Remote Sensing of Forest Health Trends in the Northern Green Mountains of Vermont

Michael G. Olson

University of Vermont
REMOTE SENSING OF FOREST HEALTH TRENDS IN THE NORTHERN GREEN MOUNTAINS OF VERMONT

A Thesis Presented

by

Michael G. Olson

to

The Faculty of the Graduate College

of

The University of Vermont

In Partial Fulfillment of the Requirements for the Degree of Master of Science Specializing in Natural Resources

January, 2012
ABSTRACT

Northeastern forests are being impacted by unprecedented environmental stressors, including acid deposition, invasive pests, and climate change. Forest health monitoring at a landscape scale is necessary to evaluate the changing condition of forest resources and to inform management of forest stressors. Traditional forest health monitoring is often limited to specific sites experiencing catastrophic decline or widespread mortality. Satellite remote sensing can complement these efforts by providing comprehensive forest health assessments over broad regions. Subtle changes in canopy health can be monitored over time by applying spectral vegetation indices to multitemporal satellite imagery. This project used historical archives of Landsat-5 TM imagery and geographic information systems to examine forest health trends in the northern Green Mountains of Vermont from 1984 to 2009. Results indicate that canopy health has remained relatively stable across most of the landscape, although decline was present in localized areas. Significant but weak relationships were discovered between declining forest health and spruce-fir-paper birch forests at high elevations. Possible causes of decline include the interacting effects of acid deposition, windthrow, and stressful growing environments typical of montane forests.
ACKNOWLEDGEMENTS

This research would not have been possible without the support and guidance of my advisor, Jen Pontius, and the members of my committee: Austin Troy and Brian Beckage. I would like to thank the Northeastern States Research Cooperative for providing funding for this research project. Katie White, Eleanor Regan, and William Young were invaluable in performing image processing during the beginning stages of this research. I would also like to thank the Spatial Analysis Lab for answering questions about GIS, including Ernie Buford, Jarlath O'Neil-Dunne, Keith Pelletier, and Sean McFadden. Last, I would like to thank my dad, who is responsible for cultivating my interest in the outdoors.
# TABLE OF CONTENTS

ACKNOWLEDGEMENTS ........................................................................................................... ii

LIST OF TABLES .................................................................................................................. vi

LIST OF FIGURES ................................................................................................................ viii

CHAPTER 1: LITERATURE REVIEW ..................................................................................... 1

1.1. Introduction .................................................................................................................. 1

1.2. Forest Health .............................................................................................................. 1
    1.2.1. Introduction ....................................................................................................... 1
    1.2.2. Forest Health in the Northeast ......................................................................... 4
    1.2.3. Acid Deposition ............................................................................................... 5
    1.2.4. Pests .................................................................................................................. 7
    1.2.5. Forest Decline .................................................................................................. 9
    1.2.6. Effects of Climate on Forest Health .............................................................. 10
    1.2.7. Landscape Influences on Forest Health .......................................................... 12
    1.2.8. Forest Health Monitoring Efforts .................................................................... 15

1.3. Remote Sensing ......................................................................................................... 16
    1.3.1. Introduction .................................................................................................... 16
    1.3.2. Remote Sensing of Forest Health .................................................................... 17
    1.3.3. Using Landsat To Assess Forest Health ......................................................... 18
    1.3.4. Landsat Studies of Forest Health Using Multi-temporal Imagery ................... 19
    1.3.5. Forest Health Trends Using Pixel-based Regressions of Multitemporal Landsat Imagery .................................................................................................................................................................................. 21

1.4. Spatial Statistics ......................................................................................................... 23
1.4.1. Spatial Autocorrelation .......................................................... 23
1.4.2. Spatially-Adjusted Regression ............................................... 26
1.4.3. Geographically Weighted Regression ..................................... 27

1.5. Conclusion .............................................................................. 29

1.6. Tables ..................................................................................... 31

1.7. Figures .................................................................................... 32

CHAPTER 2: REMOTE SENSING OF FOREST HEALTH TRENDS IN THE NORTHERN GREEN MOUNTAINS OF VERMONT ........................................ 33

2.1. Abstract .................................................................................. 33

2.2. Keywords ................................................................................ 34

2.3. Introduction ............................................................................. 34

2.4. Methods .................................................................................. 38
  2.4.1. Image Processing ................................................................. 38
  2.4.2. Study Region ....................................................................... 40
  2.4.3. Geospatial Database ............................................................. 41
  2.4.4. Statistical Analysis ............................................................... 45
  2.4.5. Modeling Forest Health Trends ........................................... 46
  2.4.6. Model Validation ................................................................. 48

2.5. Results .................................................................................... 49
  2.5.1. Regional Decline Trends ..................................................... 49
  2.5.2. Spatial Patterns .................................................................. 49
  2.5.3. Geospatial Database ............................................................ 50
  2.5.4. Forest Health Drivers .......................................................... 52
  2.5.5. Modeling Forest Health Trends ........................................... 57
**LIST OF TABLES**

<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Table 1</td>
<td>Forest decline equation derived from 2006 Landsat-5 TM data over the Catskill Mountains, NY (table from Pontius et al. in review a). B1 through B5 refer to band numbers that correspond to wavelengths in the electromagnetic spectrum. Band 1 is blue, band 2 is green, band 3 is red, band 4 is near-infrared, and band 5 is short-wave infrared.</td>
<td>31</td>
</tr>
<tr>
<td>Table 2</td>
<td>Forest health equation derived from 2006 Landsat TM 5 data over the Catskill Mountains, NY (table from Pontius et al. in review a). B1 through B5 refer to band numbers that correspond to wavelengths in the electromagnetic spectrum. Band 1 is blue, band 2 is green, band 3 is red, band 4 is near-infrared, and band 5 is short-wave infrared.</td>
<td>39</td>
</tr>
<tr>
<td>Table 3</td>
<td>List of data layers used in the geospatial database.</td>
<td>43</td>
</tr>
<tr>
<td>Table 4</td>
<td>Model descriptions.</td>
<td>46</td>
</tr>
<tr>
<td>Table 5</td>
<td>Descriptive statistics for continuous data layers used in the geospatial database.</td>
<td>51</td>
</tr>
<tr>
<td>Table 6</td>
<td>Forest types and forest height classes in the geospatial database. Almost 80% of forests are northern hardwoods dominated by sugar maple in the 10 to 25 meter height class.</td>
<td>52</td>
</tr>
<tr>
<td>Table 7</td>
<td>Nonparametric Spearman's Rho statistic and partial correlations for continuous variables.</td>
<td>53</td>
</tr>
<tr>
<td>Table 8</td>
<td>Nonparametric ANOVA for continuous variables. Classes not connected by same letter are significantly different.</td>
<td>56</td>
</tr>
<tr>
<td>Table 9</td>
<td>Chi-squared test for categorical variables.</td>
<td>57</td>
</tr>
<tr>
<td>Table 10</td>
<td>Model 1, mixed stepwise regression model. Significant terms are in bold (p&lt;0.001).</td>
<td>58</td>
</tr>
</tbody>
</table>
Table 11: Model 2, spatially-adjusted regression model. Significant terms are in bold (p<0.05). ................................................... 60

Table 12: Number of significant results obtained for statistical tests by variable. NS means “not significant” and N/A means “not applicable.” .............................. 63

Table 13: Comparison of significant results between a stratified random sample of ~6,000 points and a simple random sample of ~900 points............................. 64
## LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 1: Overview of processing steps used to create the forest health trend raster. Processing steps are described in detail in Pontius et al. (in review b). Figure prepared by J.A. Pontius and modified by M.G. Olson.</td>
<td>32</td>
</tr>
<tr>
<td>Figure 2: Map of the study region in northern Vermont, Landsat Row/Path boundaries, and adjacent northeastern states.</td>
<td>40</td>
</tr>
<tr>
<td>Figure 3: Histogram of the forest health trend raster. The distribution is leptokurtic, with a mean of 0.0108. Red lines divide the distribution into three sections; 95% of the data lie in the center between the red lines, with significantly improving or declining stands located in the two tails. An equal sample of points was selected from each section of the distribution.</td>
<td>42</td>
</tr>
<tr>
<td>Figure 4: Random points in the geospatial database (N = 5,948) with the forest health trend raster in the background. Red indicates decreasing forest health and blue indicates improving forest health.</td>
<td>44</td>
</tr>
<tr>
<td>Figure 5: Statistical analyses used for each data format.</td>
<td>45</td>
</tr>
<tr>
<td>Figure 6: Raster of improving and declining forest health trends within the northern Vermont study region. Red indicates declining and blue indicates increasing forest health by at least 10% on a 0 to 10 scale of perfect health to mortality. Stable pixels have been masked.</td>
<td>50</td>
</tr>
<tr>
<td>Figure 7: All-pairs Tukey-Kramer HSD test between groups after oneway ANOVAs of forest types and height classes. Higher values indicate decreasing forest health, and negative values indicate improving forest health. Classes not connected by the same letter are significantly different.</td>
<td>54</td>
</tr>
</tbody>
</table>
Figure 8: All-pairs Tukey-Kramer HSD test between groups after a one-way ANOVA of soil drainage classes. Higher values indicate decreasing forest health, and negative values indicate improving forest health. Classes not connected by the same letter are significantly different.

Figure 9: Quadratic discriminant analysis of forest health classes. Red points are declining, blue points are stable, and green points are improving forest health classes. Colored circles represent 50% contours for each class.

Figure 10: Local t values of elevation, biomass, forest height, and forest type. Red and blue points are significant (p<0.05). Red points indicate a positive coefficient (points are associated with forest decline) while blue points indicate a negative coefficient (points are associated with forest improvement).

Figure 11: Local r-squared values of geographically weighted regression model. Darker points have a better model fit, which ranges from 0.023 to 0.322.

Figure 12: Spurious patterns in the forest health trend image. The image on the left is the forest health trend raster draped over a DEM of the Green Mountains. The image on the right is the forest health index for 2008 (gray) overlain over a DEM. Missing data from cloud masks are apparent in the 2008 image, which can create spurious patterns in the forest health trend dataset.
CHAPTER 1: LITERATURE REVIEW

1.1. Introduction

Forests are an important resource in the northeastern United States and provide an array of products and services for society, including sawtimber, paper products, fuelwood, wildlife habitat, watershed protection, carbon storage, and recreational amenities. Forest-based manufacturing and forest recreation support a 19 billion dollar industry in the states of New York, Vermont, New Hampshire, and Maine (North East State Foresters Association 2007). The future condition of Northeastern forests is uncertain, however, as unprecedented stressors are impacting the region, including acid deposition, invasive pests, and climate change. In addition, development pressure and parcelization threaten to reduce the forest land base and fragment the landscape into property sizes that are uneconomical for many forest management operations (Germain et al. 2006). Comprehensive monitoring programs are needed to assess the changing condition of Northeastern forests and identify sites at risk to decline and mortality.

1.2. Forest Health

1.2.1. Introduction

"Forest health" is a term used by many land management organizations to describe the condition of forest resources and their ability to provide benefits for humans. Although the term has been defined several ways, the most intuitive, literal definition refers to the physiological condition of forest trees (Raffa et al. 2009). Trees
that are stressed and that are experiencing senescence, crown dieback, and/or reduced growth are considered less healthy than vigorous trees with full crowns. While physiological stress and mortality occur naturally in forest ecosystems, anthropogenic stressors (e.g., acid deposition), and human-mediated stressors (e.g., invasive pests and climate change) are cause for concern. Most unhealthy forests do not result from a single stressor but are caused by interacting abiotic and biotic stressors, causing tree decline and mortality that is considered excessive (Wargo and Auclair 2000).

Forest health also incorporates the concept of natural historical variability, which is the range of historical spatial and temporal conditions found in an ecosystem in the absence of humans (Landres et al. 1999). Several scientists recommend using ‘forest health’ only “when describing the extent to which ecosystem processes are functioning within natural historical variability” (Raffa et al. 2009). This definition automatically highlights invasive, non-native pests as forest health concerns, since they are human-mediated stressors that were not historically present in forests. Even native mortality agents can cause declining forest health if human influences create conditions that are outside the natural historic range of variability of an ecosystem. As an example, mountain pine beetle outbreaks in the western U.S. are partly attributable to a legacy of fire suppression, which has created mature, overstocked stands of low-vigor pines susceptible to drought. This facilitates attack by native bark beetles and causes levels of mortality which are considered unhealthy (U.S. Forest Service 2009).

In any discussion of forest health, one must remember that tree death is a common event in forest ecosystems, and mortality is a natural component of self-
thinning processes that occur during stand development (Teale and Castello 2011). Dead trees perform several beneficial ecological functions, such as providing food sources for decomposing organisms and creating habitat for cavity-nesting birds (Franklin et al. 1987). Tree mortality is of interest to forest managers regardless of its cause, however, since excessive mortality may conflict with forest management objectives. For example, recreational amenities and habitat for some wildlife species may be adversely affected when entire stands experience overstory mortality. Tree mortality is a concern for landowners and private timber companies who have invested financial resources in standing timber. Thus, it is essential to monitor tree stress and mortality across the landscape to understand the causes of tree death and their consequences for forest resources. It is important to identify sites that are at risk to forest decline and mortality so that mitigation actions can be taken to improve the health of forest stands.

