AIRBORNE IMAGE TEXTURE AND MIXTURE ANALYSIS OF A FOREST SCALE CONTINUUM: A COMPARISON WITH NDVI BIOPHYSICAL ESTIMATES, KANANASKIS ALBERTA *

Derek R. Peddle [1], Diedre P. Davidson [1], Ryan L. Johnson [1], and Ronald J. Hall [2,1]

[1] Department of Geography, University of Lethbridge, Lethbridge, Alberta, T1K 3M4 Canada.
WWW: http://home.uleth.ca/geo/derekp.htm

[2] Natural Resources Canada, Canadian Forest Service, 5320-122 St., Edmonton, AB. T6H 3S5

ABSTRACT

The ability to extract information at different spatial scales from remotely sensed imagery has been shown to improve estimation of forest biophysical and structural characteristics compared to the use of vegetation indices (VI). For example, at sub-pixel scales, spectral mixture analysis (SMA) provides information on the fraction of canopy, shadow and background within a pixel. These fractions provide improved biophysical estimates since they account explicitly for background and shadow effects. Spatial discriminators such as texture measures have also improved estimation of LAI compared to image tone or VI values. That method captures important information about the spatial arrangement and patterns of image data related to forest structure. In this paper, we consider sub-pixel scale fractions (mixture analysis) and areas of pixels (texture analysis) together with image tone values to create a working framework over a more full spatial scale continuum. Information derived from these various scales are evaluated using regression analyses of individual and different combinations of image variables for predicting leaf area index (LAI) from high spatial resolution airborne multispectral video imagery of the Canadian Rockies. Shadow fraction alone was the best individual predictor of LAI ($r^2 = 0.54$) compared to NDVI ($r^2 = 0.01$). Use of all SMA fractions and the original 3 image bands (green, red, NIR) improved this to $R^2 = 0.61$. Use of texture improved this further to $R^2 = 0.70$. The texture results indicated that larger window sizes (15×15 here) and second-order measures from spatial co-occurrence matrices performed best, using several different individual measures. SMA fractions were the most important, for which we found shadow fraction optimal, with canopy fraction providing additional new information. Without SMA, the best overall result using image tone and texture and NDVI was $R^2 = 0.38$. Overall, texture was less important than SMA, although it did enable further improvements which were significant. The ability to extract information over a range of scales using mixture and texture analysis provided substantial improvements over that obtained using image data and vegetation indices.

1.0 INTRODUCTION

Leaf area index (LAI) is defined as one half the total leaf area per unit ground surface area (Chen and Cihlar, 1996). It is an important biophysical structural parameter as it can be useful in studies of ecosystem functioning and carbon exchange (Bonan, 1993). The normalized difference vegetation index (NDVI) has been a common method used to estimate LAI from remote sensing imagery. However, a number of studies have concluded that NDVI alone does not extract the full amount of biophysical information contained in remotely sensed image data, nor does it provide the desired level of information required for input to ecosystem models (Spanner *et al.*, 1990). A contributing factor to this problem is that information pertaining to forest structure exists over a range of spatial scales, yet NDVI is derived on an individual per-pixel basis (image tone) and therefore has no mechanism to capture that spatial information. For example, individual red and near-infrared image tone values in high spatial resolution airborne imagery contain little or no information about the pattern or density of forest crowns within a stand, yet this

* Presented at the Fourth International Airborne Remote Sensing Conference and Exhibition / 21st Canadian Symposium on Remote Sensing, Ottawa, Ontario, Canada, 21-24 June 1999.

can be important in accurate estimation of LAI. Indeed, at higher spatial resolutions, some NDVI values may actually decrease with increasing LAI (Wulder *et al.*, 1998) due to the increased shadowing within forest stands which progressively obscures more of the canopy area within some image pixels.

To help address these issues, image processing methods such as texture analysis (Haralick, 1979) have been used in remote sensing to capture some of the spatial information that exists over neighbourhoods of adjacent pixels and which may contain additional information related to forest land cover and structure. For example, satellite image texture has been shown to increase forest land cover classification accuracy in flat or low relief areas as well as in mountainous terrain (Peddle and Franklin, 1991). More recently, improvements in the estimation of forest LAI using NDVI have been obtained using image texture of high resolution airborne imagery in studies by Wulder *et al.* (1996, 1998).

