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AERIAL AND SATELLITE SENSOR DETECTION AND CLASSIFICATION OF WESTERN SPRUCE BUDWORM DEFOLIATION IN A SUBALPINE FOREST

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RÉSUMÉ

La détection et la classification des patrons de défoliation par la tordeuse occidentale de l'épinette (**Choristoneura occidentalis**, Freeman) dans une forêt subalpine de l'ouest de l'Oregon ont été réalisées à l'aide d'images vidéo acquises à deux altitudes à partir d'un aéronef ultra léger et à l'aide d'images numériques multibandes acquises par le capteur thématique de Landsat.

L'analyse de texture des images vidéo a donné lieu à une précision de classification de l'ordre de 78 % en référence avec un relevé de terrain de la défoliation et de l'interception de lumière du couvert forestier effectué sur 21 parcelles en septembre 1994. Les données acquises par le capteur thématique en 1993, à elles seules, ont permis d'obtenir des résultats de classification satisfaisants dans une proportion de 75 % pour quatre classes de dommages (aucun, léger, modéré et sévère) dans ces mêmes parcelles. La précision cartographique était de l'ordre de 67 % d'après les résultats d'une classification (K-movennes) non dirigée modifiée. À partir d'une série de données diachroniques acquises par le capteur thématique de Landsat, une comparaison a été effectuée entre une structure forestière telle qu'elle apparaissait avant l'épidémie en 1988 et cette structure en état de défiolation à la suite de la chute de la population d'insectes en 1993, ce qui a permis d'atteindre une

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précision de 86 % dans la discrimination de trois classes de dommages (aucun, léger/modéré, sévère).

L'analyse texturale et spectrale combinée des données vidéo peut constituer une méthode complémentaire aux photographies aériennes et aux relevés de terrain classiques pour évaluer le niveau de défoliation ainsi qu'une solution de rechange à la tâche complexe que constitue la sélection des sites d'entraînement pour les classifications effectuées à l'aide d'images satellites.

SUMMARY

The detection and classification of western spruce budworm (**Choristoneura occidentalis** Freeman) defoliation patterns in a subalpine forest in western Oregon was accomplished with videographic imagery acquired at two altitudes from an ultralight aircraft and with multitemporal digital Landsat TM satellite imagery.

Image texture analysis of the aerial videographic data provided 78% classification accuracy with reference to a ground survey of defoliation and canopy light interception made on 21 plots in September 1994. The 1993 TM data alone provided 75% correct discrimination in four damage classes (none, light, moderate, severe) in these same plots. **Mapping accuracy** was 67% correct based on a modified, unsupervised K-means classification. A multitemporal TM image data set enabled the comparison of a pre-outbreak forest structure in 1988 and defoliation conditions following a collapse of the insect population in 1993, which improved the discrimination of defoliation to 86% in three damage classes (none, light/moderate, severe).

A combination of spectral and textural analysis of aerial videographic data may provide a complementary

technique to conventional photography and ground surveys in assessing defoliation, and may offer an alternative in the complex task of training site selection for satellite-derived image classification.

INTRODUCTION

erial and satellite sensor digital imagery provide a Abasis for classifying and mapping defoliation caused by insects or other agents in a wide range of forest environments through the detection of subtle changes in the spectral properties of foliage (Bucheim et al., 1985; Rock et al., 1988; Leckie et al., 1988; Franklin, 1989; Ahern et al., 1991a; Muchoney and Haack, 1994) or as a result of a reduction in the canopy leaf area (Leckie and Ostaff, 1988; Ekstrand, 1990; Ahern et al., 1991b; Brockhaus et al., 1993). Aerial digital image analysis can provide a close view of individual tree crowns or small stands; satellite digital image analysis would seem well suited for identifying canopy defoliation classes and for mapping changing patterns across large landscapes. The remote sensing techniques may provide results that are equivalent to, or better, than those obtained from aerial sketch-mapping (Franklin and Raske, 1994) or from limited ground surveys of small areas that represent different types of stands and their conditions.

