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Optimal classification methods for mapping agricultural tillage practices

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Abstract

The classification of agricultural tillage systems has proven challenging in the past using traditional classification methods due to the similarity of spectral reflectance signatures of soils and senescent crop residues. In this study, five classification methods were examined to determine the most suitable classification algorithm for the identification of no-till (NT) and traditional tillage (TT) cropping methods: minimum distance (MD), Mahalanobis distance, Maximum Likelihood (ML), spectral angle mapping (SAM), and the cosine of the angle concept (CAC). A Landsat ETM+ image acquired over southern Michigan and northern Indiana was used to test these classification methods. Each classification method was validated with 293 ground truth sampling locations collected commensurate with the satellite overpass. Classification accuracy was then assessed using error matrix analysis, Kappa statistics, and tests for statistical significance. The results indicate that of the classification routines examined, the two spectral angle methods were superior to the others. The cosine of the angle concept algorithm outperformed all the other classification routines for tillage practice identification and mapping, yielding an overall accuracy of 97.2% (Kappa = 0.959).

Keywords: Remote sensing; Classification; Spectral angle mapping; Agricultural tillage methods

1. Introduction

Production of agricultural row crops takes place on 80 million hectares of land across the United States (USDA, 2000). The implications and consequences of tillage systems, used to manage agricultural crops covering such a large area are far reaching. Two primary production methods in widespread use are traditional tillage (moldboard plow) and no-till. These two production methods exhibit dramatically different environmental impacts. The national average of erosional soil losses from traditional (also referred to as conventional) tillage practices are estimated at 8619 kg/ha/year while soil losses associated with no-till practices are estimated at 328 kg/ha/year (Aber & Melillo, 2001). Tillage systems also affect carbon sequestration rates. No-till methods have been shown to sequester carbon at a rate of up to 300 kg/ha/year while traditional tillage methods exhibit no net carbon sequestration (Robertson et al., 2000). The spatial and temporal dynamics of tillage systems are not documented systematically, even in the most intensive agricultural regions of the Midwestern United States. It is therefore of great interest to develop methods that can be routinely used to map tillage practices over large areas.

Current methods to map agricultural tillage practices consist of drive-by, or commonly referred to as windshield surveys, to sample fields on a county by county basis. The drive-by method consists of a driving transect from which the results are used to estimate/extrapolate the tillage systems used in the entire county. The Conservation Technology Information Center (CTIC) maintains a database of cropping system survey results; however, the survey method is both costly and time consuming. An additional drawback of the transect survey method is the lack of spatially explicit locations or distributions of individual fields. While these data provide useful information regarding overall spatial extent in a given county they lack the specific locational information to link many ecological and weathering processes to specific areas or watersheds. The CTIC data are also collected by a wide variety of interested parties; there is no single specific agency or group charged with collecting data over a state or region. Additionally, there is no way to ensure a particular county is surveyed on a yearly basis; the

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windshield survey may be completed one year but not the next. This creates a data set that may be complete for some counties but adjoining counties may lack data for a given year. A study of the Maumee River Basin performed by the US Geological Survey cites a complete lack of data for several counties within the study area, an all too common occurrence (Myers et al., 2000; USDA, 1993).

Remotely sensed data may offer the ability to efficiently identify agricultural tillage methods over large areas. Synoptic remotely sensed imagery allows the classification of agricultural tillage systems without the need for spatial averaging or extrapolation of results to completely assess an area; techniques required for driving transect data collection. Several classification methods exist and have been used for agricultural land use/cover classification studies (Bauer et al., 1978; Bricklemyer et al., 2002; Buechel et al., 1989; Gowda et al., 2001; McNarin & Protz, 1993; Oetter et al., 2000; VanDeventer et al., 1997). These classification routines fall into three main categories: distance based, probability based, and angular based decision rules. There is no one ideal classification routine to suit all needs and requirements (Cihlar et al., 1998; Erol & Akdeniz, 1998; Kartikeyan et al., 1998).

