A Landscape-Scale Remote Sensing/GIS Tool to Assess Eastern Hemlock Vulnerability to Hemlock Woolly Adelgid-Induced Decline

Jennifer Pontius, Richard Hallett, Mary Martin, and Lucie Plourde

Jennifer Pontius and **Richard Hallett**, research ecologists, USDA Forest Service, Northern Research Station, Durham, NH 03824; **Mary Martin**, research assistant professor, and **Lucie Plourde**, research scientist, Complex Systems Research Center, University of New Hampshire, Morse Hall, Durham, NH 03824.

Abstract

The hemlock woolly adelgid (*Adelges tsugae* Annand) (HWA) is an invasive insect pest that is causing widespread mortality of eastern hemlock (*Tsuga canadensis* (L.) Carr.). However, some stands remain living more than a decade after infestation. The ability to target management efforts in locations where hemlock is most likely to tolerate prolonged HWA infestation is critical to successful integrated pest-management programs. Here, we build a landscape-scale hemlock risk model for the Catskills region of New York based on coverage like slope and aspect derived from a traditional Digital Elevation Model (DEM). We also show that additional data layers derived from hyperspectral sensors such as NASA's Airborne Visible InfraRed Imaging Spectrometer (AVIRIS) can provide critical information for geographic information system (GIS) modeling. The initial landscape-only model was able to predict the rate of overall decline following HWA infestation for 21 plots across the Northeast with $R^2 = 0.35$, $p = 0.027$. Adding foliar N concentration to our model improved results to $R^2 = 0.79$, $p = 0.0009$. An AVIRIS-derived hemlock abundance coverage was then used to define the hemlock resource and its relative vulnerability to rapid decline. These results indicate that the inclusion of both landscape and chemical variables is critical to predicting hemlock vulnerability to HWA, and that landscape-scale modeling in a GIS platform is possible with the addition of hyperspectral remote sensing coverages. Whereas the resulting risk map covers only the Catskills region of New York, the relationships established here should be applicable to HWA infestation across the range of eastern hemlock, providing a basis for forest land management agencies to make informed management decisions.

Keywords: AVIRIS, *Adelges tsugae*, forest health, invasive insect pest, susceptibility.

Introduction

Insect pests and pathogens represent the largest and most pervasive agents of natural disturbance in North American forests, with potentially significant economic, aesthetic, and ecological consequences for northern forest ecosystems (Ayres and Lombardero 2000). In order for land managers to make successful management decisions for mitigation and treatment activities, they must know the location and extent of the host resource as well as the anticipated risk of host mortality. Traditionally, land managers have relied on plot-based field sampling efforts to supply this information. Although this is useful, a comprehensive, landscape-scale, spatially continuous coverage of the resource and its vulnerability is needed to fully assess the potential impacts on the forest resource and to devise successful management strategies.

Recently, remote sensing technologies have greatly increased the amount and quality of information that is available for landscape-scale ecological risk modeling. This information includes abundance maps for individual tree species, detailed forest decline assessments (including previsual symptoms), and foliar chemical concentrations (Foody 2002; Martin and Aber 1997; Ollinger and others 2002; Plourde and others 2007; Pontius and others 2005, 2006; Smith and others 2002). Such remote-sensing-based products, combined in a geographic information system (GIS) platform with traditional topographic-based data layers, have expanded the tools available for risk modeling. They provide the potential to greatly enhance our ability to create spatially continuous, landscape-scale models of ecosystem function and response to disturbance.

Hemlock woolly adelgid (*Adelges tsugae* Annand) is an invasive insect pest that is causing widespread mortality of eastern hemlock (*Tsuga canadensis* (L.) Carr.). Current rates of spread into uninfested areas are estimated at 10 to 15 miles per year, and all indications are that HWA will penetrate the entire range of eastern hemlock (McClure 1995a). Because HWA may infest all hemlock stands eventually, susceptibility assessments (assessments of likelihood of infestation) are not necessarily informative for long-term, landscape-scale risk modeling. However, there is evidence of differing hemlock vulnerability (ability to tolerate prolonged HWA infestation). Many infested hemlock have shown minimal resistance to *A. tsugae* and little chance for recovery (McClure 1995b). However, some stands remain living more than a decade after infestation (Pontius and others 2006). Indeed, two adjacent hemlock stands can often respond very differently to attack, with differences commonly attributed to topographic characteristics such as landscape position, slope, and aspect (Bonneau and others 1997, Hunter 1993, Orwig and others 2002, Royle and Lathrop 1999). Greenhouse studies have shown that the presence of HWA alone did not cause the death of hemlock seedlings, and that it is the combined stress of drought and infestation that ultimately leads to mortality (Sivaramakrishnan and Berlyn 1999). In the field, reduced growth rates were associated with infested trees on ridgetop and southwestern facing sites, but not with those on well-watered sites (Sivaramakrishnan and Berlyn 1999). Pontius and others (2006) found that several site factors could be used to predict hemlock decline across the Northeast. The severest hemlock decline was associated with markedly low growing-season precipitation levels, southern and western exposures, and ridgetop/side-slope positions.

All of these landscape variables are in some way related to potential soil-moisture content, indicating that water availability may be an additional stressor, accelerating decline in the drought-sensitive eastern hemlock (Bonneau and others 1997, Orwig and Foster 1999, Orwig and others 2002, Young and others 1999). Orwig and others (2002) concluded that although the duration of infestation primarily controls the intensity of hemlock decline and mortality, stands on xeric aspects succumb most rapidly.

Although significant, these landscape variables typically explain only a small portion of the overall variation in hemlock decline. Adding foliar chemistry to site factors at the plot level, Pontius and others (2006) predicted an 11-class decline rating with 98 percent one-class tolerance accuracy on an independent validation set, indicating that foliar chemistry may also play an important role in HWA dynamics and hemlock decline. Herbivory is often positively correlated with foliar nitrogen concentrations, with low nitrogen-limiting insect populations (McClure 1980, Schowalter and others 1986, White 1984). Nitrogen can be particularly limiting to insects because there is a large difference between the nitrogen concentration of plants (around 2 percent dry weight) and that of insects (approaching 7 percent) (Dale 1988). This link between nitrogen and aphid success has been documented for a variety of host species (Carrow and Betts 1973, Douglas 1993, Koritsas and Garsed 1985, McClure 1980).

For relatively immobile insects such as HWA, the nutritive quality of forage becomes even more important. McClure (1991, 1992) found that N fertilization resulted in increased relative growth rate, survivorship, and fecundity of HWA, thus increasing hemlock vulnerability and reducing the effectiveness of implanted and injected pesticides. Regionally, Pontius and others (2006) also found that foliar N concentration was the strongest correlate with HWA infestation, with higher N consistently associated with higher HWA population levels.

Although useful in identifying key factors in the hemlock decline complex, such plot-level and greenhouse-based studies do little to assist land managers in making critical planning and treatment decisions for their forests. Here, we apply a plot-level empirical model from field-based observations of hemlock decline across the Northeast to a landscape-scale GIS model for hemlock woolly adelgid risk assessment. Because of the unique ecological niche occupied by hemlock stands, it is important to identify the stands that are most likely to tolerate HWA infestations so that hemlock can be preserved as a component of forest habitats in the region. At the same time, stands likely to suffer high rates of mortality can be evaluated for integrated pest management activities or conversion to other species.

