

NOTE TO USERS

This reproduction is the best copy available.

UMI[®]



Université d'Ottawa • University of Ottawa



Université d'Ottawa • University of Ottawa

FACULTÉ DES ÉTUDES SUPÉRIEURES
ET POSTDOCTORALES

FACULTY OF GRADUATE AND
POSTDOCTORAL STUDIES

Anna PACHECO

AUTEUR DE LA THÈSE - AUTHOR OF THESIS

M.A. (Geography)

GRADE - DEGREE

Department of Geography

FACULTÉ, ÉCOLE, DÉPARTEMENT - FACULTY, SCHOOL, DEPARTMENT

TITRE DE LA THÈSE - TITLE OF THE THESIS

Contribution of Hyperspectral Remote Sensing for the Estimation of Leaf Area
Index in the Context of Precision

A. Bannari

DIRECTEUR DE LA THÈSE - THESIS SUPERVISOR

CO-DIRECTEUR DE LA THÈSE - THESIS CO-SUPERVISOR

EXAMINATEURS DE LA THÈSE - THESIS EXAMINERS

A. Desrochers

M. Sawada

K. Staenz

J.-M. De Koninck, Ph.D.

LE DOYEN DE LA FACULTÉ DES ÉTUDES
SUPÉRIEURES ET POSTDOCTORALES

DEAN OF THE FACULTY OF GRADUATE
AND POSTDOCTORAL STUDIES

**CONTRIBUTION OF HYPERSPECTRAL REMOTE SENSING TO THE
ESTIMATION OF LEAF AREA INDEX IN THE CONTEXT OF
PRECISION AGRICULTURE.**

Presented by
Anna Pacheco

A thesis submitted to the Faculty of Graduate and Postdoctoral Studies
in partial fulfillment of the requirements
for the degree of M.Sc. in Geography

REMOTE SENSING AND GEOMATIC ENVIRONMENT LABORATORY
DEPARTMENT OF GEOGRAPHY
UNIVERSITY OF OTTAWA
OTTAWA, ONTARIO
CANADA

© Anna Pacheco, Ottawa, Canada, 2004



Library and
Archives Canada

Bibliothèque et
Archives Canada

Published Heritage
Branch

Direction du
Patrimoine de l'édition

395 Wellington Street
Ottawa ON K1A 0N4
Canada

395, rue Wellington
Ottawa ON K1A 0N4
Canada

Your file Votre référence

ISBN: 0-494-01569-1

Our file Notre référence

ISBN: 0-494-01569-1

NOTICE:

The author has granted a non-exclusive license allowing Library and Archives Canada to reproduce, publish, archive, preserve, conserve, communicate to the public by telecommunication or on the Internet, loan, distribute and sell theses worldwide, for commercial or non-commercial purposes, in microform, paper, electronic and/or any other formats.

The author retains copyright ownership and moral rights in this thesis. Neither the thesis nor substantial extracts from it may be printed or otherwise reproduced without the author's permission.

AVIS:

L'auteur a accordé une licence non exclusive permettant à la Bibliothèque et Archives Canada de reproduire, publier, archiver, sauvegarder, conserver, transmettre au public par télécommunication ou par l'Internet, prêter, distribuer et vendre des thèses partout dans le monde, à des fins commerciales ou autres, sur support microforme, papier, électronique et/ou autres formats.

L'auteur conserve la propriété du droit d'auteur et des droits moraux qui protègent cette thèse. Ni la thèse ni des extraits substantiels de celle-ci ne doivent être imprimés ou autrement reproduits sans son autorisation.

In compliance with the Canadian Privacy Act some supporting forms may have been removed from this thesis.

Conformément à la loi canadienne sur la protection de la vie privée, quelques formulaires secondaires ont été enlevés de cette thèse.

While these forms may be included in the document page count, their removal does not represent any loss of content from the thesis.

Bien que ces formulaires aient inclus dans la pagination, il n'y aura aucun contenu manquant.


Canada

ABSTRACT

The estimation of Leaf Area Index (LAI) is a key parameter controlling biophysical processes of the vegetation canopy, and ultimately yield. Defined as one half the total green leaf area per unit ground surface area, LAI is an essential component of precision crop management. Direct field techniques are tedious, time-consuming and labour-intensive. Indirect techniques, such as determining gap fraction with optical instruments have proven to be a good alternative, but their use is limited to rigid field sampling techniques. Vegetation indices have been useful to estimate LAI but are limited mostly due to its background reflectance noise. LAI can be estimated using different types of data, but only hyperspectral remote sensing has the potential to distinguish effectively the crop from other field components using spectral mixture analysis. Once the crop fraction has been derived, LAI is estimated using a crop fraction inversion technique. The application of this technique under agricultural field conditions has been very limited and not rigorously validated. The main objective of this study is to validate the crop fraction inversion technique for LAI estimation, and to examine the potential for LAI estimation using hyperspectral remote sensing data in the context of precision agriculture. This research will provide a unique scientific contribution to the field of hyperspectral remote sensing and greatly contribute to the advancement of remote sensing agriculture applications in Canada.

Image data were acquired over two experimental test sites, near Clinton, Ontario and Indian Head, Saskatchewan, with the Probe-1 airborne hyperspectral sensor. Ground LAI data were collected simultaneously from sampling sites spanning fourteen fields of various crop types (beans, corn, wheat, canola and peas). Ground measurements include LAI data derived from biomass samples (LAI_G) and measured with the LAI-2000 (LAI_{2000}) and, percent-crop cover derived from vertical ground photographs (PCC_G). PCC_G and LAI_G measurements were used to validate image-derived percent-crop cover using partially-constrained unmixing (PCC_P) and LAI (LAI_I), respectively.

The use of the spectral unmixing technique employed in this study proved to be quite efficient to estimate percent-crop cover (PCC) over a broad range of crop types, with an index of agreement (D) of 0.90 and a root mean squared error (RMSE) of $\pm 11.20\%$. The

crop fraction technique for LAI estimation was less successful with a D of 0.73 and an RMSE of ± 0.96 . The use of these techniques to quantify within-crop and within-field variability of PCC and LAI showed mixed success. The PCC derived using partially-constrained unmixing (PCC_P) model was sensitive to within-crop variability for canola ($D = 0.94$ and $\text{RMSE} = \pm 10.67\%$) and wheat crops ($D = 0.85$ and $\text{RMSE} = \pm 11.77\%$) and less sensitive to within-crop variability for beans ($D = 0.64$ and $\text{RMSE} = \pm 10.83\%$), corn ($D = 0.59$ and $\text{RMSE} = \pm 12.46\%$) and pea ($D = 0.58$ and $\text{RMSE} = \pm 9.70\%$) crops. The LAI_I model was sensitive to the high variability in the canola crops ($D = 0.76$ and $\text{RMSE} = \pm 0.84$) but was less sensitive to the pea ($D = 0.47$ and $\text{RMSE} = \pm 1.05$) and corn ($D = 0.42$ and $\text{RMSE} = \pm 0.64$) crops. Results were poorer for the wheat ($D = 0.22$ and $\text{RMSE} = \pm 1.32$) and bean ($D = 0.09$ and $\text{RMSE} = \pm 0.47$) crops due to the lack of ground variability. The validation of the models was complicated by the experimental setup, which did not provide ideal conditions for ground data measurements. The biomass sampling technique used to derive LAI_G and the lack of variability within the fields provided difficulties in validating the model. Regardless, the study did demonstrate potential for the use of hyperspectral remote sensing and spectral unmixing analysis as a tool to estimate LAI in the context of precision agriculture. However, a better understanding of influential vegetation parameters, such as the stem-to-leaf ratio and the clumping index, is necessary to better recognize the full potential of hyperspectral remote sensing to estimate LAI in agricultural canopies.

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to everyone who contributed directly or indirectly to the accomplishment of this research project. First, I would like to thank Dr. Abdou Bannari, my thesis director, for his guidance and his immense patience. A particular expression of thanks to Dr. Karl Staenz, who gave me the opportunity to work on this project at the Canada Centre for Remote Sensing (CCRS), part of Natural Resources Canada, and therefore benefited from the facilities and valuable resources provided by the institution. There was an enormous amount of data in this project, and I would not have been able to carry out this research without the competent and generous assistance provided by the research team at the CCRS, especially that of Dr. Heather McNairn, Jean-Claude Deguise, Catherine Champagne, Dr. Peter White, Jiali Shang, Christian Nadeau, Rob Hitchcock, and Lixin Sun as well as the field teams at Clinton and Indian Head. I would also like to express my appreciation to Martin Chevrier of the University of Ottawa for his assistance with some of the processing tasks. I would also like to express my great gratitude for the financial support provided by the University of Ottawa Faculty of Graduate and Postdoctoral Studies and the National Science and Engineering Research Council for its assistance with academic fees, fieldwork expenses and conference participation. Last but not least, I would like to thank all my family members and friends who provided the moral support needed to complete this thesis; above all my mom, Elizabeth, Matt and Catherine.

TABLE OF CONTENTS

TITLE PAGE.....	i
ABSTRACT.....	iii
ACKNOWLEDGMENTS.....	v
TABLE OF CONTENTS.....	vi
LIST OF TABLES.....	x
LIST OF FIGURES.....	xii
ABBREVIATIONS AND ACRONYMS	xiv
1. Introduction.....	1
1.1 Objectives.....	4
1.2 Hypotheses.....	4
1.3 Thesis Structure.....	5
2. Estimating Leaf Area Index: A Literature Review.....	6
2.1 LAI Use in Precision Crop Management.....	7
2.2 LAI Estimation: Direct and Indirect Measurements.....	9
2.2.1 Direct LAI Measurements.....	9
2.2.1.1 Specific Leaf Area (SLA).....	10
2.2.1.2 Photoelectric Planimeters.....	11
2.2.1.3 Dimension Analysis.....	12
2.2.1.4 Conclusions.....	12
2.2.2 Indirect LAI Measurements.....	13
2.2.2.1 LAI-2000 Instrument	14
2.2.2.2 Using LAI-2000 Over Agricultural Canopies.....	18
2.2.2.3 Conclusions.....	20
2.3 Remote Sensing Methods.....	21
2.3.1 Vegetation Indices (VIs).....	21
2.3.1.1 Estimating LAI with Vegetation Indices (VIs)	23

2.3.1.2 Broadband versus Narrow-band Vegetation Indices (VIs).....	25
2.3.1.3 Conclusions.....	27
2.3.2 Hyperspectral Remote Sensing and Spectral Mixture Analysis (SMA).....	27
2.3.2.1 Endmember Selection.....	28
2.3.2.2 Spectral Mixture Analysis (SMA).....	31
2.3.2.3 Linear Spectral Mixture Analysis (SMA) to Estimate LAI.....	31
2.3.2.4 Contribution of Hyperspectral Remote Sensing to LAI Estimation	33
2.4 Conclusions.....	34
3. Methodology.....	35
3.1 Study Sites.....	35
3.2 Ground Data Collection.....	40
3.2.1 Field Sampling Design.....	40
3.2.2 Ground Measurements.....	41
3.2.2.1 Biomass Samples.....	41
3.2.2.2 LAI-2000 (LAI_{2000}) Measurements.....	41
3.2.2.3 Percent-Crop Cover (PCC_G) Measurements.....	44
3.2.3 Ground Data Preprocessing.....	45
3.2.3.1 Ground LAI (LAI_G) Derived from Biomass Samples.....	45
3.2.3.2 LAI-2000 (LAI_{2000}) Measurements.....	46
3.2.3.3 Percent-Crop Cover (PCC_G) Measurements.....	46
3.3 Remote Sensing Data and Preprocessing.....	46
3.3.1 Remote Sensing Hyperspectral Data Acquisition and Sensor Parameters.....	47
3.3.2 Remote Sensing Data Preprocessing.....	47
3.3.2.1 Radiometric and Spectral Calibration.....	48
3.3.2.2 Surface Reflectance Retrieval.....	49

3.3.3 Image Georeferencing.....	50
3.3.3.1 Image-to-Image Registration.....	50
3.3.3.2 Location of Ground Sampling Sites.....	52
3.4 Information Extraction.....	52
3.4.1 Endmember Selection and Extraction.....	53
3.4.2 Spectral Mixture Analysis (SMA).....	54
3.4.3 Calculation of Effective LAI (<i>e</i> LAI) and LAI.....	55
3.5 Statistical Analyses.....	56
3.6 Conclusions.....	57
4. Results and Discussion.....	59
4.1 Image Registration and Error Analysis.....	59
4.2 Spatial Field and Image Variability.....	62
4.3 Ground LAI (LAI _G) Measurements.....	64
4.3.1 Characterization of Ground LAI Estimates (LAI _G).....	65
4.3.2 Validating LAI-2000 Estimates (LAI ₂₀₀₀) With Ground LAI Measurements (LAI _G)	67
4.3.3 Adjusting Ground LAI Measurements (LAI _G) for Stem-to-Leaf Ratio.....	70
4.4 Endmember Selection and Extraction.....	73
4.5 Spectral Mixture Analysis (SMA).....	77
4.5.1 Constrained versus Partially-Constrained Unmixing.....	77
4.5.2 Validating Image Percent Crop Cover (PCC _I) With Ground Percent Crop Cover (PCC _G).....	77
4.5.3 Adjusting Image Percent Crop Cover (PCC _I) for Endmember “Impurity”	81
4.6 Deriving LAI From Crop Fraction Inversion.....	83
4.6.1 Prediction of Image <i>e</i> LAI (<i>e</i> LAI _I).....	84

4.6.2 Adjusting Image $eLAI$ ($eLAI_I$) Estimates With the Clumping Index (Ω)	85
4.6.3 Prediction of Image LAI (LAI_I).....	87
4.6.4 Sources of Error in LAI Estimation and Validation.....	88
4.7 Potential for Modelling Crop and Field Variability.....	89
4.7.1 Prediction of Image Percent Crop Cover (PCC_I) and Image LAI (LAI_I) for Single Crops.....	90
4.7.2 Prediction of PCC and LAI for Detection of Field Scale Variability.....	98
4.8 Conclusions.....	100
5. Conclusions and Recommendations.....	101
5.1 Summary and Contributions.....	101
5.2 Recommendations for Future Research	103
6. References.....	105
APPENDICES.....	118
Appendix I: Flight Line and Pass Layout for Probe-1 Images.....	119
Appendix II: Percent Crop Cover Fraction Maps Derived From Constrained (A) and Partially-Constrained (B) Unmixing.....	122
Appendix III: Leaf Area Index (LAI) Maps Derived From Crop Fraction Inversion Using Partially-Constrained Unmixing.....	128
Appendix IV: Paper Presented at the 8 th International Symposium on Physical Measurements & Signatures in Remote Sensing (January, 2001).....	134
Appendix V: Paper Presented at the 23 rd Canadian Symposium on Remote Sensing (August, 2001)	142
Appendix VI: Paper Presented at the 1 st International Symposium on Recent Advances in Quantitative Remote Sensing (September, 2002).....	150

LIST OF TABLES

Table 2.1. Vegetation indices.....	25
Table 3.1. Detailed description of studied fields for the Clinton dataset.....	38
Table 3.2. Detailed description of studied fields for the Indian Head dataset.....	39
Table 3.3. Spectral specifications for Probe-1 sensor detector modules.....	47
Table 3.4. MODTRAN3 model input parameters.....	49
Table 4.1. Results of image-to-image registration for Clinton field sites.....	60
Table 4.2. Results of image-to-image registration for Indian Head field sites.....	60
Table 4.3. Average error percentages of PCC_G and PCC derived from the hyperspectral image data for Clinton (a) and Indian Head (b) datasets.....	63
Table 4.4. Average error percentages of LAI_G and PCC derived from the hyperspectral image data for Clinton (a) and Indian Head (b) datasets.....	64
Table 4.5. LAI_G and LAI_{2000} measurements and statistics for Clinton (a) and Indian Head (b) datasets.....	66
Table 4.6. Fit statistics for LAI_G and LAI_{2000} for all crops and on a within-crop basis.....	67
Table 4.7. Estimated values of stem-to-leaf water ratio per field.....	70
Table 4.8. Fit statistics for LAI_{G_SLR} and LAI_{2000} for all crops and on a within-crop basis.....	71
Table 4.9. List of endmembers for the Clinton (a) and Indian Head (b) datasets.....	73
Table 4.10. Fit statistics for PCC_G and PCC_C (a), and PCC_P (b) for all crops.....	78
Table 4.11. Adjustment factor for each crop type.....	81
Table 4.12. Fit statistics for PCC_G and PCC_{C-ADJ} (a), and PCC_{P-ADJ} (b) adjusted for endmember “impurity” for all crops.....	81
Table 4.13. Fit statistics for LAI_G and $eLAI_I$ for all crops.....	84

Table 4.14. Clumping index (Ω) values estimated per field.....	86
Table 4.15. Fit statistics for LAI_G and LAI_I for all crops.....	87
Table 4.16. Fit statistics for PCC_G and PCC_P on a within-crop basis.....	90
Table 4.17. Fit statistics for LAI_G and LAI_I on a within-crop basis.....	94
Table 4.18. Fit statistics for PCC_G and PCC_P on a within-field basis.....	99
Table 4.19. Fit statistics for LAI_G and LAI_I on a within-field basis.....	99

LIST OF FIGURES

Figure 2.1. Spectral regions used for vegetation index calculation.....	22
Figure 3.1. Processing sequence for estimating LAI from Probe-1 hyperspectral data.....	36
Figure 3.2. Location of Clinton and Indian Head study sites.....	37
Figure 3.3. Fertilizer and seeding treatments in the study fields in the Indian Head site.....	39
Figure 3.4. Sampling design for the study fields of the Clinton site.....	42
Figure 3.5. Soil patch in field Corn-1 (a) and residue patch in field Bean-1 (b).....	43
Figure 3.6. Sampling design for the study fields of the Indian Head site.....	43
Figure 3.7. Sampling method for LAI-2000 measurements.....	44
Figure 3.8. Field collection of ground vertical photographs.....	45
Figure 4.1. Sampling site selection for the Indian Head dataset.....	61
Figure 4.2. Relationship between LAI_G and LAI_{2000} for all crops, except beans.....	68
Figure 4.3. Relationship between LAI_{G_SLR} and LAI_{2000} for all crops, except beans.....	72
Figure 4.4.a Average endmember spectra used for spectral unmixing analysis for the Clinton dataset.....	75
Figure 4.4.b Average endmember spectra used for spectral unmixing analysis for the Indian Head dataset.....	76
Figure 4.5. Relationship between PCC_G and PCC_C (a), and PCC_P (b) for all crops.....	80
Figure 4.6. Relationship between PCC_G and PCC_{C-ADJ} (a), and PCC_{P-ADJ} (b) for all crops.....	82
Figure 4.7. Relationship between LAI_G and $eLAI_I$ for all crops.....	85
Figure 4.8. Relationship between LAI_G and LAI_I for all crops.....	87

Figure 4.9. Relationship between PCC_G and PCC_P for wheat fields.....	91
Figure 4.10. Relationship between PCC_G and PCC_P for canola fields.....	91
Figure 4.11. Relationship between PCC_G and PCC_P for pea fields.....	92
Figure 4.12. Relationship between PCC_G and PCC_P for bean fields.....	93
Figure 4.13. Relationship between PCC_G and PCC_P for corn fields.....	93
Figure 4.14. Relationship between LAI_G and LAI_I for wheat fields.....	96
Figure 4.15. Relationship between LAI_G and LAI_I for canola fields.....	96
Figure 4.16. Relationship between LAI_G and LAI_I for pea fields.....	97
Figure 4.17. Relationship between LAI_G and LAI_I for bean fields.....	97
Figure 4.18. Relationship between LAI_G and LAI_I for corn fields.....	98

ABBREVIATIONS AND ACRONYMS

AIS	Airborne Imaging Spectrometer
BRDF	Bidirectional Reflectance Distribution Function
<i>casi</i>	Compact Airborne Spectrographic Imager
CCRS	Canada Centre for Remote Sensing
DGPS	Differential Global Positioning System
D	Index of agreement
DM	Dry plant matter
$eLAI$	Effective leaf area index
$eLAI_I$	Image-derived effective leaf area index
$E_{eLAI_{IC}}$	Error percentage of image leaf area index derived from constrained unmixing
$E_{eLAI_{IP}}$	Error percentage of image leaf area index derived from partially-constrained unmixing
E_{LAI_G}	Ground leaf area index error percentage
$E_{LAI_{2000}}$	LAI-2000 estimates error percentage
E_{PCC_C}	Error percentage of image percent-crop cover derived from constrained unmixing
E_{PCC_I}	Image-derived percent-crop cover error percentage
E_{PCC_P}	Error percentage of image percent-crop cover derived from partially-constrained unmixing
E_{PCC_G}	Ground percent-crop cover error percentage
EO	Earth Observation
ESA	European Space Agency
EVI	Enhanced vegetation index
FLI	Fluorescence Line Imager
FOV	Field-of-view
FWHM	Full width at half maximum

GA	Ground area
GCPs	Ground control points
GIS	Geographic Information Systems
GPS	Global Positioning Systems
HRV	High Resolution Visible
IEA	Iterative Error Analysis
IHARF	Indian Head Agricultural Research Foundation
ISDAS	Imaging Spectrometer Data Analysis System
JPL	Jet Propulsion Laboratory
LA	Leaf area
LAI	Leaf area index
LAI _I	Image-derived leaf area index
LAI ₂₀₀₀	LAI-2000 estimates
LAI _G	Ground leaf area index estimates
LAI _{G_SLR}	Ground leaf area index estimates adjusted for the stem-to-leaf ratio
LUT	Look-up table
LW	Leaf Weight
MEE	Manual Endmember Extraction
MIVIS	Multispectral Infrared and Visible Imaging Spectrometer
MSAVI2	Modified soil adjusted vegetation index 2
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NIR	Near-infrared (700 to 1000 nm)
OSAVI	Optimized soil adjusted vegetation index
PCA	Principal component analysis
PCC _C	Image percent-crop cover derived from constrained unmixing
PCC _{C_ADJ}	Image percent-crop cover derived from constrained unmixing adjusted for endmember “impurity”
PCC _G	Ground percent-crop cover derived from vertical ground photographs

PCC _I	Image-derived percent-crop cover
PCC _P	Image percent-crop cover derived from partially-constrained unmixing
PCC _{P_ADJ}	Image percent-crop cover derived from partially-constrained unmixing adjusted for endmember “impurity”
PVI	Perpendicular vegetation index
R	Red (600 to 700 nm)
R ²	Coefficient of determination
RBVC	Reflectance-based vicarious calibration
RMSE	Root mean squared error
RT	Radiative transfer
RVI	Ratio vegetation index
SAVI	Soil adjusted vegetation index
SAVI2	Soil adjusted vegetation index 2
SEL	Standard Error of leaf area index measurement (LAI-2000 instrument)
SLA	Specific Leaf Area
SMA	Spectral Mixture Analysis
SWIR	Shortwave Infrared (1000 to 2500 nm)
TLW	Total leaf weight
TM	Thematic Mapper
TSAVI	Transformed Soil Adjusted Vegetation Index
TVI	Triangular vegetation index
VI	Vegetation index
VI _s	Vegetation indices
VNIR	Visible – Near-Infrared (400 to 1000 nm)
WDVI	Weighted difference vegetation index
θ	Solar zenith angle
ϕ	Solar azimuth angle
Ω	Clumping index
μ	Foliage density

z	Canopy height
α	Incidence angle
$\bar{\alpha}$	Mean tilt angle
a	Slope of the regression line
b	Intercept of the regression line
G	Fraction of the foliage projected
K	Contact frequency
P	Probability of radiation intercepted by foliage
p	Significance level
T	Probability of radiation non-intercepted by foliage or gap fraction
S	Path length

1. INTRODUCTION

Remote sensing has undergone numerous advances since the launch of the first civilian Earth Observation (EO) satellite, Landsat, in 1972. It offers many applications in various areas such as agriculture, forestry, hydrology, and, marine and coastal management. Approximately 60% of the earth's surface is covered by vegetation, which makes agriculture and forestry applications research priority areas in remote sensing.

Multispectral remote sensing offers imagery acquired in a small number of wide spectral bands. Multispectral satellites, such as Landsat's Thematic Mapper (TM) and Spot's (Satellite Pour l'Observation de la Terre) High Resolution Visible (HRV), use discrete filters and detectors to acquire the image data. These sensors were revolutionary instruments at the time of their launch and still remain of great use for various applications. However, the small number of wide spectral channels limits the resolution of absorption features caused, for example, by plant liquid water and chlorophyll. These features are important for many applications and, they can be resolved with high spectral resolution instruments such as hyperspectral sensors.

Hyperspectral remote sensing allows simultaneous image acquisition in hundreds of contiguous narrow bands (15 nm or less). Existing hyperspectral instruments cover selected portions of the electromagnetic spectrum, e.g., in the visible and near-infrared (VNIR), short wave infrared (SWIR) and thermal infrared or a combination thereof (Edwards *et al.*, 1991). For example, the reflectance spectra from the 2000-2500 nm region can be used to identify a large range of mineral targets (Goetz *et al.*, 1985), which is not feasible with multispectral data. Hyperspectral remote sensing offers numerous possibilities for vegetation management in agriculture and forestry. This technology can be used to discriminate between vegetation types, quantify and map various biochemical parameters, such as lignin, cellulose, nitrogen,

and phosphorus and, numerous biophysical components, such as leaf area index (LAI), hydric stress, and productivity (Staenz *et al.*, 1998b; Goetz, 1992). One of the key parameters controlling biophysical processes of vegetation canopies is the LAI (Staenz *et al.*, 1998b). LAI is used in agriculture and forestry studies in order to describe the amount of vegetation cover and, then used to estimate productivity or yield of vegetation canopies. Since LAI influences the amount of reflectance of a vegetation canopy, it is directly correlated with the chlorophyll concentration of the canopy (Curran and Milton, 1983) and, thus, may be considered as one of the best indicators for potential yield (Bariou *et al.*, 1985).

The growing interest of LAI in precision agriculture results in the necessity to provide a more accurate LAI value for crop modelling purposes. The existing uncertainties for its calculation by simple vegetation indices such as the Normalized Difference Vegetation Index (NDVI) or by more sophisticated vegetation indices such as the Transformed Soil-Adjusted Vegetation Index (TSAVI) are often extremely large. These uncertainties arise from various sources such as the foliar architecture and the effects of background soil in the vegetation canopy (Chen and Cihlar, 1995a). In addition, direct LAI measurements are time-consuming and costly, and destructive in their nature while indirect measurements are more convenient (Leblanc *et al.*, 1999). With respect to indirect measurements, optical instruments are mostly used because of the rapidity of execution in which ground LAI data can be collected. These optical instruments measure the quantity of direct or diffuse light penetrating the vegetation canopy to derive LAI (Chen and Cihlar, 1995b). A few instruments exist in the current market to acquire these measures. One of the most utilized instruments for the estimation of LAI in agricultural canopies is the LAI-2000 (LI-COR, 1992).

It is possible to estimate LAI more precisely by the processing and analysis of hyperspectral data (Gong *et al.*, 1992; Curran, 1994). Multispectral data estimate LAI by considering the total amount of reflectance of a pixel from a vegetation canopy. Multispectral vegetation indices have been developed to specifically diminish the effects of soil background but they are still not ideal. It is essential to clearly distinguish the crop component from soil or weeds within a pixel in order to determine a more accurate LAI and then, to eventually integrate this parameter in a crop model (Staenz *et al.*, 1998b). Hyperspectral remote sensing has the advantage of discriminating different objects of similar

nature on the earth's surface. For example, bean and corn canopies are both vegetation canopies but have a different spectral response. Using a spectral unmixing technique, hyperspectral remote sensing allows the separation of materials within a pixel (Shimabukuru and Smith, 1991). A pixel is composed of different materials where each material represents a fraction which sums to 100%. In fact, the spectra for each pixel translate into a linear sum of all its components (Szeredi *et al.*, 2003). For example, a pixel can include fractions of 20% soil, 70% vegetation and 10% weeds. Accordingly, spectral unmixing has the advantage to distinguish different components and only uses the crop portion for LAI estimation. Thus, LAI is estimated in a more accurate fashion because it is not derived from the whole amount of vegetation (including weeds) but from the crop itself (Staenz *et al.*, 1998b).

Precision agriculture utilizes a certain number of technologies such as Global Positioning Systems (GPS), Geographic Information Systems (GIS) and remote sensing to allow farm producers to manage variability within a field (Brisco *et al.*, 1998). Studies have demonstrated that this approach optimizes crop production by minimizing the application of chemical supplements and, therefore, minimizing environmental impacts (Snyder *et al.*, 1999; Brown *et al.*, 1998). Precision agriculture makes use of the spatial variability associated with soil characteristics (Wehrhan and Selige, 1997) and crop growth. It uses these site-specific field informations in order to promote a more appropriate management strategy (Moran *et al.*, 1997). In summary, precision agriculture has the objective to optimize crop yield. This parameter can then be estimated and predicted by crop modelling, where LAI is an important input parameter. It is, therefore, not only essential that these yields are accurately estimated but that they are also provided in a timely and repetitive fashion where farmers can use the information to their benefit (Brown *et al.*, 1998; McNairn and Brown, 1999). Information from vegetation canopy characteristics, derived from high-resolution spectral data, is very useful for within-field applications, such as low or high growth detection areas, stress mapping and weed detection.

This thesis will mainly focus on LAI extraction from hyperspectral data over agricultural canopies. This parameter will be estimated using the crop fraction derived from spectral unmixing analysis. Validation will then be necessary to evaluate this method's

efficiency to accurately determine LAI. Hyperspectral LAI values will be validated against ground LAI measurements acquired simultaneously to the sensor's overflight.

1.1 Objectives

The main objective of this study is to examine the potential for LAI estimation using hyperspectral remote sensing data in the context of precision agriculture. This research has evolved around the following objectives:

- i. To investigate the correlation between ground LAI values estimated from the biomass samples and the LAI values derived from the LAI-2000 measurements.
- ii. To examine the relationship between percent-crop cover derived from hyperspectral data and percent-crop cover estimated from vertical ground photographs.
- iii. To test the ability of the methodology for LAI extraction from hyperspectral data using a linear spectral unmixing approach from which LAI can be predicted for agricultural canopies. This will be accomplished by validating LAI values derived from hyperspectral data against LAI measured on the ground.

1.2 Hypotheses

Three hypothesis were defined in the context of the research objectives as follows:

- i. LAI-2000 estimates will be reasonably correlated with the ground LAI derived from the biomass samples. The relationship between the two variables should be stronger for wheat and canola canopies given that the foliage is more randomly (haphazardly) distributed than for the other crops examined in this study.
- ii. Crop fractions derived from hyperspectral data using a spectral unmixing technique will be strongly correlated with percent-crop cover estimated from the vertical ground photographs.
- iii. LAI values derived from the hyperspectral data using a spectral unmixing approach will be correlated with the ground LAI data. Therefore, the approach for LAI estimation will be successful and provide agronomists with a more accurate LAI input for integration into crop models for yield prediction.

1.3 Thesis Structure

This current chapter presented the introduction and problematic of the thesis' research. Objectives and hypotheses were also defined in the previous sections. The thesis will then follow with a review of how LAI can be used and integrated into precision crop management, the current state of LAI estimation using direct and remote sensing techniques, and how hyperspectral remote sensing can contribute to LAI estimation (Chapter 2). Subsequently, the technique used in this study to derive LAI from hyperspectral data will be outlined in Chapter 3, including ground data collection, remote sensing data, data pre-processing and processing techniques, and statistical analysis. Chapter 4 will discuss the application of the developed methodology and the results. Finally, conclusions of this study and recommendations for future work will be presented in Chapter 5.

2. ESTIMATING LEAF AREA INDEX: A LITERATURE REVIEW

In response to the earth's rapid global climate change, well-developed countries are elaborating strategies to integrate principles of sustainable development for natural resource management. Sustainable development is now a major policy goal for the Government of Canada. This involves the achievement of an optimal balance across social, economic and environmental objectives in order to secure a high quality of life for present and future generations of Canadians. This management strategy is being implemented for all natural resources including agriculture. Sustainable agriculture is generally concerned with the need for agricultural practices to be economically viable, to meet human needs for food, to be environmentally positive, and to be concerned with the quality of life.

Consequently, resource inputs into the agriculture industry will become a fundamental requirement for the next decades, especially with the industry's effort to satisfy more rigid environmental standards. Precision agriculture is perceived as being one of the possible means to satisfy such requirements. Historically, agriculture fields have been managed as if they were homogeneous entities and, thus, uniform management practices were used (Lillesand and Kiefer, 1999). In contrast, precision agriculture or precision farming acknowledges the inherent spatial variability related to soil and crop characteristics (Bullock *et al.*, 2000). As a result, variable rate technology applies production inputs, such as fertilizer or pesticide at rates suitable to soil and plant conditions within a field (Moran *et al.*, 1997). However, obtaining temporal information, such as crop and soil conditions, that is detailed and spatially distributed is difficult and expensive (Shanahan *et al.*, 2001) and no other technique is as efficient as remote sensing (Moran *et al.*, 1997). Crop and soil information, derived from remote sensing data, has the potential to provide continuous data

throughout the field within the temporal and spatial resolution required for precision agriculture applications. Accordingly, remote sensing can provide information at a canopy (or field) scale to a site-specific scale.

Remote sensing is then considered as a tool for precision crop management by assessing soil and crop biophysical and biochemical characteristics in an indirect fashion. Extensive research has been carried out to correlate sensor signal responses to these vegetation characteristics, and transform these responses in variables useful to agriculture applications. This chapter will review the current state of research for the estimation of LAI over agricultural canopies. The first section will examine precision agriculture as a tool for precision crop management, and how LAI can be integrated and utilized with respect to this management tool. The second section will discuss the various direct and indirect techniques used to estimate LAI of vegetative canopies, mostly focusing on agricultural canopies. The third and last section will summarize and discuss remote sensing methods used to estimate LAI, such as vegetation indices and hyperspectral techniques including spectral unmixing analysis, and how hyperspectral remote sensing and its analyses techniques can contribute to the estimation of LAI.

2.1 LAI Use in Precision Crop Management

Interactions between light and vegetation have been studied extensively in the last few decades. Norman and Campbell (1989) explain that “the vegetation architecture not only affects exchanges of mass and energy between the plant and its environment, but it also may reveal a strategy of the plant for dealing with long-lasting evolutionary processes, such as adaptation to physical, chemical or biotic factors, by reflecting the organism’s vital activity or peculiarities in growth and development”. LAI is considered a crucial plant parameter given that photosynthesis takes place in the green plant portions (Clevers, 1999). This process is responsible for the development and growth of all plant elements. Thus, measurement of LAI is useful for investigating light interception and crop growth models used for yield prediction. Agronomists, crop physiologists, and crop modelers frequently integrate LAI in their studies (Baret and Guyot, 1991). The LAI of a vegetative canopy is a quantitative measure of leaf matter present in the canopy for a given surface. More specifically, LAI is defined as “one half the total leaf area per unit ground surface area”

(Chen and Cihlar, 1995b), and is a nondimensional index (Gobron *et al.*, 1997). Some authors such as Clevers (1988) have defined LAI as being the number of leaf layers one can overlay from the vegetation of a specific surface area. In the last several years, considerable research has been done in an attempt to link vegetation spectral responses to LAI. It was found that remote sensing could actually play an important role in the mapping of LAI, especially over large areas. Section 2.3 will examine how remote sensing data can be utilized to map LAI of agricultural canopies.

Precision agriculture is defined as an “information- and technology-based agricultural management system to identify, analyze, and manage site-soil spatial and temporal variability within fields for optimum profitability, sustainability, and protection of the environment” (Moran *et al.*, 1997). As mentioned in the first chapter, precision agriculture involves the integration of different technologies including GIS, GPS and remote sensing to allow management practices to be carried out on a site-specific basis. While advancements in GIS and GPS technologies progressed well in the 1970’s, digital remote sensing technology was just in its initial phase. However, remote sensing technology has considerably improved over the last decade and, consequently, has made it a more reliable tool for precision farming purposes. The launch of numerous satellites with high-spatial and -spectral resolution, the increase in repeat coverage and the greater speed with which data are being delivered and analyzed are all factors contributing to the recent success of remote sensing for precision agriculture applications. Remote sensing can further contribute to precision agriculture especially if a sequence of images is acquired during the growing season, providing spatial information on crop status prior to harvest. This could result in an opportunity for the farmer to adjust fertilization rates or apply pesticide in time to make a difference on final yield (Rydberg and Söderström, 2000).

Yield data is important in the decision-making process relative to agricultural practices. Precision agriculture can increase crop yields because it prevents local under-fertilization in a field leading to sub-optimal yields as well as local over-fertilization leading to environmental impacts due to excess discharge (Bouma, 1999). Numerous studies have examined how remote sensing can be used for the estimation of crop yield (Bouman, 1992; Moran *et al.*, 1997; Moulin *et al.*, 1998; Layrol *et al.*, 2000; Locke *et al.*, 2000; Yang and Everitt, 2000; Werner *et al.*, 2000). For instance, Wiegand *et al.* (1991) found that yield

differences within his study fields were highly associated with LAI and that it could be used for crop yield forecasting. Crop growth models are also often used to estimate yields in precision agriculture (Clevers, 1999; Werner *et al.*, 2000). Crop growth models describe the relationship between physiological processes in plants and environmental factors such as solar radiation, and temperature, water and nutrient availability. Remote sensing can be extremely useful to provide some of the inputs necessary to these models. They require crop, soil, weather and management data. Remote sensing can provide information for the first two parameters. Plummer (2000) assessed how remote sensing can be used for ecological modelling and classified this approach into four alternative strategies. In a agricultural context, these strategies are (1) to use remotely sensed data to provide estimates of variables required to drive crop growth models, (2) to use remotely sensed data to validate crop growth models, (3) to use remotely sensed data to update or adjust crop growth predictions and finally, (4) to use crop growth models to understand remotely sensed data. LAI is an important and commonly used variable given that the change in LAI over time is strongly related to the stage of crop growth (Duke, 2002). Furthermore, LAI is one of the most important parameters when describing a crop canopy. This parameter has the potential to be used for input in a crop model to predict yield.

2.2 LAI Estimation: Direct and Indirect Measurements

Estimation of the area of leaves and the surface of other assimilating plant organs is an essential part of classical growth analysis and is indispensable in many plant physiological studies (Kvet and Marshall, 1971). This section will review different techniques to measure LAI over vegetative canopies using field techniques, which are divided in two categories: direct and indirect measurements. The term ‘indirect’ will be applied to refer to the use of radiation measurements to obtain estimates of canopy vegetation amount and structure.

2.2.1 Direct LAI Measurements

The measurement of leaf area in plant canopies by direct methods usually involves an attempt to obtain a representative description of the whole canopy by observations on individual plants (Norman and Campbell, 1989). Direct LAI measurements refer to manual techniques to measure this parameter. Numerous methods exist to measure leaf area of plant

canopies using this approach. The counting squares or dot counting methods, the planimetric and gravimetric methods, the linear measurement approach, the leaf-weighting method and, leaf litterfall technique are a few examples of the many methods cited in the literature to estimate LAI directly (Kvet and Marshall, 1971; Norman and Campbell, 1989; Welles and Norman, 1991; Gower *et al.*, 1999; Ganguli *et al.*, 2000; de Jesus *et al.*, 2001; Malone *et al.*, 2002). Due to the great variety of methods developed for direct LAI measurements in plant canopies, the choice of a method will be determined by numerous factors. These factors depend, for example, whether the sampling should be destructive or non-destructive, whether the total leaf area or that of individual leaves are required. They are also influenced by the required degree of accuracy, the sample size, the morphology of the leaves, the availability of technical equipment, and the amount of time and labour (Kvet and Marshall, 1971). Researchers need to consider all these facts to facilitate the selection of the most suitable method for their study. A review of all the various methods used for direct LAI measurements is beyond the scope of this thesis. Accordingly, this section will focus on the three direct LAI methods most frequently used: the leaf-weighting method or more commonly called specific leaf area (SLA), photoelectric planimeter and dimension analysis approaches.

2.2.1.1 *Specific Leaf Area (SLA)*

The SLA can be easily used to derive LAI in agricultural canopies (Gower *et al.*, 1999). This type of measurement technique is frequently used in growth analysis of plant canopies in which it would be technically impossible to measure the area of the whole foliage (Kvet and Marshall, 1971). SLA is convenient given that biomass sampling is a common technique used for crop characterization. The SLA is defined as the area of leaf per unit of dry leaf matter. A different value should be determined for each plant species since leaf structure is essentially dependent on the specie (van Heemst, 1986), but more or less constant for non-senescent leaves. Thus, van Keulen (1986) established a table of indicative SLA values for major crops. More specifically, this direct method uses the relationship between leaf area (LA) and leaf weight (LW) of a subsample of leaves to derive LA of a larger sample (LA') of leaves just from the measurement of the total leaf weight (TLW), as

expressed in the following equation:

$$LA' = \frac{LA \times TLW}{LW} . \quad [2.1]$$

If one does not wish to calculate LA', van Keulen's (1986) SLA indicative values can be used as a substitute. LAI is then calculated by the following equation:

$$LAI = SLA \times TLW . \quad [2.2]$$

This method has been used in various studies including forestry applications (Norman and Jarvis, 1974; Waring *et al.*, 1982; Gower and Norman, 1991). However, the effort required to measure LA/LW ratio of trees is tremendous (Norman and Campbell, 1989). The leaf-weighting method is best suited for short-stature ecosystems, such as grasslands and agriculture crops (Gower *et al.*, 1999). Accordingly, numerous agriculture studies have measured LAI with this method over potato, corn, cotton, soybean, sunflower and sorghum canopies (Norman and Campbell, 1989; Ross, 1981; Daughtry and Hollinger, 1984).

2.2.1.2 Photoelectric Planimeters

Photoelectric planimeters, or automatic planimeters, are instruments used to measure LAI based on a light interception method. The common principle used is based on the intensity of light emitted from a constant source, reaching a detector which is proportional to the area of material (leaves) placed between the light source and the detector (Kvet and Marshall, 1971). Nowadays, automatic planimeters are frequently used to measure leaf area in agricultural canopies (Bouman *et al.*, 1992; Thenkabail *et al.*, 2000; Boegh *et al.*, 2002; Welles and Norman, 1991; Wilhelm *et al.*, 2000; Malone *et al.*, 2002; Staenz *et al.*, 1998b). They provide a method to accurately measure LAI of vegetation canopies (Kvet and Marshall, 1971; Daughtry and Hollinger, 1984; Norman and Campbell, 1989). An advantage of this method is that the exact areas of leaves are measured. Leaves with irregular margins or those with holes such as caused by insects or other sources of leaf damage are properly measured. The errors of measurement are probably less than 2% if these instruments are properly maintained and calibrated (Kvet and Marshall, 1971; Daughtry and Hollinger, 1984;

Norman and Campbell, 1989). Leaves tend to fold and wrinkle slightly as they move between the rollers of the area meter, causing slight differences in the total area measured. Norman and Campbell (1989) found that the LA measurement of a single intact corn leaf may be 4-8% less accurate than when the leaf is cut into pieces and the area of these pieces are measured separately. Nevertheless, these errors associated with the photoelectric planimeters are smaller than the ones found in the leaf weighting and the dimension analysis methods (Daughtry and Hollinger, 1984). LAI is then calculated by summing the LA of each leaves (LA_i) within a plant for a specific ground area:

$$LAI = \sum LA_i. \quad [2.3]$$

2.2.1.3 Dimension Analysis

The dimension analysis technique involves the estimation of LA from two simple leaf dimensions: length and width. This method can provide non-destructive area estimates within 5% error (Norman and Campbell, 1989). The general form of the leaf area/leaf dimension relationship can be expressed as follows:

$$LA = k (l \times mw), \quad [2.4]$$

where l is the length of the leaf, mw is the maximum width of the leaf, and k is a coefficient depending on the shape of the leaves (for e.g., k is 0.50 for a triangled leaf shape, 1 for a rectangle and 0.75 for grasses, such as corn, sorghum and wheat). This coefficient needs to be verified from time to time, especially when leaf shape changes with position and plant age (Kvet and Marshall, 1971; Daughtry and Hollinger, 1984). LAI is then obtained by normalizing LA values with the ground surface area. This method is often used in forestry (Gower and Norman, 1991) and agriculture where non-destructive sampling is necessary (Pearce *et al.*, 1975; Daughtry and Hollinger, 1984; Kopec *et al.*, 1987; de Jesus *et al.*, 2001).

2.2.1.4 Conclusions

Direct methods require cutting and measuring various elements of the leaf. They are straightforward, arduous and any level of detail can be obtained with enough patience and

labour (Norman and Campbell, 1989). LA measurements, obtained by direct methods, provide LAI values with high accuracy (Gower *et al.*, 1999, Ganguli *et al.*, 2000). Daughtry and Hollinger (1984) evaluated several direct methods for measuring LAI in corn canopies with respect to the magnitude of within-plot errors, the number of plants required and the relative costs per sample for each method. Direct measurements of LA measured with a photoelectric planimeter demonstrated the lowest variability. This approach requires fewer plants to be sampled and approximately the same amount of time as the leaf-weighting method to detect comparable differences. Dimensional analysis involves more plants to be measured but requires less time than the area-meter method. The method of choice really depends on the resources available, the differences to be detected, and what additional information, such as leaf weight or stalk weight, is also desired (Daughtry and Hollinger, 1984).

Since direct measurements of canopy structure are tedious, time-consuming and labour intensive in small canopies and nearly impossible in large crop or forest canopies (Welles and Norman, 1991; Welles and Cohen, 1996; Gower *et al.*, 1999), the development of instrumentation and associated theory to rapidly estimate LAI has received a great deal of attention in the past decades (Gower and Norman, 1991). Indirect methods, which are based on the close coupling between radiation penetration and canopy structure, provide such an alternative.

2.2.2 Indirect LAI Measurements

Indirect methods can be divided in three groups: spectral methods, bidirectional reflectance distribution function (BRDF) methods and gap fraction methods. Spectral methods will not be discussed in this section since the subject overlaps with section 2.3. Similarly, BRDF methods were mentioned here mainly for reference purposes. It is not a commonly used method and, hence, will not be further examined. This section will emphasize on the gap fraction methods to indirectly measure LAI.

Gap fraction methods offer a powerful tool for the estimation of LAI and leaf inclination angles of canopies for full cover or isolated single canopies and even, heterogeneous canopies (Norman and Campbell, 1989). The gap fraction of a canopy is defined as the fraction of view in some direction from beneath a canopy that is not blocked

by foliage (Welles, 1990). Gap fraction analysis uses the relationship between fraction of direct and/or indirect radiation intercepted by the canopy to estimate LAI (Wilhelm *et al.*, 2000). The equations for gap fraction computation are defined in the following section (2.2.2.1). This parameter can be measured with an hemispherical lens in the visible waveband (from below the canopy looking upward) or in the near-infrared waveband (from above the canopy looking downward) by traversing a sunward-pointed sensor beneath the canopy, with linear light sensors, or by pushing metal probes through the canopy (Norman and Campbell, 1989). The development of the gap fraction theory has led to the development of several commercial instruments to estimate LAI. Line quantum sensors, such as the LI-191SA (LI-COR), the SF-80 Ceptometer (Decagon Devices, Inc.), the Demon instrument (CSIRO, Centre for Environmental Mechanics) and the LAI-2000 (LI-COR) are all devices designed to measure gap fraction of vegetative canopies. For the purpose of this thesis, it is only relevant to further examine the LAI-2000 instrument and its application in agricultural studies.

2.2.2.1 LAI-2000 Instrument

The LAI-2000 Plant Canopy Analyzer (LI-COR, 1992) uses a fisheye light sensor that measures the attenuation of diffuse sky radiation simultaneously in five distinct angular bands about the zenith point. The image of its hemispheric view is projected onto five detectors arranged in concentric rings: 0-13°, 16-28°, 32-43°, 47-58° and 61-74°. An optical filter restricts transmitted radiation below 490 nm, minimizing the contribution of radiation that has been scattered by foliage (Welles, 1990). The LAI-2000 uses a canopy gap fraction as mentioned previously. The basic technique combines a measurement of sky brightness from a leveled sensor above the canopy with a second measurement taken beneath the canopy with the same sensor again viewing skywards. The ratio of each detector's above- and below-canopy radiation measurement is then referred to as the canopy gap fraction for that detector.

To certify the accuracy of the foliage amount and orientation calculations, a few assumptions must be made as indicated in the guidelines of the LI-COR (1992) operating manual. These assumptions are: (i) only sky radiation is seen by the sensor below the canopy (below-canopy readings do not include any radiation that has been reflected or transmitted by

foliage); (ii) foliage is randomly distributed in the canopy within certain foliage-containing envelopes such as a row crop; (iii) foliage elements are small (i.e., the sensor-foliage distance should be at least four times the leaf width); and (iv) foliage is azimuthally randomly oriented (i.e., foliage is inclined with any distribution of angles). The degree of which these assumptions are violated will affect the accuracy of the LAI. It should be noted that random foliage distribution suggest that foliage is randomly (haphazardly) distributed in space, which is almost never the case in agricultural situations since leaves are distributed according to the various structures of a crop canopy such as plant rows and stems. The same can be said about foliage inclination where some crops are described as being erectophile or planophile canopies such as wheat and peas, respectively. Thus, the concept of random leaf inclination is not very realistic as well.

