Property Value Impacts of Hemlock Woolly Adelgid in Residential Forests

Thomas P. Holmes, Elizabeth A. Murphy, Kathleen P. Bell, and Denise D. Royle

Abstract: This study estimates the economic losses attributable to a nonindigenous forest insect, the hemlock woolly adelgid (*Adelges tsuga*), using cross-sectional and difference-in-difference hedonic price models. The data span a decade of residential property value transactions in West Milford, New Jersey. Hemlock health in naturally regenerated hemlock stands was measured biannually over this period using remote sensing data and the image differencing technique. These data were linked with spatially referenced land use and land cover data, measured twice during the decade, and the locations and housing characteristics associated with parcels sold. Spatial dependence in the regression models was addressed using spatial error and fixed-effects panel data models. The empirical results demonstrated that hemlock decline consistently caused statistically significant reductions in property values both for parcels containing hemlock resources as well as for neighboring nonhemlock parcels. We conclude that failure to account for spatial spillover effects would downwardly bias estimates of economic losses and total economic losses on properties sold during the study period ranged from \$0.64 million in the parcel level cross-section model to \$2.2 million in the 0.5-km neighborhood difference-in-difference model. FOR. SCI. 56(6):529–540.

Keywords: hedonic analysis, invasive species, spatial econometrics

Biological invasions are an emerging and critical problem facing forest landowners in the United States and abroad. As economies around the world have developed, the growth in international trade has induced a steady increase in the arrival and establishment of nonindigenous species (Levine and D'Antonio 2003, Work et al. 2005, McCullough et al. 2006). Forest pests and pathogens are known to hitchhike on various commercial products as well as round-wood and packing materials (Brockerhoff et al. 2006, Haack et al. 2006, Piel et al. 2008). International phytosanitary measures have been developed to address the major economic cause of biological invasions with the goal of preventing invasive species from entering trade pathways (Mumford 2002). New policies that shift the burden of economic impacts from forest landowners and taxpayers onto parties responsible for introducing and/or spreading invasive species may be an efficient means for internalizing the economic spillovers associated with trade (Perrings et al. 2002). However, policies that seek to internalize the externalities caused by nonindigenous forest pests and pathogens will require reliable estimates of economic damages associated with forest invasive species (Holmes et al. 2009).

Since the period after European discovery of the United States, more than 450 nonindigenous phytophagous insects have become established in domestic forests, woodlots, parks, and orchards (Mattson et al. 1994, Aukema et al. 2010). Although the preponderance of non-native forest pests introduced into US forests are innocuous, a few well-known pests have caused severe ecological impacts (Liebhold et al. 1995). Despite an extensive body of literature describing the ecological impacts of non-native forest invasive species, very little is known about the economic impact of biological invasions on various sectors of the forest economy. A recent review of three nonindigenous forest pests of current concern in the United States (emerald ash borer [*Agrilus planipennis*], Asian longhorned beetle [*Anoplophora glabripennis*], and sudden oak death [*Phytophthora ramorum*]) estimated that control costs plus economic damages for these pests might total billions of dollars (General Accounting Office 2006). Furthermore, Pimentel et al. (2000) suggested that economic damages arising from the impact of nonindigenous forest pests in the United States on forest products markets are on the order of \$4.2 billion annually. Despite the importance of these studies in focusing attention on the economic aspects of biological invasions, it must be recognized that neither study used the standard neoclassic approach to economic analysis. The absence of credible estimates for a full suite of costs and economic damages arising from changes caused by nonindigenous forest pests and pathogens on timber and nontimber resources limits the ability of policymakers to evaluate tradeoffs between the loss of economic well-being and potential policy measures targeted to reducing those impacts. Consequently, theoretically sound analyses are needed, which could provide a foundation for the estimation

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Acknowledgments: We gratefully acknowledge the assistance provided by Richard Lathrop, Grant F. Walton Center for Remote Sensing and Spatial Analysis, Cook College, Rutgers University; David Butry, National Institute of Standards and Technology, Office of Applied Economics; and Robert Haight, US Forest Service, Northern Research Station and the financial support provided by Northeastern Area State and Private Forestry, US Forest Service. Any remaining issues or errors are the responsibility of the authors.

Manuscript received August 12, 2009, accepted May 11, 2010

of aggregate economic impacts from nonindigenous forest pests and pathogens.

The goal of this article was to analyze the microeconomic impacts of a nonindigenous forest pest, the hemlock woolly adelgid (*Adelges tsuga* [HWA]), on the value of residential forests using the hedonic price method. To set the context for analysis, a summary of the HWA problem is provided in the second section, along with an overview of the hedonic price method literature regarding the value of trees in residential forest landscapes. The study site and data used for analysis are described in the third section, followed by a description of empirical methods in the fourth section. Results of the empirical analysis are reported in the fifth section, and the conclusions of the study are presented in the last section.

HWA and Residential Forest Landscapes

The HWA is an exotic forest insect accidentally introduced into Virginia from Japan during the 1950s [1]. During the past half-century, the HWA has spread to hemlock forests in the Northeast, the Mid-Atlantic region, and the South. Eastern (*Tsuga canadensis*) and Carolina (*Tsuga caroliniana*) hemlocks have shown no resistance to HWA, and once trees are moderately or severely infested, there is little chance for recovery, typically resulting in tree mortality. Dramatic losses of hemlock forests throughout the eastern United States are likely unless successful control measures are found.

Eastern hemlocks are a long-lived species and individuals may approach 1,000 years of age. Hemlock stands are often found in cool, moist valleys and ravines, where they stabilize soil and helps maintain water temperatures favorable to trout species. Hemlocks also favor cool habitats found on northerly slopes. Because of the limited availability of these growing conditions, the distribution of eastern hemlocks is spatially patchy. Where pure stands occur, they typically create a cool and dark environment that contains few understory species.

Although eastern hemlock is sold as a timber species, it has little commercial value (Howard et al. 2000). Its principal economic value derives from the nontimber ecosystem services it provides. In a study of the aesthetic preferences of forest landowners in Massachusetts for 20 different forest types, Brush (1979) discovered that old Eastern hemlock stands were rated above all other sites for scenic beauty.

There is a limited, but increasingly important and expanding, body of literature that examines the contribution of tree cover to residential property values. The existing literature can be categorized from three perspectives: individual yard trees increase property value (Morales et al. 1976, Anderson and Cordell 1988, Dombrow and Sirmans 2000), forest preserves near residential locations convey property value (Tyrväinen and Miettinen 2000, Thorsnes 2002), and trees within the general forest matrix surrounding residential structures convey value (Garrod and Willis 1992, Patterson and Boyle 2002). Importantly, the focus of these studies has been to estimate the contribution of healthy trees and forests to residential property values. Although Payne et al. (1973) simulated the loss of value to residential properties due to individual tree mortality caused by the gypsy moth (*Lymantria dispar*), their method relied on the assumption that the loss in property value is exactly symmetric to the gain in property value attributable to healthy trees. Rather than impose this assumption, we directly estimated the impact of a change in forest (hemlock) health on property values.

Study Site and Data Description

Study Area

Our analysis focuses on the township of West Milford, a residential community located in the Highlands region of northern New Jersey. This study area was chosen for analysis for two reasons. First, hemlock health data for New Jersey are well documented (Royle and Lathrop 1997, 2002). Second, naturally regenerated hemlock stands form a small, but integral, component of the residential landscape in this region. West Milford is an 80-square mile township located in Passaic County. Although less than 100 miles from New York City, the landscape in the Highlands region is characterized by farms, small villages and towns, lakes, forests, and wetlands.

