Research Report 3.12

Evaluation of High Resolution Airborne Imagery and Global Positioning Systems for Monitoring Changes in Agroecosystems

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FORWARD

This report is one of a series of **COESA** (Canada-Ontario Environmental Sustainability Accord) reports from the Research Sub-Program of the Canada-Ontario Green Plan. The **GREEN PLAN** agreement, signed Sept. 21, 1992, is an equally-shared Canada-Ontario program totalling $64.2 M, to be delivered over a five-year period starting April 1, 1992 and ending March 31, 1997. It is designed to encourage and assist farmers with the implementation of appropriate farm management practices within the framework of environmentally sustainable agriculture. The Federal component will be delivered by Agriculture and Agri-Food Canada and the Ontario component will be delivered by the Ontario Ministry of Agriculture and Food and Rural Assistance.

From the 30 recommendations crafted at the Kempenfelt Stakeholders conference (Barrie, October 1991), the Agreement Management Committee (AMC) identified nine program areas for Green Plan activities of which the three comprising research activities are (with Team Leaders):

1. Manure/Nutrient Management and Utilization of Biodegradable Organic Wastes through land application, with emphasis on water quality implications

- **A.** Animal Manure Management (nutrients and bacteria)
- **B.** Biodegradable organic urban waste application on agricultural lands (closed loop recycling) (Dr. Bruce T. Bowman, Pest Management Research Centre, London, ONT)

2. On-Farm Research: Tillage and crop management in a sustainable agriculture system. (Dr. Al Hamill, Harrow Research Station, Harrow, ONT)

3. Development of an integrated monitoring capability to track and diagnose aspects of resource quality and sustainability. (Dr. Bruce MacDonald, Centre for Land and Biological Resource Research, Guelph, ONT)

The original level of funding for the research component was $9,700,000 through Mar. 31, 1997. Projects will be carried out by Agriculture and Agri-Food Canada, universities, colleges or private sector agencies including farm groups.

This Research Sub-Program is being managed by the Pest Management Research Centre, Agriculture and Agri-Food Canada, 1391 Sandford St., London, ONT. N5V 4T3.

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Objectives and Expected Outputs

Objectives	To investigate the effect of field scale topographic variation on the reflectance properties of soil. To develop a methodology for the rapid integration of image analysis, GIS and GPS techniques for use with site specific agriculture.
Expected Outputs	1. Image maps of each research site registered to elevation data (obtained by high resolution GPS) 2. A complete analysis of procedure used, detailing errors and/or limitations for the absolute(quantitative) and relative (qualitative) assessment of soil organic matter levels. 3. Assessment of the utility of high resolution imagery and GPS data for mapping agroecosystems. The evaluation of the utility of data from future satellites. 4. How imagery from high resolution satellites could be used to produce SOM maps of fields and how the spectral data could be correlated with high resolution topographic data.
Type:	Contribution Agreement, University
Spending Profile	95-97: $25.0 K, **Total:** $25.0K
Status:	Available June 1999

Executive Summary

High resolution Compact Airborne Spectral Imager (CASI) data was collected of three of the paired fields within the "Soil Organisms As Bioindicators Of Agronomic Practices" project sites. High resolution elevation data was obtained with the Leica Global Positioning System (GPS) of each of six fields. The imagery and elevation data have been registered. Soil profile sites have been located to within one meter accuracy in the imagery. Surficial soil organic matter content has been correlated to spectral response.

In an associated project Landsat thematic mapper imagery (30 m resolution) has been registered to the road network for the 10 counties in southern Ontario. The size of each field has been measured in hectares. Each large agricultural field has been numbered within major physiographic region and township.

To map changes in soil organic matter (SOM) in the future, agricultural fields can be chosen randomly within the

arc/info Geographic Information System (GIS). Samples will be chosen by slope position. Characterization of soil organic matter within pedons on various slope positions within each physiographic region will be done periodically in the future. Monitoring of tillage practices over time will aid in the selection of a method for soil sampling to measure the state of soil organic matter.

Introduction

The initial map of the distribution of organic carbon in Canadian soils has been published by Tarnocai and Lacelle (1996). The discrimination of small differences in surface soil organic carbon with high resolution airborne imagery has been demonstrated previously (Cihlar et al. 1987). The content of soil organic carbon within any cultivated soil pedon is dependent upon its vegetative history since deglaciation, the methods used to clear the forests, and subsequent agricultural soil and crop management systems. These management systems are in a continual state of flux, dependent on a better understanding of soil processes (the most recent of which are no-till conservation systems).

The technological advances within the remote sensing industry result in higher temporal, spatial and spectral resolution imagery collected via airborne or satellite platforms. The potential agricultural uses of data collected by these new methods are summarized and discussed by Hulshof (1997), Moran et al. (1997), and Goward and Williams (1997).

Statement of Deliverables

1. Image maps of each research site registered to elevation data (obtained by high resolution GPS)
2. A complete analysis of procedure used, detailing errors and/or limitations for

   The absolute(quantitative) and relative (qualitative) assessment of soil organic matter levels.

3. Assessment of the utility of high resolution imagery and GPS data for mapping agroecosystems. The evaluation of the utility of data from future satellites.
4. How imagery from high resolution satellites could be used to produce SOM maps of fields and how the spectral data could be correlated with high resolution topographic data.

Methods and Materials

The methods used to integrate the CASI and the GPS data have been presented at the 1996 Geomatics conference (Wood et al 1996) . A copy of the manuscript is included in Appendix 1. The identification of field size and boundaries on Landsat TM imagery was developed by Hulshof (1997) and presented at the 1997 Geomatics conference (Hulshof et al, 1997). A copy of the manuscript is included in Appendix 2. The methodology for selecting a random set of fields by size, physiographic unit and soil type for measurement of any parameter was developed by Hulshof (1997) and presented at the 1997 Geomatics conference (Hulshof et al,1997). A copy of the manuscript is included in Appendix 3.

Results and Discussion

The corrected CASI imagery of three sets of paired sites from the "Soil Organisms As Bioindicators Of Agronomic Practices"project are shown in figures 1 to 6. The variations of soil surface colour within fields is evident at each site. High resolution topographic surfaces of each of the six plots show that the difference in surface soil colour is mapable. These differences are clearly visible in fields without crops figure 1 (TGW) and figure 5 (NBD) and less visible within fields with young winter wheat figures 2 (TPM), figure3 (TMM), figure 4 (NMT) and figure 6 (NBS). The differentiation of surface spectral properties is possible within no-till fields with crop residue on the surface ,figure 5, (NBD), as well as fall plowed fields, figure 1 (TGW). In the fields with 11 years on no-till figure 6, (NBS) underlying differences in spectral reflectance are visible through the winter wheat canopy. Whereas within the four year no-till field , NMT (figure 4) the winter wheat canopy is thicker and spectral variation is much lower. The within-field spectral differences are measurable within plowed fields through the winter wheat canopy figure 3 (TMM) and figure 2 (TPM).

Detailed topographic and spectral images of the six plots within fields along with specific soil profile sample locations, and the distribution of ^{137}Cs and %SOM are shown in figures 7 to 12. Spectral reflectance properties are closely associated with the %SOM and slope at site TMM (figure 9), and less so at sites TPM (figure7), NBS (figure 12), NMT (figure10) and NBD (figure 11), and is not visible in site TGW (figure8). The variation in organic matter within the 0-1 cm layer for each profile within each plot are given in table 1.

Table 1. % SOM in the top 1 cm of each profile from each of three slope positions.

Site	Slope Position	% SOM	Site	Slope Position	% SOM
NBS	H M L	3.7 3.7 6.0	TPM	H M L	3.2 4.3 5.5
NMT	H M L	4.1 4.4 4.7	TMM	H M L	2.8 3.7 5.9
NBD	H M L	4.6 4.0 6.1	TGW	H M L	2.6 3.1 4.8

The variation in spectral reflectance is correlated to the SOM content of the surface 1 cm layer. The variation in SOM at the higher and middle slope positions is related to the slope gradient. At site NBD the mid-slope position has a lower SOM content than the upper position. In all sites the lower or toe slope position contains the most SOM in the surface 1 cm layer and also with depth in soil profile (Figures 7 to 12). Therefore, we predict that lower reflectance values will indicate higher amounts of SOM in the surface layer and that this indicates a greater soil profile OM content in the toeslope landscape positions.

In no-till systems SOM is progressively accumulated from the soil surface downwards (Figures 10,11,12) with time, and faunal activity produces fine aggregates of higher organic matter content within the top 3cm within 11 years (VandenBygaart, in preparation). A system of monitoring cropping and tillage practices on a field basis would produce the data required to estimate the rates of SOM aggradation. This concept could be tested by monitoring randomly selected fields from various soil physiographic units in southern Ontario. The Geographic Information System –Remote Sensing (GIS-RS) base for such a program has been developed by Hulshof (1997) for the 10 counties in southern Ontario. Figure 13 shows Essex County as an example, of a road network and LANDSAT imagery of all fields. To monitor SOM we'd require the periodic (every 3 years) purchase of high resolution EarlyBird or QuickBird Imagery while monitoring soil-crop management systems on a field basis with coarser resolution LANDSAT, SPOT, RADARSAT or ERS1, ERS2 imagery (Figure 14).

Acknowledgements

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Wood, M.D., VandenBygaart, A.J., Shepherd, P., Protz, R., and Hulshof, B. 1996. Integration of high resolution GPS and CASI Imagery for Agricultural Soil Landscape Studies. 8 th Inter. Conference on Geomatics. May ,Ottawa.

Figures

Figure 1. CASI imagery from TGW showing the digital elevation model for the sample area.

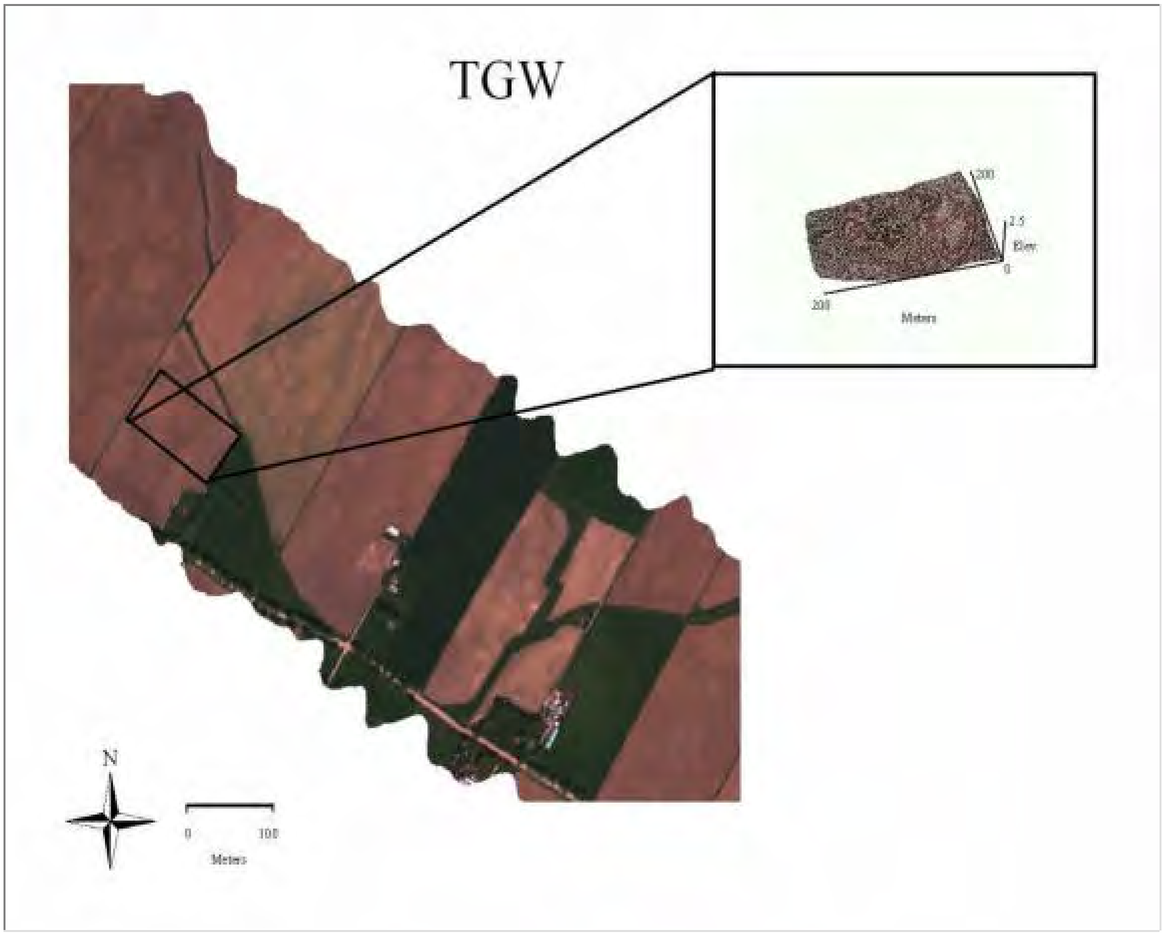


Figure 1. CASI imagery from TGW showing the digital elevation model

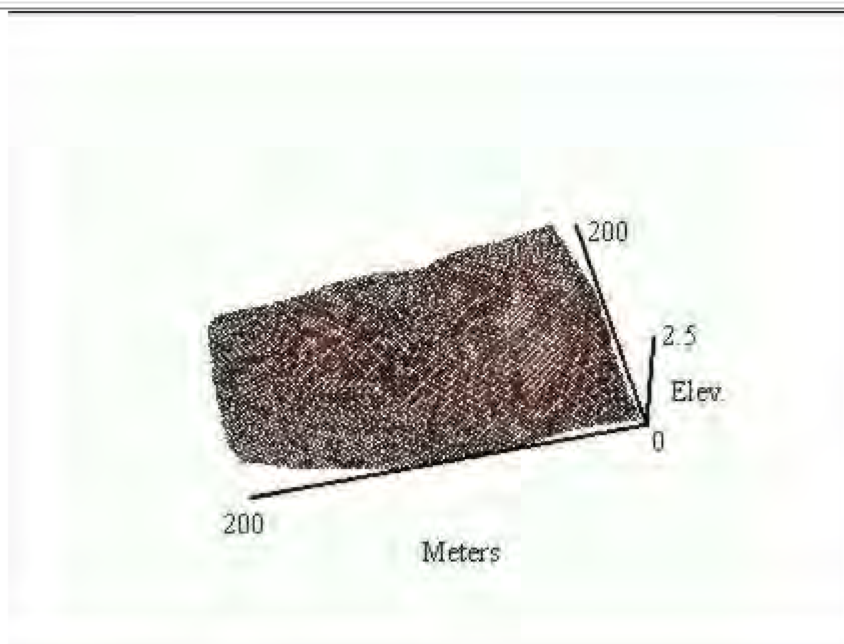


Figure 2.CASI imagery from TPM showing the digital elevation model for the sample area.

