Using Hyperspectral Technologies to Map Hemlock Decline: Pre-Visual Decline Assessment for Early Infestation Detection

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ABSTRACT

Hyperspectral remote sensing technology can help monitor hemlock health across large areas of the landscape. This study examines the capability of a commercially available sensor (Specim's AISA Eagle) to map hemlock decline due to hemlock wooly adelgid (HWA) infestation in the Catskill Mountain area of New York. The AISA Eagle was able to classify hemlock health at the tree level into an 11-class rating system with a one-class tolerance accuracy of 88 percent. The ability of this instrument to predict decline below class 4 (when dieback and transparency reach levels first noticeable in the field) is based upon "pre-visual" changes in chlorophyll content and function that are typical of incipient HWA infestation and early stress. This technology will enable land managers to assess and monitor detailed changes in forest health across the landscape so that integrated pest management programs can be effectively implemented.

KEYWORDS

Forest health, AVIRIS, remote sensing, hemlock woolly adelgid.

INTRODUCTION

One of the most pressing forest health issues currently facing North American forests is the widespread decline of eastern hemlock (*Tsuga canadensis* Carriere) due to the hemlock woolly adelgid (HWA), *Adelges tsugae* Annand. The potentially severe consequences and large scale of the HWA infestation requires that land managers be familiar with the actual location of the hemlock resource, as well as its health and infestation status.

Most assessments of decline involve time-consuming field based methods. Although these methods are valuable in monitoring gross changes over time, they are not able to identify trees in the very early stages of decline (Sampson et al. 2000) or assess large acreages, both crucial to the development of integrated pest management strategies aimed at managing the hemlock resource.

Remote sensing technologies are the most viable option to assist land managers in health assessment and monitoring at a regional scale. To date, remote sensing of forest health has been limited to the classification of coarse defoliation classes using aerial photography or multi-spectral resolution visible/NIR space-based sensors, such as Landsat Thematic Mapper (TM) (Lambert et al. 1995; Royle and Lathrop 1997 and 2002, Royle et al. 1995). When measuring decline solely as a function of defoliation, earlier signs of stress such as reductions in photosynthesis and chlorophyll content are not detected. Instruments with higher spectral resolution are needed to accurately detect such changes in vegetation condition (Treitz and Howarth 1999).

There is mounting evidence that hyperspectral instruments have the capability, not only to assess defoliation, but also to identify the early signs of stress—in some cases before visual symptoms are apparent (Cibula and Carter 1992, Mohammed et al. 1995, Zarco-Tejada et al. 2000a and 2000b). This can be explained by the tendency of stressed leaves to undergo reduction in photosynthetic activity and to lose chlorophyll. These changes alter reflectance at chlorophyll-sensitive wavelengths (Vogelmann and Rock 1988, Rock et al. 1988, Vogelmann et al. 1993, Gitelson and Merzlyak 1996, Carter and Knapp 2001).

Chlorophyll$_a$ and $_b$ content are particularly good detectors of stress because of their direct role in photosynthesis. Narrow wavebands near 700nm where changes in chlorophyll absorption are easily detectable have been recommended for early detection of forest damage (Hoque et al. 1990 and 1992) and were able to detect decreased vigor, before visual symptoms were apparent, in pine seedling canopies (Cibula and Carter 1992). Because changes in chlorophyll function typically precede changes in chlorophyll content, chlorophyll fluorescence has also been shown to be a useful tool in identifying pre-visual strain (Zarco-Tejada et al. 2000a and 2000b).

Preliminary work by the authors using an ASD FieldSpec Pro FR field spectroradiometer (Analytical Spectral Devices) highlight several indices and wavelengths that are able to track hemlock stress, including pre-visual symptoms. This work has resulted in the development of equations capable of predicting a 10-class hemlock health scale on independent data with 96% one-class tolerance accuracy (Pontius et al. In press-a). Additional work by the authors using remotely sensed hyperspectral imagery from NASA's Airborne Visible Infrared Imaging Spectrometer (AVIRIS) produced a hemlock abundance map that correctly identified hemlock dominated pixels (>50% basal area) with 88% accuracy. Reflectance at a chlorophyll sensitive wavelength (683nm) coupled with a water band index (R970/900) was able to predict plot level decline with 100 percent one-class tolerance accuracy. The extreme accuracy at the low (0-4) end of the range indicated that these wavelengths might be used to assess early decline, before visual symptoms are apparent (Pontius et al., In press-b).

