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# Estimating Nonharvested Crop Residue Cover Dynamics Using Remote Sensing

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## 1. Introduction

Non harvested above and below ground carbon must be continuously replaced to maintain the soil resilience and adaptability. The soil organic carbon (SOC) maintenance requirement is the amount of non-harvested carbon (NHC) that must be added to maintain the SOC content at the current level ($NHC_m$) (Mamani-Pati et al., 2010; Mamani-Pati et al., 2009). To understand the maintenance concept a basic understanding of the carbon cycle is needed (Mamani-Pati et al., 2009). The carbon cycle is driven by photosynthesis that produces organic biomass which when returned to soil can either be respired by the soil biota or contribute to the SOC. The rates that non-harvested biomass is converted from fresh biomass to SOC and SOC is converted to $CO_2$ are functions of many factors including, management, climate, and biomass composition. First order rate mineralization constants for nonharvested carbon ($k_{NHC}$) and SOC ($k_{SOC}$) can be used to calculate half lives and residence times. Carbon turnover calculations are based on two equations,

$$\frac{d\text{SOC}}{dt} = k_{\text{NHC}} \left[ \text{NHC}_a - \text{NHC}_m \right] \tag{1}$$

$$k_{\text{SOC}} \times \text{SOC}_e = k_{\text{NHC}} \times \text{NHC}_m \tag{2}$$

In these equations, SOC is soil organic C, $NHC_a$ is the non-harvested carbon returned to soil, $NHC_m$ is the nonharvested carbon maintenance requirement, $k_{soc}$ is the first order rate constant for the conversion of SOC to $CO_2$, and $k_{NHC}$ is the first order rate constant for the conversion of NHC to SOC (Clay et al., 2006). These equations state that the temporal change in SOC ($d$SOC/$d$t) is equal to the non-harvested carbon mineralization rate constant ($k_{NHC}$) times the difference between the amounts of carbon added to the soil ($NHC_a$) and the maintenance requirement ($NHC_m$) and that at the SOC equilibrium point ($SOC_e$), the rate that non-harvested C (NHC) is converted into SOC ($k_{NHC} \times NHC_m$) is equal to the rate that SOC is mineralized into $CO_2$ ($k_{SOC} \times SOC_e$). Through algebraic manipulation, these equations can be combined to produce the equation,

$$\frac{\text{NHC}_a}{\text{SOC}_e} = \frac{k_{\text{SOC}}}{k_{\text{NHC}}} + \frac{d\text{SOC}}{d\text{t}} \left[ \frac{1}{k_{\text{NHC}} \times \text{SOC}_e} \right] \tag{3}$$

When fit to a zero order equation, the y-intercept and slopes are $\dfrac{k_{SOC}}{k_{NHC}}$ and $\dfrac{1}{k_{NHC} \times SOC_e}$, respectively.

Based on this equation, $NHC_m$, $k_{NHC}$, and $k_{SOC}$ can be calculated using the equations, $NHC_m$ = b × $SOC_e$; $k_{NHC}$ = 1/ (m × $SOC_e$); and $k_{SOC}$ = b/(m × $SOC_e$). This approach assumed that above and below ground biomass make equal contributions to SOC; that the amount of below ground biomass is known; and NHC is known and that initial ($SOC_e$) and final ($SOC_{final}$) SOC values are near the equilibrium point. Advantages with this approach are that $k_{SOC}$ and $k_{NHC}$ are calculated directly from the data and the assumptions needed for these calculations can be tested. A disadvantage with this solution is that surface and subsurface NHC must be measured or estimated. Remote sensing may provide the information needed to calculate surface NHC, through estimating the spatial variation of crop residues which are a major source of NHC.

