MAPPING VEGETATION COVER TYPES IN THE CANADIAN BOREAL FOREST USING PIGMENT AND WATER ABSORPTION FEATURES DERIVED FROM AVIRIS

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1. BACKGROUND

Globally, the boreal forest is one of the most extensive biomes. Encompassing approximately 14.3 million km^2, or 21% of the world's forested land surface (Whittaker and Likins, 1975), it is estimated that it stores > 37% of the total amount of carbon in the biosphere (Kasischke et al., 1995). An increasing body of research indicates that high latitude continental regions (43°-65°) will be most vulnerable to large climatic perturbations resulting from global warming (Mitchell et al., 1983; Sellers et al., 1996). These changes in climate are likely to result in changes in the carbon, energy and water cycles of the boreal forest; however, the precise mechanisms and implications of these changes are still not fully comprehended (Sellers et al. 1997). In 1993, the Boreal Ecosystem-Atmosphere Study (BOREAS) was undertaken in the boreal forest of central Canada to improve our knowledge of the processes involved in the fluxes of radiative energy, sensible heat, water, trace gases and CO_2 between this biome and the troposphere. One of the primary objectives of BOREAS was to improve the parameterization and simulation modeling of these interactions at multiple scales (Sellers et al. 1997). Land cover data is an essential parameter in various BOREAS modeling efforts that seek to upscale fluxes from sub-regional to regional scales (Sellers et al. 1997; Steyaert et al., 1997). Additionally, land cover data is needed to improve remote sensing algorithms and study fire disturbance (Steyaert et al., 1997). Thus, accurate and reliable boreal forest land cover data at the sub-area, study area and regional level is critical for BOREAS flux modeling efforts.

At the regional and sub-regional scales, Steyaert et al. (1997) derived an AVHRR (1-km pixel resolution) vegetation classification based on a combination of field observations and an unsupervised cluster analysis based on NDVI. Hall et al. (1997) developed a Landsat TM physical based classification that uses canopy reflectance models to classify vegetation types and biophysical parameters. These studies produced better results than those of solely statistical methods, e.g. maximum likelihood; however, low accuracies for fen and wet conifers, two important land cover types in the boreal forest, were reported. Narrow-band airborne hyperspectral sensors, AVIRIS (224 spectral bands) and the Compact Airborne Spectrographic Imager (CASI), provide the opportunity to explore different expressions of vegetation such as reflectance vegetation indices and pigment concentration parameters that can be used to improve the results of broadband sensors. Using hyperspectral CASI imagery, Zarco-Tejada and Miller (1999) derived three red edge parameters and used them as inputs in an isodata unsupervised classification routine to map vegetation types. With an overall accuracy of 61.2% and the ability to map the fen cover type, the study provided important improvements over the TM physical classification. However, this technique was unable to classify deciduous vegetation and differentiate between wet and dry conifers, some of the functionally distinct types present in this ecosystem.

The primary objectives of our study were: (1) to improve vegetation classification of boreal forests for modeling at the sub-regional scale; (2) to test the advantages of hyperspectral AVIRIS data over satellite multispectral data (TM, AVHRR); (3) to explore alternative approaches to express land cover vegetation based on pigment and water content; and (4) to test the robustness of these techniques across multiple seasons. Two different methods of expressing pigment and water content (leaf- based vs. index-based) were explored and these results are presented here.

2. MATERIALS & METHODS

AVIRIS 1994 imagery for three seasons, fall (September 16), spring (April 19) and summer (July 21) for the BOREAS Southern Study Area, near Prince Albert, Saskatchewan (Figure 1) were converted to reflectance using the atmospheric correction routine developed by Green et al. (1991). In BOREAS, at the sub-area scale, water vapor, heat and CO_2 fluxes were measured using eddy correlation equipment installed on flux towers at two study areas within the BOREAS modeling region (~500,000 km^2). These local measurements (~ 1 km^2) have been linked to aircraft measurements to derive fluxes at the regional scale (Steyard et al., 1997). Due to the importance of flux towers to the overall BOREAS objectives, the AVIRIS images were selected to include flux tower sites. These images also contained the major vegetation types representative of the BOREAS study region. The images were georeferenced in ENVI 3.0 (Research Systems, Boulder, CO) using a panchromatic Landsat TM image as a base map, obtained from the BOREAS Information System (BORIS) archive (Goddard Space Flight Center, Greenbelt, Maryland). Two study areas were extracted: JP-FEN ("jack pine-fen"), where the dominant vegetation types were *Pinus banksiana* (jack pine) and fen; and OBS ("old black spruce"), where the dominant species was *Picea mariana* (black spruce) (Figure 1).

