Documenting no-till and conventional till practices using Landsat ETM+ imagery and logistic regression.

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The ability of agricultural lands to sequester carbon from the atmosphere and help mitigate global warming has the potential to add value to farmland through the development of carbon-credit trading. Crucial to the creation of a market-based carbon credit trading system is the monitoring and verification of agricultural practices that promote carbon storage. Using remotely sensed images for this purpose could prove more efficient and cost-effective than traditional land-based methods. Landsat Enhanced Thematic Mapper Plus (ETM+) imagery and logistic regression had >95% accuracy in verifying no-till fallow fields. Further research is needed to investigate the potential for this low-cost technology to assist in the monitoring and verification of practices that sequester carbon. Development of an accurate, low-cost, efficient means of monitoring and verifying carbon sequestering practices will further the development of cropland carbon credits, thus helping to mitigate global warming, and will add value to U.S. farmland.

Keywords: Carbon credits, carbon sequestration, Landsat ETM+, logistic regression, no-till, remote sensing, tillage

The desirability of sequestering carbon in terrestrial ecosystems to mitigate global warming has been emphasized by recent political developments, most notably the Kyoto protocol (Masood 1997). Countries that ratified the Kyoto Protocol (KP) are required to reduce their annual carbon dioxide ([CO.sub.2]) emissions. The KP, if ratified by the United States, would have required the United States to reduce its net [CO.sub.2] emissions to 7% below 1990 levels (Bruce et al. 1999). When originally negotiated in 1997, the KP recognized direct [CO.sub.2] reductions and provisionally considered agricultural sinks (i.e., offsets) as a means to meet target [CO.sub.2] reductions. At the subsequent Conference of Parties (COP 6.5) meeting in Bonn, Germany (July 2001), agricultural sinks were recognized as emission offsets because [CO.sub.2] captured by plants and sequestered (stored) in soils is a large part of the global carbon cycle (Lal et al. 1998; Kaiser 2000). More recently, at the COP 7 meeting in Marrakech, Morocco (November 2001), emission offsets were termed "emission removal units". The global terrestrial carbon pool [2100 Gt (2315 US Gt) C] is approximately three times larger than the atmospheric carbon pool [750 Gt (827 US Gt) C] (Flach et al. 1997).

The United States' decision to withdraw from the Kyoto Protocol does not exempt the U.S. from addressing [CO.sub.2] emissions. The U.S. has committed to doing its share to address the global warming issue, and will likely include direct emission reductions along with carbon sequestration as a part of that effort. National incentives, such as "green" payments for agricultural management changes and a potential market-based carbon credit trading system to offset [CO.sub.2] emissions, are being developed that will likely coincide with the targeted emission reduction commitment period scheduled in Kyoto of 2008-2012.

According to the U.S. Environmental Protection Agency (EPA) Greenhouse Gas (GHG) Inventory, agriculture plays a significant role in GHG emissions. In 1999, agriculture contributed 488 Mt (538 US Mt) of [CO.sub.2] equivalents, which is 7.2% of the total GHG emissions in the U.S. (EPA 2001). Tillage breaks up soil aggregates and stimulates soil microorganisms by increasing both the bioavailability of soil organic matter and aeration (Paustian et al. 1997; Reicosky 1997). When responding to soil aeration, soil microorganisms metabolize soil organic matter and release [CO.sub.2] as a by-product (Reicosky 1997). Continued tillage over many years has reduced the overall organic carbon content of soil by 20 to 50% (Tiessen et al. 1982; Mann 1986; Rasmussen and Parton 1994; Lal et al. 1998; Peterson et al. 1998).

Carbon dioxide removed from the atmosphere and stored in soil is a form of carbon sequestration (McConkey et al. 1999). Reduction of soil disturbance and increasing the crop residues on a field are key to sequestering carbon (Lal et al. 1998). Land management changes have the potential to sequester carbon and restore soil organic carbon (Paustian et al. 1997; Peterson et al. 1998). Agricultural land management changes, in particular the adoption of no-till management, have the potential to sequester significant amounts of carbon: 275-763 Mt (303-841 US Mt) [CO.sub.2] Eq. annually (Lal et al. 1999; Bruce et al. 1999). This represents approximately 4 to 11% of the U.S. total GHG emissions during 1999.

