Mapping Contrasting Tillage Practices in the Texas Panhandle with Landsat Thematic Mapper (TM) Data

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ABSTRACT

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, six Thematic Mapper (TM)-based logistic regression models proposed by van Deventer et al (1997) were used to distinguish conventional and conservation tillage practices in Ochiltree County located in the Texas panhandle. Accuracy assessments of tillage maps derived from Landsat 5 TM data were made using field data collected during the 2005 planting season. Logistic regression models were easy to use, cost and time effective, and produced reasonably accurate tillage maps. The “percent correct” and kappa (k) values varied from 61-83% and 0.02-0.73, respectively, with best values for logistic regression models that use TM bands 1, 3 and 5 images. This approach is promising for the rapid collection of tillage information on individual fields over large areas.

INTRODUCTION

Environmental models require information on tillage management practices to predict water holding capacity, evapotranspiration, carbon sequestration, and soil losses due to wind and water erosion from agricultural lands. Collecting this information can be time consuming, labor intensive, costly and can involve destructive sampling. Moreover, field data are limited because they provide point, rather than area information. Remote sensing techniques show promise in providing such spatial data over a large area in a time and cost-effective manner.

Conventional methods of mapping tillage practices over a large area include field survey and manual interpretation of film-products derived from sensors mounted on aerial or satellite platforms. In a 5-year study, DeGloria et al. (1986) manually interpreted the Landsat MSS data for identifying land under conventional and conservation tillage practices in the central coastal region of California. They achieved an overall classification accuracy of 81 percent. However, accuracy of their map was a function of a human interpreter's ability to identify tillage patterns on the image. Motsch et al. (1990) derived a crop residue map showing four tillage categories from Landsat TM data for Seneca County, Ohio and reported an accuracy of 68 percent. For the same study area, van Deventer 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. Similar levels of accuracy may not be achieved when these models are applied to a different geographic region. Spectral models that contain ratio and orthogonal indices are sensitive to soil types and water conditions (Huete et al., 1985). Therefore, spectral indices developed and evaluated for one geographic location must be re-evaluated if they are to be applied in another geographic location. The objective of this study is to evaluate a set of Landsat TM-based logistic regression models proposed by van Deventer et al. (1997) for their ability to identify tillage management practices.

STUDY AREA

Ochiltree County is located in the Texas Panhandle underlain by the diminishing Ogallala aquifer. The county area is about 234,911 ha with more than 70 percent of the land under row crop production. Annual average precipitation is about 562 mm and about 66 percent of the crop land is irrigated with Ogallala water. Sorghum, wheat and corn are the major crops in the county. Silty clay sherm soils with nearly level to gently sloping fields occupy nearly all of the crop land.

MATERIALS AND METHODS

The Landsat TM imagery was acquired on May 10, 2005 for mapping tillage practices in the Ochiltree County (Figure 1). A set of six TM based logistic regression models proposed by van Deventer et al. (1997) (Table 1) was used to identify tillage practices. Mapping of tillage practices and the accuracy assessment consist of three steps: 1) ground-truth data collection, 2) applying logistic regression models to determine tillage probability values for each pixel in the imagery, and 3) determining statistical measures of map accuracy, i.e., *percent correct* and *kappa (k)* values. Ground-truth data were collected from 41 randomly selected fields in Ochiltree County on the day of the satellite overpass. Ground-truth data included geographic coordinates using a handheld Global Position System (GPS), infrared and digital pictures for residue cover estimation, soil water content using the time-domain reflectometry, and soil samples for particle size distribution.