Housing Characteristics

Our empirical analysis uses 4,373 residential property transactions in West Milford township for the years 1992–2002 (Table 1). The mean (nominal) sales price (PRICE) for West Milford was $177,752 (dummy variables were used in the model specification to control for housing price inflation in these markets). The mean lot size (L_SIZE) was 0.24 ha, the average date of construction (YR_BUILT) was 1961, and the average living area (LV_AREA) was 161.93 m^2. Other housing characteristics used in the model specifications included the number of bedrooms (BEDROOMS), bathrooms (BATHS), and kitchens (KITCHENS), as well as the presence or absence of a finished basement (F_BASE). The cost of travel to the major labor market, New York City, was estimated by computing the road distance and multiplying by a constant cost per kilometer (COST_NYC). Given the importance of the proximity of water bodies as a determinant of land price (Snyder et al. 2007), a variable measuring the distance from sold parcels to the closet water body was also included (DIST_LAKE).

Landscape Characteristics

Land use and land cover (LULC) data based on LANDSAT satellite imagery were obtained from the Center for Remote Sensing and Spatial Analysis at Rutgers University (Lathrop 2000). The land classifications used in the model specification were based on a 14-class scheme, with two classes omitted to simplify analysis [2]. The resolution of individual pixels was 30 m^2. Consequently, observations on tree cover do not represent individual trees but rather represent groups of trees, or stands. LULC variables used in the analysis include highly developed land (HI_DEV: >75% impervious soil), medium and low development (LMED-_DEV: 25–75% impervious soil), deciduous forest cover

Table 1. Descriptive statistics for housing and landscape attributes measured at the parcel level

Variable (variable name, units)	West Milford Mean	S.D.	Minimum	Maximum
House price (PRICE, $)	177,752	77,595	30,000	975,000
Parcel size (LOT_SIZE, ha)	0.24	0.29	0.04	2.02
Year constructed (YR_BUILT, year)	1962	19.87	1880	2002
Bathrooms (BATHS, number)	1.84	0.80	1	5
Bedrooms (BEDROOMS, number)	3.10	0.87	1	8
Living area (LV_AREA, m^2)	161.93	61.97	74.32	458.66
Kitchens (KITCHENS, number)	1.03	0.20	1	5
Finished basement (F_BASE, dummy)	0.30	0.46	0	1
Driving cost (COST_NYC, $)	19.72	32.17	9.95	25.09
Proximity to lake (DIST_LAKE, km)	0.29	0.24	0	1.41
Wetland (WETLAND, ha)	0.01	0.05	0.00	1.28
Agricultural (AGRIC, ha)	0.00	0.01	0.00	0.30
Highly developed (HI_DEV, ha)	0.00	0.01	0.00	0.16
Low–medium development (LMED_DEV, ha)	0.15	0.12	0.00	1.22
Water body (WATER, ha)	0.00	0.01	0.00	0.36
Grass (GRASS, ha)	0.00	0.00	0.00	0.46
Coniferous forest (CONIF, ha)	0.00	0.01	0.00	0.17
Mixed forest (MIXED, ha)	0.01	0.05	0.00	1.03
Deciduous forest (DECID, ha)	0.06	0.20	0.00	1.98
Healthy hemlocks (HEALTHY_H, ha)	0.00	0.05	0.00	1.12
Moderate defoliation (MOD_H, ha)	0.00	0.03	0.00	0.87
Severe defoliation (SEVERE_H, ha)	0.00	0.03	0.00	0.53
Dead hemlocks (DEAD_H, ha)	0.00	0.03	0.00	1.10
Hemlocks (HEMLOCK, ha)	0.02	0.08	0.00	1.26
Hemlocks during impact (HEM_IMPACT, ha)	0.00	0.04	0.00	1.26

(DECID), hemlock forest cover (described below), other (nonhemlock) coniferous forest cover (CONIF), mixed (deciduous and other coniferous) forest cover (MIXED), agricultural land (AGRIC), wetlands (WETLAND), and area covered by streams, ponds, and lakes (WATER). Land cover variables were measured in hectares (Table 1) and were available for the years 1995 and 2000. For West Milford township, the transactions data encompassed about 1,804 total ha. In the empirical model specification, housing sale data were matched with the closest corresponding dates for the LULC data.

Hemlock Health

Concern regarding the spread of HWA and its impact on hemlock resources in New Jersey motivated the development of methods to monitor hemlock health, which was accomplished using the image differencing technique (Royle and Lathrop 1997, 2002). This methodology has been successfully used to map canopy defoliation by other forest pests such as gypsy moth and spruce budworm (*Choristoneura fumiferana*) and quantifies defoliation by subtracting spectral reflectance between satellite imagery for two points in time. By relating the spectral difference in reflectance to defoliation observed on the ground, various levels of defoliation can be quantified.

Four hemlock health classes were used to assign values to hemlock pixels in the study area: (1) healthy and lightly defoliated hemlocks ($<$25% defoliation), (2) moderately defoliated hemlocks (25–49% defoliation), (3) severely defoliated hemlocks (50–74% defoliation), and (4) dead hemlocks ($>$74% defoliation). Leaf-off, winter images were obtained for November 1984, November 1992, December 1994, December 1996, December 1998, and December 2001. The 1984 image was used as the base scene for image processing and change detection, because it was the preinfestation data against which all vegetation changes were compared [3]. Given that 1992 is the first year in which reliable hemlock health data were available, this is the initial year used in the empirical analysis. As was done with the LULC data, housing sale data were matched with the closest corresponding dates for the hemlock health variables.

Figure 1 shows the hectares of hemlock forest type included in residential property transactions between 1992 and 2002 in West Milford township by health class. Roughly 76 ha of hemlock forest type were located on parcels sold during the study period (representing 330 transactions). As can be seen, most of the area sold in this forest type was either healthy or moderately defoliated before the year 2000. However, a sudden decline in hemlock health occurred during the subsequent years 2000–2002, and the area of hemlocks located on parcels sold during this period increased sharply (representing 106 transactions).

Landscape Externalities

Previous research has demonstrated that LULC variables in the neighborhood of a parcel can influence transactions price (Powe et al. 1995, Geoghegan et al. 1997, Benson et al. 1998, Acharya and Bennett 2001, Geoghegan 2002, Irwin 2002, Patterson and Boyle 2002) suggesting that, to some degree, landscape attributes are public goods. To test for possible hemlock health externalities among neighboring properties, all LULC variables were measured at the parcel level, within a 0.1-km radius from the parcel centroid, and within a 0.5-km radius from the parcel centroid.

