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Assessment of Tillage Practices Using Landsat-TM 5 in Nebraska.

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ASSESSMENT OF TILLAGE PRACTICES USING LANDSAT-TM 5 IN NEBRASKA

by

Sonisa Sharma

A THESIS

Presented to the Faculty of

The Graduate College at the University of Nebraska

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Major: Natural Resource Sciences

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Ayse Kilic

Lincoln, Nebraska

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Tillage management practices are an important component to crop production and to federal and state conservation efforts and crop subsidy programs. Crop residue created by conservation tillage reduces soil erosion and reduce evaporation from exposed soil. Agro-hydrological models require information on tillage practices to estimate their impacts on soil-water-holding capacity, total evapotranspiration, carbon sequestration, water runoff and water and wind erosion for agricultural lands. Classification of tillage practices using remote sensing offers promise for the rapid collection of tillage information on individual fields over large areas. Using satellite imagery proves to be challenging due to the similarity in spectral signatures for soils and crop residues and the typically broad spectral bands used by moderate resolution satellites needed to cover large areas and with frequent revisit time. In this study, Landsat 5 images from Path 29, Row 32 in years 2008 and 2009 acquired over southeastern Nebraska (NE) were used to discriminate tillage practices using a Quadratic Discriminant Analysis (QDA). Ground truth data regarding the presence or absence of no-till practices were collected by the US Department of Agriculture–Natural Resources and Conservation Service (USDA–NRCS) at 31 locations in Adams and Fillmore Counties. Results indicated that Landsat-TM bands 1, 3, 4, 5 and 7 classified 75-91% correctly for no-till and 20-55% for till in March and May of 2008 and 2009 respectively. Similarly, the Landsat based tillage indices such as simple tillage index, and the normalized difference tillage index and Normalized difference of Bands 1 and 5 discriminated tillage practices in March and May of 2008 and 2009 images with 81-91% for no-till and 60%, 12-26% for till respectively. When prediction was performed using training model May 2009, there was 81% classification accuracy under no-till and 24 % under till for May 2008 image. The QDA approach with Landsat 5 data appears to be efficient and effective in classifying tillage practices over large areas.

**Key Words:** Reflectance, tillage, bands, remote sensing, quadratic discriminant analysis
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Chapter 1: Introduction

Tillage management practices are an important component to federal and state conservation efforts and crop subsidy programs. Tillage management is important for crop production, due to the influence of surface residue on reducing evaporation losses from the soil surface and promoting infiltration of water. The two general types of tillage practices, till and no-till, represent traditional and modern practices, and impact the amount of crop residue that covers the soil surface. Consequently, the type of tillage exhibit different environmental impacts.

Lately the scientific community has become more interested in carbon dynamics which is greatly affected by the tillage system (South et al., 2004). Many soils in United States have lost 30–50% of the carbon contained in soils prior to cultivation (Kucharik et al., 2001) and much of this loss has been attributed to soil tillage (Reicosky, 2003). Agricultural practices can either sequester carbon or promote its emission. Thus, conservation management decisions are essential for reducing atmospheric carbon dioxide (Tan et al., 2007). One example of such a practice is conservation tillage which encompasses any type of tillage system where at least 30% of the soil surface is covered with crop residue after harvest to protect from wind and water erosion (CTIC, 2004). It has been argued that widespread adoption of conservation tillage within the United States could sequester 24–40 Metric tons carbon year\(^{-1}\) (Lal et al., 2003) through reduced oxidation of the upper soil layer through reduced exposure. These statistics have been extrapolated globally to estimate that conversion of all croplands to conservation tillage could sequester 25 Gt of carbon over the
next 50 years, making adoption of tillage practices one of the key global strategies for stabilizing atmospheric CO$_2$ concentrations (Pacala and Socolow, 2004).

In recent years, numerous regression models have been developed to measure crop residue cover or to identify tillage practices from remotely sensed data. Spectral imaging from various platforms has been used at different spatial scales with varying success, ranging from 60% to 95% using regression approaches. Studies show that higher prediction accuracy can be obtained when Landsat-TM indices are used to differentiate tillage practices. A number of studies also demonstrated that the remote sensing data is somewhat challenging due to the similarity in spectral signatures for soils and crop residues and the typically broad spectral bands used by moderate resolution satellites needed to cover large areas and with frequent revisit time.

The main objective of this thesis is to determine if a particular band or combination of Landsat bands is able to classify tillage and no-tillage system for agricultural-based crop production in Nebraska. A second objective was to determine which time of the year is good for the tillage classification. Therefore, in Chapter 2, reflectance data from Path 29 Row 32 of Landsat Thematic Mapper were used for differentiation of tillage practices in Adam and Fillmore County in Nebraska using Quadratic Discriminant Analysis (QDA). QDA is an appropriate method for binomial data and for determining to which class an observation belongs, based on knowledge of the quantitative variables that best reveals the differences among the classes (Lachenbruch and Goldstein, 1979). Two different QDA were used to understand how each of the selected bands (Band 1, Band 3, Band 4, Band 5, Band 6 and Band 7) or commonly used tillage indices plays a role in differentiation of tillage practices in Nebraska.
The last chapter includes a summary of major findings in this research and the conclusions.
Chapter 2: Discriminating Tillage Practices Using Landsat-5 Thematic Mapper

2.1 Introduction

Tillage management is important for crop production, due to the influence of surface residue on reducing evaporation losses from the soil surface and promoting infiltration of water. Maintaining a residue on the surface will reduce evaporation losses from the soil surface, promote infiltration of water, and reduce soil and wind erosion. The two general types of tillage practices, till and no-till, represent traditional and modern practices, and impact the amount of crop residue that covers the soil surface. Consequently, the type of tillage can influence the crop environment. Lately the scientific community has become more interested in carbon dynamics which is greatly affected by the tillage system (South et al., 2004). Soils in the United States are estimated to have lost 30–50% of the original carbon contained in soils prior to cultivation (Kucharik et al., 2001) and much of this loss can be attributed to land-use intensification, namely soil tillage (Reicosky, 2003). Tilled soils with the extensive soil carbon loss are considered to be a depleted carbon reservoir that can be refilled (Baker et al., 2007). In United States cropland, there has been an average loss of 36 tons of carbon ha⁻¹ (Lal et al., 2003) but scientists suggest that much of this carbon can be restored over a 50 year period with appropriate management (Lal et al., 1998). Agricultural practices can either sequester carbon or promote its emission. Thus, conservation management decisions via tillage type are essential for soil sequestration of carbon dioxide and effecting a reduction of atmospheric carbon dioxide (Tan et al., 2007). Conservation tillage has been defined as encompassing any type of tillage system where crop residue covers at least 30% of the soil surface after harvest to
protect soil particles from wind and water erosion (CTIC, 2010). Conservation tillage is also practiced to reduce evaporation losses. Conservation tillage methods include no-till, strip-till, ridge-till and mulch till types. Reducing evaporation and increasing infiltration of precipitation and irrigation water maximizes agricultural water use efficiency (USDA-NRCS, 2001). It has been argued that widespread adoption of conservation tillage within the United States could sequester 24–40 Mt carbon year\(^{-1}\) (Lal et al., 2003) through reduced oxidation of the upper soil layer through reduced exposure. These statistics have been extrapolated globally to estimate that conversion of all croplands to conservation tillage could result in sequestration of 25 Gt of carbon over the next 50 years, making adoption of conservation tillage a global strategy for stabilizing atmospheric CO\(_2\) concentrations (Pacala and Socolow, 2004).