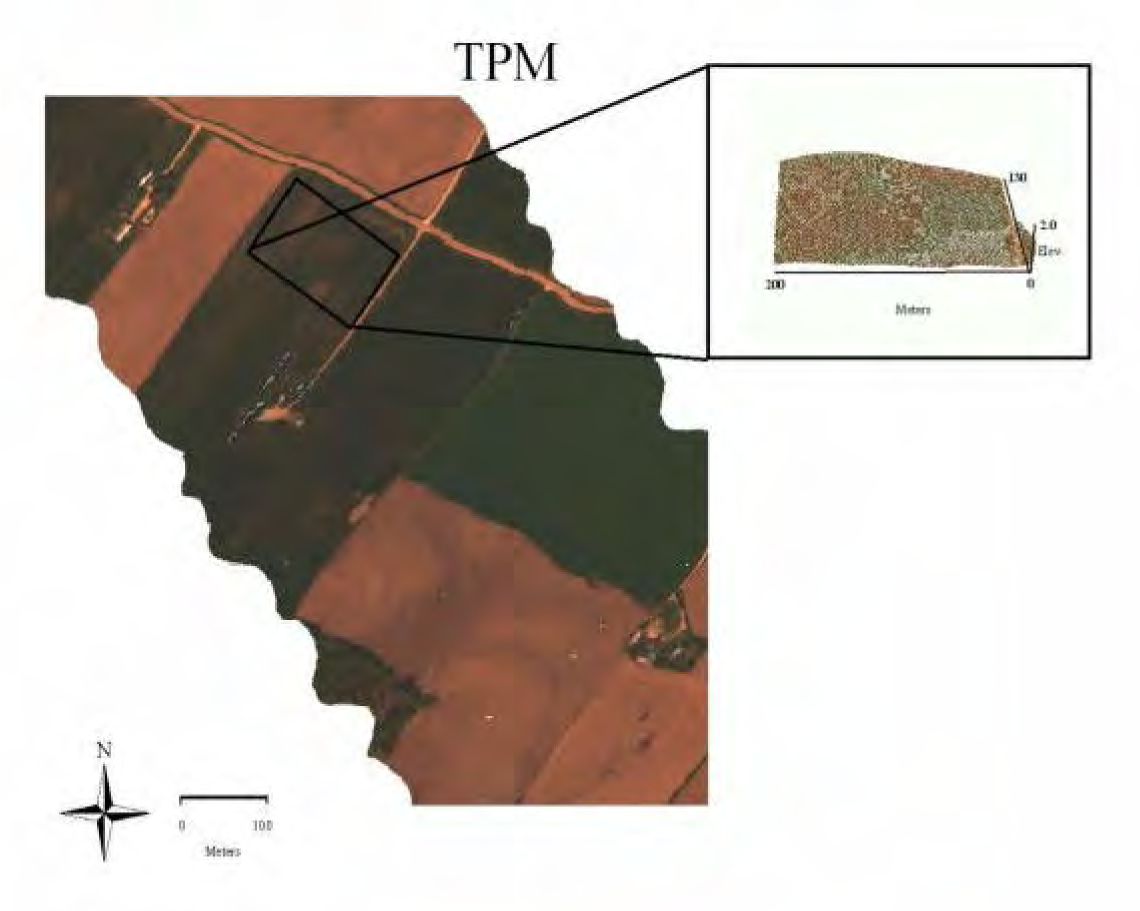


Figure 2.CASI imagery from TPM showing the digital elevation model

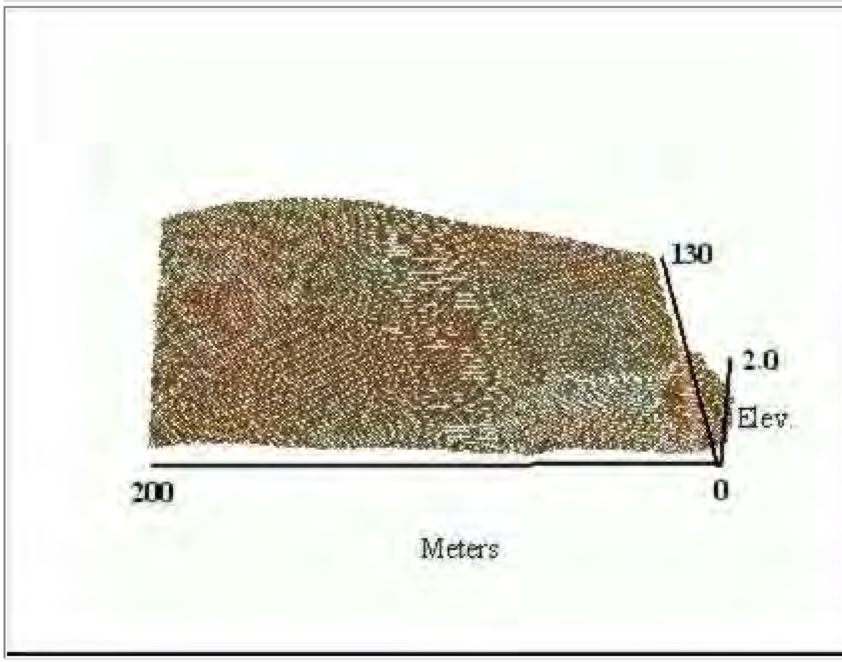


Figure 3.CASI imagery from TMM showing the digital elevation model for the sample area.

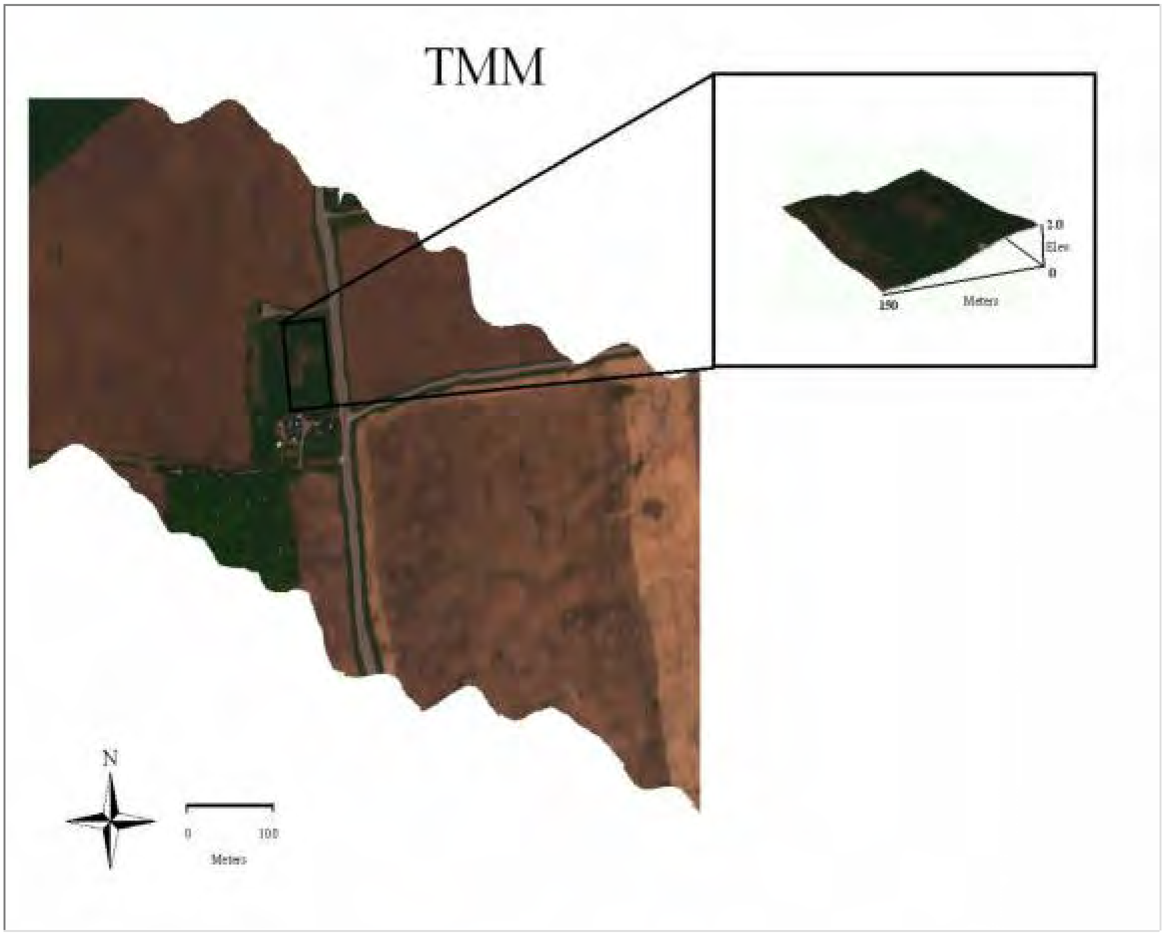


Figure 3.CASI imagery from TMM showing the digital elevation model

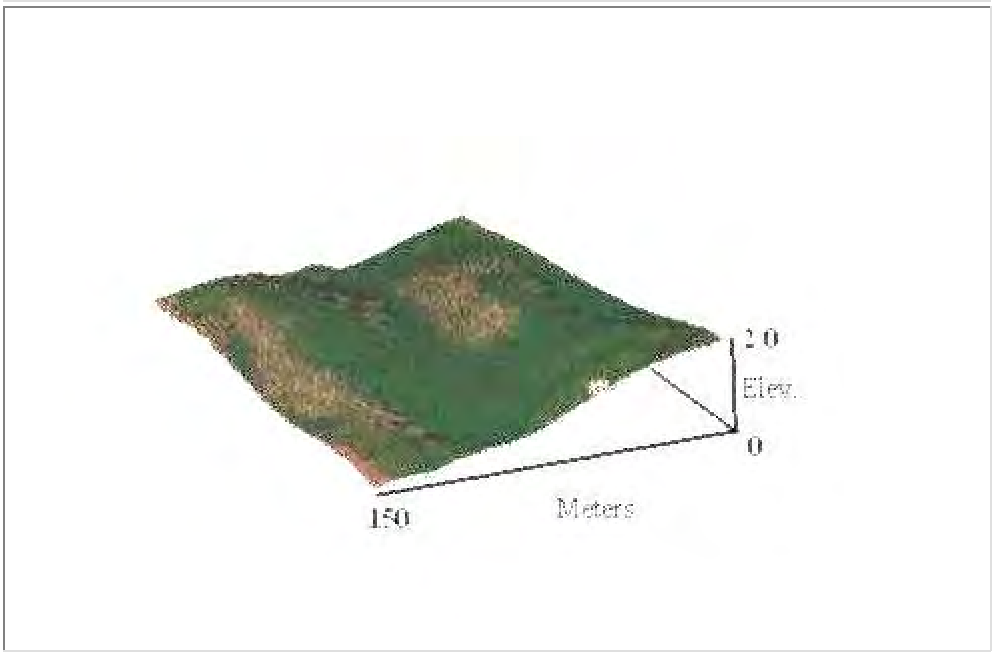


Figure 4. CASI imagery from NMT showing the digital elevation model for the sample area.

