Measuring Intensity of Tillage and Plant Residue Cover Using Remote Sensing

Namik Kemal Sonmez* and Brian Slater

1Akdeniz University, Science Faculty, Space Science and Technologies Department, 07070, Antalya, Turkey
2The Ohio State University, School of Environment and Natural Resources, 43210, Ohio, USA
*Corresponding author, e-mail address: nksonmez@akdeniz.edu.tr

Abstract
The objectives of this study were to evaluate several spectral indices for estimating soil tillage practices and determining crop residue cover using multispectral and Hyperspectral satellite images. For this purpose, Landsat satellite and EO-1 Hyperion imaging spectrometer data were acquired over agricultural fields in central Ohio, near Columbus, in April and May. According to the calculated mean normalized difference tillage index data (NDTI), in the period 2003 to 2014, area of conservation tillage fields increased at a rate of 8.41 %, while no-tillage fields decreased at a rate of 14.45 %. Comparing normalized difference index (NDI) data from 2003 and in 2014 it was determined that a reduction of 10% vegetated areas occurred. Normalized difference senescent vegetation index (NSDVI) values did not evidence significant change over a nearly 10 year period. The best determination of tillage practices was obtained using the cellulose absorption index (CAI) value calculated from Hyperspectral data. By combining information on crop classification with indexes, similar results were obtained for crop distribution over a ten year period.

Keywords: Remote sensing, hyperspectral, tillage, index.

Introduction
Remote sensing such as aerial photography has been a tool in the mapping of soils for more than 50 years. Spatial patterns in remotely sensed images and crop yield maps over several years have been analyzed to identify areas within fields with similar crop responses. Remote sensing provides efficient and objective methods of obtaining information about crop cover conditions over large areas. These techniques can provide uniform approaches for modeling the spatial variation in residue cover on a continuous surface over large areas, unlike ground based methods which rely on sampling and interpolation [Daughtry et al., 2006].

Soil tillage practices in agricultural fields are an important consideration for reducing soil erosion and increasing soil nutrient contents. Because of the different spectral-radiometric responses between bare soil and crop residue, variation in crop residue cover resulting from tillage practices will necessarily alter the spectral characteristics of the crop background
Robust spectral vegetation indices have been developed to quantify green vegetation by exploiting the characteristic shape of the green vegetation spectrum with its high reflectance of the near infrared (700-1000 nm) and its low reflectance of the visible (400-700 nm). Indices are a mathematical combination of various bands, or spectral transformations of two or more bands designed to enhance the contribution of vegetation properties and allow reliable spatial and temporal inter-comparisons of terrestrial photosynthetic activity and canopy structural variations. As a simple transformation of spectral bands, they are computed directly without any bias or assumptions regarding land cover class, soil type, or climatic conditions. They allow us to monitor seasonal, inter-annual, and long-term variations of vegetation structure, phenological, and biophysical parameters. Moreover, they are used to measure biophysical variables like chlorophyll and other pigment content, vegetation fresh or dry biomass, water content, internal structure of leaves, soil moisture, and plant surface temperature. There are a great number of vegetation indices that have been proposed, ranging from very simple to very complex band combinations.

Motsch et al. [1990] derived a crop residue map showing four tillage categories from Landsat TM data for Seneca County, USA, Ohio and reported an accuracy of 68 percent. For the same study area, VanDeventer et al. [1997] developed a set of Landsat TM-based probability models to identify tillage practices. Models classified 93 percent of the tillage attributes correctly when they were tested with independent data from 15 fields. However, development of remote sensing indices for assessing crop residue cover has been impeded, because soils and crop residues lack unique spectral signatures in the 400-1100 nm region. Crop residues and soils are often spectrally similar and differ only in amplitude at a given wavelength. Shortly after harvest, crop residues are frequently much brighter than the soil, but as the residues start to decompose they may be either brighter or darker than the soil. This makes discrimination between crop residues and soil difficult or nearly impossible using reflectance techniques in the visible and near infrared wavelengths. Efforts to enhance the discrimination of crop residues from soil have led to numerous spectral indices that incorporate the Landsat Thematic Mapper (TM) shortwave infrared bands.