Forest health is a national concern. In 2006, the Forest Health Technology Enterprise Team estimated that more than 25 percent of standing live tree volume is at risk of mortality from insects and diseases on 58 million acres of forest in the United States from 2006 to 2021 (Krist et al. 2007). In addition, climate change is predicted to alter the frequency and intensity of forest disturbances, such as drought, fire, windstorms, ice storms, introduced species, and pest and pathogen outbreaks (Dale et al. 2001). Climate change may potentially cause increasing outbreaks of drought-induced forest decline worldwide (Allen 2009), although catastrophic dieback and species change are likely occur in localized areas (Hanson and Weltzin 2000).
Resource managers must be aware of changing field conditions that may affect forest health, as flows of products and services may be reduced.

1.2.2. Forest Health in the Northeast

Forest health is of particular concern in the northeastern U.S. The Northeast has been subjected to more abiotic stressors than any region in the United States, including changes in climate, air chemistry, land use, and site alterations (Wargo and Auclair 2000). Acid deposition has been studied in the region since the 1980s and continues to be a concern (Innes 1993, Miller 2005). Invasive insect pests and pathogens are converging on the Northeast, in addition to native pests and invasive species that are already established (Dukes et al. 2009, Liebhold et al. 1995). According to the Forest Health Technology Enterprise Team, oak decline, hardwood decline, and gypsy moth defoliation are the greatest immediate concerns in the region, since these agents have the greatest potential to cause widespread crown deterioration in the near future. Beech bark disease, emerald ash borer, hemlock woolly adelgid, Asian longhorned beetle, pine engraver beetles, common pine shoot beetle, and butternut canker are species of special concern; these stressors either affect single species (e.g., butternut canker) or are emerging invasive threats (e.g., Asian longhorned beetle, Krist et al. 2007). In addition, climate change is predicted to exacerbate the effects of many insect pests and pathogens in Northeastern forests (Dukes et al. 2009) and alter the intensity and frequency of forest disturbances (Dale et al. 2001). Dominant stressors in Northeastern
forests are reviewed here, in addition to site and stand-specific landscape processes that influence forest health conditions.

1.2.3. Acid Deposition

Acid deposition results from the transformation of air pollutants – primarily sulfur dioxide (SO₂) and nitrogen oxides (NOₓ) – into sulfuric acid, nitric acid, and ammonium nitrate through reactions with atmospheric gases. Primary sources of sulfur dioxide and nitrous oxides are fossil fuel-burning electricity plants and industrial facilities. Acidic particulates can be deposited to the Earth as rain (wet deposition) or as dry particles and gases (dry deposition). Acidification results when acid deposition inputs exceed the buffering capacity of terrestrial or aquatic ecosystems (Schwartz 1989).

Vigorous research was conducted on acid rain and forest decline during the 1980s, with efforts concentrated in central Europe and the northeastern United States (Pitelka 1989). Some researchers postulated that acid rain and air pollution would cause "Waldsturben," defined as catastrophic dieback and growth decline of forest ecosystems (Schutt and Cowling 1985). This assertion was questioned by many scientists (Kandler 1993, Skelly and Innes 1993), who proposed that the Waldsturben phenomenon was overstated and that numerous other factors contribute to forest decline besides acid deposition. The current scientific consensus is that forest decline results from numerous interacting stressors (Paoletti 2010), and the effects of acid deposition on forest ecosystems are less serious than previously believed (Menz and
Seip 2004). There is still concern that anthropogenic acid deposition is depleting base cations from forest soils, however, which may predispose stands to decline (Miller 2005, Schaberg et al. 2001).

Some of the first studies on acid deposition-induced forest decline were done in Vermont. Siccama et al. (1982) discovered declines of red spruce (*Picea rubens* Sarg.) in high-elevation spruce-fir forests at several sites in northern Vermont. Declines were observed in all size classes and were most prevalent at high elevations. Subsequent research showed that declines were occurring in other species, as well. Vogelmann and others (1985) found significant density declines in sugar maple, beech, mountain maple, and striped maple on Camels Hump Mountain from 1965 to 1983. Significant declines in aboveground biomass were found for red spruce, balsam fir, and mountain maple, and significant biomass declines were observed in montane forest types. Red spruce decline was observed in other parts of the Northeast, including Whiteface Mountain in the Adirondack Mountains (Scott et al. 1984), high elevation forests in New Hampshire (Johnson and Siccama 1983), and low-elevation spruce forests in Maine (Jagels 1986). Crown dieback and reductions in basal area and density were typical symptoms at these sites (Johnson and Siccama 1983).

Several scientists predict that acid deposition will be a major stressor of forests in the 21st century, although impacts will vary by region. Fowler and others (1999) predict a 624% increase in the area of global forests at risk to acidification between 1985 and 2050, although most of this increase will be in developing sub-tropical and tropical regions. Acidification in the northeastern U.S. is predicted to stabilize or
decline (Driscoll et al. 2001), although nutrient deficiencies resulting from leaching of base cations from forest soils continues to be a concern (Schaberg et al. 2001). Maps have been developed for Vermont and New Hampshire that estimate regions for which critical loads of nitrogen and sulfur have been exceeded (Miller 2005). Critical loads indicate the level of acid deposition an ecosystem can tolerate before nutrients are leached from the ecosystem. Models produced by Miller (2005) indicate that critical loads were exceeded in approximately 30 percent of the forested area in Vermont and 18 percent of the forested area in New Hampshire from 1999 to 2003. Although field assessments were not conducted to verify if forests showed symptoms of nutrient stress where critical loads were exceeded, any nutrient limitations that occurred could predispose trees to decline and mortality.

1.2.4. Pests

Numerous native and exotic insects, fungi, and pathogen pests attack forests in the northeastern United States. Common pests that have caused defoliation, dieback, or mortality of mature trees are reviewed here, in addition to some emerging pests that have the potential to cause extensive mortality throughout the region.

The gypsy moth (Lymantria dispar) is a defoliating insect native to Eurasia that was introduced to Massachusetts around 1869 (Liebhold et al. 1995). Since its introduction, the pest has expanded throughout the northeastern United States, causing outbreaks of defoliation on a cycle of approximately 10 to 11 years (Liebhold et al. 2000). Quercus and Populus are preferred hosts, although larvae may feed on other
deciduous trees. Gypsy moths continue to defoliate forests in the Northeast and are one of the top contributors to the estimated 58 million forested acres that are at risk to pest mortality from 2006 to 2021 (Krist et al. 2007).

Beech bark disease is a complex formed by the non-native scale insect Cryptococcus fagisuga and one of three species of pathogenic fungi: Nectria coccinea var. faginata, Nectria ochroleuca, and Nectria galligena (Witter et al. 2004). N. coccinea var. faginata is introduced while the other two species are native. The scale insects feed on beech sap and open wounds in trees, which are then infected by one or more of the Nectria fungi. Cankers form on tree boles, resulting in crown dieback and mortality (Griffin et al. 2003). Beech bark disease is widespread in the Northeast and continues to cause mortality throughout the region (Krist et al. 2007). In Vermont, approximately twenty percent of beech basal area had poor crowns in 2007, mostly from the impacts of beech bark disease (Morin et al. 2011).

The spruce budworm (Choristoneura fumiferana) is a native insect that causes extensive damage in spruce-fir forests. Balsam fir is the preferred host species, but larvae also feed on spruce, pine, hemlock, and tamarack. Larvae feed on the buds and needles of trees, causing partial defoliation, top-kill, or mortality when outbreaks are severe (Royama 1984). Spruce budworm outbreaks continue to occur in the Northeast, and spatial models predict significant basal area losses from this insect in the future (Krist et al. 2007).

Several exotic forest pests are expanding their range in Northeastern forests. These include emerald ash borer (Agrilus planipennis), hemlock woolly adelgid
(Adelges tsugae), Sirex woodwasp (Sirex noctilio), and Asian longhorned beetle (Anoplophora glabripennis), which cause mortality in ash, hemlock, pines, and hardwoods, respectively. Currently these species have a limited distribution in the Northeast, though their ranges will expand if early eradication efforts are unsuccessful (Krist et al. 2007). Emerald ash borer and Asian longhorned beetle are of particular concern, since they could do considerable damage to the valuable hardwood timber resources of the region.

1.2.5. Forest Decline

Forest decline is a complex of interacting stressors that causes premature deteriorations in tree health. A unique feature of forest decline diseases is that they are not attributable to a single causal agent (Wargo and Auclair 2000). Symptoms of declining trees include crown dieback, reduced growth rates, and reduced levels of starch reserves in roots. Forest decline has been observed in many genera in the U.S., including Abies, Acer, Picea, Pinus, Populus, and Quercus (Allen 2009). In the Northeast, decline diseases have been observed in oaks, sugar maple (Duchesne et al. 2002), red spruce, and paper birch (Halman et al. 2011). Localized incidences of forest decline continue to be observed in the region by state and federal agencies (Vermont Dept. of Forests, Parks, and Recreation 2009), and oak and hardwood decline are predicted to be leading causes of mortality from 2006 to 2021 (Krist et al. 2007).

Sugar maple decline is of particular concern in the Northeast because of this species’ prevalence in the region and its value for veneer, sawtimber, maple syrup, and
fall foliage displays. Horsley and others (2000) examined sugar maple declines in northwestern Pennsylvania and found that declining stands were associated with interactions between nutrient-deficient sites (located primarily on ridgetops and in unglaciated regions) and insect defoliation. Horsley et al. (2002) expanded on this research and identified several interacting abiotic and biotic factors that can cause declines in sugar maple stands. These included soil moisture deficiencies, late spring frosts, atmospheric deposition, insect attacks, and *Armillaria* root disease.

Calcium is an important nutrient for sugar maple health in the Northeast. In a study at the Hubbard Brook Experimental Forest, Juice et al. (2006) observed healthier sugar maple crowns and better regeneration after the addition of wollastonite (CaSiO$_3$) to a forested watershed. Maples in a reference watershed had poorer crowns, lower concentrations of foliar calcium, and poorer seedling establishment and growth. Acid deposition may reduce sugar maple health on poor and marginal sites, since it may leach calcium, magnesium, and manganese nutrients essential for tree nutrition (Long et al. 2009). The status of base cations in soils and the biogeochemical processes that deplete and replenish them may become serious concerns for forest managers in the future (Schaberg et al. 2010).

### 1.2.6. Effects of Climate on Forest Health

Climate is a fundamental factor that affects the distribution of vegetation. Extreme or unusual climatic events can cause declines in tree health, however. Auclair (1996) proposed that thaw-freeze and root-freeze events in winter and early spring
triggered major episodes of dieback in mature northern hardwoods during the 20th century. Late spring frosts can kill emerging leaves, rendering trees susceptible to decline if refoliation is incomplete (Vermont Dept. of Forests, Parks, and Recreation 2010). Trees growing on sites that experience frequent climate extremes, such as frost pockets, may exhibit poor crown conditions and decline. Hough (1945) observed stunted, open-grown eastern hemlock trees growing in a frost pocket in the Allegheny Plateau of Pennsylvania. Tree crowns had been pruned by unseasonable frosts, forming dense "witches brooms." Hardwoods were not as severely affected as hemlock, but regeneration of all species was poor. Frost pockets have also been associated with oak decline in the eastern U.S. (Wargo 1983).

Climate change is predicted to exacerbate the effects of many insect pests and pathogens in Northeastern forests. The northern range limits of some species, such as hemlock woolly adelgid, are defined by minimum winter temperatures that kill overwintering pest populations. An amelioration of minimum winter temperatures may allow the adelgid to spread northward, causing dieback and decline of this species. Similar effects may occur for other insect pests, such as the forest tent caterpillar and beech bark disease, although the responses of these species to climate change are difficult to predict (Dukes et al. 2009). Nationwide, climate change will alter the intensity and frequency of forest disturbances, such as windstorms, ice storms, fire, and drought (Dale et al. 2001), and the Northeast is not exempt from these effects. In the future, Northeastern forests are predicted to experience more frequent disturbances from pests in addition to weather-related stressors produced by a changing climate.
1.2.7. **Landscape Influences on Forest Health**

Forest management organizations that oversee large land holdings must be able to manage resources on a landscape scale. Many site-specific landscape processes affect forest health (Gerhardt and Foster 2002, Swanson et al. 1988), and identification of sites at risk to decline can enable managers to plan for stress events. Factors associated with forest health can be categorized as site factors, stand factors, and disturbance events. Site factors include topography (elevation, aspect, and slope), soil type, site quality, and microclimate. Stand factors include forest type, stand density, stand maturity, tree vigor, and stand age. Disturbance events can be divided into two general categories: biotic and abiotic. Abiotic disturbance events include weather-related events, such as droughts, windthrow, ice storms, and wildfires, as well as anthropogenic stressors, such as acid deposition and ozone pollutants. Biotic disturbance agents include native and introduced insect pests and pathogens. These factors are reviewed below.

