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Sugar Maple Decline Assessment Based on Spectral and Textural Analysis of Multispectral Aerial Videography

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This paper presents an application of digital airborne multispectral videography in sugar maple decline assessment. Large scale four-band video imagery of several test plots located in sugar maple stands was acquired using a four-camera video system. Various spectral and texture features were computed for individual trees selected from the video data within and around two of the test plots. The features included principal components, a band ratio, and first-order and second-order texture transforms. They were evaluated through correlation with results of color/color IR photographic interpretation of decline for the same trees. The most significant features were selected to form a numerical maple decline index model, which was then applied to evaluate decline of trees in all test plots. The results agreed well with results from ground surveys. The combination of spectral and textural analysis of aerial multispectral video imagery is an objective, quantitative, and inexpensive means for maple decline assessment on a single tree basis. It provides comparative information on tree health and can serve as an alternative or complementary technique to conventional photography and ground surveys.

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INTRODUCTION

Sugar maple (*Acer saccharum*) decline has become a severe problem in northeastern American forest regions in recent years due to the interaction of several biotic and abiotic stress factors such as acid rain, soil nutrient deficiencies, increased ozone pollution, and so on (McIlveen et al., 1989). Providing timely and accurate assessment of the level and extent of damage is essential to the management of this economically important tree species.

Advantages of using remote sensing techniques to detect and assess maple decline are related to the progression of decline symptoms. There are five general stages of decline: 1) leaf chlorosis and premature autumn leaf discolouration followed by early leaf fall, 2) progressive deterioration of young twigs and branches of increasing sizes, 3) progressive dieback of buds, twigs, and branches from the upper outermost parts of the crown resulting in significant loss of foliage, 4) decline of part or almost all of the leaf crown, and 5) death/recovery of affected trees (Dessureault, 1986). These changes are manifested in airborne multispectral imagery through changes in crown spectral reflectance and texture characteristics. Spectral reflectance variations include changes in the magnitude of crown reflectance in the visible and near-IR regions of the spectrum and shifts in the position of the crown spectral reflectance curve between the red and near-IR regions (the "red edge"). Crown texture variations related to decline are spatially manifested in changes in leaf orientation and changes in the proportion of shadows, exposed branches, and background reflectance contributions. There is, therefore, high potential for application of large scale multispectral imaging and analysis in assessment of individual tree decline.

Multispectral video imaging, a recently developed remote sensing technique, has proven to be useful in many forest applications using both analogue and digital image analysis methods (King and Vlcek, 1990; Yuan et al., 1987; Vlcek et al., 1986). In particular, large scale video can provide a close view of individual tree crowns at a fraction of the cost of multispectral scanning or ground surveys. The main purpose of this study was to evaluate the capability of multispectral aerial video imaging in comparison to conventional ground surveys for sugar maple decline assessment. A maple decline index model incorporating video image spectral and textural characteristics was developed with the aid of aerial photographic interpretation. The model was then compared to a ground-based model currently utilized by the Ontario Ministry of Environment (OME).

DATA ACQUISITION

Multispectral aerial video imagery of six observation plots established by the OME was acquired on 16 August 1988 between 11:30 and 15:00 EST from an altitude of 410 m AGL. The sensor which was used was a four-camera video system developed at the Faculty of Forestry, University of Toronto (King and Vlcek, 1990; Vlcek and King, 1985). It included four aligned black-and-white solid-state video cameras each with a different bandpass filter, a sequential switcher which pro-

Figure 1. Example four-band original video data of STEED site.

vided frame-rate multiplexed video from all cameras that was recorded on a single VCR, and a color encoder which provided color/false color imagery from any three selected cameras that was recorded on a second VCR. The cameras were RCA TC-2800 models equipped with Canon 2/3 in., 16 mm focal length TV lenses. The interference filters which were used were: Band 1 (430–470 nm), Band 2 (530–570 nm), Band 3 (665–675 nm), and Band 4 (780–820 nm). Digitization of the recorded black-and-white band sequential video frames at 512×480 sampling rate was conducted using a Matrox PIP-1024a frame grabber capable of freezing four consecutive video frames (spectral bands). The resulting ground pixel sizes were: 0.48 m (H) $\times$ 0.38 m (V). Registration of individual video bands was then conducted to eliminate shifts due to aircraft translation in the interval between generation of each video frame (1/30 s). Figure 1 is an example of four-band video for one of the sites (STEED) near Peterborough Ontario. The spectral bands are: upper left, Band 1; upper right, Band 2; lower left, Band 3; lower right, Band 4. A linear contrast enhancement has been applied to each image so that all four bands could be displayed simultaneously.

