Modeling Landscape-Level Impacts of HWA in Shenandoah National Park

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Abstract

Eastern hemlock is in decline in many parts of its range in the eastern United States due primarily to infestation by the hemlock woolly adelgid (HWA). In Shenandoah National Park, HWA rapidly killed many hemlock stands after first appearing in 1989. While the severity of hemlock decline in Shenandoah National Park may preclude saving the hemlock forest component, an examination of the progression of decline across the landscape may provide insight into management potential for other areas under threat from HWA. We are exploring the potential to use satellite remote sensing and geospatial modeling as a tracking tool for HWA decline in the mountainous terrain of Shenandoah National Park. Pre- (1984) and post- (1997) infestation Landsat TM images were processed to remove atmospheric and topographic influences. Corrected pre-infestation images were used to classify hemlock stand areas and were used as a mask for subsequent analysis. Normalized difference vegetation indices (NDVI) were computed for both images, and assessed for rates of decline. Rates of decline from satellite imagery were compared to measures of hemlock decline from field plots, and to terrain characteristics through the use of regression tree statistical modeling techniques. Satellite image-based decline measures compare favorably to field estimates of decline, and show associations with landscape variables, especially elevation. However, variability in the post-infestation imagery shows only weak association with landscape variables, suggesting uniform decline by 1997, or the influence of unmeasured fine- or coarse-scale parameters. Landscape analysis provides a useful tool for managers to track and assess the progression of eastern hemlock decline due to HWA, even in areas of high relief.

Keywords:

HWA, satellite imagery, landscape variability.

Introduction

Eastern hemlock (*Tsuga canadensis*) comprises about 1% by area of the forest in Shenandoah National Park (SNP), Virginia, and occurs in cool, moist, hillside, and ravine environments (Teetor 1988). While only a small fraction of the overall forest area, eastern hemlock is valued as a natural and cultural resource by park managers and the public as it provides shading to stream habitats and unique environments for wildlife and park visitors. Field observations by SNP park resource managers have documented a severe and rapid decline of eastern hemlocks in many stands since 1989 when hemlock woolly adelgid (HWA) (*Adelges tsugae*) was first observed in the park. HWA was first introduced into the eastern United States in the 1950s (McClure 1987) and has since spread north and west to infest eastern hemlock stands in Connecticut, New Jersey, Pennsylvania, Maryland, Virginia, and West Virginia. In areas of intense infestation, defoliation by HWA has resulted in almost total eastern hemlock mortality. In some areas, infestation, defoliation, and tree mortality have advanced at such a rapid pace that near complete elimination of hemlocks trees from some forests has been observed within a span of only 3 or 4 years (McClure 1991). In other areas, HWA is present but only minor defoliation has been observed to date. The progression of HWA-induced decline has been remarkably swift in SNP, but preliminary studies suggested that not all stands declined at the same rate, depending on their location on the landscape (Young et al., unpublished data).

The patchy nature of eastern hemlock decline suggests landscape-level environmental factors may be influencing the rate of decline. Landscape pattern and structure play an important role in governing the spread and severity of insect pests in forest ecosystems by directly influencing insect populations and dispersal capabilities, or indirectly by influencing host tree health and distribution (Castello et al. 1995; Perry 1988). Powers et al. (1999) used landscape analysis to evaluate Douglas fir bark beetle dynamics and host tree susceptibility at multiple scales and found that landscape-scale phenomena were more strongly correlated with beetle kill events than individual tree health factors. McClure (1990) found that wind, birds, deer, and human activities, all of which are moderated to some extent by landscape structure, disperse HWA. Bonneau (1997) found that eastern hemlock stands located on cold, moist, north, or northeast aspects were generally healthier than stands in drier or more exposed areas of Connecticut. Landscape-scale impacts from forest defoliating insects allow the use of geospatial technologies (e.g., satellite remote sensing and geographic information systems) for tracking and modeling forest health, and researchers have successfully used satellite-based remote sensing to evaluate forest health impacts of HWA and other defoliating insects in Connecticut (Bonneau et al. 1999) and New Jersey (Royle and Lathrop 1997).