In addition to the benefit of recharging soil organic carbon (SOC) in the soil, conservation tillage can increase soil and phosphorus retention compared with that of conventional tillage methods. Tillage practices influence wind and water erosion, which in turn have implications for non-point source pollution of pesticides, fertilizers, and sediment (Bricklemyer et al., 2005) due to their influence on erosion and chemical runoff. Reduction in erosion and runoff will improve soil, water and aquatic ecosystem quality (Mickelson et al., 2001). The many benefits of conservation tillage have resulted in the creation of policies that encourage farmers to adopt these practices (Lal et al., 1998; Hache et al., 2007). Under conservation tillage management, there is less evaporation during early growing season. The conservation of water helps to overcome short drought periods without severe moisture stresses developing in the plants. Possible side effects of conservation tillage, however, are an increased dependency on herbicides and a slower
soil warming on poorly drained soils, potential for nitrogen fertilizer losses, and medium to high labor and fuel requirements (Mask et al., 1994). Also the extra water conserved in no-till can be detrimental under heavy precipitation causing denitrification loss (Blevins et al., 1983).

Crop residue left on the surface by conservation tillage reduces evaporation by increasing reflection of solar radiation, shading the moist soil surface from solar radiation, protection of the soil from aerodynamic exchanges of vapor and heat, and providing an insulation cover over the soil surface, thereby reducing its warming. All of these effects reduce energy availability to the soil surface and evaporation (Klocke et al., 2009; van Donk et al., 2010). The overall reduction in evaporation by crop residue is not well understood or quantified. FAO-56 (1998) suggested that crop residue may reduce evaporation from bare soil by 5% for every 10% of surface covered by organic residue.

In order to understand the efficacy of conservation programs and fully quantify the benefits of conservation tillage, it is important to distinguish between conventional and conservation tillage practices and to quantify the aerial extent of coverage on a large scale. For example, agro-hydrological models require information on tillage management practices to estimate water-holding capacity, evapotranspiration, carbon sequestration, and soil losses due to wind and water erosion on agricultural lands (Gowda et al., 2007). In addition, federal and state conservation and crop subsidy programs often need to monitor tillage types and amounts of surface crop residue.

In recent years, numerous regression models have been developed to measure crop residue cover or to identify tillage practices (Thoma et al., 2004; Daughtry et al., 2005;
Sullivian et al., 2006; Gowda et al., 2008). Studies show that higher prediction accuracy can be obtained when Landsat-TM indices are used to differentiate tillage practices in biogeochemical models linked to Geographic Information Systems (Daughtry et al., 2005).

Crop residue cover data are currently not surveyed systematically and vary from one location to another. The USDA Natural Resources Conservation Service (NRCS) generally collects Crop residue cover data visually using a line-transect method (Morrison et al., 1993). The Conservation Technology Information Center (CTIC) provides assessments of conservation tillage practices, but collects data using annual roadside surveys of crop residue levels, which is subjective and limited in geographic extent. CTICs tillage data are available at county, state, and regional levels; county level tillage practices data regarding residue management from the CTIC were recently aggregated to 8-digit Hydrologic Unit watersheds and made available for inclusion in U.S. Geological Survey (USGS) National Water-Quality Assessment Area Characterization dataset (Baker, 2011). The National Agricultural Statistics Service (NASS) crop acreage data relies on survey respondents and is only available at state and county level. These inventory data are either too coarse to provide field level tillage details or are inconsistent to support the simulation of the impact of crop management on water quantity at the field scale. Furthermore, spatial and temporal gaps in crop and tillage inventory data restrict the ability to simulate the impact of crop management on water quality, water conservation, or carbon sequestration at broad scales (Jarecki et al., 2005; Saseendran et al., 2007).
Thus, there is a strong need to develop methods to routinely monitor agricultural management practices over large areas. Spectral imaging from various platforms has been used to identify conventional and conservation tillage practices at different spatial scales with varying success. Landsat-TM is a commonly used satellite dataset for this purpose (Table 1). Landsat-TM has a spatial resolution of 30 m, which allows discriminating variables of interest (e.g. vegetation, landcover, landuse, etc.) on field level. A number of Landsat Tillage Indices as well as sensor indices have been developed using combinations of Landsat-TM bands (Table 2).

In a five year study, Landsat Multispectral Scanner (MSS) images as in Table 2 were used to manually identify land under conventional and conservation tillage practices in the central coastal region of California, involving photo interpretation of enlarged Landsat film products reproduced on 35mm color transparencies and projected onto base maps at a scale of 1:63,360 (De Gloria et al., 1986). They achieved an overall classification accuracy of 81%. However, accuracy of their map was a function of a human interpreter's ability to identify tillage patterns on the image. In Seneca County of Ohio, Landsat 5 TM-based probability models classified 93% of the tillage attributes correctly when they were tested with independent data from 15 fields (Van Deventer et al., 1997). Sullivan et al. (2008) stated that normalized difference tillage and simple tillage indices based on Landsat-TM performed best with an overall accuracy of 71% and 78%, respectively. For an agricultural region located in Montana, Bricklemyer et al. (2006) developed and evaluated logistic regression models based on Landsat Enhanced Thematic Mapper Plus (ETM+). They achieved an overall classification of 95%. Similarly, Vina et al. (2003) reported 77% accuracy when they used Ikonos-based logistic
regression models using bands 4 and 3. Analysis by Gowda et al. (2008) indicates that the combination of TM bands 5 with band 4 or 6 may provide consistent and acceptable results when they are applied in the same geographic region. Watts et al., 2009 studied that there could be more differentiation between no-till and minimum till with the presence of high temporal/spatial resolution data.
Table 1: Wavelength and resolution of each band in Landsat bands

