SATELLITE MONITORING OF CROPLAND-RELATED CARBON SEQUESTRATION PRACTICES IN NORTH CENTRAL MONTANA

by

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ABSTRACT

This study used an object-oriented approach in conjunction with the Random Forest algorithm to classify agricultural practices set forth in carbon contract agreements associated with the Chicago Climate Exchange (CCX), including tillage (till or no-till (NT)), conservation reserve (CR), and crop intensity. The object-oriented approach allowed for per-field classifications and the incorporation of contextual elements in addition to spectral features. Random Forest is an advanced classification method that avoids data over-fitting and incorporates an internal classification accuracy assessment. Landsat satellite imagery was chosen for its continuous coverage, cost effectiveness, and image accessibility.

Classification (2007) results included producer's accuracies of 91% for NT and 31% for tillage when applying Random Forest to image-objects generated from a May Landsat image. Low classification accuracies likely were attributed to the miss-classification of conservation-based tillage practices as NT. Crop and CR lands resulted in producer's accuracies of 100% and 90%, respectively. Crop and fallow producer's accuracies were 95% and 82% in the 2007 classification; misclassification within the fallow class was attributed to pixel-mixing problems in areas of narrow (>100 m) strip management. A between-date normalized difference vegetation index approach was successfully used to detect areas "changed" in vegetation status between the 2007 and prior image dates; classified "changed" objects were then merged with "unchanged" objects to produce final classification maps of crop versus fallow.

Resulting statistics showed that 22% of lands classified as CR had occurred outside of the Conservation Reserve Program (CRP). Field survey results were applied for tillage analysis because of low image classification rates and indicated that 56% of the evaluated region was under NT in 2007, with 44% practicing some form of tillage. Crop intensity estimates indicated that only 5% was under continuous cropping. These observations show the potential for the increased NT and continuous cropping. The application of carbon sequestration estimates to the land use data predict that approximately 59,497 t C yr^{-1} might be sequestered through the universal adoption of NT and a 1.0 rotation (continuous cropping). Financial incentives through carbon credit programs might motivate land managers to make these management changes and to maintain CR lands.

CHAPTER 1

INTRODUCTION

Greenhouse Gases

Human activity has long contributed to atmospheric pollution; yet man-influenced global climate change was not recognized until the late twentieth century. Swedish scientist Svante Arrhenius first suggested in 1886 that increased atmospheric emissions, primarily from fossil fuel carbon dioxide (CO_2) release, would ultimately raise the Earth's temperature (Rodhe et al., 1997). Recent studies have shown an increase in Earth's mean annual surface temperature by over 0.6 °C since 1860 (IPCC, 2007). Atmospheric CO_2 modeling and the monitoring of CO_2 levels in Greenland ice sheets have provided additional evidence to support this hypothesis (Oeschger et al., 1984; Wang et al., 1976; Manabe and Wetherald, 1975; Ramanathan, 1975).

Carbon dioxide remains the primary anthropogenic greenhouse gas within the atmosphere, followed by methane (CH_4) and nitrous oxide (N_2O). The 2005 atmospheric concentrations and associated radiative forcings are presented in Table 1.1. Radiative forcing is defined as the change in the balance between solar radiation entering the atmosphere and the Earth's emitted radiation.

Greenhouse Gas	**Conc.**	**Radiative Forcing (Wm^2)**
Carbon Dioxide (CO_2)	379 ppm	1.66 ($\pm$ 0.17)
Methane (CH_4)	1,745 ppb	0.48 ($\pm$ 0.05)
Nitrous oxide (N_2O)	319 ppb	0.16 ($\pm$ 0.02)

Table 1.1. 2005 Atmospheric Greenhouse Gas Concentrations (IPCC, 2007).

The largest sources for CO_2 emissions (> 0.1 Mt CO_2 yr^{-1}) involve fossil fuel and/or biomass use resulting from the oxidation of carbon (C) from the burning of fossil fuels, industrial processes, and the processing of natural gas (IEA-GHG, 2002). Agriculture is also a substantial contributor to greenhouse gas emissions with agricultural byproducts estimated to produce 13% of the annual greenhouse gas emissions; associated land use and the burning of biomass contribute an additional 10% (EDGAR, 2000). It has been estimated that a standard tillage-based corn-wheat-soybean system in the Midwestern US contributes an average of 110 g m^2 CO_2 equivalents per yr; about half of this potential is attributed to N_2O release, followed by CO_2 and CH_4, with system inputs such as nitrogen (N) fertilizer, carbonate-based lime, and fuel also accounted for in the estimation (Robertson et al., 2000).

Political and social response to climate change has been relatively slow, as it was not until the 2003 Kyoto Protocol that international climate policy was attempted; the US failed to ratify the protocol (Bohringer and Vogt, 2003). Local and state action, meanwhile, has made headway in addressing the climate change issue in the US. Eight states sued the five largest emitters of CO_2 in the US in July 2004, claiming that CO_2 released by utility companies contributed to global warming (Stokstad, 2004). Ten states have also sued the Environmental Protection Agency (EPA) over its decision not to further regulate CO_2 (Barrett, 2006). It might be only a matter of time before Federal regulations mandate emission controls.

Regional Carbon Mitigation

Montana is campaigning to use an estimated 1.1 billion tonnes of coal reserves to produce synthetic diesel fuel and to supply additional coal-burning power plants (Schweitzer, 2007). These developments have important economic value, but might constitute a significant increase in regional C emissions. The Big Sky Carbon Sequestration Partnership (BSCSP), a collaboration of 14 public and private organizations and two indigenous tribes, is working to develop a local economy where C sequestering practices will offset coal-related atmospheric CO_2 pollution (Capalbo, 2005). The Consortium for Agricultural Soils Mitigation of Greenhouse Gases (CASMGS) also has been established to provide information and technology pertaining to C sequestration strategies and is based at Colorado State University in Fort Collins (http://www.casmgs.colostate.edu). Current projects include investigating the feasibility of pumping CO_2 into basalt/carbonate reservoirs and unrecoverable coal seams. Terrestrial C storage is also being considered.

Carbon-trading programs have been used to mitigate CO_2 released from industrial activities, where polluting entities purchase permits to emit CO_2 into the atmosphere. Monies resulting from permits are then used to support C sequestering activities. The European Union Emission Trading Scheme (EU ETS) is the largest multi-national greenhouse gas emissions trading scheme in the world and was created in conjunction with the United Nations Framework Convention on Climate Change (UNFCCC) and contains the world's only mandatory C trading program (PCGCC, 2006). Having commenced operation in 2005, EU ETS caps the amount of CO_2 that can be emitted from large industrial bodies within European Union (EU) countries. Concluding remarks within a recent ETS Commission review emphasized that the streamlining and expansion of this entity is of the “utmost importance” in order to reduce greenhouse gas emissions “in a cost-effective manner to serve as a role model for schemes in other parts of the world” (EU ETS, 2006, p. 10).

Concern has arisen pertaining to Europe’s market-based approach. Lingering reservations were voiced within a 2006 International Emissions Trading Association market report (Dawson, 2006) despite previous dialog among the industry and business community and representatives from the EU in an attempt to address the scheme’s effect on market competitiveness (IISD, 2005). Dawson, commodities director at Barclays Capital, London, also alluded to the need for further determination of the scheme’s ability in driving long-term C investments and reducing of global emissions (Dawson, 2006). Fluctuations in emission permit allocations have lead to instability in C market prices; C trading prices have ranged from 9 Euro/t CO_2 in December 2004 to a record high of 30 Euro/t CO_2 in April 2006, followed by a decrease to under 10 Euro/t CO_2 the following May (Grubb and Neuhoff, 2006).

Voluntary C trading markets such as the United Kingdom Emissions Trading Scheme (UK ETS) and the Chicago Climate Exchange (CCX) are also in existence but suffer from low trading rates due to lack of government-driven regulations concerning C emissions (Taiyab, 2006). The CCX is a relatively small entity consisting of trade members from within the US, Canada, and Mexico. Carbon shares on the CCX remained around $5 US per t CO_2 as of August 2007, with the annual trade volume fluctuating below the initial 40,000 t CO_2 and reaching a low of 27,500 t CO_2 in 2006 (CCX, 2007a). Speculated rises in voluntary C trading (resulting in increased share prices) will likely result from the anticipation of future C regulations stemming from anticipated policy shifts and an increased sense of “personal responsibility” amongst non-profit and charitable organizations, or “green” corporations (Taiyab, 2006).

Per-ha offset issuance rates for agricultural C sequestration are a function of market trading prices. CCX rates have ranged from \$0.4 to about \$3.0 (t CO_2 ha^{-1} yr^{-1}); estimated C sequestration credits are allocated based on region and management type, with higher credit allocations given to land under no-till (NT) and conservation reserve (CR) management within humid to sub-humid or irrigated systems (CCX, 2007b).

The National Carbon Offset Coalition (NCOC), in conjunction with the BSCSP, is currently enrolling farmers from across north central Montana in a pilot cropland sequestration program in an attempt to generate C credits for trading on the CCX. The NCOC acts as an Offset Aggregator, meaning a CCX-registered entity that serves as an administrative and trading representative on behalf of multiple individual participants. Agricultural producers under this program will sign a contract, agreeing to implement and maintain a management system(s) that will facilitate soil C (SC) increase. Examples include the addition of cover crops, the reduction or elimination of summer fallow, improved fertilization and irrigation management, and soil erosion control practices such as NT. Farmers with current CR program contracts also have the opportunity to be included in the C program. Carbon credits will be based on average C sequestration values estimated through the CarbOn Management Evaluation Tool (COMET) model or

CCX-based rates. Direct sampling, used to verify predicted amounts, will occur at least every 10 yr.

Management practices must be monitored annually to ensure that farmers comply with contract guidelines. Chicago Climate Exchange regulations specify that the monitoring and validation process must occur through a third party. Physical verification would be costly and inefficient, as project sites are scattered across the region. Satellite imagery analysis might present a feasible alternative and would allow for the remote identification of crop rotations, tillage practices, and CR land. Project auditors could then determine if land-use practices were in accordance with contract specifications.

The following research is a response to the need for the development of remote sensing methodologies pertaining to the identification and monitoring of agricultural lands for SC sequestration purposes within north central Montana. Secondly, the intent was also to utilize the resulting land management data to provide an estimate of the region's potential to mitigate CO_2 by means of cropland soil. Two primary objectives were addressed:

1) determine if remote sensing can be used to identify accurately agricultural practices specified in NCOC C-contract agreements. These practices include NT, grassland-based CR, and crop intensity. Conservation Reserve, for purposes of this study, includes lands within the Conservation Reserve Program (CRP) and "other" grasslands characteristic to those within the CRP; and

2) estimate the amount of C sequestration that could be contributed by the universal adoption of these practices throughout the region in 2007.

This thesis is organized into four additional chapters. Chapter two consists of a literature review spanning two sections. The first section pertains to SC sequestration and its relation to soil organic matter and agricultural practices influencing the rate of soil organic production and mineralization. The second section addresses the potential for remote sensing in classifying agricultural management practices and satellite imagery options available for regional analyses. Chapter three pertains to the object-oriented classification of agricultural management practices in accordance to objective one; the use of change detection in determining cropping intensity (from 2004-2007) in accordance to objective one is also discussed. Chapter four encompasses methodology used in estimating regional C sequestration potential as outlined by objective two and chapter five provides a summary and conclusion of the project.

Referenced Literature

Barett, D. 2006. 10 states sue EPA over global warming. April 27. CBS News Washington. Last Accessed 29 August 2007 <http://www.cbsnews.com/stories/2006/04/27/tech/main1553669.shtml>

Bohringer, C., and C. Vogt. 2003. Economic and environmental impacts of the KyotoProticol. Centre for European Economic Research (ZEW), Mannheim. 17 pp.

Capalbo, S., R. Smith, P. Tomski, J. Antle, D. Brown, and P. Rich. 2006. Big Sky carbon sequestration partnership-phase II. Semi-annual progress report. Big Sky Carbon Sequestration Partnership.

Chicago Climate Exchange (CCX). 2007a. Market data: CCX CFI Monthly Summary. Last Accessed 20 August 2007 <http://www.chicagoclimatex.com/market/data/monthly.jsf>

Chicago Climate Exchange (CCX). 2007b. Soil carbon management offsets. Exchange Publication.

Dawson, P. 2006. Wider, longer, deeper: The EU ETS as the template for international emissions trading post-2012. Kirkman, A. (Ed.), The 2006 International Emissions Trading Association Greenhouse Gas Market Report, "Financing response to climate change: moving to action". 144 pp.

Emission Database for Global Atmospheric Research (EDGAR). 2000. Global emission inventories information system. Version 3.2.

European Union Emission Trading Scheme (EU ETS). 2006. Communication from the Commission to the Council, the European Parliament, the European Economic and Social Committee and the Committee of the Regions: Building a global carbon market-report pursuant to Article 30 of Directive 2003/87/EC. Commission of the European Communities. Brussels, 10.11.2006 COM(2006)676.

Grubb, M., and K. Neuhoff. 2006. Allocation and competitiveness in the EU emissions trading scheme: policy overview. Climate Policy, 6: 7-30.

Intergovernmental Panel of Climate Change (IPCC). 2007. Fourth assessment report (AR4): Climate Change 2006. In press.

International Energy Agency-Greenhouse Gas Programme (IEA GHG). 2002a. Building the Cost Curves for CO2 Storage, Part 1: Sources of CO2, PH4/9, July. 48 pp.

International Institute for Sustainable Development (IISD). 2005. Summary of the seminar on linking the Kyoto project-based mechanisms with the European Union Emissions Trading Scheme. Vol. 115. 7 pp.

Manabe, S., and R. T. Wetherald. 1975. The effects of doubling the CO_2 concentration on the climate of a general circulation model. Journal of Atmospheric Sciences, 32: 3-15.

Oeschger, H., J. Beer, U. Siegenthaler, B. Stauffer, W. Dansgaard, and C.C. Langway. 1984. Late glacial climate history from ice cores. Climate Processes and Climate Sensitivity. Geophysical Monograph, 29: 299-306.

Pew Center for Global Climate Change (PCGCC). 2006. European Union-Emission Trading System White Pages. 20 pp.

Ramanathan, V. 1975. Greenhouse effect due to chlorofluorocarbons: climate implications. Science, 190: 50-52.

Robertson, G., E.A. Paul, and R.R. Harwood. 2000. Greenhouse gases in intensive agriculture: contributions of individual gases to the radiative forcing of the atmosphere. Science, 289: 1922-1925.

Rodhe, H., R. Charlson, E. Crawford. 1997. Svente Arrhenious and the greenhouse effect. Ambio, 6: 2-5.

Schweitzer, B. 2007. Govenor's Hot Topics: Frequently asked questions about synthetic fuel. Last Accessed 17 September 2007 <http://governor.mt.gov/hottopics/faqsynthetic.asp>

Stokstad, E. 2004. States sue over global warming. Science, 305: 590.

Taiyab, N. 2006. Exploring the market for voluntary carbon offsets. International Institute for Environment and Development (IIED). 36 pp.

Wang, W.C., Y.L. Yung, A.A. Lacis, T. Mo, and J.E. Hansen. 1976. Greenhouse effects due to man-made perturbations of trace gases. Science, 194: 685-690.

CHAPTER 2

LITERATURE REVIEW

Agriculture and Soil Carbon Sequestration

Soil Organic Matter

Soil organic carbon (SOC) is estimated to make up two-thirds of terrestrial C, of which 4% is in an annual flux between atmosphere and land (Post et al., 1990; Schlesinger, 1995). Soil OC is the main component of soil organic matter (SOM). Each molecule of SOM contains 58% C on average; however organic C content can vary considerably with molecular composition (Stevenson and Cole, 1999). There are many forms of SOM ranging from visually identifiable particulates to organic acid complexes. Three primary categories of organic materials are found within the soil: ‘active’ or ‘labile’, ‘intermediate’ or ‘slow’, and ‘inert’, ‘recalcitrant’, ‘passive’, or ‘stable’ SOM (Wander, 2004).

Active SOM consists of cells embodied within living organisms and relatively un-decomposed material and constitutes about 5% of total SOM. The half-life ranges from days to a few years and is greatly influenced by management practices (Christensen, 1992). Varying rates of plant input and microbial activity contribute to seasonal fluctuations within this fraction.

Resilient C pools are more resistant to decay and increase as fresh residues and SOM fractions decompose (Swift et al., 1979). Intermediate SOM has a half-life of a few years to decades and consists of amino compounds, glycoprotein, within-aggregate particulate OM, and acid/base hydrolysable and mobile humic acids. Twenty to 40% of SOM falls within this fraction. Inert SOM has a half-life of decades to centuries and includes lignins, charcoal, humin, and nonhydrolysable SOM, and accounts for 60-70 % of the organic fraction.

Respiration processes release C into the atmosphere. Soil microfauna and plant systems facilitate organic material as an energy source, releasing 6 molecules of CO_2 for each molecule of glucose ($C_6H_{12}O_6$). This process is demonstrated by the following equation:

Eq. 2.1 $$C_6H_{12}O_6 + 6O_2 \rightarrow 6\ CO_2 + 6\ H_2O + \text{Energy}$$

Many models have been developed to explain and quantify the amount of CO_2 release (White et al., 2000; Fang and Moncrieff, 1999; Parton et al., 1988). Processes that affect microbial respiration include SOC (a food source), available nitrogen (N), soil moisture, temperature, and aeration. Respiration generally increases with aeration and decreases with higher levels of soil water. Microbial activity also increases as temperatures rise above 0° C (below which microbial activity is minimal) and is optimized by a C:N ratio of 8:1to 15:1 (Stevenson and Cole, 1999). Soil respiration has also been found to be more spatially variable in spring than in fall (Rochette et al., 1990).

Management practices that sequester C mainly contribute to active SOM, with little influence on the intermediate and inert fractions. The amount of C stored in the active fraction will gradually increase over time until reaching a saturation point where increases are no longer observed. It is estimated that 25 Pg C were released from 1700 to 1990 through the conversion from forests to agricultural lands and from the cultivation of prairie soils (Houghton et al., 1999; Graph 2.1). A sharp decrease in C sequestration is evident around 1900 (a time of increased cultivation within the US) followed by a lag in the early 1970s possibly due to soil conservation measures and farm abandonment. Carbon release also diminished following the 1900s with the depletion of active SOC. Sequestration occurs as management practices are adjusted to promote an increase in C inputs until reaching the original pre-management flux where annual SC inputs equals released CO_2.

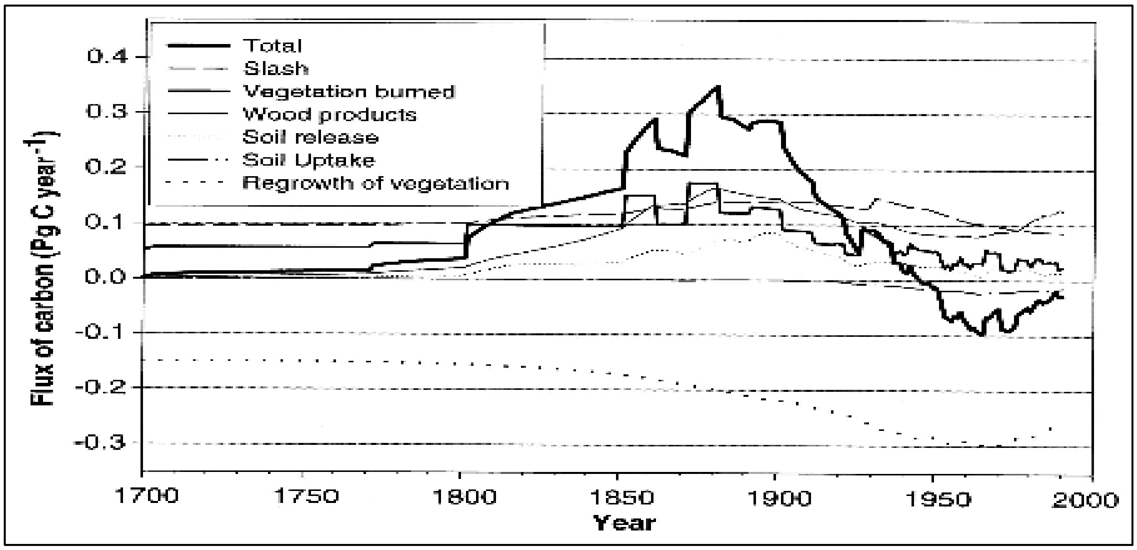

Figure 2.1. US CO_2 Released From Agricultural Practices (Houghton et al., 1999, p. 575).

Carbon sequestration is estimated to occur from 10 to 20 yr following management change (Kern and Johnson, 1993). The amount of C that a particular soil can sequester varies and is partially dependent on climatic factors. A short summer season and cool mean annual temperatures are less favorable for microbial activity, contributing to C storage as C inputs exceed carbon dioxide (CO_2) release. An analysis of long-term Canadian experiments found that SOC could be sequestered for 25 to 30 yr at a rate of 50 to 75 g C m^{-2} yr^{-1} (Dumanski et al., 1998).

Agricultural Management and Soil Organic Matter

Land management practices have a profound effect on SOM. Traditional US agriculture has included tillage, which is primarily used in crop seedbed preparation and weed control. The mechanization of farming during the 20th century has allowed tractors to replace the horse-drawn plow, further increasing soil disturbance over larger areas as cultivation became less time intensive (Padgitt et al., 2000). Tillage practices and land use intensification have led to substantial reductions in SOM.

Improvements in biochemical weed control (primarily herbicide) and planting implements have decreased the need for plowing. A better understanding of agro-ecosystem dynamics has also led to the identification of alternative practices that facilitate soil preservation. The best approach to replacing lost SOM is to cease cultivation for a period, returning the land to a more natural state. Three basic guidelines have been identified to maximize SOM, if cropping must be continued: (1) minimizing soil disturbance and erosion; (2) retaining crop residues within the soil; and (3) increasing water and nutrient efficiencies within the cropping system (Paustian et al., 2000). Practices that adhere to these guidelines include mixed-crop rotations, cover crops, and NT management practices (Angers and Mehuys, 1989; Beare et al., 1994). Other SOM facilitating practices include compost/manure application and conversion to pasture.

Soil OC is directly related to the amount of plant residue present in the soil (Ortega et al., 2002). In a NT system, seeding occurs directly into intact, un–tilled soil.

Coverage in conservation tillage management (including NT) often exceeds 30%, while tillage practices leave no more than 15% of the ground surface covered with plant residue (Marland et al., 2003). No-till seeding techniques primarily consist of air drill and disk seeders. Air drill seeders insert the seed directly into soil with varying levels of disturbance. Disks on a disk seeder, or disk drill, create an indentation within the soil followed by the placement and burial of seeds into the furrow. The resulting degree of soil disturbance following seeding has not been well studied, particularly within NT systems.

Carbon increases are well documented in systems implementing NT practices. One study observed that sequestration occurred within the top 8 cm of soil (Kern and Johnson, 1993). Another showed increases in both active and slow C pools in a 0-10 cm depth after 12 yr of NT (Sherrod et al., 2005). Soil CO_2 emissions might also be reduced through NT. A 10-yr analysis of cropping practices in the US indicated that NT farming had far less global-warming potential than tillage or organic systems due to decreased soil respiration (Robertson et al., 2000).

Practices such as fallow rotations, where the land is left bare for a period of time to conserve moisture, decrease beneficial residues through normal decay cycles. Soil OC loss (as compared to baseline SOC levels) was reported within a dryland wheat-fallow rotation study in North Dakota, even through NT had been incorporated (Halvorson et al., 2002). Conversion to NT management without fallow dramatically increased SOM in surface soils in a semi-arid region of the Great Plains (Campbell and Zentner, 1993; Sherrod, 2003). Another study showed an increase in SOC levels to a 20-cm depth within a continuous winter wheat system in a semiarid portion of the southern United States (Dao, 1998).

Crop rotations, a series of dissimilar crops grown in the same space in sequential seasons, have also been found to aid in C sequestration. A global data analysis of C studies showed that enhanced rotation complexity added an average of 20 +/- 12 g C m^{-2} yr^{-1} (West and Post, 2002). Carbon retention might also be increased by adding N-fixing legumes or deep rooted species into a rotation (Drinkwater et al., 1998; Ingram and Fernandes, 2001). It has been demonstrated that SC is increased in rotations which exclude periods of fallow. A dryland study near Havre, MT observed that a continuous wheat and wheat-lentil rotation conserved C and crop residue better than a wheat-fallow rotation (Sainju et al., 2006).

Agricultural Statistics for Carbon Estimates

The collection of regional land-use information is of great importance, as it provides the means to predict C storage over a large area. This opens the potential to incorporate more accurate per-state estimations into the National C Map, which identifies and quantifies the effect of human activity and natural disturbances on US C sources and sinks (Lucier et al., 2006). Agencies, non-profit and government alike, currently rely on impractical methods for collecting farm census information, mainly in the form of surveys and drive-by validation; agricultural statistics are often outdated by two years or more as a result of this time-consuming process. Models are often used in lieu of survey-based statistics but the lack of data to support process models across a wide range of soil and land management scenarios continues to be a major limitation (Daughtry et al., 2002).

Recent advances in remote sensing of vegetation and soils can potentially provide the biophysical parameters required by models to more accurately predict C dynamics across landscapes. It has been suggested that the only practical source of land cover data is remote sensing, which offers a map-like format, consistency, cost effectiveness, and availability of data over a range of spatial and temporal scales (Foody, 2000). Remotely sensed data could then be used for verification and comparison of C storage on a regional basis. Satellites provide a stable and predictable platform for image sensors, allowing for wide-area coverage. Satellite image analysis would allow information to be updated on an annual basis at a fraction of the cost, providing land-use information that could be used to predict C sequestration for the entire region. It is likely that field site visits for audits will be used in conjunction with a remote sensing program designed to estimate annual sequestration (ISCC, 2003).

Carbon Sequestration Models

It is often necessary to use computer modeling techniques in estimating C flux, as direct soil measurements are often limited spatially. Models such CQESTR and Century have been used to produce scientifically reliable estimates in the absence of SOC data (Brown, 2005). The CQESTR model is a quantitative field level SOC sequestration planning and prediction tool whereas Century is more appropriate for regional-scale estimates in absence of field-specific data (Rickman et al., 2001). Parameters for this model include crop residue and root biomass production, tillage type and timing, average temperature, N content, and soil layering information. Although literature concerning CQESTR accuracy is minimal, one study reported CQESTR predictions to only vary from measured soil data from Wisconsin and Kentucky from -0.3% to +0.02% OM (Rickman et al., 2001).

The most widely used soil C models for large area analyses are the Century and the Rothamsted (Roth-C) models (Coleman and Jenkinson, 1996). The Roth-C model solely predicts SOC and requires fewer data inputs than Century; parameter values for plant residue C are required, however. Accurate estimates of plant residue can be very difficult to obtain over a large area. Century, on the other hand, is a broader ecosystem-based model that incorporates sub-models also capable of simulating biogeochemical fluxes of C, N, phosphorus (P), and sulfur (S) in addition to primary biomass production and water balance (Al-Adamat et al., 2007). Parameters for the SOC module include soil texture, plant N, P, and S content, plant lignin content, atmospheric and soil N inputs, baseline soil mineral pools, and temperature and precipitation averages on a per-month basis (Mellilo et al., 1995).

Century and Roth-C also differ in their compartmentalization of the conceptual soil carbon pools and mineralization rates. The C pools in the mineral soil, from the most labile to the most recalcitrant to decomposition, are called 'fast', 'slow', and 'passive' in the Century model and 'microbial biomass', 'humified organic matter', and 'inert' in the Roth-C (Davidson and Janssens, 2006). The Roth-C model consists of two additional C pools, microbial biomass and humified OM, as opposed to the inert, decomposable plant material, and resistant plant material, accounted for in the Century model (Figure 2.2). Both the Roth and Century models have been tested against data from long-term agricultural field trials in a variety of climate zones, including arid and semi-arid regions.

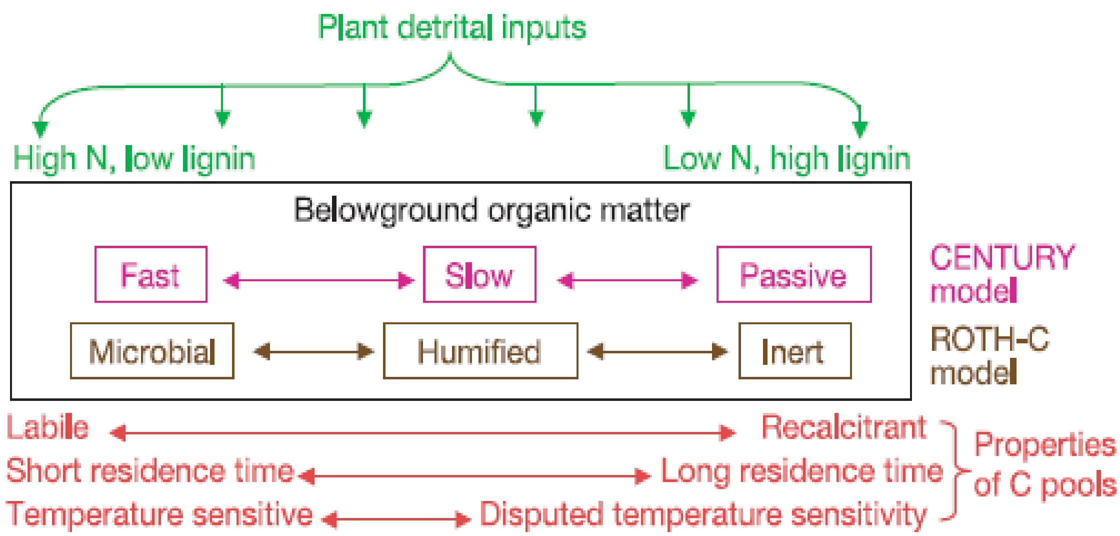

Figure 2.2. Diagram of properties of conceptual soil carbon stocks (Davidson and Janssens, 2006, p.168).

Soil Organic Carbon additions in the Century model is controlled primarily by nitrogen availability (Melillo et al., 1995). Elevated CO_2 influences net primary productivity predictions by altering the C:N ratio of decomposing OM, as well as soil moisture. The SOM sub-model includes three SOM pools (active, slow, and passive) with different potential decomposition rates, above and below ground litter pools, and a surface microbial pool (decomposition of surface litter). A possible limitation within the Century model is the assumption that the soil profile (20 cm depth) is of uniform texture, where as models such as EPIC 5125 allow soil profile information to be incorporated on a per layer basis (Post et al., 2001). EPIC, however, is designed to model soil-plant-atmosphere properties and does not specifically predict soil C storage.

The Century model has been used widely for estimating C storage in grassland, agricultural, and forest systems world wide (Murty et al., 2002; Schimel et al., 2000; Motavalli et al., 1994; Burke et al., 1991). One study found that the Century model accurately reproduced the observed SOM development (sequestered C) determined through field experimentation across a variety of crop rotations in Denmark (Foereid and Hǿgh-Jensen, 2004). This study also evaluated model sensitivity to parameter values. The authors found using average climate data did not introduce large errors (1-5%) into SOC predictions. Another study examined the accuracy of Century V4 in determining SOC within European agricultural systems; a regression between observed and simulated changes in SOC yielded a significant relationship (r^2 of 0.51), with greater success found in simulating SOM in grass and crop systems than forest systems (Kelly et al., 1997). The authors concluded that these findings reinforce the utility of Century as a tool for predicting SOM dynamics.

Bias in the Century model resulting from soil texture has been suggested. While an early study reported that the Century model adequately estimated SOC values for various soil textures and climates in the Great Plains grasslands, explaining over 88% of the variability for coarse, medium, and fine-textured soils (Parton et al., 1987), a recent study comparing NT and tillage at five dryland farm sites in north-central Montana found that the Century model overestimated SOC by an average of 10% (Bricklemyer et al., 2007). This study suggested that the Century model is particularly sensitive to the effects of clay content when predicting total SOC, but not the rate of change in SOC.

The Voluntary Reporting Carbon Management Tool (COMET-VR) model is essentially a user-friendly interface for the Century model and reduces the extent of user-defined parameters needed for SOC prediction. This tool is available on-line (http://www.cometvr.colostate.edu), making it readily accessible to the public and private sectors, and was developed by Colorado State University and the USDA Agricultural Research Service (ARS) to aid agricultural producers in estimating SOC changes. The NCOC plans to use COMET to predict SOC sequestration for fields under C contract.

Sequestration values can be obtained by providing COMET with state, county, parcel size, and surface soil texture. Information for landscape position (lowland vs. upland) and historical (pre-1970s), recent (1970s to mid-1990s) management is also required. Additional parameter data needed for Century computations stem from a pre-defined pool of region-specific climatic and bio-physical data; land management data are provided at a major land resource area (MLRA) 1:7,500,000 scale, while climate data are set at the county level. Generated values are provided as total English tons C per year and total CO_2 equivalent. COMET predictive accuracy is less than that of the Century model, due to the use of more generalized parameterization.

Monitoring and Validation of Land Management Through Satellite Imagery Mapping

Field-based SOC analyses require time-consuming soil sampling and costly lab analysis. Accurate estimation of SOC is also difficult to obtain due to spatial and temporal variability and influence by sampling design (Bricklemyer et al., 2006). Visible near-infrared diffuse reflectance spectroscopy (VNIR-DRS) is currently being investigated as a fast, in-field alternative to traditional lab analysis (Brown et al., 2006). VNIR-DRS can reduce time and effort, but worker expense would still prevent the annual monitoring of multiple farm fields, limiting per-field validation to 1:10 yr intervals.

Remote sensing has been attempted for large-area SOC estimation. A study in eastern Washington found a significant correlation between SOC and Landsat Thematic Mapper (TM) reflectance ratio values, implying that TM data might help in estimating surface SOC levels (Wilcox et al., 1994). These findings reflect an earlier investigation that observed TM ratios blue/near-IR, red/near-IR, and mid-IR(band 5)/near-IR were useful in SOC prediction (Frazier and Cheng, 1989). Reflectance values from digital aerial photography were also found to yield SOC predictions very similar to measured surface C (Chen et al., 2000).

These results are encouraging, yet a definitive relationship between soil radiance and SOM remains distant as most attempts have failed to accurately predict OC across a wide range of soil types and moisture levels (Scharf et al., 2002). Vegetative cover and post-harvest residue also can obstruct soil visibility, diminishing the accuracy of SOM estimations. Remote sensing ultimately is limited to surface C detection, a disadvantage that cannot be overcome with current technology. Carbon must be evaluated deeper within the soil column for adequate monitoring (Reeder et al., 1998; Mann, 1986).