This study examines the use of supervised classification routines based on several decision rules. Arguably the most basic supervised classification routines are the distance based classification classifiers. Distance-based classifiers such as minimum distance rely primarily on mean spectral values of distinct classes, ignoring variance within classes. The primary advantage of these classification methods lies in the relatively quick processing time to perform the classification. Contemporary processing speeds achieved by commonly available computers have negated this advantage.

Probability classification routines offer, in most cases, higher degrees of classification accuracy over distance-based classifiers. These classification routines incorporate both the mean and variance of the data set into the classification decision rule. The utilization of variance into the classification decision rule provides additional data on which to base the classification, thereby improving overall classification accuracy. The accuracy of a maximum likelihood classification routine depends heavily on an accurate estimation of the covariance matrix. To accurately estimate the covariance matrix, a sufficient number of pixels for each class training site must be readily available. However, even if great care is taken to ensure a statistically significant number of training pixels are used to generate reference signatures, the underlying decision rule still requires an assumption of data normality with well defined variances in each spectral band (Sohn & Rebello, 2002). These assumptions are generally not met using multispectral data sets; spectral bands obtained from remotely sensed imagery typically exhibit skewed or non-normal distributions. Given the inherent limitations and assumptions that must be met with maximum likelihood classification decision rules in order to accurately estimate the variance/covariance matrix, it is evident that spectrally similar reflectance patterns may be misclassified. Hybrid classification techniques which involve clustering (unsupervised) before the application of the maximum likelihood classification (supervised) exist which in theory addresses the multimodality problem (Craighead & Craighead, 1982; Tømmervik et al., 2003; Tømmervik & Lauknes, 1987). However, the hybrid classification is a complex and time consuming process that is of limited use if the results of this study are to be adopted or used by a wide variety of researchers or agencies.

Angular-based classifiers such as Spectral Angle Mapping (SAM) use a classification decision rule based on spectral angles formed between a reference spectrum and an unclassified pixel in n-dimensional space where n is the number of spectral bands available. A vector is plotted in n-dimensional space for an unknown pixel from the origin. The angle this vector forms with the vectors of reference signatures is compared and the pixel is assigned to the reference class forming the smallest angle with the unknown pixel vector. An advantage of this method is that SAM is relatively insensitive to illumination and albedo effects (Sohn et al., 1999). Because the vectors of both the unclassified pixel and the reference spectra extend through all the possibilities in brightness levels, variations between pixels due to illumination or albedo effects will have little effect on the vector as a whole.

The cosine of the angle concept (CAC) algorithm takes SAM a step further by calculating the normalized dot product, the cosine of the angle formed between the vector representing the unclassified pixel and the vector representing the reference spectra multiplied by the lengths of the vectors. Therefore, the CAC effectively incorporates the length of the vectors of the reference signatures which adds additional information to the classification. In comparison, SAM uses only the angle formed between the vectors as the decision rule.

The spectral signatures of soils and senescent crop residues are very similar to one another and traditional classification routines have not proven robust enough to successfully differentiate the two. The objective of this paper is to examine five classification routines, including two angular-based classifiers, to determine which method is best suited for the identification and mapping of agricultural tillage systems using Landsat images in the Midwest region. An additional goal is to use data, software and methods that are accessible and repeatable by a wide variety of agencies and researchers with varying levels of expertise.

2. Study area

The study area is delimited by Landsat WRS 2 nominal scene for Path 21/Row 31 (Fig. 1), that encompasses a 185

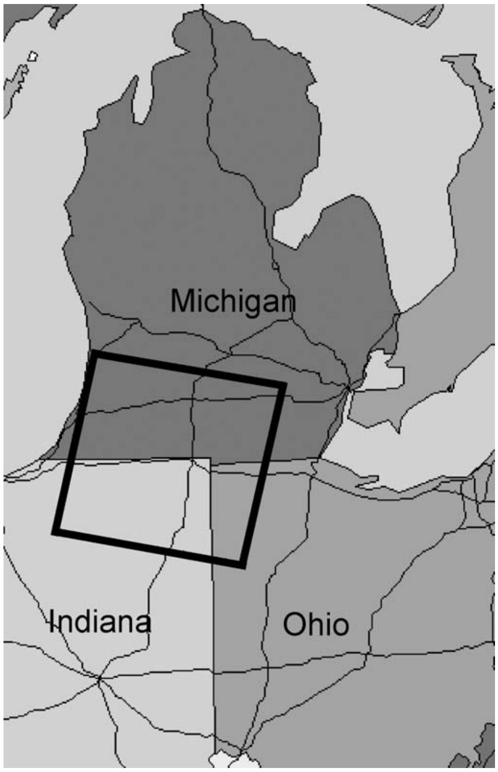

Fig. 1. Study area delineated by Landsat Path 21/Row 31.