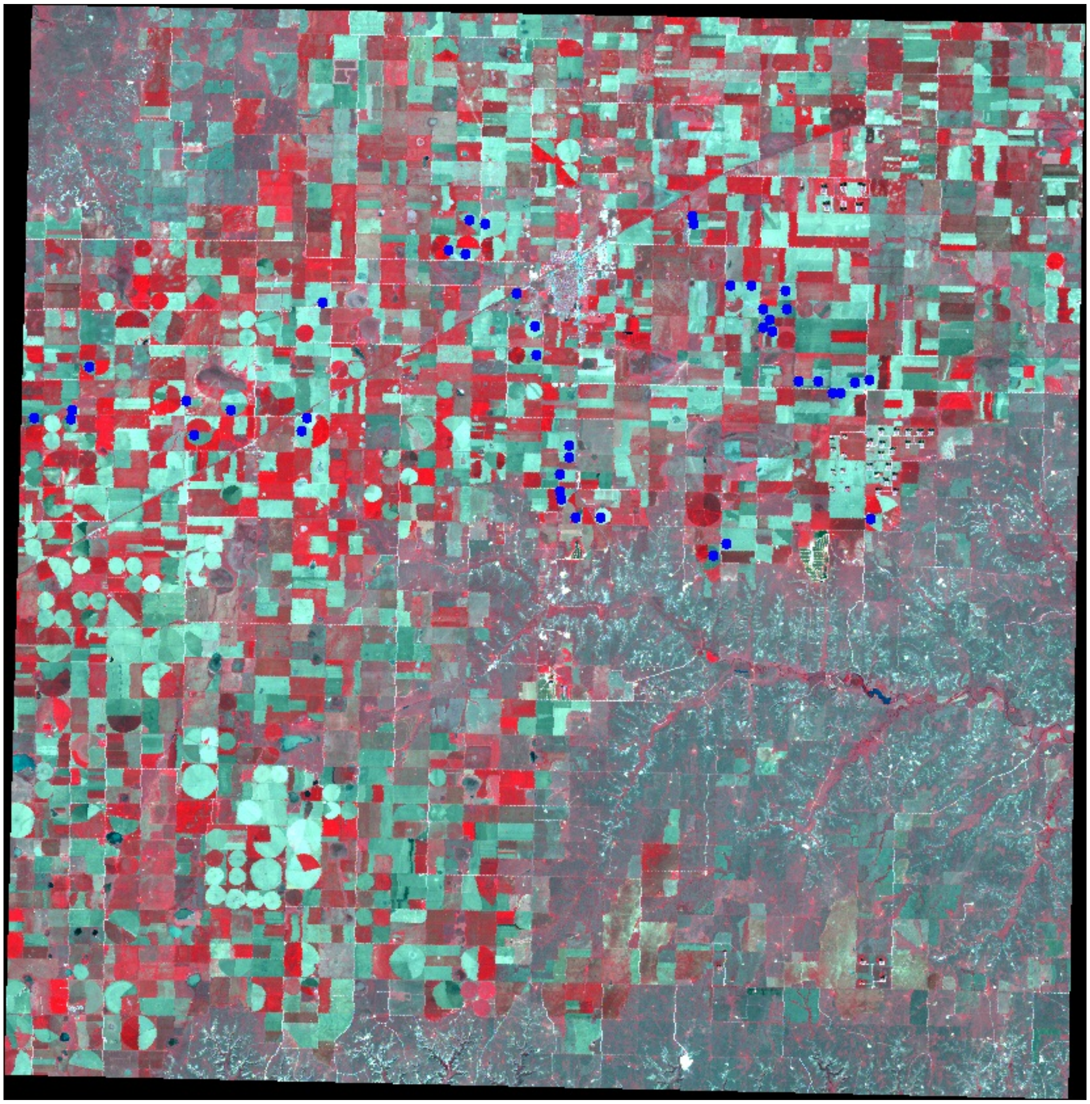

Figure 1. Ground-truth locations on Landsat TM imagery of Ochiltree County acquired on May 10, 2005 for mapping tillage practices.

The Landsat TM-based logistic regression models (SAS, 1990) used in this study have the form:

$$\log it(p) = \ln\left[\frac{p}{1-p}\right] = \alpha + \beta X \quad \textbf{(1)}$$

where p is the response probability for a specific tillage management practice, X is an independent response variable based on reflectance, α is the intercept parameter, and β is a vector of slope parameters. In this study, p is the conventional tillage probability and varies between 0 and 1. The ideal p values for 100% conservation and 100% conventional tillage are 0 and 1, respectively. The p value, expressed as a fraction, is:

$$p = \frac{e^{\log it(p)}}{1 + e^{\log it(p)}} \quad \textbf{(2)}$$

Table 1. Landsat TM-based logistic regression models proposed by van Deventer et al. (1997)[1].

Model	Band or Index[2]	Intercept	Slope	Cut-off Tillage Probability
I	TM5	10.215	-0.072	0.62
II	R15	-19.404	29.949	0.56
III	M15	8.785	40.947	0.56
IV	D35	10.931	0.135	0.44
V	STI	45.218	-23.998	0.64
VI	NDTI	30.464	-99.483	0.62

[1] Intercept and slope terms are for each logit equation. For example, logit(p) = 45.218 - 23.998 STI.
[2] R15 = (Band 1 / Band 5), M15 = (Band 1 - Band 5) / (Band 1 + Band 5), D35 = Band 3 - Band 5, STI = (Band 5 / Band 7) NDTI = (Band 5 - Band 7) / (Band 5 + Band 7).

Logistic regression models require users to specify a cut-off response probability to classify the outcome of an event occurring. For example, in this study, whenever the tillage probability of a pixel was less than the cut-off tillage probability value, the pixel was classified as conservation tillage. Selection of a cut-off response probability will normally depend on the application.