Identifying agricultural practices that increase sequestration offers an alternative to direct soil C analysis. This investigation will attempt to detect three primary land-use practices, tillage types (NT vs. tillage), cropping intensity, and CR land, although sequestration is influenced by other management factors as well. The incorporation of surface residues and the minimization of soil disturbance (Bricklemyer et al*.,* 2006), for example, will not be evaluated in this study as they were excluded from C contract specifications.

Tillage vs. No-Till

Satellite imagery has been used to detect conservation tillage practices (Bricklemyer et al., 2006; South et al., 2004; Andrés et al., 2003). Successful investigations have been limited to areas of fallow, avoiding increased spectral interference and reduced soil visibility due to vegetative canopy. Investigators in one study predicted dryland tillage with 80% accuracy through manual interpretation of Landsat imagery, but were faced with commission errors from tillage being wrongly classified as NT (DeGloria et al., 1986; DeGloria et al., 1985). Logistic regression applied to Landsat Enhanced Thematic Mapper Plus (ETM+) imagery yielded >95% accuracy in verifying NT in Montana dryland fallow with surface wheat stubble (Bricklemyer et al*.,* 2002). Another study used the spectral angle mapper algorithm with ETM+ data to differentiate tillage practices under crop residue, resulting in a classification accuracy of 97% (South et al., 2004).

The classification of tillage practices in crop-covered fields has been relatively unsuccessful. A Texas study using Landsat TM imagery with logistic regression was able to separate tillage from NT in fields under sorghum, wheat, and soybean cover with 83% accuracy, but failed to achieve the 85% accuracy standard for spatial data (Gowda et al., 2005; Lillesand and Kiefer, 2000). A study in north-central Montana applied logistic regression to ETM+ data and was able to predict NT under dryland spring wheat, winter wheat, and barley with 94% accuracy, but found that tillage was often classified as NT, lowering tillage accuracy to 80% (Bricklemyer, 2006). Tillage accuracy must be improved before this approach can be considered successful.

Canopy interference might be avoided if imagery were acquired in early spring prior to plant emergence. One drawback is that spring cloud cover could minimize the opportunity for “clear view” imagery. Winter wheat canopy (emergence is pre-winter) and continuous crop rotations present additional complications for acquisition of bare-soil imagery. Two alternate approaches to tillage classification are presented in this review with these limitations in mind, the object-oriented (O-O) classification and sub-pixel analysis techniques.

A per-field analysis is the most likely alternative to traditional pixel-based classification. Agricultural fields are defined as individual objects, and then classified according to spectral and object-related features unique to each land-use type. The leading software for contextual classification of Earth observation imagery is Definiens Professional (formerly eCognition and currently being replaced by Definiens Developer), which is capable of O-O analysis (www.definiens-imaging.com).

Object segmentation is the first step in the Definiens Professional (Definiens AG, Boulder) analysis process and uses scale**,** color**,** smoothness, and compactness to create image objects. Segmentation begins by grouping together similar “seed” pixels into a larger object. The objects continue to merge until all like areas represent a distinctive feature such as a tree, rooftop, or in this case agricultural fields.

Sample and/or knowledge-based supervised classification can be applied once segmentation has been accomplished. Definiens Professional incorporates visual elements such as tone, shape, texture, area, and context, while traditional methodology has been limited to using spectrally-based information in the classification process (eCognition User Guide 4.0, 2004). This approach is especially useful when classifying objects that retain stable shape boundaries, although their interior characteristics are constantly changing (Blaschke and Strobl, 2001).

A few studies have examined Definiens object delineation accuracy, including a Definiens sponsored case study that remotely identified European farm fields cropped with winter wheat, oats, barley, and grasslands (Fockelmann, 2001). These crops were delineated from color-infrared aerial imagery (1-m resolution) with three bands (green, red, and infrared) spanning a 2.6-km by 2.68-km area. Final results were described as satisfactory, but statistical data was not provided. Another study evaluated eCognition 3.0 abilities using IKONOS high-resolution imagery over urban and rural landscape. It found overall segmentation results to be acceptable with a 16% difference between actual and predicted areas (Meinel and Neubert, 2004). There is still great uncertainty as to how well agricultural-related object segmentation will perform at both the farm-based and regional levels.

Sub-pixel analysis offers a third approach to tillage classification. Cover types in small patches or strips might become obscured by surrounding land cover in coarse resolution imagery (Bastin, 1997). The spectral properties of vegetation and bare soil are often included within the same pixel with 30-m ETM+ resolution. Un-mixing mixed-pixel signatures might help to identify land-cover classes present at the sub-pixel level, separating soil spectral information from areas under canopy cover.

A study examining sub-pixel accuracy found that linear-mixture and regression models showed significant correlation between land cover proportions when applied to three-band (visible, near-infrared, and middle infrared) airborne imagery (Foody and Cox, 1994). The fuzzy c-means classifier, however, often outperforms linear-mixture classification as it is less influenced by the degree of between-class signature separation (Bastin, 1997). Linear optimization techniques have also been used in sub-pixel development, yielding a classification accuracy of >89% for water, wetland, and dry-land vegetation at 500-, 200-, and 100-m resolution (Verhoeye and Wulf, 2001). Other approaches used to map multiple classes at the sub-pixel scale include Hopefield neural networks and genetic algorithms, while fuzzy classification tree analysis can be useful for data with a high degree of uncertainty and noise (Chiang and Hsu, 2002; Mertens et al., 2003; Tatem et al., 2001).

Vegetation indices might offer a second approach in determining tillage practices under canopy cover. Radiometer-based studies have found that the greenness vegetation index (GVI) is strongly dependent on soil brightness (Huete et al., 1984). Index values were also found to be lower for dark-colored and low reflecting soils than for light-colored and high reflecting soils under similar vegetative cover (Huete et al., 1985). Decreased surface roughness and increased surface residue, both of which are found under NT conditions, can increase surface reflectance (Stoner et al., 1980; van Deventer et al., 1997).

To determine the relationship between the vegetation index and background soil properties a regression analysis would still be needed. It has been suggested that this is an unnecessary step, as the application of a regression analysis to individual bands explains more variability than regression against a vegetation index (Lawrence and Ripple 1998; Ripple, 1994). Vegetation indexes might have more validity in tillage management analysis when applied indirectly. Areas with unhealthy vegetation tend to reflect more light in the visible spectrum than in the near-infrared (NIR). This results in a lower index value (Gamon et al., 1995). The thought is that higher index values (indicating greater canopy cover) could then be excluded from training objects, using only areas with reduced vegetation or bare soil in the classification process. This approach is limited, however, as bare soil tends to reflect equal amounts of red and NIR.

Crop Rotation Systems

Traditional cropping systems have included monocultures of wheat and barley followed by periods of fallow. This management approach, however, does not facilitate optimal SC storage. Research has demonstrated that C sequestration can be increased by creating a more complex crop rotation (especially with the addition of N-fixing and deep-rooted plants) (West and Post, 2002).

Fields must be classified to current crop type before crop-rotation patterns can be identified. Satellite image analysis has had success in remotely identifying certain crop types. An initial study used ERTS-1 imagery and semi-automatic analysis to identify field and vegetable crops with 82 to 90% accuracy (Johnson and Coleman, 1973). A more recent study in north central Montana used June and July ETM+ imagery with boosted classification tree analysis (BCTA) to detect six crop types (spring wheat, winter wheat, barley, alfalfa, lentil, and CRP) with 97% accuracy (Bricklemyer et al., 2006). Class accuracy ranged from 88-99%.

The main disadvantage with pixel-based classification is that it usually results in a visually-confusing pixilated display that makes it difficult to visually relate to on a per-field basis and does not represent the reality that fields are managed for single crops in a given year. An O-O approach would reduce the pixilated effect, creating larger classification units, resulting in a land cover map that is more realistic and visually appealing (Stuckens et al., 2000). Statistical evaluation and export procedures could become entirely automated if Definiens was used in the classification process, decreasing image processing costs.

Relatively few investigations have used an O-O approach to crop classification. A study in California attempted to use Definiens to discriminate between agricultural crops using MODIS imagery and seasonal Normalized Difference Vegetation Index (NDVI) values, but failed to yield conclusive results (Hansen et al., 2006). A more detailed analysis of land cover in a Michigan watershed used two Landsat TM images (acquired in April and August) to compare Definiens classification accuracy with a mixed unsupervised/supervised approach in ERDAS Imagine (Brooks et al., 2006). Identified crop types included alfalfa, corn, soybeans, wheat, mixed grass, and CRP. These resulted in a total class accuracy of 68% with Definiens and 55% with the mixed approach. Individual class accuracies for Definiens ranged from 91.3 to 35.6% with wheat being the lowest (due to a lack of cloud free imagery during wheat's peak growing season). It is thought that the study might have achieved greater accuracy by incorporating user knowledge with the fuzzy membership function instead of using the “click and classify” approach, as user knowledge can greatly affect performance (O’Brien and Irvine, 2004).

Another study found that giving higher weighting to ETM+ bands 3, 4, 5 (Red, NIR, and Short Wave Infrared (SWIR)) increased field segmentation accuracy due to their sensitivity to spectral vegetation features (Sugumaran, 2004). This study also observed that Definiens outperformed the maximum-likelihood per-pixel classifier in identifying wetlands, mixed forest, impervious surface, bare/fallow soil, urban grasslands, and open water with an overall accuracy of 90.7% using the 15-m resolution panchromatic band (band 8) and 73.9% with the 30-m resolution bands.

Conservation Reserve

Using satellite imagery to identify grassland-based conservation reserve (CR) land has posed certain challenges. Although CR land is commonly planted with native grass, shrubs and trees can also be incorporated. While disturbance is heavily restricted under CR contract, haying is allowed once every five years from July to October and grazing is allowed once every three years from February to November (Deschamps, 2006). The variable land patterns within CR are the result of these different management factors and vegetation types, making accurate classification difficult. Remotely distinguishing CR from prairie grasslands is also an issue that must be resolved.

Attempts have been made to determine CR land by identifying changes from agricultural fields to grassland. One study achieved 97% accuracy using post-classification change detection to identify lands converted from cropland to grassland during a six-year period (Price et al., 1997). This land-use change is most often associated with CR. Another study in Kansas took a multi-seasonal and multi-year approach to CR mapping, using Landsat TM imagery from 1987 and 1992 for May, July, and September, achieving 88% accuracy (Egbert et al., 1998). This study also attempted to locate CR land by identifying the conversion of agriculture land to grassland. The identification of CR through land-use change is helpful, but it fails to identify land already under CR.

Vegetation indexes have been used in the differentiation of CR land. One study found that the GVI worked best for discriminating between CR, grazed, and hayed land (Price et al., 2002). A similar study achieved 90% accuracy in discriminating between CR, grazed, and hayed land by applying NDVI to Kansas Landsat TM scenes acquired in spring, summer, and fall (Guo et al., 2003). Study results found that the spectral reflectance at CR sites was consistently higher in the red portion of the visible spectrum while non-CR grassland had greater reflectance in the green portion of the visible spectrum. This indicates that there was less green plant material found on CR sites compared to grazed areas. This is likely to be less true for comparing CR to dry-land crops. Accuracy was also plant-type dependent as user's accuracy for cool crop (C3 plants)/CR was 91% compared to 82% for warm crop (C4 plants)/CR.

Landsat TM satellite imagery, GIS data, and derived features such as a NDVI and band ratios were compiled into a complex multi-source geospatial database in a more creative attempt at CR identification (Song et al., 2003). Applying a decision tree classifier (DTC) and a support vector machine (SVM) to the multi-source database, the study was able to obtain a 5-10% improvement in classification accuracy over a maximum likelihood classifier used in ERDAS Imagine.

These attempts demonstrate a wide array of approaches taken in the identification of CR land. The challenge is that classification accuracy is strongly dependent on carefully selected imagery and well-defined study areas with minimal complexity. It is doubtful that these methods could accurately classify CR land over a diverse regional area.

Spectral and structural pattern recognition might be useful in defining areas of CR. The distinctive rectangular or circular patterns common in most agricultural practices add an additional means to distinguish CR land from native grasslands. The Definiens segmentation process should be able to incorporate these field-based features into the classification process. This method is unproven, however, as studies using an O-O approach to CR classification have not been identified at this time.

Change Detection Analysis

Multiple years must be compared to detect annual changes in agricultural management practices. These comparisons are essential in determining crop rotations. Annual monitoring requires additional effort; nonetheless, it is critical in confirming that C contract agreements have been honored. Two approaches to change detection are commonly used: a comparative analysis of independently-produced classifications and a simultaneous analysis of multi-temporal data (Lambin and Strahler, 1994; Malila, 1980). A comparative analysis of independently-produced classification data would require the entire area of interest to be reclassified on a yearly basis, a process far too time-consuming for the purposes of this study. Applying a change analysis model to unclassified multi-date imagery is more feasible, especially when analyzing the amount of data found at a regional scale.

Change-vector analysis (CVA) is a commonly used multivariate pixel-based technique that detects changes present in multispectral data between acquisition dates (Johnson and Kasischke, 1998; Malila, 1980). Locations with minor changes in spectral responses are identified as unchanged from the base year, and only potentially changed locations need to be reclassified. Potential advantages of CVA include simultaneous change detection of cover conditions as well as cover change in all multispectral input layers. This sensitivity makes CVA more appropriate in cases where all change must be detected or when this step must occur before a particular area of change can be identified (Johnson and Kasischke, 1998).

Image transformations are often applied to multi-date imagery prior to CV analysis. The tasseled cap is one such transformation and combines six non-thermal Landsat bands, resulting in brightness, greenness, and wetness components that are sensitive to vegetative change (Dymond et al., 2002). This often improves classification results and adds additional information to assist the change detection process. A disadvantage of the tasseled cap transformation is that it does not incorporate multi-temporal imagery.

Change vector direction and multispectral change magnitude are two types of output information produced through CVA. These indicators are limited because they only show the direction and magnitude of change without directly determining what actually occurred. The user must then decide a level of no change, above which further investigation is necessary. Spectral data from the unchanged areas must then be used to classify the change. Per-pixel CVA is very sensitive to subtle changes due to seasonality, vegetative growth, and condition in addition to detecting abrupt changes in land-cover types (Lambin and Strahler, 1994). Detection of per-field change is more appropriate in this study as pixel-based change detection would only complicate the interpretation and re-classification process.

A study using Definiens-based O-O change detection identified structural changes at a Canadian nuclear facility with IKONOS-2 high-resolution imagery. Pixel-based classification was avoided under the assumption that shadow effects would cause multiple false signals, making interpretation complex and unclear (Niemeyer and Canty, 2001). A multivariate alteration detection (MAD) was applied to each image layer, and individual objects were then defined through segmentation. Four classes were used to identify Digital Number (DN) changes in grey values and vegetation, changes DN-, changes DN+, changes vegetation-, and changes vegetation+. The multiple image layers were simultaneously classified to produce a change/no-change image but results were not discussed.

Another example of O-O analysis is a preliminary study that compared the Definiens approach to pixel-based change analysis using a multi-temporal Landsat TM/ETM+ sequence acquired over Alberta foothills. A tasseled cap transformation was first applied to derive an enhanced wetness difference index. A regression tree analysis was applied after segmentation to determine which variables to use for the classification membership function. Overall accuracy for forestry, mining, oil and gas, and transportation change detection was 84% compared to 59% in the pixel-based routine, with individual class accuracies of 70-90% (McDermid et al., 2006)

Image Classification Algorithms

Methodologies used for the automated classification of digital imagery are often referred to as either supervised or unsupervised (Jensen, 2005). Unsupervised clustering attempts to identify underlying feature distributions by organizing spectral data into groups according to homogeneous characteristics. These classifiers are often used when there is uncertainty concerning the characteristics of land cover features within a landscape. Unsupervised clustering techniques provide a means for obtaining optimum information for the selection of training regions used in subsequent supervised classification (Lillesand et al., 2000). The K-means classifier is a popular clustering-based approach in which a user-defined number of spectral clusters are arbitrarily located within a multidimensional measurement space. Data pixels are then assigned membership to the closest cluster. The re-clustering process continues until there is no significant change in the location of the class mean vector between successive iterations of the algorithm. The Iterative Self-Organizing Data Analysis Technique (ISODATA) takes a similar approach, but allows iterations to vary in the number of generated clusters through merging, splitting, and deleting of the previous spectral groups.

Supervised classification requires a prior understanding pertaining to spectral classes within the landscape of interest. This approach also requires reference data or surface locations for which the class type is known. Spectral information from these locations is then used to "train" an image classifier; the trained algorithm then classifies the remaining "unknown" pixels (Jensen, 2005). Algorithms used within supervised classification can be further divided into parametric and non-parametric classifiers.

Parametric Classifiers Parametric classifiers are based on the assumption that all data follow a similar distribution from which model parameters can be estimated (Hardin, 1994). The minimum-distance-to-means (nearest neighbor) and parallelepiped classifier are examples of elementary approaches to supervised classification. The minimum-distance approach first determines the mean band spectral value for each class type. A pixel is assigned to a class based on shortest Euclidean distance in spectral space between the unclassified pixel and mean class values (Lillesand et al., 2000). Problems associated with the minimum-distance lies in its insensitivity to different degrees of variance within class spectral response. This classifier becomes problematic when classes are in close proximity with high spectral variance. The parallelepiped classifier classifies pixels according to class range. If an unknown pixel lies within a class maximum and minimum value in spectral space, the pixel will be assigned to that class. Problems arise when there is high covariance, or overlap, amongst classes.

The maximum likelihood classifier has been the most widely used method in classifying remote sensing data and evaluates both the variance and covariance in spectral response during the classification process (Ediriwickrema and Khorram, 1997). This process computes the relative likelihoods for each pixel within an image. The probability of a pixel belonging to a predefined set of *m* classes is calculated and a pixel is assigned to the class where the probability is the highest (Jensen, 2005).

The likelihood function $L(\Theta;y)$ supplies an order of preference or plausibility among possible values of Θ based on the observed y (Sprott, 2000). The relative likelihood is the likelihood standardized with respect to its maximum to obtain a unique representation not involving an arbitrary constant.

Eq. 2.2 $$R(\Theta;y) = L(\Theta;y)/\sup_s L(\Theta;y) = L(\Theta;y)/(\Theta^{\wedge hat};y).$$

The maximum likelihood estimate $\Theta^{\wedge hat}$ is the most plausible value of Θ in that it makes the observed sample most probable. The relative likelihood $R(\Theta;y)$ measures the plausibility of any specified value of Θ relative to that of $\Theta^{\wedge hat}$. Non-linear optimization is used to estimate the likelihood in order to find optimal parameters that maximize the log-likelihood. Probability density functions are computed, assuming that the data follows a Gaussian, or normal, distribution. A multidimensional normal distribution is described as a function of a vector location in multispectral space by (Richards and Jia, 1999):

Eq. 2.3 $$P(x) = 1/\left((2\pi)^{N/2}/\textstyle\sum/^{1/2}\right)\exp\{-1/2(x-m)^t \textstyle\sum-1(x-m)\}$$

Where x is a vector location in N dimensional spectral space: m is the mean position of the spectral class (the position in which a pixel is most likely to be found within a class distribution), and $\sum$ is the covariance matrix of the distribution which describes the spread in spectral space. Such a distribution describes the chance of finding a pixel belonging to a particular class at any given location in multispectral space (Richards and Jia, 1999). It is assumed that prior probabilities for each class are not known and that each class has an equal probability of occurring.

Non-Parametric Classifiers The major drawback associated with parametric-based models is that they assume that the dataset has a particular statistical distribution, which is usually not found with multisource data incorporating ancillary information in addition to spectrally-derived information (Huange, 2001). These parametric approaches assume that land use classes can be modeled by probability distributions and can be described by the parameters of these distributions. The ability of minimum-distance and parallelepiped to correctly classify a spectral feature becomes diminished when the data does not follow a normal distribution and can not handle multiple data sets that do not follow the same distribution. Non-parametric models make no assumption concerning the data distribution, thus avoiding associated error. These methods, which include decision trees, artificial neural networks, and expert systems, have demonstrated better performance on land cover classification than traditional parametric-based methods (Richards and Jia, 1999). Non-parametric rule-base methods can include ordinal and nominal datasets, which allows continuous data such as spectral bands and vegetation indices to be used in conjunction with categorical data.

The classification of multi-source remote sensing data has been described as challenging as a convenient multivariate statistical model is generally not available for the data (Gislason et al., 2006). Fortunately improvements in programming language have provided various options in classifying non-Gaussian, multi-source data. These include tree-based data mining approaches based on linear classifiers segmented by nodes (representing decisions) used to partition the data into similar spectral groups. Popular variations of decision-tree analysis are discussed below.

Classification tree analyses (CTA) or classification and regression tree algorithms are used increasingly in remote sensing analysis. These algorithms work to create a classification model through the repeated binary splitting of heterogeneous training data representing two or more class types until reaching a terminal node, or end point, where stopping criteria is met (Breiman, 1993; Lawrence et al., 2004; Lawrence and Ripple, 2000). Splits within the tree serve to further reduce heterogeneity within sub-samples, therefore minimizing deviance in the response variable (Lawrence and Wright, 2001). CTA does not rely on assumptions regarding the distribution of the data as it is a non-parametric technique. Classification TA is also advantageous as a wide diversity of data can be used as inputs into the classification, including raw spectral bands or derived spectral information, topographic information, and other GIS layers.

Inaccuracies and outliers in the data can adversely affect CTA. Unbalanced data in certain classes can also affect the performance of CTA with the analysis dividing heavily represented classes rather than splitting out lightly represented classes. Over fitting also occurs with CTA classifiers; this is when a tree explains the deviance within a training set so tightly that it might no longer explain the distribution of the remaining data.

Boosting and bagging techniques generally increase classification accuracy in tree-based approaches. Bagging is based on training many classifiers samples boot-strapped (sampled with replacement) from a training set. This process reduces variance in the classification. Alternatively, boosting uses an iterative re-training approach where incorrectly classified samples are given increased weighting as the iterations progress.

Boosting is considered to produce more accurate classifications than bagging as it reduces classification variance and bias but is both computationally slow and sensitive to overtraining and noise (Gislason et al., 2006). CART® (Salford Systems) is a statistical package implementing boosted CTA. The decision tree software, See5® (C5.0 for Unix) also incorporates boosting but differs from CART in its use of a normalized information gain (a measure of difference in entropy between subset attributes) instead of the Gini index as a criteria for splitting tree nodes.

The Gini index of node impurity (Eq. 2.4) is based on the sum of the squared probabilities *p* of membership for each target category in the node (Lerman and Yitzhaki, 1984). It reaches its minimum (zero) when only one class is present at a node or all data samples in a node belong to one class. The maximum is reached when class sizes at each node are equal.

Eq. 2.4
$$i(p) = \sum_{i \neq j} p_i p_j = 1 - \sum_j p_j^2$$

Stochastic gradient boosting (SGB) is a hybrid of boosting and bagging approaches (Friedman, 1999). A random subset of the data is selected at each step of the boosting process. A number of small classification trees are developed instead of the full trees, and each tree is summed and an observation is classified according to the most common classification among trees. Stochastic GB has reduced sensitivity to inaccurate training data, outliers, and unbalanced training sets. Stochastic GB is also resistant to over fitting as small classification trees are used at each step of boosting. TreeNet® is a popular software that incorporates SGB (Salford Systems, 2001).

A study comparing CTA with SGB against three different data sets, using IKONIS 4-m resolution multispectral data, found that SGB (via TreeNet) produced > 90% User's and Producer's accuracies for Tree, Water, Meadow, and Rock classes and overall accuracies of > 95% (Lawrence et al., 2004). Classification TA class accuracies ranged from 61-100% with 84% overall accuracy. Classification of Probe-1 hyperspectral data for water, conifer, deciduous, developed, range, and disturbed classes resulted in 83% overall accuracy with the CTA and 93% accuracy with the SGB. Although CTA accuracies for Landsat-7 ETM+ data representing the GreaterYellowstone Ecosystem yielded an overall accuracy of only 64%, two percentages higher than those for the SGB, the authors noted that certain class accuracies showed substantial improvements through SGB.

Another study found that SGB resulted in classification accuracy improvements when classifying non-wet, wetland, and riparian areas land types in Southwestern Montana when using Landsat-7 ETM+ imagery combined with topographic and soil data (Baker et al., 2006). Overall classification accuracy was 73% for the CTA and 86% for SGB; producers and users accuracies for each class were also substantially greater when using SGB.

The Breiman Clutler Classification (BCC) approach, alternatively referred to as the Random Forest (RF) classifier, is considered to be an improved form of bagging, and is comparable to boosting in terms of accuracy (Gislason et al., 2006; Breiman, 2001). It has been claimed that this classifier is "unexcelled in accuracy among current algorithms" (Lawrence et al., 2006; Breiman and Cutler, 2005). Random Forest is superior to many tree-based algorithms as it is not sensitive to noise or overtraining, as the resampling is not based on weighting as occurs in boosted methods.

Random Forest uses bagging to form an ensemble of classification and regression trees (CART-like classifiers) featuring identically distributed random vectors (Θ_k) with an input pattern *x* (Breiman, 2001; Gislason et al., 2006). Random vectors are generated independent of past random vectors but with the same distribution. Splits at each node are determined with the Gini index using random subsets of input variables. Classification occurs when each tree in the "forest" casts a unit vote for the most popular class at input *x* resulting in a classified output determined by a majority vote. The margin function for RF is as follows, where I(·) is the indicator function (Breiman, 2001):

Eq. 2.5 $$mg(X,Y) - av_k I(h_k(X) = Y - \max av_k I(h_k(X) = j\ )$$

This margin function measures the extent to which the average number of votes at X,Y for the right class exceeds the average vote for any other class. Thus a larger margin indicates more confidence in a classification.

Unlike CART analysis, trees in RF are not pruned. Over fitting does not occur within random forests, following the Strong Law of Large Numbers. This law states that the sample mean M_n converges to the distribution mean μ with a probability of one (Pal, 2005). In other words if *Zt* is a sequence of *n* random variables drawn from a distribution with mean μ with a probability of one, the limit of a sample averages of the *Z*'s goes to μ as the sample size *n* goes to infinity. If there are *M* input variables, a number $m << M$ is specified so that m variables are selected at random out of the M and the best split is used for a particular node.

Forest error is dependent on the correlation between any two trees in the forest and the strength of each individual tree in the forest (Breiman and Cutler, 2005). Increased correlation between trees increases the forest error rate. A low error rate indicates a strong classifier; hence increasing the "strength" decreases the forest error rate. Correlation problems are avoided as only random subsets of the variables are evaluated for a split at each node. Reducing m reduces both the correlation and the strength (and vice versa). This value, m, is the only adjustable parameter in RF, for which the algorithm is somewhat sensitive.

A problem often associated with the classification of spectral imagery is a relatively small quantity of training data available for classifying an abundance of spectral data (Ham et al., 2005). Sample statistics of the training data might also not be representative of the true probability distribution of the individual class signatures. Generalization of the resulting classifiers is often poor, resulting in reduced mapping quality over extended areas. An internal accuracy measure within the algorithm is advantageous as reference data does not need to be partitioned by the analysis into separate sets for training and validation. Instead, all available "ground" data can be brought into the forest.

Test set accuracy is estimated in RF by running out-of-bag (OOB) samples (training set data that are not in the bootstrap for a particular tree) down through a tree as a form of cross-validation. Out-of-bag estimation is described as follows (Breiman, 2001). The process starts with a training set, T. From this you form bootstrap training sets, T_k. From these training sets, classifiers h(x, T_k) are constructed. These classifiers vote to form a bagged predictor. For each y, x in the training set, aggregate the votes only over those classifiers for which T_k does not contain y, x. The OOB estimate for the generalization error is the error rate of the OOB classifier on the training set.

It is important to note that the OOB accuracy estimates in RF tend to have lower accuracy than training sample accuracy measurements due to each bootstrap using 2/3 of the training samples, so that each tree can only use the remaining 1/3 of the training sample to estimate OOB accuracy. For larger training, the OOB error approaches the test set error. A study comparing OOB accuracy assessments with the traditional error matrix approach for resulting rangeland classifications reported that the OOB estimates were within 3% of the independent accuracy assessments, with most less than 1% apart (Lawrence et al., 2006). The authors cautioned, however, that OOB estimation is only reliable given an absence of bias in the reference data.

The remote sensing community has increasingly used RF for land cover classifications. A study evaluating ten ground-cover classes (consisting of Colorado forest types and a water class) found that the RF algorithm had greater overall accuracy (83%) than the CART algorithm (78%), but was less accurate than the 1R boosting CTA algorithm (85%) (Gislason et al., 2006). The 1R classifier (Witten and Frank, 1999) is described as a very simple classifier that splits the data range into sections, or “buckets”. The algorithm then finds the class from which the most training samples fall into each bin and uses this information to classify. Random Forest, however, was superior to the boosting classifier in computational efficiency. It was mentioned that the total OOB accuracy was over 5% lower than the associated test set accuracy, for reasons mentioned previously.

Another study evaluating agricultural land use classification of wheat, potato, sugar beet, onion, peas, lettuce, and beans using Landsat-7 ETM+ data resulted in 88% total accuracy, with 87% and 87% accuracy for decision trees using boosting and bagging (Pal, 2003). Class accuracies were not provided. Random Forest showed greater accuracy with the introduction of 8% noise into the data set, resulting 87% total class accuracy, compared to 86% with bagging and 83% in boosting.

A study within Madison County, Montana used RF to classify hyperspectral data for weed mapping. Overall accuracy for spotted knapweed was 84% while leafy spurge accuracy was 86% (Lawrence et al., 2006). The authors reported that these accuracies were substantially greater than classifications reported in other studies, resulting from the use of conventional tree-based, spectral angle mapper, and maximum likelihood classifiers.

Limitations in using RF for classification of satellite imagery include the great complexity in the algorithm's computational process. Random Forest is a black box model that produces results too excessively complex to comprehend, unlike some decision tree classifiers whose resulting classification rules can be evaluated to facilitate a qualitative understanding. In other words, the analyst is unable to deduce classification rules based on an evaluation of the forest-generating process. The randomForest package, however, does allow for the generation of variable importance plots. These plots provide insight in determining which predictors were of greater importance in creating the forest. Data size limitations within R, the platform for which the randomForest package operates, might also pose problems as R is only capable of handling between 2-3 Gb of data depending on system settings. A randomForest package recently released for S-plus statistical software (Insightful) might alleviate this problem as S-plus can handle larger data sets than R.

Object-Oriented Analysis

Classification Options Two classification options are available within the Definiens Professional O-O software package, a "fuzzy" based nearest-neighbor classifier and the building of membership functions. Working in a multidimensional feature space, objects evaluated for classification are compared to mean values associated with user specified training objects (eCognition 4.0, 2004). These mean values can include band-wise spectral information, contextual information such as object shape, size, texture, and any thematic information incorporated into the program prior to object segmentation. The algorithm then searches for the closest sample object to the unclassified object in feature space and assigns the object to that class. Class assignments are further determined by values ranging from 0 (no assignment) to 1 (full assignment). The closer an object is located to a certain sample in feature space, the higher the membership degree given. The distance is computed as follows:

$$\sum \sqrt{\left(\frac{v_f^{(s)} - v_f^{(o)}}{\sigma_f} \right)^2}$$

Eq. 2.6

Where d is the distance between sample object s and image object o, vf(s) is the feature value of the sample object for feature f, vf(o) is the feature value of the image object for feature f, and σ is the standard deviation of the feature value for feature f (in this manner, all features values are compiled together in the distance decision process).

A multidimensional membership function $z(d)$ is also computed (Eq. 2.7), based in the distance d.

Eq. 2.7 $$z\,(d) = e^{-k * d\text{^}2}$$

The parameter k is the natural log of the inverse function slope. The function slope equals $z\,(d)$ for d=1. The function slope is the membership value of an image object to a class. The default value for the function slope (Eq. 2.8) in Definiens is 0.2, however

Eq. 2.8 $$k = \ln\,(1 \,/\, \text{function slope}\,)$$

adjustments to the function slope can be made to account for known feature properties. A smaller function slope requires image objects to be closer to sample objects in feature space if they are to be included within a particular class.

Membership functions in Definiens consist of rule sets stating feature space criteria that an object must meet before inclusion into a particular class. These rule sets can be incorporated by the way of results from the nearest neighbor classification analysis or through direct user specification. Class hierarchies are formed by grouping child classes under parent classes. There might be an overarching “tree” class where all classes under the tree hierarchy might have similar feature properties, but enough feature differences are present that further “child” rules can be used to separate the trees into sub-species. This process is very similar to ERDAS Imagine’s Knowledge Engineer package, where the user builds a knowledge base represented as a tree diagram consisting of class definitions, rules, and variables to create a classification model.

"Fuzzy" memberships result when class descriptions overlap and objects belongs to several classes but with different degrees of membership in each class. In other words, the nearest neighbor algorithm not only provides information concerning which class an unclassified object has the minimum distance to but also the second and third best distances. This information provides the analyst with an opportunity to further refine the classification process to account for classification errors by evaluating the fuzzy results and adding additional rules or combinations of several conditions that must be fulfilled before an object can be assigned to a certain class. Fuzzy rules can be incorporated where the range of a particular membership value might fall within a range, instead of above or below a set value.

The determination of rules to be incorporated within the membership function can result from prior knowledge or through the evaluation of tools within the Definiens package. These tools include the sample editor, which displays the feature histograms for the sample objects, and a Feature Space Optimization Tool, which shows class seperability based on sample data feature statistics. It is also possible to manually import training rules derived from external data mining packages such as the classification and regression tree options featured in many statistical programs. Other techniques have included the inclusion of both pixel- and object-based data derived from image segmentation in Definiens into a Bayesian neural network resulting in 85% total accuracy for developed, grassland, deciduous, coniferous, water, wetland, and bare soil classes

(Song et al., 2005). Another study combined information gleaned from an ISODATA unsupervised classification and object-based classification rules generated in See5 data mining software into ERDAS Imagine's Knowledge Engineer to design a rules-based decision tree approach in classifying tidal marsh land (Hurd et al., 2006). The classified images were used as input variables with the addition of band-derived principle components, NDVI, Tasseled Cap Wetness, and an elevation DEM to improve classification accuracy.

<u>Object-Oriented Segmentation</u> Various methodologies have been used in the attempt to glean field-based information from digital imagery (Geneletti and Gorte, 2003; Evans et al., 2002; Torre and Radeva, 2000). Superimposing manually delineated field boundaries over pixel-based thematic maps for land-use analysis is one such example (Ozdarici and Turker, 2006; Aplin et al., 1999). This approach is highly labor intensive and does not directly link class types with field objects (De Wit and Clevers, 2004). Image-object segmentation offers a more practical solution to field-based delineation and analysis. The ideal segmentation process will result in image objects, which are integrated entities that exhibit an intrinsic scale and are composed of structurally connected parts or pixels (Hay et al., 2001).