Aerial remote sensing of forest defoliation has been reported using a wide range of sensors and analysis techniques (Ahern et al., 1991a). The accuracy of digital aerial forest defoliation assessment may be increased through multispectral band manipulation (Leckie et al., 1992) and through image texture analysis (Ghitter et al., 1995). For example, image ratios, normalization, or principal components analysis can improve the signal-to-noise ratio by removing differences associated with variable illumination, thereby possibly increasing the ability to detect subtle colour changes. Other noise-inducing factors, attributed to variation in the transmissivity of the atmosphere or to instrument sensitivity, also may be reduced. Image texture analysis allows for spatial variability in tree-level damage that reflect differences within tree crowns or among trees within a stand. In 1991 Yuan et al. reported reasonably good results with multispectral texture analysis in aerial video detection and classification of sugar maple decline. The application of digital aerial video imagery with texture analysis in conifer forest defoliation assessment and scaling to satellite imagery has not been tested.

Few examples of operational forest defoliation assessment by satellite remote sensing exist, partly because of the difficulty in covering a large area with sufficient detail at acceptable levels of accuracy. One requirement is for sets of cloud-free images over a series of years or seasons (Beaubien, 1994). The multispectral data should be stratified by forest structure *prior* to image analysis to predict defoliation accurately (Ekstrand, 1994). This stratification may be based on digital forest inventory data or from multitemporal remote sensing observations of stand structure made prior to the defoliation (Khorram *et al.*, 1990; Brockhaus and Khorram, 1992). Once defoliation is noted, it is often difficult to obtain a sufficient number of homogeneous training sites (McCaffrey and Franklin, 1993; Bucheim and Lillesand, 1989; Bolstad and Lillesand, 1991) representing easily recognized stages of defoliation, as, for example, when foliage is red.

A large-scale Western Spruce budworm (Choristoneura occidentalis Freeman [Lepidoptera: Tortricidae]) infestation between 1989 and 1993 in the Cascade Mountains of western Oregon afforded an opportunity to assess the ability of aerial and satellite sensor systems to detect various levels of defoliation in a relatively homogenous subalpine coniferous forest. An ultralight Near-Earth-Observation-System (McCreight et al., 1994) collected aerial videographic data over the defoliated stands on two missions in September and October 1994. To utilize better the inherent advantages of satellite digital analyses, we investigated the possibility of extending aerial digital image analyses validated on a few precisely located training sites to satellite image analysis of a larger area. We discriminated and mapped defoliation using the aerial video data, 1993 Landsat TM digital data, and also examined the possibility of increased defoliation discrimination through change detection analysis using a 1988 (pre-outbreak) Landsat TM image.

This paper outlines the logical steps in the multitemporal and multisensor digital analysis of forest defoliation, with examples and quantitative assessments of discrimination and mapping accuracy for four digital data sets, compared to field observations of defoliation acquired using ocular estimates and light absorption data acquired at 21 locations along a transect through the stands of interest.

STUDY AREA AND DATA COLLECTION

The study was centred on a 150- to 200-year-old subalpine forest at Santiam Pass, Oregon (Lat. 44° 25' N, Long. 121° 50' W) at an elevation of 1460 m (Figure 1). Mountain Hemlock (*Tsuga mertensiana*), subalpine fir (*Abies lasiocarpa*), Engelmann Spruce (*Picea engelmanii*) with some scattered Western White Pine (*Pinus monticola*) comprised the predominant cover type. On the southern edge of this forest, a young stand of Lodgepole Pine (*Pinus contorta*) has replaced the dominant type following a wildfire in 1967. The leaf area index of the older forest averaged <3 before the insect outbreak (Runyon *et al.*, 1994). A sparse cover of huckleberry (*Vaccinium membranaceum*) represented the only significant ground vegetation in leaf at the time of the study.

The area receives >200 cm of precipitation annually, mostly as snow. The growing season is less than four months (Franklin and Dyrness, 1973). Meteorological data were collected at the site between 1989 and 1991 as part of the Oregon Transect Ecosystem Research (OTTER) project (Runyon *et al.*, 1994). The NASA project was a multiple aircraft campaign (see the special issues of *Ecological Applications* (Peterson and Waring, 1994) and *Remote Sensing of Environment* (Goward *et al.*, 1994a)).

Field Assessment of Defoliation

Two estimates of defoliation were acquired on September 15, 1994, at 21 field plots located on a random transect



Figure 1.