Traditionally crop residue cover estimates have relied on visual estimation through road side surveys, line-point transect or photographic methods (CTIC, 2004; McNairn and Protz, 1993; Serbin et al., 2009 a). However, such ground-based survey methods tend to be time-consuming and expensive and therefore are inadequate for crop residue quantification over large areas (Daughtry et al., 2005; Daughtry et al., 2006). The need to improve these estimates has prompted much research on the extraction of surface residue information from aerial and satellite remote sensing (Bannari et al., 2006; Daughtry et al., 2005; Gelder et al., 2009; Serbin et al., 2009 a & b; Thoma et al., 2004). Previous research has shown crop residues may lack the unique spectral signature of actively growing green vegetation making the discrimination between crop residues and soils difficult (Daughtry et al., 2005). Daughtry and Hunt (2008) reported that dry plant materials have their greatest effect in the short wave infra-red (SWIR) region between 2000 and 2400 nm related to the concentration of ligno-cellulose in dry plant residue.

Other studies have proposed the Cellulose Absorption Index (CAI), the Lignin Cellulose Absorption index (LCA) and the Shortwave Infrared Normalized Difference Residue Index (SINDRI) for estimating field residue coverage (Daughtry et al., 2005; Daughtry et al., 2006; Thoma et al., 2004; Serbin et al., 2009 c). However, neither CAI, LCA nor SINDRI are currently practical for use in spaceborne platforms (Serbin et al., 2009 a). For example, EO-1 Hyperion which was sensitive to the spectral ranges of CAI and LCA (2100 and 2300 nm wavelengths), is past its planned operational lifetime and suffers bad detector lines (USGS, 2007), while the shortwave infrared (SWIR) detector for ASTER satellite failed in April, 2008 (NASA, 2010; Serbin et al., 2009 c). Therefore, indices that utilize the multispectral wavelength ranges (450-1750 nm) appear to be the most viable economical alternative. The objective of this research was to assess if remote sensing can be used to evaluate surface crop residue cover, and the amount of nonharvested biomass returned to soil.

## 2. Materials and methods

### 2.1 Study area

A randomized block field experiment was conducted in South Dakota (SD) in the years 2009 and 2010. The coordinates at the site were 44° 32'07"North and 97° 22' 08"West. Soil at the site was a fine-loamy, mixed, superactive, frigid typic calciudoll (Buse). The treatments considered were residue removed (baled) or returned (not baled) with each treatment

replicated 36 times. The field was chisel plowed and corn was seeded at the site during the first week of May in 2009 and 2010. The row spacing was 76 cm and the population was 80,000 plants per hectare. Following physiological maturity in October, grain and stover yields were measured. In all plots corn residue was chopped after harvesting. In residue removal plots, stover was baled, and removed. The amount of residue remaining after baling was measured in at 16 locations that were 0.5806 m² in size. For these measurements, the stover was collected, dried, and weighed. Approximately 56% (±0.08) of the corn residue was removed by this process. Following residue removal, soil surface coverage was measured using the approach by Wallenhaupt (1993) on 27th November 2009 and 13th November 2010.

## 2.2 Field measurements and model development

Spectral reflectance measurements of corn residues were collected with a Cropscan handheld multispectral radiometer (Cropscan Inc., Rochester, Minnesota) under clear sky conditions between 10 a.m. and 3 p.m. for all the field sites on 28th November 2009 and 13th November 2010. The Cropscan radiometer measures incoming and reflected light simultaneously. It measures within the following band widths, 440-530 (blue), 520-600 (green), 630-690 (red), 760-900 (near infra red, NIR), 1550-1750 (mid infra red, MIR), for wide (W) bands, and 506-514, 563-573, 505-515, 654-666, 704-716, 755-765, 804-816, 834-846, 867-876, 900-910, 1043-4053 nanometer (nm) for narrow wavelength bands.

The Cropscan radiometer was set at a height of 2 m above ground, so as to approximate a 1 m² spatial resolution on the ground. The Cropscan was calibrated by taking five spectral radiance readings on a standard reflectance, white polyester tarp, before beginning the scanning and after the whole field had been scanned. Scanning errors were minimized by following the protocols as reported by Chang et al. (2005). For calculations it is assumed that the irradiance flux density at the top of the radiometer is identical to the target. Reflectance data were corrected for temperature and incident light angles, relative to top of the sensor. Based on measured reflectance information, four wide reflectance bands and four indices derived from the wide spectral bands were calculated (Table 1).

