Remote sensing for crop residue cover recognition: a review

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Abstract: The application of conservation tillage in recent years was due to the changing of attitudes from conventional agriculture to sustainable agriculture. Soil and water quality have been affected directly by tillage and planting practices. Due to the different advantages of conservation tillage on soil, water and crop quality, these methods have been adopted by scientists and farmers quickly. These advantages were consist of improving soil and water quality, prevention of wind and water erosion and also, reducing soil surface evaporation , greenhouse gases and fuel consumption. By the definition, in conservation tillage, more than 30% of the soil surface covered by the left crop residues. Generally, line-transect method has been used to estimation of crop residue cover (CRC). In spite of the deriving accurate CRC data by line–transect method, the application of this method in large areas is extremely time consuming and costly. Therefore, researchers found that the percentage of CRC can be estimated accurately by processing of satellite remote sensing data. Tillage indices and textural features are two most applicable approaches in remote sensing CRC assessment. The aim of this study was reviewing the conclusions of different researchers and assessment of remote sensing methods in order to finding the best method for estimating the CRC using satellite data. We found that hyper-spectral cellulose absorption index (CAI) has been the best fit with CRC. Multi-spectral indices like normalized difference tillage index (NDTI) and simple tillage index (STI) also demonstrated a good fit with CRC.

Keywords: sustainable agriculture, conservation tillage, remote sensing, satellite imagery, textural features, tillage indices

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1 Introduction

Due to the rapid development of machine technology and necessity of maximum production conservation of soil, water and natural resources is a serious challenge. Since 1994, the topic of sustainable agriculture has been discussed by various researchers. The new agricultural approach is based on sustainable agriculture. Many definitions of sustainable agriculture have been expressed by various institutions, organizations and researchers. Finally, the U. S. congress in the 1990s provided a comprehensive definition that sustainable agriculture is an integrated system of plant and animal production practices which, satisfy human food and fiber needs, enhance environmental quality and the natural resource base upon which the agricultural economy depends, and enhance the quality of life for farmers and society as a whole. One of the topics of sustainable agriculture is different tillage methods which severely effect on soil properties and water consumption. Therefore, conservation tillage was introduced as an alternative to conventional tillage. According to the conservation Technology Information Center (CTIC) in a conservation tillage system more than 30 percent of crop residue must be left on the soil surface after tillage and planting practices. In order to estimation of crop residue cover (CRC) different methods have been developed by many

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researchers but in recent years, remote sensing methods is taken into consideration due to the significant reduction in time and labor costs. In this study, we aim to a) review the advantages of conservation tillage, b) study of the different CRC detection methods and c) concentrate on remote sensing methods in particular.

2 Advantages of conservation tillage

Saving water at soil in semi-arid regions is very important in rain fed cultivations. Generally, at a place that saturated of water vapor, crop residues are able to absorb water about of 80%-90% of its weight, while clay soils absorb 15%-20% at the same conditions (Arshad and Azooz, 1996).

Existence of the crop residue on the soil surface also reduces soil compaction about two-thirds compared to the uncovered soil. Moreover, at the depth of 25-30 cm, the bulk density of plowed soil is less than unplowed soil (Osunbitan et al., 2005). Wang et al. (2012) demonstrated that conservation tillage (no tillage and reduced tillage) increases the bulk density on top of the soil surface compared to the conventional tillage, but it reduces it in subsurface layers.

Residue cover on the soil surface also increases soil permeability about 25%-50% compared to the conventional tillage methods (Daniel et al., 1999).

One of the problems related to farming at arid and semi-arid regions is SOM deficiency. Studies showed annually, 5-7 million hectares of agricultural fields lacked their fertility (Steiner et al, 1998). Bai et al. (2008) found that over 23 years about one fifth of agricultural fields lacked their fertility. Soil erosion in the conventional farming system is three times more than conservation tillage (Montgomery, 2007). Soil biological, physical and chemical attributes depended to soil organic carbons (Chan et al., 2008). Crop residue can improve content of SOM and soil nitrogen in a long term cultivation (Cassman et al., 1996). Anyanzwa et al. (2010) investigated effects of conservation tillage, CRC and cultivation systems on SOM at corn-bean cultivation system. They found that crop residue has been the most increasing on the content of SOM and soil nitrogen.

3 CRC measurement methods

There are different methods to estimation of the crop residue consist of computation method, line-transect method, photo comparison and remote sensing.