At the other end of the scale continuum, information at sub-pixel scales has been shown to provide substantially improved estimates of forest biophysical information compared to NDVI. In a series of studies using spectral mixture analysis (SMA), sub-pixel scale fractions such as sunlit canopy, background and shadow have consistently provided better estimates of LAI, biomass, net primary productivity and other biophysical structural variables compared to image tone or vegetation indices in a variety of boreal and mountain study sites with both deciduous and coniferous forests using satellite and multi-scale high resolution airborne imagery (Hall *et al.*, 1996; Peddle, 1997; Peddle *et al.*, 1999; Peddle and Johnson 1999). The central basis for these improvements has been that NDVI does not account explicitly for the influence of forest canopy, ground vegetation, and shadows on spectral reflectance (Spanner *et al.* 1990), whereas SMA provides this information directly.

Recognising that both image texture analysis and spectral mixture analysis provide improvements over NDVI, it was prudent for us to test the use of both methods together to determine if a synergistic forest image processing method might emerge. The idea is to possibly exploit the information which can be extracted over a more full range of spatial scales, that is, from scales which involve many pixels (texture computed from pixel windows) to scales which involve areas smaller than an individual pixel (sub-pixel scale fractions from SMA). From an information content perspective, we are essentially testing whether the information provided by texture analysis is unique and separate from, or redundant with, the new information provided by SMA fractions.

We have also taken this concept one step further by integrating spatial texture analysis and sub-pixel scale mixture analysis directly. This was done by first deriving SMA fraction images, and then performing a spatial image texture analysis on those fraction images. The idea here is to evaluate the spatial patterns of sub-pixel scale mixtures which may exist over a landscape (e.g. the spatial arrangement, variability and randomness of shadow fractions over a given pixel window). In this paper, we test these image processing methodologies for predicting leaf area index (LAI) using high spatial resolution airborne imagery of a montane forest environment in the Canadian Rockies.

2.0 STUDY AREA AND DATA COLLECTION

2.1 STUDY AREA AND AIRBORNE IMAGERY

The study area was centered at 51°1'13"N 115°4'20"W on the eastern slopes of the Rocky Mountains and straddles Barrier Lake in Kananaskis Provincial Park, Alberta, Canada. This $77 km^2$ region includes a full range of terrain aspects with slopes ranging from 3° to 30°. This montane region has forest species such as lodgepole pine, white spruce and trembling aspen, with some scattered Douglas-fir and balsam poplar, as described in more detail in Peddle and Johnson (1999) and Johnson *et al.* (1999).

The digital remote sensing data were obtained July 1996 from a multispectral video (MSV) camera system comprised of three CCD monochrome video cameras with filters centered in the green (537.1 nm), red (617.2 nm), and near-infrared (NIR, 718.9 nm), as described in Roberts (1995). In this research, a multi-resolution image data set was acquired at different altitudes and pixel scales; this study was based on imagery acquired at 500 ft with a spatial resolution of 30 cm, the highest resolution in the data set. Radiometric and geometric corrections were performed as part of initial preprocessing by Gerylo *et al.* (1997).

2.2 FIELD MEASUREMENT OF LAI

Field data were collected in 1996 and 1997 involving measurements of LAI, crown closure, tree diameter, species and tree spacing. Fourteen plots were identified which contained homogeneous or near homogeneous forest species over a square 10×10m area. All plots used in this paper contained aspen. LAI was estimated in the field using a Decagon[1] AccuPAR hand-held ceptometer which measured canopy photosynthetically active radiation (PAR 400-700nm). PAR values were obtained below the forest canopy near ground level, while measurements obtained in nearby clearings served as above canopy measurements of PAR. These measurements were input to equations that derive LAI as a function of the amount of PAR, as described in Peddle and Johnson (1999). Measurements were obtained at each corner and in the center of each plot, for a total of $5 \times 14 = 70$ LAI sites. These plots were located in the airborne imagery with reference to GPS data acquired in the field and visual alignment of image data with reference to plot information.

