Using Spatial Co-Occurrence Texture to Increase Forest Structure and Species Composition Classification Accuracy

S.E. Franklin, A.J. Maudie, and M.B. Lavigne

Abstract

The analysis of forest structure and species composition with high spatial resolution (≤ 1 m) multispectral digital imagery is described in an experiment using spatial co-occurrence texture analysis and maximum-likelihood classification. The objective was to determine if higher forest species composition classification accuracies would result in comparison to the use of spectral response patterns alone. Increased accuracy was obtained when using texture at all levels of a classification hierarchy. At the stand level, accuracies were on the order of 75 percent in agreement with field surveys, an improvement of 21 percent over the accuracy obtained using spectral data alone; in stands grouped according to species dominance/co-dominance, the accuracy improved still further to 80 percent. The overall classification accuracy in a highly generalized lifeform classification was 100 percent. This represented a 33 percent increase in accuracy over that which could be obtained, in a classic spectral "signature" classification approach, using spectral response patterns alone.

Introduction

The use of high spatial resolution remote sensing data to classify forest structure (St-Onge and Cavayas, 1997) and identify forest species composition (Franklin *et al.*, 2000) within forest stands continues to interest forest scientists, managers, and practitioners (Hudson, 1987; Sali and Wolfson, 1992; Baulies and Pons, 1995; Leckie *et al.*, 1995; Meyers *et al.*, 1996; Pitt *et al.*, 1997). The objective of achieving accuracies that meet or exceed those currently achieved by aerial photointerpretation techniques (Congalton and Mead, 1983; Gillis and Leckie, 1993) may soon be feasible given continued improvements in computing, image understanding, and image analysis techniques (Green, 2000). Image classification is one possible method for use in this application. One of the challenges in using high spatial resolution remotely sensed imagery in digital classification is that the interclass spectral variability of surface features can increase with increasing spatial resolution. The result is a reduction in class statistical separability (Hay *et al.*, 1996). With traditional classifiers, which rely on the concept of a "spectral signature," this often translates into a poor classification accuracy for individual tree species (Hughes *et al.*, 1986) and aggregated estimates of species composition (Franklin, 1994). In general, it is thought that, rather than relying on multispectral image spectral signatures alone, digital classification of species composition and forest structure should be augmented with texture measures (St-Onge and Cavayas, 1995). Texture can be used in the classification or, alternatively, the process of per-pixel classification can be supplemented or replaced with another approach, such as texture segmentation (Lobo, 1997). Much work remains to be done on how and where texture analysis can be effective in forestry remote sensing applications (Lark, 1996; Wulder *et al.*, 1996; Bruniquel-Pinel and Gastellu-Etchegorry, 1998).

A large degree of variability can exist in the development of a classification signature using high spatial resolution image data. In Figure 1, approximately 1-m pixels are shown of a forest stand adjacent to a logging road T-intersection. Large standard deviations, relative to the mean spectral response, typically result in forested scenes in most spectral bands. The difficulties in using spectral signatures comprised of the mean and standard deviation are obvious, giving rise to the notion that some measure of spatial variability would be useful in signature generation (Figure 2). Texture analysis attempts to measure this scene variance for use in the classification process. Traditionally, texture has been defined as the spatial variation in image tones or colors (Haralick *et al.*, 1973). In images of forest cover, spatial variation may be caused by changes in species type, crown closure, or stem density.

Different stem densities can create different texture patterns, even though they have the same species composition (Figure 3). In the first set (Figure 3; top row labeled as group 1A and 1B), the first image contains data from a mature spruce stand with approximately 500 stems per hectare. The second image (group 1B) contains data from a spruce plantation, but with approximately 3000 stems per hectare. In the second set (Figure 3; middle row labeled as 2A and 2B) the difference between two hardwood stands with different crown closures is shown. Group 2A illustrates image data from a mature intolerant hardwood stand with a canopy that was almost completely closed. Group 2B was acquired over a stand which had a much more open canopy, with a measured crown closure of 30 to 50 percent. The open canopy created a larger shadow component than that represented by the first stand, resulting in different textures. Figure 3 also contains examples of two mixed-wood stands (bottom row, labeled as groups 3A and 3B). First, group 3A is a 70 percent hardwood and 30 percent softwood mixed-wood stand. This stand can be compared to group 3B, a mixed-wood stand with 60 percent softwood and 40 percent hardwood. Each of these stands had similar structure (i.e., shadow