We are exploring the use of remote sensing and geospatial modeling techniques to track eastern hemlock decline in the rugged terrain of Shenandoah National Park, and we present here initial results from this analysis. Shenandoah National Park straddles a ridge of the Blue Ridge Mountains in northwestern Virginia, and is topographically complex with numerous coves and deep ravines. Eastern hemlock occurs as a mixed forest component along stream drainages and as nearly pure stands in high elevation coves. Although remote sensing has been shown to be a valuable tool for monitoring forest vegetation, the steep topography of SNP poses special challenges for tracking decline of eastern hemlock. The steep stream corridors and sheltered coves where hemlock occurs in the park also are some of the most difficult areas to map using satellite imagery, due to heavy topographic shadowing in those areas.

We are attempting to answer two basic questions in this research: Can hemlock decline be measured using satellite imagery in the topographically challenging environment of SNP?; and can hemlock decline due to HWA be associated with landscape attributes?

Methods

We are using satellite remote sensing investigations, field data collection, and landscape modeling to assess eastern hemlock decline in Shenandoah National Park. For this analysis, we acquired and analyzed Landsat TM satellite images from 1984 and 1997. Field data collection was accomplished in the fall of 1998 and summer of 1999. Landscape variables were derived using GIS from digital elevation models and other digital geospatial data. We used exploratory statistical modeling to assess relationships between image-based measures of decline and field collected hemlock-health attributes.

Satellite Image Interpretation. We acquired several Landsat Thematic Mapper (TM) satellite images for use in this study. The Landsat TM imaging satellite records reflected visible and near-infrared light as digital images over broad areas. This satellite captures wavelengths tuned for vegetation study in repeatable, multi-spectral, medium-scale images (Lillesand and Kiefer 2000). Images acquired include a pre-infestation scene from April 12, 1984, and a post-infestation scene from April 16, 1997. Other imagery from the spring of 1989, 1992, and 1994 was acquired to assess the time sequence of defoliation, but we focus here on results only from the pre-(1984) and post-(1997) infestation endpoints. Imagery was acquired to correspond to seasonal deciduous leaf-off periods so that vegetation response of eastern hemlock could be isolated. Several preprocessing steps were required to normalize the satellite imagery prior to assessment of changes in vegetation condition. Each Landsat TM image was reprojected into a common coordinate system (UTM zone 17, NAD 1927). Having an exact geographic alignment between images of different dates is critical during a change detection procedure.

It also was critical to insure radiometric consistency between images (i.e., to be sure that each image is displaying features in the same manner spectrally). Differences in atmospheric conditions, completed a topographic shading, or sensor calibration could be detrimental to detecting differences in forest cover over time. Therefore, we performed a "dark-object subtraction" to remove haze, topographic normalization to control for topographic shading, and then normalized each image to a radiometric master scene to account for sensor calibration differences or other scene-level differences. Dark-object subtraction was completed according to Chavez (1988). This procedure adjusts for atmospheric haze in satellite imagery by subtracting the reflectance from known dark objects (e.g., dark shadows) from visible and near-infrared wavelength bands. Due to the pronounced relief in SNP and the shadows cast by low sun angles during spring satellite acquisitions, it was critical to adjust the imagery to remove topographically induced differences in vegetation reflectance. Topographic normalization was performed using the backward radiance correction transformation proposed by Colby (1991). This method adjusts for differential reflectance patterns due to slope orientation to incident sunlight. Finally, images were radiometrically normalized to a master scene to adjust for sensor calibration differences between image dates using a procedure based on Coppin and Bauer (1994). Resulting normalized images minimized spurious differences between vegetation reflectance (Figure 1).

We computed an index of vegetation vigor for the pre- and post-infestation images using the