3.0 METHODS

3.1 MIXTURE ANALYSIS

Spectral mixture analysis image endmembers were selected from all 3 bands of the high-resolution 500 ft MSV imagery (Peddle and Johnson, 1999). It was not possible to use field reference endmembers from a spectroradiometer because the image data could not be converted to surface reflectance since radiometric calibration ground spectra co-incident with image acquisition were not available. As in the earlier study, a two-endmember model was used (sunlit canopy and shadow) as the high canopy density obscured the forest floor (background endmember) in these plots (Peddle and Johnson, 1999). The mixture analysis of the 14 image scenes and 70 LAI sites was performed using ENVI (1998) software. The output produced from the analysis was a set of shadow fraction images and canopy fraction images, where each pixel values corresponded to the magnitude of shadow and canopy derived from the SMA for each pixel, respectively.

3.2 TEXTURE ANALYSIS

First-order and second-order texture analyses were completed using ENVI (1998) software applied to the 14 airborne images containing the forest test plots. Texture was also computed from shadow and canopy fraction images, and of NDVI images to provide a full spatial analysis of all image tone and sub-pixel scale features. First-order texture measures were calculated directly from pixel values within a specified window. In this study, values for mean, range, variance, entropy and skewness were computed. Second-order texture measures involved a two-step process in which spatial co-occurrence matrices were computed to capture the spatial arrangement of digital pixel values, from which various texture measures were then derived. Here, texture measures of homogeneity, contrast, dissimilarity, entropy, second moment, correlation, mean and variance were calculated from the co-occurrence matrices, using a quantisation level of 255 and a distance increment of 1. All texture analyses were run separately using window sizes of 3×3, 5×5, 9×9, and 15×15 to evaluate the textural information which may exist over different spatial scales. Since each forest plot was of dimension 10×10m, we used a maximum window size of 15×15 equivalent to a 4.5×4.5m area for these 30cm pixels, so that the maximum window dimension was less than half the overall plot size. Texture values were computed for each pixel in a given plot. Texture measures derived from pixel windows near the edge of plots included some pixels outside the plot. This did not affect the analysis since the plots were positioned at or near individual scene centers, resulting in ample image data being available outside the plots which contained the same forest species and stand characteristics as in the plot. Further, four of the five LAI measurements per plot were obtained at the plot corners, near the image plot boundary.

3.3 LAI PREDICTION

The data set of image bands (red, green, NIR), mixture fraction images (shadow, canopy fraction) and texture images (first and second order variables) were assembled and the pixel values at the locations of the 70 LAI sites

[1] The mention of trade names is for information only.

within the plots were extracted from each image. NDVI ([NIR-red]+[NIR+red]) was also computed for each pixel and added to this data set. Regression analysis was used to assess the ability of image tone, texture, mixture analysis variables, and NDVI values as independent variables for predicting the dependent variable LAI. For the texture variables, different window sizes, texture measures, and input image bands were tested, including evaluation of texture derived from mixture fraction images and NDVI. Individual independent variables were evaluated for predicting LAI with reference to the magnitude of the coefficient of determination (r^2) for simple linear regression. Various combinations of independent variables were tested in a series of multiple regression analyses. The ability to predict LAI was assessed using the coefficient of multiple determination for multiple regression (R^2). Since the number of independent variables differed over the various data set combinations tested, adjusted R^2 values were reported instead of R^2 values alone, the latter of which can be artificially inflated by the mere presence of extra independent variables in the model. This adjustment, based on the number of degrees of freedom, reduces the magnitude of R^2 appropriately, thus making it statistically valid to compare R^2 values obtained from different numbers of independent variables. All R^2 results reported here are adjusted R^2 values. All regressions used a confidence level of 95%. The quality of fit was limited in this study to adjusted R2 values: other measures such as statistical significance of the regression coefficients, root mean square error, and plots of standardized residuals will be incorporated into a future report of this work.