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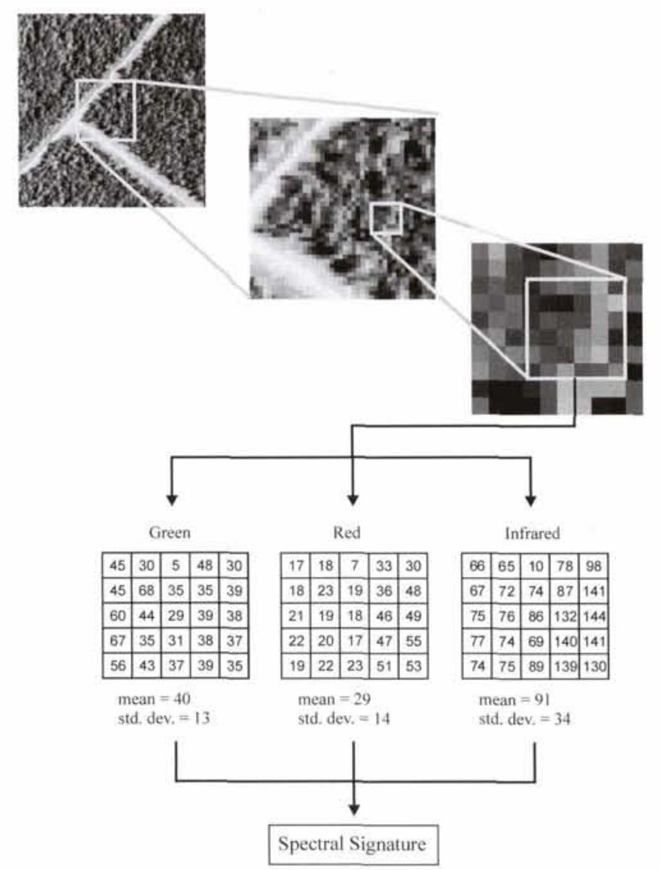

Figure 1. A high spatial resolution classification spectral signature. Adapted with permission from Franklin (2001).

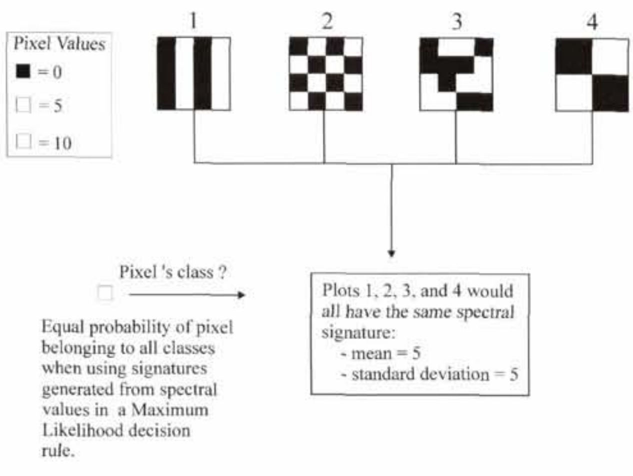

Figure 2. Simplified example of texture windows with same spectral signatures. Adapted with permission from Franklin (2001).

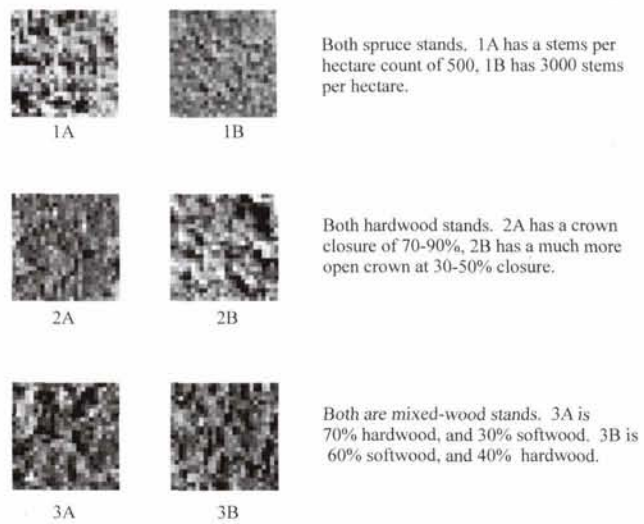

Figure 3. Examples of image texture variability in different forest stands.

component is similar). However, these image textures appear different because of different combinations of species, resulting in different variations in tone.