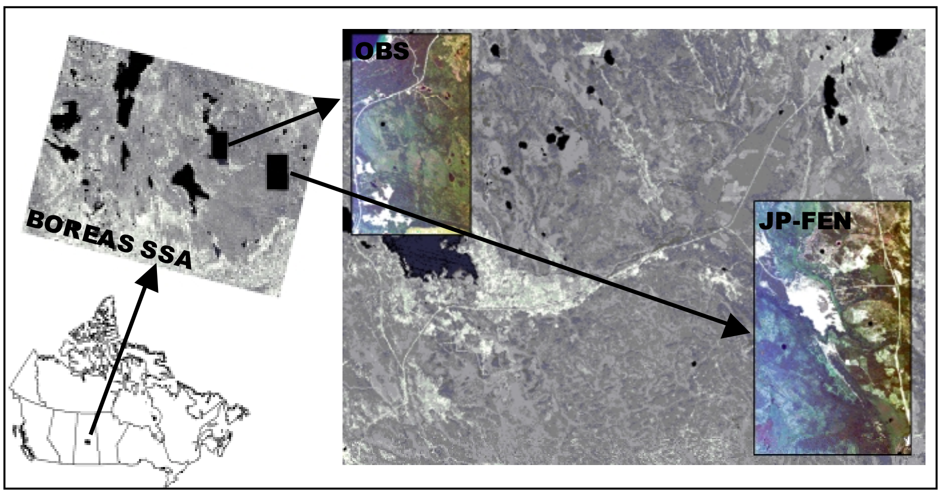

Figure 1. BOREAS Southern Study Area (SSA) and the sub-areas, old black spruce (OBS)

SSA forest cover data from the Saskatchewan Environment and Resource Management, Forestry Branch-Inventory Unit (SERM-FBIU), processed by BOREAS Staff Science team into binary raster files, were obtained from BORIS (Gruszka, 1998). This classification was prepared using aerial photography coupled with field visits and included 20 vegetation classes (Table 1). Landsat TM physical vegetation classification produced by BOREAS staff science based on the methodology developed by Hall et al. (1997) was obtained as a raster binary image from the BORIS archive (Hall, 1999). Both the TM and SERM classifications were then reclassified to match the seven ecologically significant land cover types outlined in Table 1. These seven classes were based on the needs of the various BOREAS science teams, as described by Zarco-Tejada and Miller (1999).

We decided to represent land cover types based on two alternate methods of expressing pigment and water content in vegetation. The first used a combination of leaf types representing varying mixtures of the principal pigment groups present in photosynthetic vegetation and a linear spectral decomposition procedure, spectral mixture analysis, to obtain the relative abundance of those leaf types (the “leaf-based approach”). The second used a combination of several reflectance indices that provide information on pigment and water abundance (the “index-based approach”). The products of these processes were then used as inputs in a supervised maximum likelihood classification to distinguish land cover types.

Table 1. Reclassification of the SERM-FBIU and Landsat TM land cover classifications into seven ecologically significant classes used in this study.

SERM-FBIU Classification	**TM Spectral Trajectories Classification**	**Maximum Likelihood AVIRIS Classification**
Class	Class	Class
White Spuce Jack Pine	Dry Conifer	Dry Conifers
Black Spruce Spruce/Pine Tamarack	Wet Conifer New Regeneration Conifer Medium Age Regeneration Conifer	Wet Conifers
Mixed Spruce-Fir/Broadleaf Mixed Jack Pine/Broadleaf Mixed Broadleaf/Spruce-Fir Mixed Broadleaf/Jack Pine	Mixed (Conifer & Deciduous)	Mixed
Aspen	Deciduous New Regeneration Deciduous Medium Age Regeneration Deciduous	Deciduous
Treed Muskeg Clear Muskeg	Fen	Fen
Brushland Clearing Burn-over Disturbed, Cut or Burn Disturbed/Jack Pine Regeneration Experimental Area Flooded Land	Disturbed Fire Blackened	Disturbed
Water	Water	Water