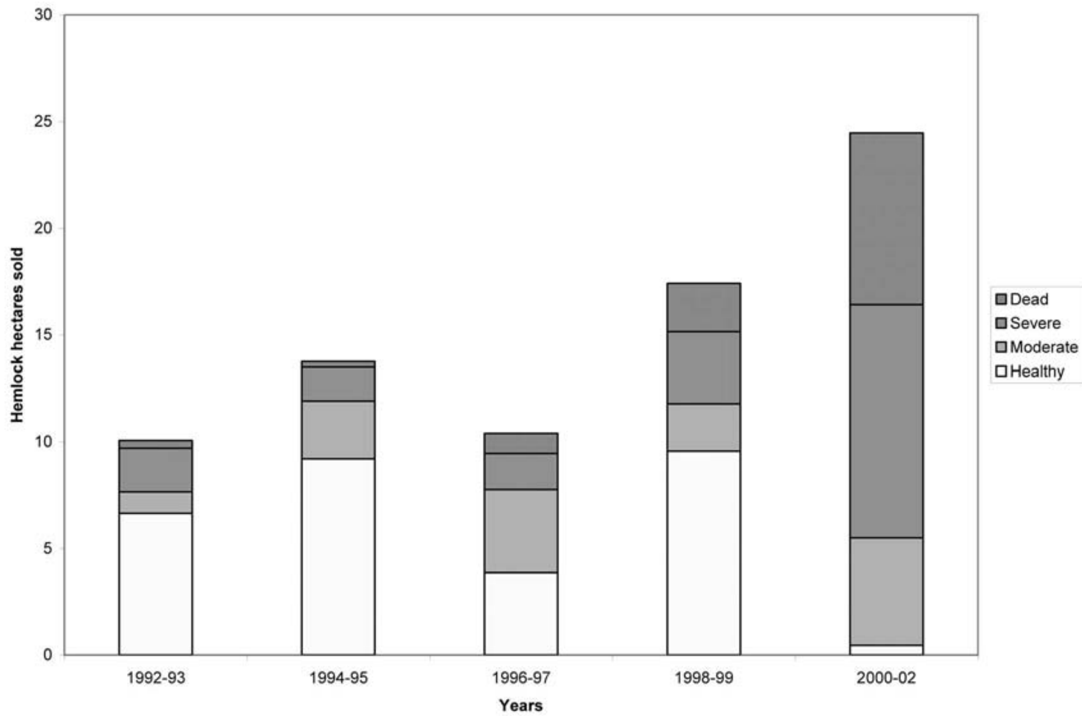

Figure 1. Trend of hemlock health on parcels sold in West Milford, NJ.

Statistically significant parameter estimates for landscape variables within the neighborhood of parcels containing hemlock forest cover type signifies that tree health (decline) is a public good (bad).

Empirical Methods

Hedonic Price Model

The hedonic price model, which provides the theoretical foundation for our analysis, is based on the idea that the price of a good represents the sum of values associated with the qualities or attributes that comprise the good (Palmquist 1991). Attributes are provided by sellers, represented by an offer curve for each attribute holding all other attributes constant, and demanded by buyers, represented by a bid curve for each attribute. The hedonic price function represents the equilibrium position between buyers and sellers and is characterized by the locus of tangencies between offer and bid curves for each attribute.

Localized changes in an environmental attribute, such as hemlock health in residential forests, affect a relatively small number of properties, and the hedonic price function for the entire market remains unaffected. Under these conditions, the first-stage hedonic price function can be used to compute changes in economic welfare resulting from the change in an environmental attribute (Taylor 2003).

To understand the theoretical argument, consider residential property owners with hemlock stands who, when faced with a decrease in the health of their stands, are no longer situated at their preferred combination of attributes given the hedonic price schedule. If these property owners were able to move, at zero cost, to an alternative location that maintained their preferred combination of attributes, they would remain at an identical level of welfare (Palmquist 1991). However, when faced with the sale of the property with a diminished level of forest amenity, they would face a capital loss due to the loss of amenity value (as well as possible landscape restoration costs) and would be willing to pay an amount equal to the capital loss to avoid the change in amenity. The total welfare loss for the community can then be computed as the sum of the losses for each property that is affected by the decline in amenity value.

It should be recognized that a loss in property value due to a reduction in forest health is likely to be a transitory phenomena. Residential hemlock forests that experience decline and mortality will not remain in a degraded state over long periods of time. Rather, we anticipate that landowners will take actions to restore degraded residential forests to an improved condition. Managerial actions may include the removal of dead and dying trees, planting alternative tree species, or encouraging the natural regeneration of desired tree species. Unfortunately, our data do not span a sufficient period to evaluate the evolution of property values subsequent to the period of hemlock decline. However, at the end of the period for which we have hemlock health data (2002), less than one-third of the hemlock component of parcels sold was categorized as dead. Thus, it is likely that property value losses will continue to accrue in this housing market as hemlocks in the moderate and severe defoliation categories transition into the dead category.

Cross-Section Hemlock Health Model

The structure of our data allows alternative econometric models to be specified to evaluate the economic impacts of hemlock decline on economic welfare. The first specification uses detailed information on the hemlock health classes. This specification assumes that the impact of hemlock health status on property value is constant over the study period but may vary by health class. Because patches of hemlocks located within parcels or neighborhoods may exhibit multiple health classes at any point in time, this specification also imposes the assumption that property buyers and sellers can decompose overall hemlock health impacts into impacts associated with specific health classes.

In general, the hedonic price model is specified by linking the variation in prices of residential properties with the variation in measured attributes using linear regression methods. A semilogarithmic hedonic price function can be specified as

$$\ln(\mathbf{P}_{it}) = \mathbf{Z}_{it}\boldsymbol{\beta} + \boldsymbol{\tau}_t + \boldsymbol{\varepsilon}_i, \qquad (1)$$

where $\ln(\mathbf{P}_{it})$ is an $N \times 1$ vector of the natural log of price for parcel i in year t, $\mathbf{Z}$ is an $N \times M$ matrix containing explanatory variables, $\boldsymbol{\beta}$ is an $M \times 1$ vector of parameter estimates, $\boldsymbol{\tau}_t$ is a vector of parameters associated with $T - 1$ dummy variables that capture temporal price inflation for all parcels sold in year t (relative to a base year), and $\boldsymbol{\varepsilon}$ is an $N \times 1$ vector of errors, which are distributed normally with zero mean and variance of σ^2 [4]. The semilogarithmic functional form is widely used in applied research and yields the interpretation that estimated model parameters represent the proportional change in price resulting from a unit change in the associated explanatory variable.

The impact of hemlock decline on property value in the cross-section model can then be specified as

$$\ln(\mathbf{P}_{it}) = \mathbf{Z}_{it}\boldsymbol{\beta} + \boldsymbol{\tau}_t + \mathbf{H}_{it}\boldsymbol{\theta} + \boldsymbol{\varepsilon}_i, \qquad (2)$$

where $\mathbf{H}_{it}$ is a $N \times 4$ matrix containing data on hemlock health classes (healthy, moderate decline, severe decline, and dead), and $\boldsymbol{\theta}$ is a 4×1 vector of parameters that capture the impact of hemlock health status on the logarithm of sales price.

Difference-in-Difference Hemlock Health Model

A second framework for computing changes in economic welfare due to hemlock decline is the difference-in-difference model. In contrast to the cross-section model, this specification does not impose the assumption that the economic impact of hemlock health classes remains constant over time or that buyers and sellers can decompose the overall impact of hemlock decline into impacts associated with specific hemlock health classes. Rather, this specification is based on the idea that a gradual reduction in forest health will have a benign impact on property values until a threshold is reached at which point property values decline (the period of impact). Thus, this model specification takes a more holistic view of the impact of hemlock health on residential property transactions, suggesting that buyers and sellers take account of the overall health of hemlocks (or, more generally, the landscape condition) on parcels and within neighborhoods when making property transactions.