km by 180 km area covering about 22 counties (approximately 1.7 million ha) in southwestern Michigan, northern Indiana, and northeastern Ohio. This area is dominated by agricultural land use with intermixed forested areas. Agriculture has been a dominant activity in the region since the early 1800s when European settlement occurred. Cropping systems in the area are typical of the US Corn Belt, comprised mainly of corn and soybean production. Alfalfa and winter wheat are also produced throughout the region but spatially account for very little of the overall landscape. The 22 counties collectively produced $1.7 billion in agricultural sales for the year 2000 (USDA, 2000).

Soils in the area developed on glacial drift and outwash plains and include well and poorly drained Alfisols, Mollisols, and Entisols. The major soil associations of the study area are predominantly Alfisols of which Udalfs are the dominant suborder (USDA, 1991). Most soils in this region are sandy loam to silty clay loams of moderate fertility. The outwash plains support primarily loamy sands. Sandy loams or loamy sands are commonly associated with the end and ground moraines of the area (Albert, 1995).

No-till and conventional tillage methods are the primary agricultural production methods found throughout the study area. Traditional or conventional tillage consists of a combination of moldboard plowing, disking, and tilling to condition and loosen the soil, mix in organic matter, and to prepare a flat and uniform seed bed. Moldboard plowing creates a soil surface highly susceptible to erosion, due to burial of crop residues, until the crop has grown sufficiently to provide protection from environmental conditions such as wind and water crosion. Traditional tillage techniques are the primary mechanism for carbon dioxide release from agricultural soils (Reicosky, 1996). Moldboard plowing, which inverts the soil surface, was initially required to convert native ecosystems such as grassland and forested areas into agricultural production. Additionally, before the advent of effective herbicides, moldboard plowing was the primary method of initial weed control in agricultural fields. The tradition of moldboard plowing has remained a standard method of field preparation throughout 20th century.

No-till practices are characterized by leaving stubble or residue from the previous year's crop on the soil surface, dramatically reducing soil erosion. The stubble prevents erosion by protecting the soil surface from disaggregating raindrop impacts and by creating barriers to overland flow. This keeps the topsoil in place on the farmer's field preventing it from blowing or washing away over the years. Enhanced carbon sequestration rates are an additional long-term benefit associated with no-till systems (Robertson et al., 2000). Conservation tillage practices cover a variety of methods implemented at the field level. A generally accepted definition of a conservation tillage system is one that leaves more than 30% of the crop residue on the soil surface after planting. Ridge till, mulch till, and no-till are examples of conservation tillage practices that can be found in use across the Midwestern United States.

3. Data description

A Landsat 7 ETM+ image (Path21/Row 31), acquired on May 27, 2002, was used in this study. The May 27th image was selected to coincide with planting activities. At this point in the production cycle farmers using traditional tillage methods will have their fields plowed in preparation of planting while fields utilizing no-till methods will consist of crop residue from the previous growing season. The pixel size of the six bands used (b1, b2, b3, b4, b5, and b7) is 30 m by 30 m and the image covers an area of 185 km by 180 km (Fig. 1). This image was delivered geometrically and radiometrically corrected. Subsequent preprocessing included (1) conversion of digital numbers to radiance, (2) radiance to top-of-atmosphere reflectance and (3) top of atmosphere reflectance to surface reflectance using the 5S radiative transfer model (Tanre et al., 1990).