3.1 Crop residue estimation using computation method

This is a simple and not precise method to crop residue estimation without the presence of the farm. Al-Kaisi et al. (2002) developed this method for corn and soybean. Table 1 showed remained residues on the soil surface after practices. To reach to final crop residue, we should multiply remained residues of practices.

Table 1 Remained crop residue after different practices (Al-Kaisi et al., 2002)

Practice	Corn, %	Soybean, %
After harvest	90-95	80-90
Winter decomposition	80-90	70-80
plow	02- 07	00-02
Chisel (twisted shank)	40-50	10-20
Disk (offset and deep)	25-40	10-20
Para plow	65-75	35-45
Chisel (straight shank)	50-60	30-40
Disk (tandem, shallow)	40-70	25-35
Anhydrous applicator	75-85	45-55
Field cultivator	80-90	55-65
Plant	80-90	80-90
Till-plant	55-65	55-65

3.2 Line-transect method

Line transect is a simple and precise method to CRC estimation. The equipment for this method is a 30 m measuring tape which can be easily divided into 100 parts with 30 cm intervals (Figure 1). At each location, the tape was stretched diagonally across the rows and the number of markings intersecting the crop residue counted. This counting was repeated but in the perpendicular direction of the first state. Average counted marks in a location indicated the percentage of CRC (Al-Kaisi et al., 2002).

3.3 Photo comparison method

Photos can provide an estimate by comparing fields to percentages in photos that show a known percentage of crop residue. Perspectives from angles are misleading, so look straight down when comparing photos (Figure 2). Accuracy of this method is less than line transect method.

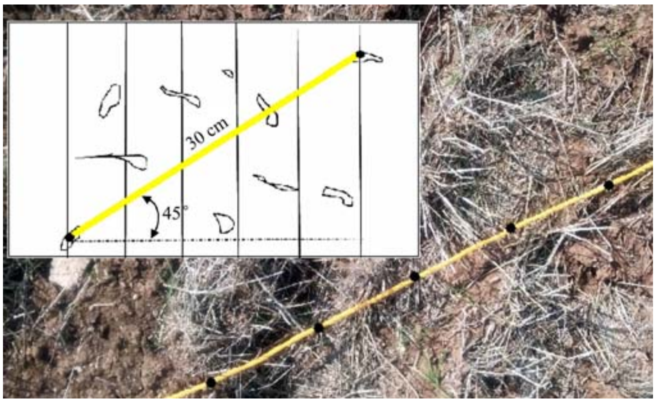

Figure 1 The schematic of line-transect method on wheat residue cover

25%

50%

75%

90%

Figure 2 Wheat CRC estimation using photo comparison

3.4 Remote sensing from satellites and aircraft

Primary efforts to use of remote sensing to CRC mapping refers to 1975. Thereafter possibility of remote sensing crop residue estimation has been investigated in laboratory and field scales. Since spectral reflectance of soil and residue are similar at the vision and near infrared (400-1900 nm) range (Figure 3), chemical absorption property recognition is obvious at the range of shortwave infrared (1900-2500) (Serbin et al., 2009a).

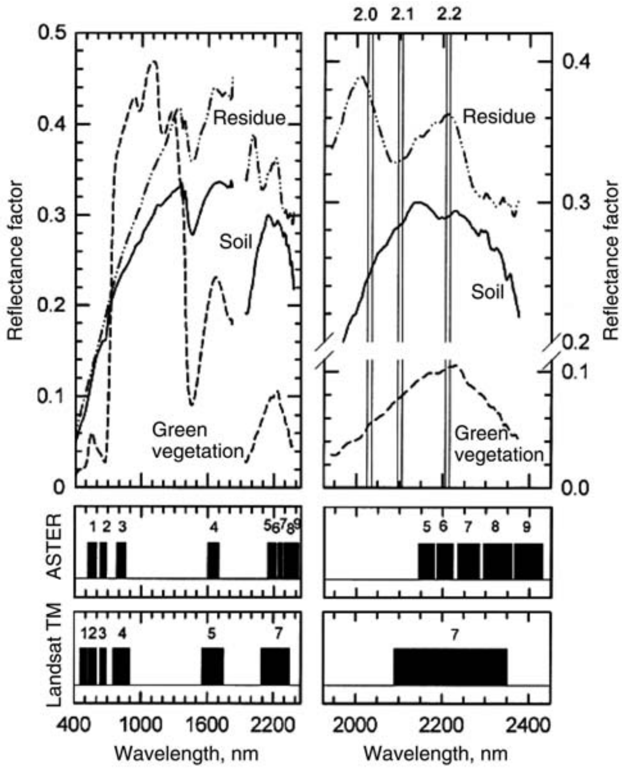

Figure 3 Examples of field spectra for green vegetation, soil, and corn residue. Locations of Landsat-7 TM, advanced spaceborne thermal emission and reflection_ (ASTER), and cellulose absorption index (CAI) bands are shown (Dauthery et al., 2005)

