Satellite mapping of conservation tillage adoption in the Little River experimental watershed, Georgia

D.G. Sullivan, T.C. Strickland, and M.H. Masters

Abstract: Conservation tillage is a commonly adopted best management practice for improving soil quality and reducing erosion. However, there are currently no methods in place to monitor conservation tillage adoption at the watershed scale. The primary objective of this study was to evaluate the usefulness of Landsat TM data as a tool to depict conservation tillage in a small Coastal Plain watershed. Satellite imagery was used to calculate four commonly used indices: Normalized Difference Vegetation Index, Crop Residue Cover Index, Normalized Difference Tillage Index, and the Simple Tillage Index. Ground truth data consisted of a windshield survey, assigning each site a tillage regime (conventional or conservation tillage) at 138 locations throughout the watershed and surrounding areas. A logistical regression approach was used on two subsets of the data set ($n = 20$ or $n = 44$) to determine the influence of the number of ground control points on the success of modeling the occurrence of conservation tillage. The most accurate model was re-applied to the satellite image and evaluated using an independent sample of 94 survey sites. Results indicate that the normalized difference tillage and simple tillage indices performed best, with an overall accuracy of 71% and 78% for models developed using $n = 20$ and $n = 44$ sample locations, respectively. Errors were typically in the form of commission. Results are encouraging and suggest that currently available satellite imagery can be used for rapid assessment of conservation tillage adoption using minimal a priori information.

Key words: conservation tillage—crop residue cover—near-infrared—remote sensing

In the Southeastern United States, long and often drought-prone growing seasons necessitate management practices that improve agricultural water use efficiency. Agricultural water use efficiency is particularly critical in the Southeastern United States where increasing public demand on water and increasingly expensive operation costs continue to challenge producers. The USDA National Agricultural Statistics Service estimates that the average fuel expenses per farm have increased nearly two-fold between 1997 and 2006 (USDA 2007). However, conservation tillage with residue management shows promise as a tool to maximize agricultural water use efficiency, which may lessen fuel costs associated with irrigation. In a recent study, Sullivan et al. (2006a) estimated conservation tillage adoption can potentially reduce statewide irrigated water requirements from 4% to 14% in Georgia. Estimates were based on the current conservation tillage adoption rate (~30%) for row-crop agriculture in the state. More importantly, this research showed that increasing conservation tillage adoption to 40% in intensively row-cropped counties could increase overall water savings by 1% to 6% compared to estimated savings at the current adoption rate. Considering the impact that conservation tillage can have at the farm, watershed, and state scales, methodologies for rapid assessments of conservation tillage adoption are necessary. Remote sensing of crop residue cover is one method that shows promise for watershed-scale delineation of conservation tillage adoption.

Research regarding crop residue spectra has varied according to the spectral and spatial resolution of the remote sensing platform, surface soil characteristics, and crop residue composition. Most studies have shown that crop residue and soil are spectrally similar, increasing in reflectance throughout the visible and near-infrared, differing primarily in the magnitude of spectral response (Baumgardner et al. 1985; Aase and Tanaka 1991; Daughtry et al. 1995; Sullivan et al. 2004). Some plot-scale research indicates that differences in the magnitude of response in visible and near-infrared is sufficient to separate conventional from conservation tillage and, in some cases, to quantify percent residue cover (Aase and Tanaka 1991; Biard and Baret 1997; Sullivan et al. 2004; McMurtrey et al. 1993). Others suggest spectral differences in the visible and near-infrared regions are poorly correlated with crop residue coverage, demonstrating instead the usefulness of middle infrared spectra where residues exhibit an absorption feature that is absent from soil spectra (Daughtry et al. 1996, 2001; Nagler et al. 2000).

More recently, investigations using thermal infrared spectra have shown great promise as a tool for rapid delineation of conservation tillage and estimation of crop residue cover (Sullivan et al. 2004). Sullivan et al. (2004) demonstrated that high resolution thermal infrared imagery was more sensitive to differences in crop residue cover amounts (0%, 10%, 30%, 50%, or 80%) compared to reflectance spectra. Under dry conditions, thermal infrared data explained greater than 95% of the variability in crop residue cover amount compared to >77% using reflectance spectra.

Within the last decade, researchers have investigated both multispectral and hyperspectral satellite remote sensing platforms, such as Landsat TM and EO-1 Hyperion, as tools to derive maps of conservation tillage adoption (van Deventeer et al. 1997; Gowda et al. 2001, 2003; Thoma et al. 2004; Daughtry et al. 2005, 2006). Early efforts by van Deventeer et al. (1997) used a combination of Landsat TM bands to differentiate between conventional tillage and conservation tillage at 27 farm sites in Ohio. Conventional and conservation tillage sites were differentiated using logistical regression analysis and the resulting probability cut-off values. Results indicated that