<table>
<thead>
<tr>
<th>Landsat</th>
<th>Wavelength (μm)</th>
<th>Resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thematic Mapper (TM)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Band 1</td>
<td>0.45-0.52</td>
<td>30</td>
</tr>
<tr>
<td>Band 2</td>
<td>0.52-0.60</td>
<td>30</td>
</tr>
<tr>
<td>Band 3</td>
<td>0.63-0.69</td>
<td>30</td>
</tr>
<tr>
<td>Band 4</td>
<td>0.76-0.90</td>
<td>30</td>
</tr>
<tr>
<td>Band 5</td>
<td>1.55-1.75</td>
<td>30</td>
</tr>
<tr>
<td>Band 6</td>
<td>10.40-12.50</td>
<td>120</td>
</tr>
<tr>
<td>Band 7</td>
<td>2.08-2.35</td>
<td>30</td>
</tr>
<tr>
<td>Multispectral Scanner (MSS)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Band 1</td>
<td>0.5-0.6</td>
<td>60</td>
</tr>
<tr>
<td>Band 2</td>
<td>0.6-0.7</td>
<td>60</td>
</tr>
<tr>
<td>Band 3</td>
<td>0.7-0.8</td>
<td>60</td>
</tr>
<tr>
<td>Band 4</td>
<td>0.8-1.1</td>
<td>60</td>
</tr>
<tr>
<td>Enhanced Thematic Mapper Plus(ETM+)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Band 1</td>
<td>0.45-0.52</td>
<td>30</td>
</tr>
<tr>
<td>Band 2</td>
<td>0.52-0.60</td>
<td>30</td>
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<tr>
<td>Band 3</td>
<td>0.63-0.69</td>
<td>30</td>
</tr>
<tr>
<td>Band 4</td>
<td>0.76-0.90</td>
<td>30</td>
</tr>
<tr>
<td>Band 5</td>
<td>1.55-1.75</td>
<td>30</td>
</tr>
<tr>
<td>Band 6</td>
<td>10.40-12.50</td>
<td>60*30</td>
</tr>
<tr>
<td>Band 7</td>
<td>2.08-2.35</td>
<td>30</td>
</tr>
<tr>
<td>Band 8</td>
<td>0.52-0.90</td>
<td>15</td>
</tr>
</tbody>
</table>
Table 2: List of Landsat based indices as well other sensor indices

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Tillage Index</th>
<th>Band ratios</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat-TM</td>
<td>Simple Tillage Index (STI)</td>
<td>$\frac{\text{Band 5}}{\text{Band 7}}$</td>
<td>Van Deventer et al., 1997</td>
</tr>
<tr>
<td></td>
<td>Normalized Difference Tillage Index</td>
<td>$\frac{(\text{Band 5} - \text{Band 7})}{(\text{Band 5} + \text{Band 7})}$</td>
<td>Van Deventer et al., 1997</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>M15</td>
<td>$\frac{(\text{Band 1} - \text{Band 5})}{(\text{Band 1} + \text{Band 5})}$</td>
<td>Van Deventer et al., 1997</td>
</tr>
<tr>
<td>Hyperion</td>
<td>Cellulose Absorption Index (CAI)</td>
<td>0.5$(R_{20}+R_{22})-R_{22}$</td>
<td>Daughtry, 2001</td>
</tr>
<tr>
<td>Landsat ETM+</td>
<td>Normalized Difference Vegetation Index</td>
<td>$\frac{(\text{Band 4} - \text{Band 3})}{(\text{Band 4} + \text{Band 3})}$</td>
<td>Burgan, 1993</td>
</tr>
<tr>
<td>Landsat MSS</td>
<td>Ratio vegetation Index (RVI)</td>
<td>$\frac{\text{Band 4}}{\text{Band 2}}$</td>
<td>Singh, A. 1988</td>
</tr>
<tr>
<td></td>
<td>Normalized vegetation index (NVI)</td>
<td>$\frac{(\text{Band 4} - \text{Band 2})}{(\text{Band 4} + \text{Band 2})}$</td>
<td>Singh, A. 1988</td>
</tr>
<tr>
<td></td>
<td>Transformed vegetation index</td>
<td>$\sqrt{\frac{(\text{Band 4} - \text{Band 3})}{(\text{Band 4} + \text{Band 3}) + 0.5}}$</td>
<td>Singh, A. 1988</td>
</tr>
</tbody>
</table>

Additionally, hyperspectral data from satellite platforms show promise to develop tools for delineation of conservation tillage adoption. NASA Langley Research Center in 2011 classified 80% of fields correctly into two different tillage practices (till and no-till) by using the cellulose absorption index (CAI) using reflectance’s in the shortwave mid-infrared region (2.0-2.2 μm range), corresponding to Landsat TM Band 7. The spatial
resolution of hyperion image is 30 m and temporal resolution of every 16 days like Landsat-TM. This is a sensor that is deployed on NASA’s EO-1 platform (Zhang et al., 2008) The CAI correlates linearly with crop residue fraction (Makar et al., 2011).

\[ \text{CAI} = 0.5 \left( \frac{\rho_{2000} - \rho_{2200}}{\rho_{2100}} \right) \]  

Unfortunately, the hyperspectral images are not readily available for every state and the images are expensive. Moreover, the aerial extent of the image is very small compared to Landsat 5-TM images. Landsat imagery provides a long-term synoptic view of the Earth at 30 meter spatial resolution.

In summary, there have been a number of efforts in recent years that used satellite data from different sensors to classify tillage practices of agricultural fields. These studies noted the accuracies of classification ranging from 60% to 95% using regression approaches. However, regression models do not provide in depth information on the level of significance of the results. The models assume that F-test as a standard statistical test to assess their quality but it is not true. If the models had been developed from subset of large variables, then the F-test would not be a test of significance because of selection bias (Livingstone and Salt, 2005). In addition, Bricklemyer et al., 2006 and Watts et al., 2009 showed that the tillage classification accuracy is good when there is crop residue cover on the fields, but do not provide information on the critical time of year for robust classification accuracy.

Several method such as, tasseled cap (TC) transformation of Landsat-TM (Crist and Cicone, 1984 a, b) were considered since TC had been used in several disturbance-mapping projects because of its ability to highlight relevant vegetation changes (Healey
et al., 2005). Ratios of bands such as TM7/TM5 or the Normalized Difference Vegetation Index (Rouse et al., 1973) were examples which partially fulfill the functions of providing information on the change detection on lands. Brightness, the first feature, is a weighted sum of all the bands, and was defined in the direction of principal variation in soil reflectance. It thus measured soil total reflectance. The second feature, Greenness, is a contrast between the near-infrared bands and the visible bands. Cellular structure in plants scatters infrared radiation and plant pigments (e.g. chlorophyll) absorbs the visible spectrum, thereby producing high greenness values. A third feature, termed Yellowness, was originally defined in the spectral direction expected to correspond to plant senescence (Kauth and Thomas, 1979) as in Fig. 1. Transition zone view is the intermediate phase between soil and vegetation view.

**Fig 1**: TM Tasseled Cap Transformation-North Carolina Sub-Scene: (a) Plane of Vegetation view, (b) Plane of soils view, (c) Transition Zone view (From Christ and Cicone, 1984)
Since, the band ratios partially fulfill the operation of TC transformation and as well as there is not much information on the land cover types on the fields selected; these ideas did not work well. The TC transformation is most appropriate for regional applications where atmospheric correction is not feasible (Huang et al., 2001). The transformation has potential application in finding out the major forest attribute as species, age and structure (Cohen et al., 1995). However, there is a major problem with applying the reflectance factor based transformation directly to at-satellite reflectance images: the greenness value of soil increases as its brightness value increases, making it difficult to differentiate bright soil pixels from some dark green vegetation pixels using the greenness alone (Huang et al., 2001; Cohen et al., 2001). So, using TC transformation to differentiate tillage practices did not seem feasible. Instead, Principal component analysis (PCA) was also viewed as alternative option.