An alternative approach for discriminating crop residues from soils is based on a broad absorption band near 2100 nm that is associated with cellulose and lignin in crop residues [Daughtry, 2001]. From a practical standpoint, indices such as cellulose absorption index (CAI), and the lignin cellulose absorption index (LCA), which are based on cellulose-associated broad absorption features (2100 nm and 2300 nm wavelength) appearing in the reflectance spectra of crop residues in a particular laps of time. According to Daughtry et al. [2005], tillage intensity classes were correctly identified in >90% of the fields in a limited test using aircraft hyperspectral imagery. While absent in the reflectance spectra of soils, these bands are unsuitable for mapping residue cover, largely because most satellite sensors are not sensitive within the specified spectral range [Paul, 2012].

Research on utilizing Landsat TM and ETM+ sensors for crop residue cover (CRC) monitoring tasks has yielded mixed results. Some studies found low, or very low, correlations between Landsat-based tillage indices and CRC field data. Although, the Normalized Difference Tillage Index (NDTI) was found to be the most effective, it was not as effective as cellulose absorption index (CAI) [Zheng et al., 2013].
**Materials and Methods**

**Materials**

The test site was a 7.5 km x 100 km area that included portions of Delaware, Morrow, Franklin and Pickaway counties in central Ohio. The counties centroids are 40°27' 48" N and 82°56'18" W; 39°33'03" N and 83°07'50" W (Fig. 1).

![Figure 1 - Study area.](image-url)
Delaware and Morrow Counties lie in north-central Ohio; Franklin and Pickaway counties lie in south-central Ohio. Those are respectively at elevations ranging from 220-310 m above sea level. Agriculture has been a dominant activity in this region with maize, wheat and soybean crops. Agricultural lands have been gradually replaced by urban development in the central part of the study area, represented by the city of Columbus. Ohio has a great diversity of soils, some of which are very productive. In the study area soils were formed as glacial deposits of Wisconsinan age, with relatively subdued topography on till plains. The dominant agricultural soils are Mollisols and Alfisols, which normally occur in drainage toposequences from moderately well drained crests and shoulder slopes (Udalfs) to somewhat poorly drained lower slopes, and poorly drained depressions (Aqualfs and Aquolls). These soils have lower lime content, and naturally become more acid under weathering conditions.

In this study Landsat 5 data was acquired from April 2003, EO-1 Hyperion imaging spectrometer and Landsat 7 ETM data’s were acquired from April 2004, Landsat 8 OLI was acquired from May 2014 for mapping tillage practices in central Ohio. In order to evaluate some indices, crop residue cover and categorize soil tillage intensity in agricultural fields, ground-truth data were collected from 48 randomly selected fields north and south of Columbus on the same date of the satellite overpass [Gowda et al., 2006].

**Methods**

The implementation process involved three steps: a) pre-processing, b) applying spectral indices to determine tillage probability values for each pixel in the imagery, and c) making statistical analyses by using image classification and accuracy assessment.

Before using data for detecting tillage practices, a series of pre-processing operations were performed on four images including geometric and radiometric corrections. Geometric correction of satellite images involves modeling the relationship between the image and ground coordinate systems. Both images were rectified to a common Universal Transverse Mercator (UTM) WSG84 Datum, Zone 17 coordinate system. Radiometric correction of remotely sensed data is normally carried out to reduce the influence of inconsistencies that may affect the ability to quantitatively analyze as well as to interpret the images. These images were geo-registered and Digital numbers (DNs) were converted to radiance then to reflectance using the method and the calibration coefficients described in Chander and Markham [2003]. Both images were atmospherically corrected using the specific software tool embedded in ERDAS Imagine (based on the ATCOR algorithm, http://www.geosystems.de/atcor/index.html) in order to take into account the variations in solar illumination conditions; the atmospheric scattering and absorption.

Indices are a mathematical combination of various bands or spectral transformations of two or more bands designed to enhance the contribution of vegetation properties and allow reliable spatial and temporal inter-comparisons of terrestrial photosynthetic activity and canopy structural variations. As a simple transformation of spectral bands, they are computed directly without any bias or assumptions regarding land cover class, soil type, or climatic conditions. They allow us to monitor seasonal, inter-annual, and long-term variations of vegetation structure, that are phenological, and biophysical parameters. Moreover, they are used for measurements of biophysical variables: chlorophyll and other pigment content, fresh or dry biomass of vegetation, water content, internal structure of leaves, soil moisture,
and plant surface temperature. There are a great number of vegetation indices that have been proposed, ranging from very simple to very complex band combinations [Jwan Al-doski et al., 2013].