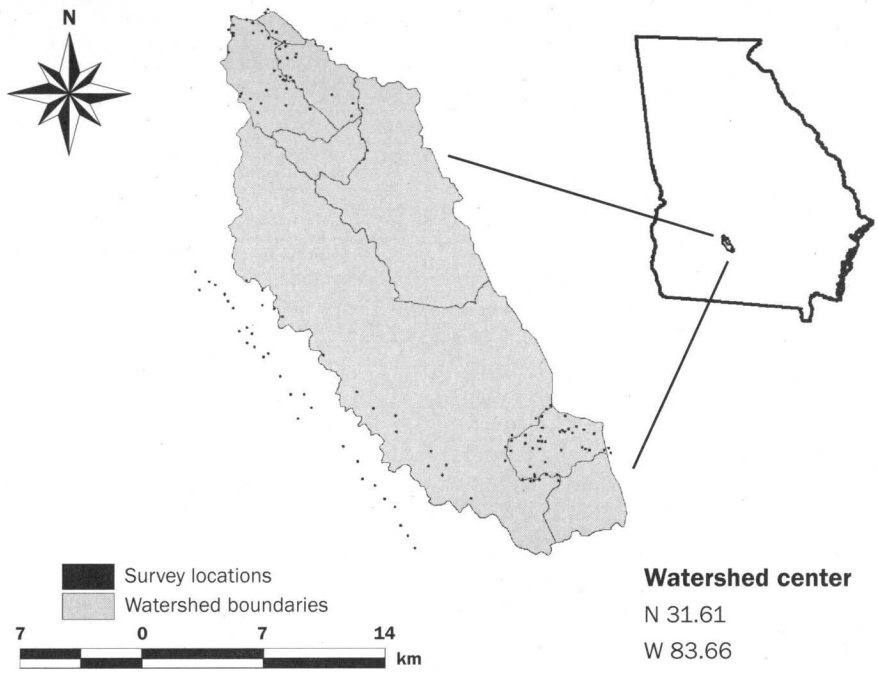
Dana G. Sullivan is a soil scientist and **Timothy C. Strickland** is a research leader at the Southeast Watershed Research Laboratory, USDA Agricultural Research Service, Tifton, Georgia. **Mark H. Masters** is a resource economist at the Flint River Water Policy Center in Albany, Georgia.

a combination of Landsat bands 5 and 7 (Simple Tillage Index [STI] and Normalized Difference Tillage Index [NDTI]) provided a classification accuracy of 93% using 15 independent field locations for verification.

Gowda et al. (2001) tested the strength of the tillage indices developed by van Deventeer et al. (1997) at 84 field locations in Minnesota. Using the same probability cut-off values assigned by van Deventeer et al. (1997), Gowda et al. (2001) demonstrated that Landsat band 5 accurately classified 77% of the field locations as conservation or conventional tillage. Alternately, using a combination of Landsat bands 3 and 5, along with a site-specific probability cut-off value, 70% of field sites were accurately classified. Gowda et al. (2001) attribute the observed accuracies to the strong relationship observed between increasing cover and reflectance in Landsat band 5 (1.55 to 1.75 μm). A primary limiting factor in greater classification accuracy was likely associated with soil organic carbon, which was greater than 4% for many of the soils studied. After evaluating the classification accuracy, Gowda et al. (2003) used the conservation tillage map as a means to identify (or eliminate) factors related to the adoption of conservation tillage. To do this, the relationship between conservation tillage placement and slope steepness was evaluated across several subwatersheds in the Minnestoa River basin. Because soil loss is often a function of terrain steepness, terrain steepness was chosen to determine if the reason for conservation tillage adoption was related to soil conservation or some other factor. Across subwatersheds, conservation practice placement was weakly correlated with terrain steepness, suggesting something other than soil loss was a driving factor in conservation tillage adoption.

More recently, researchers have applied the tillage indices suggested by van Deventeer et al. (1997) over a greater number of field sites and soils. Thoma et al. (2004) compared the accuracies of satellite-derived tillage maps to windshield surveys and line-transect estimates of cover. Results suggested that tillage indices developed by van Deventeer et al. (1997) poorly explained variability in cover amount (r^2 = 0.02 to 0.56). Daughtry et al. (2006) reported similar results in Iowa, showing tillage indices were only weakly correlated with crop residue cover. However, Thoma et al. (2004) showed classification improvement using the Crop Residue Index Multiband Model (Biard and Baret 1997), having coefficients of determination ranging from 30% to 64%. Actual classification accuracies using the Crop Residue Index Multiband Model were within 9% of the traditional windshield survey approach when tillage regime was divided into two tillage categories: conventional (residue cover < 30%) and conservation tillage (residue cover > 30%).

Figure 1
Little River Experimental Watershed boundaries and windshield survey locations.



Hyperspectral satellites also show promise as tools for delineation of conservation tillage adoption. Daughtry et al. (2005) and (2006) used hyperspectral remote sensing data to calculate the cellulose absorption index based on absorption features in crop residue at 2.103, 2.113 and 2.123 μm. Daughtry et al. (2005) demonstrated a strong linear relationship between crop residue cover and the Cellulose Absorption Index. Perhaps more importantly, land use separation using a combination of the normalized difference vegetation index and the Cellulose Absorption Index resulted map classification accuracies of 72% to 86% (classes: conventional tillage, reduced tillage, conservation tillage, and green vegetation).

Currently, there is no national monitoring of conservation tillage adoption in the United States. The Conservation Technology Information Center conducted the most recent survey in 2004. Considering the need for spatially representative assessments of conservation tillage a rapid and repeatable method of watershed scale assessments is critical. Currently available satellite imagery shows promise as a tool for delineating conservation tillage adoption. The objectives of this study were to (1) evaluate four different reflective indices as tools to identify conservation tillage adoption in a small Coastal Plain Watershed, (2) determine a minimum number of survey sites necessary to develop a reliable conservation tillage model and (3) develop and assess a satellite derived conservation tillage map using an independent data set.

Materials and Methods

Study Site. The Little River Experimental Watershed (LREW), near Tifton, Georgia, is approximately 334 km^2 (129 mi^2) and is located in the headwaters of the Upper Suwannee River Basin (figure 1). The LREW is typical of a Southeastern Coastal Plain watershed consisting primarily of low gradient streams and sandy to sandy loam surface soil textures. While a range in surface soil properties can be found (coarse sand, sand, loamy fine sand, loamy sand, and sandy loam), loamy sand surface textures comprise nearly 80% of the watershed. Land use within the watershed is made up of 31%

agriculture, 10% pasture, 28% riparian forest, 22% upland forest, and 7% urban area based on the classification of 2003 Landsat 5 imagery (Bosch et al. 2006). Agricultural areas consist predominantly of row-crop (cotton [*Gossypium hirsutum* L.], corn [*Zea mays* L.], peanut [*Arachis hypogaea*]), and vegetable production.