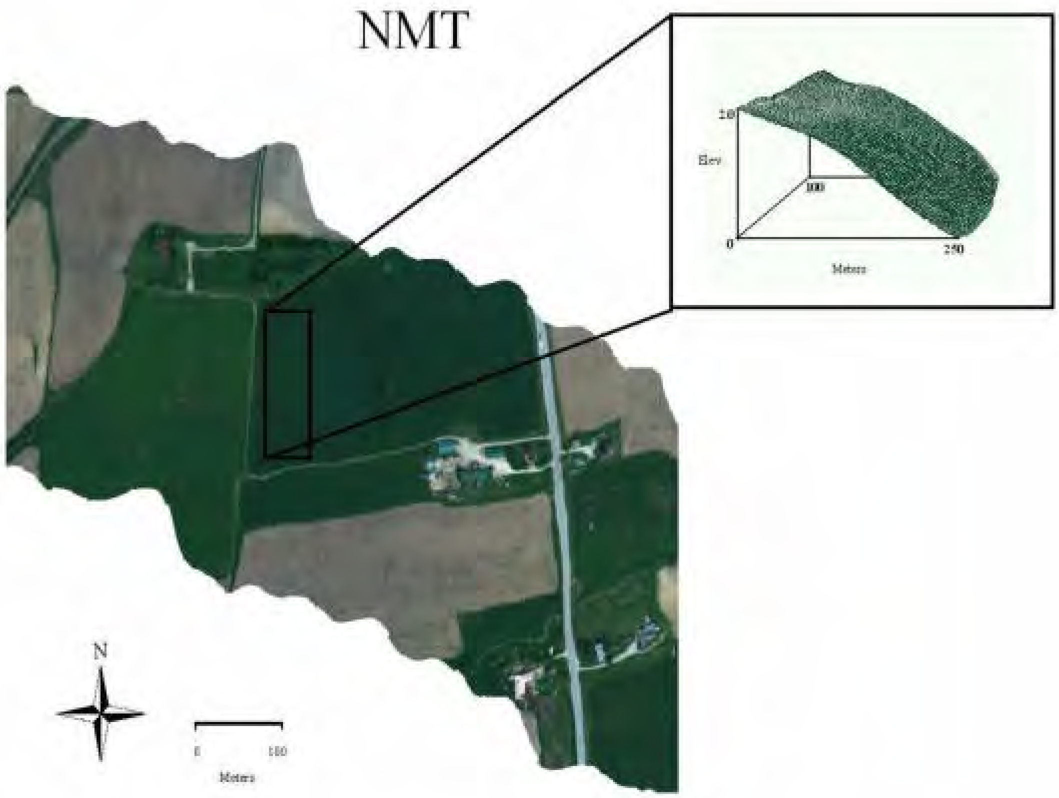


Figure 4. CASI imagery from NMT showing the digital elevation model

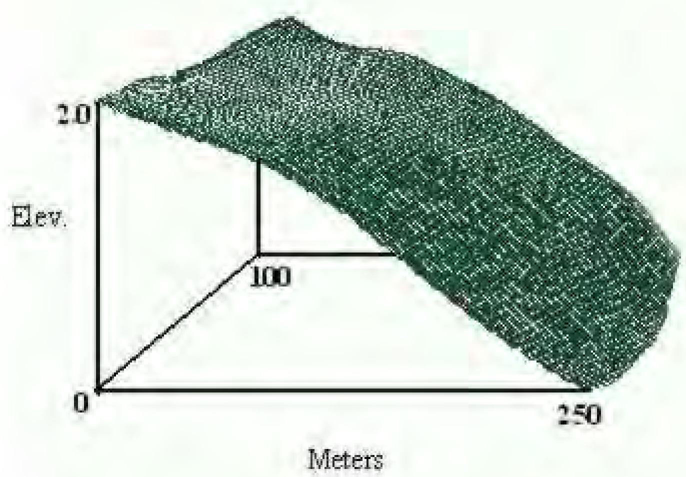


Figure 5. CASI imagery from NBD showing the digital elevation model for the sample area.

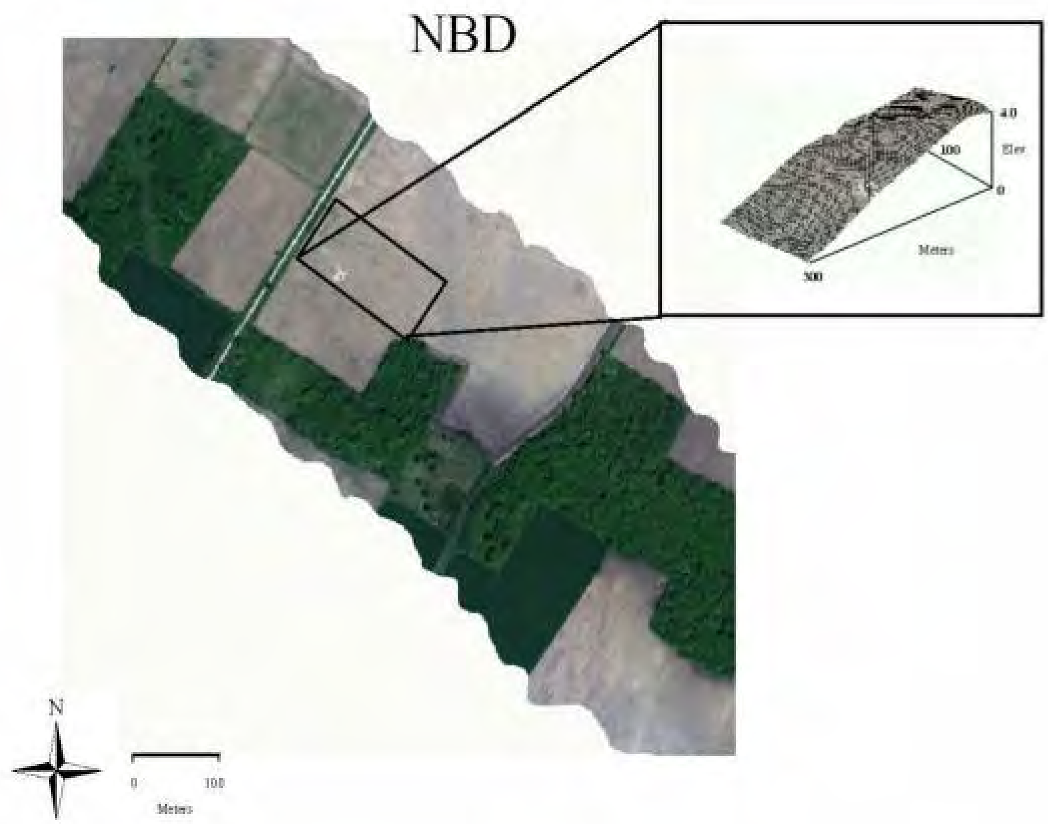


Figure 5. CASI imagery from NBD showing the digital elevation model

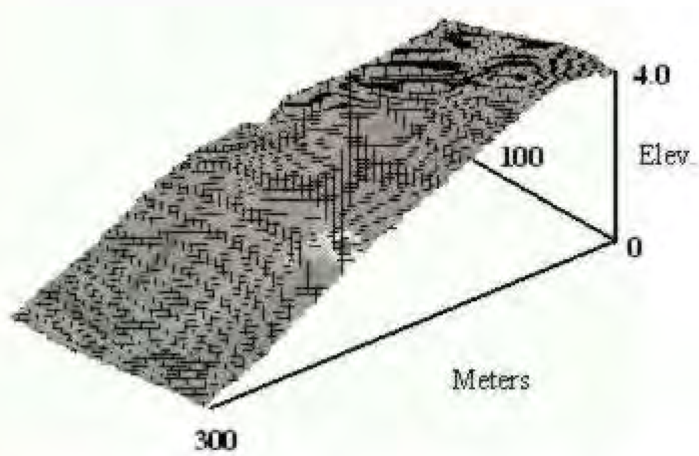


Figure 6. CASI imagery from NBS showing the digital elevation model for the sample area.

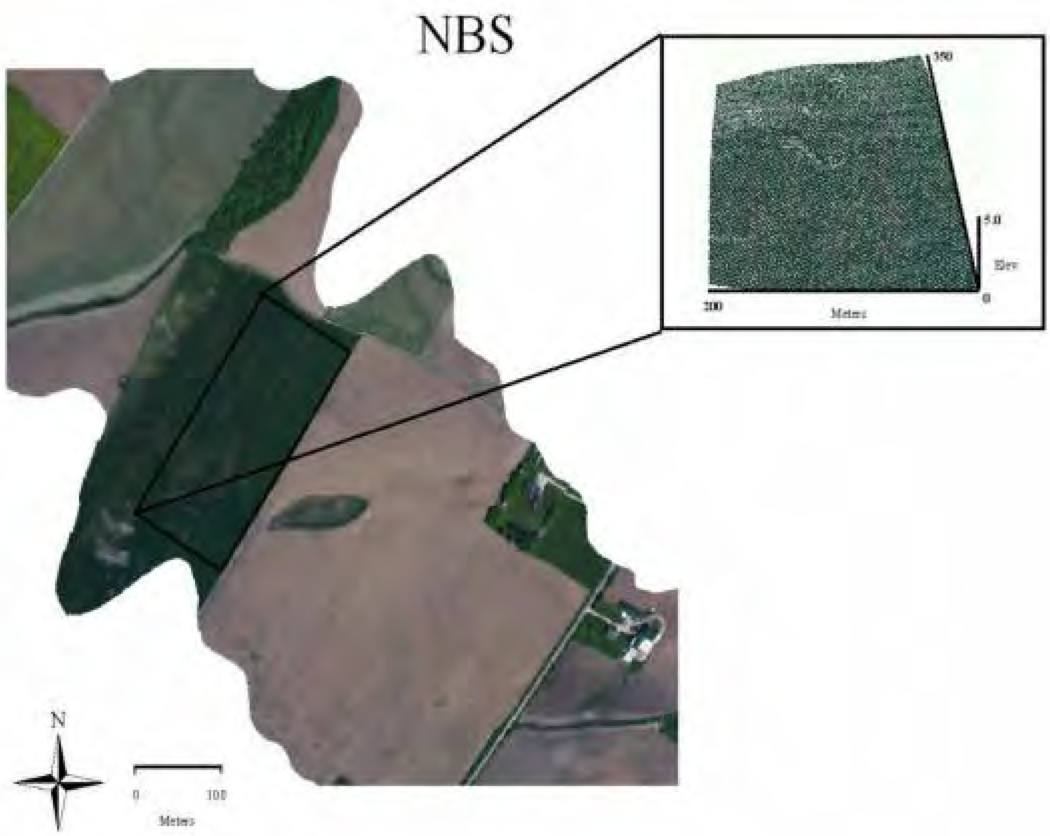


Figure 6. CASI imagery from NBS showing the digital elevation model.

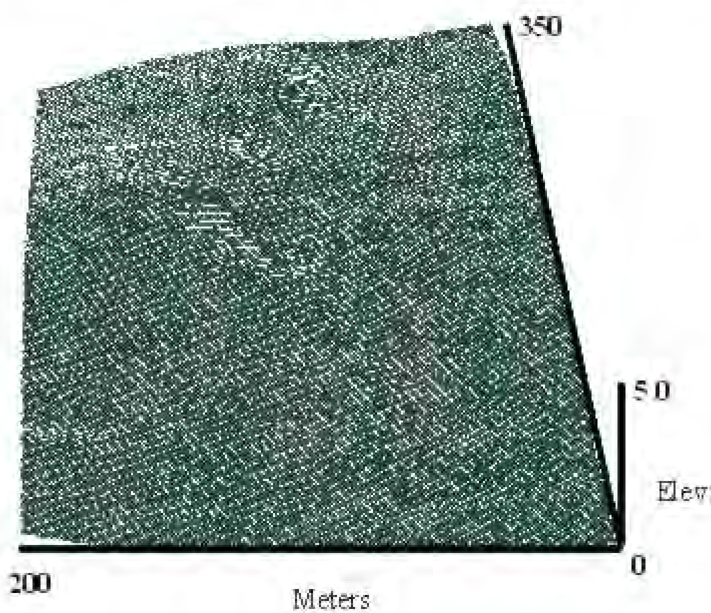


Figure 7. Digital elevation models with draped CASI spectral imagery, and the distribution of ^{137}Cs and SOM with soil depth at each of the slope positions for TPM