Actually three main broadband spectral indices were used to identify tillage practices. These indices were prepared with the Erdas Imagine program [ERDAS, 2011] and then calculated using Landsat satellite imaging systems. The prepared indexes used in this study are summarized in the Table1.

**Table 1 - Calculated indexes.**

| Bands | Wavelengths (nm) | Index                                      |
|-------|-----------------|-------------------------------------------|
| TM3   | 630-690         | *Mean normalized difference tillage index* [Van Deventer et al., 1997]  
        |                  | NDTI = (SWIR1-SWIR2) / (SWIR1+SWIR2)   |
| TM4   | 760-900         |                                           |
| TM5   | 1550-1750       |                                           |
| TM7   | 2080-2350       |                                           |
| OLI5  | 851-879         | *Normalized difference index* [McNairn and Protz, 1993]  
        |                  | NDI = (NIR1-SWIR2) / (NIR1+SWIR2)    |
| OLI6  | 1566-1651       |                                           |
| OLI7  | 2107-2294       |                                           |
| R2031 | 2026-2036       | *Normalized difference senescent vegetation index* [Qi et al., 2002]  
        |                  | NDSVI = (SWIR1-RED2) / (SWIR1+RED2)  |
| R2211 | 2206-2216       |                                           |

TM: Landsat Thematic Mapper (Landsat 5, Landsat 7), OLI: Operational Land Imager (Landsat 8), Rx: Hyperspectral bands

The explained broadband spectral indices were weakly correlated to crop residue cover. Therefore, a cellulose absorption index (CAI) was used as an alternative approach for discriminating crop residues (Tab.1). The cellulose absorption index was calculated using the corrected Hyperion (hyperspectral imaging systems) data.

In the classification process, the Supervised Classification method was performed using the maximum likelihood algorithm based on a set of user-defined classes and training areas, by creating the appropriate spectral signatures from satellite images. Over 50 training areas were repeatedly selected from the whole study area by drawing a polygon around training sites of interest. In this supervised classification process, Jeffrey-matusita index (JM) of training region were calculated. According to the results, best average separability of bands was 1404.61, 1399.06, 1410.29 for the years 2003, 2004 and 2014, respectively. The signatures can be said to be totally separable in the bands being studied for JM between 0 and 1414 [ Erdas, 2011].

Over the years, a number of image classifiers have been developed. Maximum likelihood classification has been found to be the most accurate and commonly used classifier, when data distributional assumptions are met (Yacuoba et al., 2009). This classifier is based on
the decision rule that the pixels of unknown class membership are allocated to those classes with which they have the highest likelihood of membership.

The land use cover types were stratified according to the U.S. Geological Survey’s Land-Use/Land-Cover classification system for Use with Remote Sensor Data [Anderson et al., 1976]. Land use/cover class maps were divided into seven main classes and classification maps were generated. These classes were explained in the Table 2.

| Major Land Cover Type | Description of Land Cover Classes |
|------------------------|-----------------------------------|
| Urban-vegetation       | Residential areas                  |
| Urban                  | Commercial and industrial areas    |
| Water Bodies           | Rivers and lakes                   |
| Forest and shrub land  | Mature trees, shrubby plants and growing close together |
| Agricultural land      | Rain fed cropping, plated and irrigated crops, wheat parcels |
| Soil Conservation tillage | At least 30% of the soil surfaces were covered with residue after planting |
| Soil Tillage           | Maximum 30% of the soil surfaces were covered with residue. |

Both index results and image classification results cannot be complete unless its accuracy has been assessed. To determine the accuracy of results, a sample of testing pixels is selected on the classified images and their class identity is compared with the reference data (ground truth). The choice of a suitable sampling scheme and the determination of an appropriate sample size for testing data play a key role in the assessment of classification accuracy. To evaluate the accuracy of the classified images, an error matrix was used based on random sampling method in which 232 points were automatically selected from a reference image. Overall accuracy and kappa values were computed by applying user’s accuracy and producer’s accuracy of each class.

Another accuracy assessment process was performed by using a random sampling scheme for each index. For this purpose, various maps, field data, and images of the same dates, were used as reference data. Ground truth measurements of the area also played an important role in this process. To evaluate the accuracy of the indexes, an error matrix was used based on random sampling method in which 90 points were automatically selected from reference image. In the error matrix utility, the reference class values were compared with the class values in a cxc matrix, where c is the number of classes.