Many different object-segmentation techniques have been developed within the last 20 years and can be generally classified as either boundary-based or region-based. Boundary-based methods detect object boundaries according to areas of discontinuity. These methods do not directly lead to object generation as the contours obtained are seldom closed, requiring additional algorithms to complete the process (Carleer et al., 2005; Hay et al., 2003). Edge detectors, watershed segmentation processes, neural nets, and pyramids are examples of boundary-based algorithms.

Region-based algorithms directly result in image segmentation by grouping areas according to homogeneity. Definiens Professional, the leading commercial O-O software, incorporates a multi-resolution bottom-up region growing approach in which segmentation starts by merging individual pixels or 'seeds' into groups which continue to be merged until a user-defined threshold, based on size (scale) and weighted heterogeneity measures, is reached (eCognition User's Manual, 2004). The heterogeneity criterion includes a combination of color (spectral reflectance) and shape (smoothness and compactness). Resulting field object boundaries are then treated as vector polygons, with contextual and topological information linked together. The objects are also connected within a hierarchical network that can represent image information at different spatial resolutions simultaneously, with each object knowing its neighborhood, super-objects, and sub-objects (Benz et al., 2004). A texture and region-based multi-scale algorithm (MSEG) is currently being developed and has shown promise in producing segmentations similar to those generated by the Definiens multi-resolution algorithm (Tzotsos et al., 2006).

Image segmentation is not an aim in itself, but a means of obtaining optimal information for further processing. The segmentation step is critical as it generates the object primitives that will be treated as a whole during subsequent analyses. Incorrectly defined objects can decrease classification accuracy, while field-based area statistics might be erroneous without proper object delineation. The literature discussing optimal segmentation parameters for land-use delineation, particularly with consideration to agricultural fields, is minimal. There is no unique solution to object segmentation and that adjustments to heterogeneity measures must be made by trial and error until the desired outcome is reached, as delineation results are often case-specific (Hay and Castilla, 2006; Radoux and Defourny, 2006).

Recommendations have been made concerning the multi-resolution segmentation of Landsat imagery. Giving higher weighting to Landsat ETM+ bands 3, 4, 5 (Red, NIR, and Mid-Infrared) was found to increase the segmentation accuracy of agricultural fields, as these spectral ranges are influenced by vegetative features (Sugumaran et al., 2004). It was also mentioned that giving zero weight to the Landsat ETM+ (or TM) band six (thermal) might avoid deteriorated segmentation accuracy due to the lower spatial resolution of this band (eCognition Users Guide 4.0, 2006; Yan, 2006). No literature reference has been made concerning segmentation error due to within-field management patterns. One option would be to adjust the segmentation scale parameter until the fields are segmented solely by exterior perimeter features, thus avoiding the delineation of within-field stripping. An alternative idea is taken loosely from a study in which segmentation was applied to NDVI values in an attempt to delineate urban regions according to relative vegetation amount (Arefi and Hahn, 2005). An image composite consisting of low NDVI values (representative of low to non-vegetated area) taken from two consecutive years might remove within-field patterns caused by cropped strips, after which segmentation could be applied accordingly.

Literature is also lacking concerning the evaluation of segmentation accuracy. Segmentation results have been largely subjected to human interpretation by visually referencing image-objects to those created by manual delineation or to the original image (Zhang, 1997; Benz, 2004). This approach is both subjective and inconsistent. Objective methods for determining the segmentation accuracy of remotely sensed data have not been thoroughly evaluated (Darwish et al., 2003). A positional quality technique, which takes into account error bias, has been proposed as an additional guideline for accuracy evaluation (Radoux and Defourny, 2005).

Moderate Resolution Satellite Imagery

A variety of satellite imagery has been used in studying land-use change, including synthetic aperture radar and SPOT medium-resolution imagery. Landsat imagery remains the preference in this study because of its continuous coverage, unparalleled image accessibility, and cost-effectiveness.

The Landsat program (initially called ERS - Earth Resources Survey) has provided a continuous stream of remote sensing data for monitoring and managing the Earth's resources since 1972 (LPSO, 2006). There are currently two Landsat satellites in orbit, Landsat 5 and 7. Landsat 5 was launched in 1984 and features Thematic Mapper (TM) multispectral scanning. Thematic Mapper includes seven spectral bands that collect data simultaneously, including three bands within the visible spectrum, one near-infrared (IR) band, two middle-IR bands, and one thermal-IR band. Spatial resolution is 28.5 m (120 m for thermal IR). Landsat 7 has been in operation since 1999 and includes Enhanced Thematic Mapper Plus (ETM+) capabilities. Improvements over Landsat 5 include increased spatial resolution in the thermal-IR channel (from 120 m to 60 m) and the addition of a panchromatic band with 15-m resolution. Enhanced Thematic Mapper also features an increased effective dynamic range over that of TM, resulting from adjustments in sensor gain (NASA, 2006) It has been said that no other system matches Landsat 7's combination of synoptic coverage, high spatial resolution, spectral range, and radiometric calibration (NASA, 2006).

Landsat 5 and 7 have shown long-term reliability in delivering world-wide satellite coverage; nonetheless technical problems have occurred. A malfunction with the solar array on Landsat 5 prevented battery recharge and suspended imagery collection for a three-month period starting November 2005 (USGS, 2006a). Problems with a downlink transmitter shut down image transmission for two weeks starting March 17, 2006. Landsat 7 is currently operating without a scan line corrector and is tracing imagery in a zig-zag pattern along the ground line track, resulting in a 22% loss of data in each scene (USGS, 2006b).

Problems have been identified in using the Landsat 7 gap data in a regional field-based approach. Data gaps range from no gaps in the middle of a scene to 14-pixel gaps (420 m) at the edge (Kurtz, 2006). Two gap-filled options are available to replace the missing data; one incorporates imagery from two consecutive 16-day ETM+ image scenes (as gaps are often random), while the other uses an automatic interpolation method to create non-real data based on pixel data located adjacent to gaps. The first approach becomes problematic due to phenologically-influenced image differences, while the second reduces image accuracy and is only recommended when image presentation is of great importance.

Thematic Mapper imagery is collected by Earth-receiving stations, including the EROS Data Center in South Dakota, where it is processed and distributed in either corrected or uncorrected format. Three levels of imagery are available: 1G, 1P, and 1T. Levels 1P and 1T are only accessible to United States Geological Survey (USGS) approved researchers. Level 1G includes radiometric and geometric correction and is geo-referenced to a user-defined map projection. Level 1P includes the features of Level 1G, but with the addition of ground control points to improve image accuracy. Level 1T includes accuracy improvements through control points as well as digital elevation model (DEM) topographic relief correction. The data for Levels 1G, 1P, and 1T are provided in a rescaled 8-bit unsigned integer (DN) format. Corrections for the Memory Effect (ME), an image artifact associated with Landsat 5, are automatically applied to all image levels.

Alternative image sources must also be considered to ensure the ability of sustained monitoring as launching the next generation of Landsat sensors has been met with ongoing delays. Sensors most comparable to Landsat include the Satellite Pour l'Observation de la Terre (SPOT) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), both of which span a 60-km^2 footprint. These footprints are roughly half that of Landsat 5 and 7. SPOT sensors 4 and 5 consist of five multispectral bands at 20- and 10-m spatial resolution, respectively. ASTER features 14 spectral bands; spatial resolution is 15 m in the visible and NIR spectrum, 30 m in the middle infrared (MIR), and 90 m in the thermal infrared. The radiometric resolutions corresponding to the sensor bands are presented in Table 2.1.

	Green	**Red**	**NIR**	**MIR**	**Thermal**
SPOT	0.50-0.59	0.61-0.68	0.78-0.85	1.58-1.75	NA
ASTER	0.52-0.60	0.63-0.69	0.76-0.86	1.6-2.43*	8.13-11.65**
* Spanning 6 Bands ** Spanning 5 bands					

Table 2.1. Band Spectral Resolution (μm) for SPOT and ASTER data.

Referenced Literature

Al-Adamat, R., Z. Rawajfih, M. Easter, K. Paustian, K. Coleman, E. Milne, P. Falloon, D.S. Powlson, and N.H. Batjes. 2007. Predicted soil organic carbon stocks and changes in Jordan between 2000 and 2030 made using the GEFSOC Modeling System. Agriculture, Ecosystems, and Environment, 122: 35-45.

Andrès, V., A.J. Peters, and J. Lei. 2003. Use of multispectral Ikonos imagery for discriminating between conventional and conservation agricultural tillage practices. Photogrammetric Engineering and Remote Sensing, 63: 537-544.

Angers, D.A., and G.R. Mehuys. 1989. Effects of cropping on carbohydrate content and water stable aggregation of a clay soil. Canadian Journal of Soil Science, 69: 373-380.

Aplin, P., P. M. Atkinson, and P.J. Curran. 1999. Fine spatial resolution simulated satellite sensor imagery for land cover mapping in the United Kingdom. Remote Sensing of Environment, 68: 206-216.

Arefi, H., and M. Hahn. 2005. A hierarchical procedure for segmentation and classification of airborne LIDAR images. Geoscience and Remote Sensing Symposium, 7: 4950-4953.

Baker, C., R. Lawrence, C. Montagne, and D. Patten. 2006. Mapping wetlands and riparian areas using Landat ETM+ imagery and decision-tree-based models. Wetlands, 26: 465-474.

Bastin, L. 1997. Comparison of fuzzy c-means classification, linear mixture modeling and MLC probabilities as tools for unmixing coarse pixels. International Journal of Remote Sensing, 18: 3629-3648.

Beare, M.H., P.F. Hendrix, and D. C. Coleman. 1994. Water-stable aggregates and organic matter fractions in conventional and no-tillage ultisols. Soil Science Society of America Journal, 58: 777-786.

Benz, U.C., P. Hofmann, G. Willhauck, I. Lingenfelder, and M. Heynen. 2004. Journal of Photogrammetry and Remote Sensing, 58: 239-258.

Blaschke, T., and J. Strobl. 2001. What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. GeoBit/GIS, 6: 12-17.

Breiman, L., and A. Cutler. 2005. Random Forests. Last Accessed 15 August 2007 <http://www.stat.berkeley.edu/users/breiman/RandomForests/cc_home.htm>

Breiman, L. 2001. Random forests. Machine Learning, 45: 5-32.

Breiman, L. 1996. Out-of-bag estimation. Last Accessed 10 August 2007 <ftp.stat.berkeley.edu./pub/users/breiman/OOBestimation.ps>

Breiman, L. 1993. Classification and regression trees. Chapman and Hall-CRC press, Boca Raton, Fl. 368 pp.

Bricklemyer, R.S., P.R. Miller, P.J. Turk, K. Paustian, T. Keck, and G.A. Nielsen. 2007. Sensitivity of the Century model to scale-related soil texture variability. Soil Science Society of America Journal, 71: 784-792.

Bricklemyer, R.S., Lawrence, R.L., Miller, P.R., and Battogtokh, N. 2006. Monitoring and verifying agricultural practices related to soil carbon sequestration. Agriculture, Ecosystem and Environment, 118: 201-210.

Bricklemyer, R.S., Lawrence, R.L., and Miller, P.R. 2002. Documenting no-till and conventional till practices using Landsat ETM+ imagery and logistic regression. Journal of Soil and Water Conservation, 57: 267-274.

Brooks, C.N., D.L. Schaub, R.B. Powell, N.H.F. French, and R.A. Shuchman. 2006. Multi-temporal and multi-platform agricultural land cover classification in southeastern Michigan. ASPRS Annual Conference, 1-5 May 2006, Reno, NV., 12 pp.

Brown, D.J., K.D Shepherd, M.G. Walsh, M.D. Mays, and T.G. Reinsch. 2006. Global soil characterization with VNIR diffuse reflectance spectroscopy. Geoderma, 132: 273-290.

Brown, J. 2005. Depositing carbon in the bank; the soil bank, that is. Interview in USDA News and Events, 28 February 2005. Last Accessed 5 August 2007 <http://www.ars.usda.gov/is/AR/archive/feb01/bank0201.htm>

Burke, I.C., T.G.F. Kittel, W.K. Lauenroth, P. Snook, C.M. Yonker, and W.J. Parton. 1991. Regional analysis of the Central Great Plains: Sensitivity to climate variability. Bioscience, 41: 685-692.

Campbell, C.A., and R.P. Zentner. 1993. Soil organic matter as influenced by crop rotations and fertilization. Soil Science Society of America Journal, 57: 1034-1040.

Carleer, A.P., O. Debeir, and E. Wolff. 2005. Assessment of very high spatial resolution satellite image segmentations. Photogrammetric Engineering and Remote Sensing, 71: 1285-1294.

Chen, F., D.E. Kissel, L.T. West, and W. Adkins. 2000. Field-scale mapping of surface soil organic carbon using remotely sensed imagery. Soil Science Society of America Journal, 64: 746-753.

Chiang, I., and J. Y. Hsu. 2002. Fuzzy classification trees for data analysis. Fuzzy Sets and Systems, 130: 87-99.

Christensen, B.T. 1992. Physical fractionation of soil and organic matter in primary particle size and density separates. Advances in Soil Science, 20: 1-90.

Coleman, K., and D.S. Jenkinson. 1996. RothC-26.2-A model for the turnover of carbon in soil. In: Powlson, D.S., P. Smith, and J.U. Smith (Eds.), Evaluation of soil organic matter models using existing, long-term datasets. NATO ASI Series I, 38: 237-246.

Dao, T.H. 1998. Tillage and crop residue effects on carbon dioxide evolution and carbon storage in a Paleustoll. Soil Science Society of America Journal, 62: 250-256.

Darwish, A., K. Leukert, and W. Reinhardt. 2003. Image segmentation for the purpose of object-based classification. Proceedings of IGARSS 2003, 3: 2039-2041.

Daughtry, C.S.T., Hunt, E.R., and Doraiswamy, P.C. 2002. Assessing carbon dynamics in agriculture using remote sensing. International Symposium on Evaluation of Terrestrial Carbon Storage and Dynamics by In-situ and Remote Sensing Measurements. pp. 28-35.

Davidson, E.A., and I.A. Janssens. 2006. Temperature sensitivity of soil carbon decomposition and feedbacks to climate change. Nature, 440: 165-173.

DeGloria, S.D., Wall, S.L., Benson, A.S., and M.L. Whiting. 1986. Monitoring conservation tillage practices using Landsat multispectral data. Journal of Soil and Water Conservation, 40: 187-189.

DeGloria, S.D., Wall, S.L., and A.S. Benson. 1985. Monitoring conservation tillage practices in San Luis Obispo County, California, using Landsat multispectral scanner film projects. Resource Survey Institute, Benicia, CA. 32 pp.

De Wit, A.J.W., and J.G.P.W. Clevers. 2004. Efficiency and accuracy of per-field classification for operational crop mapping. International Journal of Remote Sensing, 25: 4091-4112.

Dumanski, J., R. L. Desjardins, C. Tarnocai, D. Monreal, E.G. Gregorich, V. Kirkwood, and C. A. Campbell. 1998. Possibilities for future carbon sequestration in Canadian agriculture in relation to land use changes. Climate Change, 40: 81-103.

Deschamps, D. 2006. Executive Director of Montana Farm Service Agency. Personal Communication. CRP monitoring.

Drinkwater, L.E., P. Wagoner, and M. Sarrantonio. 1998. Legume-based cropping systems have reduced carbon and nitrogen losses. Nature, 396: 262-265.

Dymond, C.C., D.M., Mladenoff, and V.C. Radeloff. 2002. Phenological differences in Tasseled Cap indices improve deciduous forest classification. Remote Sensing of Environment, 80: 460-472.

eCognition User Guide for Version 4.0. 2004. Definiens Imaging, Munich, Germany. 479 pp.

Ediriwickrema, J., and S. Khorram. 1997. Hierarchical maximum-likelihood classification for improved accuracies. IEEE Transactions on Geoscience and Remote Sensing, 35: 810-816.

Egbert, S.L., Lee, R.Y., Price, K.P., and R. Boyce. 1998. Mapping conservation reserve program (CRP) grasslands using multi-seasonal Thematic Mapper imagery. Geocarto International, 13: 17-24.

Emission Database for Global Atmospheric Research (EDGAR). 2000. Global emission inventories information system. Version 3.2.

Evans, C., R. Jones, I. Svalbe, and M. Berman. 2002. Segmenting multispectral Landsat TM images into field units. Geoscience and Remote Sensing, 5: 1054-1064.

Fang, C. and J. B. Moncrieff. 1999. A model for soil $C0_2$ production and transport 1: model development. Agricultural and Forest Metrology, 95: 225-236.

Fisette, T., R. Chenier, M. Maloley, P.Y. Gasser, T. Huffman, L. White, R. Ogston, and A. Elgarawany. 2006. Methodology for a Canadian agricultural land cover classification. Lang, S., T. Blaschke, and E. Schopfer (Eds.), Proceedings of the 1st International Conference on Object-based Image Analysis, International Society for Photogrammetry and Remote Sensing. 6 pp.

Fockelmann, R. 2001. Agricultural parcel detection with eCognitioin 2.0. Definiens eCognition Application Notes, 2: 1-2.

Foereid, B., and H. Høgh-Jensen. 2004. Carbon sequestration potential of organic agriculture in northern Europe-a modeling approach. Nutrient Cycling in Agroecosystems, 68: 13-24.

Foody, G.M. 2000. Mapping land cover from remotely sensed data with a softened feedforward neural network classification. Journal of Intelligent and Robotic Systems, 29: 433-449.

Foody, G.M., and D.P. Cox. 1994. Sub-pixel land cover composition estimation using a linear mixture model and fuzzy membership functions. International Journal of Remote Sensing, 15: 619-631.

Frazier, B.E., and Y. Cheng. 1989. Remote sensing of soils in the eastern Palouse region with Landsat Thematic Mapper. Remote Sensing of Environment, 28: 317-325.

Friedman, J.H. 1999. Stochastic gradient boosting. Last Accessed 4 September 2007 <http://www.salford-systems.com/treenet.html>

Gamon, J.A., C.B. Field, M.L. Goulden, K.L. Griffen, A.E. Hartley, G. Joel, J. Penuelas, and R. Valentini. 1995. Relationships between NDVI, canopy structure, and photosynthesis in three Californian vegetation types. Ecological Applications, 5: 28-41.

Geneletti, D., and B. G. H. Gorte. 2003. A method for object-oriented land cover classification combining Landsat TM data and aerial photographs. International Journal of Remote Sensing, 24: 1273-1286.

Gislason, P.O., J.A. Benediktsson, and J.R. Sveinsson. 2006. Random Forests for land cover classification. Pattern Recognition Letters, 27: 294-300.

Gowda, P.H., Peters, R.T., and T.A. Howell. 2005. Mapping tillage practices in the Texas Panhandle with Landsat Thematic Mapper (TM) data. Wetting Front News. USDA-ARS Conservation and Production Research lab, 7: 5-7.

Guo, X., Price, K.P., and J. Stiles. 2003. Grasslands discriminate analysis using Landsat TM single and multitemporal data. Photogrammetric Engineering and Remote Sensing, 69: 1255-1292.

Halvorson, A.D., B. J. Wienhold, and A.L. Black. 2002. Tillage, nitrogen, and cropping system effects on soil carbon sequestration. Soil Science Society of America Journal, 66: 906-912.

Ham, J., Y. Chen, M.M. Crawford, and J. Ghosh. 2005. Investigation of the random forest framework for classification of hyperspectral data. International Journal for Remote Sensing, 243: 492-500.

Hansen, D., C. Curlis, and B. Simpson. 2006. Techniques for discrimination between agricultural and similar land cover types with fuzzy logic and spectral polygon characteristics. ASPRS Annual Conference 1-5 May 2006, Reno, NV. 9 pp.

Hardin, P.J. 1994. Parametric and nearest-neighbor methods for hybrid classification: a comparison of pixel assignment accuracy. Photogrammetric Engineering and Remote Sensing, 60: 1439-1448.

Hay, G., and G. Castilla. 2006. Object-based image analysis: strengths, weaknesses, opportunities and threats. Lang, S., T. Blaschke, and E. Schopfer (Eds.), Proceedings of the 1st International Conference on Object-based Image Analysis, International Society for Photogrammetry and Remote Sensing. 3 pp.

Hay, G.J., T. Blaschke, D.J. Marceau, and A. Bouchard. 2003. A comparison of three image-object methods for the multiscale analysis of landscape structure. Journal of Photogrammetry and Remote Sensing, 57: 327-345.

Hay, G.J., D.J. Marceau, P. Dube, and A. Bouchard. 2001. A multiscale framework for landscape analysis: object-specific analysis and upscaling. Landscape Ecology, 16: 471-490.

Houghton, R.A., J.L. Hackler, and K.T. Lawrence. 1999. The U.S. carbon budget: contributions from land-use change. Science, 285: 274-578.

Huange, Z. 2001. Combining non-parametric based models for multisource predictive forest mapping. Proceedings of the 6th International Conference on GeoComputation, 24-26 September 2001, Brisbane, Australia. 5 pp.

Huete, A.R., R.D. Jackson, and D.F. Post. 1985. Spectral response of a plant canopy with different soil backgrounds. Remote Sensing of Environment, 17: 37-53.

Huete, A.R., D.F. Post, and R.D. Jackson. 1984. Soil spectral effects on 4-space vegetation discrimination. Remote Sensing of Environment, 15: 155-165.

Hurd, J.D., D.L. Civco, and M.S. Gilmore, S. Prisloe, and E.H. Wilson. 2006. Tidal wetland classification from Landsat imagery using an integrated pixel-based and object-based classification approach. ASPRS 2006 Annual Conference 1-5 May 2006, Reno, NV. 11 pp.

Idaho Soil Conservation Commission (ISCC). 2003. Measuring and modeling net carbon sequestration. In: Chapter 5, Carbon Sequestration on Idaho Agriculture and Forest Lands. 194 pp.

Ingram, J.S.I., and E.C.M. Fernandes. 2001. Managining carbon sequestration in soils: conceps and terminology. Agriculture, Ecosystems, and Environment, 87: 111-117.

Jensen, J.R. 2005. Introductory digital image processing. Pearson Publishing, Upper Saddle River, NJ. 526 pp.

Johnson, C.W., and V.B. Coleman. 1973. Semi-automated crop inventory from sequential ERTS-1 imagery. Symposium on Significant Results Obtained from the Earth Resources Technology Satellites, Vol. 1: Technical Presentations. Freden, S.C. (Ed.), National Aeronautics and Space Administration, Washington, D.C. 10 pp.

Johnson, R.D., and E.S. Kasischke. 1998. Change vector analysis: A technique for the multispectral monitoring for land cover and condition. International Journal of Remote Sensing, 19: 411-426.

Kelly, R.H., W.J. Parton, G.J. Crocker, and P.R. Grace. 1997. Simulating trends in soil organic carbon in long-term experiments using the century model. Geoderma, 81: 75-90.

Kern, J.S., and M.G. Johnson. 1993. Conservation tillage impacts on national soil and atmospheric carbon levels. Soil Science Society of America Journal, 57: 200-210.

Kurtz, R. 2006. Personal Communication. Landsat specialist at USGS EROS data center. Problems with Landsat 7 gap-filled data. rkurtz@usgs.gov.

Lambin, E.F. and A.H. Strahler. 1994. Change-vector analysis in multitemporal space: a tool to detect and categorize land-cover change processes using high temporal-resolution satellite data. Remote Sensing of Environment, 48: 231-244.

Landsat Project Science Office (LPSO). 2006. Landsat 7: Science data user's handbook. Greenbelt, Maryland. NASA Goddard Space Flight Center.

Lawrence, R.L., S. D. Wood, and R.L. Sheley. 2006. Mapping invasive plants using hyperspectral imagery and Breiman Cutler classifications (RandomForest). Remote Sensing of Environment, 100: 356-362.

Lawrence, R., A. Bunn, S. Powell, and M. Zambon. 2004. Classification of remotely sensed imagery using stochastic gradient boosting as a refinement of classification tree analysis. Remote Sensing of Environment, 90: 331-336.

Lawrence, R.L., and A. Wright. 2001. Rule-based classification systems using classification and regression tree (CART) analysis. Photogrammetric Engineering and Remote Sensing, 67: 1137-1142.

Lawrence, R. L. and W.J. Ripple. 2000. Fifteen years of revegetation of Mount St. Helens: a landscape-scale analysis. Ecology, 81: 2742-2752.

Lawrence, R.L. and W.J. Ripple. 1998. Comparisons among vegetation indices and bandwise regression in a highly disturbed, heterogeneous landscape. Remote Sensing of Environment, 64: 91-102.

Lerman, R.J., and S. Yitzhaki. 1984. A note on the calculation and interpretation of the Gini index. Economic Letters, 15: 363-368.

Lillesand, T.M., and R.W. Kiefer. 2000. Remote Sensing and Image Interpretation. 4th ed. Wiley and Sons, New York, NY. 763 pp.

Lucier, A., M. Palmer, H. Mooney, K. Nadelhofferik, D. Ojima, and I. Chavez. 2006. Ecosystems and climate change: Research priorities for the US Climate Change Program-recommendations from the Scientific Community. SS-92-06. University of Maryland Center for Environmental Science, Chesapeake Biological Laboratory.

Malila, W. 1980. Machine processing of remotely sensed data and soil information systems and remote sensing and soil survey. Proceedings of the Sixth Annual Symposium, 3-6 June 1980, West Lafayette, IN. pp. 326-336.

Mann, L.K., 1986. Changes in soil carbon storage after cultivation. European Journal of Soil Science, 142: 279-288.

Marland, G., T.O. West, B. Schlamadinger, and L. Canella. 2003. Managing soil organic carbon in agriculture: the next effect on greenhouse gas emissions. Tellus, 55B: 613-621.

McDermid, G.J., A. Pape, M.S. Chubey, and S.E. Franklin. 2006. Object-oriented analysis for change detection. Unpublished paper. Department of Geography, University of Calgary. 4 pp.

Meinel, G., and M. Neubert. 2004. A comparison of segmentation programs for high resolution remote sensing data. Proceedings of the ISPRS 20th Congress Istanbul, Volume 35. 6 pp.

Melillo, J.M., J. Borchers, J. Chaney, H. Fisher, A. Haxeltine, A. Janetos, D.W. Kicklighter, T.G.F. Kittel, A.D. McGuire, R. McKeown, R. Neilson, R. Nemani, D.S. Ojima, T. Painter, Y. Pan, W.J. Parton, L. Pierce, L. Pitelka, C. Prentice, B. Rizzo, N.A. Rosenbloom, S. Running, D.S. Schimel., S. Sitch, T. Smith, and I. Woodward. 1995. Vegetation/ecosystem modeling and analysis project comparing biogeography and biogeochemistry models in a continental-scale study of terrestrial ecosystem response to climate change and CO_2 doubling. Global Biogeochemical Cycles, 9:407-437.

Mertens, K.C., L.P.C. Verberke, E.I. Ducheyne, and R.R. De Wulf. 2003. Using generic algorithms in sub-pixel mapping. Remote Sensing of Environment, 91: 225-236.

Metherell, A.K., L.A. Harding, C.V. Cole, and W.J. Parton. 1993. Century soil organic matter model environment. Agroecosystem Version 4.0, USDA-ARS, Ft. Collins, Colorado.

Motavalli, P.P., C.A. Palm, W.J. Parton, E.T. Elliot, S.D. Frey. 1994. Comparison of laboratory and modeling simulation methods for estimating soil carbon pools in tropical forest soils. Soil Biology and Biochemistry, 26: 935-944.

Murty, D., M.U. F. Kischbaum, R.E. Mcmurtrie, and H. Mcgilvray. 2002. Does conversion of forest to agricultural land change soil carbon and nitrogen? A review of literature. Global Change Biology, 8:105-123.

NASA, 2006. Landsat 7-About Landsat. Last Accessed 2 August 2007 <http://landsat.gsfc.nasa.gov/about/landsat7.html>

Niemeyer, I. and M. J. Canty. 2001. Knowledge-based interpretation of satellite data by object-based and multi-scale image analysis in the context of nuclear verification. Proceedings of the 2001 International Geoscience and remote sensing symposium, Sydney, Australia. pp. 2982-2984

O'Brien, M.A., and J.M. Irvine. 2004. Information fusion for feature extraction and the development of geospatial information. Special Issue of the 7th International Conference on Information Fusion, Stockholm. pp. 976-982.

Ortega, R.A., G.A. Peterson, and D.G. Westfall. 2002. Residue accumulation and changes in soil organic matter as affected by cropping intensity in no-till dryland ecosystems. Agronomy 94: 994-954.

Ozdarici, A., and M. Turker. 2006. Field-based classification of agricultural crops using multi-scale images. ISPRS Mid-Term Symposium 'From Pixels to Processes', Enschede, The Netherlands. 7 pp.

Padgitt, M., D. Newton, R. Penn, and C. Sandretto. 2000. Production practices for major crops in U.S. agriculture, 1990-1997. Statistical Bulletin No. 969. Economic Research Service. US Department of Agriculture. 104 pp.

Pal, M. 2005. Random forests for land cover classification. International Journal for Remote Sensing, 26: 217-222.

Parton, W.J., J.W.B. Steward, and C.V. Cole. 1988. Dynamics of C, N, P and S in grassland soils: a model. Biogeochemistry, 5: 109-131.

Paustian, K., J. Six, E.T. Elliot, and H.W. Hunt. 2000. Management options for reducing $C0_2$ emissions from agricultural soils. Biogeochemistry, 48: 147-163.

Pew Center for Global Climate Change (PCGCC). 2006. European Union-Emission Trading System White Pages. 20 pp.

Post, W.M., R.C. Izaurralde, L.K. Mann, and N. Bliss. 2001. Monitoring and verifying changes of organic carbon in soil. Climate Change, 51: 73-99.

Post, W.M., T.H. Pong, W.R. Emmanuel, A.W. King, V.H. Dale, and D.L. de Angelis. 1990. The global carbon cycle. American Scientist, 78: 310-326.

Price, K.P. Guo, X., Stiles, J.M. 2002. Optimal Landsat TM band combinations and vegetation indices for discrimination of six grassland types in eastern Kansas. International Journal of Remote Sensing, 23: 5031-5042.

Price, K.P., Egbert, S.L., Nellis, M.D., Lee, R.Y., and Boyce, R. 1997. Mapping land cover in a High Plains agro-ecosystem using a multi-date Landsat Thematic Mapper modeling approach. Transactions of the Kansas Academy of Science, 100: 21-33.

Radoux, J., and P. Defourny. 2006. Influence of image segmentation parameters on positional and spectral quality of the derived objects. Lang, S., T. Blaschke, and E. Schopfer (Eds.), Proceedings of the 1st International Conference on Object-based Image Analysis, International Society for Photogrammetry and Remote Sensing. 5 pp.

Reeder, J.D., Schuman, G.E., and Bowman, R.A. 1998. Soil C and N changes on conservation reserve program lands in the Central Great Plains. Soil and Tillage Research, 47: 339-349.

Richards, J.A., and X. Jia. 1999. Remote sensing digital image analysis: an introduction. Springer, New York, NY. 363 pp.

Rickman, R.W., C.L. Douglas, Jr., S.L. Albrecht, L.G. Bundy, and J.L. Berc. 2001. CQUESTR: a model to estimate carbon sequestration in agricultural soils. Journal of Soil and Water Conservation, 56: 237-244.

Ripple, W.J. 1994. Determining coniferous forest cover and forest fragmentation with NOAA-9 advanced very high resolution radiometer data. Photogrammetric Engineering and Remote Sensing, 60: 533-540.

Robertson, G., E.A. Paul, and R.R. Harwood. 2000. Greenhouse gases in intensive agriculture: contributions of individual gases to the radiative forcing of the atmosphere. Science, 289: 1922-1925.

Rochette, P., R.L. Desjardins, and E. Pattey. 1990. Spatial and temporal variability of soil respiration in agricultural fields. Canadian Journal of Soil Science, 71: 189-196.

Sainju, U.M., A. Lenssen, T. Caesar-Tonthat, and J. Waddell. 2006. Tillage and crop rotation effects on dryland soil and residue carbon and nitrogen. Soil Science Society of America Journal, 70: 668-678.

Salford Systems. 2001. TreeNet Data mining tool software. Salford Systems, San Diego, CA.

Scharf, P.C., J.P. Schmidt, N.R. Kitchen, K.A. Sudduth, S.Y. Hong, J.A. Lory, and J.G. Davis. 2002. Remote sensing for nitrogen management. Journal of Soil and Water Conservation, 57: 518-524.

Schimel, D., J. Melillo, H. Tian, A.D. McGuire, D. Kicklight, T. Kittel, N. Rosenbloom, S. Running, P. Thorton, D. Ojima, W. Parton, R. Kelly, M. Sykes, R. Neilson, and B. Rizzo. 2000. Contribution of increasing CO2, and climate to carbon storage by ecosystems in the United States. Science, 287: 2004-2006.

Schlesinger, W.H. 1995. An overview of the carbon cycle. Lal., R., J.M. Kimble, E. Levine, and B.A. Stewart (Eds.), Soils and global change. Lewis Publishers, Boca Raton, FL. pp. 9-36.

Sherrod, L.A., G.A. Peterson, D.G. Westfall, and L.R. Ahuja. 2005. Soil organic carbon pools after 12 years in no-till dryland agroecosystems. Soil Science Society of America Journal, 69: 1600-1608.

Sherrod, L.A., G.A. Peterson, D.G. Westfall, and L.R. Ahuja. 2003. Cropping intensity enhances soil organic carbon and nitrogen in a no-till agroecosystem. Soil Science Society of America Journal, 67: 1533-1543.

Smith, P., J.U. Smith, D.S. Powlson, W.B. McGill, J.R.M. Arah, O.G. Chertov, K. Coleman, U. Franko, S. Folking, D.S. Jenkinson, L.S. Jensen, R.H. Kelly, H. Klein-Gunnewiek, A.S. Komarov, C. Li, J.A.E. Molina, T. Mueller, W.J. Parton, J.H.M. Thornley, A.P. Whitmore. 1997. A comparison of the performance of nine soil organic matter models using datasets from seven long-term experiments. Geoderma, 81: 153-225.

Song, M., D.L., Civco, and J.D. Hurd. 2005. A competitive pixel-object approach for land cover classification. International Journal of Remote Sensing, 26: 4981-4997.

Song, X., Fan, G., and Rao, M.N. 2003. Machine learning approaches to multisource geospatial data classification: application to CRP mapping in Texas County, Oklahoma. 2003 IEEE Workshop on Advances in Techniques for Analysis of Remotely Sensed Data, 27-28 October 2003, Greenbelt, MA. pp. 202-211.

South, S., Qi, J., Lusch, D.P. 2004. Optimal classification methods for mapping agricultural tillage practices. Remote sensing of Environment, 91: 90-97.

Sprott, D.A. 2000. Statistical Inference in Science. Springer, New York, NY. 245 pp.