Aerial color and color IR photography were acquired at the same time as the videography by the Ontario Centre for Remote Sensing (OCRS). The cameras utilized were Vinton 70 mm format cameras with 76 mm focal length lenses. The films employed were Kodak Aerocolor 2445 negative and Kodak Aerochrome 2443 IR. A 500 nm cut-on filter was used on the camera containing IR film.

The six OME plots were typically 20 m $\times$ 20 m and were located in representative mature sugar maple woodlots in southern Ontario. All trees in the upper and intermediate canopy of each plot had been assessed using a ground-based decline index model developed by the OME (McLaughlin et al., 1985). Of the six sites which were flown over, all were covered by photography but only four were successfully covered by video due to its narrower view angle and the difficulty of locating the plots from the aircraft. For the two plots not covered by video, representative plots nearby were delineated which could also be located in the photography. Field visits were made to each of the sites immediately following data acquisition to identify plot locations on the aerial photographs and visually assess the decline status of each plot.

DATA ANALYSIS METHODOLOGY

Tree Crown Sampling Procedure

In the video imagery of each site individual trees were identified in and around the plots in the central portion of the scene. A subimage of these trees was created by reducing all surrounding areas to an image value of zero. A square window was delineated in each tree crown for derivation of spectral and texture features. Selection of tree window size was critical because too large a window would include some boundary shaded pixels which could increase variations of pixel values while too small a window would not reflect the actual tree crown spectral and texture patterns. In this study the window size was determined in accordance with the tree size. Experience revealed that an appropriate window size for a tree crown was one that included at least 70–80% of the total pixels falling on the crown (Yuan et al., 1987). Most importantly, the window was always located within the sunlit portion of the tree to avoid tree boundary and shadow effects and maintain sampling consistency.

Image Preprocessing

Since image texture statistics are sensitive to variations in imaging conditions, data normalization is commonly conducted prior to analysis (Van Gool et al., 1985). In this study imaging conditions differed between sites due to variations in time of imaging and camera aperture settings. This resulted in relative translation, compression or expansion of grey level distributions. To normalize the data in the subimage of tree crowns for each site, the band mean was subtracted from each pixel and the result was divided by the standard deviation. This produced grey level distributions with means of zero and unit standard deviations.

Table 1. Spectral and Textural Features Evaluated

Spectral Feature	*Texture Feature*
BND 1: 430–470 nm	MED: mean Euclidean distance
BND 2: 530–570 nm	CON: contrast
BND 3: 665–675 nm	ENT: entropy
BND 4: 780–820 nm	ASM: angular second moment
NDR: $\frac{(\text{Band 4} - \text{Band 3})}{(\text{Band 4} + \text{Band 3})}$	
PC1: principal Component 1	
PC2: Principal Component 2	

In addition, prior to conducting the texture analysis, the data were compressed from 8-bit (256 grey levels) to 6-bit (64 grey levels). This process did not change the actual grey level distributions but greatly reduced computation time using a microcomputer.

Calculation of Spectral and Texture Features for Model Development

Two plots, STEED and MILLER, which exhibited different decline symptoms were selected for detailed analysis and decline model derivation. Fifty-six and 22 trees were sampled at each site, respectively. The low number of trees at the MILLER site was due to lower density and degree of uniformity in the canopy. A number of spectral and texture features (listed in Table 1) were computed for each tree at both sites.

(*a*) *Spectral Features*. In addition to the four original spectral bands, three transformed spectral features were used: two principal components and one ratio component. Principal component transformation is a useful technique in multispectral image analysis to reduce data dimensionality by derivation of uncorrelated principal components formed by linear combinations of the original spectral variables. The covariance matrix from which the linear coefficients were derived was constructed from the normalized four-band window samples of all 78 maple trees in the two sites. Since the first two components usually account for most of the data variation, and that variation was caused mainly by relative tree health, they were selected as two spectral features. The ratio which was tested was the normalized difference band ratio (NDR): $(IR-R)/(IR+R)$. It was selected because it can reduce radiometric variations with view angle and is sensitive to vegetation conditions (Jackson, 1983). These spectral features were calculated for each sampled tree by taking the average of the values for all pixels within the delineated crown window.