| Vegetation Index | Equation (modified) | Reference |
|---|---|---|
| **Normalized Difference Vegetation Index (NDVI$_w$)** | NDVI$_w$= (R$_{830}$-R$_{660}$)/(R$_{830}$+R$_{660}$) | Rouse et al. 1974 |
| **Green Normalized Difference Vegetation Index$_w$ (GNDVI$_w$)** | GNDVI$_w$ = (R$_{830}$-R$_{560}$)/(R$_{830}$+R$_{560}$) | Daughtry et al. 2000 Gitelson and Merzlyak 1996 |
| **Normalized Difference Water Index (NDWI$_w$)** | NDWI$_w$= (R$_{830}$-R$_{1650}$/(R$_{830}$+R$_{1650}$) | Gao 1996 |
| **Blue Normalized Difference Vegetation Index (BNDVI$_w$)** | BNDVI$_w$= (R$_{830}$-R$_{485}$)/(R$_{830}$+R$_{485}$) | Hancock and Dougherty 2007 |

Table 1. Spectral band combinations (indices)

## 2.3 Statistical analysis

Proc Mixed available within the Statistical Analysis System (SAS Institute, North Carolina) software, was used to determine reflectance differences in the residue removed and returned plots. Correlation (r) coefficients between reflectance values and weights of stover returned and % surface residue cover were determined. Finally, graphs of percent residue cover versus spectral band and index for the models with the highest correlations were compared.

# 3. Results and discussion

In 2009, 28.8 % of the soil was covered with residue in the removed (baled) plots, while in 2010, 54% of the soil was covered with residue (Table 2). In the residue returned (not baled) plots, the surface cover was 100 and 70%, in 2009 and 2010, respectively. The residue removal plots (28.8% cover) in 2009 had the lowest reflectance in the green, red, and NIR bands, while the residue returned plots in 2010 had the highest reflectance in the green, red, NIR, and MIR bands. These results imply that corn residues have a relative high albedo, compared to soil. Slightly different results would be expected in soybean (*Glycine max*) where Chang et al. (2004) did not detect reflectance differences between bare and soybean residue covered soil.

| Year | Residue | Percent Cover | Weight Mg/ha | Blue W. | Green W. | Red W. | NIR W. | MIR W. | NDVIw | GNDVIw | BNDVIw | NDWIw |
|------|---------|------|------|------|------|------|------|------|------|------|------|------|
| 2009 | Removed | 28.8 d | 3.7a | 4.60 c | 6.50 c | 8.84 c | 13.75 d | 19.50 b | 0.22b | 0.36b | 0.50b | -0.0035b |
| 2009 | Returned | 100 a | 7.1b | 7.72 a | 11.10 ab | 15.60 b | 23.05 c | 24.02 a | 0.20c | 0.35c | 0.50b | 0.026a |
| 2010 | Removed | 54.2 c | 2.7c | 6.60 b | 11.22 b | 16.53 b | 26.6 b | 26.61 a | 0.24a | 0.41a | 0.60a | -0.15c |
| 2010 | Returned | 70.0 b | 5.5d | 7.18 a | 12.28 a | 18.16 a | 28.91 a | 27.30 a | 0.23ab | 0.41a | 0.60a | 0.02ab |
| p-value | | 0.0001 | 0.001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0005 | 0.0001 | 0.0047 | 0.1691 | 0.0001 |
| | | | | | | | | | | | | |
| 2009 | | 64.4 | 10.9 | 6.2 | 8.77 | 12.2 | 18.4 | 21.76 | 0.21b | 0.36 | 0.50 | -0.08 |
| 2010 | | 62.1 | 7.1 | 6.9 | 11.75 | 17.3 | 27.74 | 26.96 | 0.23a | 0.41 | 0.60 | 0.011 |
| p-value | | 0.464 | 0.001 | 0.14 | 0.0010 | 0.0002 | 0.0001 | 0.0368 | 0.013 | 0.0001 | 0.0001 | 0.0003 |

*Values within a column that have different letters are significantly different at the 0.05 probability level.