This study was designed to determine if similar hyperspectral techniques from a commercially available remote sensing platform could be used to predict early hemlock decline symptoms in the Catskills State Park, New York. The hyperspectral instrument used in this study was the airborne AISA Eagle, measuring 130 contiguous bands from 400nm – 970nm, with 3nm spectral resolution, and 2m spatial resolution. Our objectives are to: (1) present the key wavelengths and/or stress indices most strongly correlated with hemlock decline, (2) use this information to develop a simple linear equation to predict decline using a minimal number of variables, and (3) discuss the potential of commercially available hyperspectral sensors.

METHODS

Ground truth data from 65 canopy-dominant hemlocks in the Catskills (Figure 1) were collected using methods specifically designed to quantify the various sequential symptoms of decline that follow adelgid infestation. This included the percent of terminal branchlets with new growth, percent transparency (quantified using a concave spherical densiometer), percent fine twig dieback, and live crown ratio (USDA Forest Service Crown Rating Guide). Raw health data was normalized by assigning a decline value to each measurement (Table 1). This normalized data was then averaged for each tree to determine the decline rating that best described the trees' overall status (where 0 = perfect health and 10 = dead). Species data, GPS location and canopy position were recorded across the imagery for an additional 465 trees for species mapping, including over 20 species. Geographic location data was collected for all trees using a Trimble GeoXT global positioning system with sub-meter accuracy.

On September 3, 2004, hyperspectral data from Helicopter Applicators, Inc.'s AISA Eagle was obtained for a 25,000 acre region of the Catskills State Park (Figure 1). Atmospheric corrections were conducted in house by Helicopter Applicators, Inc. Individual passes were mosaicked together and geometrically registered to USGS 1m resolution digital orthoquads using a polynomial degree 2 warping method (ENVI 4.0 software, Research Systems, Inc). Reflectance spectra were then extracted for pixels corresponding with the ground truth data locations. A mask of all shadow resulting from cloud cover, steep northern aspects, and canopy geometry was applied before application of predictive equations.