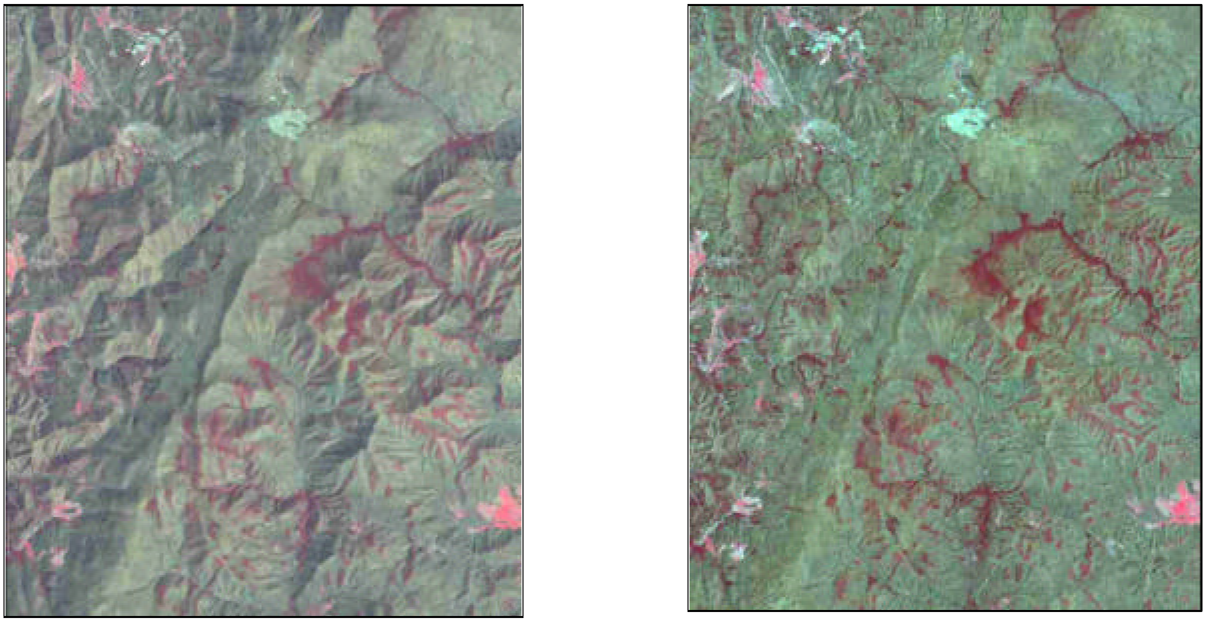

Figure 1. Examples results of 1984 satellite image atmospheric correction and topographic normalization in Shenandoah National Park, before (left) and after (right). Notice reduction in shadows and haze.

Normalized Difference Vegetation Index or NDVI (Jensen 1996). This index is calculated as a ratio of near-infrared to red reflectance for each pixel in the image. Since healthy vegetation reflects strongly in the near-infrared portion of the spectrum, and absorbs the red portion, a ratio of near-infrared to red reflectance highlights vegetation in multispectral imagery. The formula for calculation of the NDVI is: NDVI = (NIR – Red) / (NIR + Red) where NIR is near-infrared reflectance from Landsat TM wavelength band 4 and Red is red reflectance from Landsat TM wavelength band 3. Values of the NDVI range from –1 to 1, and higher (positive) values represent healthier, more vigorous vegetation. The NDVI has been widely applied in remote sensing studies of vegetation condition (Jensen 1996). We applied the mask of pre-infestation hemlock stands to NDVI transformations of the normalized 1984 and 1997 imagery to examine the change in NDVI in hemlock stands.

Field Data Collection. We collected information in the field to compare measures of hemlock decline from NDVI with measures of tree health from vegetation plots. The purpose of field plots was to to record coniferous tree species dominance, stand characteristics, and hemlock health for evaluating potential imagery-derived vegetation indices. We used landscape data from GIS to randomly locate sample plots in known hemlock areas, stratified by topography and image reflectance types. We visited 58 sites in the fall of 1998 and the summer of 1999. Site coordinates were located in the field using a handheld GPS receiver capable of receiving the U.S. Military precise positioning service (PPS) with a potential real-time locational accuracy of ± 4 meters.

Each full plot was centered on a point and was 30 meters in diameter. At each plot we measured basal area, diameter, species, density, canopy position, and crown closure of trees; presence of understory conifers; and health (if hemlock) of significant (e.g., greater than 8 cm dbh) coniferous trees. At a subset of plots we recorded only conifer diameter, basal area, species, canopy position, and health of hemlocks in a 15-meter diameter plot. Hemlock health was observed visually for each tree and recorded on a six-number scale developed by SNP personnel for their annual hemlock health surveys (Table 1). We re-scaled the SNP crown health measurement using the mid-point of the class (i.e., percentage foliage), and calculated the mean health value by plot.