The LAI-2000 essentially measures two structural components of the vegetative canopy: foliage amount and foliage orientation. As a beam of radiation passes through some distance of the vegetation canopy, there is a certain probability that it will be intercepted by foliage. The probability of interception is proportional to the path length, foliage density and foliage orientation. If the foliage elements are small compared to the overall canopy dimensions, and are randomly distributed (in the region through which the beam passes), then a beam of radiation for a given zenith (θ) and azimuth angle (ϕ) has a probability of non-interception, $T(\theta, \phi)$, as follows:

$$T(\theta, \phi) = \exp[-G(\theta, \phi) \mu S(\theta, \phi)], \quad [2.5]$$

where $G(\theta, \phi)$ is the fraction of the foliage projected along the direction (θ, ϕ) , μ is the foliage density (m^2 foliage per m^3 canopy), and $S(\theta, \phi)$ is the path length within the canopy. ϕ is eliminated from the equation since the LAI-2000 optical sensor averages over the azimuth angles. Equation 2.5 can then be rewritten as:

$$G(\theta) \mu = -\frac{\ln(T(\theta))}{S(\theta)} \equiv K(\theta), \quad [2.6]$$

where $K(\theta)$ is the contact frequency (Miller, 1967) which is equivalent to the average number of contacts per unit length of travel that a probe would make passing through the canopy at θ . Miller (1967) gives an exact solution for μ :

$$\mu = 2 \int_0^{\pi/2} \frac{-\ln(T(\theta))}{S(\theta)} \sin \theta \, d\theta. \quad [2.7]$$

In a full homogeneous canopy, LAI is related to μ and canopy height (z), and z in turn is related to S by the θ :

$$\mu = \frac{LAI}{z}, \quad [2.8]$$

$$S(\theta) = \frac{z}{\cos \theta}. \quad [2.9]$$

Substituting equations 2.8 and 2.9 into equation 2.7 yields an expression for LAI as follows:

$$LAI = 2 \int_0^{\pi/2} -\ln(T(\theta)) \cos \theta \sin \theta \, d\theta. \quad [2.10]$$

Since z cancels out in equation 2.10, it is numerically identical to equation 2.6 when $S(\theta) = 1/\cos \theta$. Thus, equation 2.7 can be used either for LAI or μ . If the distances are $1/\cos \theta$, the calculations should then be interpreted as LAI; otherwise, μ is determined. The LAI-2000 solves equation 2.7 numerically with the following equation:

$$LAI \text{ or } \mu = 2 \sum_{i=1}^5 \frac{-\ln(T_i)}{S_i} W_i, \quad [2.11]$$

where i is each individual measurement, T_i represents the five gap fractions (ratio of below-canopy measurements and above-canopy measurements) and W_i is equal to $\sin \theta \, d\theta$, which is

set to 0.034, 0.104, 0.160, 0.218, and 0.494 for the five view angles of view of the LAI-2000 sensor. The corresponding S_i values ($=1/\cos\theta$) are set to 1.008, 1.087, 1.270, 1.662, and 2.670. These values are stored in the control box where they are accessible to the user. If these values are modified to reflect the actual path lengths, observed by the sensor through the canopy, μ is then computed rather than LAI.

According to Lang (1986), the LAI-2000 also determines the canopy's foliage orientation by measuring the mean tilt angle ($\bar{\alpha}$) of the foliage. He determined that $dG(\theta)/d\theta$ is related to $\bar{\alpha}$. The fraction of the foliage ($G_\alpha(\theta)$) of such a canopy projected along the θ is as follows (Wilson and Reeve, 1959):

$$G_\alpha(\theta) = \begin{cases} \cos\alpha \cos\theta & (\text{for } \alpha + \theta \leq \pi/2) \\ \frac{2}{\pi} \sin\theta \sin\alpha \sin\beta + \left[1 - \frac{2\beta}{\pi}\right] \cos\theta \cos\alpha & (\text{for } \alpha + \theta > \pi/2) \end{cases} \quad [2.12]$$

where

$$\cos\beta = \frac{\cos\alpha \cos\theta}{\sin\alpha \sin\theta}. \quad [2.13]$$

The parameter $\bar{\alpha}$ of the curves (average slopes of the curves of $G_\alpha(\theta)$ as a function of various leaf tilt angles) in the region between $\theta = 0.436$ (25°) and $\theta = 1.134$ (65°) is described by a 5th order polynomial as follows:

$$\bar{\alpha} = a_0 + a_1x + a_2x^2 + a_3x^3 + a_4x^4 + a_5x^5, \quad [2.14]$$

where $x = dG(\theta)/d\theta$,

$$a_0 = 56.81964,$$

$$a_1 = 46.84833,$$

$$a_2 = -64.62133,$$

$$a_3 = -158.6914,$$

$$a_4 = 522.0626, \text{ and}$$

$$a_5 = 1008.149.$$

The LAI-2000 determines $\bar{\alpha}$ by dividing the five $K(\theta)$ values by LAI or μ to obtain $G(\theta)$ (Equation [2.6]). A straight line is fit to the five $G(\theta)$ values, and the slope of that line is used in equation [2.14] to predict $\bar{\alpha}$. A confidence indicator for $\bar{\alpha}$ is computed by adding the standard error of the slope to the value of the slope. The resulting value is then used as the independent variable in equation [2.14] to calculate a second inclination angle, which is subtracted from $\bar{\alpha}$. Because of the steep slope at the extreme angles, the $\bar{\alpha}$ estimation becomes more uncertain near these extremes. The software in the LAI-2000 instrument forces $\bar{\alpha}$ predictions to be between 0 and 90° (Welles and Norman, 1991).

The LAI-2000 is lightweight, portable, and easily carried on by a single operator while traversing large areas. The instrument is also a fast and inexpensive technique to measure LAI. Although this instrument is relatively easy to use, it has some disadvantages. The use of the LAI-2000 is restricted to certain sky conditions. This may be a limiting factor in certain climates where isolate clouds are common and, at high latitudes in the winter (too narrow range of sun angles) (Welles, 1990). The instrument is optimally used during complete overcast conditions and at low solar zenith angles (sunrise and sunset), as the direct sunlight can substantially lower the LAI estimates especially in canopies with large gaps. These limitations may restrict the number of samples that can be measured in a day and force intricate planning of data collection (Wilhelm *et al.*, 2000). However, it is still possible to overcome this problem by shading the sensor and the canopy being measured. Another potential weakness of the LAI-2000 approach is the requirement for above canopy radiance reference measurements. The sky conditions may change between the reference and below canopy readings, generating errors in the measurements (Welles, 1990). In order to obtain the most accurate LAI value from the LAI-2000, it is essential that measurements are done under suitable sky conditions and that the sampling technique follows the guidelines established in the LAI-2000 operating manual (LI-COR, 1992).

2.2.2.2 Using LAI-2000 Over Agricultural Canopies

Many agricultural studies have tested and validated the ability of the LAI-2000 to estimate LAI in crop canopies (Welles and Norman, 1991; Hicks and Lascano, 1995; Gilabert *et al.*, 1996; Welles and Cohen, 1996; Miller-Goodman *et al.*, 1999; Ganguli *et al.*,

2000; Wilhelm *et al.*, 2000; de Jesus *et al.*, 2001; Malone *et al.*, 2002). Results from several studies will be summarized in the following section.

Welles and Norman (1991) conducted an experiment on various crop canopies (soybeans, winter wheat and prairie grass) to compare LAI-2000 (LAI_{2000}) estimates with those determined by an electronic area meter (LI-COR LI-3100). Results from this investigation revealed that the LAI-2000 underestimated LAI by up to 15%. Variations in sky brightness patterns caused variations in LAI estimates in winter wheat of less than 10%, while the presence of direct solar radiation increased LAI errors to more than 30%. Another study investigated the applicability of the LAI-2000 to measure LAI in common bean canopies (de Jesus *et al.*, 2001). A high correlation ($R^2 = 0.97$) was observed between ground LAI (LAI_G) measurements and LAI_{2000} estimates. Malone *et al.* (2002) also evaluated the use of the LAI-2000 to estimate LAI in manually defoliated soybean crops. LAI_{2000} estimates were analogous to LAI_G measurements at defoliation levels between 0 and 33% and were higher at the 67% and 100% defoliation levels. This overestimation of LAI was due to the LAI-2000 detecting more pod, petiole, and stem tissue at higher defoliation levels (Hunt *et al.*, 1999). However, the effect of non-leaf plant tissue on the LAI estimate should be less as LAI increases in a canopy (Malone *et al.*, 2002).

Hicks and Lascano (1995) investigated the use of the LAI-2000 to estimate LAI in cotton canopies. LAI_{2000} estimates agreed well with LAI_G measures in the range of 0.5 to 3.5. The best agreement between LAI_{2000} and LAI_G estimates was made around solar noon by shading both the sensor and sampling area. The parallel transect approach consistently underestimated LAI_G , because the sensor's field-of-view (FOV) is limited to the sparse portion of the canopy while the perpendicular FOV transect approach overestimated LAI_G by viewing only the most dense portion of the canopy. Nonetheless, the average of the parallel and perpendicular transects agreed well with LAI_G . This was also found in the study of Welles and Norman (1991).

Miller-Goodman *et al.* (1999) evaluated the use of the LAI-2000 to quantify changes in canopy density and architecture in response to defoliation by cattle and to determine advantages and drawbacks of the LAI-2000. It was concluded that the LAI-2000 provided a rapid, accurate method for quantification of foliage density reduction attributed to certain grazing treatments. The LAI-2000 allowed detection of differences in LAI as pastures

entered the dormant season where ungrazed areas had higher LAI than any of the grazed pastures. The use of the LAI-2000 instrument was beneficial for this type of research since it was less time-consuming than classical methods (Knight, 1973; Stringer *et al.*, 1995). In contrast, Ganguli *et al.* (2000) found that LAI₂₀₀₀ estimates showed a poor correlation ($R^2 = 0.67$) in comparison with LAI_G derived using other non-destructive techniques for standing crop in shortgrass plains.

Wilhelm *et al.* (2000) validated the use of the LAI-2000 to estimate LAI in corn canopies. The objective of the study was the comparison of LAI estimates derived from three instruments (AccuPAR, LAI-2000 and SunScan) with LAI_G. It was found that all instruments generally underestimated LAI compared to LAI_G. In addition, the LAI-2000 gave distinctly different LAI₂₀₀₀ estimates in comparison to the AccuPAR and SunScan instruments. These results were expected since the LAI-2000 uses a different approach for determining LAI than the other two instruments (Wilhelm *et al.*, 2000). Previous research (Grantz and Williams, 1993; LI-COR, 1992) suggested that deleting data from the fifth ring (61-74°) could improve LAI₂₀₀₀ estimates in vertical canopies or in situations where the FOV of the sensor is less than 3 times the crop height. Accordingly, when LAI-2000's estimates were recalculated from data of rings 1 through 4, the relationship between LAI₂₀₀₀ estimates and LAI_G improved and were similar to all three instruments.

2.2.2.3 Conclusions

The LAI-2000 measures LAI by computing foliage density and foliage orientation using a gap fraction method. The instrument is light-weighted, easy to use and is not time-consuming or labour intensive. The LAI-2000 also has specific sampling guidelines that need to be followed to ensure satisfactory data output. Sky conditions are also a limiting factor for the use of the LAI-2000. In spite of these issues, the LAI-2000 is a common instrument used to estimate of LAI from agriculture canopies. However, inconsistencies in the results from the various studies presented in the previous section suggest caution in using this instrument as the only means for ground LAI acquisition.

2.3 Remote Sensing Methods

In the last decade, the development of functional relationships between crop characteristics and remote spectral observations has been governing agriculture-applied studies (Baret and Guyot, 1991). LAI is a key parameter used to assess biophysical processes of the vegetation canopy, and as such, it has captured a great deal of interest in the field of remote sensing. Accordingly, a variety of remote sensing methods has been developed to measure LAI of vegetation canopies. Some of these methods include vegetation indices (VIs), reflectance models and spectral unmixing analysis using hyperspectral data. The following chapter will discuss how VIs and spectral unmixing analysis can estimate LAI. Reflectance models will not be discussed here as it is beyond the scope of this thesis.

2.3.1 Vegetation Indices (VIs)

A vegetation index (VI) is a quantitative measure qualifying the vigor of vegetation (Bannari *et al.*, 1995). The most commonly used VIs utilizes the information contained in the red and near-infrared wavelength regions (Figure 2.1) of the electromagnetic spectrum (Baret and Guyot, 1991). Numerous natural surfaces are about equally as bright in the red and near-infrared part of the spectrum with the notable exception of green vegetation. Red light is strongly absorbed by photosynthetic pigments (such as chlorophyll a) found in green leaves, while near-infrared light either passes through or is reflected by live leaf tissues, despite their color. Therefore, areas of bare soil having little or no green plant material will appear identical in both the red and near-infrared wavelengths, while areas with much green vegetation will be very bright in the near-infrared and very dark in the red part of the spectrum.

The propagation and use of VIs can be attributed to the simplicity with which large amounts of satellite data can be processed with minimum computational effort per pixel, thus, facilitating valuable large spatial- and temporal-scale analyses (Bouman, 1992; Myneni and Williams, 1994). An ideal vegetation index is, in theory, an index that is particularly sensitive to vegetative covers, insensitive to soil brightness, soil color, atmospheric effects, environmental effects, solar illumination geometry and sensor viewing conditions (Jackson, 1983). Consequently, caution should be taken when estimating LAI from VIs if

these effects are unknown (Baret and Guyot, 1991). The next section will discuss some of these issues.

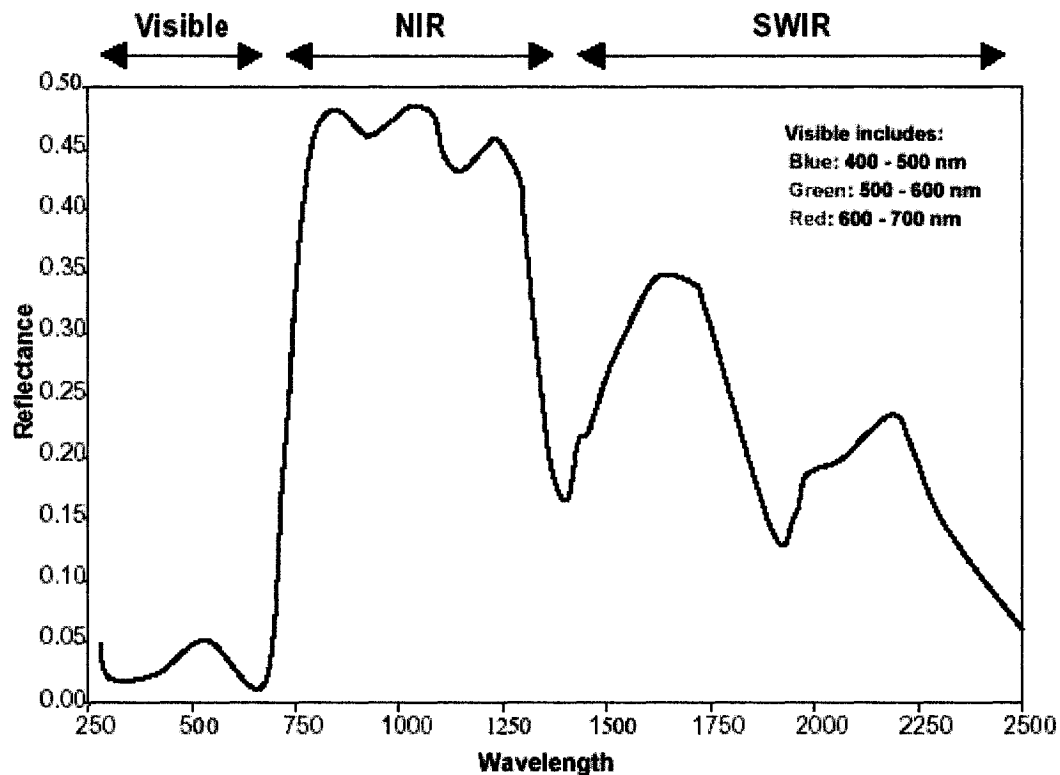


Figure 2.1. *Spectral regions used for vegetation index calculation.*

Multiple studies have demonstrated that VIs are well correlated with LAI and that LAI can then be estimated using VIs over agriculture canopies (Holben and Fan, 1980; Wiegand and Richardson, 1990; Elvidge and Chen, 1995; Myneni and Williams, 1994; Carlson and Ripley, 1997; Bouman *et al.*, 1992; Bouman, 1992; Clevers, 1989). A summary of the most common VIs is listed in Table 2.1. Not all studies have shown the same performance consistency for the estimation of LAI from VIs, although, successful VIs are common throughout the literature. Holben and Fan (1980) found that LAI and the ratio vegetation index (RVI) was most highly correlated, which was also illustrated in other studies (e.g., Curran and Milton, 1983). The RVI increases until maximum LAI is reached and then decreases slowly with decreasing LAI (Best and Harlan, 1985). Broge and Mortensen (2002) found that from all VIs examined, the soil adjusted vegetation index 2 (SAVI2) was the best predictor for LAI estimation in wheat canopies, which was confirmed

by other authors such as Major *et al.* (1990). Rondeaux *et al.* (1996) found that the TSAVI and the optimized SAVI (OSAVI) provided better LAI estimation in the context of homogeneous canopies such as grass and agriculture crops at mid-latitudes. Broge and Leblanc (2000) illustrated that the RVI once again, and the modified soil adjusted vegetation index 2 (MSAVI2) were the best LAI predictors for low and high vegetation densities, respectively. RVI was less sensitive to variations in canopy structure or atmospheric conditions while MSAVI2 was more sensitive to canopy effects. MSAVI2 was very sensitive to atmospheric effects and its use might be compromised if atmospheric conditions are of concern. In general, VIs which were corrected or adjusted for soil properties offer a better LAI estimation.

2.3.1.1 *Estimating LAI with Vegetation Indices (VIs)*

One important limitation when VIs are used to estimate LAI is the existence of a saturation level for the VIs when LAI reaches high values. Many studies have demonstrated that the relation between VIs and LAI undergoes an obvious decrease in sensitivity above a loosely defined threshold and can be fitted to an exponential equation (Broge and Mortensen, 2002; Baret *et al.*, 1989; Clevers, 1989; Carlson and Ripley, 1997). The threshold value is generally around 2-3 (Price, 1992; Liu and Huete, 1995), although it has been shown that the LAI threshold value can be found near values of 3-4 (Curran and Milton, 1983; Sellers, 1987). NDVI increases almost linearly with increasing LAI and then enters an asymptotic regime in which NDVI increases very slowly with increasing LAI. Baret and Guyot (1991) and Carlson and Ripley (1997) also found that NDVI is sensitive to variations in the fractional cover until a full cover is attained. The decrease in sensitivity of NDVI with respect to higher LAI values is due to the large attenuation of reflectance of solar radiation from the underlying soil surface or lower leaf stories when the ground surface is fully concealed by leaves (Carlson and Ripley, 1997). Studies have generally found that the asymptotic region for LAI initiates at NDVI values of 2 for soybeans (Holben and Fan, 1980), 3 for corn (Gallo *et al.*, 1985) and 2.5 for wheat (Asrar *et al.*, 1984). TSAVI and soil adjusted vegetation index (SAVI) also reach an asymptotic regime when LAI is higher than 3 (Baret and Guyot, 1991). Bouman (1992) also found that the weighted difference vegetation index (WDVI) reacted little to further increases of LAI once a value of 4 was achieved.

Overall, the asymptotic nature of the VIs and LAI relationship limits the use of VIs for estimating LAI_G in high-density vegetation canopies.

Soil properties including brightness, color, moisture and types greatly influence the spectral behaviour of agriculture canopies. Baret and Guyot (1991) investigated the potentials and limits of various VIs for estimating LAI by considering the effect of several soil factors on simulated reflectance data. Results demonstrated that NDVI and, to a lesser degree, the perpendicular vegetation index (PVI) were highly influenced by the variation of soil optical properties especially for low vegetation cover. NDVI will provide mediocre information about a vegetation canopy when the soil background is unknown (Rondeaux *et al.*, 1996). On the contrary, TSAVI and to a lesser degree SAVI demonstrated some potential in estimating LAI. It was noted that VIs such as the PVI, SAVI and TSAVI formulated to minimize the soil background effect, highly reduce the noise for low LAI. van Leeuwen and Huete (1996) also found that the SAVI was a better LAI predictor than the NDVI. The SAVI demonstrated a great variability between SAVI responses and differences between the optical properties of green leaves, litter and bark. North (2002) also found that SAVI was the best VI for LAI estimation over green vegetation properties even though the performance of most indices was quite similar. Broge and Leblanc (2000) compared different VNIR spectral reflectance-based VIs for estimation of LAI from simulated data using the PROSPECT leaf optical model (Jacquemoud and Baret, 1990) coupled with the SAIL canopy reflectance model (Verhoef, 1984). They demonstrated that generally the SAVI2 was the least influenced by background reflectance to predict LAI and was, therefore, the best estimator of LAI.

The leaf angle distribution can also affect the response of VIs. Jackson and Pinter (1986) examined the effect of canopy architecture on the spectral response of wheat canopies. The analysis demonstrated that radiation reflected in a vertical direction was significantly larger for planophile than erectophile vegetation canopies. Overall, the RVI was a better LAI predictor for the erectophile canopy while the PVI was better for the planophile canopy during the early season. This situation was reversed for the period of maximum greenness. These authors concluded that architecturally different canopies with the same LAI value can result in different VI values.

Table 2.1. *Vegetation indices (where ρ_{NIR} is the reflectance in the NIR, ρ_R is the reflectance in the red (R), ρ_B is the reflectance in the blue, a and b is the slope the intercept in the soil line respectively, and L is a constant = 0.5 to minimize soil brightness).*

Vegetation Index	Acronym	Formula	Author and Year
Ratio Vegetation Index	RVI	$\frac{\rho_{NIR}}{\rho_R}$	Pearson and Miller (1972)
Normalized Difference Vegetation Index	NDVI	$\frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R}$	Rouse <i>et al.</i> (1974)
Perpendicular Vegetation Index	PVI	$\frac{\rho_{NIR} - a\rho_R - b}{\sqrt{1 + a^2}}$	Richardson and Wiegand (1977)
Soil Adjusted Vegetation Index	SAVI	$\frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R + L} (1 + L)$	Huete (1988)
Soil Adjusted Vegetation Index 2	SAVI2	$\frac{\rho_{NIR}}{\rho_R + b/a}$	Major <i>et al.</i> (1990)
Transformed Soil Adjusted Vegetation Index	TSAVI	$\frac{a(\rho_{NIR} - a\rho_R - b)}{a\rho_{NIR} + \rho_R - ab}$	Baret <i>et al.</i> (1989)
Modified Soil Adjusted Vegetation Index 2	MSAVI2	$\frac{1}{2} \left[2(\rho_{NIR} + 1) - \sqrt{(2\rho_{NIR} + 1)^2 - 8(\rho_{NIR} - \rho_R)} \right]$	Qi <i>et al.</i> (1994)
Optimized Soil Adjusted Vegetation Index	OSAVI	$\frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R + 0.16}$	Rondeaux <i>et al.</i> (1996)
Weighted Difference Vegetation Index	WDVI	$\rho_{NIR} - a \times \rho_R$	Clevers (1989)
Enhanced Vegetation Index	EVI	$\frac{2.5(\rho_{NIR} - \rho_R)}{L_c + \rho_{NIR} + 6\rho_R - 7.5\rho_B}$	Boegh <i>et al.</i> (2002)
Triangular Vegetation Index	TVI	$0.5(120(\rho_{NIR} - \rho_G) - 200(\rho_R - \rho_G))$	Broge and Leblanc (2000)

2.3.1.2 Broadband versus Narrow-band Vegetation Indices (VIs)

During the last decade, advances in imaging spectrometry have established a new group of VIs based on narrower bands, the shape of the reflectance curve and the position of its absorption features (Broge and Mortensen, 2002). Numerous studies have demonstrated that derivative spectral indices (based on the red-edge position) are very perceptive to LAI variations, minimizing at the same time spectral noise generated by the soil background reflectance and atmospheric effects (Baret *et al.*, 1989; Demetriades-Shah *et al.*, 1990; Fillela and Peñuelas, 1994; Leblanc *et al.*, 1999).

Several studies have established a good correlation between hyperspectral VIs and LAI. Boegh *et al.* (2002) explored the feasibility of airborne hyperspectral reflectance data to predict LAI over agricultural fields such as winter and spring barley, peas, winter wheat, grass, corn and beets. The enhanced vegetation index (EVI), which has the capability to measure variations in LAI of canopies with high vegetation density, was the best predictor for LAI estimation for crop types analyzed in this study. Thenkabail *et al.* (2000) also investigated the relationship between hyperspectral reflectance measurements and LAI over five different agricultural crops (cotton, potato, soybeans, corn, and sunflower). The red (R) and near-infrared (NIR) narrow bands were found to be the best hyperspectral predictors for LAI estimation, more specifically the R and NIR bands centered at 682-nm and 920-nm. In comparison to all other soil-adjusted VIs, the narrow band TSAVI was the best LAI predictor.

Other studies have compared the performance of broadband and narrow-band VIs to estimate LAI in agriculture canopies. Broge and Mortensen (2002) compared prediction accuracies of VIs to estimate LAI from commonly used satellite-based VIs with those of narrow-band hyperspectral VIs recently suggested in the literature. The results from this comparison revealed that the narrow-band VIs were not highly superior to the broadband VIs for the estimation of LAI. Broge and Leblanc (2000) carried out a similar study that examined the relationship of analogous VIs and LAI based on simulated data. Broadband indices were found to be less affected by external factors when estimating LAI. In general, they seem to be somewhat better for the estimation of LAI than hyperspectral indices were, including the ones derived with waveform analysis techniques. Indeed, all broadband indices, except for the triangular vegetation index (TVI), showed more sensitivity to the effects introduced in their study, such as illumination geometry, canopy architecture and leaf biochemistry. However, they were also more affected by the soil background reflectance.

On the other hand, Elvidge and Chen (1995) compared the capability of broadband and narrow-band R and NIR VIs to accurately predict LAI on two plant species: pinyon pine and a big sagebrush. The results showed that broadband VIs do not accurately estimate LAI when plant canopies are discontinuous and when spectral variations in background rock, soil and litter materials occur. The background effects were mostly significant in the broadband version of the NDVI and RVI, while the TSAVI and SAVI2 minimized these effects.

However, PVI and SAVI were the best indices to maximise the decrease of the background effects to some degree. The authors concluded that the soil background effects considerably decreased using narrow-band derivative-based VIs, which is in agreement with Demetriades-Shah *et al.* (1990).

2.3.1.3 Conclusions

The ideal choice of a VI is still very much related to the purpose of the study and the type of vegetation examined as well as the amount of prior information available (Rondeaux *et al.*, 1996). Overall, the studies confirm that the estimation of LAI of a vegetation canopy on the basis of VIs is not straightforward. Many disturbing factors can influence on the accuracy of LAI estimation. Soil properties and leaf angle distribution are a few of the many factors that were discussed in the previous section. Although VIs are adjusted to diminish soil background effects and should improve LAI estimation in agricultural situations because of the large gaps between plant rows, results are still not convincing. More importantly, LAI cannot be accurately estimated in high-density vegetation cover, since VIs become insensitive at that point. The advent of hyperspectral indices has improved LAI predictability in some cases (Elvidge and Chen, 1995; Demetriades-Shah *et al.*, 1990), but results are not consistent (Broge and Mortensen, 2002; Broge and Leblanc, 2000). Remote sensing has demonstrated its potential for mapping LAI, but the limitations and uncertainties of these present models are enough incentive to research alternative remote sensing methods to estimate LAI.

2.3.2 Hyperspectral Remote Sensing and Spectral Mixture Analysis (SMA)

During the last two decades, the field of remote sensing has considerably progressed and technological advances have allowed the simultaneous acquisition of images in hundreds of narrow contiguous bands in specific regions of the electromagnetic spectrum (Adams *et al.*, 1993). This technique is called imaging spectroscopy, or more commonly called hyperspectral remote sensing.

The spectral resolution of this technology is close to the one found in laboratories and field measurements, thus, enhancing the ability to identify, from aircrafts or spacecrafts, materials on the earth's surface. All earth surface materials have specific characteristic

features in their spectra, which are related to their composition. This is especially true for identifying minerals, which show strong absorption in specific narrow regions of the SWIR or for vegetation with specific chlorophyll or liquid water absorption features in the VNIR. The significance of hyperspectral remote sensing relies in its capability to acquire a full reflectance spectrum for each pixel in the imagery. The reflectance spectrum in the 400-2500 nm region can be utilized to distinguish a large variety of surface cover materials which is not possible with broadband sensor technology (Goetz *et al.*, 1985).

Numerous hyperspectral sensors have been developed to survey the earth's surface and retrieve high-spectral information for various applications such as geology, forestry, agriculture, hydrology, and oceanography to only name a few (Staenz, 1992; Curran, 1994). The hyperspectral technology was first implemented on aircrafts with the National Aeronautics and Space Administration (NASA) Jet Propulsion Laboratory's (JPL) Airborne Imaging Spectrometer (AIS) and Moniteq's Fluorescence Line Imager (FLI) in the early eighties. First hyperspectral sensors are now in space, such as the EO-1's Hyperion sensor and the European Space Agency's (ESA) CHRIS sensor.

The advent of hyperspectral remote sensing not only requires new technology for instruments, but also new analytical approaches and techniques to manipulate and process data and extract information from hundreds of spectral bands at a time (Goetz *et al.*, 1985; Staenz, 1992). Several new techniques have been developed to analyze hyperspectral data such as new classification techniques (Staenz, 1996), spectral signature matching (Staenz, 1996), endmember selection, and linear spectral mixture analysis (SMA) (Adams *et al.*, 1986; Boardman, 1995; Tompkins *et al.*, 1997; Neville *et al.*, 1999; García-Haro *et al.*, 1999; Feng *et al.*, 2003; Szeredi *et al.*, 2003). The last two techniques are linked and are of relevance for this thesis, and will be further discussed in the next sections. Nonlinear mixing models are another method used for unmixing analysis. However, they will not be further examined for the purpose of this thesis.

2.3.2.1 Endmember Selection

Each pixel within a hyperspectral data cube provides a single spectrum which, generally represents a mixture of materials. The spectrum is influenced by the spectral properties of the components' mix and, the relationship between the major geophysical and

biophysical properties of the surface and the hyperspectral remotely sensed data (Tompkins *et al.*, 1997). The purpose of SMA is to unmix the spectrum of each pixel into its components. Accordingly, SMA requires the initial step to retrieve these components or “endmembers”. When spectral unmixing analysis is done correctly, image endmembers replicate all or most of the pixel spectra (Adams *et al.*, 1993).

Strahler *et al.* (1986) defined endmembers as “the features recognizable in a scene as being meaningful for an observer, and constitute abstractions of real objects that can be regarded as having uniform properties”. Endmember selection is the most important step to successfully unmix a reflectance data cube and produce valid fractional abundances of the study site. Improper endmember selection and extraction can lead to meaningless fraction maps, especially if the endmembers spectra are inaccurate in a physical sense (Tompkins *et al.*, 1997). In general, the exact number and the identification of the endmembers within a reflectance cube may be unknown and, thus, interpretation of the fraction maps becomes a difficult task. This problem is further complicated as the selection of endmembers is highly influenced by the scale (spatial resolution) of the data, the scattering by surface components or other factors such as illumination and viewing geometry. Selecting endmembers from vegetative imagery is even more difficult since the spectral behaviour of the different vegetation types is very similar (Deguise *et al.*, 1999). Operationally, it is very problematic to find “pure” pixels (i.e., completely covered by a single material) at the spatial resolution of airborne sensors (≈ 5 m) (McNairn *et al.*, 2001a; Pacheco *et al.*, 2001a; Pacheco *et al.*, 2002). This problem will be further complicated with the advent of satellite sensors with spatial resolutions in the order of 30 m.

Various methods are used to select and extract endmembers spectra from hyperspectral datasets (Boardman, 1995; Tompkins *et al.*, 1997; Neville *et al.*, 1999; García-Haro *et al.*, 1999; Feng *et al.*, 2003; Szeredi *et al.*, 2003). Endmember selection methods reviewed in the literature can be divided in two groups: manual and automatic endmember selection. Manual selection include endmembers spectra (1) extracted directly from pixels of known target materials, (2) extracted from spectral libraries either measured in the field or extracted from the imagery, and (3) derived from transformed image data (e.g., principal component analysis (PCA)). The latter technique uses pixel spectra displayed within a solid geometric figure where the number of vertices is equal to the dimensionality of the data.

Some automatic selection methods exist such as the Iterative Error Analysis (IEA), which uses constrained unmixing to successfully select endmembers (Szeredi *et al.*, 2003). The IEA method is most useful in extracting endmembers from the data cube since it requires “pure” pixels in the image data. This procedure is also easy to understand and implement (Szeredi *et al.*, 2003).

The advantages for the use of automatic selection methods to generate endmembers over manual methods are the elimination of human interaction and process time and the reproduction of corresponding results each time the method is used (Bateson and Curtiss, 1996; Szeredi *et al.*, 2003). Manual methods for endmember selection have certain limitations. Endmembers are normally extracted through trial-and-error process where the pixels in a scene, that are expected to represent the endmembers, are selected and the fraction images for those endmembers are computed (Boardman, 1995). The first set of endmember fractions are then evaluated using the residual errors of the SMA model, from available field data, and notes. The use of a reference endmember, either from field measurements or a spectral library, is dependent on a well-calibrated image and that the reference spectrum effectively represents the spectral variability of the endmember in the imagery. In-situ validation becomes then necessary. Furthermore, the conception of a spectral library for agricultural applications is very complex due to the exhaustive crop, weed, residue and soil conditions a vegetation canopy can undergo. Thus, extensive fieldwork would be required for a library-based method for selecting endmembers (Bateson and Curtiss, 1996). Finally, endmembers derived from transformed image data offers the advantage of not requiring prior knowledge of the image scene or the spectral properties of constituents within the scene. This method is time-consuming and the endmember selection may be difficult if the pixel data clouds do not show the extremities where the endmembers are located (Tompkins *et al.*, 1997; Staenz *et al.*, 2000). On the other hand, computer visualization tools allow manipulation of the pixel cloud, enabling the operator to locate the extremities, and, thus, the endmember spectra (Neville *et al.*, 1999). This method is considered subjective since different users could find, to some extent, different endmembers (Bateson and Curtiss, 1996).

2.3.2.2 Spectral Mixture Analysis (SMA)

Linear SMA assumes that the source of the spectral signature from a pixel is produced by more than one spectrally distinct component (Schwarz, 1998). The fundamental assumption of linear SMA is that generally each pixel on the surface is a physical mixture of several constituents weighted by surface abundance, and the spectrum of the mixture is a linear combination of the endmember reflectance spectra. Linear unmixing is implemented in two manners, the unconstrained version and the constrained version. The general equations that express linear constrained SMA are (Boardman, 1992):

$$R_b = \sum_{i=1}^m f_i r_{bi} + e_b \quad [2.15]$$

where

$$\sum_{i=1}^m f_i = 1.0 \quad [2.16]$$

and R_b is the reflectance of a pixel in band b , f_i is the fractional abundance of endmember i , m is the total number of endmembers, r_{bi} is the reflectance in band b of endmember i , and e_b is the residual error in band b of the model.

Unconstrained linear unmixing is the more common of the two since it is easier to implement and computationally more efficient (Schwarz, 1998). Although, it is more difficult to interpret since the fractions are not constrained to sum to 1 as it is the case for constrained linear unmixing. Regardless of the difficulties to select endmembers, linear unmixing is a method whose benefits have been constantly recognized over the past decade (Tompkins *et al.*, 1997). At the present time, it is obvious from the literature that there is basically no endmember selection method, which can be broadly employed in environmental applications with much confidence in the accuracy of the results (Schwarz, 1998).

2.3.2.3 Linear Spectral Mixture Analysis (SMA) to Estimate LAI

Linear SMA approaches have been extensively used in geology, soil, land cover and forestry applications (Mustard, 1993; Zhang *et al.*, 1998; Staenz *et al.*, 2000; Peddle *et al.*,

1999; Piwowar and Peddle, 1999; Lévesque and King, 2003). Limited research has been done where the combination of hyperspectral data and spectral mixture analysis are used to estimate LAI, particularly over agricultural canopies (Lelong *et al.*, 1998; Staenz *et al.*, 1998b).

Lelong *et al.* (1998) used linear SMA to map agronomic variables such as LAI over wheat crops using Multispectral Infrared and Visible Imaging Spectrometer (MIVIS) data. The general approach used in this study is similar to the one utilized in this thesis but the techniques vary somewhat. A PCA method was used to select four endmembers: fresh developed wheat, water-deficient wheat, soil and shade. Spectral unmixing was then performed on the reflectance cube in order to separate wheat from other spectral constituents. As a result, endmember fraction images and their residual were generated. This empirical method resulted in good correlations between LAI_G measurements and LAI estimated from hyperspectral data.

Another approach using linear SMA has been developed by Staenz *et al.* (1998b) to estimate LAI. This technique was validated on hyperspectral reflectance data from the Compact Airborne Spectrographic Imager (CASI) over four agricultural canopies: beans, canola, wheat and potatoes. Details and equations of this approach are listed in section 3.4 in the methodology chapter, since the purpose of this thesis is to validate this particular approach. The approach involves in a first step, to retrieve endmembers from the reflectance data themselves and to perform constrained linear spectral unmixing to define crop, soil, and other endmember fractions in the reflectance cube. Once this is completed, the crop fraction is used as input to an LAI algorithm, which takes into account the gap fraction (crop fraction inversion) and calculates LAI values on a pixel basis. LAI estimates derived from the hyperspectral data were compared to LAI_G measurements. Overall, the validation results demonstrated that the spectral unmixing analysis provided an absolute measure of LAI accurate to within 0.9, two thirds of the time. Some of the model errors were related to the difficulty of positioning the sampling sites in the imagery due to geometric distortions of the remotely sensed imagery and, uncertainties of the foliage distribution for each crop. In general, this analysis demonstrated potential for using linear SMA to estimate LAI over agricultural canopies. Results between LAI_G measurements indicated a reasonable correlation with LAI estimates derived from the hyperspectral data.

2.3.2.4 Contribution of Hyperspectral Remote Sensing to LAI Estimation

The high spectral dimensionality of hyperspectral data permits the extraction of quantitative information never before possible with broadband imaging sensors (Staenz *et al.*, 1997). Consequently, this technology allows a more accurate identification of a wide range of materials on the earth's surface. This is significant for agriculture applications since a greater range of crop and soil conditions can be detected. For example, hyperspectral remote sensing will be able to identify areas of low and high crop water stress and crop growth within agriculture fields. Several studies have found hyperspectral remote sensing useful for precision agriculture applications (Staenz *et al.*, 1998b; Deguise *et al.*, 1999; Clevers, 1999; Bechdol *et al.*, 2000; Garegnani *et al.*, 2000; Pacheco *et al.*, 2001a; Pacheco *et al.*, 2002; Champagne, 2002). For example, weed detection is rather difficult with multispectral data, while hyperspectral remote sensing can more easily identify weed infestation and provide information for site-specific herbicide application. In particular, hyperspectral data is exploited in precision agriculture to: (1) improve the detection of within-field variability with respect to crop production, (2) determine the cause of within-field spatial variability, and (3) parameterize and validate crop models (Moran *et al.*, 1995; Staenz *et al.*, 1998b).

Furthermore, hyperspectral remote sensing can estimate canopy LAI with an accuracy greater than what would be expected with a multispectral sensor depending on the technique used (see Section 2.3.1.2). The techniques associated with broadband remote sensing data consider the total amount of the vegetation canopy within a pixel to estimate LAI (Staenz *et al.*, 1998b; Pacheco *et al.*, 2002). In addition, VIs that are sensitive to the soil background do not completely eliminate its influence when deriving LAI estimates, especially over low vegetation densities. Consequently, it is essential for precision agriculture applications to distinguish the crop from the other vegetation present in the pixel, such as weeds, volunteer crops, and even soil. LAI can then be estimated using the reflectance contribution of the crop fraction only and as a result, derive a more accurate LAI estimate.

The motivation to establish a more robust LAI estimate from remote sensing is to link this variable to crop growth and, subsequently, to crop yield models. Although the current status of crop modeling cannot be recognized as satisfactory (Sirotenko, 2001), the inputs

into the crop model are not satisfactory either. The accumulation of errors with respect to the different input parameters and together with possible inaccuracies in the model equations, can lead to model results that are quite far from measured field data (Wallach *et al.*, 2001). As a result, the more accurate and refine the LAI estimation, the more accurate the modelled yield estimation will be.

2.4 Conclusions

The operational use of precision agriculture has been challenged by the necessity for accurate growth models to relate plant biophysical properties to canopy reflectance. Crop yield models require correct and precise inputs, such as LAI, in order to provide accurate crop yield forecasting. LAI from agriculture canopies can be quantified using various techniques. Although direct methods are straightforward and precise, they are time-consuming and labour intensive. Indirect methods, such as optical instruments, represent an alternative but are still not ideal. Remote sensing methods, on the other hand, are a solution for providing fast and accurate estimation of LAI over large agriculture areas. VIs are very common and useful to estimate LAI but a review of the literature has acknowledged that they possess limitations (due mostly to soil background noise) and results are inconsistent. Hyperspectral remote sensing and SMA, however, seem to demonstrate much potential for the estimation of LAI over agricultural canopies. This approach offers an accurate and very precise method where only the crop vegetation will be used as input to estimate LAI. The application and validation of this approach over different crop types and environmental conditions is necessary to fully determine and understand its strengths and limitations. The following chapter (Chapter 3) will describe in detail the methodology used to derive LAI from hyperspectral image data.

3. METHODOLOGY

The following chapter describes the methodology used in this thesis. Study sites and ground data collection, including field methods to estimate LAI_G measurements, will be discussed. Remote sensing data acquisition parameters will be described, preprocessing and information extraction and, statistical analyses will be examined. A flowchart summarizes all processing steps (Figure 3.1).

3.1 Study Sites

Two agricultural sites, characterized by various crop types and site conditions, were chosen for this study. Field campaigns were carried out during the growing seasons in Clinton (Ontario) in 1999 and Indian Head (Saskatchewan) in 2000.

Data were acquired from an agricultural region near Clinton (43° 40' N; 81 ° 30' W), in southern Ontario, located 21 km east of Lake Huron (Figure 3.2). Crops in this agricultural region were composed mainly of beans, corn, forage crops and small grains (wheat and barley). Within this general study site, six fields were selected for reference measurements. These fields included three white bean fields (*Phaseolus vulgaris* L.) and three corn fields (*Zea mais* L.). The bean fields were seeded in early May and the corn fields in late May. No treatments were applied within these fields. Details of these fields are given in Table 3.1.

Data were also acquired in an agricultural region near Indian Head (50° 32' N; 103 ° 40' W), in southern Saskatchewan, situated 68 km east of Regina (Figure 3.2). The fields used for validation purposes were located on a precision test farm of the Indian Head Agricultural Research Foundation (IHARF). Eight 12-hectare fields were selected for intense sampling and validation purposes. Four of the eight fields were seeded with wheat

(*Triticum aestivum* L.), two with canola (*Brassica napus* L.) and two with peas (*Lathyrus aphaca* L.). To increase field variability, variable fertilizer treatments were applied to the wheat and canola fields while variable rate seeding treatments were performed in the pea fields. Each field was divided into four sections of approximately three hectares in width to delimit treatments (Figure 3.3). Details of these fields are given in Table 3.2.

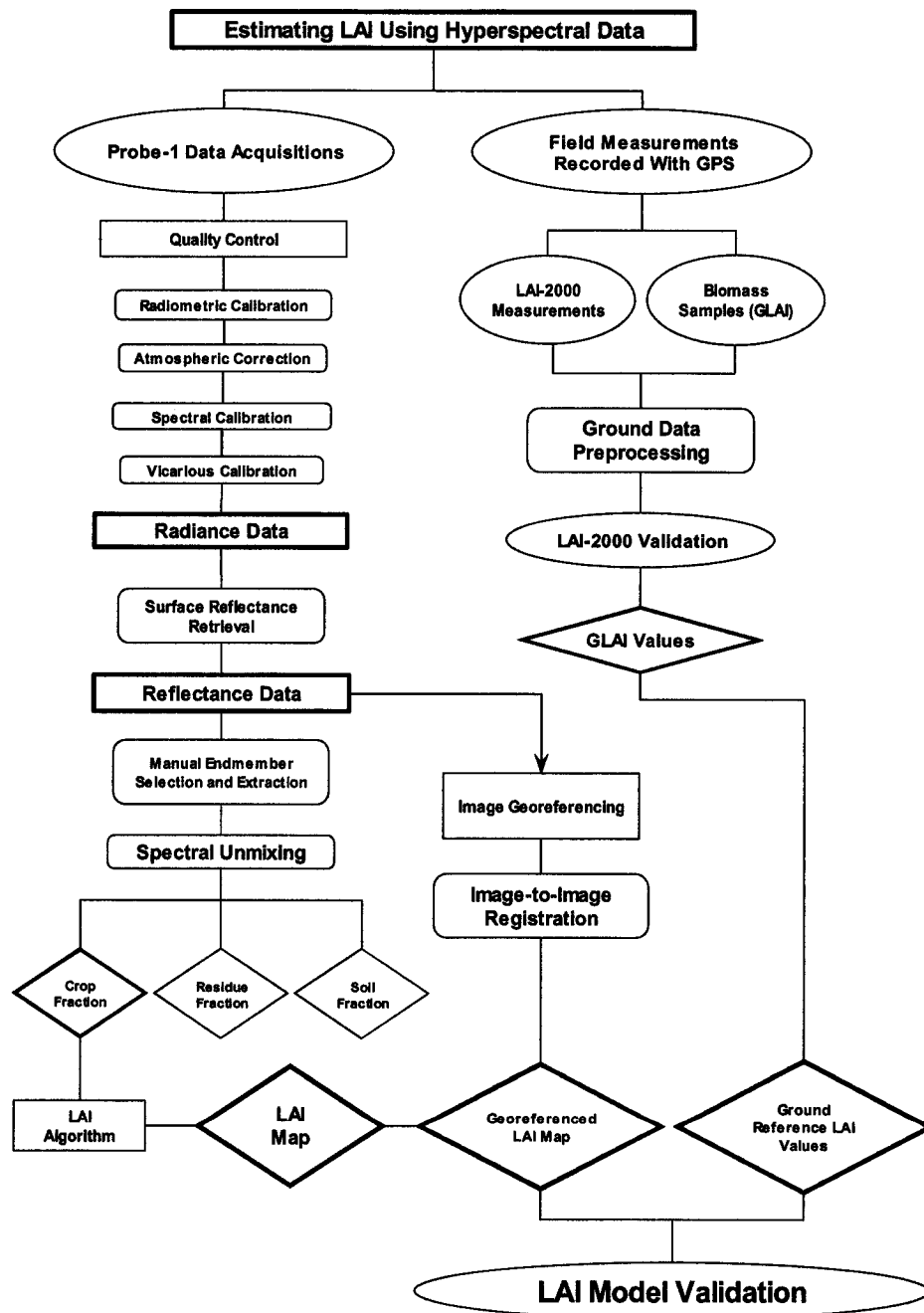


Figure 3.1. Processing sequence for estimating LAI from Probe-1 hyperspectral data.