2.1 Leaf-based Approach

Because pigment spectra in isolated extracts can differ markedly from those in the intact leaf, we decided to model the landscape based on leaf spectra. *Liquidambar styraciflua* (sweetgum), a common street tree native to the Eastern U.S., was chosen because leaves of this species display all possible combinations of major plant pigment groups (chlorophylls, carotenoids and anthocyanins). Thus, with this species, it was possible to obtain spectral endmembers of leaf "types" representing varying pigment concentrations, including relatively pure spectra of each of these pigments. Leaf spectra in the visible/NIR (400-1100 nm) for ten sweetgum leaf types, representing widely varying levels of pigmentation, were collected using a portable spectrometer (Unispec, PP Systems, Haverhill, MA). Figure 2 shows four representative spectra. The leaves were collected in the vicinity of the California State University, Los Angeles campus in the fall of 1998. Additionally, 100 pixel-averaged soil and water spectra obtained from the JP-FEN July 21 AVIRIS scene were added. The spectra were interpolated to match 1994 AVIRIS bands 13 – 32 and 35 – 67 (489.67 – 991.44 nm). The leaf spectra were then converted into an ENVI spectral library and used as input in a linear spectral mixture analysis (SMA) routine to extract the leaf endmember fractions of those leaf types for the OBS and JP-FEN image cubes. The result of this procedure was a 12-band image cube with each band representing one of the endmembers used in the SMA process. One image was created for each of the endmembers used for the process and for each pixel a value representing the fraction of that endmember was produced.

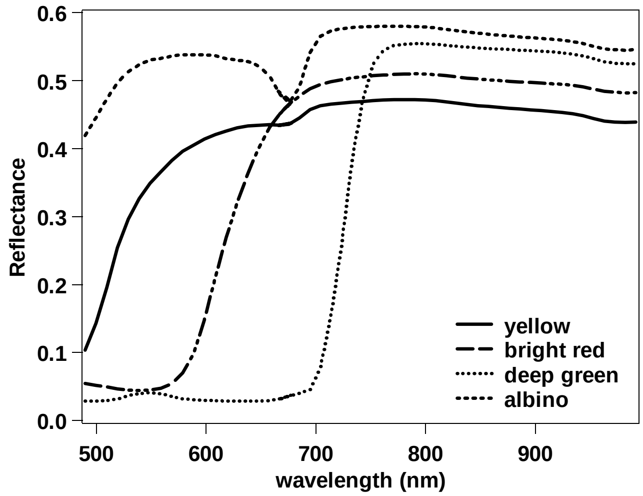

Figure 2. Leaf spectra for four representative *Liquidambar styraciflua* leaf types exhibiting different concentrations of chlorophyll, carotenoids and/or anthocyanins.

2.2 Index-based Approach

Seven reflectance indices were selected to characterize the physiological state of the vegetation composition of the two study areas. These indices are indicators of pigment content, photosynthetic rates, canopy structure or water content (Table 2) and their effectiveness has been widely explored at the leaf and canopy scales (Gamon et al. 1992, 1997; Gamon and Surfus, 1999; Gao, 1996; Gitelson and Merzylak, 1994; Peñuelas et al., 1994, 1995; Peñuelas and Filella, 1998). Using the original 224-channel AVIRIS image cube for the two areas, the reflectance indices were calculated. The formulas for these indices are provided in Table 2. Figure 3 gives a visual representation of the information in Table 2. AVIRIS wavelengths were interpolated to obtain the exact bands employed in the index formulas using linear interpolation.

Table 2. Seven reflectance vegetation indices calculated from the original AVIRIS image cube and used in the maximum likelihood analysis to derive land cover types.

INDEX	FUNCTION	FORMULATION	REFERENCE
Modified normalized Difference vegetation index (mNDVI)	Leaf chlorophyll content	$(R_{750}-R_{705})/(R_{750}+R_{705})$	Gitelson and Merzlyak (1996)
Red/green ratio	Anthocyanins/chlorophyll	$R_{600-699}/R_{500-599}$	Gamon and Surfus (1999)
Photochemical reflectance index (PRI)	Xanthophyll cycle pigment activity	$(R_{531}-R_{570})/(R_{531}+R_{570})$	Gamon and Surfus (1999)
Water band index (WBI)	Leaf water content	R_{900}/R_{970}	Peñuelas et al. (1997)
Normalized difference water index (NDWI)	Leaf water content	$(R_{857}-R_{1241})/(R_{857}-R_{1241})$	Gao (1993)
Summed green reflectance	Green vegetation cover	$\sum_{n=500}^{599} Rn$	Unpublished
Normalized difference vegetation index (NDVI)	Green vegetation cover	$(R_{895}-R_{675})/(R_{895}+R_{675})$	Modified from Tucker (1979)

