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Estimating Mean Field Residue Cover on Midwestern Soils Using Satellite Imagery

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ABSTRACT

Knowledge of residue cover is crucial for targeting conservation efforts to reduce soil erosion, runoff, and associated environmental impacts; however, a rapid, accurate, inexpensive methodology is not currently available. Previous studies have shown mixed results detecting crop residue using Landsat residue indices, but conditions generally included poor soil color contrast, emergent vegetation, or categorized residue cover. Our objectives were to evaluate a new normalized difference residue index (NDRI), along with other indices, over multiple image dates in 2005 and 2006 on dark soils in north-central Iowa. An automated method for field boundary delineation was used. The NDRI, using Landsat Bands 3 and 7, performed best overall, explaining 81% of the residue cover differences overall, 78% before emergence, and 9% after emergence. The normalized difference tillage index (NDTI), using Landsat Bands 5 and 7, also performed well explaining 68% of the variation overall, 86% before emergence, and 6% after emergence. Introduction of an empirical correction of the influence of green vegetation improved index performance. The NDTI outperformed the NDRI after green vegetation correction, explaining 67% of the variation versus 63%. The NDTI also returned the best RMSE (0.11) under preemergence conditions, and 0.15 after green vegetation correction. Generally, indices utilizing Landsat Band 7, which contain lignin and cellulose absorption bands absent in soil, returned the best residue detection results. Indices utilizing Landsat Band 4, where the reflectance of green vegetation is high, had difficulty detecting residue cover, especially after plant emergence.

Soil erosion remains a significant environmental problem despite decades of research into erosion mechanics and prediction and billions of dollars spent on soil conservation practices. It contributes to local and global problems of reduced topsoil depth and, along with streambank erosion, to excess sediment and nutrient problems in inland and coastal waterbodies, costing billions of dollars per year (Pimentel et al., 1995). To combat these problems, cost-effective best management practices, such as maintaining high levels of residue cover, have been developed to improve environmental quality. Maintaining increased amounts of residue on the soil surface has been shown to reduce water runoff and soil erosion (Blough et al., 1990), and build SOC (Halvorson et al., 2002, Moorman et al., 2004), all while reducing fertilizer and fuel inputs and maintaining a healthy environment for plant growth. Consequently, adoption of minimum or no tillage techniques has increased residue cover and decreased erosion significantly over the past few decades; however, 28% of the nation's total cropland still erodes at levels above the soil loss tolerance rate (USDA-Natural Resource Conservation Service, 2006), indicating that more cropland would benefit from conservation tillage. Erosion risk and adoption of conservation tillage varies across geographic regions, creating the need for targeted education efforts about conservation tillage practices, monitoring of conservation tillage adoption, and modeling of the impacts of tillage and residue harvesting. Current methods for assessing residue cover and conservation tillage adoption utilize ground-based observations which dramatically increase the time and cost required to produce an estimate. Remote sensing could provide consistent, inexpensive, and accurate estimates of residue cover over large areas.

Remote sensing has been repeatedly evaluated as a method to provide rapid and inexpensive estimates of residue cover with varying degrees of success. Initial attempts (Gausman et al., 1975) reported difficulties in estimating residue cover from the bands observed by the early Landsat multispectral scanner due to the similarity of soil and residue spectra. However, Viña et al. (2003) successfully used similar wavelengths with Ikonos high spatial resolution data to correctly classify conventional and conservation tillage fields 76% of the time using logistic regression.

The addition of shortwave infrared bands in the Thematic Mapper (TM) on Landsats 4 and 5 and the Enhanced Thematic Mapper Plus (ETM+) on Landsat 7 facilitated additional research into residue cover indices; however, the results are

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Abbreviations: CAI, cellulose absorption index; CRIM, crop residue index multiband; DN, digital numbers; ETM+, Enhanced Thematic Mapper Plus; LCA, lignin cellulose absorption index; NDRI, normalized difference residue index; NDSVI, normalized difference senescent vegetation index; NDVI, normalized difference vegetation index; NDTI, normalized difference tillage index; SACRI, soil adjusted crop residue indices; TM, Thematic Mapper.

mixed. McNairn and Protz (1993) found that the normalized difference index with Band 5 (NDI5, Eq. [2]) using TM Bands 4 and 5 was most strongly related to percentage residue cover with 65% of light colored sandy soils and 92% of darker colored silty soils being accurately classified into three residue categories. Van Deventer et al. (1997) used logistic regression on Landsat TM imagery of glacial till and lake plain soils in Ohio and found that the functionally equivalent indices, the NDTI (Eq. [4]) and the Soil Tillage Index (STI = TM5/TM7), were the best predictors of conservation tillage status by correctly classifying fields 93% of the time over both soil types.

Alternatively, both Biard and Baret (1997) and Arsenault and Bonn (2005) found that, with ground-based radiometers collecting radiance representing TM Bands 2, 3, 4, and 5, a crop residue index multiband (CRIM) model performed better (r^2 up to 0.954) than the NDI5, NDTI, and soil adjusted crop residue indices (SACRI; Biard et al., 1995). Gowda et al. (2001) evaluated the NDTI, STI, and four other models proposed by van Deventer et al. (1997) on southern Minnesota soils and found that models using TM Band 5 or the difference of TM Bands 3 and 5 correctly classified fields into conservation and conventional tillage categories 70 and 77% of the time, respectively. Soil organic matter, soil moisture content, and soil color were also found to be important in predicting residue cover. Bricklemyer et al. (2002) found that logistic regression adequately (>95%) identified no-till fallow fields from tilled fields on light colored soils in Montana. Bricklemyer et al. (2006) found similar conclusions to Bricklemyer et al. (2002) with logistic regression identifying no-till fields (94%) better than Classification Tree Analysis or Boosted Classification Tree Analysis; emergent vegetation was noted as a problem. Although logistic regression may be well suited to estimating a field's no-till status, it does not provide information on the actual fraction of residue cover which is helpful in determining which tillage operations were conducted at what time.