Stevenson, F.J., and M.A. Cole. 1999. Cycles of Soil. John Wiley and Sons, Hoboken, NJ. 448 pp.

Stoner, E.R., M.R. Baumgardner, R.A. Weismiller, L.L. Biehl, and B.F. Robinson. 1980. Extension of laboratory-measured soil spectra to field conditions. Soil Science Society of America Journal, 44: 572-574.

Stuckens, J., P.R. Coppin, and M.E. Bauer. 2000. Integrating contextual information with per-pixel classification for improved land cover classification. Remote Sensing of Environment, 71: 282-296.

Sugumaran, R, J. Harken, and J. Gerjevic. 2004. Using remote sensing data to study wetland dynamics in Iowa. Iowa Space Grant Final Technical Report. University of Northern Iowa, Cedar Falls. 16 pp.

Swift, R.S. 2001. Sequestration of carbon by soil. Soil Science, 166: 858-871.

Swift, M.J., O.W. Heal, and J.M. Anderson. 1979. Decomposition in terrestrial ecosystems. Blackwell Scientific Publications, Oxford. 372 pp.

Tatem, A.J., H.G. Lewis, P.M. Atkinson, and M.S. Nixon. 2001. Multiple-class land-cover mapping at the sub-pixel scale using a Hopfield neural network. International Journal of Geographical Information Science, 3: 184-190.

Torre, M., and P. Radeva. 2000. Agricultural-field extraction on aerial images by region-competition algorithm. Proceedings, 15th International Conference on Pattern Recognition, 1: 313-316.

Tzotsos, A., C. Iosifidis, and D. Argialas. 2006. Integrating texture features into a region-based multi-scale image segmentation algorithm. Lang, S., T. Blaschke, and E. Schopfer (Eds.), Proceedings of the 1st International Conference on Object-based Image Analysis, International Society for Photogrammetry and Remote Sensing. 6 pp.

United States Geological Survey (USGS). 2006a. Landsat 5 team overcomes problem with solar array. Project News. Last Accessed 15 August 2007 <http://landsat.usgs.gov/project_facts.gov>

United States Geological Survey (USGS). 2006b. SLC-off products: background. Landsat Products. Last Accessed 20 August 2007 <http://landsat.usgs.gov/data-products.gov>

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

Verhoeye, J., and R. De Wulf. 2001. Land cover mapping at sub-pixel scales using linear optimization techniques. Remote Sensing of Environment, 79: 96-104.

Wander, M. 2004. Soil organic matter fractions and their relevance to soil function. Magdoff, M., and W. Weil (Eds.), Soil Organic Matter in Sustainable Agriculture. CRC Press, Boca Raton, Fl. 416 pp.

West, T.O., and W.M. Post. 2002. Soil organic carbon sequestration rates by tillage and crop rotation: a global data analysis. Soil Science Society of America Journal, 66: 1930-1946.

White, M.A., P.E. Thornton, S.W. Running, and R.R. Nemani. 2000. Parameterization and sensitivity analysis of the BIOME-BGC terrestrial ecosystem model: net primary production controls. Earth Interactions, 4: 1-5.

Wilcox, C.H., Frazier, B.E., and Ball, S.T. 1994. Relationship between soil organic carbon and Landsat TM data in Eastern Washington. Photogrammetric Engineering and Remote Sensing, 60: 777-781.

Witten, I.H., and E., Frank. 1999. Data Mining-Practical Machine Learning Tools With Java Implementations. Morgan Kaufmann, San Francisco, CA. 525 pp.

Yan, G., J.F. Mas, B.H.P. Maathuis, Z. Xiangmin, and P.M. Van Dijk. 2006. Comparison of pixel-based and object-oriented image classification approaches- a case study in a coal fire area, Wuda, Inner Mongolia, China. International Journal of Remote Sensing, 27: 4039-1055.

Zhang, Y.J. 1997. Evaluation and comparison of different segmentation algorithms. Pattern Recognition Letters, 18: 963-974.

CHAPTER 3

SATELLITE MONITORING OF CROPLAND CARBON SEQUESTRATION PRACTICES IN NORTH CENTRAL MONTANA

Introduction

Increased soil carbon sequestration is attributed to the utilization of cropland management practices such as no-till (NT), conservation reserve (CR), and cropping intensity. No-till management is where the soil surface remains undisturbed through the use of specialized planting techniques and chemical fallowing instead of mechanical soil cultivation (tillage). Conservation Reserve is the practice of converting marginal cropland into diverse perennial plant cover, and is not confined to lands under the Conservation Reserve Program (CRP). Increased cropping intensity results from reduced summer fallowing, a period during which land is left in an un-vegetated state for water storage purposes. Farmers within north central Montana are being encouraged to implement these practices as part of a cropland carbon trading program first initiated through the Big Sky Carbon Sequestration Partnership (Capalbo, 2006) in collaboration with the National Carbon Offset Coalition (NCOC). Sequestered carbon can then be purchased through entities such as the Chicago Climate Exchange (CCX) to mitigate greenhouse gas emissions.

The development of methodology for the validation and monitoring of these practices through remote sensing is needed for carbon contract purposes. Current methods are limited to drive-by field validation, a costly and time consuming process

(Dodge, 2007). Remote monitoring of cropland practices also would facilitate an increased documentation of regional agricultural management trends, as US cropping statistics are often limited by inconsistent data sources and infrequent collection periods (Daughtry et al., 2006; Sullivan et al., 2006; South et al., 2004).

Pixel-based classifications have been attempted for NT, grassland-based CR, and field vegetative status (cropped vs. fallow). These results, however, are often confusing due to within-field mixed classifications, resulting in single fields being erroneously mapped as having multiple management practices. Thematic pixels within a raster-based image often provide no indication of spatially-confined management patterns, making the interpretation of land use patterns difficult in the absence of reference field boundaries.

A more meaningful understanding of landscape patterns might be found through an object-oriented (O-O) approach, examining pixel relationships within cropland parcels. Field-based image objects, resulting from image delineation, would provide a more realistic portrayal of agricultural practices, since management practices are generally uniform within fields. These objects, from an image processing standpoint, serve as integrated entities that exhibit an intrinsic scale and are composed of structurally connected parts or pixels (Hay et al., 2003).

The commercial O-O software Definiens Professional incorporates a multi-resolution, bottom-up region growing approach in which segmentation starts by merging individual pixels or ‘seeds’ (Navulur, 2007). Merging of the resulting groups continues until a user-defined threshold, based on size (scale) and weighted heterogeneity measures, is reached. Object-based features such as object mean and standard deviation (the mean or standard deviation of all pixels within an object), object texture (measures the variation of pixel values within an object) and neighborhood relationship measures can be incorporated into the classification process in addition to spectral information. Neighborhood relationship data might include mean value differences between an object, or measures concerning the proportion of an object boarder shared with neighboring objects having a certain characteristic. Object-oriented analysis is most often applied to high-resolution imagery, as it provides a way to remove unwanted noise due to pixel heterogeneity (Niemeyer and Canty, 2001; Chubey et al., 2006; Yu et al., 2006). Few O-O studies (e.g., Schneevoigt et al., 2008; Yan et al., 2006; Brooks et al., 2006; Block et al., 2005) have attempted to analyze moderate resolution imagery.

Peer-reviewed research concerning the O-O analysis of cropland management practices is lacking and has not included tillage and grassland-based CR classifications. A few pixel-based studies have mapped NT and tillage on surfaces with bare to minimal cover with resulting class accuracies 90% or greater (South et al., 2004; Bricklemyer et al., 2002). Studies attempting to identify tillage management in the presence of vegetative cover have had limited success. One study achieved 83% total tillage accuracy, but only attempted analysis during early stages of crop growth (Gowda et al., 2005). Another study achieved producer's and user's accuracies of 99% and 95% for NT and 29% and 80% for tillage (Bricklemyer et al., 2006). The results from this study are inadequate for carbon contract validation due to a low NT producer's accuracy, indicating that many tilled fields were wrongly classified as NT. This would be unacceptable for carbon contract validation as violations of NT management agreements might not be detected.

The identification of grassland-based CR through satellite image mapping techniques has been problematic as it is often spectrally similar to other management practices. Perennial plant cover might be classified as a small-grain crop, or vice versa, while patches of bare-soil might be classified as NT. Among-site diversity in vegetation and management also make it difficult to define classification rules that adequately represent data sets with high spectral variability (Daly, 2001). Increased CR accuracies have been reported through the inclusion of multi-temporal techniques (Price et al., 1997; Egbert et al., 1998; Egbert et al., 2002). The multi-temporal mapping of CR sites is advantageous in agricultural regions practicing crop-fallow management as parcels under continuous annual vegetation are more likely to be grassland than crop. The incorporation of ancillary data such as elevation and slope has also been reported to increase CR accuracy (Song et al., 2003).

Mapping cropping intensity requires crop and fallow to be classified annually in a crop rotation. Cropping intensity increases with the number of growing seasons that a field is kept under live plant cover as opposed to dead residual plant cover or bare soil. A comparison of between-year classification differences would allow for the establishment of crop intensity patterns. Compound error might be avoided by classifying annual crop and fallow practices through a change-vector approach, as the reliability of between-map comparisons will reflect, at best, the product of the two map accuracies (Congalton and Green, 1999). Change vector analysis (CVA) is often used to detect radiometric change between multispectral data sets (Johnson and Kasischke, 1998), with differences in spectral features between two image dates indicating the magnitude and direction of movement within and between classes over time (Coppin et al., 2004). Class change is assigned to pixels whose vector components exceed a user defined threshold. Reference class information (based on initial classification maps) from “unchanged” pixels can then be used as training data for the classification of potentially “changed” pixels (Nackaerts et al., 2005).

Per-pixel CVA is often sensitive to subtle within-class changes due to seasonality, vegetative growth, and condition (Lambin and Strahler, 1994). Per-field change detection might be more appropriate within cropland studies process, where annual changes occur on a field basis. Object-based change detections have included a neighborhood correlation method in which change between two images was indicated by movement in slope and intercept values (Im et al., 2007) and a classification based on a between-date covariance matrix (Bontemps and Defourny, 2007).

The majority of object-based studies have not utilized advanced classification techniques. Simple classifiers such as the nearest neighbor (NN) (Stow et al., 2007; Lucas et al., 2007; Kamagata et al. 2006) are often used, although continued advancements in image classification algorithms have made the use of these methods increasingly obsolete within pixel-based analyses (Gislason et al., 2006). A NN-based classification is often chosen due to its incorporation within the Definiens O-O software. The NN algorithm presumably provides greater computational efficiency and handling of feature space overlap when dealing with hierarchical classification (Yu et al., 2006;

Definiens, 2006). This algorithm might also be advantageous as it does not assume a statistical distribution.

A disadvantage to the NN approach is its insensitivity to class variance within feature space. False class assignments might be made if the distance between an object value and the true class mean exceeds the distance between an object value and a false class mean due to greater variability within that class (Richards and Jia, 2006; Lillesand et al., 2004). Definiens somewhat alleviates this problem by creating fuzzy NN classifications through the assignment of membership functions, which allow an analyst to evaluate the best two class options and edit the final classification as needed. The closer an object is to a reference or training object, the higher the membership function will be in a range of 0 (no classification) to 1 (full assignment to one class). This option is most useful in situations where a minimal number of features can be used to separate one class from another. Rule-based classifications can also be performed within Definiens Professional, allowing the incorporation of expert knowledge or rule sets derived from the Definiens Feature Space Optimization Tool or external decision tree classification algorithms (Navulur, 2007).

Advanced image classification algorithms that have been used within pixel-based analyses include, but are not limited to, boosting and/or bagging-based classification tree analysis (CTA) (Lawrence et al., 2004; Lawrence and Wright, 2001; Baker et al., 2001) and the CTA-based Random Forest (Lawrence et al., 2006; Ham et al., 2005; Prasad et al., 2006). Applying these classification algorithms to O-O analysis is beneficial as they have the processing capability to handle the extensive data sets often derived through O-

O segmentation (Chubey et al., 2006). The utilization of basic CTA-based models within O-O studies is also suggested as generated classification rule sets are readily incorporated into the Definiens platform to produce an object-based class map (Yongxue et al., 2006), although this is not true for boosted and bagged approaches. Advanced CTA algorithms, utilizing boosting and bagging, produce black-box results where the analyst is unable to see the resulting classification rule sets. Classification trees are advantageous over more simple algorithms as they do not rely on assumptions regarding data distributions and can incorporate a wide diversity of data types into the model building process (Lawrence and Wright, 2001). Studies have not been identified that provide a quantitative comparison of differences in O-O classification accuracies resulting from the use of CTA-based algorithms and more traditional classification methods.

The Breiman Clutler classification algorithm, alternatively referred to as the Random Forest (RF) classifier, is superior to many tree-based algorithms as it is not sensitive to noise or overtraining. It has been suggested that RF is “unexcelled in accuracy among current algorithms” (Breiman and Cutler, 2005). Random Forest uses a bagging-based approach to form an ensemble of CTA-like classifiers by randomly selecting 2/3 of the data during tree creation and using a random subset of variables for each splitting node within the trees (Breiman, 2001; Gislason et al., 2006). This process is repeated, generating a group of trees. Each tree in the resulting forest casts a unit class vote; a plurality decision is used to determine the final classification (Breiman, 2001).

Another advantage to using RF is its internal accuracy measure, which potentially makes it unnecessary to partition reference data into separate sets for training and validation. All available reference data can instead used to develop the classification model. Test set accuracy is estimated in RF by running out-of-bag (OOB) samples (training set data that are not in the bootstrap for a particular tree) down through a tree as a form of cross-validation (Breiman, 2001). Out-of-bag error estimates approach test set errors with larger data sets. A study comparing OOB accuracy assessments with the traditional error matrix approach reported that the OOB estimates were within 3% of the independent accuracy assessments, with most less than 1% apart (Lawrence et al., 2006). The authors cautioned, however, that OOB estimation is only reliable given an absence of bias in the reference data.

The remote sensing community has increasingly used RF for pixel-based land cover classifications. A study evaluating forest vegetation found that the RF algorithm resulted in a greater overall accuracy than a CTA-based approach (Gislason et al., 2006). Another study reported that RF classified crop types with greater accuracy than boosting and bagging-based classification trees (Pal, 2003). Studies using RF for O-O classification have not been identified.

The objective of this study was to determine if NT and grassland-based CR management, as specified within carbon-contract agreements between the NCOC and Montana farmers, could be accurately identified through an O-O RF classification of moderate resolution Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) imagery. Cropping intensity was also evaluated, in addition to the primary objective, as CCX guidelines specify that carbon credits will not be allocated in years incorporating summer fallow (CCX, 2008). Crop intensity mapping was analyzed through O-O change threshold mapping.

Methods

Study Area Description

This study attempted to remotely classify cropland management practices within north central Montana. This region is roughly bounded by the communities of Great Falls, Fort Benton, Havre, Cut Bank, and Conrad (Figure 3.1). Counties within the geographical extent of this study include Toole, Liberty, Hill, Blaine, Pondera, Chouteau, Fergus, Judith Basin, Wheatland, Meagher, Broadwater, Lewis and Clark, Teton, and Cascade.

The Golden Triangle region falls within a semi-arid grassland/shrub (steppe) biotic regime (NRCS, 2007a). Soil type can vary considerably throughout the region (NRCS, 2007b); clay-dominant textures are reportedly common in many cropland fields throughout the region, with more sandy soils expected within elevated field locations and areas prone to water erosion.

Precipitation patterns are extremely important to dryland farmers within the region. Timely spring rain allows farmers to produce wheat, barley, and other cool-season crops in an otherwise semiarid climate. Temperature and especially precipitation vary strongly within the region. Annual average minimum temperatures have ranged from -0.7 °C Havre to -0.9 °C in Great Falls, with annual average maximum temperatures ranging from 12.7 °C in Havre to 15.5 ºC in Fort Benton (NWS, 2007). Annual average precipitation ranges from 265 mm in Chester, 318 mm Cut Bank, and 373 mm in Great

Falls (WRCC, 2006). Spring and summer temperatures within north central Montana were reported to be about 1.9°C above average from 2006-2007 and about 0.55°C below average from 2004-2005 (NWS, 2007).

Dryland wheat and barley are the primary crop exports within north central Montana, with market price and fall soil moisture conditions driving the decision to plant spring or winter wheat. Oat, pea, lentil, flax, camelina, safflower, and canola occasionally might be planted to target alterative markets but have contributed to a minute proportion of total cropped hectares (CTIC, 2004). A wheat-fallow rotation is common throughout the region; continuous cropping is rarely implemented and is considered by many producers to be too risky due to unreliable late spring and early summer precipitation (Farkell, 2007).

Four data subsets were identified within the general study area for the analysis of crop and fallow patterns. These subsets were located near Dutton (18,500 ha), Chester (11,250 ha), between Big Sandy and Fort Benton (7,646 ha), and near Great Falls (13,014 ha) (Figure 3.2). Chester was chosen as it represented a drier than average climate within the 2004-2007 period (~250 mm annual precip.), while Great Falls represented a wetter than average climate (~390 mm annual precip.) (HPRCC, 2008). Annual precipitation in the Dutton and Big Sandy/Fort Benton areas was near average (~290 - 320 mm).

Reference Data Collection

Locations for training data were randomly identified throughout the region. The final data collection points were chosen based on their proximity to public roadways to avoid land access issues. Data collection occurred early June 2007, by which time a field phase is known certainly for that year, with the exception of chemically managed fallow that may be tilled subsequently during the hot summer period. Collected reference field information included vegetative status (cropped or fallow), crop type, and tillage management (tilled or NT). The classification of tillage management as either “tilled” or “NT” was based on specifications within NCOC field contract specifications. The determination of tillage management within a field included an examination of stubble position (stubble in a NT field should generally be in a relatively upright position), soil surface disturbance, and the establishment of soil surface crusts. It is noted that many of the fields classified as tillage had high levels of surface residue but also showed indication that there had been surface disturbance between the stubble rows.

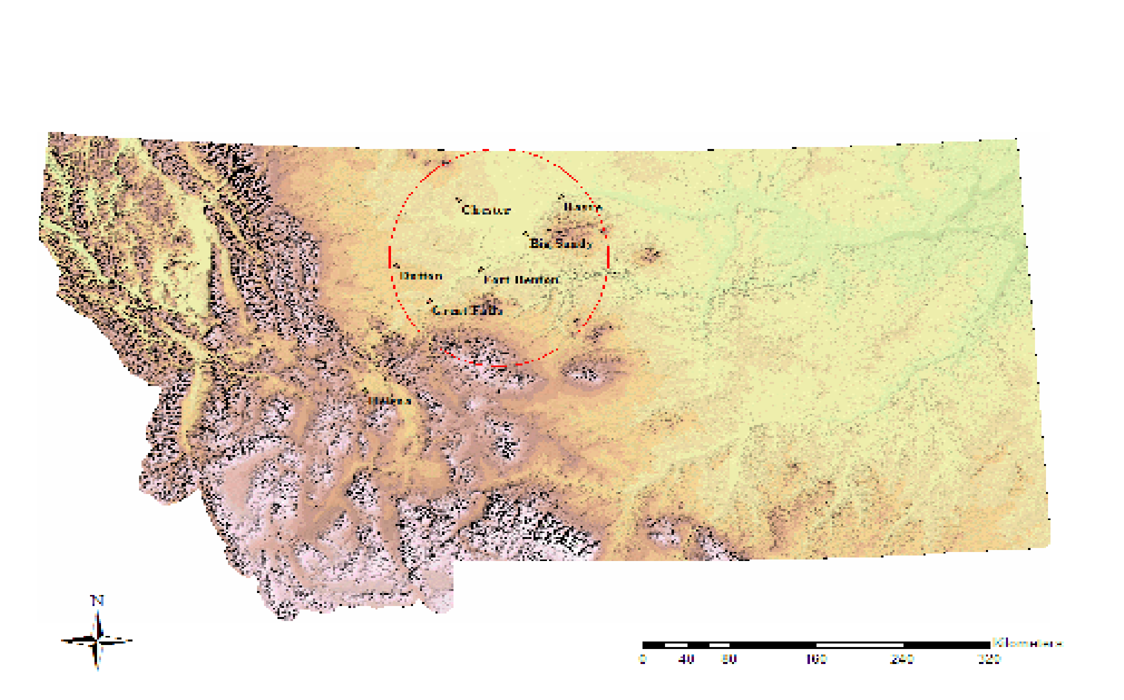

Figure 3.1. Geographic location (within the red circle) of the remote sensing cropland validation study, Montana, USA. Map colors reflect elevation gradients, ranging from gentle lowland prairies in the east, to the more mountainous regions of the west.

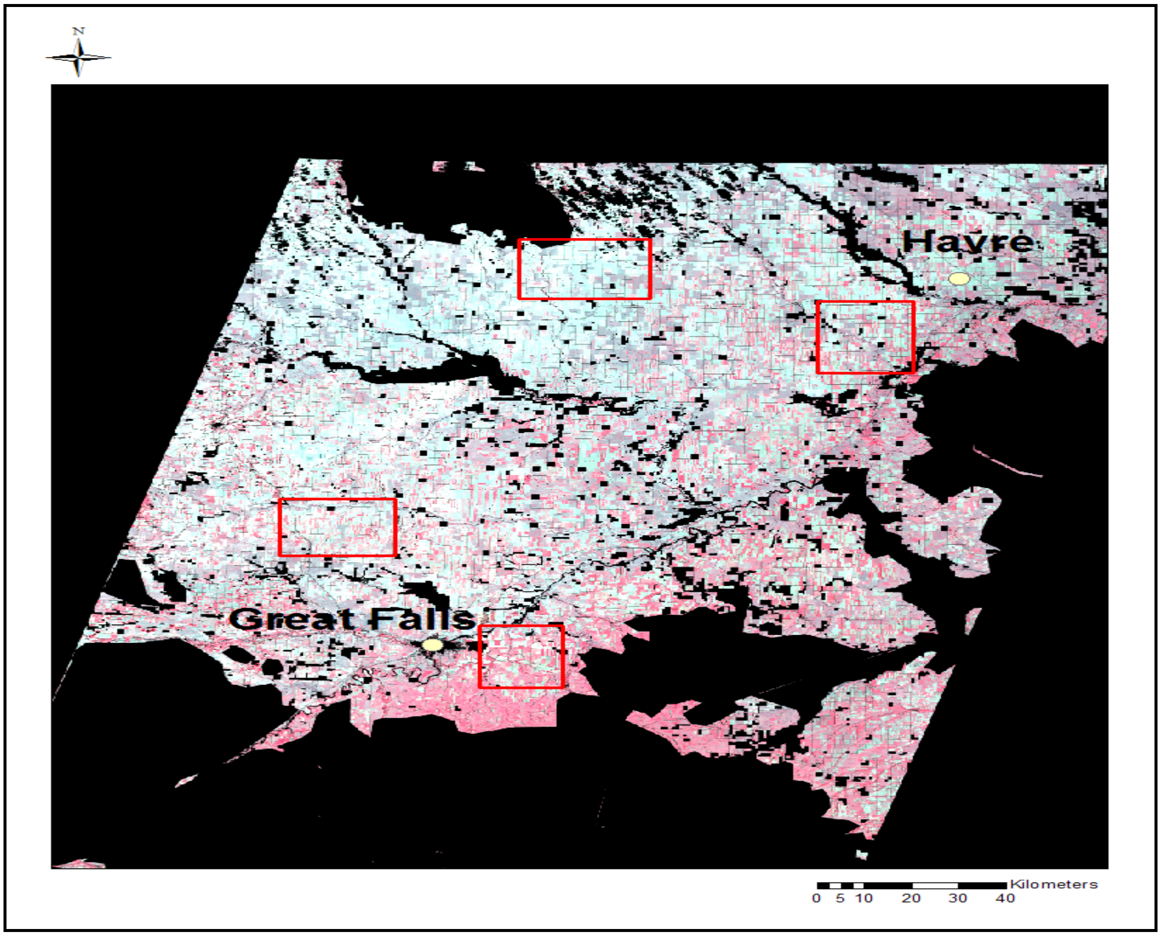

Figure 3.2. Data subset locations (outlined in red) used for identifying crop and fallow practices from 2004-2007 as seen within two Landsat images (May 2007) where non-cropland data has been removed ("black" locations represent no data). The imagery is displayed in standard false color where areas with higher amounts of photosynthetically active vegetation are represented by a more "reddish" color.

Verbal communication with farmers throughout the region confirmed that conservation tillage, where only a chisel plough is used once prior to planting, for residue management. Although some of these practices can result in minimal levels of soil disturbance can be relatively minimal, it would still be considered "tillage" under NCOC carbon contract agreement definitions (NCOC, 2008).

Rangeland data included vegetation type and the relative percent of soil surface covered by the vegetative canopy. Conservation Reserve Program (CRP) data were provided by the Montana Farm Service Agency (MFSA) to represent grassland management similar to that of the CRP under the assumption that spectral signatures between CRP and CR-based lands did not differ. The CRP sites used within the classification model-building process were randomly selected from the data pool. The resulting 2007 cropland data set included information for 78 NT-fallow, 138 NT-cropped, 48 tilled-fallow, 148 tilled-cropped, and 113 CR field sites. The actual number of field sites utilized within the model-building process was scene-dependent due to cloud masking and missing pixel information resulting from the Landsat ETM+ scan-line gaps.

Satellite Data Collection

Satellite data consisted of Landsat TM and ETM+ image sets spanning path/row 39-26 and 39-27 (Table 3.1). Images were selected according to image quality and the degree of atmospheric interference (primarily due to clouds). Landsat data were chosen over other satellite image sources due to its cost effectiveness, relatively large footprint, and temporal coverage. The authors recognize that some error might have been introduced into the model-building process as the 2007 image dates did not match that of the June field data collection period, thus there might have been some change in field management status between the time of image data collection and on-site field reference. The extent of this error is unknown.

Year	2004	2005	2006	2007
Date 1	9 Jul	12 Jul	31 Jul	15 May
Date 2	27 Sep	6 Sep*	1 Sep	11 Aug*
* Denotes that image is Landsat scan-line-corrector-off ETM+ instead of TM.				

Table 3.1. Landsat satellite image dates.

Satellite Image Pre-Processing

Image scenes 39-26 and 39-27 were mosaicked to form one continuous image for each analyzed date. The NN resampling method was used in this and all subsequent processes. Seams within the resulting image mosaics were visually analyzed on a band-by-band basis to validate that the smooth integration of image edges had occurred. Geometric polynomial models based on generated tie points were use to rectify the study imagery to a reference TM image used in the creation of the non-agricultural mask template. Root Mean Squared Error (RMSE) was less than one-half pixel in all cases (Table 3.2). The RMSE is used as a measure of resulting geometric accuracy and accounts for both random and systematic error in the geometrically corrected image (Kutner et al., 2004).

The mosaicked images were examined for spectral irregularities, haze, and clouding. Visual enhancement of clouds and haze was facilitated by displaying TM and ETM+ image bands four (near infrared) as red, two (green) as green, and six (thermal) as blue. Pixels contaminated with cloud, haze, and shadow were identified through a maximum likelihood supervised classification and excluded from image analyses.

Image	# Tie Points	RMSE (pixels)
11 Aug, 07	273	0.27 $\pm$ 0.09
15 May, 07	140	0.17 $\pm$ 0.09
06 Sep, 06	70	0.14 $\pm$ 0.06
31 July, 06	217	0.20 $\pm$ 0.01
06 Sep, 05	170	0.36 $\pm$ 0.05
12 July, 05	194	0.20 $\pm$ 0.05
27 Sep, 04	103	0.13 $\pm$ 0.04
9 July, 04	217	0.20 $\pm$ 0.05

Table 3.2. Geometric Sample Point Accuracy

Image data were then converted to exo-atmospheric reflectance to minimize between-image differences due to earth-sun distance and solar angle (Chander et al., 2007; SDH-L7, 2006). Further data correction techniques were used to normalize the 2004-2006 imagery to the 2007 imagery to minimize between-image data differences unrelated to land use change. These techniques included regression-based normalizations (Jensen, 2005) where data values for pseudo-invariant pixel features (~32), such as concrete strips, roadways, and deep water bodies, were identified within a 2007 and prior image date.

A standard linear regression was applied to the pseudo-invariant feature data to obtain the regression equation used to normalize a prior image data set to the 2007 data. A two-sample t-test for means, based on an alpha value of 0.05, was used to compare prior and "corrected" data to determine if improvement through normalization had occurred. The t-test consisted of 22 data points representative of pseudo-invariant features within the same general locations as those used to generate the regression model.

Dark object subtraction techniques (Song et al., 2001) were also used to reduce the discrepancy between image data prior to the regression-based normalization, if it was observed that these techniques improved overall normalization results. In most cases the means for the normalized and the 2007 base data differed significantly ($\alpha = 0.05$) but showed improvement as the resulting *p*-value, or the probability of obtaining a test statistic value at least as extreme as the one observed, decreased following the normalization.

Normalized Difference Vegetation Indices (NDVI), representative of relative photosynthetically active vegetation densities (Tucker and Sellers, 1986), and the Tasseled Cap components associated with soil brightness, vegetation greenness, and surface wetness (Crist et al., 1986; Huang et al., 2002) were also derived from each image date to be included as model predictors. Our rationale was that the addition of these indices might better allow for node splitting within the model.

An image mask was created to exclude non-agricultural land from the project area. Spatial data pertaining to non-agricultural areas were collected from the Natural Resource Information Service (NRIS, 2007) in shapefile format and included water bodies, wetlands, transportation systems, public lands, and cities (Appendix 1, Table 1). A 15-m radius buffer was applied to point and line features to ensure that the spatial extent was at least 30 m, the common Landsat pixel width. The vector-based features were converted into a raster-based template that was used to recode non-agricultural image data to zero. Spatial data provided by the MFSA also were used to exclude rangeland from the study area, while the MFSA-based CRP data were also used to remove known CR land from the cropland tillage and crop/fallow classifications.

Image segmentation was conducted within Definiens Professional Earth LDH (Large Data Handling) O-O software, using the multi-resolution segmentation algorithm (Benz et al., 2004). Definiens Professional was chosen as it provides segmentation, object analysis, and vector export within one package. Two segmentation strategies were used, representing parcel management strips and within-strip sections of spectral and textural similarity (Figure 3.3). The within-strip segmentation was used to reduce the inclusion of both crop and bare soil within an image-object. A strip-based segmentation was determined to be suitable for tillage and CR classifications, as it was unlikely that these management types would vary within field-based boundaries. Vector information representing taxable field parcels, provided by the Montana Department of Administration, was also included within the segmentation process to ensure that generated objects were constrained within ownership boundaries.

Figure 3.3. Object segmentation results (red vector lines) for parcel management strips (left) and within-strip sections (right). Black parameter lines represent taxable field boundaries.

Initial segmentations were applied to a May 2007 Landsat TM image. The image segmentation parameters were determined heuristically. The resulting image objects were exported from Definiens in Arc shapefile format and utilized as a vector-based template for the remaining image segmentations. The use of object templates served to produce objects with identical footprints. A spatial join was used to add the object-based data to the reference management data set for use in both model training and validation of accuracy.

Image Classification

2007 Image Classifications The randomForest package (S-Plus®) was used to generate classification models for NT and till, CR and cropland, cropped and fallow. Object-based spectral, textural, and neighborhood parameters were included within the model building process (Appendix 1, Table 2). Initial forest models were built using 500 generated classification trees, the default number. Model tree adjustments were based on an analysis of model error as influenced by the number of RF trees. Classification matrices and associated class accuracies were determined through the internal OOB accuracy assessment (Breiman, 2001).

Data sets examined in the generation of class models included those from individual image dates (early summer; late summer) or predictive parameters incorporating both image dates. A May TM pixel-based tillage model was also examined, in addition to the object-based models, to ascertain any improvements in tillage accuracy that might be attributed to the inclusion of object-based textural and neighborhood parameters into the model. Various cluster analyses including K-means, divisive hierarchical clustering, and a fuzzy partitioning method were also used to determine the degree of spectral similarity within the tillage field validation data. This

information provided a further source of understanding pertaining to classification error within the NT and tillage model. Data sets were then run through the generated RF models to provide object classifications for the 2007 season. Class predictions were exported and joined with the existing vector objects within a GIS platform according to field object identification numbers. This allowed for an efficient way to examine spatial relationships between cropland management class predictions, spectral image data, and various other data sets.

2004-2006 Image Classifications. Fall images from 2004-2006 also were classified for crop and fallow practices in order to determine 4-yr vegetation patterns spanning from 2004-2007. The multi-date crop and fallow classifications were applied only to objects within the four study area subsets to reduce the computation time associated with image-object generation (Figure 3.2). The resulting crop vegetation pattern data allowed for the determination of crop intensity within an agricultural field.

Change Vector Analysis and an NDVI threshold method were examined for the detection of "unchanged" image objects, or those having the same class type (fallow or cropped) between the 2007 and a prior image date. Between-year vegetative change within the study area is most common due to crop-fallow rotations; areas of no change, or fields under continuous cropping, are relatively infrequent. "Unchanged" areas, or those cropped in both the 2007 and prior image dates, were determined using object-based data from the May 2007 and July 2004-2006 images as these dates provided the best distinction between photosynthetically active (cropped) and photosynthetically inactive (fallow) field areas. The CVA consisted of object-based spectral means for the red and near-infrared (NIR) bands. These bands were chosen to detect management changes as they are sensitive to photosynthetic activity. Photosynthetically active vegetation strongly absorbs energy between 0.63 and 0.69 μm (red) and strongly reflects energy between 0.7 and 1.2 μm (NIR) (Jensen, 2005).

Change vectors (CV) were generated according to a distance measure based on the Pythagorean Theorem (Eq. 3.1), where Red_1 and Red_2 represent multi-year object-mean values for the red portion of the measured electromagnetic spectrum and NIR_1 and NIR_2 represents multi-year values for the near-infrared portion of the spectrum.

Eq. 3.1 $$CV = ((Red_1 - Red_2)^2 + (NIR_1 - NIR_2)^2)^{0.5}$$

Objects representing possible management changes between image dates were visually identified through a comparison of image data and were used as reference points in the determination of appropriate thresholds to separate “changed” from “unchanged”. No clear threshold values were identified through the analysis of CV values from these reference object areas. A more apparent change threshold value was determined within the between-date NDVI difference values, as was also reported by Lyon et al. (1998).