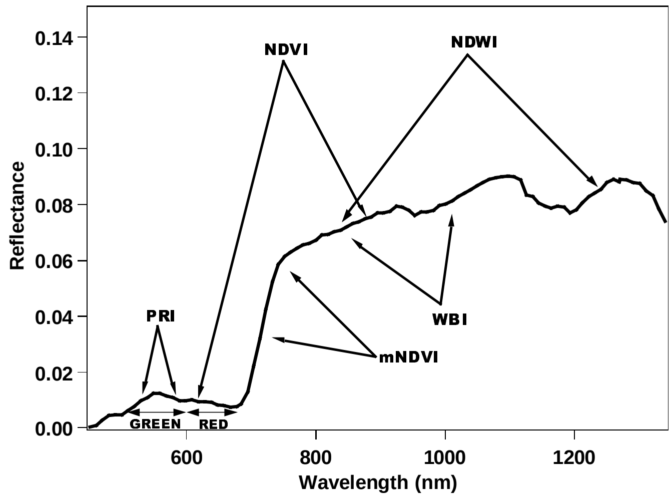

Figure 3. Jack Pine (*Pinus banksiana*) spectrum from AVIRIS illustrating the wavebands used for the reflectance indices classification.

A set of training pixels was selected to be used in a maximum likelihood classification routine. The selection was based on the 20 vegetation types from the SERM-FBIU land cover classes listed in Table 1. A region of interest (ROI) of 100 pixels per cover type were chosen for the analysis; however, for the burn-over, disturbed/jack pine regeneration, experimental area and flooded land classes, this was not possible because of limited spatial extent. To simplify the analysis, we decided to combine them into a single "disturbed"cover class. Pixels from the above mentioned classes in addition to the disturbed, cut or burn cover type were selected for the disturbed training pixel set. In order to achieve a more statistically representative training set, sample pixels were randomly selected across the entire image. To minimize over-representation and under-representation of large and small cover types, respectively, the number of pixels for all classes were kept equal (Richards, 1995). Both the leaf-type and index image cubes for the three seasons were classified using maximum likelihood (Richards, 1995). So that all pixels would be classified, no threshold value was placed on the process. The resulting images were reclassified into the seven BOREAS cover types.

Accuracy of the AVIRIS classifications was assessed using a second set of pixels selected across the image. The 17-meter-pixel AVIRIS mosaics for the two study areas were re-sampled to 30 meter-pixel images using a 1st degree polynomial nearest neighbor warping routine (Richards, 1995). This allowed comparisons to the SERM-FBIU and spectral trajectories Landsat TM classifications. A region of interest (ROI) of 700 pixels, 100 per cover type, was selected from the SERM-FBIU reclassified image. Careful consideration was taken to avoid selecting pixels used in the maximum likelihood procedure. The test pixels were subsequently overlaid on the leaf-type and index-based maximum likelihood images and their labels were checked against those of SERM.

3. RESULTS

The results of the two AVIRIS classification methods for JP-FEN and OBS for summer (July 21) are presented in Figure 4, panels C & G (leaf-based) and D & H (index-based). A visual comparison of both methods to the SERM and TM classifications indicates that both AVIRIS classification methods tend to correspond better to the SERM-FBIU than does the TM classification. Table 3 presents a summary of the results of the contingency tables developed for the AVIRIS maximum likelihood classifications. The table displays both “user’s accuracy” (the total number of correctly classified pixels of a class of all the pixels classified as that class), and “overall accuracy” (the total number of pixels for all classes correctly classified).