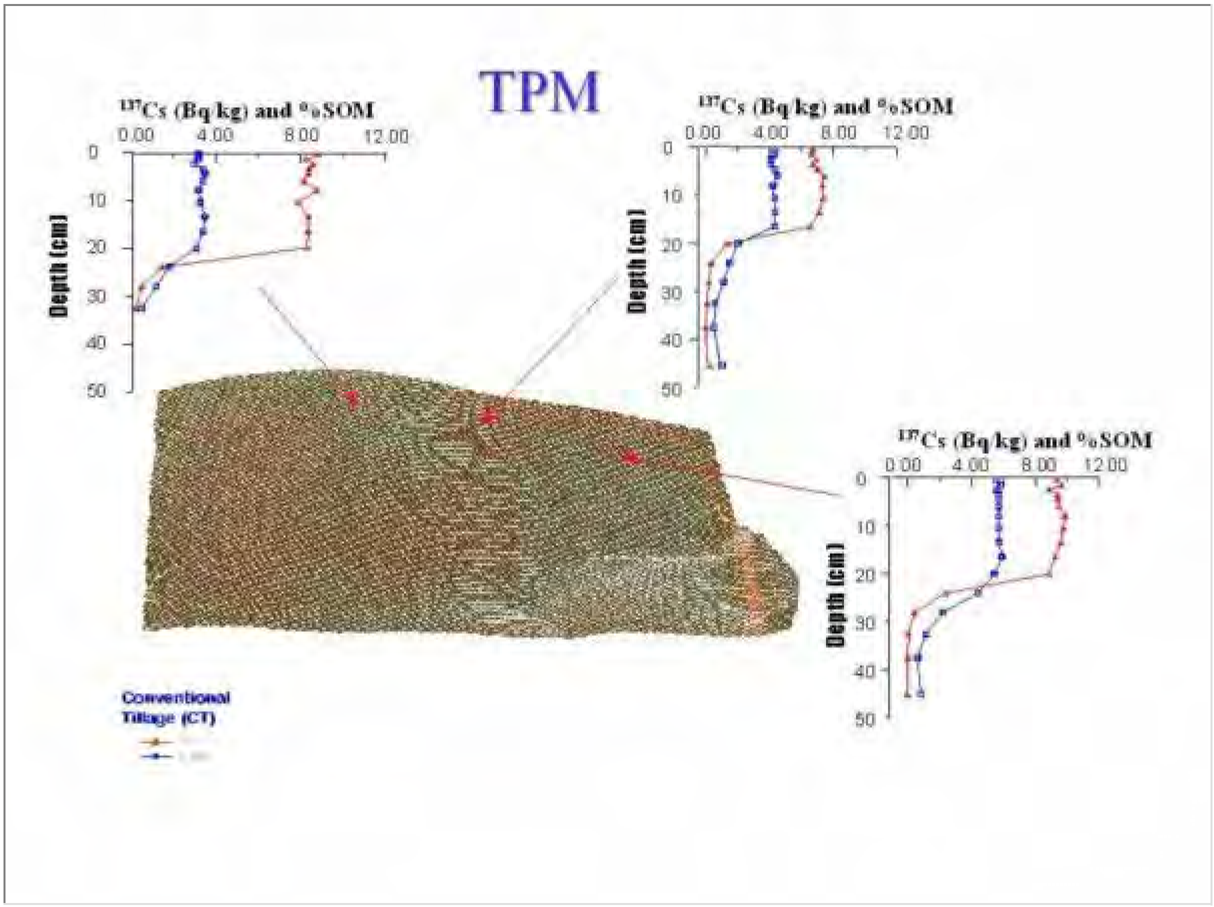


Figure 8. Digital elevation models with draped CASI spectral imagery, and the distribution of ^{137}Cs and SOM with soil depth at each of the slope positions for TGW

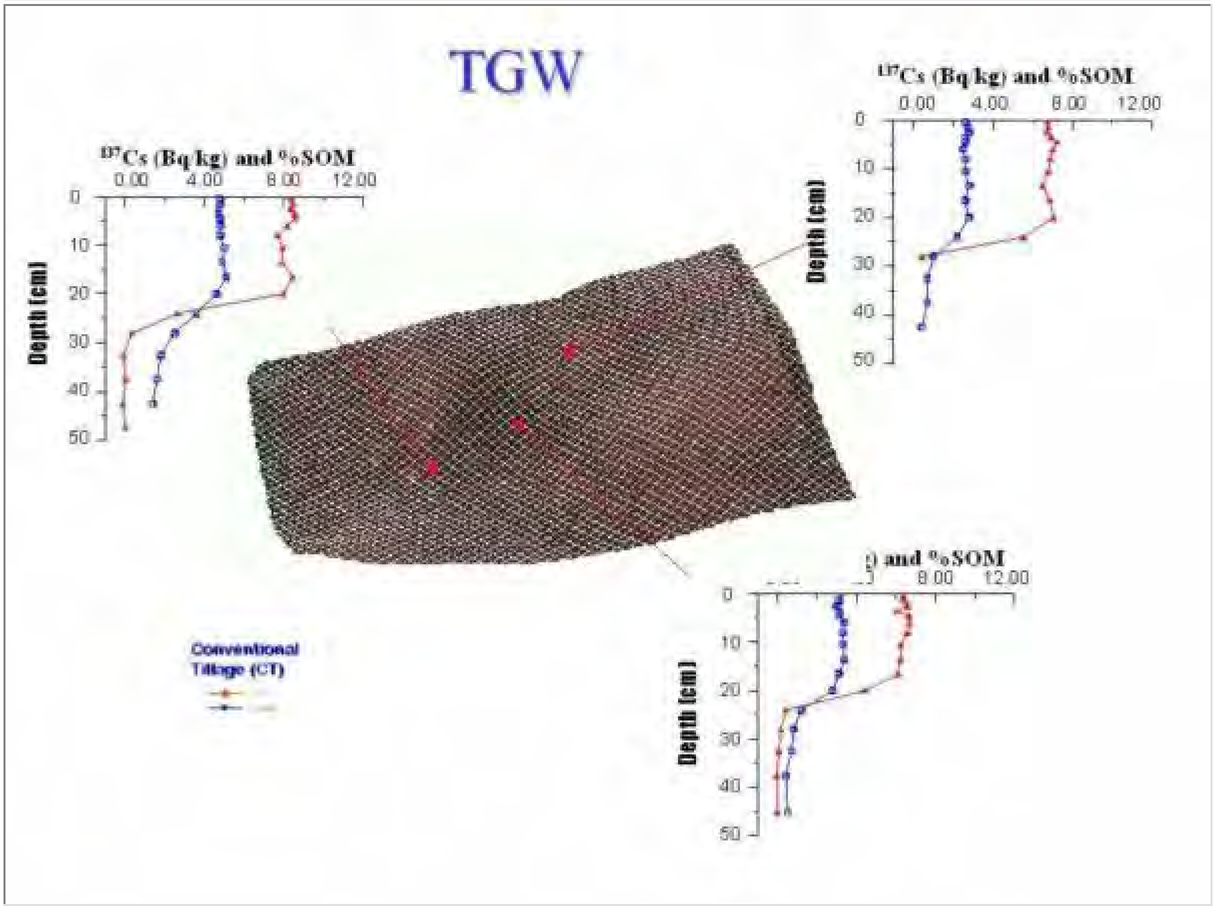


Figure 9. Digital elevation models with draped CASI spectral imagery, and the distribution of ^{137}Cs and SOM with soil depth at each of the slope positions for TMM

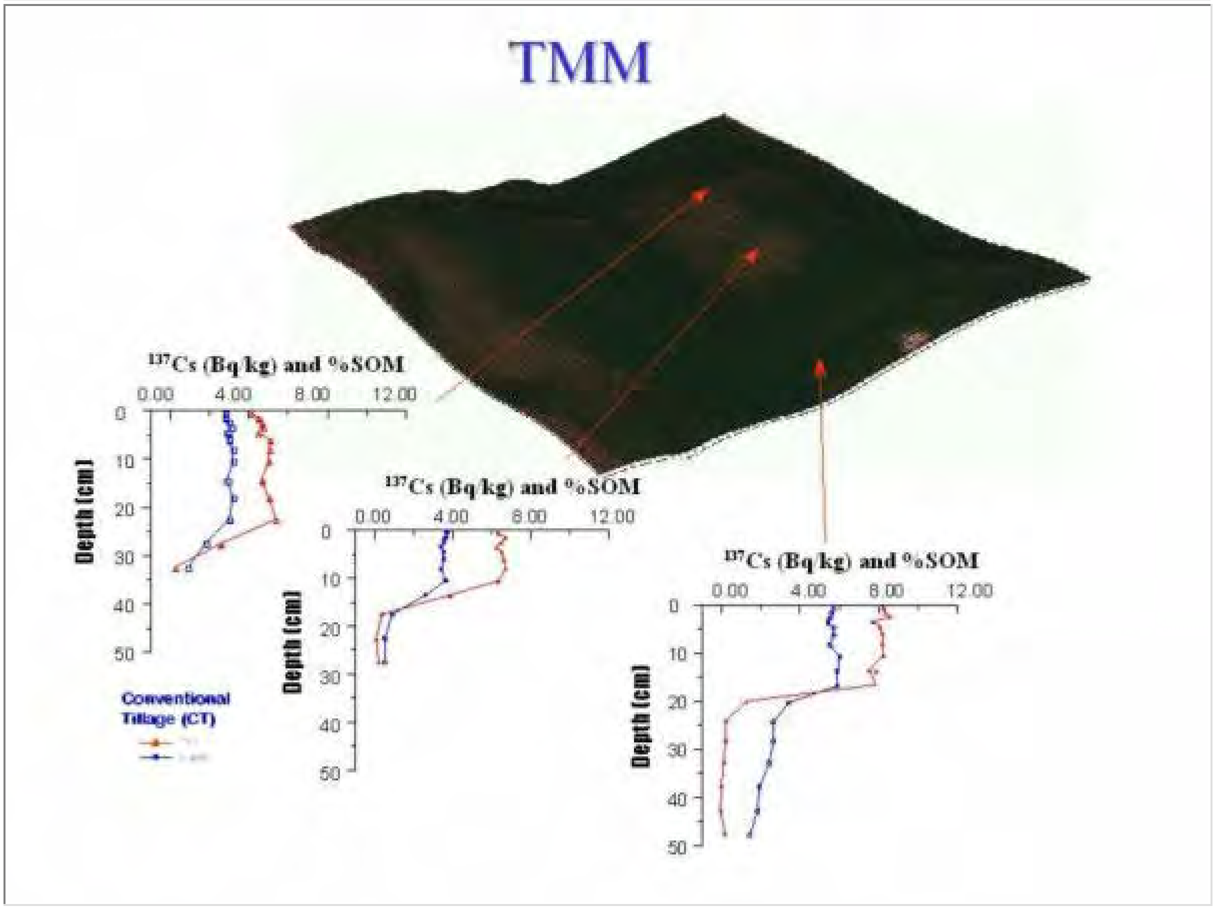


Figure 10. Digital elevation models with draped CASI spectral imagery, and the distribution of ^{137}Cs and SOM with soil depth at each of the slope positions for NMT

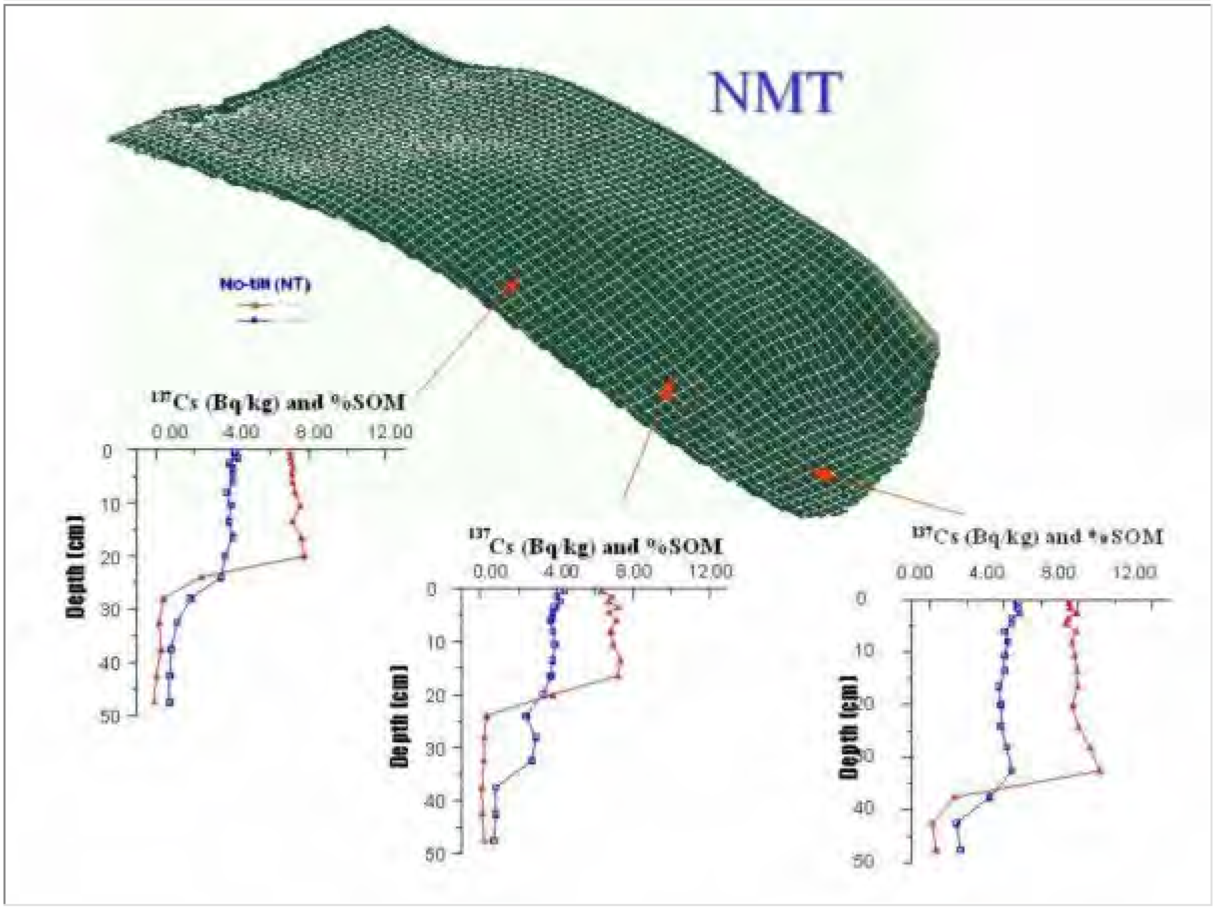
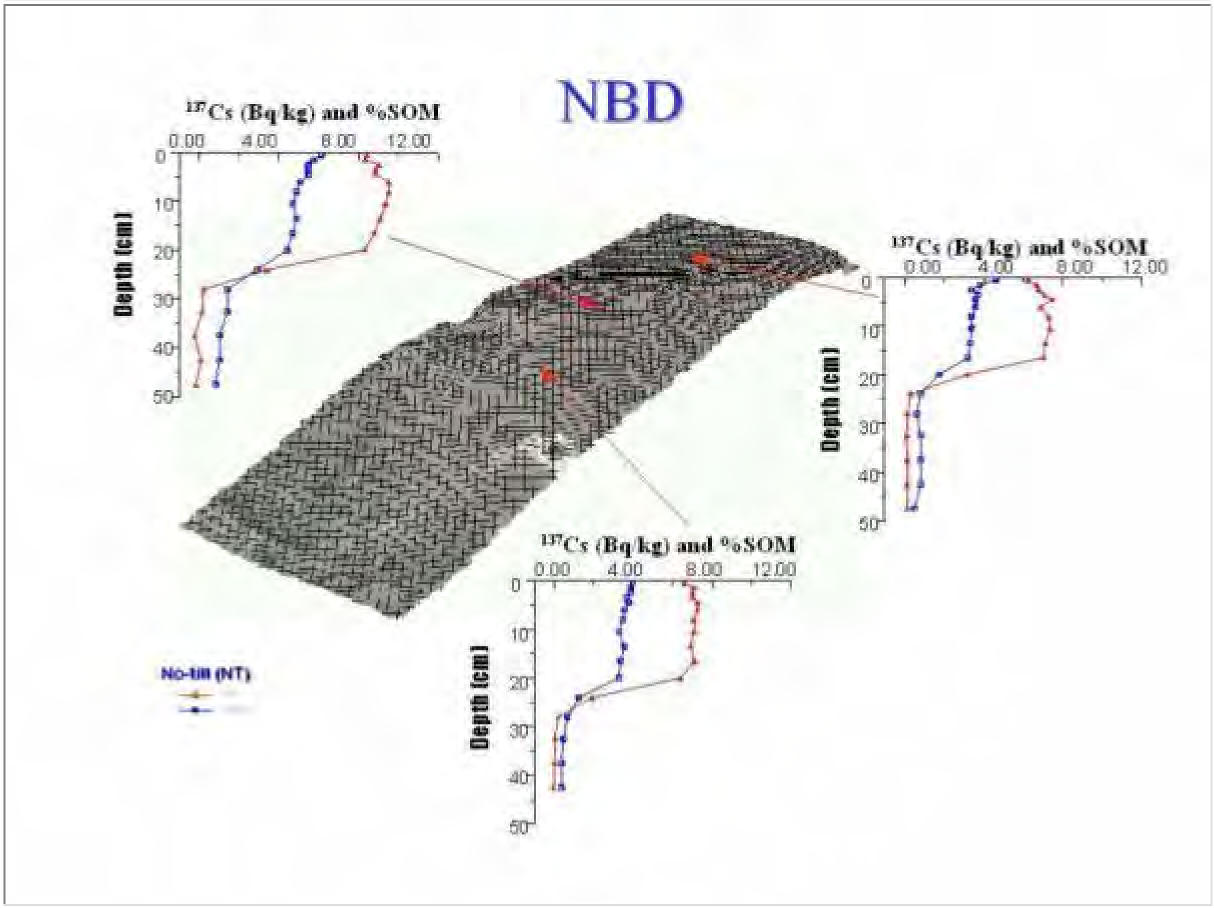


