Evaluation of the Cellulose Absorption Index (CAI) for estimation of crop residue cover and soil carbon

Guy Serbin[1*], Craig S. T. Daughtry[1], E. Raymond Hunt, Jr.[1], Paul C. Doraiswamy[1], David J. Brown[2]

[1] USDA-ARS Hydrology and Remote Sensing Laboratory, 10300 Baltimore Ave. Bldg. 007 Rm. 104 BARC-West, Beltsville, MD 20705 USA (*Corresponding author email: guy.serbin@gmail.com, telephone: +1-301-504-5250, fax: +1-301-504-8931)

[2] Department of Land Resources and Environmental Sciences, Montana State University, USA

Introduction

- The use of conservation tillage practices has been shown to improve soil structure, reduce soil erosion, and increase levels of soil organic carbon (SOC) content.
- Conservation tillage methods often employ the use of crop residues to cover the soil, protecting it from wind and water, and also providing lignin and cellulose, which contribute to SOC.
- A number of remote sensing methods were developed for remote estimation and assessment of crop residue cover (CRC), most notably the Cellulose Absorption Index (CAI) and ASTER Lignin-Cellulose Index (LCA, Daughtry et al., 2005).
- These estimates of CRC can then be used as inputs in soil carbon models.
- However, individual soils have differing compositions, which may affect base CAI values, and thus, bias estimates.
- While most satellite systems utilize sensors with broad spectral bands which may limit the use of CAI, hyperspectral satellite and airborne systems allow for the use of this index.

Study objectives

- The purposes of this study are to:

1. Evaluate CAI values for shortwave infrared (SWIR) spectra of over 4,100 soils from Brown et al. (2006), and compare them with soil components.
2. Evaluate CRC using CAI values for hyperspectral imagery acquired over Indiana on 29 May 2006.

Experimental methods

Soil spectra were acquired from a number of sources, including:

- Laboratory and field measurement using the Analytical Spectral Devices FieldSpec Pro (Boulder, CO) spectro-radiometer.
- Laboratory measurements used a DC-stabilized lighting source and 1º or 18º fore-optics, as seen in Fig. 1.

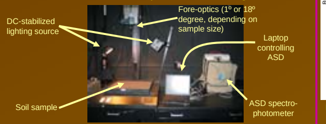
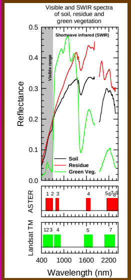


Fig. 1. Laboratory setup for spectral measurements

- 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 acquired from online spectral libraries, including Elvidge (1990), and Karl Norris (USDA Instrumentation Laboratory, Beltsville, MD).

Remote sensing of crop residues, vegetation, and soil



- Satellite remote sensing of vegetation frequently utilizes broad spectral bands in the visible and shortwave infrared (SWIR), such as those used by ASTER and Landsat TM (Fig. 2).
- In the visible and SWIR portion of the spectrum below 1900 nm, crop residues and soils appeared very similar to one another, but differ greatly from green vegetation.
- In the SWIR portion of the spectrum above 1900 nm, crop residues showed a distinct absorption at 2100 nm which is not shared by soils or by green vegetation (which can appear similarly in this region).
- This absorption was related to cellulose and lignin in dry residues.
- Unfortunately, both ASTER and Landsat TM bands either are too broad, or do not sample the 2100 nm absorption feature.
- Thus, hyperspectral measurements are needed to discriminate between crop residues and bare soils, which are achieved using the cellulose absorption index.

The Cellulose Absorption Index (CAI)

$$CAI = 100 \cdot [0.5\,(R_{2.0} + R_{2.2}) - R_{2.1}] \qquad (1)$$

where $R_{2.0}$, $R_{2.1}$, and $R_{2.2}$ denote the mean reflectances of the 2026 nm – 2036 nm, 2096 nm – 2106 nm, and 2206 nm – 2216 nm bands, respectively.

Spectral properties of soils and residues

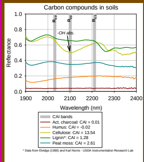


Fig. 3. Spectra of carbon compounds in soils.

Spectral reflectance properties of soil carbon (Fig. 3)

- Dry crop residues had distinctive spectral features which distinguished them from living vegetation and mineral and organic matter in soils.
- Crop residues consisted mainly of cellulose and lignin, which exhibited spectral absorptions around 2100 nm, relating to alcoholic –OH groups in the molecular structure (Curran, 1989).
- CAI was positive if the reflectance spectra between 2026 nm and 2216 nm are concave, and negative if convex; if spectra were more or less straight then values were in the vicinity of zero.

- Cellulose had stronger absorptions than lignin, and hence, higher values of CAI.
- Humus (degraded organic residues) and inorganic C (activated charcoal) exhibited much lower reflectances than lignin or cellulose and without the diagnostic absorptions.
- Peat moss, which was relatively undegraded plant organic matter (Fig. 3), showed intermediate values between humus and crop residues and had a signature that was similar in shape to cellulose, albeit darker and flatter (Fig. 4).