Table 1. Hemlock Health Classification Developed by SNP Biologists and Used in Assessments of Hemlock Tree Health.

Crown Health Indicator	Definition	Re-Scaled (Midpoint)
1	85 to 100% crown intact	92.5
2	50 to 85% crown intact	67.5
3	15 to 50% crown intact	32.5
3X	0 to 15% crown intact	7.5
4	Dead from HWA	0
5	Dead from other/unknown	0

Landscape Variables. We summarized landscape information using GIS. The goal of this analysis was to examine environmental gradients that may influence the rate of hemlock decline directly by affecting HWA populations or HWA dispersal, or indirectly by influencing hemlock habitat suitability and stress. GIS data layers used in this analysis were a digital elevation model (DEM) of the park, maps of streams, roads, and trails. The DEM was derived from standard USGS 1:24,000 scale digital elevation files where each cell represents 0.09 ha of ground area (30 m by 30 m). We used the DEM to produce maps of elevation, slope, slope direction (e.g., aspect), slope shape, moisture index, and relative solar illumination. Slope direction was translated to a measure of "northness" by a cosine transform such that aspect varied from -1 (south) to 1 (north) (Roberts 1986). A measure of slope shape was calculated from the DEM following methods outlined in McNab (1991). A measure of solar illumination was calculated from a hill-shading function using the sun's position and height above the horizon at the summer solstice (Marsh 1983) to highlight those areas likely to be in shadow. A relative topographic moisture index was calculated from the DEM following Anderson and Merrill (1998).

We used GIS distance functions to create maps of distance to roads, trails, and streams. In this process, lines representing roads, trails, and streams were converted to a binary representation where presence or absence of the linear feature is recorded on each cell of the map as 1 or 0 respectively. The result of the distance calculation is a continuous surface recording the relative distance of each pixel in the park from linear features.

Statistical Analyses. Landscape and NDVI variables were summarized for pixel areas within the hemlock mask image, and translated into a table for statistical analysis. Field data was tabulated by sample point and overlaid on 1984 and 1997 satellite images to record NDVI values around each sample location. The goal of this analysis was to examine change in NDVI from 1984 to 1997, to assess correspondence between field collected attributes of hemlock health and NDVI, and to assess potential relationships between hemlock decline and landscape features. Our aim was to use exploratory data analysis to identify potential avenues for further research as we collected additional data on the rate and nature of hemlock defoliation from remote sensing investigations. We assessed the relationship between NDVI and field measures of hemlock crown damage using scatter plots with fitted regression lines and simple correlation analysis. We used regression tree-based models to assess relationships between NDVI change in hemlock areas and landscape attributes. Regression tree models are non-parametric exploratory modeling techniques that do not assume any distribution in the predictor variables, which can be either categorical or continuous variables (Breiman et al. 1984). These models are fitted to the dependent variable (in this case NDVI or NDVI change) by recursively splitting the dataset based on the independent variables (e.g., the landscape variables). The result is a tree or mobile graph showing the partitioning of the data set (on the dependent variable), and the "proportional reduction in error" value (similar to a multiple squared R value). When the dependent variable is categorical, these models are termed "classification trees"; when the dependent variable is continuous, the models are termed regression trees. CART models are useful as exploratory tools because they can uncover "non-additive behavior" or interactions among variables easier than can linear models such as multiple regression (Clark and Pregibon 1993).

Results

Results from NDVI calculated from the satellite images show a generalized decrease in vegetation vigor from 1984 to 1997 in areas classified as hemlock (Table 2). A total of 22,211 0.09 ha pixels (1998.99 ha) were classified as hemlock from the 1984, pre-infestation image. Of this total, vegetation vigor as measured by the NDVI decreased in 97.6% (1951.38 ha) of the areas originally classified as hemlock. In 42.2% (844.2 ha) of the area classified as hemlock, the NDVI measurement decreased by greater than 50% (Table 3). A comparison of image-measured NDVI decline to hemlock defoliation measured at field plots showed a fairly good correspondence (Figure 2). The average health of hemlocks across all canopy classes in hemlock-dominated field sites was correlated to NDVI difference from 1984 to 1997, regardless of the presence of understory conifers.