Fractional residue cover estimation directly from indices can provide this information. Thoma et al. (2004) compared NDI5, STI, NDTI, CRIM, and multiple linear regression models using raw digital numbers (DN) and two different radiometric correction methods against measured residue cover for fields in southern Minnesota. Indices calculated using DN performed better than either correction method, and the linear regression models best predicted the overall residue cover of corn (*Zea mays* L.) and soybean [*Glycine max* (L.) Merr.] followed by NDTI, STI, NDI5, and CRIM, ranked by the coefficients of determination (Thoma et al., 2004). Accuracy of predictions also varied depending on residue type, soil color, and imagery date, with a decrease in accuracy of tillage indices from November to March to June. Although no data were provided on the amount of green vegetation in the scene, it could be hypothesized that the decreasing accuracy was due to increasing amounts of green vegetation.

Research by Daughtry et al. (2005, 2006) and Daughtry and Hunt (2008) indicates that high spectral resolution indices utilizing specific absorption features of cellulose and lignin, such as the cellulose absorption index (CAI; Daughtry, 2001) and lignin cellulose absorption index (LCA; Daughtry et al., 2005), may provide much better quantification of crop residue than the NDTI, NDI5, or the normalized difference senescent vegetation index (NDSVI, Eq. [5]; Qi et al., 2002), especially in challenging conditions such as variable soil moisture and light soil color. However, in addition to these problems, it should be noted that in both studies, fields with up to 30% vegetation cover were combined with preemergent fields which could cause green vegetation to obscure index response; a problem also noted by Sullivan et al. (2006).

Although the recent research into CAI and LCA is encouraging, there are no plans for use of such sensors in an operational program, limiting their use to research applications for the foreseeable future. Alternatively, Landsat 5 TM and Landsat 7 ETM+ image collection, although currently of limited capabilities, will be followed by the Landsat Data Continuity Mission, indicating that additional research into TM imagery for large scale estimation of residue cover under field conditions is still needed. This leads to the objectives for this paper: (i) develop a new residue index and evaluate, along with previously developed indices, its ability to detect residue on high contrast dark soils in the presence and absence of green vegetation; and (ii) evaluate methods to enhance the accuracy of residue indices in the presence of green vegetation.

MATERIALS AND METHODS

Remote Sensing Imagery Collection

Thirty-meter Landsat 5 TM imagery of the target fields was collected on 3 Apr., 30 May, and 6 June 2005, and 15 Apr. and 2 June 2006. Images were received as GeoTIFF single band images, which were merged into a seven band scene. Each scene was then georeferenced using the ERDAS IMAGINE 9.0 (Leica Geosystems AG, St. Gallen, Switzerland) Georeferencing Wizard using 10-m aerial photography as the reference and red band for correlation. The RMSE for each of the five scenes were less than 0.5 pixels. Images were visually inspected for cloud cover and impacted fields were removed from surface residue calculation and soil/residue line calibration.

Surface soil moisture conditions have been previously shown to impact soil reflectance and classification results (van Deventer et al., 1997; Daughtry and Hunt, 2008). The focus of this research on production remote sensing meant that detailed investigations into soil surface moisture were not conducted; however, precipitation records were analyzed and it was noted that between 2 to 4 d had passed since significant precipitation (>0.25 mm) on all dates, which allowed the surface layer to dry for most fields.

Ground Data Collection

Digital images of the soil surface were captured in 51 corn, 31 soybean, and one alfalfa (*Medicago sativa* supsp. *sativa*) field in the April to June 2005 tillage season, and 36 corn, 29 soybean, and 1 alfalfa field in the April 2006–June 2006 tillage season resulting in 293 unique combinations of field and imagery date. Residue cover type was categorized by the most recent crop. Tillage practices were documented and included moldboard plow, chisel plow, ripper, disk ripper, field cultivator, and no-till, with cover fraction ranging from near-zero to as high as possible (near 100% residue coverage of soil in corn and 60% in soybean residue). Fields were located in Boone, Story, and Hamilton counties on the Des Moines lobe of central Iowa, where soils consist of both glacial till and lake plain soils. Digital photographs were collected at three to seven locations