Figure 11. Digital elevation models with draped CASI spectral imagery, and the distribution of ^{137}Cs and SOM with soil depth at each of the slope positions for NBD



[Figure 12.](#) Digital elevation models with draped CASI spectral imagery, and the distribution of ^{137}Cs and SOM with soil depth at each of the slope positions for NBS

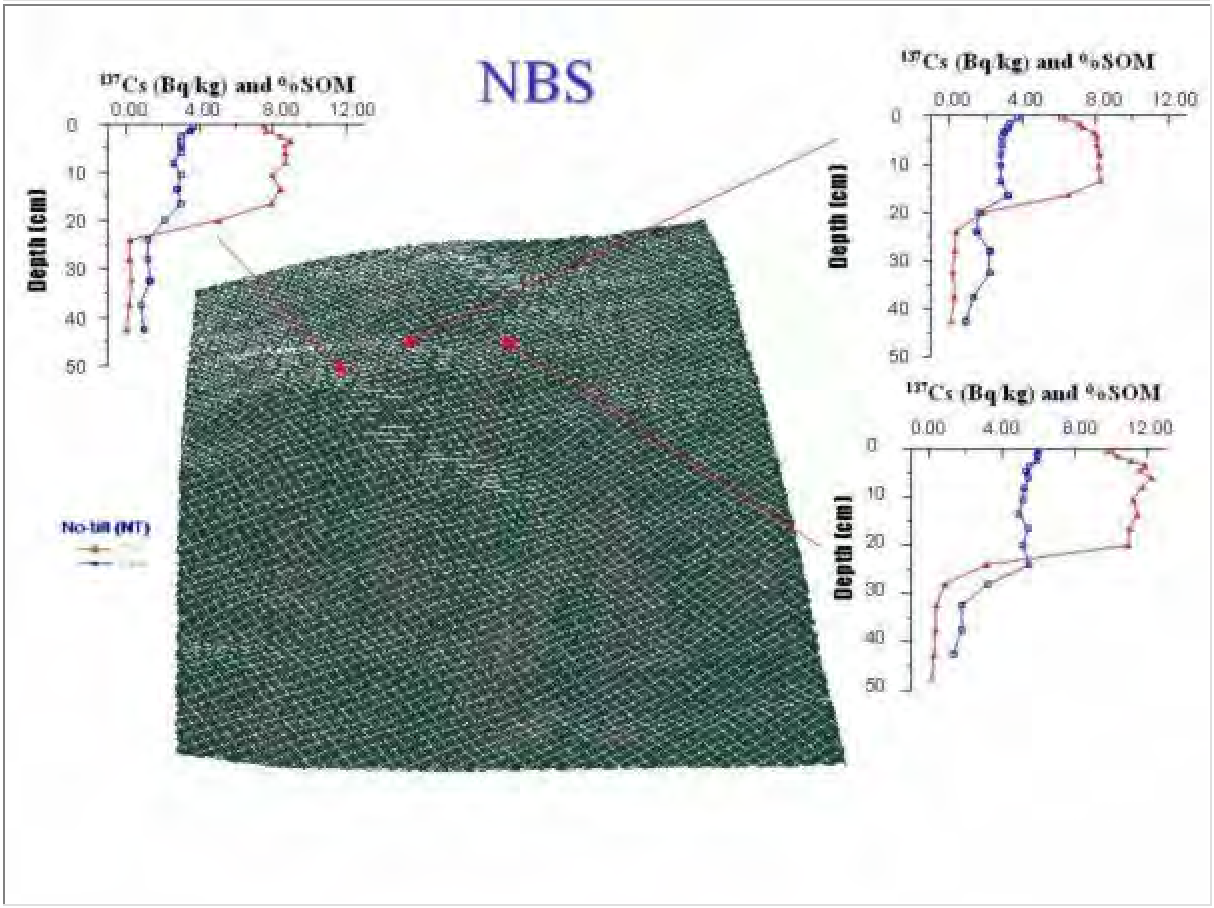
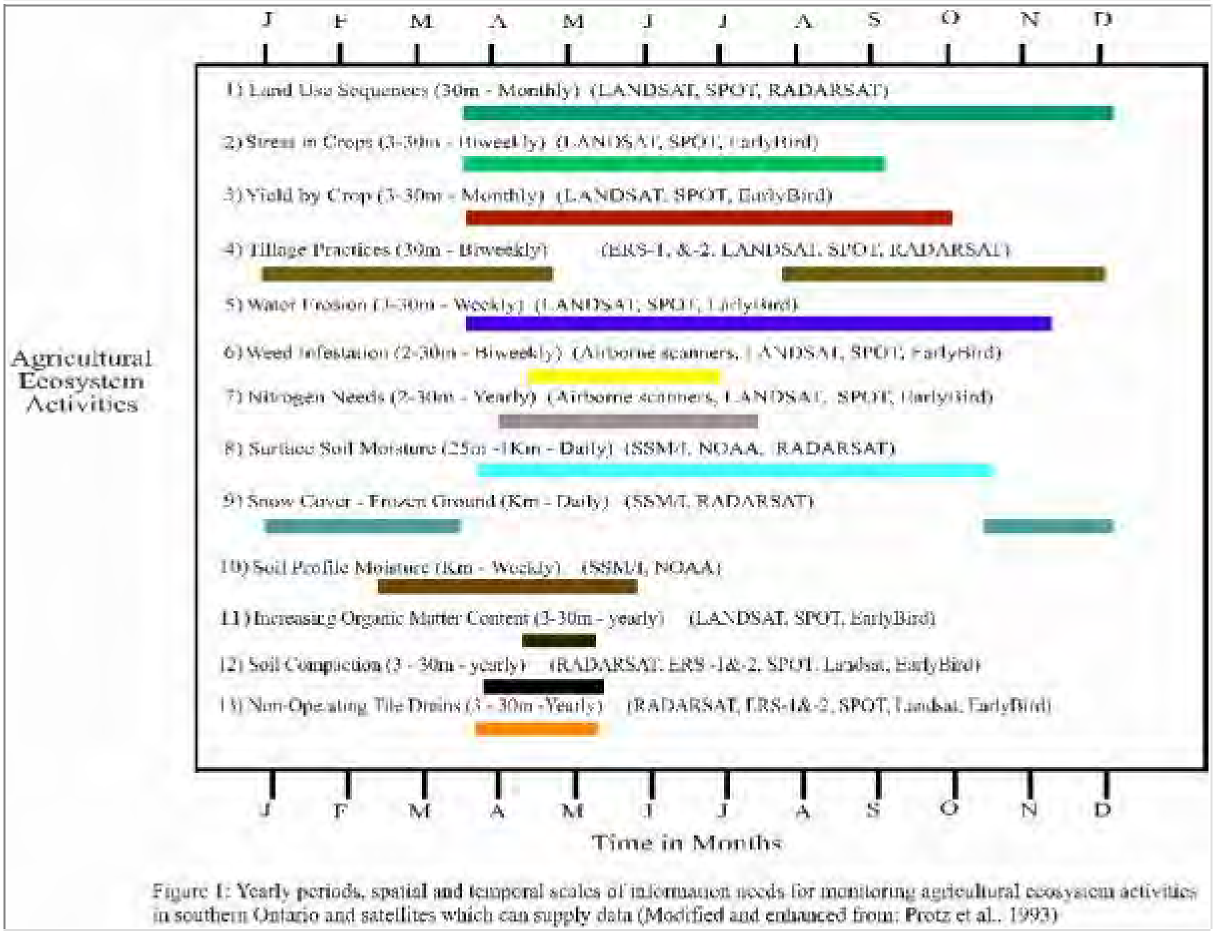


Figure 13. LANDSAT imagery of Essex county showing the road network.

Figure 14. Yearly periods, spatial and temporal scales of information needs for monitoring agricultural ecosystem activities in southern Ontario and satellites which can supply data.



Appendix 1

Wood, M.D., VandenBygaart, A.J., Shepherd, P., Protz, R., and Hulshof, B. 1996. Integration of high resolution GPS and CASI Imagery for Agricultural Soil Landscape Studies. 8 th Inter. Conference on Geomatics. May,Ottawa.

Integration of High Resolution GPS and CASI Imagery for Agricultural Soil Landscape Studies

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Abstract

The analysis of high resolution (~ 1 m) digital airborne imagery provides an excellent opportunity to develop the techniques and methodologies for the use of the next generation of high resolution satellite imagery. Integration of this imagery with accurate field scale Digital Elevation Models (DEM) derived from Differential Global Positioning Systems (DGPS), affords an opportunity to study the effect of small scale topographic changes and tillage practices on the reflectance characteristics of an individual agricultural field.

In the spring of 1995, a Compact Airborne Spectrographic Imager (CASI) collected imagery in the visible and IR regions

over six study sites throughout southern Ontario. The sites exhibited both conventional and conservation tillage practices. Reflectance from the conservation till (no till) sites varied considerably less than their conventional counterparts, showing little effect of topography on reflectance. The conventional tillage plots exhibited a response to topography, with high slope areas showing a higher return in the three optical wavelengths while foot slope regions tended to return low reflectance values.

Introduction

Remote sensing is evolving an important source of information about agriculture and agricultural systems. The use of remote sensing techniques can provide information over a large area in a relatively short period of time. Comprehensive agricultural monitoring schemes have been proposed (Clevers et al., 1994; Smith et al., 1995) by use existing satellite technologies to monitor crop growth and agricultural practice. Recent technological innovations in agriculture such as GPS and site specific farm management have precipitated a need to move towards smaller scales of digital data not available from today's satellites. Currently, the smallest scale form of digital map data is that of 1:5000 and 10 m pixels of satellite imagery (SPOT). Giles (1996) utilized SPOT HRV to classify slope units, however the study was conducted in a mountainous area in the Yukon and only was concerned with large scale variation. Generally, topographic variation within the field scale rarely varies more than 3 meters, and soil properties can change rapidly over 10 meters. As a consequence of this the inadequacy of this data for field scale monitoring becomes apparent. With impending availability of high resolution optical commercial imagery from spaceborne platforms, coupled with increasingly more accurate GPS receivers, the need for high resolution digital spectral imagery and accurate large scale survey and mapping can perhaps be filled.

The use of high resolution airborne imagery for the investigation of soil properties has been used successfully by Cihlar et al. (1987) who investigated the relationship between soil organic matter and reflectance as measured by a MEIS scanner.