Declining canopy conditions may be related to topographical features in some forest types. In the Northeast, soils on high-elevation mountain ranges are often thin and nutrient-poor (Siccama et al. 1982), making montane forests susceptible to secondary stressors and decline (Wargo and Auclair 2000). In addition, high-elevation forests experience increased loading of acidic precipitation and cloud deposition (Driscoll et al. 2001, Miller 2005), which can exacerbate nutrient limitations by leaching base cations essential for tree growth (e.g., Ca$^{2+}$, K$^+$, and Mg$^{2+}$; Driscoll et al. 2001).
2001, Schaberg et al. 2001). Aspect also affects acid deposition loading in the Northeast. Prevailing winds carry sulfur and nitrate emissions from the Midwest to the northeastern U.S. and Canada. In general, west-facing slopes receive higher inputs of acid deposition than east-facing slopes (Lazarus et al. 2006). Peart (1991) found red spruce on west-facing slopes to have higher acid deposition-induced winter injury than east-facing slopes on Mt. Moosilauke, New Hampshire. Lazarus et al. (2006) found that red spruce winter injury increased with the degree to which plots faced west and south. A third topographical factor associated with forest health is slope. Steep slopes are often associated with thinner, nutrient-poor soils, factors which can predispose trees to premature decline. Slope was identified as a significant parameter when modeling sites at risk to oak decline in the southeastern United States (Oak et al. 1996), and Lazarus et al. (2006) found that red spruce growing on steep slopes at high elevations experienced more winter injury than spruce growing on gentler slopes.

In addition to topography, soil properties influence tree health. Plant water availability is influenced by soil texture, drainage, and depth to the water table. Drought is stressful to trees, and water stress can predispose trees to attacks by secondary agents, leading to canopy decline (McLaughlin 1998, Wargo and Auclair 2000). Mature oak stands growing on droughty, south-facing slopes are especially susceptible to gypsy moth defoliation (Liebhold et al. 1995), and oak decline in the southeastern U.S. is often associated with shallow and/or excessively drained soils (Oak et al. 1996). In addition to water availability, soil fertility has a major influence on the growth, vigor, and health of trees. Forests growing on nutrient-poor soils are
predisposed to crown dieback, decline, and attack by pests, since trees already stressed by nutrient limitations have fewer resources to devote to defense (Wargo and Auclair 2000). Soil fertility has been identified as an important factor in the health of eastern forests (Federer et al. 1989), including sugar maple forests in Pennsylvania (Horsley et al. 2000) and New Hampshire (Juice et al. 2006) and paper birch stands in Vermont (Halman et al. 2011).

Stand dynamics influence tree health and susceptibility to decline. Dense stands are often at higher risk to pest attack, since competition for light, water, and nutrients places stress on individual trees and decreases stand vigor. Stressed trees, in turn, have fewer resources to devote to defense against insects, fungi, and pathogens (Wargo and Auclair 2000). Stand age is also important. Mature and over-mature stands may exhibit cohort senescence, especially if they are even-aged, making them susceptible to perturbations by climatic and biotic agents (Wargo and Auclair 2000). Species composition is also a factor, as species-specific stressors operate only in stands in which hosts are present. Several species-specific pests are present in the Northeast, including beech bark disease, white pine blister rust, and hemlock woolly adelgid. Stressors specific to forest types are present, as well, including spruce budworm, which defoliates both balsam fir and red spruce in spruce-fir forests (Royama 1984).

The importance of disturbances on forest condition and stand developmental processes is widely recognized (Chadwick and Oliver 1996, Franklin et al. 2002). While disturbances are natural processes in forest ecosystems, anthropogenic disturbances and stressors caused by invasive pests can have disruptive effects on forest
ecosystems. Even natural disturbances that are within historic ranges of variability – such as windthrow, mortality due to native pests, and forest fires – are detrimental to some forestry objectives (e.g., sawtimber production and aesthetic concerns) and must be monitored and managed.

1.2.8. Forest Health Monitoring Efforts

Maps and models of the current and future health of forest ecosystems are needed by resource managers, policy makers, and citizens to inform sustainable management of forest resources. In the U.S., forest health is monitored by state and federal natural resource management agencies. The U.S. Forest Service’s Forest Inventory and Analysis (FIA) and Forest Health Monitoring (FHM) programs track changes in national forest health indicators, including crown condition, mortality, and lichen diversity (Smith 2002, Tkacz 2008). In Vermont, the Division of Forestry works in partnership with the U.S. Forest Service to monitor forest health, performing aerial surveys of canopy condition on an annual basis (Vermont Dept. of Forests, Parks, and Recreation 2011). To examine future changes in forest condition, the Forest Health Technology Enterprise Team developed risk assessment maps to predict basal area mortality from insect pests and pathogens from 2006 to 2021 (Krist et al. 2007). The authors estimate that 58 million acres are at risk, where risk is defined as the expectation that 25 percent or more of live trees greater than one inch in diameter are expected to die in a given stand. Map resolution is one kilometer, making it suitable for regional and state-level planning, but it is less useful when considering individual forest
parcels. Monitoring approaches are needed that can assess actual and predicted forest health at a smaller scale. This would enable the early detection of incipient forest stressors, which could guide management actions to protect vulnerable stands (Zirlewagen et al. 2007). Remote sensing technologies have shown promise as a means to monitor and map forest health conditions.

1.3. Remote Sensing

1.3.1. Introduction

Remote sensing is the observation of electromagnetic radiation reflected or emitted from distant objects. Remote sensing offers powerful tools for natural resource management, enabling monitoring of broad geographic regions where field data collection would be impractical or prohibitively expensive (Kennedy 2009). Aerial photographs have been used for decades for many forest management applications, including cover type mapping, stand delineations, and the detection of forest damage (Franklin 2001, Ciesla 2000). The advent of satellite platforms in the 1970s increased the number of remote sensing applications for forest management purposes. The estimation of biophysical parameters, such as basal area, tree height, aboveground live biomass, and canopy condition has become possible within reasonable margins of error for some forest management applications (Franklin 2001). Satellite imagery may not be the most effective medium when conducting forest inventories at local scales where a high degree of precision is required, however (Holmgren and Thuresson 1998).
Nonetheless, satellite remote sensing is an additional tool available to resource managers to acquire information on the condition of forest resources.

1.3.2. Remote Sensing of Forest Health

Remote sensing is routinely used by land management organizations to assess forest health conditions (Ciesla 2000, Franklin 2001). Much of this work involves delineation of canopy senescence and dieback using aerial sketch mapping and aerial photography. Some authors have suggested that vegetation mortality should be a key indicator of forest and range health in large-scale natural resource surveys – such as those conducted by the U.S. Forest Service and the Natural Resource Conservation Service – as remote sensing may be the most cost-effective method to monitor mortality over broad regions (Olson and Schreuder 1997). Tree mortality is currently being used as a leading forest health indicator by the U.S. Forest Service’s Forest Inventory and Analysis Program, which measures crown condition variables in the field to assess forest condition and health (Schomaker et al. 2007, U.S. Forest Service 2009).

Satellite remote sensing can play a role in landscape-scale monitoring efforts of forest health, since the spectral signatures of healthy and dead forest canopies can be differentiated in many forest ecosystems (Franklin et al 2003; see Wang et al. 2007 for an example). The location, extent, and rate of change in canopy stress and mortality are useful pieces of information for natural resource managers.
1.3.3. Using Landsat To Assess Forest Health

Landsat is an earth monitoring satellite launched and operated by NASA. The Landsat program has been in operation since 1972, and the Landsat archive includes over thirty years of data over much of the Earth’s surface (Williams et al. 2006). The satellite has a swath of 183 kilometers, a return interval of sixteen days, and a spatial resolution of 30 meters. Spectral resolution varies by sensor; spectral information for Landsat-5 TM is collected in seven discrete bands that range from the blue portion of the visible spectrum to the thermal infrared. Ecological applications of the imagery are numerous, with a spatial and spectral resolution appropriate for studies of landscape change (Cohen and Goward 2004).

Many researchers have used Landsat imagery to examine forest health. Rock et al. (1986) tested the ability of Landsat TM to detect forest damage in Vermont, concluding that the unique spectral signatures of damaged forests can be measured and mapped from broadband satellite imagery. Most subsequent studies have focused on severe decline symptoms for a particular species classified into a few categories of crown damage at one point in time. In conifers, Franklin et al. (2003) used Landsat TM imagery to identify lodgepole pine decline caused by mountain pine beetles. Imagery was stratified using field inventory data of structural attributes unrelated to decline, and a maximum-likelihood algorithm separated damaged, “red-attacked” forest from undamaged forest with 73% accuracy. Lambert et al. (1995) used a Landsat-5 TM image to examine damage to Norway spruce stands in the Krusne Hory Mountains of the Czech Republic. Stands were separated into light, moderate, and heavy defoliation
classes with 71-75% accuracy. In hardwoods, Cunningham et al. (2008) mapped the vegetation condition of riparian Eucalyptus forests along the Murray River floodplain in Australia using Landsat-7 TM imagery, separating stands into classes of good, declining, poor, degraded, and severely degraded. Live basal area, plant area index, crown vigor, and epicormic growth were used as indicators of forest condition, and models created using artificial neural networks had the highest predictive power of stand condition at new locations ($R^2 = 0.78$).

1.3.4. Landsat Studies of Forest Health Using Multi-temporal Imagery

While remote sensing methods have been developed to quantify forest health at one point in time, the ability to use many years of data to examine trends in forest health is more complicated and time-consuming. Because of this, the literature on forest health trends is not as robust as the theory and application of the technology for the assessment of a single image. A few researchers have studied forest health changes using two Landsat images. A common method is to apply vegetation indices, such as NVDI, to pre-damage and post-damage images, then use change detection techniques to map changes in forest health. In conifers, Royle and Lathrop (1997) detected and mapped hemlock defoliation by the hemlock woolly adelgid in the New Jersey Highlands, separating stands into four damage classes (healthy/light, moderate, severe, and dead) based on field-measured canopy defoliation. Vegetation index difference was correlated with hemlock damage ($R^2 = 0.73$), and stands could be predicted within one-half damage class with 64% accuracy for four classes, 70-72% for three classes,
and 78-92% for two classes. Change detection studies using pre- and post-damage images have also been done on hardwoods. Wang et al. (2007) separated oak stands into five categories (no change, recovery, dying, died-back, and other) following a 1999 drought using the normalized difference water index (NDWI). NDWI was applied to two Landsat images from 1992 and 2000, and a difference classification was produced by subtracting spectral information from the 1992 image from the 2000 image. When validated on field-measured U.S. Forest Service Forest Inventory and Analysis data on tree condition, the classification had an overall accuracy of 75.95%. Arsenault et al. (2006) separated declining aspen stands into light, moderate, and severe damage by applying the infrared simple ratio (ISR) to 1998 and 2004 Landsat-5 TM imagery. A linear relationship was found between aspen crown dieback and relative change in ISR ($R^2 = 0.7$). Olthof et al. (2004) used two years of Landsat-5 TM imagery to map sugar maple forest damaged by an ice storm in eastern Ontario. Stand condition was separated into three classes based on percent crown loss: low (0-25%), medium (26-50%), and high (51%+). Stands with low to moderate damage were discriminated from severely damaged stands with 69% accuracy.

Several researchers have examined forest health changes over longer periods of time using three or more Landsat images. Diem (2002) applied the vegetation index (VI) to three years of Landsat MSS imagery (1972, 1986, and 1992) and compared them to field-measured foliar ozone damage in ponderosa pine forests in southern Arizona. VI increased for two study sites, corresponding to increasing precipitation over the study period. However, VI increased less at the site receiving more ozone
damage. Diem proposed that ozone damage caused the reduction in VI, though the association was not confirmed. Vogelmann (2002) examined changes in near-infrared reflectance (NIR, a common measure of pixel "greenness") in the Green Mountains of northern Vermont and found that NIR reflectance declined from 1976 to 1991, followed by a “green-up” from 1991 to 1999. He attributed this to forest decline and recovery following acid deposition, though his conclusions were not verified by field assessments. In a subsequent study, Vogelmann (2009) examined changes in the Shortwave Infrared/Near Infrared Index (SWIR/NIR) in eight autumnal Landsat TM images from 1988 to 2006 in the San Pedro Parks Wilderness Area of New Mexico. He found that increases in SWIR/NIR were associated with spruce-fir dieback, the cause of which was likely due to the interaction of droughty soils and defoliating insects, as was suggested by site visits.