Principal Component Analysis (PCA) has been widely used for reducing variability in higher dimensional data sets to lower dimensional ones for data analysis, visualization, feature extraction or data compression. PCA is appropriate when we have obtained measures on a number of observed variables and wish to develop a smaller number of linear combinations of those variables (called principal components) that will account for most of the variance in the observed variables. However, the PCA is less useful when the goal is to identify a criterion to select the spectral channels/bands that are used in training in Discriminant analysis (Bandos et al., 2007). Even though they are useful for pattern recognition, they are not very useful for discrimination.
In summary, there have been a number of efforts in recent years that used satellite data from different sensors to classify tillage practices of agricultural fields. All the methods previously used do not an analysis for best time for tillage identification. Moreover F-tests are used as test of significance in logistic regression models but one issue with unequal sets of data (14 as till fields and 17 as no-till fields) is the selection bias. In order to overcome these problems, Quadratic Discriminant Analysis (QDA) will be investigated as a potential method to discriminate between unequal number of till and no-till practices. The Landsat-5 imagery was chosen among the freely available satellite imagery since the spatial resolution of 30 meters allows the classification at the field level and provides more information about the surface status when tillage or planting occurred. So, the specific objectives were to:

1) Determine if a particular band or combination of Landsat bands is able to classify tillage and no-tillage systems,

2) Determine which time of year is critical for the classification, and

3) Test the ability of the model for predicting tillage practices in an independent dataset.
2.2 **Materials and Method**

Mapping of tillage practices and the accuracy assessment in this study consist of five steps: 1) selecting ground-truth data, 2) quadratic discriminant analysis (i.e., train the model based on ground-truth data, 3) determining statistical measures of map accuracy, i.e., percent correct, 4) determining the significance of the discriminate function for till and no-till fields, and 5) determining the equation to predict the tillage practices.

### 2.2.1. Ground-Truth Field Study Sites

The selected field sites were located in Adams and Fillmore Counties in Nebraska ([Fig. 2](#)). Adams and Fillmore Counties lie in south-central Nebraska. Counties centroids are at latitude and longitude are 40.5861 N and 98.3884 W; 40.527 N and 97.5959 W, respectively with elevations ranging from 457-520 m above sea level. Adams and Fillmore Counties receive on average 508 to 762 mm (20 to 30 inches) of rain and 381 to 558 mm (15 to 22 inches) of snowfall annually ([http://www.climod.unl.edu](http://www.climod.unl.edu)). Agriculture has been a dominant activity in this region with maize and soybean crops.
Fig 2: Location of till and no-till fields in Adams and Fillmore County, Nebraska, USA. The township, range, and section shape file for each county is overlaid on the Landsat False Color Composite (bands 4, 3, 2) of May 11, 2008 image.

Ground-truth data were collected from 31 randomly selected fields in Adams and Fillmore Counties within Landsat Path 29 and Row 32 for years 2008-2009, months March and May. The legal description (township, range, and section) for these fields with their tillage management classes (no-till and till) were provided by the NRCS (National Resource Conservation Service) (personal communication, Sandra Weber, October 3, 2011). This format was converted to latitude and longitude by using the web tool ScanTek Systems Inc (http://www.legallandconverter.com). Out of 31 fields, 14 fields were reported as tilled fields and 17 were reported as no-tilled fields. We selected
Landsat images in early growing seasons since these will lack vegetative cover. In the mid growing season, soil as well as crop residue cover will be covered by vegetation making it difficult to distinguish soil and crop residue during this time period. Crop residues and soils are often spectrally similar and differ only in amplitude at a given, narrow wavelength (Aase and Tanaka, 1991). Shortly after harvest, crop residues are frequently much brighter than soil, but as the crop residues weather and decompose they may be either brighter or darker than the soil (Nagler et al., 2000). This makes discrimination between crop residues and soil difficult, or nearly impossible, using reflectance values in the visible and near-infrared wavelengths only.

Landsat 5 images from Path 29 Row 32 were obtained from the USGS Earth Resource Observation and Science (EROS) Center (http://www.edcsns17.cr.usgs.gov/EarthExplorer). In this study, Bands 1, 3, 4, 5, 6 and 7 from Landsat-TM are analyzed. Band 1 is capable of differentiating soil and rock surface from vegetation. Band 3 can differentiate between soil and vegetation. Band 4 is useful for crop identification and more in distinguishes between bare and croplands. Band 5 separated forest lands, croplands distinctly. Band 6 is useful to estimate soil moisture. Band 7 separated land and water clearly (http://web.pdx.edu/~emch/ip1/bandcombinations.html). A lot of researcher used band 1, 3, 4, 5, 6 and 7 to discriminate tillage practices (Van Deventer et al., 1997; Daughtry et al., 2001; Vina et al., 2003; Bricklemyer et al., 2006; Gowda et al., 2008). A subset of the large image encompassing all the study area was selected. The acquisition dates for the suitable Landsat 5 images were March 08, and May11, 2008 and March 11 and May 14,
2009; satellite overpass on path 29, row 32, were usually between 11:00 a.m. to 11:10 a.m. Central Standard Time.

Images were prepared and processed within Earth Resources Data Analysis System (ERDAS) (Leica Geosystem Geospatial Imaging, Norcoss, GA.). The Lat/Long coordinates and False Color Composite of Landsat imagery (as a base map) was used to create field polygons. Digital numbers (DNs) were converted to radiance then to reflectance using the method and the calibration coefficients that are described in Chander and Markham (2003) for Landsat-TM. Surface reflectance for all selected bands were calculated for each Landsat-TM using published methodologies coded in ERDAS Imagine 2011 (Tasumi et al., 2006). Next, we created specific subsets of full image by extracting the surface reflectance data for each no-till and tilled field. Reflectance values for selected bands (Band 1, 3, 4, 5, 6 and 7) were pulled from the images for each field at a 30m resolution. Surface reflectance was used for statistical analysis. Band 2 was not used for analysis since Band 2 and 3 are used for the same purpose in differentiating the soil from vegetation.
2.2.2 Quadratic Discriminant Analysis of No-till vs. tillage

The term discriminant analysis (Fisher 1936; Lachenbruch 1975, 1979; Gnanadesikan 1977; Klecka 1980; Hand 1981, 1982; Silverman, 1986) refers to several different types of analyses. Classificatory discriminant analysis is used to classify observations into two or more known groups on the basis of one or more quantitative variables (Cooley and Lohnes 1971; Tatsuoka 1971; Kshirsagar 1972). Classification can be done by either a parametric method or a nonparametric method in the DISCRIM procedure in SAS (SAS 9.2, Cary, NC: SAS Institute Inc., 2000-2008). A parametric method is appropriate only for approximately normal within-class distributions. The method generates either a linear discriminant function (the within class covariance matrices are assumed to be equal) or a quadratic discriminant function (the within class covariance matrices are assumed to be unequal). Quadratic Discriminant Analysis (QDA) is an appropriate method for binomial data and for determining to which class an observation belongs, based on knowledge of the quantitative variables that best reveals the differences among the classes (Lachenbruch and Goldstein, 1979).