This study was able to account for 50 - 94 % of the variabilty in the soil organic matter.

This paper investigates the effect of field scale topographic variation on the reflectance properties of soil. It also attempts to develop a methodology for the rapid integration of image analysis, GIS and GPS techniques for use with site specific agriculture.

Methodology

Two distinct forms of digital data were collected for this study (1) digital airborne imagery and (2) spot elevations from differential GPS. The analysis can be divided into two parts, first, the image processing of the CASI (Compact Airborne Spectrographic Imager) data using EASI/PACE and second the production of the elevation model in SKI and ARC/INFO.

Image Processing

Multi spectral imagery was collected over twelve sites in Southern Ontario using the CASI sensor. Only six sites will be discussed in this paper, namely those from a controlled bio indicators Green Plan project funded by Agriculture and Agri food Canada (AAFC).

Data from six spectral bands, three in visible and three in the infrared region, were imaged at a spatial resolution of between 1.5 and 2.0 m. The imagery was corrected for roll, pitch and yaw as well as radiometrically calibrated using the methodology outlined by Harron (1995). The imagery was then geocorrected using a correction algorithm developed at ISTS specifically for CASI imagery. With data registered to world co-ordinates, the experimental sites were located and clipped from the image for processing ease.

Differential GPS and GIS processing

Using the WILD GPS System from Leica, the experimental sites were surveyed generating accurate global X,Y, Z locations. The GPS system allows for an automated logging of X,Y,Z position on a specified time interval, this permits the operator to just walk over the plot area while the GPS automatically logs the spot elevations. In order to ensure spatial coherency between the GPS and CASI imagery, features clearly visible in the imagery were located using the GPS, these acted as control points to transform the data sets into the same relative space. The points generated in the survey were then differentially corrected using Leica's SKI differential software. This ensured the relative accuracy of the survey by correcting for the selective availability and ionospheric fluctuations.

The X,Y,Z points were transferred to the ARC/INFO GIS via an ASCII interchange format. Once in the GIS, a grid surface or lattice was interpolated from the points using the GRID subsystem in ARC/INFO. Surface values were generated using a procedure specifically developed for the generation of DEM's called TOPOGRID. From this surface, a three dimensional model was visualized and contours generated at a specific contour interval. The coverages were then transformed using the control points to define the transformation. Once the coverages were transformed, the CASI imagery was imported into ARC/INFO where it was draped on top of the topographic model.

Results and Discussion

Of the six sites, two were chosen for analysis. To investigate the effect of tillage patterns on spectral reflectance, both conventional till and conservational tillage were represented in the sites. The total change in elevation over each of the sites was 2 to 3 meters with relatively simple slopes. It was evident that two primary factors were influencing the reflectance of each of the sites, those being the effect of topography and tillage effects.

Tillage effects on reflectance

The mean, maximum and minimum reflectance values for each of the six CASI bands are shown in **Table 1**, and illustrate the effect of tillage patterns on reflectance. The conservational tillage (no till) showed less variation in reflectance for all six bands. This is in response to the homogenizing effect of the stubble or crop residue left on the field after harvest. The amount of crop residue found on the field is highly variable depending on the crop type and the specific conservation tillage practice. The movement of the crop residue from the upper slope to the lower slope tends to be slow and dependant on intense rain and degree of slope.

The no till study site, exhibiting only a 3 m total change in elevation, has a very gentle slope and likely very little movement of crop residue occurs down slope. This results in a fairly uniform distribution of stubble over the entire field which could account for the observed lack of reflectance variation of the no till site. In order to investigate the effect of topography on a no till site, a much more complex slope and varied terrain would be needed.

a: Spectral reflectance in the visible range with 25 cm contour intervals. Pixel size 1.5m x 1.5m .

b: Three dimensional topographic model of the study sitegenerated from high precision GPS survey. Vertical exaggeration 7.5 times.

c: Combined spectral reflectance of red, green, and blue wavelengths draped over the topographic model to show influence of slope on spectral reflectance.

Appendix 2

Hulshof, B.,Protz,R., Wood,M., and Fischer,J. 1997. Identification of agricultural field size and boundaries from Landsat TM data in southern Ontario. International Symposium in the Era of Radarsat 1997. May, Ottawa.

Identification of agricultural field size and boundaries from Landsat TM data in southern Ontario.

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Abstract

Providing accurate information derived from satellite data on agroecosystems requires ground truth cognizant of spatial and temporal variations that occur on a regional scale. To better understand the interactions between satellite data and agroecosystems training areas need to be identified. It is in this context that all large agricultural fields (those greater than 14.5 hectares in size) were identified in southern Ontario from Landsat TM data.

To facilitate the identification of large fields from Landsat TM data a rigid unsupervised classification procedure was developed. The classification successfully identified large fields. The spatial resolution of Landsat TM data and natural variability in crops due to soil, topography, nutrient status and available moisture were found to be limiting factors in the identification of large fields.

Introduction

Agriculture is an important industry in Ontario, in 1995 the total farm gate receipts were 6.09 billion dollars (Ministry of Agriculture, Food and Rural Affairs, 1996). The success of the agricultural industry is dependent on many variables such as crop type, soil moisture, nutrient availability and soil type. Many of these variables affecting field crops can be monitored using remotely sensed data throughout the growing season (see Figure 1). Ultimately, satellite data should be able to provide accurate, up-to-date information on agroecosystems at a regional scale.

With the pending launch of up to ten new satellites in the next two years it becomes possible to have high resolution data on a timely basis (Corbley, 1996). To ensure that information derived from the satellite data is accurate, ground truthed sites will be required throughout southern Ontario. **The objective of this paper is to identify all large fields in southern Ontario for satellite data validation**. These ground truth sites will be used to validate satellite data as training areas and improve our understanding of the correlations between satellite imagery and agroecosystems.

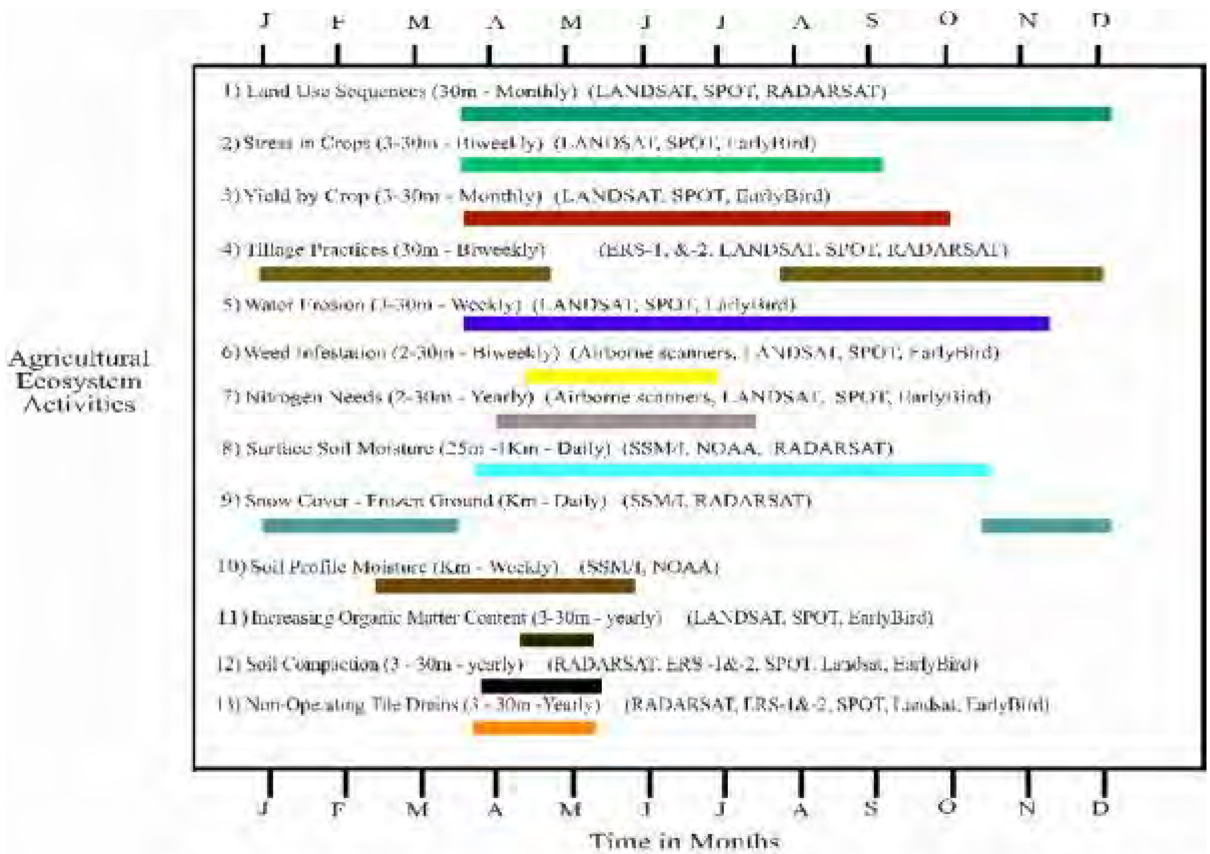

Figure 1: Yearly periods, spatial and temporal scales of information needs for monitoring agricultural ecosystem activities in southern Ontario and satellites which can supply data (Modified and enhanced from: Protz et al., 1993)

Study Area and Data Sets

The study area is located in southern Ontario. It includes the 10 counties of Lambton, Kent, Essex, Middlesex, Elgin, Oxford, Brant, Haldimand-Norfolk, Hamilton-Wentworth, and Niagara (see figure 2).

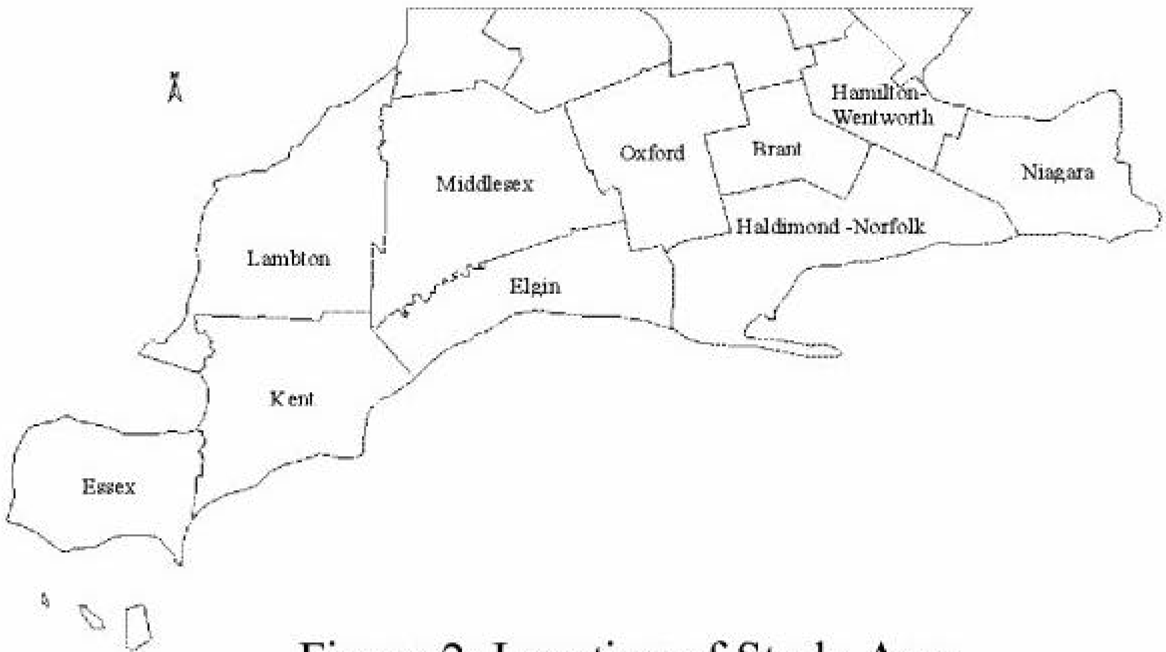

Figure 2: Location of Study Area

Landsat Thematic Mapper (TM) for southern Ontario was kindly provided by the Provincial Remote Sensing Office (PRSO). This consisted of four relatively cloud free satellite scenes mosaiced together. Each of these scenes was processed separately due to the different spectral and temporal characteristics of each image. The satellite imagery was acquired in the summer on dates ranging from August 1988 to June 1993 in Landsat TM bands two (0.52 to 0.60 m m), three (0.63 to 0.69 m m) and four (0.76 to 0.90 m m). On July 19, 1990 colour infrared aerial photographs were taken of the Oxford test strip. These photos were used to verify classification results.

The digital road network of primary and secondary roads covers the ten counties in the study area and was purchased from Desktop Mapping. The data is based on 1:50000 National Topographic Data Base (NTDB) topographic map sheets and has a accuracy of ± five meters of the true ground location (Geomatics Canada, 1995).

Methodology

Large fields are defined as agricultural fields larger than 14.5 hectares. This is based on Swain and Davis's (1978) recommendation that 10*n* to 100*n* pixels be used in training areas (" *n*" being the number of bands used). Assuming three to six bands are used in a supervised classification, a minimum of 30 and maximum of 600 pixels should be used in a training area. If 169 RADARSAT standard resolution or Landsat TM pixels of 25 meters are used and a 55 meter buffer along field edge are included in the calculations then the required field size is 14.5 hectares (McNairn and Protz, 1993).

