice of atmospheric correction. This indicated atmospheric correction may be unimportant if scenes were collected at times of atmospherically clear conditions. However, cloud interference will remain a vexing problem. Too often cloudy conditions occur coincident with satellite overpass.

Figure 7
(a) Relationship between measured corn residue cover and CRIM computed residue cover for June and November 2001 scenes. (b) Relationship between measured soybean residue cover and CRIM computed residue cover for June and November 2001 scenes.

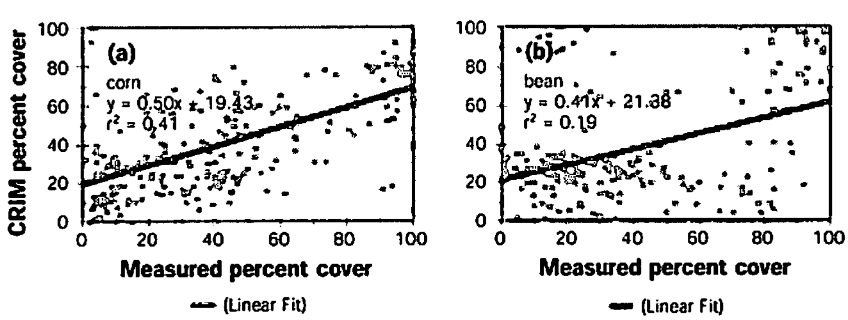


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Table 7. Classification accuracy by month of year for fields using COST corrected pixels in the CRIM model for three ETM+ scenes.

Number of Categories[§]	Bean + Corn Mar	Bean + Corn Jun	Bean + Corn Nov	Corn Mar	Corn Jun	Corn Nov	Bean Mar	Bean Jun	Bean Nov
	% Fields correctly classified by CRIM								
5[α]	22	15	32	21	33	30	25	38	38
3[β]	51	33	62	56	54	47	39	65	55
2[ε]	58	45	80	65	64	79	68	65	79

[§] The number of categories between 0 and 100% into which residue cover was grouped for classification assessment.

[α] Categories were: 0-15, 16-30, 31-50-51-75, 76-100%

[β] Categories were: 0-30, 31-75, 76-100%

[ε] Categories were: 0-30, 31-100%

and Water Conservation District offices for their cooperation in identifying transects along which residue measurements were made.

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