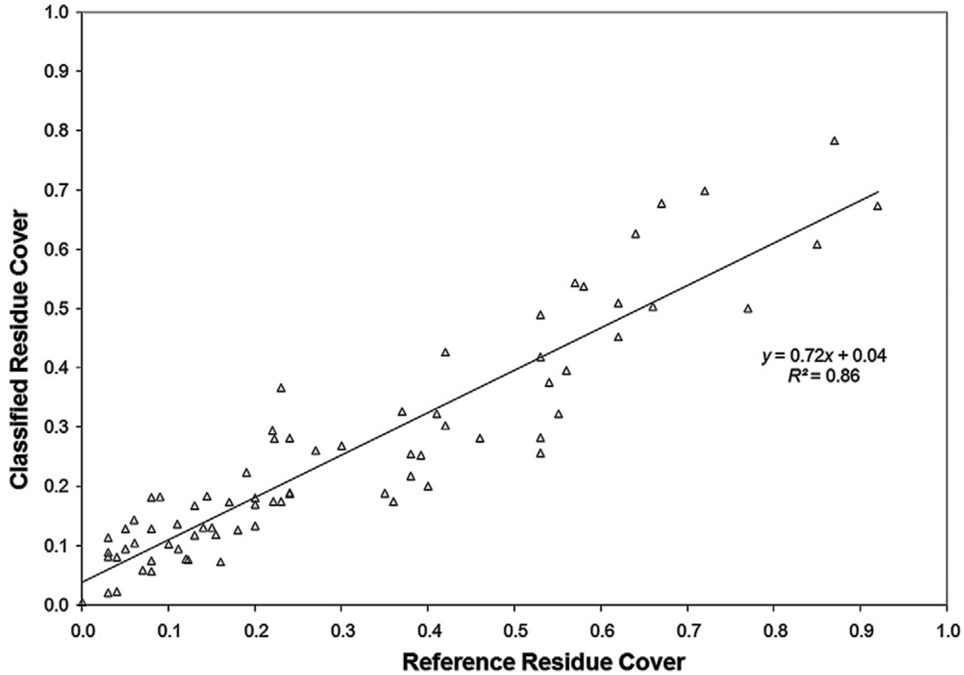

Fig. 1. Comparison of two estimates of fractional residue cover from digital photographs. Reference estimates were calculated using a regular 100-point grid and classified estimates were from unsupervised classification with classes identified by visual inspection.

per field. Locations were distributed around a random starting point and separated by about 30 m to obtain approximately one sample per 30-m pixel. Sample locations were captured with a wide area augmentation system (WAAS)-enabled GPS and were rephotographed after residue cover changed due to tillage or after 45 d had elapsed, whichever came first. Images were collected approximately 0.8 m above the soil surface using five- and seven-megapixel digital cameras aimed straight down to obtain approximately 1 m^2 of soil surface coverage per image.

Soil/residue images were saved in TIFF format and classified into 50 unsupervised categories using ERDAS IMAGINE 9.0. These categories were then assigned into residue and nonresidue classes by visual inspection. Accuracy was validated by projecting 10% of the photographs (n = 75) on a regular 100-point grid and determining the number of points covered by residue. This reference residue cover correlated well to classified residue cover with an r^2 of 0.86 and an RMSE of 0.07 (Fig. 1). However, the linear regression of reference to classified residue cover could not be described by a 1:1 regression at the 0.05 confidence level. Thus, the classified residue cover was corrected to reference residue cover using the regression shown in Fig. 1. After bias correction and consideration of the limitations of residue cover determination discussed in Laflen et al. (1981) and Morrison et al. (1995), especially in fields of high residue cover, the classification method was deemed accurate for further use.

Field boundaries of the sampled fields for index calculation were determined using the methodology given in Gelder et al. (2008), with the 2008 USDA Farm Service Agency (FSA) Common Land Unit (CLU) map (USDA-Farm Service Agency, 2007) and 2004 and 2005 USDA National Agricultural Statistics Service (NASS) Cropland Data Layers (CDL) (USDA-National Agricultural Statistics Service, 2007) as inputs. Field boundaries were buffered inwards by 45 m to remove georectification errors and fencerow and buffer strip impacts.

Spectral Index Development

Crop residue generally exhibits increasing reflectance throughout the visible and near-infrared wavelengths and decreases in the mid-infrared due to cellulose and lignin absorption at 2.1 and 2.3 μm, respectively (Fig. 2); however, the exact reflectance values depend on many factors including species, moisture content, and age of the residue (Nagler et al., 2000). Green vegetation, however, shows a significantly different response, with reflectance increasing sharply from Band 3 to Band 4 in growing plants, and decreasing by half from Band 4 to Band 5 and again by half from Band 5 to Band 7. Utilizing this knowledge of spectral reflectance, a normalized difference index utilizing Landsat Bands 7 and 3, where vegetation reflectance is similar, was hypothesized by the authors to minimize effects of green vegetation on residue detection. This index will be referred to as the NDRI.

$$\text{NDRI} = (\text{TM3} - \text{TM7})/(\text{TM3} + \text{TM7}) \quad [1]$$

Additional normalized difference indices tested also include the two indices of McNairn and Protz (1993),

$$\text{NDI5} = (\text{TM4} - \text{TM5})/(\text{TM4} + \text{TM5}) \quad [2]$$

$$\text{NDI7} = (\text{TM4} - \text{TM7})/(\text{TM4} + \text{TM7}) \quad [3]$$

the NDTI index of van Deventer et al. (1997),

$$\text{NDTI} = (\text{TM5} - \text{TM7})/(\text{TM5} + \text{TM7}) \quad [4]$$

and the NDSVI (Qi et al., 2002).

$$\text{NDSVI} = (\text{TM 5} - \text{TM3})/(\text{TM5} + \text{TM3}) \quad [5]$$