Location of the study area (labelled site 4) in the subalpine zone of western Oregon; sites 1, 2, 3, 5, and 6 represent other forest types that were part of the OTTER experiment (see Peterson and Waring, 1994; Goward *et al.*, 1994a).

through the subalpine forest stands of interest. An approximately 10 by 10 m sampling area was used for each plot. First, ocular estimates of defoliation as a percentage of the tree foliage were obtained by three field staff and averaged to produce a single estimate of defoliation in the field. These estimates were grouped into four categories of defoliation for the upper third of the crown: none (no visible defoliation), light (1–24% defoliation), moderate (25–49% defoliation), and severe (more than 50% defoliation, including dead trees). This is a standard field method for defoliation assessment, and was used by Franklin and Raske (1994) in their satellite remote sensing study of Eastern Spruce budworm defoliation of Balsam Fir forests in western Newfoundland.

Second, Photosynthetically Active Radiation (PAR) was measured with a sunfleck ceptometer (Decagon SF-80) in single-sensor mode in each sample plot (Pierce and Running, 1988). A total of 100 readings were acquired when traversing the plot, but only the average value was recorded. The PAR observation for each plot was converted to leaf area index estimates assuming a light extinction coefficient (k) of 0.5 (after Jarvis and Leverenz, 1983):

$$LAI = (\ln I_z / I_o) / -k \tag{1}$$

where I_z is the PAR measurement per plot and I_0 is the incoming solar radiation measured in open areas at frequent intervals throughout the sampling period (restricted to the local hours 1000–1400).

Remote Sensing Observations

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Near-Earth-Observing-System

Aerial video imagery were acquired from 300 m above ground on September 7, 1994, and 2000 m above ground on October 2, 1994, over the Santiam Pass using the system described by McCreight et al. (1994). The video data were recorded with a Sony CCD-TR5 Video-8 camera with the automatic exposure gain control operable. Each image frame was time-tagged in milliseconds, and the GPS coordinates were recorded in an image trailer using the NavStar (P-code) Global Positioning System. A Matrox graphics board, driven by Decision Images PC-software (v 3.24; Decision Images Inc., 1989), was used to frame-grab and colour composite selected video scenes into RGB colour space, which were then transferred to the PCI EASI/PACE processing system (v 5.2; PCI Inc., 1993) running on a SUNSPARC 10 workstation. The resolution of the video imagery was determined to be approximately 1 m² pixel for the September 7 data and 2 m² pixels for the October 2 data through measurements of common features (road cuts, clearings, and small buildings, for example).

Recent improvements in aerial videography suggest that these data may be calibrated (King, 1992) and used as a surrogate for some types of

environmental field data (Neale and Crowther, 1994), as a tool for assessing satellite image land-cover classification accuracy (Marsh *et al.*, 1994), and as a general source of resource information for updating GIS data bases (Bobbe *et al.*, 1993). However, in radiometric terms, the video imagery in this study are not calibrated. No adjustment of the video imagery for the automatic gain control settings and possible non-uniform CCD sensitivity was made; only raw DN values were used in the digital image analysis. Lens vignetting was offset by sampling only within the middle onethird of each video frame.

The field locations were identified on the video imagery with small pixel windows (10 by 10 pixels for the September 7 data, 5 by 5 pixels for the October 2 data). The video imagery were not georeferenced or resampled to a geographic grid since only the scene centres were tagged with GPS coordinates and the field sites were often located away from the frame centres.

Landsat TM digital image data

Landsat TM imagery acquired September 30, 1993, were geometrically registered to a second geocoded scene acquired August 31, 1988, with less than 0.6 pixel RMSE at 19 ground control points scattered across a quadrant scene. A cubic convolution resampling algorithm was used to determine pixel values in a 25 m grid. The image solar conditions were 37° elevation and 147° azimuth, and 46° elevation, 138° azimuth, respectively. The data were then transformed into TM Tasseled Cap brightness, greenness, and wetness indices (Crist *et al.*, 1986).

An atmospheric correction (Richter, 1990) was applied to the two image dates, but the impreciseness of the scattering model in 1993, when smoke and haze from burning fields to the west of the study area dominated the scene, led to obvious errors in the change detection procedures (see also Muchoney and Haack, 1994). Therefore, raw DN values were used in the satellite image analysis techniques.

METHODS

Aerial Image Processing

Linear discriminant analysis was used to test the ability of the aerial videographic digital data to separate the defoliation levels, and multiple regression was used to show the relationships between the aerial video and the percentage of defoliation as estimated from the canopy light interception measurements. The original 21 field plots served to assess the accuracy of the discrimination, but uncertainty in geometric locations of image pixels and field sites make these comparisons more tentative than in the satellite remote sensing discrimination.