Spectral reflectance is 400-1000 nm for vegetation and it is not appropriate for soil and residue recognition (Dauthery et al., 1997). Soil and crop residue are similar at the reflectance point of view and the only difference between them is in visible and near infrared wavelength range that this made difficult for residue recognition from the soil (Biard and Baret, 1997; Streck et al., 2002). Soil spectral properties are a function of multiple factors, including mineralogy and composition, water content, grain size, structure, and soil organic matter. Crop residue and soil can be very similar spectral below 1,920 nm (Figure 3), as shown by Daughtry et al. (2005), except for an absorption feature around 1,440 nm shared with vegetation and atmospheric water vapor. However, above 1,920 nm, the O-H bending and C-O stretches combination exists at 2,101 nm for cellulose and other sugars, which is not found in common soil minerals and provides a clear contrast between soils and crop residues (Serbin et al., 2009b).

3.4.1 Tillage indices

Tillage indices are including multi-spectral and hyper-spectral. Technically speaking, this classification depends on the type of passive sensor that installed on the platform of the imagery. The both sensors can produce spectral images with several bands (available multispectral and hyper-spectral sensors have 7-12 and 220-250 bands, respectively) at visible, near infrared, shortwave infrared and long wave infrared (thermal). Table 2 shows tillage indices in order to detection the crop residue from the soil and vegetation.

Table 2 Satellite indices in order to residue cover crop identifying

Sensor	Tillage indices	Formula	Description
AVIRIS Hyperion	CAI	$100\times[0.5(R_{2030}+R_{2210})-R_{2100}]$	R2030 and R2210 are the reflectance of the shoulders at 2030 nm and 2210 nm, R2100 is at the center of the absorption
ASTER	LCA SINDRI	100(2×B6–B5–B8) (B6–B7)/(B6+B7)	B5, B6, B7, B8: ASTER shortwave infrared bands 5, 6, 7, and 8
Landsat TM, ETM+ and OLI	STI NDTI MCRC NDI5 NDI7	B5/B7 (B5–B7)/(B5+B7) (B5–B2)/(B5+B2) (B4–B5)/(B4+B5) (B4–B7)/(B4+B7)	B2, B4, B5, B7: Landsat bands 2, 4, 5, and 7
ALI MODIS	NDTI	(B5–B7)/(B5+B7)	B5 and B7

In order to the estimation of CRC linear regression of the model were employed which are based on the multi-spectral and hyper-spectral tillage index. consist of normalized difference tillage index (NDTI) (Daugthry, 2001), normalized difference senescent vegetation index (NDSVI) (Serbin et al., 2008) and normalized difference vegetation index (NDVI) are also remote sensing techniques for vegetation analysis.

Landsat based indices could be used successfully in the diagnosis residue, while, these indices were less effective in areas with different soils (Daugthry et al., 2005), due to weak dissimilarity between soil and residue and that, these indices were strongly influenced by green vegetation (Gill and Phinn, 2008). The results of Aguilar et al (2012) also indicated that hyper-spectral data are able to estimate CRC more accurately than multi-spectral data. CAI and shortwave infrared normalized difference residue index (SINDRI) are two spectral index that provided acceptable results of detection of the residue. Serbin et al. (2009b) found that due to the soils are content of mineral materials, CAI hyper-spectral index is able to detect the residue from the soil accurately, but excessive accumulation of minerals in the soil can lead to errors in the detection of residues. Eskandari et al. (2016) studied the relation between CRC and tillage indices through hyper-spectral spectrometer imagery. They investigated four tillage indices consist of CAI, NDTI, SINDRI and lignin-cellulose absorption (LCA) index. The results showed that CAI had a linear relationship with CRC, which the comparative intensity of cellulose and lignin absorption features near 2100 nm could be measured by it.

There was another index based on Landsat spectrum wavelength known as minimum NDTI which evaluated at several areas and different times in order to CRC estimation. Results showed that this index was capable to estimate CRC. Accuracy of CRC estimation with use of minNDTI almost was equal to CAI results (Zheng et al., 2012). At dry residue spectral reflectance, absorption features near 2100 nm is obvious entirely that these features could not be seen about the soil (Dauthry et al., 2004; Nagler et al., 2000).

