Application of remote sensing based tillage mapping technique to evaluate water quality impacts of tillage management decisions in Upper White River Basin

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ABSTRACT

Tillage practices directly impact runoff processes, erosion and water quality in agricultural watersheds. Consequently, environment models require tillage information for water quality modeling but often this information is not available at required spatial and temporal scales. Remote sensing approach facilitates tillage mapping at a larger scale than the conventional surveying methods. Models based on remote sensing can classify contrasting tillage practices with accuracy of 80% to 92%. The objectives of this study were to use reflectance based logistic regression models to classify contrasting tillage practices in agricultural watersheds using Landsat imagery. This study is conducted in the Upper White River Basin (7,000 km^2) located in central Indiana, an agricultural watershed with corn-soybean rotation. A single tillage practice can have different level of impact at different slope classes within the watershed therefore; the tillage system information is coupled with the slope classes within a watershed using geographic information system (GIS). This can identify the optimum slope class for a tillage system for minimum sediment loss. The tillage data derived are input in the Soil and Water Assessment Tool (SWAT) model to evaluate the distribution of tillage practices and their impacts on runoff, sediment, and pollutant losses.

INTRODUCTION

Tillage information is crucial in environmental and watershed modeling as it has a direct impact on soil and water quality but often this information are not available at required spatial and temporal scales. Remote sensing approach facilitates tillage mapping at a larger scale than the conventional surveying methods. The conventional method of crop residue cover and tillage practices assessment is done from roadside surveys in selected counties of the U.S. The survey is not done every year for each county and therefore leads into data inconsistency. Also, manual data collection from roadside surveys is often time-consuming, labor-intensive and costly. There is no program that can objectively monitor tillage over broad areas. Remote sensing can be an effective tool in differentiating contrasting tillage practices over a large spatial area in a time- and cost-effective manner.

Models based on remote sensing can classify contrasting tillage practices with an accuracy of 80% to 92%. Different tillage practices have different level of impact on runoff processes, erosion and water quality in agricultural watersheds. Sediment erosion from agricultural watershed is major pollutant for stream and river impairment. The U.S. Environmental Protection Agency and state agencies working on implementing Total Maximum Daily Loads (TMDLs) to address agricultural non-point source pollution require specific knowledge of prevailing tillage patterns as well as their location for adoption of conservation practices to reduce non-point source pollution. Watershed studies have shown that the adoption of conservation tillage (CT) 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. The Conservation Technology Information Center (CTIC) has defined CT as any tillage and planting system that has >30% residue cover after planting, reduced tillage (RT) as 15 to 30% residue cover, and intensive tillage as <15% residue cover (CTIC, 2000). Conservation tillage system, or crop residual management, is recognized as a cost-effective means of significantly reducing soil erosion and maintaining productivity.

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.

In recent years, numerous spectral models have been developed to measure crop residue cover or identify contrasting tillage practices. They exploit the characteristic shape of the green vegetation spectrum by combining the low reflectance of the visible with the high reflectance of the near infrared to identify and quantify green vegetation (Daughtry, 2004). Many spectral indices had been used to enhance the Landsat Thematic Mapper (TM) signal from crop residues which include Normalized Difference Tillage Index, Simple Vegetation Index (NDTI; STI; van Deventer et al., 1997) and Normalized Difference Index (NDI; McNairn and Protz, 1993). These indices utilize the relative difference in reflectance from soil and vegetative reflectance.

Daughtry et al. (2005) evaluated several spectral indices for crop residue cover using satellite multispectral and hyperspectral data and to categorize soil tillage intensity in agricultural fields. 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.

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. The objective of this study was 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

This study is conducted in the Upper White River Basin (UWRB; 7,000 km^2) located in central Indiana, an agricultural watershed with corn-soybean rotation (Table 2). It extends across sixteen (16) counties including significant portions of Hancock, Marion, Hendricks, Johnson, Hamilton, Morgan, Boone, Tipton, Madison, Henry, Delaware, and Randolph Counties, as well as smaller portions of Owen, Monroe, Brown, and Clinton Counties. The city of Indianapolis is located in Marion County. Typical planting dates for major crops (Corn and Soybean) in the Indiana vary from May5 – May 20 for Corn to May 15 – June 5 for Soybean (NASS, 1997).