Tillage practices are typically either a rip and bed operation or conservation tillage in the form of strip tillage. In a strip tillage system, a winter cover crop is established late October or early November and killed approximately three weeks prior to planting in the spring. Beds are prepared using a fluted coulter to cut debris in front of an in-row subsoil shank (depth = 33 cm [13 in]), followed by a set of two wavy coulters, which till a 30 to 46 cm (12 to 18 in) strip for planting. Rip and bed operations are designed to incorporate a majority of crop residue cover using a subsoil shank followed by two bed shapers (concave disks), which create a round bed. In 2004, the Conservation Technology Information Center reported that approximately 30% of row crop producers used some form of conservation tillage in Georgia (2004).

The LREW is one of twelve USDA Agricultural Research Service benchmark watersheds participating in the USDA Natural Resources Conservation Service Conservation Effects Assessment Project-Watershed Assessment Studies. Monitoring conservation tillage adoption within the watershed will contribute to national efforts designed to evaluate the impact that federal conservation programs may be having on soil and water quality.

Ground Truth. In the spring of 2007, a comprehensive windshield survey was conducted throughout the LREW and surrounding areas (figure 1). Windshield surveys were conducted coincident with satellite data acquisition on March 25, 2007. Surveyed fields were selected from three sub-watersheds as well as two new transects identified during a 2005 windshield survey as having a range in conventional and conservation tillage sites. All surveyed fields were delineated on the satellite image and numbered. The survey identified each field as conventional (<30% crop residue cover), conservation (>30% cover), pasture, or live vegetative cover. The conservation tillage cut-off amounts were based on USDA Natural Resources Conservation Service requirements for crop residue cover at planting. In all there were 138 farm locations consisting of 61 conservation tillage sites and 77 conventional tillage sites.

Table 1
Landsat 5 specifications and indices calculated.

Band	Wavelength (μm)	Spatial resolution (m)
B1	0.45 to 0.52	30
B2	0.52 to 0.60	30
B3	0.63 to 0.69	30
B4	0.76 to 0.90	30
B5	1.55 to 1.75	30
B7	2.08 to 2.35	30

Notes: Normalized Difference Vegetation Index (Rouse et al. 1974) = (B4 – B3)/(B4 + B3). Modified Crop Residue Cover Index (Sullivan et al. 2006b) = (B5 – B2)/(B5 + B2). Simple Tillage Index (van Deventeer et al. 1997) = (B5/B7). Normalized Difference Tillage Index (van Deventeer et al. 1997) = (B5 – B7)/(B5 + B7).

Satellite Imagery. Satellite imagery was acquired via Landsat 5 on March 25, 2007. Data were provided in 8-bit digital format, corrected for sensor gains and offsets only. Reflective bands used in this study encompass the 0.45 to 2.35 μm spectral range (table 1) and have a spatial resolution of 30 m (98 ft). The spatial resolution of Landsat imagery was previously evaluated for conservation tillage mapping in the Southeastern Coastal Plain of Georgia (Sullivan et al. 2007a). Results indicated that soil variability was adequately captured within 40 m (131 ft) of the sampling location. Thus, background contributions to crop residue assessment were similar within the range of Landsat spatial resolution.

An area centered on the LREW measuring 930 km^2 (359 mi^2) was extracted from the satellite image. The subset image was geo-referenced in ERDAS using 1999 US Geological Survey digital ortho-quadrangles. Twenty distributed and easily identifiable ground control points were selected within each image.

Digital information corresponding to surveyed fields was extracted and used to calculate four remotely sensed indices: (1) Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1974), (2) modified Crop Residue Cover (CRC) Index (Sullivan et al. 2006b), (3) STI (van Deventeer et al. 1997), and (4) NDTI (van Deventeer et al. 1997) (table 1). The CRC is typically calculated as a ratio of Landsat band 5 and Landsat band 1; however, due to noise in band 1, the CRC Index was calculated using band 2.

To extract data, a 20-m (66-ft) buffer was created around each sampling location. The 20-m buffer was selected to correspond with the spatial resolution of Landsat 5 and ensure that an area representative of the sample location was extracted. All pixels falling within the buffered area were extracted and averaged. Data were collated within a spreadsheet along with the corresponding tillage regime.

Model Development. A logistical regression analysis (SAS Institute, Cary, North Carolina) was used to distinguish conventional from conservation tillage sites using remotely sensed data. Two subsamples of the surveyed dataset were randomly selected for analysis (n = 20 and n = 44). Within each dataset an equivalent number of conventional and conservation tillage sites were selected. The remaining sites were retained for model validation (n = 94).

All sampling locations identified as conservation tillage were assigned a value of 1, and all other sampling locations were assigned a value of 0. The linear regression was used to determine the relationship between remotely sensed data and tillage regime using the following equation:

$$\text{Logit}\,(p) = \alpha + \beta X, \qquad (1)$$

where p is the response variable (predictor of tillage regime), α is the intercept, β is the slope (alpha = 0.10), and X is the observed tillage index value. The logistical regression proceeds iteratively using a jack-knife approach to generate parameter estimates of ordinal data. The jack-knife approach reduces bias in the error term by using a random selection of data points with each iteration, thus generating an independent data set for error term estimation.