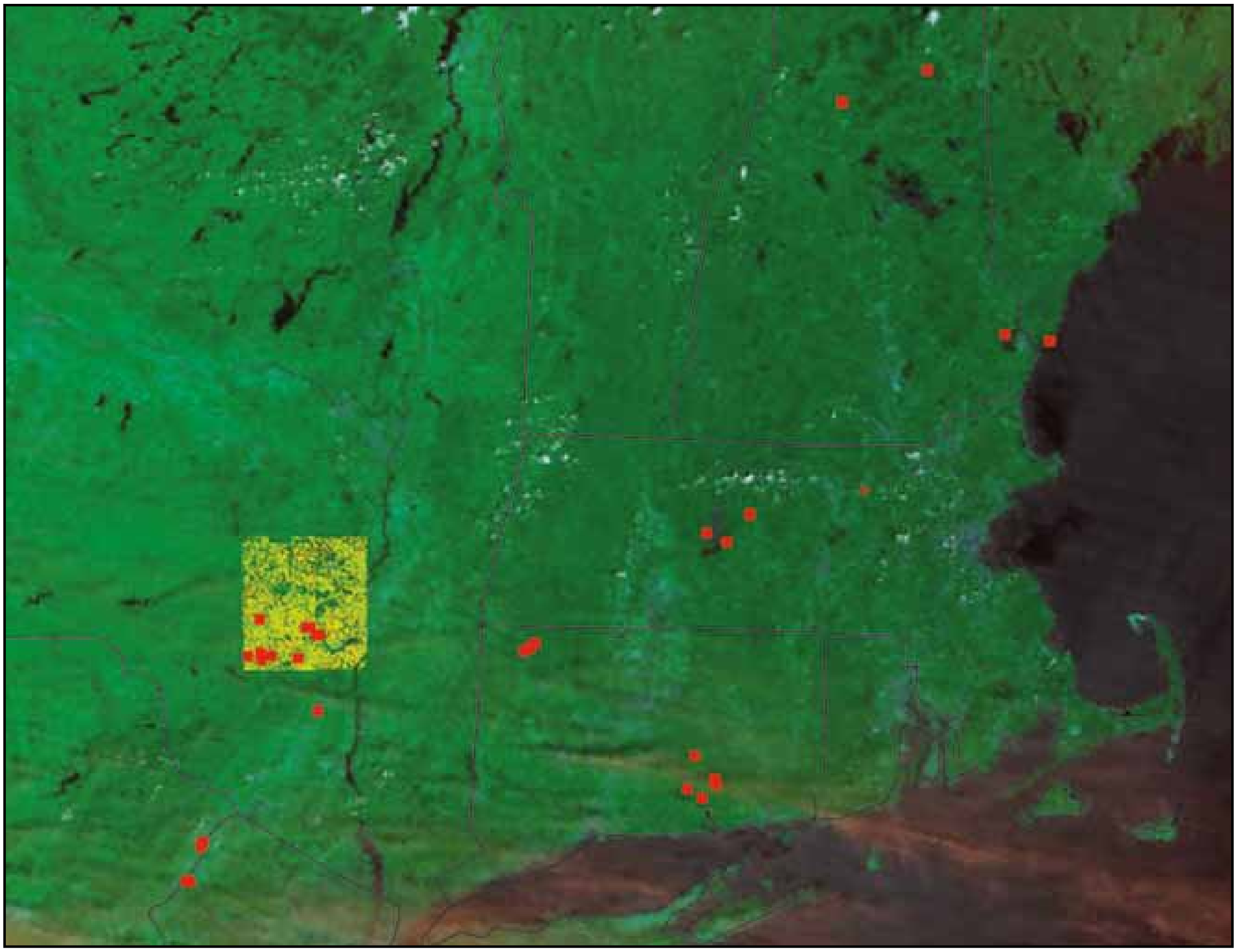

Figure 1—The study area spanned the full range of hemlock health and infestation histories over 11 states in the Northeast. Of the 48 total plots, 27 were concentrated in the Catskills region of New York, where hyperspectral coverages were available for GIS modeling.

Objectives

The goal of this work was to build a data-driven, empirical decline model for hemlock vulnerability to HWA that could be applied to a spatially continuous GIS model. Here we considered variables that were identified in previous research to be linked to HWA/hemlock decline and that were available in landscape-scale, wall-to-wall coverages. Using plot-level data from a regional set of infested hemlock stands, our specific objectives were to:

1. Develop and evaluate data-driven, quantitative linear models to predict the average rate of decline following HWA infestation based on (1) only landscape variables and (2) landscape variables plus foliar N concentrations.
2. Use the most effective model to incorporate key variables into a GIS model to map relative risk to hemlock on a landscape scale in the Catskills region of New York.

Methods

Plots in mature hemlock (where hemlock occupies >50 percent of the canopy) were established across a wide range of hemlock health, HWA infestation levels, site characteristics, and stand demographics. This included 48 sites characterizing the extremes of hemlock resistance and vulnerability to HWA from Pennsylvania to Maine (Figure 1). At each plot, a minimum of five hemlocks was sampled yearly between 2001 and 2005. Whereas statistical models were based on

Table 1—Decline ratings

Class	Overall decline status	New growth	Canopy transparency	Fine twig dieback	Live crown
		---------------------------*Percent*---------------------------------			
0	Perfect health	> 98	0 to 3	0	> 97
1	Very healthy	96 to 98	2 to 5	-	91 to 96
2	Healthy	94 to 96	4 to 7	5	78 to 90
3	Pre-visual decline	86 to 94	6 to 9		64 to 77
4	Decline first visible	69 to 86	8 to 12	10	52 to 63
5	Early decline	48 to 69	11 to 18	15	42 to 51
6	Moderate decline	23 to 48	17 to 26	20 to 30	30 to 41
7	Severe decline	4 to 23	25 to 40	35 to 45	20 to 29
8	Extremely unhealthy	2 to 4	39 to 64	50 to 60	10 to 19
9	Death imminent	1 to 2	63 to 67	65 to 80	1 to 10
10	Dead	0	> 67	85 to 100	0

Overall summary decline ratings were calculated by averaging the class assignment for each measured variable according to Table 1. These class assignments were then averaged to summarize overall decline status.

plot-level data, development of a landscape-scale GIS risk coverage was limited to the Catskills region of New York where hyperspectral imagery was available.

Field and Laboratory Methods

Each plot was sampled and evaluated yearly for a suite of decline symptoms, foliar chemistry, and HWA infestation levels. Site, stand, climate, and soil physical and chemical characteristics by genetic horizon were added for all plots by the final year of the study. Here we considered only those variables that would be available as digital landscape-scale coverages. This included slope, aspect, and landscape position derived from a digital elevation model (DEM). Additional data layers of foliar N (Martin and Aber 1997, Smith and others 2003), and percentage hemlock basal area (Pontius and others 2005) derived from hyperspectral sensors were also considered for inclusion in the second model.

Rather than rely on a nominal variable of vulnerable/tolerant for model development, a continuous overall decline value was calculated for all trees. This overall decline value was assessed using methods specifically designed to quantify the various, sequential symptoms that follow *A. tsugae* infestation. This included the percentage of terminal branchlets with new growth, percentage transparency (quantified using a concave spherical densiometer (Pontius and others 2002), percentage fine twig dieback, and live crown ratio (USDA Forest Service 1997).

Because the goal was to calculate one summary variable to describe hemlock decline, we designed a method to normalize and then average all measured health variables into one value. Individual measurements for each variable were first normalized and rescaled to a 0 to 10 category value based on the quantile distribution cut-offs from a database of over 1,000 northeastern hemlock measurements (Table 1). These new normalized category values were then averaged to determine one summary decline rating that best described overall tree status (a continuous variable where 0 = perfect health, 10 = dead). These summary values were averaged over all trees for each plot yearly for the duration of the study.