(*b*) *Texture Features*. The texture representation methods employed were a first-order texture transformation, and a second-order co-occurrence transformation. These were selected because first-order texture transformations are simple, fast, and easy to implement whereas the second-order co-occurrence method is more generally accepted as a better texture representation method (Wezka et al., 1975); Conners and Harlow, 1980).

One first-order feature, mean Euclidean distance (MED), was tested. It is the average grey level distance of surrounding pixels to the centre pixel in a window. Therefore, MED is a local property feature which indicates the variability around the centre pixel (Irons and Peterson, 1981). It was computed for each tree from all four spectral bands.

The second-order texture method is based on the estimation of second-order joint conditional probability functions. Each of the functions is the probability of going from grey level i to grey level j in an image given an intersample distance (in terms of pixel units) and an angular sampling direction. The estimated probability values are written in matrix form (i.e., co-occurrence matrix) from which a number of texture measures can be derived.

Three second-order features, contrast (CON), entropy (ENT), and angular second moment (ASM) were used. Contrast (CON) is a measure of the overall amount of local variation in a window (i.e., it is proportional to the range of grey levels). Entropy (ENT) is a statistical measure of uncertainty. It is low if image texture is relatively smooth and high if the texture is structured. It can be used as a measure of the absence of a distinct structure or organization of image patterns. Angular second moment (ASM) is a measure of homogeneity. A small ASM indicates a spread of values in the co-occurrence matrix and a large ASM indicates that the image is quite homogeneous. The details of the algorithms and computations for these features are given in Haralick (1979).

These three second-order texture features were computed from the normalized Band 2 image of tree crown windows because it displayed the best image contrast and sharpness, resulting in good visual appearance of different texture patterns. The intersample spacing for the co-occurrence matrix was 1 pixel and an average of eight sampling angles were used to ensure rotationally invariant texture.

Evaluation of Spectral and Texture Features

A tree-by-tree comparison of each video-based spectral and texture feature to the ground-based

OME decline index for the STEED and MILLER sites was not possible because it was too difficult to match OME numbered trees with visibly identifiable tree crowns in the video images. Therefore, evaluation of each feature was done through a statistical comparison with photo interpretation results. Stereoscopic color and color IR photo interpretation was based on three variables: chlorosis or tonal variations (four levels), visible branches (four levels), and crown texture (four levels). The sum of these three variables was used as a photo decline index [PDI—see Vlcek et al. (1989) for details]. Sites visits which included visual analysis of trees exhibiting a broad range of decline confirmed the PDI to be indicative of tree health. Correlations between PDI and the spectral and texture features were calculated and the best variables were selected for the maple decline index model.

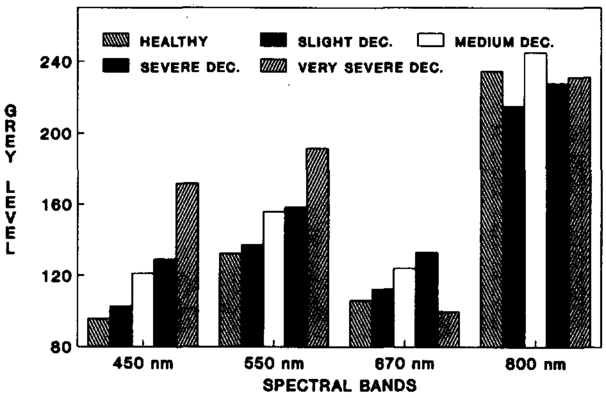

Figure 2. Spectral comparison of five maple trees.