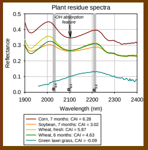


Fig. 4. Crop residue and vegetation spectra.

Spectral properties of plant residues and vegetation (Fig. 4)

- While dry plant residues showed distinct absorptions at 2100 nm and 2330 nm, live vegetation (green lawn grass) did not show them, and thus, can be distinguished apart.
- Residue spectral properties varied with age and phenology;
- As residue aged, cellulose content decreased relative to that of lignin, and thus, CAI values decreased;
- Species with thicker stems had higher CAI values and lasted longer in the field.

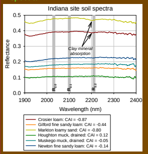


Fig. 5. Spectra of Fulton Co., IN soils.

Spectra of soils from Indiana field site (Fig. 5)

- Soils from Fulton Co., Indiana showed relatively flat spectra excepting two soils with a characteristic clay mineral absorption at around 2200 nm.

- Soils with large amounts of organic matter had higher CAI values and were darker than those with low SOC.

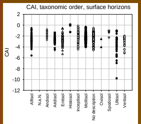


Fig. 6. CAI for surface horizons as grouped by taxonomic order.

Fig. 6: Surface soil layer CAI values calculated from Brown et al. (2006) and Indiana soil spectra.

- 705 soil spectra used from Brown et al. (2006) and Indiana.
- Most soil orders showed similar ranges of values with minor variations.

- Some soils, e.g., certain ultisols, showed very CAI low values
- In general, soil order was not a strong indicator of soil CAI, due to broad ranges.
- Surface soil mineralogy and organic matter content will dominate soil spectral properties.
- Histosols, oxisols, and spodosols insufficiently sampled.

Linear spectral mixing model

- A linear spectral mixing model was used to estimate residue cover at nadir as a function of residue cover:

$$R_{M,\lambda} = R_{S,\lambda} \cdot (1\text{-}f_R) + R_{R,\lambda} \cdot f_R \qquad (2)$$

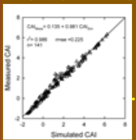


Fig. 7. Measured vs. simulated CAI values.

where R denotes reflectance and the subscripts M, S, R, and λ denote mixture, soil, residue, and wavelength, respectively. f_R denotes the fractional cover of the crop residue.

- When looking at nadir, soils and residues mixed according to Eq. (2) with excellent correlation between simulated and measured values (Fig. 7).

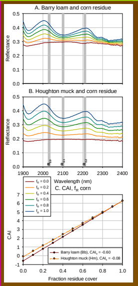


Fig. 8. Spectral mixing of corn residue with (a) Barry loam and (b) Houghton muck. (c) CAI values for both soil-residue mixtures.

Spectral mixing of residues at nadir

- Simulations of spectral mixing were performed for two Indiana soils as seen in Fig. 8a-c.
- Both soils can be found adjacent to one another in the field, and had different values for CAI_S.
- Houghton muck had a much higher SOC and a slightly higher CAI_S.
- As higher proportions of corn residue were added to the scene, the spectra appeared to be more like corn.
- The relationship between CAI and fR,corn was linear for both soils.
- Lower proportions of corn showed significant differences between soils; these lessened as $f_{R,corn}$ increased.
- This showed that soil composition can have a significant effect upon CAI values, and thus residue cover estimates, and should be taken into account.

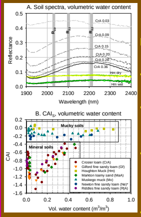


Fig. 9. Spectra (a) and CAI values (b) for two Indiana soils as a function of water content. *denotes mucky surface layer.

Effect of soil water content on CAI_S (Fig. 9a-b)

- Soil brightness was inversely related to water content.
- Soils with low SOC (mineral soils) were brighter than those with high SOC (mucky soils).
- Mineral soils showed CAI minima at water contents of ~0.1 m³/m³, due to water content effects on spectrum shape, particularly at $R_{2.0}$.
- Mucky soils showed little effect of water on CAI, as this parameter had little effect on spectral shape.

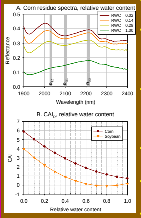


Fig. 10. (a) Corn residue spectra and (b) corn and soybean CAI values as a function of volumetric water content.

Effect of soil water content on CAI_R (Fig. 10a-b)

- As relative water content (RWC or degree of saturation) increased crop residues darkened throughout measured spectra.
- Increasing water content affected $R_{2.0}$ the most, by making the spectra less concave between $R_{2.0}$ and $R_{2.2}$, and thus, decreasing CAI_R.
- Corn showed a consistent decrease in CAI_R with RWC.
- Soybean achieved minimal CAI_R values at about 60% RWC.
- Under wet conditions, residue cover estimation may not be feasible for soils when $CAI_S \approx 0$.

Results: Hyperspectral remote sensing of crop residue cover

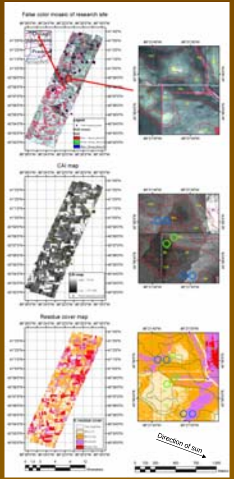


Fig. 11. Maps of Indiana test site.