Annual average precipitation is about 1040.13 mm and 942 mm for Marion and Hamilton counties, respectively in UWRB. The dominant soil in UWRB is mainly Crosby-Treaty-Miami (headwaters areas) and Miami-Crosby-Treaty (downstream areas). These two soil type cover about 78% of the UWRB soil type. The most common conventional tillage system in Indiana for Corn crop is moldboard plowing.

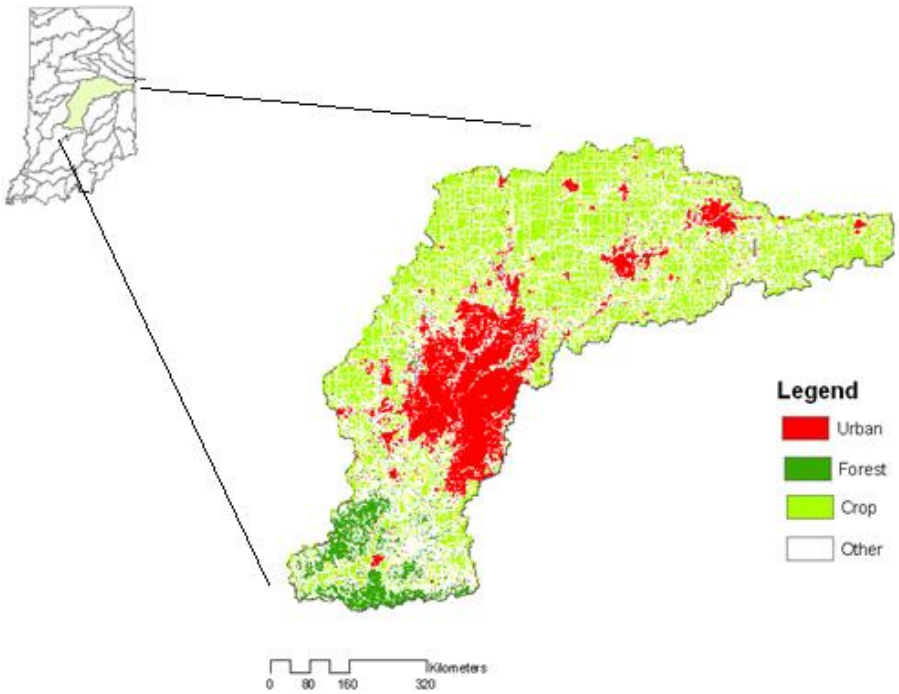

Figure 1 : Upper White River Basin (UWRB) in central Indiana with major land use classes.

MATERIALS AND METHODS

Table 1: Land use classification for Upper White River Basin

Land Use	Area
Agricultural Land	57.1%
Urban	23.9%
forest	14.4%
Water	0.4%
Other	4.1%

Developing and evaluating the tillage models consisted of four steps: (1) groundtruth data collection, (2) remote sensing data acquisition, (3) development of models using the linear logistic regression modeling technique, and (4) evaluation of models. Two Landsat TM scenes were acquired, one on 8th May 2003 for UWRB area (Path 21/Row 31-32) and the other on 25th July 2003 (Path 21/Row 31-32), for developing and evaluating Landsat TM-based tillage models. First image 8th May 2003 is during the time 70% of tillage was been done at central Indiana to prepare tillage classification maps (NASS, 2003) and the second image 25th July 2003 is during the crop growing season to classify land use (agricultural and non-agricultural land) in UWRB. Six TM based logistic regression models proposed by van Deventer et al. (1997) were used to identify contrasting tillage practices (Table 2). The Landsat TM-based logistic regression models (SAS, 1990) used in this study has the form:

$$\mathrm{Logit(p)} = \ln\left(\frac{\mathrm{p}}{1-\mathrm{p}}\right) = \alpha + \beta \mathrm{X} \quad (1)$$

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

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. Logistic regression models require users to specify a cut-off response probability to classify the outcome of an event occurring. The p values below the cut-off value were classed as conservational tillage whereas values above cut-off value were classed as conservational tillage. 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.