The change threshold values were then applied within a GIS platform to highlight all “no-change” objects. These objects were exported into a separate vector-based shapefile. Training data for cropped were taken from randomly selected “no-change” objects. “Cropped” class data were also obtained from randomly selected “changed” objects identified based on a visual examination of the data. This step was needed as areas of “no-change” or continuous crop are not often practiced within the general study area, but might be more common in localized areas. Training data for the fallow class were also based on randomly selected “changed” objects because areas of “fallow-fallow” were not identified. These data were used to generate the RF models for the 2004-2006 image-object classifications. Training object data used to create the 2006 model included 85 cropped and 126 fallow sites, object data used to create the 2005 model included 73 cropped and 70 fallow sites, and 111 cropped and 112 fallow sites were used in the 2004 model. The final number of data points used in the generation of each model were based on results from a random object selection where 230 locations were generated within the study region; object locations that did not fall within areas of masked or "no data" were used to train the models. The resulting classifications were merged with the "unchanged" object classifications to produce a final class layer. A simple database analysis within a GIS platform was used to determine the four-year cropping patterns.

Results

Tillage Type

The highest classification accuracies for tillage type were generated using the May 2007 data set and included information from 113 NT-cropped, 61 NT-fallow, 70 tilled-cropped, and 22 tilled-fallow field locations (Figure 3.4). This model consisted of 500 trees, with 13 variables examined at each node split. Total model accuracy was 70%, with low user's and producer's accuracies (31%, 67%) in the tillage class (Table 3.3).

The most important variables for the classification, as observed within the variable importance plots, were the object mean value for wetness followed by the object standard deviation for greenness. It was observed that the 2007 August-based model was more likely to misclassify NT cropped sites as tilled. Lower tillage class accuracies were observed for the 2007 May pixel-based model, although the pixel-based model resulted in the lowest overall model error (~21%). This model included data from 118 NT-cropped, 56 NT-fallow, 34 tilled-cropped, and 22 tilled-fallow sites; 450 trees were included within the forest and 13 variables were examined at each node split. Near-infrared reflectance was found to be the most important variable in the generation of the pixel-based model.

Conservation Reserve

The greatest classification accuracies pertaining to the discrimination of CR land from small-grains crop were obtained through the May-based model (Table 3.3). Data utilized in the building of this model included 304 cropland (95 till and 209 NT) and 127 CR sites. Total model accuracy was 99%, with 100% producer's accuracy in the cropland class (96% user's) and 90% in the CR class (100% user's) (Figure 3.5). Classification error primarily resulted from the misclassification of CR as NT-cropped and tilled-crop.

This model consisted of 500 trees, with 13 variables examined at each node split. Predictive parameters found to be the most important for model generation included the non-directional grey level co-occurrence (GLCM) standard deviation for brightness, followed by the mean object value for thermal, the minimum pixel value for green, the object standard deviation for blue, and the GLCM mean for red. The GLCM is a measure of texture within pixel gray levels within a certain object (Herold et al., 2003).

Crop and Fallow

The August-based RF model was able to distinguish senesced crop from fallow with greater than 82% accuracy (Figure 3.6). Data from 188 cropped and 67 fallow sites were used in building the model. The RF variable importance plot indicated that object textural measures such as within-object contrast and homogeneity were often used as model predictive parameters, suggesting that object-derived information allowed for greater predictive ability under certain conditions. Textural measures related to object-based wetness were also found to influence model accuracy, with wetness being greater on cropped surfaces.

Misclassification errors within the fallow category were attributed to objects located within landscapes characterized by narrow (< 100-m wide) crop and fallow strip management. This was likely due to the within-pixel mixing of crop and fallow spectral signatures. The object-based classification tended to favor the "cropped" class, resulting in a classification bias under these conditions.

Discussion

It has been stated that "the ultimate goal (of remote sensing) is to mirror, elucidate, quantify and to describe surface patterns in order to contribute to an understanding of underlying phenomena and processes" (Blaschke and Strobl, 2001, p. 12). A pixel, when examined as a single unit, does not inherently provide information concerning landscape patterns and spatial relationships. Instead, when landscape objects of interest are distinct and at a scale where they consist of a large number of pixels, it makes more sense to examine an image based on localized spatio-temporal and functional structures, which tend to create regions of heterogeneity within the greater landscape (Burnett and Blaschke, 2003).

Model	Overall Accuracy	Classification Matrix			Producer's	User's
No-Till & Tillage			**NT**	**Till**	**NT**	**Till**
May Pixel-based	76%	**NT**	161	13	92%	79%
		Till	43	13	23%	50%
May Object-based	71%	**NT**	160	14	91%	71%
		Till	63	29	31%	67%
August Object-based	57%	**NT**	101	35	74%	61%
		Till	64	31	33%	47%
May + August Object-based	54%	**NT**	93	43	68%	60%
		Till	63	32	34%	43%
Crop & CR			**Crop**	**CR**	**Crop**	**CR**
May Object-based	97%	**Crop**	304	0	100%	96%
		CR	12	115	90%	100%
May + August Object-based	91%	**Crop**	87	19	82%	88%
		CR	12	219	95%	92%
August Object-based	88%	**Crop**	99	27	79%	85%
		CR	17	214	93%	89%
Crop & Fallow			**Crop**	**Fallow**	**Crop**	**Fallow**
August Object-based 07	91%	**Crop**	178	10	95%	93%
		Fallow	12	55	82%	84%
May + August Object-based 07	77%	**Crop**	149	14	91%	79%
		Fallow	39	29	43%	67%
May Object-based 07	67%	**Crop**	145	18	89%	71%
		Fallow	58	10	15%	36%
September Object-based 06	96%	**Crop**	80	5	94%	95%
		Fallow	4	122	96%	96%
September Object-based 05	93%	**Crop**	68	5	93%	93%
		Fallow	5	65	92%	92%
July Object-based 04	93%	**Crop**	103	8	93%	93%
		Fallow	7	105	93%	93%

Table 3.3. Classification (OOB) accuracy for tillage, CR, crop and fallow.

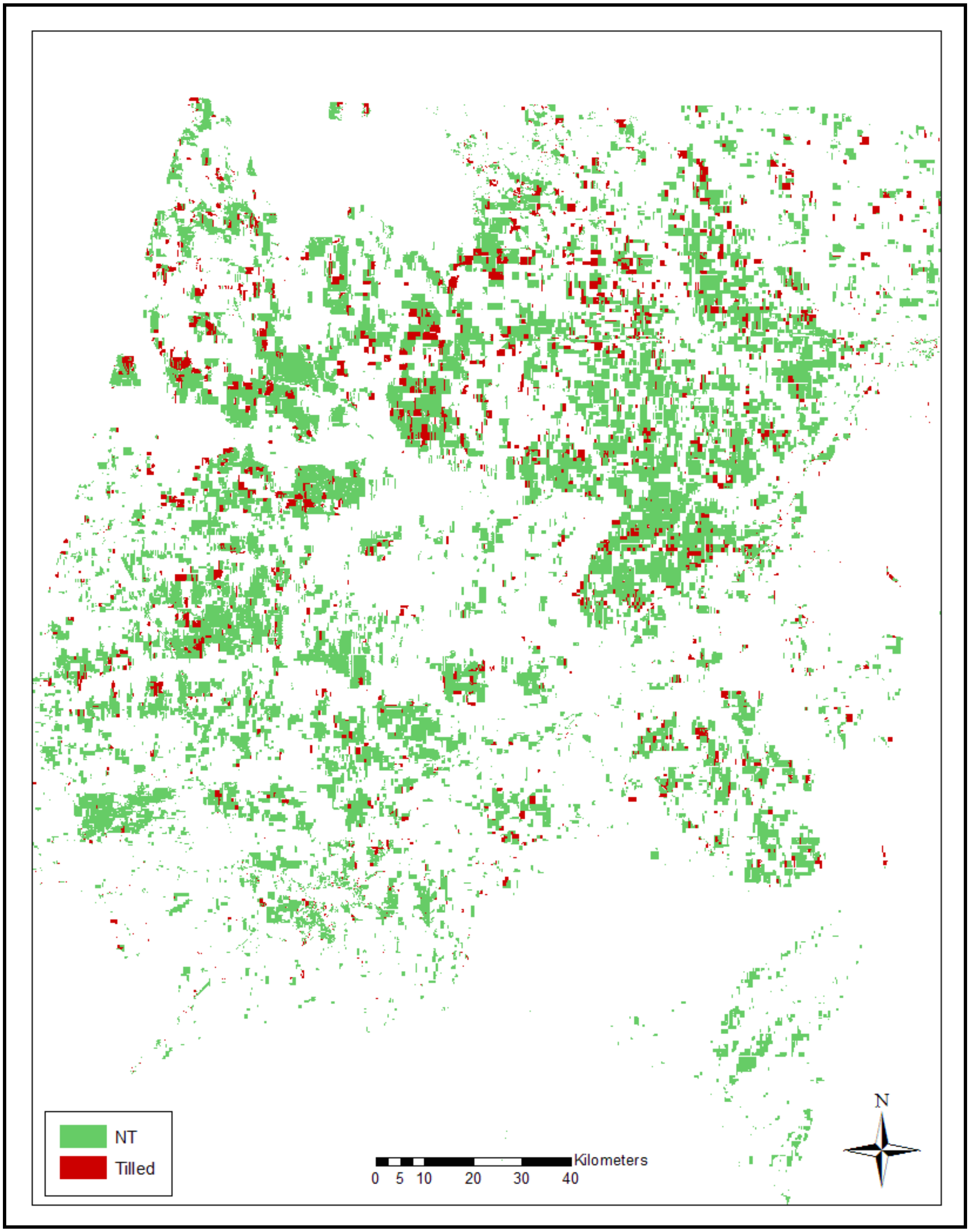

Figure 3.4. Classified tillage (red) and NT (green) within north central Montana in 2007.

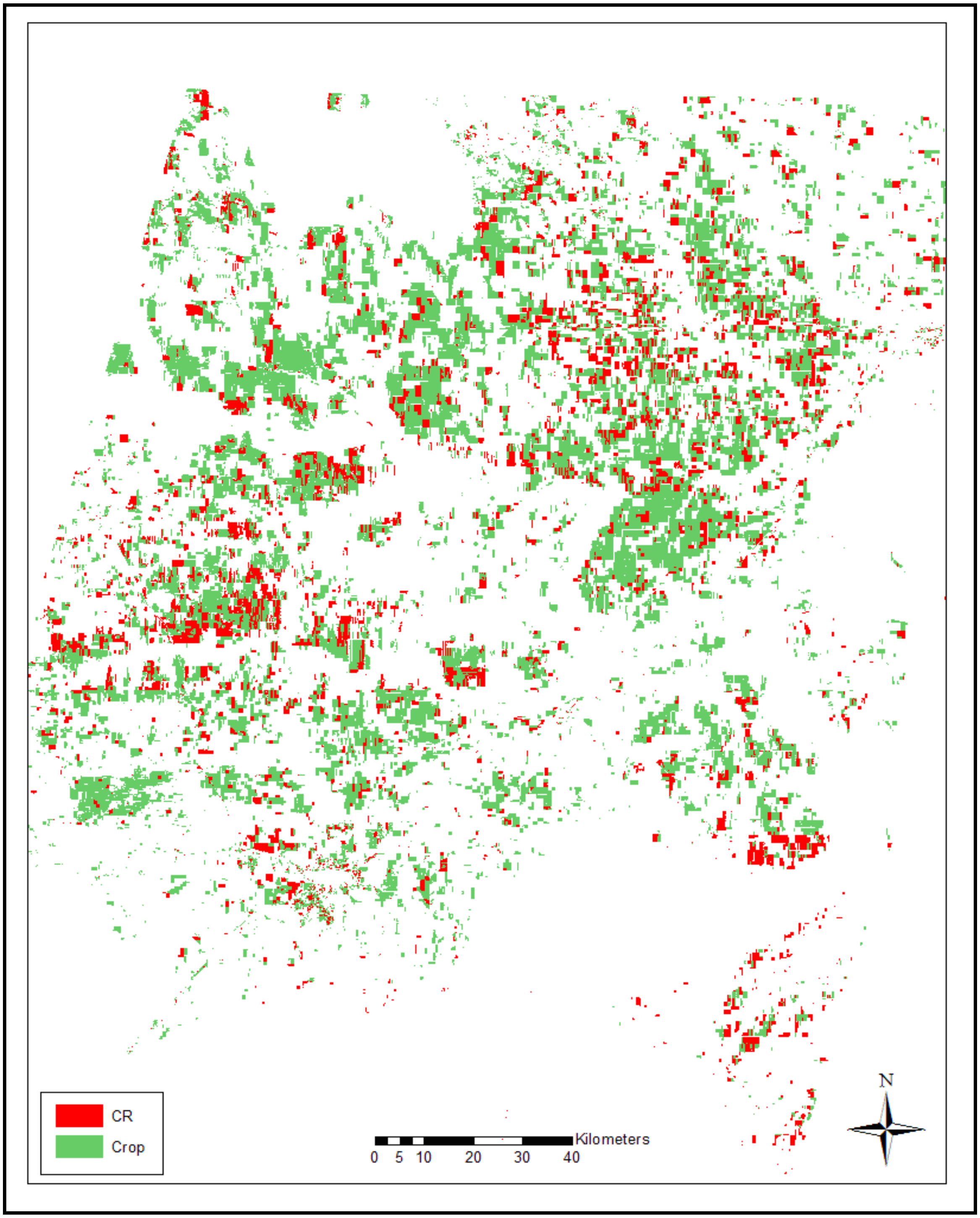

Figure 3.5. Classified CR (red) and cropland (green) in 2007 within north central Montana.

The O-O approach provides a way to incorporate landscape patterns into an analysis by first deriving spatial, morphological, and contextual information through image segmentation (Navulur, 2007). This information can then be incorporated into the classification process, in addition to spectral information. The resulting vector-based units can also be incorporated into a geographic information system for further spatial analyses.

The objective of this study was to identify cropland management types within agricultural systems defined, in part, by anthropogenic boundaries stemming from land ownership. Landscape patterns resulting from varied cropping management within ownership parcels were also used to define individual object units for image analysis and classification purposes. It was expected that the object-based classification of tillage type, CR, and crop and fallow would yield high class accuracies through the addition of object-based parameters. Classification success, however, was varied.

Tillage Type

Past studies have reported difficulty in the distinction of tillage from NT in situations where the soil surface is covered by established crop canopy and plant residues. One pixel-based study applying logistic regression to late June TM data successfully classified NT under crop canopy with a 99% producer's accuracy, but failed to adequately classify tillage (29% producer's) (Bricklemyer et al., 2006). It was expected that the object-based approach utilized within this study, aided by the RF algorithm, would yield higher classification accuracies than those generated through the logistic regression approach. The O-O classification, however, produced results very similar to those reported by Bricklemyer et al. (2006). The tillage producer's accuracy was unacceptable for mapping purposes (31%), although the NT producer's accuracy was acceptable (91%).

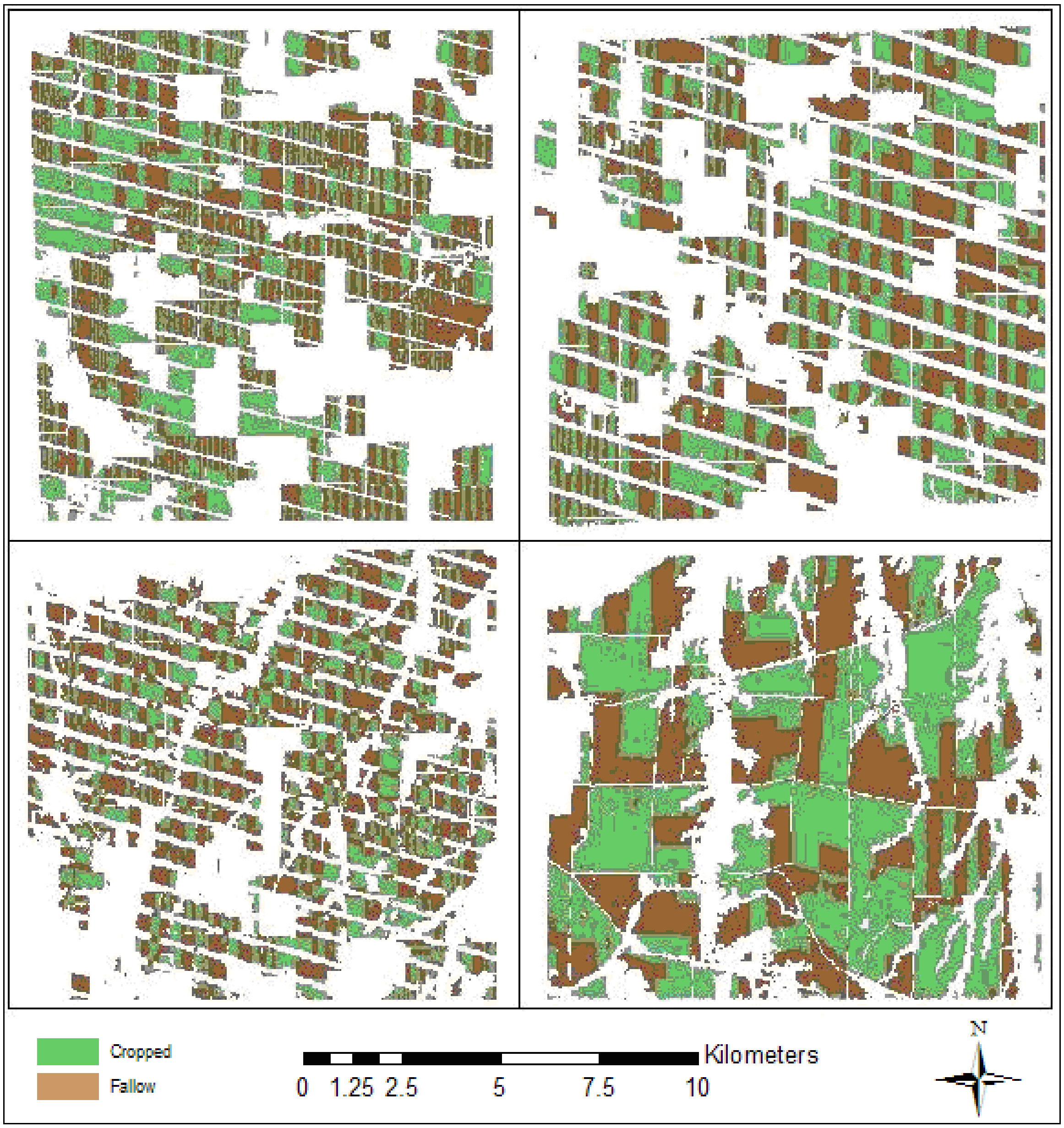

Figure 3.6. 2007 crop (green) and fallow (brown) classifications for the Chester (top left), Big Sandy (top right), Dutton (bottom left), and Great Falls (bottom right) areas.

The RF algorithm theoretically should outperform logistic regression, as it is more robust to noise and outliers (Guo et al., 2004). Studies have demonstrated the superiority of RF to logistic regression and other popular algorithms in classifying a variety of data sets (Qi et al., 2006; Hothorn and Lausen, 2005; Lee et al., 2005). The pixel-based RF model yielded a NT producer's accuracy of 92%, with only a 23% user's accuracy for tillage. This suggests that the lower classification accuracies generated by the RF approach compared to the Bricklemyer et al. (2006) study might be attributed to differences between study data sets.

The May data used within this study should have allowed for the increased detection of surface disturbances as vegetative canopy was lower than those reported within the late June data. The study site information incorporated into the RF-based models might also have reflected a greater degree of variability within regional cropland management as it reflected a larger number of study site locations than those used by Bricklemyer et al. (2006). It has also been noted that the survey-based data collection methods utilized by the Bricklemyer et al. (2006) study might have introduced a slight bias towards NT sites, possibly resulting in a bias within the classification model.

The inability of various cluster analysis algorithms to separate NT from conservation-based tillage given May data-based spectral, textural, and object neighborhood information suggests that there is substantial overlap between class feature characteristics. The May data should have minimized vegetation-based spectral similarities between NT and tillage, as senesced crop canopy was avoided. We believe that a large part of the class confusion was a function of the wide use of conservation tillage within the regions. Similarities between NT and other forms of conservation tillage likely stem from little difference in crop surface residues amounts between class types. Conservation tillage, by definition, leaves at least 30% of the soil surface covered by crop residue (CTIC, 2004). No-tillage is an extreme form of conservation tillage. Alternative management types might include the use of V-blades (Kuepper, 2001), chisel ploughs or light duty tandem disks to prepare the soil prior to planting or for weed management on fallow land (Uri, 2000). These tillage types result in a greater amount of soil disturbance compared to NT but do not fully mix surface residues into the soil as would moldboard ploughs or heavy duty tandem disks, or repeated operations of chisel ploughs and/or light duty tandem disks, thus preserving surface residue amounts.

Managers might decide to incorporate minimal tillage methods, as opposed to strictly adhering to a NT system, in the event that surface residue density begins to impede the proper function of planting equipment, or to control chemically tolerant weeds in the hot droughty summer and fall periods. This observation was confirmed through verbal communication with area farmers during the 2007 field data collection period. Many managers had reported that contracted combine crews had set cutting lengths too tall in years previous, resulting in the need to reduce surface residue amounts through tillage or burning prior to planting crops for the 2007 season.

Conservation Reserve

A RF O-O classification based on May TM data was able to successfully separate CR from cropland with producer’s accuracies of 90% and 100%. Previous pixel-based studies had relied on more elaborate multi-year techniques to achieve similar accuracies (Egbert et al., 2003; Price et al., 1997). Classification error within the May-based model primarily resulted from the misclassification of CR as NT-cropped and tilled-crop. The misclassified sites were often those under recent conversion from cropland to CR, as was determined by an examination of data supplied through the MFSA. It was also observed that the misclassification rate was greater at late vegetative maturity (late August), suggesting that there are greater spectral and textural differences between the management classes during early stages of growth.

An analysis of model predictive parameters used in the data splitting process suggests that object-based texture played a role in the discrimination of crop from CR. Both the textural standard deviation for brightness and the textural mean for red demonstrated some degree of importance in the predictive variable plot. The high standard deviation in the texture for brightness likely resulted from greater variation within cropland surface albedo due to patches of soil exposure, straw stubble, and vegetation than might be expected at CR locations, which generally feature a more uniform grassland surface.

Increased object texture exhibited within the red portion of the spectrum might have resulted from un-evenness in soil exposure throughout site locations, possibly driven by the incorporation of spectral signatures from both cropped and fallowed strips within some objects as well as patterns resulting from crop row spacing. Conservation Reserve sites were also characterized, on average, by a higher mean object thermal value than cropped sites. It is suspected that this might have resulted from higher evapotranspiration at the CR sites due to higher photosynthetically active plant biomass densities. This observation is given further support as the average minimum pixel value within each object was found to be greater for CR sites than for cropland sites, also indicative of greater vegetative coverage. The average standard deviation for object reflectance in the blue band was also slightly higher for CR sites than cropland fields, possibly due to differences in surface moisture and evapotranspiration.

Crop and Fallow

It has been shown that crop and fallow can be accurately classified within Landsat ETM+ imagery using simple NDVI differencing techniques (Xie et al., 2007), as were used to detect objects continuously cropped between 2004 and 2007; however, the incorporation of multiple spectral and object-based data parameters into a RF classification approach allowed the identification of crop and fallow in a post-photosynthetic state. This is of value for years when cloud or smoke cover limits the availability of image scene dates. Imagery collected too early might not allow for the detection of early-emergence spring crops, while those collected late summer or early fall would not provide spectral signatures from active crop vegetation, especially in a dryland setting.

Random Forest model accuracies for the classification of crop vs. fallow ranged from 92 to 96%, which were similar to those reported by Xie et al. (2007) (~93% total accuracy) using a spectral angle mapping algorithm and a NDVI threshold approach. That the RF model was able to produce results similar to the Xie et al. (2007) study which used pre-senesced vegetation data, despite the use of data representing post-photosynthetic vegetation, suggests that the incorporation of textural and neighborhood parameters into the classification model increases the classifier's predictive abilities. A purely spectrally-based classifier would likely have difficulty in distinguishing between fallow (with surface stubble) and recently harvested (cropped) fields compared to the relative ease by which a fallow field might be separated from a green, cropped field.

The use of a threshold to separate "unchanged" (crop-crop) from "changed" (crop-fallow or fallow-crop) objects within NDVI-difference values provided a direct way to determine change in crop-vegetation status between the May 2007 and prior image dates, despite a temporal difference of more than a month between the reference and preceding image dates. The use of May data, however, restricted the ability to detect late planted spring wheat crop that was still in periods of early emergence. It is suggested that late June or early July imagery be used when possible to avoid this situation. Using a change vector approach incorporating the red and NIR bands did not provide a direct means to determine objects unchanged in between-year vegetation status as an appropriate threshold was not easily apparent and varied between the agricultural regions analyzed within the sub-analysis.

Conclusion

The adequate separation of NT from conservation tillage management through spectral and textural-based satellite mapping is unlikely given the current technology. Specifically, we see difficulty in discovering a contracted farmer who has agreed to follow NT practices, but is in fact practicing a less extreme form of conservation tillage. Physical validation of tillage management within carbon contract sites will likely be necessary, complimented by satellite-based classifications to detect heavy tillage disturbances. The re-evaluation of tillage management classes included within carbon contracts might also be considered to address the appropriateness of including only NT within carbon contract agreements, as opposed to more flexible management options incorporating other types of conservation tillage, as results in this study showed great similarity in surface spectral characteristics (specifically surface residues) between NT and sites thought to be under conservation-based tillage management. Alternatively, greater emphasis might be made on using relative surface residue amounts to indicate degrees of tillage usage and field disturbance.

Results from this study indicate that the incorporation of object-based parameters into a RF model has the ability to distinguish cropland from grassland-based CR using image data collected at early stages of vegetative growth (~May). The misclassification of CR as cropland might be problematic, however, for fields under recent conversion to CR. Study results also showed the ability of an object-based RF model to separate crop from fallow within a dryland, post-photosynthesis landscape. Results also imply that the use of moderate-resolution imagery (~30 m) might not be appropriate in agricultural landscapes where narrow (<100 m) crop strip management patterns are used, as misclassification was often common within these areas due to spectral mixing. An NDVI threshold approach was found to accurately separate continuously cropped objects from those under a crop-fallow rotation within a multi-year setting. Applying the NDVI threshold to vector-based objects within a GIS platform allowed for the classification of "changed" objects and the merging of the newly classified objects with those "unchanged" to produce a final class maps showing crop and fallow status. It is then possible to determine crop intensity based on the multi-year analysis of the thematic data resulting from these multi-year classification

Referenced Literature

Baker, C., R. Lawrence, C. Montagne, and D. Patten. 2006. Mapping wetlands and riparian areas using Landsat ETM+ imagery and decision-tree-based models. Wetlands, 26: 465-474.

Benz, U.C., P. Hofmann, G. Willhauck, I. Lingenfelder, and M. Heynen. 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS Journal of Photogrammetry and Remote Sensing, 58: 239-258.

Blaschke, T., and J. Strobl. 2001. What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. GeoBIT and GIS, 6:12-17.

Block, M., P. Xofis, J. Mitchley, G. Rossner, and M. Wissen. 2005. Object-oriented methods for habitat mapping at multiple scales. Case studies From Northern Germany and Wye Downs, UK. Journal for Nature Conservation,13: 75-89.

Bontemps, S., and P. Defourny. 2007. Mapping forest change in Borneo in 2000-2006 by a multispectral statistically-based detection technique with SPOT-VEGETATION. In Proceedings of the 4th Annual International Workshop on the Analysis of Multi-temporal Remote Sensing Images, Leuven, Belgium, 18-20 July 2007. pp. 1-6.

Breiman, L., and A. Cutler. 2005. Random Forests. Last Accessed 15 December 2007 <http://www.stat.berkeley.edu/users/breiman/RandomForests/cc_home.htm>

Breiman, L. 2001. Random forests. Machine Learning, 45: 5-32.

Bricklemyer, R.S., R.L. Lawrence, P.R. Miller, and N. Battogtokh. 2006. Predicting tillage practices and agricultural soil disturbance in north central Montana with Landsat imagery. Agriculture, Ecosystems and Environment, 114: 210-216.

Bricklemyer, R.S., R.L. Lawrence, and P.R. Miller. 2002. Documenting no-till and conventional till practices using Landsat ETM+ imagery and logistic regression. Journal of Soil and Water Conservation, 57: 267-272.

Brooks, C.N., D.L. Schaub, R.B Powell, N.H.F. French, and R.A. Shuchman. 2006. Multi-temporal and multi-platform agricultural land cover classification in southeastern Michigan. Proceedings of the 2006 ASPRS Annual Conference, 1-5 May 2006, Reno, NV. pp 178-190.

Burnett, C., and T. Blaschke. 2003. A multi-scale segmentation/object relationship modeling methodology for landscape analysis. Ecological Modeling, 168: 233-249.

Capalbo, S.M. 2005. Big Sky Carbon Sequestration Partnership phase II: proposal summary and overview. 7 pp.

Chander, G., B. L. Markham, and J.A. Barsi. 2007. Revised Landsat 5 Thematic Mapper radiometric calibration. IEEE Geoscience and Remote Sensing Letters, 4: 490-494.

Chicago Climate Exchange (CCX). 2008. Soil carbon management offsets. CCX Guidelines: Agricultural Soil Carbon. 2 pp.

Chubey, M.S., S.E. Franklin, and M.A. Wulder. 2006. Object-based analysis of Ikonos-2 imagery for extraction of forest inventory parameters. Photogrammetric Engineering and Remote Sensing, 72: 383-394.

Congalton, R., and K. Green. 1999. Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. CRC Press, Boca Raton, FL. 133 pp.

Conservation Technology Information Center (CTIC). 2004. Conservation tillage and other tillage types in the United States (1990-2004). National Crop Residue Management Survey. Conservation Technology Information Center, West Lafayette, Indiana, USA.

Coppin, P.R., E. Lambin, I. Jonckheere, K. Nackaerts, and B. Muys. 2004. Digital change detection methods in ecosystem monitoring: a review. International Journal of Remote Sensing, 25: 1565-1596.

Crist, E.P., R. Laurin, and R.C. Cicone. 1986. Vegetation and soils information contained in transformed Thematic Mapper data. In Proceedings of IGARSS ’86 Symposium, 8-11 September 1986, Zurich, Switzerland. pp.1465-1470.

Daly, P. 2001. Remote sensing for crop assessment. A report to the Franklin Conservation District, Pasco WA. 4 pp.

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

Definiens. 2006. Definiens Professional User’s Guide, 5.0. Definiens Professional White Pages. 479 pp.

Dodge, T. 2007. Personal communication. National Carbon Offset Coalition, Butte, MT.

Egbert, S.L., S. Park, K.P. Price, R. Lee, J. Wu, and M. Duane Nellis. 2002. Using conservation reserve program maps derived from satellite imagery to characterize landscape structure. Computers and Electronics in Agriculture, 37: 41-156.

Egbert, S.L., R.Y. Lee, K. P. Price, and R. Boyce. 1998. Mapping conservation reserve program (CRP) grasslands using multi-seasonal Thematic Mapper imagery. Geocarto International, 13: 1010-6049.

Farkell, J. 2007. Personal Interview. Centrol Agricultural Consultant. Tillage and cropping systems near Conrad, Montana.

Gislason, P.O., J.A. Benediktsson, and J.R. Sveinsson. 2006. Random forests for land cover classification. Pattern Recognition Letters, 27: 294-300.

Gowda, P.H., Peters, R.T., and T.A. Howell. 2005. Mapping tillage practices in the Texas Panhandle with Landsat Thematic Mapper (TM) data. USDA-ARS Conservation and Production Research Lab. Wetting Front News, 7: 5-7.

Guo, L., Y. Ma, B. Cukie, and H. Singh. 2004. Robust prediction of fault-proneness by random forests. Proceedings of the 15th International Symposium on Software Reliability Engineering., 2-5 November 2004, Saint-Malo, France. pp. 417-428.

Ham, J., Y. Chen, M.M. Crawford, and J. Ghosh. 2005. Investigation of the random forest framework for classification of hyperspectral data. International Journal of Remote Sensing, 243: 492-500.

Hay, G.J., T. Blaschke, D.J. Marceau, and A. Bouchard. 2003. A comparison of three image-object methods for the multiscale analysis of landscape structure. ISPRS Journal of Photogrammetry and Remote Sensing, 57: 327-345.

Herold, M., X. Liu, and K.C. Clarke. 2003. Spatial metrics and image texture for mapping urban land use. Photogrammetric Engineering and Remote Sensing, 69: 991-1001.

High Plains Regional Climate Center (HPRCC). 2008. Climate summary maps and archived station data. Last Accessed 22 April 2008 < http://www.hprcc.unl.edu>

Hothorn, T., and B. Lausen. 2005. Bundling classifiers by bagging trees. Computational Statistics and Data Analysis, 49:1068-1078.

Huang, C., B. Wylie, L. Yang, C. Homer, and G. Zylstra. 2002. Derivation of a tasseled cap transformation based on Landsat 7 at-satellite reflectance. International Journal of Remote Sensing, 23: 1741-1748.

Im, J., J.R. Jensen, and J.A. Tullis. 2007. Object-based change detection using correlation image analysis and image segmentation. International Journal of Remote Sensing, 25: 1143-1161.

Jensen, J.R. 2005. Introductory Digital Image Processing: A Remote Sensing Perspective. Pearson Prentice Hall, Upper Saddle River, NJ. 526 pp.

Johnson, R.D., and E.S. Kasischke. 1998. Change vector analysis: a technique for the multispectral monitoring of land cover and condition. International Journal of Remote Sensing, 19: 411-426.

Kamagata, N., K. Hara, M. Mori, Y. Akamatsu, Y. Li, and Y. Hoshino. 2006. A new method of vegetation mapping by object-based classification using high resolution satellite data. Journal of the Japan Society of Photogrammetry and Remote Sensing, 45: 43-49.

Kuepper, G. 2001. Pursuing conservation tillage systems for organic crop production. National Center for Appropriate Technology. 28 pp.

Kutner, M.H., C.J. Nachtsheim, J. Neter and W. Li. 2004. Applied Linear Statistical Models (5th ed.). McGraw-Hill/Irwin, New York, NY. 1396 pp.

Lambin, E.F. and A.H. Strahler. 1994. Change-vector analysis in multitemporal space: a tool to detect and categorize land-cover change processes using high temporal-resolution satellite data. Remote Sensing of the Environment, 48: 231-244.

Lawrence, R.L., S. D. Wood, and R.L. Sheley. 2006. Mapping invasive plants using hyperspectral imagery and Breiman Cutler classifications (RandomForest). Remote Sensing of Environment, 100: 356-362.

Lawrence, R., A. Bunn, S. Powell, and M. Zambon. 2004. Classification of remotely sensed imagery using stochastic gradient boosting as a refinement of classification tree analysis. Remote Sensing of Environment, 90: 331-336.

Lawrence, R.L., and A. Wright. 2001. Rule-based classification systems using classification and regression tree (CART) analysis. Photogrammetric Engineering and Remote Sensing, 67: 1137-1142.