Soil	Circle color	CAI	f_R (%)
Bb	Green	-0.42	4.0
Mx	Green	0.62	27.9
Bb – Mx diff.		*1.04*	*24.0*
Gf low view angle	Blue	0.12	16.6
Gf high view angle	Blue	1.00	36.9
Gf high – low view angle		*0.88*	*20.3*

Table 1. Observed CAI and f_R biases caused by soil type and incidence angle.

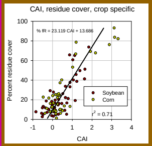


Fig. 12. CAI and CRC ground estimate correlations for (a) all residues and (b) corn and soybean measured separately.

Fig. 11. Maps of Indiana test site

- Remotely sensed hyperspectral imagery of Indiana acquired from aircraft from SpecTIR Inc. (Sparks, NV) in strips, which were subsequently mosaicked together, and used to calculate CAI.
- These data were compared against residue data from a number of field sampling points.
- The subsequent regression for all CRC estimates was used to generate a five class-class residue cover map via decision tree analysis.
- Regression equation (Fig. 12) not entirely accurate (r^2 = 0.71), such that low CRC estimates were smaller than 0% or larger than 100% (these are classified in the 0-15% and 60-100% bins, respectively).
- SSURGO soil maps (USDA-NRCS Soil Data Mart) were also used to help distinguish soil units.
- When closely observing fields, some soil units can clearly be distinguished from others in both false-color maps and CAI maps (e.g., Muskego muck (Mx) bordering Barry loam (Bb), green circles), showing that soil composition can affect CAI, as seen in Table 1.
- This in turn shows that soil composition can bias residue cover estimates, even in the same field, in agreement with results from Fig. 8.
- View angle was also shown to affect CAI estimates along swath edges (blue circles), where the sensor sees more residue than it would at nadir, resulting in a positive bias, as seen in Table 1.
- View angle effects are greatest in the opposite direction from the sun, but are still significant for high View angle pixels facing the sun.
- Class areas and statistics for classified areas in Residue cover map can be seen in Table 2.

f_R class	Areal %	Area (km²)
0-15%	26.18	24.57
15-30%	32.10	30.12
30-60%	22.70	21.31
60-100%	19.02	17.85

Table 2. Statistics for classified pixels in f_R map (Fig. 11).

Accuracy of remote residue cover estimates (Fig. 12)

- Ground truth field estimates of CRC utilized the line-point transect method (Morrison et al., 1993), and included residue type.
- Differences in soil CAI_S or water contents were not accounted for here.
- Regression equation can result in over- and under-estimation of residue cover.

Conclusions

- CAI is sensitive to residue cover type, age, and wetness.
- Soil spectral properties, and thus, CAI_S are dependent on soil composition.
- Soils that are rich in degraded organic matter (mucky) will have CAI_S values around 0
- Mineral soils will have lower CAI_S values.
- Mineral soils were affected more by water content than mucky soils.
- Water content also affects CAI_R.
- Water content affects $R_{2.0}$ more than $R_{2.1}$ and $R_{2.2}$.
- Local differences in soil composition affect remote estimates of residue cover.
- View angle effects from aircraft remote sensing are a concern.

Acknowledgments

- Humus Products of America, Richmond, TX for providing a sample of humus WP-80 powder.

References

Brown, D.J., K.D. Shepherd, M.G. Walsh, M.D. Mays, and T.G. Reinsch. 2006. Global soil characterization with VNIR diffuse reflectance spectroscopy. Geoderma 132:273-290.

Curran, P.J. 1989. Remote sensing of foliar chemistry. Remote Sensing of Environment 30:271-278.

Daughtry, C.S.T., E.R. Hunt Jr., P.C. Doraiswamy, and J.E. McMurtrey III. 2005. Remote sensing the spatial distribution of crop residues. Agronomy Journal 97:864-871.

Elvidge, C.D. 1990. Visible and near infrared reflectance characteristics of dry plant materials. International Journal of Remote Sensing 11:1775-1795.

Morrison Jr., J.E., C. Huang, D.T. Lightle, and C.S.T. Daughtry. 1993. Residue cover measurement techniques. Journal of Soil Water Conservation 48:479.

Norris, K. USDA Instrumentation Lab, Beltsville, MD (data downloaded from Thermo Fisher Scientific, Inc., Available URL: "http://spectra.galactic.com/" [Accessed January 2007]).

Soil Survey Staff, National Soil Survey Characterization Data, Soil Survey Laboratory, National Soil Survey Center, USDA-NRCS, Lincoln, NE. Available URL: "http://ssldata.nrcs.usda.gov/". [Accessed December 2006].

Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. Soil survey of Fulton County, Indiana [Online WWW]. Available URL: "http://soildatamart.nrcs.usda.gov/Survey.aspx?State=IN" [Accessed October 2006].