Table 2 : Landsat TM-based logistic regression models proposed by van Deventer et al. (1997).

Model	Band	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

Six logistic regression models were used with different values for abscissa 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). Model III was based on the normalized difference between TM bands 3 and 5 (M15). Model IV was based on the difference between TM bands 3 and 5 (D35). 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).

Tillage probability values (p) for each pixel in the TM image was calculated using model-builder module in ERDAS imagine, image processing software for 8th May 2003 image. The second image acquired on 25th July 2003 was used to classify land use class into agricultural and non- agricultural using ArcGIS software.

RESULTS AND DISCUSSION

Table 3 shows percentage of agricultural land in UWRB (county-wise) under conventional and conservational tillage practices (ISDA, 2004). This data was based on tillage survey conducted by the Indiana State Department of Agriculture (ISDA). Based on this survey data, about 56% of the fields surveyed adopted conventional tillage in the UWRB. The model results for percentage of conservational and conservational tillage in UWRB is shown in Figure 2. The Table 4 shows that model R15 and M15 has closer classification result than other models. The model STI and NDTI did not perform well in present study. This is consistent with results presented in Gowda et al. (2006) to Ochiltree County in the Texas Panhandle where they found that STI and NDTI models performed poor than other models which may be due to fact that TM Bands 5 and 7 are sensitive to organic matter content and soil water conditions. Also, in the same study, they found R15 and M15 models performed better than other models in classifying conservational and conservational tillage practices.

Table 3: Percentage area of Conventional tillage and Conservational tillage in UWRB counties (ISDA, 2004).

Counties UWRB	Conservational Tillage (%)	Conventional Tillage (%)
Randolph	74	26
Delaware	78	22
Hendricks	60	41
Hamilton	40	61
Morgan	33	68
Madison	19	81
Johnson	49	51
Henry	52	48
Tipton	4	95
Hancock	30	70
Average	**43.9**	**56.3**