1.3.5. Forest Health Trends Using Pixel-based Regressions of Multitemporal Landsat Imagery

In addition to traditional forest health classes used to assess condition with remote sensing applications, more detailed and accurate predictive decline equations have been developed for application to multispectral satellite imagery, such as Landsat. A forest health equation has been created by Pontius and others (in review a) that can be applied to multiple Landsat images to quantify trends in forest health, regardless of species. This equation is based on modified hyperspectral vegetation indices that are sensitive to forest stress symptoms, such as reductions in canopy water content, total
chlorophyll content, chlorophyll florescence, and the ratio of carotenoids to chlorophyll a (Table 1). This equation was calibrated on a range of forest decline symptoms, including fine twig dieback, crown transparency, and live crown ratio, on over 50 plots in the Catskill Mountains of New York with a range of species composition, canopy health, and topographic position ($R^2 = 0.621$, $p<0.0001$). Pontius et al. (in review b) applied this algorithm to 26 years of Landsat imagery from 1984 to 2009 for Landsat Row 29, Paths 12, 13, and 14; these images cover northeastern New York, northern Vermont, northern New Hampshire, and western Maine. This resulted in a continuous decline rating for each 30 meter forested pixel for the entire study area. Yearly forest health images were stacked into one multi-band raster, where each band represents a different year. A custom IDL script (ITT Visual Information Solutions, Boulder, Colorado) was written to run a linear regression on each pixel in the image, where yearly forest health values represent independent data points in each regression. The slope of the regression line for each pixel represents whether forest condition is improving, declining or has remained stable.

Examination of this data by year shows that average forest health conditions have not changed significantly in northeastern New York, northern Vermont, northern New Hampshire, and western Maine (Pontius et al. in review b). However, local changes in forest condition are not detectable by examination of averages over the entire study area, and additional analyses are necessary to identify site-specific patterns in forest health trends across the landscape. This thesis research uses geographic information systems to build a geospatial database from the forest health trend raster
produced by Pontius et al. (in review b) and site-specific environmental GIS layers. This database can be analyzed using traditional inferential statistics and spatial statistical methods. The study's objective is to identify site and stand factors that are associated with changes in forest health, which will yield insights into the causal agents of forest decline. This information can be used to guide management efforts aimed at mitigating declining forest health and increasing the resilience of Northeastern forest ecosystems.

1.4. Spatial Statistics

Spatial patterns and processes are important in ecological relationships (Fortin et al. 2002), and unique statistical methods are necessary to examine spatial processes. Traditional statistical approaches often do not consider the location of observations and their effects on other observations in the dataset. In spatial statistics, location is an important component of analyses that allows one to incorporate the effects of spatial autocorrelation.

1.4.1. Spatial Autocorrelation

Autocorrelation refers to the correlation between a variable and itself (Fortin and Dale 2005). Spatial autocorrelation implies that an observation is correlated with nearby observations in space, and there is a lack of independence among observations that are neighbors. Spatial autocorrelation can occur at local scales (i.e., patches in the case of vegetation) or global scales (i.e., a gradient change in forest species
composition with increasing latitude). Global spatial autocorrelation implies autocorrelation processes operating over an entire study area, while local autocorrelation may occur in discrete regions within a study area. Spatial autocorrelation can be positive or negative. With positive spatial autocorrelation, nearby observations are more similar to each other than distant observations. Negative spatial autocorrelation indicates spatial disaggregation of observations; observations that are near each other are systematically dissimilar to distant observations (Fortin and Dale 2005).

Spatial autocorrelation can be either a hindrance or a property of interest when conducting statistical analyses, depending on the research question. The mere presence of spatial autocorrelation can allow one to identify patches of similarity in a dataset, which may indicate an ecological process. For example, the physiological health of trees may exhibit positive spatial autocorrelation, since stressors acting on an individual tree – such as acid deposition, drought, or defoliating insects – are likely to be operating on nearby trees. Spatial autocorrelation processes operate at both local and global scales, and the selection of the observational unit can affect one's ability to detect these processes. Continuing the forest health example, positive spatial autocorrelation may exist at the stand scale in addition to the scale of individual trees. The same local disturbances that cause patches of declining tree health (acid deposition, drought, insect outbreaks, etc.) can operate on stands that are similar in species composition, age, and density – all of which can be important factors that predispose stands to decline. However, adjacent stands can differ markedly in composition and
structure. Thus, positive spatial autocorrelation may be weaker at the stand-scale than at the scale of individual trees. Positive spatial autocorrelation in forest health may also exist on the scale of broader landscapes, such as high-elevation mountains, where the interaction of acid deposition and harsh growing conditions can create large patches of poor tree health.

Several statistical tests have been developed to examine global and local autocorrelation. For global spatial autocorrelation, the Moran's I index or Geary's c statistics estimate the degree of spatial autocorrelation for an entire study area and summarize it as a single index value (Fortin and Dale 2005). With Moran's I, positive spatial autocorrelation is present if the index is close to one, negative autocorrelation is present if values are close to -1, and index values near zero indicate global spatial autocorrelation is not present in the data. With Geary's c, index values close to 0 indicate strong positive spatial autocorrelation, values close to 1 indicate no autocorrelation, and values close to 2 indicate negative autocorrelation (Fortin and Dale 2005). Local spatial autocorrelation tools include Local Moran, Local Getis, or the Getis-Ord hotspot analysis. The Getis-Ord hotspot analysis measures local spatial clustering and the direction of the cluster value. When applied to spatial forest health data, this tool can identify local patches of healthy and unhealthy forests across the landscape, yielding insights into the ecological processes causing forest health patterns.

While spatial autocorrelation can yield useful information on ecological patterns, it can also indicate pseudo-replication in datasets where each observation is assumed to be independent. When spatial autocorrelation is present in a dataset, it can
cause one to overestimate the number of independent samples – the effective sample size. In the case of linear regression, if the effective sample size, N, is too big, it inflates the t statistic. One may identify significant independent variables when they are not significant; p values become unreliable. Regression diagnostics can be used to test for autocorrelation, including running a Moran's I test on the residuals using a neighbor weight matrix. If residuals are autocorrelated, one can attempt to transform the data so that the residuals assume constant variance, which is one of the assumptions of OLS regression.

1.4.2. Spatially-Adjusted Regression

Another approach to account for spatial autocorrelation in a model is to adjust the alpha level to a more conservative value (e.g., from 0.05 to 0.01). However, this could be overly conservative, causing one to fail to reject the null hypothesis and cause a Type II error. One could also attempt to isolate independent observations, although this approach would be wasteful of data and it would be difficult to determine whether or not observations are truly independent. One solution is to employ spatially-adjusted regression, which adjusts the effective sample size to account for spatial autocorrelation. Two approaches are the simultaneous autoregressive (SAR) and conditional autoregressive (CAR) models, which calculate a neighbor weight matrix (the spatial position of each observation and their relation to other observations) to adjust the effective sample size. CAR may be more appropriate for local (first-order) spatial autocorrelation, while SAR may be more appropriate for higher-order patterns.
of autocorrelation (Shekhar and Xiong 2008). Spatially-adjusted linear regression generally reduces the number of significant variables identified in ordinary least squares regression.

1.4.3. Geographically Weighted Regression

Geographic location is important when modeling spatial relationships. In ordinary least squares regression, the relationship between dependent and independent variables is assumed to be constant (stationary) throughout the study region from which data were obtained, and a global model is created to describe these relationships. In reality assumptions of stationarity are often violated, as the relationship between two parameters, such as soil fertility and forest health, can vary from one geographic region to another. Additionally, often a set of local models can fit a dataset better than a single "one size fits all" global model. Non-stationarity is the concept that the relationship between dependent and independent variables vary in space. Geographically-weighted regression (GWR) allows one to model non-stationary relationships, using software such as GWR 3 (GWR 3.0, M. Charlton, A.S. Fotheringham, and C. Brunsdon, University of Newcastle, UK). GWR runs a separate regression for each observation using a spatial kernel that weights nearby observations with a distance decay function. GWR then compares the output of the local regressions to the output of an OLS global regression (Brunsden et al. 1998). The Akaike Information Criterion (AIC) is computed for both the global and local models, and minimization of the AIC determines which model is a better fit of the data (Fotheringham et al. 2002). The AIC
provides a better measure of model performance than the coefficient of determination because it accounts for the number of degrees of freedom in the model and identifies an acceptable tradeoff between complexity and model fit (Lazarus et al. 2006). GWR computes local coefficients, local r-squared values, and local t values for each local regression. These can be imported into a GIS to map local regression outputs over the study area. Examination of local regression outputs can yield insights into the underlying processes causing spatial patterns. For example, local R² values can indicate geographic regions where the model performs poorly, hinting at missing parameters that might improve model performance. Local t values can indicate geographic regions for which a particular parameter is statistically significant. Local coefficients can indicate the magnitude of the relationship between dependent and independent parameters in addition to whether the relationship is positive or negative. A Monte Carlo test can be performed to see if parameters are significantly non-stationary.

Geographically weighted regression can be a useful tool to examine landscape patterns in forestry. Wang and others (2005) used GWR to estimate net primary production (NPP) of forest ecosystems in China. Parameters included altitude, temperature, precipitation, and time-integrated NDVI. The GWR model performed better than an OLS model by taking the local variation of parameters into account, as R² values increased from 0.58 to 0.66. Kimsey et al. (2008) used GWR to model site index for douglas-fir in northern Idaho. The GWR model predicted site index better than multiple least squares regression, reducing the error sum of squares by 53%.
GWR has also been used in forest health assessments. Perry et al. (unpublished) modeled sugar maple mortality in the Northeast with GWR using parameters of the calcium:aluminum ratio, exchangeable magnesium, latitude, and longitude. The model did a poor job of predicting sugar maple mortality because it did not include additional parameters associated with sugar maple decline, such as slope and glacial geology. Nonetheless, it provided a foundation for future forest health modeling efforts with GWR. Lazerus et al. (2006) examined landscape patterns of winter spruce injury in the northeastern U.S. using GWR. Only one term – the interaction between elevation and north-south orientation – was significantly nonstationary, indicating that winter injury was uniformly severe at high elevations at northern latitudes, while at lower elevations injury was more severe on south-facing slopes. These examples show that GWR can be a useful tool to model spatial ecological processes across forested landscapes.

1.5. Conclusion

Invasive pests, air pollutants, and climate change are affecting forest resources around the world, and monitoring systems are needed to evaluate impacts from these stressors. Satellite remote sensing provides cost-effective methods to monitor forest stress and mortality at a landscape scale. The Landsat satellite, in particular, has an archive of historical remote sensing data over much of the Earth's surface, with imagery dating to 1972. This archive can be used to examine changes in forest health over time. An innovative forest health trend dataset has been created by Pontius and others (in review b) for the Northeastern U.S., where pixel-based regressions were run on
modified hyperspectral vegetation indices applied to multitemporal Landsat imagery from 1984 to 2009. This thesis uses the northern Green Mountains of Vermont as a case study to examine changes in forest health over the past quarter-century using this dataset. A geospatial database of forest health trends and associated site-specific environmental factors was developed for the region, with the aim of identifying factors associated with declining forest health using traditional and spatial statistical methods. Results from this project may be applicable to forests throughout the Northeast, and the research approach used in this study may be applied to forests in other regions of the world where historical archives of remote sensing imagery are available.
1.6. Tables

Table 1: Forest decline equation derived from 2006 Landsat-5 TM data over the Catskill Mountains, NY (table from Pontius et al. in review a). B1 through B5 refer to band numbers that correspond to wavelengths in the electromagnetic spectrum. Band 1 is blue, band 2 is green, band 3 is red, band 4 is near-infrared, and band 5 is short-wave infrared.

<table>
<thead>
<tr>
<th>Term</th>
<th>Coefficient</th>
<th>Sensitivity</th>
<th>Reference</th>
<th>Landsat TM based formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-51.763</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B5</td>
<td>0.946</td>
<td>Canopy water content</td>
<td>Yilmaz et al. 2008</td>
<td>B5</td>
</tr>
<tr>
<td>Aoki</td>
<td>0.706</td>
<td>total chlorophyll</td>
<td>Yabuki &amp; totsuka 1981</td>
<td>B2, B4</td>
</tr>
<tr>
<td>MCARI2</td>
<td>-0.236</td>
<td>total chlorophyll</td>
<td>Haboudane et al. 2005</td>
<td>$\frac{1.5 \times (2.5 \times (B4 - B3)) - (1.3 \times (B4 - B2))}{2 \times B4 + 1 - (6 \times B4 - 5 \times \sqrt{B3} - 0.5)}$</td>
</tr>
<tr>
<td>SIPI</td>
<td>54.536</td>
<td>carotenoids/chlorophyll</td>
<td>Penuelas et al. 1995</td>
<td>$\frac{B4 - B1}{B4 - B3}$</td>
</tr>
<tr>
<td>Flo</td>
<td>0.451</td>
<td>chlorophyll fluorescence</td>
<td>Mohammed et al. 1995</td>
<td>$\frac{B4 - B2}{B5 - B3}$</td>
</tr>
</tbody>
</table>
1.7. Figures

For every pixel, predicted health status is plotted for all years. A line is fit to this data and the slope of that line (long term trend in health status) becomes the new forest health “trend” value for that pixel.

The forest health trend coverage will be used in a GIS analysis to determine what site, stand or landscape characteristics (if any) are related to spatial patterns in forest decline across the northeast.