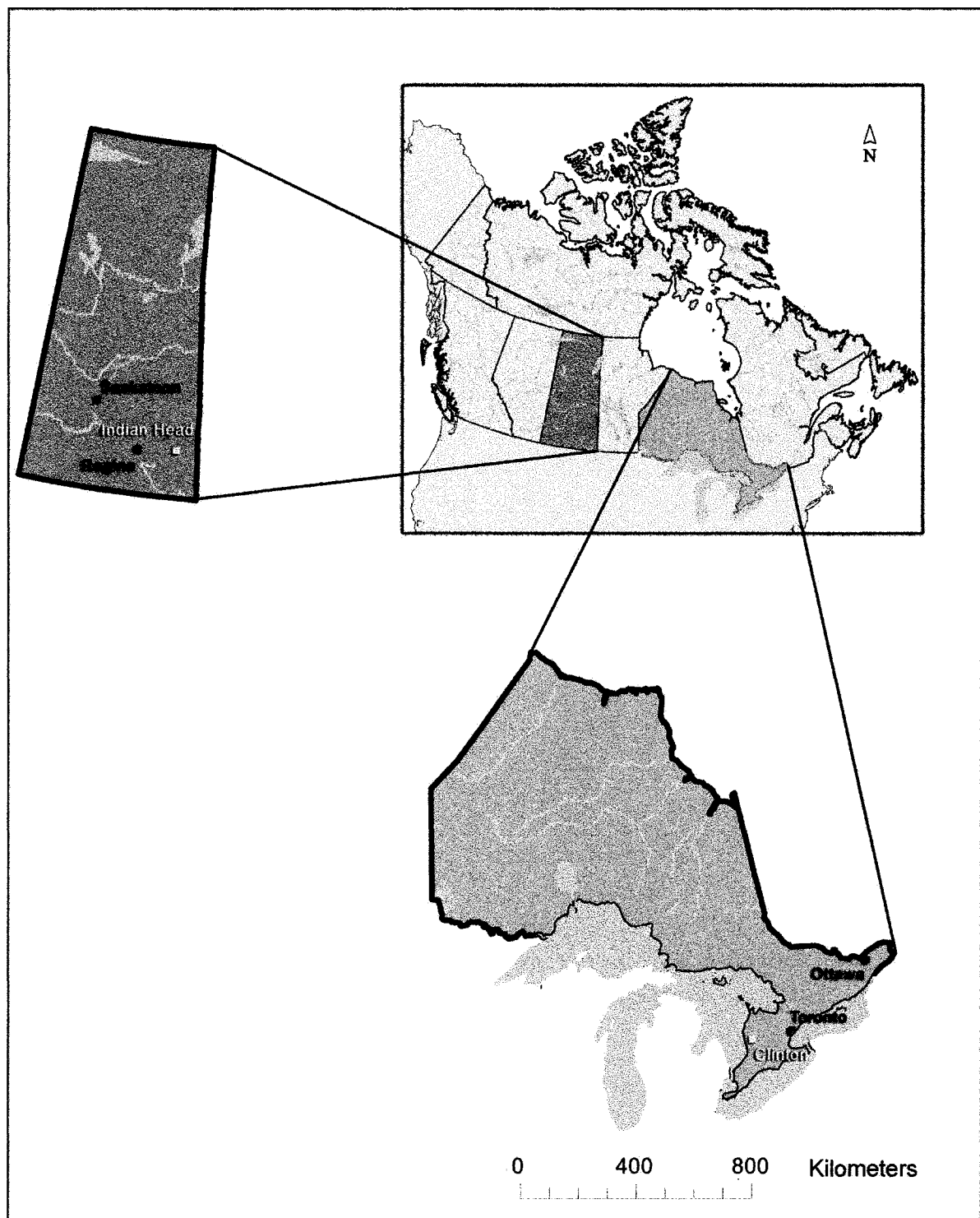


Figure 3.2. *Location of Clinton and Indian Head study sites.*

Table 3.1. *Detailed description of studied fields for the Clinton dataset.*

Field ID	Crop Type	Patches	Details
Bean-1	White Bean	• Three bare soil patches • One double seeded patch • One residue patch	• Has a potential for white mould (based upon manure application) or for insect damage. • Significant corn residue. • Approximately 75 acres.
Bean-2	White Bean	• Three bare soil patches	• In wheat in 1996, soybeans in 1997 and corn in 1998. • Sloped from south to north. • Significant corn residue (no-till). • Approximately 65 acres.
Bean-3	White Bean	• None	• Approximately 47 acres.
Corn-1	Corn	• Two bare soil patches • Two weed patches • Two double seeded patches	• In hay for the last 5 years. • Has a large perennial weed problem. • Has significant topography. • Approximately 75 acres.
Corn-2	Corn	• Three bare soil patches • One weed patch	• Has had a perennial weed problem, primarily with nutsedge. • Partly manured in the spring. • In soybeans in 1997 and wheat in 1998. • Approximately 73 acres.
Corn-3	Corn	• None	• Approximately 90 acres.

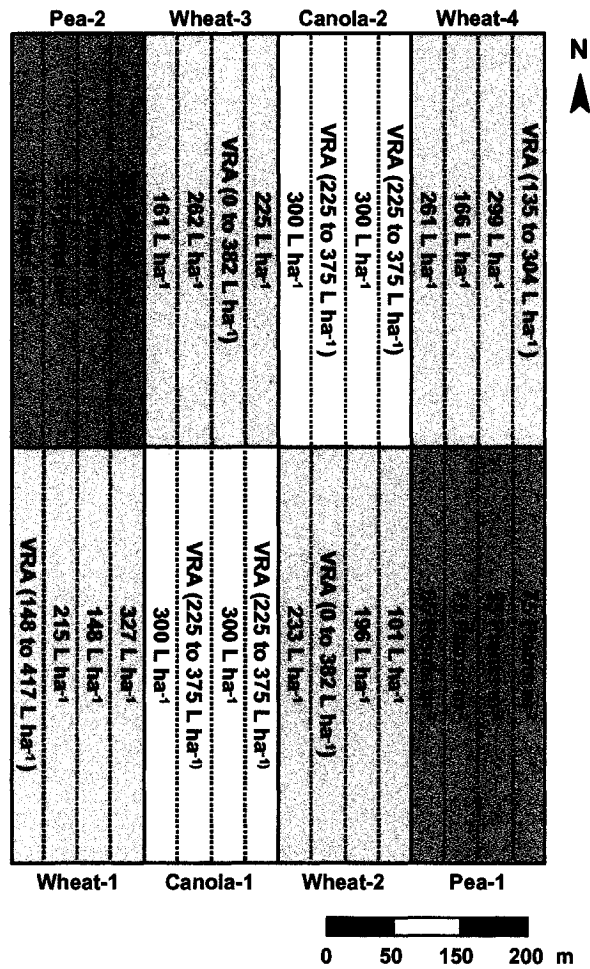


Figure 3.3. Fertilizer and seeding treatments in the study fields in the Indian Head site.

Table 3.2. Detailed description of studied fields for the Indian Head dataset.

Field Name	Crop Type	Hybrid	Seeding Date and Rate	Nitrogen Treatments
Canola-1	Canola	SW Flare LL	May 17 th - 27.2 kg ha ⁻¹	Variable rate
Canola-2	Canola	SW Flare LL	May 9 th - 27.2 kg ha ⁻¹	Variable rate
Pea-1	Pea	Swing	May 3 rd - 180.8 kg ha ⁻¹ and 244.8 kg ha ⁻¹	None
Pea-2	Pea	Swing	May 5 th - 180.8 kg ha ⁻¹ and 244.8 kg ha ⁻¹	None
Wheat-1	Wheat	AC Barry	May 17 th - 134.8 kg ha ⁻¹	Variable rate
Wheat-2	Wheat	AC Barry	May 20 th - 134.8 kg ha ⁻¹	Variable rate
Wheat-3	Wheat	AC Barry	May 20 th - 134.8 kg ha ⁻¹	Variable rate
Wheat-4	Wheat	AC Barry	May 20 th - 134.8 kg ha ⁻¹	Variable rate

3.2 Ground Data Collection

LAI_G measurements and a large set of ancillary data were collected for each of the studied sites. Field sampling design, field measurement methods and ground data processing will be discussed in this section.

3.2.1 Field Sampling Design

Ground measurements were collected from June 24 to July 7, 1999 in support of the Clinton hyperspectral dataset. Approximately 10 sampling sites were selected per field to reflect within-field variability, based on elevation and soil maps (Figure 3.4). There were sixty sampling sites in total. All sites were marked with a flag and the location of the flag was recorded with a Differential Global Positioning System (DGPS) unit. During recording, the geodetic datum was set to WGS-84 while the coordinate system was set to geographic (longitude/latitude). Four of the six bean and corn fields were considered primary sites and two fields were back-up fields. “Pure” crop (achieved by double seeding), weed, residue and bare soil patches were created. In 4 of the 6 fields, these patches were located in different areas within the fields, where variability in soil and vegetation cover among the patches was maximized. Each patch was approximately 20 m by 20 m in dimension (Figure 3.5). The location of each patch was measured with a DGPS unit. These patches were used for the endmember selection process discussed later in the Information Extraction section (see section 3.4). Further details of these patches are found in Table 3.1.

Ground measurements were collected from June 26 to July 8, 2000 for the Indian Head dataset. A rectangular grid was overlaid on all the fields with an 80 m vertical and a 50 m horizontal spacing. This grid contained 308 points regularly distributed over the eight fields (Figure 3.6). Only 96 points were selected for sampling purposes. These points were selected to cover within-field variability resulting from various nitrogen and variable rate seeding treatments. The location of all sampling sites were recorded with the same GDPS as in Clinton and settings were identical. Similarly to the Clinton site, 20m-by-20m “pure” patches of crop, residue and soil were established in an adjacent field to the IHARF site.

3.2.2 Ground Measurements

This section will describe the various ground measurements collected during the field campaigns. These include LAI_G measured from biomass samples, LAI_{2000} and percent-crop cover (PCC_G) measurements estimated from ground vertical photographs.

3.2.2.1 Biomass Samples

Measurements of plant fresh and dry mass were made on the day of image data acquisition. At each site, all above-ground crop biomass samples were harvested within a 0.5m-by-0.5m area for all crops except corn. Six corn plants were harvested at each sampling site. Three replicate samples were collected at each site. These samples were immediately weighed to establish wet weight, and then oven-dried at 105°C for 48-72 hours until no change in weight was noticed by further drying. Corn samples were subset once fresh weight and a ratio of total to subset weight was determined for scaling.

3.2.2.2 LAI_{2000} (LAI_{2000}) Measurements

LAI_{2000} measurements were acquired using the LI-COR LAI_{2000} instrument. These measurements were carried out from June 26 to July 5, 1999 and from June 30 to July 5, 2000 during the Clinton and the Indian Head field campaign, respectively. Three LAI measurements were taken at each sampling site in order to minimize errors and, thus, to provide a representative LAI average. Measurements were acquired along 2-m transects coinciding with a diagonal between two plant rows (Figure 3.7). Transects were located within an area of 2-3 m surrounding the center of the sampling site.

One reference measurement was taken above the crop canopy and four measurements were taken below the vegetation canopy, for each sampling site. These measurements were collected along the transect at regular spacing intervals. The LAI_{2000} was employed during overcast conditions only.

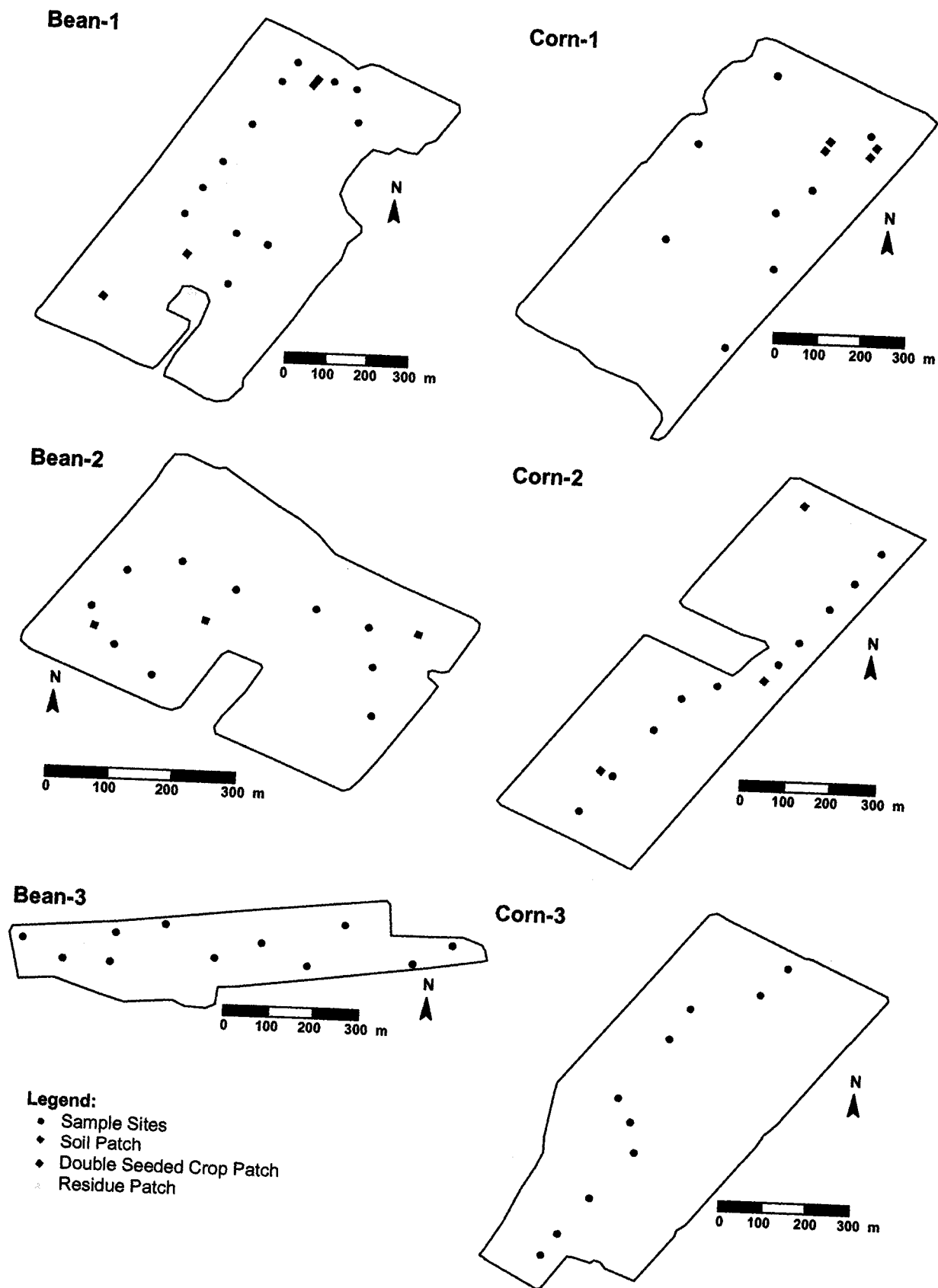


Figure 3.4. *Sampling design for the study fields in the Clinton site.*

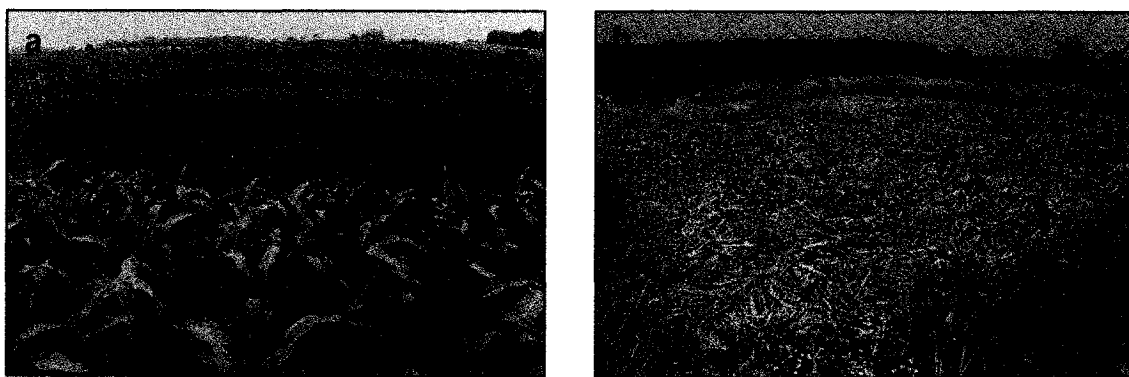


Figure 3.5. *Soil patch in field Corn-1 (a) and residue patch in field Bean-1 (b).*

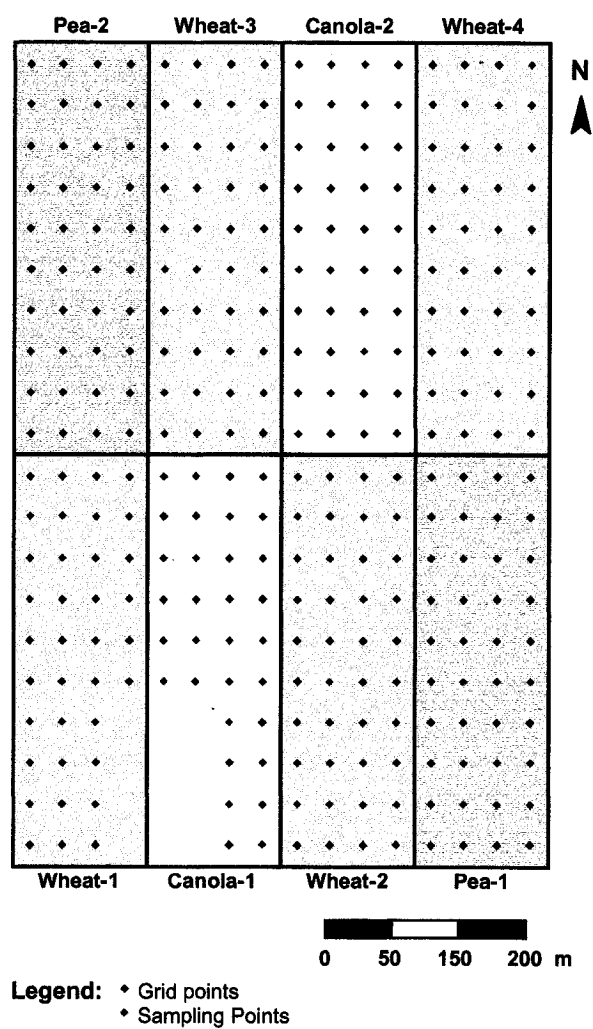


Figure 3.6. *Sampling design for the study fields in the Indian Head site.*

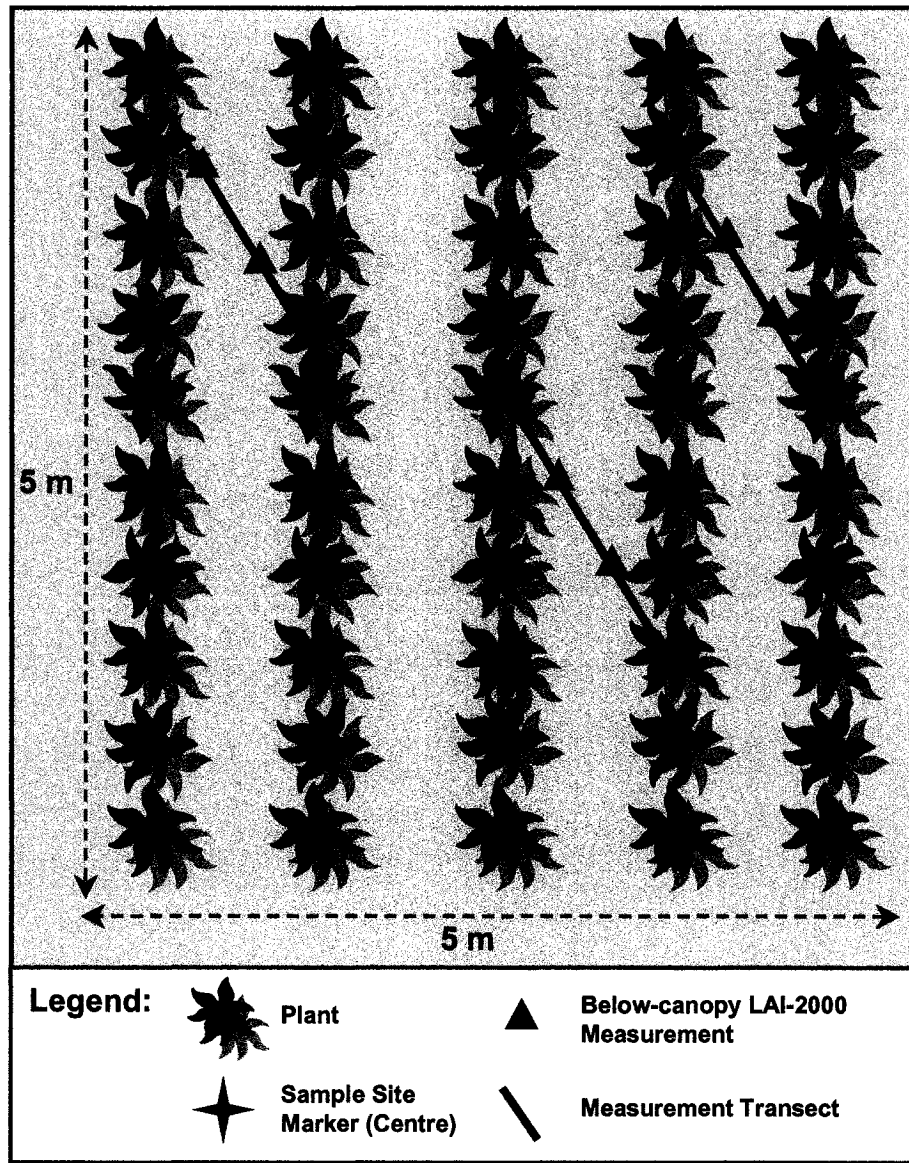


Figure 3.7. *Sampling method for LAI-2000 measurements.*

3.2.2.3 Percent-Crop Cover (PCC_G) Measurements

PCC_G were collected from June 24 to July 7, 1999 and from July 2 and July 4, 2000 during the Clinton and the Indian Head field campaign, respectively. PCC_G was calculated from vertical photographs taken with a 35-mm camera equipped using 28 mm lens. The camera was mounted on an overhead mast and used at a height of 2 m above ground (Figure 3.8). In this configuration, the camera viewed a ground area of about 4 m². Since the Probe-1 data has a pixel size of 25 m², photographs were acquired within 3 to 4 m of the center of the

sampling site locations for greater site representation. Three photographs were taken at each sampling site and in each patch.



Figure 3.8. *Field collection of ground vertical photographs.*

3.2.3 Ground Data Preprocessing

Ground measurements required some preprocessing before final values could be used for data analysis. This section will discuss preprocessing requirements for LAI_G , LAI_{2000} and PCC_G .

3.2.3.1 Ground LAI (LAI_G) Derived from Biomass Samples

Gravimetric crop water content, derived from biomass samples, was calculated with the following equation:

$$\frac{(wet\ weight - dry\ weight)}{wet\ weight} \quad [3.1]$$

Dry plant matter (DM) was then calculated by subtracting the wet weight to the total plant weight. LA and LAI was calculated with the following equations:

$$LA = DM \times SLA \quad [3.2]$$

$$LAI_G = LA / GA \quad [3.3]$$

where SLA values were derived from van Keulen (1986) and GA is the ground surface area. LAI_G values were averaged per sampling site and only the mean value was used for statistical analyses.

3.2.3.2 LAI-2000 (*LAI₂₀₀₀*) Measurements

LAI₂₀₀₀ values were directly extracted from the instrument and did not require further data processing (LI-COR, 1992). For each sampling site, LAI values from all replicates were averaged and only the mean value was retained for further statistical analysis.

3.2.3.3 Percent-Crop Cover (*PCC_G*) Measurements

The vertical photographs were digitized in three channels (blue, green and red) and processed with PCI ImageWorks (PCI Geomatics, 2000). Unsupervised classification was carried out using ten classes: three classes for soil, three classes for leaf cover, two for residue, one for soil shadow, and one for leaf shadow. These classes were then aggregated to form three major components: leaf cover, residue and soil. Once the classification was completed, percentages of leaf, soil and residue cover were determined for each photograph. Final PCC_G was then calculated from the average of the three replicate photographs.

3.3 Remote Sensing Data and Preprocessing

Sensor data acquisition parameters and preprocessing techniques were analogous for both study sites. This section will describe the various remote sensing data parameters and the preprocessing technique for both datasets with any differences between the two sites noted.

3.3.1 Remote Sensing Hyperspectral Data Acquisition and Sensor Parameters

Remote sensing data were acquired using the airborne Probe-1 hyperspectral sensor (ESSI Inc., 2001) on July 7th, 1999 and on June 28th, 2000 over the Clinton and Indian Head sites, respectively (See Appendix I). Probe-1 is a “whiskbroom style” instrument that collects data in the cross-track direction by mechanical scanning and in the along-track direction by movement of the airborne platform. This sensor acquires upwelling radiance in 128 bands in the VNIR and the SWIR regions of the electromagnetic spectrum. The at-sensor radiance is dispersed by four spectrographs onto four linear detector arrays with 32 bands each. This sensor covers a wavelength region from 437.9 nm to 2506.7 nm almost continuously with small gaps in the strong 1380 nm and 1870 nm atmospheric water vapor absorption. Table 3.3 lists specific parameters for each detector module. The bandwidths at full width half maximum (FWHM) varies from 13.3 nm to 22.3 nm with a spectral sampling interval of 10.7 nm to 19.8 nm. The aircraft was flown at an altitude of around 2780 m (above sea level) resulting in a swath width of 2.56 km (512 pixels) and a spatial resolution of 5 m at nadir. The Probe-1 sensor was mounted on an active 3-axis. A non-differential GPS was recording the location of the aircraft during the flight.

Table 3.3. *Spectral specifications for Probe-1 sensor detector modules.*

Detector Modules	Spectral Range	Spectral Bandwidth	Spectral Sampling Interval
1	437.9 - 904.3 nm	13.7 - 20.7nm	10.7 - 18.3 nm
2	896.3 - 1355.3 nm	13.3 - 22.3 nm	12.5 - 19.8 nm
3	1394.7 - 1801.1 nm	14.6 - 17.8 nm	11.7 - 15.6 nm
4	1977.6 - 2506.7 nm	16.7 - 21.5 nm	13.9 - 18.9 nm

3.3.2 Remote Sensing Data Preprocessing

Image preprocessing was carried out using the Imaging Spectrometer Data Analysis System (ISDAS), a software package developed at the CCRS (Staenz *et al.*, 1998a). Data preprocessing involves three components: radiometric and spectral calibration and surface reflectance retrieval.

3.3.2.1 Radiometric and Spectral Calibration

A laboratory calibration was completed on the Probe-1 sensor in April 1999 (Clinton dataset) and in April 2000 (Indian Head dataset) to obtain dark current signal, radiometric coefficients, and to ascertain the centre position of the spectral bands. However, a vicarious calibration of the sensor was required to correct for errors in gains and band centers, which resulted from the stresses experienced during transportation, installation and operation between the laboratory calibration and the overflight (Secker *et al.*, 2001). Vicarious calibration is an absolute calibration method, which produces a new set of gains that can be used to replace those derived in the laboratory. It is also used to correct errors in the laboratory spectral calibration since shifting of the band wavelength positions may have occurred.

To achieve spectral calibration of the Probe-1 data, the raw spectrum (digital numbers) recorded by the sensor was converted to radiance using the radiometric gains and offsets derived in the laboratory. Surface reflectances were then computed with the MODTRAN3 (Berk, 1989) radiative transfer (RT) code, in combination with a look-up table (LUT) approach (Staenz and Williams, 1997). Table 3.4 presents the various parameters used as inputs to the RT code. The derived reflectance spectra were then analyzed to evaluate the band's wavelength and center position using five known atmospheric absorption features: 760 nm (oxygen), 940 nm and 1130 nm (water vapour) and, 2005 nm and 2055 nm (carbon dioxide). Wavelength shifts were then calculated, which best corrected the reflectance to obtain a smooth spectrum in the regions of these absorption features. These shifts were then applied to the Probe-1 data.

A reflectance-based vicarious calibration (RBVC) was conducted using accurate ground-based reflectance measurements of specific targets at each study site. A 20m-by-20m asphalt surface and a 5m-by-5m bare soil patch were chosen as the calibration sites for Clinton and Indian Head, respectively. A portable GER3700 field spectroradiometer (Geophysical and Environmental Research Corporation, 1990) was used to acquire ground-based reflectance measurements. This instrument measures radiance over a spectral range from 300 nm to 2500 nm using 704 spectral bands varying from 1.5 nm to 9.5 nm in width. Ground reflectance was calculated by ratioing target radiance to the radiance obtained from a calibrated 10inch-by-10inch white Spectralon panel (Labsphere, 2001). The Spectralon

radiance was acquired immediately prior to the target radiance. The average of five spectra was convolved with Gaussian response profiles to match the bandwidths and the band centers of the Probe-1 sensor. The calibration sites were then visually located in the Probe-1 imagery and an average spectrum was extracted for each target. The spectra from these targets were then matched to the averaged GER spectra. The differences between the two spectra were calculated and the Probe-1 radiometric coefficients were adjusted to minimize the absolute reflectance difference until an error threshold was reached, which was set to 0.02%. This process is computed in ISDAS with an iterative numerical technique and provides a new set of optimal gains with each iteration (Secker *et al.*, 2001). These new gains were then applied to the raw digital numbers to calculate at-sensor radiance for each dataset.

Table 3.4. *MODTRAN3 model input parameters for the atmospheric correction of the Probe-1 data.*

Input Parameters/Dataset	Clinton 1999	Indian Head 2000
Date	1999:07:07	2000:06:28
Greenwich Mean Time (GMT)	14:47:00	17:10:00
Aircraft heading	180°	110°
Sensor altitude (above sea level)	2778 m	2780 m
Terrain elevation (above sea level)	340 m	579 m
Solar zenith angle	39.68°	34.35°
Solar azimuth angle	108.79°	132.55°
Atmospheric model	Midlatitude Summer	Midlatitude Summer
Aerosol model	Continental (rural)	Continental (rural)
Water vapour content	1.5 g/cm ²	1.5 g/cm ²
Ozone column (as per model)	0.319 cm-atm	0.319 cm-atm
CO2 mixing ratio (as per model)	357.5 ppm	357.5 ppm
Horizontal visibility	50 km	50 km

3.3.2.2 Surface Reflectance Retrieval

The calibrated at-sensor radiance data were converted to surface reflectance using the reflectance retrieval tool implemented in ISDAS to compensate for atmospheric scattering and absorption effects. The procedure is based on a LUT approach to decrease considerably the number of RT code runs (Staenz and Williams, 1997). Two five-dimensional raw LUTs with tunable breakpoints were generated with a selected RT code to provide additive and multiplicative coefficients for the removal of scattering and atmospheric effects. The LUTs dimensions include wavelength, pixel position, atmospheric water vapor, aerosol optical

depth and terrain elevation. The MODTRAN3 RT code was applied to the Clinton and Indian datasets, respectively using a Midlatitude Summer atmosphere model and a Continental-Rural aerosol model. Other input parameters are listed in Table 3.4. The raw LUTs are then convolved with the sensor characteristics. Once the convolved LUTs were generated, they were then used in combination with a curve-fitting technique in the 940 nm and 1130 nm water vapor absorption regions, to estimate the atmospheric water vapor content on a pixel-by-pixel basis from the data cube (Green *et al.*, 1991; Gao and Goetz, 1990). Finally, the column atmospheric water vapor estimates, were used on a per pixel basis for interpolation of the LUTs to retrieve surface reflectance. The resulting reflectance spectra were then examined for quality assessment purposes. This process revealed band-to-band errors in the 820 to 1000 nm region as a result of uncertainties in atmospheric modelling and calibration. These errors were removed using an 8-nm Gaussian smoothing window in that specific wavelength region.

3.3.3 Image Georeferencing

Airborne imagery generally contains considerable geometric distortion induced by the variations in the pitch, yaw, and roll of the aircraft during image acquisition as well as the attitude and speed of the aircraft. These attitude effects must be eliminated to ensure accurate correspondence between ground measurement locations and image pixel locations. A non-differential GPS (on-board the aircraft) registers the location of the aircraft during Probe-1 image acquisition, but unfortunately the system was not working at the time of image acquisitions. Therefore, this georeferencing system was not exploited to validate the ground sampling locations in the imagery. Instead, high spatial resolution ortho-rectified aerial photographs and Ikonos imagery was used to establish sampling site locations via an image-to-image registration technique. This procedure was performed on both Clinton and Indian Head datasets. This section describes the geo-referencing procedure for both datasets underlining any differences between the two.

3.3.3.1 Image-to-Image Registration

A reversed image-to-image registration process was used to determine ground sampling locations in the Probe-1 imagery. To preserve the radiometric integrity of each

pixel in the imagery, no registration of the Probe-1 data was performed in order to avoid resampling of the image pixels. Alternatively, sampling site locations were located on the Probe-1 image by initially determining their location on a geo-referenced image and then warping this image to match the Probe-1 imagery. As indicated in section 3.2.1, all sampling site locations were measured with a DGPS during the field campaign. The positions of these sampling sites were then marked on digital aerial orthophotos for the Clinton dataset and on a 4-m orthorectified multispectral Ikonos image for the Indian Head dataset. The Clinton orthophotos were georeferenced using 10 ground control points (GCPs) measured with a GPS (± 1 m accuracy). These GCPs were then matched to pixels within the orthophotos with an accuracy of ± 5 m or less. The Indian Head orthorectified Ikonos image was georeferenced using 12 GCPs measured with the same GPS as for the Clinton dataset. Georeferencing was done using the same geodetic datum (WGS-84) to ensure ground sampling locations were compatible with image sampling locations. Finally, the ground sampling locations were “burned” into the orthophotos and Ikonos image to ensure that the sampling site positions would remain visible once the georeferenced images were warped to the Probe-1 imagery.

The georeferenced orthophotos and Ikonos image were then registered to the Probe-1 imagery and warped using 1st, 2nd or 3rd order polynomials using the GCP Works module of the PCI Software (PCI Geomatics, 2000). The orthophotos and Ikonos image were used as the “slave” images and the Probe-1 imagery was used as the “master” to ensure that the Probe-1 images would maintain radiometric fidelity. For each field in the Clinton dataset, 21 to 49 GCPs were identified on a visual basis at the corners of each field or at any other points clearly noticeable in both the “slave” and “master” images (i.e., intersections of rivers, roads, house corners, etc). Due to significant distortion of the Clinton hyperspectral imagery, a third order polynomial fit was used for all fields. For individual fields in the Indian Head dataset, 8 to 20 points were selected as GCPs in both images and only first and second order polynomial fits were applied to the data. Even though all of the study fields in Indian Head were located within a single flight line, the warping process was done separately for each of the eight fields. For both datasets, GCPs were distributed uniformly over the imagery to ensure a good image fit. A cubic convolution-resampling scheme was applied in the registration procedure, which uses a four-by-four pixel window to compute a brightness

value as the weighted average of the nearest sixteen pixels. Finally, sampling site pixel and corresponding line coordinates from the warped orthophotos and IKONOS were kept for each sampling site and retained for data extraction.

3.3.3.2 Location of Ground Sampling Sites

For both study sites, hyperspectral image data were acquired during several consecutive flight lines, providing dual coverage of the same geographical area. Only one pass of the two Probe-1 image acquisitions was selected for the analysis of the Clinton dataset. The selection criteria were a combination of the radiometric quality of the data (based on acquisition time influencing the sun-sensor viewing geometry), the root mean squared error (RMSE) of the polynomial fits and a visual assessment of geometric integrity of the fields for each flight line. Image data were extracted from a 3-by-3-pixel window centred on the sampling site to eliminate errors in case of incorrect sampling site location.

In regards to the Indian Head dataset, two flight lines were acquired over the same area covering all fields, identified as Pass 1 and Pass 2. The high radiometric and geometric quality of both flight lines required a more detailed approach to establish which pass to extract image data on a sampling site basis. The Ikonos image was warped to the hyperspectral images of the two passes on a field-by-field basis in order to geometrically match the field boundaries of the Ikonos image with those of the hyperspectral data. Pixel and line coordinates were extracted from the most geometrically accurate pass for each sampling site. The ground locations were chosen based on a combination of the RMSE (minimum value) for each polynomial fit and a visual assessment of the field boundaries fit and intra-field geometric accuracy. Intra-field geometric accuracy was an issue for specific fields. Certain areas within a field appeared to be more distorted in one flight line but other areas of the same field were more distorted in the other flight line.

3.4 Information Extraction

This section will discuss the various processing steps performed on the remote sensing data once the surface reflectance data was retrieved. The processing was done similarly for both datasets. This includes endmember selection and extraction, spectral unmixing and the calculation of the eLAI and LAI values.

3.4.1 Endmember Selection and Extraction

A Manual Endmember Extraction (MEE) approach was used to select and extract endmembers from the reflectance cube. Accordingly, endmember spectra were manually extracted from the image data based on prior knowledge of the fields. The endmember selection was carried out on an individual field basis. For each field, two or three endmembers were identified and then extracted from the imagery for spectral unmixing purposes. The endmember selection included three different components: vegetation (crop), soil and residue. However, not all fields contained residue and this particular endmember was not included for spectral unmixing analysis on certain fields. It should also be noted that a crop shadow endmember was not included in the endmember selection and extraction process given that the leaf shadow on leaves or soil would be automatically classified in the crop and soil endmember fractions, respectively. The spectral response of shadow would only vary in amplitude and not in the signature itself.

For the Clinton dataset, corn and white bean spectra were extracted as the crop endmembers. Soil was also selected as an endmember for all fields while only white bean fields contained residue. Since the availability of pure pixels under natural field conditions was problematic, patches of crop, residue and bare soil were artificially created on some of the fields (see Table 3.1). Endmember spectra were then extracted directly from the image data within these 20 m by 20 m patches. Since these patches did not exist on all investigated fields, some endmember spectra from one field were used for the other two fields of the same crop type.

For the Indian Head dataset, five endmembers were selected and then extracted from the reflectance cube data. Endmembers included crop spectra of wheat, canola, peas, soil and residue spectra. Soil and residue endmembers were extracted from “patches” created in the northeast area of the IHARF site. However, similar patches were not created for the crop endmembers wheat, canola and peas. In order to overcome the absence of these patches, a few days following the Probe-1 overflight, a quicklook image of the hyperspectral data was taken out in the field for validation purposes. Areas of high crop vigor were noted on the imagery and thus, the crop endmembers were then extracted directly from those areas of the imagery. A spectral array was created containing each of the endmembers necessary for spectral unmixing analysis.

3.4.2 Spectral Mixture Analysis (SMA)

Constrained and partially-constrained linear spectral mixture or unmixing analysis (SMA) was performed on both hyperspectral datasets using an algorithm implemented in ISDAS (Boardman, 1995; Endsley, 1995). Constrained linear spectral unmixing is defined by equation [2.14] in section 2.3.2.2. Partially-constrained linear spectral unmixing is a recently-introduced option in ISDAS, which relaxes the constraint that the fractions sum to one. If constrained linear spectral unmixing is performed on a data cube using an incomplete list of endmembers, the constrained unmixing algorithm will force the fraction of some of the pixels to get assigned to an inappropriate endmember since the algorithm requires unit sum (Shang *et al.*, 2003). The partially-constrained unmixing algorithm, however, allows the sum of fractions to be smaller than 1. The equation for partially-constrained unmixing can be summarized as follows:

$$\sum_{i=1}^m f_i \leq 1.0. \quad [3.4]$$

where f_i is the fractional abundance of endmember i , m is the total number of endmembers and the sum of the endmembers (Σ) is smaller or equal to 1.

Spectral unmixing was completed using the full spectral range from 437.9 nm to 2506.7 nm. Probe-1 reflectance cubes were unmixed on a field-by-field basis for the Clinton dataset. All fields were covered with the same overflight with respect to the Indian Head dataset. As a result, a series of fraction maps were derived from the hyperspectral Probe-1 data for each individual field. Constrained unmixing generated in each one crop and soil fraction maps while residue fraction maps were produced for specific fields only. Partially-constrained unmixing generated the same fraction maps as constrained unmixing, with an additional fraction map from reflectance contribution that was not assigned to either the crop, soil or residue endmember. These fraction maps determine the relative contribution of each of the endmembers to the total reflectance recorded for each pixel. The values range from 0 to 1 where 0 indicates a low abundance and 1 a high one. Finally, the percent crop cover (PCC) fraction maps were validated with the ground vertical photographs taken during each field campaign. Spectral unmixing analysis was carried out similarly for both datasets. Only endmember spectra inputs varied for each dataset and each field.

3.4.3 Calculation of effective LAI (*eLAI*) and LAI

Effective LAI (*eLAI*) and LAI values were extracted from the hyperspectral data using ISDAS. When canopy foliage distribution is not affected by foliage clumping, *eLAI* is computed. For each of the fields, crop fraction maps derived from the hyperspectral data were used as input to generate *eLAI* and LAI maps. Unlike other methods, this approach uses the crop portion of vegetation only (excluding soil, residue, weeds or volunteer crops) to estimate LAI. *eLAI* can be calculated according to the following formula (Ross, 1981):

$$eLAI = \frac{\cos \alpha}{G} (-\ln P), \quad [3.5]$$

where *P* is the probability of a view line or a beam of radiation at an incidence angle α passing through a horizontally uniform plant canopy with random leaf angular and spatial distribution and *G* is the mean projection coefficient of unit foliage area on a plane perpendicular to α .

To estimate *eLAI* from hyperspectral data, *G* (α) can be determined at 0.5 for plants which have randomly distributed leaf angles such as agricultural crops (Norman, 1979). The incidence angle α corresponds to the sensor viewing zenith angle. Probe-1 is assumed to acquire data at a viewing angle of 0° (nadir looking). *P* represents the gap (non-vegetation) fraction, which is determined by spectral unmixing as follows (Staenz *et al.*, 1998b):

$$P = 1 - fc, \quad [3.6]$$

where *fc* is the fraction of the crop endmember. *eLAI* is then derived from hyperspectral data substituting equation 3.1 into 3.3 (Staenz *et al.*, 1998b):

$$eLAI (fc) = -2 \ln (1 - fc). \quad [3.7]$$

LAI values are then computed with the following equation (Chen *et al.*, 1991):

$$LAI = \frac{eLAI}{\Omega}, \quad [3.8]$$

where Ω is the clumping index. This parameter varies between 0 and 1 for clumped canopies, but can be larger than 1 for regularly distributed foliage.

3.5 Statistical Analyses

Statistical analyses were carried out similarly for both the Clinton and Indian Head datasets. Statistical analyses were computed with the Statistica software (StatSoft Inc. 1994). Various statistics were computed including means and standard deviations for both ground measurements (observed values) and image data (predicted values). Standard deviation statistics allowed the evaluation of data variability. This parameter was reported in all cases as an error percentage of the average value extracted from ground measurements (E_{PCC_G} , E_{LAI_G} , $E_{LAI_{2000}}$) and the image data (E_{PCC_C} , E_{PCC_P} , $E_{eLAI_{IC}}$, $E_{eLAI_{IP}}$). As for the spatial field variability within the imagery, errors were evaluated by computing average and maximum errors on a crop-by-crop and field-by-field basis. These errors were estimated from the set of error percentages calculated for each sampling of each individual crop type or field.

To validate the PCC, $eLAI$ and LAI models implemented in ISDAS, ground measurements and image data values were compared using the 1:1 line. Ideally, observed and predicted values should have a correspondence of 1:1. An index of agreement reflects the degree to which the observed value is accurately estimated by the predicted value. The index of agreement was calculated as follows (Willmott, 1982):

$$D = \left[\frac{\sum_{i=1}^n (P_i - O_i)^2}{\sum_{i=1}^n (|P'_i| + |O'_i|)^2} \right], \quad [3.9]$$

where P_i is the predicted value at sample i , O_i is the observed value at sample i , P'_i is the difference between P_i and the average of the predicted values, and O'_i is the difference between O_i and the average of the observed values and n is the number of values. A perfect model would have a D value of 1.

The RMSE was used as an additional measure to supplement the index of agreement described above. This statistic also quantifies the relationship for models that should ideally

have a 1:1 relationship between observed and predicted values. This error measure was calculated with the following equation (Willmott, 1982):

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (P_i - O_i)^2}{n}} .$$

The RMSE indicates the magnitude of the average error produced by a model. This error is reported in the same units as the observed and predicted values. Scatterplots displaying observed and predicted variables were also generated as graphic aids in evaluating the relationship between the variables (Willmott, 1982).

The relationship between observed and predicted values were also analyzed using a linear regression model. The slope (a), the intercept (b), and the coefficient of determination (R^2) of the regression model were calculated and used to evaluate the strength of the linear relationship between observed and predicted values. Significance levels (p) were calculated for each correlation. Regression models rarely produce a scatterplot where all points fall on a regression line, with a slope of 1.0 and an intercept of 0.0. Therefore, these parameters are fundamental to the statistical analysis of the regression model. Systematic linear over- or under- predictions generate characteristic variations in the slope and intercept values, which can help to interpret the major sources of error. LAI₂₀₀₀ estimates were correlated with LAI_G. Also, PCC derived from the image data (PCC_I) were correlated with PCC_G and eLAI and LAI values derived from the crop fraction maps (eLAI_I; LAI_I) were correlated with LAI_G measurements. Correlations were run on data pooled from both datasets, for each crop type, and finally for each individual field.

3.6 Conclusions

This chapter described the study sites and the ground measurement techniques as well as the remote sensing data processing techniques used to complete the data analysis. LAI_G measurements and Probe-1 hyperspectral remote sensing data were acquired over two agricultural sites: Clinton (Ontario) in 1999 and Indian Head (Saskatchewan) in 2000. Investigated crops included white beans, corn, wheat, canola and peas. LAI_G measurements were derived from biomass sampling and were also acquired with the LAI-2000. Percent-

crop cover measurements were also collected within the fields. The entire remote sensing data processing was performed in ISDAS. Hyperspectral Probe-1 imagery required preprocessing steps such as radiometric and spectral calibration, and surface reflectance retrieval. Probe-1 data analysis included endmember selection and extraction, constrained linear spectral unmixing analysis (SMA) and calculation of *eLAI* and LAI values. Finally, statistical analyses were described. The next chapter (Chapter 4) will examine the application of the proposed methodology. Results will be presented and discussed.

4. RESULTS AND DISCUSSION

This chapter will examine and discuss the results obtained from the application of the methodology described in Chapter 3. The errors from the image registration procedure will be quantified and analyzed. The variability of the ground measurements will also be assessed. LAI_{2000} estimates will be validated against the LAI_G measurements and the relationship between both variables will be examined. The endmember selection and extraction process will be thoroughly evaluated. PCC_G measurements will be validated against PCC_I and both spectral unmixing algorithms will be assessed. Finally, LAI_G measurements will be compared to LAI_I values. Validation will be examined on pooled data (Clinton and Indian Head), on a crop-by-crop and field-by-field basis. Sources of errors in the LAI estimation and validation will also be analyzed.

4.1 Image Registration and Error Analysis

The accuracy with which ground-sampling sites are located in remote sensing imagery is crucial for the validation of any models using image data. A diligent effort was carried out during the field campaigns to match the ground sampling resolution to the spatial resolution of the remote sensing image data (25-m²). Also, the hyperspectral Probe-1 imagery was registered to high-spatial resolution imagery improving the registration accuracy of the ground sampling locations in the hyperspectral image data. Nevertheless, this image registration process is never ideal and errors are often introduced in this procedure. An appreciation and understanding of the errors are essential to conduct further analysis. This section will examine the results of the image registration technique.

As discussed in Section 4.3.2, the hyperspectral sensor flew twice over each study site generating two images over each field. For the Clinton dataset, one pass was chosen per field in order to perform image registration. This was done based on visual assessment of the geometric integrity of each field for both passes. Pass 1 achieved better geometry for White Bean-1, Corn-2 and Corn-3 while Pass 2 demonstrated a better fit for White Bean-2, White Bean-3 and Corn-1 (Table 4.1). A large number of GCPs were collected for each field of the Clinton dataset given that the fields were very large (~47 to ~90 acres) in comparison to the fields of Indian Head. Generally, geometric registration aims for sub-pixel accuracy (i.e., when the root mean square error (RMSE) is less than one pixel). This was achieved for most of the fields in both datasets (Tables 4.1 and 4.2). Fields Corn-1 and Corn-3 had higher RMSE values of 1.23 and 1.19, respectively, which is still an acceptable error.

Table 4.1. *Results of image-to-image registration for Clinton field sites (where RMSE is the root mean square error for the polynomial fitting between the orthophotos and the Probe-1 imagery).*

Field Name	Selected Pass	Number of GCPs	RMSE (Pixels)
White Bean -1	Pass 1	49	0.54
White Bean -2	Pass 2	28	0.45
White Bean-3	Pass 2	36	0.48
Corn-1	Pass 2	46	1.23
Corn-2	Pass 1	21	0.12
Corn-3	Pass 1	41	1.19

Table 4.2. *Results of image-to-image registration for Indian Head field sites (where RMSE is the root mean square error for the polynomial fitting between the Ikonos imagery and the Probe-1 imagery).*

Field Name	Number of GCPs – Pass 1	Number of GCPs – Pass 2	RMSE (Pixels) – Pass 1	RMSE (Pixels) – Pass 2
Wheat-1	13	20	1.92	0.50
Wheat-2	10	8	0.25	0.49
Wheat-3	11	12	0.45	0.62
Wheat-4	12	16	0.19	0.27
Canola-1	12	14	0.45	0.50
Canola-2	10	11	1.42	0.73
Pea-1	10	12	0.27	0.27
Pea-2	11	10	0.22	0.74

In contrast to the Clinton dataset, selection of the overpass for the Indian Head dataset was done on a ground sampling site basis. Selection was mostly based on the geometric integrity of the fields, since RMSE values were comparable between passes for several fields (Table 4.2). Image data for Wheat-1 and Pea-2 were selected from Pass 1 while data for all the other fields were chosen from Pass 2 (Figure 4.1). Similarly to Clinton, the polynomial warping for both passes of the Indian Head dataset resulted in a good fit, achieving an accuracy of less than a sub-pixel for all selected fields except Wheat-1 and Canola-2 (1.92 and 1.42, respectively) as shown in Table 4.2. The large RMSE value (1.92) for Wheat-1 (Pass 1) can be attributed to the large geometric distortion surrounding sampling points 42 and 44. Consequently, image data for these sampling points only were derived from Pass 2 (RMSE = 0.50), which preserved better geometric integrity of that area (Figure 4.1).