A definitive classification accuracy assessment requires the use of ground truth as part of the sampling design (Magnussen, 1997). We acquired ground-truth data throughout the study area covering 1555 km of driving transects. These transects provided the ground truth data regarding tillage method. The 3.2 m positional accuracy (Wilson,

Table 1
Comparison of classification accuracies from the five classification methods

Classification methods	Overall classification accuracy (TT, CT)	kappa statistics
Mahalanobis classifier (MC)	72.88%	0.61
Maximum likelihood (ML)	72.88%	0.61
Minimum distance (MD)	78.82%	0.72
Spectral angle mapping (SAM)	96.10%	0.92
Cosine of the angle concept (CAC)	97.27%	0.96

2001) of the Wide Area Augmentation System (WAAS) enabled Garmin GPS V to provide enough detail to easily locate and identify agricultural fields within the 30 m by 30 m pixels of the imagery. Fields of interest, large agricultural targets with clearly discernable crops and tillage systems, were recorded by collecting a GPS way point. A total of 317 fields were logged as way points during the transect survey. These 317 fields were used primarily for classification accuracy assessments (293), but also provided known ground truth points to collect spectral signatures (24) from the Landsat image to be used as training sites in the classification routines.

4. Methodology

4.1. Classification methods used

Five classification methods were selected to examine their suitability for detecting no-till cropping practices: minimum distance (MD), Mahalanobis Classifier (MC), Maximum Likelihood (ML), Spectral Angle Mapping (SAM), and Cosine of the Angle Concept (CAC). The Landsat image was independently classified by each of these methods to identify no-till practices. The resulting classified maps were then compared with the remaining field survey data to assess their accuracy.

4.2. Training signatures

From the 317 field survey data points, 24 selected fields were used to identify areas in the ETM+ image to collect training signatures. Half of these were traditional tillage (TT) sites, and the other half were no-till (NT) sites. During the signature selection process, individual regions of interest were drawn to contain at least 900 pixels in order to obtain a representative spectral signature of the class. The individual training signatures were then merged into two signatures, NT and TT. The 24 selected training sites were eliminated from the accuracy assessment portion of this analysis. The remaining 293 ground truth locations were used in the accuracy assessment portion of the study.

The training sites and field survey data points for the two tillage systems investigated, traditional tillage and no-till, were selected during the drive-by transect survey based on extremes of the two groups. Only clearly undisturbed no-till fields were used as ground truth locations for the no-till class, and only moldboard plowed fields were used in the conventional tillage class. This dichotomous classification of tillage systems neglects to directly address the continuum of conservation tillage methods that may exist from mulch till to no-till in terms of crop residue on the soil surface explicitly. Erosion and carbon sequestration benefits of conservation tillage systems also span a continuum of benefits directly related to the amount of crop residue left on the soil surface. However, the classification products derived using only the two extremes of the classes, as in the case of this study, provides a greater level of spatial detail regarding cropping systems than is currently available. Future work will involve the investigation of how much crop residue on the soil surface is sufficient for classification into the conservation tillage class using no-till conservation tillage systems for the classification end member.

4.3. Classification comparison

For each classification method, an error matrix was generated to examine and display errors of commission and omission, producer's accuracy, user's accuracy, and overall classification accuracy. An error matrix provides an easily interpreted data matrix with the main diagonal comprised of correctly classified pixels. The error matrices were examined and analyzed using a method outlined by Congalton (1983) that involves computing the variance of the error matrices as well as the row and column residuals to calculate Kappa variance.

Table 2
Error matrices of the five classification methods

Class	Reference totals	Classified totals	Number correct	Producer's accuracy	User's accuracy
Mahalanobis classifier					
TT	89	88	55	61.80%	62.50%
NT	204	205	171	83.82%	83.41%
Maximum likelihood					
TT	89	88	55	61.80%	62.50%
NT	204	205	171	83.82%	83.41%
Minimum distance					
TT	89	65	52	58.43%	80.00%
NT	204	227	190	93.14%	83.70%
Spectral angle mapping					
TT	89	95	87	97.75%	91.58%
NT	204	198	196	96.08%	98.99%
Cosine of the angle concept					
TT	89	94	88	98.88%	93.62%
NT	204	199	198	97.06%	99.50%

TT = traditional tillage.
NT = no-till.