4.0 RESULTS AND DISCUSSION

4.1 IMAGE TONE FOR PREDICTING LAI

4.1.1 Regression Results from Individual Image Tone Variables

Each of the six image tone variables were first tested for their ability to predict LAI (Table 1). Of the three image bands, NIR provided the highest r^2 of 0.15. The best overall result was obtained from the mixture analysis shadow fraction ($r^2 = 0.54$), while the NDVI result was quite low ($r^2 = 0.01$). These are almost identical to results obtained in boreal forest aspen stands in BOREAS (Peddle, 1997), while in conifer stands we typically see $r^2 = 0.30$ to 0.45 with NDVI compared to $r^2 = 0.70$ to 0.80 from shadow fraction with LAI (Peddle, 1997; Peddle *et al.*, 1999). The canopy fraction ($r^2 = 0.12$) was substantially lower than shadow fraction, yet, as we shall see later, this proved to nonetheless contain new information not provided by shadow fraction or other variables. The significantly higher shadow fraction result ($r^2 = +0.39$) serves as a basis for further improvements in subsequent tests. Compared to NDVI, the ability to quantify sub-pixel scale fractions appears to be critical for predicting LAI.

Table 1: Prediction of LAI using individual image tone variables alone. Regression coefficients of determination (r^2) shown for each of the 3 image bands, NDVI, and spectral mixture analysis fraction of shadow (SMA S) and canopy (SMA C).

Image Band	r^2 with LAI	Image Variable	r^2 with LAI
Green	0.11	NDVI	0.01
Red	0.12	SMA S	0.54
NIR	0.15	SMA C	0.12

4.1.2 Multiple Regression Results from Combinations of Image Tone Variables

We first tested various combinations of image tone variables that did not include any mixture fraction variables (Table 2). The highest result was obtained using all 3 bands with NDVI (R^2 =0.17). When shadow fraction (SMA S) was included, all results were R^2 =0.54 or greater. The use of image bands and NDVI with SMA S provided little or no improvement (maximum R^2 =0.55). This is essentially the same as SMA S alone (Table 1). However, canopy fraction (SMA C) with SMA S provided an improvement (R^2 =0.60), but again when image bands and NDVI were used with both fractions, the improvements were very small (R^2 =0.61). The image bands and NDVI appear to contribute no additional or new information not already provided by mixture fractions. In contrast to this, the shadow and canopy fractions each contribute different and useful information for the prediction of LAI. This is quite significant, since we have never tested different mixture fractions together in this way. It would appear that to obtain optimal results from mixture fraction tone values, the use of several fractions may be recommended.

Table 2: Prediction of LAI using combinations of image tone variables. Coefficient of multiple determination for multiple regression (adjusted R^2) values shown for the 3 image bands [Green(G), Red(R),NIR], NDVI, and fractions of shadow (SMA S) and canopy (SMA C).

Image Variables	R^2 with LAI	Image Variables	R^2 with LAI
NIR, NDVI	0.16	SMA S, NIR, NDVI	0.54
G, R, NIR, NDVI	0.17	SMA S, G, R, NIR	0.55
SMA S, NIR	0.54	SMA S, G, R, NIR, NDVI	0.55
SMA S, NDVI	0.54	SMA S, SMA C, G, R, NIR	0.61
SMA S, SMA C	0.60	SMA S, SMA C, G, R, NIR, NDVI	0.61

4.2 IMAGE TONE AND TEXTURE FOR PREDICTING LAI

4.2.1 Overview of Results from All Texture Analyses

In these experiments, we tested 5 first-order and 8 second-order texture measures over 4 different window sizes for computing texture from 6 different image tone variables. Further, we tested a large variety of different combinations of variables in a series of multiple regression analyses. This produced a very large set of results which were impractical to present or discuss here. Instead, we have extracted the major themes from these results, which are discussed first in more general terms in this section, and followed by more in-depth interpretations with reference to summary tables in subsequent sections.

We found that texture provided some new and useful information to improve the prediction of LAI. In general, window size had the greatest overall influence on texture performance. For all texture measures, we consistently found a steady increase in predictive ability as window size was increased. Accordingly, we list results from the minimum (3×3) and maximum (15×15) window sizes only, to illustrate the range of results obtained. In terms of different first-order texture measures, entropy and skewness yielded substantially lower results or were unrelated to LAI, therefore, we show results from mean, range, and variance only since these were the most useful within that group. Second-order texture measures generally performed better than first-order measures, suggesting that forest structural information was captured more effectively using the two-step method in which spatial patterns are first extracted using co-occurrence matrices. For these results, we listed only the three best measures (homogeneity, contrast, dissimilarity) based on an overall assessment, although we note that other measures also performed almost as well as those reported here. To provide some direct insight into first-order and second-order measures, we include both types of measures in the initial set of texture results reported.