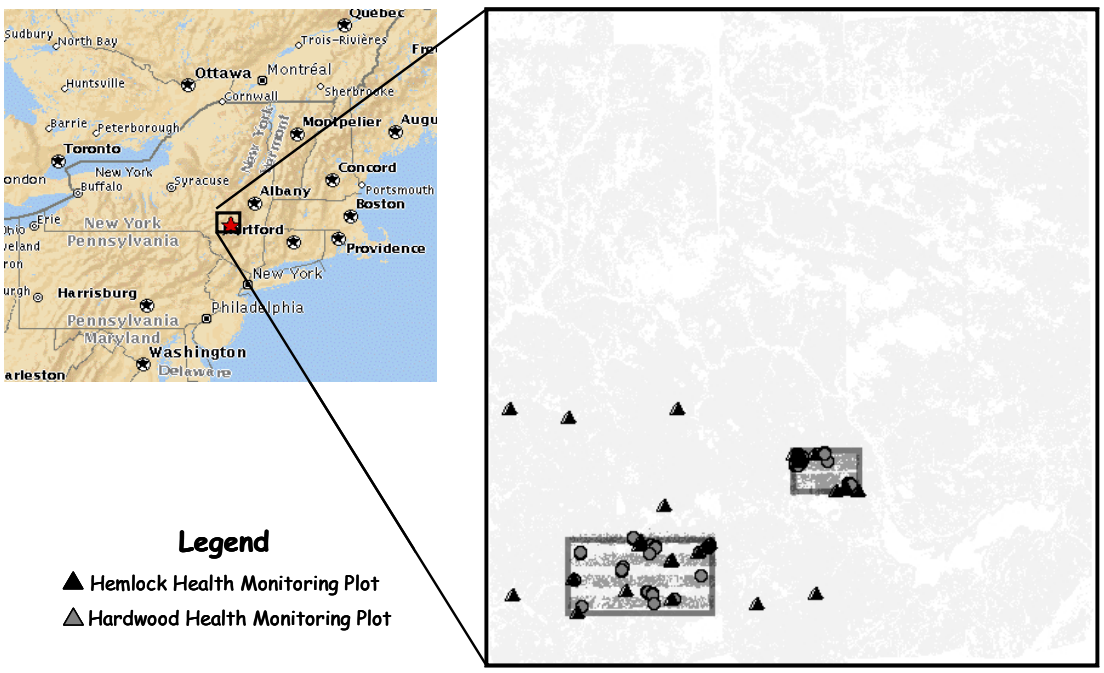

Figure 1. Grey rectangles represent the 2004 HAI study area, comprising a 25,000-acre subset of the original 2001 AVIRIS Catskills imagery (large black square). A series of hemlock health and hardwood plots were establised for ground truth in health calculations and species mapping.

Table 1. A summary of the typical values observed for each measured characteristic by decline class. The best-fit categories for each of the individual measurements were averaged to determine one overall decline rating for each tree.

Decline Class	Health Status	Characteristics
0	Perfect health	100% new growth Negligible canopy transparencey Negligible fine twig dieback Greater than 90% photosynthetically active canopy
1	Very healthy	Over 90% new growth 6-9% canopy transparency Negligible fine twig dieback 80-89% photosynthetically active canopy
2	Healthy (typical forest co-dominant)	Over 85% of branches produce new growth 10-14% canopy transparency Less than 5% fine twig dieback 70-79% photosynthetically active canopy
3	Earliest decline	80-85% of branches produce new growth 15-19% canopy transparency 5-10% fine twig dieback 65-69% photosynthetically active canopy
4	Light decline	75-79% of branches produce new growth 20-24% canopy transparency Approaching 10% fine twig dieback 60-64% photosynthetically active canopy
5	Light to moderate decline	70-74% of branches produce new growth 25-29% canopy transparency 10-15% fine twig dieback 50-59% photosynthetically active canopy
6	Moderate decline	60-69% of branches produce new growth 30-34% canopy transparency Up to 15% fine twig dieback 40-49% photosynthetically active canopy
7	Moderate to severe decline	40-59% of branches produce new growth 35-39% canopy transparency 15-20% fine twig dieback 30-39% photosynthetically active canopy
8	Severe decline	20-39% of branches produce new growth 40-44% canopy transparency Up to 20% fine twig dieback 20-29% photosynthetically active canopy
9	Death imminent	Less than 20% of branches produce new growth Greater than 45% canopy transparency Greater than 25% fine twig dieback Less than 20% photosynthetically active canopy
10	Dead	100% defoliation

Previously established stress detecting wavelengths and indices (Pontius et al. In press-a; Table 2) were related to decline data to determine the strongest stress correlates (Kleinbaum et al 1998). These were then entered into a stepwise linear regression with conservative significance cutoff limits to avoid over-fitting (probability to enter = 0.250, probability to leave = 0.01). Mallow's Cp and PRESS statistics were used to compare the predictive abilities of various models (Kozak and Kozak 2003). Full double-cross validation (jackknifed residuals) were used in lieu of independent validation to assess predictive abilities (Kozak and Kozak 2003). After establishing the best-fit hemlock decline model, the resulting equation was applied to all non-shadowed hemlock pixels within the imagery.

Table 2. A list of existing indices included in our analyses that are known to have strong relationships with stress-specific physiological responses.