Formation of Maple Decline Index Model

The linear regression models obtained from the above analysis only showed the linear relationship between the selected features and PDI within the immediate area of each plot. For comparisons between plots with different site conditions a healthy tree was selected at each site as a reference. The spectral and texture features of all other sampled trees were compared to the reference tree and a linear video decline index model was proposed as follows:

$$\mathrm{VDI} = a_1 + a_2 S_d + a_3 T_d$$

where

VDI = video decline index for a sampled tree,

S_d = spectral distance between the sampled tree and the reference (healthy) tree,

T_d = texture distance between the sampled tree and the reference (healthy) tree,

a_1, a_2, a_3 = regression coefficients to be determined.

The derived model was applied to all sampled trees in the six sites and a mean maple decline index was determined for each site. The site indices were then ranked and compared to the ranking of the average OME ground-based indices for the same sites.

RESULTS

Figure 2 shows the variation within each spectral band of the mean grey levels (7×7 pixel window) for five trees ranging from healthy to severely declining at the STEED site. The standard deviations of these data ranged from 3.7% to 7.9% of the corresponding mean values. Observing within each band, some patterns are evident in the grey level variation with decline. In Bands 1 and 2, the grey level increases with increasing level of decline. Adjacent decline levels are not all significantly different in brightness but there are significant differences ($\alpha = 0.05$) between healthy and declining trees. In Band 3 the trend is the same except for the severely declining tree which had almost no foliage. A possible explanation for this is that healthy background vegetation which was highly absorbing in the red region was visible to the sensor. In Band 4, no clear trend is apparent because the images were overexposed, resulting in saturation of many pixels.

Texture variations with decline were also evident in the raw data. For declining trees, the variation in crown grey levels (measured by the

Table 2. Correlations of Seven and Four Texture Variables vs. Photo Decline Index

	BND1	BND2	BND3	BND4	NDR	PC1	PC2	MED	CON	ENT	ASM
r	0.32	0.22	0.46	−0.51	−0.11	0.35	0.56	0.45	0.79	−0.22	0.06

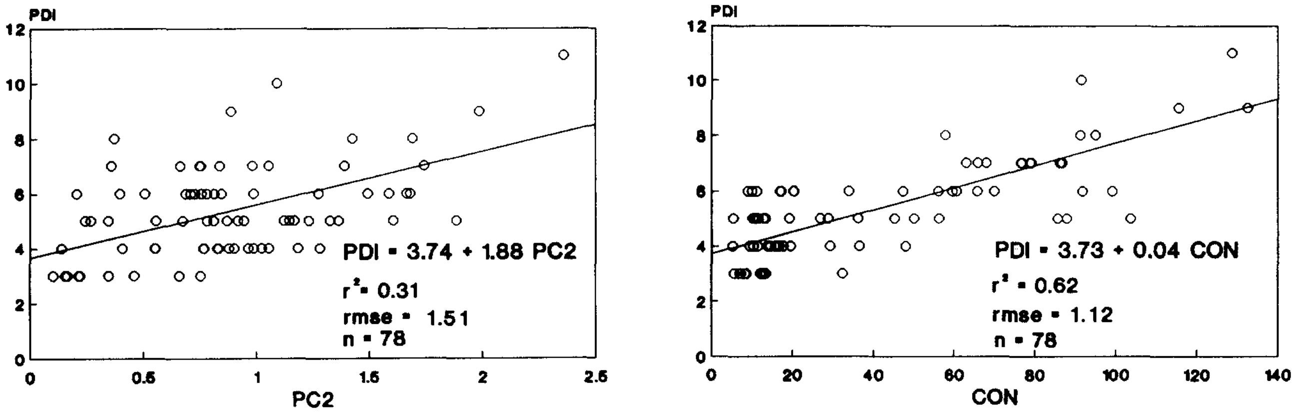

Figure 3. Linear regression analysis of video data spectral and texture variables with the photo decline index from STEED and MILLER sites (PDI = Photo Decline Index, PC2 = 2nd principal component, CON = contrast texture measure, n = number of trees, r^2 = determination coefficient, RMSE = root mean square error).

standard deviation) in relation to the mean crown brightness was found to be greater than that for healthy trees. Thus, it became apparent that both spectral and texture features should be included in a decline model.

Results of correlation analysis of the seven spectral features and four texture features with the photo decline index (PDI) for the combined STEED and MILLER sites are given in Table 2. The second principal component spectral feature (PC2) and the CON texture feature had the highest linear relationship with PDI. Bands 3 and 4 showed the next highest correlations but they had no visible linear (or curvilinear) trend.