The logistic regression is a non-linear approach designed to estimate the probability of occurrence. In this study, we were interested in determining the probability of

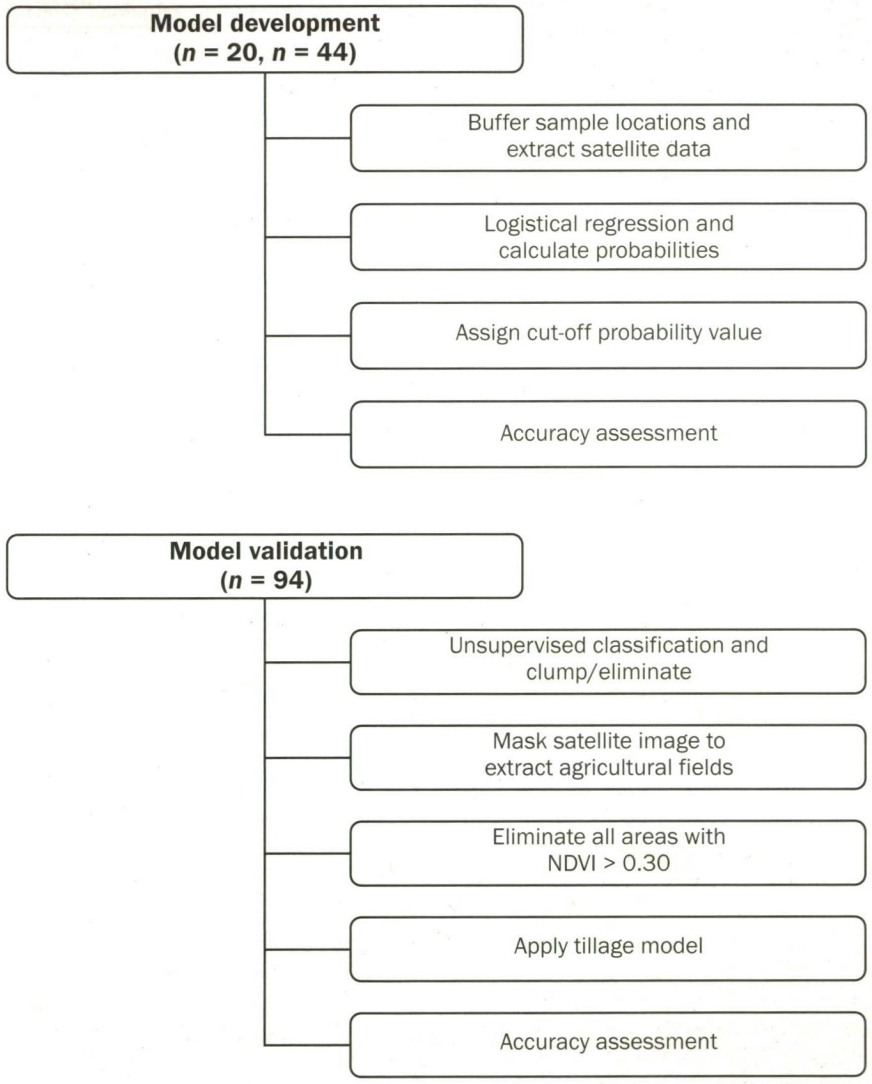
observing conservation tillage. The probability (p) of observing conservation tillage is calculated using the predictor as follows:

$$p = e^{\text{logit}(p)}/1 + e^{\text{logit}(p)} . \quad (2)$$

Probability cut-off values were then determined by comparing the calculated probability at each sample location to the observed tillage regime. A cut-off value was selected for each remotely sensed index, where a majority of sample locations were accurately identified as conservation tillage (van Deventeer et al. 1997). Based on the probability cut-off value, all observations where p was less than the cut-off were classified as conventional, and all observations where p was greater than or equal to the cut-off were classified as conservation tillage.

Model results were evaluated based on three different metrics: (1) Akaike criterion, (2) probability cut-off value, and (3) observed errors (total, commission, and omission). The Akaike criterion is a relative measure of the goodness of fit. Models exhibiting low Akaike values are an indication that those models explain a greater proportion of the variability in tillage regime. The probability cut-off level was used as a qualitative indication of the likelihood that a tillage regime would be accurately classified. Thus, higher probability cut-off values suggest greater confidence in tillage classification. Finally, errors of commission and omission were determined by comparing the observed tillage regime to the classified tillage regime. Errors of commission convey the percentage of conventional tillage sites that were mislabeled as conservation tillage. Errors of omission indicate the percentage of conservation tillage sites that were mislabeled as conventional tillage.

Figure 2
Schematic delineating the algorithms used to develop and validate conservation tillage map (figure 4) using Landsat 5 imagery.



Model Validation. The tillage model having the lowest Akaike criterion and greatest overall accuracy was applied to the LREW satellite image as a test of robustness. Once a classified tillage map was produced, an accuracy assessment was conducted using sample locations retained for model validation (n = 94).

The tillage model was applied in a series of steps (figure 2). First, the georeferenced LREW image was entered into an unsupervised classification to locate all farms within the image field of view. The unsupervised classification assigns pixels to a specified number of classes based on an Iterative Self-Organizing Data Analysis Technique (Tou and Gonzalez 1974). The Iterative Self-Organizing Data Analysis procedure repeatedly groups pixels within a minimum Euclidean distance to a specified class. The iterative procedure continues until a minimum convergence factor or maximum number of iterations has been reached. Ten classes were established and used to identify agricultural fields within the watershed.

Next, contiguous classes (clumps) were identified within the classified image, and clumps with fewer than two pixels per class were "eliminated." The eliminate function is an iterative smoothing procedure that recodes pixel values in clumped areas with the values associated with nearby larger clumps (Leica Geosystems 2003). This was done to smooth the classified image, so that whole farms were accurately represented based on the classification of surrounding pixels. Whole farms were extracted from the unclassified satellite image using the classified thematic map as a mask.