It is these variations that are of interest in the application to derive structural estimates and species composition classifications from high spatial detail image texture measures (Franklin *et al.*, 2000). The initial questions relate to the issue of how texture can be extracted from the image, and how the extracted texture relates to variations within stands that are measured on the ground. We reasoned that further work with texture would be warranted if simple texture procedures produced significantly higher classification accuracies for species composition and structure; others, notably Hay *et al.* (1996), have adopted a different logic, arguing that texture should be optimized for the phenomena under investigation, and then applied. Such work has not yet been translated into usable texture procedures in practical forestry applications; instead, simpler measures appear able to provide reasonable results in similar applications (He and Wang, 1992; Wilson, 1996; Martin *et al.*, 1998). In a species composition analysis of airborne imagery, we wanted to use a texture procedure and texture measures that would at least have some chance of being used in operational settings—because they are readily available. Therefore, the central objective of this research was to assess whether the inclusion of textural information derived from readily available spatial co-occurrence texture measures in a maximum-likelihood classifier would improve species composition classification accuracies when compared to per-plot agreement with field surveys.

Study Area and Data Collection

The study area is situated in the Fundy Model Forest (FMF) in southeastern New Brunswick (Figure 4). The FMF is a 420,000-hectare working forest that contains towns and villages, industrial freehold land, Crown Land, Fundy National Park, and many small private woodlots. The FMF is part of a model forest network including Canadian and international efforts to de-velop model forests for the purposes of research (Natural Resources Canada, 1997). The study area is characterized by a wide variety of forest species and forest conditions. Hardwood species are predominantly red maple (*Acer rubrum* L.), white birch (*Betula papyrifira* Marsh.), and trembling aspen (*Populus tremuloides* Michx.), with yellow birch (*Betula alleghaniensis* Britton.), grey birch (*Betula popufolia* Marsh.), sugar maple (*Acer saccharum* Marsh.), striped maple (*Acer pensylvanicum* L.), white ash (*Fraxinus americana L.*), and beech (*Fagus grandifolia* Ehrh.) also present in smaller quantities. The dominant softwood species are jack pine (*Pinus banksiana* Lamb.), balsam fir (*Abies balsamea* (L.) Mill.), white pine (*Pinus strobus* L.), and white spruce (*Picea glauca* (Moench) Voss), with