Six models were used with different values for X in Eq. (1). Model I was derived from TM band 5. Model II was based on the ratio of TM bands 1 and 5 (R15 index). Model III was based on the normalized difference between TM bands 3 and 5 (M15 index). Model IV was based on the difference between TM bands 3 and 5 (D35 index). Model V was based on the ratio of TM bands 5 and 7 (Simple Tillage Index - STI). Model VI was based on the normalized difference between TM bands 5 and 7 (Normalized Difference Tillage Index - NDTI).

The ERDAS Imagine®, an image processing software was used extract brightness values for each of the ground-truth location. The ground-truth locations on the image were identified using the geographic coordinates recorded during the field visit. Tillage probability value for each location was calculated using a spreadsheet and ranked for further analysis. The crop residue cover was estimated by classifying the infrared images using Multispec®, an image processing software developed by the Purdue Research Foundation. Cut-off probability values were determined by comparing ground-truth data with calculated tillage probability values to maximize mapping accuracy.

Error matrices (Campbell, 1987) were developed for all regression models to determine overall classification accuracy (*percent correct*) and *kappa (k)* values. *Percent correct* is calculated by dividing the sum of correctly classified fields by the total number of fields examined. The "*k* value is a measure of the difference between two maps and the agreement that might be contributed solely by chance matching of the two maps" (Campbell, 1987). The *k* value is calculated using:

$$k = \frac{Observed - Expected}{1 - Expected} \quad \textbf{(3)}$$

where, "observed" is the *percent correct* and "expected" is an estimate of the chance agreement to the "observed." A *k* value of +1.0 indicates perfect accuracy of the classification.

RESULTS AND DISCUSSIONS

Table 2 presents tillage and crop residue types from 41 randomly selected ground-truth data locations in Ochiltree County during the 2005 planting season. Out of 41 fields, conservation tillage was found in 19 fields and about 53% of these fields had wheat residue. Conventional tillage was found in 22 fields, and only 18% these had wheat residue. About 37% of the conservation and 36% of conventionally tilled fields had sorghum residue. Soybean fields accounted for 32% of the conventionally tilled fields and none under conservation tillage.

Table 2. Tillage and crop residue characteristics of randomly selected fields for ground-truth data in Ochiltree County.

Tillage	**N**[1]	**Crop residue**				
		Sorghum	**Soybean**	**Corn**	**Wheat**	**Others**
Conservation	19	7	0	2	10	0
Conventional	22	8	7	2	4	1
Total	41	15	7	4	14	1

[1] N - Number of ground truth data fields.

Table 3. *Percentage Correct* and kappa (*k*) values for tillage management practice maps derived using TM based logistic regression models.

Model	Band or Index	Cut-off Probability[1]	Percent Correct	Kappa Value (*k*)
I	TM5	0.10	71	0.52
II	R15	0.10	83	0.73
III	M15	0.10	83	0.73
IV	D35	0.10	80	0.69
V	STI	0.99	61	0.03
VI	NDTI	0.99	61	0.02

[1] *Cut-off probability values associated with maximum percent correct* and *k* values

Table 3 presents the best cut-off probability for each tillage model and resulting overall classification accuracy and k values. The regression models that use TM bands 1 and 5 (Model II and III) gave the highest *percent correct* and *k* values followed by the regression model that uses differences between TM bands 3 and 5 (Model IV). Models II and III performed equally and gave *percent correct* and k values of 83% and 0.73, respectively. Similar values were found with model IV. The TM band 3 is present in all three models indicating that reflectance values in the mid-infrared spectral range (1.55 - 1.75 µm) are sensitive to crop residue, and generally show higher reflectance in conservation tillage fields than in conventionally tilled fields.

Models V and VI performed more poorly than all other models. This may be due to the fact that TM Bands 5 and 7 are sensitive to organic matter content and soil water conditions. In the Ochiltree County, a majority of soils are silty clay texture, and soil water content is usually low compared to that in northern Ohio. Also, models V and VI are ratio-based models which are generally sensitive to soil background (Huete et al., 1985). For this reason, the ratio of TM bands 5 and 7 in model V were smaller (< 1.7) than the range of values (1.7 to 2.1) reported in van Deventer (1997). As a result, models V and VI achieved their maximum *percent correct* and *k* values at a cut-off probability of 0.99.

CONCLUSIONS

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, six Thematic Mapper (TM)-based logistic regression models proposed by van Deventer et al (1997) were used to distinguish conventional and conservation tillage practices in Ochiltree County located in the Texas panhandle. Accuracy assessments of tillage maps derived from Landsat 5 TM data were made using field data collected during the 2005 planting season. Logistic regression models were easy to use, cost and time effective, and produced reasonably accurate tillage maps. The "percent correct" and kappa (k) values varied from 61-83% and 0.02-0.73, respectively, with best values for logistic regression models that use TM bands 1, 3 and 5 images. This approach is promising for the rapid collection of tillage information on individual fields over large areas.

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