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Economic analysis of carbon sequestration in Montana has shown that increasing soil organic carbon would be more efficient if conducted on a market-based "per ton C" payment rather than a governmental "green" payment on a "per acre" basis that would be similar to the Conservation Reserve Program (CRP) (Antle et al. 2000). The estimated marginal cost for carbon sequestered on a "per acre" payment to producers to seed land into permanent grass ranges from $34 to $500 [MT.sup.-1] C ($31 to $450 US [t.sup.-1] C), compared to $12 to $150 [MT.sup.-1] C ($11 to $135 US [t.sup.-1] C) in a system that would compensate farmers for adopting a continuous cropping system (Antle et al. 2000). The theory behind "per ton" market-based carbon credits is that [CO.sub.2] emitters, such as fossil fuel energy producers, can purchase sequestered carbon for use as an offset to direct [CO.sub.2] emission reductions. Emitters would purchase carbon credits to meet their emission reduction targets. Monitoring and verification of agricu ltural practices that promote carbon sequestration will be a critical part of "green" payments and carbon-credit contracts.

For states like Montana, where large areas of land are in agriculture, ground-based monitoring of agricultural practices would be costly and labor-intensive. Remote sensing might provide a more efficient and cost-effective method of documenting carbon-sequestering practices for carbon-credit contract fulfillment. Thus far, use of remote sensing to determine tillage practices has been limited, especially in dryland wheat regions. Conservation tillage practices including no-till have been mapped with 80% accuracy in the central coast region of California using manual interpretation of 35 mm color Landsat Multispectral Scanner (MSS) film transparencies (DeGloria et al 1986). Landsat- 5 Thematic Mapper (TM) data were used to determine tillage practices in a corn/soybean rotation in Ohio using middle infrared bands (TM bands 5 and 7) in a Simple Tillage Index and a Normalized Difference Tillage Index with map accuracy of 93% (Van Deventer et al. 1997). Percent groundcover was estimated for a corn/soybean/wheat sys tem using TM bands 3,4,5, and 7 in a Cellulose Absorption Index and estimations of relative water content, which was then related to tillage type (Daughtry 2001). RADARSAT C-band HH-radar backscatter used to determine tillage types has had mixed results (McNairn et al. 1996; Colpitts 1998).

Our objective was to determine if no-till and conventionally tilled agricultural systems could be accurately documented using Landsat 7 Enhanced Thematic Mapper Plus (ETM+) imagery. We expected the spectral signatures of conventional till and no-till management to differ in response to soil disturbance, which might affect soil surface roughness and moisture, as well as stubble coverage, thus resulting in differences in reflectance (Swain and Davis 1978; Stoner et al. 1980). Other potential uses of ETM+ imagery include creating inventories of national tillage practices and estimating inputs for erosion models such as the Water Erosion Prediction Project (WEPP) and carbon dynamics models such as CENTURY.

Methods and Materials

Our study site was located in an agricultural region north of Chester, Montana (48[degrees] 42’ 03" N, 110[degrees] 58’ 44" W). Dryland wheat production dominates the study area, and conventional tillage practices are variable. Commonly used tillage implements in the study area include the tandem disc, chisel plough, cultivator, rod weeder, and hoe drill seeder. Conventionally tilled fallow ground in the study area consisted of two to three passes with a cultivator and rod weeder by the end of July. In our area of interest, no-till is defined as chemical fallow followed by direct seeding into the previous crop’s stubble. All of the no-till fields were owned and operated by a cooperating producer. We acquired an ETM+ image of the study area for July 22, 2000 (Figure 1). We chose the July image date to ensure that any tillage during the fallow phase would have occurred, even in eco-fallow systems that initially begin the fallow season with chemical weed control before switching to tillage for subsequent weed co ntrol. Ground truth data were obtained by the producer identifying fields under conventional and no-till management practices in the area.

Digital brightness values (DNs) of fallow ground under no-till and conventional tillage practices were extracted from the imagery using ERDAS Imagine image processing software. The common practice of crop/fallow strip-farming in conventional tillage systems is commonly abandoned for block farming in no-till systems. Crop/fallow strips in conventional tillage systems create different field patterns than block farming in no-till systems, and could have potentially confounded the analysis of the spectral response of tillage. Additionally, as spring wheat matured, tillage response could have been masked or hidden by strong canopy reflectance. We specifically sampled fallow ground to reduce the effects of field patterning and canopy interference. For the conventionally tilled fields, the centermost pixels in fallow strips were chosen to reduce pixel mixing at the interface of fallow and cropped ground. We followed the same procedure for no-till fields, choosing pixels from the centers of the fallow fields to reduc e the effects of pixel mixing. Choosing the fallow pixels in this fashion ensured "pure" tillage signatures of fallow ground.