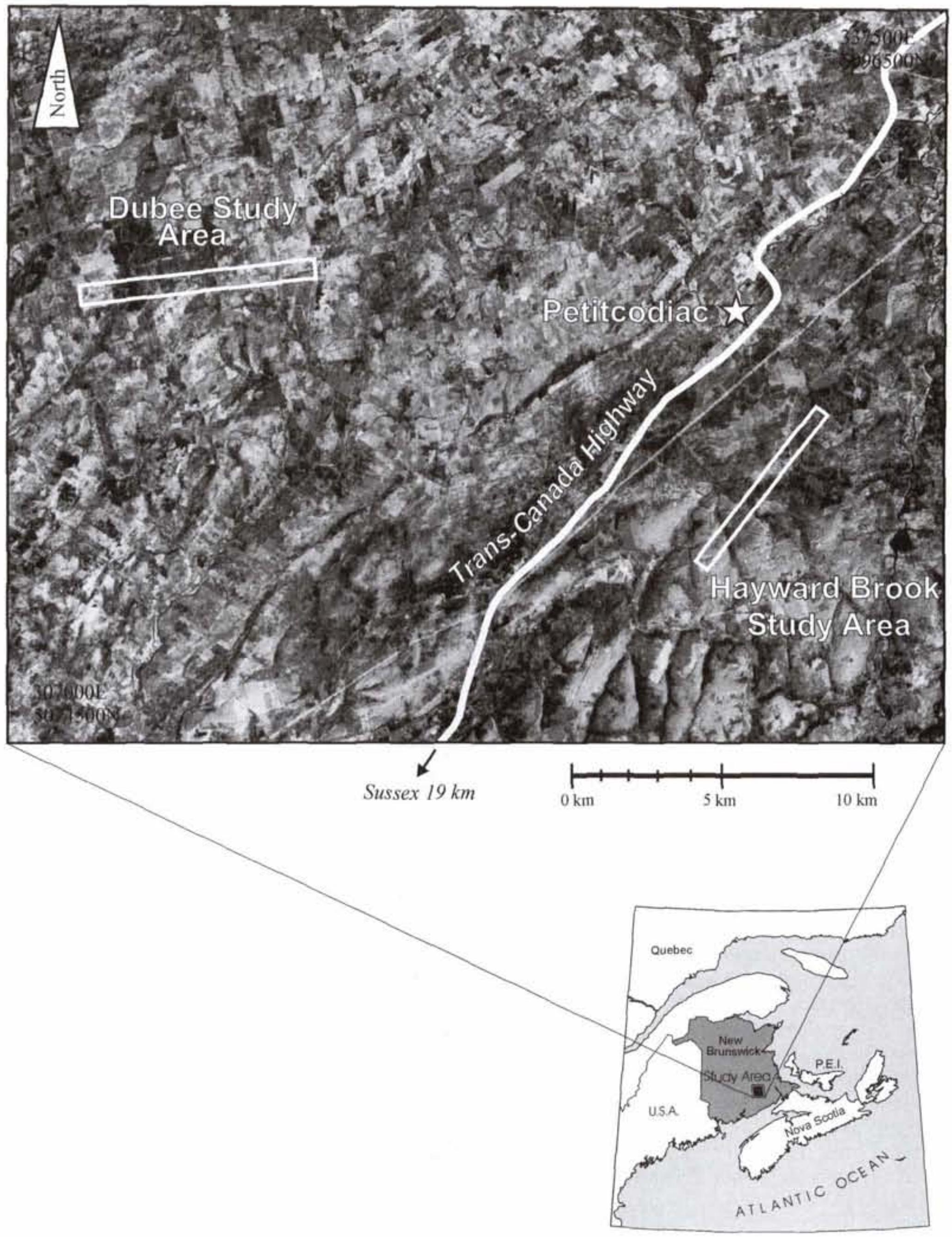

Figure 4. Location of the study area and flight lines in southeastern New Brunswick.

some red spruce (*Picea rubens* Sarg.) and red pine (*Pinus resinosa* Ait.). Due to glaciation, the area is underlain with a thick overburden of unconsolidated diamicton (till), resulting in a hummocky topography and erratic drainage patterns.

Airborne Data

The Fundy Model Forest Compact Airborne Spectrographic Imager (CASI) data set was acquired on 31 July 1995 under favorable atmospheric conditions. The data were geometrically corrected (to inertial navigation system accuracy with known Global Positioning System (GPS) points observed in the imagery), and were atmospherically adjusted using spectroradiometric observations of pseudo-invariant features located throughout the study area. The image data set is composed of two flight lines of approximately 8 km each in length, an average width of 500 m, with a spatial resolution of 1 m^2, and five bands centered at 565.0, 645.4, 665.1, 711.0, and 750.6 nm. The two flight lines are referred to as Dubee and Hayward Brook (see Figure 4). The Dubee flight line had a wide range of forest-cover types, including plantations, naturally regenerating stands, reclaimed farm land, and second and third generation mature stands. In contrast, the Hayward Brook flight line was covered entirely by mature stands with the exception of one jack pine plantation. On both flight lines, active harvesting was in progress and a substantial percentage of the area in the imagery had been cutover. The flight lines were recorded at different azimuths.

Field Data Collection

A modified systematic sampling method (utilizing a grid or transect) was employed (Muller *et al.*, 1998) to identify areas to be sampled on the ground. All transects were identified on the georeferenced imagery and then later verified on the ground to ensure sample areas had not been altered by harvesting or other disturbances. Two plots of each forest inventory stand type represented in the image were selected from a random list of coordinates on each transect. One plot was used for training the classifier and the other plot was used for assessing the classification accuracy. A total of 48 plots was sampled in 24 different stand types. Sampling occurred on a transect with a spacing of 100 meters, and all samples were taken at a minimum distance of 50 meters from any disturbance. To minimize the effects of sensor look geometry, no points were sampled within 100 meters of the edge of the image.

Bitterlich Horizontal Point Sampling (plotless cruising) (Avery and Burkhart, 1994) was used to collect measurements of diameter at breast height (dbh), crown diameter, tree height, height to live crown, crown closure, and tree age in July 1998. A basal area prism factor of 2 was used. All cruising was conducted in accordance with procedures recommended by the New Brunswick Department of Natural Resources and Energy (1996). From the crown diameter and tree height measurements, bivariate regression analysis was performed to determine the relationship between dbh and height, and dbh and crown diameter for each species. Most relationships were either linear or logarithmic with the exception of the Black Spruce height prediction which was best described by an exponential relationship. The dbh versus height relationship yielded an average r^2 value of 0.68 while dbh versus crown diameter provided an average r^2 of 0.77. Once these relationships were established, tree height and crown diameter were predicted for all trees measured.