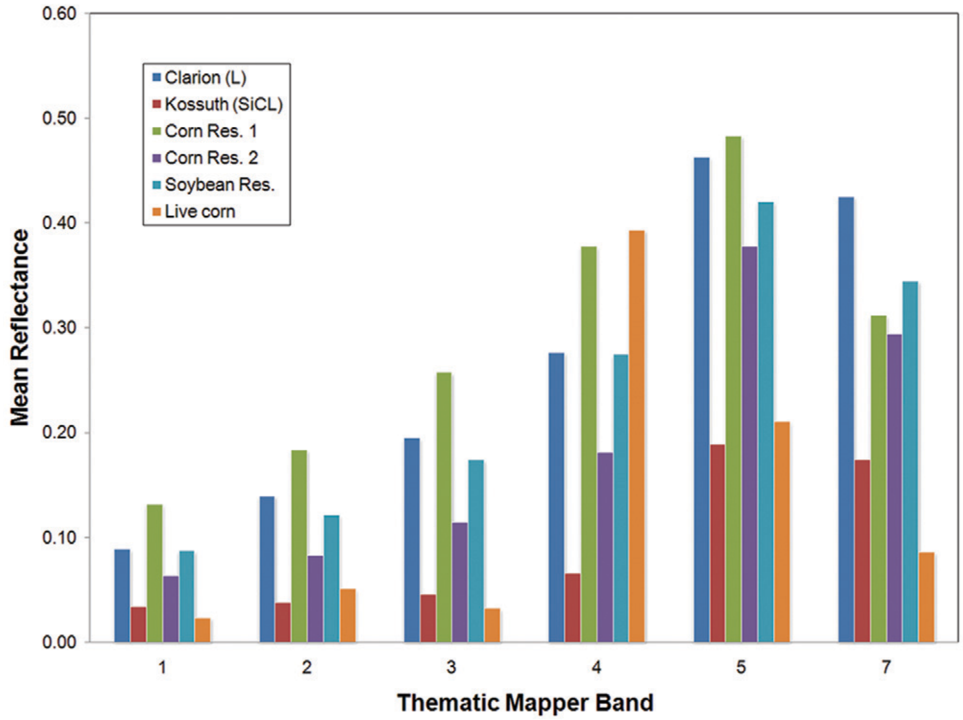

Fig. 2. Dry soil, dry residue, and green vegetation reflectance across Thematic Mapper Band 1 (0.45–0.52 μm), Band 2 (0.52–0.60 μm), Band 3 (0.63–0.69 μm), Band 4 (0.76–0.90 μm), Band 5 (1.55–1.75 μm), and Band 7 (2.08–2.35 μm). Values are means from 1 nm resolution spectra (C.S.T. Daughtry and G. Serbin, unpublished data, 2008).

Implementation of the CRIM was more complex and required selection of spectral bands for computation of characteristic soil and residue lines before index calculation began (Fig. 3). Based on previous research by Thoma et al. (2004), Landsat TM Bands 3, 4, 5, and 7 were chosen for analysis. The soil line and residue line for each band combination of the CRIM was calculated as the regression line of DN in one band versus the reference band (Fig. 3). Difficulty in locating fields defining

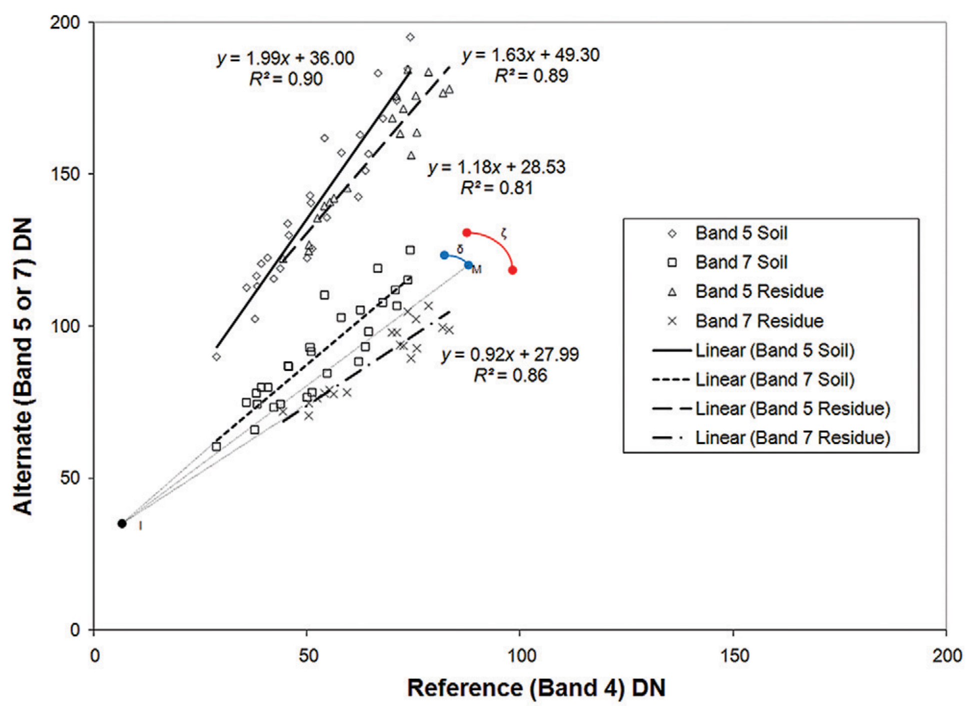

Fig. 3. Crop Residue Index Multiband (CRIM) concept in two-dimensional space with data from Bands 4, 5, and 7. I is the soil and residue line intersection, M is a field with unknown residue cover, δ (blue arc) is the angle between M and the soil line, and ζ (red arc) is the angle between the soil and residue lines.

pure soil and residue lines necessitated the use of fields with >0.50 mean residue cover fraction to define the residue line and the use of fields with <0.10 mean residue cover fraction to define the soil line. One complication with the use of impure soil and residue lines is that the range of resulting residue cover estimates, shown by the angle ζ in Fig. 3, is now compressed. To correct for this error, ζ was divided by the mean residue cover of the fields used to compute the residue line to expand the range back to 1.00. Estimates of residue cover less than the soil line were assigned a value halfway between the mean residue cover of the fields used to define the soil line and 0.