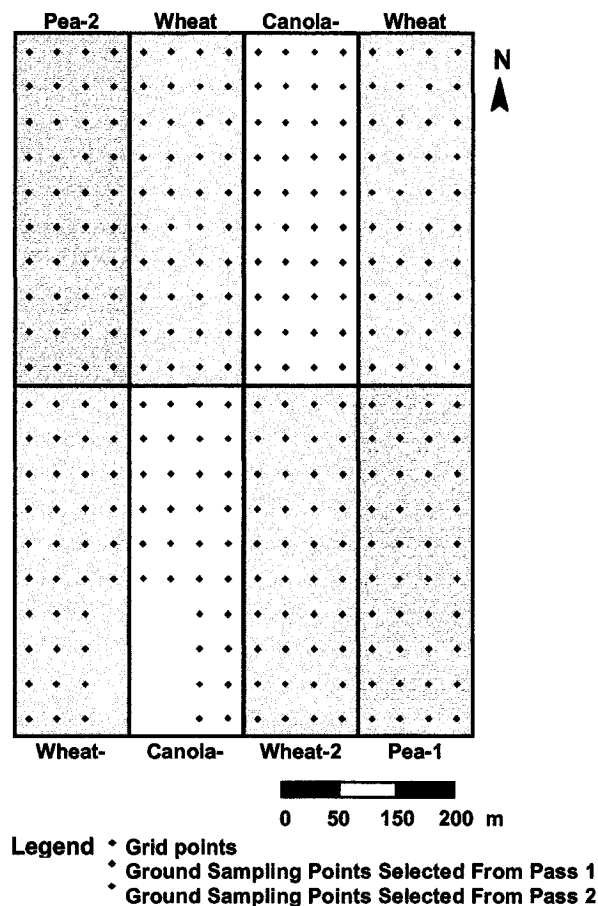


Figure 4.1. *Sampling site selection for the Indian Head dataset.*

4.2 Spatial Field and Image Variability

The spatial variability of the ground measurements and the image data were assessed and is presented in this section. For each sample site, ground measurements were averaged from three replicates and the variability of these measurements was calculated. PCC_I and $eLAI_I$ were extracted from a 3-by-3 pixel window (to eliminate errors from image-to-image registration procedure) and the variability within that window was evaluated.

The overall variability in both ground measurements and image data was generally lower for fields investigated in Clinton (Tables 4.3a and 4.4a) in comparison to the results from Indian Head (Tables 4.3b and 4.4b). The spatial variability of the PCC_G measurements in Clinton and Indian Head was much higher than the spatial variability found in PCC_C and PCC_P . As for the LAI_G , $eLAI_{IC}$ and $eLAI_{IP}$ measurements, the spatial variability was comparable for the Clinton dataset (ranging from 3.18% to 5.45%), while the error percentages varied to a much greater extent for Indian Head (ranging from 5.94% to 17.36%). The $eLAI_{IC}$ difference was as high as 416.28% within the 3-by-3 pixel window in the Indian Head dataset compared to 22.65% for Clinton.

For the Clinton dataset, spatial variability was higher within the bean fields than the corn fields in both PCC_G and LAI_G measurements. This was also reflected in the image data where errors were higher in bean fields for PCC_C , PCC_P , $eLAI_{IC}$ and $eLAI_{IP}$. In regards to the Indian Head dataset, spatial variability was much higher within canola fields compared to the other crop types for ground and especially image values. The variable fertilizer treatments applied in the canola fields were responsible for this high variability. Errors were similar between wheat and pea fields.

Overall, variability in the image values was generally lower than for ground measurements, except for $eLAI_{IC}$ and $eLAI_{IP}$ values of the Indian Head dataset and in some cases for the Clinton dataset. Consequently, the impact of extracting image data from erroneous pixels due to the image-to-image registration procedure was overall decreased by the low variability within the image data, especially for the PCC. The average error values for both ground and image values were retained for each field in the data analysis.

Table 4.3. Average error percentages of PCC data between 3 ground sampling replicates and from the hyperspectral image data (3-by-3 pixel window) for Clinton (a) and Indian Head (b) datasets. The error percentages are given as a proportion of the average where E_{PCC_G} is the error percentage for ground percent crop cover, E_{PCC_C} and E_{PCC_P} are the error percentages for percent crop cover derived from the image data using constrained unmixing and partially-constrained unmixing, respectively.

a)

Clinton							
Crop Type	Field ID	E_{PCC_G}		E_{PCC_C}		E_{PCC_P}	
		Mean	Max	Mean	Max	Mean	Max
Bean	Bean-1	21.05	34.61	4.30	6.56	3.69	5.84
	Bean-2	10.53	20.54	3.11	6.04	3.28	8.38
	Bean-3	14.01	28.58	4.50	14.70	4.92	14.70
	<i>Bean (mean)</i>	<i>15.19</i>	<i>34.61</i>	<i>3.97</i>	<i>14.70</i>	<i>3.96</i>	<i>14.70</i>
Corn	Corn-1	11.53	20.38	0.89	1.48	1.43	3.46
	Corn-2	5.83	13.99	0.79	2.50	3.57	13.80
	Corn-3	7.12	16.97	1.29	6.09	1.81	7.10
	<i>Corn (mean)</i>	<i>8.16</i>	<i>20.38</i>	<i>0.99</i>	<i>6.09</i>	<i>2.27</i>	<i>13.80</i>
Clinton (mean)		11.68	34.61	2.48	14.70	3.12	14.70

b)

Indian Head							
Crop Type	Field ID	E_{PCC_G}		E_{PCC_C}		E_{PCC_P}	
		Mean	Max	Mean	Max	Mean	Max
Wheat	Wheat-1	16.81	30.01	4.21	7.29	4.66	10.05
	Wheat-2	11.49	24.77	9.77	59.49	10.05	62.71
	Wheat-3	16.56	34.85	6.10	15.27	6.34	15.95
	Wheat-4	13.60	33.91	11.79	85.98	5.62	9.38
	<i>Wheat (mean)</i>	<i>14.61</i>	<i>34.85</i>	<i>7.97</i>	<i>85.98</i>	<i>6.67</i>	<i>62.71</i>
Canola	Canola-1	36.88	79.01	48.38	292.70	48.73	288.52
	Canola-2	39.26	141.42	9.51	38.62	9.26	38.69
	<i>Canola (mean)</i>	<i>38.07</i>	<i>141.42</i>	<i>28.95</i>	<i>292.70</i>	<i>28.99</i>	<i>288.52</i>
Pea	Pea-1	16.61	31.34	5.92	8.24	6.52	11.82
	Pea-2	11.45	30.23	5.62	11.12	6.40	12.56
	<i>Pea (mean)</i>	<i>14.03</i>	<i>31.34</i>	<i>5.77</i>	<i>11.12</i>	<i>6.46</i>	<i>12.56</i>
Indian Head (mean)		20.33	141.42	12.66	292.70	12.20	288.52

Table 4.4. Average error percentages of LAI data between 3 ground sampling replicates and from the hyperspectral image data (3-by-3 pixel window) for Clinton (a) and Indian Head (b) datasets. The error percentages are given as a proportion of the average where E_{LAI_G} is the error percentage for ground LAI derived from the biomass samples, $E_{LAI_{2000}}$ is the error percentage for the LAI-2000 measurements, $E_{eLAI_{CI}}$ and $E_{eLAI_{CP}}$ are the error percentages for LAI derived from the image data using the PCC values from constrained unmixing and partially-constrained unmixing, respectively.

a)

Clinton									
Crop Type	Field ID	E_{LAI_G}		$E_{LAI_{2000}}$		$E_{eLAI_{CI}}$		$E_{eLAI_{CP}}$	
		Mean	Max	Mean	Max	Mean	Max	Mean	Max
Bean	Bean-1	3.18	6.79	9.21	39.02	4.86	7.33	4.18	6.72
	Bean-2	3.15	6.41	9.94	35.99	3.57	6.97	3.77	9.60
	Bean-3	6.55	14.17	8.65	26.79	5.34	16.38	5.82	16.38
	<i>Bean (mean)</i>	<i>4.29</i>	<i>14.17</i>	<i>9.27</i>	<i>39.02</i>	<i>4.59</i>	<i>16.38</i>	<i>4.59</i>	<i>16.38</i>
Corn	Corn-1	7.13	19.01	7.36	17.48	1.61	2.64	2.49	6.12
	Corn-2	7.20	15.91	4.00	11.75	1.51	4.68	5.95	22.65
	Corn-3	5.46	19.26	9.95	36.34	2.20	9.49	2.89	10.22
	<i>Corn (mean)</i>	<i>6.60</i>	<i>19.26</i>	<i>7.10</i>	<i>36.34</i>	<i>1.77</i>	<i>9.49</i>	<i>3.78</i>	<i>22.65</i>
	Clinton (mean)	5.45	19.26	8.19	39.02	3.18	16.38	4.18	22.65

b)

Indian Head									
Crop Type	Field ID	E_{LAI_G}		$E_{LAI_{2000}}$		$E_{eLAI_{CI}}$		$E_{eLAI_{CP}}$	
		Mean	Max	Mean	Max	Mean	Max	Mean	Max
Wheat	Wheat-1	4.83	8.68	11.90	24.15	6.69	11.56	7.61	13.61
	Wheat-2	4.97	15.44	11.47	30.38	11.67	70.77	12.29	75.53
	Wheat-3	2.76	5.49	14.71	50.55	9.54	27.06	9.90	27.06
	Wheat-4	5.53	23.03	14.44	81.56	13.10	90.15	6.96	11.63
	<i>Wheat (mean)</i>	<i>4.52</i>	<i>23.03</i>	<i>13.13</i>	<i>81.56</i>	<i>10.25</i>	<i>90.15</i>	<i>9.19</i>	<i>75.53</i>
Canola	Canola-1	7.05	14.11	30.94	110.23	60.88	416.28	66.10	410.76
	Canola-2	13.26	40.24	48.41	268.39	17.55	68.74	17.22	68.90
	<i>Canola (mean)</i>	<i>10.16</i>	<i>40.24</i>	<i>39.68</i>	<i>268.39</i>	<i>39.21</i>	<i>416.28</i>	<i>41.66</i>	<i>410.76</i>
Pea	Pea-1	5.36	9.23	14.81	37.72	8.29	11.80	8.98	16.04
	Pea-2	3.74	8.70	15.68	78.91	8.68	18.60	9.79	21.46
	<i>Pea (mean)</i>	<i>4.55</i>	<i>9.23</i>	<i>15.25</i>	<i>78.91</i>	<i>8.49</i>	<i>18.60</i>	<i>9.38</i>	<i>21.46</i>
	Indian Head (mean)	5.94	40.24	20.30	268.39	17.05	416.28	17.36	410.76

4.3 Ground LAI (LAI_G) Measurements

Destructive LAI_G measurements are time-consuming and labour intensive. Alternative methods have been developed to measure LAI of plant canopies which are

more practical and faster, such as estimating gap fraction with the LAI-2000 instrument. These estimations can be used to validate LAI values derived from remote sensing data assuming the ground sampling technique was adequate with respect to the canopy structure and that measurements were properly acquired. This section will examine the descriptive statistics and the spatial field variability of the LAI_G and LAI_{2000} measurements. The LAI_{2000} will also be validated against the LAI_G .

4.3.1 Characterization of Ground LAI Estimates (LAI_G)

LAI_G measurements and statistics are presented in Tables 4.5a and b per field and crop basis for the Clinton and Indian Head dataset, respectively. These measurements show a much higher variability (N) for the Clinton dataset than the Indian Head dataset with variance values of 7.00 and 0.58, respectively. Corn fields had the highest LAI_G values followed by pea, canola, wheat and bean fields. The LAI-2000 instrument consistently underestimated the LAI_G of the crop canopies. This was particularly true for the corn fields where only an LAI_{2000} of 2.19 was estimated in comparison to a LAI_G of 6.78. Consequently, variation of the corn LAI_{2000} estimates was much lower than the LAI_G . LAI_{2000} ranged from 0.88 for beans to 2.18 for corn canopies. The LAI_{2000} values indicate a higher average LAI for canola than for peas, which is in contrast to the LAI_G .

In comparison to the other crops, wheat and canola fields from the Indian Head dataset had the most comparable LAI results with differences of 35% and 30%, respectively. These results can be explained by the assumption that the LAI-2000 instrument requires the foliage to be randomly distributed within foliage-containing envelopes to provide accurate LAI measurements (LI-COR, 1992). This assumption is especially valid for canola and wheat canopies where row structure is much less apparent than in other canopies used in this analysis. Although wheat canopies are a row-structured crop, leaf elements become randomly distributed as the crop grows and the row-structure is then less apparent. Welles and Norman (1991) also found a similar variation (30%) between LAI_G and LAI_{2000} estimates in wheat canopies. The large variation found can partially be explained by the different sampling dates especially for the Clinton dataset. In Indian Head, temperature and precipitation remained stable throughout the field campaign while in Clinton a large amount of precipitation on July 1st

and 2nd initiated a rapid and substantial growth of the plant canopies, resulting in a discrepancy between the LAI_G and the LAI₂₀₀₀ measurements.

Table 4.5. Ground LAI measurements (LAI_G and LAI₂₀₀₀) and statistics for Clinton (a) and Indian Head (b) datasets (where LAI_G is the LAI derived from the biomass samples; LAI₂₀₀₀ is the LAI estimated with the LAI-2000; SEL/LAI is the standard error of LAI in percentage; α is the average; σ is the standard deviation; and v is the variation). The date refers to the date of the ground data collection. Sky conditions refer to the sky conditions present at the time of the LAI-2000 estimates.

a)

Clinton										
Field Name	LAI _G				LAI ₂₀₀₀					
	α	σ	v	Date	α	σ	v	SEL/LAI (%)	Date	Sky Conditions
Bean-1	1.70	0.13	0.02	July 7	0.85	0.18	0.03	44.87	July 3	Overcast
Bean-2	1.94	0.14	0.02	July 7	0.67	0.15	0.02	54.03	June 28	Cloudy
Bean-3	1.91	0.28	0.08	July 7	1.12	0.22	0.05	43.07	June 29	Cloudy
<i>Bean (mean)</i>	<i>1.85</i>	<i>0.22</i>	<i>0.05</i>		<i>0.88</i>	<i>0.26</i>	<i>0.07</i>	<i>47.32</i>		
Corn-1	6.22	1.53	2.33	July 7	2.18	0.34	0.11	4.67	June 30	Overcast
Corn-2	7.36	1.31	1.72	July 7	2.44	0.23	0.05	3.17	June 29	Overcast
Corn-3	6.76	0.84	0.71	July 7	1.89	0.39	0.15	3.27	June 30	Overcast
<i>Corn (mean)</i>	<i>6.78</i>	<i>0.51</i>	<i>0.26</i>		<i>2.19</i>	<i>0.39</i>	<i>0.15</i>	<i>3.70</i>		
<i>Clinton (mean)</i>	<i>4.32</i>	<i>2.65</i>	<i>7.00</i>		<i>1.51</i>	<i>0.73</i>	<i>0.54</i>			

b)

Indian Head										
Field Name	LAI _G				LAI ₂₀₀₀					
	α	σ	v	Date	α	σ	v	SEL/LAI (%)	Date	Sky Conditions
Wheat-1	2.39	0.26	0.07	June 28	1.60	0.34	0.12	6.92	July 4	Overcast
Wheat-2	2.11	0.28	0.08	June 28	1.28	0.36	0.13	9.63	July 2	Overcast
Wheat-3	2.12	0.13	0.02	June 28	1.72	0.52	0.27	11.16	July 3	Cloudy
Wheat-4	2.22	0.29	0.08	June 28	1.18	0.33	0.11	9.57	July 2	Overcast
<i>Wheat (mean)</i>	<i>2.21</i>	<i>0.27</i>	<i>0.07</i>		<i>1.43</i>	<i>0.46</i>	<i>0.21</i>	<i>9.32</i>		
Canola-1	2.38	0.39	0.16	June 28	1.63	0.83	0.68	12.42	July 4	Overcast
Canola-2	3.51	1.00	0.99	June 28	2.57	1.33	1.78	8.68	July 6	Overcast
<i>Canola (mean)</i>	<i>2.95</i>	<i>0.79</i>	<i>0.63</i>		<i>2.08</i>	<i>1.19</i>	<i>1.43</i>	<i>10.55</i>		
Pea-1	3.38	0.41	0.16	June 28	1.46	0.49	0.24	7.27	July 2	Overcast
Pea-2	3.56	0.35	0.12	June 28	1.70	0.53	0.28	9.24	July 3	Cloudy
<i>Pea (mean)</i>	<i>3.47</i>	<i>0.39</i>	<i>0.15</i>		<i>1.58</i>	<i>0.52</i>	<i>0.28</i>	<i>8.26</i>		
<i>Indian Head (mean)</i>	<i>2.71</i>	<i>0.76</i>	<i>0.58</i>		<i>1.63</i>	<i>0.78</i>	<i>0.61</i>			

LAI₂₀₀₀ estimates were more closely examined with respect to the standard error for the LAI estimates (SEL) provided by the instrument and the conditions during the measurement acquisition. Results are also provided in Tables 4.5a and b. The ratio of SEL and the LAI₂₀₀₀ value indicates the percentage range of the true average LAI value. For example, the corn canopies have an error of 3.70% which means that the true LAI value of 2.19 is within a range of $\pm 3.70\%$. Overall, the average SEL value was lower for corn, followed by peas, wheat, canola and beans. As a rule, errors greater than 10% should not consider LAI₂₀₀₀ measurements as accurate and, therefore, measurements should be eliminated from the dataset and not be used for further analysis. This was actually the case for the bean fields where the average SEL/LAI value was 47.32%. It is also interesting to note that the SEL values were in general slightly larger when measurements were acquired in non-ideal sky conditions, i.e. when clouds or sun patches were present.

4.3.2 Validating LAI-2000 Estimates (LAI₂₀₀₀) with Ground LAI Measurements (LAI_G)

LAI₂₀₀₀ estimates were validated against the LAI_G measurements. Validation was only done for the corn, wheat, canola and pea canopies since the standard error of the LAI₂₀₀₀ was too large for the bean fields. Table 4.6 summarizes the statistics and a scatter plot of the results is given in Figure 4.2.

Table 4.6. Fit statistics for LAI derived from the biomass samples (LAI_G) and estimated with the LAI-2000 (LAI₂₀₀₀) for all crops and on a within-crop basis (where E_{LAI_G} and $E_{LAI_{2000}}$ are the standard deviations as a percentage of the mean values; a and b are the slope and intercept of the least squares regression line; RMSE is the root mean square error; D is the index of agreement; and R^2 is the coefficient of determination). R^2 values in bold are significant at $p < 0.05$.

Field	LAI _G	LAI ₂₀₀₀	E_{LAI_G} (%)	$E_{LAI_{2000}}$ (%)	a	b	RMSE ($\pm$)	D	R^2
All Crops	3.85	1.82	6.02	16.89	0.20	1.05	2.40	0.52	0.22
Corn	6.78	2.19	6.60	7.10	0.18	0.94	4.61	0.29	0.31
Wheat	2.21	1.43	4.52	13.13	0.91	-0.58	0.88	0.38	0.27
Canola	2.95	2.08	10.16	39.68	0.91	-0.56	1.19	0.72	0.50
Pea	3.47	1.58	4.55	15.25	0.70	-0.86	1.94	0.26	0.27

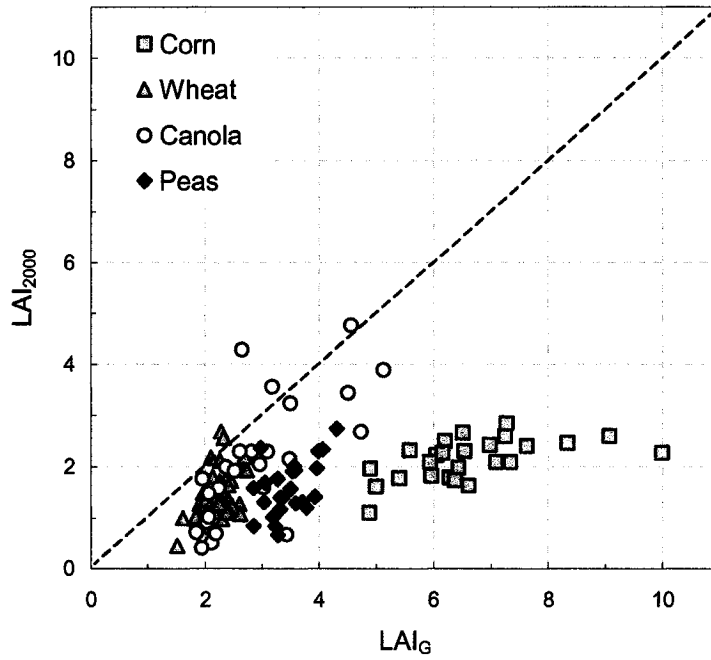


Figure 4.2. Relationship between LAI derived from the biomass samples (LAI_G) and LAI-2000 measurements (LAI_{2000}) for all crops, except beans.

As mentioned previously in Section 4.3.1, Figure 4.2 also reveals that the LAI-2000 instrument generally underestimated LAI_{2000} for the crop canopies investigated for this study. This was especially the case for corn canopies where LAI_G values ranged from around 5 to 10 compared to around 1 to 3 for LAI_{2000} estimates. The relationship between LAI_G and LAI_{2000} measurements is much better with the canola crop where a linear trend following the 1:1 line is noticeable.

The visual assessment of the scatter plots collaborates well with the statistics in Table 4.6. Indeed, the slope of the regression line (a) for all crops excluding bean fields is 0.20, indicating that the relationship is not close to the 1:1 line. A model that approximates the 1:1 line relationship suggests that the empirical observations are a good predictor of the ground observations. The overall RMSE of 2.40 indicates a poor relationship between LAI_G and LAI_{2000} . The index of agreement (D) between the two variables was very poor with a D of 0.40. The correlation was also very poor with a coefficient of determination (R^2) of 0.22 indicating that only 22% of the variation is accounted by the regression model.

When examining results at a crop level, the slope of the regression line was quite high (0.91) for the wheat and canola canopies indicating a close approximation to the 1:1

line. However, the intercept was negative for both wheat and canola crops with values of -0.58 and -0.56 , respectively. The close proximity of the regression line to the 1:1 line can be explained by the fact that the LAI-2000 instrument is more adequate to estimate LAI of canopies with random foliage distribution. The negative intercepts were probably caused by the poor variability within these crops and random variation attributable to field measurement error (Steel and Torrie, 1980), which was actually somewhat higher for canola (39.68%) than for wheat canopies. The generally poor coefficient of determination was higher for the canola fields ($R^2 = 0.50$) in comparison to the average R^2 of the other crops ($R^2 \approx 0.28$).

The analysis of the relationship between LAI_G and LAI_{2000} measurements demonstrated a poor relationship between the two variables. Several studies have validated the use of the LAI-2000 to effectively measure LAI in crop canopies (see Section 2.2.2.2), which contradicts the results of this present study. Therefore, these poor results were most likely due to the method of biomass sampling. In fact, the mass of water calculated for plant water content was made on pooled samples of above-ground biomass, without discriminating between stem and leaf water content. The majority of an agricultural plant canopy is made up of leaves, and it is the leaf elements that dominate the scattering of radiation within the canopy (Allen and Richardson, 1968). This is especially true for a broadleaf canopy with a planophile leaf angle distribution where the leaf surface is reflecting and, thus, absorbing the greater proportion of the incident radiation. Consequently, the effect of stem reflectance can be more or less disregarded (Knipling, 1970). On the other hand, the stem water content is a significant portion of the total canopy biomass, especially in the early stages of growth and in plant canopies with bulkier stems such as corn. Water allocation varies considerably within a plant among leaves, stems and roots (Cornelissen *et al.*, 1996). As a result, the plant water content values were corrected for the stem-to-leaf ratio to eliminate the effect of stem water content in these measurements and, subsequently, the LAI_G values were adjusted to be representative of the true LAI in the crop canopies.

4.3.3 Adjusting Ground LAI Measurements (LAI_G) for Stem-to-Leaf Ratio

The stem-to-leaf ratio is an extremely variable quantity related to the dry matter distribution characteristics of the plant. The actual proportion of leaves, stems, roots and storage organs in the total plant biomass at a specific period of the plants' growth stage depends on the growth rates, which are directly affected by environmental conditions, more importantly temperature and day length (van Heemst, 1986). They are also related to the ability of the plant to adapt to environmental change. However, the complexity of this process can be slightly diminished with two basic assumptions. Firstly, an estimate of the stem-to-leaf ratio can be determined under ambient growing conditions from measured values made under similar growing conditions. Secondly, it can also be assumed that dry matter partitioning is more strongly related to crop type than to individual growing conditions (van Heemst, 1986). For this analysis, measured and modelled dry matter partition as a function of crop growth stage were taken from Champagne (2002) in which stem-to-leaf ratios were determined for individual crop fields used in this study (Table 4.7).

Table 4.7. *Estimated values of stem-to-leaf water ratio per field.*

Field	Crop Type	Days After Sowing	Estimated Stem-to-Leaf Ratio
Bean-1	White Bean	~ 50	0.50
Bean-2	White Bean	~ 50	0.50
Bean-3	White Bean	~ 50	0.50
Corn-1	Corn	~ 60	0.45
Corn-2	Corn	~ 60	0.45
Corn-3	Corn	~ 60	0.45
Wheat-1	Wheat	39	0.75
Wheat-2	Wheat	39	0.75
Wheat-3	Wheat	39	0.75
Wheat-4	Wheat	39	0.75
Canola-1	Canola	50	0.70
Canola-2	Canola	42	0.80
Pea-1	Pea	56	0.85
Pea-2	Pea	54	0.85

LAI₂₀₀₀ estimates were once again validated against the LAI_G measurements adjusted for stem-to-leaf ratio (LAI_{G_SLR}). Table 4.8 summarizes the statistics calculated for all crops excluding beans and for each individual crop type. A scatter plot of the results is also presented in Figure 4.3. The LAI_{G_SLR} average value was 2.14 in comparison to 3.41 for LAI_G which is much more comparable to the average LAI₂₀₀₀ value of 1.62. LAI₂₀₀₀ measurements only vary around 25% in comparison to almost 50% when no stem-to-leaf ratio adjustment was done on the LAI_G values. The slope has a value of 0.54 and an RMSE of 0.92 which indicates a better 1:1 line relationship than what was achieved when the stem-to-leaf ratio was not considered. Also, correlations were improved with a D of 0.75 and an R² of 0.43. The improvement of the relationship between LAI_{G_SLR} and LAI₂₀₀₀ estimates was also noticeable in the scatter plot where data points aligned much closer to the 1:1 line, although LAI₂₀₀₀ values are still clearly underestimated.

Table 4.8. *Fit statistics for LAI derived from the biomass samples adjusted for stem-to-leaf ratio (LAI_{G_SLR}) and estimated with the LAI-2000 (LAI₂₀₀₀) for all crops and on a within-crop basis (where $E_{LAI_{G_SLR}}$ and $E_{LAI_{2000}}$ are the standard deviations as a percentage of the mean values; a and b are the slope and intercept of the least squares regression line; RMSE is the root mean square error; D is the index of agreement; and R² is the coefficient of determination). R² values in bold are significant at $p < 0.05$.*

Field	LAI _{G_SLR}	LAI ₂₀₀₀	$E_{LAI_{G_SLR}}$ (%)	$E_{LAI_{2000}}$ (%)	a	b	RMSE (±)	D	R ²
All Crops	2.31	1.74	6.02	16.89	0.54	0.50	0.92	0.67	0.29
Corn	2.98	2.14	6.60	7.10	0.40	0.94	0.96	0.50	0.31
Wheat	1.65	1.42	4.52	13.13	1.21	-0.58	0.46	0.54	0.27
Canola	2.21	2.08	10.16	39.68	1.01	-0.15	0.87	0.79	0.48
Pea	2.95	1.58	4.55	15.25	0.83	-0.86	1.44	0.29	0.27

On a crop-to-crop basis, all RMSE values decreased considerably particularly for the corn canopies (from 4.61 to 0.96) where the stem-to-leaf ratio had the most influence. D values also increased for all crops. This was significant for the corn and wheat canopies which have similar plant canopy structure. Adjusting the stem-to-leaf ratio had less influence on the relationships for the canola and pea canopies where D values increased only slightly (from 0.72 to 0.76 and from 0.26 to 0.29, respectively).

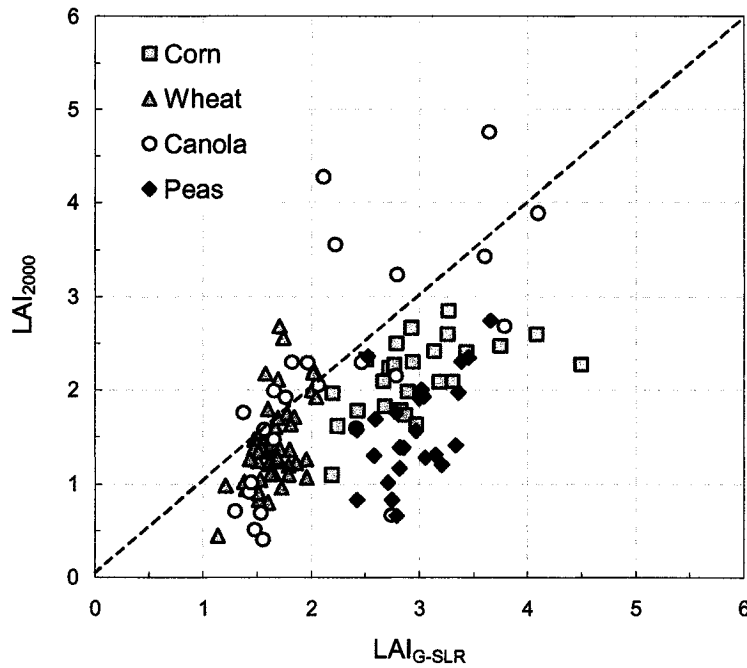


Figure 4.3. Relationship between LAI derived from the biomass samples adjusted for stem-to-leaf ratio (LAI_{G_SLR}) and LAI-2000 measurements (LAI_{2000}) for all crops, except beans.

Similarly to other studies (Hicks and Lascano, 1995; Miller-Goodman *et al.*, 1999), the LAI-2000 instrument seems to generally provide satisfactory results in estimating LAI for most of the crop canopies examined in this study, especially in canola crops. Unfortunately, LAI_{2000} estimates for the bean canopies could not be analysed, as the standard error was too high. Beans were very small (~18 cm of height) at the time of measurement with large gaps (~45 cm) between rows. Thus, the instrument did not provide accurate LAI estimation of the beans. Also, a discrepancy in the sampling dates added to the problem. LAI_{2000} estimates in corn canopies were underestimated, similarly to Wilhelm *et al.* (2000). Validation in the canola fields was very good but large variations in the LAI_{2000} measurements suggest caution in using these estimates for future analysis. Finally, given that pea crops are mostly planophile canopies, i.e. leaf inclination angle is less than 26.76° (Goel, 1988), the LAI-2000's assumption that canopy foliage should be azimuthally and zenithally randomly oriented was not respected and justifies the poor relationship between the LAI_G and the LAI_{2000} estimates. Although the relationship between LAI_G and LAI_{2000} values were considerably improved when the stem-to-leaf ratio was adjusted, the LAI_{2000} estimates will not be used for further analysis.

LAI_{G_SLR} values will be used instead and will be referred to as LAI_G in the following sections.

4.4 Endmember Selection and Extraction

Endmember selection and extraction was carried out based on prior knowledge of the fields and in-situ validation during the field campaign. Tables 4.9a and b summarizes the endmember selection and extraction process for the Clinton and Indian Head datasets, respectively.

Table 4.9. List of endmembers retrieved from the Clinton (a) and Indian Head (b) datasets where the type of averaged endmember spectrum, the field or region where they were extracted from, the number of spectra collected per endmember and the number of pixels used per spectra are defined.

a) Clinton				
Averaged Endmember Spectrum	Field or Region	Extraction Area	Number of Spectra	Number of pixels used per spectra
Bean Vegetation	Bean-1	Double seeded patch	1	5
Corn Vegetation	Corn-1	Two double seeded patches	2	5
Soil	Bean-1	Three soil patches	3	5
	Bean-2	Three soil patches	3	5
	Corn-1	Two soil patches	2	5
	Corn-2	Three soil patches	3	5
Residue	Bean-1	Residue patch	1	2
b) Indian Head				
Averaged Endmember Spectrum	Field or Region	Extraction Area	Number of Spectra	Number of pixels used per spectra
Crop Vegetation	Wheat-2	High-vigor crop area	1	3
	Wheat-3	High-vigor crop area	1	2
	Wheat-4	High-vigor crop area	1	3
	Canola-1	High-vigor crop area	1	2
	Canola-2	High-vigor crop area	1	3
	Pea-1	High-vigor crop area	1	3
	Pea-2	High-vigor crop area	1	2
Soil	NE of IHARF	Soil patch	1	4
Residue	Canola-2	High-density residue area	1	3

For the Clinton dataset, endmember components included bean, corn, soil and residue. More specifically, the bean endmember spectrum was created from the average of five “pure” pixels extracted in the single double seeded bean patch for the whole dataset located in the Bean-1 field. The corn endmember spectrum was created from the average of five “pure” pixels extracted in each of the two double seeded patches in the Corn-1 field. This corn endmember spectrum was used to unmix the reflectance cube for Corn-2 and Corn-3 fields, since “pure” patches of vegetation were not created in these fields. Due to the variation in soil composition and the much easier task of creating soil patches, a soil endmember spectrum was generated for each field. In the bean fields, the same averaging procedure was used for the Bean-1 and Bean-2 fields, where three soil patches were located in each field. An average of the soil endmember spectra from the Bean-1 and the Bean-2 fields were used to unmix the Bean-3 field. In Corn-1, the soil endmember spectrum was created from the average of two sets of five “pure” pixels in each patch, whereas in the Corn-2 field, five “pure” pixels were averaged for each of the three patches present in the field. Soil patches were not created in the Corn-3 field. In this case, the soil endmember spectra of each field were averaged and used as an endmember for the Corn-3 field. Finally, only one “pure” residue patch was created within the entire fields. The residue patch was located in the Bean-1 field and the average of only two “pure” pixels was used to form the residue endmember, which was used to unmix all reflectance cubes for the Clinton dataset.

For Indian Head, three endmembers were selected per pass to unmix the reflectance cubes: a vegetation endmember composed from the average of wheat, canola and pea endmember spectra, a soil endmember and a residue endmember. Wheat, canola and pea endmembers spectra were averaged since these endmembers have a similar spectral response. Due to the difficulty in creating “pure” endmember patches, only one soil patch was generated which was representative of the soil composition for the eight fields studied. As discussed in Section 3.4.1, endmembers were selected and extracted based on field validation of the quicklook hyperspectral imagery. Wheat endmember spectra were extracted from high vigor crop areas. Only two to three “pure” pixels were available to form the endmembers. One wheat endmember was extracted per field with the exception of Wheat-1, and then averaged to form one average wheat endmember

spectra. Field validation was not performed on the Wheat-1 field due to lack of time. The exact same procedure was used for the canola and pea to generate the endmember spectra. As mentioned previously, a soil endmember spectrum was extracted from the average of a few “pure” soil pixels in a patch located northeast of the fields. Finally, a residue endmember spectrum was created from the average of four “pure” pixels located in the Canola-2 field. The final endmember spectra used for unmixing purposes are illustrated in Figures 4.4a and b for Clinton and Indian Head, respectively.

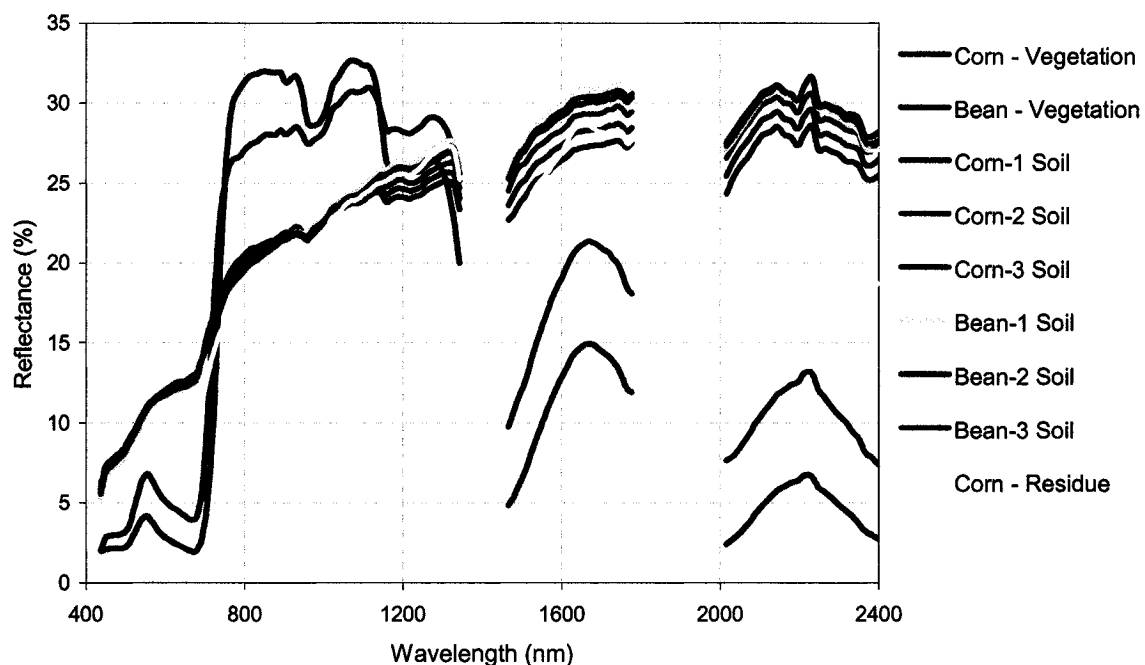


Figure 4.4a *Average endmember spectra used for spectral unmixing analysis for the Clinton dataset. Gaps in the reflectance spectra are due to noisy bands, which were removed.*

In examining Figure 4.4a more carefully, it can be noted that the corn and bean vegetation spectra were similar in shape but differed in magnitude. The bean spectra had higher reflectance compared to the corn spectra in the VIS region and lower reflectance than the corn spectra in the NIR region of the electromagnetic spectrum. Corn leaves are much thicker and greener than the bean leaves and, therefore, absorb and reflect more radiation in the VIS and NIR regions, respectively. The soil spectra for the corn were very similar until the 1200-nm region where the soil spectra for Corn-2 had higher

reflectance followed by Corn-3 and Corn-1, which indicates that soil was generally brighter for the Corn-2 field. The same observation can be made for the soil spectra in the bean fields, but the distinction was less obvious than in the corn fields. The residue spectrum was similar to the soil spectra in the VNIR region of the electromagnetic spectrum. However, it differs considerably in the SWIR II region (2000-2400 nm). The specific absorption feature near 2100 nm that is characteristic to residue is noticeable in both Figures 4.4a and b. It is important to note that the soil and residue spectra have a little trough at the chlorophyll-well (~680 nm), indicating absorption of radiation and, consequently, the presence of some vegetation. It can then be concluded that the soil and residue spectra were lightly contaminated by vegetation for the Clinton dataset.

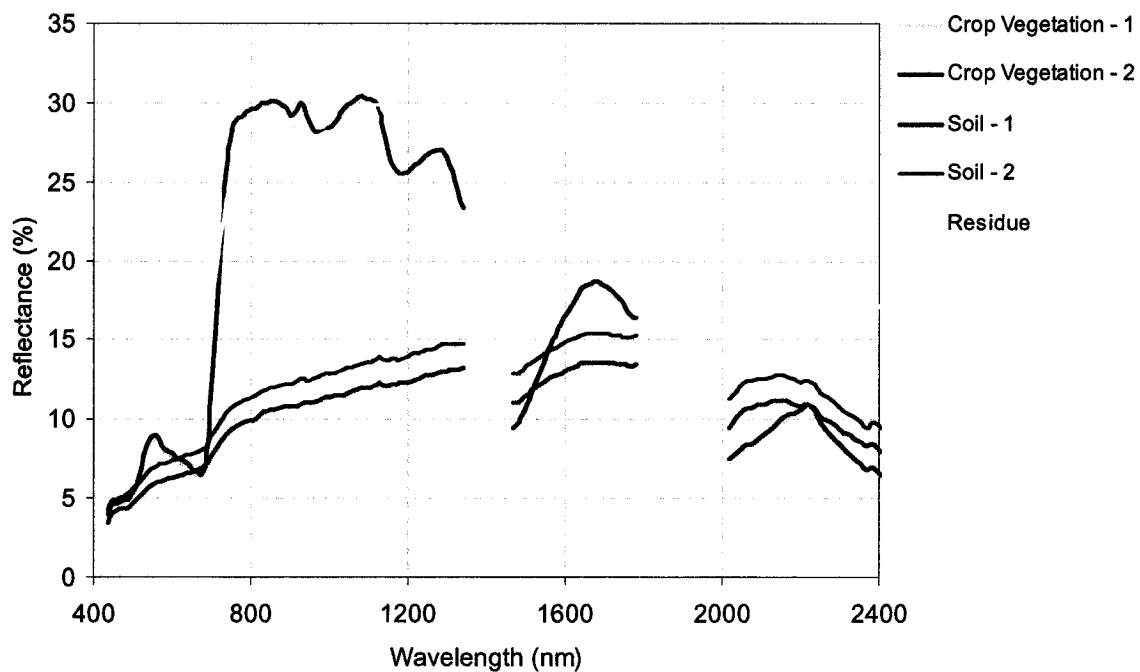


Figure 4.4b *Average endmember spectra used for spectral unmixing analysis for the Indian Head dataset. Gaps in the reflectance spectra are due to noisy bands, which were removed. In the legend, 1 and 2 indicate endmember spectra extracted from Pass 1 and 2, respectively.*

Figure 4.4b demonstrates that the average vegetation spectra were analogous in both shape and magnitude for both passes in Indian Head. Also, the amplitude of the soil spectrum for Pass 2 was slightly higher with a maximum reflectance of approximately 16% near 1650 nm in comparison to 14% for Pass 1. The residue spectrum for Indian

Head also shows its typical absorption feature near 2100 nm. The shape of the residue spectrum near 680 nm clearly indicates that the spectrum is very much contaminated with vegetation. Although this method of selecting and extracting endmembers is successful, it is subjective and like other manual endmember extraction methods, no measure of error is available.

4.5 Spectral Mixture Analysis (SMA)

Linear spectral mixture analysis (SMA) was conducted on all reflectance cubes for the Clinton and Indian Head datasets. For Clinton, only one pass was used for each field while for Indian Head, both passes were processed as they were both necessary for crop fraction value extraction, since results from the image-to-image registration process were better from one pass to the other for various sampling sites (see Section 4.1.1).

4.5.1 Constrained versus Partially-Constrained Unmixing

PCC_I derived from constrained unmixing (PCC_C) and partially-constrained unmixing (PCC_P) were computed for all canopies of the Clinton reflectance dataset and for all canopies in both passes of the Indian Head reflectance dataset (see appendix II). When visually examining the crop fraction maps for the Clinton dataset, it can be noted that the partially-constrained unmixing method decreased the crop fraction. This is mostly the case for corn canopies, where PCC_C were on average 94% and decreased to an average of 88% for PCC_P . It is also evident that there is not very much variability within the fields, especially for corn fields where PCC_I values cover a range of 9% on average. For Indian Head, the partially-constrained unmixing did not have as much effect on the reduction of the PCC_I in comparison to the Clinton dataset. Also, PCC variability within the fields is much larger for Indian Head due to the effect of the different nitrogen treatments applied on the fields.

4.5.2 Validating Image Percent Crop Cover (PCC_I) with Ground Percent Crop Cover (PCC_G)

PCC_I derived from the constrained and partially-constrained unmixing were validated against the percent crop cover estimated from ground vertical photographs

(PCC_G). The relationship between the two variables was assessed on an agricultural canopy level (including all bean, corn, wheat, canola and pea canopies). Statistics were generated from this relationship and are given in Table 4.10a for constrained unmixing and in Table 4.10b for partially-constrained unmixing.

Table 4.10. *Fit statistics for PCC derived from the ground vertical photographs (PCC_G) and the reflectance data using constrained unmixing (PCC_C) (a) and partially-constrained unmixing (PCC_P) (b) for all crops (where E_{PCC_G} , E_{PCC_C} and E_{PCC_P} are the standard deviations as a percentage of the mean values; a and b are the slope and intercept of the least squares regression line; RMSE is the root mean square error; D is the index of agreement; and R^2 is the coefficient of determination). R^2 values in bold are significant at $p < 0.05$.*

a) Constrained Unmixing									
Field	PCC _G (%)	PCC _C (%)	E_{PCC_G} (%)	E_{PCC_C} (%)	a	b	RMSE (±%)	D	R^2
All Crops	49.42	66.55	18.01	9.53	0.93	19.61	23.04	0.72	0.52

b) Partially-Constrained Unmixing									
Field	PCC _G (%)	PCC _P (%)	E_{PCC_G} (%)	E_{PCC_P} (%)	a	b	RMSE (±%)	D	R^2
All Crops	49.42	65.08	18.01	9.67	0.87	22.02	21.90	0.73	0.51

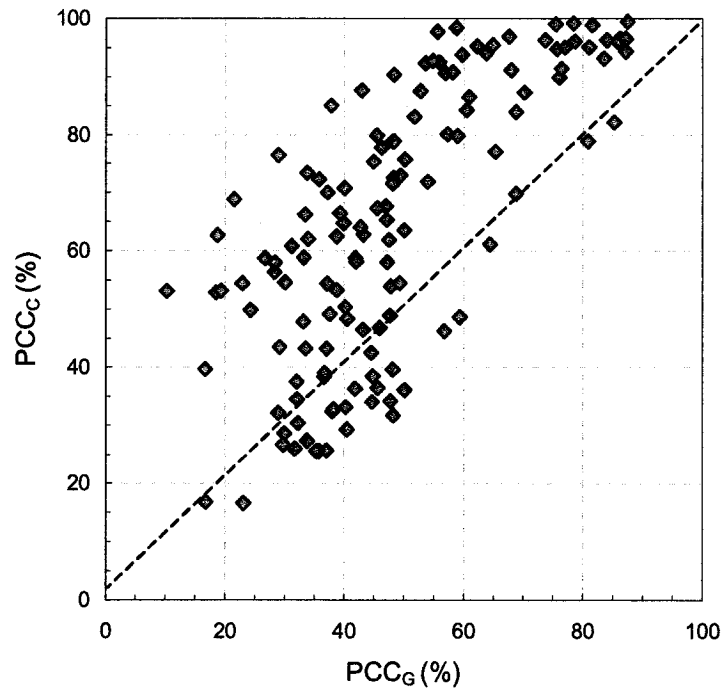
The correlations between PCC_G for all crops and both PCC_C and PCC_P were very similar, where the relationship for PCC_C had a D value of 0.72 and an R^2 of 0.52 and the relationship for PCC_P had a D value of 0.73 and an R^2 of 0.51. The RMSE values for both methods were also close to one another with values of ±23.04% and ±21.90% for PCC_C and PCC_P, respectively. The scatter plots as shown in Figures 4.5a and b also demonstrated the strong similarity of both relationships. Generally, the graphs reveal a linear relationship between the two variables but the PCC_I values were clearly almost consistently overestimating the ground observations which results in data points not fitting the 1:1 line.

The consistent overestimation of the PCC_I compared to the PCC_G measurements were caused by two reasons. The first one is related to what the hyperspectral sensor actually “senses”. When solar radiation penetrates through a vegetation canopy, the radiation is scattered and reflected, and its direction and spectral composition are

transformed in a complex manner by the vegetation (Goel, 1988). The canopy reflectance is the sum of the reflectance of all vegetation components such as leaves, stalks, stems, bark, flowers, etc. Accordingly, the hyperspectral sensor essentially measures spectral reflectance from the total volume of the canopy (McNairn *et al.*, 2001a), which includes the aforementioned components of the plant. Accordingly, the hyperspectral sensor measures PCC_I by incorporating the 3-dimensional structure of the canopy whereas the PCC_G values derived from the photographs can only view and measure 2-dimensional plant area (including leaves, stalks, stems). The PCC_I is a reflection of the actual vegetation amount in the canopy as it considers the total volume of the canopy while PCC_G is more representative of the true PCC of the canopy. Vegetation canopies can be represented by the same vegetation volume but have very different vegetation covers and, thus, generating an error in the estimation of true PCC. Despite this discrepancy, the hyperspectral sensor was successful in estimating PCC.