Using crown diameter, the percentage of crown area per species for each plot was determined, from which the species composition of each plot was labeled based on its percentage of crown composition (Martin *et al.*, 1998). The result is a plot label which is a better estimate of species composition than using a simple linear relationship between number of stems and species composition (e.g., eight jack pine stems and two white birch stems equals jack pine 80 percent and white birch 20 percent), because the crown area technique describes the percentage of the forest canopy that each species is contributing to the spectral response. This procedure is similar to the aerial photointerpretation of species composition which is also based on crown composition rather than stem composition. The stand types and field data for each of the plots measured in the Hayward Brook and Dubee flight lines are compiled in Table 1.

Methods

The most common algorithm available for estimation of texture is based on the gray-level spatial co-occurrence matrix (Haralick *et al.*, 1973; Haralick, 1979; Haralick, 1986; Jensen, 1996). This is one of many possible texture analysis methods available, but choosing an optimal texture algorithm is not straightforward (Connors and Harlow, 1980). In one recent study, Carr and Pelon de Miranda (1998) found that semivariance textures produced higher classification accuracies when classifying microwave images, and spatial co-occurrence texture measures produced higher classification accuracies when classifying optical imagery. Spatial co-occurrence texture analysis requires the user to identify five different control variables (Franklin and Peddle, 1987; Marceau *et al.*, 1990; Franklin *et al.*, 1996):

- window size,
- the texture measure(s),
- input channel (i.e., spectral channel to measure the texture of)
- quantization level of output channel (8-bit, 16-bit, or 32-bit), and
- the spatial component (i.e., the interpixel distance and angle during co-occurrence computation).

Assuming that multiple texture measures from the co-occurrence matrix are computed using different spectral channels, multiple window sizes to capture "scale" differences (Ahearn, 1988), more than one quantization level, and at least four possible directions (spatial component), the result would be many thousands of different possible combinations that could be used to generate texture channels for a single application. This output would overwhelm even the most sophisticated classifer. Because in this initial research we were interested primarily in whether an increase in the usefulness of the relationship between species composition classification and imagery could be established based on texture, recommendations from previous research with this imagery were used to select a texture measure (Wulder *et al.*, 1998; Franklin *et al.*, 2000). A test of the optimal window size was conducted using a subsample of the available plots; larger window sizes (19 by 19) were found to provide more stable texture measures and, therefore, were adopted in this study.

Maximum-likelihood classification was selected as the method of comparing the performance of the image data with the field assessment in the 48 plots studied. First, the image data were classified based on the signatures derived in the training areas and the classifications were compared to the results in the test areas. Second, this process was repeated, but using only the texture data in the classification. Third, the effect of adding a texture measure on the classification accuracy was determined by repeating this classification process with the addition of texture to the signature for each class. These steps were executed at three levels of a classification hierarchy; first, considering all of the stands surveyed (Table 1) as an instance of a separate, unique class; second, by merging stands with similar species composition and structure to create stands labeled by dominance/co-dominance (black spruce, white and red spruce, jack pine, white pine, tolerant hardwoods, intolerant hardwoods, several mixedwoods); and finally, by merging stands with similar species composition and structure labeled by dominance/co-dominance into lifeform classes (softwood, hardwood, mixedwood).

Results

The trend of higher accuracy when using texture in the classification accuracy results was expected and found in this study (Table 2): classification accuracy increased when using the combined spectral and texture data (75 percent) compared to classification using only the spectral data alone (54 percent) or the texture data alone (70 percent). The increase in accuracy attributable to the addition of texture was 21 percent. As well, the expected trend of increasing accuracy with fewer classes was found. At Level 2 (based on species dominance/co-dominance classes), the classification accuracy improved from 61 percent (spectral data alone) to 80 percent (using combined spectral and texture data). At Level 3 (based on lifeform classes), the improvement resulting from the texture analysis was 33 percent. The classification accuracy, using spectral and texture data in lifeform classes, was 100 percent correct in the 24 available test plots. However, even though this accuracy is impressive, the amount of detail in the classification is such that little practical use would result. Foresters are much more interested in remote sensing image classifications that preserve spatial detail rather than remove it—smoothly varying forest stand depictions are all too common as a product of aerial photointerpretation in which polygonal data are created as homogeneous generalizations at the expense of spatial detail (Lowell *et al.*, 1996).