The QDA was employed with surface reflectance data of Landsat-TM bands to classify fields of known tillage (till and no-till), using PROC DISCRMIN in SAS software (http://support.sas.com/documentation/cdl/en/statug/63347/HTML/default/viewer.htm#statug_discrim_sect004.htm). No-tilled and tilled fields were classified as “0”, and “1”, respectively. The QDA was used to test for equality of covariance matrix for tillage practices.
The surface reflectance of band 1, 3,4,5,6 and 7 of Landsat-5 TM were used in the analysis. There were total 8 classes as till, no-till of March 2008, March 2009, May 2008 and May 2009. Cross-Validation (Leave-one out field) was used. It involved using single observation from original sample as the validation model and the remaining observation as training models. The equation for QDA was as follows:

\[
Q_i = \text{const}_i + \left[ l_1, l_3, l_4, l_5, l_7 \right],
\]

\[
\left[ \begin{array}{c}
Band 1 \\
Band 3 \\
Band 4 \\
Band 5 \\
Band 7 \\
\end{array} \right] + \left[ \begin{array}{c}
q_{11} \\
q_{13} \\
q_{14} \\
q_{15} \\
q_{17} \\
\end{array} \right],
\]

\[
\left[ \begin{array}{c}
Band 1 \\
Band 3 \\
Band 4 \\
Band 5 \\
Band 7 \\
\end{array} \right] + \left[ \begin{array}{c}
q_{31} \\
q_{33} \\
q_{34} \\
q_{35} \\
q_{37} \\
\end{array} \right],
\]

\[
\left[ \begin{array}{c}
Band 1 \\
Band 3 \\
Band 4 \\
Band 5 \\
Band 7 \\
\end{array} \right] + \ln(n_i/N).
\]

Where,

\[ Q_i = \text{equation for either till (1) or no-till (0)} \]

\[ l_1...l_7 = \text{linear score for each band} \]

\[ q_{11}...q_{77} = \text{quadratic coefficients that are based on mean constant, linear coefficients, covariance matrix, and proportions in training group used to classify test group} \]

\[ \text{Const}_i = \text{constant value that are used found in either till/no-till management} \]

\[ \frac{n_i}{N} = \text{proportions in teaching group used to classify test group} \]

In addition, the significant tillage indices was investigated for middle infrared bands (TM bands 5 and 7) in a Simple Tillage Index, a Normalized Difference Tillage Index (Van Deventer et al. 1997 (Table 2). After that, with reflectances, the classification accuracy was obtained using most significant tillage indices. Since the proportion of observations in each group is unequal, \( \ln(n_i/N) \) was used. Here, \( n_i \) is the number of till/no-till cases to be classified. \( N \) is the number of till/no-till cases of teaching group and \( i \) is the number of cases in the group which is either till or no-till.
2.2.2.1. *Formulate the Hypothesis*

The null hypothesis in the QDA states that the means of all discriminant functions in all groups are equal. Acceptance of the null hypothesis indicates no significant discrimination between the mean of each bands for tillage practices. Thus, if the means for the selected bands are not significant, there was no separation between the till and the no-till fields. The significance of the means of all discriminant functions was found by Mahalanobis distance (MD) (Mahalanobis, 1936).

The **Mahalanobis distance** is the squared distance between two observation vectors i and j.

\[
MD (ij) = \sqrt{(\mu_i - \mu_j)^T \Sigma^{-1} (\mu_i - \mu_j)}
\]  

(3)

Where,

\(\Sigma = \) common covariance matrix

\(\mu_i\) and \(\mu_j\) are the mean reflectance for band 1 through band 7.

\(T = \) transpose of the matrix

This equation assumes a common variance for the groups. The MD accounts for the variance of each variable and the covariance between variables and assumes that the data are normally distributed. The MD used to determine how close an individual spectrum sample is to the center of its group. The QDA was used for five bands (Band 1, Band 3, Band 4, Band 5 and Band 7) to classify two groups (Till or no-till) for all pixels.
associated in each of the sub-images by computing a sample’s distance from each band center in MD units.

2.2.2.2. The significance of the Discriminant Function

In stepwise QDA, specified predictors (selected bands and the Landsat based indices as in Table 2) were entered sequentially based on their ability to discriminate between the groups (Till/no-till) (Thompson, 1995). Discriminant function analysis is broken into a 2 step process: (1) testing significance of a set of discriminant functions, and; (2) classification.

An $F$ test was calculated for each predictor by conducting a univariate analysis of variance where the groups (Till/No-till) were treated as the categorical variable and the predictor as the criterion variable. The predictor with the lowest value of p-value less than alpha at 5% level was the first to be selected for inclusion in the discriminant function. A second predictor was added based on the lower adjusted or partial p-value test, taking into account the predictor already selected. Each predictor selected was tested for retention based on its association with other predictors selected. The process of selection and retention was continued until all predictors meeting the significance criteria for inclusion and retention had been entered in the discriminant function.
2.2.2.3. Estimate the Discriminant Function Coefficient

Canonical correlation measures the extent of association between the mean discriminant scores (D) and the groups (i.e., selected bands and the Landsat based tillage indices). A canonical discriminant function coefficient (CDFC) provides relative importance of each variable and is defined as a linear combination of the variables that yield the highest possible multiple correlation with the groups. Chi-square test was applied to determine whether the within covariance matrices in the discrimination function were significant or not (Morrison, D.F. 1976).

2.2.2.4. Interpret the Results

The classification which results from the predictive ability of discriminant function coefficients (also known as a prediction matrix) contains the number of correctly classified and misclassified cases. The classification % accuracy was calculated as follows:

\[
\text{Classification } \% \text{ accuracy} = \frac{\text{Number of pixel classified correctly}}{\text{Total Number of pixel}}
\]  

The classification also provides the order in which the variables were selected; the order indicates their importance in discriminating between the groups. The ability to discriminate between two classes is represented below in Fig. 3. The test for the statistical significance of the discriminant function is a generalized measure of the distance between the group centroids. If the overlap in the distribution is small, the discriminant function separates the groups well. If the overlap is large, the function is a poor discriminator between the groups. Canonical discriminant analysis plot derives a linear combination of
the variables that has the highest possible multiple correlation with the groups. The variable defined by the linear combination is the first canonical variable or canonical component. The second canonical correlation is obtained by finding the linear combination uncorrelated with the first canonical variable that has the highest possible multiple correlation with the groups. The relative size of canonical correlation provides a measure of the relationship between categorical variable and predictor variables as in Fig 3.

Fig 3: Canonical Discriminant Analysis plots where the curve represents a poor and good distribution.