The soil adjusted crop residue index (SACRI; Biard et al., 1995), a derivative of both the normalized difference indices and the soil line concept, was also tested. It uses the slope (α) and intercept (β) of the soil regression line in Bands 4 and 5:

$$\mathrm{SACRI} = \alpha(\mathrm{TM4} - \mathrm{TM5} - \beta)/(\alpha\mathrm{TM4} + \mathrm{TM5} - \alpha\beta) \quad [6]$$

Analyzing the effects of green vegetation on residue cover indices necessitates the use of an index to estimate the presence and amount of live vegetation in the scene. The normalized difference vegetation index (NDVI; Rouse et al., 1974):

$$\mathrm{NDVI} = (\mathrm{TM4} - \mathrm{TM3})/(\mathrm{TM4} + \mathrm{TM3}) \quad [7]$$

was found sensitive to vegetative cover under low green vegetation fractions in corn (Gitelson et al., 2002).

Spectral Index Calculation

To calculate normalized difference indices on all fields, the 292 unique combinations of imagery dates and field boundaries were randomly divided into 195 calibration and 97 validation fields. To calculate CRIM and SACRI indices, the 195 calibration fields were further partitioned into soil and residue line calibration fields with <0.13 (n = 28, mean residue fraction = 0.07) and > 0.70 (n = 19, mean residue fraction = 0.87) residue cover fractions, respectively. The remaining calibration fields (n = 148) were used to increase validation to 245.

Index values were calculated using the mean DN over the sampled field. The DN were used because they consistently performed better in all classifications attempted by Thoma et al. (2004) and are computationally simpler than atmospherically corrected values; however, this can create problems when comparing different imagery dates. For the normalized difference indices and SACRI, the calibration data set was used to establish a linear least squares regression of index value versus residue cover. This linear regression was used to estimate residue cover on validation fields between zero and 100% The r^2 and RMSE were then calculated between mean classified residue cover and mean index estimated residue cover on both calibration and validation data sets.

To analyze the effects of vegetation on residue indices, fields were partitioned into pre- and postemergent categories using an NDVI of 0.065, the highest NDVI recorded in either the 3 Apr. 2005 or 15 Apr. 2006 preemergent images. The NDVI range of bare soil fields (fractional residue cover < 0.10, n = 15) was −0.054 to 0.062, and representative values for corn residue and green grass were 0.01 to 0.05 and 0.50 to 0.58, respectively. The 195 calibration fields from the overall analysis were decreased to 76 calibration fields by the 0.065 breakpoint and rejected fields were moved to validation, resulting in 40 preemergent and 176 postemergent validation fields for normalized indices. The 0.065 criteria also reduced the fields available to calibrate CRIM and SACRI a and b coefficients to 11 soil fields (mean residue fraction = 0.07) and 16 residue fields (mean residue fraction = 0.87). As before, linear regressions on the calibration data set were used to estimate residue cover, and r^2 and RMSE were calculated. Regressions were tested for date-specific responses by dummy variable coding.

Normalized Difference Vegetation Index Correction of Residue Indices

To investigate the possibility of correcting for the influence of green vegetation on residue cover indices, the postemergent fields (NDVI > 0.065) were divided into calibration (n = 118) and validation fields (n = 58). The difference between the residue cover index predicted from the measured residue cover and the calculated residue index was plotted versus the NDVI, and an increase in error with increasing NDVI was observed (Fig. 4). Least squares linear regressions were calculated for all indices and mean field NDVI was used to correct the index estimated residue cover to between zero and 100% The observed residue cover and the corrected residue cover estimate were used to calculate r^2 and RMSE.

RESULTS AND DISCUSSION

Overall Residue Indices

Normalized residue indices for all fields, shown in Table 1, returned validation r^2 between 0.01 and 0.81 with RMSE ranging from 0.15 to 0.50. The NDRI, which was selected to be resistant to vegetation impacts, performed best with a validation r^2 of 0.81 and RMSE of 0.15. The NDI5 and SACRI performed worst, with r^2 of near 0.00 and RMSE greater than 0.4; this is very poor, considering estimates were restricted to between 0.0 and 1.0, limiting possible error.

The CRIM soil and residue regression equations used to develop the CRIM and SACRI are shown in Table 2, along with associated r^2 values. The CRIM indices for all fields returned similar results to the normalized residue indices, shown in Table 3. $\mathrm{CRIM}_{5,7}$ performed best with an r^2 of 0.52 and RMSE of 0.14 and the $\mathrm{CRIM}_{4,5}$ performed worst with r^2 of 0.02 and RMSE of 0.42.

Overall, the best performing indices utilized TM Band 7, likely due to the cellulose and lignin absorption bands evident in residue and plants but absent in soils. Combinations of Band 7 with either Band 3 (NDRI, $\mathrm{CRIM}_{3,7}$) or Band 5 (NDTI, $\mathrm{CRIM}_{5,7}$) performed best, although combinations with Band 4, (NDI7, $\mathrm{CRIM}_{4,7}$) or the CRIM indices utilizing Band 7 in conjunction with 3 or 4 other bands, did not perform well. Errors in the indices utilizing Bands 4 and 5 are likely due to the similarity of soil and residue lines in these bands, this is shown in Fig. 3. This error also contributes to the trend of generally decreasing accuracy with increasing index dimensionality by impacting all three and four band CRIM models that include Bands 4 and 5. Errors in the three and four band implementations of the CRIM model estimates are also due to the approximations involved with solving the over-determined linear equations to compute the CRIM.

