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Improved crop residue cover estimates obtained by coupling spectral indices for residue and moisture

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ABSTRACT

Remote sensing assessment of crop residue cover (f_R) and tillage intensity can improve predictions of the environmental impact of agricultural practices and promote sustainable management. Spectral indices for estimating f_R are sensitive to soil and crop residue water contents, therefore the uncertainty of f_R estimates increases when moisture conditions vary. Our goals were to evaluate the robustness of spectral residue indices based on the shortwave infrared region (SWIR) for estimating f_R and to mitigate the uncertainty caused by variable moisture conditions on f_R estimates. Ten fields with center pivot irrigation systems (eight partially irrigated and two uniformly dry fields) were identified in Worldview-3 satellite imagery acquired for a study site in Maryland (USA). The fields were mid-irrigation at the time of imagery acquisition, allowing comparison of residue cover under dry and wet conditions. Fields were subdivided into approximately equal-size wedges within the dry and wet portions of each field, and the SWIR bands were extracted for each pixel. Two crop residue indices (Normalized Difference Tillage Index (NDTI); Shortwave Infrared Normalized Difference Residue Index (SINDRI) and a water index (WI) were calculated. Reflectance in each band was moisture-adjusted based on the WI difference between wet and dry wedges, and updated NDTI and SINDRI were calculated. Finally, the probability density distributions of f_R estimated from the residue indices were calculated for each field. SINDRI was more robust than NDTI for estimating f_R. Moisture corrections of spectral bands reduced the root mean square error of NDTI f_R estimates from 22.7% to 4.7%, and SINDRI f_R estimates from 6.0% to 2.2%. The mean and variance of the probability density distribution of f_R estimated from residue indices, before and after moisture correction, were greatly reduced in the partially irrigated fields, but only slightly in fields with uniform water distribution. The estimation of f_R should be based on SINDRI if appropriate bands are available, but f_R can be reliably estimated by combining NDTI with a water content index to mitigate the uncertainty caused by variable moisture conditions.

1. Introduction

Maintaining crop residues on the soil surface is a key component of conservation agriculture promoted by the Food and Agriculture Organization of the United Nations to make more sustainable cropping systems (FAO, 2015). The soil is often completely covered by crop residues after harvest, but residue cover decreases as the soil is tilled or residues are removed for fuel or feed. Crop residue fractional cover (f_R) reduces soil erosion and runoff, and therefore the amount of nutrients and agrochemicals that reach surface waters (Delgado, 2010). Tillage intensity is the main management practice that controls f_R and a reduction in tillage is associated with increasing soil organic matter and water retention capacity (Hobbs et al., 2008). In addition, tillage intensity is often a key variable in models, such as EPIC (Izaurralde et al., 2006) and SWAT (Gassman et al., 2007), that predict the overall impact of agricultural systems on soil organic carbon, greenhouse gas emissions, and water quality. These models require geospatial information on landscape topography, soil properties, weather and climate, crop type and management practices, including soil tillage intensity. Appropriate databases exist for all of these requirements except for soil tillage intensity. Thus, the capability to assess f_R and soil tillage intensity can help to improve predictions of the impact of agricultural practices across landscapes and further promote sustainable management of our resources.

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Table 1
Spectral bands used for the crop residue cover indices SINDRI (Shortwave Infrared Normalized Difference Residue Index) and NDTI (Normalized Difference Tillage Index) and the water index (WI).

Band[a]	Wavelengths, nm		Equation	Reference
Residue index				
SWIR6	2185–2225	SINDRI	$\frac{100\,(\text{SWIR6} - \text{SWIR7})}{\text{SWIR6} + \text{SWIR7}}$	Serbin et al., 2009
SWIR7	2235–2285			
OLI6	1570–1650	NDTI	$\frac{\text{OLI6} - \text{OLI7}}{\text{OLI6} + \text{OLI7}}$	Van Deventer et al., 1997
OLI7	2110–2290			
Water index				
SWIR3	1640–1680	WI	$\frac{\text{SWIR3}}{\text{SWIR5}}$	Quemada and Daughtry (2016)
SWIR5	2145–2185			

[a] SWIR3, SWIR5, SWIR6 and SWIR7 are Worldview-3 bands at the designated wavelengths; and OLI6 and OLI7 are Landsat OLI bands simulated with Worldview-3 [OLI6 = average bands (2, 3, 4), OLI7 = average bands (5, 6)].

Currently, in selected counties in the U.S., only qualitative information on crop residue management is available from farmer interviews and road-side surveys (CTIC, 2015). The quantitative standard used by the U.S. Department of Agriculture-Natural Resources Conservation Service (USDA-NRCS), the line-point transect, is impractical for wide-scale use because of time and human resources constraints (Corak et al., 1993; Thoma et al., 2004). Only remote sensing has the potential for monitoring f_R over large areas in a timely and cost effective manner (Zheng et al., 2014).

Early remote sensing methods for assessing f_R were often based on the relatively broad spectral bands of Landsat and similar satellites (Biard and Baret, 1997). Although these multispectral satellites typically have only a few relatively broad spectral bands, they provide global coverage and have been used to assess f_R at regional scales (Van Deventer et al., 1997; Thoma et al., 2004; Sullivan et al., 2008; Zheng et al., 2012). The Normalized Difference Tillage Index (NDTI) (Van Deventer et al., 1997) is generally one of the best of the Landsat-based tillage indices for estimating f_R (Table 1). The corresponding bands of Landsat 4 and 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper (ETM +), Landsat 8 Operational Land Imager (OLI), and Sentinel-2 may be used.