4.2.2 Regression Results from Individual Texture Variables

To provide a thorough and unbiased test of texture, we analysed each of the selected texture measures derived from each image tone variable. Separate linear regressions were performed using each texture variable alone for predicting LAI, to assess the independent information content provided by texture (Table 3). Texture window size was quite important, with consistent improvements found with larger windows over the four window sizes tested. The average improvement from a window size of 3 to 15 was an increase in r^2 =+0.08. Second-order texture variables showed a greater average improvement with increased window size (r^2 =+0.11) compared to first-order texture (r^2 =+0.05). The best first-order texture measure at each window size was range (average r^2 =0.13), while among second-order variables, dissimilarity was the best at all window sizes (average r^2 =0.16). Texture dissimilarity computed over a 15×15 window size produced the best overall texture results.

Table 3: Prediction of LAI using individual image texture (Tx) variables alone. Regression coefficients of determination (r^2) values shown for first-order texture variables range, mean, variance (VAR), and second-order texture variables homogeneity (HMG), contrast (CON), and dissimilarity (DIS) derived from green, red, near-infrared (NIR), spectral mixture analysis shadow fraction (SMA S), canopy fraction (SMA C), and NDVI, using 3×3 and 15×15 window sizes.

Texture Measure	Green Tx 3	Green Tx 15	Red Tx 3	Red Tx 15	NIR Tx 3	NIR Tx 15	SMA S Tx 3	SMA S Tx 15	SMA C Tx 3	SMA C Tx 15	NDVI Tx 3	NDVI Tx 15
Range	.11	.14	.10	.14	.14	.25	.12	.17	.11	.10	.10	.09
Mean	.09	.17	.10	.16	.13	.25	.02	.02	.14	.28	.00	.00
VAR	.09	.14	.07	.14	.09	.18	.09	.16	.09	.09	.09	.15
HMG	.05	.14	.04	.13	.06	.19	.12	.21	.00	.22	.00	.20
CON	.10	.07	.09	.16	.12	.27	.10	.20	.00	.21	.00	.17
DIS	.13	.07	.11	.16	.16	.29	.13	.24	.13	.25	.11	.19

In terms of absolute performance, perhaps the most significant result was obtained by texture analysis of the image bands. Image band texture variables alone were better predictors of LAI compared to image tone variables for each of the 3 bands. This is quite significant, since it suggests that texture may actually be more important than tone for these bands. The largest improvement was found with the NIR band, which increased from an r^2=0.15 (tone) to 0.29 (texture dissimilarity), the highest of any of the texture results. NDVI texture dissimilarity increased the r^2 from 0.01 (tone) to 0.19 (texture). A similar, though less dramatic, improvement was found with texture derived from the canopy fraction image, for which the r^2 increased from 0.12 (tone) to 0.25 (texture dissimilarity), with the first-order mean variable having an r^2 =0.28, the second-highest individual texture result. Shadow fraction image texture also provided a good result (dissimilarity r^2 =0.24), although this was much lower than the original fraction tone value (0.54). The differences between canopy and shadow fraction in terms of tone and texture predictive abilities for LAI further illustrates the differences in information contained in these two mixture fractions. Overall, texture appears to be more necessary for image bands and NDVI, than with mixture fractions.

4.2.3 Multiple Regression Results from Combinations of Tone and Texture Variables

Based on results from the previous section, we used the texture dissimilarity measure from a 15×15 window applied to all image tone variables, and tested a variety of tone and texture variable combinations (Table 4). Space does not permit a full treatment of all these results; instead, we summarise the major trends. The best result obtained from an exhaustive test of different combinations of image bands and NDVI tone and texture (i.e. no mixture fractions) was R^2 =0.38, using all available variables. This was an improvement over image bands and NDVI tone alone (R^2=0.17, Table 2) and image and NDVI texture alone (R^2 = 0.36), suggesting that both image tone and, in particular, image texture are important. However, the level of predictive ability (R^2=0.38) using tone and texture from all image bands and NDVI (8 variables) is still unacceptably low, and still significantly less than shadow fraction alone (r^2=0.54, Table 1).