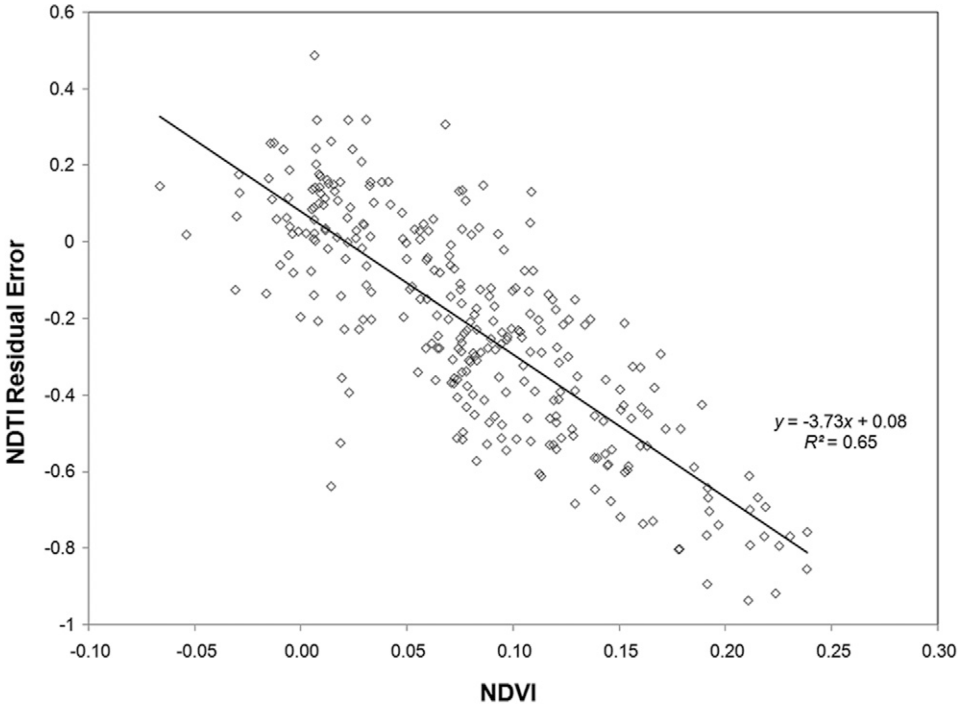

Fig. 4. Residual error (actual – predicted residue cover) plotted against normalized difference vegetative index (NDVI) for all fields. Predicted residue cover was estimated using residue cover versus index value for only preemergent fields (Eq. [17]).

Table 1. Fractional residue cover (FRC) estimates for all fields.

	Linear regression		Calibration (n = 195)		Validation (n = 97)	
Index†	Equation	Eq.	r^2	RMSE	r^2	RMSE
NDRI	FRC = 0.183 × NDRI – 0.358	[8]	0.56	0.18	0.81	0.15
NDI5	FRC = 0.043 × NDI5 – 0.453	[9]	0.04	0.44	0.05	0.46
NDI7	FRC = 0.124 × NDI7 – 0.266	[10]	0.21	0.31	0.23	0.35
NDTI	FRC = 0.073 × NDTI + 0.214	[11]	0.59	0.17	0.68	0.18
NDSVI	FRC = –0.092 × NDSVI + 0.531	[12]	0.34	0.26	0.67	0.20
SACRI	FRC = 0.251 × SACRI – 1.475	[13]	0.01	0.51	0.01	0.50

† ND15 and ND17, additional normalized difference indices of McNairn and Protz (1993); NDRI, normalized difference residue index; NDSVI, normalized difference senescent vegetation index; NDTI, normalized difference tillage index; SACRI, soil adjusted crop residue indices.

Dummy variable tests show that date was a significant factor (P < 0.10) in all residue cover index models. There are multiple explanations for this result, from differences in irradiance to soil moisture differences to green vegetation. The effects of green vegetation will be tested in the next section.

Residue Indices by Emergence Status

Table 4 shows results from the analysis of the normalized residue indexes broken out into pre- and postemergent categories. The regression of preemergent index value against residue cover returned higher r^2 than the overall regression for all indices, with r^2 varying from 0.32 to 0.86. This translated into better r^2 and RMSE for predicting residue cover on the preemergent validation dataset, with the NDRI and NDI7 both having r^2 better than 0.7 and the NDTI producing an r^2 of 0.86. RMSE also fared well, with NDRI, NDI7, and NDTI yielding RMSEs of 0.16, 0.16, and 0.11, respectively.

Most CRIM indices calibrated using preemergent fields did not show the same degree of improvement when compared with the indices calibrated using all fields, shown in Table 5. The $CRIM_{5,7}$ was still the best performing index, with r^2 increasing to 0.84 from 0.52 and RMSE remaining the same at 0.14.

Table 2. Crop residue index multiband (CRIM) and soil adjusted crop residue indices (SACRI) overall soil and residue lines.

Bands	Soil line (n = 28)	r^2	Residue line (n = 19)	r^2
3, 4	$1.304x + -6.009$	0.76	$1.252x + -9.124$	0.94
3, 5	$2.841x + 13.061$	0.82	$2.003x + 36.744$	0.80
3, 7	$1.761x + 11.304$	0.80	$1.123x + 21.366$	0.76
4, 5	$1.993x + 36.003$	0.90	$1.631x + 49.295$	0.89
4, 7	$1.179x + 28.532$	0.81	$0.921x + 27.995$	0.86
5, 7	$0.618x + 3.479$	0.98	$0.565x + 0.089$	0.97

Table 3. Validation (n = 245) of crop residue index multiband (CRIM) predictions for fractional residue cover.