To understand this model, let $P^{\mathrm{h,tb}}$ represent the price of a parcel either containing hemlock (h) cover or a parcel located within the neighborhood of a hemlock-containing parcel, during years (t) in which the change in hemlock health is benign (b). Let $P^{\mathrm{h,tn}}$ represent the price of a parcel either containing hemlock cover or a parcel located within its proximity, during years (t) in which the change in hemlock health induces a nonoptimal (n) bundle of attributes for property owners. Further, let $P^{\mathrm{nh,tb}}$ represent the price of a nonhemlock parcel or a parcel located within the proximity of a nonhemlock parcel, during period tb (as described above). Finally, let $P^{\mathrm{nh,tn}}$ represent the price of a nonhemlock parcel or a parcel located within its proximity during period tn. Then, the welfare loss due to hemlock decline can be expressed as

$$\{\mathrm{E}[P^{\mathrm{h,tb}}|\mathbf{Z}] - \mathrm{E}[P^{\mathrm{h,tn}}|\mathbf{Z}]\} - \{\mathrm{E}[P^{\mathrm{nh,tb}}|\mathbf{Z}] - \mathrm{E}[P^{\mathrm{nh,tn}}|\mathbf{Z}]\}, \qquad (3)$$

where $\mathrm{E}[\cdot]$ is the expectations operator and Z is a vector containing household and landscape attributes.

The first expression on the left-hand side of Equation 3 represents the difference in price for parcels influenced by hemlock resources before and after the impacts of hemlock decline are registered in the market. The second expression represents the difference in price for parcels that do not have or are not located in the proximity of hemlock cover types and represents the overall changes in market conditions during the study period.

The impact of hemlock decline on property value in the difference-in-difference model is specified using two related variables. The first variable, $\mathrm{HEMLOCK}_{\mathrm{it}}$, specifies the total area of hemlock trees on parcels or within the defined spatial buffers sold throughout the entire period covered by the data record. A second hemlock variable, $\mathrm{HWA\_IMPACT}_{\mathrm{it}}$, is specified to evaluate the impact of hemlock decline at the point in time at which holding hemlock stands becomes nonoptimal (from the sellers perspective) [5]. Adding these variables to Equation 1, the specification of the hedonic price equation is now

$$\ln(\mathbf{P}_{it}) = \mathbf{Z}_{it}\boldsymbol{\beta} + \boldsymbol{\tau}_t + \varphi\mathrm{HEMLOCK}_{it} + \delta\mathrm{HWA\_IMPACT}_{it} + \boldsymbol{\varepsilon}_i, \qquad (4)$$

where φ registers the marginal influence of hemlock forest cover on parcel price and δ registers the impact of hemlock decline relative to hemlock stands sold during the benign period [6].

Spatial Error Models

The assumption that the error term ε in Equations 2 and 4 is distributed normally with zero mean and variance of σ^2 is often violated when property value transactions are analyzed. Because the empirical specifications in Equation 2 and 4 cannot include all of the factors that influence property prices, omitted variables and their associated bias are relevant empirical issues (Kuminoff et al. 2009). We estimated spatial error models in response to concerns over omitted variables that are likely to be spatially correlated, such as unobserved neighborhood attributes. If spatial error dependence is present but ignored in the model specification, ordinary least-squares regression will produce unbiased parameter estimates, but the standard errors associated with these estimates will be biased (inefficient). Thus, parameter estimates that are, in fact, statistically significant may appear as insignificant if spatial errors are ignored (and vice versa).

One approach to handling spatially correlated errors is to construct a spatial weights matrix to provide structure for the error dependencies (Anselin 1988). This strategy has been used in previous hedonic property value studies (Holmes et al. 2006, Donovan et al. 2007), and we use this strategy in the current study. In general, the spatial error model can be specified as modifying the errors shown in Equation 2 (for the cross-section model) and Equation 4 (for the difference-in-difference model) as a spatial autoregressive process:

$$\boldsymbol{\varepsilon} = \lambda \mathbf{W} \boldsymbol{\varepsilon} + \mu, \tag{5}$$

where $\mathbf{W}$ is a N $\times$ N spatial weights matrix, λ is the parameter estimate on $\mathbf{W}$, and μ is the independent and identically distributed equation error [7]. The spatial error models for the cross-section and difference-in-difference specifications were estimated using GeoDa software (Anselin et al. 2006).

The construction of the spatial weights matrix is problematic when cross-section observations are unequally distributed across space, as is typical in property value studies. The specification chosen by the analyst for the spatial weights matrix can cause differences in parameter estimates, and it is difficult to test among alternative specifications for this matrix (Bell and Bockstael 2000). For the data used in our analysis, two problems arise in the specification of $\mathbf{W}$ shown in Equation 5. First, property value transaction data used in our study are, indeed, unequally distributed across space. For the analysis reported here, $\mathbf{W}$ is specified using the minimum (arc) distance for which each parcel has a neighbor. Second, the transactions data used in our analysis contain many repeat sales of individual properties. The presence of many repeat sales in our data (roughly one-third of the recorded transactions) did not allow us to discard those observations. Instead, this situation was handled by slightly offsetting the coordinates of parcels where repeat sales occurred to create a unique set of locations that could be used in constructing $\mathbf{W}$. However, this method differs from the standard convention of setting the diagonal elements of $\mathbf{W}$ equal to zero (i.e., unobserved spatial errors are not correlated at a single location). Although this procedure preserves the full set of observations for analysis, it will induce a high spatial autocorrelation among identical locations that have been spatially offset. By increasing the level of spatial autocorrelation among elements of $\mathbf{W}$, too much variation in the dependent variable may be attributed to omitted variables in the model specification.

Because this methodology may confound the interpretation of the econometric results, an alternative approach for handling spatially correlated errors was used. Pope (2008) and Kuminoff et al. (2009) suggested the use of a fixed-effects panel model for handling the problem of spatially correlated omitted variables. To implement this model, a vector of spatial dummy variables is specified as a vector of fixed-effects in a panel model. In our implementation of this model, omitted variables are captured using dummy variables identified by census blocks. Thus, the cross-section and difference-in-difference models, respectively, can be specified to include spatially correlated errors,

$$\ln(\mathbf{P}_{it}) = \mathbf{Z}_{it}\boldsymbol{\beta} + \boldsymbol{\tau}_t + \mathbf{H}_{it}\theta + \boldsymbol{\omega}\text{BLOCK}_{j|i} + \boldsymbol{\varepsilon}_i, \tag{6}$$

$$\ln(\mathbf{P}_{it}) = \mathbf{Z}_{it}\boldsymbol{\beta} + \boldsymbol{\tau}_t + \varphi\text{HEMLOCK}_{it} + \delta\text{HWA\_IMPACT}_{it} + \omega\text{BLOCK}_{j|i} + \boldsymbol{\varepsilon}_i, \tag{7}$$

where $\boldsymbol{\omega}$ is a vector of fixed-effects parameters and $\text{BLOCK}_{j\ i}$ is a vector of dummy variables identifying spatial neighborhoods as census block j containing parcel i. The fixed-effects parameters capture the (time-invariant) impacts of omitted neighborhood variables. The hypothesis that all of the $\boldsymbol{\omega}$ are equal can be evaluated using a likelihood ratio test (Greene 1997).

Results and Discussion

In all of the models we estimated, the spatial autocorrelation parameter estimate λ was statistically significant at the 0.01 level, providing evidence that omitted variables, related to the variation in housing prices, were spatially autocorrelated. Estimates of λ ranged from roughly 0.80 to 0.82, suggesting a high degree of spatial autocorrelation among equation errors (which may reflect, to some degree, the method used to handle repeat sales data). Further, the likelihood ratio tests on the vector of parameters $\boldsymbol{\omega}$ indicated that the fixed-effects models were statistically superior to the ordinary least-squares models with a single constant, providing further evidence that omitted variables had a systematic impact on property values. The hypothesis that all $\boldsymbol{\omega}$ estimates were equal was rejected at the 0.01 level in every model. In general, the goodness of fit statistic (adjusted R^2) suggested that the fixed-effects models were superior to the spatial error model specifications. Further, Moran's I-statistic was computed for the errors in the fixed-effects models. Results of this analysis showed that the fixed-effects models were successful in eliminating positive spatial autocorrelation in the residuals [8].