Index	Formula	Primary Absorbance Feature	Citation
Carter and Miller Stress	$CMS = \frac{R694\ nm}{R760\ nm}$	Chlorophyll content	Carter and Miller 1994
Curvature Index	$CI = \frac{R683\ nm \bullet 2}{R675\ nm \bullet R691\ nm}$	Chlorophyll a & b content; chlorophyll fluorescence	Zarco-Tejada et al. 2002
Derivative Chlorophyll Index	$DCI = \frac{FD705\ nm}{FD723\ nm}$	Chlorophyll fluorescence	Zarco-Tejada et al. 2002
Chlorophyl Fluorescence	$CF = \frac{FD690\ nm}{FD735\ nm}$	Chlorophyll flurorescence; photosynthetic activity	Mohammed et al. 1995
Normalized Difference Vegetation Index	$NDVI = \frac{R800\ nm - R680\ nm}{R800\ nm + R680\ nm}$	Chlorophyll content and energy absorption	Deblonde & Cihlar 1993; Gamon et al. 1997; Myneni et al. 1995; Rousse et al. 1974
Photo-chemical Reflectance Index	$PRI = \frac{R531\ nm - R570\ nm}{R531\ nm + R570\ nm}$	Xanthopyll Cycle Activity	Gamon et al. 1990; Gamon et al. 1997; Rahman et al. 2001
Red Edge Inflection Point	$REIP = \lambda FD\ max$	Chlorophyll a content; green vegetation density	Gitelson et al. 1996; Rock et al. 1988; Vogelmann et al. 1993
Ratio Vegetation Index	$RVI = \frac{R800\ nm}{R680\ nm}$	Chlorophyll content	Pearson and Miller 1972; Royal and Lathrop 2001
Water Band Index	$WBI = \frac{R970\ nm}{R900\ nm}$	Canopy water content	Carter 1993; Penuelas et al. 1997; Tucker 1980

RESULTS AND DISCUSSION

An examination of the average spectra for various decline classes highlights the spectral changes that accompany hemlock decline (Figure 2). Although the full spectrum is obviously different, our goal was to identify a smaller subset of variables that may account for the maximum variability in spectral signatures. Building off of the key variables identified in previous benchtop hyperspectral work (Pontius et al. In press-a), several wavelengths and stress indices were significantly correlated with hemlock decline using the AISA Eagle sensor (Table 3). Of these, only R680, R760, SD737, and RVI were retained in the final stepwise, linear regression model to predict hemlock decline (Table 4). This model predicted decline on the 41 sample ground truth data set ($R^2 = 0.75$ and RMSE = 0.81). Treated as a class variable, declining trees could be identified within one health class with 88% accuracy (Figure 3).

While this model works well on an empirical basis, it is also important that there be a theoretical framework for the relationships witnessed. In the predictive model presented here, two of the four terms are wavelengths of known chlorophyll absorption (Mohammed et al. 1995, Carter and Miller 1994, Pearson and Miller 1972, Zarco-Tejada et al. 2002a, Carter and Knapp 2001). Miller et al. (1990) identified leaf chlorophyll content, as one of the most significant factors affecting plant vigor.

Chlorophyll$_a$ content, captured by R680 and RVI, is a particularly good indicator of stress because of its direct role in photosynthesis. Such narrow wavebands are sensitive to early stress induced decreases in leaf chlorophyll content (Carter 1993) and have been recommended for early detection of forest damage (Hoque et al. 1990 and 1992). In hemlock, Royle and Lathrop (1997) used RVI calculated from Landsat TM to predict and map four hemlock defoliation based damage classes with 64% accuracy.

Chlorophyll fluorescence sensitive wavelengths were also retained for the final model, including: 680nm and 760nm. Fluorescence is inversely related to photosynthetic rates, (D'Ambrosio et al. 1992, Schreiber and Bilger 1994, Larcher 1994) making it a good measure of relative photosynthetic activity. Because changes in photosynthetic function typically precede changes in chlorophyll content, chlorophyll fluorescence has been shown to be a useful tool in identifying pre-visual strain in other studies as well as the predictive equation presented here (Zarco-Tejada et al. 2000a and 2000b).

The SD737 was the final key term in predicting hemlock decline. This location has a strong -OH absorbance feature (Osborne and Fearn 1986). Although -OH bonds are found in many structures, one of the most obvious and most common in plant tissues is water. Water sensitive wavelengths have been identified in early ASD and AVIRIS decline surveys (Pontius et al. In press-a). It is possible that reflectance at this location is picking up slight differences in the canopy water content of subject trees.