In the original stand classifications, several of the classes were thought to be "texturally" distinct. For example, two

TABLE 1. FOREST STAND TYPES AND FIELD MEASUREMENTS OF STRUCTURE

a) Hayward Brook image stands, classes, and field measurements of structure					
Stand	Class	Crown Closure	Stems/ha	Understory	Midstory
1	JP10	4	5500	—	—
2	TH6 IH2 SW2	2	650	hw	hw
3	WP3 SP2 TH2 IH2	4	800	mw	mw
4	SP7 WP1 HW2	3	1350	mw	—
5	WP5 SP3 HW2	4	900	mw	—
6	JP5 SP3 HW2	2	830	mw	—
7	TH3 IH3 SW4	3	650	mw	—
8	IH7 SW3	3	800	mw	mw
9	IH6 TH3 SW1	3	950	sw	—
10	TH5 IH4 SW1	3	900	mw	—
11	IH6 TH4	4	2100	mw	—
12	IH7 TH3	4	2200	mw	—
13	PI5 SP3 HW2	3	870	mw	—
14	IH7 TH3	4	2100	mw	—
15	SW8 HW2	3	1000	mw	—
16	HW6 SW3	3	725	mw	—
17	HW9 SW1	3	925	mw	—
b) Dubee image image stands, classes, and field measurements of structure					
Stand	Class	Crown Closure	Stems/ha	Understory	Midstory
18	BS8 BF2	2	550	—	—
19	BS8 BF2	4	1700	—	—
20	SP10	5	800	—	—
21	SP10	5	5700	—	—
22	JP10	4	1300	—	—
23	TH4 IH4 SP2	1	700	sw	—
24	TH5 IH4 bF1	4	300	hw	—
25	IH5 TH5	4	500	hw	—
26	IH5 TH5	regenerating stand, approx. 5 years			—
27	IH5 TH4 SP1	3	2200	mw	—
28	IH9 TH1	3	900	mw	—
29	IH9 TH1	regenerating stand, approx. 3 years			—
30	TH4 IH4	4	400	hw	—

TABLE 2. OVERALL CLASSIFICATION ACCURACY USING SPECTRAL DATA ALONE, TEXTURAL DATA ALONE, AND COMBINED SPECTRAL AND TEXTURAL DATA IN THREE HIERARCHICAL LEVELS

	Accuracy (%)		
	Classification Level*		
Classification	1	2	3
Spectral data alone	54	61	67
Texture data alone	70	76	70
Combined spectral and texture data	75	80	100

*Note the levels correspond to classes in a hierarchy as follows;
Level 1 = each stand in Table 1 considered a unique class (30 classes)
Level 2 = merging of stands into classes organized according to dominant/co-dominant species; classes consisted of black spruce, white (and red) spruce, jack pine, white pine, tolerant hardwoods, intolerant hardwoods (10 classes)
Level 3 = lifeform classes (softwood, hardwood, mixedwood dominated by hardwoods or softwoods, 6 classes)

hardwood stands with the same species composition represented by stands 25 and 26 had quite different structures. The large crowns of stand 25 were anticipated to cast much larger shadows, resulting in a more coarse texture that would not be confused with the fine texture produced by the smaller, more close-growing crowns in a regenerating stand (e.g., stand 26). Spectrally, the two stands were confused, but the differences in structure and the resulting texture were sufficient for the classifier to distinguish between them. The texture classification also separated two black spruce stands with differing density. In another case, stand 1 (jp10), the only plantation class on the Hayward Brook Image, was anticipated to be reasonably distinct using image data from the spectral channels alone. Instead, the jack pine stand was confused with the white pine stands. The texture data allowed this stand to be separated from the other pine stands; the interpretation was that a *lack of texture* in the pine plantation provided useful information to the classifier. The largest improvement by texture was found in the classification and separation of the mixedwood stands. Such classes have long been problematic in digital classifications of forest cover, and are quite often grouped into one class (Franklin *et al.*, 2000), despite the obvious unsuitability of this grouping for the purposes of the user. This study suggests that more detailed mixedwood classes are possible if texture is incorporated into the classification.

The classification accuracies obtained in this study (approximately 75 percent average at the lower class detail end of the hierarchies), and the amount of increase due to the use of texture (between 19 and 33 percent), are comparable to results obtained in similar applications of airborne multispectral image texture in forest inventory classifications (Franklin *et al.*, 2000). A 17 percent increase in the classification accuracies of seven volume classes in fourteen Alberta conifer stands by including texture measures in the classification procedure was earlier obtained by Franklin and McDermid (1993). A maximum classification accuracy of 75 percent was reported. St-Onge and Cavayas (1997) incorporated texture in a more advanced image segmentation method, similar to that used by Lobo (1997), and found 80 percent classification accuracies in several forest-cover and density classes with high spatial resolution imagery. Those results were obtained on a much smaller sample of sites with less variability and suggested the more detailed stand-by-stand analysis presented in this paper. These studies suggest that further work is required to fully document the value of airborne multispectral image texture analysis in forest inventory classification work.