The plot shows a modest linear relationship (R^2 of .334), but reveals some potential problems in comparing these measurements. For example, heavy defoliation of hemlocks was measured at some field plots, but was not reflected in the change in NDVI. Field plots that did not have understory conifers show a better fit to image-based NDVI (R^2 of .4614), most likely due to elimination of areas with mixed pixels. However, there are still some areas showing high defoliation in the field that are not reflected by image-based NDVI change.

Results of regression tree analysis (Figure 3) in areas classified as hemlock demonstrate partitioning of the dependent variable (in this case post-infestation NDVI in 1997) based on landscape variables. The 22,211 - 0.09 ha pixels are split into groups based on the most important predictor variable. Reading down the tree graph allows an examination of the main factors influencing the dependent variable. In this case elevation was most important for predicting levels of 1997 NDVI.

Table 2. Results of NDVI in 22,211 - 0.09 Ha Pixels (1998.99 Total Ha) From Image Areas Classified as Hemlock on 1984 and 1997 Normalized Satellite Images (i.e., Hemlock Mask)

	1984 Image Mask	*1997 Image Mask*
Minimum NDVI	0.341152	0.275638
Maximum NDVI	0.627978	0.515480
Mean NDVI	0.513097	0.392805
Std. Deviation of NDVI	0.060181	0.061806

Table 3. Change in NDVI From 1984 to 1997 in Each of 22,211 - 0.09 Ha Pixels

NDVI Change Type	*# of 0.09 Ha Pixels*	*Total Area (ha)*	*% of Total Area*
Decrease > 50%	9380	844.2	42.2
Decrease < 50%	12302	1107.18	55.4
Increase < 50%	328	29.52	1.5
Increase > 50%	201	18.09	<1

Hemlock areas at elevations lower than 749 meters had much lower average NDVI than those at higher elevations. Beyond the first split, areas that are closer to streams had lower average NDVI (second level on left), and areas at the highest elevations had the highest NDVI.

Overall, the model fit is low (proportional reduction in error or PRE of 26%) suggesting that variability in NDVI in 1997 imagery was only weakly associated with landscape factors. By this time, there had been almost 10 years of HWA defoliation in the park and decline due to HWA may have progressed in most stands to a somewhat uniform level. The remaining variability in NDVI (not explained by this model) may be due to other factors such as boosting of the NDVI signal from other regenerating conifers, or from depression of infrared reflectance due to exposure of water under defoliated canopies. It will be instructive to assess NDVI change at intermediate time periods to fully understand the progression of decline based on landscape position and vegetation characteristics.

A regression tree model of NDVI change from 1984 to 1997 (Figure 4) shows a more complex model with more interactions, but a poorer overall fit (12.8%). The most important factors in this model are distance to streams and elevation. Those areas that were closer to streams and at low elevations had the most change in NDVI, while those hemlock stands on steep slopes and at high elevations had the lowest levels of NDVI change. Again, more work needs to be done to investigate the reasons for poor model fit. Data analysis of each of the 22,211 individual pixels may be introducing noise into the data analysis, especially if there is a slight misregistration in the geospatial data. It may be more telling to examine contiguous pixels or stands as one unit for analysis.