The second reason is related to the endmember selection and extraction process. In order to minimize errors in selecting and extracting endmembers, “pure” patches were generated. Even though precautions were taken to avoid the contamination of “pure” patches, the examination of the endmembers’ spectra in section 4.3 revealed that the “pure” patches were not exactly pure. In Clinton, the crop patches were double-seeded in order to obtain full vegetation cover and, thus, enabled the extraction of a pure crop endmember. During the field campaign, it was evident that the “pure” crop patches were not 100% composed of vegetation and that the soil background was apparent up to some degree. In Indian Head, the “pure” crop endmembers were extracted from high-density crop areas. The soil background was also apparent and these areas were small in size and the reflectance from surrounding material (soil and residue) could have contributed to the contamination of the crop endmember spectra. Despite this problem, the crop endmembers were still selected from the purest pixels available in the reflectance cubes and spectral unmixing analysis was carried out using two or three spectrally distinctive endmembers per field. This enabled reasonably good estimation of PCC_I .

a)



b)

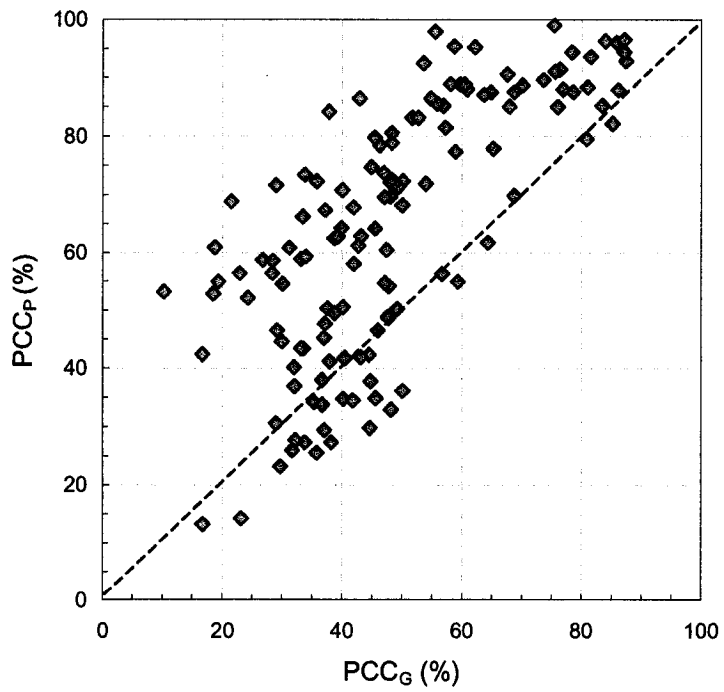


Figure 4.5. Relationship between PCC derived from the ground vertical photographs (PCC_G) and reflectance data using constrained unmixing (PCC_C) (a) and partially-constrained unmixing (PCC_P) (b) for all crops.

4.5.3 Adjusting Image Percent Crop Cover (PCC_I) for Endmember “Impurity”

An adjustment factor was introduced in the PCC_I computation to take into account the potential error associated with the endmembers’ “impurity”. The adjustment factor was calculated for Clinton using the same procedure used for the estimation of PCC where ground vertical photographs were identified for the crop patches. For Indian Head, endmembers were extracted in high-density crop growth areas using the Probe-1 field validation (see Section 3.5.1). The field validation also included written observations, which visually assessed the PCC for the specific sites where endmembers were extracted. The “true” average PCC_G (averaged on a crop basis) was ratioed against the PCC_I values derived for each individual sampling site. Adjustment factors were then computed for each crop type and are presented in Table 4.11. Statistics derived from this adjustment to the PCC_C and PCC_P values are given in Tables 4.12a and b together with scatter plots as shown in Figures 4.6a and b.

Table 4.11. *Adjustment factor for each crop type.*

Crop Type	Adjustment Factor
Bean	0.3955
Corn	0.7170
Wheat	0.8200
Canola	0.8250
Pea	0.8000

Table 4.12. *Fit statistics for PCC adjusted for endmember “impurity” for all crops. The PCC were derived from the ground vertical photographs (PCC_G) and the reflectance data using constrained unmixing (PCC_{C-ADJ}) (a) and partially-constrained unmixing (PCC_{P-ADJ}) (b) (where $E_{PCC_{G-ADJ}}$, $E_{PCC_{C-ADJ}}$ and $E_{PCC_{P-ADJ}}$ are the standard deviations as a percentage of the mean values; a and b are the slope and intercept of the least squares regression line; RMSE is the root mean square error; D is the index of agreement; and R^2 is the coefficient of determination). R^2 values in bold are significant at $p < 0.05$.*

a) Constrained Unmixing									
Field	PCC_G (%)	PCC_{C-ADJ} (%)	E_{PCC_G} (%)	$E_{PCC_{C-ADJ}}$ (%)	a	b	RMSE (±%)	D	R^2
All Crops	49.42	46.86	18.01	9.53	0.91	1.38	11.06	0.91	0.71
b) Partially-Constrained Unmixing									
Field	PCC_G (%)	PCC_{P-ADJ} (%)	E_{PCC_G} (%)	$E_{PCC_{P-ADJ}}$ (%)	a	b	RMSE (±%)	D	R^2
All Crops	49.42	45.84	18.01	9.67	0.87	3.15	11.20	0.90	0.69

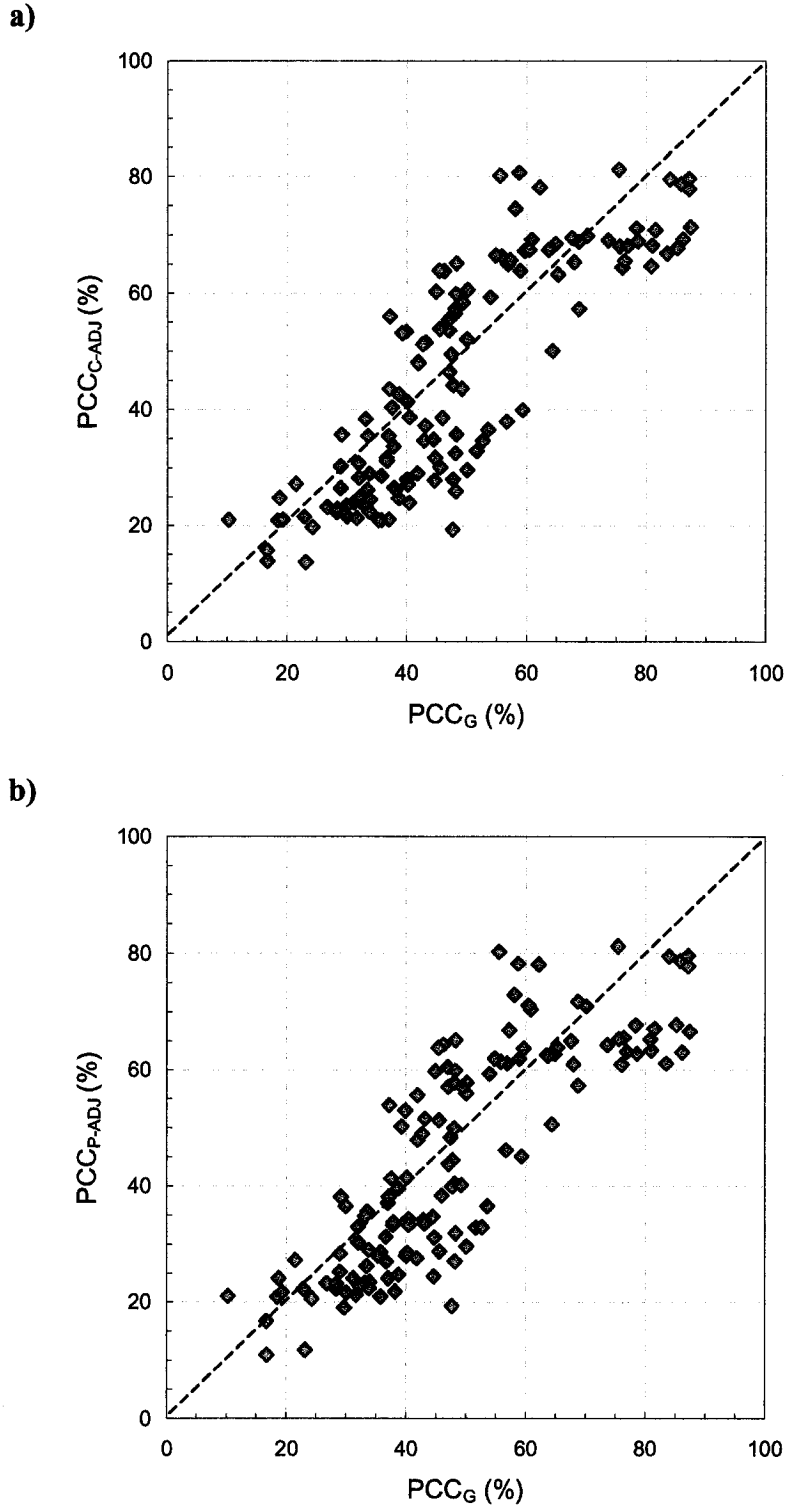


Figure 4.6. Relationship between PCC derived from the ground vertical photographs (PCC_G) and reflectance data using constrained unmixing (PCC_{C-ADJ}) (a) and partially-constrained unmixing (PCC_{P-ADJ}) (b) adjusted for endmember “impurity”, for all crops.

The scatter plots depicting the relationship between the PCC_G and the adjusted crop fractions, derived from constrained (PCC_{C_ADJ}) and partially-constrained unmixing (PCC_{P_ADJ}), clearly illustrate a better fit to the 1:1 line than the unadjusted PCC (see Figures 4.5a and b in section 4.4.2). Tables 4.12a and b indicate that D values increased considerably once the PCC_I values were adjusted for spectral “impurity” (from 0.72 to 0.91 for PCC_{C_ADJ} and from 0.73 to 0.90 for PCC_{P_ADJ}). This was also reflected for the RMSE, which was reduced from $\pm 23.04\%$ and $\pm 21.90\%$, to $\pm 11.06\%$ and $\pm 11.20\%$ for PCC_{C_ADJ} and PCC_{P_ADJ} , respectively. Average PCC_I values were also much more comparable with PCC_{C_ADJ} and PCC_{P_ADJ} values. R^2 values also increased considerably from 0.52 and 0.51 to 0.71 and 0.69 for PCC_{C_ADJ} and PCC_{P_ADJ} , respectively.

Both constrained and partially-constrained unmixing methods worked extremely well and are good predictors of PCC in agricultural canopies. Although, for further analysis, only the PCC_{P_ADJ} values will be considered as this method relaxes the constraint that image fractions sum to one. This algorithm is much more lenient and recognizes that it is possible that not all endmembers were identified within the scene. In agriculture canopies, these endmembers could include shadow, weeds, pebbles, water puddles, etc. For example, a water puddle was present in the north area of the Pea-5 field (see Appendix II), and almost 50% of its pixels were contributing to the PCC_{C_ADJ} values. However, when examining the PCC_{P_ADJ} values, the reflectance contribution was reduced to almost 0% indicating that the “partially-constrained unmixing” algorithm detected the water and classified it as being a different endmember than crop, soil or residue. This can also be noted in the Bean-1 reflectance cube where shadow was classified in the “other endmember” fraction image when partially-constrained unmixing was used. Therefore, partially-constrained unmixing was a much better model for this study to describe actual field conditions of vegetation canopies. To facilitate reading, PCC_{P_ADJ} will be referred as PCC_P from this point on.

4.6 Deriving LAI from Crop Fraction Inversion

The application of specific methods to derive plant biophysical parameters from remotely-sensed imagery such as LAI requires that these methods be validated rigorously and independently. The method in which hyperspectral data and spectral unmixing

analysis are employed to derive crop fraction and then use crop fraction inversion to estimate LAI has not been thoroughly evaluated. Staenz *et al.* (1998b) has developed this technique to estimate LAI in bean, canola, wheat and potato canopies and concluded that the proposed technique had potential to estimate LAI over agricultural canopies. This section will discuss the validation of the technique used to estimate LAI and some of the factors influencing the technique's performance.

4.6.1 Prediction of Image $eLAI_I$ ($eLAI_I$)

$eLAI_I$ maps were computed using the PCC_P values for each individual field for both the Clinton and Indian Head datasets (see Appendix III). Average values extracted for each sample site from a 3-by-3-pixel window were compared to LAI_G values estimated from biomass samples. Various statistics were calculated and are summarized in Table 4.13. A scatter plot of the results is also presented in Figure 4.7.

Table 4.13. Fit statistics for LAI derived from the biomass samples (LAI_G) and image ($eLAI_I$) calculated for all crops (where E_{LAI_G} and E_{eLAI_I} are the standard deviations as a percentage of the mean values; a and b are the slope and intercept of the least squares regression line; RMSE is the root mean square error; D is the index of agreement; and R^2 is the coefficient of determination). R^2 values in bold are significant at $p < 0.05$.

Field	LAI_G	$eLAI_I$	E_{LAI_G} (%)	E_{eLAI_I} (%)	a	b	RMSE ($\pm$)	D	R^2
All Crops	2.14	1.39	6.02	13.72	0.53	0.29	1.01	0.68	0.37

Average LAI_G measurements and average $eLAI_I$ differed somewhat significantly with values of 2.14 and 1.39, respectively. Also, the scatter plot illustrating the relationship between LAI_G measurements and $eLAI_I$ values demonstrated an inadequate fit to the 1:1 line. Data points were mostly located below the 1:1 line indicating that the hyperspectral image data was underestimating the LAI_G mainly due to foliage clumping resulting from the distinct row structure found in most of the studied crop canopies. This issue will be addressed in the following section. However, the D value was somewhat satisfactory with a value of 0.68 and an RMSE of ± 1.01 . This was also reflected to some extent on the regression line, which had a slope of 0.53 indicating a certain deviation between the regression line and the 1:1 line, but a relatively low intercept of 0.29. These

results are not surprising and are actually expected since the LAI_G values have been adjusted to the clumping index while the image data is still influenced by this factor and requires an adjustment.

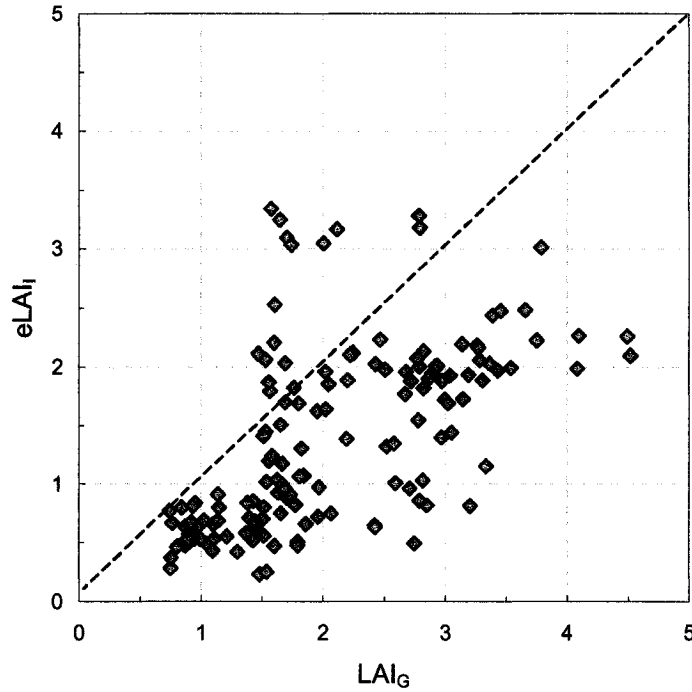


Figure 4.7. Relationship between LAI derived from the biomass samples (LAI_G) and image $eLAI$ ($eLAI_I$) for all crops.

4.6.2 Adjusting Image $eLAI_I$ ($eLAI_I$) Estimates with the Clumping Index (Ω)

As discussed in the previous section, hyperspectral remote sensing data generally underestimated LAI_G estimates of the crop canopies. This is mainly attributable to the occurrence of foliage clumping within agriculture canopies. Foliage clumping can occur on two levels: within the plant itself and within the canopy, i.e. within and between plant rows. For example, bean leaves are grouped closely on a stem which in turn, is attached to other stems including the main stem of the plant. Also, crop plants are usually planted close to each other within a row generating foliage clumping. Hence, foliage clumping is directly related to plant growth and becomes an important factor as the crop matures.

Ω values were roughly estimated with the classified ground vertical photographs using the following equation (Chen and Cihlar, 1995b):

$$\Omega = \frac{(1 + F_G) \ln(F_T)}{\ln F_V}, \quad [4.1]$$

where F_G is the fraction of exposed soil between rows, F_T is the total fraction of exposed soil, and F_V is the fraction of exposed soil within the rows. Ω values were generated for each field since this quantity can vary extremely among fields (Table 4.14). Ω values that approach 1 indicate a canopy with leaves that are randomly distributed. In this case, the Canola-2 and the Bean-2 fields were the ones closest to that value with clumping indexes of 0.89 and 0.85, respectively. Ω for the Bean-1 and Wheat-4 fields were very low, which indicates that those fields were very clumped. This was mostly caused by the isolation of each plant row due to the small size of the bean and wheat plants, and because the foliage clumping within the plant rows was very distinct. Once Ω has been applied to $eLAI_I$ values, these values will be referred as LAI_I values (see Equation 3.8).

Table 4.14. *Clumping index (Ω) values estimated per field derived from vertical ground photographs.*

Field	Estimated Clumping Index (Ω)
Bean-1	0.33
Bean-2	0.85
Bean-3	0.78
Corn-1	0.60
Corn-2	0.74
Corn-3	0.59
Wheat-1	0.57
Wheat-2	0.60
Wheat-3	0.75
Wheat-4	0.38
Canola-1	0.67
Canola-2	0.89
Pea-1	0.59
Pea-2	0.72

4.6.3 Prediction of Image LAI (LAI_I)

LAI_I maps were computed by considering Ω values for each individual field for both the Clinton and Indian Head datasets. Average LAI_I values (3-by-3 window) were extracted from the hyperspectral image data and were compared to LAI_G measurements. Statistics and a scatter plot describing the relationship between the two variables were generated and are presented in Table 4.15 and Figure 4.8, respectively.

Table 4.15. Fit statistics for LAI derived from the biomass samples (LAI_G) and image with adjustment for foliage clumping (LAI_I) for all crops (where E_{LAI_G} and E_{LAI_I} are the standard deviations as a percentage of the mean values; a and b are the slope and intercept of the least squares regression line; RMSE is the root mean square error; D is the index of agreement; and R^2 is the coefficient of determination). R^2 values in bold are significant at $p < 0.05$.

Field	LAI_G	LAI_I	E_{LAI_G} (%)	E_{LAI_I} (%)	a	b	RMSE ($\pm$)	D	R^2
All Crops	2.14	2.12	6.02	13.72	0.68	0.76	0.96	0.73	0.31

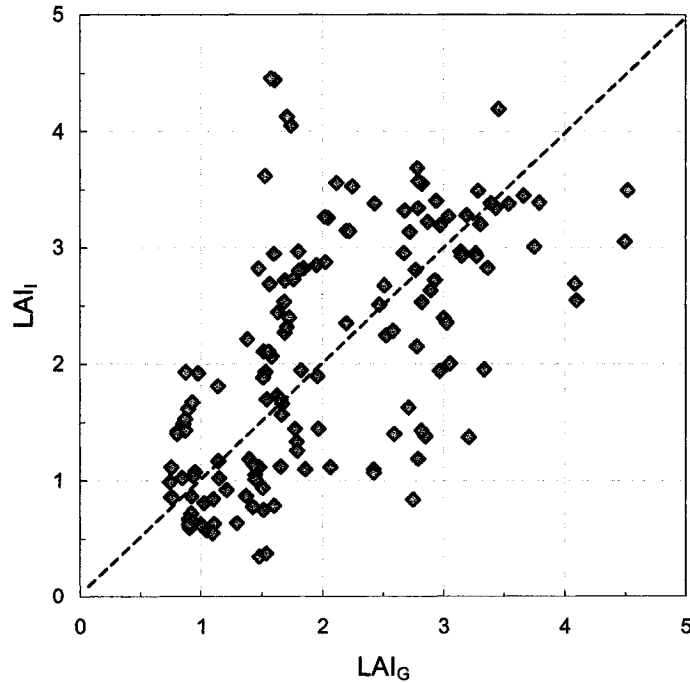


Figure 4.8. Relationship between LAI derived from the biomass samples (LAI_G) and image LAI adjusted for foliage clumping (LAI_I) for all crops.

Average LAI_G and average LAI_I were quite comparable with values of 2.14 and 2.12 respectively. The scatter plot illustrates a much better relationship between the two variables where data points are closer to the 1:1 line. D is also better with a value of 0.73 and an RMSE of ± 0.96 . Even though, the scatter plot follows the general linear trend of the 1:1 line, some variability is still unexplained. This is also reflected in the slope of the regression line with a value of 0.68 clearly indicating that there is some inconsistency between the two variables examined.

4.6.4 Sources of Error in LAI Estimation and Validation

Various sources of error in the LAI estimation have been discussed throughout this study. However, it is useful to re-evaluate these error sources to fully grasp and understand the assumptions and implications that are made in both the estimation of image LAI and in the validation procedure employed. Errors can be introduced at several stages of the analysis such as in the pre-processing, analysis and validation of the image data.

Radiometric calibration of the hyperspectral sensor is essential and will affect the surface reflectance retrieval from the radiance data. Uncertainties in the reflectance will have an influence on any analysis that is carried out using this data (Green *et al.*, 1991). This source of error was significantly minimized by calibrating the radiance data using a vicarious calibration technique (Secker *et al.*, 2001). Another source of error lies in the estimation of parameters used in the MODTRAN3 RT code. However, the sensitivity of the LAI estimation technique to variable RT code inputs is beyond the scope of this thesis. The location of the ground sample sites in the hyperspectral imagery is yet another important source of error, which was previously assessed and discussed in section 4.1.

Furthermore, the LAI_I extraction technique is dependent on the crop fractions, which in turn are dependent on the spectral unmixing analysis and the endmember selection and extraction. Any errors introduced in these analysis procedures can be accumulated and affect the LAI_I values. This is why much caution was used to identify scene endmembers within the endmember selection process. In addition, crop fractions were first validated against percent crop cover before these were used to estimate LAI.

This actually helped to determine that the use of selected endmembers provided an overestimation of crop cover due to their lack of “purity”. However, some variability was unexplained when validating crop fractions.

Hyperspectral image LAI data validation was affected by several sources of uncertainty. One obvious limiting factor lies in the technique how biomass samples were collected. The separation of plants into leaf and stem constituents was done subsequently to the field campaign using dry matter partitioning ratios derived from the existing literature. These values are greatly influenced by crop growth conditions and can be quite variable. Consequently, the errors in the estimation of the partitioning ratios would significantly impact the results of the validation. On the other hand, as discussed in Section 4.3.3, neglecting to convert the measured plant water content values to stem and leaf constituents would lead to erroneous LAI results. An additional source of error is the estimation of foliage clumping in the crop canopies. This parameter was estimated using the most representative photograph of the conditions within each field but foliage clumping can be quite variable within a field and occasionally even within a sample site. However, for better representation of the field conditions, foliage clumping could have been estimated for each three vertical photograph replicates and averaged per sampling location and then adjusted individually for each sampling site. Foliage clumping was roughly estimated from ground vertical photographs, but a more robust field technique should be used to adequately estimate this parameter, such as the Tracing Radiation and Architecture of Canopies (TRAC) instrument (Leblanc *et al.*, 2002).

4.7 Potential for Modelling Crop and Field Variability

For remote sensing models to retrieve plant biophysical parameters and to be efficient tools in precision agriculture, they must be able to detect within-crop and within-field variations that is of interest to the agriculture industry. This section will discuss the within-crop and within-field divergences of the PCC and LAI estimations for the evaluation of the sensitivity of the models to subtle variation of field conditions. Both parameters were assessed for within-crop and within-field variability, since they are directly related to each another.

4.7.1 Prediction of Image Percent-Crop Cover (PCC_i) and Image LAI (LAI_i) for Single Crops

The robustness of the models was evaluated within each individual crop type. Statistics and scatter plots were generated to aid in the evaluation of the performance of the models.

In regards to PCC estimation (Table 4.16), the model was overall a very good predictor of PCC for wheat ($D = 0.85$) and canola ($D = 0.94$). The results were less satisfactory for beans ($D = 0.64$), corn ($D = 0.59$) and peas ($D = 0.58$). The wheat and canola fields revealed large crop cover variability (Figures 4.9 and 4.10, respectively) with the canola fields showing the largest one. This is probably due to the different seeding dates for the two canola fields. Canola-2 was seeded eight days prior to Canola-1, producing a more phenologically developed crop with higher percent crop cover. The large variability within the wheat fields was most likely due to different seeding rates applied in the fields (see Appendix 1), resulting in different crop densities across the fields. According to the scatter plots, pea fields (Figure 4.11) also demonstrated a good variability in PCC (from both ground and imagery data) also as a result of different seeding rates within the fields. Although, D was relatively low ($D = 0.58$) for peas, the RMSE value was the best among all crops studied (RMSE = 9.70%).

Table 4.16. Fit statistics for PCC derived from the ground vertical photographs (PCC_G) and image using partially-constrained unmixing (PCC_P) on a within-crop basis (where E_{PCC_G} and E_{PCC_P} are the standard deviations as a percentage of the mean values; a and b are the slope and intercept of the least squares regression line; RMSE is the root mean square error; D is the index of agreement; and R^2 is the coefficient of determination). R^2 values in bold are significant at $p < 0.05$.

Field	PCC_G (%)	PCC_P (%)	E_{PCC_G} (%)	E_{PCC_P} (%)	a	b	RMSE ($\pm\%$)	D	R^2
Bean	32.48	25.78	15.19	3.96	0.32	15.48	10.83	0.64	0.52
Corn	71.16	62.85	8.16	2.27	0.20	48.91	12.46	0.59	0.38
Wheat	48.53	47.17	14.61	6.67	1.01	-1.70	11.77	0.85	0.59
Canola	48.86	44.96	38.07	28.99	0.95	-1.23	10.67	0.94	0.81
Pea	46.09	48.45	14.03	6.46	1.23	-8.33	9.70	0.58	0.58

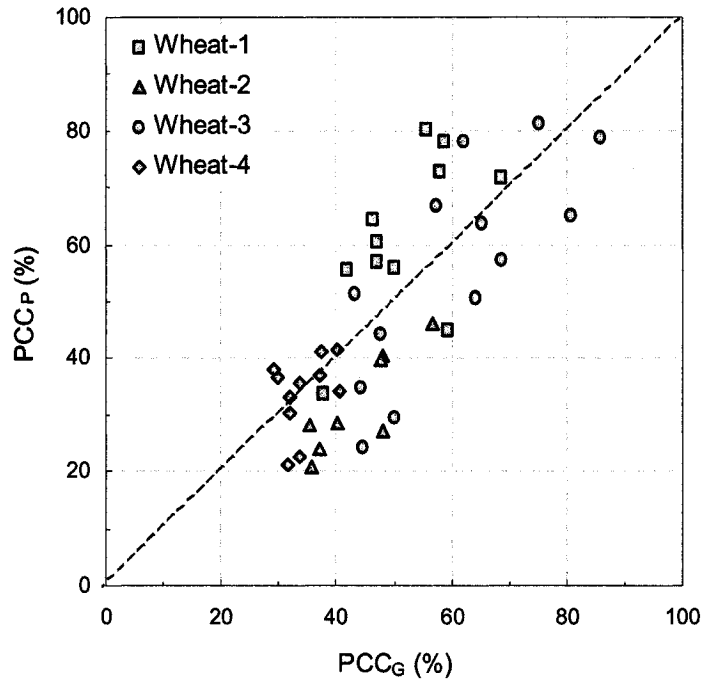


Figure 4.09. Relationship between PCC derived from the ground vertical photographs (PCC_G) and reflectance data using partially-constrained unmixing (PCC_P) for wheat fields.

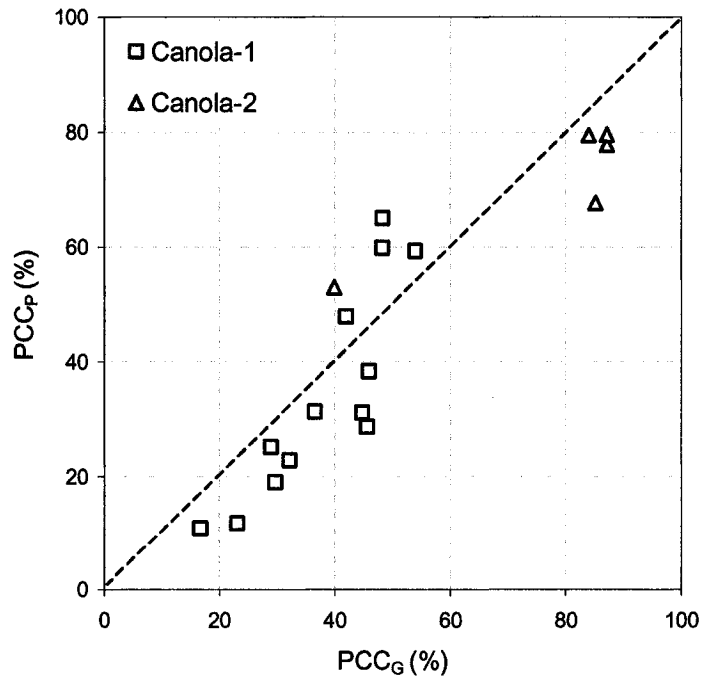


Figure 4.10. Relationship between PCC derived from the ground vertical photographs (PCC_G) and reflectance data using partially-constrained unmixing (PCC_P) for canola fields.

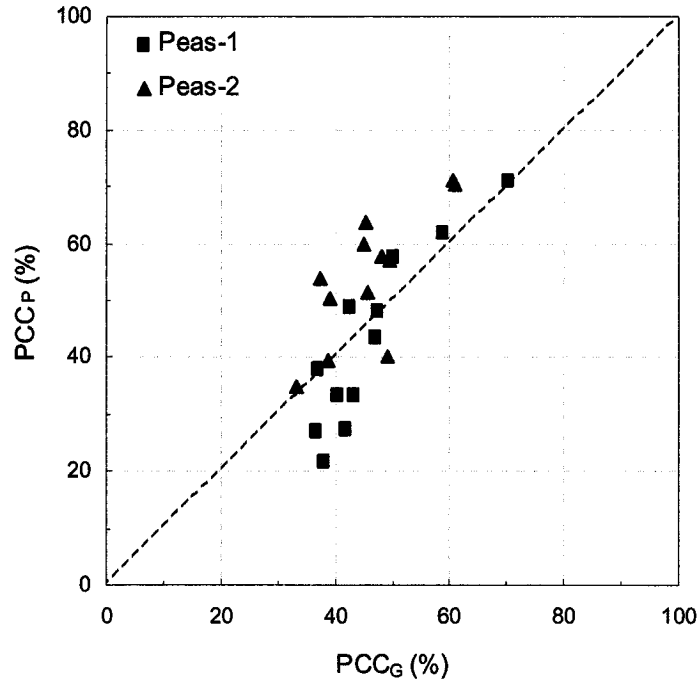


Figure 4.11. Relationship between PCC derived from the ground vertical photographs (PCC_G) and reflectance data using partially-constrained unmixing (PCC_P) for pea fields.

The predicted model values for beans and corn (Figures 4.12 and 4.13, respectively) had a weaker linear relationship with the PCC_G . RMSE values were somewhat similar to the other canopies but D values were much lower than in canola and wheat fields. The lower variability range in the data for the bean and the corn fields studied can, to some extent, explain this poorer relationship. The variability range in the PCC_G was lower in the bean (45%) and corn (40%) fields in comparison to the average variability within the other crops (56%). This was especially the case for the image data values where variability was no more than 20% compared to average variability of 60% for the other crops. The bean and corn fields were more homogeneous as a result of the absence of applied treatments unlike the fields in Indian Head, where the various treatment applications artificially increased intra-field variability. Generally, the model to estimate PCC was insensitive to a limited range of variability.

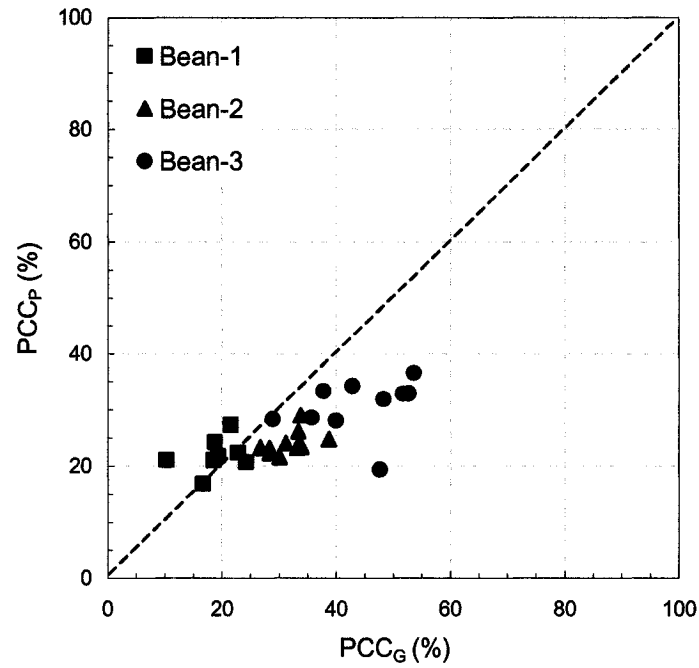


Figure 4.12. Relationship between PCC derived from the ground vertical photographs (PCC_G) and reflectance data using partially-constrained unmixing (PCC_P) for bean fields.

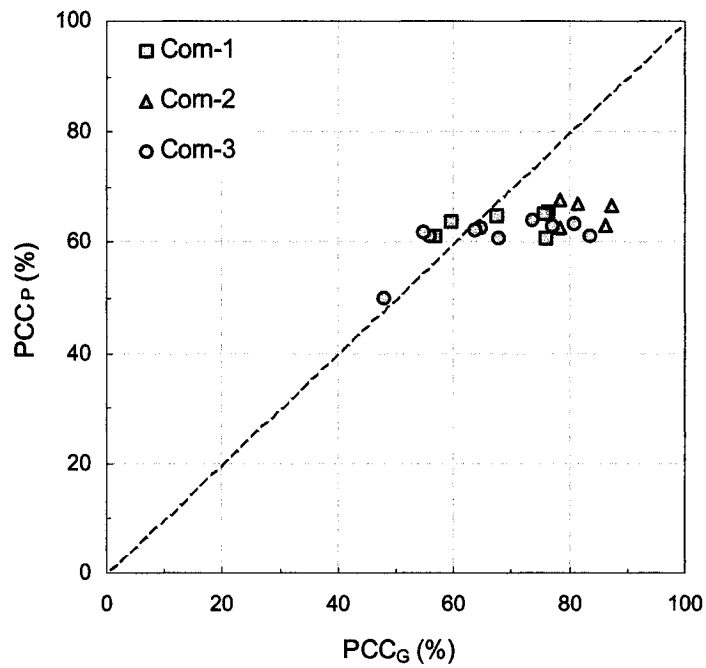


Figure 4.13. Relationship between PCC derived from the ground vertical photographs (PCC_G) and reflectance data using partially-constrained unmixing (PCC_P) for corn fields.

Concerning LAI estimation (Table 4.17), the model was overall a good predictor for canola ($D = 0.76$), which is analogous to the performance of the PCC estimation model for the canola canopies. Results were less successful for pea ($D = 0.47$) and corn ($D = 0.42$) fields and even less for wheat ($D = 0.22$) and bean ($D = 0.09$) fields. However, RMSE values were lower for beans (± 0.47) and corn (± 0.64) than for peas (± 1.05). The reason for this inconsistency is not obvious from the statistical analyses. Overall, the LAI_G variability was very low for all canopies (Figures 4.14 to 4.18) with values varying within 0.5 units for bean, 1.0 for wheat, 2.0 for peas, 2.5 for corn and 3.0 for canola fields.

Table 4.17. Fit statistics for LAI derived from the biomass samples (LAI_G) and image (LAI_I) on a within-crop basis (where E_{LAI_G} and E_{LAI_I} are the standard deviations as a percentage of the mean values; a and b are the slope and intercept of the least squares regression line; RMSE is the root mean square error; D is the index of agreement; and R^2 is the coefficient of determination). R^2 values in bold are significant at $p < 0.05$.

Field	LAI_G	LAI_I	E_{LAI_G} (%)	E_{LAI_I} (%)	a	b	RMSE ($\pm$)	D	R^2
Bean	0.93	1.04	4.29	4.59	-0.98	1.95	0.47	0.09	0.07
Corn	2.98	3.11	6.60	3.78	0.06	2.94	0.64	0.42	0.01
Wheat	1.65	2.36	4.52	9.19	2.19	-1.26	1.32	0.22	0.14
Canola	2.21	1.96	10.16	41.66	0.96	0.01	0.84	0.76	0.42
Pea	2.95	2.14	4.55	9.38	1.82	-3.23	1.05	0.47	0.49

The variability of the LAI_I was fairly better for some crops, such as wheat (5.0 LAI units), canola (4.0 LAI units) and peas (3.0 LAI units), white beans (1.5 LAI units) and corn (2.0 LAI units) had a smaller LAI_I variability range (Figures 4.14, 4.15, 4.16, 4.17 and 4.18, respectively). The low LAI_G variability in the bean canopies inhibited, to a certain degree, a 1:1 relationship. This is also reflected on the regression line statistics where the R^2 is 0.07, the slope is -0.98 and the intercept is 1.95. The slope of the regression line being negative indicates that while the LAI_G increases, the LAI_I decreases. The low LAI_G variability within the wheat fields is partially responsible for the poor LAI_I estimation. The lack of variability in the LAI_G values in comparison to the PCC_G (see Figure 4.9) also suggests that the LAI_G measurements were possibly not accurately estimated. In addition, LAI_I was highly overestimated for the Wheat-1 field which could suggest an error in the Ω value applied to this specific field. As for the corn fields, the

scatter plot seems to imply that LAI_I saturates at LAI_G values close to 4. Actually, all figures suggest this with the exception of LAI_I values of Wheat-1. The pea fields were also characterized by a low LAI_G range resulting in a regression slope of 1.82 and an intercept of -3.23 . Finally, the canola fields were the crop type showing the best model performance ($D = 0.76$) with a regression slope very close to 1 ($a = 0.96$) and an intercept of almost 0 ($b = 0.01$).

The somewhat poor relationships between the LAI_G and the LAI_I within-fields can be the result of a few issues. The LAI_G data does not provide the model with the required variability in order to perform a robust validation. Overall, the model seems to have a problem with its prediction ability at low LAI_G values. It is generally over-predicting low LAI_G values, especially in the bean and wheat canopies. There are two possible reasons for this both related to the LAI_G measurements. Firstly, deriving LAI from the biomass samples was not ideal since the SLA was not calculated based on the dataset used in this study, but was derived from van Keulen's (1986) SLA indicative values for major crops (see Section 3.2.3.1). The SLA was also calculated using the dry plant matter, while LAI_I was derived from fresh (wet) plant matter, which causes an inconsistency between the LAI_G measurements and the LAI_I data. Secondly, the poor estimation of the fraction of the stem-to-leaf water content used in adjusting the biomass estimates may be a source of error. In addition, these estimates may be uncertain as a result of the uneven emergence of crops influenced by soil and climate conditions, which could affect the phenological stage of the crop and, thus, the dry matter-partitioning ratio (van Heemst, 1986). To some extent, the rough estimation of foliage clumping when adjusting the $eLAI_I$ data can also contribute to erroneous results. The combination of these problems could explain the large scatter in the data given that the application of a constant value to all samples would not solve the problem.

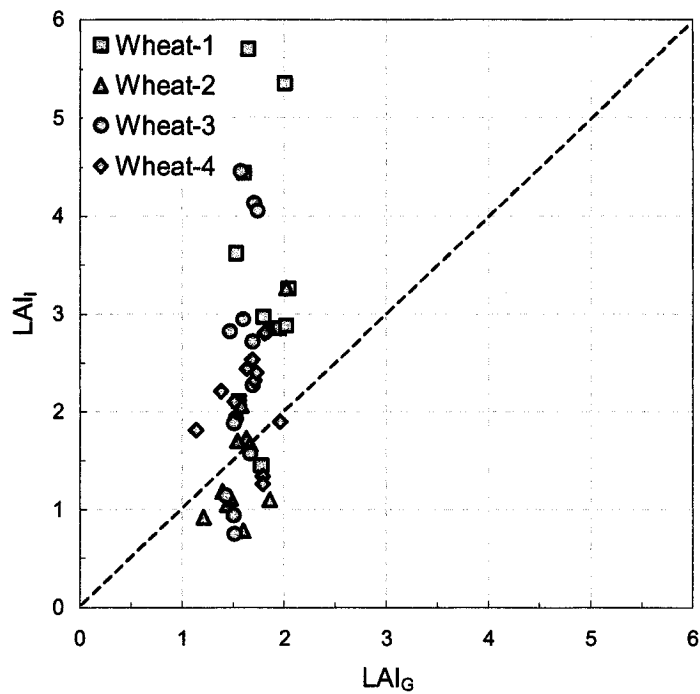


Figure 4.14. Relationship between LAI derived from the biomass samples (LAI_G) and image LAI (LAI_I) for wheat fields.

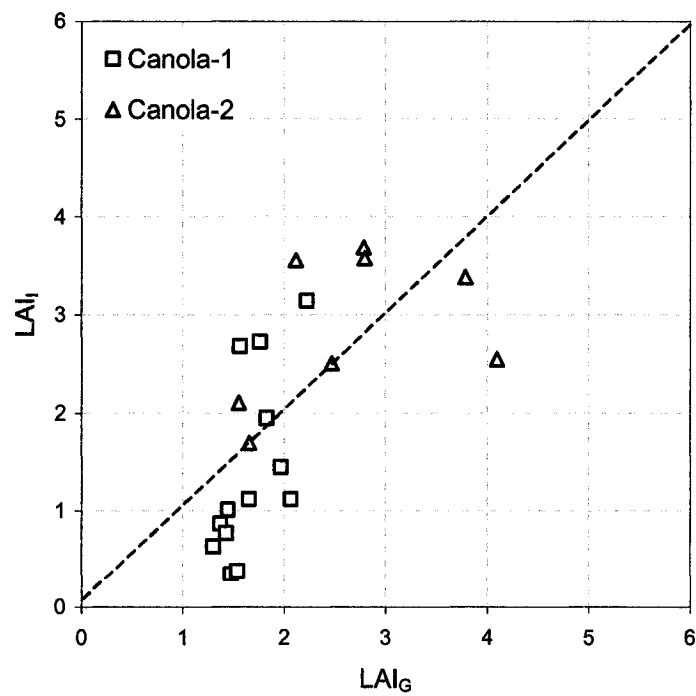


Figure 4.15. Relationship between LAI derived from the biomass samples (LAI_G) and image LAI (LAI_I) for canola fields.

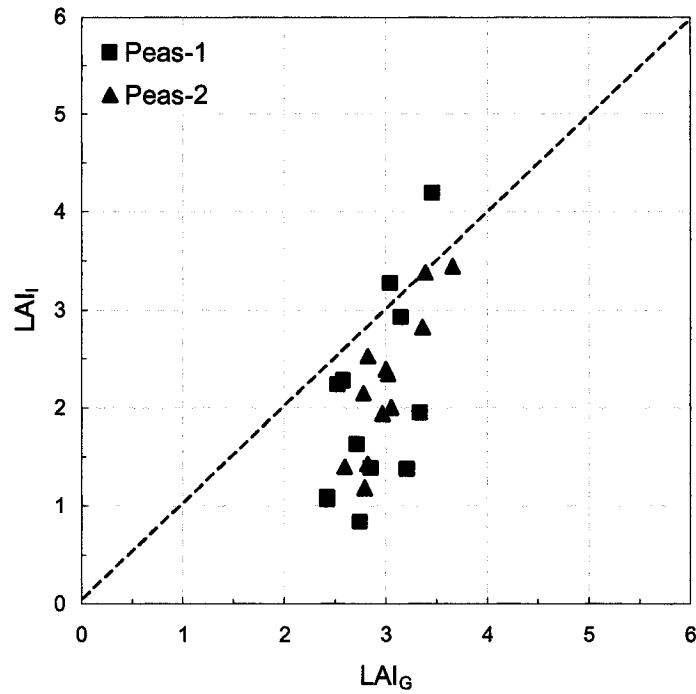


Figure 4.16. Relationship between LAI derived from the biomass samples (LAI_G) and image LAI (LAI_I) for pea fields.

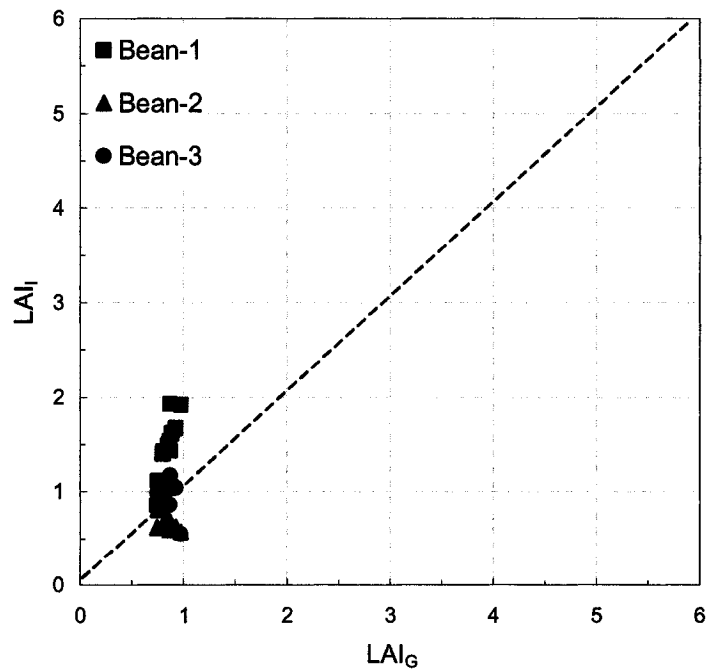


Figure 4.17. Relationship between LAI derived from the biomass samples (LAI_G) and image LAI (LAI_I) for bean fields.

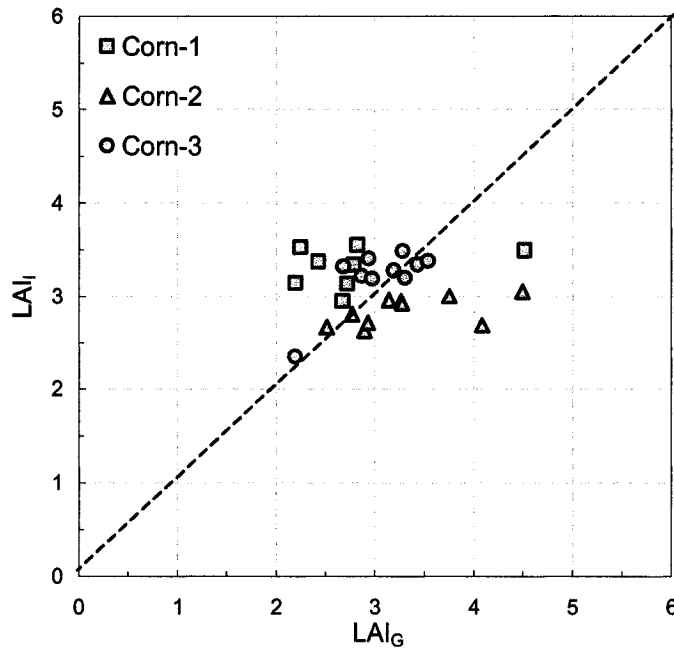


Figure 4.18. Relationship between LAI derived from the biomass samples (LAI_G) and image LAI (LAI_I) for corn fields.

4.7.2 Prediction of PCC and LAI for Detection of Field Scale Variability

Precision agriculture must not only be sensitive to within-crop variability, but should more significantly be able to detect plant physiological variations existing within an individual field. To establish the model's ability to predict PCC and LAI, the model fit was calculated on an individual field level. Statistics were only generated to describe the various relationships between both parameters (Tables 4.18 and 4.19).

The within-field model performance differed somewhat from the within-crop variability. Generally, the model was a good PCC predictor for canola, pea and wheat fields and a weaker predictor for corn and bean fields. As for the LAI_I estimation model, the best results were generally found in the canola fields followed by the corn, pea, bean and wheat fields. In general, D values are much lower for the LAI_I estimation model (0.28 to 0.88) than for the PCC_I estimation model (0.22 to 0.65). It is relevant to note that fields with relatively high R^2 values are statistically significant on the 95% level. The reason that the other fields did not read this significance is partially due to the small amount of sampling sites for those fields.

Table 4.18. Fit statistics for PCC derived from the ground vertical photographs (PCC_G) and image using partially-constrained unmixing (PCC_P) on a within-field basis (where E_{PCC_G} and E_{PCC_P} are the standard deviations as a percentage of the mean values; a and b are the slope and intercept of the least squares regression line; RMSE is the root mean square error; D is the index of agreement; and R^2 is the coefficient of determination). R^2 values in bold are significant at $p < 0.05$.

Field	PCC_G (%)	PCC_P (%)	E_{PCC_G} (%)	E_{PCC_P} (%)	a	b	RMSE ($\pm\%$)	D	R^2
Bean-1	19.02	21.84	21.05	3.69	0.21	17.86	5.04	0.48	0.09
Bean-2	31.77	24.10	10.53	3.28	0.29	14.86	8.22	0.43	0.23
Bean-3	43.95	30.60	14.01	4.92	0.16	23.38	15.50	0.45	0.08
Corn-1	68.69	63.58	11.53	1.43	0.09	57.33	9.05	0.53	0.14
Corn-2	82.40	65.43	5.83	3.57	-0.05	69.62	17.55	0.28	0.01
Corn-3	67.02	61.12	7.12	1.81	0.21	47.12	11.09	0.61	0.37
Wheat-1	51.88	61.40	16.81	4.66	0.95	12.24	14.37	0.64	0.37
Wheat-2	43.63	31.88	11.49	10.05	1.00	-11.96	12.54	0.62	0.73
Wheat-3	60.77	55.88	16.56	6.34	1.02	-5.82	12.40	0.84	0.60
Wheat-4	34.30	33.75	13.60	5.62	0.61	12.73	6.22	0.54	0.13
Canola-1	38.17	34.74	36.88	48.73	1.40	-18.72	10.43	0.86	0.74
Canola-2	76.66	71.54	39.26	9.26	0.51	32.74	11.29	0.85	0.83
Pea-1	46.16	42.76	16.61	6.52	1.38	-21.16	8.30	0.88	0.79
Pea-2	46.02	54.15	11.45	6.40	1.04	6.24	10.91	0.73	0.58

Table 4.19. Fit statistics for LAI derived from the biomass samples (LAI_G) and image (LAI_I) on a within-field basis (where E_{LAI_G} and E_{LAI_I} are the standard deviations as a percentage of the mean values; a and b are the slope and intercept of the least squares regression line; RMSE is the root mean square error; D is the index of agreement; and R^2 is the coefficient of determination). R^2 values in bold are significant at $p < 0.05$.