Conclusion

The objective of this study was to determine whether spatial co-occurrence texture measures—readily available and easily understood—could be used to generate higher forest species composition classification accuracies in New Brunswick forest stands than the use of spectral response patterns alone. Increased accuracy was obtained when using texture at all levels of a classification hierarchy. At the stand level, accuracies were on the order of 75 percent in agreement with field surveys, an improvement of 21 percent over the accuracy obtained using spectral data alone; in stands grouped according to species dominance/co-dominance, the accuracy improved still further to 80 percent. The overall classification accuracy in a highly generalized lifeform classification was 100 percent. These results are consistent with those reported for similar high spatial detail image texture studies in New Brunswick and elsewhere, and are also thought to be reasonable when compared to the accuracy of forest species composition analysis using aerial photointerpretation of similar stands. The ability to accurately classify forest structure and species composition using high spatial resolution ($\leq$ 1m) multispectral digital imagery may contribute to the development of new methods to produce forest stand inventories.

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References

Ahearn, S.C., 1988. Combining Laplacian images of different spatial frequencies (scales): Implications for remote sensing analysis, *IEEE Transactions on Geoscience and Remote Sensing*, 26:826–831.

Avery, T.E., and H.E. Burkhart, 1994. *Forest Measurements, Fourth Edition*, McGraw-Hill, Boston, Massachusetts, 331 p.

Baulies, F., and X. Pons, 1995. Approach to forest inventory and mapping by means of multi-spectral airborne data, *International Journal of Remote Sensing*, 16:61–80.

Bruniquel-Pinel, V., and J.P. Gastellu-Etchegorry, 1998. Sensitivity of high resolution images of forest to biophysical and acquisition parameters, *Remote Sensing of Environment*, 65:61–85.

Carr, J.R., and F. Pellon de Miranda, 1998. The semivariogram in comparison to the co-occurrence matrix for classification of image texture, *IEEE Transactions on Geoscience and Remote Sensing*, 36:1945–52.

Congalton, R.G., and R.A. Mead, 1983. A quantitative method to test for consistency and correctness in photointerpretation, *Photogrammetric Engineering & Remote Sensing*, 49:61–74.

Connors, R., and C. Harlow, 1980. A theoretical comparison of texture algorithms, *IEEE Transactions of Pattern Analysis and Machine Intelligence*, 2:204–222.

Franklin, S.E., 1994. Discrimination of subalpine forest species and canopy density using digital CASI, SPOT PLA and Landsat TM data, *Photogrammetric Engineering & Remote Sensing*, 60:1233–1241.

———, 2001. *Remote Sensing for Sustainable Forest Management*. CRC Press, Boca Raton, Florida, 391 p.

Franklin, S.E., R.J. Hall, L.M. Moskal, A.J. Maudie, and M.B. Lavigne, 2000. Incorporating texture into classification of forest species composition from airborne multispectral images, *International Journal of Remote Sensing*, 21:61–79.

Franklin, S.E., and G.J. McDermid, 1993. Empirical relations between digital SPOT HRV and CASI spectral response and lodgepole pine (*Pinus contorta*) forest stand parameters, *International Journal of Remote Sensing*, 14:2331–2348.

Franklin, S.E., and D.R. Peddle, 1987. Texture analysis of digital image data using spatial co-occurrence, *Computers and Geosciences*, 17:1151–1172.

Franklin, S.E., M.A. Wulder, and M.B. Lavigne, 1996. Automated derivation of geographic windows for use in remote sensing digital image texture analysis, *Computers and Geosciences*, 22:665–673.

Gillis, M.D., and D.G. Leckie, 1993. *Forest Inventory Mapping Procedures across Canada*, Information Report PI-X-114. Petawawa National Forestry Institute, Forestry Canada, Ottawa, Ontario, Canada, 79 p.

Green, K., 2000. Selecting and interpreting high-resolution images, *Journal of Forestry*, 98:37–39.

Haralick, R.M., 1979. Statistical and structural approaches to texture, *Proceedings of the IEEE*, 67:786–804.

———, 1986. Statistical image texture analysis, *Handbook of Pattern Recognition and Image Processing* (T.Y. Young and K.S. Fu, editors), Academic Press, New York, N.Y., pp. 247–279.