2.3.2.5 Assess the validity of Quadratic Discriminant Analysis

The validity of Quadratic Discriminant Analysis for the application of distinguishing between tilled and no-tilled fields involved two steps: 1) develop training models using the significant bands and the Landsat based indices in one of the images and 2) use the
training model to validate in other images as in equations 2 and 3. All the steps of quadratic discriminant analysis is summarized as in Fig. 4.

![Diagram showing the steps of quadratic discriminant analysis]

**Fig 4:** Methodology of Quadratic Discriminant Analysis

2.3. **Determining the equation to predict tillage practices**

Quadratic Discriminant Analysis (SAS 9.2, Cary, NC: SAS Institute Inc., 2000-2008) was used to identify the Landsat bands and tillage indices which worked best in training and validating tilled and no-tilled fields. Once the significant spectral bands were selected, the classification was performed using the selected spectral bands. The training model was selected based on the best classification accuracy on tillage management. The remaining images were used as the classifying models. The same approach was used with the Landsat based tillage indices.
In addition, models were also evaluated based on their F-value. Once the training model (Eq. 2) was obtained, the training model was used to classify the percentage of accuracy in the rest images.

3. Results

3.1.1. Formulate the hypothesis

It was hypothesized there was separation or not between the till and the no-till field means for the selected bands and Landsat based tillage indices. The significance test was found using Mahalanobis Distance (MD). All the MD was significant for the selected bands and the tillage indices at the 5% level. So, there was separation between till and no-till fields.

3.1.2. Selection of the Best Vegetation Indices

The next step was the stepwise QDA in which all the pixels from each significant band respectively from four of the images were used to discriminate between two groups (Till/no-till). The stepwise QDA was performed on bands 1, 3, 4, 5, 6 and 7 of all four images i.e March and May of year 2008 and 2009. These bands were found useful in classifying tillage practices (Sullivian et al., 2008; Thoma et al., 2004; Van Deventer et al., 1997; Vina et al., 2003). Table 4 provides information on the significance of each selected band as well as the Landsat tillage indices. Band 3 was the most important band to discriminate tillage practices followed by Band 1, 5, 7, 4 and 6, respectively.
Table 3: Stepwise Summary for bands using all the pixels from four of the images.

<table>
<thead>
<tr>
<th>Step</th>
<th>Number In</th>
<th>Entered</th>
<th>Label*</th>
<th>Partial R Squared</th>
<th>F-Value</th>
<th>Pr&gt;F</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>B3</td>
<td>B3</td>
<td>0.57</td>
<td>6420.70</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>B1</td>
<td>B1</td>
<td>0.77</td>
<td>15793.4</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>B5</td>
<td>B5</td>
<td>0.37</td>
<td>2761.59</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>B7</td>
<td>B7</td>
<td>0.38</td>
<td>2929.96</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>5</td>
<td>5</td>
<td>B4</td>
<td>B4</td>
<td>0.28</td>
<td>1854.38</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>6</td>
<td>6</td>
<td>B6</td>
<td>B6</td>
<td>0.14</td>
<td>761.09</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

*B3: Band 3, B1= Band 1, B5= Band 5, B7= Band 7, B4= Band 4, B6= Band 6

As in Table 4, Band 3 was the most important band to discriminate among till and no-till fields.

A Landsat-TM tillage indices developed by van Deventer et al., (1997) as in Table 2 was used in step QDA to know which indices were more significant to identify tillage practices. All the pixels from all the four images were used. As in Table 4, NDTI was most important in discriminating tillage practices followed by STI and M15.

Table 4: Stepwise Summary for Landsat based indices developed by van Deventer et al. 1997 on all the pixels from all four images.

<table>
<thead>
<tr>
<th>Step</th>
<th>Number In</th>
<th>Entered</th>
<th>Label*</th>
<th>Partial R Square</th>
<th>F-Value</th>
<th>Pr&gt;F</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>NDTI</td>
<td>NDTI</td>
<td>0.79</td>
<td>17772.5</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>M15</td>
<td>M15</td>
<td>0.27</td>
<td>1770.84</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>STI</td>
<td>STI</td>
<td>0.19</td>
<td>1150.45</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

*NDTI: Normalized Difference Tillage Index

* M15: Normalized Difference between bands 1 and 5

* STI: Simple Tillage Index
3.1.3. Estimate the Discriminant Function Coefficient

Since the Chi-Square value is significant at the 0.001 level, the separate within covariance matrices were used in the discriminant function for the QDA approach.

3.1.4. Accuracy assessment of Tillage Practices

When individual images (March 8, 2008; March 11 2009; May 11, 2008 and May 14, 2009) were examined, May 14, 2009 images had the best accuracy for the training dataset. The comparison was made on the basis of correctly classified pixels out of total pixels. For May 2009, there is a 66% classification accuracy in till and 75% in no-till (Table 6 and 7).

For May, 2009, classification % accuracy in no-till was 75% \( \left[ \frac{1555}{1555 + 698} \times 100\% \right] \) and 66% for till \( \left[ \frac{1328}{1328 + 506} \times 100\% \right] \).
Table 6: Individual classification accuracy for four candidate models using Bands 1, 3, 4, 5, 6 and 7.

<table>
<thead>
<tr>
<th>All pixels</th>
<th>Till</th>
<th>No-till</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correctly Classified pixels</td>
<td>Incorrectly Classified pixels</td>
</tr>
<tr>
<td>March 2008</td>
<td>1173</td>
<td>1389</td>
</tr>
<tr>
<td>March 2009</td>
<td>1792</td>
<td>3548</td>
</tr>
<tr>
<td>May 2008</td>
<td>1203</td>
<td>2635</td>
</tr>
<tr>
<td>May 2009</td>
<td>1328</td>
<td>506</td>
</tr>
</tbody>
</table>

Every of the image was treated as a candidate model. All the significant bands were used to classify in one model at a time. As in Table 6, in May 2009, 1328 pixels were correctly classified as till, 506 pixels were incorrectly classified as till and 1555 pixels were correctly classified as no-till, 698 pixels were incorrectly classified as no-till.

When step QDA was performed in the Landsat tillage indices, NDTI was important indices to discriminate so in Table 7, NDTI was used to see how many pixels will be classified correctly as till and no-till. NDTI was tested in each of the four models at a time.

Table 7: Individual classification accuracy for four candidate model using tillage indices NDTI

<table>
<thead>
<tr>
<th>All pixels</th>
<th>Till</th>
<th>No-till</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correctly Classified pixels</td>
<td>Incorrectly Classified pixels</td>
</tr>
<tr>
<td>March 2008</td>
<td>145</td>
<td>2417</td>
</tr>
<tr>
<td>March 2009</td>
<td>1532</td>
<td>3808</td>
</tr>
<tr>
<td>May 2008</td>
<td>799</td>
<td>3039</td>
</tr>
<tr>
<td>May 2009</td>
<td>719</td>
<td>1307</td>
</tr>
</tbody>
</table>

- NDTI = Normalized Difference Tillage Index
In both cases, there is greater percent classification accuracy for no-till.