The number of years since infestation was determined based on the first year that any HWA was witnessed on any hemlock within the plot. This is often first noticed at very low infestation levels (less than 5 percent infestation), typically well before the first year that HWA populations reach outbreak levels. In order to maximize accuracy of initial infestation dates, plots were selected from stands where monitoring and sampling have been conducted yearly by State, Federal, local, or private groups. We then calculated the change in overall plot-level decline from initial infestation to the current year to determine the dependent variable:

average yearly decline since infestation. This continuous output variable represents how rapidly health deteriorates and allows for flexibility in interpretation, depending on the needs of the user.

In addition to decline variables, the five canopy dominant hemlocks on each plot were sampled yearly between 2001 and 2005 for foliar chemical analyses. Needles were dried at 70 °C and ground to pass a 1-mm-mesh screen. A NIRSystems spectrophotometer was used to measure foliar nitrogen (N) concentrations (Bolster and others 1996). Dried and ground foliage was digested using a microwave-assisted, acid digestion procedure (US EPA 1995) and analyzed for calcium, potassium, magnesium, manganese, and phosphorus using an inductively coupled plasma spectrometer. Plot-level average chemistry was used from all years to compare to decline rates.

Slope and aspect were measured at plot center for each plot. Local physiography was assessed based on methods presented in Bailey and others (2004), where plots are assigned an ordinal classification based on landscape position as it relates to nutrient and moisture retention (streambeds and flats = 1, benches and toe slopes = 2, gentle midslopes = 3, moderate midslopes = 4, severe upper slopes = 5, and summit and shoulder positions = 6).

Predictive Model Calibration

Data from plots that are known to have been infested for at least 4 years were used to calibrate a linear, mixed stepwise model of average decline since infestation. In a mixed platform, forward and backward steps are enlisted. The most significant terms are entered first. Then any variables that become insignificant as the model becomes more complex are removed. It continues removing terms until the remaining terms are significant, when it changes back to the forward direction. Variables were retained under our mixed stepwise platform if the p-value was less than 0.1 and the variance inflation factor was below 2.0 (identifies potential autocorrelation between variables). The final model was then used to link key variables in a landscape-scale GIS model using ESRI® ArcGIS version 9.1.

GIS Data Layers Used for Mapping Risk in the Catskills

Hemlock vulnerability to HWA is complex and linked to multiple site, climatic, stand, and chemical factors (Pontius and others 2006). Here, we were limited to those variables for which raster-GIS coverages are available for inclusion in a landscape-scale risk assessment of the Catskills. This included the following.

Topographic Features—
Topographic variables such as slope, aspect, and landscape position can easily be derived from DEMs using the 3D Analyst available in ArcToolbox (ESRI® ArcMap v.9.1). Here we used a digital raster DEM with 10-m resolution from the National Elevation Data set (NED) assembled by the U.S. Geological Survey (USGS). NED is designed to provide national elevation data in a seamless form with a consistent datum, elevation unit, and projection for the conterminous United States. These can be downloaded at no charge from http://seamless.usgs.gov. The selected GIS-available topographic variables included aspect (calculated as the degrees from southwest), slope (degrees), and physiographic landscape position (classes of 1 to 6 representing the least to most xeric landscape positions following Bailey and others [2004]).

Foliar Chemistry—
The researchers involved in this project have used National Aeronautic and Space Administration's (NASA's) AVIRIS instrument to predict foliar concentrations of N, lignin, and cellulose in forested areas of New England (Martin and Aber 1997) with a high degree of accuracy. Using these same methods, we have developed a map of foliar N from 2001 AVIRIS imagery for the Catskills region of New York. Such coverages can be used to inform palatability or defensive chemical-based relationships related to risk assessment.

Hemlock Species Abundance Coverage—
Existing maps of hemlock abundance in the Catskills region were available from previous work (Pontius and others 2005). Using 2001 AVIRIS imagery, Mixture Tuned Matched Filtering in ENVI (v.4.2, ©Research Systems, Inc.

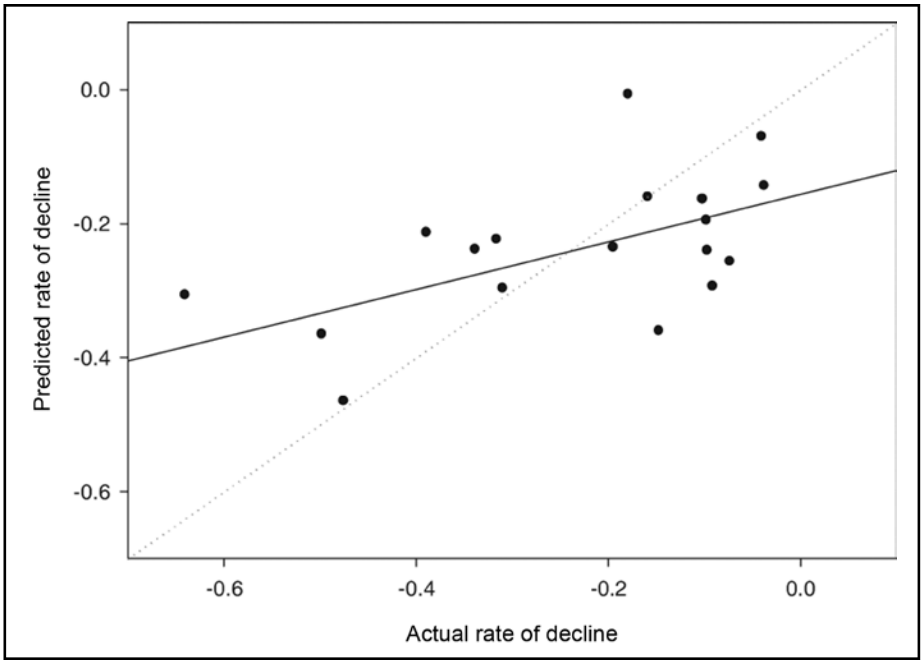

Figure 2—A stepwise linear regression model of landscape variables was only able to produce a predictive decline model that accounted for slightly more than a third of the overall variability witnessed in decline rates following infestation (R^2 = 0.35, RMSE = 0.19, p = 0.027). Variables included slope, aspect, and physiography, all discernable from digital elevation models in ArcToolbox.

2005) was used to unmix spectra and quantify the hemlock signature contribution to each pixel. The availability of this distribution coverage allowed us to isolate only those areas dominated by hemlock (greater than 40 percent hemlock basal area) for the final risk coverage.

Risk Coverage for the Catskills

The results of this model highlight which environmental variables are significant in determining hemlock decline rates and the nature of those relationships. Whereas the ultimate goal is to apply the actual quantitative predictive model based on modeled parameter estimates for each variable, final published estimates of foliar nitrogen for the region are still being finalized. To account for this inability to use direct parameter estimates for this version of the risk coverage, coverages for each of the significant predictive variables were scaled to a continuous value from 0 to 10 based on the nature of the modeled relationships. The Spatial Analyst available in ArcToolbox (ESRI® ArcMap v.9.1) was then used to add together the rescaled pixel values from each significant variable, resulting in a risk map that highlights the cumulative effect of all significant variables in terms of relative hemlock vulnerability.

Results and Discussion

The final three-term predictive model included aspect and slope (Equation 1). This model accounted for a little over a third of the variability in decline rates for the 21-plot calibration set with a p = 0.02, R^2 = 0.35, R^2*adjusted* = 0.27 and *RMSE* = 0.19 (Figure 2). A PRESS statistic for jack-knifed residuals of 1.04 indicates that, on average, if each plot was left out of the calibration and retained individually for validation, the average error would equal approximately 0.23 for the 0 to 10 scale.

$$Decline\_rate = -0.154 + (\text{aspect} \times 0.002) - (\text{slope} \times 0.118)$$

Equation 1. A landscape-variables-only model selected aspect (calculated as degrees from south) and slope (degrees) to predict the rate of decline expected following HWA infestation. This model accounted for 35 percent of the variability in the calibration set.