The classification methodology to identify large fields was developed on a 3 by 16 kilometer strip of agricultural land in Oxford county. This enabled experimentation and rapid evaluation with different classification methodologies and avoids working with cumbersome large data sets. The area was selected because of the ancillary data that was available for verification of the classification being experimented with. Available data included Landsat TM imagery from 1991, a digital road network, airphotos from 1991 and a digitized field boundaries from 1990. The classification was developed bearing in mind that it should be efficient and effective on a large scale (i.e. over southern Ontario). Once an appropriate classification methodology had been established it was applied to the remainder of southern Ontario.

There are two methods by which field boundaries can be detected, using edge detection or through the delineation of homogeneous areas (Metzger and Muller, 1996). Edge detection algorithms were found only to be effective in some areas and would leave gaps that required manual editing (Ji, 1996). This is not viable on a large area.

Large field detection using satellite data was pursued through the delineation of homogeneous areas. Supervised classification was not used because there was no ground truth data available from the image collection period. Unsupervised classification was chosen because of the efficiency in which large areas of imagery from different dates could be processed.

Before proceeding with the classification three principal components were generated from the original Landsat TM data. Principal components compress image variability into fewer channels. Up to 99 percent of the image variability was contained in the first two eigenchannels. Reducing the number of input channels for classification decreased the processing time required. Additionally, classification results from eigenchannels compared better with the field boundaries than classifications based on using the original Landsat TM data.

When classifying the entire image there was some confusion between corn and forest area, especially in August imagery. Duke (1993) also encountered this confusion in a supervised crop classification completed on imagery recorded on July 19, 1991. To remedy this a mask that separated agricultural areas from non agricultural areas was created for this paper.

It was found unsupervised classification recognized homogeneous areas or natural groupings in the image. The ISODATA algorithm used in EASI/PACE's ISOCLUS functionality was found to yield the best classification results when compared with other unsupervised classification algorithms such as K-CLUS. As in Belward *et al.* (1990) the optimal number of classes to specify was found to be 30.

The 30 classes generated through unsupervised classification were aggregated into six or seven agricultural classes utilizing PCI's Imageworks aggregation functionality. This enabled the classes to be viewed individually, as potentially aggregated classes and varying combinations of unaggregated classes. The new classes were always referenced back to the original image at full resolution in different locations throughout the frame. Results of aggregation were then compared with the original data. An advantage of aggregation was that contextual information interpreted by the analyst but not detected by the computer could improve field classification. Areas smaller than 0.81 hectares in size were eliminated using EASI/PACE's SIEVE filtering function. It was found these areas significantly increased data volume and were not of interest to this paper.

The resulting classification was exported to ARC/INFO where the individual fields were converted into polygons for size analysis. A 40 meter buffer that approximated road width was created on a road network and integrated with the field boundary coverage. Integration provided reference information to locate the fields and aided in separating individual fields where reflectance of the field had been homogenized with the surrounding road.

In ARC/INFO the fields were placed in classes based on their area starting at 14.5 hectares and increasing in 10 hectare intervals (i.e. 25 to 35 ha). Seven classes were generated the last class being those fields larger than 75 hectares in size. Final maps were generated in ARCVIEW.

Results and Discussion

The classification using Landsat TM data was successful at identifying most large fields (see Figure 3). Ground truth showed large fields where they had been identified. It was not feasible to quantify the accuracy of the classification given satellite data had been recorded between 1988 and 1993 and the large size of the study area. Most of the inaccuracies in the classification could be attributed to the 25 meter resolution of Landsat TM data or the dynamic nature of agriculture (Spectranalysis, 1995).

Temporal changes in field boundaries and crop type made it challenging to accurately assess the effectiveness of a field classification. Many farmers will change the type of crop grown and area planted from year to year to maximize profits or to plant more sustainable crop rotations. Changes that may have occurred between the dates of image acquisition dates of ground truthing (October, November 1996 and March 1997) confounded accuracy assessment.

The best classification results were obtained from imagery recorded during August, it is during this time in the growing season that crops have a full canopy but have not yet senesced. The area and crop type grown changes annually which confounded the assessment of the classification.

Figure 3: Classification of large fields on test site in Oxford county

The 25 meter spatial resolution of Landsat TM imagery was not fine enough to detect a fence line crossing through some pixels or a narrow band of trees and shrubs that separate two fields which may be as narrow as one meter. Often the reflectance measurement of the fence will become homogenized with its surroundings. Consequently the fence and field boundary remains undetectable and field size was overestimated. This complicates field boundary detection where two fields with the same crop are separated only by a fence. Higher resolution remotely sensed data will alleviate this type of error.

The spectral variability found within a field was occasionally to diverse to permit classification as one field. An example of this is a field with low lying wet areas which retarded crop growth and consequently had a darker spectral signature than the rest of the field . When compared to the surrounding crop these areas showed up dark while the remainder of the field reflected strongly and thus a field was separated into two different crop classes.

When aggregating classes the aim was to group the 30 classes generated through unsupervised classification into six or seven conceptual classes that represent agricultural fields. There was a trade off between trying to maximize the number of aggregated classes and trying to create aggregated classes that reflect the natural variability in a field. The scenario exists whereby if more than six or seven classes were created then the fields became too fragmented. Consequently, some large fields will not be detected because high within field variability, which is contrary to the objectives of this paper. However, in attempting to ensure that the natural variability in large fields was detected fewer aggregated classes were created. As aggregated classes begin to contain larger numbers of the original classes there is a tendency to classify fields larger than they actually are.

Conclusions

It was established that the most effective way to locate fields was through the identification of homogeneous areas. The method selected for classifying a fields in southern Ontario was through the use of unsupervised classification using the ISODATA algorithm. The classification methodology developed proved to be successful, identifying most fields larger than 14.5 hectares. The greatest number of fields identified occurred in the 14.5 to 25 hectare class. The optimal time to acquire imagery for the classification of large fields is August.

However, the 25 meter spatial resolution of Landsat TM and natural variability found within agricultural fields proved to be the major limiting factors in the classification. The size of some fields was overestimated due to the difficulties in detecting narrow fence lines or single furrow boundaries. Crops located on smaller fields (i.e. tobacco) will not be represented in the sampling scheme because the 25 meter pixel resolution was too coarse to detect these small fields. Higher resolution imagery is needed improve the accuracy with which large fields are identified. Fields with a broad range of natural variability and thus variations in spectral reflectance values were difficult to classify as one field.

Acknowledgements

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Appendix 3

Hulshof,B., Protz, R, and Allen, B. 1997. Objective training site sellection for regional scale satellite data validation. International Symposium in the Era of Radarsat 1997. May, Ottawa.

Objective Training Site Selection for Regional Scale Satellite Data Validation in Southern Ontario

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Abstract

The success of agriculture is dependent on many variables such as crop health, soil nutrient status, soil moisture, and soil organic matter. The aim of this paper is to account for spatial and temporal variability of these factors when selecting training sites for calibration of remotely sensed data in southern Ontario. Many methods used for the selection of training sites are subjective and consequently may reduce the classification accuracy with non-representative, biased training sites.

A stratified random sampling scheme was employed to select agricultural fields larger than 14.5 hectares to be used for calibration of satellite data. Three to four fields were located in clusters at road intersections to improve ground truthing efficiency by up to 70 percent. The number of training clusters per county ranged from 18 in Essex county to 78 in Middlesex. It was difficult to satisfy the dual objectives of selecting training areas representative of spatial variations in agriculture and creating a sampling design that is not prohibitively costly.

Introduction

Several factors provided the impetus for this paper, the major driving force being that the remote sensing industry at a stage where it can move to operational resource monitoring (Lillesand and Kiefer, 1994). The launch of up ten new satellites in the next two years creates new opportunities with high resolution imagery from satellite platforms (Corbley, 1996). Concurrently there have been advances in Geographic Information Systems (GIS), reductions in the cost of computer memory, increases in processing speed and the emergence of information delivery systems such as the internet. Remote sensing is now at a stage where we can look towards providing a comprehensive monitoring system. Agricultural activities which could be monitored using satellite data are shown in Figure 1. Agriculture, which is constantly changing, could benefit from the timeliness of remote sensed data.

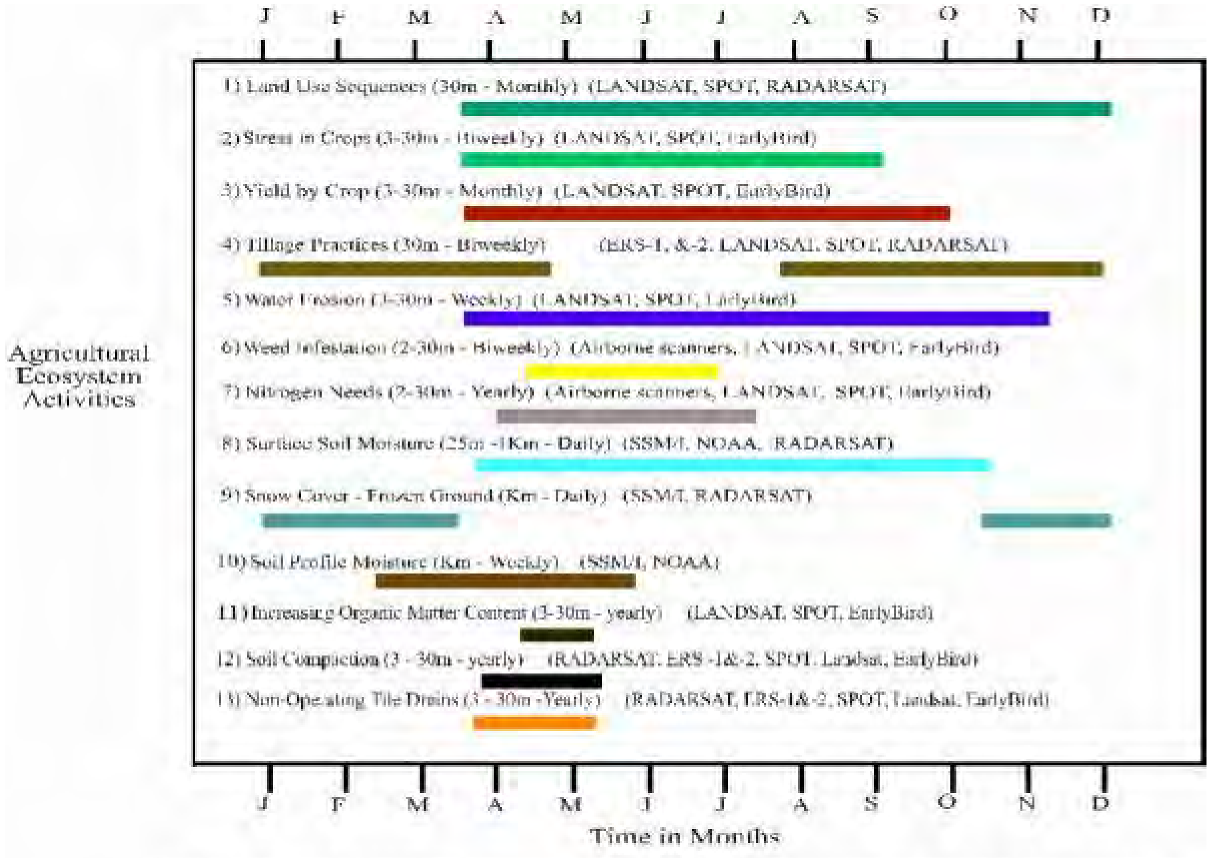

Figure 1: Yearly periods, spatial and temporal scales of information needs for monitoring agricultural ecosystem activities in southern Ontario and satellites which can supply data (Modified and enhanced from: Protz et al., 1993)

While it would appear that remote sensing is on the threshold of becoming operational, there are still many questions to be answered regarding the exact capabilities of satellites, especially future satellites. To answer these questions new satellites will need validation on agricultural test plots. As remote sensing moves from a local to a regional scale these test plots or "training sites" will need to be distributed over the agricultural landscape to represent the spatial and temporal variability in southern Ontario.

However, "collection of field data remains one of the least systematized aspects of remote sensing" (Campbell and Browder, 1995:p. 333) even though the choice of training area is an important factor in the final accuracy of a classified map (Warren *et al.*, 1990; Kershaw *et al.*, 1992). Justice and Townshend (1994) also identified a need for satellite sensor "calibration" sites. These sites would be used to parameterize biophysical properties on present and future satellites (Townshend and Justice, 1994). An equilibrium should be found between collecting sufficient ground data and being efficient enough so the cost of ground truthing does not become prohibitive (Congalton and Biging, 1992; Cochran, 1977). Warren *et al.* (1990) developed a procedure to maximize the representativeness of field sample sites and was one of the few pieces of literature that addressed the issue of objectively locating field sample sites (see also Hallum and Basu, 1978).

The objective of this paper was to establish a strategy for selecting ground truth sites for satellite data in southern Ontario. All agricultural fields larger than 14.5 hectares in southern Ontario have been identified (Hulshof *et al.* 1997). It is from these fields that training areas will be selected.

Study Area and Data Sets

The study area is located in Southern Ontario. It includes the 10 counties of Lambton, Kent, Essex, Middlesex, Elgin, Oxford, Brant, Haldimand-Norfolk, Hamilton-Wentworth and Niagara (see figure 2).

