Improved remote crop residue cover estimation by incorporation of soil and residue information

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Introduction

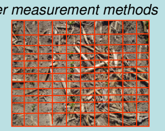
- Conservation tillage practices improve soil structure, reduce soil erosion, and increase soil organic carbon (SOC) content.

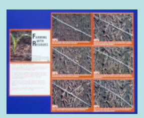

A. Conventionally tilled field


B. No-tilled field

Residue cover measurement methods


C. Line-transect.


D. Photographic.


E. Photo comparison.

- A number of remote sensing methods were developed for remote estimation and assessment of crop residue cover (CRC).
- Most remote sensing methods met with limited success, except for the Cellulose Absorption Index (CAI), which is based upon a distinct spectral feature limited mostly to residues (Daughtry et al., 2001).
- Other methods used include the ASTER Lignin-Cellulose Absorption (LCA) Index (Daughtry et al., 2005) And the Landsat TM indices NDTI (van Deventer et al., 1997), NDI (McNairn and Protz, 1993, and NDSVI (Qi et al., 2002).
- However, soils have different mineral and organic matter compositions, which may bias estimates.
- Soil water content affects spectral indices and soil reflectance.

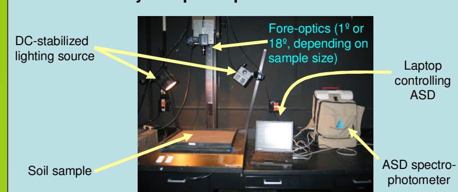
Study objectives

1. Compare crop residue vegetation indices.
2. Compare regression analyses after incorporation of soil information.

Spectral datasets

- Laboratory and field measurement using the Analytical Spectral Devices FieldSpec Pro (Boulder, CO) spectrophotometer (HRSL).
- Data from Brown et al. (2006), which were acquired from a subset of the USDA-NRCS National Soil Survey Center's Characterization Data Library (Lincoln, NE).
- Data from Jim Reeves of the USDA-ARS Environmental Management and By-Product Utilization Laboratory (EMBUL).
- Data acquired from online spectral libraries, including:
  - USGS Spectroscopy Lab Spectral Library Splib05a (Clark, et al., 2003).
  - Elvidge (1990).
  - Karl Norris (USDA Instrumentation Laboratory, Beltsville, MD).
  - Labsphere Inc.
- Hyperspectral imagery collected by SpecTIR LLC (Sparks, NV) over Fulton and Cass counties in Indiana on May 29, 2006. Ground-truth acquisition utilized line-transect data.

Laboratory setup for spectral measurements



Spectral indices used in this study

- Hyperspectral:

$$CAI = 100[(R_{2.0} + R_{2.2})/2 - R_{2.1}] \quad (1)$$

- ASTER LCA:

$$LCA = 100[2ASTER6 - (ASTER5 + ASTER8)] \quad (2)$$

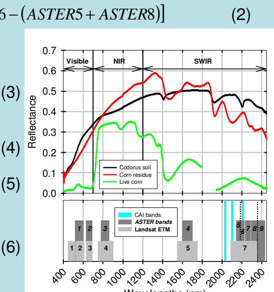
- Landsat TM:

$$NDTI = \frac{TM5 - TM7}{TM5 + TM7} \quad (3)$$

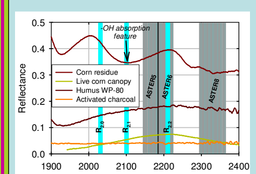
$$NDI5 = \frac{TM4 - TM5}{TM4 + TM5} \quad (4)$$

$$NDI7 = \frac{TM4 - TM7}{TM4 + TM7} \quad (5)$$

$$NDSVI = \frac{TM5 - TM3}{TM5 + TM3} \quad (6)$$



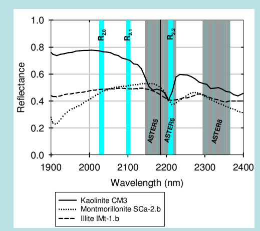
Live vegetation, residues, and soil carbon affect indices

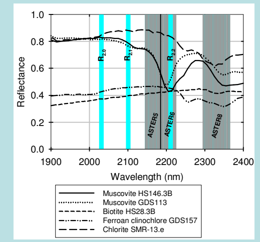


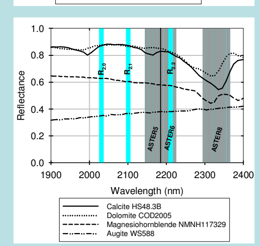
- Live vegetation is dark and shows maximum reflectance at $R_{2.2}$.
- Dry residues, which are mixtures of cellulose and lignin, are much brighter and show a clear C–OH absorption feature centered at 2101 nm.
- Humus WP-80 and activated charcoal are darker and relatively featureless.
- Narrow CAI bands capture C-OH absorption feature.
- LCA bands show similar spectral shapes and index values for live vegetation, residues, requiring NDVI to separate between the two spectral signatures.