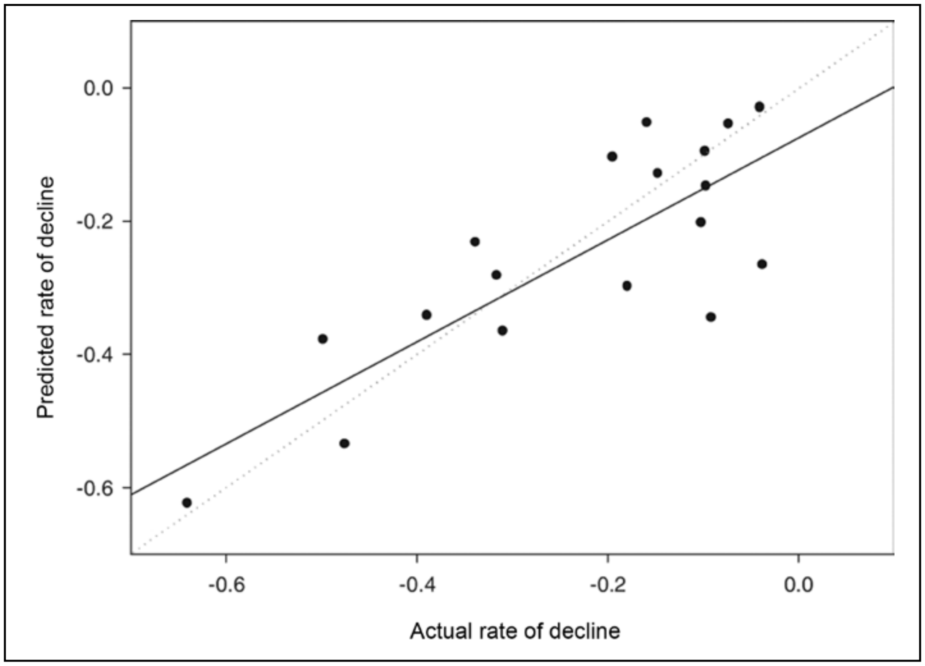

Figure 3—A stepwise linear regression model that added nitrogen as an option to the landscape-variable-only model was able to produce a predictive decline model that accounted for over two-thirds of the overall variability witnessed in decline rates following infestation (R^2 = 0. 79, RMSE = 0.13, p = 0.0009). Nitrogen coverages were possible as additions to the GIS model from 2001 AVIRIS-derived hyperspectral coverages of the Catskills region.

When we added foliar nitrogen concentrations to the mixed stepwise linear regression, model accuracy improved significantly. The resulting model based on slope, aspect, physiography, and foliar nitrogen concentration produced a p = 0.0009, R^2 = 0.79, R^2 *adjusted* = 0.69, and *RMSE* = 0.13 (Figure 3). Jack-knifed residuals resulted in a *PRESS* statistic of 0.55, or an average error of approximately 0.16 on the 0 to 10 decline rating scale.

$$\textit{Decline\_rate} = 0.643 - (\textit{aspect} \times 0.0003) - (\textit{slope} \times 0.158) + (\textit{physiography} \text{ x } 0.049) - (\textit{foliarN} \times 0.425) + ([\textit{aspect} \text{ x } \textit{slope}] \times 0.001) + ([\textit{aspect} \times \textit{foliarN}] \times 0.022)$$

Equation 2. The full GIS model again selected aspect (calculated as degrees from southwest) and slope (degrees) to predict the rate of decline expected following HWA infestation, with the addition of physiographic position and foliar nitrogen concentration. This model accounted for 79 percent of the variability in the calibration set.

Using this final model based on both landscape variables and foliar N concentrations, we combined coverages of key variables to create a map of relative hemlock vulnerability to decline following HWA infestation for the Catskills region of New York (Figure 4). The availability of a hemlock distribution coverage from previous work (Pontius and others 2005) allows us to isolate only those areas dominated by hemlock (greater than 40 percent hemlock basal area) for the final risk coverage (Figure 5). The resulting coverage of hemlock and its relative vulnerability to infestation should aid land managers in targeting management activities in the region.

Although these quantitative models were statistically significant, we wanted to ensure that there was a theoretical basis for why these variables might exert influence on hemlock decline rates. The inclusion of landscape characteristics in our risk models has a strong theoretical basis in the literature. Similar to previous HWA research discussed in the introduction, we found that stands with a demonstrated resistance to long-term HWA infestation typically occupy lower physiographic positions, such as streambeds, flats, and toe-slopes (p = 0.0076, Figure 6). In addition to physiography, resistant stands were consistently found on

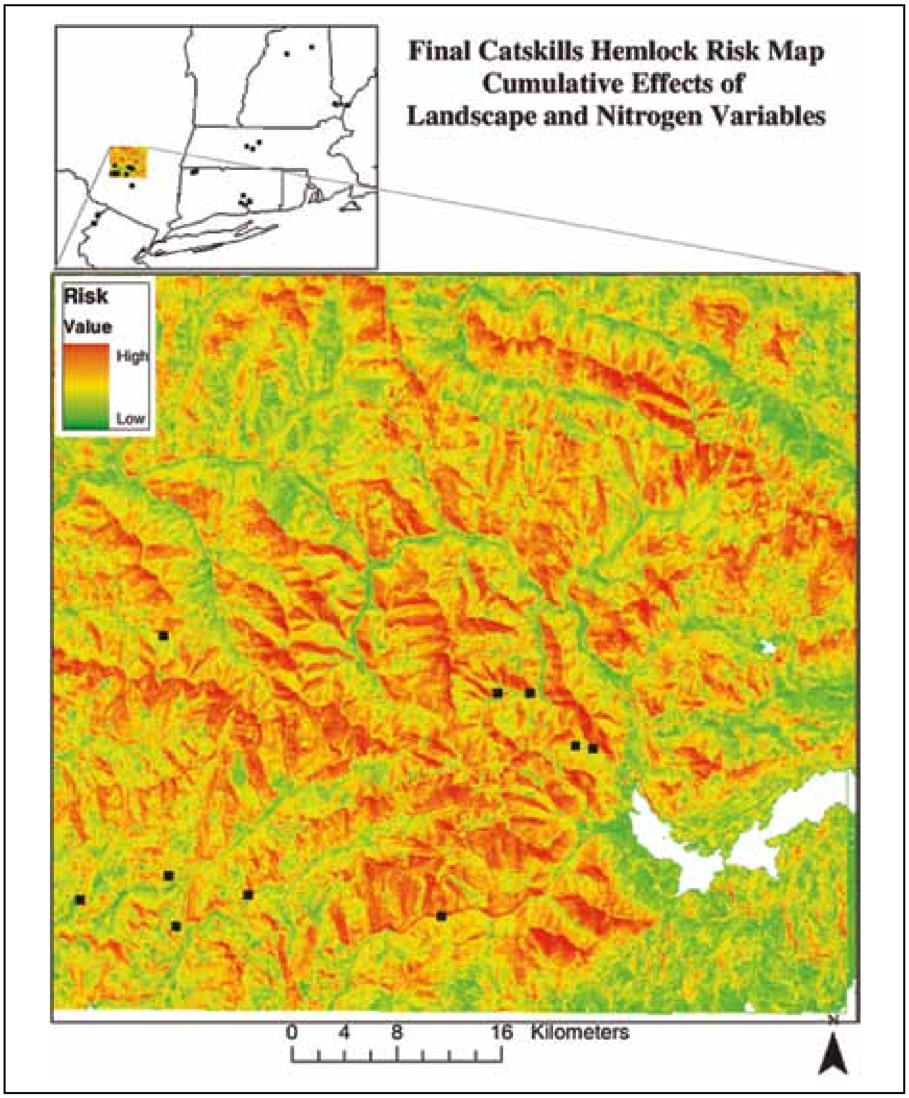

Figure 4—A spatially continuous, comprehensive map of relative hemlock vulnerability to HWA-induced decline in the Catskills, New York, summarizes the cumulative effect of key variables identified in the statistical modeling.

less steep terrain than susceptible stands across our calibration data set (p = 0.008, Figure 7). A weak yet significant correlation between aspect (in degrees from southwestern exposure) and the rate of decline (r = 0.24, p = 0.04) was also seen, with more rapid decline on southern facing exposures (p = 0.012, Figure 8). Significant interactions between aspect/slope (p = 0.06) and aspect/nitrogen (p = 0.002) indicate that aspect may be more significant when other stressors (such as steeper slopes or higher nitrogen concentrations) are involved.