We then investigated improvements to the mixture fraction results using various combinations of tone and texture. Individual mixture fraction tone and texture resulted in an increase in R^2 with canopy fraction from 0.25 (texture) to 0.30 (tone and texture), while for shadow fraction an increase from 0.54 (tone) to 0.60 (tone and texture) was found. When texture was applied to both fractions and used with the original fraction tone images, the predictive ability increased further to R^2=0.66. This was quite significant, as it showed the importance of both fractions as well as texture. Different combinations of image band and NDVI texture did not improve the SMA results, and in some cases these additional variables resulted in a slight decrease in R^2 values. Using all available variables, that is, the 8 image and NDVI tone and texture variables (which had an R^2 =0.38) together with the 4 SMA tone and texture fraction images (R^2=0.66), produced an overall R^2=0.70, which was the best result obtained in the study.

Table 4: Prediction of LAI using combinations of image tone and texture variables. Coefficient of multiple determination for multiple regression (adjusted R^2) values shown using Green, Red, NIR, NDVI, and spectral mixture analysis fractions of shadow (SMA S) and canopy (SMA C). Texture (Tx) computed as second-order dissimilarity over a 15×15 window.

Image Variables	R^2 with LAI	Image Variables	R^2 with LAI
Green Tx, Red Tx, NIR Tx, NDVI Tx	.36	SMA C, SMA C Tx	.30
Green, Green Tx, Red, Red Tx, NIR, NIR Tx, NDVI Tx, NDVI Tx	.38	SMA S, SMA S Tx	.60
		SMA S,SMA S Tx,SMA C,SMA C Tx	.66
Green Tx, Red Tx, NIR Tx, NDVI Tx, SMA S Tx, SMA C Tx	.37	Green, Green Tx, Red, Red Tx, NIR, NIR Tx, NDVI Tx, NDVI Tx, SMA S,SMA S Tx,SMA C,SMA C Tx	.70

5.0 CONCLUSIONS

The ability to extract information over different scales from remotely sensed imagery has been shown to be critical for estimating biophysical variables such as LAI. Sub-pixel scale shadow fraction was found to be the best individual predictor of LAI (r^2=0.54) compared to image tone (r^2=0.15) or NDVI (r^2=0.01). This was further improved with the addition of canopy fraction and texture variables over large image windows (R^2=0.66). A combination of mixture fractions, image and NDVI tone and texture produced the best result of R^2=0.70, which is significant for montane deciduous stands. Larger window sizes and second-order measures provided the best texture information, particularly with the original image bands. It may be useful to test larger window sizes than was practical here, or to use image semi-variance and texture to optimise window size selection (Wulder *et al.*, 1998). In this mountainous environment, we would also expect further improvements using topographic corrections. Given these results, further improvements with other forest species (e.g. spruce and pine) may be possible, for which we already have obtained good predictive capabilities for LAI and other biophysical variables using shadow fraction alone (e.g. r^2=0.74-0.85: Peddle, 1997; Peddle *et al.*, 1999). From these results, it is clear that mixture fraction variables are more important than texture measures, however, the latter also contributes additional and useful information pertaining to forest structure and is therefore worthy of consideration. This suggests that the ability to extract information at scales which are both larger and smaller than the pixel spatial resolution is important for maximising the predictive capability of forest biophysical variables using airborne remote sensing imagery.

6.0 ACKNOWLEDGEMENTS

This research was supported by NSERC Research and Equipment Grants, Alberta Research Excellence Grants, an Alberta IIPP Grant, the University of Lethbridge Research Fund, and Faculty Research Grants to Dr. Peddle. D.P. Davidson and R.L Johnson were partially funded by NRCAN-Ottawa and Alberta STEP Grants, and Graduate Student Scholarships from the University of Lethbridge. Airborne MSV data were acquired by Dr. Arthur Roberts, Simon Fraser University, and made available to this research by Dr. Steven Franklin, University of Calgary. We gratefully acknowledge collaborators, staff and students at the Universities of Lethbridge, Calgary, Regina, CFS Edmonton, the Miistakis Institute for the Rockies, and the Kananaskis Field Stations for their support and contributions to this research program.