The linear regression analysis results for PC2 and CON against PDI are shown in Figure 3. The determination coefficient (r^2) was 0.31 and 0.62, respectively. An even higher coefficient was obtained when both PC2 and CON were combined in a two-variable linear model: $PDI = 2.93 + 1.16PC2 + 0.03CON$ ($r^2 = 0.73$). The root mean square errors were also reduced from 1.51 and 1.12 for PC2 and CON, respectively, to 0.96 in the two variable model.

This model was deemed to be the best two-variable linear model from the spectral and texture features tested. It was therefore applied to all plots and an average video decline index was calculated for each plot. Table 3 shows the ranked mean VDI values beside the plot rankings based on the 1988 OME ground survey. All sites showed average decline values in the middle of the range exhibited by individual trees.

It was found that the STEED site had the lowest VDI (5.2) while the DAVIES site had the highest (8.2). The remaining sites were not significantly different from each other. These results agreed with those determined by the OME with the exception of the DAVIES site which was ranked as worst by the video method and in the middle of the group by the OME. This was because the trees within the DAVIES plot were small and it was difficult to obtain a representative sample from the video images. Consequently, many trees surrounding the plot were included in the video decline index and the level of decline of these trees was greater than the trees within the plot.

Table 3. Comparison of Ranked Average Video Decline Index Values with OME Decline Index Values

Plot	*Video Decline Index*			*OME Ground-Based Index*		
Name	*n*	*Mean VDI*	*Std. Dev.*	*n*	*Mean Index*	*Std. Dev.*
DAVIES	63	8.2	1.7	30	24.9	17.5
MILLER	23	7.0	1.5	21	52.1	20.7
MACLAUGHLIN	24	6.5	2.1	14	51.1	13.4
FINCHAM	26	6.4	1.5	28	24.0	18.0
VEITCH	56	6.3	1.5	21	14.6	14.4
STEED	47	5.2	0.7	30	9.9	15.2

For all the sites, the standard deviation of the video decline index was generally lower than the OME ground survey index in relation to their means. This can be attributed to the greater number of trees sampled for the video index at most of the sites and the more objective approach of the video method to decline assessment.

DISCUSSION

Several points of discussion are presented, below which relate to interpretation of results and current deficiencies in the methodology.

The method of individual tree sampling and assessment is applicable to other hardwood and coniferous forests. However, care should be taken when sampling tree crowns which are not regular in shape as they were in this study. In irregular crowns, bidirectional reflectance effects and shadows can affect the image brightness of different portions of the tree crown so that window location within the crown and window shape are critical.

An alternative to using a reference tree and a relative decline index model would be to calibrate the video data so that absolute comparisons could be made between sites. Calibration was not conducted because it was too costly for the size of the study. However, it should permit more quantitative study of the spectral characteristics of tree crowns in relation to physiological and chemical variations associated with decline.

When a tree begins to decline, foliage color changes or autumn colors appear up to a few weeks earlier than usual. Thus, spectral characteristics dominate and little change in image texture occurs. In the middle stages of decline, leaf orientation changes, some foliage is lost or branches are exposed, and image texture variations increase. Finally, as the tree dies, remaining foliage is minimal and texture becomes more consistent. However, branches and background reflectance (usually healthy vegetation which may counteract the decline index trend to higher values) combine to cause large variations in image tone from band to band. Thus, spectral characteristics become dominant once again. In this study most of the sampled trees were in mid-decline stages dominated by texture. Consequently, the CON texture feature was most correlated with PDI. A straight line relationship with PDI was well established since image texture variations resulting from loss of foliage and exposed branches were quite visible in the crowns. In the spectral data, neither the original bands nor the principal component transformations showed high correlation with decline ($r \leqslant 0.56$). The highest was PC2 but it did not produce a visibly linear trend with PDI. The next highest, the near-IR band (Band 4), should be investigated further because the data were slightly overexposed, possibly reducing the separability of decline levels. Bands 1 (blue), 2 (green), and 3 (red) were not as good in discriminating decline levels.