The existing literature suggests that inherently low N concentration may limit HWA success, which, in turn, may impart some measure of resistance for host trees. Under low nitrogen conditions, concentrations may not be sufficient to maintain viable HWA populations. The data presented here support this “palatability-based” relationship between nitrogen and decline rates (Figure 9). The strongest correlate with hemlock decline rates across the region was the percentage infestation (r = -0.67, p = 0.008), with higher infestation levels associated with more rapid decline rates. In turn, the strongest correlate with HWA infestation

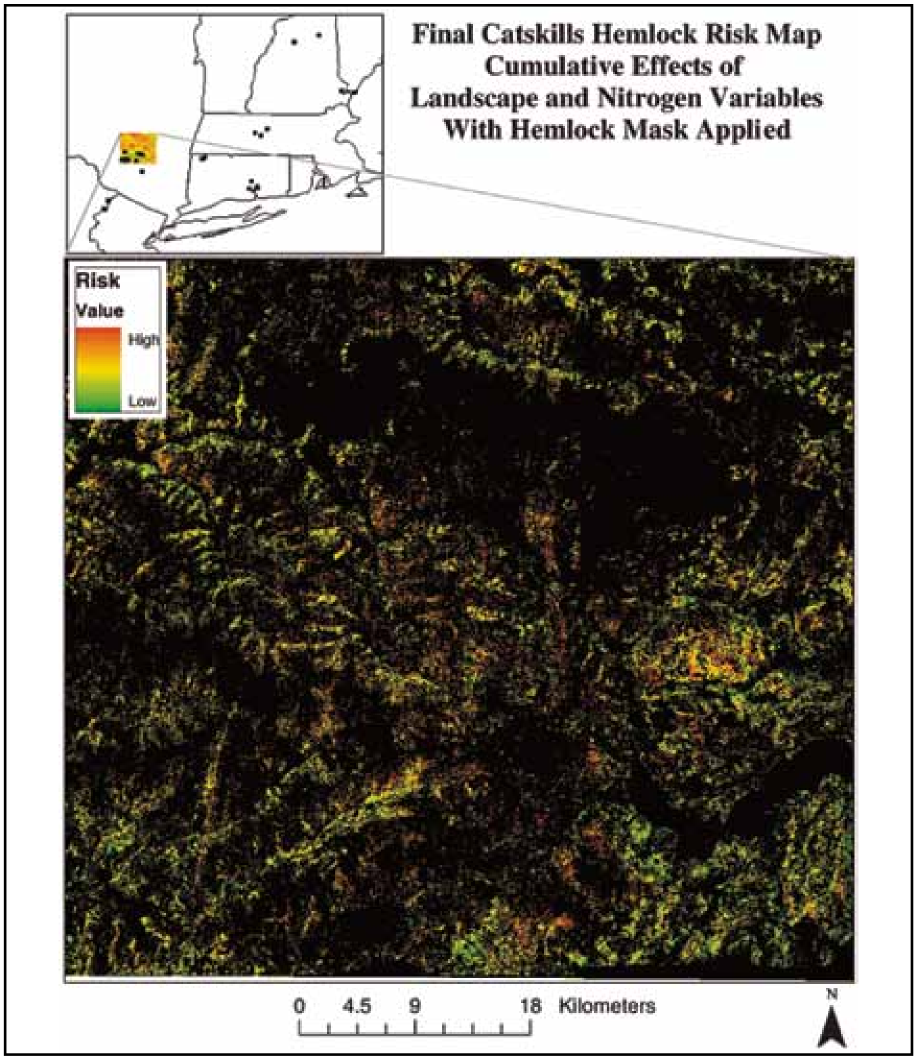

Figure 5—Masking nonhemlock pixels using an AVIRIS-derived coverage of hemlock basal area percentage produces a hemlock only risk map. This allows land managers to identify hemlock-dominated stands and their vulnerability to HWA to direct management efforts.

levels was foliar nitrogen concentration (r = 0.396, p = 0.005), with higher infestation levels associated with higher nitrogen concentrations. This may explain the significant relationship between hemlock decline rates and foliar nitrogen concentrations (r = -0.46, p = 0.004). Higher nitrogen levels support a larger, more successful adelgid population, which is able to deplete hemlock of photosynthate more rapidly, leading to more rapid decline.

Whereas these statistics and jack-knifed residuals suggest that this final landscape and foliar nitrogen model is robust enough to apply to new input data, independent validation provides a better assessment of model accuracy. As a preliminary test, this model was applied to all regional plots, regardless of infestation history, resulting in an R^2 = 0.51 and $RMSE$ = 0.142 (Figure 10). This reduction in model accuracy when newly infested plots are added is most likely due to a nonlinear decline response over the duration of infestation. Newly infested trees may decline only slightly in the first or second years because photosynthate reserves are available for injury response, defensive reaction, and continued productivity. Once these reserves have been reduced, decline becomes much more rapid. To validate this model, we will continue to track hemlock decline in the remaining plots over the next several years.

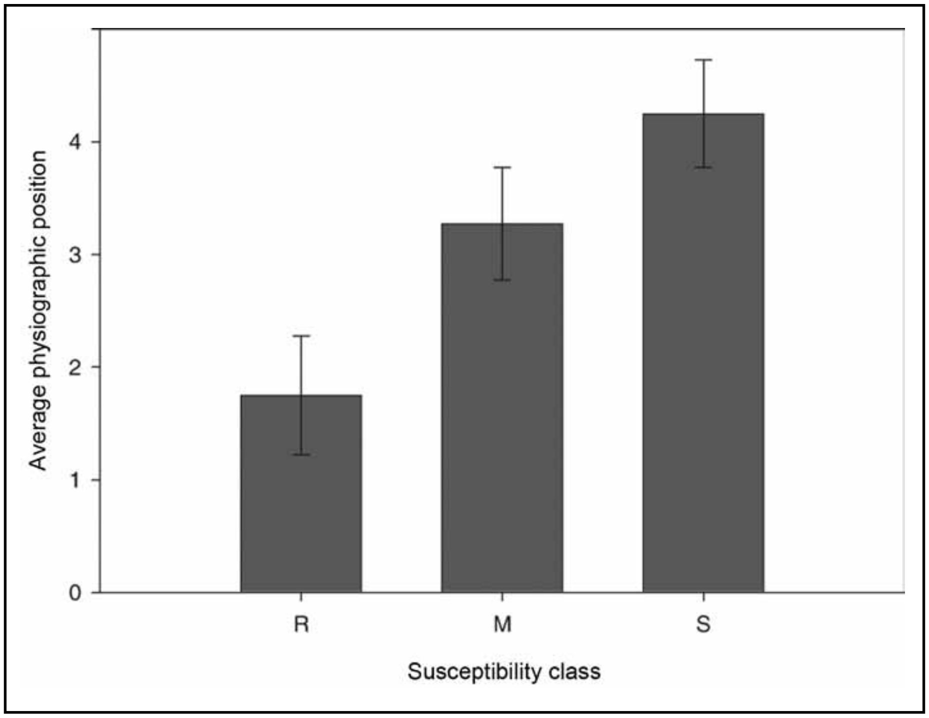

Figure 6—Resistant hemlock stands (R) were consistently found in lower landscape positions such as streambeds, flats, and toe-slopes. Susceptible stands (S) were consistently located on more xeric landscape positions (p = 0. 0076). Plots with average rates of decline (M) were generally located on midslopes. Physiographic landscape position (class 1 to 6 representing the least to most) is xeric landscape position following Bailey et al. (2004).