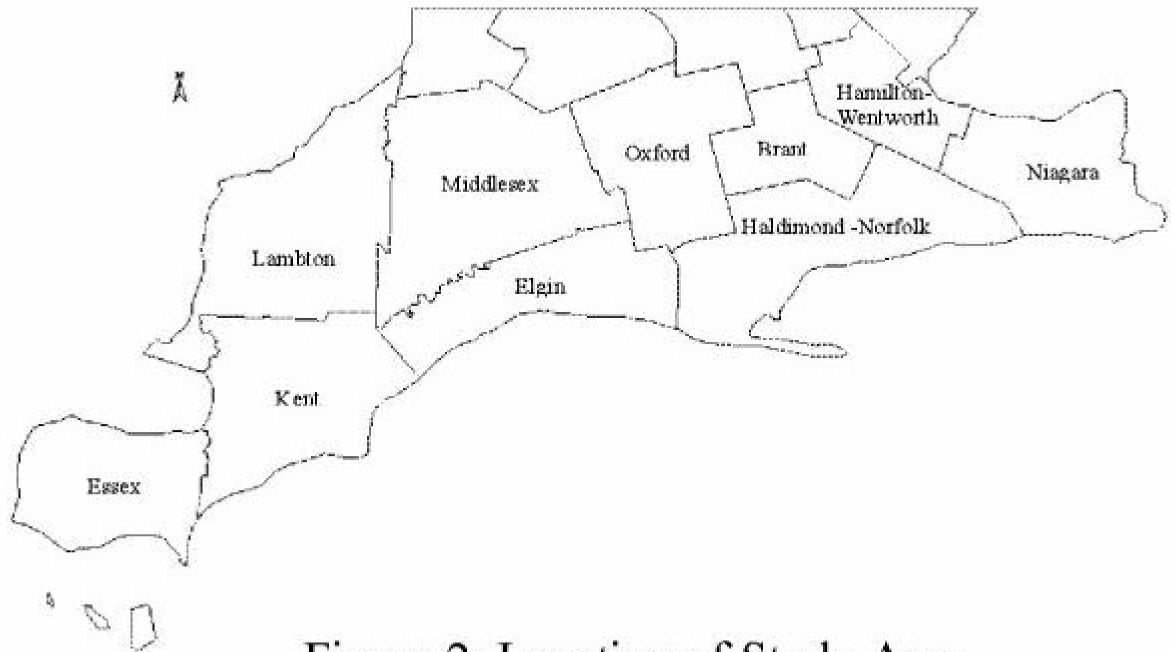

Figure 2: Location of Study Area

The training sites were selected from a classification of large fields (agricultural fields larger than 14.5 hectares) completed by Hulshof et al. (1997). The classification made available a census of large fields that can be used for monitoring agricultural dynamics in southern Ontario. The georeferenced fields were identified from Landsat TM imagery and resides as a data layer in ARC/INFO.

The primary and secondary road network was purchased from Desktop Mapping. This digital dataset covers ten counties in the study area. The data is based on 1:50000 National Topographic Data Base (NTDB) topographic map sheets and has a accuracy of ± five meters of the true ground location (Geomatics Canada, 1995). The road network was needed to locate the agricultural fields.

The minor physiographic regions digital file is based on Chapman and Putnam's (1984) map of physiography in southern Ontario. It was digitized in ARC/INFO because a high confidence coverage was not available. The boundaries of the physiographic regions are an approximation of the true boundaries

.

Methodology

The sampling strategy chosen for locating training sites in southern Ontario was stratified random sampling of clusters of fields positioned at intersections. Stratified random sampling requires that a population is divided into subpopulations that are more homogeneous in nature (Cochran,1977).

Stratification has been used in several agricultural studies to estimate subpopulation parameters (Hallum and Basu, 1978; and Guoxuiang and Dawei, 1990). Researchers have used a variety of means to stratify regional areas. Franklin et al. (1986); and Cibula and Nyquist (1987) used bioclimatic divisions (i.e. large watershed regions) to stratify their study area. Alternatively, Shasby and Carnegie (1986), and Lozano-Garcia *et al.*, (1991) used physiographic units as proposed in this paper to stratify the landscape. Stratification using natural boundaries reduces heterogeneity and yields more homogeneous areas than man-made boundaries (Hallum and Basu, 1978; Lozano-Garcia et al., 1991).

Southern Ontario was cross-stratified using the minor physiographic regions defined in Chapman and Putnam (1984) and county boundaries (Fieveson, 1978). A total of 44 sub strata were defined in the study area (see table 1). Using cross stratification enabled the identification of homogeneous areas within political boundaries and permits the comparison of classification results with census data at a county scale.

Table 1: Cross stratification of counties with minor physiographic regions and the number of training clusters in each sub stratum.

	Essex	Kent	Lambton	Elgin	Middlesex	Haldimond-Norfolk	Oxford	Brant	Hamilton-Wentworth	Niagara
Bothwell		51	2	21	9					
Caradoc					22					
Ekfrid			28		21					
Erie Spit	8	3								
Flamborough									2	
Haldimond						50		9	33	99
Horseshoe			9		40	4		19	6	
Huron Fringe			10							
Huron Slope			8		21					
Iroquois									7	26
Mount Elgin				21	31		43	8		
Norfolk 1				22		35	14	4	15	
Norfolk 2							2	19		
Oxford					6		106			
St. Clair	163	188	127		3					
Stratford					67		1			
Waterloo							3			

To improve the efficiency and reduce costs of the ground truth process, candidate training clusters are defined as road intersections having three to four large fields, not too patchy in appearance, located at an road intersection. Candidate training clusters were identified from the classification of large fields using Landsat TM data (Hulshof et al., 1997). This was done by creating a point coverage in ARC/INFO to which all potential candidate training clusters were digitized. The UTM zone 17 coordinate of each cluster was included in the coverage. The road network for the corresponding area was added to enable users to rapidly locate each cluster of fields for ground truth.

The training fields were randomly selected in clusters within each sub stratum. Based on the assumption that six to nine principal crops will be found in a sub stratum at any given time, it will be necessary to have up to 10 fields (one extra to accommodate crop failure or potential errors) of at least 14.5 hectares in area. A particular crop will only be grown once every three years since most farmers practice crop rotations on a three year cycle (i.e. corn, soybeans, wheat). To ensure that all crop types are represented a minimum of 30 large fields (three years multiplied by ten different crop types) are needed per sub stratum. Given that a minimum of three large fields appear at an intersection, ten training clusters are required per sub stratum. All training clusters were used if less than ten training clusters were identified within a sub stratum.

To facilitate random selection of training clusters, each sub stratum was renumbered from one to the total number of clusters located there. This required 44 individual coverages of the sub strata be created in ARC/INFO and the number candidate training clusters in each sub stratum was thus determined (see Table 1).

From the total of 1393 training clusters a fraction of clusters were selected using a random number generator. These random numbers corresponded to the candidate training cluster labels. The first ten random numbers or cluster labels were selected as training sites for the satellite data. If a number repeated itself the next unused cluster label was used. From this total, 350 training clusters were randomly selected from within the 44 sub strata delineated in the study area. Each of these training clusters had three to four agricultural fields located there.

Results and Discussion

Ground truthing completed on selected training cluster locations showed clusters had been successfully identified. It was not possible to visit all training clusters identified due to limited resources and the size of the study area. Sometimes fields were located a small distance from the intersection and required traveling a small distance (less than 50 meters) to locate the field because the view was obstructed by a woodlot or farmstead.

A consequence of cross stratification was that number of training sites identified ranged from 18 to 78 in a county and a total of 350 training sites were selected in southern Ontario. The greater the number of strata located in a county the higher the number of training clusters selected. There was some difficulty in trying to balance the dual goals of making the scheme as efficient as possible and trying to represent the physiography present in each county, especially in counties such as Middlesex where nine strata were identified and 78 training sites were delineated. Ideally, to be efficient fewer training clusters would have been selected. A more optimal situation occurred in Kent county with only three strata and a total of 23 training site locations (see figure 3). However balancing the need to be cost efficient and selecting representative training sites can be contradictory.

By locating the fields in clusters the number of stops required for ground truth can be reduced by up to 70 percent per sub stratum in the "best case" scenario. In the best case, three of the 10 field clusters would have four fields located at each intersection for a total of 12 large fields (three intersections multiplied by four fields). In addition, each of the fields to be used as a training cluster would have a different crop growing there. Making the reasonable assumption that up to nine principal crops will be classified in each county, this provides the required nine training sites at three stops for supervised classification.

In the worst case scenario all 10 training clusters would be needed. This situation would arise if only one crop type was found at each intersection and 10 crops were being monitored. This would require ten stops. The most probable situation is that the number of clusters requiring ground truth lies somewhere between the best and worst case scenarios outlined.

In areas such as Niagara county it was found that agriculture was characterized by smaller fields with a greater number inhomogeneities. To select only fields that appeared homogeneous in nature in this area would have meant that many fields that represent the nature of agriculture in the region would be ignored restricting the ability of the sampling scheme to represent agriculture in the area. In the central part of the study area the landscape is more rolling and field size larger. The largest fields were found in Essex county on the St. Clair clay plain.

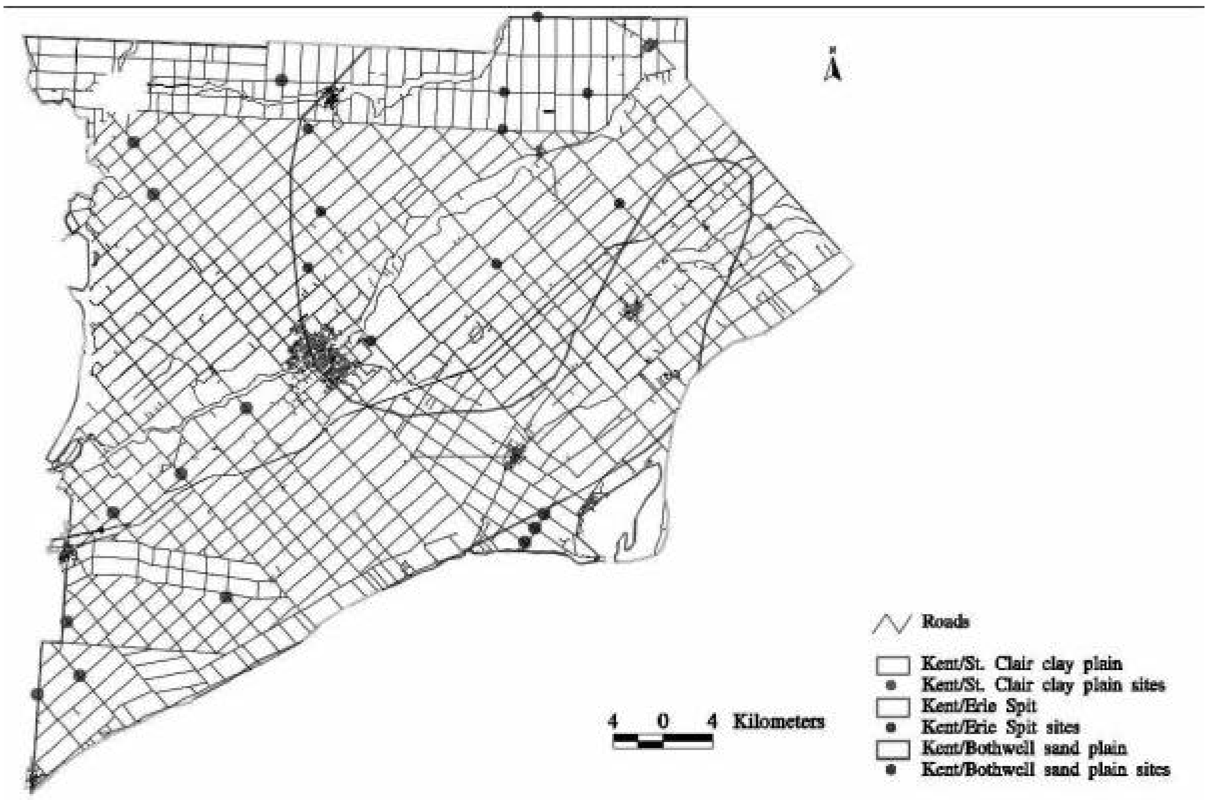

Figure 3: Training Clusters Located in Kent County

This training site selection scheme is intended to show how training areas may be objectively selected for the monitoring of agriculture. Before future users utilize this design it is essential to consider the scale of the study and the characteristics of the crops to be monitored. There are alternative units by which the study area could have been stratified, such as soil type or corn heat units. Future users need to consider their own specific needs and have available to them a census of all large fields and candidate training areas from which they can select training sites for satelllite data.

Conclusions

A total of 1393 clusters with three or more fields larger than 14.5 hectares at a road intersection were identified as candidate training areas for agroecosystem monitoring in southern Ontario. Sampling in clusters of three to four fields reduced the number of locations to be visited for ground truth by up to 70 percent. The number of strata in each county ranged from a minimum of two in Niagara and Essex to a maximum of nine in Middlesex county. The number of training areas selected in each county ranged from 18 in Essex to 78 in Middlesex. Having 78 training areas in one county decreased the efficiency of the sampling design but may be necessary to represent variations in agriculture due to physiography. Counties such as Kent with only 3 strata and 23 training areas illustrate a more uniform landscape and thus a simpler sampling situation. It was difficult to satisfy the dual objectives of selecting training areas representative of spatial variations in agriculture and to create an efficient sampling design.

Acknowledgments

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