Prior to applying the logistical regression results to the image, all farm locations with a corresponding NDVI > 0.30 were eliminated. This was done to reduce errors of estimation associated with vegetative interference (Sullivan et al. 2006b; Daughtry et al. 2005). Finally, the conservation tillage model having the highest overall accuracy and a low Akaike value was applied to the image using

equations (1) and (2). The "tillage map" was created by using the previously defined "cut-off" value to assign a tillage classification to each pixel (conventional or conservation tillage). The tillage map was validated using corresponding windshield survey sites retained for the accuracy assessment.

Results and Discussion

Model Development. Four different remotely sensed indices were used to develop a conservation tillage model based on $n = 44$ or $n = 20$ surveyed locations distributed throughout the LREW and surrounding areas. Each logistical regression model (CRC Index, NDVI, NDTI, STI) was then evaluated to determine (1) which model most accurately identified conservation tillage and (2) the minimum number of survey sites necessary to identify conservation tillage.

Using a minimum of 20 survey sites, significant model results were obtained using only the NDTI and the STI (table 2). This is not surprising when the spectral data are considered (figure 3). For instance, the NDVI is calculated using visible and near infrared regions of the light spectrum, where the spectral response properties of soil and crop residue are very similar. While the NDVI results in numerically higher values for conservation tillage sites, variability in NDVI response limits its usefulness as an indicator of tillage regime. The CRC Index combines a middle infrared band (1.55 to 1.75 μm) with a visible band (0.52 to 0.60 μm). The observed CRC Index values for conventional and conservation tillage were nearly indistinguishable. This is in contrast to previous studies, where the CRC Index more clearly differentiated among tillage regimes in similar soil conditions (Sullivan et al. 2006b, 2007b). However, those studies were conducted at the field-scale using a handheld radiometer, and Sullivan et al. (2006b, 2007b) used a shorter visible band to calculate the CRC Index (0.45 to 0.52 μm). Their study suggested that differentiation between conventional and conservation tillage may have been attributable to differences in the magnitude of response within these two regions. Thus, spectral separation between Landsat bands 2 and 5 may not have been sufficient to delineate tillage regimes in this study.

The STI and NDTI resulted in significant conservation tillage models. Although the shape of the spectral response curve is similar for conventional and conservation tillage sites in the middle infrared regions used to calculate these indices, the difference in magnitude of spectral response was much greater compared to the visible and near-infrared regions. Similar results were reported by Gowda et al. (2001), attributing separation of tillage regimes to the inclusion of Band 5. Based on our results, it is likely that the inclusion of two middle infrared bands (B5 and B7) were critical to tillage separation. Both models were positively related to tillage, indicating STI and NDTI values increase with the likelihood of observing conservation tillage.

Cut-off values for the NDTI and STI were chosen by comparing probability estimates to the observed tillage regime at the 20 survey points. The probability value that resulted in the greatest number of accurately identified sites was selected as the cut-off. The cut-off probability values for the STI and NDTI were 0.41 and 0.42, respectively. The low to moderate values suggest that there is a 41% to 42% chance of accurately depicting conservation tillage adoption. However, both models resulted in an overall accuracy of 75% with a majority of the observed errors being errors of commission (15%). In an earlier study, errors of commission were primarily a function of variability in surface soil color (Sullivan et al. 2007a). Sullivan et al. (2007a) evaluated surface soil characteristics and percent crop residue cover at five intensively sampled farm sites. Errors of commission were mostly attributable to a single field, where iron oxide contents were more than two times that observed at any other location. Because iron oxides tend to darken soil surfaces, in the current study it is likely that variability in surface soil color contributed to the observed errors. Keeping this in mind, a majority of the LREW (80%) is considered a loamy sand, and errors of commission represented only 10% of survey locations.

Fitting the model using 44 survey locations resulted in significant model results for all indices tested (table 2). The NDTI and STI performed best having overall accuracies of 75% using a cut-off value ranging from 0.60 to 0.62. The higher cut-off value is an indication of greater confidence in model performance. However, it is interesting to note that model parameters were similar compared to those using only 20 sample locations although errors were more commonly in the form of omission. The NDVI had a lower overall accuracy of 70% compared to tillage indices. Like the STI and NDTI, the NDVI exhibited a positive slope, indicating the NDVI increases with the probability of observing conservation tillage. Using the NDVI, errors of omission represented 27% of sampled locations.

Despite having the highest Akaike coefficient, the CRC exhibited an overall accuracy of 73% and a cut-off value of 0.37. The slope of the model is negative suggesting that the probability of observing conservation tillage increases with decreasing values of CRC. This is in contradiction to previously published work in this region, which suggests repeatedly that the CRC increases with increasing crop residue cover (Sullivan et al. 2006b). Using the CRC, errors were primarily commission (25%), inaccurately identifying farm sites as conservation tillage.