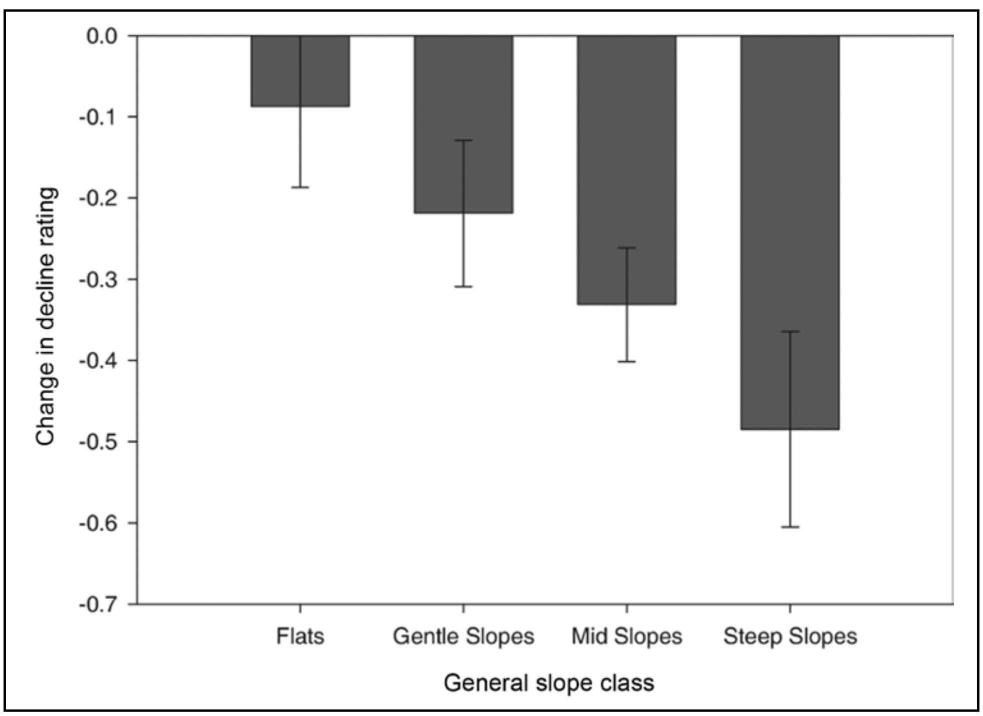

Figure 7—Susceptible stands were consistently found on steeper terrain than resistant stands (p = 0.008). Decline rating is a continuous scale from 0 (perfect health) to 10 (dead).

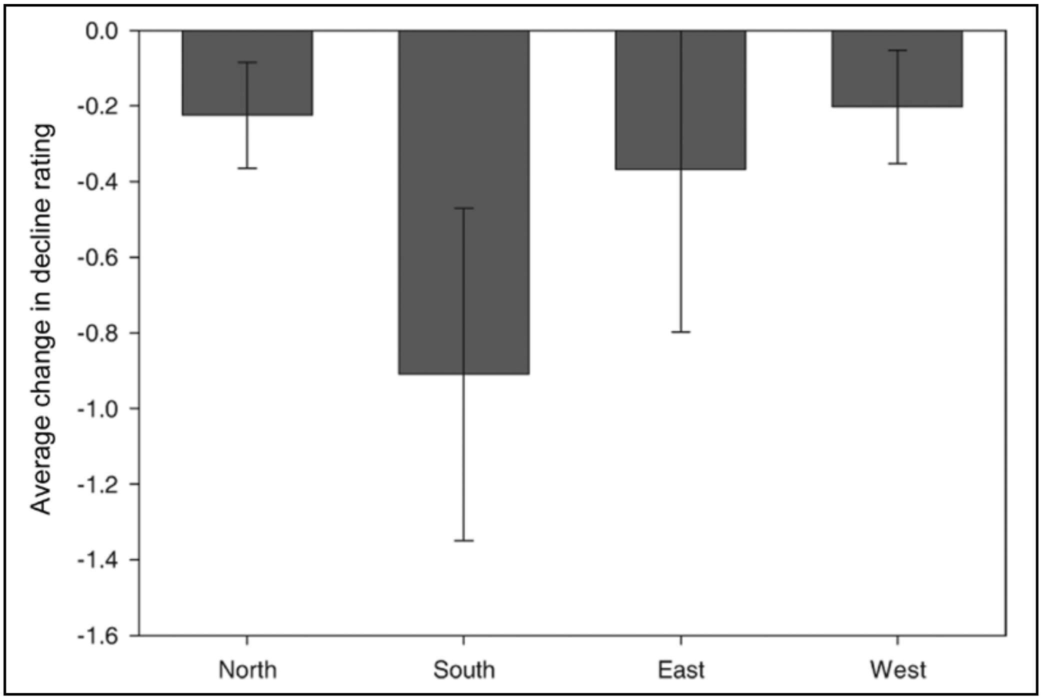

Figure 8—Southern-facing slopes experienced significantly faster decline following HWA infestation ($p = 0.012$). In addition, an interaction between aspect/slope ($p = 0.06$) and aspect/nitrogen ($p = 0.002$) indicates that the significance of aspect may come into play when other stressors (such as steeper slopes or higher nitrogen concentrations) are also a factor. Decline rating is a continuous scale from 0 (perfect health) to 10 (dead).

Conclusions

Creating an acceptable model of a complex, dynamic system is always challenging. Landscape-scale analyses increase the level of complexity by limiting the variables that are available for consideration. Here we applied knowledge- and data-driven approaches to model hemlock decline following HWA infestation. An initial review of existing literature identified potential variables for model inclusion and helped direct field measurement efforts. We used a mixed stepwise linear regression model based on plots that have been infested for at least 4 years to identify the set of landscape and chemical variables that could best predict the average rate of hemlock decline since HWA infestation. Using a continuous output variable instead of a simple tolerant/susceptible classification allows for flexibility in interpretation, depending on the needs of the user. For example, a research scientist with a limited number of HWA predator beetles to release may choose a conservative approach, selecting the stands with the lowest anticipated rate of decline and, therefore, highest probability of continued health in spite of HWA infestation. Conversely, a forester who wants to preserve a strong genetic pool of hemlock may decide not to cut any hemlock in stands that have even a marginal probability of sustaining long-term infestation with minimal health impacts.