Figure 1: Overview of processing steps used to create the forest health trend raster. Processing steps are described in detail in Pontius et al. (in review b). Figure prepared by J.A. Pontius and modified by M.G. Olson.
CHAPTER 2: REMOTE SENSING OF FOREST HEALTH TRENDS IN THE
NORTHERN GREEN MOUNTAINS OF VERMONT

M.G. Olson and J.A. Pontius

2.1. Abstract

Northeastern forests are being impacted by numerous environmental stressors, including acid deposition, invasive pests, and climate change. Forest health monitoring at a landscape scale is necessary to evaluate the changing condition of forest resources and to inform management of forest stressors. Traditional monitoring efforts have been limited to field assessments of specific species or stressors and coarse-resolution mapping of widespread decline and mortality. Satellite remote sensing can complement these efforts by providing comprehensive forest health assessments over broad regions at regular time intervals. This project used historical archives of Landsat-5 TM imagery and geographic information systems to examine forest health trends in the northern Green Mountains of Vermont from 1984 to 2009. Results indicate that forest health has remained relatively stable across most of the landscape over this 26-year period, which is likely due to the natural resilience of Northeastern forests and their rapid recovery following disturbances. Decline was present in localized areas, however, and significant but weak associations were found between declining forest health and high-elevation spruce-fir-paper birch forests. Possible
causes of decline include the interacting effects of acid deposition, red spruce winter injury, windthrow, and stressful growing environments found in montane forests.

2.2. Keywords
Forest decline, remote sensing, GIS, spatial analysis, geographically weighted regression, spruce-fir forests, acid deposition

2.3. Introduction
The northeastern United States has been a focal region for forest health research since the 1980s (Innes 1993), and a number of disturbance agents make this an intriguing area in which to study the response of forest ecosystems to interacting stressors. The Northeast has been subjected to more abiotic stressors than any region in the country, including changes in climate, air chemistry, land use, and site alterations, with indications that forest declines have been increasing in frequency and severity over the past century (Wargo and Auclair 2000). Of particular concern is acid deposition, which has been linked to declines in red spruce (Picea rubens) at high elevations (Innes 1993). Despite reductions in the deposition of sulfates after passage of the 1990 Clean Air Act amendments (Lynch et al. 2000), there is concern that continued deposition exceeds soil buffering capacity on some sites (Schaberg 2001, Miller 2005), depleting base cations essential for tree nutrition and predisposing forest stands to decline (Driscoll et al. 2001). Northeastern forests are impacted by numerous invasive insect pests and pathogens, including beech bark disease (Cryptococcus scale...
insects and *Nectria* fungi; Shigo 1972) and gypsy moth (*Lymantria dispar*; Liebhold et al. 1995, 2000, 2004). New invasive threats are converging on the region, including emerald ash borer (*Agrilus planipennis*), hemlock woolly adelgid (*Adelges tsugae*), and Asian longhorn beetle (*Anoplophora glabripennis*; Dukes et al. 2009, Krist et al. 2007). Climate change may place additional stress on forest ecosystems, altering temperature and rainfall patterns and increasing the frequency of droughts (Hanson and Weltzin 2000) and forest disturbance events (Dale et al. 2001). Climate change may contribute to increasing incidences of forest decline worldwide (Allen 2009), although catastrophic dieback and species conversion are likely to occur in localized areas (Hanson and Weltzin 2000). Warmer temperatures may increase pest metabolism and fecundity, causing more frequent and intense outbreaks of insects and pathogens in Northeastern forests (Dukes et al. 2009).

In light of concerns about Northeastern forest health, comprehensive monitoring efforts are needed to assess changes in forest resources at landscape scales. Traditional monitoring efforts include field assessments that are limited to localized areas of decline and species/stressor-specific studies that do not represent larger forest regions (Zhang et al. 2011). Large-scale aerial mapping efforts are useful to detect canopy defoliation or dieback, but they are limited to identification of severe defoliation and mortality events, and little forest inventory information is collected on mapped stands. Satellite remote sensing can complement these efforts by providing comprehensive forest health assessments over broad regions at regular time intervals.
Many researchers have used Landsat to examine forest health, as its spatial and spectral resolution is appropriate for studies of landscape change (Cohen and Goward 2004). Most studies have been limited to individual tree species categorized into broad classes of condition at one point in time (Franklin et al. 2003, Lambert et al. 2005, Cunningham et al. 2008). A common approach to monitor changes in forest health is to apply vegetation indices – such as the normalized difference vegetation index (NDVI) – to pre-damage and post-damage images. Change detection techniques are then used to classify forests into stable, improving, or declining forest health classes (Royle and Lathrop 1997, Wang et al. 2007, Arsenault et al. 2006, Olthof et al. 2004).

Several researchers have examined forest health changes over longer periods of time using three or more Landsat images. Multitemporal remote sensing assessments of forest health include the work of Diem (2002), who applied the vegetation index (VI) to three years of Landsat MSS imagery (1972, 1986, and 1992) for comparison to field-measured foliar ozone damage in Arizona ponderosa pine forests. Vogelmann (2002) examined changes in near-infrared reflectance (NIR) in the Green Mountains of northern Vermont and found that NIR declined from 1976 to 1991, followed by a “green-up” from 1991 to 1999. This was attributed to decline and recovery following trends in acid deposition, though conclusions were not verified by field assessments. In a subsequent study, Vogelmann (2009) examined changes in the Shortwave Infrared/Near Infrared Index (SWIR/NIR) in eight autumnal Landsat TM images in New Mexico. Increases in SWIR/NIR were associated with spruce-fir dieback due to the interaction of droughty soils and defoliating insects.
More sophisticated methods have been developed to examine changes in forest health over decadal time scales. Pontius and others (in review b) constructed a detailed forest health index based on hyperspectral vegetation indices that can detect subtle changes in forest condition, regardless of species or stressor. This index was applied to 15 to 18 years of Landsat-5 TM imagery from 1984 to 2009 to monitor forest health trends from northern New York to central Maine. Results indicate that although forest health fluctuates from year to year, forest health trends have remained relatively stable from 1984 to 2009.

This research used the forest health trend product produced by Pontius et al. (in review b) to examine spatial patterns and potential drivers of forest health trends in northern Vermont. Geographic information systems were used to build a geospatial database from publicly available GIS layers, and the forest health trend raster was analyzed using traditional inferential statistics and spatial statistical methods. The study's objective was to identify site and stand factors associated with changes in forest health. The following questions were investigated:

1. What are the dominant trends in forest canopy health in the northern Green Mountains?
2. Do patterns of forest health exist at a landscape scale?
3. How do forest health trends differ by forest type (e.g., northern hardwoods vs. spruce-fir)?
4. What environmental factors are associated with declines in forest health?
This research serves as a case study to test the use of geospatial technologies as forest assessment tools. If satellite imagery and GIS layers can be used to quantify forest health and identify causal and associative factors related to forest decline, the need for expensive field studies may be reduced. Information derived from geospatial forest health monitoring may be used to identify stands that are at risk to decline and mortality.

2.4. Methods

2.4.1. Image Processing

The forest health trend product created by Pontius et al. (in review b) was produced from a set of 33 growing season (June 10th to August 20th) Landsat-5 TM level 1T orthorectified images for Landsat Row 29, Paths 13 and 14 between the years of 1984 to 2009. Each image was converted to top of atmosphere reflectance using ENVI 4.6.1 software, and dark object subtraction was used to approximate at-surface reflectance. To minimize noise between images, coregistration was performed using a third-order polynomial transformation with nearest neighbor resampling; images were then histogram-matched to a control scene. Clouds and non-forested pixels were masked using an unsupervised classification and band thresholding; contamination from high-altitude cirrus clouds remained in some images, however.
A continuous forest health index, with values from 0 to 10, was predicted on each pre-processed Landsat image using an equation developed by Pontius et al. (in review a; Table 2). Based on hyperspectral vegetation indices sensitive to canopy water content, chlorophyll content, and photosynthetic function, this equation was shown to be accurate across species and through time when calibrated on data from the Catskill Mountains of New York (Pontius et al. in review a). A custom IDL script was developed to fit a linear regression to the yearly forest health images; this created a single raster of forest health trends, where the regression slope represents forest health
trends from 1984 to 2009. Pixels with values greater or less than 0.5 were masked from the image, as these extreme values were found to result from forest misclassification errors and were not related to changes in forest health. The final one-band raster coverage of forest health trends from 1984 to 2009 was used as the dependent variable in statistical analyses.

2.4.2. Study Region

![Study Region Map](image.png)

*Figure 2: Map of the study region in northern Vermont, Landsat Row/Path boundaries, and adjacent northeastern states.*

The overlap region of Landsat row 29, Paths 13 and 14 was chosen as a focal study region (Figure 2) because it contains the most years of data for the forest health trend calculation (16 and 17 years, respectively). This region encompasses
approximately 2.5 million hectares and covers a range of forest types and landforms. The predominant forest type is northern hardwoods dominated by sugar maple, with coniferous stands restricted to high-elevation mountains, old fields, and poorly-drained lowlands. Elevations range from 100 feet near Lake Champlain to over 4,000 feet on Mt. Mansfield, Camels Hump, and the Lincoln Range.

2.4.3. Geospatial Database

To explore relationships between forest health trends and environmental factors, a geodatabase was created that contained approximately 6,000 points. Because forest health had not changed significantly across most of the landscape, a stratified random sample was generated from equal numbers of declining, stable, and improving forest pixels based on z score thresholds \((z\text{-score} < -1.96 \text{ or } z\text{-score} > 1.96; \text{ Figure 3})\). This ensured that pixels with marked declining or improving forest health trends were equally represented in the random sample. Because pixels with mixed land uses can contaminate spectral signatures, a 90 meter buffer was created around road polylines for the State of Vermont (Vermont Center for Geographic Information, http://www.vcgi.org/), and sampled points within this buffer were deleted to reduce contamination of roadside development and forest edge effects. Points with less than sixteen years of data or more than five years between observations were also deleted, resulting in 5,948 points for statistical analyses.
Figure 3: Histogram of the forest health trend raster. The distribution is leptokurtic, with a mean of 0.0108. Red lines divide the distribution into three sections; 95% of the data lie in the center between the red lines, with significantly improving or declining stands located in the two tails. An equal sample of points was selected from each section of the distribution.

GIS layers were downloaded from public GIS websites (Table 3). For rasters, only datasets with fine-scale (<250 m) resolutions were retained in order to match the spatial scale of the forest health trend dataset as closely as possible. Topographical features were derived from a 30 meter digital elevation model (DEM, U.S. Geological Survey, EROS Data Center, Sioux Falls, South Dakota) and included elevation, slope, and aspect. Circular aspect data were converted to continuous east-west and north-south gradients by applying sine and cosine functions, respectively. Soil drainage and fertility tables were joined to Natural Resource Conservation Service (NRCS) Soil Survey Geographic (SSURGO) data in ArcGIS to compute ordinal soil drainage and fertility indices from soil taxonomy information (http://www.drainageindex.msu.edu/). The soil drainage index approximates the capacity of a soil to supply water to plants (Schaetzl 2009), with values ranging from 0 (xeric soils) to 99 (hydric soils). The
fertility index is a relative scale of soil fertility ranging from 0 (nutrient-poor) to 19 (nutrient-rich) (Schaetzl et al. in review). Forest type and forest height data were obtained from the LANDFIRE program (Table 3; Rollins 2009; http://www.landfire.gov/). Aboveground live dry biomass data were obtained from the U.S. Forest Service's Geodata Clearinghouse (Blackard et al. 2008; http://fsgeodata.fs.fed.us/).

**Table 3: List of data layers used in the geospatial database.**

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Resolution</th>
<th>Format</th>
<th>Accuracy</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest Health Trends</td>
<td>30 m</td>
<td>Raster</td>
<td>Correlation = 0.59 – 0.69</td>
<td>Landsat-5 TM, J. Pontius, M.G. Olson</td>
</tr>
<tr>
<td>Elevation</td>
<td>30 m</td>
<td>Raster</td>
<td>Unknown</td>
<td>U.S. Geological Survey</td>
</tr>
<tr>
<td>Slope</td>
<td>30 m</td>
<td>Raster</td>
<td>Unknown</td>
<td>LANDFIRE (Rollins 2009)</td>
</tr>
<tr>
<td>Aspect</td>
<td>30 m</td>
<td>Raster</td>
<td>Unknown</td>
<td>LANDFIRE (Rollins 2009)</td>
</tr>
<tr>
<td>Soil Drainage Index</td>
<td>N/A</td>
<td>Shapefile</td>
<td>N/A</td>
<td>NRCS SSURGO, Michigan State/USFS (Schatzl et al. 2009)</td>
</tr>
<tr>
<td>Soil Fertility Index</td>
<td>N/A</td>
<td>Shapefile</td>
<td>N/A</td>
<td>NRCS SSURGO, Michigan State/USFS (Schatzl et al. 2009)</td>
</tr>
<tr>
<td>Forest type</td>
<td>30 m</td>
<td>Raster</td>
<td>63% - 95%</td>
<td>LANDFIRE (Rollins 2009)</td>
</tr>
<tr>
<td>Forest Height (categorical)</td>
<td>30 m</td>
<td>Raster</td>
<td>76%</td>
<td>LANDFIRE (Rollins 2009)</td>
</tr>
<tr>
<td>Forest Biomass</td>
<td>250 m</td>
<td>Raster</td>
<td>Correlation = 0.39</td>
<td>U.S. Forest Service</td>
</tr>
<tr>
<td>Forest Height (continuous)</td>
<td>30 m</td>
<td>Raster</td>
<td>Correlation = 0.57 - 0.72</td>
<td>Woods Hole Research Center</td>
</tr>
<tr>
<td>Number of years with disturbance (1997 to 2009)</td>
<td>30 m</td>
<td>Raster</td>
<td>Polygon lines inaccurate by up to 150 meters or more (Schrader-Patton 2003)</td>
<td>U.S. Forest Service</td>
</tr>
</tbody>
</table>

Aerial sketch polygons of forest canopy disturbances (defoliation, discoloration, and mortality) from 1997 to 2009 were obtained from the U.S. Forest Service Forest Health Technology Enterprise Team (http://www.na.fs.fed.us/ims/aerial/viewer.htm). To convert many years of polygon data to one summary layer, polygons were rasterized
and summed using the Raster Calculator tool in ArcGIS 9.3.1 to produce a 30 meter raster with the total number of years with disturbance from 1997 to 2009.