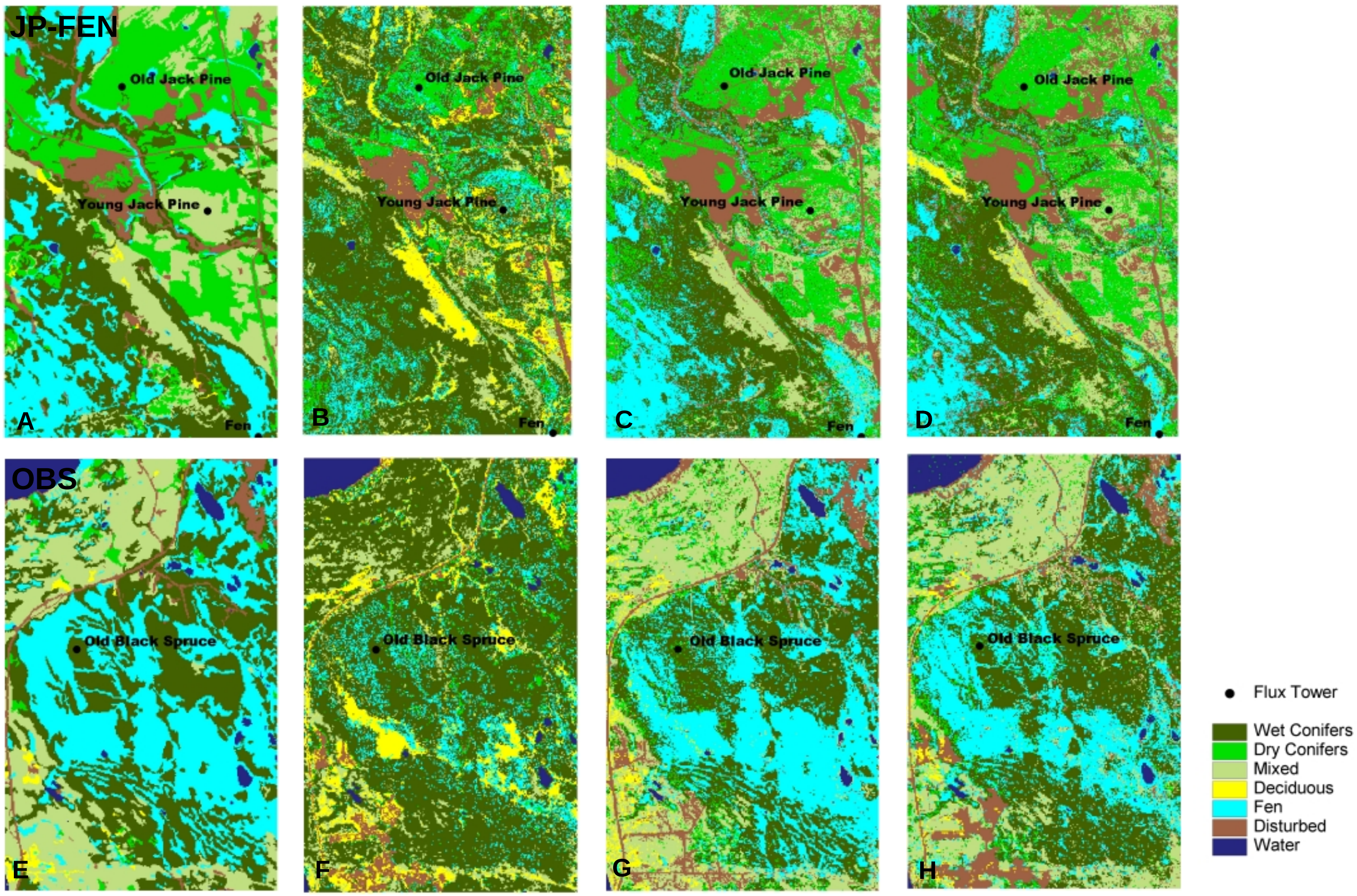

Figure 4. JP-FEN (jack pine-fen) site (top panels) and OBS (old black spruce) site (bottom panels). For the evaluation of classification accuracy, theSERM-FBIU (panels A & E), obtained from the BOREAS Information System (BORIS), was assumed to be true. The Landsat TM physical classification (panels B & F) was obtained from BORIS. The AVIRIS leaf-based (panels C & G) and index-based (panels D & H) classifications were derived from the July 21, 1994, overflight.