Hemlock vulnerability to HWA is complex and likely results from a combination of landscape and chemical factors. Because the ability to map relative risk on a landscape scale could prove to be a useful tool for managers faced with HWA, we limited ourselves to variables available in digital, raster format for inclusion in a GIS model. A model based only on topographic variables derived from a 10-m DEM was able to account for almost one-third of the variability in hemlock decline rates from infested plots across the Northeast. This is consistent with previous studies that link variables related to soil-moisture availability with hemlock vulnerability. By adding foliar nitrogen concentrations to the model, over two-thirds of the variability in hemlock decline rate following infestation can be accounted

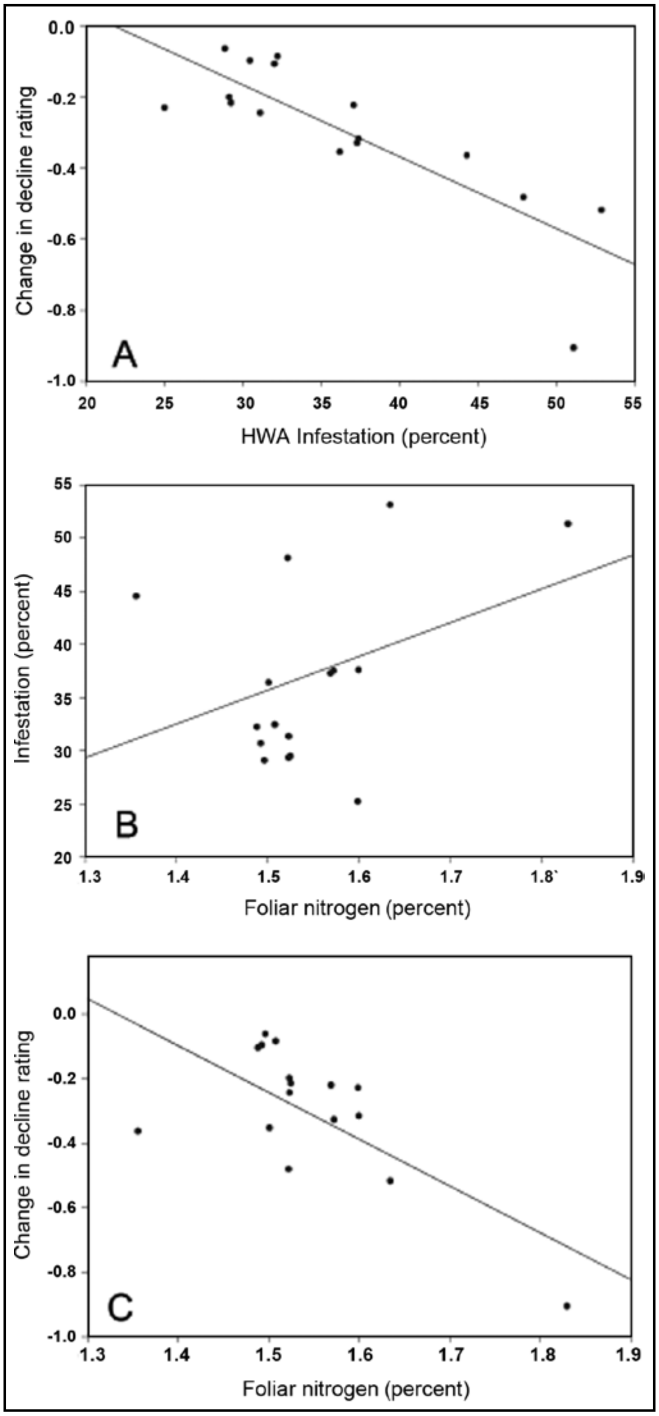

Figure 9—A. Percentage infestation was the strongest correlate with hemlock decline rates across the region (r = -0.67, p = 0.008). B. In turn, foliar nitrogen was the strongest correlate with percentage infestation (r = 0.396, p = 0.005), indicating a palatability-based relationship between nitrogen and HWA population success. C. This may be why nitrogen was a significant factor (r = -0.436, p = 0.004) in determining hemlock decline rates in the final model. Decline rating is based on several normalized variables such as dieback, transparency, live crown ratio, and new growth where 0 = perfect health and 10 = dead.

for. This is also consistent with previous fertilization and foliar chemistry studies, which identify a palatability-based relationship between foliar nitrogen and HWA population levels.

The significant improvement in model accuracy with the inclusion of chemical data highlights the value of hyperspectral data-derived coverages in risk modeling. In addition to improved predictive accuracy, hyperspectral imagery can provide spatially continuous maps of host species abundance and detailed decline assessments for model validation. This will allow land managers to better locate the host resource, identify stands to target management activities, and monitor forest health.

It is likely that the inclusion of other organic compounds, such as phenolics or other defensive chemicals would further improve this model (Bi and others 1997, Zucker and others 1992). However, the ability to use remote sensing platforms to assess secondary compound concentration has not been attempted to date. Other factors such as duration of infestation, climatic variables, and mineral nutrition likely interact, and these factors may exhibit different influence under different situations (Pontius and others 2006). In areas with available hyperspectral imagery, digital soil maps, and climate data, more complex models may soon be available to land managers. The addition of such data layers, which are not typically available for risk modeling, can be incorporated for more detailed and accurate risk maps. This type of spatially continuous information could be used by integrated pest management plans to help target specific areas on the ground where management efforts may be most effective.

This work will continue to be validated and improved in our future research efforts. By tracking infestation as it progresses through these stands and monitoring changes in hemlock health on newly infested plots, we will be better able to test the accuracy of this model. Finalized coverages of foliar nitrogen concentration will also be added to this model so that parameter estimates can be used to predict actual rates of decline instead of relative vulnerability to HWA.

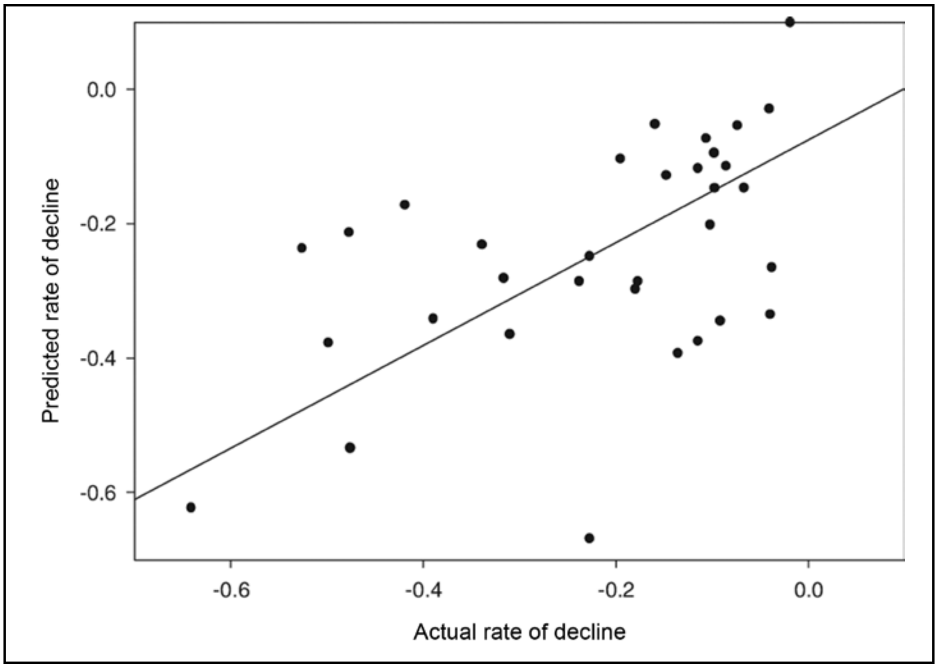

Figure 10—Actual and predicted final model results for all plots, including those excluded from calibration due to insufficient infestation periods to determine decline rates, produced a $p < 0.0001$, $r^2 = 0.51$, and RMSE = 0.14.

Literature Cited

Ayres, M.P.; Lombardero, M.J. 2000. Assessing the consequences of global change for forest disturbance from herbivores and pathogens. Science of the Total Environment. 262: 263–286.

Bailey, S.W.; Horsley, S.B.; Long, R.P.; Hallett, R.A. 2004. Influence of edaphic factors on sugar maple nutrition and health on the Allegheny Plateau. Soil Science Society of America Journal. 68: 243–252.

Bi, J.L.; Felton, G.W.; Murphy, J.B. [and others]. 1997. Do plant phenolics confer resistance to specialist and generalist insect herbivores? Journal of Agricultural Food Chemistry. 45: 4500–4504.