Broad-band image normalization has been suggested as a robust, empirical correction technique for use in video image analysis in forest surveys and other applications. For example, Leckie *et al.* (1992) found that transformed spectral features were generally better than the original spectral bands in the digital multispectral scanner detection of budworm defoliation. Therefore, image normalization based on a simple chromaticity calculation (Rees, 1990) was used to illustrate graphically the different levels of defoliation in the aerial imagery and to aid in locating field sites for sampling. More complex image manipulations based on a series of processing steps using image histograms, non-linear contrast modifications, and colour space transformations are possible, but were considered beyond the scope of the present analysis.

Video image texture processing was applied to the October 2, 1994, raw imagery in the form of spatial co-occurrence matrices (Franklin and Peddle, 1987; PCI Inc., 1993). The texture variable *homogeneity* (Haralick, 1979) for each colour band in the composite was selected based on an *ad hoc* inspection of the visual displays for additional analysis (see also Franklin and Peddle, 1990). Homogeneity (H) is computed as:

$$H = \sum_{j} \sum_{i} (P(i, j) / (1 + R(i)) - (C(i))^{2}))$$
(2)

where P(i,j) is the spatial co-occurrence matrix element, R(i) is the grey level value for a row, and C(j) is the grey-level value for a column. The measure was computed for four directions (vertical, horizontal, left, and right diagonals) and all three bands, and then averaged for a 5 by 5 pixel window corresponding to the area measured on the ground during the field survey.

Satellite Image Processing

Linear discriminant analysis (TM 1988 and 1993 data) and image classification (TM 1993 only) were used to test the ability of satellite spectral data to separate defoliation levels. Multiple regression was used to show the relationships between the 1993 TM spectral data and the percentage of defoliation as estimated from the canopy light interception measurements. Image comparisons were made by calculating TM Tasseled Cap differences derived from the 1988 and 1993 Landsat imagery. For the 1993 Landsat TM image, classification was based on a conventional modified unsupervised algorithm 'seeded' with mean class values from the field plots. The minimum distance to means (or K-means) decision rule was employed. The original 21 field plots served to assess the accuracy of these classifications, which was computed as the sum of the diagonal in the contingency tables divided by the number of classes.

Two separate procedures were required to accomplish the detection of insect damage categories using the two dates of satellite imagery, which were previously georegistered: radiometric matching of the two images; and change detection. Some degree of uncertainty in the analysis remains because of the geometric error in locating a single TM pixel corresponding to each field plot. While not definitive, these results are considered valuable as a part of this 'proofof-concept' study.

Radiometric matching

The two TM images were acquired on different dates, and therefore under different illumination and atmospheric conditions. To minimize associated radiometric differences in the two images, a modified Hall et al. (1991) radiometric normalization procedure was used. This requires that one image be selected as a reference image (1988) that will remain unchanged and that one be selected as a subject (1993) image that will be radiometrically "matched" to the reference image. One dark control set was selected in spectral space for the subject image and one was set for the reference images. For the bright control sets, two were selected for each image from both spectral and scene space. This provided four different sets of radiometrically matched images: sets 1a and 1b using spectral space control sets; and sets 2a and 2b using scene space control sets. In each set, "a" refers to one bright control set and "b" refers to the other.

To evaluate the effectiveness of each of the four radiometrically matched images, we selected in scene space several groups of image pixels (a test set) representing an array of dark to bright targets. These included water bodies, old-growth, young, and deciduous forests, and rock outcrops, all of which we assumed would have changed spectrally very little (relative to defoliated stands) between the two dates. Over all test set pixels, we calculated the mean spectral vector over all six TM reflectance bands and over the TM Tasseled Cap brightness, greenness, and wetness indices (Crist and Cicone, 1984; Crist et al., 1986). This yielded two mean vectors for the test set of the reference image (one for six-band TM space and one for three-index) Tasseled Cap space), two for the raw or unmatched image, and two for each of the four radiometrically matched images. Finally, using these mean spectral vectors, we calculated the Euclidean spectral distance between the 1988 reference test set and the five subject reference test sets. The radiometric match that provided the shortest Euclidean distance between reference and subject test sets determined which radiometrically matched TM subject image to use in the following change detection procedure.