Multiple sample sites were delineated within each tilled and no-till field. Stratified random sampling was used to divide sites within each field into training and independent validation sites. Training site data were used to develop a logistic equation to calculate the probability of fields being in conventional tillage or no-till management. Using a backwards-stepwise logistic regression procedure in the S-PLUS statistical software, we developed an equation that calculated the probability of conventional tillage based on ETM+ spectral DNs. The use of logistic regression is appropriate for binary responses (Neter et al. 1996). Our response variable of interest was binary--tilled or not tilled--and was represented by the indicator variables 1 (tilled) and 0 (not tilled). With logistic regression, the regression of predictor variables (in this case ETM+ spectral data) against the binary responses results in a probability of the till response for given spectral DNs (Neter et al. 1996).The logistic regression formula has the form:

logit ([pi]) = [[beta].sub.0]+ [[beta].sub.1][X.sub.1]+[[beta].sub.2][X.sub.2]...+[[beta].sub.(p-1)] [X.sub.(p-1)] (1)

where: logit ([pi]) is the logit mean response of the probability of conventional tillage and X's are ETM+ spectral bands (Neter et al. 1996). Solving for the probability, [pi], we find:

([[beta].sub.0]+[[beta].sub.1]+[X.sub.1]+ [[beta].sub.2][X.sub.2]...+[[beta].sub.(p-1)][X.sub.(p-1)])/1+exp ([[beta].sub.0]+ [[beta].sub.1][X.sub.1]+ [[beta].sub.2][X.sub.2]...+[[beta].sub.(p-1)][X.sub.(p-1)]) (2)

The backwards-stepwise procedure began by fitting a logistic regression model to the data using all seven ETM+ bands. Next, each predictor (i.e., ETM+ band) was systematically removed, and the residual deviance, at new degrees of freedom, was compared to a Chi-square distribution to determine the significance of that predictor to the model. After each predictor was removed and the significance of each predictor determined, the least significant predictor was removed permanently if it failed to meet the required Chi-square test (p-value [less than or equal to] 0.05). The process of removing the least significant predictor continued until all remaining predictors were significant, given the other predictors included in the model. The resulting equation contained the most significant ETM+ bands to predict the tillage system of a fallow field. The logistic equation, when solved for [pi], returned the probability of conventional tillage for each picture element (pixel) in the original image.

Applying the equation to the original image produced a map in which each pixel had a probability of being tilled, with values ranging from 0 to 1. We reclassified the probability image by classifying pixels with probabilities of less than 0.5 as not tilled and probabilities greater than or equal to 0.5 as tilled. A cutoff value of 0.5 is reasonable to use when the binary outcome is equally likely in the population of interest, and when the cost of incorrectly predicting either binary response is essentially equal (Neter et al. 1996). Thus, if the probability of conventional tillage was less than 50%, the pixel was classified as no-till. A 3 x 3 majority filter was applied to the binary image to reduce a scattered peppering of pixels. We assessed the accuracy of the resulting map on a pixel basis in terms of overall accuracy, producer's accuracy (defined as errors of omission or whether pixels were placed in the right classes), and user's accuracy (defined as errors of commission or whether pixels were what th e map indicated).

Results and Discussion

Tilled fallow sites generally had greater mean DNs than no-till fallow sites in ETM+ bands 2 [green, 0.525 - 0.605 [micro]m], 3 [red, 0.63 - 0.69 [micro]m], 4 [near infrared 0.75 - 0.90 [micro]m], 6 [thermal 10.40 - 12.5 [micro]m], and 7 [mid-infrared 2.09 - 2.35 [micro]m]. This finding was contrary to one previous study (Van Deventer et al. 1997), which found that fields with conservation tillage, including no-till, exhibited higher brightness values than tilled fields. The previous study, however, looked at corn and soybean residues using a Landsat TM image from 11 May 1990, excluded wheat stubble, and did not specifically target fallow fields. We would expect the plant residues to have different spectral signatures, for visual differences in stubble color exist. For example, soybean stubble is typically darker than wheat stubble, and older stubble (after a typical 12- to 20- month fallow period) is partially degraded and therefore visually darker than freshly harvested stubble.

The significant ETM+ bands for predicting tillage in our final logistic equation were 1 [blue, 0.45 - 0.52 [micro]m], 3,4,5 [mid-infrared, 1.55 - 1.75 [micro]m], and 7. The final equation for predicting tillage was:

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Logit ([pi]) = 66.23926 - 0.81998(band 1) + 0.35670(band 3)

+ 0.704835(band 4) - 0.85676 (band 5) + 0.48997(band 7) (3)

The final equation was highly significant (p-value < 0.001), and all individual predictor variables were significant (p-value [less than or equal to] 0.05).