Lee, J., J. Lee, M. Park, and S. Song. 2005. An extensive comparison of recent classification tools applied to microarray data. Computational Statistics and Analysis, 48: 869-885.

Lillesand, T.M., R.W. Kiefer, and J.W. Chipman. 2004. Remote Sensing and Image Interpretation, 5^{th} ed. John Wiley & Sons, NY, NY. 763 pp.

Lucas, R., A. Rowlands, A. Brown, S. Keyworth, and P. Bunting. 2007. Rule-based classification of multi-temporal satellite imagery for habitat and agricultural land cover mapping. ISPRS Journal of Photogrammetry and Remote Sensing, 62: 165-185.

Lyon, J.G. D.Yuan, R. S. Lunetta, and C. D. Elvidge. 1998. A change detection experiment using vegetation indices. ISPRS Journal of Photogrammetry and Remote Sensing, 64: 143-150.

Nackaerts, K, K. Vaesen, B. Muys, and P. Coppin. 2005. Comparative performance of a modified change vector analysis in forest change detection. International Journal of Remote Sensing, 26: 839-852.

National Carbon Offset Coalition (NCOC). 2008. Exchange soil offset eligible practices and offset issuance rates by zone. Cropland Protocol Guidelines. 23 pp.

National Weather Service (NWS). 2007. Past weather local climate information. National Oceanic and Atmospheric Administration.

Natural Resources Conservation Service (NRCS). 2007a. Major Biomes Map. Last Accessed 12 December 2007 <http://soils.usda.gov/use/worldsoils/mapindex/biomes.html>

Natural Resources Conservation Service (NRCS). 2007b. Interactive Soil Survey Map. Last Accessed 10 December 2007 <http://websoilsurvey.nrcs.usda.gov/app/WebSoilSurvey.aspx>

Natural Resources Information Service (NRIS). 2007. Collective spatial information clearinghouse for Montana. Last Accessed 12 August 2007 < http://nris.mt.gov/gis/default.asp>

Navulur, K. 2007. Multispectral Image Analysis Using the Object-oriented Paradigm. CRC Press, Boca Raton, FL. 165 pp.

Niemeyer, I., and M.J. Canty. 2003. Pixel-based and object-oriented change detection analysis using high-resolution imagery. Proceedings 25th Symposium on Safeguards and Nuclear Material Management, 13-15 May 2003, Stockholm, Sweden. pp. 2133-2136

Pal, M. 2005. Random forest classifier for remote sensing classification. International Journal of Remote Sensing, 26: 217-222.

Prasad, A.M., L.R. Iverson, and A. Liaw. 2006. Newer classification and regression tree techniques: bagging and random forests for ecological prediction. Ecosystems, 9: 181-199.

Price, K.P., Egbert, S.L., Nellis, M.D., Lee, R.Y., and Boyce, R. 1997. Mapping land cover in a High Plains agro-ecosystem using a multi-date Landsat Thematic Mapper modeling approach. Transactions of the Kansas Academy of Science, 100: 21-33.

Qi, Y., Z. Bar-Joseph, and J. Klein-Seetharaman. 2006. Classification methods for use in protein interaction prediction. PROTEINS: Structure, Function, and Bioinformatics, 63: 490-500.

Richards, J.A., and X. Jia. 2006. Remote Sensing Digital Image Analysis: An Introduction. 5th Ed. Springer, Berlin. 450 pp.

Schneevoigt, N.J., S. van der Linden, H. Thamm, and L. Schrott. 2008. Detecting alpine landforms from remotely sensed imagery. A pilot study in the Bavarian Alps. Geomorphology, 93: 104-119.

Science Data Users Handbook,-Landsat 7 (SDH-L7). 2006. National Aeronautics and Space Administration. Last Accessed 10 March 2008 <http://landsathandbook.gsfc.nasa.gov/handbook/handbook_toc.html>

Song, X., G. Fan, and M.N. Rao. 2003. Machine learning approaches to multisource geospatial data classification: application to CRP mapping in Texas County, Oklahoma. IEEE Workshop on Advances in Techniques for Analysis of Remotely Sensed Data, 27-28 October 2003, Greenbelt, MD. pp. 202-211.

Song, C., C.E. Woodcock, K.C. Seto, M.P. Lenney, and S.A. Macomber. 2001. Classification and change detection using Landsat TM data: when and how to correct atmospheric effects? Remote Sensing of Environment, 75: 230-244.

South, S., J. Qi, and D.P. Lusch. 2004. Optimal classification methods for mapping agricultural tillage practices. Remote Sensing of Environment, 91: 90-97.

Stow, D., A. Lopez, C. Lippitt, S. Hinton, and J. Weeks. 2007. Object-based classification of residential land use within Accra, Ghana based on Quickbird satellite data. International Journal of Remote Sensing, 28: 5167-5173.

Sullivan, D.G., C.C. Truman, H.H. Schomberg, D.M. Endale, and T.C. Strickland. 2006. Evaluating techniques for determining tillage regime in the southeastern costal plain and piedmont. Journal of Agronomy, 98: 236-1246.

Tucker, C.J. and P.J. Sellers. 1986. Satellite remote sensing of primary production. International Journal of Remote Sensing, 7: 1395-1416.

Uri, N.D. 2000. Perceptions on the use of no-till farming in production agriculture in the United States: an analysis of survey results. Agriculture, Ecosystems, and Environment, 77: 263-266.

Western Regional Climate Center (WRCC). 2006. Historical climate information. Last Accessed 05 April 2007 <http://www.wrcc.dri.edu/CLIMATEDATA.html>

Xie, H., Y.Q. Tian, J.A. Granillo, and G.R. Keller. 2007. Suitable remote sensing method and data for mapping and measuring active crop fields. International Journal of Remote Sensing, 28: 395-411.

Yan, G., J.F. Mas, B.H.P. Maathuis, Z. Xiangmin, and P.M. Van Dijk. 2006. Comparison of pixel-based and object-oriented image classification approaches-a case study in a coal fire area, Wuda, Inner Mongolia, China. International Journal of Remote Sensing, 27: 4039-4055.

Yongxue, L., L. Manchun, M. Liang, X. Feifei, and H. Shuo. 2006. Review of remotely sensed imagery classification patterns based on object-oriented image analysis. Chinese Geographical Science, 16: 282-288.

Yu, Q., P. Gong, N. Clinton, G. Biging, M. Kelly, and D. Schirokauer. 2006. Object-based detailed vegetation classification with airborne high spatial resolution remote sensing imagery. Photogrammetric Engineering and Remote Sensing, 72: 799-811.

CHAPTER 4

AN ESTIMATION OF SOIL CARBON SEQUESTRATON POTENTIAL RESULTING FROM NO-TILL, CROPPING INTENSITY, AND CONSERVATION RESERVE PRACTICES WITHIN NORTH CENTRAL MONTANA

Introduction

Increased demand for the mitigation of anthropogenic carbon dioxide (CO_2) has stemmed from rising concern about greenhouse gas emissions and their relation to global climate change. Geologic carbon (C) sequestration through CO_2 injection has been promoted as a means to contain large amounts of atmospheric C, but it is speculated that the technology will not be economically feasible within the near future (Schrag, 2007). Terrestrial C sequestration (Post and Kwon, 1999 might offer a practical and immediate approach to C sequestration while long-term strategies are being developed.

Soils have long been recognized as important sinks within the global C cycle (Schlesinger, 1977). The global soil pool currently is estimated to hold 2,500 Gt C, 3.3 times the amount of atmospheric C (Lal, 2004). US cropland soils alone are reported to hold 2.7 Gt C (Houghton and Hackler, 2000). This estimate reflects C storage amounts below pre-development levels, as years of intensive tillage management and summer fallowing have resulted in cropland C loss (Houghton et al., 1999). Intensive tillage practices (conventional tillage) incorporate mechanical disturbance mechanisms to prepare the soil for planting, to manage surface residue, and to control weeds. Summer fallow is the practice of leaving the soil in an un-vegetated state during the growing season for water storage purposes.

Recent increases in cropland C storage have been attributed to management changes associated with the conversion from intensive tillage to conservation tillage practices such as no-till (NT) and the enrollment of cropland within the Conservation Reserve Program (CRP) to facilitate the planting of degraded cropland into perennial vegetation (Eve et al., 2002). The incorporation of these cropland management methods allows for soil C levels to increase over time, gradually approaching, and in some cases exceeding, pre-disturbance levels. Adopting a variety of best management practices for agricultural lands, including NT and the conversion of cropland to perennial grasses, has been described as "a partial solution to the environmental problem (global warming)" (Lal et al., 1998, p.vi).

<u>Carbon Sequestration through Cropland Management</u>

The soil organic C (SOC) cycle is a complex system of input, storage, and release. Plants remove CO_2 from the atmosphere through photosynthesis; about 50% of this CO_2 is re-released through plant respiration (Ryan, 1991), while the remainder is incorporated into vegetative tissue. Plant tissues become incorporated into the soil medium, increasing organic C. This remains in the soil system until it is re-released as CO_2 through heterotrophic respiration, or it is physically removed through erosion.

Soil ecosystems vary in their ability to store C. Sequestration potential is largely controlled by climate, soil organisms, parent material, topography, and time (Post et al., 2004). Carbon sequestration rates have been positively correlated with increased soil moisture and lower mean annual temperature and been have also found to increase with higher clay content and higher lignin content (Schimel et al., 1994). Sequestration efforts can increase C levels in depleted systems until eventually reaching a saturation point where the soil can no longer hold additional C (Six et al., 2002).

Agricultural management techniques that facilitate the input of organic materials into the soil, and/or reduce decomposition rates, serve to increase soil C. Reduced tillage methods such as NT promote cool and wet micro-climatic conditions within the soil, thereby reducing the release of C into the atmosphere as CO_2 and methane (CH_4) (Carter, 1996). The amount of SOC that might be sequestered through NT management varies greatly and is often site specific. Estimated sequestration rates for the conversion from conventional tillage to conservation tillage management (mulch till, ridge till, NT, etc.) have ranged from 300-600 kg C ha^{-1} yr^{-1} within the US Great Plains (Follett and McConkey, 2000) to 100-300 kg C ha^{-1} yr^{-1} in the Canadian Great Plains (McConkey et al., 1999).

Crop intensity and crop rotation can influence C sequestration potential. The inclusion of fallow into a rotation can limit C accumulation, even in the presence of NT (Jarecki and Lal, 2003; Paustian et al., 2000; Potter et al., 1997; Staben, 1997). One study reported a loss of 113 kg C ha^{-1} yr^{-1} in an NT crop-fallow system; a nearby NT continuous crop treatment was found to sequester 233 kg C ha^{-1} yr^{-1} (Halvorson et al., 2002). Increased crop intensity, or reducing the number of years that a parcel is under summer fallow, minimizes C loss within the soil profile by sustaining the amount of plant residue deposition needed to offset CO_2 release resulting from soil respiration. Plant residue production is also facilitated by crop rotations that incorporate C4 varieties (that have higher photosynthetic efficiency) or consider plant rooting depths for soil water management purposes (Paustian et al., 1997).

Conservation reserve (CR) management is often used to restore C levels within degraded agricultural soils. Cropland is planted into perennial vegetation and often includes a mix of grass and legumes. Trees also might be incorporated into the re-vegetation process. The amount of C accumulation following the conversion from crop to CR has ranged from < 100 kg C ha^{-1} yr^{-1} to > 400 kg ha^{-1} yr^{-1} (Uri, 2001). Accumulation rates of 0-210 kg C ha^{-1} yr^{-1} have been observed in CR sites within the US Great Plains (McLauchlan, 2006). Higher sequestration rates have generally occurred in areas with greater soil moisture; the addition of trees has facilitated greater C increases than CR sites only containing perennial grass (Uri, 2001). Soils with higher levels of C depletion have also been correlated with increased C rates.

It has been estimated that 100% enrollment into CR across the Great Plains would sequester an additional 1.2-1.8 MMT C per year (Follett, 2001). This level of enrollment is impractical as it would require that all cropland be removed from production for a considerable period of time. The extent of time that a system must be left as CR before reaching pre-disturbance C levels has not been well established and is likely site-dependent. One study did not detect a significant increase in soil C after 10 years under CR; the lack of C accumulation was hypothesized to be due partially to nitrogen limitations (Baer et al., 2000). Another study assessing C change in semiarid soils found that soil C increased only slightly after six years under CR management (Robles and Burke, 1998). It has been suggested that 50 yr is the minimum recovery time needed for depleted active (those more subject to mineralization) SOC pools; more resilient C pools might require even longer recovery periods (Burke et al., 1995).

Regional Carbon Mitigation Efforts

Carbon offset programs have been developed by the US Department of Energy in an attempt to establish and promote regional C sequestration efforts. These programs were created in an attempt to mitigate projected increases in C emissions due to coal-driven energy development (Abraham, 2002). The Big Sky Carbon Sequestration Partnership (BSCSP), a branch of the National Carbon Offset Program, is currently overseeing C trading development within north central Montana (Capalbo, 2005; Young, 2003). Carbon credits result from the utilization of cropland management practices such NT and the conversion of cropland to a CR-based management. Land owners enrolled within the program are paid on a per-area basis for the implementation of these practices, according to C sequestration standards established by the Chicago Climate Exchange (CCX, 2008). Credits resulting from C increases within contracted land might then be purchased as a commodity on the CCX, a voluntary market. Each C credit, the unit upon which greenhouse gas emissions are based, represents the removal of 1 t CO_2 from the atmosphere (Bayon et al., 2007).

The amount of SOC that might be sequestered from the incorporation of NT and CR within north central Montana has not been well established. The current CCX credit assignment scheme divides US agricultural regions into six participating zones. Each zone is assigned a coarse regional approximation of soil organic C increase associated with changes in tillage management (till to NT) or the conversion to perennial vegetation.

The CCX soil C credit assignment system was established by a soil C technical advisory committee comprised of "leading experts from the academic soils science community" (CCX, 2008c, p. 4). Standardized regional sequestration rates reflect both professional opinion and available literature. Area-specific C data is currently lacking, making it necessary to apply broad C rates in place of more localized sequestration rate estimates.

Carbon credits for farmland under C contract are calculated by applying the regionally-assigned sequestration rate to the amount of land under contract agreement. North central Montana lies within "Zone C" and is assigned an estimated rate of 0.79 t CO_2 ha^{-1} yr^{-1} (CCX, 2008a) for dryland production sites under conversion from tillage to NT. Offsets are not issued in years when chemical fallowing, the process of using herbicides to prevent plant growth for increased soil water storage, occurs. The loss of credits during fallowing serves to promote the use of higher levels of cropping intensity. Higher crop intensity results with the reduction of fallowing frequency within a crop rotation pattern; the highest level of cropping intensity is continuous cropping where fallowing is removed altogether. Credits also are not given in years when residue management, through burning or physical removal, occurs. Sites under permanent grassland, or CR, are assigned a C sequestration rate of 2.47 t CO_2 ha^{-1} yr^{-1} within this region (CCX, 2008b).

A general lack of studies establishing region-specific C sequestration rates is due largely to the great cost and time involved in monitoring soil C following a management conversion. It has been suggested that it might take almost 40 yrs to detect change in soils having only a 20% increase in C (Smith, 2004). Change in SOC might be detected in as little as 10 yr in soils having a 100% increase in SOC. Study findings have suggested that it is very difficult to find change in soil C within a 5-yr period (Smith, 2004). Detection methods allowing for the more frequent monitoring of soil C are needed. Technological advancements in field spectrometry (Brown, 2007) might facilitate on-site quantification of SOC. The use of field spectrometers would likely be more time-efficient and cost-effective than traditional soil testing procedures. Measuring SOC over large areas currently remains an impractical and daunting task. Many researchers have instead chosen to use C models or generalized averages based on physical data to determine regional SOC change.

Popular C models have included the Century and Rothamsted, otherwise known as Roth-C (Coleman and Jenkinson, 1996), and the Century-based COMET model (Parton et al., 2005). Disadvantages of using these models for predictions includes the need to provide plant residue amounts into the Roth-C model and soil texture, estimates for plant and soil nutrient amounts, and plant lignin content for both models (Millino et al., 1995). The need for these parameters to generate SOC predictions makes it difficult to obtain model-based C sequestration estimates on a regional basis.

One study (Sperow et al., 2003) avoided the use of regional C models by applying generalized rates of C sequestration provided by the 2006 IPCC guidelines (Lasco et al., 2006) for agriculture greenhouse gas inventories to NT and CR land use percentage estimates supplied by the CTIC. This type of estimate might be ideal for a regional-scale analysis within Montana, as the necessary parameters needed for other methods are not readily obtainable.

There is uncertainty concerning the current percentage of agricultural land within north central Montana already under NT, CR management, and continuous cropping as these data are not available. The US Department of Agriculture conducts a national census, but this data is only obtained every five years and has not historically included tillage management or crop intensity data (USDA, 2008). The Conservation Technology Information Center (CTIC) had previously coordinated roadside transect surveys on a two-year collection basis; they now solely rely on data collected and reported by individuals on a voluntary basis due to a lack of funding and external support for a more rigorous survey program (CTIC, 2008). Data does exist for CRP land under contract with the Montana Farm Service Agency (MFSA); these statistics, however, are not readily available to parties outside the Agency. The CRP data do not account for cropland conversion to CR management having occurred outside of CRP contract.

Satellite-based Land Use Classification

Satellite image analysis has been widely used in the characterization of land cover practices (Cohen and Goward, 2004; Kerr and Ostrovsky, 2003; Lefsky et al., 2002). Image-based classifications provide a way to obtain agricultural management data in a less expensive manner than physically-based survey methods, making it possible to collect information over a wide area with greater temporal frequency. Pixel-based classifications applied to Landsat moderate-resolution imagery have yielded high accuracies for NT, but have fallen short due to problems associated with the miss-classification of tillage as NT (Bricklemyer et al., 2006). The use of a more advanced classification algorithm, such as Random Forest (RF) (Breiman, 2001), than previously used for this purpose and object-based analysis to avoid mixed classifications within single management zones (Benz et al., 2004) might improve the separation of tillage from NT. Several studies have reported high classification accuracy in detecting CR vegetation through image analysis (Price et al., 1997; Egbert et al., 1998; Egbert et al., 2002). Image analysis has also provided an efficient way to determine fallow and cropped parcels (Xie et al., 2007); crop rotation intensity might then be established through the multi-year compilation of the classification data.

Attempts have been made to quantify the amount of SOC sequestered by these management changes at a national level (Sperow et al., 2003; Eve et al. 2002; Houghton et al., 1999). Little effort has been made to assess the effect that changes in cropland management might have on SOC storage within specific regions of the US. This study attempts to bridge the regional gap in C sequestration analysis by examining the SOC storage potential for north central Montana. This was accomplished as a two-part process. Land use classification data was generated from Landsat satellite imagery and sampling to establish the percentage of cropland within north central Montana under NT and CR management in 2007. Sites considered to be under CR management for purposes of this study include those within the CRP and “other grasslands” that are characteristic of vegetation and management practices encouraged by the CRP program. A multi-year image analysis was also conducted to estimate four-year crop intensity patterns spanning from 2004-2007. Estimates for regional C sequestration attributed to the conversion to

NT systems, the conversion to NT systems in conjunction with changes in crop intensity and CR were established by applying literature-based sequestration rates to the regional land use information.

Methods

Study Area Description

This study examined cropland management practices within north central Montana and included portions of Toole, Liberty, Hill, Blaine, Pondera, Chouteau, Fergus, Judith Basin, Wheatland, Meagher, Broadwater, Lewis and Clark, Teton, and Cascade counties (Figure 4.1). This region is considered to be semi-arid steppe (NRCS, 2007a). Soil type can vary considerably throughout the region (NRCS, 2007b); clay-dominant textures are common in many cropland fields throughout the region, with more sandy soils expected within elevated field locations and areas prone to water erosion. Regional cropland topography ranges from gently rolling hills to relatively flat prairie lands.

Temperature and especially precipitation vary strongly within the region. Annual average minimum temperatures have ranged from -0.7 °C Havre to -0.9 °C in Great Falls, with annual average maximum temperatures ranging from 12.7 °C in Havre to 15.5 ºC in Fort Benton (NWS, 2007). Annual average precipitation ranges from 265 mm in Chester to 318 mm in Cut Bank and 373 mm in Great Falls (WRCC, 2006). Spring and summer temperatures within north central Montana were 1.9 ºC above average from 2006-2007 and 0.5 ºC below average from 2004-2005 (NWS, 2007).

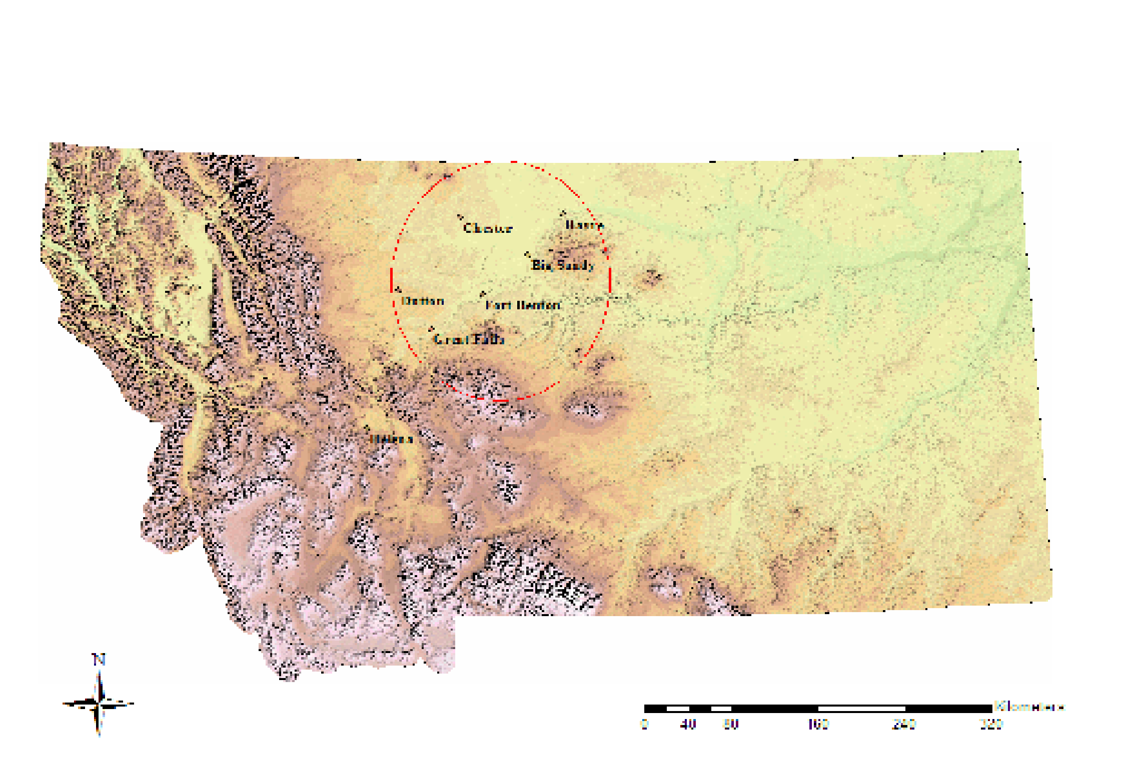

Figure 4.1. Geographic location of the remote sensing cropland validation study (within red circle), Montana, USA. Map colors reflect elevation gradients, ranging from gentle lowland prairies in the East, to the more mountainous regions of the West.

Dryland wheat is the primary export within north central Montana, with market price and weather conditions driving the decision to plant spring or winter wheat. Barley, oat, pea, lentil, flaxseed, camelina, safflower, and canola might occasionally be planted to target alterative markets but have contributed to a minute proportion of total cropped hectares (CTIC, 2004). A wheat-fallow rotation is common throughout the region; continuous cropping is rarely implemented and is considered by many producers to be risky due to unreliable late spring and early summer precipitation.

Four regional subsets were identified for the analysis of crop and fallow patterns (Figure 4.2). This step was necessary to minimize computational problems associated with data size. Cropland data located outside of the sub-regional analysis was excluded through a spatial mask. These subsets were located near Dutton (18,500 ha), Chester (11,250 ha), and Great Falls (13,014 ha) and between Big Sandy and Fort Benton (7,646 ha) (Figure 3.2). Chester was chosen as it represented a drier climate within the 2004-2007 period (~250 mm) while Great Falls represented a relatively wetter climate (~390 mm) (HPRCC, 2008). Annual precipitation in the Dutton and Big Sandy/Fort Benton areas was more moderate (~290-320 mm).

Estimation of Regional Cropland Land Use Management

2007 Cropland Survey. An estimate of regional cropland land management was established based on reference field information collected in early June 2007. Site locations were randomly identified throughout the region. The final data collection points were chosen based on their proximity to public roadways to avoid land access issues. Collected reference field information included vegetative status (cropped or fallow), crop type, and tillage management (tilled or NT). The decision to classify fields as either till or NT stemmed from National Carbon Offset Coalition (NCOC) C contract specifications. The determination of tillage management within a field included an examination of stubble position (stubble in a NT field should generally be in a relatively upright position), soil surface disturbance, and the establishment of soil surface crusts. It was noted that many of the fields classified as tillage had high levels of surface residue but also showed indication that there had been surface disturbance between the stubble rows.

Verbal communication with farmers throughout the region confirmed that conservation tillage, where only a light tillage is incorporated prior to planting for residue management purposes, is often used on a one-pass basis. The relative date of tillage was not established, but was expected to have great spatial (within-region) and temporal variability and was influenced by personal decisions, weather conditions, and crop type. This level of disturbance can be relatively minimal but would still be considered “tillage” under NCOC C contract agreement definitions (NCOC, 2008). Conservation reserve information was obtained by randomly selecting samples from CRP data provided by the MFSA. Conservation reserve parcels within the region were primarily observed as having been planted into a mix of alfalfa and grass. The resulting 2007 cropland data set included information for 78 NT-fallow, 138 NT-cropped, 48 tilled-fallow, 148 tilled-cropped, and 113 CR field sites.

Satellite-based Analyses Regional, site-specific, land use statistics for tillage, CR, and crop intensity were established through a satellite image-based classification. Non-agricultural lands were excluded from analysis through a series of data masking procedures; data provided by the MFSA were used to remove land under CRP contract from the cropland tillage classifications. Classification models were built using 2007 data collected through the cropland field survey (Table 4.1). The classifications were based on field objects to eliminate the possibility of mixed land-use predictions within management units. A detailed description of the satellite-based land-use analysis is provided in Chapter 3.

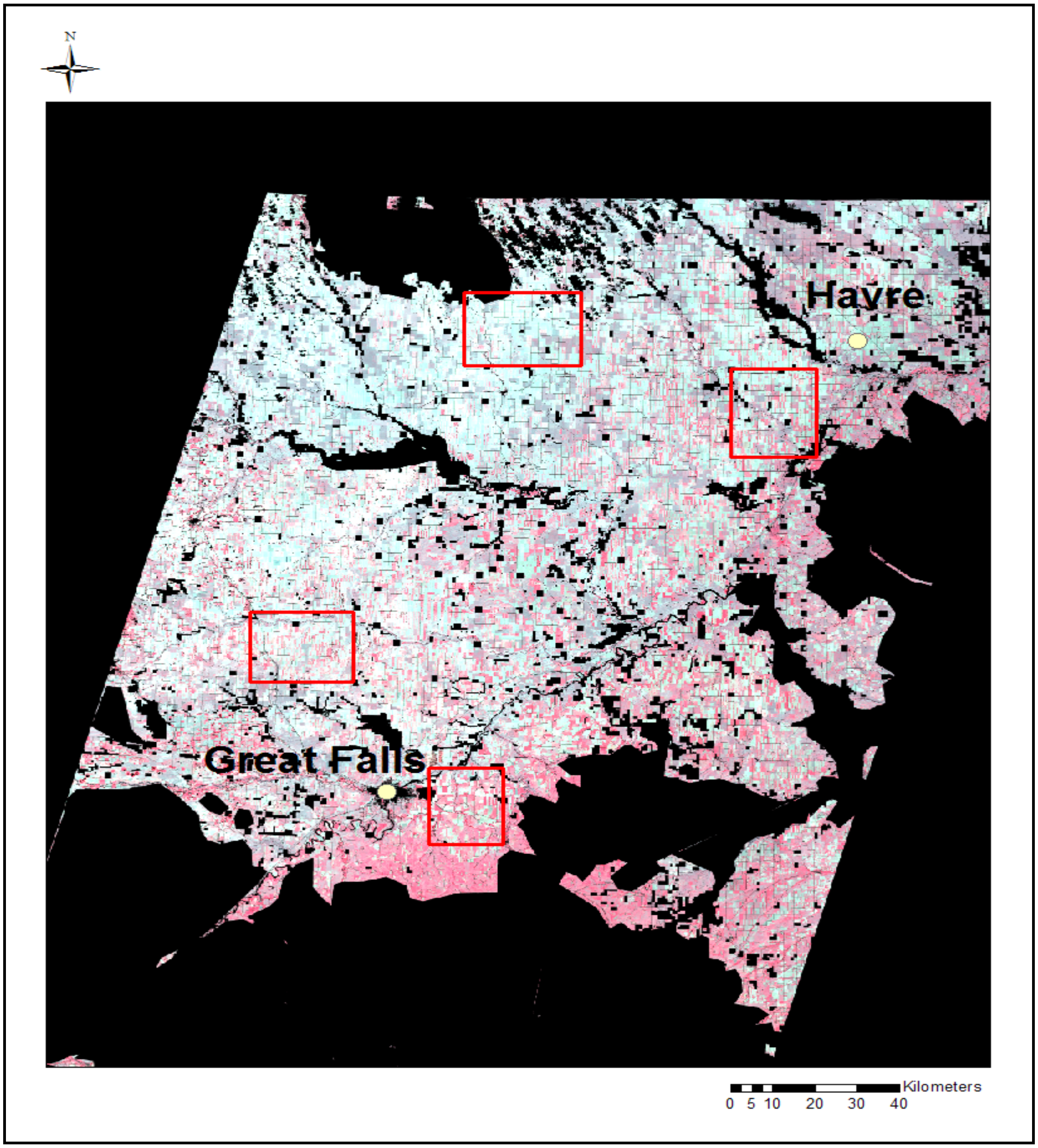

Figure 4.2. A 2007 Landsat TM image scene displaying north central Montana cropland. Data subset locations (outlined in red) used for identifying crop and fallow practices from 2004-2007, and included cropland near Chester, Big Sandy/Fort Benton, Dutton, and Great Falls.

Model	Overall Accuracy	Classification Matrix			Producer's	User's
No-Till & Tillage			**NT**	**Till**	**NT**	**Till**
May Object-based	71%	**NT**	160	14	91%	71%
		Till	63	29	31%	67%
Crop & CR			**Crop**	**CR**	**Crop**	**CR**
May Object-based	97%	**Crop**	304	0	100%	96%
		CR	12	115	90%	100%
Crop & Fallow			**Crop**	**Fallow**	**Crop**	**Fallow**
August Object-based 07	91%	**Crop**	178	10	95%	93%
		Fallow	12	55	82%	84%
September Object-based 06	96%	**Crop**	80	5	94%	95%
		Fallow	4	122	96%	96%
September Object-based 05	93%	**Crop**	68	5	93%	93%
		Fallow	5	65	92%	92%
July Object-based 04	93%	**Crop**	103	8	93%	93%
		Fallow	7	105	93%	93%

Table 4.1. Classification accuracy for tillage, CR, crop and fallow satellite image-based models.

Survey-based Tillage Management Estimates The decision was made to estimate the percentage of land-use area under NT and tillage by means of the 2007 field survey due to the high degree of error within the image-based NT and tillage classifications. Confidence intervals (95%) were applied to each percentage estimate according to standard procedures for the statistical analysis of sample proportions (Moore, 2004). It was assumed that these data were unbiased as they were collected based on random selection. The elimination of sites not accessible from roads was not believed to induce bias with respect to any management practices. The resulting percentages were then multiplied by the total cropped hectares analyzed within the May satellite-based cropland classifications following the exclusion of cropland parcels having been classified as CR (occurring outside of CRP contract) to obtain land-area estimates for tillage and NT.

Carbon Sequestration Estimates

Relevant research was reviewed for reported C sequestration rates pertaining to the conversion from tillage to NT, tillage to NT as influenced by crop intensity, and the conversion from cropland to CR. Only C sequestration data based directly on physical measurements, as opposed to model estimated data, were included in the review. Research reports of C sequestration data selection were narrowed by including only those reflecting climatic regimes similar to that of north central Montana. Data from CR were also extended to include those pertaining to areas under higher annual precipitation, as climatically similar studies were not identified. Selected data were primarily taken from studies that established sequestration rates by comparing baseline SOC data with C measurements taken after management conversion. Rates based on side-by-side comparatives, where one location was kept under tillage while a neighboring location had switched to NT management, were also included if they provided information directly relevant to the study area.

The final selection included nine studies having identified C sequestration rates associated with the conversion from tillage to NT (Table 4.2) and three studies that established SOC sequestration rates resulting from the conversion from cropland to grassland-based CR (Table 4.3). Prior cropland management for parcels evaluated within the tillage studies included some degree of summer fallowing and the planting of various crop types. Tillage implements used for cultivation purposes in "tilled" treatments within these studies reportedly included tandem disk, sweeps and rod weeder, chisel plough and mounted harrow. Data taken from these studies often represented C measurements at variable depths. Carbon data was constrained within the 0-30 cm soil depth, as the studies' analyses most often included this range. This step likely resulted in a more conservative estimate of area-based total soil C sequestration potential, as higher C amounts are expected when taking into account a greater measurement depth.

It was sometimes necessary to convert selected data from a weight-based to an area-based estimate (e.g., multiplying g C by soil density) before final C sequestration estimates could be established. Carbon sequestration rates were then averaged according to management and rotation type, with consideration taken for climate and textural similarities. A formal meta-analysis (Arnqvist and Wooster, 1995) was not attempted due to an overall lack of test statistics within individual studies. Rates reflecting C increase in fields switching from conventional tillage to NT while maintaining a continuous crop, and for fields having converted from minimal tillage (MT) to NT under various degrees of crop intensity, were not identified within the available literature.

Estimates of expected C sequestration rates pertaining to changes in tillage and rotation management also were acquired through use of a generalized C-Gain equation (McConkey et al., 1999) due to a lack of published data directly related to SOC gains resulting from minimal tillage to NT management change. Sequestration rates provided for use within the equation were based on an analysis of various tillage and crop rotation systems within the Canadian Great Plains. Carbon-Gain (C-Gain) estimates associated with the Brown and Dark Brown Canadian soil climatic zones were used, as they represented more conservative C sequestration rates and corresponded most closely with soil characteristics found in the wheat growing regions of north central Montana. Rates associated with a medium soil texture were also selected for use within the equation, as was recommended for calculations involving large areas of land (McConkey et al., 1999).