Several additional layers were considered for inclusion in the database but were omitted because of poor accuracy, incompatible spatial resolution (e.g., national-scale rasters with resolutions greater than 1 kilometer), or because they were unavailable to the public. These included layers of sulfate (SO₄) and nitrogen deposition (NOₓ) from the National Atmospheric Deposition Program (NADP; Lamb and Bowersox 2000), PRISM climate data (http://www.prism.oregonstate.edu/), and modeled acid deposition and critical load exceedances for New England (Miller 2005).

![Forest Health Trends](image)

Figure 4: Random points in the geospatial database (N = 5,948) with the forest health trend raster in the background. Red indicates decreasing forest health and blue indicates improving forest health.
The final geospatial database had a single attribute table, where each of the 5,948 stratified random points included information on each of the 11 independent GIS variables and the dependent forest health trend (Figure 4).

2.4.4. Statistical Analysis

<table>
<thead>
<tr>
<th>Site Variables</th>
<th>Forest Health Trends</th>
</tr>
</thead>
<tbody>
<tr>
<td>Continuous</td>
<td>Spearman's Rho Correlations, Regression</td>
</tr>
<tr>
<td>Categorical</td>
<td>Oneway ANOVA, Regression, Chi-squared tests</td>
</tr>
</tbody>
</table>

Figure 5: Statistical analyses used for each data format.

Because forest health trends could be tested as continuous or categorical values (declining, stable, or improving) and because of the mix of data types for independent variables (continuous and categorical), several statistical approaches were used to identify factors associated with forest health trends (Figure 5). Spearman's rho correlations, partial correlations, nonparametric one-way analysis of variance (ANOVA), and Chi-squared analyses were used to test relationships between individual variables and forest health trends. Our approach was to examine relationships from various statistical angles, giving weight only to relationships that were significant in several different analyses. This confluence of evidence minimizes the chance of Type I errors or specificity to the random sample used in the analyses. Because the large
sample size increases the likelihood that observations exhibit spatial autocorrelation, a conservative alpha level of 0.001 was used to determine significance in all non-spatial statistical tests.

### 2.4.5. Modeling Forest Health Trends

Because forest health is influenced by many interacting factors, several modeling approaches were used to predict forest health trends based on multiple variables in the geospatial database (Table 4). This included a mixed stepwise linear regression model with main-effects and 2nd order interactions (Model 1; Table 4). In order to avoid over-fitting, a conservative alpha level (p<0.001) and a maximum variance inflation factor (VIF) of 10 were used to retain model variables. The Press statistic was used to assess model stability (Allen 1974).

<table>
<thead>
<tr>
<th>Model</th>
<th>Description</th>
<th>Number of Variables*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>Mixed stepwise model</td>
<td>8</td>
</tr>
<tr>
<td>Model 2</td>
<td>Spatially-adjusted model including terms from Model 1</td>
<td>8</td>
</tr>
<tr>
<td>Model 3</td>
<td>GWR local regression model including terms from Model 1</td>
<td>8</td>
</tr>
</tbody>
</table>

*For the stepwise model, number of variables indicates the number retained after running the stepwise platform.
A discriminant analysis (Lachenbruch and Goldstein 1979) was conducted using only significant variables identified in the mixed stepwise linear regression to test the model’s ability to differentiate between declining, stable and improving stands. The resulting class accuracy provides insight into how well the three classes of forest health trends can be differentiated, which is perhaps a more meaningful measure than R-squared in the linear regression.

Because a Moran's I test detected significant spatial autocorrelation in the dataset (Moran's Index = 0.64, Z score = 14.70), a simultaneous autoregressive spatially-adjusted regression model (Model 2) was built in TIBCO Spotfire S+ (TIBCO Software, Inc.) using the variables retained in the mixed stepwise linear regression model (Model 1). Spatially-adjusted linear regression calculates a neighbor weight matrix to adjust the effective sample size (Fortin and Dale 2005), generally reducing the number of significant variables identified in ordinary least squares regression.

Geographically weighted regression (GWR) was used to explore spatial nonstationarity, which is the variation in model parameters over space (Brunsdon 1998). Ordinary least squares (OLS) regression models assume relationships between dependent and independent variables are constant throughout the study region. This may not be a realistic assumption for geospatial datasets, however. GWR identifies specific geographic regions where a given parameter is significant, which may provide information on the spatial variability of ecological processes across the landscape. GWR then compares the output of the local regressions to the output of an OLS global regression (Brunsden et al. 1998). The Akaike Information Criterion (AIC) is
computed for both the global and local models, and minimization of the AIC determines which model is a better fit of the data (Fotheringham et al. 2002). The AIC provides a better measure of model performance than the coefficient of determination because it accounts for the number of degrees of freedom in the model and identifies an acceptable tradeoff between model complexity and model fit (Lazarus et al. 2006). Outputs from GWR include spatially explicit coefficients, local r-squared values, and local t values for each input variable. These can then be imported into a GIS to map local regression outputs over the study area, providing insights into the underlying processes driving spatial patterns. The GWR model (Model 3) was created using GWR 3 software (GWR 3.0, M. Charlton, A.S. Fotheringham, and C. Brunsdon, University of Newcastle, UK) and included the independent variables identified in the mixed stepwise linear regression (Model 1). A Monte Carlo simulation (Kalos and Whitlock 2008) was performed to test whether model parameters were constant or significantly nonstationary throughout the study region.

2.4.6. Model Validation

To test the robustness of results, a new dataset was created that contained a simple random sample of 881 points for parallel analyses. Because this dataset has a smaller sample size and consisted of a simple random sample with a reduced range of forest health trends, fewer significant results should be obtained that reflect robust relationships in the entire population. The alpha level was set at 0.05, as spatial
autocorrelation should not be as problematic when fewer points are sampled throughout the study region (i.e., points are spaced farther apart).

2.5. Results

2.5.1. Regional Decline Trends

The mean forest health trend in the northern Green Mountain study region was near zero (0.0108 ± 0.0431, 95% confidence interval), indicating that most forest canopies have not experienced significant change in the past quarter century. Only 3% of all pixels had forest health trends greater than ±0.96, which represents an improvement or deterioration of more than 25% along the continuous 0 to 10 scale of perfect health to mortality. Less than 0.02% of forested pixels had trends greater than ±0.192, which represents an improvement or deterioration of more than 50% along the 0 to 10 forest health scale.

2.5.2. Spatial Patterns

Although the majority of forest health trends were stable, patches of forest decline and improvement were present in localized areas. Examination of the forest health trend raster revealed distinct clusters of declining pixels on high-elevation mountain ranges, where spruce-fir-paper birch forests predominate (Figure 6). However, patches of declining forest health trends were found at low elevations, as well. Patch size ranged from 30 m² (a single pixel) to over one square kilometer,
indicating that forest health response ranges from the scale of small groups of trees to large geographic regions.

Figure 6: Raster of improving and declining forest health trends within the northern Vermont study region. Red indicates declining and blue indicates increasing forest health by at least 10% on a 0 to 10 scale of perfect health to mortality. Stable pixels have been masked.

2.5.3. Geospatial Database

The mean forest health trend in the geodatabase sample of 5,948 points was 0.0178 ± 0.061, similar to the mean for the raster of the entire study region but with a
larger standard deviation due to the stratified random sample design (Table 5). Five LANDFIRE forest types were present in the study region (Table 6), with the majority of sample points (78%) classified as sugar maple, 14% classified as red spruce-balsam fir, 6.5% classified as hemlock-yellow birch, 1.1% classified as oak, and 0.2% classified as sugar maple-beech (the low sample size of oak and sugar maple-beech points may be insufficient to evaluate the status of these forest types in this study). Three Landfire forest height classes were present in the study region (Table 6), with over 95% of the points in the 10 to 25 meter height class and 3.2% and 1.7% in the 5 to 10 meter and 25 to 50 meter height classes, respectively. Although these categories are coarse, the point distribution is consistent with the mature condition of most forests in northern Vermont (Seymour 1995). Most forests in the 5 to 10 meter height class occur in high-elevation spruce-fir forests.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest Health Trends</td>
<td>0.0178144</td>
<td>0.061036</td>
<td>-0.4284</td>
<td>0.49456</td>
</tr>
<tr>
<td>Elevation (m)</td>
<td>1330.546</td>
<td>621.642</td>
<td>105</td>
<td>4039</td>
</tr>
<tr>
<td>Slope (°)</td>
<td>10.552</td>
<td>6.437</td>
<td>0</td>
<td>43.878</td>
</tr>
<tr>
<td>Sine of Aspect</td>
<td>-0.002106</td>
<td>0.7046</td>
<td>-1</td>
<td>1</td>
</tr>
<tr>
<td>Cosine of Aspect</td>
<td>0.0222</td>
<td>0.7094</td>
<td>-1</td>
<td>1</td>
</tr>
<tr>
<td>Soil Drainage Index</td>
<td>37.451</td>
<td>19.373</td>
<td>6</td>
<td>99</td>
</tr>
<tr>
<td>Forest biomass (Mg/ha)</td>
<td>131.704</td>
<td>31.159</td>
<td>0.0064</td>
<td>203.565</td>
</tr>
<tr>
<td>Forest height (m)</td>
<td>16.287</td>
<td>1.174</td>
<td>11.8</td>
<td>19.1</td>
</tr>
</tbody>
</table>
Almost 54 percent of the sample points had no recorded disturbances from 1997 to 2009, 26.1% had one, 11.1% had two, 5.4% had three, and less than 4% experienced four or more recorded disturbance events. The disturbance with the largest spatial extent was the 1998 ice storm; impacts from this event were mapped over approximately 20% of the state.

Table 6: Forest types and forest height classes in the geospatial database. Almost 80% of forests are northern hardwoods dominated by sugar maple in the 10 to 25 meter height class.

<table>
<thead>
<tr>
<th>Forest Type</th>
<th>Count</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hemlock-Yellow Birch</td>
<td>385</td>
<td>6.5</td>
</tr>
<tr>
<td>Oak</td>
<td>65</td>
<td>1.1</td>
</tr>
<tr>
<td>Red Spruce-Balsam Fir-Paper Birch</td>
<td>834</td>
<td>14</td>
</tr>
<tr>
<td>Sugar Maple</td>
<td>4651</td>
<td>78.2</td>
</tr>
<tr>
<td>Sugar Maple-Beech</td>
<td>13</td>
<td>0.2</td>
</tr>
<tr>
<td>Total</td>
<td>5948</td>
<td>100</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Forest Height</th>
<th>Count</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 to 10 meters</td>
<td>192</td>
<td>3.2</td>
</tr>
<tr>
<td>10 to 25 meters</td>
<td>5655</td>
<td>95.1</td>
</tr>
<tr>
<td>25 to 50 meters</td>
<td>101</td>
<td>1.7</td>
</tr>
<tr>
<td>Total</td>
<td>5948</td>
<td>100</td>
</tr>
</tbody>
</table>

2.5.4. Forest Health Drivers

Univariate Continuous Decline Trend Analyses

Spearman’s Rho correlations found that stands with declining forest health were significantly associated with higher elevations, higher forest biomass, and steeper slopes ($\rho = 0.152$, 0.1168, and 0.0849, respectively; Table 7). Partial correlations
showed that elevation was the strongest of the significant correlates (partial correlation = 0.113).

Table 7: Nonparametric Spearman's Rho statistic and partial correlations for continuous variables.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Nonparametric Spearman's Rho</th>
<th>P value</th>
<th>Partial Correlations of Significant Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elevation</td>
<td>0.152</td>
<td>p&lt;0.0001</td>
<td>0.113</td>
</tr>
<tr>
<td>Slope</td>
<td>0.0849</td>
<td>p&lt;0.0001</td>
<td>0.0746</td>
</tr>
<tr>
<td>Forest biomass</td>
<td>0.1168</td>
<td>p&lt;0.0001</td>
<td>0.0393</td>
</tr>
<tr>
<td>Soil Drainage Index</td>
<td>-0.045</td>
<td>p=0.0013</td>
<td>-0.0367</td>
</tr>
</tbody>
</table>

Nonparametric oneway ANOVAs of forest type and forest height classes were also significant, with higher decline trends in spruce-fir forests (mean trend = 0.066 than in northern hardwoods (Figure 7). The 5 to 10 meter height class had significantly higher decline trends than 10 to 25 and 25 to 50 meter height classes (mean trend = 0.071, 0.027, and -0.005, respectively; Figure 7).