Although most of the variables representing housing characteristics were statistically significant in each model specification, some irregularities in statistical significance were noted that appeared to be related to the method by which omitted variables were handled. For example, in the models for which landscape variables were measured at the parcel level (Table 2), the variable representing a finished basement (F_BASE) was significant at the 0.01 level in the spatial error model but not significant (at the 0.10 level) in the corresponding fixed-effects models. In contrast, the variable representing the distance from New York City (DIST_NYC) was statistically different from zero at the 0.05 level in the fixed-effects model parcel model (Table 2) and at the 0.10 level in the 0.1- and 0.5-km models (Tables 2 and 3) but was not significantly different from zero at the 0.10 level in the corresponding spatial error models. Thus, we suspect that the methods used to control for the variation in housing prices induced by the spatial location of unobserved variables influenced the statistical significance of some of the parameter estimates in the model specifications.

Table 2. Spatial error and fixed-effects panel models of the determinants of housing prices with landscape variables measured at the parcel level and hemlock variables specified using cross-section and difference-in-difference models

Variables	Coefficients: cross-section, spatial error	Coefficients: cross-section, fixed effects	Coefficients: difference-in-difference, spatial error	Coefficients: difference-in-difference, fixed effects
CONSTANT	2.782 (0.515)‡	—	2.717 (0.514)‡	—
YR_BUILT	0.005 (0.000)‡	0.005 (0.000)‡	0.005 (0.000)‡	0.005 (0.000)‡
BATHS (#)	0.048 (0.007)‡	0.032 (0.008)‡	0.048 (0.007)‡	0.032 (0.008)‡
BEDROOMS (#)	0.016 (0.006)‡	0.021 (0.006)‡	0.016 (0.006)‡	0.021 (0.006)‡
LV_AREA (1,000 ft^2)	0.228 (0.009)‡	0.168 (0.011)‡	0.228 (0.009)‡	0.169 (0.011)‡
KITCHENS (#)	−0.092 (0.021)‡	−0.078 (0.024)‡	−0.092 (0.021)‡	−0.078 (0.024)‡
F_BASE (dummy)	−0.027 (0.010)‡	−0.016 (0.011)‡	−0.027 (0.010)‡	−0.017 (0.011)‡
DIST_NYC (km)	0.000 (0.000)	0.005 (0.002)†	0.000 (0.000)	0.005 (0.002)†
DIST_LAKE (km)	−0.066 (0.023)†	−0.122 (0.051)†	−0.002 (0.001)‡	−0.004 (0.002)†
WETLAND (ha)	0.015 (0.082)	0.160 (0.11)	0.010 (0.082)	0.159 (0.111)
AGRIC (ha)	1.090 (0.516)†	1.365 (0.557)†	1.045 (0.516)†	1.305 (0.557)†
HI_DEV (ha)	1.245 (0.326)‡	0.679 (0.356)†	1.228 (0.326)‡	0.662 (0.356)*
LMED_DEV (ha)	0.314 (0.040)‡	0.305 (0.047)‡	0.321 (0.037)‡	0.310 (0.047)‡
WATER (ha)	1.376 (0.423)‡	0.904 (0.511)*	1.366 (0.423)‡	0.886 (0.511)*
GRASS (ha)	−1.300 (0.504)‡	−4.928 (1.021)‡	−1.295 (0.504)‡	−4.906 (1.020)‡
CONIF (ha)	−0.297 (0.576)	−0.287 (0.623)	−0.390 (0.573)	−0.354 (0.622)
MIXED (ha)	0.126 (0.099)	0.315 (0.108)‡	0.116 (0.099)	0.302 (0.108)‡
DECID (ha)	0.044 (0.022)†	0.091 (0.031)‡	0.042 (0.022)*	0.091 (0.031)‡
HEALTHY_H (ha)	−0.079 (0.094)	−0.164 (0.113)	—	—
MODERATE_H (ha)	−0.005 (0.151)	−0.072 (0.162)	—	—
SEVERE_H (ha)	**0.358 (0.158)**†	0.273 (0.182)	—	—
DEAD_H (ha)	**−0.314 (0.168)***	**−0.471 (0.182)**‡	—	—
HEMLOCK (ha)	—	—	0.032 (0.072)	−0.071 (0.092)
HEM_IMPACT (ha)	—	—	−0.173 (0.111)	**−0.229 (0.121)***
λ	0.803 (0.036)‡	—	0.798 (0.037)‡	—
Adjusted R^2	0.60	0.67	0.60	0.67
N	4,373	4,373	4,373	4,373

SE are in parentheses. Parameter estimates related to hemlock health that are significant at the 0.10 level or lower are indicated in bold. Parameter estimates on dummy variables for the year of sale (1992–2001) were all significantly different from zero at the 0.01 level, and are available from the authors upon request.
* Significance at the 0.10 level.
† Significance at the 0.05 level.
‡ Significance at the 0.01 level.

Given this recognition of the subtle influence that methods used to control for spatial correlation of omitted variables can have on econometric analysis, the consistency of results across alternative methods for handling spatial correlation can provide an indication of the robustness of the empirical results. Further, although the spatial scale at which landscape variables are most salient in the determination of residential property values is not generally known and remains an empirical question, consistency of results across spatial scales will provide a further indication of robustness in the interpretation of results.

All of the landscape variables included in the model specifications, except WETLAND, were statistically different from zero at the 0.10 level or lower in at least one of the model specifications. Notably, the parameter estimate on the landscape characteristic representing the area of a lake, pond, or stream on a parcel or within its proximity (WATER) was significantly different from zero in 10 of the 12 model specifications. The importance of water in determining property values was further demonstrated by the fact that in 9 of the 12 model specifications, the parameter estimate on the distance from the parcel centroid to the nearest water body (DIST_LAKE) was statistically significant at the 0.10 level or lower.

The statistical significance of the parameters associated with various landscape characteristics was found to vary in several instances across the spatial scales at which those variables were measured. For example, the parameters on the variable representing the area of coniferous forest species (CONIF) were not different from zero when measured at the parcel level (Table 2), significant (and positive) in all model specifications when measured at the 0.1 km level (Table 3), and significant (positive) in two of the four model specifications measured at the 0.5-km level. These results suggest that residential property owners in this market favor (nonhemlock) coniferous species within their neighborhood, but not on their parcel. In contrast, the empirical results (Table 2) suggest that property owners prefer a high level of development (HI_DEV) on their own parcel (representing factors such as driveways, decks, and swimming pools) but dislike a high degree of development within their neighborhood (Table 4).