7.0 REFERENCES

Bonan, G.B. 1993. Importance of leaf area index and forest type when estimating photosynthesis in Boreal Forests. *Remote Sensing of Environment* 43: 303-313

Chen, J. and Cihlar, J. 1996. Retrieving leaf area index of boreal conifer forests using Landsat TM images. *Remote Sensing of Environment* 55:153-162.

ENVI, 1998 Environment for Visualizing Images: ENVI/IDL User's Manuals. Research Systems Inc. Boulder, CO.

Gerylo, G., S.E. Franklin, A. Roberts, E.J. Milton and R.J. Hall. 1997. Hierarchical Alberta Vegetation Inventory (AVI) classification using aerial digital frame camera data. In Proceedings, GER'97: 9th Int. Conf. Geomatics/ 19th Canadian Symposium on Remote Sensing, Ottawa, Canada. (CD-ROM).

Hall, F.G., D.R. Peddle and E.F. LeDrew, 1996. Remote sensing of biophysical variables in boreal forest stands of *Picea Mariana. International Journal of Remote Sensing* 17(15): 3077-3081.

Haralick, R. 1979. Statistical and Structural Approaches to Texture. *Proceedings of the IEEE.* 67(5): 786-804

Johnson, R.L., D.R. Peddle, R.J. Hall and S. Mah, 1999. Spectral mixture analysis of montane forest biophysical parameters: A comparison of endmembers from airborne imagery and a field spectroradiometer. *4th International Airborne Remote Sensing Conf./21st Canadian Symp. on Remote Sensing* (these proceedings).

Peddle D.R., and S.E. Franklin. 1991. Image texture processing and data integration for surface pattern discrimination. *Photogrammetric Engineering & Remote Sensing* 57(4): 413-420.

Peddle, D.R., 1997. Remote sensing of boreal forest terrain: Sub-pixel scale mixture analysis of land cover and biophysical parameters at forest stand and regional scales. *Unpublished Ph.D. Thesis, Department of Geography, University of Waterloo.* Waterloo, Ontario, Canada. 332 p.

Peddle D.R. and R. L. Johnson. 1999. Spectral mixture analysis of airborne remote sensing imagery for improved prediction of leaf area index in mountainous terrain, Kananaskis Alberta. *Canadian Journal of Remote Sensing;* Special Issue: 20th Canadian Symposium on Remote Sensing

Peddle, D.R., F.G. Hall and E.F. LeDrew, 1999. Spectral mixture analysis and geometric optical reflectance modeling of boreal forest biophysical structure. *Remote Sensing of Environment.* 67(3): 288-297.

Roberts, A. 1995. Integrated MSV airborne remote sensing. *Canadian Journal of Remote Sensing.* 21(3):214-224.

Spanner, M., L. Pierce, D. Peterson and S. Running, 1990. Remote sensing of temperate coniferous forest LAI: Influence of canopy closure, understorey vegetation and background reflectance. *Int J Rem Sens* 11(1):95-111.

Wulder, M., S. Franklin and M. Lavigne, 1996. High spatial resolution optical image texture for improved estimation of forest stand leaf area index. *Canadian Journal of Remote Sensing.* 22(4): 441-449

Wulder, M., E. LeDrew, S. Franklin, and M. Lavigne, 1998. Aerial image texture information in the estimation of northern deciduous and mixed wood forest leaf area index (LAI). *Remote Sensing of Environment.* 64: 64-76

Proceedings of the Fourth

International Airborne Remote Sensing Conference and Exhibition/ 21st Canadian Symposium on Remote Sensing

Volume II

21-24 June 1999
Ottawa, Ontario, Canada

Published by
ERIM International, Inc.
P.O. Box 134008, Ann Arbor, MI 48113-4008, USA

The papers appearing in this two-volume set constitute the proceedings of the *Fourth International Airborne Remote Sensing Conference and Exhibition.* They reflect the authors' opinions and are published as received. Their inclusion in this publication does not necessarily constitute endorsement by ERIM International, Inc.

ISSN 1076-7924

Printed in the United States of America.