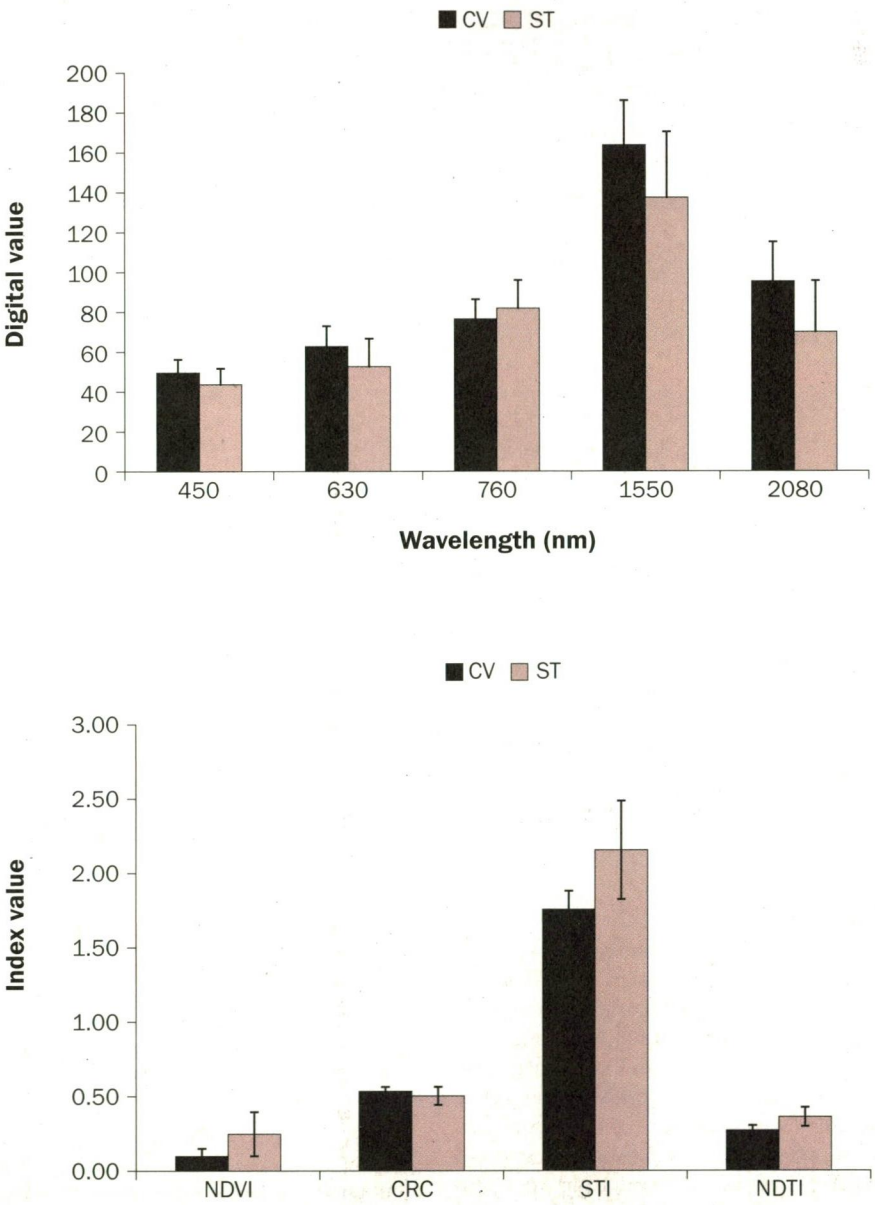
Model Validation. Because the NDTI and STI performed similarly, only results of the NDTI validation are reported here. To validate the model, model parameters

Table 2
Parameter estimates for the logistical regression used to develop a satellite-derived conservation tillage map.

n	Index	Akaike criterion	Slope	Intercept	*p*-value	Cut-off
44	NDVI	56.27	10.14	-1.25	0.03	0.65
	CRC	60.34	-22.61	12.06	0.04	0.37
	STI	49.39	6.81	-12.34	0.00	0.60
	NDTI	49.44	27.55	-7.89	0.00	0.62
20	NDVI	–	–	–	NS	
	CRC	–	–	–	NS	
	STI	25.01	6.88	-12.50	0.05	0.41
	NDTI	25.17	27.33	-7.86	0.04	0.42

Notes: Independent variables tested include the Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1974), modified Crop Residue Cover (CRC) Index (Sullivan et al. 2006b), Simple Tillage Index (STI) (van Deventeer et al. 1997), and the Normalized Difference Tillage Index (NDTI) (van Deventeer et al. 1997).

Figure 3
Average observed spectral response and index values observed for conventional (CV) and conservation strip tillage (ST) sites (n = 138).



Notes: Indices include the Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1974), modified Crop Residue Cover (CRC) Index (Sullivan et al. 2006b), Simple Tillage Index (STI) (van Deventeer et al. 1997), and the Normalized Difference Tillage Index (NDTI) (van Deventeer et al. 1997).

were applied to the image and used to transform digital values to probability estimates (figure 4). Next, using the cut-off values determined during the model development phase, each survey location was classified as conservation tillage or conventional tillage. The overall accuracy of the model was determined by comparing observed tillage regime to the model-derived tillage regime. This procedure was repeated for models developed using n = 20 and n = 44 points.