Turning to the impact of hemlock decline on property value transactions, we note a broad consistency of results across the model specifications. The parameter estimates from the cross-section model specifications demonstrate that the parameter estimates associated with the area of dead hemlocks (DEAD_H) were statistically different from zero (at the 0.10 level or lower) in four of the six model specifications. Dead hemlocks consistently had a negative impact

Table 3. Spatial error and fixed-effects panel models of the determinants of housing prices with landscape variables measured within a 0.1-km neighborhood of parcel centroid and hemlock variables specified using cross-section and difference-in-difference models

Variables	Coefficients: cross-section, spatial error	Coefficients: cross-section, fixed-effects	Coefficients: difference-in-difference, spatial error	Coefficients: difference-in-difference, fixed-effects
CONSTANT	2.376 (0.525)‡	—	2.387 (0.524)‡	—
YR_BUILT	0.005 (0.000)‡	0.005 (0.000)‡	0.005 (0.000)	0.005 (0.000)‡
BATHS (#)	0.046 (0.007)‡	0.036 (0.008)‡	0.047 (0.007)‡	0.037 (0.008)‡
BEDROOMS (#)	0.014 (0.006)‡	0.020 (0.007)‡	0.015 (0.006)‡	0.020 (0.006)‡
LV_AREA (1,000 ft^2)	0.246 (0.009)‡	0.187 (0.011)‡	0.244 (0.009)‡	0.186 (0.011)‡
KITCHENS (#)	−0.090 (0.021)‡	−0.078 (0.024)‡	−0.090 (0.021)‡	−0.077 (0.024)‡
F_BASE (dummy)	−0.038 (0.010)‡	−0.025 (0.011)†	−0.037 (0.010)‡	−0.025 (0.011)†
COST_NYC ($)	0.000 (0.000)	0.000 (0.000)*	0.000 (0.000)	0.004 (0.002)*
DIST_LAKE (km)	−0.003 (0.027)†	−0.004 (0.002)‡	0.000 (0.002)	−0.004 (0.002)†
WETLAND (ha)	0.030 (0.037)	0.005 (0.020)	0.035 (0.037)	−0.011 (0.049)
AGRIC (ha)	0.131 (0.054)†	0.016 (0.080)	0.133 (0.054)†	0.010 (0.080)
HI_DEV (ha)	0.015 (0.042)	0.005 (0.057)	0.015 (0.042)	0.004 (0.057)
LMED_DEV (ha)	0.062 (0.032)*	0.028 (0.045)	0.067 (0.032)†	0.030 (0.045)
WATER (ha)	0.203 (0.037)‡	0.103 (0.053)†	0.210 (0.037)‡	0.105 (0.053)*
GRASS (ha)	0.091 (0.044)†	0.046 (0.058)	0.099 (0.504)†	0.048 (0.058)
CONIF (ha)	0.274 (0.091)‡	0.253 (0.123)†	0.279 (0.091)‡	0.256 (0.122)†
MIXED (ha)	0.064 (0.037)*	0.095 (0.053)*	0.081 (0.037)†	0.100 (0.053)*
DECID (ha)	0.064 (0.035)*	0.041 (0.046)	0.072 (0.035)†	0.043 (0.046)
HEALTHY_H (ha)	−0.002 (0.017)	0.009 (0.026)	—	—
MODERATE_H (ha)	−0.002 (0.030)	−0.024 (0.036)	—	—
SEVERE_H (ha)	0.025 (0.020)	0.003 (0.028)	—	—
DEAD_H (ha)	**−0.047 (0.020)**†	**−0.082 (0.034)**†	—	—
HEMLOCK (ha)	—	—	0.007 (0.010)	0.004 (0.021)
HEM_IMPACT (ha)	—	—	**−0.042 (0.015)**‡	**−0.049 (0.015)**‡
λ	0.811 (0.035)‡	—	0.807 (0.035)‡	—
Adjusted R^2	0.60	0.66	0.60	0.66
N	4,373	4,373	4,373	4,373

SE in parentheses. Parameter estimates related to hemlock health that are significant at the 0.10 level or lower are indicated in bold. Parameter estimates on dummy variables for the year of sale (1992–2001) were all significantly different from zero at the 0.01 level and are available from the authors upon request.
* Significance at the 0.10 level.
† Significance at the 0.05 level.
‡ Significance at the 0.01 level.

on property value transactions when they occurred either on a parcel or within 0.1 km of the parcel centroid (four of four parameter estimates were statistically different from zero) [9]. Conversely, dead hemlocks did not convey an impact on property price when located within 0.5 km of the parcel centroid [10]. These results are complemented by results from the difference-in-difference models. In these model specifications, the parameter estimates on the variable specifying the time period during which hemlock decline conveyed a reduction in property values (HEM_IMPACT) were statistically significant in five of the six model specifications (and the parameter estimate was significant at the 0.12 level in the remaining model specification).

These results demonstrate that hemlock decline in this housing market had a negative impact not only on parcels where hemlock stands were located but also on neighboring parcels that were devoid of hemlock trees. These spillover effects suggest that hemlock decline is a public bad. Further, although our results suggest that the economic losses due to hemlock decline are largely driven by the presence of dead hemlock trees on parcels and within neighborhoods, after a certain period of time other dynamic factors come into play. That is, once the stage of hemlock decline reaches a threshold level, as captured in the difference-in-difference model by a temporal reference point, all hemlock-related transactions impart a negative impact on property prices. During this period of impact, which is anticipated to extend beyond the period of time recorded in this study, all hemlock stands, regardless of health category, are viewed as an undesirable landscape feature. This shift in value may reflect the perception that all hemlocks in the residential forest matrix will ultimately exhibit premature mortality.

The per unit area loss in property value due to a decline in hemlock health can be computed by multiplying the parameter estimates associated with Dead_H in the cross-section model and HEM_IMPACT in the difference-in-difference model, by the average property value. Then, the aggregate economic losses to properties sold in West Milford townships due to HWA can be estimated by multiplying the per unit area losses by the area of hemlock stands on properties sold during the period of impact (Table 5) [11]. These estimates represent a lower bound of the loss in economic welfare in this housing market due to hemlock decline, as they do not include welfare impacts on properties that sustained hemlock-related losses but were not sold.

As can be seen in Table 5, specific model specifications had systematic impacts on estimates of economic losses. In particular, economic losses estimated using the fixed-effects model specifications were consistently larger than the losses estimated using the spatial error model (except for the

Table 4. **Spatial error and fixed-effects panel models of the determinants of housing prices with landscape variables measured within a 0.5-km neighborhood of parcel centroid and hemlock variables specified using cross-section and difference-in-difference models**