Our map of predicted tillage (Figure 2) showed that, within sample fields, predicted tillage practices were highly uniform, with only scattered erroneous predictions. Some of the neighboring fields showed mixed results because of misclassification where growing crops were present. The accuracy assessment of the predicted tillage map (Table 1) showed individual class accuracies ranging from 92 to 98% and an overall accuracy of 95% (KHAT = 0.90, which is an estimated difference between actual agreement in the error matrix and chance agreement, Congalton and Green 1999). Accuracy could also be assessed by the correct classification of fields (based on the predominant classification within each field),rather than individual pixels, since individual fields should not contain a mixture of tillage practices. Using a field-based measure of accuracy, all classification accuracies were 100%.

Care must be taken when analyzing the relationships of individual bands as expressed in the logistic regression equation because (1) the presence of some bands in the equation can influence the relationships of other bands and (2) the equation predicts the logit of the probability, which is not readily interpretable. Transformation of the logit of the probability to the probability itself results in a more useable predictor. Because each pixel in the image has a predicted probability associated with it, decision makers have the flexibility to be conservative or liberal in their reclassification judgments by varying the cutoff point to a value other than 0.5. We can, however, understand why fallow areas are spectrally distinguishable depending on tillage practices. No-till fields have standing stubble that is both spectrally distinct from bare soil and provides shading that might reduce spectral reflectance. Conventional tillage, on the other hand, reduces the amount of standing stubble and alters the surface texture of the soil, which might in turn affect soil brightness.

Incorporating actively growing wheat fields into the analysis would increase the robustness of the model. We expect that this approach would be successful since trial fields that had actively growing crops between fallow strips were classified properly. Including actively growing crops in the analysis would place additional demands on the data set to account for varying types of crops and variable crop stages resulting from differing planting dares. It is important to remember that the logistic model presented in this study is scene-dependent and specific to fallow fields. Alternatively, analyzing post-tillage and pre-emergence fields in early spring would give the best "pure" tillage signatures. Early spring weather conditions in Montana, however, are typically not conducive to quality, cloud-free imagery. The use of quality cloud-free, reasonably priced ETM+ imagery and the knowledge of a limited number of no-till and conventional till fields, however, should enable others to successfully map tillage practi ces using logistic regression.

Summary and Conclusion

We demonstrated that ETM+ imagery was able to successfully document tillage practices in fallowed, dryland wheat stubble fields. The accuracies of our method of classification (>95% on a pixel basis and 100% on a field basis) exceeded the United States Geological Survey (USGS) mapping standards for remotely sensed data (minimum level of interpretation accuracy using remotely sensed data should be at least 85%, Lillesand and Kiefer 2000), demonstrating that our method should be more than adequate for documentation of these practices. The reasonable cost of ETM+ data (currently less than $0.01 [km.sup.-2](S.066 [mi.sup.-2])) [mi.sup.-2])) makes this approach financially attractive as compared to alternative ground-based approaches for documenting tillage practices over large areas.

Landsat ETM+ imagery also has potential applications related to carbon credit trading and carbon sequestration. Not only can ETM+ data be used to document tillage practices quickly and efficiently, as shown in this study, it could also be used as a tool to verify that practices outlined in carbon credit contracts are indeed being followed. Additionally, it could be used for constructing an efficient ground-truth sampling design for measuring SOC. By looking at annual patterns and variations in vegetation and groundcover, ETM+ data users could target representative areas of fields for SOC sampling. Finally, Landsat ETM+ data could be used to create a national inventory of current tillage practices and for estimating inputs to erosion and ecological process-based models such as WEPP and the CENTURY model, respectively. The WEPP model simulates potential losses of the soil resource resulting from runoff and erosion (Laflen et al. 1991). The CENTURY model

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estimates soil organic carbon changes over long periods ba sed on macro-environmental gradients, management, and soil and plant properties (Parton et al. 1987). Analysis of ETM+ imagery has potential to be used for identifying tillage practices and crop types, and for estimating vegetation coverage, crop biomass, yield, and soil characteristics such as surface texture (Barnes and Baker 2000), which are inputs for the CENTURY model as well as erosion models. Further work is needed to develop the full potential of Landsat ETM+ data for applications related to carbon-credit trading and carbon sequestration.

Table 1

Accuracy assessment for prediction of tillage using Landsat ETM+ Imagery and logistic regression.

		Reference Data(number ofpixels)		
		No-till	Till	Total
Class Data	No-till	292	6	298
	Till	24	309	333
	Total	316	315	631
Producer’s Accuracy		92%	98%	
User’s Accuracy		98%	93%	
Overall Accuracy		95%		

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