Field	LAI_G	LAI_I	E_{LAI_G} (%)	E_{LAI_I} (%)	a	b	RMSE ($\pm\%$)	D	R^2
Bean-1	0.85	1.49	3.18	4.18	1.31	-0.62	0.36	0.28	0.76
Bean-2	0.97	0.65	3.15	3.77	0.01	0.54	0.42	0.22	0.00
Bean-3	0.96	0.94	6.55	5.82	-0.05	0.78	0.30	0.38	0.00
Corn-1	2.80	3.31	7.13	2.49	-0.05	1.84	1.05	0.39	0.09
Corn-2	3.31	2.84	7.20	5.95	0.10	1.77	1.32	0.41	0.29
Corn-3	3.04	3.22	5.46	2.89	0.36	0.80	1.17	0.39	0.59
Wheat-1	1.80	3.46	4.83	7.61	-0.12	2.19	0.78	0.22	0.00
Wheat-2	1.59	1.51	4.97	12.29	1.29	-1.14	0.75	0.39	0.45
Wheat-3	1.59	2.43	2.76	9.90	5.09	-6.26	0.87	0.23	0.31
Wheat-4	1.67	2.16	5.53	6.96	0.08	0.69	0.89	0.28	0.01
Canola-1	1.66	1.40	7.05	66.10	1.33	-1.28	0.87	0.44	0.37
Canola-2	2.66	2.88	13.26	17.22	0.31	1.75	0.84	0.65	0.17
Pea-1	2.87	2.02	5.36	8.98	0.99	-1.66	1.74	0.28	0.35
Pea-2	3.02	2.25	3.74	9.79	1.47	-2.83	1.43	0.29	0.74

A closer examination of the individual field results led to a few observations. High D values (> 0.73) and relatively low RMSE ($\approx 10.00\%$) characterized the results for the pea fields. Low variability of PCC values within-fields explained the poorer results found in the bean and corn canopies. D values were relatively close to 0.45 for beans while these differed significantly within the three corn fields. Corn-3 had a D value of 0.61 in comparison to 0.28 for Corn-2. The extremely low variability within Corn-2 ($E_{PCC_G} = 5.83$) explains the low D value. Once again, the seeding rate treatments in the fields of the Indian Head dataset were an important factor, increasing the variability within each field. The ability of the LAI estimation model to perform well within individual canola fields was illustrated by the highest D values (0.44 for Canola-1 and 0.65 for Canola-2). LAI_G variability within individual corn fields seemed to be detected by the model (D values around 0.40) even though RMSE values were relatively high (average RMSE of 1.18). However, this model seems to be insensitive within each pea, wheat and bean fields with D values lower than 0.38.

4.8 Conclusions

The image-to-image registration procedure used in this study was overall successful and proved to be an efficient way to locate ground-sample sites in the imagery which cannot be geometrically corrected in order to keep the radiometric integrity. Ground variability was also examined and revealed that the fields used for this study were not ideal since variability was quite low, especially for the bean and corn fields. The validation of the LAI_{2000} measurements against the LAI_G demonstrated that the use of the LAI-2000 instrument in agriculture canopies is not straightforward and that the sampling technique has to strictly follow the guidelines in the LAI-2000 operating manual (LI-COR, 1992) as described in section 2.2.2.1 of this thesis. Generally, constrained and partially-constrained unmixing analysis is an accurate method to determine PCC. Finally, LAI estimated from crop fraction inversion has potential to estimate LAI over agricultural canopies. Errors in the LAI estimation model were thoroughly evaluated and these should be considered and corrected for future research. The next chapter (Chapter 5) will summarize the results of this study and list recommendations for future research.

5. CONCLUSIONS AND RECOMMENDATIONS

The following chapter will present a brief summary of the thesis and contributions to the research on leaf area index (LAI) estimation using hyperspectral remote sensing are also demonstrated. Finally, recommendations are put forward to improve future research.

5.1 Summary and Contributions

A spectral unmixing technique for the prediction of LAI was validated and evaluated in relation to its practical application to precision agriculture. The results indicate that the model used for this study has several strengths and weaknesses. Overall, the model provides a fairly good indicator of LAI when samples from multiple fields and crop types are compared. Combining the measures from all fields and crop types in this study illustrated that for a wide range of plant types and field conditions, the estimation of LAI using this model is accurate, with an index of agreement (D) of 0.73 and a Root Mean Square Error (RMSE) of ± 0.96 . However, some variability in the model is still unexplained and further research using this technique is required to fully understand its potential. This will be discussed more thoroughly in the next section (5.2).

The calculation of the foliage clumping improved the results in terms of average LAI values. Average image LAI (LAI_I) values were much more comparable to the ground LAI (LAI_G) for bean, corn, canola and pea canopies than for wheat. However, adjusting the image effective LAI ($eLAI_I$) values with the clumping index only increased the D value from 0.68 to 0.73 and, decreased the RMSE from ± 1.01 to ± 0.96 . A more robust field estimation of this parameter is necessary to fully assess its influence. Also, the method for percent-crop cover (PCC) estimation did not account for 10% of the variability. Thus, this relatively small

error was translated to the LAI estimation model as well. In addition, some of the deviation in the model can be related to the errors involved in locating the sample sites in the Probe-1 imagery. Although these were minimal, they still exist and could have affected, to some extent, the model's overall performance. Errors related to the estimation of LAI_G from the ground biomass samples are certainly an issue in regards to the validation of this LAI extraction technique. The conversion of leaf area (LA) to LAI was not ideal since SLA values were not available for the datasets used in this study. This was also a problem for the estimation of the stem-to-leaf ratio.

The use of the spectral unmixing technique employed in this study proved to be quite efficient to estimate ground PCC (PCC_G). The effect of the “impurity” of endmembers to the spectral unmixing analysis was revealed when crop fractions were adjusted for pixel “impurity”. Adjusting the crop fractions for the lack of “pure” endmembers increased the D values from 0.72 to 0.91 and decreased RMSE from $\pm 23.04\%$ to $\pm 11.06\%$ for constrained unmixing and increased the D values from 0.73 to 0.90 and decreased RMSE from $\pm 21.90\%$ to $\pm 11.20\%$ for partially-constrained unmixing. The results indicate that the two spectral unmixing algorithms were equally successful. This suggests that the endmember spectra, selected within the reflectance cube itself, were really representative of the field conditions. Thus, the contribution of other small components (e.g., shadow) was very minimal and does not influence the results. This finding is important as it simplifies the endmember selection and extraction process by eliminating the crop shadow influence on the spectral unmixing analysis. The results also show that the manual endmember extraction (MEE) technique is appropriate for endmember selection and extraction when endmembers are known and well identified in the hyperspectral image.

The use of the spectral unmixing technique to quantify within-crop and within-field PCC and LAI variability showed mixed success. The PCC model was sensitive to the high variability in the canola (D = 0.94 and RMSE = $\pm 10.67\%$) and wheat crops (D = 0.85 and RMSE = $\pm 11.77\%$). However, this level of variability was somewhat artificial since the crops were subject to variable rate treatments. This is evident in the results for corn and beans, in which the model was not as sensitive to the level of variability found in beans (D = 0.64 and RMSE = $\pm 10.83\%$) and corn (D = 0.59 and RMSE = $\pm 12.46\%$) under ambient field conditions. The somewhat poor results for pea crops (D = 0.58 and RMSE = $\pm 9.70\%$) are

possibly due to the classification process used for the ground vertical photographs where pea stems and residue were difficult to distinguish. The LAI_I model was sensitive to the high variability in the canola crops ($D = 0.76$ and $RMSE = \pm 0.84$), but did not predict LAI accurately for the pea ($D = 0.47$ and $RMSE = \pm 1.05$) and corn canopies ($D = 0.42$ and $RMSE = \pm 0.64$). Results were even poorer for the wheat ($D = 0.22$ and $RMSE = \pm 1.32$) and bean crops ($D = 0.09$ and $RMSE = \pm 0.47$). The inconsistency in these results is generally due to the lack of variability within-crops and even more so within-fields. Thus, statistical analyses become more difficult to interpret. The results are also affected by the inadequate estimation of the plant's stem-to-leaf ratio and the plant's and canopy's foliage clumpiness. To validate the LAI model thoroughly, improved methods are required to estimate these parameters more precisely.

5.2 Recommendations for Future Research

Several issues must be addressed in order to successfully implement this model into precision agriculture. The general ineffectiveness of the model in predicting LAI_I at a within-crop or within-field level must be further investigated, since it has broad implications for the operational use of remote sensing to estimate LAI in the context of precision agriculture applications. The model should be further tested later in the growing season to determine if the early growth stage of the plants in this study was contributing to the lack of sensitivity. A multi-temporal dataset in a variety of structurally different crops, such as the ones in this study, covering a full growing season would benefit this type of research. LAI would certainly vary between the different growth stages of the crops and result in greater variability within the dataset. The collection of ground measurements also requires a great deal of consideration to ensure that the measurements collected are comparable to the data extracted from the remote sensing data.

Another issue that must be addressed is the threshold of sensitivity that is indispensable for application of LAI estimation to precision agriculture. The limited range of LAI_G especially in bean and wheat fields prohibited the model to accurately assess its performance with respect to these crops. Once the model has been further validated confirming a good LAI predictability, the model could be operationally used for precision agriculture applications.

Other issues in terms of the model's sensitivity should also be addressed. The implications of using this model during reproductive stages of growth needs to be investigated, since the development of fruit on the plants might influence the spectral response measured by the sensor. In fact, future studies should examine LAI of individual plant components (stems, leaves, fruit, etc.) in order to distinguish the influence of these various components on the spectral response of the sensor.

Finally, greater synergy is required between remote sensing derived-LAI and agronomic modeling. Agriculture models are often limited in their application to precision agriculture by the lack of data inputs, while remote sensing is most often perceived as the solution for this problem. To make sure that this is feasible, the limitations of remote sensing to estimate LAI, and ultimately incorporate this data in agronomic models must be explicitly addressed to ensure that emphasis is put on the integration of measurable quantities into these models.

6. REFERENCES

- Adams, J.B., Smith, M.O. and Johnson, P.E. (1986). Spectral mixture modeling: A new analysis of rock and soil types at Viking Lander 1. *Journal of Geophysical Research*. **91**: 8113-8125.
- Adams, J.B., Smith, M.O. and Gillespie, A.R. (1993). Imaging spectroscopy: Interpretation based on spectral mixture analysis. In *Remote Geochemical Analysis: Elemental and Mineralogical Composition*. (C.M. Pieters and P.A.J. Englert, Eds). Cambridge University, Cambridge. pp. 145-166.
- Allen, W.A. and Richardson, A.J. (1968). Interaction of light with a plant canopy. *Journal of the Optical Society of America*. **58** (8): 1023-1028.
- Asrar, G., Fuchs, M., Kanemasu, E.T. and Hatfield, J.L. (1984). Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat. *Agronomy Journal*. **76**: 300-306.
- Bannari, A., Morin, D., Bonn, F. and Huete A.R. (1995). A review of vegetation indices. *Remote Sensing Reviews*. **13**: 95-120.
- Baret, F. and Guyot, G. (1991). Potentials and limits of vegetation indices for LAI and APAR assessment. *Remote Sensing of Environment*. **35**: 161-173.
- Baret, F., Guyot, G. and Major, D.J. (1989). TSAVI: A vegetation index which minimizes soil brightness effects on LAI and APAR estimation. *Proceedings of the 12th Canadian Symposium on Remote Sensing*. Vancouver, Canada. pp. 1355-1358.
- Bariou, R., Lecamus, D. and Le Henaff, F. (1985). Indices de végétation. *Dossiers de télédétection*, Centre Régional de télédétection, Université de Rennes 2, France. 80 pages.
- Bateson, A. and Curtiss, B. (1996). A method for manual endmember selection and spectral unmixing. *Remote Sensing of Environment*. **55**: 229-243.

Bechdol, M.A., Gualtieri, J.A., Hunt, J.T., Chettri, S. and Garegnani, J. (2000). Hyperspectral imaging: A potential tool for improving weed and herbicide management. *Proceedings of the 5th International Conference on Precision Agriculture*. Madison, Wisconsin, USA. CD-ROM.

Berk, A., Bernstein, L.S. and Robertson, D.C. (1989). MODTRAN: A moderate resolution model for LOWTRAN7. *Final report, GL-TR-0122*. AFGL, Hanscom AFB, Maryland, 42 pages.

Best, R.G. and Harlan, J.C. (1985). Spectral estimation of green leaf area index of oats. *Remote Sensing of Environment*. **17**: 27-36.

Boardman, J.W. 1995. Analysis, understanding and visualization of hyperspectral data convex sets in N-Space. *Proceedings of SPIE's International Conference on Imaging Spectrometry*, Orlando, Florida. **2480**: 14-20.

Boardman, J.W. 1992. Automating spectral unmixing of AVIRIS data using convex geometry, in *Summaries of the 4th Airborne Geoscience Conference* (R.O. Green, Eds), JPL Publication 93-26. Jet Propulsion Laboratory, Pasadena, California, USA. Volume 1, pp. 11-14.

Boegh, E., Soegaard, H., Broge, N., Hasager, C.B., Jensen, N.O., Schelde, K. and Thomsen, A. (2002). Airborne multispectral data for quantifying leaf area index, nitrogen concentration, and photosynthetic efficiency in agriculture. *Remote Sensing of Environment*. **81**: 179-193.

Bouma, J. (1999). Precision agriculture: a unique tool to unify production and environmental requirements in agriculture. *Proceedings of the 4th International Conference on Precision Agriculture*. Madison, Wisconsin, USA. CD-ROM.

Bouman, B.A.M. (1992). Accuracy of estimating the leaf area index from vegetation indices derived from crop reflectance characteristics, a simulation study. *International Journal of Remote Sensing*. **13**(16): 3069-3084.

Bouman, B.A.M., van Kasteren, H.W.J. and Uenk, D. (1992). Standard relations to estimate ground cover and LAI of agricultural crops from reflectance measurements. *European Journal of Agronomy*. **1**(4): 249-262.

Brisco, B., Brown, R.J., Hirose, T., McNairn, H. and Staenz, K. (1998). Precision agriculture and the role of remote sensing: a review. *Canadian Journal of Remote Sensing*, **24**(3): 315-327.

Broge, N.H. and Mortensen, J.V. (2002). Deriving green crop area index and canopy chlorophyll density of winter wheat from spectral reflectance data. *Remote Sensing of Environment*. **81**: 45-57.

- Broge, N.H. and Leblanc, E. (2000). Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density. *Remote Sensing of Environment*. **76**: 156-172.
- Brown, R.J., McNairn, H., Wood, D., Staenz, K. and Deguise, J.-C. (1998). Assessing crop vigor from high spatial and high spectral optical imagery. *20th Canadian Symposium on Remote Sensing*. Calgary, Alberta, Canada. May 11-14. Pp. 33-35.
- Bullock, P., Brisco, B. and Hirose, T. (2000). Remote sensing for improving crop management. *2nd International Conference on Geospatial Information in Agriculture and Forestry*. Lake Buena Vista, Florida, USA. January 10-12. Volume 2, pp. 487-494.
- Carlson, T.N. and Ripley, D.A. (1997). On the relation between NDVI, fractional vegetation cover, and leaf area index. *Remote Sensing of Environment*. **62**: 241-252.
- Champagne, C. (2002). Remote sensing of plant water content for precision agriculture: the potential for hyperspectral modeling. *MSc. Thesis, Department of Geography, University of Ottawa*, Ottawa, 114 pages.
- Chen, J.M. and Cihlar, J. (1995a). Quantifying the effect of canopy architecture on optical measurements of leaf area index using two gap size analysis methods. *IEEE Transactions on Geoscience and Remote Sensing*. **33**(3): 777-787.
- Chen, J.M. and Cihlar, J. (1995b). Plant canopy gap-size analysis: theory for improving optical measurements of leaf area index. *Applied Optics*. **34**(27): 6211-6222.
- Chen, J.M., Black, T.A. and Adams, R.S. (1991). Evaluation of hemispherical photography for determining plant area index and geometry of a forest stand. *Agricultural and Forest Meteorology*. **56**: 129-143.
- Clevers, J.G.P.W. (1999). The use of imaging spectrometry for agricultural applications. *Journal of Photogrammetry & Remote Sensing*. **54**: 299-304.
- Clevers, J.G.P.W. (1989). The application of a weighted infra-red vegetation index for estimating leaf area index by correcting for soil moisture. *Remote Sensing of Environment*. **29**: 25-37.
- Clevers, J.G.P.W. (1988). The derivation of a simplified reflectance model for the estimation of leaf area index. *Remote Sensing of Environment*. **25**: 53-69.
- Cornelissen, J.H.C., Castro Diez, P. and Hunt, R. (1996). Seedling growth, allocation and leaf attributes in a wide range of woody plant species and types. *Journal of Ecology*. **84**: 755-765.
- Curran, P.J. (1994). Imaging spectrometry. *Progress in Physical Geography*. **18**(2): 247-266.

Curran, P.J. and Milton, E.J. (1983). The relationship between the chlorophyll concentration, LAI and reflectance of a simple vegetation canopy. *International Journal of Remote Sensing*. **4**(2): 247-255.

Daughtry, C.S.T and Hollinger, S.E. (1984). Costs of measuring leaf area index of corn. *Agronomy Journal*. **76**: 836-841.

Deguisse, J.-C., Staenz, K. and Lefebvre, J. (1999). Agricultural applications of airborne hyperspectral data: weed detection. *4th International Airborne Remote Sensing Conference and Exhibition/21st Canadian Symposium on Remote Sensing*. Ottawa, Ontario, Canada, 21-24 June. Volume 2, pp. 352-358.

de Jesus Jr., C.W., Ribeiro do Vale, F.X., Resende Coelho, R. and Costa, L.C. (2001). Comparison of two methods for estimating leaf area index on common bean. *Agronomy Journal*. **93**: 989-991.

Demetriades-Shah, T., Steven, M.D. and Clark, J.A. (1990). High resolution derivative spectra in remote sensing. *Remote Sensing of Environment*. **33**(1): 55-64.

Duke, C. (2002). The integration of remote sensing information products and crop growth models for predicting crop productivity and for assessing the environmental impact of cropping practices. *Department of Land Resource Science, University of Guelph*. Ontario, Canada. 64 pages.

Edwards, G., Jaton, A. and Thomson, K.P.B. (1991). La manipulation des données hyperspectrales. *Téledétection et Gestion des Ressources*. **7**: 295-299.

Elvidge, C.D. and Chen, Z. (1995). Comparison of broad-band and narrow-band Red and Near- Infrared vegetation indices. *Remote Sensing of Environment*. **54**: 38-48.

Endsley, H.H. (1995). Spectral unmixing algorithms based on statistical models. *Proceedings of SPIE's International Symposium on Imaging Spectrometry*, Orlando, Florida. Volume 2480, pp. 14-22.

ESSI Inc. (2001). About Probe-1. Kalispell, MT., www.earthsearch.com/technology.

Feng, J., Rivard, B. and Sánchez-Azofeifa, A. (2003). The topographic normalization of hyperspectral data: Implications for the Selection of Spectral End Members and Lithologic Mapping. *Remote Sensing of Environment*. **85**: 221-231.

Filella, I. and Peñuelas, J. (1994). The red edge position and shape as an indicator of plant chlorophyll content, biomass and hydric status. *International Journal of Remote Sensing*. **15**(7): 1459-1470.

Gallo, K.P., Daughtry, C.S.T. and Bauer, M.E. (1985). Spectral estimation of absorbed photosynthetically active radiation in corn canopies. *Remote Sensing of Environment*. **17**: 221-232.

- Ganguli, A.C., Vermeire, L.T., Mitchell, R.B. and Wallace, M.C. (2000). Comparison of four nondestructive techniques for estimating standing crop in shortgrass plains. *Agronomy Journal*. **92**: 1211-1215.
- Gao, B.C. and Goetz, A.F.H. (1990). Column atmospheric water vapor and vegetation liquid water retrieval from Airborne Imaging Spectrometer data. *Journal of Geophysical Research*. **95**: 3549-3564.
- García-Haro, F.J., Gilabert, M.A. and Meliá, J. (1999). Extraction of endmembers from spectral mixtures. *Remote Sensing of Environment*. **68**: 237-253.
- Garegnani, J., Gualtieri, J.A., Chettri, S., Robinson, J., Hunt, J.P., Bechdol, M. and Vermeullen, A. (2000). Preliminary tests of the utility of hyperspectral image data to precision farming. *IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*. Honolulu, Hawaii, USA. July 24-28. Volume 5, pp. 2519-2521.
- Geophysical and Environmental Research Corporation (1990). GER 3700 Spectroradiometer User's Manual, version 2.1. 55 pages.
- Gilabert, M.A., Gandía, S. and Meliá, J. (1996). Analyses of spectral-biophysical relationships for a corn canopy. *Remote Sensing of Environment*. **55**: 11-20.
- Gobron, N., Pinty, B. and Verstraete, M.M. (1997). Theoretical limits to the estimation of the leaf area index on the basis of Visible and Near-Infrared remote sensing data. *IEEE Transactions on Geoscience and Remote Sensing*. **35**(6): 1438-1445.
- Goel, N.S. (1988). Models of vegetation canopy reflectance and their use in estimation of biophysical parameters from reflectance data. *Remote Sensing Reviews*. **4**(1): 16-25.
- Goetz, A.F.H. (1992). Imaging spectrometry for earth observations. *Episodes*. **15**(1): 7-14.
- Goetz, A.F.H., Vane, G., Solomon, J.E. and Rock B.N. (1985). Imaging spectrometry for earth remote sensing. *Science*. **228**(4704): 1147-1153.
- Gong, P., Pu, R. and Miller, J.R. (1992). Correlating leaf area index of Ponderosa Pine with hyperspectral CASI data. *Canadian Journal of Remote Sensing*. **18**(4): 275-282.
- Gower, S.T., Kucharik, C.J. and Norman, J.M. (1999). Direct and indirect estimation of leaf area index, f_{APAR} , and net primary production of terrestrial ecosystems. *Remote Sensing of Environment*. **70**: 29-51.
- Gower, S.T. and Norman, J.M. (1991). Rapid estimation of leaf area index in conifer and broad-leaf plantations. *Ecology*. **72**(5): 1896-1900.
- Grantz, D.A. and Williams, L.E. (1993). An empirical protocol for indirect measurement of leaf area index in grape (*Vitis vinifera* L.). *HortScience*. **28**: 777-779.

- Green, R.O., Conel, J.E., Margolis, J.S., Brugge, C.J. and Hoover, G.L. (1991). An inversion algorithm for the retrieval of atmospheric and leaf water absorption from AVIRIS radiance with compensation for atmospheric scattering. *Proceedings of the Third Annual Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) Workshop*. Pasadena, California, JPL Publication 91-28, pp. 51-61.
- Hicks, S.K. and Lascano, R.J. (1995). Estimation of leaf area index for cotton canopies using the LI-COR LAI-2000 plant canopy analyzer. *Agronomy Journal*. **87**: 458-464.
- Holben, B.N. and Fan, C.-J. (1980). Spectral assessment of soybean leaf area and leaf biomass. *Photogrammetric Engineering and Remote Sensing*. **46**: 651-656.
- Hunt, T.E., Haile, F.J., Hoback, W.W. and Higley, L.G. (1999). Indirect measurement of insect defoliation. *Environmental Entomology*. **28**: 1136-1139.
- Huete, A.R. (1988). A Soil-Adjusted Vegetation Index (SAVI). *Remote Sensing of Environment*. **25**: 295-309.
- Jackson, R.D. and Pinter Jr., P.J. (1986). Spectral response of architecturally different wheat canopies. *Remote Sensing of Environment*. **20**: 43-56.
- Jackson, R.D. (1983). Spectral Indices in n-space. *Remote Sensing of Environment*. **13**: 409-421.
- Jacquemoud, S. and Baret, F. (1990). PROSPECT: A model of leaf optical properties spectra. *Remote Sensing of Environment*. **34**: 75-91.
- Knight, D.H. (1973). Leaf area dynamics of a shortgrass prairie in Colorado. *Ecology*. **54**: 891-896.
- Knipling, E.B. (1970). Physical and physiological basis for the reflectance of visible and near infrared radiation from vegetation. *Remote Sensing of Environment*. **1**: 155-159.
- Kopec, D.M., Norman, J.M., Shearman, R.C. and Peterson, M.P. (1987). An indirect method for estimating turfgrass leaf area index. *Crop Science*. **27**: 1298-1301.
- Kvet, J. and Marshall, J.K. (1971). Assessment of leaf area and other assimilating plant surfaces. In Z. Sestak et al. (ed.) *Plant photosynthetic production: Manual of Methods*. Dr.W. Junk. The Hague, Netherlands. Pp. 517-574.
- Labsphere (2001). A guide to reflectance coatings and materials. North Sutton, NH., http://www.labsphere.com/tech_info/docs/Coating_&_Material_Guide.pdf.
- Lang, A.R.G. and Yueqin, X. (1986). Estimation of leaf area index from transmission of direct sunlight in discontinuous canopies. *Agricultural and Forest Meteorology*. **37**: 229-243.

- Lang, A.R.G. (1986). Leaf area and average leaf angle from direct transmission of sunlight. *Australian Journal of Botany*. **34**: 349-355.
- Layrol, L., Hedoin, E., Lepoutre, D. and François, O. (2000). Matching multispectral yield and images data. *Proceedings of the 5th International Conference on Precision Agriculture*. Madison, Wisconsin, USA. CD-ROM.
- Leblanc, S.G., Chen, J.M. and Kwong, M. (2002). Tracing Radiation and Architecture of Canopies: TRAC MANUAL, Version 2.1. Canada Centre for Remote Sensing, Natural Resources Canada. Ottawa (Ontario), Canada. 25 pages.
- Leblanc, S.G., Chen, J.M., Miller, J.R. and Freemantle, J. (1999). Compact Airborne Spectrographic Imager (CASI) used for mapping LAI of cropland. *4th International Airborne Remote Sensing Conference and Exhibition / 21st Canadian Symposium on Remote Sensing*. Ottawa, Ontario, Canada. June 21-24. Volume 1, pp. 297-308.
- Lelong, C.C.D., Pinet, P.C. and Poilvé, H. (1998). Hyperspectral imaging and stress mapping in agriculture: a case study on wheat in Beauce (France). *Remote Sensing of Environment*. **66**: 179-191.
- Lévesque, J. and King, D.J. (2003). Spatial analysis of radiometric fractions from high-resolution multispectral imagery for modelling individual tree crown and forest canopy structure and health. *Remote Sensing of Environment*. **84**: 586-602.
- LI-COR. (1992). LAI-2000 Plant Canopy Analyzer - Operating manual. *LI-COR*, Lincoln, Nebraska, USA.
- Lillesand, T.M. and Kiefer, R.W. (1999). Remote sensing and image interpretation. John Wiley & Sons, Inc.. USA. 724 pages.
- Liu, Q. and Huete, A. (1995). A feedback based modification of the NDVI to minimize canopy background and atmospheric noise. *IEEE Transactions on Geoscience and Remote Sensing*. **33**: 457-465.
- Locke, C.R., Carbone, G.J., Filippi, A.M., Sadler, E.J., Gerwig, B.K. and Evans D.E. (2000). Using remote sensing and modeling to measure crop biophysical variability. *Proceedings of the 5th International Conference on Precision Agriculture*. Madison, Wisconsin, USA. CD-ROM.
- Major, D.J., Baret, F. and Guyot, G. (1990). A ratio vegetation index adjusted for soil brightness. *International Journal of Remote Sensing*. **11**(5): 727-740.
- Malone, S., Herbert, D.A.Jr. and Holshouser, D.L. (2002). Evaluation of the LAI-2000 Plant Canopy Analyzer to estimate leaf area index in manually defoliated soybean. *Agronomy Journal*. **94**: 1012-1019.

- McNairn, H., Deguise, J.C., Pacheco, A., Shang, J. and Rabe, N. (2001a). Estimation of crop cover and chlorophyll from hyperspectral remote sensing. *23rd Canadian Remote Sensing Symposium*. Saint-Foy, Québec, Canada, August 21-24. CD-ROM.
- McNairn, H., Deguise, J.-C., Secker, J. and Shang, J. (2001b). Development of remote sensing image products for use in precision farming. *3rd European Conference on Precision Farming*, Montpellier, France, June 18-20. pp. 259-263.
- McNairn, H. and Brown, R.J. (1999). Remote sensing in support of crop management. *United Nations/China/European Space Agency (ESA) Conference on Space Application for Promoting Sustainable Agriculture*. Beijing, China, September 14-17. CD-ROM.
- Miller, J.B. (1967). A formula for average foliage density. *Australian Journal of Botany*. **15**: 141-144.
- Miller-Goodman, M.S., Moser, L.E., Waller, S.S., Brummer, J.E. and Reece, P.E. (1999). Canopy analysis as a technique to characterize defoliation intensity on Sandhills Range. *Journal of Range Management*. **52**(4): 357- 362.
- Moran, M.S., Inoue, Y. and Barnes, E.M. (1997). Opportunities and limitations for image-based remote sensing in precision crop management. *Remote Sensing of Environment*. **61**: 319-346.
- Moran M.S., Maas, S.J. and Pinter, P.J. (1995). Combining remote sensing and modeling for estimating surface evapotranspiration and biomass production. *Remote Sensing Reviews*. **12**: 335-353.
- Moulin, S., Bondeau, A. and Delecolle, R. (1998). Combining agricultural crop models and satellite observations: from field to regional scales. *International Journal of Remote Sensing*. **19**(6): 1021-1036.
- Mustard, J.F. (1993). Relationships of soil, grass, and bedrock over the Kaweah Serpentine Melange through spectral mixture analysis of AVIRIS data. *Remote Sensing of Environment*. **44**: 293-308.
- Myneni, R.B. and Williams, D.L. (1994). On the relationship between FAPAR and NDVI. *Remote Sensing of Environment*. **49**: 200-211.
- Neville, R.A., Staenz, K., Szeredi, T., Lefebvre, J. and Hauff, P. (1999). Automatic endmember extraction from hyperspectral data for mineral exploration. *4th International Airborne Remote Sensing Conference and Exhibition / 21st Canadian Symposium on Remote Sensing*. Ottawa, Ontario, Canada, 21-24 June. Volume 2, pp. 891-897.
- Norman, J.M. and Campbell, G.S. (1989). Canopy structure. In R.W. Pearcy et al. (ed.) *Plant physiological ecology: Field methods and instrumentation*. Chapman & Hall, London and New York. Pp. 301-325.

- Norman, J.M. (1979). Modelling the complete crop canopy. In Int. B.J. Barfield and J.F. Gerber (Editors), *Modification of the Aerial Environment of Plants. American Society of Agricultural Engineers*. St. Joseph, Michigan, USA. Pp. 249-277.
- Norman, J.M. and Jarvis, P.G. (1974). Photosynthesis in Sitka Spruce (*Picea sitchensis* (Bong.) Carr.). III. Measurements of canopy structure and interception of radiation. *Journal of Applied Ecology*. **11**: 375-398.
- North, P.R.J. (2002). Estimation of f_{apar} , Lai, and vegetation fractional cover from ATSR-2 imagery. *Remote Sensing of Environment*. **80**: 114-121.
- Pacheco, A., Bannari, A., Staenz, K., McNairn, H. and Deguise, J.-C. (2002). Validating LAI using hyperspectral imagery over agricultural canopies. *1st International Symposium on Recent Advances in Quantitative Remote Sensing*. Torrent, Valencia (Spain), September 16-20. Pp. 210-215.
- Pacheco, A., Bannari, A., Deguise, J.-C., McNairn, H. and Staenz, K. (2001a). Application of hyperspectral remote sensing for LAI estimation in precision farming. *23rd Canadian Remote Sensing Symposium*. Saint-Foy, Québec, Canada, August 21-24. Volume 1, pp. 281-287.
- Pacheco, A., Bannari, A., Staenz, K., and McNairn, H. (2001b). LAI measurements in white beans and corn canopies with two optical instruments. *8th International Symposium of Physical Measurements & Signatures in Remote Sensing*, Aussois, France, January 8-12. Pp. 374-379.
- PCI Geomatics (2000). Using PCI software. Richmond Hill, ON. 540 pages.
- Pearce, R.B., Mock, J.J. and Bailey, T.B. (1975). Rapid method for estimating leaf area per plant in maize. *Crop Science*. **15**: 691-694.
- Pearson, R.L. and Miller, L.D. (1972). Remote mapping of standing crop biomass for estimation of the productivity of the short-grass prairie, Pawnee National Grasslands, Colorado. *Proceedings of the 8th International Symposium on Remote Sensing of Environment*. Ann Harbor, Michigan. Pp. 1357-1381.
- Peddle, D.R., Hall, F.G. and LeDrew, E.F. (1999). Spectral mixture analysis and geometric-optical reflectance modeling of boreal forest biophysical structure. *Remote Sensing of Environment*. **67**: 288-297.
- Piwowar, M.P. and Peddle, D.R. (1999). Assessing annual forest ecological change in western Canada using temporal mixture analysis of regional scale AVHRR imagery over a 14-year period. *Proceedings of the 4th International Airborne Remote Sensing Conference and Exhibition / 21st Canadian Symposium on Remote Sensing*. Ottawa, Ontario, 21-24 June. Volume 2, pp. 848-855.

- Plummer, S.E. (2000). Perspectives on combining ecological models and remotely sensed data. *Ecological Modelling*. **129**:169-186.
- Price, J.C. (1992). Estimating Vegetation Amount From Visible and Near Infrared Reflectances. *Remote Sensing of Environment*. **41**: 29-34.
- Qi, J., Chehbouni, A., Huete, A.R., Kerr, Y.H. and Sorooshian, S. (1994). A modified soil adjusted vegetation index. *Remote Sensing of Environment*. **47**: 1-25.
- Richardson, A.J. and Wiegand, C.L. (1977). Distinguishing vegetation from soil background information. *Photogrammetric Engineering and Remote Sensing*. **43**: 1541-1552.
- Rondeaux, G., Steven, M. and Baret, F. (1996). Optimization of soil-adjusted vegetation indices. *Remote Sensing of Environment*. **55**: 95-107.
- Rouse, J.W., Haas, R.W., Schell, J.A., Deering, D.W. and Harlan, J.C. (1974). Monitoring the vernal advancement and retrogradation (greenwave effect) of natural vegetation. *NASA/GSFCT Type III Final Report*. Greenbelt, USA.
- Ross, J. (1981). The radiation regime and architecture of plant stands, *Dr. W. Junk Publishers*. 391 pages.
- Rydberg, A. and Söderström, M. (2000). Potential crop growth assessment from remotely sensed images compared to ordinary yield maps. *Proceedings of the 5th International Conference on Precision Agriculture*. Madison, Wisconsin, USA. CD-ROM.
- Schwarz, J. (1998). Classification of hyperspectral data. *MSc. Thesis, School of Computer Science, Carleton University, Ottawa*, 180 pages.
- Secker, J., Staenz, K., Gauthier, R.P. and Budkewitsch, P. (2001). Vicarious calibration of airborne hyperspectral sensors in operational environments. *Remote Sensing of Environment*. **76**: 81-92.
- Sellers, P.J. (1987). Canopy reflectance, photosynthesis and transpiration II. The role of the biophysics in the linearity of their dependence. *Remote Sensing of Environment*. **21**: 143-183.
- Shanahan, J.F., Schepers, J.S., Francis, D.D., Varvel, G.E., Wilhelm, W.W., Tringe, J.M., Schlemmer, M.R. and Major, D.J. (2001). Use of remote-sensing imagery to estimate corn grain yield. *Agronomy Journal*. **93**: 583-589.
- Shang, J., Staenz, K., Lévesque, J., Neville, R.A., Howarth, P. and Morris, B. (2003). Mine tailings characterization using Probe-1 data (*to be submitted to Remote Sensing of Environment*).
- Sirotenko, O.D. (2001). Crop modeling: advances and problems. *Agronomy Journal*. **93**: 650-653.

- Shimabukuru, Y.E. and Smith, J.A. (1991). The least squares mixing models to generate fraction images from remote sensing on multispectral data. *IEEE Transactions on Geoscience and Remote Sensing*. **29**: 16-20.
- Snyder, C., Havlin, J., Kluitenberg, G. and Schroeder, T. (1999). Evaluating the economics of precision agriculture. *Proceedings of the 4th International Conference on Precision Agriculture*, St. Paul, Minnesota, USA. CD-ROM.
- Staenz, K., Nadeau, C., Secker, J. and Budkewitsch, P., (2000). Spectral unmixing applied to vegetated environments in the Canadian Arctic for mineral mapping. *Proceedings of XIX ISPRS Congress*. Amsterdam, The Netherlands. July 15-23, CD-ROM, 8 pages.
- Staenz, K., Schwarz, J. W., Vernaccini, L., Vachon, F. and Nadeau, C. (1999). Classification of hyperspectral agricultural data with spectral matching techniques. *Proceedings of the International Symposium on Spectral Sensing Research (ISSSR 99)*. Las Vegas, Nevada, United States, October 31 - November 4. CD-ROM, 12 pages.
- Staenz, K., Szeredi, T. and Schwarz, J. (1998a). ISDAS- A system for processing/analyzing hyperspectral data. *Canadian Journal of Remote Sensing*. **24**(2): 99-113.
- Staenz, K., Deguise, J.-C., Chen, J. M., McNairn, H., Szeredi, T. and McGovern, M. (1998b). The use of hyperspectral data for precision farming. *ISPRS Commission VII Symposium*. Budapest, Hungary. September 1-4. Pp. 38-42
- Staenz, K. and Williams, D.J. (1997). Retrieval of surface reflectance from hyperspectral data using a look-up table approach. *Canadian Journal of Remote Sensing*. **23**(4): 354-368.
- Staenz, K., Szeredi, T., Brown, R.J., McNairn, H. and van Acker R. (1997). Hyperspectral information extraction techniques applied to agricultural CASI data for detection of within-field variations. *International Symposium, Geomatics in the Era of RADARSAT (GER'97)*. Ottawa, Canada. May 25-30. CD-ROM.
- Staenz, K. (1996). Classification of a hyperspectral agriculture data set using band moments for reduction of the spectral dimensionality. *Canadian Journal of Remote Sensing*. **22**(3): 248-257.
- Staenz, K. (1992). A decade of imaging spectrometry in Canada. *Canadian Journal of Remote Sensing*. **18**(4): 187-197.
- StatSoft, Inc. (1994). STATISTICA for WINDOWS, release 5.0., User's Manual. Tulsa, Oklahoma, USA. 1098 pages.
- Steel, R.G. and Torrie, J.H. (1980). Principles and procedures of statistics: A biometrical approach. *McGraw-Hill, Inc.*, USA. 633 pages.

- Strahler, A.H., Woodcock, C.E. and Smith, J.A. (1986). On the nature models in remote sensing. *Remote Sensing of Environment*. **20**: 121-139.
- Stringer, W.C., Bridges, W.C., Pinkerton, B.W., Chrestman, R.E. and Rice, J.S. (1995). Non-destructive measurements of canopy volume to estimate grazing activity. *Crop Science*. **35**: 581-584.
- Szeredi, T., Staenz, K. and Neville, R.A. (2003). Automatic endmember selection: Part 1 Theory (to be submitted to *Remote Sensing of Environment*).
- Thenkabail, P.S., Smith, R.B. and De Pauw, E. (2000). Hyperspectral vegetation indices and their relationship with agricultural crop characteristics. *Remote Sensing of Environment*. **71**: 158-182.
- Tompkins, S., Mustard, J.F., Pieters, C.M. and Forsyth, D.W. (1997). Optimization of endmembers for spectral mixture analysis. *Remote Sensing of Environment*. **59**: 472-489.
- van Heemst, H.D.J. (1986). Crop phenology and dry matter distribution. In *Modelling of Agricultural Production*. H.van Keulen and J.Wolf (eds), Pudoc Wageningen. Pp. 26-38.
- van Keulen, H. (1986). Plant data. In *Modelling of Agricultural Production*. H.van Keulen and J.Wolf (eds), Pudoc Wageningen. Pp. 235-247.
- van Leeuwen, W.J.D. and Huete, A.R. (1996). Effects of standing litter on the biophysical interpretation of plant canopies with spectral indices. *Remote Sensing of Environment*. **55**: 123-138.
- Verhoef, W. (1984). Light scattering by leaf layers with application to canopy reflectance modeling: The SAIL model. *Remote Sensing of Environment*. **16**: 125-141.
- Wallach, D., Goffinet, B., Bergez, J.-E., Debaeke, P., Leenhardt, D. and Aubertot, J.-N. (2001). Parameter estimation for crop models: A new approach and application to a corn model. *Agronomy Journal*. **93**: 757-766.
- Waring, R.H., Schroeder, P.E. and Oren, R. (1982). Application of the pipe model theory to predict canopy leaf area. *Canadian Journal of Forest Research*. **12**: 556-560.
- Wehrhan, M.J.G. and Selige, T.M. (1997). Airborne remote sensing to support precision farming. *IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*. Singapore, Singapore. August 3-8. Volume 1, pp. 101-103.
- Welles, J.M. and Cohen, S. (1996). Canopy structure measurement by gap fraction analysis using commercial instrumentation. *Journal of Experimental Botany*. **47**(302): 1335-1342.
- Welles, J.M. and Norman, J.M. (1991). Instrument for indirect measurement of canopy architecture. *Agronomy Journal*. **83**: 818-825.

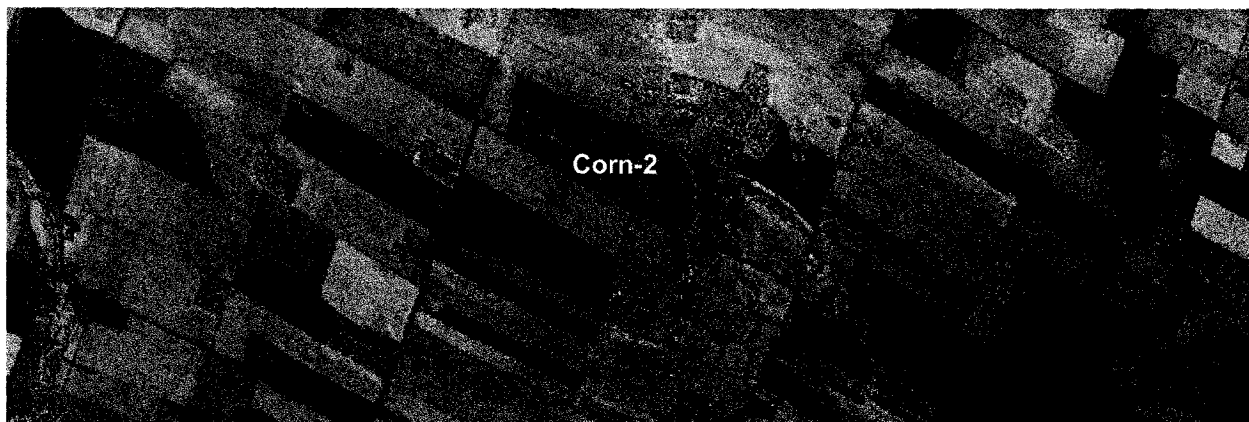
- Welles, J.M. (1990). Some indirect methods of estimating canopy structure. *Remote Sensing Reviews*. **5**(1): 31-43.
- Werner, S., Dölling, S., Jarfe, A., Kühn, J., Pauly, J. and Roth, R. (2000). Deriving maps of yield-potentials with crop models, site information and remote sensing. *Proceedings of the 5th International Conference on Precision Agriculture*. Madison, Wisconsin, USA. CD-ROM.
- Wiegand, C.L., Richardson, A.J., Escobar, D.E. and Gerbermann, A.H. (1991). Vegetation indices in crop assessments. *Remote Sensing of Environment*. **35**: 105-119.
- Wiegand, C.L. and Richardson, A.J. (1990). Use of spectral vegetation indices to infer leaf area, evapotranspiration and yield: II. Results. *Agronomy Journal*. **82**: 630-636.
- Wilhelm, W.W., Ruwe, K. and Schlemmer, M.R. (2000). Comparison of three leaf area index meters in a corn canopy. *Crop Science*. **40**: 1179-1183.
- Willmott, C.J. (1982). Some comments on the evaluation of model performance. *Bulletin American Meteorological Society*. **63**(11): 1309-1313.
- Wilson, W. and Reeve, J.E. (1959). Inclined point quadrats. *New Phytologist*. **59**: 1-8.
- Yang, C. and Everitt, J.H. (2000). Relationships between yield monitor data and airborne multispectral digital imagery. *Proceedings of the 5th International Conference on Precision Agriculture*. Madison, Wisconsin, USA. CD-ROM.
- Zhang, L., Li, D., Tong, Q. and Zheng, L. (1998). Study of the spectral mixture model of soil and vegetation in PoYang Lake area, China. *International Journal of Remote Sensing*. **19**(11): 2077-2084.