Variables	Coefficients: cross-section, spatial error	Coefficients: cross-section, fixed-effects	Coefficients: difference-in-difference, spatial error	Coefficients: difference-in-difference, fixed-effects
CONSTANT	2.354 (0.603)‡	—	2.381 (0.600)‡	—
YR_BUILT	0.005 (0.000)‡	0.005 (0.000)‡	0.005 (0.000)‡	0.005 (0.000)‡
BATHS (#)	0.049 (0.007)‡	0.035 (0.008)‡	0.049 (0.007)‡	0.036 (0.008)‡
BEDROOMS (#)	0.014 (0.006)‡	0.019 (0.007)‡	0.014 (0.006)‡	0.019 (0.006)‡
LV_AREA (1,000 ft^2)	0.245 (0.009)‡	0.187 (0.011)‡	0.244 (0.009)‡	0.187 (0.011)‡
KITCHENS (#)	−0.084 (0.021)‡	−0.068 (0.024)‡	−0.084 (0.021)‡	−0.067 (0.024)‡
F_BASE (dummy)	−0.035 (0.010)‡	−0.024 (0.011)†	−0.034 (0.010)‡	−0.024 (0.011)†
COST_NYC ($)	0.000 (0.000)	0.004 (0.002)*	0.000 (0.000)	0.004 (0.002)*
DIST_LAKE (km)	−0.001 (0.001)	−0.004 (0.002)‡	−0.001 (0.001)	−0.004 (0.002)‡
WETLAND (ha)	0.005 (0.005)	−0.005 (0.008)	0.005 (0.040)	−0.004 (0.008)
AGRIC (ha)	0.010 (0.005)†	0.001 (0.001)	0.010 (0.005)†	0.001 (0.010)
HI_DEV (ha)	−0.002 (0.004)	−0.019 (0.010)*	0.001 (0.004)	−0.018 (0.010)*
LMED_DEV (ha)	0.005 (0.005)	0.004 (0.008)	0.005 (0.002)†	−0.003 (0.008)
WATER (ha)	0.010 (0.005)‡	−0.001 (0.008)	0.010 (0.004)‡	−0.000 (0.008)
GRASS (ha)	0.001 (0.007)	0.006 (0.012)	0.001 (0.007)	0.005 (0.012)
CONIF (ha)	0.012 (0.007)*	0.004 (0.012)	0.012 (0.007)*	0.004 (0.012)
MIXED (ha)	0.005 (0.005)	−0.002 (0.008)	0.007 (0.004)*	0.001 (0.008)
DECID (ha)	0.005 (0.005)	0.005 (0.008)	0.004 (0.004)	−0.004 (0.008)
HEALTHY_H (ha)	0.000 (0.000)	**0.004 (0.002)***	—	—
MODERATE_H (ha)	−0.000 (0.002)	0.004 (0.003)	—	—
SEVERE_H (ha)	0.000 (0.002)	0.002 (0.003)	—	—
DEAD_H (ha)	−0.002 (0.002)	0.000 (0.003)	—	—
HEMLOCK (ha)	—	—	0.000 (0.000)	0.003 (0.002)
HEM_IMPACT (ha)	—	—	**−0.001 (0.000)**‡	**−0.002 (0.001)**†
λ	0.819 (0.033)‡	—	0.818 (0.034)‡	—
Adjusted R^2	0.60	0.66	0.60	0.66
N	4,373	4,373	4,373	4,373

SE are in parentheses. Parameter estimates related to hemlock health that are significant at the 0.10 level or lower are indicated in bold. Parameter estimates on dummy variables for the year of sale (1992–2001) were all significantly different from zero at the 0.01 level and are available from the authors upon request.
* Significance at the 0.10 level.
† Significance at the 0.05 level.
‡ Significance at the 0.01 level.

Table 5. **Aggregate economic losses on properties sold in West Milford township, New Jersey, under alternative model specifications**

Landscape scale	Cross-section: Dead trees: hemlock area (ha)	Cross-section: Loss/ha (total loss $): Spatial error	Cross-section: Loss/ha (total loss $): Fixed-effects	Difference-in-difference: Period of impact: hemlock area (ha)	Difference-in-difference: Loss/ha (total loss $): Spatial error	Difference-in-difference: Loss/ha (total loss $): Fixed-effects
Parcel	11.45	55,781 (638,730)	83,798 (959,546)	20.64	NS	40,734 (840,774)
0.1 km	140.71	8,345 (1,174,226)	14,571 (2,050,226)	222.87	7,467 (1,664,089)	8,798 (1,960,885)
0.5 km	2472.60	NS	NS	6027.61	350 (2,108,287)	350 (2,108,287)

Values reported in the table are total, not annual, losses. NS, parameter estimate on economic loss was not statistically different from zero at the 0.10 level or lower in the econometric model.

0.5-km neighborhood model, in which the impacts were equal). This result may be due to excess filtering of the spatially correlated omitted variables associated with the repeat sales data. The spatial error model procedure used to remove variation in the housing prices associated with spatially correlated omitted variables (to create independent observations) may have, in fact, removed some portion of the true independent variation induced by hemlock decline, thus lessening the estimated impact. Further, within the spatial error and fixed-effects model specifications, the economic losses associated with cross-section models were larger than the corresponding losses estimated by the difference-in-difference models. This result may be due to the fact that the cross-section models focus specifically on the impact of dead trees on housing values.

To place the aggregate economic losses reported in Table 5 in context, it is helpful to think about the average impacts on parcels, which can be computed using sample estimates of the average affected forest area within the relevant parcels. For example, in the cross-section parcel models, the average area of dead hemlock on parcels containing hemlock is roughly 0.04 ha [12]. Multiplying this area by the estimated loss per hectare yields a parcel level loss of $2,231 and $3,352 (in the spatial error and fixed-effects models, respectively). As the average price of parcels sold containing hemlocks was roughly $212,539, these losses represent 1.05 and 1.6% of the parcel price. Applying this methodology to the difference-in-difference fixed-effects parcel-level model, it was estimated that the average economic loss per parcel was $2,444 (1.2% of the parcel price). These estimates are similar to, but more conservative than, estimates of the contribution of healthy trees to residential property values in Athens, Georgia (Anderson and Cordell 1988) [13].

It is also apparent that hemlock decline and mortality cause a loss in value on properties containing hemlock stands as well as on neighboring properties. Thus, a loss of tree health is a public bad, and failure to incorporate spatial externalities in the model specifications would lead to downwardly biased estimates of economic losses. For example, the economic losses estimated by considering impacts only on properties where hemlocks occur ranged from $638,730 to $840,774. However, by including hemlock-related impacts within 0.1 km of parcel centroids, economic losses ranged from $1,174,226 to $1,960,885. Finally, economic losses on properties where hemlocks occur within 0.5 km of parcel centroids were estimated to be $2,108,287 in the difference-in-difference model.

Conclusions

Within the study area, hemlock decline and mortality in naturally regenerated residential forests was associated with an economic loss equivalent to roughly 1–1.6% of the sales price for parcels containing hemlocks. In addition, changes in hemlock health consistently caused statistically significant reductions in property values on neighboring nonhemlock parcels. Severe loss of tree health in residential forest settings is a public bad, and economic models need to recognize negative spillovers when economic impact assessments are conducted.

Despite the fact that hemlock stands are a relatively rare landscape feature in our study area, precise identification of the location of hemlock resources using remote sensing data, combined with the use of spatial econometric methods to control for spatial autocorrelation of omitted variables, resulted in a consistent set of economic loss estimates. As the study area used in this analysis represents a sample drawn from a population of residential forest sites that are experiencing hemlock decline, it is anticipated that similar methods could be used to estimate economic losses in other locations. A better understanding of how parameter values associated with changes in forest health vary across housing markets and forest types would provide a more robust foundation for estimating the overall impacts of forest invasive species on residential property values.

Spatial econometric analyses that control for spatially correlated variables that are not included in model specifications appear to be essential for isolating economic impacts associated with relatively rare landscape features. We suggest that further research is needed to refine these methods so that the most efficient and unbiased estimates of economic losses can be obtained. For example, future researchers should evaluate the relationship between the scale at which spatial correlation among omitted variables is specified and the resulting parameter estimates, whether using spatial error or fixed-effects models. In addition, robust methods are needed to conduct spatial econometric analyses of hedonic property value data in situations in which many repeat observations are included in the analysis.

The time span used in the analysis reported here covered 11 years. Although this is a relatively long period for a hedonic price study, it was deemed necessary because changes in hemlock health in response to an HWA infestation take a long time to develop (unlike other natural disturbances, such as wildfires). Although we were able to account for housing price inflation and changes in landscape characteristics during the period of analysis, future researchers should consider improved methods for handling the long time periods required for the economic analysis of pest impacts on residential property values.