Accuracies varied with method, AVIRIS scene, season, and cover type, as indicated in Table 3. Of the two methods, slightly higher accuracies were obtained with the leaf-based method (Figure 4, panels C & G) (overall accuracy 66.6 - 80.1% for the leaf-based method, vs. 56.6 –73.3% for the index-based method). Of the two scenes, higher accuracies were obtained with the JP-Fen scene (overall accuracy 72.7-80.1% for the JP-Fen scene vs. 56.6-75.6 for the OBS scene). Season also had a slight effect on accuracy, but this effect was not consistent across methods and scenes. For example, using the leaf-based method for the JP-Fen scene, spring and fall yielded slightly higher overall accuracies than summer (80 – 80.1% for spring and fall vs. 73.7% for summer). However, the same method for the OBS scene yielded the highest overall accuracy in summer (75.6%). Within a scene and method, accuracies varied with cover type. Not surprisingly, the highest user's accuracy were obtained with water (99-100%). Of the different vegetation types, the lowest user's accuracies were obtained with the mixed class (e.g., 47.2 - 62.6 % for JP Fen using the leaf-based method). On the other hand, the other vegetation classes all yielded better results, with user accuracies ranging as high as 91.4% (deciduous class for JP Fen in fall, using the leaf-based method).

A comparison of the AVIRIS-based classification methods to earlier Landsat TM classifications (Hall et al., 1997) revealed substantial improvements over these previous classifications. With Landsat TM, overall accuracies for our two study regions were 54.7% (JP-Fen) and 44.9% (OBS) (Table 4; Figure 4 panels B & F). By contrast, AVIRIS imagery, using even the weakest, index-based method, yielded higher overall accuracy values (72.7 – 73.3% for JP-Fen, and 56.6 – 68% for OBS, depending upon season) (Table 3). Using the stronger, leaf-based method, overall accuracies were even higher (73.7 - 80.1% for JP-Fen, and 66.6 - 75.6% for OBS). Thus, regardless of location, method, or season, AVIRIS imagery yielded markedly better cover classifications than other standard methods based on Landsat TM.

Table 3. Summary of the contingency matrix results for the AVIRIS leaf-type and index based maximum likelihood classifications for JP-FEN and OBS for the three study seasons. The original matrices were derived using a 700-pixel sample, 100 per cover type.

	AVIRIS Maximum Likelihood Classifications					
	JP-FEN			**OBS**		
	Spring	**Summer**	**Fall**	**Spring**	**Summer**	**Fall**
LEAF BASED **User's Accuracies (%)**						
Wet Conifers	75.7	73.9	80.2	58.1	66.1	52.4
Dry Conifers	74.5	81.9	86.4	67.7	72.5	77.3
Mixed	62.6	47.2	55	52.7	51	41.8
Deciduous	85.5	90.9	91.4	89.8	82.9	69.6
Fen	83.3	65.9	87.9	74.3	80.6	82
Disturbed	83.2	79.8	73.1	85.8	91.3	84.8
Water	100	100	100	100	100	100
Overall Accuracy (%)	80.1	73.7	80	72.6	75.6	66.6
INDEX BASED User's Accuracies (%)						
Wet Conifers	69.2	70.2	77.8	56.9	56.7	57.4
Dry Conifers	70.4	73	63.6	54.3	75	31
Mixed	50.9	52.5	45.2	43.3	46.1	35.4
Deciduous	79.3	90	94.9	62.5	90.5	38.2
Fen	74.3	74.4	80	79.3	65.1	82.7
Disturbed	69.7	67.8	76.7	86.9	59.9	58
Water	99	100	100	100	100	100
Overall Accuracy (%)	72.7	73.1	73.3	66.9	68	56.6

Table 4. Summary of the contingency matrix results for the Landsat TM physical classification for JP-FEN and OBS. This classification was produced using a September 9, 1994 image. The original matrices were derived using a 700-pixel sample, 100 per cover type.

LANDSAT TM SPECTRAL TRAJECTORIES	JP-FEN	OBS
User's Accuracies (%)		
Wet Conifers	40.0	28.6
Dry Conifers	72.7	50.0
Mixed	29.9	47.4
Deciduous	46.3	30.0
Fen	49.4	75.8
Disturbed	100.0	100.0
Water	99.0	100.0
Overall Accuracy (%)	54.7	44.9

4. DISCUSSION

Both techniques presented in this work offer improvements over other vegetation cover products for this region. This is not surprising, considering they both make use of the rich information content present in hyperspectral data. The slightly better results using the leaf-based method may be due to the fact that the leaf-based method uses more of the spectral information present in the AVIRIS imagery than the index-based method. Because it uses *all* spectral information within the 489.67 to 991.44 nm region, the leaf-based method appears to have more power to distinguish cover classes than the index-based method, which is based on a more limited number of spectral bands. On the other hand, the index method has the potential advantage that it also yields index images that are themselves of functional significance. For example, using a simple combination of the NDVI and PRI indices, it is possible to derive a map of photosynthetic fluxes for this region (Rahman et al., 2000).