APPENDICES

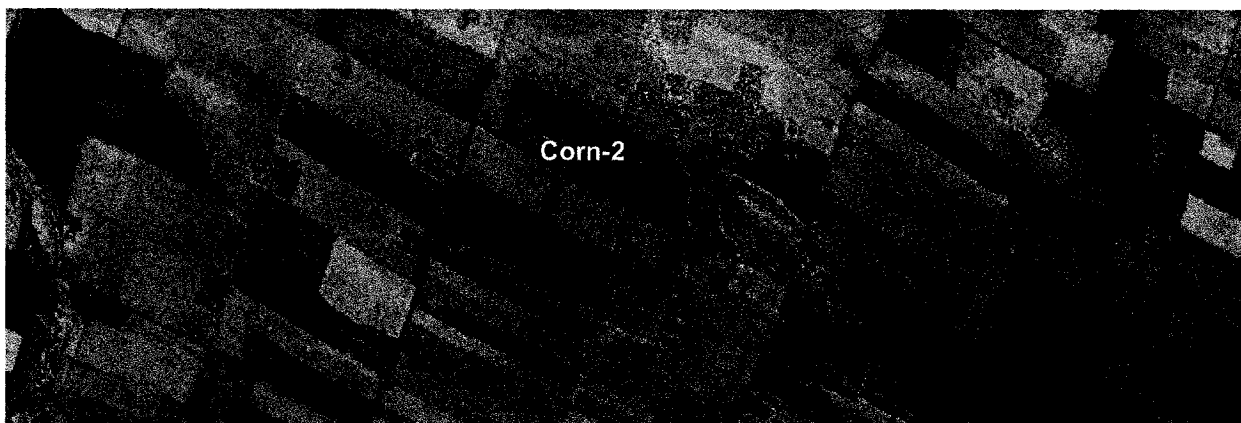
**APPENDIX I: FLIGHT LINE AND PASS LAYOUT FOR
PROBE-1 IMAGES**

A. Clinton, Ontario (Study fields outlined and identified in each flight line. Flight line 3 not shown.)

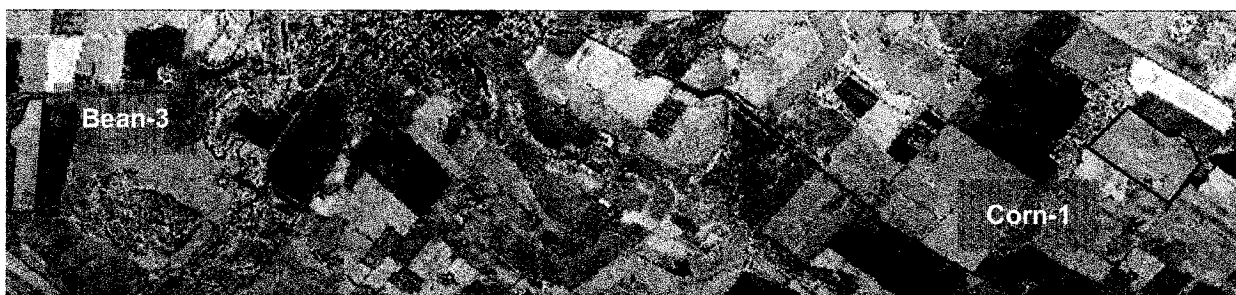
Flight line 1, Pass 1 (flown at 9:27 Eastern Standard Time)



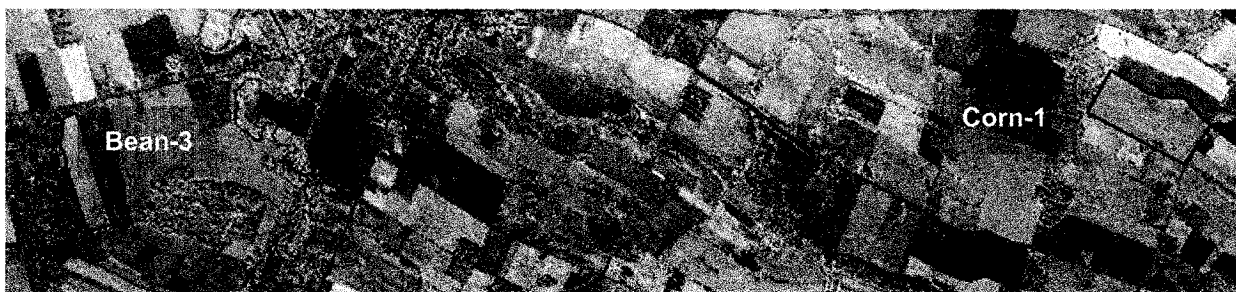
Flight line 1, Pass 2 (flown at 10:12 Eastern Standard Time)



Flight line 2, Pass 1 (flown at 9:47 Eastern Standard Time)

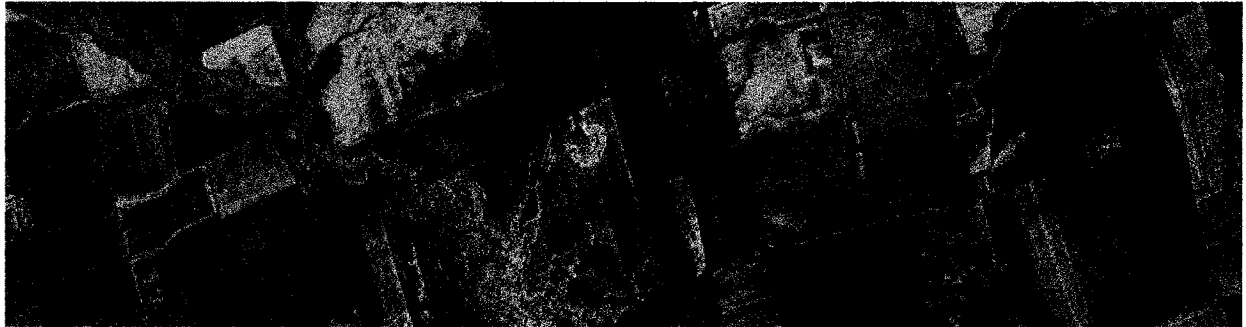


Flight line 2, Pass 2 (flown at 9:53 Eastern Standard Time)



B. Indian Head, Saskatchewan (Study fields outlined and identified in each flight line.)

Flight line 1, Pass 1 (flown at 11:10 Central Standard Time)



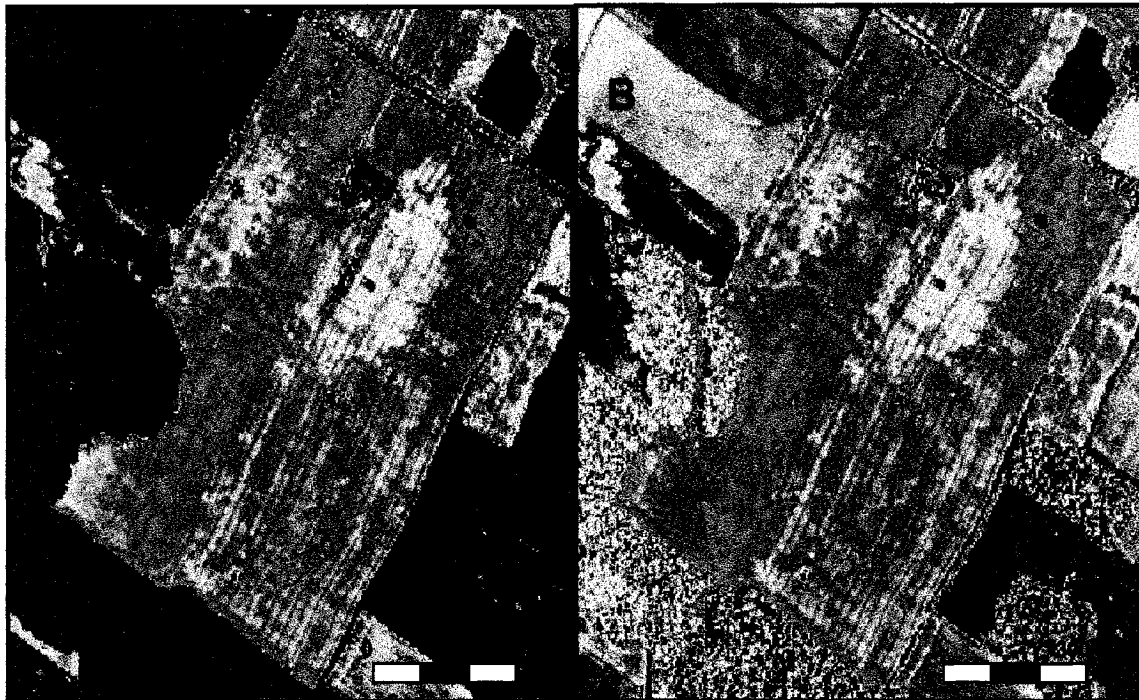
Flight line 1, Pass 2 (flown at 11:15 Central Standard Time)



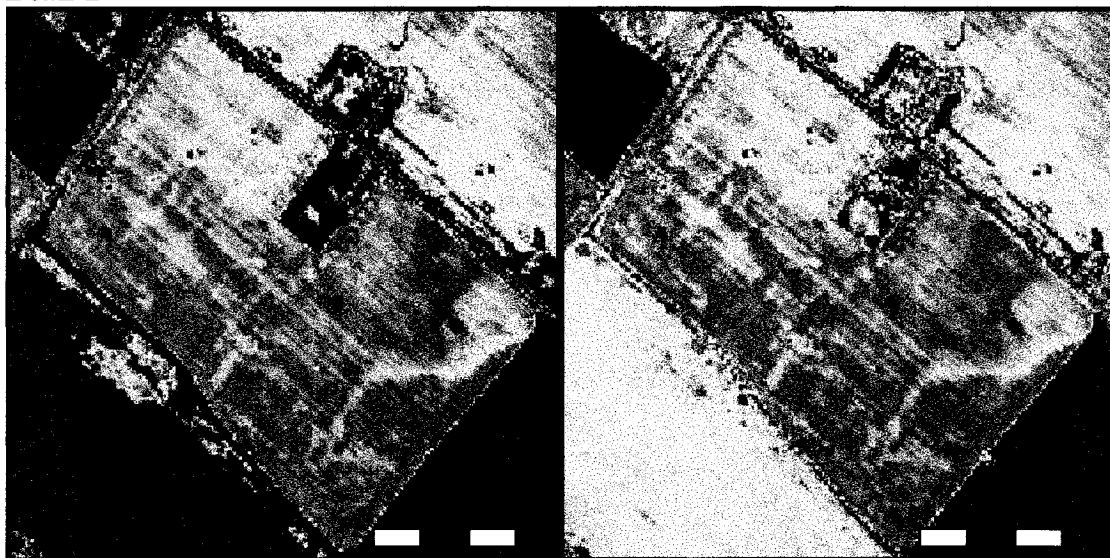
**APPENDIX II: PERCENT-CROP COVER FRACTION MAPS
DERIVED FROM CONSTRAINED (A) AND PARTIALLY-
CONSTRAINED (B) UNMIXING**

Clinton Site

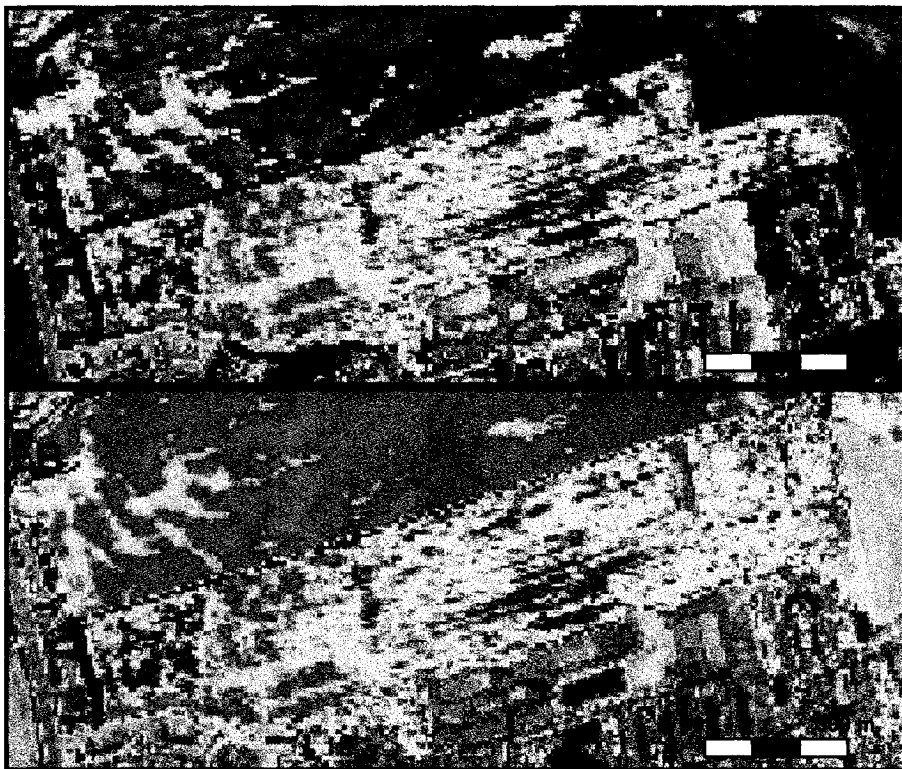
Bean-1



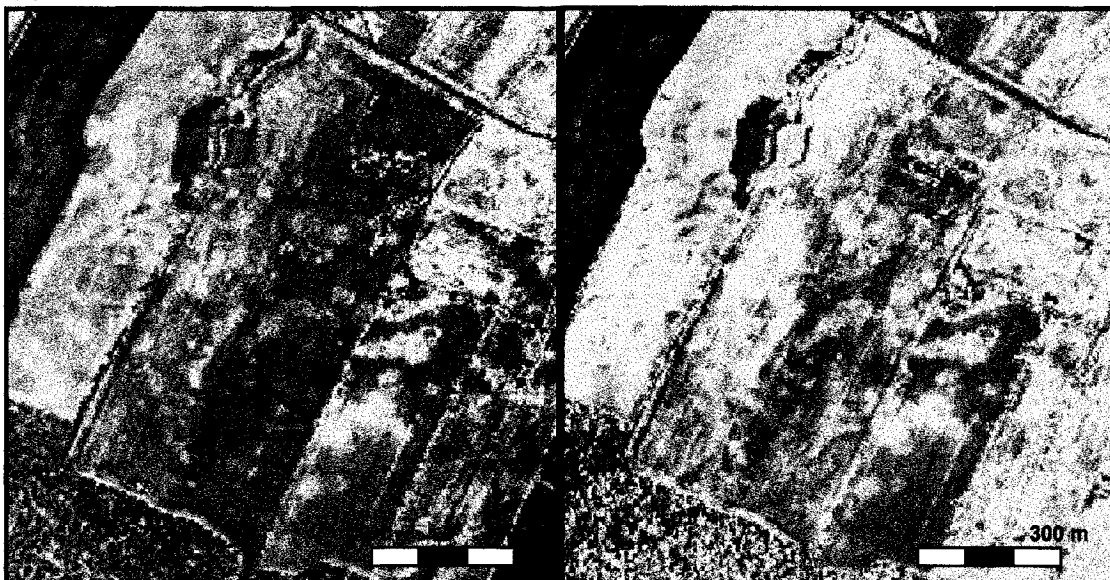
Bean-2



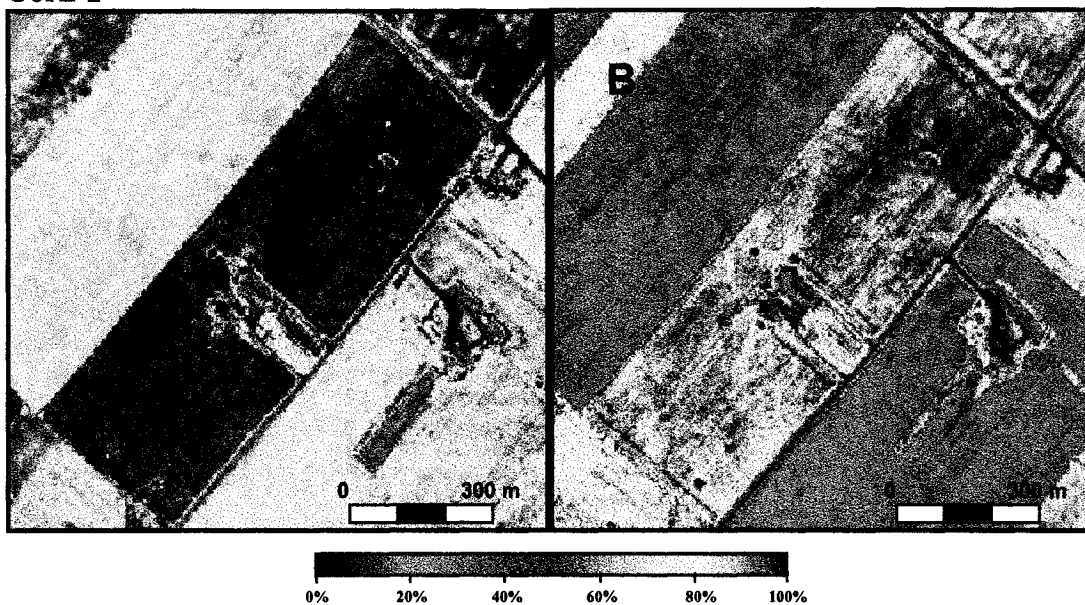
Bean-3



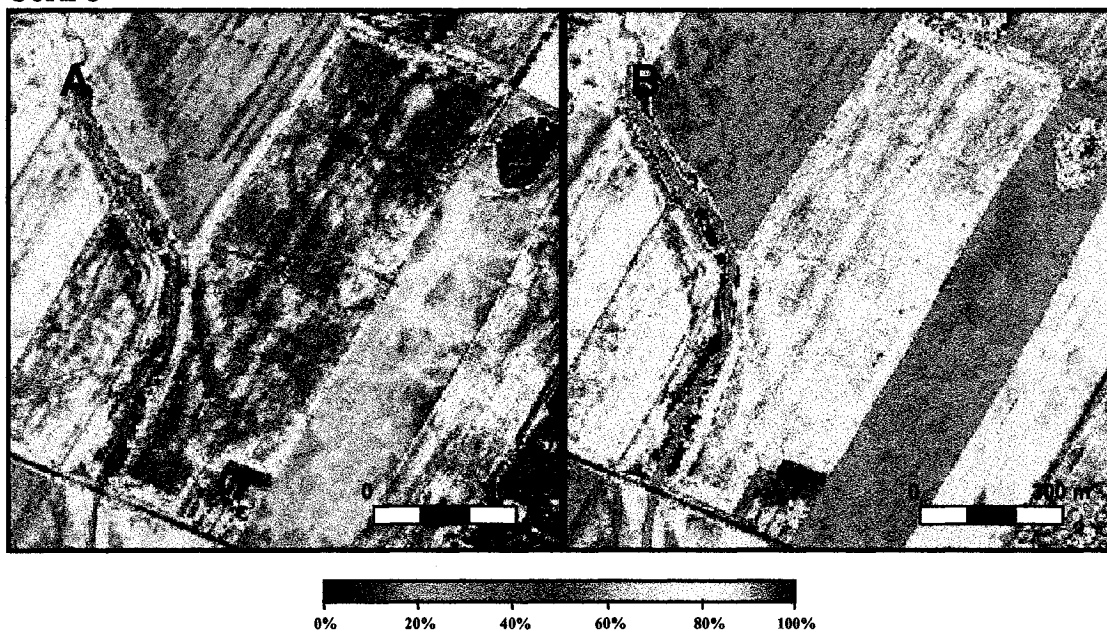
Corn-1



Corn-2

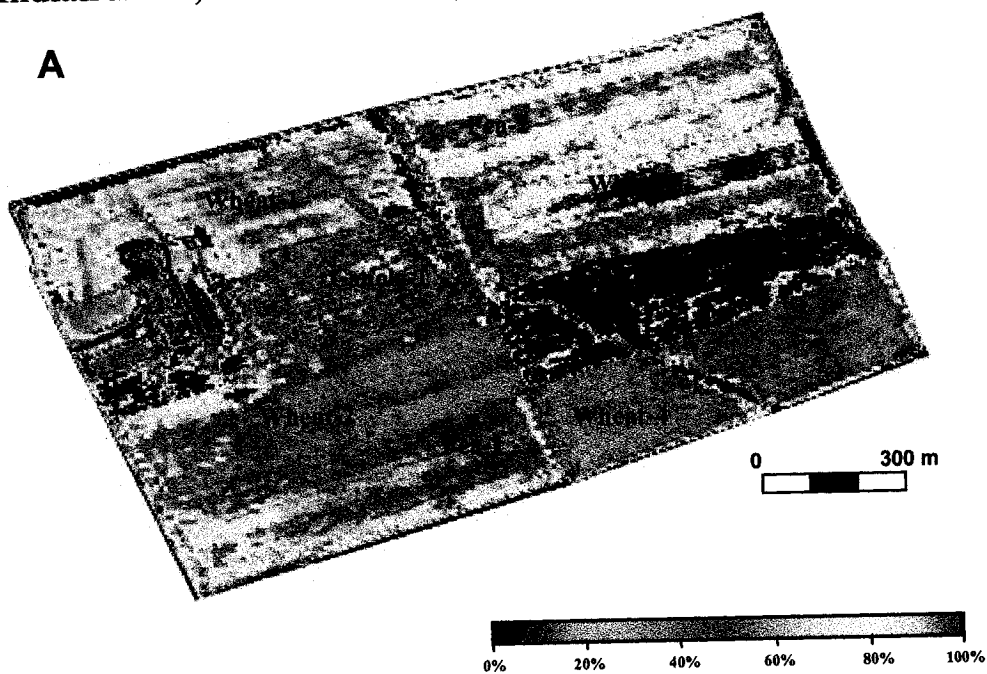


Corn-3

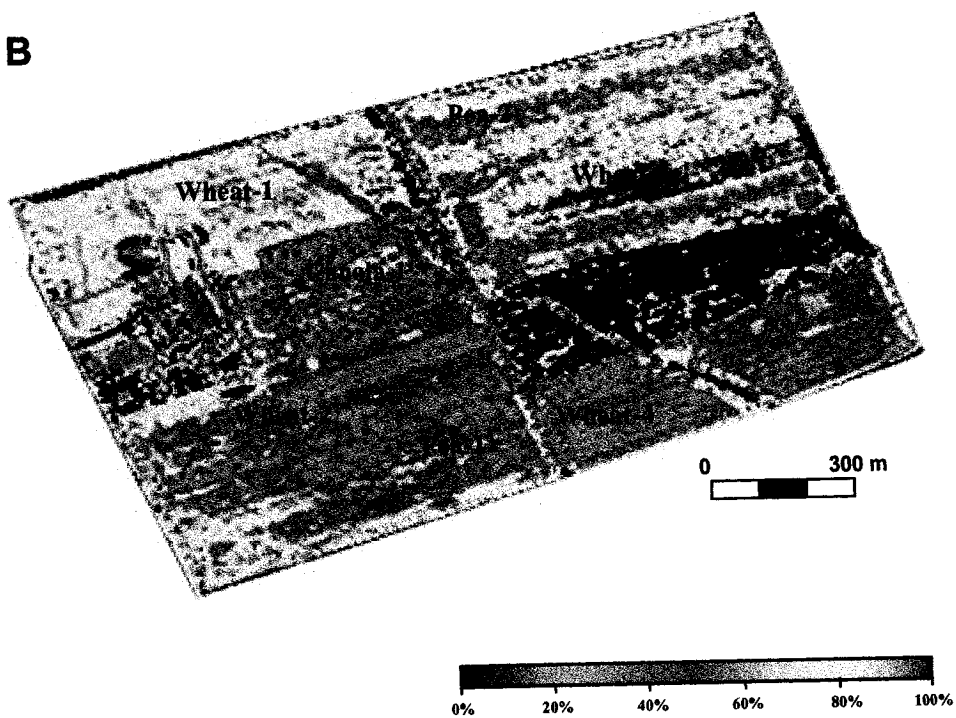


Indian Head, Saskatchewan (Pass 1)

A

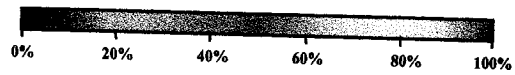
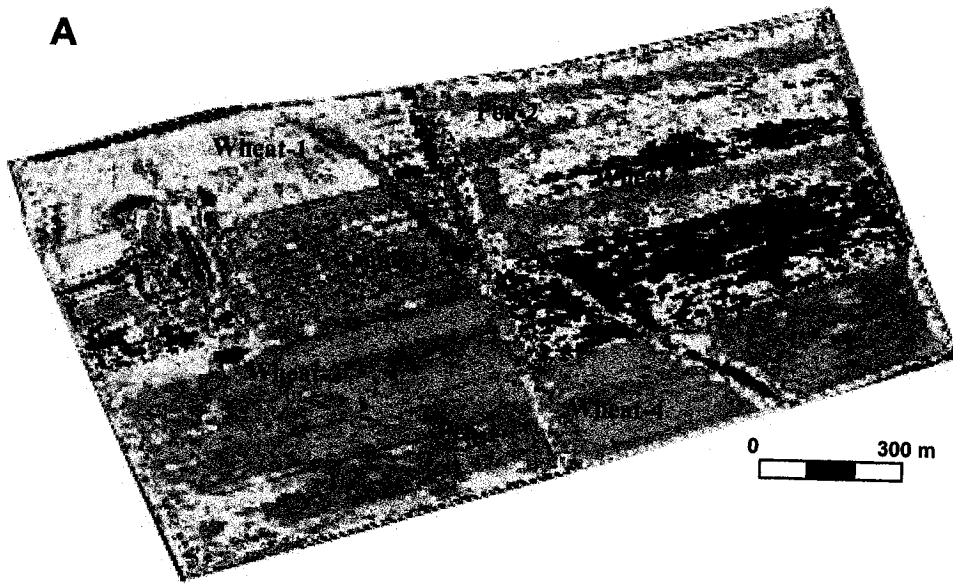


B

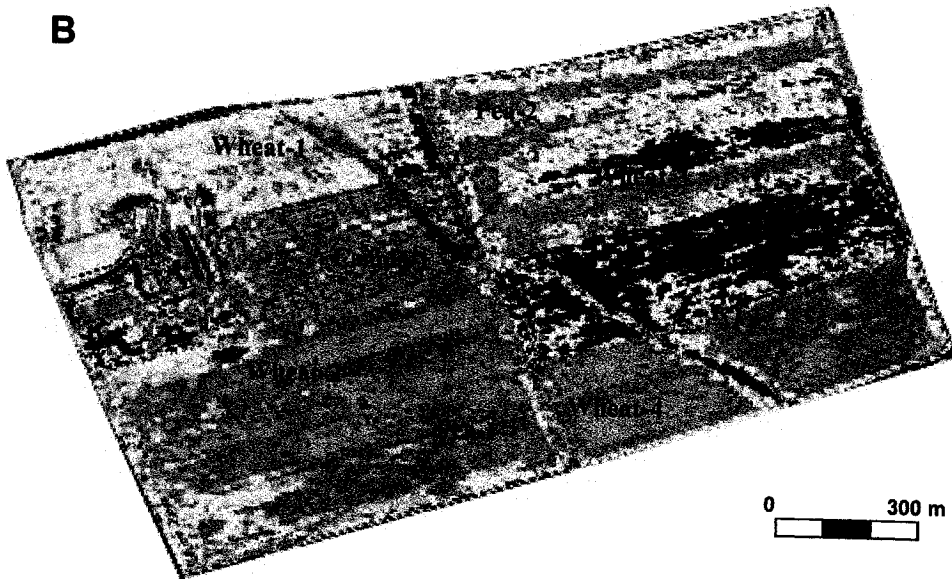


Indian Head, Saskatchewan (Pass 2)

A



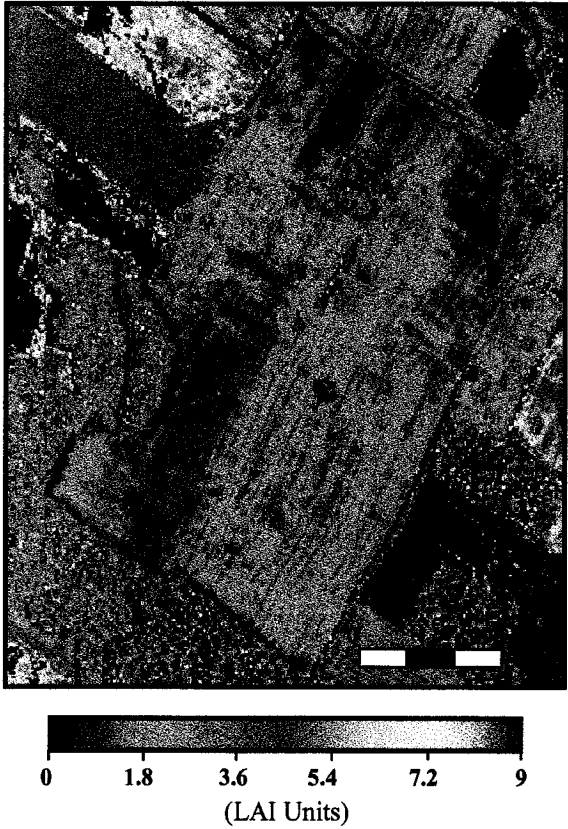
B



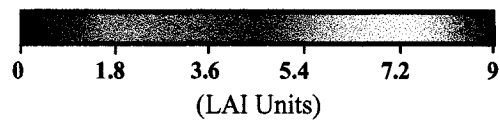
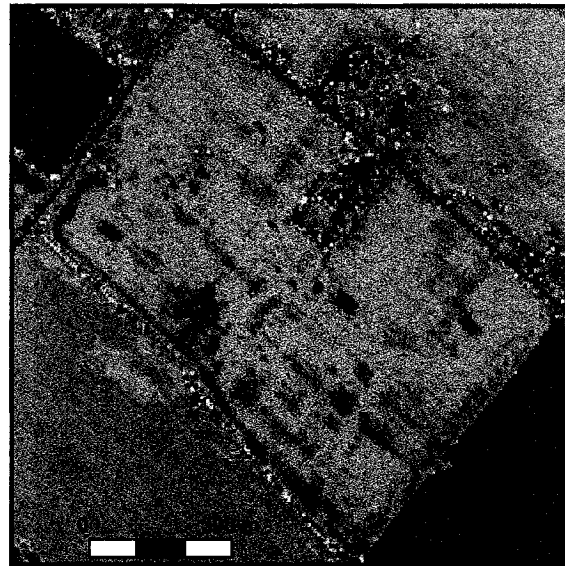
**APPENDIX III: LEAF AREA INDEX (LAI) MAPS DERIVED FROM
CROP FRACTION INVERSION USING PARTIALLY-CONSTRAINED
UNMIXING**

Clinton Site

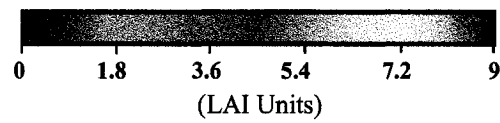
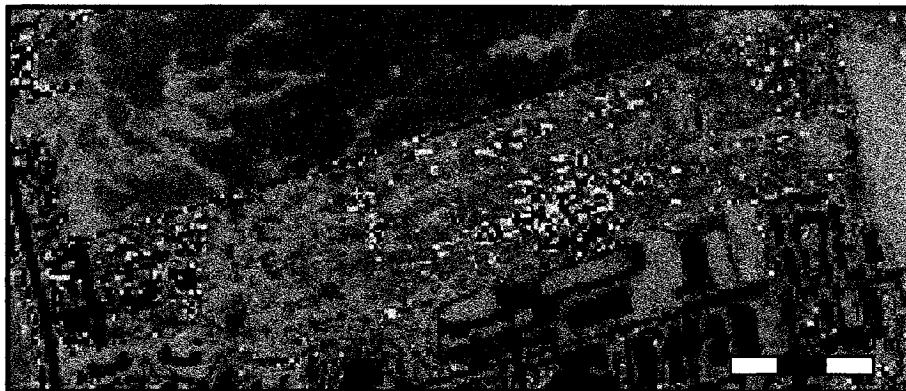
Bean-1



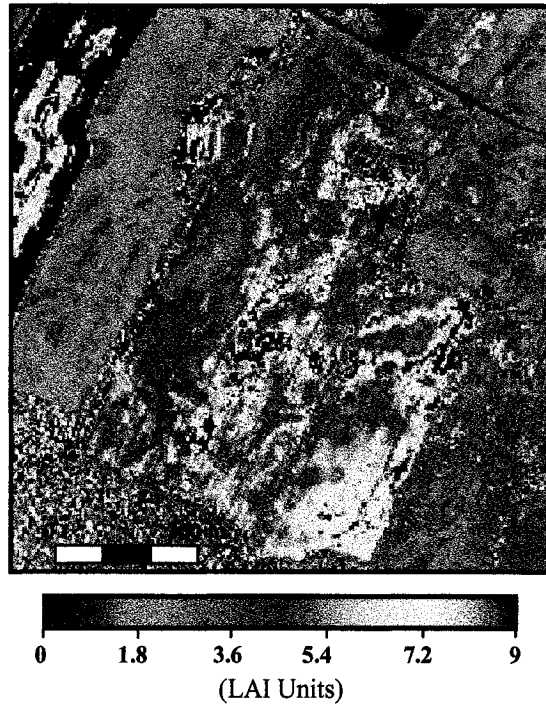
Bean-2



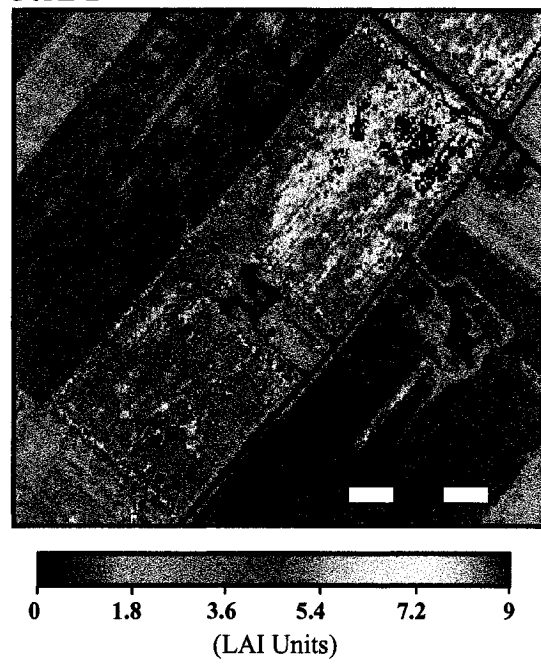
Bean-3



Corn-1



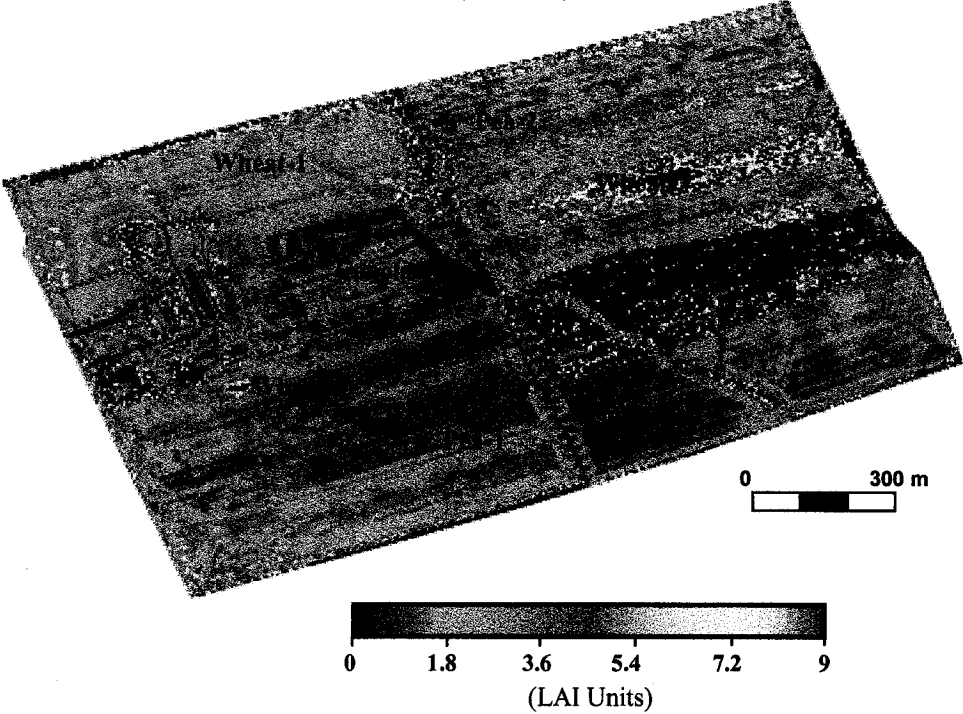
Corn-2



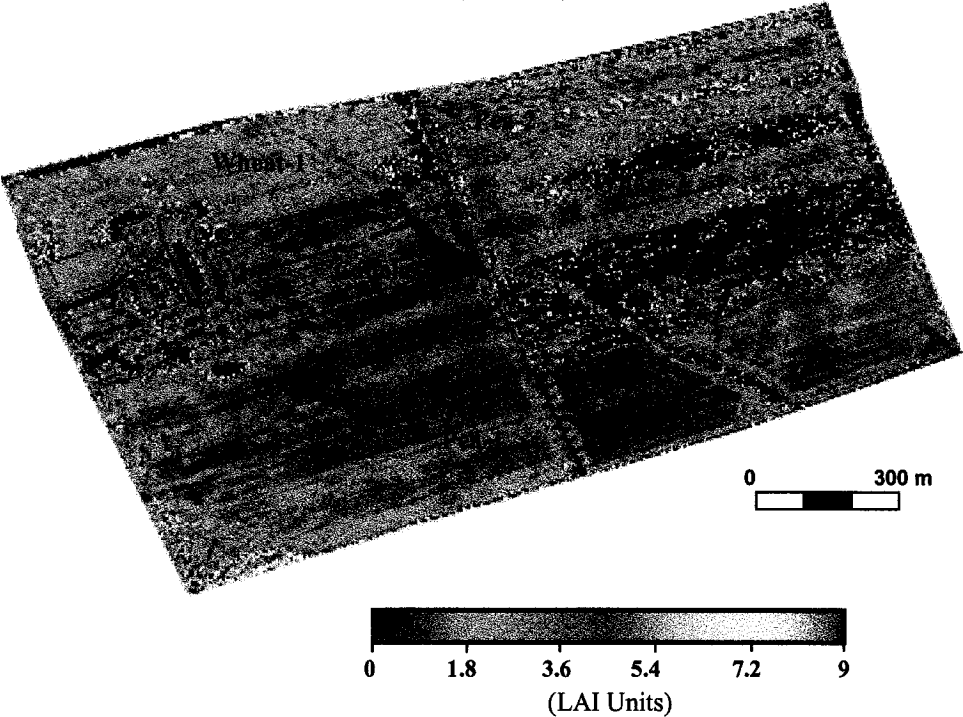
Corn-3



Indian Head, Saskatchewan (Pass 1)



Indian Head, Saskatchewan (Pass 2)



**APPENDIX IV: PAPER PRESENTED AT THE 8TH INTERNATIONAL
SYMPOSIUM ON PHYSICAL MEASUREMENTS & SIGNATURES IN
REMOTE SENSING, AUSOIS, FRANCE. 8-12 JANUARY, 2001.**

PP. 374-379.

http://www.ccrs.nrcan.gc.ca/ccrs/rd/sci_pub/bibpdf/13220.pdf

LAI MEASUREMENTS IN WHITE BEANS AND CORN CANOPIES WITH TWO OPTICAL INSTRUMENTS

Anna PACHECO¹, Abdou BANNARI¹, Karl STAENZ² and Heather MCNAIRN²

¹*Remote Sensing and Geomatics of Environment Laboratory
Department of Geography, University of Ottawa, P.B. 450, Succ. A,
Ottawa (Ontario) Canada K1N 6N5
E-mail : anna.pacheco@ccrs.nrcan.gc.ca
E-mail: abannari@uottawa.ca*

²*Canada Centre for Remote Sensing, 588 Booth Street,
Ottawa (Ontario) Canada K1A 0Y7
E-mail : heather.mcnairn@ccrs.nrcan.gc.ca
E-mail : karl.staenz@ccrs.nrcan.gc.ca*

ABSTRACT - Leaf Area Index (LAI) is a parameter used to describe the percentage of vegetation cover and to estimate productivity or yield of agriculture and forest canopies. LAI can be estimated using different techniques such as destructive sampling, vegetation indices and optical instruments. This paper investigates LAI measurements in white beans and corn canopies using two optical instruments, the LI-COR LAI-2000 and the Tracing Radiation and Architecture of Canopies (TRAC), a prototype instrument designed by the Canada Centre for Remote Sensing (CCRS). LAI estimates provided by each instrument are compared and analysed. Also, further investigation is done in regards to the percent crop cover data and LAI values from the LAI-2000 and the TRAC. Preliminary results indicate that LAI measurements with the LAI-2000 and the TRAC do not correlate very well. It was also found that LAI-2000's LAI estimates correlate better with the percent crop cover than the TRAC. Accordingly, the LAI-2000 provides LAI values that are more accurate than those provided with the TRAC.

1. INTRODUCTION

In the two last decades, there has been extensive developments of functional relations between crop characteristics and remote sensing that have been used in many agricultural studies. Agronomists, crop physiologists and crop modellers often use Leaf Area Index (LAI), a key parameter controlling biophysical processes of the vegetation canopy [Stae 00]. The LAI is defined as one half the total green leaf area per unit ground surface area [Chen 92]. This parameter is used in agricultural or forestry studies to describe the percentage of vegetation cover and to estimate productivity or yield [Mora 95; Boum 92; Wien 91]. The uncertainties in the LAI estimations with vegetation indices such as Normalized Difference Vegetation Index (NDVI) and Simple Ratio are often very large [Chen 95]. Direct measurements are also time consuming, expensive and destructive in their nature whereas indirect methods are more suitable and often used [Lebl 99]. One of these techniques includes optical instruments that are favoured by the speed of the data collection.

These instruments measure the penetrating light in the vegetation canopy where LAI is derived. Several instruments exist on the market such as the LI-COR LAI-2000 and the Tracing Radiation and Architecture of Canopies (TRAC), a prototype designed by the Canada Centre for Remote Sensing (CCRS). There has been numerous studies done in the forest environment with these two optical instruments. Although the LAI-2000 has been utilised before in some agricultural studies, the TRAC instrument has not been used in agricultural research. Both instruments measure LAI but not in the same fashion.

The LAI-2000 only takes gap fraction into account whereas the TRAC takes into consideration two elements of the canopy, the gap fraction and the clumping index. The gap fraction is the percentage of gaps in the canopy at a given solar zenith angle and the clumping index can be quantified by the difference between the measured gap fraction and the gap fraction after the gap removal [Chen 00]. When the clumping effects are not considered, the LAI is underestimated since it is based only on the gap fraction of the vegetation canopy. Therefore, the TRAC measures LAI while the LAI-2000 only measures effective LAI (eLAI). The main objective of this paper is to investigate the relationship between the LAI values from the two optical instruments with the percentage crop cover determined by vertical ground photographs in white beans and corn canopies.

2. MATERIAL AND METHODS

2.1. Study Site

The LAI data were acquired on agricultural sites in Clinton, Ontario, Canada (43° 40' N, 81° 30' W). Clinton is a rural area near Huron Lake, 20 km east of the town Goderich. This area is an agricultural region composed mainly of white beans, corn and grain (wheat and barley) fields. The field campaign was held from June 24 to July 8, 1999. These dates were chosen to ensure the plants were at a certain growth stage to facilitate LAI measurements.

2.2. Ground Data Collection

Two different crops were investigated, corn and white beans. LAI data were acquired from three fields of each crop type. Approximately ten sampling sites were selected per field according to within-field variability. Sample sites were located in different soil type, soil moisture, slope angle and aspect. The number of sample sites varied from one field to another in proportion to their surface area.

LAI measurements were carried out with two optical instruments, the LAI-2000 and the TRAC. Three LAI measurements were taken at each sample site in order to minimise errors and, thus, provide a good LAI average of the sample site. For the LAI-2000, 10 m transects were done diagonally between two plant rows whereas the TRAC measurements were done perpendicular to the plant rows. Each transect was 10 m in length in order to represent a surface area of 20 m² around the sample site. The LAI-2000 had to be used during overcast conditions or during sunrise or sunset. No measurements could have been made during periods of direct sun because the more sunlit

leaves the sensor can view, the larger are the underestimation of LAI. The LAI-2000 measures the attenuation of diffuse sky radiation at five zenith angles (7° , 23° , 38° , 53° and 68°) simultaneously [LI-C 90]. One reference measurement was taken above the canopy per sample site and four measurements were taken below the vegetation canopy. At each measurement, five canopy transmittance values are calculated from the five zenith angles of the optical sensor that is used to calculate foliage amount and foliage orientation. The LAI-2000 allows the estimation of eLAI, which does not consider the clumping index parameter. The clumping effect assumes that canopy foliage is spatially distributed according to a certain pattern [Chen 00].

The TRAC instrument also has specific operation conditions. Compared to the LAI-2000, the TRAC measurements have to be collected during a clear day. TRAC measurements are acquired along transects and the user has to walk at a steady pace, about 0.3 meter per second. This instrument measure transmitted direct light at a high frequency giving a time series of solar photosynthetic photon flux density along a certain transect. First, the TRAC has to take a reference measurement above the vegetation canopy and, subsequently the user has to walk along a transect and record measurements below the vegetation. These measurements determine different parameters such as LAI, eLAI, gap size and clumping index [Chen 00].

Finally, the percent crop cover was estimated from vertical photographs taken with a camera

mounted on a tripod following specific acquisition parameters. The focal length was 28 mm. The aperture was set at 22 mm while the camera viewed an area of 2.3 m^2 . Approximately 80 % of the sample sites were photographed. The photographs were taken within 3 to 4 meters of the sample site locations.

2.3. Methodology

LAI values and other parameters such as effective LAI were extracted from the LAI-2000 and the TRAC instruments. True LAI values will not be compared considering the LAI-2000 does not provide this parameter. Therefore, effective LAI from both instruments will be analysed.

The vertical photographs were digitised in three channels (blue, green and red) and processed with PCI ImageWorks. Unsupervised classification was carried out using ten classes: three classes for soil, three classes for leaf cover, two for residue, one for soil shadow, and one for leaf shadow. These classes were then aggregated to form three major components: leaf cover, residue, and soil. After the classification was done, percentage of leaf cover, soil cover and residue was estimated for each photograph.

Correlation between different variables is done using a Pearson coefficient that reflects the extent of a linear relationship between two data sets. Several correlations are examined in this paper such as eLAI values in regards to the LAI-2000 and the TRAC instrument. Also, the relationship between the percent crop cover from the ground data and eLAI values from the TRAC and the LAI-2000 is investigated. Finally, these different variables are also examined on a crop level. Since eLAI values from biomass sampling are not available, it is important to mention that percent crop cover is used as a reference.

3. RESULTS AND DISCUSSION

The correlation coefficient (r) between eLAI values from the LAI-2000 and the TRAC is presented in Figure 1. This figure demonstrates a positive but weak correlation of 0.38 between the two variables. It is also important to note that white beans have lower eLAI values (from approximately 0.5 to 1.5) while corn crops have higher eLAI values (from approximately 1.6 to 2.9) in both sets of data.

Figures 2 and 3 illustrate the relationship between the same two variables but on a corn and white bean level only. The relationship between the LAI-2000 and the TRAC is stronger in white bean crop ($r = 0.59$) than in corn ($r = -0.39$). The relationship is actually negative with respect to the corn crops. Similar results were obtained by Leblanc [00] when comparing LAI values for both instruments in deciduous forest canopies. LAI-2000's LAI was systematically lower than the TRAC values because the TRAC instrument takes into consideration a lower gap fraction and the foliage clumping. These results indicate that the LAI-2000 and the TRAC do not give the same eLAI values. Although, they are better correlated on the white bean crop than the corn, results still reveal a weak relationship between the two instrument measurements.

Furthermore, in order to examine which of the two instruments gives a more realistic view of ground LAI, eLAI values from the LAI-2000 and the TRAC were compared with the percentage of crop cover as illustrated in Figures 4 and 5. It is important to mention that although percent crop cover is not really an LAI value, it will provide us some indication of the foliage quantity, which is what LAI

measure. It is clearly demonstrated in these figures that percent crop cover is better correlated with eLAI values from the LAI-2000 ($r = 0.90$) than the TRAC ($r = 0.49$). The two correlation coefficients have a difference of 0.41, which is statistically significant. Qi *et al.* [97] also found a good relationship between plant projected areas determined by destructive sampling and LAI-2000 estimates. These results are encouraging for the use of the LAI-2000 instrument.

The percent crop cover and the LAI-2000's eLAI relationship was further investigated on a crop level. The results are depicted in Figures 6 and 7. They indicate a relationship with correlation coefficients of around 0.60, which are lower than considering all crops together. Accordingly, there is no particular difference between the white beans and the corn crops. The LAI-2000 instrument estimated both crops with the same accuracy even though the foliage architecture is different for both crops. Indeed, white beans have wider and rounder, but smaller leaves while the corn has leaves that are longer and narrower.

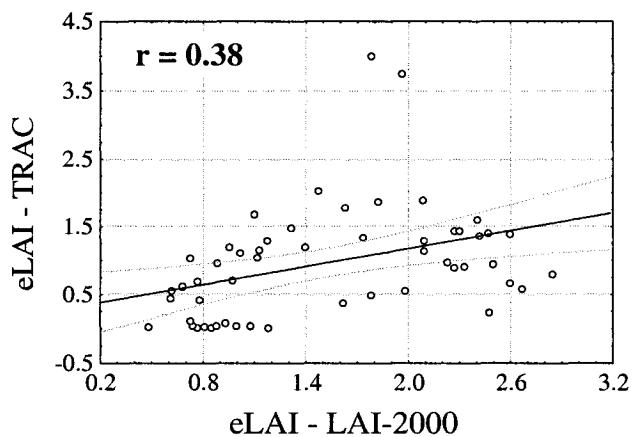


Figure 1. LAI-2000 eLAI versus TRAC eLAI of White Bean and Corn Canopies

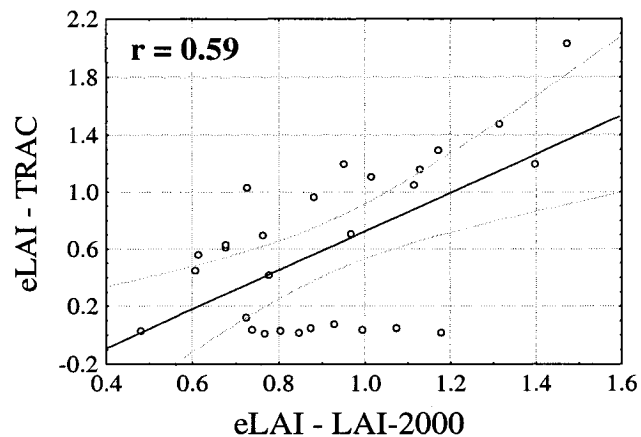


Figure 2. LAI-2000 eLAI of White Bean Canopies.

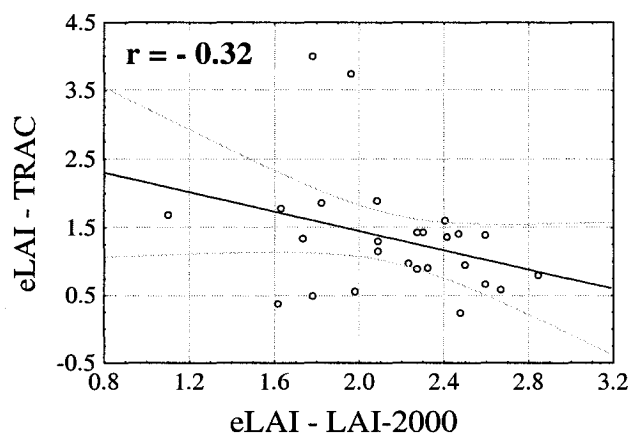


Figure 3. LAI-2000 eLAI versus TRAC eLAI of Corn Canopies.

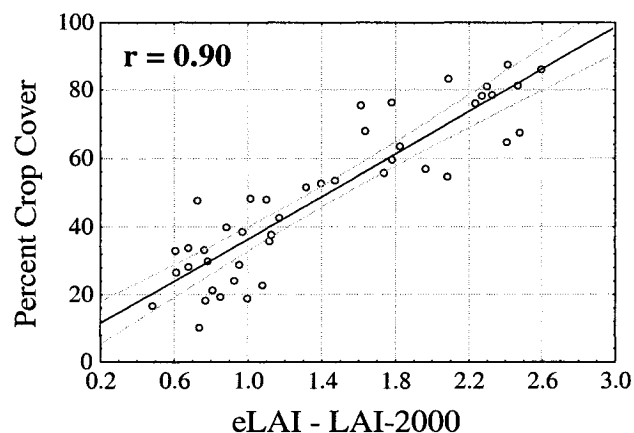


Figure 4. LAI-2000 eLAI versus of Percent Crop Cover of White Bean and Corn Canopies.