After converting the 0 to 99 soil drainage index to five broad categories (xeric, dry, well-drained, mesic, and hydric), significant differences were found between drier soil types (xeric and dry) and wetter soil types (well-drained, mesic, and hydric; Figure 8). Most soils classified as xeric or dry in the study region are found at higher elevations, while wetter soils are predominantly found in alluvial valleys and low to mid-elevation forests.
Figure 7: All-pairs Tukey-Kramer HSD test between groups after oneway ANOVAs of forest types and height classes. Higher values indicate decreasing forest health, and negative values indicate improving forest health. Classes not connected by the same letter are significantly different.
Figure 8: All-pairs Tukey-Kramer HSD test between groups after a oneway ANOVA of soil drainage classes. Higher values indicate decreasing forest health, and negative values indicate improving forest health. Classes not connected by the same letter are significantly different.

Univariate Categorical Decline Trend Analysis

By re-coding continuous forest health trends to a class variable (where trends $< -0.05 = \text{Improving}; \text{trends} > 0.05 = \text{Declining}; -0.05 < \text{trends} < 0.05 = \text{Stable}$), relationships between continuous variables were examined for consistency. Similar to results obtained using the continuous forest health trend variable, stands in the declining class were associated with significantly higher elevations, steeper slopes, drier soils, and higher biomass (Table 8).
Table 8: Nonparametric ANOVA for continuous variables. Classes not connected by same letter are significantly different.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>P value</th>
<th>Means Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elevation</td>
<td>p&lt;0.0001</td>
<td>Class Mean</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Declining A 1468.87</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Stable B 1343.75</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Improving C 1036.01</td>
</tr>
<tr>
<td>Slope</td>
<td>p&lt;0.0001</td>
<td>Class Mean</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Declining A 11.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Stable B 10.41</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Improving B 9.98</td>
</tr>
<tr>
<td>Forest biomass</td>
<td>p&lt;0.0001</td>
<td>Class Mean</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Declining A 134.76</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Stable B 131.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Improving C 115.45</td>
</tr>
<tr>
<td>Soil Drainage</td>
<td>p&lt;0.0001</td>
<td>Class Mean</td>
</tr>
<tr>
<td>Index</td>
<td></td>
<td>Declining A 38.26</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Stable B 35.92</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Improving B 34.92</td>
</tr>
</tbody>
</table>

Chi-squared tests on categorical site variables and forest health trend classes (Table 9) showed a higher proportion of spruce-fir than expected in the Declining class ($\chi^2 = 42.96$), with lower numbers than expected in the Stable and Improving classes ($\chi^2 = 11.9$ and 6.0, respectively). Other significant deviations included more oak in the Improving class than expected ($\chi^2 = 18.67$) and fewer sugar maple in the Declining class than expected ($\chi^2 = 12.47$). The proportion of stands in the 5 to 10 meter height class was higher than expected in the Declining class ($\chi^2 = 54.56$) and lower than expected in the Stable class ($\chi^2 = 14.11$). There were also significantly more xeric soils than expected in the Declining class ($\chi^2 = 27.65$) and more soils of moderate fertility (classes 6-7 and 8-9) than expected in the Improving class ($\chi^2 = 29.98$ and 31.46, respectively).
### Table 9: Chi-squared test for categorical variables.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>P value</th>
<th>Chi-squared Test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Cell Chi^2</td>
</tr>
<tr>
<td>Forest Type</td>
<td>p&lt;0.0001</td>
<td>Declining</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Improving</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Stable</td>
</tr>
<tr>
<td>Forest Height</td>
<td>p&lt;0.0001</td>
<td>Declining</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Improving</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Stable</td>
</tr>
<tr>
<td>Drainage Index</td>
<td>p&lt;0.0001</td>
<td>Declining</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Improving</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Stable</td>
</tr>
<tr>
<td>Fertility Index</td>
<td>p&lt;0.0001</td>
<td>Declining</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Improving</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Stable</td>
</tr>
</tbody>
</table>

### 2.5.5. Modeling Forest Health Trends

*Multivariate Linear Regression*

The mixed stepwise linear regression model predicting continuous forest health trends retained variables of elevation, biomass, forest height classes, forest type, and number of disturbance events ($R^2 = 0.044$, Table 10, Model 1). Forest decline was associated with higher elevations, higher biomass, spruce-fir forest types, and the 5 to 10 meter height class. Relationships between disturbances and forest health trends were more complicated, with no ordinal trend. Forest health decreased at sites with zero disturbances and increased at sites with one or two disturbances. Similar
Table 10: Model 1, mixed stepwise regression model. Significant terms are in bold (p<0.001).

| Parameter Estimates | Estimate | Std Error | t Ratio | Prob>|t| |
|---------------------|----------|-----------|---------|-------|
| Intercept           | -0.048134| 0.012787  | -3.76   | 0.0002* |
| Elevation           | 1.57E-05 | 1.92E-06  | 8.19    | <.0001* |
| Forest Type {O&SM&H-YB: S-F&SM-B} | -0.003872| 0.001398  | -2.77   | 0.0056  |
| Forest Type {O&SM:H-YB} | -0.00701  | 0.001621  | -4.32   | <.0001* |
| Forest Height {25-50 m&10-25 m:5-10 m} | -0.008355| 0.002356  | -3.55   | 0.0004* |
| Biomass             | 0.0001088 | 2.79E-05  | 3.9     | <.0001* |
| Forest Height (continuous) | 0.00256 | 0.000745 | 3.44    | 0.0006* |
| Disturbance Class {0&1-2:3-4&5-8} | 0.0051337 | 0.001542 | 3.33    | 0.0009* |
| Disturbance Class {0:1-2} | 0.0035893 | 0.000904 | 3.97    | <.0001* |

**Discriminant Analysis**

Approximately 52.5% of forest health trend points were classified correctly as declining, stable, or improving in a quadratic discriminant analysis. While there were significant differences between the cluster means (95% confidence intervals of the
means for forest health classes were separated in space), there was considerable overlap in the contour regions containing 50% of the points (Figure 9).

Figure 9: Quadratic discriminant analysis of forest health classes. Red points are declining, blue points are stable, and green points are improving forest health classes. Colored circles represent 50% contours for each class.

*Spatially-adjusted Regression*

In the spatially-adjusted regression model (Model 2) only forest type, forest height, and disturbance class were significant (Table 11). A Moran's I test revealed that residuals were still spatially autocorrelated in the model, possibly indicating that spatial autocorrelation occurs at several scales that cannot be accounted for with a single neighbor weight matrix.
Table 11: Model 2, spatially-adjusted regression model. Significant terms are in bold (p<0.05).

| Term                              | Estimate | Std Error | t Ratio | Prob>|t| |
|-----------------------------------|----------|-----------|---------|-----|---|
| Intercept                         | 0.0177   | 0.0143    | 1.2414  | 0.2145 |
| Elevation                         | 0.00E+00 | 0.0000    | 1.2527  | 0.2104 |
| Forest Type {O&SM&H-YB:S-F&SM-B}  | -0.0029  | 0.0013    | -2.1927 | 0.0284 |
| Forest Type {O&SM:H-YB}           | -0.0024  | 0.0016    | -1.5573 | 0.1194 |
| Forest Height Class {25-50 m&10-25 m:5-10 m} | -0.0085 | 0.0024    | -3.6007 | 0.0003 |
| Biomass                           | 0        | 0.0000    | -0.4424 | 0.6582 |
| Forest Height (continuous variable)| 0.0005   | 0.0008    | 0.6941  | 0.4877 |
| Disturbance Class {0&1-2:3-4&5-8} | 0.0004   | 0.0016    | -0.2561 | 0.7979 |
| Disturbance Class {0:1-2}         | 0.002    | 0.0009    | 2.2373  | 0.0253 |

Geographically Weighted Regression

The geographically weighted regression model (Model 3, $R^2 = 0.217$, AIC = -17040.6) was a significant improvement (p<0.0001) over the mixed stepwise regression in Model 1 ($R^2 = 0.043$, AIC = -16374.1). A Monte Carlo test found elevation, biomass, forest height, and forest type to be significantly nonstationary, indicating that their significance is dependent upon geographic location. Local t values indicated that each variable was significant only within specific regions (Figure 10). No relationships were found that were significant throughout the entire study region.
Figure 10: Local t values of elevation, biomass, forest height, and forest type. Red and blue points are significant (p<0.05). Red points indicate a positive coefficient (points are associated with forest decline) while blue points indicate a negative coefficient (points are associated with forest improvement).

Local $R^2$ values were plotted in ArcGIS to evaluate variability in model performance across the landscape (Figure 11). Model fit was best in regions of extreme
elevation, including the Mt. Mansfield region, the Lincoln Peak region, and the area south of Jay Peak. Model fit was poorer in the northeastern and east-central portion of the study area.

Figure 11: Local r-squared values of geographically weighted regression model. Darker points have a better model fit, which ranges from 0.023 to 0.322.

2.5.6. Consistent Variables Related to Decline

Considering all statistical tests, elevation, biomass, forest type, forest height class, and soil drainage were repeatedly significant (Table 12). Slope was significant for two statistical tests, while remaining variables either were significant in only one statistical test or were not significant in any tests.
Table 12: Number of significant results obtained for statistical tests by variable. NS means “not significant” and N/A means “not applicable.”

<table>
<thead>
<tr>
<th></th>
<th>Elevation</th>
<th>Slope</th>
<th>Biomass</th>
<th>Forest Height</th>
<th>Forest Type</th>
<th>Forest Height Class</th>
<th>Soil Drainage Index</th>
<th>Fertility Index</th>
<th>Disturbance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oneway ANOVA</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.001</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td>Oneway ANOVA of Forest Health Classes</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>N/A</td>
<td>N/A</td>
<td>p&lt;0.0001</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Spearman’s Rho Correlations</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>NS</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Chi-squared Tests</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.01</td>
</tr>
<tr>
<td>Linear Regression</td>
<td>p&lt;0.001</td>
<td>NS</td>
<td>p&lt;0.001</td>
<td>p&lt;0.001</td>
<td>p&lt;0.001</td>
<td>p&lt;0.001</td>
<td>p&lt;0.001</td>
<td>NS</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>Number of Significant Tests [p&lt;0.001]</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>4</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

2.5.7. Model Validation

Several consistent significant results were obtained when the stratified random sample (N=5,948) and the simple random sample (N=881) were compared (Table 13). Forest type, forest height class, and soil drainage were significant in two or more tests in the simple random sample, indicating that relationships between declining forest health and spruce-fir-paper birch forests, the five to ten meter height class, and drier soils are relatively robust.

Elevation, slope, forest height (continuous), and soil fertility were not significant in any statistical tests in the simple random sample. Disturbance was significant in the chi-squared test, and biomass was marginally significant in a oneway ANOVA of forest health classes. All these variables exhibit collinearity with elevation and may be
insignificant because of undersampling of high-elevation montane forests, which are relatively rare compared to other forest types in the study region.

Table 13: Comparison of significant results between a stratified random sample of ~6,000 points and a simple random sample of ~900 points.

<table>
<thead>
<tr>
<th></th>
<th>Elevation</th>
<th>Slope</th>
<th>Biomass</th>
<th>Forest Height</th>
<th>Forest Type</th>
<th>Forest Height Class</th>
<th>Soil Drainage Index</th>
<th>Fertility Index</th>
<th>Disturbance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stratified Random Sample, N=5,948 points</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oneway ANOVA</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td>Oneway ANOVA of Forest Health Classes</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>p&lt;0.0001</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Spearman’s Rho Correlations</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>NS</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Chi-squared Tests</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.01</td>
</tr>
<tr>
<td>Spearman’s Rho Correlations</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>NS</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>N/A</td>
<td>NS</td>
</tr>
<tr>
<td>OLS Linear Regression</td>
<td>p&lt;0.001</td>
<td>NS</td>
<td>p&lt;0.001</td>
<td>p&lt;0.001</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>NS</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>Simple Random Sample, N=881 points</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oneway ANOVA</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>p&lt;0.01</td>
<td>p&lt;0.05</td>
<td>p&lt;0.01</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td>Oneway ANOVA of Forest Health Classes</td>
<td>NS</td>
<td>NS</td>
<td>N/A</td>
<td>N/A</td>
<td>p=0.0534</td>
<td>NS</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Spearman’s Rho Correlations</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Chi-squared Tests</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>p&lt;0.001</td>
<td>p&lt;0.001</td>
<td>NS</td>
<td>NS</td>
<td>p&lt;0.05</td>
</tr>
<tr>
<td>Spearman’s Rho Correlations</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>p&lt;0.0001</td>
<td>p=0.054</td>
<td>NS</td>
<td>p&lt;0.01</td>
<td>NS</td>
</tr>
<tr>
<td>OLS Linear Regression</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>p&lt;0.0001</td>
<td>p&lt;0.0001</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td># Significant Tests In Both Datasets</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

2.6. Discussion

2.6.1. Northeastern Forest Health

Results from this study indicate that the canopy health of most forests in northern Vermont has not changed significantly from 1984 to 2009 (i.e., forest health trends are near zero). This stability is partially a result of limitations of the remote sensing methods used to quantify forest health trends. Forest health trend values
represent the change in photosynthetic capacity of a 30 m² forest canopy. Individual tree crowns may die within a pixel, but large portions of the 30 m² canopy would have to be impacted – with minimal regrowth or regeneration – for the spectral signature to register a significant change. The Landsat TM platform is able to detect decline in stands that experience catastrophic stress events, such as fire, logging, or mountain pine beetle outbreaks. Catastrophic disturbances are relatively uncommon in the Northeast, however. Disturbance regimes are dominated by fine-scale (24 – 126 m²) canopy gaps caused by pests, windthrow, and age-induced senescence, with return intervals of 50 to 200 years for any given stand (Seymour et al. 2002). Stand replacing disturbances by wind and fire are less common, with return intervals exceeding 800 years and patch sizes ranging from 2 to 200 hectares (Seymour et al. 2002). Thus, extensive declines in forest health are not expected on a 26-year time scale, although small canopy gaps may form in localized areas from pests or age-induced senescence.