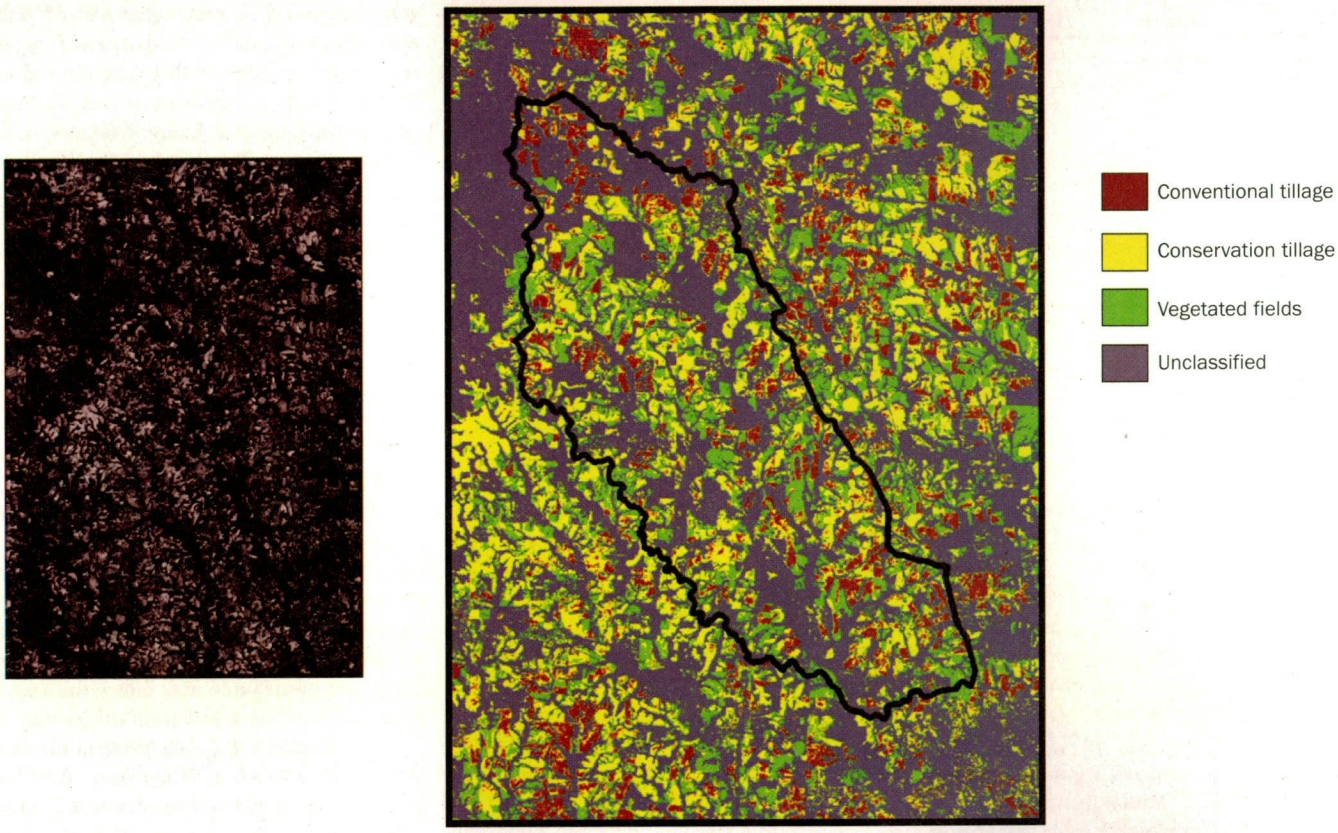
When the NDTI models were applied to the LREW image, overall accuracy ranged from 71% to 78% for models developed using 20 and 44 survey points, respectively. Although model parameters were similar using either approach, slight differences in the n = 44 parameters led to increased certainty in the resulting tillage map. This result was manifested in the higher cut-off value associated with the n = 44 model, suggesting greater confidence in tillage delineation. Errors in either case were primarily errors of commission and likely reflect variability in surface soil mineralogy as previously mentioned. Using the n = 44 model, errors of commission represented only 15% of all survey locations. Moreover, only 7% of conservation tillage sites were omitted from the final tillage map. These results are slightly lower than those reported by van Deventeer et al. (1997) using the NDTI to segregate conventional and conservation tillage fields with 93% accuracy in glacial till soils.

It should also be noted here that the usefulness of the model was tested within a 930 km^2 (359 mi^2) area. Similarity in surface soil attributes was key to the successful application of our model. Application of the model presented here over a larger or more variable watershed would require some a priori information regarding surface soil attributes and how those attributes may affect the indices used to derive a conservation tillage map.

Conservation Tillage Adoption in the Little River Experimental Watershed. A tillage map was derived from the Landsat 5 image depicting the distribution of conventional tillage, conservation tillage, and vegetated agricultural areas as well as the distribution of unclassified areas (figure 4). Unclassified areas correspond to riparian or upland forest, surface water bodies (ponds), or urban land use categories. The vegetated fields are denoted in green and correspond to areas where the NDVI was > 0.30. These fields are very likely either winter cover crops that have not yet been killed or pasture. It is not uncommon for producers in this region to maintain a winter cover crop and then clean till in preparation for the spring crop. Because the satellite imagery was acquired prior to killing the winter cover and bed preparation in these areas, the model could not be used to assign a tillage regime in those locations. These data demonstrate the need for multiple satellite images during the planting season to accommodate variable planting times for cotton, corn and peanut. The vegetated fields represent 10% of the total area classified and 26% of all agricultural areas.

The remaining 30% of the subset image was classified as non-vegetated. These pixels were subdivided into conservation tillage (>30% crop residue cover) and conven-

Figure 4
Satellite (Landsat 5) derived map of probability and resulting conservation tillage map for the Little River Experimental Watershed and surrounding areas.



tional tillage (<30% crop residue cover). Conservation tillage has been adopted for approximately 70% of the cropped area. This estimate does not include currently vegetated areas, and in practice this estimate would be adjusted based on the analysis of subsequent satellite images. Adoption was fairly evenly distributed throughout the image.

Summary and Conclusions

Results suggest that satellite-derived conservation tillage maps can be rapidly produced with a high degree of confidence in the Southeastern Coastal Plain of Georgia. By combining a simple land use classification algorithm, with two remotely derived indices, conservation (>30% crop residue cover at planting) and conventional tillage (<30% crop residue cover at planting) regimes were delineated within the LREW. Results varied based on the number of ground control points used to generate model parameters, ranging from 71% to 78% accuracy. Accuracy was best when a minimum of 22 conventional and 22 conservation tillage sites were surveyed. With the model fit using 44 sites, errors of commission represented 15% of all surveyed locations, compared to 20% for the model fit with 20 ground control points.

Remote sensing techniques show great promise as a tool for rapid watershed scale assessments of conservation tillage adoption. Regular assessments of conservation tillage adoption at the watershed scale could facilitate federal conservation program implementation, natural resource inventories, soil and water quality models, and evaluation of conservation practice effects. Methods presented here demonstrate the usefulness of currently available satellite imagery to produce basic tillage maps using a limited number of ground control points.