Bolster, K.L.; Martin, M.E.; Aber, J.D. 1996. Determination of carbon fraction and nitrogen concentration in tree foliage by near infrared reflectance: a comparison of statistical methods. Canadian Journal of Forest Research. 26: 590–600.

Bonneau, L.R.; O'Dell, T.C.D.L.; Broderick, S.H.; Sheilds, K.S. 1997. The impact of hemlock woolly adelgid on the health of eastern hemlock: an update from Connecticut. Storrs, CT: University of Connecticut Cooperative Extension System. [Not paged].

Carrow, J.R.; Betts, R.E. 1973. Effects of different foliar-applied nitrogen fertilizers on balsam woolly aphid. Canadian Journal of Forest Research. 3: 122–139.

Dale, D. 1988. Plant-mediated effects of soil mineral stresses on insects. In: Heinrichs, E.A., ed. Plant stress-insect interactions. New York: John Wiley: 35–110.

Douglas, A.E. 1993. The nutritional quality of phloem sap utilized by natural aphid populations. Ecological Entomology. 18: 31–38.

Foody, G.M. 2002. Status of land cover classification accuracy assessment. Remote Sensing of Environment. 80: 185–201.

Hunter, A.F. 1993. Gypsy-moth population sizes and the window of opportunity in spring. Oikos. 68: 531–538.

Koritsas, V.M.; Garsed, S.G. 1985. The effects of nitrogen and sulphur nutrition on the response of brussels sprout plants to infestation by the aphid *Brevicoryne brassicae*. Annals of Applied Biology. 106: 1–15.

Martin, M.E.; Aber, J.D. 1997. High spectral resolution remote sensing of forest canopy lignin, nitrogen, and ecosystem processes. Ecological Applications. 7: 431–443.

McClure, M.S. 1980. Foliar nitrogen: a basis for host suitability for elongate hemlock scale, *Fiorinia externa* (Homoptera: Diaspididae). Ecology. 61: 72–79.

McClure, M.S. 1991. Nitrogen fertilization of hemlock increases susceptibility to hemlock woolly adelgid. Journal of Arboriculture. 17: 227–229.

McClure, M.S. 1992. Effects of implanted and injected pesticides and fertilizers on the survival of *Adelges tsugae* (Homoptera: Adelgidae) and on the growth of *Tsuga canadensis*. Journal of Economic Entomology. 85: 468–472.

McClure, M.S. 1995a. Biology of *Adelges tsugae* and its potential for spread in the Northeastern United States. In: Salom, S.M.; Tigner, T.C.; Reardon, R.C., eds. Proceedings of the first hemlock woolly adelgid review. Morgantown, WV: U.S. Department of Agriculture, Forest Service: 16–24.

McClure, M.S. 1995b. *Diapterobates humeralis* (Oribatida: Ceratozetidae): an effective control agent of hemlock woolly adelgid (Homoptera: Adelgidae) in Japan. Population Ecology. 24: 1207–1215.

Ollinger, S.V.; Smith, M.L.; Martin, M.E. [and others]. 2002. Regional variation in foliar chemistry and soil nitrogen status among forests of diverse history and composition. Ecology. 83: 339–355.

Orwig, D.A.; Foster, D.R. 1999. Stand, landscape, and ecosystem analyses of hemlock woolly adelgid outbreaks in southern New England: an overview. In: McManus, K.A.; Shields, K.S.; Souto, D.R., eds. Proceedings of the symposium on sustainable management of hemlock ecosystems in Eastern North America. Newtown Square, PA: U.S. Department of Agriculture, Forest Service: 123–125.

Orwig, D.A.; Foster, D.R.; Mausel, D.L. 2002. Landscape patterns of hemlock decline in New England due to the introduced hemlock woolly adelgid. Journal of Biogeography. 29: 1475–1487.

Plourde, L.C.; Ollinger, S.V.; Smith, M.L.; Martin, M.E. 2007. Species classification for a northern temperate forest using spectral unmixing of hyperspectral remote sensing imagery. Photogrammetric Engineering and Remote Sensing. 73: 7, 828–840.

Pontius, J.; Hallett, R.; Martin, M. 2002. Examining the role of foliar chemistry in hemlock woolly adelgid infestation and hemlock decline. In: Onken, B.; Reardon, R.; Lashomb, J., eds. Proceedings of the symposium on hemlock woolly adelgid in the Eastern United States. Morgantown, WV: U.S. Department of Agriculture, Forest Service: 86–99.

Pontius, J.A.; Hallett, R.A.; Jenkins, J.C. 2006. Foliar chemistry linked to infestation and susceptibility to hemlock woolly adelgid (Homoptera: Adelgidae). Environmental Entomology. 35: 112-120.

Pontius, J.A.; Hallett, R.A.; Martin, M.E. 2005. Using AVIRIS to assess hemlock abundance and early decline in the Catskills, New York. Remote Sensing of Environment. 97: 163–173.

Royle, D.; Lathrop, R. 1999. The effects of site factors on the rate of hemlock decline: a case study in New Jersey. In: McManus, K.A.; Shields, K.S.; Souto, D.R. Proceedings of the symposium on sustainable management of hemlock ecosystems in Eastern North America. Newtown Square, PA: U.S. Department of Agriculture, Forest Service: 103–104.

Schowalter, T.D.; Hargrove, W.W.; Crossley, D.A., Jr. 1986. Herbivory in forested ecosystems. Annual Review of Entomology. 31: 177–196.

Sivaramakrishnan, S.; Berlyn, G.P. 1999. The role of site conditions in survival of hemlocks infested with the hemlock woolly adelgid: amelioration through the use of organic biostimulants. In: McManus, K.A.; Shields, K.S.; Souto, D.R., eds. Proceedings of the symposium on sustainable management of hemlock ecosystems in Eastern North America. Newtown Square, PA: U.S. Department of Agriculture, Forest Service: 201–202.

Smith, M.L.; Martin, M.E.; Plourde, L.; Ollinger, S.V. 2003. Analysis of hyperspectral data for estimation of temperate forest canopy nitrogen concentration: comparison between an airborne (AVIRIS) and a spaceborne (Hyperion) sensor. IEEE Transactions on Geoscience and Remote Sensing. 41: 1332–1337.

Smith, M.L.; Ollinger, S.V.; Martin, M.E. [and others]. 2002. Direct estimation of aboveground forest productivity through hyperspectral remote sensing of canopy nitrogen. Ecological Applications. 12: 1286–1302.

USDA Forest Service. 1997. Forest health monitoring 1997 field methods guide. Internal Rep. Research Triangle Park, NC: U.S. Department of Agriculture, Forest Service, National Forest Health Monitoring Program. [Not paged].

U.S. Environmental Protection Agency [US EPA]. 1995. Method 3052: microwave assisted acid digestion of siliceous and organically based matrices. In: Test methods for evaluating solid waste. 3rd ed., 3rd update. Vol. SW-846. Washington, DC.

White, T.C.R. 1984. The abundance of invertebrate herbivores in relation to the availability of nitrogen in stressed food plants. Oecologia. 63: 90–105.

Young, J.; Snyder, C.; Akerson, J.; Hunt, G. 1999. Assessment of landscape correlates of eastern hemlock decline due to hemlock woolly adelgid. In: McManus, K.A.; Shields, K.S.; Souto, D.R., eds. Proceedings of the symposium on sustainable management of hemlock ecosystems in Eastern North America. Newtown Square, PA: U.S. Department of Agriculture, Forest Service: 134.

Zucker, William V. 1982. How aphids choose leaves: the roles of phenolics in host selection by a galling aphid. Ecology. 63(4): 972–981.

Continue