Six scenarios were evaluated using the generalized C-Gain equation. This equation was used to provide sequestration rates associated with conversion from conventional tillage to NT for purposes of comparison with the literature-based estimates, and to provide an estimate for C sequestration in fields having changed from minimum tillage to NT. Estimates were calculated for conventional tillage to NT systems with crop intensity changes of 0.5 (5 of 10 yrs cropped as opposed to fallow) to 1.0 (continuous crop), 0.75 to 1.0, and for tillage to NT without a change in crop intensity. Estimates also were made for MT to NT under a 0.5 to 1.0 and a 0.75 to 1.0 rotation, and without a change in intensity. Conventional tillage management was defined as a system where both fall and spring tillage occurred, resulting in 100% surface disturbance (McConkey et al., 1999). No-till was described as a system using both tillage and herbicides for weed control, but not including fall tillage, and where 50% surface disturbance does not occur more than once during the spring. Calculated sequestration rates did not reflect system changes in fertilization rates or landscape type.

Regional C estimates associated with the conversion of cropland to NT or tillage management as influenced by crop intensity, or the conversion of cropland to CR-based management, were obtained by multiplying sequestration rates (derived from both the literature and the generalized C-Gain calculations) by the total estimated hectares under each management type. The broad-scale sequestration rates supplied by the CCX (CCX, 2008a; CCX, 2008b) were also evaluated and applied to obtain CCX-based regional sequestration estimates for the conversion from tillage to NT and the conversion from cropland to CR. Land-use area for NT and tillage used to estimate regional C were those derived from the 2007 field survey.

Three different scenarios were reflected within the tillage-based sequestration estimates. The first regional C sequestration estimate was based on the assumption that all "tilled" land was under a more traditional management system characterized by intensive soil disturbance. The second scenario was based on the assumption that all "tilled" land was under a reduced tillage management. The third scenario represented the average sequestration amounts of both estimates for the intensive tillage and the reduced tillage scenarios. Literature-based rates (those not incorporating negative sequestration amounts) were used to represent changes from intensive tillage to NT, within the averaged cross-tillage estimates.

Study	Location	Mean Annual Precip. (cm)	Mean Annual Temp. (°C)	Climate	Soil Texture	Management Comparison	Years Since Mgmt. Change	Sampling Depth (cm)	Total SOC Seq. (g/m^2)	~ Rate ($g/m^2/yr$)
No-Till										
1. Black and Tanaka (1997)	South Central North Dakota	40	5.0	CT	SiL	Till to NT-SW/F	6	0-15	-23	-3.8
					SiL	Till to NT SW/WW/SF			14	2.4
2. Bricklemyer (2003)	North Central Montana	26	5.0	CS	SL	Till vs. NT-W/F	7	0-10	186	Avg. 26.5 (15.7-47.1)
		36	7.5		CL, C	Till vs. NT-W/F	6		371	Avg. 61.8 (36.6-96.6)
3. Campbell et al. (2001)	Saskatchewan	42	2.0	CT	C	Till to NT-W/F	10	0-15	393	39.3
						Till to NT- F/W/W			521	52.1
						Till to NT-W/W/W			195	19.5
4. Halvorson et al. (2002)	South Central North Dakota	41	12.0	CT	SiL	Till to NT-SW/WW/SF	12	0-30	140	11.6
					SiL	Till to NT-SW/F			-190	-15.8
5. McConkey et al. (2003)	Saskatchewan	33	3.3	CS	SL	MT vs. NT-W/W,W/F	11	0-15	340	31.0
					SiL	MT vs. NT-W/W,W/F	12		180	15.0
					C	MT vs. NT-W/W,W/F	11		410	37.0
6. Sainju et al. (2007)	North East Montana	36	~ 6.0	CS	SL	NT-SW/SW vs. FST-SW/SW	21	0-21	170	8.1
7. West and Six (2007), Aase and Pikul (1995), Black (1973)	North East Montana	36	~ 6.0	CS	SL	Till to NT-SW/B	9	0-9	-	37.5-45.0

Table 4.2. Carbon sequestration rates for the conversion from tillage-based cropland to no-till (NT), and tillage-based cropland to NT as influenced by crop intensity (key is shown following Table 4.3). Studies reflect cropland management that had included some degree of summer fallowing prior to treatment initiation (most often a 0.5 crop intensity).

Study	Location	Mean Annual Precip. (cm)	Mean Annual Temp. (ºC)	Climate	Soil Texture	Comparison Type	Years Since Mgmt. Change	Sampling Depth (cm)	Total SOC Seq. (g/m^2)	~ Rate ($g/m^2/yr$)
CRP										
8. Burke et al. (1995)	North East Colorado	36	16	CT	SiL, SiCL	Till to CR	53	0-10	82-200	3.1
9. Gebhart et al. (1994)	Kansas	53	12	CT	SiL	Till to CR	5	0-15*	47	9.3
10. Post and Kwon (2000), White et al. (1976)	North Central South Dakota	~58	~15	CT	No Data	Till to CR	8	0-7	148	18.5

Table 4.3. Carbon sequestration rates for the conversion from cropland to conservation reserve (CR) (key is shown below). *Depths were adjusted to reflect shallow surface measurements, as are presented within the other literature referenced here.

Key for Tables 4.2 & 4.3

Tillage Management Type	Climate Type	Soil Texture	Crop Type	
NT = No-till	CS = Cool, Semi-arid	SiL = Silt Loam	B = Barley	SW = Spring Wheat
MT = Minimum Till	CSH = Cool, Sub-humid	SL = Sandy Loam	CR = Grassland Conservation Reserve	WW = Winter Wheat
FST = Fall and Spring Conventional Tillage	CT = Cool, Temperate	L = Loam	GM = Legume Green Manure	W = Wheat (undefined)
		CL = Clay Loam	SF = Sunflower	
		C = Clay		

Results

Cropland Statistics

The satellite-based image analysis (Table 4.4) identified 24% of the study area as being under grassland-based CR management as opposed to cropland (Figure 4.3). Data from the MFSA had indicated that only 2% of the study area was under CRP contract. Classification results also predicted that 18% of the evaluated cropland was under some form of tillage-based management in 2007 while 82% was under NT (Table 4.4). The resulting NT classifications were likely in error due to a high percentage of tillage being misclassified as NT. The 2007 cropland field survey results estimated that 56% of the evaluated region had practiced NT management in 2007, while 44% had incorporated some other form of tillage management during 2007. Systems under a 0.5 crop intensity (2004-2007) included 66% of the cropland area analyzed (Table 4.5), 29% was under a 0.75 crop intensity, and 5% was under a 1.0 crop intensity. There appeared to be no connection between crop intensity and localized MAP within the regional subsets.

Cropland Carbon Sequestration Estimates

The average sequestration rate reported for land converted from cropland to perennial CR management (specifically grass/legume cover) was 10 g C m^{-2} yr^{-1}, reported for depths in the 0-15 cm range. The highest reported sequestration rate for CR occurred within South Dakota (Gebhart et al., 1994), in an area with higher precipitation and more moderate MAT. The lowest (Burke et al., 1995) occurred in a more arid portion of Colorado.

Image Classifications			Roadside Survey			
Management Type	**Hectares**	**%**	**Hectares**	**95% CI**	**%**	**95% CI**
NT vs. Tillage						
NT	434,970	82	296,261	269,809-322,713	56	51-61
Tillage	94,067	18	232,776	118,504-259,228	44	40-49
Total Land Area	529,037	100	529,037	-	100	-
Crop Intensity						
0.5	33,249	66	-	-	-	-
0.75	14,820	29	-	-	-	-
1.0	2,344	5	-	-	-	-
Total Land Area	50,413	100	-	-	-	-
CR vs. Cropland						
Grassland-based CR	188,549	24	-	-	-	-
Cropland	590,898*	76	-	-	-	-
Total Land Area	779,447	100	-	-	-	-

Table 4.4. 2007 cropland tillage and grassland-based conservation reserves (CR) statistics. Land use data for tillage and no-till (NT) were derived from satellite-based image analyses and the 2007 roadside survey results; CR data were derived solely from satellite-based image analyses. Crop intensity estimates were only made for select areas within the region. Total land area within the CR analyses is the sum of total evaluated cropland and Conservation Reserve Program (CRP) hectare information provided by the Montana Farm Service Agency. * Hectare-based totals for cropland within the CR classification are greater than total hectares within the tillage-based classification resulting from the misclassification of some CR as cropland.

	Regional Crop Intensity Estimates		
Management Type	**0.5**	**0.75**	**1.0**
NT	195,532 (178,074-212,991)	85,916 (78,213-93,587)	14,813 (13,490-16,136
Tillage	153,632 (139,666-171,090	67,505 (61,368-75,176)	11,639 (10,581-12,961)

Table 4.5. Crop intensity estimates, derived from applying image classification-based crop intensity percentages (see Table 4.4) to total land area by tillage type (tilled or no-till (NT)).

Sequestration rates reported from Saskatchewan, North Dakota, and Montana (Table 4.2) show a wide range of potential C sequestration associated with the conversion from to NT. The averaged rate was 24 g C m^{-2} yr^{-1} in systems where the change to NT included a 0.5 crop rotation (Table 4.6); this rate increased considerably (38 g C m^{-2} yr^{-1}) when excluding the negative sequestration rates reported by two North Dakota studies, both under a spring wheat/fallow rotation (Black and Tanaka, 1997; Halvorson et al., 2002). Only one study reflected C sequestration estimates for a more intermediate crop intensity. The rate for a fallow/wheat/wheat system (0.67 crop intensity) was reported at 52 g C m^{-2} yr^{-1}(Campbell et al., 2001). The degree to which this solitary observation represents this level of crop intensity is unknown due to a lack of additional studies having evaluated similar rotations within the region.

The literature-based results also showed that converting from a more intensive tillage-based management (under a 0.5 crop intensity, or crop/fallow rotation) to a NT system with a 1.0 crop intensity sequestered an average of 23 g C m^{-2} yr^{-1} (Table 4.6). The highest reported sequestration rates within either crop intensity occurred under a wheat/fallow system and a spring wheat/barley system in north central Montana (Bricklemyer, 2003).

Sequestration rates associated with the C-Gain equations (Table 4.7) were slightly higher than the literature-based estimates and did not account for the possibility of C loss associated with management change. Systems converting from a more heavy tillage to NT while also switching from a 0.75 to a 1.0 or a 0.5 to a 1.0 crop intensity were estimated to sequester around 30 and 40 g C m^{-2} yr^{-1} (McConkey et al., 1999). Increased C sequestration associated with the conversion from MT to NT was estimated to be 20 g C m^{-2} yr^{-1} for systems also converting from 0.75 to 1.0 crop intensity and 30 g C m^{-2} yr^{-1} in systems converting from 0.5 to 1.0 (McConkey et al., 1999).

Management Change		**SOC Sequestration Rate (Ave.)**	**Min. Rate**	**Max. Rate**
		g m^{-2} yr^{-1}	g m^{-2} yr^{-1}	
Till to Grassland-based CR		10.3	3.1	18.5
Till to NT w/ Fallow	A	24.0	-15.8	61.8
	B	37.5		
Till to NT w/o Fallow	A	23.0	2.4	45.0
	B	-		
Till to NT (Avg. Across Rotation)	A	23.5	-6.7	53.4
	B	37.5		

Table 4.6. Reported carbon sequestration rates associated with changes from tillage to no-till (NT) management, and from cropland to conservation reserve (CR) management. “A” denotes averages having included negative sequestration rates and “B” denotes the exclusion of negative sequestration rates.

Management Change		**Δ SOC**
Tillage Type	**Crop Rotation**	(g m^{-2} yr^{-1})
Till to NT	no change	20
	0.75 to 1.0	30
	0.5 to 1.0	40
MT to NT	no change	10
	0.75 to 1.0	20
	0.5 to 1.0	30

Table 4.7. Carbon sequestration estimates associated with changes in tillage and crop rotation management as estimated through a C-Gain equation (McConkey et al., 1999).

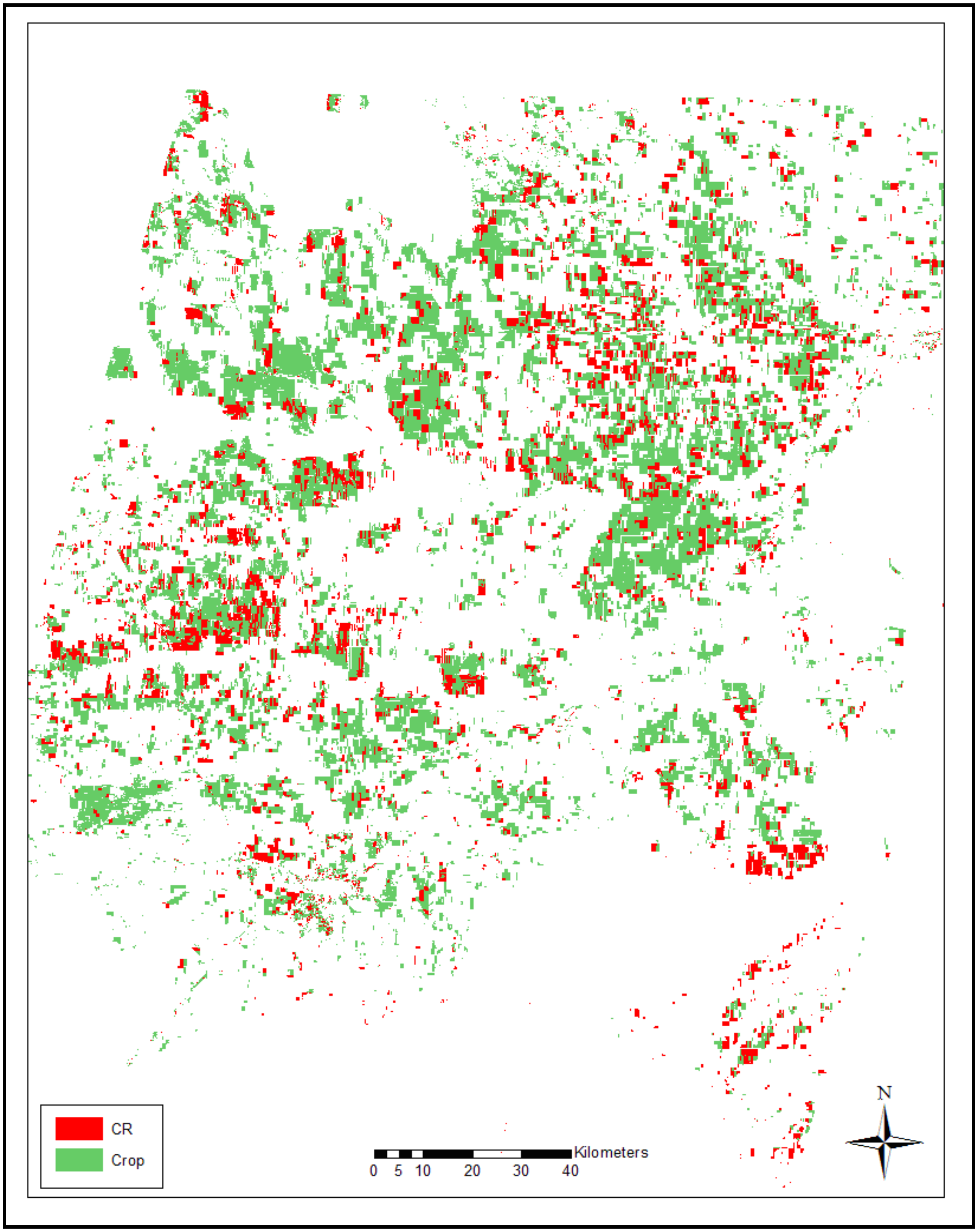

Figure 4.3. Classified conservation reserve (CR) (red) and crop (green) in 2007 within north central Montana.

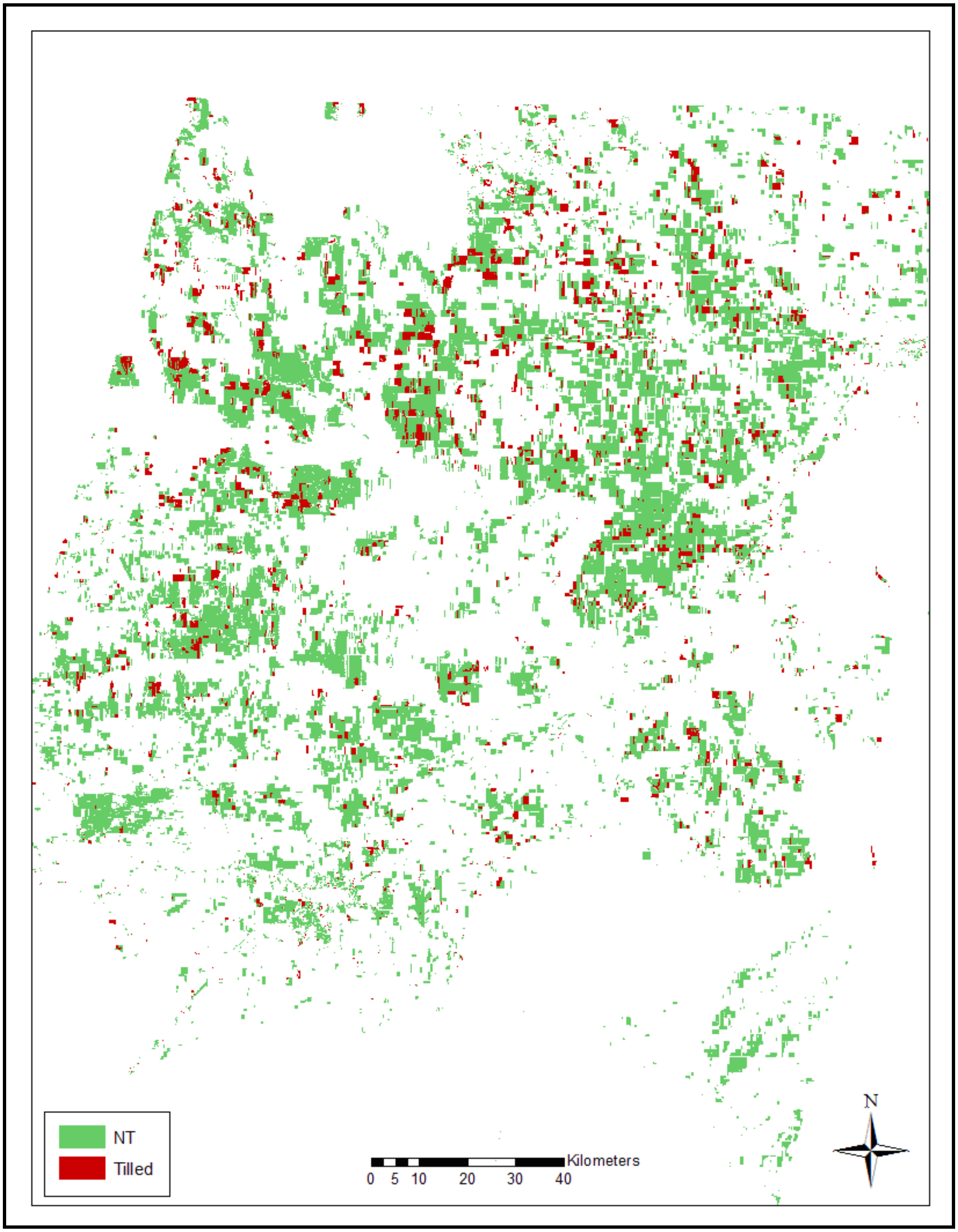

Figure 4.4. Classification map for tillage (red) and no-till (NT) (green) within north central Montana in 2007. The high percentage of NT is attributed to the misclassification of tillage as NT (see Table 4.1).

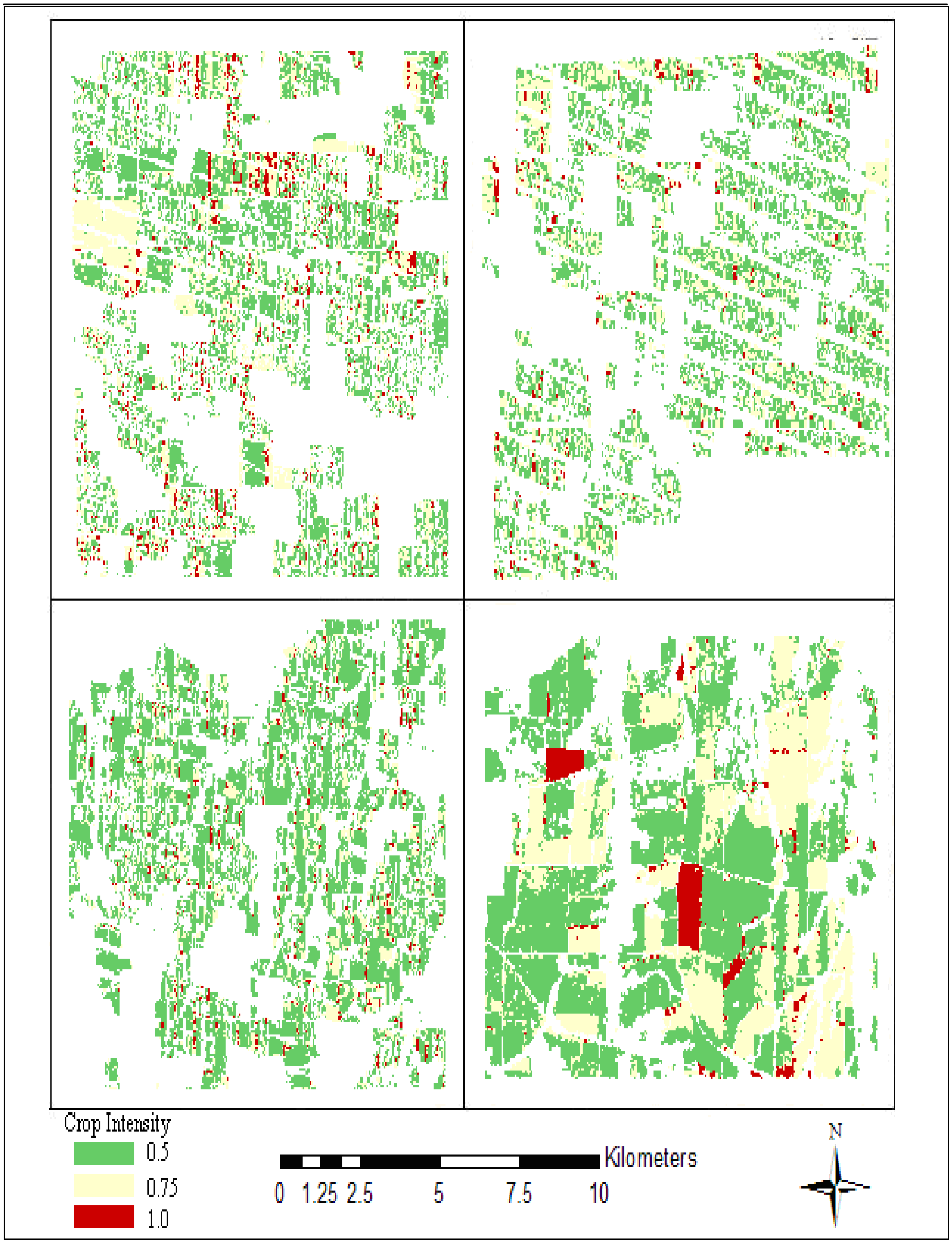

Figure 4.5. Crop intensity (2004-2007) classifications for the Chester (top left), Big Sandy and Fort Benton area (top right), Dutton (bottom left), and Great Falls (bottom right) areas.

Regional Carbon Estimates

The difference between CRP data provided by the MFSA and the image-based CR classifications provided an estimate that 174,199 ha cropland was under perennial grass/legume vegetation, outside of 2007 CRP contract agreements (Table 4.4; Table 4.8). The conversion of this land to perennial grass/legume vegetation was estimated to have provided an additional 17,420 t C yr^{-1} (Table 4.9). A much larger sequestration estimate (116,713 t C yr^{-1}) resulted from using the CCX broad-scale rate associated with the conversion from cropland to CR.

Based on land-use and sequestration rate estimates, the universal change to NT and a 1.0 crop intensity within the study area would sequester approximately 59,497 (54,089-66,258) t C yr^{-1} (Table 4.12), averaged across tillage management type (semi-intensive tillage and MT). If this universal conversion represented all tillage management as previously having been under a more intensive tillage, then sequestration might be 57,239 (52,036-63,744) t C yr^{-1} (Table 4.10). If the universal conversion represented all tillage management as previously having been under MT, the resulting sequestration is estimated to be 60,755 (55,232-67,658) t C yr^{-1} (Table 4.11). The lower sequestration estimate for the conversion from semi-intensive tillage to NT reflects the incorporation of mainly literature-based estimates; these estimates were lower than the C-Gain estimates when considering an increase in crop intensity.

Sequestration estimates for the conversion from a semi-intensive tillage management to NT while maintaining 0.5 crop intensity, according to literature-based rates, were 55,866 t C yr^{-1} (including negative values into the rate estimate) and 87,291 t C yr^{-1} (excluding negative values from the rate estimate). The CCX-based sequestration estimate for the universal conversion from a tillage-based system to NT regardless of crop intensity was 51,211 (46,555-57,030) t C yr^{-1} (Table 4.12), slightly lower than both the literature and C-Gain-based sequestration estimates.

Management Type	Rate (t C ha^{-1} yr^{-1})	Land Area (ha)	Δ SOC (t yr^{-1})	Referenced Table (Studies Footnoted)
Crop to CR	0.10	188,549	18,855	4.3 [8,9,10]
	0.67		126,328	CCX, 2008b

Table 4.8. Estimated carbon sequestration potential (2007) within north central Montana for the conversion of cropland to grassland-based conservation reserve (CR). These lands include those within the CRP program and "other" grasslands having characteristics similar to those within CRP. See Tables 4.4 and 4.5 for land area calculations. [8] Burke et al. (1995), [9] Gebhart et al. (1994), [10] White et al. (1976).

Management Type	Rate (t C ha^{-1} yr^{-1})	Land Area (ha)	Δ SOC (t yr^{-1})	Referenced Table (Studies Footnoted)
Crop to CR	0.10	174,199	17,420	4.3 [8,9,10]
	0.67		116,713	CCX, 2008b

Table 4.9. Regional carbon estimates associated with grassland-based conservation reserve (CR) within north central Montana having occurred independent of 2007 CRP program contracts. [8] Burke et al. (1995), [9] Gebhart et al. (1994), [10] White et al. (1976).

Management Type	Crop Intensity Adjustment	Rate ($t\ C\ ha^{-1} yr^{-1}$)	Land Area (ha)	Δ SOC ($t\ yr^{-1}$)	Referenced Table (Studies Footnoted)
Till to NT	0.5 Crop (No Δ in Intensity)	0.24	232,776 (211,615-259,228)	55,866 (50,788-62,215)	4.3 [1,2,3,4,6]
		0.38**		88,455 (80,414-98,507)	4.3 [2,3,6]
	Δ from 0.75 to 1.0 (Avg. Across Intensity)	0.26	67,505 (61,368-75,176)	17,551 (15,956-19,546)	4.3 [1-7]
		0.29**		19,576 (17,797-21,801)	4.3 [1-7]
	Δ from 0.5 to 1.0	0.23	153,632 (139,666-171,090)	35,335 (32,123-39,351)	4.3 [1,3,4,7]
		-		-	-
	Δ from 0.5 to 1.0	0.40		61,453 (55,866-68,436)	4.4 [11]
	Δ from 0.75 to 1.0	0.30	67,505 (61,368-75,176)	20,252 (18,410-22,553)	4.4 [11]
	No Δ in Intensity*	0.20	11,639 (10,581-12,961)	2,328(2,116-2,592)	4.4 [11]

Table 4.10. Estimated carbon sequestration potential within north central Montana for cropland converting from a heavy tillage management to no-till (NT). * Represents a change from till to NT while keeping a 1.0 crop intensity. ** Indicates the exclusion of negative sequestration rates. [1] Black and Tanaka (1997), [2] Bricklemyer (2003), [3] Campbell et al. (2001), [4] Halvorson et al. (2002), [5] McConkey et al. (2003), [6] Sainju et al. (2007), [7] West and Six (2007), [7] Pikul and Aase (1995), [7] Black (1973), [11] McConkey et al. (1999).

Management Type	Crop Intensity Adjustment	Rate ($t\ C\ ha^{-1}\ yr^{-1}$)	Land Area (ha)	Δ SOC ($t\ yr^{-1}$)	Referenced Tables
MT to NT	No Δ in Intensity*	0.10	11,639 (10,581-12,961)	1,164 (1,058 - 1,296)	4.4
	Δ from 0.75 to 1.0	0.20	67,505 (61,368 - 75,176)	13,501 (12,274 - 15,035)	4.4
	Δ from 0.5 to 1.0	0.30	153,632 (139,666 - 171,090)	46,090 (41,900 - 51,327)	4.4

Table 4.11. Estimated carbon sequestration potential (McConkey et al., 1999) within north central Montana for cropland converting from minimum till (MT) management to no-till (NT). * Represents the change from MT to NT while keeping a 1.0 crop intensity. See Tables 4.4 and 4.5 for land area calculations.

Management Type	Crop Intensity Adjustment	Rate (t C ha^{-1} yr^{-1})	Land Area (ha)	Δ SOC (t yr^{-1})	Referenced Table
Till to NT (Averaged Across Tillage Management Type)	No Δ in Intensity*	0.23	11,639 (10,581 - 12,961)	2,677 (2,434-2,981)	4.10, 4.11
	Δ from 0.75 to 1.0	0.25	67,505 (61,368 - 75,176)	16,876 (15,342-18,794)	4.10, 4.11
	Δ from 0.5 to 1.0	0.26	153,632 (139,666 - 171,090)	39,944 (36,313-44,483)	4.10, 4.11
	Intensity not considered	0.22**	232,776 (211,615 - 259,228)	51,211 (46,555-57,030)	CCX,2008a

Table 4.12. Estimated carbon sequestration potential within north central Montana for cropland converting from tillage to no-till (NT), averaged across tillage management type. * Indicates the change from till to NT while maintaining current crop intensity. ** The CCX-based rate represents the broad-scale conversion from various degrees of tillage management to NT. See Tables 4.4 and 4.5 for land area calculations.

Discussion

Cropland soils have the potential to store additional C through management changes, including conversion from tillage-based to NT systems, converting cropland to CR, and increasing cropping intensity. Carbon trading programs such as the CCX provide financial incentives for cropland management change. North central Montana has been identified by the CCX as a region acceptable for inclusion within the cropland soil C trading scheme. A lack of cropland statistics has made it difficult to determine what percentage of the region is already under NT and CR-based management and what proportion currently practices continuous cropping. The potential of north central Montana to sequester additional C through the incorporation of these management practices has not been previously established.

Land-Use Statistics

Cropland Land-use data for this portion of north central Montana shows potential for an increased conversion to NT tillage management and higher degrees of crop intensity. This study estimated that in 2007, 56% of the cropland in north central Montana evaluated within this study was under NT and 44% were still under some form of tillage management. Currently only 5% of the evaluated cropland had incorporated a 1.0 crop intensity. Conservation tillage statistics for 2004 estimated that 37% of this region was under NT and 63% were under some form of tillage-based management (CTIC, 2004). Differences between these statistics suggest that NT has quickly become the new "convention", replacing traditional tillage systems. These differences also might have resulted from inaccuracy within the CTIC estimates.

The field survey conducted within this study did not separate fields under semi-intensive tillage from those under a MT management, as it adhered to a simple "tillage" or "NT" classification as defined by NCOC C-contract agreement guidelines. The separation of different degrees of tillage management would have proven valuable, in hindsight, as it would have allowed for the determination of land area under a semi-intensive tillage or MT. Regional C estimates could then have been adjusted accordingly. Crop intensity percentage estimates were not greater in sub-regions with higher MAP. It was expected that the Great Falls area would have had a greater proportion of cropland under continuous rotation (1.0 crop intensity) and that Chester, a notably drier area, would have had the least amount of land under a 1.0 rotation, but study results showed that these areas did not differ greatly (5% Great Falls, 7% Chester), with Chester being slightly higher than Great Falls. The Dutton and Big Sandy/Fort Benton areas were found to have the highest percentages of crop-fallow (77 and 70%, respectively), although annual precipitation in these areas was between that of Chester and Great Falls. These findings show that the decision to incorporate a higher cropping intensity might often be subject to a greater influence by cultural practices than by localized annual precipitation. Offering financial incentives through C credit payments for reduced fallow might facilitate a greater percentage of this region to implement increased crop intensity. Carbon credit payments presumably would have to be high enough to offset financial risks associated with yearly cropping within a dryland setting.

Conservation Reserve An estimated 24% of the evaluated region was under a grassland-based CR management in 2007, 22% greater than the area shown to be under CRP contract with the MFSA. This percentage reflects observations noted during field data collection, where 16% of lands designated as cropland appeared to be in some form of "unmanaged" grassland state. It is likely that many of these parcels had previously been under CRP contract but were not re-incorporated into cropland following contract termination for reasons unknown, or had recently been implemented into the program but were not yet reflected within the CRP database. A portion of these parcels might have voluntarily adopted CR management outside of the CRP program, possibly because openings into the CRP program were not available at that time. There is some likelihood that these parcels might have been under contract with the Conservation Security Program (CSP), a government-sponsored program to promote land conservation. Land under the CSP program would not have been reflected within the CRP statistics. It is unlikely that the percentage of land removed from crop production within this region will ever be substantially higher than the current percentage unless financial gains associated with the incorporation of cropland into CR became higher than profits resulting from crop production.

Regional Cropland Sequestration

The regional analysis of C sequestration potential represents a rough estimate at best. It is estimated that the evaluated portion of north central Montana might sequester around 59,497 t C yr^{-1} through the universal adoption of NT practices and a 1.0 crop intensity. This number roughly equates to the amount of C (in the form of CO_2) emissions released annually by 145,569 cars (Schiermeier, 2006). The conversion of this cropland to NT management under a 1.0 crop intensity, and the maintaining of land currently under CR management within this relatively small percentage (11%) of Montana cropland has the ability to sequester 0.63 % of the projected annual CO_2 equivalents emitted by the District of Columbia, USA (DC-AQD, 2005).