Relative susceptibility of hemlock to HWA has been linked to various site and landscape factors related to water availability (Bonneau et al. 1997, Onken 1995, Royle and Lathrop 1999). Drier conditions stress already weakened tress, making them more susceptible to HWA

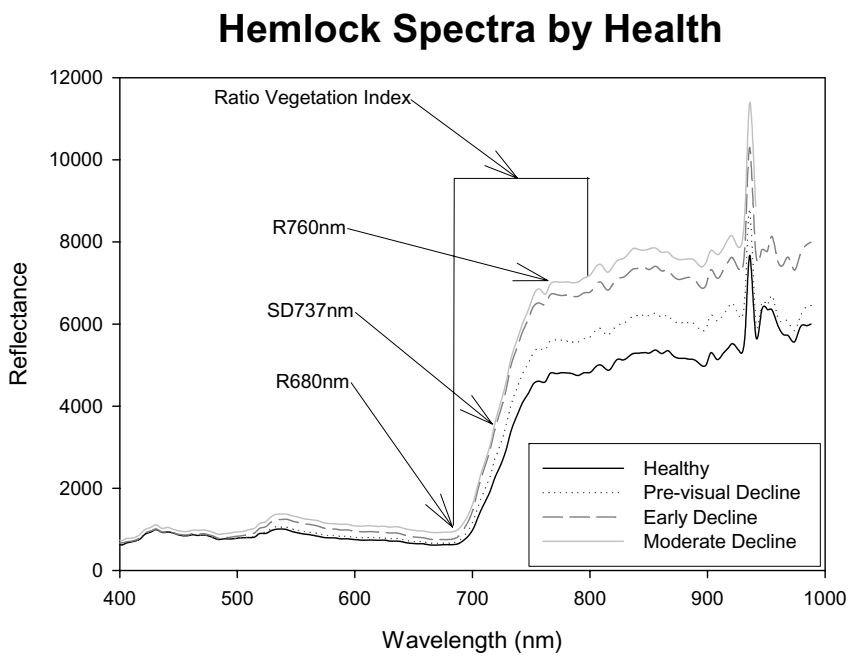

Figure 2. A close look at the average spectra for various decline stages highlight those wavelengths found to be significant in predicting hemlock decline.

Table 3. Previously developed ASD- and AVIRIS-based decline equations were applied to decline data with significant correlations ($p<0.0001$). Pairwise correlations between key AISA Eagle variables and hemlock decline are listed in order of correlation strength.

Variable	Correlation*	Absorbance Feature	Citation
R680**	**0.70**	Chlorophyll$_a$ & Fluorescence	Mohammed et al. 1995
R552	**0.53**	Chlorophyll$_a$	Penuelas et. al. 1997
PRI	**-0.53**	Xanthophyll Cycle Activity	Gamon et al. 1990; 1997
CMS	**0.49**	Chlorophyll Content	Carter and Miller 1994
NDVI	**-0.33**	Chlorophyll Content	Deblonde and Cihlar 1993
Fluorescence	**0.30**	Chlorophyll Fluorescence	Mohammed et al. 1995
R760**	**0.27**	Chlorophyll Fluorescence	Carter and Miller 1994
SD737**	0.17	OH Bonds	Osborne and Fearn 1986
RVI**	-0.12	Chlorophyll Content	Pearson and Miller 1972

***Boldface** indicates significant correlations at the 0.1 level.
**Signifies a significant variable retained in the final predictive stepwise model.

Table 4. The final AISA Eagle based linear regression equation for predicting hemlock decline, where RVI = R800/R680.