	Overall	
CRIM	r^2	RMSE
3,4,5,7	0.32	0.29
3,4,5	0.16	0.24
3,4,7	0.43	0.23
3,5,7	0.41	0.24
4,5,7	0.08	0.35
3,4	0.25	0.29
3,5	0.27	0.29
3,7	0.50	0.20
4,5	0.02	0.42
4,7	0.14	0.26
5,7	0.52	0.14

Table 4. Fractional residue cover (FRC) estimates for pre- and postemergent (NDVI > 0.065) fields.†

	Preemergence							Postemergence validation (*n* = 176)	
	Linear regression		Calibration (*n* = 76)		Validation (*n* = 40)				
Index‡	Equation‡	Eq.	r^2	RMSE	r^2	RMSE		r^2	RMSE
NDRI	FRC = 0.156 × NDRI – 0.329	[14]	0.62	0.19	0.78	0.16		0.09	0.15
NDI5	FRC = 0.084 × NDI5 – 0.495	[15]	0.43	0.26	0.50	0.24		0.01	0.61
NDI7	FRC = 0.186 × NDI7 – 0.326	[16]	0.66	0.18	0.73	0.16		0.03	0.47
NDTI	FRC = 0.087 × NDTI + 0.203	[17]	0.84	0.12	0.86	0.11		0.06	0.26
NDSVI	FRC = –0.058 × NDSVI + 0.498	[18]	0.29	0.31	0.58	0.24		0.04	0.19
SACRI	FRC = 0.529 × SACRI – 1.619	[19]	0.37	0.28	0.32	0.29		0.02	0.69

† NDVI, normalized difference vegetation index.

‡ ND15 and ND17, additional normalized difference indices of McNairn and Protz (1993); NDRI, normalized difference residue index; NDSVI, normalized difference senescent vegetation index; NDTI, normalized difference tillage index; SACRI, soil adjusted crop residue indices.

Table 5. Validation of crop residue index multiband (CRIM) predictions for fractional residue cover by emergence status.

	Preemergence (*n* = 89)		Postemergence (*n* = 156)	
CRIM	r^2	RMSE	r^2	RMSE
3,4,5,7	0.38	0.29	0.02	0.26
3,4,5	0.31	0.33	0.00	0.25
3,4,7	0.50	0.28	0.02	0.26
3,5,7	0.34	0.32	0.29	0.24
4,5,7	0.42	0.26	0.01	0.32
3,4	0.29	0.35	0.02	0.26
3,5	0.29	0.32	0.14	0.24
3,7	0.52	0.21	0.40	0.22
4,5	0.17	0.35	0.00	0.41
4,7	0.44	0.20	0.03	0.24
5,7	0.84	0.14	0.30	0.14

However, even though r^2 improved for all but one index, RMSE did not always improve greatly. This could be explained by the decrease in r^2 of many of the soil and residue regression equations (Table 6) used in determining the CRIM. This decrease is likely due to the smaller number of fields utilized in the preemergent calibration datasets.

Comparison of the preemergent validation and postemergent validation datasets in Tables 4 and 5 show the importance that even small amounts of green vegetation can have on the accuracy of residue cover indices. For all indices, r^2 values decreased greatly when green vegetation was present, although RMSE did not always increase. This apparent incongruity is generally due to the limitation of residue cover estimates to between zero and one.

Although preemergent fields returned fairly high r^2 and RMSE values, they still did not explain all observed differences in reflectance. There are likely many complicating factors remaining, such as variations in soil color and soil moisture status, inaccurate determination of actual residue cover due to sampling limitations, variations in atmospheric conditions, and differing reflectance of corn and soybean residues at different decomposition states.

Table 6. Crop residue index multiband (CRIM) and soil adjusted crop residue indices (SACRI) preemergent soil and residue lines.

Bands	Soil line (*n* = 11)	r^2	Residue line (*n* = 16)	r^2
3,4	1.354*x* + –13.525	0.97	1.225*x* + –8.569	0.98
3,5	3.001*x* + –1.787	0.71	1.984*x* + 36.712	0.83
3,7	1.938*x* + 0.241	0.59	1.107*x* + 21.423	0.81
4,5	2.286*x* + 25.322	0.79	1.667*x* + 47.540	0.89
4,7	1.499*x* + 16.818	0.67	0.923*x* + 27.875	0.86
5,7	0.705*x* + –5.602	0.98	0.555*x* + 1.337	0.97

Dummy variable tests of preemergent fields showed significant date effects for some, but not all of the residue cover index models. Date was not a significant factor for the NDTI and was of borderline significance in the NDRI ($P = 0.0867$); however, all other models showed significant date effects. The difference in results from the previous all-field analysis indicates that green vegetation has differing impacts on different indices.

Residue Index Correction by Normalized Difference Vegetation Index

The residual error between index estimated residue cover and observed residue cover versus NDVI for the NDTI is shown in Fig. 4. Regressions calculated for all indices are shown in Tables 7 and 8, along with r^2 and RMSE values for calibration and validation datasets. Some indices, such as the NDSVI and $CRIM_{4,5}$, showed almost no improvement when accounting for NDVI except for that realized by adjusting to the average residue index; however, other indices such as the NDI5, NDI7, NDTI and the $CRIM_{5,7}$ showed increases in accuracy

Table 7. Fractional residue cover corrections for postemergent field.