Kappa statistics were generated to provide an additional measure of classification assessment. Kappa values range from -1 to $+1$ with a value of zero indicating that chance agreement equaled the effect of the classifier and a value of $+1$ indicating a perfectly effective classification with no contribution from chance agreement. Any negative value indicates a very poor classification in which chance agreement is more important than classification effect. Montserud and Leamans (1992) evaluated Kappa statistics and classification methodologies and propose that a Kappa value of 0.75 or greater indicates very good to excellent classification performance. Kappa statistics were also used to evaluate the statistical difference between the possible classification pairings. A standardized *Z*-test incorporating the overall Kappa score and Kappa variance was used to determine if a pairing of classification algorithms resulted in statistically significant results.

5. Results

Of the five classification routines examined, only two provided overall classification accuracy results of greater than 85%: SAM and CAC. Table 1 summarizes the overall classification accuracies of the five methods and Table 2 contains the error matrices for each classification.

An examination of the individual land use/land cover type classification accuracies indicates that the SAM and CAC classification routines were the only classification routines to achieve >85% classification accuracy (both producer's and user's) for the conventional tillage and no-till classes.

The Kappa statistics and measures of variance derived from the classification error matrices were examined to determine if the results of the classification methods were statistically different from one another at a 95% confidence interval. Table 3 shows that of all the possible pairings of the classification methods, only the pairing of ML and MC classifiers were not significantly different examined at a 95% confidence level (*Z*-Score < 1.96).

Table 3
Z-test of classification results to determine significant differences among the five classification methods using a 95% confidence level (*Z*-Score < 1.96)

Classification pairing	*Z*-Score
ML vs. MC	0.08
MD vs. ML	2.08
MD vs. MC	2.16
SAM vs. MD	2.53
SAM vs. ML	4.65
SAM vs. MC	4.73
CAC vs. SAM	5.10
CAC vs. MD	7.15
CAC vs. ML	9.13
CAC vs. MC	9.22

The mean data values of the no-till and traditional tillage classes were relatively similar to one another, so that both the minimum distance and the Mahalanobis distance decision rules frequently cross-classified them. As a result, the MC and ML produced the poorest overall accuracy of the five methods tested (77.8%) with Kappa = 0.61.

6. Discussion

The best classification of no-till vs. traditional tillage systems was achieved using spectral angle classification techniques. Of the five classification routines investigated, only the two methods based on spectral angles satisfied the requirement of at least 85% classification accuracy, a commonly accepted guideline (Foody, 2002). The underlying mechanism and explanation of the success of spectral angle classification techniques, over the distance and probability based classification routines, lies in the ability of spectral angle mapping techniques to account for illumination and brightness effects. Linear scaling of spectral reflectance patterns above and below the mean reflectance values due to illumination and brightness effects is a commonly encountered phenomenon when working with remotely sensed data sets.

Individual land use/land cover types captured in remotely sensed synoptic imagery exhibit a range of reflectance values throughout the spatial extent of the data product. These variations are caused by lighting and illumination effects such as shadowing and are also exacerbated by the atmosphere. While the overall reflectance for any particular land use/land cover may be higher or lower than the mean reflectance values across the electromagnetic spectrum, the reflectance pattern is a linearly scaled version of the mean overall reflectance pattern (Sohn et al., 1999). While individual land use/land covers exhibit a range of linearly scaled possibilities, this knowledge can be used advantageously within the spectral angle classification decision rule.

Traditionally, distance and probability based classification methods rely on decision rules that do not account for the linear scaling of overall reflectance patterns. Oftentimes, the linear scaling of overall reflectance patterns are mistakenly classified as altogether different land use/land cover classes. Spectral angle mapping techniques, on the other hand, incorporate linearly scaled reflectance patterns into the decision rule avoiding the problem of misclassifying land use/land covers that are linearly scaled versions of a particular reflectance pattern.