Change detection

With the GPS data collected in the field, we obtained TM Tasseled Cap brightness, greenness, and wetness values for single pixels within each of the 21 ground reference plots from both the 1988 and 1993 imagery. Using these values, we calculated the temporal differences in brightness, greenness, and wetness between 1988 and 1993 for each pixel. These temporal-difference data were entered into a discriminant function analysis to determine the spectral separability of the four defoliation classes. The analysis was repeated after combining the light and moderate defoliation classes into a single class, and then again after combining the none and light classes, and the moderate and severe classes, to yield three and two defoliation classes, respectively. Also, the discriminant analysis was conducted using the six spectral values themselves (brightness, greenness, and wetness in both 1988 and 1993) rather than the temporal differences.

RESULTS

Field Estimates of Defoliation

The relationship between the leaf area estimates derived from the field PAR readings and the ocular estimate of percentage of defoliation was strong ($R^2 = 0.839$, y = -0.503x+ 6.474; see **Figure 2** for grouped data by defoliation category). This relationship suggests that the current defoliation level of each sample point may be adequately characterized by the 1994 leaf area estimates. No notable regrowth was observed in the field.

Aerial Image Analysis

The aerial videographic data were regressed on the field estimates of percentage of defoliation (Table 2). As ex-



Figure 2.

Plot of LAI estimates derived from ceptometer field observations of light interception over four defoliation classes grouped by stand for the 21 field sites. The 95% confidence intervals are shown as dashed lines.

Table 1.

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Mean 1993 TM digital number spectral response and differences between percentage of defoliation measured at 21 sample locations. The defoliation classes were derived by ocular estimation of the tree foliage in a 10 by 10 m area by three field staff and then averaged and grouped into four categories: none (no visible defoliation), light (1–24% defoliation), moderate (25–50% defoliation), and severe (more than 50% defoliation).

	1993 TM DN					
	Band					
	1	2	3	4	5	7
Defoliation Class						
None	32	11	8	16	14	5
Light	33	11	9	15	19*	7
Moderate	33	11	9	16	20*	7
Severe	34	11	10	17	21*	8
* significant difference with some defoliation	e between	n sample	es with n	o defolia	ation and	those

pected, the low altitude video data were poorly related to the defoliation, probably as a result of the increased variability (1 m² pixels) and the uncertainty in locating the exact field site in the imagery (only the exact scene centres have GPS-determined geographic coordinates). The higher-altitude data set, with lower spatial resolution, illustrates a stronger, though still weak, relationship ($\mathbb{R}^2 = 0.339$).

The discrimination of damage classes using the aerial videographic data resulted in 68% accuracy (October 2 high-altitude videography) and 60% accuracy (September 7 low-altitude videography) (**Table 3**). The videography results show that healthy and lightly defoliated trees were the

least separable, but that severe defoliation had the highest discrimination (**Figure 3**). Image texture analysis provided a substantive increase in accuracy for the video imagery (which are inherently textural). For example, the overall or mean accuracy for the four defoliation classes increased from 68% to 78% following texture analysis. The improved discrimination occurred in the healthy, light, and moderate defoliation classes.

Satellite Image Analysis

Mean TM spectral response

The mean spectral response in TM bands showed a characteristic small increase in visible reflectance and a comparatively larger increase in reflectance in the mid-infrared bands with increased defoliation (**Table 1**). Only the increase in band 5 was statistically significant in the sample. This increase in mid-infrared reflectance with decreased vegetation amounts may be a response to the moisture status of the canopy or structure differences. Increased blue reflectance may be a direct response to the increased exposure of lichens in the canopy in this sample (Goward *et al.*, 1994b).

The TM were regressed on the percentage of defoliation estimates (Table 2). An R² value of 0.568

Table 2.

Multiple regression results for the 1993 TM and 1994 aerial video spectral response and field estimates of percentage of defoliation based on field ceptometer readings of light interception at 21 sites in September 1994. Light interception was converted to leaf area index estimates using Equation 1, which were then grouped according to the level of defoliation. The grouped relationship between defoliation

and LAI is shown in Figure 2.

	R ²	F-test
Sample		
TM 1993	0.568	5.262
September 1994 Video (1 m pixels)	0.150	2.525
October 1994 Video (2 m pixels)	0.339	2.907

Table 3.