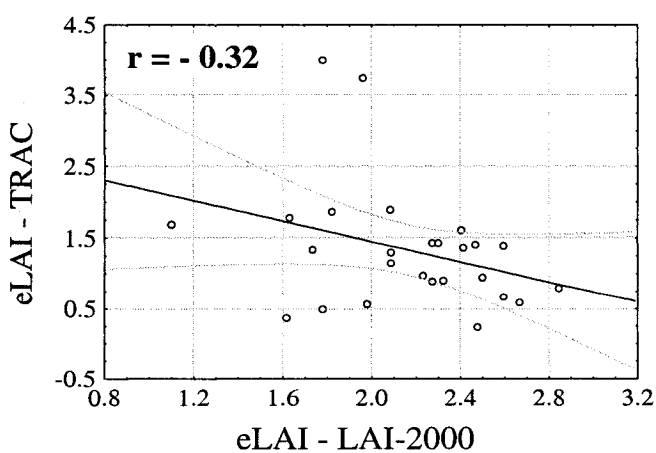


Figure 5. TRAC eLAI versus Percent Crop Cover in White Bean and Corn Canopies.

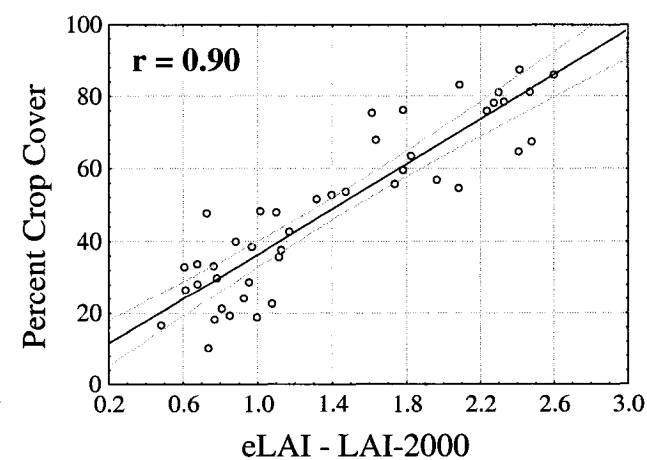


Figure 6. LAI-2000 eLAI versus Percent Crop Cover in White Bean Canopies.

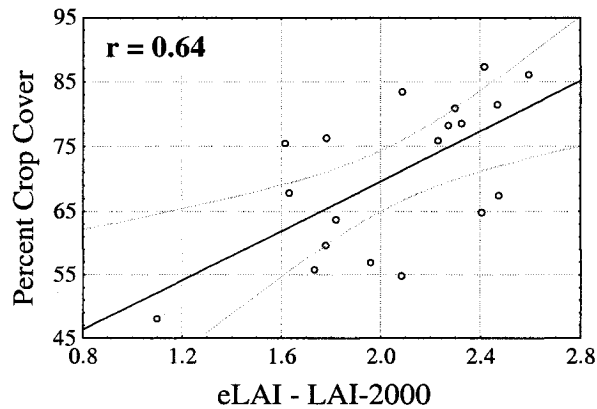


Figure 7. LAI-2000 eLAI versus Percent Crop Cover of Corn Canopies.

3. CONCLUSIONS

In this paper, the relationships between the LAI estimated from two optical instruments, the LAI-2000 and the TRAC, and the percent crop cover have been studied in two different crop canopies, white beans and corn. Preliminary results indicate that eLAI values extracted from the LAI-2000 and the TRAC do not correlate very well. Furthermore, LAI-2000's eLAI has been found to correlate better with the percent crop cover than the TRAC. Accordingly, the LAI-2000 provides eLAI values that are more accurate than those provided with the TRAC.

4. ACKNOWLEDGEMENTS

The authors would like to thank the Natural Sciences and Engineering Research Council of Canada (NSERC) and CCRS for their financial support. Thanks to Joanne Ellis (Noetix Research Inc.) for her contribution to the data processing and Jean-Claude Deguise and Sylvain Leblanc (CCRS) for their technical support.

5. REFERENCES

- [Boum 92] Bouman B.A.M., "Linking Physical Remote Sensing Models with Crop Growth Simulation Models, Applied for Sugar Beet", *International Journal of Remote Sensing*, Vol. 13, pp. 2565-2581.
- [Chen 92] Chen, J. M., T. A. Black: "Defining Leaf Area Index for Nonflat Leaves", *Plant Cell Environment*, Vol. 15, pp. 421-429.

- [Chen 95] Chen, J. M., J. Cihlar: "Plant Canopy Gap-Size Analysis Theory for proving Optical Measurements of Leaf Area Index", *Applied Optics*, Vol. 34, N. 27, pp. 6211-6222.
- [Chen 00] Chen, J.M., S.G. Leblanc, M. Kwong: "Manual for TRAC (Tracing Radiation and Architecture of Canopies", *Canada Centre for Remote Sensing*, 2000.
- [Lebl 98] Leblanc, S. G., J. M. Chen: "LAI Measurements in Deciduous and Coniferous Forests with Two Optical Instruments", Proceedings Scaling and Modelling in Forestry: Applications in Remote Sensing and GIS, International Workshop, March 19-21, 1998, University of Montreal, Montréal (Québec) Canada.
- [LI-C 90] LI-COR: "Instruction Manual for LAI-2000", *LI-COR*, 1990.
- [Mora 95] Moran, M.S., S.J. Maas, P.J. Pinter: "Combining Remote Sensing and Modeling for Estimating Surface Evapotranspiration and Biomass Production", *Remote Sensing Reviews*, Vol. 12, pp. 335-353.
- [Qi 97] Qi, J., M.S. Moran, P.J. Pinter, M. Helfert (1997) "Accuracy Assessment of LAI-2000 Instrument for Plant Projected Area and Biomass Estimations". USDA, Agricultural Research Service, Annual Research Report, Water Conservation Laboratory, Phoenix, Arizona (<http://www.uswcl.ars.ag.gov/publicat/index/QRS3.htm>).
- [Stae 00] Staenz, K., J.-C. Deguise, J. M. Chen, H. McNairn (2000) "Estimation of Leaf Area Index (LAI) from Crop Fraction Using Hyperspectral Data", *Submitted to International Society for Photogrammetric and Remote Sensing*.
- [Wieg 91] Wiegand, C.L., A.J. Richardson, D.E. Escobar, A.H. Gerbermann: "Vegetation Indices in Crop Assessments", *Remote Sensing of Environment*, Vol. 35, pp. 105-119.

**APPENDIX V: PAPER PRESENTED AT THE 23RD CANADIAN
SYMPOSIUM ON REMOTE SENSING , SAINTE-FOY (QUEBEC),
CANADA. 21-24 AUGUST, 2001. PP. 281-287.
http://www.ccrs.nrcan.gc.ca/ccrs/rd/sci_pub/bibpdf/13158.pdf**

APPLICATION OF HYPERSPECTRAL REMOTE SENSING FOR LAI ESTIMATION IN PRECISION FARMING

Anna Pacheco, Abdou Bannari

Remote Sensing and Geomatics of Environment Laboratory
Department of Geography, University of Ottawa, P.B. 450, Succ. A,
Ottawa (Ontario), Canada, K1N 6N5
E-mail : anna.pacheco@ccrs.nrcan.gc.ca
E-mail: abannari@uottawa.ca

Jean-Claude Deguise, Heather McNairn and Karl Staenz

Natural Resources Canada, Canada Centre for Remote Sensing, 588 Booth Street,
Ottawa (Ontario), Canada, K1A 0Y7
E-mail : heather.mcnairn@ccrs.nrcan.gc.ca
E-mail : jean-claude.deguise@ccrs.nrcan.gc.ca
E-mail : karl.staenz@ccrs.nrcan.gc.ca

Abstract

Leaf Area Index (LAI) is a key parameter controlling biophysical processes of the vegetation canopy. LAI helps to estimate productivity of agriculture and forest canopies, which can then serve as input to crop modelling. LAI can be measured using different approaches such as destructive sampling, optical ground-based instruments and optical imagery. Hyperspectral data has the advantage of distinguishing different target types within a pixel using spectral unmixing analysis as a tool to separate such spectral signatures. This paper investigates the relationship between ground-based effective LAI (eLAI) measurements estimated with the LI-COR LAI-2000 and eLAI values derived from Probe-1 hyperspectral surface reflectance data. This data were collected together with ground-based eLAI data during the summer of 1999 in Clinton, an agricultural area in South Western Ontario, Canada. The crops investigated for this study are corn and white beans. Correlations between ground eLAI and eLAI values derived from hyperspectral data produced encouraging results. Correlations were not strong when analysis was done on a single crop type. However, correlation results are good ($r = 0.91$) when data from all canopies are considered.

1. Introduction

Leaf Area Index (LAI) is a key parameter used to assess biophysical processes of the vegetation canopy. Defined as one half the total green leaf area per unit ground surface area (Chen and Black, 1992), LAI is used to describe the percentage of vegetation cover and to estimate productivity of agriculture and forest canopies. LAI can be estimated using different approaches such as destructive sampling, optical ground-based instruments and optical imagery. The

methods associated with multispectral data consider the total amount of the vegetation canopy in a pixel to estimate LAI. However, it is essential in agriculture to distinguish the crop from the other constituents such as residue and weeds in a pixel in order to estimate a more accurate LAI.

Hyperspectral remote sensing has the advantage of distinguishing different target types within a pixel and uses spectral unmixing analysis as a tool to separate spectral signatures. This paper

investigates the application of hyperspectral remote sensing to the estimation of LAI in the context of precision farming. The correlations between ground LAI measurements, estimated with the LI-COR LAI-2000 (LI-COR, 1990), and LAI values derived from Probe-1 hyperspectral surface reflectance data will be analysed.

2. Study Site

The LAI data were acquired from agricultural sites in Clinton, Ontario, Canada ($43^{\circ} 40' \text{ N}$, $81^{\circ} 30' \text{ W}$) (Figure 1). This area is an agricultural region composed mainly of bean, corn and small grain (wheat and barley) fields. The field campaign was carried out from June 24 to July 8, 1999. These dates were chosen to ensure the plants were at a certain growth stage to facilitate LAI measurements.

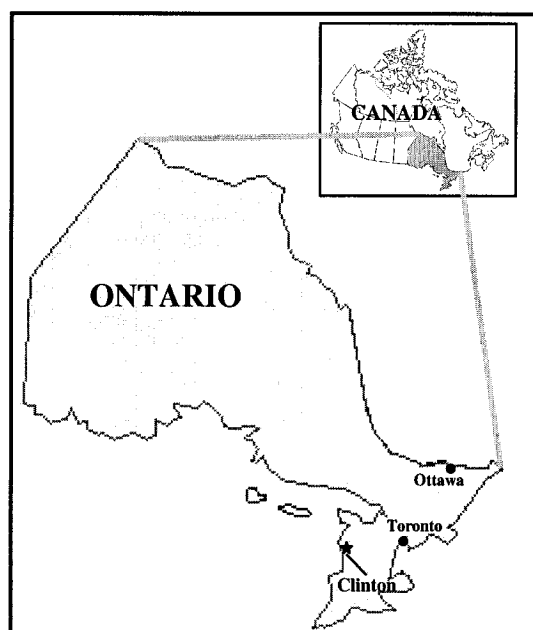


Figure 1: Study site location: Clinton, Ontario, Canada.

3. Data Acquisition

Two different crops were investigated, corn and white beans. LAI data were acquired from three fields of each crop type. In order to reflect within-field variability, approximately ten

sampling sites were selected per field: sampling sites were located in areas of different soil types and elevation. Ground-based LAI measurements and hyperspectral airborne data were acquired within a week to ensure both data sets were analogous for validation purposes.

3.1. Ground Data Collection

Ground LAI measurements were acquired using the LI-COR LAI-2000. The instrument algorithms only measures effective LAI (eLAI) (LI-COR, 1990). It does not take into consideration the clumping index of the crop canopy. The clumping effect assumes that canopy foliage is spatially distributed according to a non-random pattern (Chen and Cilhar, 1995). Using this same data set, previous research reveals that eLAI values acquired with the LAI-2000 have a very good correlation ($r = 0.90$) with percent ground cover (Pacheco *et al.*, 2001).

Three eLAI measurements were taken at each sampling site in order to minimise errors and, thus, provide a representative eLAI average of the sample site. Measurements were acquired along 2 m diagonal transects between two plant rows within an area of 2 to 3 m surrounding the centre of the sampling site. The LAI-2000 had to be employed during overcast conditions or periods of low sun angles (sunrise and sunset).

The LAI-2000 measures the attenuation of diffuse sky radiation at five zenith angles (7° , 23° , 38° , 53° and 68°) simultaneously (LI-COR, 1990). At each sampling site, one reference measurement was taken above crop canopy and four measurements were taken below. For each eLAI measurement, five canopy transmittance values are calculated from the five zenith angles of the optical sensor, which are utilised to calculate foliage amount and orientation.

3.2. Hyperspectral Airborne Data

Hyperspectral imagery was acquired over the Clinton area on July 7, 1999 with the Probe-1 hyperspectral airborne sensor (Earth Search Sciences Inc., 2001). The data were collected over the wavelength range from 430 nm to 2500 nm in 128 bands. The bandwidths at full width

of half maximum (FWHM) varies from 13 nm to 22 nm with a spectral sampling interval range of 10 nm to 20 nm. The aircraft was flown at an altitude of 2500 m resulting in a pixel size of 5 m by 5 m.

The Probe-1 sensor was mounted on an active 3-axis gyro-stabilized real time motion compensation system. A non-differential GPS was recording the location of the aircraft during the flight but no attitude measurements were made.

4. Analysis Approach

4.1. Data Preprocessing

The raw imagery was radiometrically calibrated using a reflectance-based vicarious calibration method (Secker *et al.*, 2001). Reflectance spectra from a uniform bare soil target were acquired using a GER3700 field spectroradiometer and applied with this method to generate a new set of calibrated gains to convert the raw digital numbers (DN) from Probe-1 to at-sensor radiance. Atmospheric correction was then performed on the calibrated radiance data. Surface reflectance was computed on the hyperspectral cubes using the surface reflectance retrieval procedure in Imaging Spectrometer Data Analysis System (ISDAS) (Staenz and Williams, 1997; Staenz *et al.*, 1998).

To preserve the spectral integrity of each pixel in the imagery, no geometric correction of the Probe-1 data was attempted. To locate the Probe-1 pixels where ground sampling was done in each field, a reversed image to image registration process was used. All sampling site locations were accurately measured with a differential GPS during the field campaign. The positions of these sites were digitally marked on a series of aerial ortho-photos of the area. These marked ortho-photos were then registered by a polynomial fit to the Probe-1 imagery until the boundaries of each field used in this study fit the boundaries of the same field in the original Probe-1 imagery. The pixel-line locations of the Probe-1 data of the sampling site markers were relocated by this

reverse process and used for the correlations between the eLAI derived from the hyperspectral data and the ground eLAI measurements presented in this paper.

4.2. Endmember Extraction and Spectral Unmixing

The first step in this method is to find the endmembers of the crop canopies, which are the basic spectral constituents of the pixels within the corn and white bean fields. Based on ground cover knowledge of these fields, three endmember spectra were manually extracted from the reflectance image cubes: vegetation (crop), soil and residue. Since the availability of pure pixels under natural field conditions is problematic, pure patches of soil, crop and residue were created on the fields (McNairn *et al.*, 2001). Endmember spectras were then extracted from the canopy within these 20 m by 20 m patches. Although these patches were not exactly “pure”, the selected endmember spectra were the “purest” spectra available from the data cube. Double crop density patches constituted about 80% crop and the residue patch did contain a small amount of green grass. However, soil patches were 100% soil.

A constrained linear spectral unmixing method was conducted on the hyperspectral data using an algorithm implemented in ISDAS (Staenz *et al.*, 1998). Spectral unmixing was done using the full spectral range from 430 nm to 2500 nm. For each field, reflectance cubes were unmixed using the endmembers mentioned previously. As a result, fraction maps were generated for the various endmembers.

4.2. eLAI Extraction and Validation

eLAI values were extracted from the hyperspectral data using an algorithm implemented in ISDAS (Staenz *et al.*, 2001). The crop fraction for each of the fields was used as in input to produce the eLAI map (Figure 2).

eLAI can be calculated according to this formula (Ross, 1981):

$$eLAI = \frac{\cos \alpha}{G} (-\ln P) \quad (1)$$

where P is the probability of a view line or a beam of radiation at an incidence angle α passing

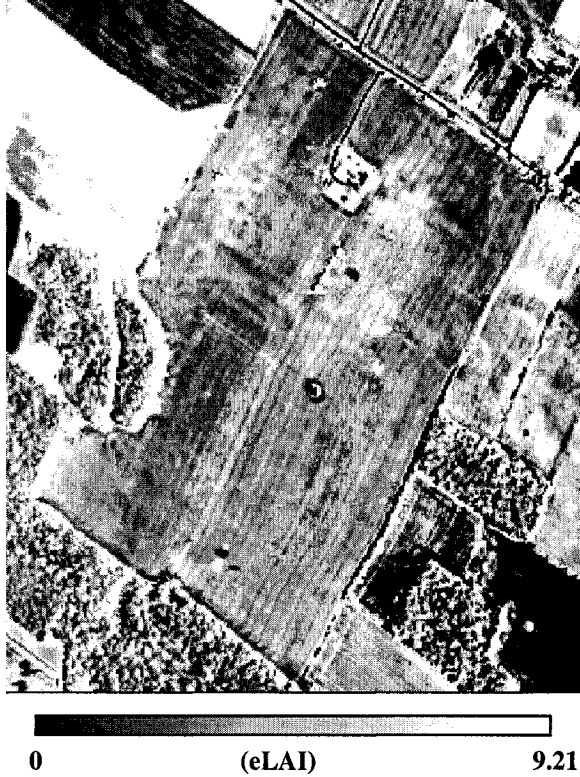


Figure 2: eLAI map of a white bean field derived from Probe-1 hyperspectral reflectance data.

through a horizontally uniform plant canopy with random leaf angular and spatial distribution and G is the mean projection coefficient of unit foliage area on a plane perpendicular to α .

To estimate eLAI from hyperspectral data, $G(\alpha)$ can be determined at 0.5 for plants which have randomly distributed leaf angles such as agricultural crops (Norman, 1979). The incidence angle α corresponds to the sensor viewing zenith angle. Probe-1 is usually flown at a view angle of 0° (nadir looking). Also, P represents the gap (non-vegetation) fraction, which is determined by spectral unmixing as follows:

$$P = 1 - f_c \quad (2)$$

where f_c is the fraction of the crop endmember. eLAI is then derived from hyperspectral data according to the following formula:

$$eLAI(f_c) = -2 \ln(1 - f_c) \quad (3)$$

For each sampling site, eLAI values were estimated using a 3 by 3 pixel window average centred on the sampling site markers. Correlations were generated between the eLAI estimates from the hyperspectral data and the ground eLAI measurements acquired with the LI-COR LAI-2000.

5. Results and Discussion

Results from the correlations between ground eLAI measurements using the LAI-2000 and eLAI values derived from the hyperspectral data cubes are presented in Table 1. Correlation coefficients were calculated for each crop type, white beans and corn, and on pooled data from all six fields. Correlations were not computed on a field-by-field basis since the number of sample points was too small and variability in eLAI values within a field was almost non-existent. Only ten sample points were chosen per field and thus, more sample points would be necessary and greater variability is required to generate a good valid relationship between ground eLAI and eLAI values derived from the hyperspectral data on a field-by-field basis.

The correlation coefficients generated for each crop type differ significantly. Indeed, the correlation between the ground eLAI measurements and the hyperspectral eLAI values are much higher for the corn ($r = 0.69$) than for the white beans ($r = 0.16$) (Figures 3 and 4). The difference of growth stage between the two crops was important: the three corn fields were much more developed than the white beans. Since the white bean crops were small in size, errors might have occurred when ground eLAI measurements were taken with the LAI-2000. In fact, the LAI-2000 instrument determines eLAI values and estimates simultaneously a standard error for the eLAI determination (SEL). It was noted that SEL values were considerably higher for white beans. Corn fields have an average SEL value of

0.04 in comparison to 0.47 for white beans. The low correlation between ground eLAI and eLAI values derived from the hyperspectral data can also be justified by the limitations in the endmember selection. Most of the fields were using the “purest” pixels of endmembers extracted from other fields of the same crop to perform spectral unmixing. Although selecting endmembers directly from the reflectance cube itself was the best method available for endmember extraction, it could have generated some errors in the output of eLAI values from the hyperspectral data.

Finally, when all corn and white beans canopies are considered, the correlation coefficient ($r = 0.91$) between ground eLAI and eLAI values derived from the hyperspectral data is quite good (Figure 5). Although correlation results are good between ground eLAI and eLAI derived from hyperspectral data, they do not translate into a perfect linear relationship. The eLAI values derived from the remote sensing data overestimates eLAI in comparison with eLAI values measured from the LAI-2000 instrument. The range of eLAI values is also greater for eLAI estimated from hyperspectral data than from LAI-2000. These problems can be observed on all correlation figures (Figure 3, 4 and 5). Further investigation is necessary in order to improve understanding of eLAI estimation from hyperspectral data. Nevertheless, preliminary results are very encouraging for the estimation of eLAI from hyperspectral remote sensing data.

Crop Canopies	Correlation Coefficient (r)*
White Bean Fields	0.16
Corn Fields	0.69
All Canopies	0.91

*All correlations were significant at a probability level of <0.05 .

Table 1: Correlations between ground eLAI measurements and eLAI values derived from the PROBE-1 hyperspectral data.

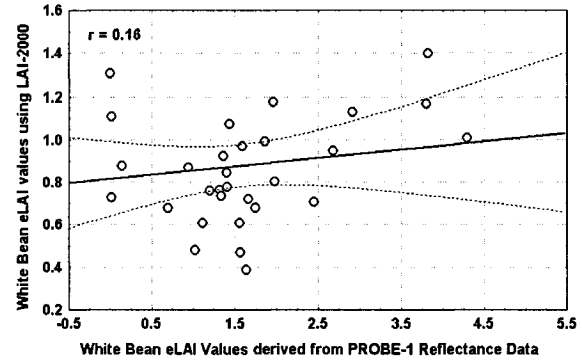


Figure 3: Correlations between ground eLAI measurements and eLAI values derived from the PROBE-1 hyperspectral data for white bean canopies.

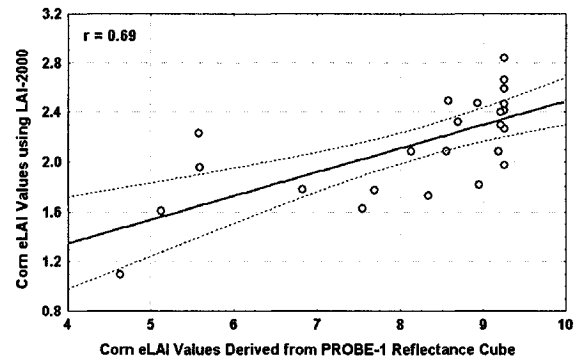


Figure 4: Correlations between ground eLAI measurements and eLAI values derived from the PROBE-1 hyperspectral data for corn canopies.

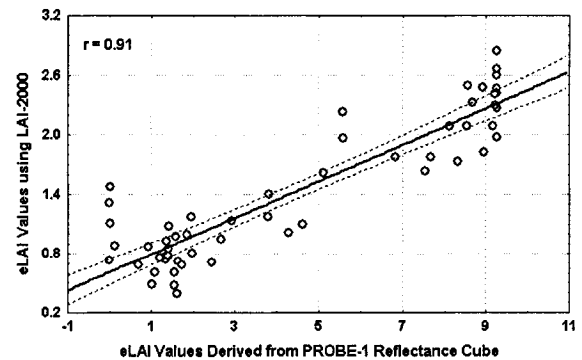


Figure 5: Correlations between ground eLAI measurements and eLAI values derived from the PROBE-1 hyperspectral data for white bean and corn canopies.

6. Conclusions

Probe-1 hyperspectral data were acquired over the Clinton, Ontario area in 1999. Study site includes three white bean and three corn canopies. Simultaneous with the Probe-1 acquisition, ground eLAI measurements were taken using the LI-COR LAI-2000. eLAI values were estimated from the crop fraction once spectral unmixing was conducted. Preliminary results indicate a good relationship between ground-based eLAI and eLAI derived from hyperspectral data. For each individual field, correlations were not calculated since within-field variability was almost non-existent. Results demonstrate a very low correlation between ground eLAI and eLAI derived from hyperspectral data in white bean canopies. Plants from this crop type were not very developed at the time of the measurements and consequently, a greater error is present in the eLAI values. Also, limitations with the endmembers selection may introduce an error in the eLAI estimates from hyperspectral data. In regards to corn canopies, correlation coefficient indicates an interesting relationship. Thus, hyperspectral data was sensitive to variability in ground eLAI values from different canopies. However, this method should be tested on a multi-temporal data set where greater variability is either existent or induced. Nevertheless, correlation between ground eLAI values and eLAI estimates derived from the hyperspectral data reveals a good relationship and demonstrates encouraging results for future analysis.

7. Acknowledgements

The authors would like to thank the Canada Centre for Remote Sensing (CCRS) and the Natural Sciences and Engineering Research Council of Canada (NSERC) for their financial support. Special thanks to Rob Hitchcock at CCRS for performing the atmospheric correction of the PROBE-1 data. The authors also acknowledge the support of Christian Nadeau for his technical assistance with ISDAS.

8. References

- Chen, J.M. and Black, T.A. (1992), "Defining Leaf Area Index for Nonflat Leaves", *Plant Cell Environment*, 13:2565-2581.
- Chen, J.M. and Cihlar, J. (1995), "Plant Canopy Gap-Size Analysis Theory for Improving Optical Measurements of Leaf Area Index", *Applied Optics*, 34 (27): 6211-6222.
- Earth Search Sciences Inc., (2001), About Probe-1, www.earthsearch.com/technology.
- LI-COR (1990), "Instruction Manual for LAI-2000", *LI-COR*.
- McNairn, H., Deguise, J.-C., Pacheco, A., Shang, J. and Rabe, N. (2001), "Estimation of Crop Cover and Chlorophyll From Hyperspectral Remote Sensing", (Submitted to the 23rd Canadian Symposium on Remote Sensing, Quebec, Canada, August 21-24).
- Norman, J.M. (1979), "Modelling the Complete Crop Canopy", Int. B.J. Barfield and J.F. Gerber (Editors), Modification of the Aerial Environment of Plants, *American Society of Agricultural Engineers*, St. Joseph, Michigan, 249-277.
- Pacheco, A., Bannari, A., Staenz, K. and McNairn, H. (2001), "LAI Measurements in White Beans and Corn Canopies With Two Optical Instruments", 8th International Symposium on Physical Measurements & Signatures in Remote Sensing", Aussois, France, January 8-12, 374-379.
- Ross, J. (1981), "The Radiation Regime and Architecture of Plant Stands", *Dr. W. Junk Publishers*.
- Secker, J., Staenz, K., Gauthier, R.P. and Budkewitsch B. (2001), "Vicarious calibration of airborne hyperspectral sensors in operational environments", *Remote Sensing of Environment*, 76: 81-92.

Staenz, K., Deguise, J.-C., Chen, J.M. and McNairn, H. (2001), "Estimation of Leaf Area Index (LAI) from Crop Fraction Using Hyperspectral Data", (*Submitted to the ISPRS Journal*).

Staenz, K. and Williams, D.J. (1997) "Retrieval of Surface Reflectance from Hyperspectral Data

Using a Look-up Table Approach", *Canadian Journal of Remote Sensing*, **23** (4): 354-368.

Staenz, K., Szeredi, T. and Schwarz J. (1998) "ISDAS – A System for Processing/ Analyzing Hyperspectral Data", *Canadian Journal of Remote Sensing*, **24** (2): 99-113.

**APPENDIX VI: PAPER PRESENTED AT THE 1ST INTERNATIONAL
SYMPOSIUM ON RECENT ADVANCES IN QUANTITATIVE REMOTE
SENSING, TORRENT (VALENCIA), SPAIN.
16-20 SEPTEMBER, 2002. PP. 210-215.**

VALIDATING LAI USING HYPERSPECTRAL IMAGERY OVER AGRICULTURAL CANOPIES

Anna Pacheco^{1*}, Abdou Bannari¹, Karl Staenz², Heather McNairn² and Jean-Claude Deguise²

¹*Remote Sensing and Geomatics of Environment Laboratory, Department of Geography, University of Ottawa, P.O. Box 450, Stn. A, Ottawa (Ontario), Canada, K1N 6N5.*

²*Canada Centre for Remote Sensing, Natural Resources Canada, 588 Booth St., Ottawa (Ontario), Canada, K1A 0Y7.*

*corresponding author: anna.pacheco@ccrs.nrcan.gc.ca

ABSTRACT *Hyperspectral remote sensing has gone through rapid development over the past two decades and interest is growing in the application of hyperspectral data to precision farming. Defined as one half the total green leaf area per unit ground surface area, Leaf Area Index (LAI) is a key parameter controlling biophysical processes of the vegetation canopy. LAI can be estimated using different approaches but only hyperspectral remote sensing has the potential to distinguish effectively the crop from other field components. The objective of this study is to validate eLAI estimation of agricultural canopies from Probe-1 airborne hyperspectral data acquired over two agricultural sites in Canada, near Clinton (Ontario) and Indian Head (Saskatchewan) during the growing seasons of 1999 and 2000, respectively. Using the LAI-2000 (LI-COR), ground eLAI measurements were collected simultaneously to the image acquisitions on various crops (corn, white beans, wheat, canola and peas). Preliminary results indicate that hyperspectral data was sensitive to variability in ground eLAI values from different canopies and demonstrates encouraging results for future analysis.*

1 INTRODUCTION

Hyperspectral remote sensing has gone through rapid development over the past two decades and interest is growing in its application to precision farming. However, crop growth is very dynamic and monitoring the condition of agricultural crops is challenging. Leaf Area Index (LAI) is a key parameter used to assess biophysical processes of the vegetation canopy. Defined as one half the total green leaf area per unit ground surface area (Chen and Black, 1992), LAI is used to describe the percentage of vegetation cover and to estimate productivity or yield of the vegetation canopies. LAI can be estimated using different approaches such as destructive sampling, optical ground-based instruments and optical remote sensing imagery. The techniques associated with multispectral

data consider the total amount of the vegetation canopy to estimate LAI. Within this context, it is essential for agricultural applications to distinguish the crop from the other vegetation such as weeds or volunteer crops present in a pixel in order to estimate a more accurate LAI. Hyperspectral data has the advantage of discriminating different target materials within a pixel using spectral unmixing analysis.

The objective of this study is to validate LAI estimation of agricultural canopies using hyperspectral imagery in the context of precision farming. More specifically, this research paper will investigate the correlation between ground eLAI measurements estimated with the LAI-2000 (LI-COR), an optical instrument often used to measure LAI in agricultural and forest canopies, and eLAI values derived from hyperspectral imagery. As a result, a model developed by Staenz *et al.* (2002) for the estimation of LAI using

hyperspectral data will be tested on various agricultural crops (white beans, corn, wheat, canola and peas). This model requires the input of crop endmember fractions, which are derived from spectral unmixing. This technique is successfully used in geological and environmental applications (Staenz *et al.*, 2000; Lévesque *et al.*, 2000; Nadeau, 2002) but has not been rigorously validated for agricultural applications. This study will also examine the potential of spectral unmixing to determine percent crop cover estimates on a crop-by-crop basis.

2 MATERIAL AND METHODS

LAI data and airborne hyperspectral imagery were acquired from two agricultural sites in Canada characterized by various crop types and site conditions. Field campaigns were carried out during the growing seasons in Clinton, Ontario (43° 40' N, 81° 30' W) in 1999 and in Indian Head, Saskatchewan (50° 33' N, 103° 36' W) in 2000.

At the Clinton site, six fields were chosen for ground validation measurements: three white bean (*Phaseolus vulgaris* L.) and three corn (*Zea mais* L.) fields. Surface cover in these fields included crop vegetation, residue from the previous crop and soil. In order to facilitate spectral unmixing analysis of the hyperspectral imagery, 20 m by 20 m pure patches of double seeded crop, soil and residue were established in some of the fields at the beginning of the season.

For the Indian Head site, fields used for ground validation purposes were located on the precision agricultural test farm of the Indian Head Agricultural Research Foundation (IHARF). Eight fields were selected for intense sampling: four wheat (*Triticum aestivum* L.), two canola (*Brassica napus* L.) and two pea (*Lathyrus aphaca* L.) fields. Crop vegetation, residue and soil constituted ground surface coverage for these fields. Similarly to the Clinton site, crop patches were selected within the aforementioned fields while soil and residue patches were established in an adjacent field.

Ground-based measurements and hyperspectral airborne data were acquired within a week to ensure both data sets were analogous for validation purposes. Between 9 and 13 sampling sites were selected per field in order to reflect within-field variability. These sites were chosen based on elevation and soil maps.

2.1 Ground Data Collection

Ground LAI measurements were collected using the LAI-2000 (Plant Canopy Analyser, LI-COR) which

estimates LAI as a function of incoming diffuse solar radiation at the top and at the bottom of the vegetation canopy. These estimates were made at five zenith angles (7°, 23°, 38°, 56° and 68°) simultaneously (LI-COR, 1990). Therefore, the LAI-2000 was utilized during overcast conditions only. It is also important to consider that the instrument measures the effective LAI (eLAI) by making the assumption of a random spatial distribution of leaves (Chen and Cihlar, 1995). However, regular and equal spacing of crop plants in agricultural canopies reduces this effect considerably.

Three eLAI measurements were taken at each sampling site to minimise errors and thus, provide a representative eLAI average of the area. Measurements were acquired along 2 m diagonal transects between two plant rows within an area of 2 to 3 m surrounding the centre of the sampling site. For each set of measurements, one reference was taken above the crop canopy and four measurements were acquired below. Five canopy transmittance values are then calculated from the five zenith angles of the optical sensor, which are utilised to determine foliage amount and orientation.

Percent ground cover was calculated from vertical photographs taken with a 35-mm camera equipped with a 28-mm lens. The camera was mounted on an overhead mast at a height of 2 m above ground. In this configuration, the camera viewed a ground area of approximately 4 m². Photographs were taken 3 to 4 m from the centre of the sample site locations. Three photographs were taken at each sampling site in order to obtain percent ground cover representative of the area covered by one hyperspectral imagery pixel.

2.2 Image Data Acquisition and Preprocessing

Airborne hyperspectral Probe-1 (Earth Search Sciences Inc., 2001) imagery were acquired on July 7, 1999 and on June 28, 2000 for the Clinton and the Indian Head test sites respectively. The Probe-1 is a "whiskbroom style" instrument that collects data in a cross-track direction by mechanical scanning and in an along-track direction by movement of the airborne platform. This sensor collects upwelling radiance from 128 bands in the visible and near infra-red (VNIR) and short-wave infra-red (SWIR) wavelength regions from 437.9 nm to 2056.7 nm almost continuously. The bandwidths at full width of half maximum (FWHM) varies from 13.3 nm to 22.3 nm with a spectral sampling interval of 10.7 nm to 19.8 nm. The aircraft was flown at an altitude of 2500 m above ground resulting in a swath width of 2.56 km (512 pixels) and a spatial resolution of 5 m at nadir.

The Probe-1 sensor was mounted on an active 3-axis gyro-stabilized real-time motion compensation system. A non-differential GPS was recording the location of the aircraft during the flight but no attitude

measurements were made. To preserve the spectral integrity of each pixel in the imagery, no geometric correction of the Probe-1 data was made. A reversed image-to-image registration process was used to locate the Probe-1 pixels where ground samples were acquired. During the field campaign, all sampling site locations were accurately measured with a differential GPS unit. The position of these sites were digitally marked on a series of aerial ortho-photos of the area for the Clinton dataset and on a panchromatic ortho-rectified Ikonos image for the Indian Head site. The marked ortho-photos and the ortho-rectified Ikonos image were then registered using a polynomial fit to the Probe-1 imagery. The pixel-line locations of the sampling site markers on the Probe-1 imagery were relocated by this reverse process and used for the correlations between the crop fractions and eLAI values derived from the hyperspectral data and the percent crop cover and ground eLAI measurements presented in this paper.

Image preprocessing was carried out using the Imaging Spectrometer Data Analysis System (ISDAS), a software package developed at the Canada Centre for Remote Sensing utilized for hyperspectral data processing and analysis (Staenz *et al.*, 1998). The Probe-1 raw digital numbers (DN) were first radiometrically calibrated using a reflectance-based vicarious calibration technique (Secker *et al.*, 2001). Reflectance spectra from an uniform target were acquired with a GER-3700 field spectroradiometer and used with this technique to generate a new set of gains to convert the DNs to radiance. A bare soil patch was selected as such a target for the Clinton site while an asphalt area was employed for the Indian Head site. These recalibrated radiance data were then converted to reflectance using the surface reflectance retrieval procedure implemented in ISDAS (Staenz and Williams, 1997).

3 ANALYSIS APPROACH

The vertical ground photographs were digitised in three channels (blue, green and red) and processed with PCI ImageWorks (PCI Geomatics, 1997) for classification purposes. An unsupervised classification was carried out using ten classes: three classes for soil, three for leaf cover, two for residue, one for soil shadow, and one for leaf shadow. These classes were then aggregated to form three major components: leaf, residue and soil cover. Once the classification was completed, percentages of leaf, soil and residue cover were determined for each photograph and averaged per sampling site to finally determine the percent ground cover.

Constrained linear spectral unmixing was performed on the hyperspectral data using an algorithm implemented in ISDAS (Staenz *et al.*, 1998).

Endmember spectra were selected and manually extracted from the reflectance image data based on knowledge of the fields. For the Clinton data set, these spectra were extracted from the pure patches created intentionally for the purpose of endmember selection and from specific areas of the fields where there is a high pixel purity level. Crop density patches were not “pure” but did constitute about 80 % crop cover and the residue patch did contain a small amount of green grass. However, soil patches were 100 % soil. For the Indian Head site, only the soil patch was used for endmember extraction. Crop endmember spectra were retrieved from the fields where high crop density had been identified and the residue endmember spectra was extracted from a very dense residue patch identified on one of the fields.

Spectral unmixing was conducted on the Probe-1 data using the full spectral range. For the Clinton site, only three endmembers categories were used to unmix the hyperspectral cube: crop vegetation according to the crop type of the field, soil and residue. For the Indian Head site, all fields are at the same location and thus, five endmembers were used to perform spectral unmixing on all fields at once: wheat, canola, pea, soil and residue. As a result, fraction maps of these endmembers were then derived from the hyperspectral Probe-1 data.

The eLAI values were estimated from the hyperspectral data using an algorithm implemented in ISDAS (Staenz *et al.*, 2002). Crop fractions from each of the fields were used as input to generate eLAI maps. eLAI can be calculated as follows (Ross, 1981):

$$eLAI = \frac{\cos \alpha}{G} (-\ln P), \quad (1)$$

where P is the probability of a beam of radiation at an incidence angle α passing through a horizontally uniform plant canopy with random leaf angular and spatial distribution and G is the mean projection coefficient of unit foliage area on a plane perpendicular to α .

To estimate eLAI from hyperspectral data, G (α) can be determined at 0.5 for plants, which have randomly distributed leaf angles such as agricultural crops (Norman, 1979). The incidence angle α corresponds to the sensor viewing zenith angle. Probe-1 is usually flown at a view angle of 0° (nadir looking). Also, P represents the gap (non-vegetation) fraction, which is determined by spectral unmixing as follows:

$$P = 1 - f_c, \quad (2)$$

where f_c is the fraction of the crop endmember. eLAI is then derived from hyperspectral data according to the following formula:

$$\text{eLAI}(f_c) = -2 \ln(1 - f_c). \quad (3)$$

For each sampling site, eLAI values were estimated from the hyperspectral imagery using a 3-by-3 pixel window average centred on the sampling site locations. Correlations were generated between the eLAI estimates from the hyperspectral data and the ground eLAI measurement acquired with the LAI-2000.

4 RESULTS AND DISCUSSION

Results from both sets of correlations (percent crop cover versus crop fractions derived from the hyperspectral data and ground eLAI measurements versus Probe-1 eLAI values) are presented in Table 1. Correlation coefficients were calculated for each crop type and on pooled data from all crops. Correlations were not computed on a field-by-field basis since the number of sample points was too small and variability in eLAI values within a field was almost non-existent.

Crop Canopies	Correlation Coefficients (r)*	
	Percent Crop Cover vs Crop Fractions	LAI-2000 eLAI Values vs Probe-1 eLAI Values
All Crops	0.728	0.690
Corn	0.696	0.695
White Beans	0.743	0.161
Wheat	0.741	0.597
Canola	0.875	0.568
Peas	0.645	0.589

* All correlations were significant at a probability level of <0.05.

Table 1: Correlation coefficients between percent crop cover and LAI-2000 eLAI values and crop fractions and eLAI values derived from hyperspectral Probe-1 data.

A good correlation was found between the Probe-1 derived crop fraction, and the percent crop cover acquired during the Clinton and Indian Head field campaigns. A correlation coefficient (R-value) of 0.728 was achieved when the crop fractions derived from spectral unmixing were regressed against percent crop cover calculated from the photographs. When correlations are examined on a crop specific level, correlations differ significantly from one crop to another. Overall, crop fractions were all positively correlated with the percent crop cover. Hence, these results indicate that spectral unmixing has the

potential to provide information on the extent of crop ground cover. Although correlations are significant, it is clear that some variability is still unexplained. Spectral reflectance from 3-dimensional targets like crop canopies is also dependent upon canopy architecture. Thus, further analysis is planned utilizing more detailed crop measurements such as canopy architecture properties. The unexplained variance could also be related to limitations in the endmember selection, and this requires further investigation. Endmembers were selected from double seeded patches or high-density areas of crop that were not exactly "pure".

As for the relationship between ground eLAI and eLAI derived from hyperspectral data, a correlation coefficient of 0.690 was found for all the data of both field campaigns. Similarly to the crop fractions and percent crop cover relationships, correlations vary considerably when they are observed at a crop specific level. Correlation coefficient for the white bean crops is low. This can be explained by the difference of growth stage between the corn and the white beans at the time of the Clinton field campaign. The white bean fields were not well developed and large gaps existed between the plant rows and between each of the plants along a row. Furthermore, plants were very small in certain areas of the fields, plant height was no more than 15 cm. Thus, errors might have occurred when ground eLAI measurements were acquired with the LAI-2000. In fact, it was noted that the standard error of the eLAI (SEL) values were considerably higher for white beans than for the rest of the crops. Furthermore, all limitations found in the spectral unmixing analysis process are carried to the eLAI estimation since the crop fraction is used as input to the eLAI algorithm.

Following a more precise examination of the regression plot for the eLAI Probe-1 values and the LAI-2000 eLAI values (Figure 2), it can be noticed that eLAI values derived from remote sensing data overestimate eLAI measured with the LAI-2000 instrument. The range of eLAI values is also greater for eLAI estimated from hyperspectral data than from the LAI-2000. Further investigation is necessary in order to improve the understanding of eLAI estimation from hyperspectral data. Nevertheless, preliminary results are very encouraging and this study demonstrates a large potential for the application of hyperspectral remote sensing to LAI estimation in agricultural crops.

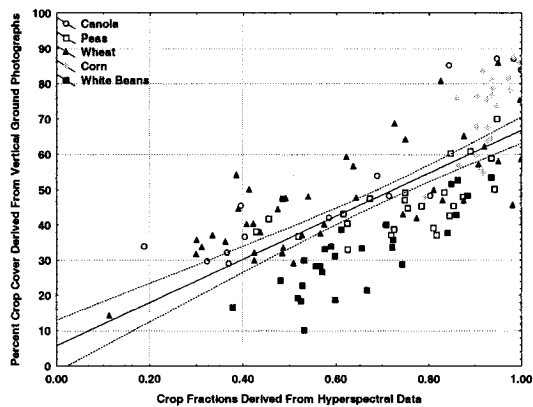


Figure 1: Correlation plot between percent crop cover calculated from vertical ground photographs and crop fractions derived from hyperspectral Probe-1 data.

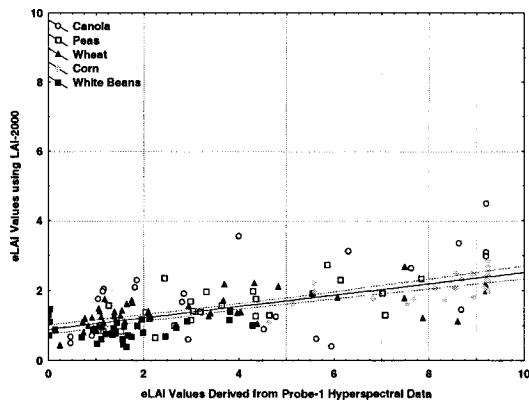


Figure 2: Correlation plot between ground eLAI values measured with the LAI-2000 and eLAI values derived from hyperspectral Probe-1 data.

5 CONCLUSIONS

Probe-1 hyperspectral data were acquired over the Clinton (Ontario) and the Indian Head (Saskatchewan) agricultural sites in 1999 and 2000, respectively. Various crops were used for the investigation: corn, white beans, wheat, canola and peas. Simultaneously to the Probe-1 acquisition, percent crop cover was derived from vertical ground photographs and eLAI measurements were taken using the LAI-2000 instrument. Crop fractions were generated using spectral unmixing analysis, which in turn, were used as input to the eLAI estimation. Validation of these map products using ground data indicated that crop fractions derived from spectral unmixing were correlated with percent crop cover. LAI-2000 eLAI and eLAI values estimated from the hyperspectral data also demonstrated a fair correlation. Thus, hyperspectral data was sensitive to variability in percent crop cover and ground eLAI values for

different crop types and illustrates encouraging results for future analysis.

6 ACKNOWLEDGMENTS

The authors would like to thank Robin Smith from Woodroffe High School in Ottawa, for classifying all the ground cover photos and calculating the classification statistics for the Indian Head data set. Special thanks to Robert Hitchcock of Prologic Systems Ltd. for performing the atmospheric correction of the Probe-1 data. Thanks also goes to Jeff Secker of DRDC and Christian Nadeau of MDA for implementing the eLAI algorithm module in ISDAS.

7 REFERENCES

- Chen, J.M. and Black, T.A., 1992, Defining Leaf Area Index for Nonflat Leaves. *Plant Cell Environment*, **13**, 2565-2581.
- Chen, J.M. and Cihlar, J., 1995, Plant Canopy Gap-Size Analysis: Theory for Improving Optical Measurements of Leaf Area Index. *Applied Optics*, **34** (27), 6211-6222.
- Earth Search Sciences Inc., 2001, About Probe-1. www.earthsearch.com/technology.
- Lévesque, J., Staenz, K. and Szeredi, T. 2000. The Impact of Spectral Band Characteristics on Unmixing of *casi* Data for Monitoring Mine Tailings Site Rehabilitation. *Canadian Journal of Remote Sensing*, **26**(3), 231-240.
- LI-COR, 1992, LAI-2000 Plant Canopy Analyzer - Instruction Manual. *LI-COR*, Lincoln, Nebraska.
- Nadeau, C., Neville R.A., Staenz K., O'Neill N.T., and Royer A., 2002, Atmospheric Effects on the Classification of Surface Minerals in an Arid Region Using SWIR Hyperspectral Imagery and a Spectral Unmixing Technique. *Canadian Journal of Remote Sensing* (in press).
- Norman, J.M., 1979, Modelling the Complete Crop Canopy. In Int. B.J. Barfield and J.F. Gerber (Editors), *Modification of the Aerial Environment of Plants*, American Society of Agricultural Engineers, St. Joseph, Michigan, pp. 249-277.

PCI Geomatics, 1998. Using PCI Software, Version 6.3, PCI Geomatics: Richmond Hill, Ontario, 990 pages.

Staenz, K. and Williams D.J., 1997, Retrieval of Surface Reflectance from Hyperspectral Data Using a Look-Up Table Approach. *Canadian Journal of Remote Sensing*, **23**(4), 354-368.

Ross, J., 1981, The Radiation Regime and Architecture of Plant Stands, *Dr. W. Junk Publishers*.

Secker, J., Staenz, K., Gauthier, R.P. and Budkewitsch, P., 2001, Vicarious Calibration of Airborne Hyperspectral Sensors in Operational Environments. *Remote Sensing of Environment*, **76**, 81-92.

Staenz, K., Szeredi, T. and Schwarz, J., 1998, ISDAS - A System for Processing/Analyzing Hyperspectral Data, Technical Note. *Canadian Journal of Remote Sensing*, **24**(2), 99-113.

Staenz, K., Nadeau, C., Secker, J. and Budkewitsch, P., 2000, Spectral Unmixing Applied to Vegetated Environments in the Canadian Arctic for Mineral Mapping. *Proceedings of XIX ISPRS Congress*, Amsterdam, The Netherlands, July 15-23, 8 p.

Staenz, K., Deguise, J.-C., Chen, J.M. and McNairn, H., 2001, Estimation of Leaf Area Index (LAI) from Crop Fraction Using Hyperspectral Data (*submitted to the Canadian Journal of Remote Sensing*).