**Results and discussion**

Three broadband spectral indices were used to identify tillage practices. The result of this process was a set of 8-bit gray scale images representing the amount of tillage practices present at each time. The NDTI, NDI and NDSVI results of the years are given in the Table 3 and Figure 2.
The calculated NDTI data, in the period from the 2003 to 2014, conservation tillage fields increased at a rate of 8.41 %, while no-tillage fields decreased at a rate of 14.45 % (Fig. 3). These results are directly related to crop management systems periodically that vary from year to year. To evaluate the accuracy of the NDTI data, the total accuracy assessments
for the years 2003, 2004 and 2014 were calculated. As seen on the Table 3, 71.11 % (K = 0.4966), 73.33 % (K = 0.4578) and 75.56 % (K = 0.6276) accuracy was reached, respectively.

These results show that agriculture practices may be determined by using tillage index derived from Landsat satellites [Sullivan et al., 2008]. Also, Daughtry et al. [2005] reported that higher prediction accuracy can be obtained when Landsat-TM indices are used to differentiate tillage practices.

Between normalized difference index (NDI) data from 2003 and in 2014 it was determined that a reduction of 10% vegetated areas occurred (Fig. 4).

Normalized different index is known to be directly related to the change of vegetation. The overall accuracy of the computed normalized difference indexes was 80.00 % (K = 0.6447), 74.40 % (K = 0.6093) and 81.11 % (K = 0.7109) for the years 2003, 2004 and 2014, respectively (Tab. 3).
Table 3 - NDVI, NDTI and NDI changes for ten year-periods.

| NDTI       | 2003     | 2004     | 2014     | Changes between 2003 and 2014 |
|------------|----------|----------|----------|-------------------------------|
|            | ha       | %        | ha       | %        | ha       | %        |                      |
| Conserv.Till. | 5613.70  | 7.20     | 1295.77  | 1.66     | 12167.72 | 15.61    | 8.41                |
| Tillage    | 16693.00 | 21.41    | 15753.94 | 20.21    | 18731.12 | 24.03    | 2.61                |
| No-tillage | 26735.10 | 34.29    | 31774.04 | 40.75    | 15470.62 | 19.84    | -14.45             |
| Urban      | 27623.39 | 35.43    | 27939.26 | 35.84    | 30303.20 | 38.87    | 3.44                |
| Lake       | 1298.62  | 1.67     | 1200.86  | 1.54     | 1291.24  | 1.66     | -0.01              |
| Total      | 77963.81 | 100.00   | 77963.87 | 100.00   | 77963.90 | 100.00   | 0.00                |

Classification Accuracy (%)  
71.11  
73.33  
75.56  

Kappa Statistics  
0.4966  
0.4578  
0.6276  

| NDI         | 2003     | 2004     | 2014     | Changes between 2003 and 2014 |
|-------------|----------|----------|----------|-------------------------------|
|            | ha       | %        | ha       | %        | ha       | %        |                      |
| Little or no Veg. | 11181.77 | 14.34    | 19071.46 | 24.46    | 14133.68 | 18.13    | 3.79                |
| Bare Soil  | 8378.57  | 10.75    | 10477.36 | 13.44    | 10686.38 | 13.71    | 2.96                |
| Vegetation | 29464.87 | 37.79    | 19081.56 | 24.47    | 21552.08 | 27.64    | -10.5              |
| Urban      | 27631.76 | 35.44    | 28035.98 | 35.96    | 30301.86 | 38.87    | 3.42                |
| Lake       | 1306.99  | 1.68     | 1297.58  | 1.66     | 1289.90  | 1.65     | -0.02              |
| Total      | 77963.96 | 100.00   | 77963.94 | 100.00   | 77963.90 | 100.00   | 0.00                |