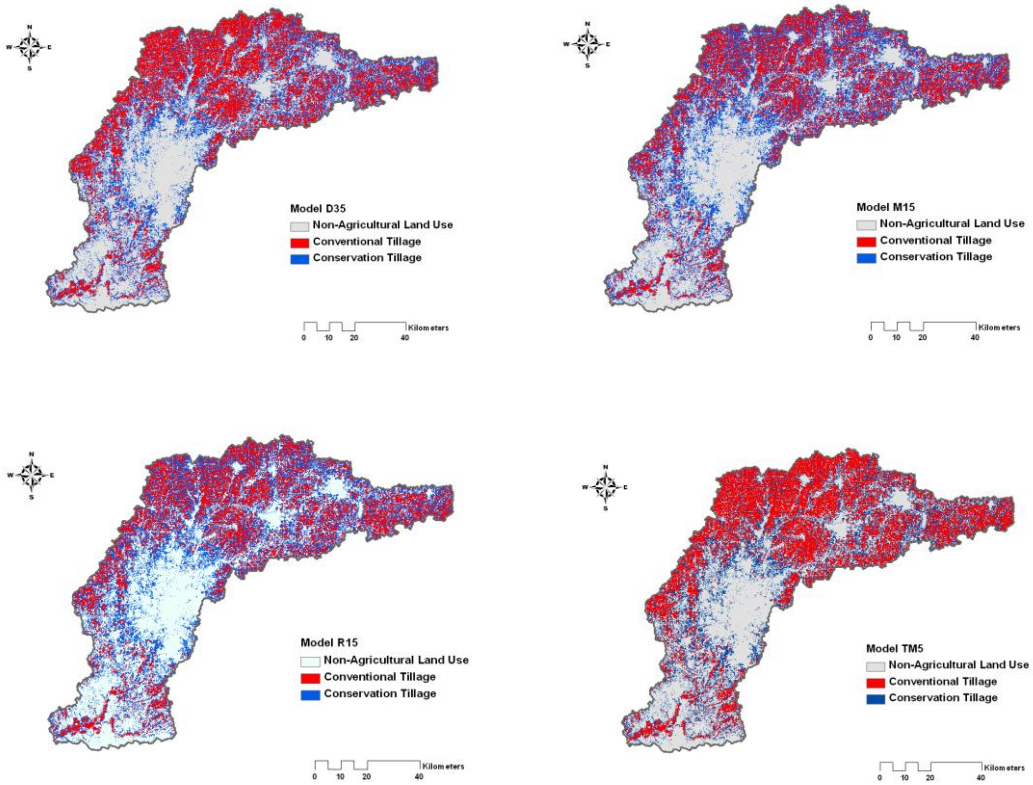

Figure 2 : Conventional tillage and Conservational tillage classification in UWRB obtained from logistic regression models D35 = Band 3 - Band 5, M15 = (Band 1 - Band 5) / (Band 1 + Band 5), R15 = (Band 1 / Band 5) and TM5.

Table 4: Percentage area of Conventional tillage and Conservational tillage in UWRB obtained from logistic regression models.

Model	Conservational Tillage (%)	Conventional Tillage (%)	Error Conventional Tillage (%)
TM5	59.5	40.4	15.8
R15	46.4	53.6	2.7
M15	45.8	54.2	2.1
D35	53.8	46.2	10.1

CONCLUSIONS

Tillage information is crucial in environmental and watershed modeling as it has a direct impact on soil erosion. 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 the UWRB located in central Indiana. Logistic regression models were easy to use, cost and time effective, and produced reasonably accurate tillage maps. The results were compared with county level data available from Indian State Department of Agriculture. This approach is useful in locating contrasting tillage information over large basin which can be applied to water quality models Soil and water Assessment Tool (SWAT) for more precise study for nonpoint source pollution from agricultural watersheds.

REFERENCES

Angle, J.S., Mcclung, G., Mcintosh, M.S., Thomas, P.M. and Wolf, D.C., (1984). *Nutrient losses in runoff from conventional and no-till corn watersheds.* Journal of Environmental Quality, 13, pp. 431–435.

CTIC, (2004). National Survey of Conservation Tillage Practices. Conservation technology Information Center, West Lafayette, IN., http://www.ctic.purdue.edu/CTIC/CRM.

Daughtry, C. S. T., Hunt, E. R., Jr., & McMurtrey, J. E., III (2004). *Assessing crop residue cover using shortwave infrared reflectance.* Remote Sensing of Environment, 90, 126−134.

Daughtry, C.S.T., Hunt Jr., E.R., Doraiswamy, P.C., McMurtrey III, J.E.,(2005). *Remote sensing the spatial distribution of crop residues*. Agron. J. 97, 864–871.

ISDA, (2008). *Conservation Tillage Program*. http://www.in.gov/isda/2354.htm#

Gowda P. H., Peters, R. T. Howell, T. A., (2006). *Mapping Contrasting Tillage Practices in the Texas Panhandle with Landsat Thematic Mapper (TM) Data*, ASCE Conf. Proc. 200, 298

Logan, T.J. and Adams, J.R., (1981). *The Effects of Conservation Tillage on Phosphate Transport from Agricultural Land, Corps of Engineers' Technical Report Series*. LakeErie Wastewater Management Study, Buffalo, NY, Bethesda: ASPRS.

Mcnairn, H., Boisvert, J.B., Major, D.J., Gwyn, Q.H.J., Brown, R.J. and Smith, A.M.,(1996). *Identification of agricultural tillage practices from C-band radar backscatter*. Canadian Journal of Remote Sensing, 22, pp. 154–162.

NASS, 2003. *Weekly Weather and Crop Bulletin*. http://usda.mannlib.cornell.edu/MannUsda/

SAS, (2005). *Categorical Data Analysis Using Logistic Regression Course Notes*, Book Code 60712 (Cary, NC: SAS Institute Inc.).

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