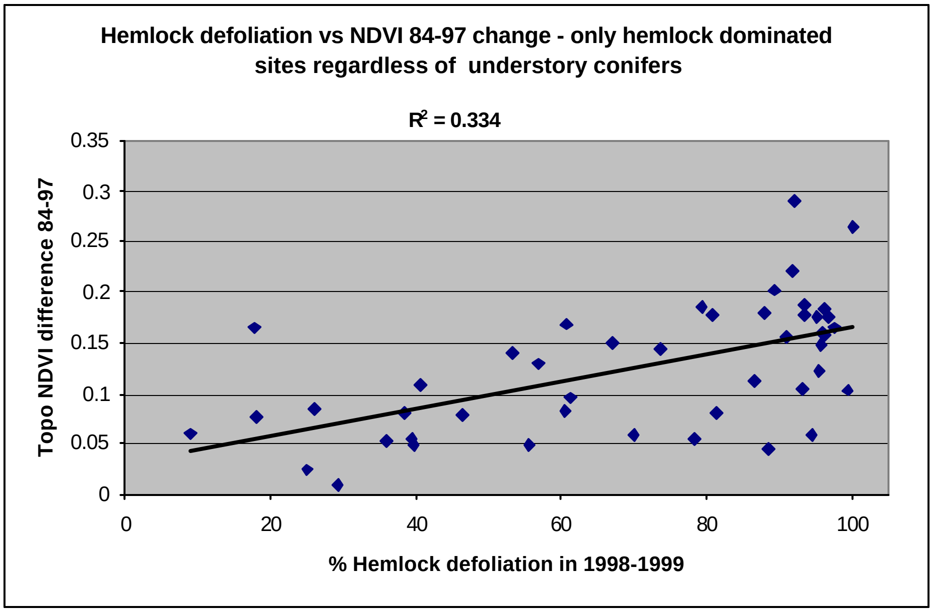

Figure 2a.

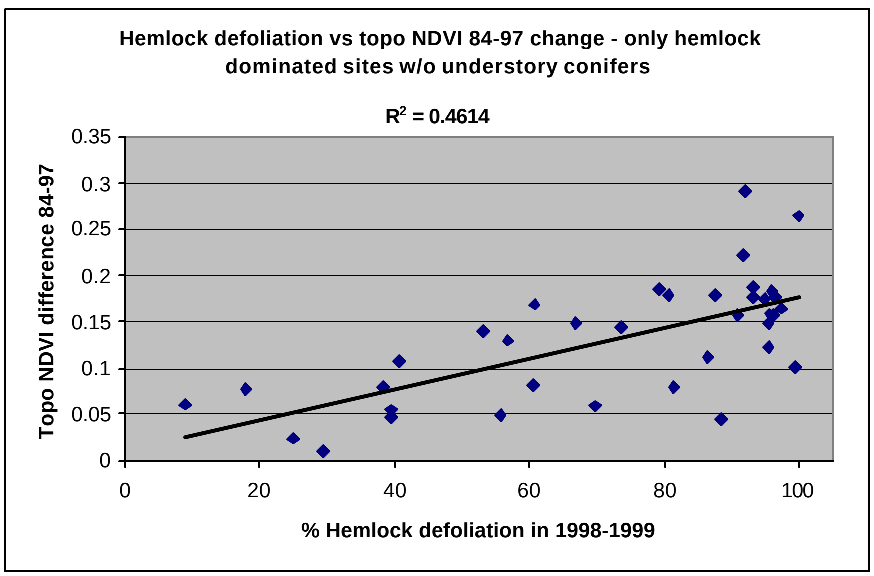

Figure 2b.

Figures 2a and 2b. Results from comparison of 1984 to 1997 satellite imagery derived NDVI decline and field-measured defoliation of eastern hemlock. Field plots dominated by hemlock, but regardless of understory conifers (2a), and field plots dominated by hemlock but without understory conifers (2b).