Classification Accuracy (%)  
80.00  
74.44  
81.11  

Kappa Statistics  
0.6447  
0.6093  
0.7109  

| NDSVI       | 2003     | 2004     | 2014     | Changes between 2003 and 2014 |
|-------------|----------|----------|----------|-------------------------------|
|            | ha       | %        | ha       | %        | ha       | %        |                      |
| Senescent  | 6686.51  | 8.58     | 6926.68  | 8.88     | 7817.47  | 10.03    | 1.45                |
| Modrt. Sensc. | 24355.58 | 31.24    | 21889.56 | 28.08    | 24609.50 | 31.57    | 0.33                |
| No-senescent | 17977.08 | 23.06    | 19814.16 | 25.41    | 13945.20 | 17.89    | -5.17              |
| Urban      | 27634.77 | 35.45    | 28035.98 | 35.96    | 30301.88 | 38.87    | 3.42                |
| Lake       | 1310.00  | 1.68     | 1297.58  | 1.66     | 1289.92  | 1.65     | -0.03              |
| Total      | 77963.94 | 100.00   | 77963.96 | 100.00   | 77963.97 | 100.00   | 0.00                |

Classification Accuracy (%)  
60.00  
58.89  
57.78  

Kappa Statistics  
0.4000  
0.383   
0.3667  

For the calculated normalized difference senescent vegetation index (NDSVI) values a significant change couldn’t be determined over a nearly 10 year period. The overall accuracy of NDSVI results was 60.00 % (K= 0.4000), 58.89 % (K= 0.3833) and 57.78 % (K= 0.3667) for the years 2003, 2004 and 2014, respectively. As can be seen from the
results, the NDSVI calculation was not successful in determining cover. Also, this index exhibited the lowest accuracy.

![Figure 5 - NDSVI changes for ten year-period.](image)

According to Daughtry et al. [2005], tillage intensity classes were correctly identified in >90% of the fields in a limited test using aircraft hyperspectral imagery. While absent in the reflectance spectra of soils, these bands are unsuitable for mapping residue cover, largely because most satellite sensors are not sensitive within the specified spectral range [Paul, 2012]. An alternative approach for discriminating crop residues from soils is based on a broad absorption band near 2100 nm that is associated with cellulose and lignin in crop residues [Daughtry, 2001]. From a practical standpoint, indices such as cellulose absorption index (CAI), and the lignin cellulose absorption index (LCA) which are based on cellulose associated broad absorption features (2100 nm and 2300 nm wavelength) appearing in the reflectance spectra of crop residues. In the study, Cellulose absorption index (CAI) result was shown in Table 4 and Figure 6.

**Table 4 - Cellulose absorption index from EO1 Hyper spectral data.**

| CAI_EO1          | 2004        |
|------------------|-------------|
|                  | ha | %  |
| Cellulose Absorbtion |  6419.90  |  8.23  |
| Moderate Cell. Abs.  |  19448.57 |  24.95 |
| No Cell. Absorbtion |  22761.87 |  29.20 |
| Urban 2004(ha)     |  28035.99 |  35.96 |
| Lake              |  1297.59  |  1.66  |
| Total             |  77963.92 | 100.00 |
| Classification Accuracy(%) |  88.89 |
| Kappa Statistics   |     0.8159 |
In this study, the most accurate determination of tillage practices was obtained using the cellulose index value calculated from Hyperspectral data. As seen in Table 2, the overall accuracy of CAI results was 88.89 % (K= 0.8159) for the year 2004. These findings are similar to those obtained by Van Deventer et al. [1997]. As can be seen from the accuracy assessment results the NDI data and supervised classification obtained relatively high accuracy. Both normalized difference index calculation and supervised classification results indicate that during the last decade, reduction in the vegetation cover in the area has occurred. In the classified images, the pattern of the changes between 2003 and 2014 are presented in the Table 5.
Table 5 - Comparison of areas and rates of changes in land use/cover classes between 2003 and 2014.

| LU/LC Classes          | Landsat 7 ETM 2003 | Landsat 5 TM 2004 | Landsat 8 OLI 2014 | Changes between 2003 and 2014 |
|------------------------|--------------------|--------------------|--------------------|--------------------------------|
|                        | ha     | %     | ha     | %     | ha     | %     | %   |
| Urban (Urbveg+Urban)   | 31826.4| 40.82 | 30283.41| 38.84 | 36863.9| 47.28 | 6.46|
| Waterbodies            | 1526.72| 1.96  | 1538.59| 1.97  | 1462.20| 1.88  | -0.08|
| Forest                 | 8761.84| 11.24 | 13223.3| 16.96 | 5214.91| 6.69  | -4.55|
| Agricultural Lands     | 14246.6| 18.27 | 11963  | 15.34 | 12003.80| 15.40 | -2.88|
| Soil Conserv.Tillage   | 12563.7| 16.11 | 10047.82| 12.89 | 7560.67| 9.70  | -6.42|
| Soil Tillage           | 9037.78| 11.59 | 10907.4| 13.99 | 14857.80| 19.06 | 7.47 |
| Totals                 | 77963.04| 100   | 77963.52| 100   | 77963.28| 100   | 0   |
| Classification Accuracy(%) | 80.60   | 83.19  | 85.78  | 0.7666 | 0.7917 | 0.8257 |