Table 2. Variation in residue cover over several wavelengths reflected from corn residues on the ground near Badger site, SD in the years 2009 and 2010.

| | Blue | Green | Red | NIR | MIR |
|------|------|------|------|------|------|
| | | | r | | |
| Residue returned (ton/ha) | 0.39 | 0.30 | 0.27 | 0.22 | 0.002 |
| % residue cover | 0.61 | 0.56 | 0.53 | 0.48 | 0.24 |
| | NDVIw | GNDVIw | NDWIw | BNDVIw | |
| Residue returned (ton/ha) | -0.35 | -0.24 | 0.35 | -0.19 | |
| % residue cover | -0.34 | -0.15 | 0.47 | 0.01 | |

Table 3. The correlation between the amounts of residue returned in 2009 and 2010 to the soil and the ground cover with surface reflectance. r values greater than 0.174 are significant at the 0.05 level.

The correlation coefficient between the residue returned in ton/ha and percent residue cover with surface reflectance are shown in Table 3. The correlation coefficients between residue returned and reflectance ranged from 0.002 in the MIR band to 0.39 in the blue band. For the % surface residue cover, higher r values were observed. These results suggest that surface reflectance measurements were better at predicting the crop residue coverage than residue amount. The highest r value between % ground cover and reflectance was observed for the blue band. The different bands previously have been reported for different uses (http://landsat.usgs.gov/best_spectral_bands_to_use.php). The blue band is useful for distinguishing soil from vegetation, while green is useful for assessing plant vigor. The NIR (770-900 nm) and short-wave infrared (1550 – 1750 nm) discriminates biomass content from soil moisture content. Although blue has a high correlation with surface residue cover, atmospheric scattering may reduce its suitability for space-based sensors (Lillesand and Kiefer, 2000; Wang et al., 2010).

The amount of residue retained on the soil was correlated to NDVI, GNDVI, and NDWI, while the percent coverage was correlated to NDVI and NDWI. Of the indices determined, $NDWI_w$ had the highest r value with percent residue cover followed by $NDVI_w$, $GNDVI_w$, and $BNDVI_w$ respectively. It is important to note, that the results are limited by the boundary conditions of the experiment. Although only the percent residue cover and residue weights versus the reflectance were analyzed, other factors such as soil cover, color or moisture could have impacted the reflectance values (Barnes et al. 2003; Daughtry et al., 2005; Daughtry et al., 2006; Pacheco and McNairn, 2010; Thoma et al., 2004).

A comparison of the reflectance data across years for the blue band suggests that a zero order equation ($y = 4.31 + 0.036x$; $r^2 = 0.38$) could explain the relationship between reflectance and surface coverage (Fig. 1). Slightly different results were observed for the $NDWI_w$ indices where a second order quadratic equation ($y = -0.22 + 0.005x – 0.0000263 x^2$; $R^2 = 0.26$) was used to describe the relationship with surface coverage. The graph of % residue cover versus $NDWI_w$ flattens after the 60 % residue cover which implies that $NDWI_w$ may saturate with increasing coverage. A limitation of this study is that only one site was analyzed, therefore any models generated would be suitable for the specific site and only after fall harvest. Other errors can occur when extrapolating plot measurements data to the whole field coverage. In future, research that confirms the finding for other sites and harvesting approach needs to be conducted.

