Remote Sensing of Crop Residue and Non-photosynthetic Vegetation

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Introduction

- Conservation tillage practices, which leave increased quantities of crop residue cover, improve soil structure, reduce soil erosion, and increase soil organic carbon (SOC) content.
- Technology for biofuels from cellulosic ethanol could result in a reduction in conservation tillage and surface residues, which could further deplete soil organic carbon stocks.

A. Conventionally tilled field

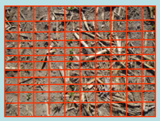
B. No-tilled field

- The quantity of non-photosynthetic vegetation is also an important indicator of rangeland quality and soil health, and also predicts potential for forest and range wildfires.

C. Rangeland

Residue cover measurement methods

D. Line-transect.



E. Photographic.

F. Photo comparison.

- Field methods currently used for crop residue cover estimation are tedious and subject to operator bias.
- A number of remote sensing methods were developed for remote estimation and assessment of crop residue cover.
- 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).
- Globally, soils have different mineral and organic matter compositions, which may bias estimates.

Study objective

Evaluate spectral indices for detection of crop residue/non-photosynthetic vegetation and make recommendations for future satellite sensor bands.

Spectral datasets

- 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).
- 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.

Spectral indices used in this study

- Hyperspectral/narrow-band:

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

- ASTER:

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

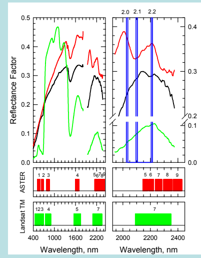
- Landsat TM:

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

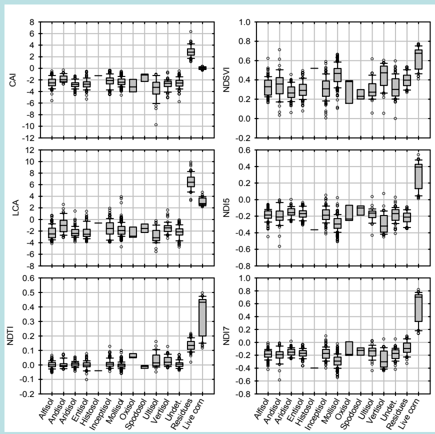
$$NDI5 = \frac{TM4 - TM5}{TM4 + TM5} \quad (4)$$

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

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

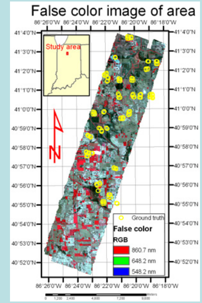


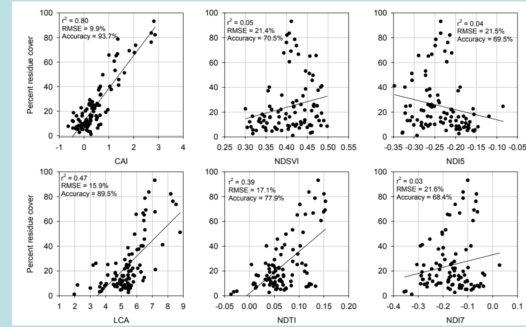
CAI is better for assessing residue cover than ASTER or Landsat TM-based indices

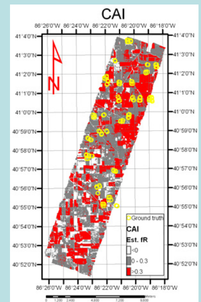


- Soil index values are dependent upon mineralogy, SOC, and particle size.
- CAI separates residues best from soils and green photosynthetic vegetation.
- LCA also shows good separation among residue, most soils, and green photosynthetic vegetation.
- However, LCA is sensitive to mineral absorptions, e.g., carbonates.
- All Landsat TM-based indices show higher significantly higher values for green vegetation than soils or residues.
- Thus, any green photosynthetic vegetation will strongly bias Landsat TM index values for non-photosynthetic vegetation/crop residue.
- While green vegetation affects CAI and LCA, it is less of an issue.
- Green vegetation is particularly an issue if acquisitions become delayed after planting due to weather, or if fields have abundant weeds.
- Of the Landsat TM indices, NDTI has the best separation between soils and residues; other indices show poor or no separation.

Airborne SpecTIR data show that CAI has the highest accuracy

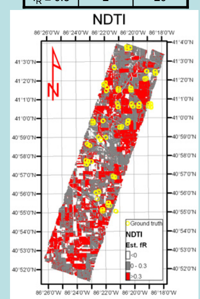






CAI — Ground data

Class	$f_R < 0.3$	$f_R \geq 0.3$
$f_R < 0.3$	69	4
$f_R \geq 0.3$	2	20



NDTI — Ground data

Class	$f_R < 0.3$	$f_R \geq 0.3$
$f_R < 0.3$	57	7
$f_R \geq 0.3$	14	17

- CAI had the highest r^2 and lowest RMSE of any of the indices.
- CAI also had the highest accuracy for separating residue classes.
- LCA also produced acceptable results with respect to accuracy.
- NDTI fared the best for Landsat-TM based indices, but was not as effective for residue cover estimation as CAI or LCA.
- NDSVI, NDI5, and NDI7 were ineffective for residue cover estimation.
- Two-sample *Z*-test of the *k*-hat statistic from show NDTI is significantly less accurate than CAI (Z = 2.99, where $Z_{critical}$ = 1.96 and P = 0.9986) for classification of residue cover.

Recommendations for future sensors

- **Thus, we recommend for future multispectral sensors that Landsat TM band 7 be replaced with multiple SWIR bands similar to ASTER, by including the CAI bands.**
- **The CAI bands should be centered at 2031, 2101, and 2211 nm with a narrow band width to detect cellulose absorption.**
- **Including CAI bands in future sensors would benefit the following monitoring applications:**
  - **Tillage determination and carbon sequestration**
  - **Rangeland health and soil quality**
  - **Brush and forest fire risk**
- **These multiple SWIR bands could be averaged to provide an equivalent Landsat TM7 band for data continuity.**

References

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