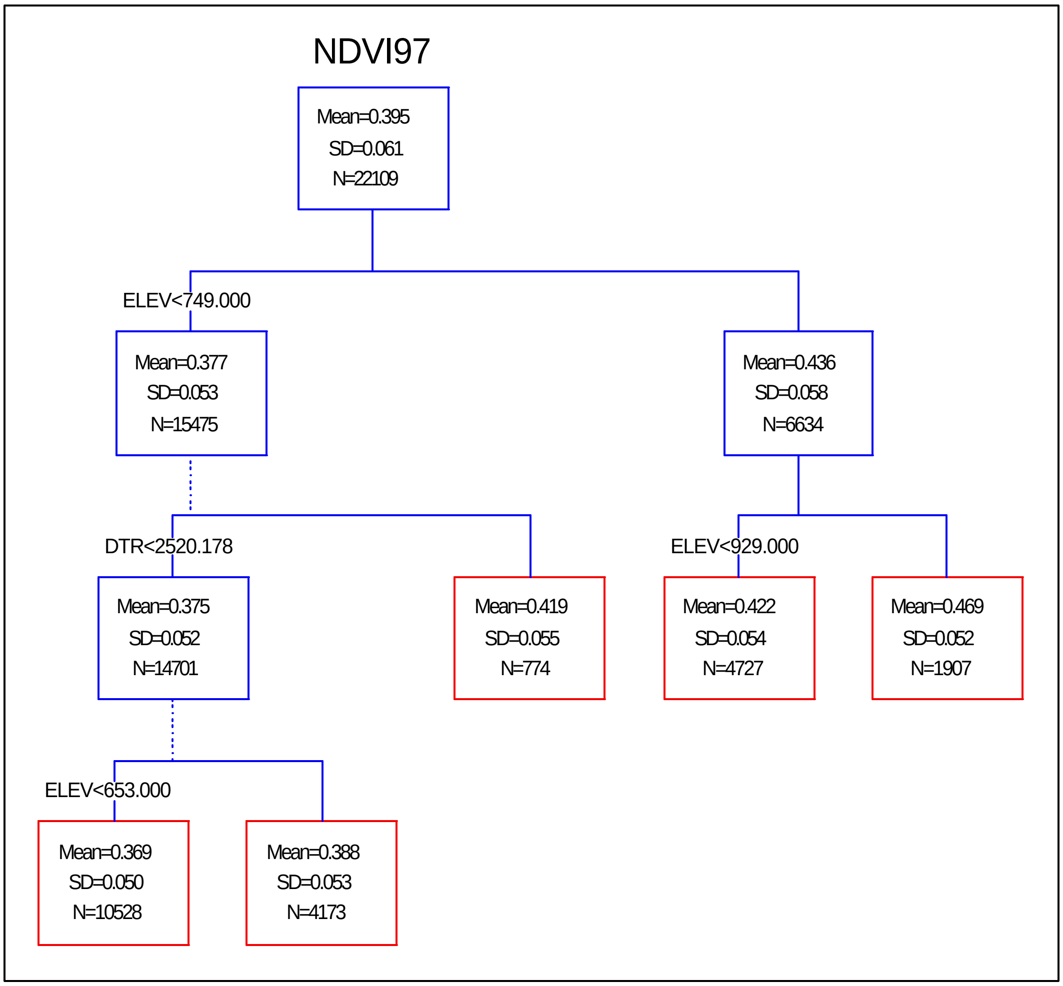

Figure 3. Regression Tree model of 1997 NDVI (NDVI 97) compared to landscape attributes. Tree splits on elevation (ELEV), then distance to trails (DTR). Mean NDVI values are higher at higher elevations and further from streams. Proportional reduction of error for this model is 26.3% (0.263).