The apparent stability of Northeastern forests also results from the study’s temporal scale. Quarter-century trends may mask stress events that impact stands over shorter time intervals. For example, the most catastrophic and widespread stress event on record from 1984 to 2009 is the 1998 ice storm. While many stands were heavily impacted, most forests quickly recovered. Rhodes et al. (2002) found that leaf area index at research plots in Hubbard Brook, New Hampshire, had reached pre-storm levels within three years, with no significant differences between damaged and undamaged stands (Weeks et al. 2009). Shortle et al. (2003) attributed ice storm recovery to sprouting in species such as ash, sugar maple, and beech, while others
attributed recovery to lateral ingrowth of surviving trees (Weeks et al. 2009). While the ice storm caused significant damage to tree crowns, its impact on quarter-century trends in the photosynthetic capacity of forest canopies appears to have been negligible.

Stable forest health trends must be interpreted with caution, as forests are dynamic ecosystems, and numerous forest health concerns in have been documented in Northeastern forests over the past quarter century (Pitelka and Raynal 1989, Siccama et al. 1982, Vogelmann et al. 1985, Williams and Liebhold 1995, Wargo and Auclair 2000). Of particular concern is red spruce decline at high elevations (Siccama et al. 1982, Vogelmann et al. 1985, Nowacki et al. 2010), beech bark disease (Evans et al. 2005, Griffin et al. 2003), and sugar maple and paper birch decline (Horsley et al. 2002, Halman et al. 2011). Instead of contradicting results of these studies, this research suggests that declining trees are replaced relatively quickly with no significant decline in canopy photosynthetic capacity over long (quarter-century) time scales.

Northern hardwood forests are relatively diverse (North and Keeton 2008), with several different overstory species capable of growing on a particular site (Leak et al. 1987). Diverse forests are more resilient to disturbances because many species are functionally redundant. When one species is eliminated from an ecosystem, another species that occupies a similar niche may take its place, resulting in negligible losses in net primary production (Thompson et al. 2009). Regeneration of northern hardwoods is facilitated by disturbances, and the species composition of the future stand depends on the type of disturbance, the size of canopy gaps, the level of soil disturbance, and biological legacies (Leak et al. 1987, North and Keeton 2008). Even where intensive
harvests have occurred, such as clearcuts, sites are typically occupied by dense stands of saplings within ten years (DeGraaf et al. 1993). It is relatively uncommon for a stand to die-back and revert to a non-forest habitat, such as herbaceous meadows, for long periods of time. Herbaceous glades have been observed in high-elevation spruce-fir forests, but their longevity and the role of disturbances in their formation is unclear (Reiners and Lang 1979).

It appears that species diversity and favorable growing conditions found in northern hardwood forests maximize growth and regeneration in spite of recurring stress events. While individual trees – and perhaps even species – may be lost from a site, other species take advantage of light and nutrient resources and quickly replace declining trees in the canopy. When monitoring forest health with Landsat at decadal time scales, the regenerative capacity of Northeastern forests appears to mask temporary declines in forest canopies.

2.6.2. Forest Health Drivers

While forest health has remained relatively stable in the majority of forests in the northern Green Mountains, patches of decline were present in localized areas. Declining forest health was consistently associated with higher elevations, spruce-fir-paper birch forest types, stand heights of five to ten meters, and drier soils. All of these characteristics are associated with high-elevation montane forests, indicating that spruce-fir-paper birch forests have experienced more decline than other forest types from 1984 to 2009.
Acid deposition-induced decline of high-elevation red spruce and paper birch has been documented in the Northeast since the 1980s (Schaberg et al. 2011, Lazerus et al. 2006, Halman et al. 2011, Miller 2005). High levels of nitrate and sulfate deposition accelerate leaching of base cations from soils (Knoepp and Swank 1994, Bailey et al. 1996, Likens et al. 1998, Markewitz et al. 1998, Swistock et al. 1999), resulting in low calcium and magnesium availability and increased availability of toxic elements, such as aluminum (Driscoll et al. 2001). Calcium depletion at high elevations reduces the cold tolerance of red spruce, resulting in severe winter injury (Dehayes et al. 1999, Shaberg et al. 2011). Several widespread winter injury events have been documented in northern Vermont from 1984 to 2009, resulting in severe decline at some locations (Lazerus et al. 2004, Lazerus et al. 2006).

In addition to acid deposition, high-elevation spruce-fir forests generally grow on thin soils where windthrow is a common occurrence (Siccama 1982, Lorimer and White 2003). It is possible that wind disturbances explain some of the declining forest health trends observed in this study. Climate change may also be impacting spruce-fir forests by increasing the number damaging freeze-thaw events. In the Green Mountains, spruce-fir forests are being displaced by hardwoods along the northern hardwood-boreal forest ecotone (Beckage et al. 2008), and models predict that this forest type will decrease in New England in future climate scenarios (Tang and Beckage 2010). Thus, the future health of spruce-fir forests in the Northeast is uncertain.
2.6.3. Modeling Forest Health Trends

While the OLS linear regression in Model 1 was significant, the low coefficient of determination ($R^2 = 0.044$) indicates that only a small proportion of the variability in forest health trends was explained. Many factors influence forest health, and accurate GIS data with an appropriate spatial scale are not always available. Two notable factors are acid deposition and disturbance events. While national datasets of sulfate and nitrogen deposition have been created by the National Atmospheric Deposition Program (Lamb and Bowersox 2000), the 2.5 kilometer resolution of these rasters was inappropriate for this study. GIS rasters of cumulative acid deposition, critical loads, and critical load exceedances have been developed for Vermont at a 30 meter spatial scale (Miller 2005), but they were not available to the public when this research was conducted. GIS layers for defoliation and decline events are not available prior to 1997, leaving a large omission in the database for disturbances early in the study period. Other factors that would explain more variability in forest health trends include droughts, distributions of pests and pathogens, stand density and basal area, forest harvesting activities, and fine-scale mortality events not typically recorded in aerial sketch maps.

In addition to missing variables, GIS datasets have higher levels of error associated with them compared to traditional field measurements. Error in GIS layers is compounded from positional, temporal, modeling, image classification, and calibration errors (Bolstad and Smith 1992). For example, the NOAA C-CAP land cover dataset, which was used to mask non-forested land uses when the forest health
trend dataset was produced, reported an overall accuracy of 85%. Fifteen percent of the pixels classified as forest in this study may be a non-forest land use, such as agriculture or pasture, and may cause spurious forest health trends.

Error is also present in the equation used to predict yearly forest health. In the Catskills, this equation was able to predict a continuous, 0 to 10 decline rating over 3 years of imagery with an $R^2$ of 0.55. However, the accuracy of this equation in our study region is limited to comparisons with averages of USFS Forest Inventory and Analysis (FIA) dieback measurements from 2000 to 2008. Significant positive correlations were found for both hardwoods ($r=0.59$) and softwoods ($r=0.69$; Pontius et al. in review b).

The Landsat Row 29, Path 13 and 14 images used for the forest health trend calculation had an average USGS-reported cloud cover of four percent. USGS estimates proved to be unreliable, however, as approximately twenty percent of image pixels were removed because of cloud contamination, including high altitude cirrus clouds that might impact spectral reflectance values. Examination of yearly forest health images indicated that several years had unusually high or low values on the forest health index scale. Spurious patterns in the forest health trend raster were produced if these images contained holes in the data from cloud masks (Figure 12).
Figure 12: Spurious patterns in the forest health trend image. The image on the left is the forest health trend raster draped over a DEM of the Green Mountains. The image on the right is the forest health index for 2008 (gray) overlain over a DEM. Missing data from cloud masks are apparent in the 2008 image, which can create spurious patterns in the forest health trend dataset.

Ideally, data would be available for every year from 1984 to 2009 for each pixel. Data volume was reduced, however, because images with less than 20% cloud cover were not available for each growing season, and pixels with cloud contamination were masked. The average number of years of data for each pixel was $7.46 \pm 4.77$, with a maximum of 18 years. While not ideal, most long term studies of forest health have used two (pre- and post-disturbance) to eight years of data (Vogelman 2009), making this the most comprehensive temporal assessment of forest health to date.

The geographically weighted regression predicted forest health trends better than the OLS stepwise regression ($R^2 = 0.217$ and 0.044, respectively). This indicates that factors that affect forest health vary by geographic location. While it is intuitive that forest health issues are site-specific, GWR results illustrate that relationships
between forest types, stand attributes, soil properties, disturbance, and forest health depend upon the unique ecological processes operating at specific geographic locations. General statements about factors related to forest health at a landscape scale should be interpreted with caution.

2.6.4. future research

The landscape-scale approach used in this study is useful to identify general trends in forest health and site-specific environmental factors associated with forest decline over the past quarter-century. However, field assessments are necessary to identify specific drivers of forest health at the scale of forest stands. Researchers in our lab group are collecting site, stand, soil, and tree core data across a range of forest health trends to validate the relationships found in this study and to identify other potential drivers of forest health (Weverka et al. in prep). Field visits to declining sites have discovered spruce-fir stands with "storks nest" crowns (Jagels 1986) and stands declining from beech bark disease. Tree mortality has also been discovered at sites with stable forest health trends, however (Weverka personal communication), and future research will investigate if there is significantly more tree mortality at sites with declining forest health trends than sites with stable trends.

2.7. conclusion

Results of this study indicate that the canopy health of most forests in northern Vermont has not changed significantly from 1984 to 2009. The stability of these
forests is likely due to a lack of widespread, catastrophic disturbances in the region and the natural resilience of Northeastern forests. While fine-scale dieback and mortality are common, ingrowth and regeneration appear to maintain a photosynthetically stable forest canopy at decadal time scales. Although accuracy of forest health models was limited by a lack of key ecological variables and error inherent in GIS datasets, forest decline was significantly associated with high-elevation spruce-fir-paper birch forests. These results highlight the sensitivity of this forest type in the Northeast, as the future of spruce-fir forests is uncertain under projected climate change scenarios and continued acid deposition.

While it is reassuring to find evidence that Northeastern forest canopies are resilient to stressors over decadal time scales, “forest health” encompasses more than canopy photosynthetic capacity and net primary productivity. Changes in species and structural conditions have important implications for human values of forest resources. If high-value trees, such as sugar maple, are replaced by less valuable species, such as red maple, the forest products industry will be negatively impacted. Aesthetic values can be somewhat subjective, but any reduction in the maple component of Northeastern forests will likely mute fall foliage displays. Human values of forest resources must be considered along with metrics of ecosystem productivity when considering forest health issues in the Northeast.


Ciesla, W.M. 2000. Remote sensing in forest health protection. USDA Forest Service FHTET Report No. 00-03.


Johnson, A.H., Siccama, T.G. 1983. Acid deposition and forest decline. Environmental Science and Technology 17(7), 294A-305A.


Pontius, J.A., Martin, M.E., Olson, M.G., Regan, E.M.D., Young, W.L., White, K.M.
Rhodes, A.G., Hamburg, S.P., Fahey, T.J., Siccama, T.G., Hane, E.N., Battles, J.,
Cogbill, C., Randall, J., Wilson, G. 2002. Effects of an intense ice storm on
the structure of a northern hardwood forest. Canadian Journal of Forest
Research 32(10), 1763-1775.


Rollins, M.G. 2009. LANDFIRE: a nationally consistent vegetation, wildland fire,

Royama, T. 1984. Population dynamics of the spruce budworm Choristoneura

Using Landsat TM data and change detection techniques. Forest Science 43,
327-335.

decline: a case study in New Jersey, in: McManus, Katherine A.; Shields,
Kathleen S.; Souto, Dennis R., eds. Proceedings: Symposium on sustainable
Rep. NE-267, 103-109. Newtown Square, PA: U.S. Department of
Agriculture, Forest Service, Northeastern Forest Experiment Station.

Service Research Paper NE-535.


Vermont Department of Forests, Parks and Recreation. 2011. 2010 Vermont Forest Health Highlights. Available from:


