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Remote sensing of contrasting tillage practices in the Texas Panhandle

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Tillage information is crucial in environmental modelling as it has a direct impact on water holding capacity, evapotranspiration, carbon sequestration and water quality. In this study, a set of Landsat Thematic Mapper (TM)-based linear logistic models were developed for mapping tillage practices and verified with an independent dataset. For data collection purposes, 35 and 41 commercial fields were randomly selected in Moore and Ochiltree counties, respectively, in the Texas Panhandle. Tillage survey was planned and conducted to coincide with Landsat 5 satellite overpasses during the 2005 planting season and two TM scenes were acquired. Using the Moore County dataset, seven logistic regression models were developed and these were evaluated with the data collected from Ochiltree County. The overall classification accuracy of the models varied from 86% to 91% with the Moore County dataset. These models were evaluated against independent Ochiltree County dataset and resulted in somewhat less accurate (classification accuracy of 67–85%) but still useful results. Analysis of these results indicates that logistic regression models that have indices derived from the combination of TM band 5 with bands 4 or 6 may provide consistent and acceptably accurate results when they are applied in the same geographic region.

1. Introduction

Tillage has a direct impact on soil and water quality. Consequently, environmental models require information on tillage management practices to predict carbon sequestration potential (Lal *et al.* 1999), and soil and nutrient losses due to wind and water erosion (Dalzell *et al.* 2004, Gowda and Mulla 2006) from agricultural lands. Studies have shown that the adoption of conservation tillage methods can substantially reduce soil and phosphorus (P) losses compared with conventional tillage methods as they retain at least 30% of the soil surface covered with crop residue after a crop is planted. Conservation tillage includes no-till, ridge-till, strip-till, mulch-till and reduced-till. A 12-year (1983–1994) monitoring study by Ghidey and Alberts (1998) on 28 natural rainfall erosion plots on a silt loam soil near Kingdom City, Missouri, showed that annual surface runoff decreased by 5% with chisel plowing when compared to conventional tillage. Chisel tillage also lowered soil losses by 31% compared to conventional tillage. In a study on fine-loamy soil at Morris, Minnesota, Ginting *et al.* (1998) reported higher P losses associated with

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mouldboard plough (1.30 kg/ha) *versus* ridge tillage (0.16 kg/ha). Higher P losses associated with mouldboard plough were due to higher runoff and sediment losses. Logan and Adams (1981) found that conservation tillage practices were effective in reducing sediment and sediment-bound P losses by 89%. Similar results were observed by Angle *et al.* (1984) in their study on a Manor loam soil in Howard County, Maryland, where total P losses were 8 and 161 g/ha from corn plots with conservation and conventional tillage systems, respectively.

The US Environmental Protection Agency and state pollution control agencies are currently addressing agricultural non-point source pollution by developing and implementing Total Maximum Daily Loads (TMDLs) on water quality limited sections of rivers and streams. Sediment from cropland is one of the primary pollutants leading to impairment of rivers and lakes. The TMDL development process requires site-specific knowledge of topography, soil and tillage management practices to identify and target potential sources of non-point source pollution, as water quality varies across soils and topographic conditions (Dalzell *et al.* 2004). Knowledge of prevailing patterns for adoption of tillage systems in relation to topography within a watershed is important for appropriate allocation of limited funds to target crucial sources of agricultural non-point source pollution (Gowda *et al.* 2003). It is also helpful to evaluate the success of conservation programmes that are promoting adoption of conservation tillage practices to reduce non-point source pollution. Collecting tillage information manually at individual fields on a regional scale can be time-consuming, labour-intensive and costly. Moreover, field data are limited because they provide point- rather than area-based information. Remote sensing techniques promise considerable improvements 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 Multi-Spectral Scanner (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%. However, the 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 Thematic Mapper (TM) data for Seneca County, northern Ohio, and reported an accuracy of 68%.

In recent years, numerous spectral models have been developed to measure crop residue cover or identify contrasting tillage practices. Daughtry *et al.* (2006) evaluated several spectral models for estimating crop residue cover using Landsat TM data. They found weak relationships between Landsat TM indices and crop residue cover. Similar results were reported in Minnesota (Thoma *et al.* 2004). However, these studies reported higher prediction accuracy when crop residue cover was classified into two categories (>30% and <30%), indicating that Landsat TM indices are useful in identifying contrasting tillage practices.

Linear logistic regression modelling is an appropriate technique for modelling binary responses (Neter *et al.* 1996). Numerous studies (van Deventer *et al.* 1997, Vina *et al.* 2003, Bricklemyer *et al.* 2006) have successfully used this technique to develop remote sensing-based models for classifying contrasting tillage practices at a regional scale. The linear logistic regression model (SAS 2005) has the form:

$$\mathrm{logit}(p) = \ln\left[\frac{p}{1-p}\right] = \alpha + \beta X \tag{1}$$

where p is the response probability for a specific tillage management practice and varies between 0 and 1, X is an independent response variable based on reflectance, α is the intercept parameter, and β is a vector of the slope parameter. The p value, expressed as a fraction, is:

$$p = \frac{\mathrm{e}^{\mathrm{logit}(p)}}{1 + \mathrm{e}^{\mathrm{logit}(p)}} \tag{2}$$

The LOGISTIC procedure in SAS (2005) uses a one-step jackknife procedure to obtain new parameter estimates when classifying ordinal data. The method reduces the bias associated with estimating the error count based on the same dataset that was used to develop the logistic regression equation. It is necessary to specify a cut-point response probability to classify the outcome of an event occurring. In efforts to develop logistic models, knowledge of the actual outcome is known and the cut point (p value) that results in most fields being correctly classified is reported as the cut point response probability. The ideal cut-point probability for binary responses is 0.5; however, the selection of a cut-point response probability will normally depend on the application.

For an agricultural region located north of Chester, Montana, Bricklemyer *et al.* (2006) developed and evaluated a logistic regression model based on Landsat Enhanced Thematic Mapper Plus (ETM+) data. They reported an overall classification accuracy of 95% when the model was used to separate conventional tillage systems from conservation tillage systems. Vina *et al.* (2003) reported 77% overall classification accuracy with their Ikonos-based logistic regression models. van Deventer *et al.* (1997) developed a set of Landsat TM-based probability models for discriminating conservation tillage from conventional tilled fields in Seneca County, northern Ohio. In their study, models using the ratio and the normalized differences of TM bands 5 and 7 classified 93% of the tillage attributes correctly evaluated with independent data from 15 fields. However, the accuracy level was reduced to 77% when these models were applied in the Lower Minnesota River Basin (Gowda *et al.* 2001). In addition, the cut point probability values that gave higher classification accuracy were significantly different from the values reported in van Deventer *et al.* (1997), possibly because TM bands 5 and 7 are sensitive to organic matter content and soil water conditions (McNairn *et al.* 1996). Ratio-based models are also generally sensitive to soil background (Huete *et al.* 1985). In the Lower Minnesota River Basin, the majority of the soils are clay and loam in texture, and the soil water content is usually high compared to that in northern Ohio. For this reason, the ratios of TM bands 5 and 7 were smaller (<1.7) in the Minnesota River Basin than the range of values (1.7–2.1) reported by van Deventer *et al.* (1997).

Linear logistic regression models based on Landsat TM data have the ability to identify contrasting tillage practices at a regional scale with acceptable tillage mapping accuracy (van Deventer *et al.* 1997) and cost of the imagery. Table 1 presents spatial and spectral resolutions of the Landsat TM data. However, these models should be evaluated thoroughly before using them in different geographic regions to adjust the cut-point probability values in order to attain higher classification accuracy, or new models may need to be developed when existing

Table 1. Landsat 5 Thematic Mapper (TM) sensor specifications.

Band	Wavelength region (μm)	Spatial resolution (m)
1	0.45–0.52 (Blue)	30
2	0.52–0.60 (Green)	30
3	0.63–0.69 (Red)	30
4	0.76–0.90 (NIR)	30
5	1.55–0.75 (MIR)	30
6	10.4–12.5 (TIR)	120
7	2.08–2.35 (MIR)	30

NIR, near infrared; MIR, mid-infrared; TIR, thermal infrared.

models are insensitive to tillage classes. In either case, ground truth data are needed. Given the options, it is preferable to develop region-specific tillage models for mapping tillage practices to maintain greater tillage classification accuracy. In this study, the main objective was to develop and evaluate a set of Landsat TM-based linear logistic regression models to identify contrasting tillage practices on semi-arid agricultural systems in the Texas Panhandle.

2. Study area

This study was conducted with tillage data collected from 76 commercially operated farms (31 in Moore County and 41 in Ochiltree County) in the Texas Panhandle underlain by the Ogallala Aquifer (figure 1), which is being depleted by excessive

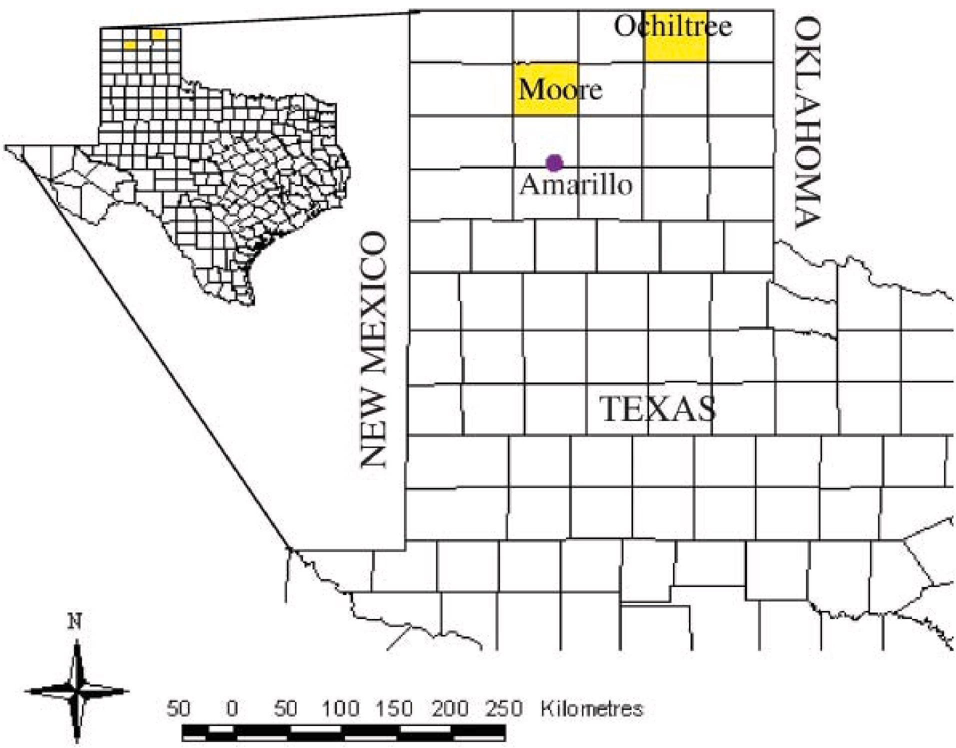

Figure 1. Location of Moore and Ochiltree counties in the Texas Panhandle, USA.

pumping. The Moore County is in the north-central part of the Panhandle and has a total area of 236 826 ha. Two-thirds of the land is in the nearly level, smooth uplands of the High Plains (USDA-SCS 1975) and most of it is under row crop production. Corn, sorghum and wheat are the major crops in the county. In 2004, Moore County ranked fifth in corn production and accounted for about 5.7% of total corn produced in the state (NASS 2005). The area of Ochiltree County is 234 911 ha, with more than 70% of the land under row crop production. Sorghum, wheat and corn are the major crops in the county. In 2004, Ochiltree County ranked eighth in sorghum production and accounted for about 2.4% of the total sorghum produced in the state (NASS 2005). Typical planting dates for major crops in the study area vary from the second week of April to the third week of May. Annual average precipitation is about 481 and 562 mm for Moore and Ochiltree counties, respectively. Crop water needs are supplemented with groundwater from the underlying Ogallala Aquifer. Nearly level to gently sloping fields with silty clay soils of the Sherm series occupy nearly all of the crop land in both Moore and Ochiltree counties. Conventional tillage practices in the study area usually consist of offset disk in autumn. Common conservation tillage practices are no ploughing in the autumn and sweep or disk ploughing at planting that leaves at least 30% of the surface covered with crop residue after planting.

3. Materials and methods

Developing and evaluating the tillage models consisted of four steps: (1) ground-truth data collection, (2) remote sensing data acquisition, (3) development of models using the linear logistic regression modelling technique, and (4) evaluation of models using statistical measures of classification accuracy (i.e. percentage correct and kappa (k) values). Two Level-1 processed, precision-corrected Landsat TM scenes were acquired, one on 10 May 2005 for Ochiltree County (Path 30/Row 35) and the other on 17 May 2005 for Moore County (Path 31/Row 35), for developing and evaluating Landsat TM-based tillage models. On the day of the Landsat 5 satellite overpass, ground-truth data were collected from 35 and 41 randomly selected commercial fields planted with major crops in Moore and Ochiltree counties, respectively. Ground-truth data included geographic coordinates obtained using a handheld Global Positioning System (GPS), infrared images taken at 2-m height using the Agricultural Digital Camera (ADC, Dycam Inc., Chatsworth, CA, USA) and digital pictures for residue cover taken with a 5-megapixel digital camera.

The crop residue cover was estimated by classifying the infrared images using Multispec© image processing software developed by the Purdue Research Foundation. Tillage practices were assigned a class value of 0 for conventional tillage and 1 for conservation tillage. In this study, the p in equation (1) is the conservation tillage probability. Therefore, the ideal p values for 100% conventional and 100% conservation tillage are 0 and 1, respectively. Tillage classification was based on the percentage of the soil surface covered with crop residue. We defined conservation tillage systems as those that retained at least 30% of the soil surface covered with crop residue after a crop is planted.

Ground-truth pixel locations on each image were identified using the GPS coordinates for extracting spectral reflectance data for each TM band image. In Landsat TM data, reflectance values are stored as brightness values (or digital numbers) in the 8-bit format. The raw brightness values for ground-truth pixels were extracted and analysed using image processing software. For model development and evaluation, mean reflectance data from 9 pixels (ground-truth pixel and surrounding 8 pixels) were used. Table 3 presents the mean brightness values for Moore and Ochiltree counties. The Moore County dataset was used for model development and the Ochiltree County dataset was used for testing the models.

For logistic regression model development, TM indices were developed with all possible combinations of two bands from all seven Landsat 5 TM bands. The TM indices included difference indices, sum indices, product indices, ratio indices and normalized difference indices. A linear logistic regression analysis was performed for the tillage variable with (1) the brightness value for each TM band, (2) each difference, sum, product and normalized difference index, and (3) stepwise, backward and forward analysis, where successive significant TM bands and indices were added or insignificant TM bands and indices were deleted from the logistic regression model. Finally, the tillage models that yielded an overall classification accuracy of 75% or more were identified to match with the accuracy levels reported with county-level tillage transect surveys commonly conducted in the USA for collecting tillage information (Thoma *et al.* 2004). The selected models were evaluated against the Ochiltree County dataset for their ability to accurately identify conservation and conventional tillage systems. Two methods were used to determine tillage classification accuracy. In method I, cut-point probabilities derived from the Moore County dataset were used, whereas in method II, cut-point probabilities were determined by comparing ground-truth data with tillage probability values to maximize the tillage classification accuracy.

For the purpose of model evaluation, error matrices (Campbell 1987) were developed for all logistic regression models to determine the overall classification accuracy (percentage correct) and k values. Percentage correct was 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' (Congalton and Green 1999). The k value is calculated as:

$$k = \frac{\text{Observed} - \text{Expected}}{1 - \text{Expected}} \qquad (3)$$

where 'Observed' is the percentage 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.

4. Results and discussion

Table 2 presents ground-truth data collected in the Moore and Ochiltree counties, respectively, during the 2005 planting season. The Moore County dataset consists of 19 fields in conservation tillage and 16 fields in conventional tillage. About 53% of the conservation and 50% of conventionally tilled fields had corn residue. Sorghum residue was found in three fields in each tillage category and five out of nine fields with wheat residue were conventionally tilled. The mean soil organic carbon and soil moisture contents were 1.39% and $0.22\,m^3\,m^{-3}$, respectively, in conventionally tilled fields. Out of 41 fields in Ochiltree County, conservation tillage was found in 20 fields and about 50% of these fields had wheat residue. Conventional tillage was found in 21 fields and only 19% of these had wheat residue. About 40% of the conservation and 33% of conventionally tilled fields had sorghum residue. Soybean fields accounted for 33% of the conventionally tilled fields and none under

Table 2. Tillage and crop residue characteristics of randomly selected commercial fields for ground-truth data in Moore and Ochiltree counties, Texas, during the 2005 pre-planting season.

Tillage	Number of fields	Crop residue				
		Corn	Soybean	Sorghum	Wheat	Others
Moore County						
Conservation tillage	19	10	1	3	4	1
Conventional tillage	16	8	–	3	5	–
Total	35	18	1	6	9	1
Ochiltree County						
Conservation tillage	20	2	0	8	10	–
Conventional tillage	21	2	7	7	4	1
Total	41	4	7	15	14	1

conservation tillage. Fields with conservation tillage generally exhibited higher mean brightness values than did conventionally tilled fields (table 3). This is consistent with results reported by van Deventer *et al.* (1997) and Stoner *et al.* (1980) but contrary to Bricklemyer *et al.* (2006), who found that conventionally tilled fields exhibited higher brightness values than did conservation tillage in Montana.

For the most significant logistic regression models (table 4), the cut-point probabilities that yielded the greatest classification accuracy varied from 0.5 to 0.57 and were close to the theoretical cut-point probability of 0.5. Models with combinations of TM bands 1, 4, 5 and 6 were shown to be useful for tillage identification purposes with the best results obtained with the model that used TM band 5 (model I). This model accurately classified 32 (91%) out of the 35 fields sampled in Moore County.

When using the Ochiltree County dataset to test the proposed logistic regression models, method I performed poorly (percentage correct and k values of 67% and 0.35, respectively, table 5) even though model I provided the highest percentage correct (91%) with the Moore County data. The poor performance was partly due to differences between Moore and Ochiltree counties in TM band 5 brightness values.

Table 3. Mean brightness values for each field in Moore and Ochiltree counties.

Tillage practice and statistic	TM1	TM2	TM3	TM4	TM5	TM6	TM7
Moore County							
Conservation tillage							
Mean	105.2	53.8	71.9	81.6	157.3	132.2	85.6
Standard deviation	10.2	5.3	6.4	7.5	13.2	13.3	6.1
Conventional tillage							
Mean	97.8	48.5	63.3	73.3	132.1	131.6	75.3
Standard deviation	8.3	3.7	5.5	6.7	15.9	11.9	8.8
Ochiltree County							
Conservation tillage							
Mean	102.2	53.3	73.7	82.6	181.2	162.4	110.9
Standard deviation	5.9	4.6	7.2	8.7	13.9	2.1	16.0
Conventional tillage							
Mean	93.7	47.7	64.4	72.2	157.2	162.0	99.7
Standard deviation	8.9	5.8	8.9	9.7	17.8	3.4	11.6

TM1, TM2, etc. are TM bands 1, 2, etc.

Table 4. Landsat 5 TM-based logistic regression models for mapping tillage practices in Moore County, Texas.

Model	Cut-point (%)	Correct predictions (%) All fields	Conservation tillage	Conventional tillage
I. logit(p)=−23.041+0.159 TM5	57	91.4	94.7	87.5
II. logit(p)=−17.845+0.279 TM5−0.172 TM6	50	85.7	89.5	81.3
III. logit(p)=−7.511−0.342 D15+0.248 D16	50	85.7	89.5	81.3
IV. logit(p)=12.7435−94.386 R35+61.036 R36	53	85.7	84.2	87.5
V. logit(p)=11.036−80.056 R45+53.910 R46	53	85.7	84.2	87.5
VI. logit(p)=−10.560−92.692 NDTI45+67.643 NDTI46	53	85.7	84.2	87.5
VII. logit(p)=−10.006−32.593 NDTI15+84.196 NDTI56	50	85.7	89.5	81.3

D15=difference in bands 1 and 5; D16=difference in bands 1 and 6; R35, R36, R45 and R46=ratio of bands 3 and 5, 3 and 6, 4 and 5, and 4 and 6, respectively; NDTI45, NDTI46, NDTI15 and NDTI56=normalized difference between bands 4 and 5, 4 and 6, 1 and 5, and 5 and 6, respectively.