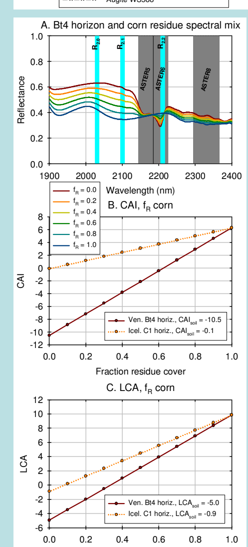
Compound	Library	CAI	$R_{2.1}$	LCA	*ASTER6*	N
Activated charcoal	HRSL	0.0	0.04	-0.1	0.04	1
Carbon	Splib05	0.1	0.01	-0.1	0.01	1
Cellulose	HRSL, Elvidge, EMBUL	10.8 ~ 18.0	0.38 ~ 0.69	14.9 ~ 20.9	0.42 ~ 0.84	11
Lignin	Elvidge, Karl Norris	1.1 ~ 1.5	0.36 ~ 0.73	5.9 ~ 7.6	0.47 ~ 0.73	3
Humus WP80	HRSL	0.0	0.18	1.5	0.19	1
Corn residue	HRSL	1.2 ~ 6.3	0.27 ~ 0.39	3.3 ~ 9.9	0.30 ~ 0.42	39
Cotton residue	HRSL	1.5	0.34	6.9	0.36	1
Soybean residue	HRSL	1.1 ~ 4.6	0.27 ~ 0.39	3.4 ~ 9.2	0.29 ~ 0.43	27
Wheat residue	HRSL	2.9 ~ 6.0	0.27 ~ 0.34	7.1 ~ 10.0	0.31 ~ 0.37	7
Green corn canopy	HRSL	-0.4 ~ 0.3	0.03 ~ 0.23	2.1 ~ 7.7	0.05 ~ 0.24	43

Soil mineralogy affects spectral indices









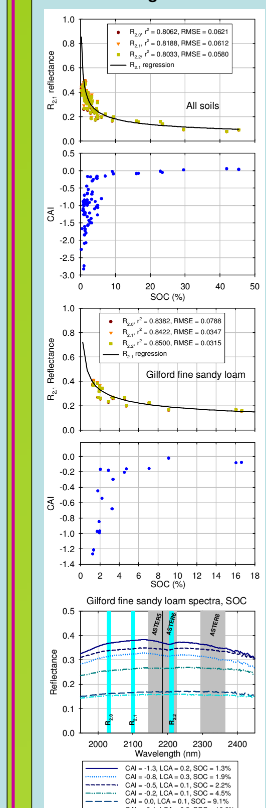
- Certain common soil minerals have absorptions which can bias spectral indices.
- Minerals which negatively bias CAI and LCA increase index contrast and can potentially improve accuracy; those which positively bias soils can have the opposite effect.
- Common clay minerals (kaolinite, montmorillonite, and illite) have absorption which affect $R_{2.2}$ and ASTER6, and can bias these soils negatively.
- Muscovite mica negatively biases CAI and LCA.
- Chlorites can negatively bias CAI and positively bias LCA.
- Biotites minimally bias both indices.
- Calcite, dolomite, and Mg-hornblende (amphibole) affect ASTER6 and can positively bias LCA, but minimally affect CAI.
- Common soil minerals are either CAI-neutral (CAI ≈ 0) or negative.
- Many common soil minerals are LCA positive; some are of similar values or exceed values of soil residues.
- These minerals then affect soil spectral properties, as seen with a kaolinic soil from Venezuela, with a CAI value of -10.5.
- These soils mix linearly with residue according to:

$$R_{mix,\lambda} = f_r \cdot R_{residue,\lambda} + (1 - f_r) \cdot R_{soil,\lambda} \quad (7)$$

where λ denotes wavelength and f_r the residue cover fraction.

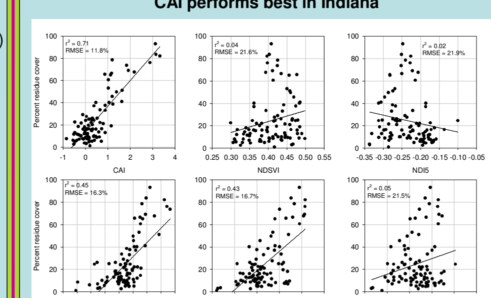
- CAI_{soil} range: -10.5 to ≈ 0.
- LCA_{soil} range: -12.4 to 8.3.
- CAI_{soil} and LCA_{soil} were linearly correlated to r^2 = 0.4137 for 3755 soils in Brown et al. (2006).
- Landsat TM indices are more dependent on relative differences between TM band reflectances, CAI and LCA on spectral shape.