The angle that defines a spectral signature or class does not change and the vectors forming the angle from the origin delineate and contain all possible positions for the spectra (Sohn & Rebello, 2002). These parameters encompass all the possible combinations of illumination for the spectra. Changes in reflectance due to illumination effects are still within the class angle, only the magnitude of the vector changes (Sohn et al., 1999). The fact that the spectra of the same type are approximately linearly scaled versions of one another due to illumination and topographic variations is utilized to achieve accurate classification results (Sohn et al., 1999).

As reported by Sohn and Rebello (2002), the cosine of the angle approach is well suited for discriminating linearly scaled spectra in feature space. This is due to the fact that linearly scaled reflectance spectrums, when compared to the reference spectrum, result in cosine of the angle value differences of zero or very close to it (Sohn & Rebello, 2002). Atmospheric and topographic effects also act to linearly scale reflectance patterns. Such effects may brighten or darken the overall observed reflectance spectrum, but it remains a linearly scaled version of the reference reflectance spectrum.

The cosine of the angle concept, utilizing the normalized dot product, provides an additional level of discrimination into the classification decision rule over SAM. The SAM algorithm does not take into account the length of the vectors forming the angle into the decision rule while the CAC method does. The incorporation of the length of the vectors into the decision rule provides additional differentiation into the CAC decision rule over SAM. When working with spectrally similar reference signatures, as is the case in this study, the incorporation of the length of the vectors provides additional information to incorporate into the decision rule thereby increasing classification accuracy between spectrally similar reference signatures. Fig. 2 provides an illustration of the CAC and SAM decision rules. The SAM decision rule will classify the unknown pixel as belonging to reference signature 1, due to the fact that the angle formed between the unknown pixel and reference signature 1 is smaller than the angle formed between it and reference signature 2. The CAC decision rule on the other hand will classify the unknown pixel as belonging to reference signature 2. Even though the angle formed between the unknown pixel and reference signature 2 is larger, the incorporation of the length of the vectors, using the normalized dot product, provides an additional level of discrimination between very similar reference signatures.

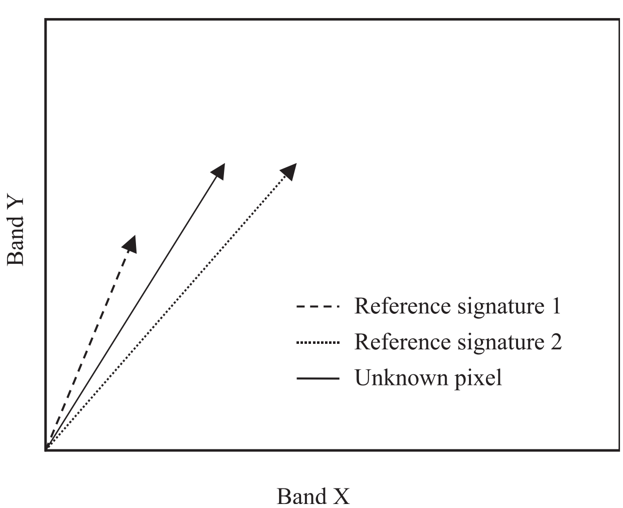

Fig. 2. Illustration of SAM and CAC decision rule.

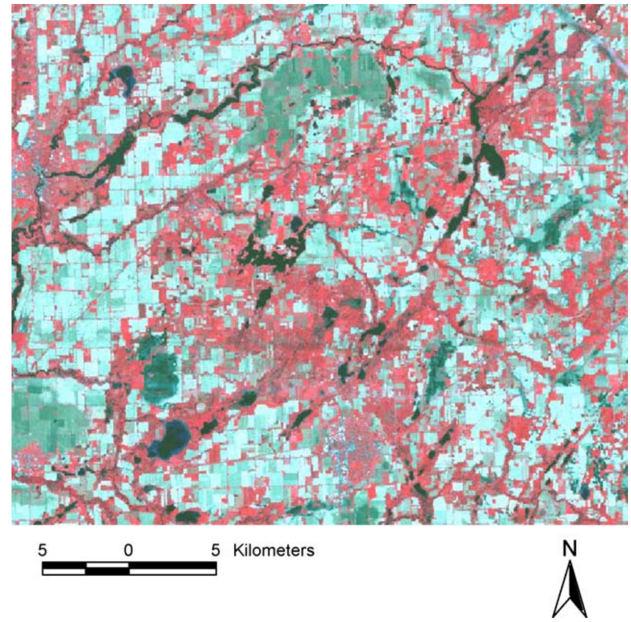

Fig. 3. Subset of study area, false color infrared (bands 4, 3, 2).