Term	Estimate	Standard Error	Prob>|t|
Intercept	-7.249	1.840	
R680	0.012	0.002	<0.0001
R760	-0.001	0.000	0.0016
SD737	0.007	0.002	0.0020
RVI	1.169	0.271	0.0001

Rsquare = 0.75
RMSE = 0.81
Terms = 4
N = 41

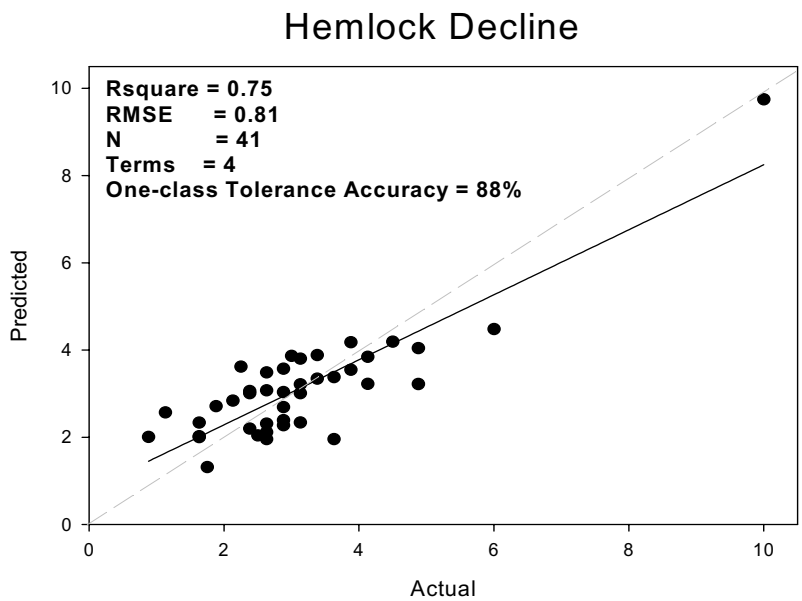

Figure 3. Using the four-term linear regression equation based on R680, R760, SD737, and RVI, decline rating was predicted with an R^2 = 0.75 and RMSE = 0.81. Converting this data to a class variable showed 88% one-class tolerance accuracy. The accuracy below decline class 4 indicates that this technology could be used to identify trees in the very early stages of decline.

and decline. There is also evidence that HWA injects toxic saliva at feeding sites (McClure et al. 1996): it is postulated that the toxic effects of this saliva may include a constricting effect on xylem, which could lead to leaf dehydration following infestation (Shields et al. 1995). Although we did not directly measure leaf water content, it is plausible that trees experiencing the most significant decline and highest infestation levels may be suffering from water stress, leading to significance at water-sensitive wavelengths.

Applying this equation to the full extent of the AISA Eagle imagery, more severe decline is evident in the eastern region, coinciding with the area along the Hudson River and Ashokan Reservoir where HWA has the longest infestation history (Figure 4). Average jackknifed residuals of 0.13 indicate that this equation should also work on independent data within the same range of decline (Kozak and Kozak 2003). While these results are promising, a more rigorous validation covering the full range of decline symptoms in the Catskills with independent validation is required to adequately test how robust this model is.