Different remote sensing methods have been employed for quantification of crop residue consist of the CAI, NDTI, SINDRI and LCA. Serbin et al. (2008) designed an experiment to compare these indices to detect CRC that led to the following conclusions. CAI had the highest R^2 and lowest Root Mean Square Error (RMSE) of any of the indices and it also had the highest accuracy for separating residue classes. However, NDTI was the best for Landsat-TM based indices, but was not as effective for residue cover estimation as CAI or LCA.

In order to validate the accuracy of results, the results of each method validated against the ground control data which were collected by GPS in field operation.

3.4.2 Textural features analysis

Textural features analysis can apply to textural feature extraction through processing techniques. An image texture is a set of metrics calculated in image processing designed to quantify the perceived texture of an image. Image texture showed the information about the spatial arrangement of color or intensities in an image or selected region of an image (Shapiro and Stockman, 2001).

Textural features analysis accomplished by three main methods, including Wavelet Fourier based, Variogram based and gray level co-occurrence matrix (GLCM) based that GLCM most widely used for structural vegetation parameters (Wood et al., 2012; Blaschke et al., 2014). The co-occurrence matrix captures numerical features of a texture using spatial relations of similar gray tones (Haralick and Shanmugam, 1973; Feizizadeh and Blaschke, 2013).

Numerical features computed from the co-occurrence matrix can be used to represent, compare, and classify textures. In order to textural feature analysis using GLCM, first order statistics and second order statistics are applied (Wood et al., 2012). To calculate second order statistics (Table 3) pixel values come in the form of a GLCM matrix.

Table 3 Textural features computed from a GLCM matrix with the statistic formula

Index	Formula	Description
Contrast	$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$	A measure of the amount of local variation in pixel values among neighboring pixels. It is the opposite of homogeneity.
Correlation	$\sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_i)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right]$	Linear dependency of pixel values on those of neighboring pixels.
Entropy	$\sum_{i,j=0}^{N-1} P_{i,j}(-\ln P_{i,j})$	Shannon-diversity. High when the pixel values of the GLCM have varying values. Opposite of angular second moment.
Standard deviation	$\sigma_i = \sqrt{\sigma_i^2}$	Gray level standard deviation of pixels in the GLCM window. In order to calculate of GLCM's standard deviation, in the first step GLCM variance was calculated as following $\sigma_i^2 = \sum_{i,j=0}^{N-1} P_{i,j}(i-\mu_i)^2 \sigma_j^2 = (j-\mu_i)^2$.
Mean	$\mu_i = \sum_{i,j=0}^{N-1} i(P_{i,j})$	Gray level average in the GLCM window.
Dissimilarity	$\sum_{n=0}^{N-1} n\left\{\sum_{i=1}^{N}\sum_{j=1}^{N} p(i,j)\right\}$	Similar to contrast and inversely related to homogeneity.
Homogeneity	$\sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j)$	A measure of homogenous pixel values across an image.
Angular second moment	$\sum_i \sum_j \{p(i,j)\}^2$	High when the GLCM is locally homogenous. Similar to Homogeneity.

To identify CRC using textural features method, very few studies has been accomplished. Jin et al. (2015) studied correlation between textural features and CRC using Landsat images. They found that all eight textural features indicators in this study, including mean, variance, homogeneity, contrast, dissimilarity, entropy, correlation and second moment have correlation with CRC, but the strongest correlation was belong to mean band 3 with R^2 of 0.71.

4 Conclusions and future

Conservation agricultural systems due to improving soil and water quality, increasing soil organic carbon and reducing wind and water erosion, evaporation, soil surface temperature greenhouse gases and fuel consumption have been considered seriously by scientists, experts and farmers. Remote sensing methods are non-destructive methods that can use satellite data to provide a lot of information about different situations that can be applied in the detection of soil and crop conditions. In recent years, satellite data widely used in agricultural experiments and activities. According to the obtained results from the estimation of the residues using hyper-spectral CAI and multi-spectral NDTI, it is expected that in the future, the method of remote sensing replaces with other methods for estimation of CRC especially in large areas. Nowadays, landsat8 and sentinel 2a produce comprehensive coverage images in fixed time periods. Also, these images are up to date and free for civilization and research activities. Results of this study are important for identifying the most effective remote sensing based indices for CRC analysis. Results are also important for developing new insight in this field of sciences by means of applying new methods, comparing results and identifying the most effective techniques.

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