For the Landsat bands, the differences in reflectance of soils and crop residues are small and the accuracy of estimating f_R is often poor (Serbin et al., 2009; Quemada and Daughtry, 2016). However, in the 2100–2350 nm wavelength region, crop residues have absorption features associated with cellulose and lignin that are absent in the spectra of soils and green vegetation (Kokaly and Clark, 1999). Various spectral indices based on detecting these absorption features have been proposed (Daughtry, 2001; Serbin et al., 2009), but are not available using Landsat.

Advanced multispectral imagers, e.g., the Worldview-3 (WV-3) (SIC, 2017) and Advanced Spaceborne Thermal Emission and Reflection radiometer (ASTER) (Abrams, 2000), include multiple bands in the cellulose and lignin absorption region. The most robust crop residue index for these advanced multispectral sensors is the Shortwave Infrared Normalized Difference Residue Index (SINDRI) (Serbin et al., 2009), which can be calculated using the SWIR band 6 (2185–2225 nm) and 7 (2235–2285 nm) of WV-3 (Table 1). These WV-3 bands also correspond to ASTER bands A6 and A7. However, the ASTER SWIR sensor is no longer available due to detector failure in April 2008. Worldview-3 has 3.7-m spatial resolution for the SWIR bands, and is well suited for studying episodic events, but its narrow swath width is not suited for mapping large areas in a timely manner.

Water in the crop residues and soils reduces reflectance at all wavelengths, attenuates the cellulose and lignin absorption features, and reduces the contrast between soil and crop residues (Daughtry and Hunt, 2008; Wang et al., 2013). Thus, the uncertainty of f_R estimates increases as moisture content of the soil and residue increases, and any method to accurately monitor soil tillage intensity must account for variations in water content. Quemada and Daughtry (2016) showed that SINDRI and NDTI accurately estimated f_R when moisture conditions were relatively dry (i.e., relative water content (RWC) < 0.25), but when scene moisture conditions varied from dry to wet the uncertainty of f_R estimates increased. Although SINDRI was more robust to changes in moisture conditions than NDTI, a multivariate linear model that used pairs of spectral indices, one for RWC and one for f_R, improved estimates of f_R using SINDRI. In contrast, NDTI was very sensitive to water content and corrections were unreliable when RWC > 0.25.

In practice, water contents of soils and crop residues often vary spatially due to minor changes in local topographic relief. Therefore, a robust protocol is required to estimate f_R from indices calculated using satellite imagery under varying moisture conditions.

Our goal is to propose a method that mitigates the uncertainty caused by variable moisture conditions on remotely sensed estimates of crop residue cover. Specific objectives were to 1) evaluate the robustness of SWIR-based spectral residue indices under various moisture conditions and 2) develop a reliable method to mitigate the uncertainty caused by variable moisture conditions on estimates of crop residue cover. To achieve this goal, we compared the dry and wet portions of partially-irrigated fields that had been captured mid-irrigation by WV-3 imagery, assuming that residue cover was consistent across each field.

2. Material and methods

2.1. Dataset of field satellite images

Space-borne WV-3 images were acquired on 14 May 2015 over a study site in the Choptank River watershed of eastern Maryland (USA) (Fig. 1). These images were inspected and determined to be properly projected and free of clouds over the study site fields, thus no re-projection or cloud masking were performed. MODTRAN (Spectral Sciences Inc., Burlington, MA, US) was used for atmospheric correction, producing coefficients for converting image radiance values to surface reflectance values. R software was used to apply MODTRAN coefficients to radiance imagery and to output surface reflectance imagery. Individual surface reflectance images were then mosaiced to cover the region of study using ENVI (Harris Geospatial, Boulder, CO, USA).

On the day of imagery acquisition soils were somewhat dry, and irrigation was underway on a number of fields. The dataset used in this paper was composed of 10 fields with full or semi-circular irrigation pivots identified in the WV-3 images. When the images were acquired (12:06 Eastern Daylight Time), the irrigation systems in fields 1 to 8 were operating and, as a result, these fields had clearly identifiable areas with differing water content due to irrigation status (recently irrigated versus not-yet-irrigated). Inside each field, various wet and dry wedges were differentiated based on visual analysis of the image. For each of the wedges, the SWIR bands were extracted from each pixel and the mean and standard error were calculated (Table 2). The 3.7 m resolution of WV-3 image was resample to 4 m. The average size of each wedge was 9433 m^2, each pixel represented 16 m^2 and, therefore, the average number of pixels per wedge was 590. The wedge in which each pivot arm was actively spraying water was deleted, along with various anomalies such as wheel tracks and shallow drainage ditches.

Fields 9 and 10 had not been recently irrigated and thus had relatively uniform water contents when the WV-3 image was acquired. They were chosen to provide a measure of uniformity of the indices in the absence of irrigation. Both fields were subdivided into wedges following the procedure defined for fields 1–8 providing a measure of the expected spatial variation of WI and f_R within a field. The complete dataset contained 10 fields and 98 wedges. Fig. 1c shows an example of identified fields.