Haralick, R.M., K. Shanmugan, and I. Dinstein, 1973. Textural features for image classification, *IEEE Transactions on Systems, Man, and Cybernetics*, 3:610–621.

Hay, G.J., K.O. Niemann, and G.F. McLean, 1996. An object-specific image texture analysis of H-resolution forest imagery, *Remote Sensing of Environment*, 55:108–122.

He, D.C., and L. Wang, 1992. Unsupervised textural classification of images using the texture spectrum, *Pattern Recognition*, 25:247–255.

Hudson, W.D., 1987. A study to evaluate multispectral imagery digital data for classifying and mapping coniferous forests in the northern Lower Peninsula of Michigan, USA, *Canadian Journal of Remote Sensing*, 13:39–42.

Hughes, J.S., D.L. Evans, and P.Y. Burns, 1986. Identification of two southern pine species in high resolution aerial MSS data, *Photogrammetric Engineering & Remote Sensing*, 52:1175–1180.

Jensen, J.R., 1996. *Introductory Digital Image Processing: A Remote Sensing Perspective*, Prentice Hall, Upper Saddle River, New Jersey, 316 p.

Lark, R.M., 1996. Geostatistical description of texture on an aerial photography for discriminating classes of land cover, *International Journal of Remote Sensing*, 17:2115–2133.

Leckie, D., J.R. Gibson, N.T. O'Neil, T. Piekutwoski, and S.P. Joyce, 1995. Data processing and analysis for MIFUCAM: A trial of MEIS imagery for forest inventory mapping, *Canadian Journal of Remote Sensing*, 21:337–356.

Lobo, A., 1997. Image segmentation and discriminant analysis for the identification of land cover units in ecology, *IEEE Transactions on Geoscience and Remote Sensing*, 35:1136–1145.

Lowell, K.E., G. Edwards, and G. Kucera, 1996. Modeling heterogeneity and change in natural forests, *Geomatica*, 50:425–440.

Marceau, D.J., P.J. Howarth, J.M. Dubois, and D.J. Gratton, 1990. Evaluation of the grey-level co-occurrence matrix method for land cover classification using SPOT imagery, *IEEE Transactions on Geoscience and Remote Sensing*, 28:513–517.

Martin, M.E., S.D. Newman, J.D. Aber, and R.G. Congalton, 1998. Determining forest species composition using high spectral resolution remote sensing data, *Remote Sensing of Environment*, 65:249–254.

Meyer, P., K. Staenz, and K.I. Itten, 1996. Semi-automated procedures for tree species identification in high spatial resolution data from digitized colour infrared-aerial photography, *Journal of Photogrammetry and Remote Sensing*, 51:5–16.

Muller, S.V., D.A. Walker, F.E. Nelson, N.A. Auerbach, J.B. Bockheim, S. Guyer, and D. Sherba, 1998. Accuracy assessment of a land-cover map of the Kuparuk River Basin, Alaska: Considerations for remote regions, *Photogrammetric Engineering & Remote Sensing*, 46:619–628.

New Brunswick Department of Natural Resources and Energy (DNRE), 1996. *New Brunswick Integrated Land Classification System*. New Brunswick Department of Natural Resources and Energy, Fredericton, New Brunswick, Canada (variously paged).

Pitt, D.G., R.G. Wagner, R.J. Hall, D.J. King, D.G. Leckie, and U. Runesson, 1997. Use of remote sensing for forest vegetation management: A problem analysis, *Forestry Chronicle*, 73:459–477.

Sali, E., and H. Wolfson, 1992. Texture classification in aerial photographs and satellite data, *International Journal of Remote Sensing*, 13:3395–3408.

St-Onge, B.A., and F. Cavayas, 1995. Estimating forest stand structure from high resolution imagery using semivariogram estimates, *International Journal of Remote Sensing*, 16:1999–2021.

———, 1997. Automated forest structure mapping from high resolution imagery based on directional semivariogram estimates, *Remote Sensing of Environment*, 61:82–95.

Wilson, B.A., 1996. Estimating coniferous forest structure using SAR texture and tone, *Canadian Journal of Remote Sensing*, 22:382–389.

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

Wulder, M.A., E.F. LeDrew, S.E. Franklin, and M.B. Lavigne, 1998. Aerial image texture information in the estimation of deciduous and mixedwood forest leaf area index (LAI), *Remote Sensing of Environment*, 64:64–76.

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