Percent accuracy for four defoliation classes using linear discriminant functions comprising the 1993 TM data and the two aerial videographic samples and the field estimates of defoliation class at the 21 field sites. The TM discrimination used bands 1, 3, 4, 5, and 7 in raw digital number format; the aerial videographic discrimination used R,G,B raw signals sampled in small windows surrounding each field site location. Texture was derived for these bands using the homogeneity statistic (see Equation 2).

	TM 1993	Digital Videographic Data (RGB format)		
		September 1994 (1 m pixels)	October 1994 (2 m pixels)	October 1994 with texture
Defoliation Class				
None	100	33	50	70
Light	72	75	54	72
Moderate	66	66	66	70
Severe	60	66	100	100
Mean	75	60	68	78

was obtained for the TM image samples. This relationship is consistent with that shown by Franklin and Raske (1994) using SPOT satellite data acquired during an Eastern Spruce budworm infestation in Newfoundland ($\mathbb{R}^2 = 0.515$ based on 56 samples). In that study and others (Ekstrand, 1994), much stronger relationships between remotely sensed spectral response and defoliation were reported following stratification of the forest samples to reduce variance due to other factors. For example, when controlling for stand age, density, and height class, Franklin and Raske (1994) reported \mathbb{R}^2 values up to 0.74 between SPOT spectral response and percentage of defoliation.

Classification of forest defoliation

The discrimination of damage classes using the 1993 Landsat satellite data set resulted in an overall classification accuracy of 75% (**Table 3**). These results are again consistent with accuracies reported elsewhere for the satellite detection of spruce budworm defoliation (Bucheim *et al.*, 1985; Franklin and Raske, 1994). In this study, the healthy samples



Figure 3.

RGB colour space video image enhancement of small area adjacent to field survey showing severely damaged trees (purple), light/moderately damaged trees (light blue), healthy trees (light green), soil background (pink), and understorey vegetation (orange). The image has been generated from three chromaticity indices followed by a histogram equalization and contrast stretch.

had the highest discrimination and the severe defoliation was the least separable. Most of the confusion was between pixels in adjacent classes.

Maps of the defoliation classes were produced using the K-means decision rule applied to the 1993 Landsat TM image. Two maps were produced (Figures 4a, 4b), one from a modified supervised algorithm where the classes were 'seeded' with means and standard deviations based on the field sample and the other using a completely unsupervised approach where only the number of initial cluster centres (10) was specified. In both classifications, TM bands 1, 3, 4, 5, and 7 were selected. Bands 2 and 3 were similar to other visible bands or showed no difference across the range of defoliation classes (Table 1). The maps were subjected to a 7 by 7 modal (or rank) filter and checked for accuracy at the 21 field sites; they were consistent with those obtained in the earlier discriminant tests (Table 3). For example, Figure 4a was found to be 67% in agreement with the field plots with the highest accuracies obtained in the healthy (100%), followed by the light/moderate (61%) and the severe defoliation classes (40%).

Image change detection

Prior to radiometric matching, the 1988 and 1993 images were spectrally quite different from each other. In multispectral TM space, the radiometric matching test sets were separated prior to matching by a mean of over 30 DN (**Figure 5**). The darker targets (water and conifer forest) were separated by around 25 DN, whereas the deciduous



Figure 4a, 4b.

Unsupervised (top) and modified unsupervised (bottom) K-means classification of the 1993 TM image into defoliation classes (none, light/moderate, severe) in a small subarea approximately 2 km by 2 km, Santiam Pass. Mapping accuracy tested at the 21 locations surveyed in the field was approximately 67% overall.

forest and rock outcrop targets were separated by about 50 DN. Radiometric matching using control sets from spectral space (sets 1a and 1b) cut the Euclidean distances between the test sets of the two dates nearly in half, with both bright control sets from spectral space having roughly the same effect.



Figure 5.

Euclidean spectral distances for the difference in 1988 and 1993 images prior to radiometric matching and after matching using four different bright scene component control sets. See the text for details.

The two bright control sets from scene space had quite different effects on the spectral properties of the subject image (Figure 5). Set 2a was less effective than either of the sets from spectral space, whereas set 2b was much more effective than any other set. Using the subject image radiometrically matched with set 2b, one can expect that differences in spectral properties between the 1988 and 1993 images are considerably more likely to be due to real scene spectral changes than to effects of different illumination and atmospheric conditions at the times the images were collected. This is the case whether one chooses to work with the original TM bands or the Tasseled Cap indices.