Similar results have been obtained in supervised classification data. As seen on Figure 7, after 2003 the agricultural lands decreased which may be replacement with urban areas. The urban areas (urban veg.+urban) accounted for 40,82 % of the total land in 2003 which increased to 47,28 % until 2014, whereas the agricultural lands decreased from 18, 27% to 15,40 % in the same period.

Figure 7 - Classified images.
The forest areas accounted for 11.24% of the total land in 2003 which decreased by 6.69% until 2014. The overall accuracy of supervised classification results was 80.60% (K=0.7666), 83.19% (K=0.7917) and 85.78% (K=0.8257) for the year 2003, 2004 and 2014, respectively (Tab. 5). These results showed that forest areas decreased and may have been replaced by urban and agricultural areas. According to Evans-Cowley and Gough [2006], due to increasing number of people choosing to live in Ohio townships, dramatic changes have occurred in land use. The results are consistent with many researchers.

Cellulose absorption index (CAI) is based on cellulose associated broad absorption features (2100 nm and 2300 nm wavelength) appearing in the reflectance spectra of crop residues. Also, crop residues are related to tillage practices. In another stage of the study, correlation analyses were performed between NDTI data and CAI (Fig. 8). It was found that high correlation existed between normalized difference tillage index calculated from Landsat data and the cellulose absorption index calculated from Hyperspectral satellite data.

As seen in Figure 8, there was high linear correlation between NDTI data from 2003, 2004 and 2014 and the CAI data which was dated 2004 (R²=0.9592, R²=0.8204 and R²=0.8759, respectively).
As a result of this study, it was demonstrated that Landsat-TM and Hyperspectral data can be used in determining tillage practices and crop residue cover efficiently.

Conclusion
The purpose of this paper was to review, and provide new insights on the application of remote sensing techniques to characterize residue cover and thus tillage intensity. Tillage information is crucial in environmental modeling as it has a direct impact on soil erosion and water holding capacity of agricultural soils. A remote sensing approach is promising for the rapid collection of tillage information on individual fields over large areas. In this study, three Thematic Mapper (TM) indices and one Hyperspectral index were used to map tillage practices in central Ohio. Accuracy assessments of maps derived from Landsat 5 TM, Landsat 7 ETM and Landsat 8 OLI data’s and EO-1 Hyperion were made using field data collected during the 2003, 2004 and 2014 planting seasons. The “percent correct” and kappa (k) values varied from 58-89% and 0.37-0.82, respectively, with best values for index models that use Hyperion bands. Cellulose absorption index (CAI) models were found to be easy to develop, cost and time effective, and produced reasonably accurate tillage classification results.

However, using satellites to map crop residues is still at its infancy possibly due to the inherent difficulties in separating the crop residue spectral signatures from soil. Paul [2012] reported that the long path that still remains towards achieving sufficient progress in residue mapping, in which measuring and estimating spatial variability in residue is determined by several factors, such as residue type, residue moisture, soil moisture, soil types, and time of year, soil organisms, and pH which influence residue decomposition rate, age of residue and so forth.

These results showed that crop residue cover and soil tillage intensity can be determined efficiently using advanced remote sensing techniques, which has been a dominant activity in this region with maize, wheat and soybean crops. This approach is promising for the rapid collection of tillage information on individual fields over large areas, because hyperspectral and advanced multispectral sensors includes CAI bands for crop residue and non-photosynthetic vegetation detection.

References
Anderson J.M., Hardy E.E., Roach J.T., Witmert R.E. (1976) - *A Land Use Classification System for Use with Remote Sensing Data.* U.S. Geological Survey Professional, 964, Washington D.C., Government Printing Office.

Chander G., Markham B. (2003) - *Revised Landsat-5 TM radiometric calibration procedures and postcalibration dynamic ranges.* IEEE Transactions on Geosciences and Remote Sensing, 41 (11): 2674-2677. doi: http://dx.doi.org/10.1109/TGRS.2003.818464.