	Regression		Calibration		Validation	
Index†	Equation‡	Eq.	r^2	RMSE	r^2	RMSE
NDRI	error = 0.973 × NDVI + 0.023	[20]	0.38	0.14	0.63	0.14
NDI5	error = –3.260 × NDVI + –0.112	[21]	0.15	0.18	0.35	0.16
NDI7	error = –3.538 × NDVI + 0.070	[22]	0.34	0.16	0.52	0.15
NDTI	error = –2.377 × NDVI + 0.153	[23]	0.47	0.14	0.67	0.15
NDSVI	error = 0.066 × NDVI + 0.063	[24]	0.03	0.24	0.07	0.17
SACRI	error = 1.385 × NDVI + 0.237	[25]	0.02	0.17	0.07	0.28

† ND15 and ND17, additional normalized difference indices of McNairn and Protz (1993); NDRI, normalized difference residue index; NDSVI, normalized difference senescent vegetation index; NDTI, normalized difference tillage index; SACRI, soil adjusted crop residue indices.

‡ NDVI, normalized difference vegetation index.

Table 8. Fractional residue cover corrections for postemergent crop residue index multiband (CRIM) indices.

	Regression		Calibration (n = 118)		Validation (n = 58)	
CRIM	Equation†	Eq.	r^2	RMSE	r^2	RMSE
3,4,5,7	error = –0.762 × NDVI + 0.344	[26]	0.05	0.14	0.13	0.12
3,4,5	error = 0.792 × NDVI + 0.101	[27]	0.01	0.21	0.04	0.14
3,4,7	error = –0.762 × NDVI + 0.344	[28]	0.05	0.14	0.13	0.12
3,5,7	error = –0.004 × NDVI + 0.204	[29]	0.35	0.12	0.15	0.13
4,5,7	error = –5.121 × NDVI + 0.453	[30]	0.22	0.18	0.05	0.23
3,4	error = –0.762 × NDVI + 0.344	[31]	0.05	0.14	0.13	0.12
3,5	error = –0.165 × NDVI + 0.241	[32]	0.19	0.13	0.07	0.13
3,7	error = –0.123 × NDVI + 0.204	[33]	0.45	0.11	0.28	0.11
4,5	error = –5.596 × NDVI + 0.422	[34]	0.07	0.25	0.02	0.25
4,7	error = –4.315 × NDVI + 0.417	[35]	0.29	0.16	0.15	0.18
5,7	error = –1.864 × NDVI + 0.184	[36]	0.55	0.10	0.40	0.11

† NDVI, normalized difference vegetation index.

as measured by increases in both r^2 and RMSE. These results indicate that it should be possible to at least partially correct for effects of green vegetation on the better performing residue indices. However, even though the RMSEs of the best corrected indices were about equal to preemergent conditions with values near 0.15, it should be noted that the best correlation coefficients of the corrected estimates were not as high as preemergent conditions.

Comparison with Previous Studies

The coefficients of determination from this analysis are much greater than those reported by either Daughtry et al. (2005, 2006) or Thoma et al. (2004). Estimates are likely much better than Daughtry et al. (2005) study due to two reasons. First, this study was conducted on darker soils than the light Chesapeake Bay area soils, leading to better contrast with residue in TM Bands 5 and 7. Also, the Daughtry et al. (2005) study only excluded fields with a vegetation fraction > 0.30, making results similar to that of the overall regression; these results had much lower accuracy than the preemergence regression. These differences could account for the decreased residue cover fraction intercept and coefficient of determination of the NDTI relationship found in the Daughtry et al. (2005) study. It should be noted that the 1.00 residue cover fraction value from both studies converge near an NDTI of 0.30, indicating this value may be consistent.

Improvements over Daughtry et al.'s (2006) study are likely due to the slower than average beginnings to the 2005 and 2006 crop seasons in central Iowa. This slowed the rate of field work and planting, and resulted in fewer fields with emergent vegetation at the same time as in the Daughtry et al. (2006) study.

The reasons for improvement over the analysis by Thoma et al. (2004) are not as clear. Thoma et al. (2004) worked on dark colored soils similar to those in this study, but they did not take green vegetation impacts into account or stratify r^2 values out by image date. They did evaluate classification accuracy by image date, with November images having greater classification accuracy than March, which were greater than June. This corresponds with the effects of green vegetation shown in this study.

CONCLUSIONS

Residue cover indices are capable of estimating residue cover on the dark-colored soils of central Iowa under conditions of both pre- and postemergent vegetation; however, increasing vegetation cover did reduce index accuracy. On both pre- and postemergent fields, the NDRI was the best indicator of residue cover due to the use of TM Bands 3 and 7 which minimize the effects of green vegetation. On preemergent fields the NDTI and $CRIM_{5,7}$, which both use TM Bands 5 and 7, were the best indicators of residue cover. The exclusion of vegetation covered fields also increased the performance of indices that do not use TM Band 7, such as NDI5 and NDSVI, increasing applicability to satellite systems beyond Landsat. However, the sensitivity of all indices except the NDTI to changes in imagery date when calibrated on preemergent fields indicates that most indexes are not appropriate for use without atmospheric correction. Thus, additional research is needed into atmospheric correction and the impacts of soil color, moisture status, and crop type on residue cover indices, as residue cover indices did not explain all variation in index values. Implementation of residue cover remote sensing will also require a more rigorous assessment of index accuracy. Further investigation of the impacts of green vegetation showed that there was a linear relation between the residual error of some indices and NDVI. Application of least squares linear regression to this error enabled more accurate estimation of residue cover in the presence of green vegetation, although postemergent estimates were still not as accurate as those made under preemergent conditions. Continuing research into correction of this error using linear regression and other methods is warranted. The loss of accuracy with increasing NDVI underscores the need for timely remote sensing observations to reduce the impact of green vegetation on scene reflectance.

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