With AVIRIS, the availability of spectral information at 10 nm intervals provides the opportunity to formulate and test narrow-band indices that have been previously developed at leaf and canopy scales. This potential is simply not available with multispectral sensors such as TM and AVHRR. Previous applications of these indices to AVIRIS images have been limited (e.g. Gamon et al., 1995); in this study when applied *in concert* to properly calibrated and atmospherically-corrected AVIRIS imagery, they are clearly able to distinguish different cover types. A similar conclusion has recently been reported with AVIRIS data from the Santa Monica Mountains in southern California (Gamon and Qiu, 1999).

Both index-based and leaf-based methods rely on the presence of universal water and pigment absorption features that are fundamental to all vegetation, regardless of type, location, or season. Thus, further development of the approaches presented here should provide robust methods for mapping cover types. The good results regardless of cover type and season, including spring dates when snow was still present, support our conclusion that these methods may have wide applicability. At present, the limitation of these methods is that they both require some degree of information about the identity of surface types as training sets. Some knowledge of how pigment expression or index values vary with cover type is needed for these methods to work. This type of information is only now beginning to become available for limited geographic regions (e.g. Gamon and Qiu, 1999). Thus, at present, a strong limitation to the broad applicability of these methods is the limited availability and coverage of hyperspectral sensors and their properly calibrated and atmospherically corrected products.

The results of the accuracy assessment for the TM classification undertaken in this work indicate values lower than those provided by the BORIS staff scientists in their experimental report in which an overall accuracy of 83% for the entire TM scene was noted (Hall, 1999). In this study, using our sample pixels, the TM classification's overall accuracy was only 54.7% for the JP-FEN study area and 44.9% for OBS. According to our analysis, most of the error in the TM classification arose from the misclassification of fen as wet conifers and of dry conifers as wet conifers. Another source of error for this classification was the misclassification of mixed stands (conifers and deciduous) as deciduous vegetation.

As discussed earlier, modeling the potential of the boreal forest to become either a carbon sink or source demands an accurate knowledge of the distribution of the different cover classes present in this ecosystem (Sellers et al. 1997; Steyaert et al., 1997). The TM physical classification developed by the BOREAS Staff Science team has been an invaluable source of information in the modeling of fluxes in the boreal forests of Canada at the sub-regional scale (BOREAS annual meeting 1999). Nevertheless, as Hall et al. (1997) acknowledged, this classification had difficulty identifying important cover types such as fen, an important source of methane in this ecosystem, and wet and dry conifers. According to the results of our study study, both leaf- and index-based methods show noticeable improvements in overall accuracy as well as in the identification of those cover types. Improved mapping of the functionally distinct cover types could yield improvements in estimates of CO_2 and methane flux for this region. An initial attempt to map CO_2 fluxes from AVIRIS imagery has been presented by Rahman et al. (2000) in this volume.

5. CONCLUSIONS

By transforming an AVIRIS image cube into reflectance index and leaf type maps and using them as inputs in a maximum likelihood routine, vegetation types in the boreal forests of Canada have been correctly classified with overall scene accuracy rates up to 80.1%. These results are notably higher than the TM spectral trajectory classification, used as a parameter in numerous flux models in the BOREAS project, as well as the more recent red-edge based classification by Zarco-Tejada and Miller (1999). These two new classification methods were able to classify fen, wet conifer and deciduous classes at higher accuracy than the previously mentioned classifications. Additionally, it should be noted that our accuracy assessments were based on the SERM-FBIU vegetation maps, which were derived from field observation and aerial photography, with their own inherent errors; consequently, we believe actual classification accuracies may be somewhat higher than reported here. The results indicate that pigment and water content expressions can be applied to detect functionally significant features in the landscape. Further investigation is focusing on developing more fundamental, quantitative derivations of pigment and water content at the landscape level for the purpose of modeling carbon and water vapor fluxes.

6. ACKNOWLEDGEMENTS

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