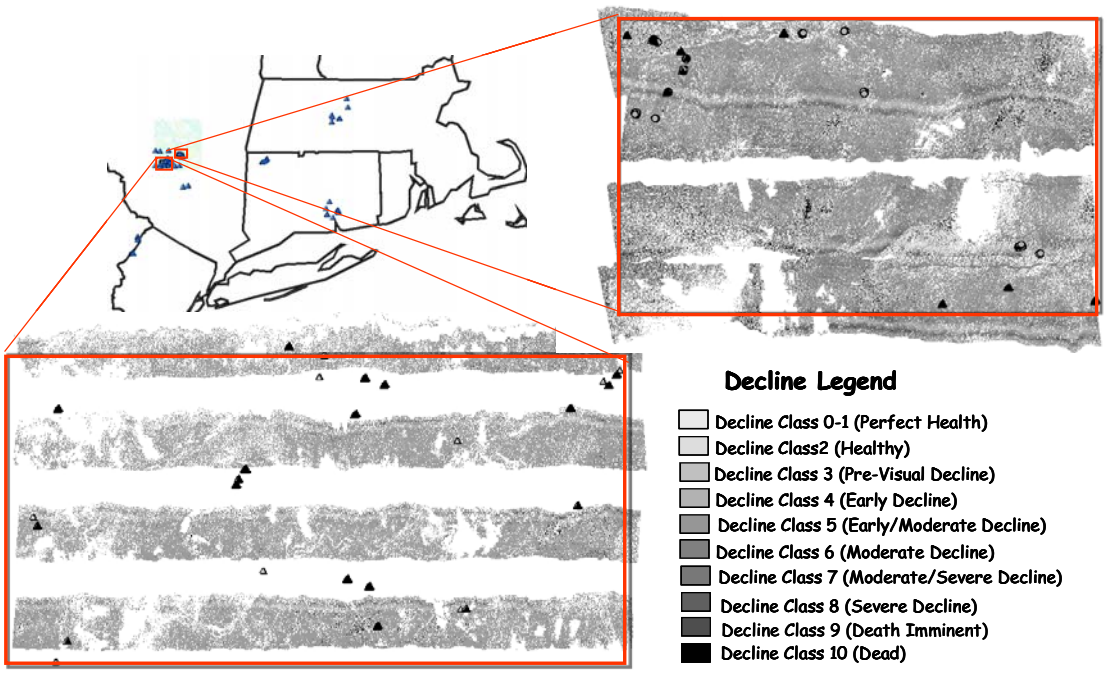

Figure 4. Applied to all pixels, the decline prediction highlights more severe decline symptoms in the eastern portion of the Catskills where HWA has the longest history in hemlock stands. Other stressors are not excluded from this analysis. The obvious gaps in coverage and spectral artifacts (striping) highlight data acquisition problems to be aware of when purchasing imagery.

IDENTIFICATION OF PRE-VISUAL DECLINE SYMPTOMS

Early symptoms of stress in forest species include reductions in photosynthetic activity and chlorophyll content (Mohammed et al. 1995). Such changes are not readily detectible from the ground in mature stands. This is why most forest health ratings rely on defoliation measurements such as transparency or dieback (USDA Forest Service Crown Rating Guide). Up until decline class 4, both of these measurements are below what is typically first categorized as decline in the field (fine twig dieback below 5% and transparency below 15%). Therefore, any results that are successfully able to differentiate between healthy samples (decline class 0) and samples in decline category 4 are most likely picking up changes in chlorophyll content and function before defoliation symptoms are apparent. Prediction accuracy in the low end of the decline range (0-4) was within a one-class tolerance 92% of the time. These results indicate that this technology can be used to detect tree health before visual symptoms are apparent across the landscape.

CROSS-INSTRUMENT APPLICATION

In order for this technology to be applicable on a large spatial and temporal scale, the relationships presented here must also be shown to work on other datasets. The initial selection of wavelengths for examination with the AISA Eagle imagery was based on results from previous ASD and AVIRIS work. All three instruments demonstrated similar relationships between key wavelengths and decline. We believe this indicates that the work presented here will prove robust enough for application to other narrow-band sensors from multiple remote sensing platforms.

Because the ratios or pairs of wavelengths used to calculate indices highlight significant features while correcting for geometrical and background effects (Baret and Guyot 1991), cross-instrument application could be direct. Such simple transformations have been closely correlated with plant characteristics without the sensitivity to external variables such as sun angle or instrument variability (Pinty et al. 1993). Ongoing work will focus on indices and ratios in order to speed processing time.

However, this is not to say that ground truth data will not continue to be necessary in hyperspectral work. The input of known spectra to any predictive model will always increase accuracy and ensure that predictions are as robust as possible. In addition, ground truth data will enable land managers to know the accuracy of their maps and limitations of predictive coverages they are using in their management plans.

CONCLUSIONS

These results indicate that a simple four-term linear regression model based on chlorophyll$_a$, fluorescence, and water absorption features is able to accurately predict a detailed hemlock decline rating system (88% one-class tolerance accuracy). The one-class tolerance accuracy at the extreme low end of the decline scale (0, healthy to 4, pre-visual decline) was 92%, indicating that hyperspectral sensors could be used to detect trees in the very early stages of decline.

There is little evidence that these technologies can diagnose causal agents, as stress may be related to a variety of factors. However, our ground truth data suggests that most declining hemlocks in this region are currently impacted by HWA. These techniques would provide a much-needed tool for the early detection of stressors such as HWA infestation, and will allow forest land management agencies to focus biological control efforts on incipient infestations before trees are severely impacted.

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