Acknowledgements

This project was partially funded and supported by the Flint River Water Planning and Policy Center and the US National Aeronautics and Space Administration. The project benefited from the technical support of H.L. Batten, Nicole Apperson, Andrea Johnson, and Jaime Fulmer.

References

Aase, J.K., and D.L. Tanaka. 1991. Reflectances from four wheat residue cover densities as influenced by three soil backgrounds. Agronomy Journal 83(4):753-757.

Bosch, D.D., D. Sullivan, and J. Sheridan. 2006. Hydrologic impacts of land-use changes in Coastal Plain watersheds. Transactions of the ASABE 49(3):423-432.

Baumgardner, M.F., L.F. Silva, L.L. Biehl, and E.R. Stoner. 1985. Reflectance properties of soils. Advances in Agronomy 38:1-44.

Biard, F., and F. Baret. 1997. Crop residue estimation using multiband reflectance. Remote Sensing of Environment 59(3):530-536.

Conservation Technology Information Center. 2004. National Crop Residue Management Survey. West Lafayette, IN. http://www.conservationinformation.org/?action=members_crm.

Daughtry, C.S.T., J.M. McMurtrey III, E.W. Chappelle, W.P. Dulaney, J.R. Irons, and M.B. Satterwhite. 1995. Potential for discriminating crop residues from soil by reflectance and fluorescence. Agronomy Journal 87(2):165-171.

Daughtry, C.S.T., J.M. McMurtrey III, E.W. Chappelle, W.J. Hunter, and J.L. Steiner. 1996. Measuring crop residue cover using remote sensing techniques. Theoretical and Applied Climatology 54(1-2):17-26.

Daughtry, C.S.T. 2001. Discriminating crop residue from soil by shortwave infrared reflectance. Agronomy Journal 93(1):125-131.

Daughtry, C.S.T., E.R. Hunt, Jr., P.C. Doraiswamy, and J.M. McMurtrey III. 2005. Remote sensing the spatial distribution of crop residues. Agronomy Journal 97(3):864-878.

Daughtry, C.S.T., P.C. Doraiswamy, E.R. Hunt Jr., A.J. Stern, J.E. McMurtrey III., and J.H. Preuger. 2006. Remote sensing of crop residue cover and soil tillage intensity. Soil and Tillage Research 91(1-2):101-108.

Gowda, P.H., B.J. Dalzell, D.J. Mulla, and F. Kollman. 2001. Mapping tillage practice with Landsat Thematic Mapper based logistic regression models. Journal of Soil and Water Conservation 56(2):91-96.

Gowda, P.H., D.J. Mulla, and B.J. Dalzell. 2003. Examining the targeting of conservation tillage practice to steep vs. flat landscapes in the Minnesota River Basin. Journal of Soil and Water Conservation 58(1):53-57.

Leica Geosystems. 2003. ERDAS Imagine 8.7, 1991-2003. Atlanta, GA: Leica Geosystems GIS and Mapping LLC.

McMurtrey, J.E. III, E.W. Chappelle, C.S.T. Daughtry, and M.S. Kim. 1993. Fluorescence and reflectance of crop residue and soil. Journal of Soil and Water Conservation 48(3):207-213.

Nagler, P.L., C.S.T. Daughtry, and S.N. Goward. 2000. Plant litter and soil reflectance. Remote Sensing of Environment 71(2):207-215.

Rouse, J.W., R.H. Haas Jr., J.A. Schell, and D.W. Deering. 1974. Monitoring vegetation systems in the Great Plains with ERTS. *In* Proceedings of the ERTS-1 Symposium, 3rd, 309-317. Greenbelt, MD, December 10-15, 1974. Washington, DC: NASA.

Sullivan, D.G., J.L. Fulmer, T.C. Strickland, J.N. Shaw, M. Masters, and H. Yao. 2007a. Assessing spatial and spectral resolution requirements for mapping crop residue cover. *In* Proc. 6th European Conference on Precision Agriculture, Skiathos, Greece. 3-6 June 2007.

Sullivan, D.G., J.N. Shaw, P. Mask, D. Rickman J. Luvall, and J.M. Wersinger. 2004. Evaluation of multispectral data for rapid assessment of in situ wheat straw residue cover. Soil Science Society of America Journal 68(6):2007-2013.

Sullivan, D.G., J.N. Shaw, A. Price, and E. Van Santen. 2007b. Spectral reflectance properties of winter cover crops in the Southeastern Coastal Plain. Agronomy Journal 99:1587-1596.

Sullivan, D.G., C.C. Truman, H.H. Schomberg, D.M. Endale, and D.H. Franklin. 2006a. Potential impact of conservation tillage on conserving water resources in Georgia. Journal of Soil and Water Conservation 62(3):145-162.

Sullivan, D.G., C.C. Truman, T.C. Strickland, H.H. Schomberg, D.M. Endale, and D.H. Franklin. 2006b. Evaluating techniques for determining tillage regime in the Southeastern Coastal Plain and Piedmont. Agronomy Journal 98(5):1236-1246.

Thoma, D.P., S.C. Gupta, and M.E. Bauer. 2004. Evaluation of optical remote sensing models for crop residue cover assessment. Journal of Soil and Water Conservation 59(5):1-9.

Tou, J.T., and R.C. Gonzalez. 1974. Pattern recognition principles. Reading, MA: Addison-Wesley.

USDA National Agricultural Statistics Service. 2007. Farm production expenditures: Fuel expenditures by year. Washington, DC: USDA National Agricultural Statistics Service. http://www.nass.usda.gov/Charts_and_Maps/Farm_Production_Expenditures/arms3cht7.asp.

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