### 3.1.5. Model Development

The resulting equations 7 and 8 were obtained using equation 2 on May 2009 model as training model and May 2008 model were used as classifying models.

\[ Q_{(no-till)} = -23.30 + [491.92 \times \text{Band 1} - 592.61 \times \text{Band 3} + 41.29 \times \text{Band 4} + 442.26 \times \text{Band 5} - 223.14 \times \text{Band 7} + \begin{bmatrix} -5033 & 4885 & 567 & -1468 & 297 \\ 4885 & -5390 & -174 & 1292 & 130 \\ 567 & -518 & 588 & -522 \\ -1468 & 1292 & 588 & -3017 & 450 \\ 297 & 130 & -522 & 2450 & -2405 \end{bmatrix}_{\text{Band}} + \ln \left( \frac{5088}{1552} \right) \] (7)

\[ Q_{(till)} = -9.62 + [893.52 \times \text{Band 1} - 753.38 \times \text{Band 3} - 30.83 \times \text{Band 4} + 118.35 \times \text{Band 5} + 21.11 \times \text{Band 7} + \begin{bmatrix} -11978 & 10925 & 582 & 52 & -1953 \\ 10925 & -10601 & -500 & -193 & 2230 \\ 582 & -500 & -285 & 683 & -535 \\ 52 & -193 & 683 & -2878 & 2747 \\ -1953 & 2230 & -535 & 2747 & 3141 \end{bmatrix}_{\text{Band}} + \ln \left( \frac{3883}{1127} \right) \] (8)

The above equation gave a classification of 92% in no-till and 12% in till using bands 1, 3, 4, 5, 6 and 7 for all the pixels of all till and no-till of May of 2008 and 2009. When equation 2 was used with May 2009 image to classified/validate in March 2008 and 2009 images, the accuracy in classifying no-till areas was 56% and 54% whereas for till, it was 42 and 31% respectively (Table 8).
Table 8: Validation/classification in rest of the three models using May 2009 as training model and the classifiers are all the pixels from till/no-till of March and May of 2008 and 2009.

<table>
<thead>
<tr>
<th></th>
<th>All pixels</th>
<th>Till</th>
<th>No-till</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correctly Classified pixels</td>
<td>Incorrectly Classified pixels</td>
<td>Correct % classification</td>
</tr>
<tr>
<td>March 2008</td>
<td>1073</td>
<td>1489</td>
<td>42</td>
</tr>
<tr>
<td>March 2009</td>
<td>1632</td>
<td>3708</td>
<td>31</td>
</tr>
<tr>
<td>May 2008</td>
<td>452</td>
<td>3386</td>
<td>12</td>
</tr>
</tbody>
</table>

The quadratic values in the matrix were taken from the classification group (May 2008, March 2009 and March 2008). The training group classifies the sample unit or subject into the population that has the largest quadratic score function. Subject is assigned to a group if it has the highest probability to fall into that group. The equations are used to give a new observation score for no-till and for till. The new observation is then assigned to the group with the highest score.

3.1.6. Validation of Tillage Practices

Since May 2009 image is the good image among the rest of the four images, this image was used as training model to classify in other images. Here, a May image from year 2008 had good percentage of classification with year May 2009 images so the test group here was May 2008 (eqs 7 and 8)
4. Discussion

Quadratic discriminant analysis (QDA) is able to classify no-till vs. till practices for March and May 2008 and 2009, respectively. Of the four images investigated, only the image of May 2009 gave good individual classification accuracy for both of the tillage practices. These results indicate that best classification of no-till vs. conventional tillage system was achieved using Landsat-TM bands 1, 3, 4, 5, 6 and 7. QDA provided for Adams and Fillmore Counties in Southeastern Nebraska 31-66% classification accuracy for cropland under till management and 75-96 % for cropland under no-till management. Images were selected for times representing crop pre-emergence. For May 2009, the cropland under no-till management were classified correctly 75% of the time while those under conventional tillage were classified correctly 66% of the time.

These results are comparable to results reported elsewhere using airborne and hyper spectral images in a corn/soybean rotation in Ohio Landsat- TM were used to determine tillage practices in a simple Tillage Index and a Normalized Difference Tillage Index (NDTI) with accuracy of 93 % (Van Deventer et al., 1997). TM bands 1, 2, 3 and 4 were found useful for identifying soil properties (Van Deventer et al., 1997). NDTI was able to discriminate tillage practices with an accuracy 0f 71 %( Sullivan et al., 2008). The significant TM bands for predicting tillage in our final discriminant equation were band 1, 3, 4, 5, 6 and 7. TM bands 5 and 7 are sensitive to organic matter content and soil water condition (Gowda et al., 2006). Combinations of TM bands 5 with 4 or 6 provide consistent and acceptable results when they are applied in the same geographic region (Gowda et al., 2008). Models with combinations of TM bands 1, 4, 5 and 6 are useful to differentiate tillage practices (Gowda et al., 2007). Band 6 is useful to detect change in
temperatures. This band could be significant help to distinguish between till and no-till fields.

Landsat -TM data can be used to document tillage practices quickly and efficiently as shown in this study. A set of Landsat TM-based models were developed and evaluated for identifying contrasting tillage practices in Nebraska. The training models is able to validate 54-96% in no-till fields whereas 12-42% in till fields. The Quadratic discriminant analysis offers a promising approach to collect information rapidly over larger areas in individual’s fields. This approach provided the information about the significance of bands and Landsat indices. Moreover, it provided an equation which we can use in other year image to predict the classification % accuracy of tillage differentiation. Data from the May 2009 image served as the training dataset to classify in the remaining three images (March 2008, 2009 and May 2008) with TM bands 1, 3, 4, 5, 6 and 7. This training dataset yielded a classification accuracy of 92% for cropland under no-till and 12% for cropland under conventional tillage for May 2008 image. Cropland under no-till was more accurately classified using QDA with Landsat based tillage indices NDTI as in Table 2 (85% accuracy compared to 35% accuracy for cropland under conventional tillage). Other months were not chosen since we really want to see whether we can differentiate tillage practices if there is not much crop residue on the fields. As in the literature, crop residue cover hinder in the spectral reflectance of soil and cause the classification accuracy to be lower. But, in our study, the crop residue does not hinder our work so some crop residue cover in the field will work. Cloud cover in the image can be a problem, especially with Landsat coverage since the overpass is every 16 days.
Chapter 3: Summary and Conclusion

This research focused on acquiring county level GPS data and Landsat 5 TM image in NE that represents locations of till and no-till fields. Reflectances on specified fields were calculated in ERDAS Imagine 2011. Differentiation of tillage filed based on reflectance was analyzed using quadratic Discriminant Analysis (QDA). To test field based reflectance in the study area, each field was assigned a numerical value (1 for till and 0 for no-till). The reflectances for each field within the study area were given quadratic values in the classification group. The test group classifies the sample unit into the population that had the largest quadratic score. Following conclusions can be drawn from this research.