## 4. Conclusion

The main objective of this study was to investigate the potential of remote sensing to assess residue coverage. The research showed that surface reflectance was more closely correlated with percent cover than the amount of residue returned. Of the spectral band widths measured, reflectance in the blue range provided the most consistent results across the two years. $NDWI_w$ had a higher correlation with residue returned and % cover than $NDVI_w$, $GNDVI_w$, or $BNDVI_w$. Future studies should not only consider more field sites, but incorporate factors such as the decomposition rates of residues on spectral reflectance and harvesting approaches (see Daughtry et al. 2010), so as to develop an accurate and standard approach for mapping residue cover in real time over large geographic areas.
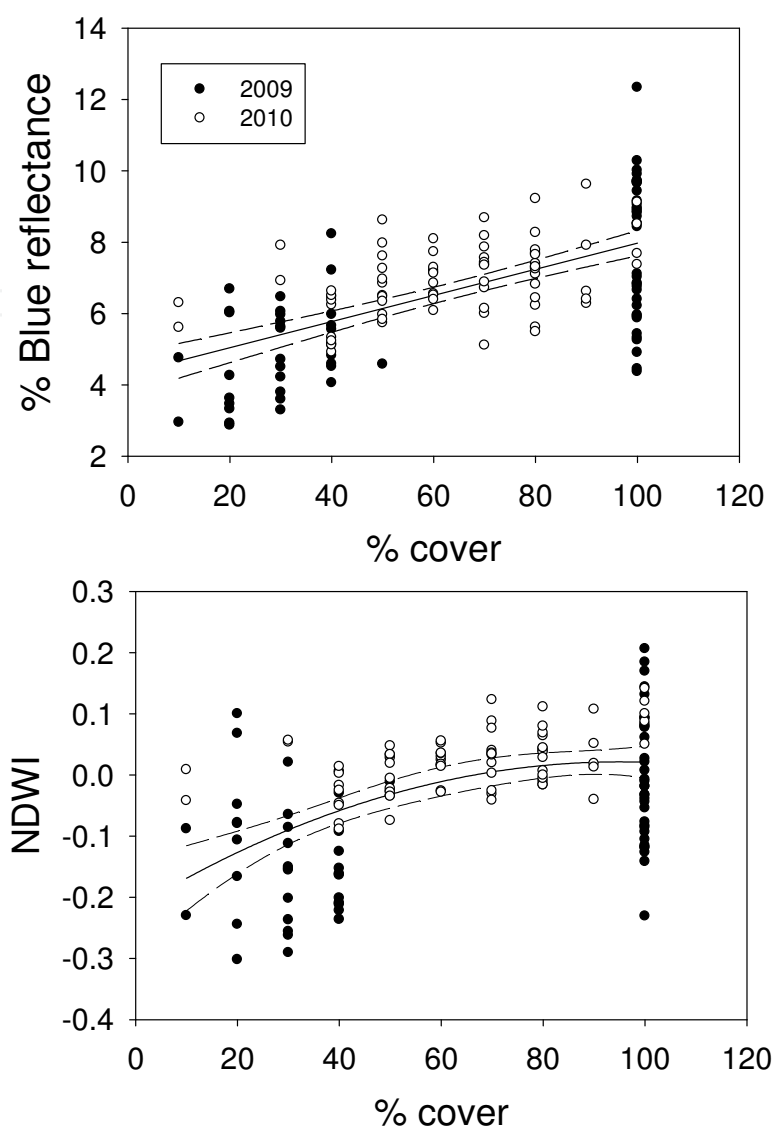
Fig. 1. Percent residue cover versus spectral bands (top) and NDWI$_w$ index (below)

## 5. Acknowledgements

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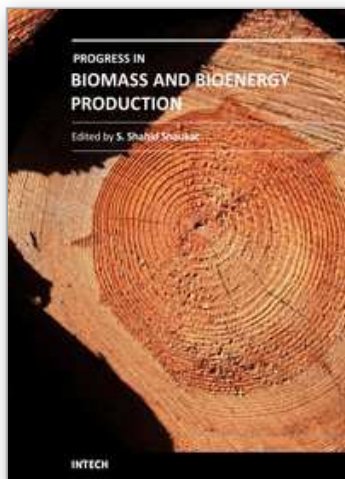
**Progress in Biomass and Bioenergy Production**

Edited by Dr. Shahid Shaukat

Alternative energy sources have become a hot topic in recent years. The supply of fossil fuel, which provides about 95 percent of total energy demand today, will eventually run out in a few decades. By contrast, biomass and biofuel have the potential to become one of the major global primary energy source along with other alternate energy sources in the years to come. A wide variety of biomass conversion options with different performance characteristics exists. The goal of this book is to provide the readers with current state of art about biomass and bioenergy production and some other environmental technologies such as Wastewater treatment, Biosorption and Bio-economics. Organized around providing recent methodology, current state of modelling and techniques of parameter estimation in gasification process are presented at length. As such, this volume can be used by undergraduate and graduate students as a reference book and by the researchers and environmental engineers for reviewing the current state of knowledge on biomass and bioenergy production, biosorption and wastewater treatment.

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