The mean brightness value for conservation tillage in Moore County was about 2.9% higher than that for Ochiltree County (table 3). Similar variation was found for conventional tillage. Although the absolute percentage difference was small, it made a large difference on the logarithmic scale. Therefore, models using a single spectral band may perform better when they are developed and used in spectrally similar environmental settings (e.g. Gowda *et al.* 2001). Models V and VI performed better (percentage correct and k values of 85% and 0.7, respectively, table 5). Model V uses R45 (TM band 4/TM band 5) and R46 (TM band 4/TM band 6), and model VI uses NDTI45 (normalized difference between TM bands 4 and 5) and NDTI46 (normalized difference between TM bands 4 and 6) as independent variables, which means that they are functionally equivalent (Perry and Lautenschlager 1984). This is

Table 5. Statistical performance of Landsat 5 TM-based logistic regression models used for mapping tillage practices in Ochiltree County, Texas.

Model no.	Method I Cut-off probability*	Method I Percentage correct	Method I Kappa value (k)	Method II Cut-off probability†	Method II Percentage correct	Method II Kappa value (k)
I	0.57	67	0.35	0.99	73	0.46
II	0.50	76	0.52	0.84	83	0.66
III	0.50	78	0.56	0.90	85	0.70
IV	0.53	80	0.60	0.53	80	0.60
V	0.53	85	0.70	0.53	85	0.70
VI	0.53	85	0.70	0.53	85	0.70
VII	0.50	80	0.60	0.75	83	0.66

*Cut-off probability values derived from the Moore County data.
†Cut-off probability values associated with maximum percentage correct.

because NDTI45 and NDTI46 can be rewritten as (R45–1)/(R45 + 1) and (R46–1)/(R46 + 1), respectively.

Four models (I–III and VII) performed slightly better with method II (table 4) but at higher point probability values than those with method I. Models V and VI produced the best results and performed equally well (% correct and k of 85% and 0.70, respectively). The cut-point probability values that produced the largest percentage correct and k values were the same as the cut-point probability values reported for the Moore County data, indicating that these models are transferable within the Texas Panhandle region. As expected, model I, which uses TM band 5, provided the least accurate map.

The TM band 5 or indices that contain TM band 5 were present in all models, indicating that reflectance values in the mid-infrared spectral range (1.55–1.75 μm) are highly sensitive to crop residue, and generally show higher reflectance in conservation tillage fields than in conventionally tilled fields (table 3). However, poor performance of model I with the Ochiltree County dataset indicated that the TM band 5 alone is not sufficient to identify contrasting tillage practices. This is because the magnitude of brightness values may vary from county to county for a variety of reasons such as differences in soil colour, organic matter and soil moisture contents. For instance, the mean brightness value for conservation tillage in Moore County (157.3) in the mid-infrared range was 13% smaller than that for Ochiltree County (table 3).

5. Conclusions

The availability of accurate information on prevailing tillage practices will aid the assessment and adoption of appropriate tillage practices to reduce soil erosion and nutrient losses. Using a linear logistic regression technique, a set of Landsat TM-based statistical models was developed for identifying contrasting tillage practices in the Texas Panhandle. Tillage data from Moore and Ochiltree counties were used to develop and evaluate the models. The overall classification accuracy for the seven models developed with the Moore County dataset varied from 86% to 91%. Testing of these models against the independent dataset produced somewhat poorer but still acceptable results with an overall classification accuracy of 67–85%. Analysis of the results indicated that the logistic regression models that have indices of TM band 5 with bands 4 and 6 may provide consistent and accurate results when they are applied to the Texas Panhandle. This is consistent with results reported by van Deventer *et al.* (1997) and Bricklemyer *et al.* (2006). However, further evaluation of these models in different geographic regions is needed to evaluate their regional usefulness for identifying contrasting tillage practices. Logistic regression models were found to be easy to use, cost- and time-effective, and produced reasonably accurate tillage classification results. This approach is promising for the rapid collection of tillage information on individual fields over large areas. However, success of remote sensing-based tillage models depends on the availability of cloud-free Landsat TM data immediately after the planting season.

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