Analysis of the reflectance data indicated that quadratic discriminant analysis proved useful tool to differentiate tillage practices in Nebraska. Timing of acquisition of image is very crucial.

Band 1, 3, 4, 5, 6 and 7 were very crucial to identify the tillage practices. The validation procedure works better if the same months are used in different years (i.e. May 2009 worked better for May 2008).

QDA will be useful approach to identify tillage practices in different local field and weather conditions though locally developed models will be more accurate. With the availability of freely available Landsat products, there will be possibility to find out the tillage history at local as well as global scale. Furthermore, real time series of tillage data will be useful in agro hydrological models to estimate water-holding capacity, evapotranspiration, carbon sequestration, and soil losses due to wind and water erosion on different sets of agricultural lands as rangeland to cropland. Recently launched
Landsat-8 with benefit of high altitude cloud detection will be another outbreak for monitoring tillage operation worldwide

References


Leica Geosystems (2011), ERDAS Imagine 11.0.5, Atlanta, GA. *Leica Geosystems GIS Mapping LLC*


LIST OF APPENDICES

*SAS code for the analysis*

ODS RTF;
PROC IMPORT OUT= WORK.fay
   RANGE="Sheet1$";
   GETNAMES=YES;
   MIXED=NO;
   SCANTEXT=YES;
   USEDATE=YES;
   SCANTIME=YES;
RUN;
DATA fay_2;
SET fay;
mon=50000;
IF Month="March" THEN mon=30000;
TYM=Year + mon + (100000*till);
RUN;
PROC IMPORT OUT= WORK.Fay1
   RANGE="Sheet1$";
   GETNAMES=YES;
   MIXED=NO;
   SCANTEXT=YES;
   USEDATE=YES;
   SCANTIME=YES;
RUN;
DATA fay_3;
SET fay1;
mon=50000;
IF Month="March" THEN mon=30000;
TYM=Year+mon+(100000*till);
RUN;
PROC IMPORT OUT= WORK.fay2
   RANGE="Sheet1$";
   GETNAMES=YES;
   MIXED=NO;
   SCANTEXT=YES;
   USEDATE=YES;
   SCANTIME=YES;
RUN;
DATA fay_4;
SET fay2;
mon=50000;
IF Month="March" THEN mon=30000;
TYM=Year+mon+(100000*till);
RUN;
PROC IMPORT OUT= WORK.fay3
RUN;
Data fay_5;
Set fay3;
Mon=50000;
If month="march" then mon=30000;
Tym=year+mon+(100000*till);
Run;
/* significance of bands*/
Data all; set fay_2 fay_3 fay_4 fay_5;
If tym=32008 then mark=1;
if tym=132008 then mark=2;
If tym=52008 then mark=3;
if tym=152008 then mark=4;
If tym=32009 then mark=5;
if tym=132009 then mark=6;
If tym=52009 then mark=7;
if tym=152009 then mark=8;
Run;
Proc sort data=all out=alls; by year month till; run;
/*proc univariate data=alls plot;var b1 b2 b3 b4 b5 b6 b7; by year mon; run; */
Proc candisc data=alls out=outcan distance; class mark; var b1 b3 b5 b7; run;
/*proc corr data=outcan; with can1-can7; var b1-b7; run;*/
Goptions reset=all gaccess=gsasfile gsfmode=append autofeed dev=pslmo;
Goptions horigin=1in vorigin=2in;
Goptions hsize=6in vsize=8in;
Symbol1 value='1';
Symbol2 value='2';
Symbol3 value='3';
Symbol4 value='4';
Symbol5 value='5';
Symbol6 value='6';
Symbol7 value='7';
Symbol8 value='8';
Run;
Proc gplot data=outcan; where mark=1 or mark=2 or mark=3 or mark=4 or mark=5 or mark=6 or mark=7 or mark=8;
Plot can2*can1=mark; run;
Proc gplot data=outcan; where mark=1 or mark=2 or mark=3 or mark=4 or mark=5 or mark=6 or mark=7 or mark=8;
Plot can3*can1=mark; plot can3*can2=mark; run;
Proc stepdisc data=alls;
   class tym;
   var b1 b3 b4 b5 b6 b7;
Run;
proc discrim data=alls canonical distance tcorr method=normal pool= test ;
class TYM; priors prop;
   var B1 B3 b4 B5 b6 B7;
run;
/* Training and validation */
proc discrim data=fay_5 outstat=may9B1357 canonical method=normal pool= test metric = full
  /*list crosslist listerr crosslisterr outcross=cross out=lister*/ ;
class TYM; priors prop; *id LAT;
var B1 B3 b4 B5 B6 B7;
run;
proc discrim data=fay_4 outstat=may8B1357 canonical method=normal pool=test metric=full
   /* list crosslist listerr crosslisterr outcross=cross out=lister */;
class TYM; priors prop; *id LAT;
var B1 B3 B4 B5 B6 B7;
run;
proc discrim data=fay_3 outstat=mar9B1357 canonical method=normal pool=test metric=full
   /* list crosslist listerr crosslisterr outcross=cross out=lister */;
class TYM; priors prop; *id LAT;
var B1 B3 B4 B5 B6 B7;
run;
proc discrim data=fay_2 outstat=mar8B1357 canonical method=normal pool=test metric=full
   /* list crosslist listerr crosslisterr outcross=cross out=lister */;
class TYM; priors prop; *id LAT;
var B1 B3 B4 B5 B6 B7;
run;
proc discrim data=may9B1357 testdata=fay_4 testout=may9_may81357;
class TYM;
run;
proc print data=may9B1357; run;
/* proc print data=may9_may81357; run; */
proc discrim data=may9B1357 testdata=fay_3;
class TYM; run;
proc discrim data=may9B1357 testdata=fay_2;
class TYM; testclass TYM;
run;
NDTI=(B5-B7)/(B5+B7);
STI=(B5/B7);
M15=(B1-B5)/(B1+B5);
proc print NDTI STI;
proc STEPDISC data=alls;
class TYM;
var NDTI STI M15;
run;
proc discrim data=fay_5 outstat=may9B1357 canonical method=normal pool=test metric=full
   /* list crosslist listerr crosslisterr outcross=cross out=lister */;
class TYM; priors prop; *id LAT;
var NDTI;
run;
proc discrim data=fay_4 outstat=may8B1357 canonical method=normal pool=test metric=full
   /* list crosslist listerr crosslisterr outcross=cross out=lister */;
class TYM; priors prop; *id LAT;
var NDTI;
run;
proc discrim data=fay_3 outstat=mar9B1357 canonical method=normal pool=test metric=full
   /* list crosslist listerr crosslisterr outcross=cross out=lister */;
class TYM; priors prop; *id LAT;
var NDTI;
run;
proc discrim data=fay_2 outstat=mar8B1357 canonical method=normal pool=test metric=full
   /* list crosslist listerr crosslisterr outcross=cross out=lister */;
class TYM; priors prop; *id LAT;
var NDTI;
run;
Ods rtf close;