Regardless of which control set one evaluates, the Euclidean distances for TM bands and the Tasseled Cap indices are quite similar. This indicates that brightness, greenness, and wetness capture most of the spectral information in the TM data, as demonstrated by Cohen *et al.* (in press) using totally different methods.

Discriminant analysis using the temporaldifference data provided classification accuracies that were not particularly high for the 21 ground plots. The highest accuracy achieved was 67% for three classes (**Table 4**). That lower accuracies were evident for two classes is a function of the shift in class boundaries. Using data from the six indices (three

for each time period) in the discriminant analysis, rather than the temporal differences, yielded significantly improved results. For three defoliation classes, 86% accuracy in classification was achieved (Table 4).

Standardized coefficients for the discriminant functions used to classify the ground plot data into three defoliation classes using the six index values help to explain the increased accuracy over the use of the temporal-difference data (**Table 5**). The first discriminant function, significant at the 0.026 level, weights most heavily the 1988 wetness values. After that, the temporal contrast in brightness and

Table 4.

Percentage of accuracy for different numbers of defoliation classes using discriminant function analysis with multi-date TM imagery and data from 21 ground reference plots. For the defoliation classes: "four" is equivalent to the original four classes; "three" combines light and moderate classes; and "two" combines the none and light classes and the moderate and severe classes. Imagery used were: (three difference images) 1993 TM minus 1988 TM Tasseled Cap brightness, greenness, and wetness, and (six indices, three from two different dates) the brightness, greenness, and wetness

images from 1993 and 1988.

	Number of Defoliation Classes			
Imagery Used	Four	Three	Two	
Differences (3)	48	67	57	
Indices (6)	67	86	86	

Table 5.

Coefficients for the two discriminant functions used to classify the data from 21 ground reference plots using the 1993 and 1988 Tasseled Cap brightness, greenness, and wetness images (six indices) for three defoliation classes (see Table a). Significance (p) values for Discriminant Function

(DF) 1 and DF 2 are 0.026 and 0.304, respectively.

Index	DF1	DF2
1988 brightness	-0.788	1.214
1993 brightness	0.963	-09.986
1988 greenness	0.459	-0.604
1993 greenness	-0.438	1.003
1988 wetness	-1.495	0.584
1993 wetness	-0.251	-0.461

greenness are important. Very little weight is assigned to the 1993 wetness value. This in effect means that, although the contrast in brightness and greenness is important, brightness and greenness are most useful indicators of defoliation only after the original wetness values are accounted for. As wetness is very strongly related to forest structure (Cohen and Spies, 1992; Cohen *et al.*, in press; Fiorella and Ripple, 1993), this means that by first accounting for variations in initial stand structure, the results of change detection in forested ecosystems can be done much more accurately.

CONCLUSION

Defoliation in a subalpine forest caused by Western Spruce budworm during an outbreak from 1988 to 1993 was detected and classified using digital aerial videographic data acquired from an ultralight aircraft at two altitudes in 1994 and multitemporal Landsat TM satellite imagery.

The discrimination of low-altitude videographic data (approx. 1 m² pixels) acquired in September 1994 was 60% in agreement with the field survey, and the discrimination of high-altitude videographic data (approx. 2 m² pixels) acquired three weeks later was 68% in agreement with the field survey. This level of discrimination improved to 78% following the application of image texture processing to derive homogeneity measures over small windows (5 by 5 pixels). Mapping accuracy, based on tests of the 21 field sites classified with a modified unsupervised algorithm applied to the 1993 TM data, was approximately 67% correct. This is consistent with previous studies on satellite remote sensing of budworm damage (see, for example, Franklin and Raske, 1994) and is probably close to the maximum level of accuracy that can be achieved with these methods and data across this range of forest types and defoliation conditions.

A significant increase in discrimination was observed (to 86% correct) when an account of variations in initial stand structure was made using the Tasseled Cap transformation of the georegistered 1988 TM data. This improvement is comparable to that reported elsewhere following stratification of satellite sensor data by forest inventory data (Ekstrand, 1994; Franklin and Raske, 1994). A logical next step would be to drive a satellite image classification based on training data derived from the aerial videographic image analysis without requiring additional, or perhaps any, ground-based field surveys.

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