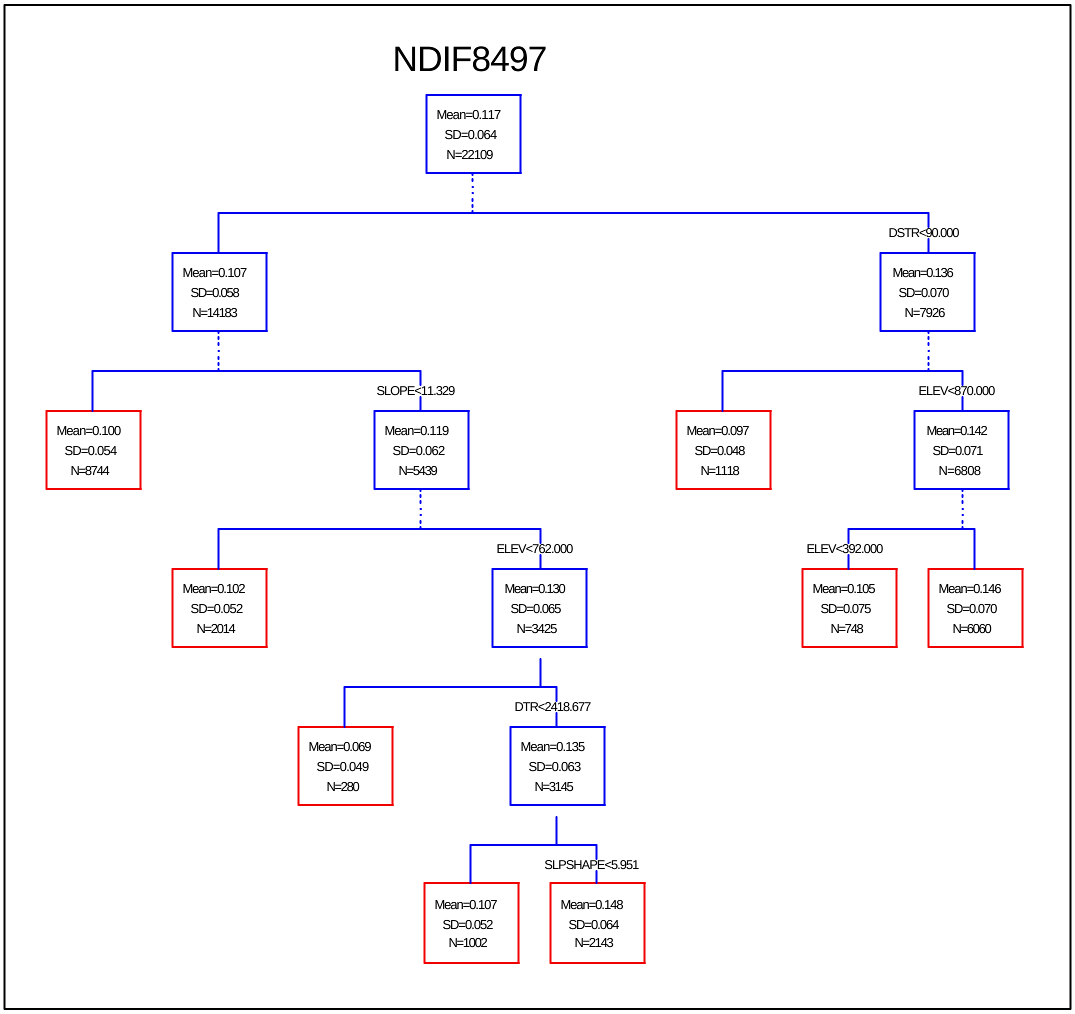

Figure 4. Regression Tree model of 1984 to 1997 NDVI change (NDVI97) compared to landscape attributes. Tree splits on distance to streams (DSTR), slope (SLOPE), elevation (ELEV), distance to trails (DTR), and slope shape (SLPSHAPE). NDVI change is higher for areas close to streams and at low elevations. NDVI change also is greater in areas of low slope and low elevation that are closer to trails. Proportional reduction of error for this model is 12.8% (0.128).

Discussion

In summary, our most important finding of this research so far is that remote sensing and landscape modeling can be used to track hemlock decline over large areas, even in areas of high relief, if attention is paid to proper image correction and calibration for atmospheric, radiometric, and topographic influences. Image-based measures of vegetation vigor correspond fairly well with field-based measures, but vegetation response from understory conifers may confuse the signal returned to the satellite, especially in the fairly coarse 0.09 ha pixels of Landsat imagery.

This study and other preliminary work point to the fact that hemlock decline as measured by change in NDVI shows association with landscape variability in Shenandoah National Park. However, the signal evidenced by looking at only pre- and post-infestation imagery is weak. More work is needed to assess whether this weak signal is related to the level of decline evident by 1997, or if factors operating at other scales such as soil nutrients, drought, or air pollution are more important for influencing rates of hemlock decline due to HWA.

Regression tree models appear to provide an excellent avenue for analysis of the relationship between hemlock decline and landscape structure. Regression tree models uncovered interactions between landscape variables that would not have been apparent using linear regression modeling. This technique also will be valuable for creating predictive models of areas on the landscape likely to be most heavily impacted, thus management activities can be better directed without reliance on extensive field surveys. One output of CART models is a set of "decision rules" that can be directly translated into map form using GIS to classify areas according to their potential for hemlock decline.

There appears to be an interaction between landscape structure and hemlock decline in Shenandoah National Park. However, much work remains to uncover the mechanisms responsible for this interaction. We are optimistic that relationships between hemlock decline and landscape structure will be made clearer through the use of more time sequence maps of the rate and location of hemlock decline. Hopefully, this will allow us to provide better estimates of vulnerable landscape types in other national park units that are threatened from the hemlock wooly adelgid. This information should be invaluable for assessing potential biological impacts to bird, amphibian, and mammal communities that depend on eastern hemlock for some portion of their life cycle.

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