Soil organic carbon affects spectral indices



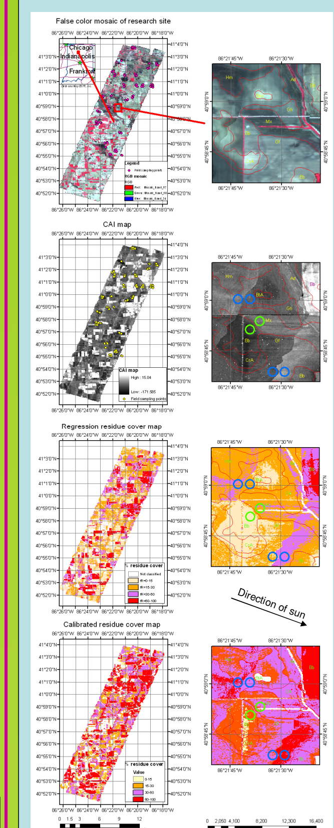
- SOC affected soil reflectivity, and thus, spectral indices.
- SOC levels and reflectance spectra were acquired for 77 soils from across the USA (most from IA and IN).
- SOC and reflectance showed good correlation with power regression.
- Each spectral band needs to be correlated separately, then indices calculated.
- This in turn will affect CAI values.
- As SOC increased, reflectance decreased, and CAI approached a value of zero.
- Above that decrease in reflectance was minimal.
- Decrease in reflectance affected all wavelengths.
- Most variability in reflectance and CAI occurred below SOC values of 5%.
- Small changes in SOC at low SOC contents are more significant than at higher contents.
- SOC effectively coats soil particles, decreasing soil mineral reflectance properties.

CAI performs best in Indiana



- CAI was compared alongside calculated equivalent ASTER and TM bands from SpecTIR hyperspectral imagery.
- CAI performed the best, followed by LCA and NDTI.
- NDSVI, NDI5, and NDI7 fared poorly.

Using soil and residue information to improve residue cover estimation

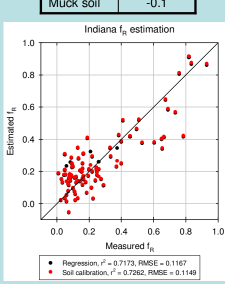


- Hyperspectral imagery were masked to eliminate non-agricultural fields, clouds, shadows, water, live vegetation.
- CAI map shows high and low residue fields.
- SWIR bands showed incidence angle effects (blue circles, effects greatest opposite direction from sun, but still significant for high view angle pixels toward sun).
- SSURGO soil maps (USDA-NRCS Soil Data Mart) were used to help distinguish soil units.
- Soil units were distinguished from others in both false-color maps and CAI maps (e.g., Muskego muck (Mx) bordering Barry loam (Bb), green circles).
- Soil composition can bias residue cover estimates in the same field.
- Eqs. (1) and (7) were combined and reorganized to calculate residue cover:

$$f_r = \frac{CAI_{pixel} - CAI_{soil}}{CAI_{residue} - CAI_{soil}} \quad (8)$$

- SSURGO data used to create three broad soil classes- mineral, muck (organic), and non-agricultural soils.
- Non-ag. soils excluded from analysis.
- Excel solver was used to determine CAI values of residues, and mineral and muck soils.
- Method shows slight improvement over simple linear regression.
- Mineral and muck soil data used in conjunction with CAI to estimate f_R, and thus, minimize need for soil calibration.
- A few locations misclassified by SSURGO.
- A SOC map used in conjunction with remote sensing data will improve residue cover estimates if soil mineralogy doesn't vary.

Material	CAI
Residue	3.7
Mineral soil	-0.6
Muck soil	-0.1



f_R class	Reg. area %	Reg. area (km^2)	Calibration area %	Calibration area (km^2)
0-15%	26.18	24.57	30.77%	27.06
15-30%	32.10	30.12	28.79%	25.31
30-60%	22.70	21.31	21.70%	19.08
60-100%	19.02	17.85	18.74%	16.47
Total	**100**	**93.85**	**100**	**87.92**

- Table above shows summary of differences between regression and calibration approaches in determining residue cover classes using CAI.
- Calibration method excluded about 6.3% of the area covered by regression.
- Most excluded soils were "prairie potholes" and inundated soils which could be lumped with muck soils.
- Data would be more accurate without view angle bias- a good spaceborne or high-altitude airborne hyperspectral sensor would be ideal for residue mapping.

Conclusions

- CAI is the most accurate of all the indices tested in this study, followed by LCA and NDTI.
- CAI is the least affected by soil mineralogy and SOC for residue estimation; residue is CAI-positive, soils are around zero or less.
- CAI most accurate when incorporating soil mineralogy and SOC information.
- Soil mineral and SOC maps can be used to generate CAI_{soil} maps, which when used with remotely measured CAI and residue CAI with Eq. (8) to determine f_R.
- This approach can minimize need for ground truth acquisition around time of sensor overpass.
- ASTER LCA is similarly sensitive to vegetation and residue; NDVI needed to mask out green fields or correct data.
- Some common soil minerals are strongly LCA-positive, making use of this index problematic.
- Normalized difference TM indices work well on specific soils, but are not universally applicable.

Acknowledgements

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