The ability of the CAC classification to classify targets along a continuum of brightness conditions is illustrated in Figs. 3 and 4. The false color infrared composite image (Fig. 3) contains an area in the upper center of the image illustrates a zone of varying soil reflectance due to soil moisture. The low-lying area is comprised of noticeably darker soil reflectance than the surrounding area. The CAC

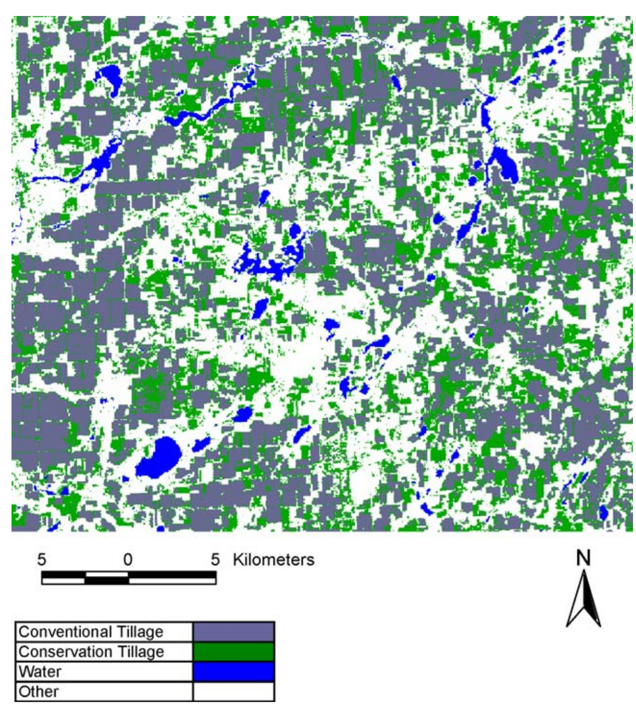

Fig. 4. Subset of study area, CAC classification results.

classification result, Fig. 4, illustrates the ability of the CAC decision rule to account for variations in brightness and illumination. The MD, ML, MC, and SAM classifiers were unable to account for this change in brightness and misclassified the area.

These results provide a method to map the spatial and temporal dynamics of agricultural tillage practices over broad geographic areas. Future research will focus on scaling the results of this study area to the larger midwestern region of the United States. The findings of scaled up research can then be used as input into carbon modeling algorithms to determine the impact of agricultural tillage systems across the landscape as they relate to the overall carbon budget. Additionally, these spatially explicit data about agricultural cropping practices can be used for a wide variety of environmental studies such as the assessment of water quality and soil erosion over entire watersheds. The potential also exists to use these methods for monitoring compliance with conservation measures or perhaps in the future carbon credits.

Through the analysis of classification results we have identified that the cosine of the angle concept outperformed other classifiers in identifying tillage practices. The optimal classification method, CAC, provides a means to begin the work of identifying agricultural tillage practices over larger geographic areas. This method, relying upon spectral angles rather than magnitude, reduces the external effects of soil color, soil moisture content, and even illumination effects.

With respect to our secondary goal of using data, software, and methods that are widely available and accessible we have mixed results. Landsat data are widely accessible and available; however, with the failure of the scan line corrector within the ETM+ instrument the amount of usable data has decreased. Software utilized in the course of this research relied primarily upon two commonly available remote sensing software systems, Erdas Imagine and ENVI. Erdas Imagine was used for image processing and classification with the exception of the SAM and CAC classifiers. ENVI has a built-in SAM classifier and was used for the SAM classification. For the CAC classification, we used a program coded (in C) from the University of Maryland at Baltimore (Dr. Sohn). Work is currently underway to develop standalone programs that will enable others to use the CAC and SAM techniques and make them freely available.

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