Daughtry C.S.T. (2001) - *Discriminating crop residues from soil by shortwave infrared reflectance.* Agronomy Journal, 93: 125-131. doi: http://dx.doi.org/10.2134/agronj2001.931125x.

Daughtry C.S.T., Hunt Jr. E.R., Doraiswamy P.C., McMurtrey III J.E. (2005) - *Remote sensing the spatial distribution of crop residues.* Agronomy Journal, 97: 864-871. doi: http://dx.doi.org/10.2134/agronj2003.0291.

Daughtry C.S.T., Doraiswamy P.C., Hunt Jr. E.R., Stern A.J., McMurtrey III J.E., Prueger
J.H. (2006) - Remote sensing of crop residue cover and soil tillage intensity. Soil & Tillage Research, 91: 101-108. doi: http://dx.doi.org/10.1016/j.still.2005.11.013.

ERDAS (2011) - ERDAS Field Guide.

Evans-Cowley J.S., Gough M.Z. (2006) - Land Use Planning and Zoning in Ohio Townships. Journal of Extension, 44 (4). Available online at: http://www.joe.org/joe/2006august/rb5.php.

Gowda P., Peters R., Howell T. (2006) - Mapping Contrasting Tillage Practices in the Texas Panhandle with Landsat Thematic Mapper (TM) Data. World Environmental and Water Resource Congress 2006, pp. 1-7. doi: 10.1061/40856(200)298.

Jwan Al-doski J., Mansor S.B, Shafri H.Z.M. (2013) - NDVI Differencing and Post-classification to Detect Vegetation Changes in Halabja City, Iraq. IOSR Journal of Applied Geology and Geophysics, 1 (2): 01-10. doi: http://dx.doi.org/10.9790/0990-0120110.

McNairn H., Protz R. (1993) - Mapping corn residue cover on agricultural fields in Oxford County, Ontario, using Thematic Mapper. Canadian Journal of Remote Sensing, 19: 152-159. doi: http://dx.doi.org/10.1080/07038992.1993.10874543.

Motsch B., Schaal G., Lyon J.G., Logan T.J. (1990) - Monitoring crop residue in Senaca County, Ohio. Proceedings of the ASPRS Meeting, Cleveland, Ohio, pp. 66-76.

Paul O.V. (2012) - Remote Sensing, Surface Residue Cover and Tillage Practice. Journal of Environmental Protection, 3: 211-217. doi: http://dx.doi.org/10.4236/jep.2012.32026.

Qi J., Marsett R., Heilman P., Biedenbender S., Moran M.S., Goodrich D.C., Weltz M. (2002) - RANGES improves satellite-based information and land cover assessments in Southwest United States. EOS, Transaction, American Geophysical Union, 83 (51): 601-606. doi: http://dx.doi.org/10.1029/2002EO000411.

Sullivan D.G., Strickland T.C., Masters M.H. (2008) - Satellite mapping of conservation tillage adoption in the Little River experimental watershed, Georgia. Journal of Soil and Water Conservation, 63 (3): 112-119. doi: http://dx.doi.org/10.2489/jswc.63.3.112.

Van Deventer A.P., Ward A.D., Gowda P.H., Lyon J.G. (1997) - Using Thematic Mapper data to identify contrasting soil plains and tillage practices. Photogrammetric Engineering & Remote Sensing, 63 (1): 87-93.

Yacuoba D., Guangdao H., Xingping W. (2009) - Assemsent of Land Use Cover Changes Using NDVI and Dem in Puer and Simao Counties, Yunnan Province, China. World rural observations, 1 (2): 1-11.

Zhao D., Yang T., An S. (2011) - Effects of crop residue cover resulting from tillage practices on LAI estimation of wheat canopies using remote sensing. International Journal of Applied Earth Observation and Geoinformation, 14 (2012): 169-177. doi: http://dx.doi.org/10.1016/j.jag.2011.09.003.

Zheng B., Campbell J.B., Serbin G., Daughtry C.S.T. (2013) - Multitemporal remote sensing of crop residue cover and tillage practices: A validation of the minNDTI strategy in the United States. Journal of Soil and Water Conservation, 68 (2): 120-131. doi: http://dx.doi.org/10.2489/jswc.68.2.120.

© 2016 by the authors; licensee Italian Society of Remote Sensing (AIT). This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution license (http://creativecommons.org/licenses/by/4.0/).