The spectral and texture features (PC2 and CON) used in the model complemented each other and improved the correlation with the photo decline index significantly. However, both variables were given equal weight in the model when either one may dominate at different stages of decline as discussed above. If a full decline range was to be modeled, the spectral and textural variations should be weighted according to the decline level.

For OME purposes, evaluation of the precision of the video decline index should be conducted in relation to their established ground survey index. (It is, however, open to question whether ground assessment of a phenomenon which proceeds from the top of the tree downwards is appropriate). In this study correlation with the OME decline index was not possible on an individual tree basis because the ground plot boundaries were difficult to identify in the aerial imagery. In addition, there were many small irregularly shaped codominant or intermediate trees in the plots which confounded tree identification. Future study will incorporate plot targeting and identification of specific trees on the ground and in the video imagery for determination of model precision.

CONCLUSIONS

There is a close relationship between sugar maple decline and spectral/texture features in aerial multispectral video imagery. The changes in spectral and spatial patterns of maple tree crowns resulting from decline were well quantified through development of a linear model, relating the associated changes in image characteristics. Aerial multispectral video is useful as an alternative or complementary means to conventional photography and ground surveys for maple (and other hardwood) decline assessment on an individual tree basis because it provides more quantitative and objective modeling capabilities.

Individual tree assessment using multispectral video could be adopted to replace ground surveys in multistage sampling. Integration of satellite data, high altitude photography, large scale video imaging, and subsequent ground checking would be beneficial to a regional forest damage survey in terms of accuracy, time, and cost.

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REFERENCES

Connors, R. W., and Harlow, C. A. (1980), A theoretical comparison of texture algorithms, *IEEE Trans. Pattern Anal. Machine Intelligence* PAM1-2 (3):204–222.

Dessureault, M. (1986), Forest decline: an international problem, in *Proc. Maple Growers Assoc., Quebec Ministry of Agric.*, 15 pp.

Haralick, R M. (1979), Statistical and structural approaches to texture, *Proc. IEEE* 67(5):786–804.

Irons, J. R., and Petersen, G. W. (1981), Texture transforms of remote sensing data, *Remote Sens. Environ.* 11:359–370.

Jackson, R. (1983), Spectral indices in n-space, *Remote Sens. Environ.* 13:409–421.

King, D., and Vlcek, J. (1990), Development of an airborne multispectral video system and its application in forestry, *Can. J. Remote Sens.* 16 (1):15–22.

McIlveen, W. D., McLaughlin, D. L., and Arnup, R. W. (1989), A survey to document the decline status of the sugar maple forest of Ontario: 1986, Ont. Ministry of Environ. Publication, ISBN 0-7729-6253-7, 22 pp.

McLaughlin, D. L., Linzon, S., Dimma, D., and McIlveen, W. (1985), Sugar maple decline in Ontario, Tech. Report No. ARB-144-85-Phyto, Ontario Ministry of Environment, 18 pp.

Van Gool, L., Dewaele, P., and Oosterlinck, A. (1985), Survey: texture analysis anno. 1983, *Comput. Vis. Graphics Image Process.* 29:336–357.

Vlcek, J., and King, D. (1985), A 4-camera video sensor and its applications in natural resources, in *Proc. 19th Int. Symp. on Remot Sensing of Environ.* Ann Arbor, MI, pp. 483–489.

Vlcek, J., Jayasinghe, D., King, D., and Yuan, X. (1986), Spectral and spatial classification of land cover types in multispectral aerial video imagery, in *Proc. 26th Fall Symp. of the SPSE*, Crystal City, VA, pp. 84–87.

Vlcek, J., King, D., and Yuan, X. (1989), Final report on determination and evaluation of aerial video and photographic maple decline index, Ontario Ministry of Environment Contract A05521, 33 pp.

Weszka, J. S., Rosenfeld, A., Carton, E. J., Kirby, R. L., and Mohr, J. M. (1975), A comparative study of texture measures for terrain classification, Report TR-361, Computer Vision Laboratory, Computer Science Center, Univ. of Maryland.

Yuan, X., King, D., Cadeau, F., and Vlcek, J. (1987), Multispectral video survey of a northern Ontario forest, in *Proc. 53rd Meeting ASPRS*, Baltimore, MD, pp. 140–147.