The C sequestration estimates associated with the conversion to NT, increased crop intensity, and CR are not static, and are expected to decrease in the years following management change. There is much uncertainty concerning the duration of C sequestration following alterations in cropland management. A system having converted from tillage to NT was predicted to peak 5-10 yr following the change, reaching equilibrium after 15-20 yr (West and Post, 2002). Another estimate has predicted that a change from tillage to NT will sequester C at a constant rate for 20 yr, followed by a steadily decline in net C gains for 20 yr before reaching equilibrium (Marland et al., 2003). The duration of C sequestration is expected to be less in systems that have not undergone significant SOC losses; hence a system converting from intensive tillage to NT is expected to have greater potential for C storage than a system converting from reduced tillage to NT. Further research is needed to quantify the amount of time that sequestration might occur under different cropland systems as knowledge in this area is generally lacking.

Site-specific C sequestration rates are expected to be both a product of climate and biophysical conditions. Differences in C sequestration amounts might also result from variations in seeding rate, time of seeding, the type of planting equipment used, and other aspects of cropland management. Current knowledge has identified certain management practices warrant consideration for the optimization of SOC storage (Lal et al., 1998), although uncertainty remains concerning the physical and biological controls over SOC storage potential and the degree to which each influences C storage. These include optimal fertilizer management, the incorporation of organic manures (Sommerfeldt et al., 1988), crop varieties and crop rotation systems (Kruminsky et al., 2007; Miller et al., 2002; Beck et al., 1998), the elimination of summer fallow (Li and Feng, 2002; Paustian et al., 2000, Lyon et al., 1998).

The elimination of summer fallow might be of particular importance as one study (Li and Feng, 2002) found that total organic C input in systems incorporating fallow must be 1.5 times that of systems under continuous cropping to prevent a decrease in SOC levels. A careful consideration to particular crop rotations suited for semi-arid regions with variable precipitation patterns is essential in facilitating a continuous cropping system that can adequately sustain plant biomass production and manage drought, as might have been reflected within the sequestration rates reported for systems under increased crop intensity.

Considerations for Carbon-Credit Allocations

Tillage Management Sequestration rates used by the CCX for C-credit allocation purposes might not adequately reflect the sequestration potential under some conditions within north central Montana. The literature-based estimates for C sequestration resulting from the change from a semi-intensive tillage system to NT was 16 g C g m^{-2} yr^{-1} higher than the currently assigned CCX rate for systems maintaining a 0.5 crop intensity and 7 g C m^{-2} yr^{-1} higher when considered across various degrees of crop intensity. The difference was only 1 g C m^{-2} yr^{-1} between the literature-based and the CCX estimate for till to NT while also implementing a 1.0 crop intensity. This suggests that the CCX sequestration rate for Region C might under-account for C storage potential in north central Montana associated with the conversion to NT in some cases.

Another limitation of the current CCX-based rate for NT is the lack of distinction in the range of C storage potential that might exist for systems converting from various forms of tillage-based management to NT. Current CCX policy allows for the application of one tillage-to-NT rate and does not adjust C-credits according to previous tillage management history. Research has shown that greater sequestration might result in systems converting from more intensive tillage to NT than in systems converting from MT to NT as C depletion is more prevalent in soils with greater disturbance, resulting in the ability to hold more C before reaching an equilibrium between C input and release due to mineralization.

Concern has also been raised whether the binary separation of tillage management (NT from tillage) is the most appropriate approach to C-credit assignment within the northern Great Plains. Little variation in surface residue amounts and soil disturbance between cropland under NT and other forms of conservation tillage was observed in a study examining the classification of NT lands from other management types based on the spectral reflectance patterns of cropland surfaces (Chapter 3). One study found that cropping implements used in NT systems release the lowest amount of CO_2 following mechanical soil disturbance, followed by those used in a strip tillage system (Reicosky, 2007), however the extent of difference between CO_2 release resulting from NT and strip tillage might vary considerably under different soil conditions and equipment operation. Consideration should also be given to the amount of soil disturbance that might result from seed drills used within NT systems. There is currently a lack of research quantifying differences in C storage that might result from the use of different seeders (disk seeder vs. commercial air drill seeder vs. custom built seeders) within a NT system.

<u>Conservation Reserve</u> The highest-reported sequestration rate identified within the literature was ~0.3 t C ha^{-1} yr^{-1} (White et al., 1976) and was considerably lower than the CCX-based rate (~0.7 t ha^{-1} yr^{-1}). The White et al. (1976) rate reflects an alfalfa system in South Dakota with a MAP of 580 mm. Lands within north central Montana do not often have pure alfalfa crops within a non-cropland setting, and MAP throughout the

region is often much lower (~250-390 mm) than that reported by White et al. (1976). It is thought that the CCX rate currently assigned to land having been converted from cropland to CR within this region might better reflect a system under optimal moisture and nutrient levels. This rate might be unrepresentative of typical CR systems found throughout portions of the semi-arid northern Great Plains, particularly those without routine nitrogen application and subject to drought conditions. Nitrogen is often a limiting factor in SOC increase within CR systems (Purakayastha et al., 2008). Adequate nitrogen management, or the planting of nitrogen-producing legumes, might help increase SOC production within CR systems. This was also reflected within a Saskatchewan study analyzing C storage resulting from the conversion from a tilled fallow system to continuously-cropped alfalfa, where the reported sequestration rate was 0.4 t ha^{-1} yr^{-1} (Wu et al., 2003), closer to that of the CCX rate.

It is also important to recognize that the CCX rate encompasses a regional area spanning over half the US, incorporating many different climatic regions. While the current CCX rate might be appropriate for some regional locations, further thought might be given to the refinement of C rates based on more localized data. The regional C sequestration potential for grassland, reported within this study, likely represents a conservative value as it also includes forms of grassland vegetation that are thought to be less productive than CRP lands, or those were legumes had been incorporated.

Conclusions and Thoughts for Future Policy

A publication by the Canadian Parliamentary Research Branch concerning C markets and agricultural soil emphasized the great difficulty in predicting the value that farmers place on soil C and the degree to which financial incentives need to increase before property owners would consider a land management change (Forge, 2001). The document also made reference to the inability to measure site-specific, annual C sequestration amounts following a management change. These unknowns remain. Further research efforts are needed to quantify the extent that cropland management adjustments can increase C sequestration rates, across variable physical and biological conditions, and will be essential to the refinement of regional C storage potential estimates. Additional data pertaining to SOC flux and land use management will improve the understanding of regional sequestration rate variability. Technological advances in SOC monitoring equipment are needed to allow for the efficient and cost-effective monitoring of C gains on land under C contracts.

Sequestration rates currently being used to estimate cropland C storage for market trading purposes represent broad-scale estimates that might not adequately account for differences in sequestration according to variations in cropland management, as influenced by localized climatic effects, soil type, degree of soil disturbance, and residue input. C-credit markets must make further efforts to address the current state of knowledge within their policies to ensure that contracted C sequestration amounts are accurately represented within the cropland soil environment. Further effort within the scientific community is needed to provide additional C sequestration data within the region, reflecting the possible impact that variations within cropland management (crop rotation type, seeder types and timing of planting, soil disturbance resulting from degrees of tillage, etc.) might have pertaining to C sequestration potential.

Referenced Literature

Aase, J.K., and J.L. Pikul. 1995. Crop and soil response to long-term practices in the northern Great Plains. Agronomy Journal, 87: 652-656.

Abraham, S. 2002. Remarks by Spencer Abraham, Secretary of Energy, U.S. Department of Energy, to the National Coal Council, 21 November 2001. US Department of Energy Archives: Fossil Energy. Last Accessed 2 January 2008 < http://www.fossil.energy.gov/news/speeches/2002/02_sec_ncc_112102.html>.

Arnqvist, G., and D. Wooster. 1995. Meta-analysis: synthesizing research findings in ecology and evolution. Trends in Ecology and Evolution, 10: 236-240.

Baer, S.G., C.W. Rice, and J.M. Blair. 2000. Assessment of soil quality in fields with short and long term enrollment in the CRP. Journal of Soil and Water Conservation, 33: 142-152.

Bayon, R., A. Hawn, and K. Hamilton. 2007. Voluntary carbon markets: an international business guide to what they are and how they work. Earthscan Press, London. 164 pp.

Beck, D.L., J.L. Miller, and M.P. Hagny. 1998. Successful no-till on the central and northern plains. American Society of Agronomy Annual Meeting, 18-22 October 1998. Baltimore, MD. 15 pp.

Benz, U.C., P. Hofmann, G. Willhauck, I. Lingenfelder, and M. Heynen. 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS Journal of Photogrammetry and Remote Sensing, 58: 239-258.

Black, A.L., and D.L. Tanaka. 1997. A conservation tillage-cropping system study in the Northern Great Plains of the United States. E.A. Paul, E.T. Elliott, K. Paustian, and C.V. Cole (Eds.), Soil Organic Matter in Temperate Agroecosystems. CRC Press, Boca Raton, FL., pp. 335-340.

Black, A.L. 1973. Soil property changes associated with crop residue management in a wheat-fallow rotation. Soil Science Society of America Proceedings, 37: 943-946.

Breiman, L. 2001. Random forests. Machine Learning, 45: 5-32.

Bricklemyer, R.S., R.L. Lawrence, P.R. Miller, and N. Battogtokh. 2006. Predicting tillage practices and agricultural soil disturbance in north central Montana with Landsat imagery. Agriculture, Ecosystems and Environment, 114: 210-216.

Bricklemyer, R.S. 2003. Sensitivity of the Century model for estimating sequestered soil carbon using coarse and fine-scale map data sources in north central Montana. M.S. Thesis. Montana State University, Bozeman. 136 pp.

Brown, D.J. 2007. Using a global VNIR soil-spectral library for local soil characterization and landscape modeling in a 2nd-order Uganda watershed. Geoderma, 140: 444-453.

Burke, I.C., W.K. Lauenroth, D.P. Coffin. 1995. Soil organic matter recovery in semiarid grasslands: implications for the conservation reserve program. Ecological Applications, 3: 793-801.

Capalbo, S.M. 2005. Big Sky Carbon Sequestration Partnership phase II: proposal summary and overview. 7 pp.

Campbell, C.A., F. Selles, G.P. Lafond, and R.P. Zentner. 2001. Adopting zero tillage management: impact on soil C and N under long-term crop rotations in a thin Black Chernozem. Canadian Journal of Soil Science, 81: 139-148.

Carter, M.R., and B.A. Stewart. 1996. Analysis of soil organic matter storage in agroecosystems. In Carter, M.R., and B.A. Stewart (Eds.), Structure and Organic Matter Storage in Agricultural Soils. CRC Press, Boca Raton, Fl. pp. 3-11.

Chicago Climate Exchange (CCX). 2008. Soil carbon management offsets. CCX Guidelines : Agricultural Soil Carbon. 2 pp.

Chicago Climate Exchange (CCX). 2008a. CCX agricultural soil carbon sequestration offset project guidelines. CCX White Pages. 26 pp.

Chicago Climate Exchange (CCX). 2008b. CCX agricultural grass soil carbon sequestration offset project guideline. CCX White Pages. 12 pp.

Chicago Climate Exchange (CCX). 2008c. Overview and frequently asked questions: Chicago Climate Exchange offsets for carbon capture and storage in agricultural soils. CCX White Pages. 12 pp.

Cohen, W.B., and S.N. Goward. 2004. Landsat's role in ecological applications of remote sensing. BioScience, 54: 535-545.

Coleman, K., and D.S. Jenkinson. 1996. RothC-26.2-A model for the turnover of carbon in soil. In: Powlson, D.S., P. Smith, and J.U. Smith (Eds.). Evaluation of soil organic matter models using existing, long-term datasets. NATO ASI Series I, vol. 38. Springer, Berlin, pp. 237-246.

Conservation Technology Information Center (CTIC). 2008. Cropland roadside transect survey: procedures for using the cropland roadside transect survey for obtaining tillage/crop residue data. Conservation Technology Information Center, West Lafayette, IN. 20 pp.

Conservation Technology Information Center (CTIC). 2004. Montana cropland conservation tillage statistics by county, 2004. Conservation Technology Information Center, West Lafayette, IN.

District of Columbia Air Quality Division (DC-AQD). 2005. District of Columbia greenhouse gas emissions inventories and preliminary projections. Internal Document prepared by the Bureau of Environmental Quality. 16 pp.

Egbert, S.L., S. Park, K.P. Price, R. Lee, J. Wu, and M. Duane Nellis. 2002. Using conservation reserve program maps derived from satellite imagery to characterize landscape structure. Computers and Electronics in Agriculture, 37: 41-156.

Egbert, S.L., R.Y. Lee, K. P. Price, and R. Boyce. 1998. Mapping conservation reserve program (CRP) grasslands using multi-seasonal Thematic Mapper imagery. Geocarto International, 13: 1010-6049.

Eve, M.D., M. Sperow, K. Paustian, R. F. Follett. 2002. National-scale estimation of changes in soil carbon stocks on agricultural lands. Environmental Pollution, 116: 431-438.

Follett, R.F. 2001. Soil management concepts and carbon sequestration in cropland soils. Soil and Tillage Research, 61: 77-92.

Follett, R.F., and B. McConkey. 2000. The role of cropland agriculture for C sequestration in the Great Plains. In: Proceedings of the Conference on Great Plains Soil Fertility, 8: 1-15.

Forge, F. 2001. Carbon sequestration by agricultural soils. Canadian Parliamentary Research Branch. 13 pp.

Gebhart, D.L., H.B. Johnson, H.S. Mayeux, and H.W. Polley. 1994. The CRP increases soil organic carbon. Journal of Soil and Water Conservation, 49: 488-492.

Halvorson, A.D., B.J. Wienhold, and A.L. Black. 2002. Tillage, nitrogen, and cropping system effects on soil carbon sequestration. Soil Science Society of America Journal, 66: 906-912.

High Plains Regional Climate Center (HPRCC). 2008. Climate summary maps and archived station data. Last Accessed 22 April 2008 < http://www.hprcc.unl.edu/>

Houghton, R.A., and J.L. Hackler. 2000. Changes in terrestrial carbon storage in the United States I: The role of agriculture and forestry. Global Ecology and Biogeography, 9: 125-144.

Houghton, R.A., J.L. Hackler, and K.T. Lawrence. 1999. The U.S. carbon budget: contributions from land-use change. Science, 285: 574-578.

Jarecki, M.K., and R. Lal. 2003. Crop management for soil carbon sequestration. Critical Reviews in Plant Sciences, 22: 471-502.

Kerr, J.T., and M. Ostrovsky. 2003. From space to species: ecological applications for remote sensing. Trends in Ecology and Evolution, 18: 299-305.

Krupinsky, J.M., S.D. Merrill, D.L. Tanaka, M.A. Liebig, M.T. Lares, and J.D. Hanson. 2007. Crop residue coverage of soil influenced by crop sequence in a no-till system. Agronomy Journal, 99: 921-930.

Lal, R. 2004. Soil carbon sequestration impacts on global climate change and food security. Science, 304: 1623-1627.

Lal, R., J.M. Kimble, R. Follett, and C.V. Cole. 1998. The potential of U.S. cropland to sequester carbon and mitigate the greenhouse effect. CRC Press, Boca Raton, FL. 128 pp.

Lasco, R.D., S. Ogle, J. Raison, L. Verchot, R. Wassmann, K. Yagi, S. Bhattacharya, J.S. Brenner, J.P. Daka, S.P. Gonzalez, T. Krug, Y.Li, D.L. Martino, B.G. McConkey, P. Smith, S.C. Tyler, W. Zhakata, R.L. Sass, and X. Yan. 2006. Cropland. In: 2006 IPCC Guidelines for National Greenhouse Gas Inventories, Volume 4: Agriculture, Forestry, and Other Land Use. IPCC. 66 pp.

Lefsky, M.A., W.B. Cohen, G.G. Parker, and D.J. Harding. 2002. Lidar remote sensing for ecosystem studies. BioScience, 52: 19-30.

Li, X., and Y. Feng. 2002. Carbon sequestration potentials in agricultural soils. AIDIS-CANADA Environmental Project. 11 pp.

Lyon, D.J., W.W. Stroup, and R.E. Brown. 1998. Crop production and soil water storage in long-term winter wheat-fallow tillage experiments. Soil and Tillage Research, 49: 19-27.

Marland, G., T.O. West, B. Schlamadinger, and L. Canella. 2003. Managing soil organic carbon in agriculture: the net effect on greenhouse gas emissions. Tellus B, 55: 613-621.

Mayerle, G. 2005. Prairie soil carbon balance project. 2005 Direct Seeding Conference, 15-16 Feb. 2005. Saskatoon, Saskatchewan. Saskatchewan Soil Conservation Society Association. Last Accessed 12 May 2008. <http://ssca.usask.ca/conference/2001proceedings/m.>

McConkey, B.G., B.C. Liang., C.A. Campbell, D. Curtin, A. Moulin, S.A. Brandt, and G.P. Lafond. 2003. Crop rotation and tillage impact on carbon sequestration in Canadian prairie soils. Soil and Tillage Research, 74: 81-90.

McConkey, B.G., B.C. Liang, and C.A. Campbell. 1999. Estimating gains of soil carbon over 15-yr period due to changes in fallow frequency, tillage system, and fertilization practices for the Canadian Prairies (an expert opinion). Publication #379M0209. Agriculture and Agri-Food Canada. 14 pp.

McLauchlan, K. 2006. Agricultural impacts on soil carbon and nutrients: a review. 2006. Ecosystems, 9: 1364-1382.

Melillo, J.M., J. Borchers, J. Chaney, H. Fisher, A. Hazeltine, A. Janetos, D.W. Kicklighter, T.G.F. Kittel, A.D. McGuire, R. McKeown, R. Neilson, R. Nemani, D.S. Ojima, T. Painter, Y. Pan, W.J. Parton, L. Pierce, L. Pitelka, C. Prentice, B. Rizzo, N.A. Rosenbloom, S. Running, D.S. Schimel., S. Sitch, T. Smith, and I. Woodward. 1995. Vegetation/ecosystem modeling and analysis project comparing biogeography and biogeochemistry models in a continental-scale study of terrestrial ecosystem response to climate change and CO_2 doubling. Global Biogeochemical Cycles, 9: 407-437.

Miller, P.R., B.G. McConkey, G.W. Clayton, S.A. Brandt, J.A. Staricka, A. M. Johnston, G.P. Lafond, B.G. Schatz, D.D. Baltensperger, and Karnes E. Neill. 2002. Pulse crop adaptation in the northern Great Plains. Agronomy Journal, 94: 261-272.

Moore, D.S. 2004. The basic practice of statistics, 3ed. Freeman, New York, N.Y. 674 pp.

National Carbon Offset Coalition (NCOC). 2008. Exchange soil offset eligible practices and offset issuance rates by zone. Cropland Protocol Guidelines. 23 pp.

Natural Resources Conservation Service (NRCS). 2007a. Major Biomes Map. Last Accessed 12 December 2007 <http://soils.usda.gov/use/worldsoils/mapindex/biomes.html>

Natural Resources Conservation Service (NRCS). 2007b. Interactive Soil Survey Map. Last Accessed 10 December 2007 <http://websoilsurvey.nrcs.usda.gov/app/WebSoilSurvey.aspx>

National Weather Service (NWS). 2007. Past weather: local climate information. National Oceanic and Atmospheric Administration. Last Accessed 3 May 2008. <http://www.nws.noaa.gov>

Parton, W.J., D.S. Ojima, and D.S. Schimel. 2005. CENTURY: Modeling Ecosystem Responses to Climate Change, Version 4 (VEMAP 1995). Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, Tennessee, U.S.A.

Paustian, K., J. Six, E.T. Elliott, and H.W. Hunt. 2000. Management options for reducing CO_2 emissions from agricultural soils. Biogeochemistry, 48: 147-163.

Paustian, K., H.P. Collins, and E.A. Paul. 1997. Management controls on soil carbon. In. Paul, E.A., K.A. Paustian, E.T. Elliot, and C.V. Cole (Eds.), Soil Organic Matter in Temperate Agroecosystems. CRC Press, Boca Raton, Fl. pp. 15-40.

Post, W.M., R. C. Izaurralde, J.D. Jastrow, B.A. McCarl, J.E. Amonette, V.L. Bailey, P.M. Jardine, T.O. West, and J. Zhou. 2004. Enhancement of carbon sequestration in US soils. BioScience, 54: 895-908.

Post, W.M., and K.C. Kwon. 2000. Soil carbon sequestration and land-use change: processes and potential. Global Change Biology, 6: 317-327.

Potter, K.N., O.R. Jones, H.A. Torbert, and P.W. Unger. 1997. Crop rotation and tillage effects on organic carbon sequestration in the semiarid southern Great Plains. Soil Science, 162: 140-147.

Price, K.P., Egbert, S.L., Nellis, M.D., Lee, R.Y., and Boyce, R. 1997. Mapping land cover in a High Plains agro-ecosystem using a multi-date Landsat Thematic Mapper modeling approach. Transactions of the Kansas Academy of Science, 100: 21-33.

Purakayastha, T.J., D.R. Huggins, and J.L. Smith. 2008. Carbon sequestration in native prairie, perennial grass, no-till, and cultivated palouse silt loam. Soil Science Society of America Journal, 72: 534-540.

Reicosky, D.C. 1997. Tillage-induced CO_2 emissions from soil. Nutrient Cycling in Agroecosystems, 49: 273-285.

Robles, M.D., and I.C. Burke. 1998. Soil organic matter recovery on conservation reserve program fields in southwestern Wyoming. Soil Science Society of America, 62: 725-730.

Ryan, M.G. 1991. Effects of climate change on plant respiration. Ecological Applications, 1: 157-167.

Sainju, U.M., T. Caesar-TonThat, A.W. Lenssen, R.G. Evans, and R. Kolberg. 2007. Long-term tillage and cropping sequence effects on dryland residue and soil carbon fractions. Soil Science Society of America Journal, 71: 1730-1739.

Schiermeier, Q. 2006. Putting the carbon back: the hundred billion tonne challenge. Nature, 442: 620-623.

Schimel, D.S., B.H. Braswell, E.A. Holland, R. McKeown, D.S. Ojima, T.H. Painter, W. J. Parton, and A.R. Townsend. 1994. Climatic, edaphic, and biotic controls over storage and turnover of carbon in soils. Global Biogeochemical Cycles, 8: 279-293.

Schlesinger, W.H. 1977. Carbon balance in terrestrial detritus. Annual Review of Ecology and Systematics, 8: 51-81.

Schrag, D.P. 2007. Preparing to capture carbon. Science, 315: 812-813.

Six, J., R.T. Conant, E.A. Paul, and K. Paustian. 2002. Stabilization mechanisms of soil organic matter: Implications for C-saturation of soils. Plant and Soil, 241: 155-176.

Smith, P. 2004. How long before a change in soil organic carbon can be detected? Global Change Biology, 10: 1878-1883.

Sommerfeldt, T.G., C. Chang, and T. Entz. 1988. Long-term annual manure applications increase soil organic matter and nitrogen, and decrease carbon to nitrogen ratio. Soil Science Society of America Journal, 52: 1668-1672.

Sperow, M., M. Eve, and K. Paustian. 2003. Potential soil C sequestration on U.S. agricultural soils. Climate Change, 57: 319-339.

Staben, M.L., D.F. Bezdicek, M.F. Fauci, and J.L. Smith. 1997. Assessment of soil quality in conservation reserve program and wheat-fallow soils. Soil Science Society of America Journal, 61: 124-130.

Uri, N.D. 2001. The potential impact of conservation practices in US agriculture on global climate change. Journal of Sustainable Agriculture, 18:109-131.

US Department of Agriculture (USDA). 2008. 2007 census of agriculture. National Agricultural Statistics Service. Last Accessed 10 May 2008 < http://www.agcensus.usda.gov/Publications/2007/index.asp>

West, T.O., and J. Six. 2007. Considering the influence of sequestration duration and carbon saturation on estimates of soil carbon capacity. Climatic Change, 80: 25-41.

West, T.O., and W.M. Post. 2002. Soil organic carbon sequestration rates by tillage and crop rotation: a global data analysis. Soil Science Society of America Journal, 66: 1930-1946.

Western Regional Climate Center (WRCC). 2006. Historical climate information. Last Accessed 5 April 2007 <http://www.wrcc.dri.edu/CLIMATEDATA.html>

White, E.M., C.R. Krueger, and R.A. Moore. 1976. Changes in total N, organic matter, available P, and bulk densities of a cultivated soil 8 years after tame pastures were established. Agronomy Journal, 68: 581-583.

Wu, T., J.J. Schoenau, F. Li, P. Qian, S. S. Malhi, and Y. Shi. 2003. Effect of tillage and rotation on organic carbon forms of chernozemic soils in Saskatchewan. Journal of Plant Nutrition and Soil Science, 166: 328-335.

Xie, H., Y.Q. Tian, J.A. Granillo, and G.R. Keller. 2007. Suitable remote sensing method and data for mapping and measuring active crop fields. International Journal of Remote Sensing, 28: 395-411.

Young, L.M. 2003. Carbon sequestration in agriculture: The U.S. policy context. American Journal of Agricultural Economics, 85: 1164-1170.

CHAPTER 5

CONCLUSION

Regional cropland carbon (C) trading will require a timely and cost-effective method for the validation of land use management as described within C contract agreements. Increased emphasis on facilitating cropland for C sequestration purposes, within future state and national policies, will likely result in a greater need for more frequent collection of regional cropland land use statistics. These statistics provide the basis for the estimation of cropland C sequestration potential within a given region.

Satellite-based analyses can provide a low-cost means for regional land use classification. Satellite imagery from moderate-resolution sources such as Landsat can provide data for land surface features on a monthly basis. Satellite-based image data are well suited for large-area analyses; the data obtained within two Landsat image scenes provided information for the entire project area (a substantial portion of north central Montana). Data used to create the classification models were collected through a one-time field survey; the image-based data in conjunction with the roadside survey likely allowed for land-use classification results to be obtained more efficiently and with lower costs than would have occurred in through a traditional regional survey. The use of image-objects within the classification process allowed land use classifications to be based on management parcels constrained by ownership boundaries. Information contained within these image-objects could then be easily managed within a GIS platform for further spatial analysis.

The Random Forest (RF) algorithm proved to be an extremely effective classification method capable of handling the detailed object-based parameter sets derived during the image segmentation process. Resulting forest-based classifications were easily incorporated into the shapefiles, so that each image-object was correctly coded according to the predicted land use classification. Random Forest also proved to be desirable as it is easily obtainable and user-friendly. S-plus® statistical software offers a randomForest package with large data-set capability; a RF package is also available within the R statistical software (a free statistical system available on the internet).

This study examined satellite-based land use classifications for tillage, conservation reserve (CR), and crop intensity patterns. While accurate classification results were obtained for conservation reserve and the multi-year separation of crop from fallow, used in determining crop intensity, we were unable to successfully separate tillage from no-till (NT). Study results indicate that the binary separation of NT from tillage ("tillage" envelops various degrees of tillage management into one class), in accordance to Chicago Climate Exchange (CCX)-based C contract agreements, might not be possible due to spectral and textural similarities in surface characteristics between NT and certain forms of tillage (likely conservation-based tillage). It is thought the adequate separation of NT from conservation tillage management through spectral and textural-based satellite mapping is unlikely given the current technology, due to similarities in surface residue coverage and soil disturbance levels. In other words, satellite-based image classification methods are currently unable to detect C contract violations resulting from light tillage disturbances in areas that are allegedly under NT management.

It is possible, however, to determine intensive tillage disturbances under minimal vegetation cover, as has been reported by other studies using satellite-image analysis. In hindsight, field data collection for these sites would have allowed for the separation of heavy tillage management during the classification process. Land area information for heavy tillage management would have then facilitated the refinement of regional C sequestration potential estimates, as sites under intensive tillage management might have greater potential to hold soil C upon conversion to NT management.

The classification of grassland-based CR lands from cropland and crop from fallow can be achieved successfully through Landsat satellite image-based analyses, incorporating image-objects and the RF classifier. Misclassifications between crop and fallow were attributed to within-pixel spectral mixing problems associated with the use of a moderate-resolution sensor (Landsat-based pixels represent 30 m^2 of land surface coverage). Pixels representing land areas where narrow field strip management (strips are < 100 m wide) is practiced, where cropped and fallow occurred side by side in an alternating pattern, were more likely to incorporate spectral data from both crop and fallow (hence the spectral mixing). We had hoped to avoid this problem by segmenting the imagery used for the crop and fallow classifications into very small, within-strip, image-objects according to spectral and textural similarities. The use of higher resolution imagery is suggested for the future mapping of crop and fallow in areas incorporating strip management. Normalized Difference Vegetation Index differencing was an effective method in determining field areas having changed from the original vegetative status (cropped or fallow) when attempting a multi-year analysis for the determination of crop intensity patterns. By classifying only "changed" image-objects and then merging the newly classified objects with the "unchanged" objects, we were able to avoid compound classification error within the multi-year (2004-2007) crop intensity analysis.

Land use statistics obtained through image analyses and the 2007 roadside cropland survey showed the potential for an increased conversion from tillage to NT and to higher degrees of cropping intensity within north central Montana. No-till management is currently estimated (for 2007) at 56%, with land under continuous cropping at only 5%. Financial incentives provided through cropland carbon contracts might encourage an increase in the adoption of NT and increased crop intensities. These incentives might also encourage the maintaining of lands currently under CR management.

The analysis of literature-based cropland C sequestration rates associated with changes from tillage-based management to NT and from cropland to grassland-based CR highlights the need for additional region-specific research. Specifically, future research will need to determine sequestration rates associated with the change from more moderate tillage management (reduced tillage; forms of conservation tillage) to NT management under various degrees of crop intensity (reduced fallow) and crop rotation types. Past research has focused more on C sequestration associated with switching from a system under intensive tillage management to NT.

Future studies should also address the degree of surface soil disturbance that occurs from the use of various forms of NT seeder implements. Further examination of the impact of increased crop intensity on soil organic C amounts is also needed, as many of the reported sequestration rates for systems under continuous crop were less than rates in systems incorporating some degree of fallow. It might be that certain crop rotations are more appropriate for use in continuously cropped systems because they better optimize soil water use. Sequestration rates appropriate for climatic conditions within north central Montana were largely absent for CR lands and resulted in the incorporation of sequestration data reported by studies having occurred in locations having higher annual precipitation into the literature-based analysis. The establishment of sequestration rates for the conversion from cropland to grassland-based CR under similar climatic conditions to those found within north central Montana is needed to obtain a better estimate of sequestration potential associated with this management change.

Like any emerging system, there is room for improvement within the US C market. The analysis of literature-based C sequestration rate estimates has highlighted the potential need for the re-adjustment of sequestration rates used by the CCX for the establishment of C credits associated with a cropland management change, namely those for the conversion from till to NT and for the conversion from cropland to grassland-based CR. The current CCX rate for NT is 0.22 t C ha^{-1} yr^{-1} and is less than many of the sequestration rates observed for various scenarios examining changes from tillage-based systems to NT.

Available literature shows that the application of a single sequestration rate, having no consideration for previous tillage management history, might be in error, as systems having been previously under intensive tillage are thought to have a greater C storage capacity due to higher levels of C depletion. Results from study analyses also indicate that the current CCX rate associated with lands having converted from cropland to grassland-based CR (0.67 t C ha^{-1} yr^{-1}) might be more appropriate for systems with optimal soil moisture and nitrogen levels and is much higher than C rates reported within the literature. The re-evaluation of sequestration rates used by the CCX is suggested to provide more accurate estimates of cropland C storage potential within this region for C-credit purposes.

APPENDIX A

DATA USED IN MASKING PROCESS AND GENERATED FROM OBJECT-ORIENTED ANALYSIS

Category	**File ID**	**Format**	**Date Published**	**Agency**	**File Description**
Wetland	x48110.shp	Point	2007	US Fish and Wildlife	Provides point locations of wetlands; includes data pertaining to wetland classification and flooding frequency.
Wetland	x48108.shp	Point	" "	" "	" "
Wetland	l48110.shp	Polygon	" "	" "	Provides area locations of wetlands; includes data pertaining flooding frequency
Wetland	l48108.shp	Polygon	" "	" "	" "
Wetland	p48108.shp	Polygon	" "	" "	" "
Wetland	p48110.shp	Polygon	" "	" "	" "
Lakes and Creeks	hd43a.shp	Polygon	2000	US Geological Service	" "
Lakes	hd49p.shp	Polygon	" "	" "	Provides lake locations as polygons.
Wild and Scenic Rivers	wildscenic.shp	Polygon	2000	" "	Provides river locations as polygons.
Roads and Highways	rd16.shp	Line	1990	Census	Provides Montana roadways and US highway locations as line features.
Roads	rds2000.shp	Line	2000	Census	Provides county and city roads as line features (road names are not given).
Cities	ct2.shp	Polygon	1991	US Geological Service	Provides Montana town and city locations as polygon features.
Montana Land Use	lu23.shp	Polygon	1993	" "	Provides generalized land use information for Montana lands.
Fish and Wildlife	fwplands.shp	Polygon	2007	US Fish and Wildlife	Provides spatial location of Fish and Wildlife land.
Landowner	lab105.shp	Polygon	1992	US Geological Service	Provides general landowner information in polygon format.
Railways	rail2003.shp	Line	2003	Bureau of Transportation	Provides railway locations.

Table 1. Data used in the masking of non-agricultural lands, obtained from the Natural Resource Information Service

Object Data Features	Description
Layer Mean (All layers)	The average of all pixels found within an image object. Includes computations for Blue, Green, Red, NIR, MIR, Thermal, MIR2, Panchromatic (if ETM+), NDVI, Brightness, Greenness, and Wetness layers.
Layer Standard Deviation (All layers)	The standard deviation calculated from all pixels within an image object.
Min-Pixel Value (All layers)	The lowest pixel value within an image object.
Max-Pixel Value (All layers)	The highest pixel value within an image object.
Mean Difference to Brighter Neighbors (All layers)	The layer mean difference computed for each neighboring object, weighted with regard to between-object border length or the area covered by the neighbor objects. A distance of zero is given for direct neighbors.
Contrast to Neighborhood Pixels (All layers)	Calculates the mean difference between pixel values and surrounding pixel values.
GLCM Homogeneity-All Directions (All layers)	A texture measure concerning the amount of local variation within an image object. Values are weighted by the inverse of the contrast weight, with weights decreasing exponentially according to their distance to the diagonal.
GLCM Mean (All layers)	A texture measure where the pixel values are weighted by the frequency of their occurrence in combination with neighbor pixel values.
GLCM Standard Deviation (All layers)	A measure of the dispersion of values around the texture mean.
GLCM Dissimilarity (All layers)	A texture measure of the amount of local variation within the image object; values increase linearly and dissimilarity will be high if there is high contrast within a localized region.
GLCM Contrast-All Directions (All layers)	A measure similar to the GLCM mean, differed by all spatial directions (0, 45, 90, 135) being summed prior to inclusion within the texture calculations.
*GLCM is the grey level co-occurrence matrix and is a tabulation of how often different combinations of pixel grey levels occur within a given object.	

Table 2. Object-based predictive parameters generated through image segmentation within the Definiens Professional software package.