Forest invasive species can affect a suite of goods and services valued by people. This study demonstrates that non-native forest pests can produce large economic losses to private property owners in residential forests. Other non-native forest pests, such as sudden oak death and the emerald ash borer, appear poised to cause major losses to residential property owners along the California coast and in the mid-western United States, respectively. A full accounting of the current and imminent economic losses due to the full constellation of non-native forest pests is essential for the development of informed policy that can meaningfully address the economic and ecological threats imposed by these ongoing threats to forest health.

Endnotes

[1] The HWA also occurs in western North America where it was probably introduced during the 1920s, although some evidence suggests that HWA may be native to this region.

[2] Two minor classes were omitted from the analysis: bare land and scrub.

[3] Ground-truth evaluations were conducted by evaluating hemlock canopy conditions for 142 field plots in northern New Jersey. Accuracy was 82%. Defoliated hemlocks were detected in the 1992 image, although it is uncertain precisely when the infestation began.

[4] Alternatively, housing prices could be deflated before model estimation using a statewide housing price index. In the analyses reported here, parameter estimates on the year-of-sale dummy variables were very highly correlated with the New Jersey house price index reported by the Federal Reserve Bank of St. Louis.

[5] The relevant time period for this impact variable is identified by interacting a dummy variable representing the impact period with the variable HEMLOCK. As defined in Equation 3, this impact period is designated as tn.

[6] The empirical specification can be linked to the difference-in-difference model by substituting the notation shown in 4 into Equation 3: $[(\varphi + \tau_{tb}) - (\delta + \varphi + \tau_{tn})] - [\tau_{tb} - \tau_{tn}]$ = the welfare loss $= -\delta$. It is anticipated that the sign on $\delta > 0$. Therefore, the welfare *loss* is expected to be positive.

[7] For each property transaction location (row), the positive and symmetric matrix **W** identifies those locations (columns) that belong to its neighborhood. The weight matrix was specified using a minimum distance so that each observation included at least one neighbor, and the rows of **W** were standardized so that the sum of the cells in each row equaled unity. The weights matrix acts to provide a spatially weighted average of values occurring in the neighborhood of each location. Fixed weights were used for the spatial average.

[8] Moran's I-statistics were computed using ARCGIS 9 software. We note that, although the fixed-effects models were successful in eliminating positive spatial autocorrelation of the residuals, a very small degree of negative spatial correlation remained.

[9] We note that the parameter estimates on healthy hemlocks (HEALTHY_H) were not statistically different from zero at conventional levels of significance in these model specifications. Thus, there appears to be an asymmetric impact of healthy versus unhealthy trees on property values at these spatial scales.

[10] The parameter estimate on healthy hemlocks (HEALTHY_H) was positive and statistically different from zero at the 0.10 level in this model specification. This result is asymmetric with the impact of unhealthy trees on property values at this spatial scale.

[11] The average loss per affected household is computed as Household loss = (average property value) × (% loss due to hemlock decline, per ha) × (average no. ha per impacted household). Then, the loss to the community is computed as Total loss = (Household loss) × (total no. households impacted). The average number of ha per affected household is computed as (Total hemlock ha affecting households)/(total no. households affected). Thus, the total loss to the community is computed as (average property value) × (% loss per ha) × (Total hemlock ha affecting households).

[12] The average size of a parcel containing hemlock was roughly 0.36 ha. Thus, dead hemlocks covered roughly 11% of the parcel, on average.

[13] Anderson and Cordell (1988) estimated that landscaping with trees increased the sales value of residential property in Athens, Georgia, by roughly 3.5–4.5%.

Literature Cited

ACHARYA, G., AND L.L. BENNETT. 2001. Valuing open space and land use patterns in urban watersheds. *J. Real Estate Finan. Econ.* 22(2/3):221–237.

ANDERSON, L.M., AND H.K. CORDELL. 1988. Influence of trees on residential property values in Athens, Georgia (U.S.A.): A survey based on actual sales prices. *Landsc. Urban Plan.* 15(1):153–164.

ANSELIN, L. 1988. *Spatial econometrics: Methods and models.* Kluwer Academic Publishers, Dordrecht, The Netherlands. 304 p.

ANSELIN, L., I. SYABRI, AND Y. KHO. 2006. GeoDa: An introduction to spatial data analysis. *Geog. Anal.* 38(1):5–22.

AUKEMA, J., D.G. MCCULLOUGH, B. VON HOLLE, A. LIEBHOLD, K. BRITTON, AND S. FRANKEL. 2010. *Temporal accumulation of nonindigenous forest pests in the continental U.S.* Working Paper, National Center for Ecological Analysis and Synthesis, Santa Barbara, CA. 24 p.

BELL, K.P., AND N.E. BOCKSTAEL. 2000. Applying the generalized-moments estimation approach to spatial problems involving microlevel data. *Rev. Econ. Stat.* 82(1):72–82.

BENSON, E.D., J.L. HANSEN, A.L. SCHWARTZ, AND G.T. SMERSH. 1998. Pricing residential amenities: The value of a view. *J. Real Estate Finan. Econ.* 16(1):55–73.

BROCKERHOFF, E.G., J. BAIN, M. KIMBERLEY, AND M. KNÍCEK. 2006. Interception frequency of exotic bark and ambrosia beetles (Coleoptera: Scolytinae) and relationship with establishment in New Zealand and worldwide. *Can. J. For. Res.* 36:289–298.

BRUSH, R.O. 1979. The attractiveness of woodlands: Perceptions of forest landowners in Massachusetts. *For. Sci.* 25(4): 495–506.

DOMBROW, J.M.R., AND C.F. SIRMANS. 2000. The market value of mature trees in single-family housing markets. *Appr. J.* 68(1):39–43.

DONOVAN, G.H., P.A. CHAMP, AND D.T. BUTRY. 2007. Wildfire risk and housing prices: A case study from Colorado Springs. *Land Econ.* 83(2):217–233.

GARROD, G., AND K. WILLIS. 1992. The amenity value of woodland in Great Britain: A comparison of economic estimates. *Environ. Res. Econ.* 2(4):415–434.

GENERAL ACCOUNTING OFFICE. 2006. *Invasive forest pests: Lessons learned from three recent infestations may aid in managing future efforts.* General Accounting Office, Washington DC. 118 p.

GEOGHEGAN, J. 2002. The value of open spaces in residential land use. *Land Use Policy* 1991(1):91–98.

GEOGHEGAN, J., WAINGER, L.A., AND N.E. BOCKSTAEL. 1997. Spatial landscape indices in a hedonic framework: An ecological economics analysis using GIS. *Ecol. Econ.* 23(2):251–264.

GREENE, W.H. 1997. *Econometric analysis.* 3rd ed. Prentice Hall, Upper Saddle River, NJ. 1075 p.

HAACK, R.A. 2006. Exotic bark- and wood-boring Coleoptera in the United States: Recent establishments and interceptions. *Can. J. For. Entomol.* 36(2):269–288.

HOLMES, T.P., J. AUKEMA, B. VON HOLLE, A. LIEBHOLD, AND E. SILLS. 2009. Economic impacts of invasive species in forests: Past, present and future. *Ann. NY Acad. Sci.* 1162:18–38.

HOLMES, T.P., E.A. MURPHY, AND K.P. BELL. 2006. Exotic forest insects and residential property values. *Ag. Res. Econ. Rev.* 35(1):155–166.

HOWARD, T., P. SENDAK, AND C. CODRESCU. 2000. Eastern hemlock: A market perspective. P. 161–166 in *Proc. of symp. on Sustainable management of hemlock ecosystems in eastern North America.* US For. Serv. Gen. Tech. Rep. GTR-NE-267.

IRWIN, E. 2002. The effects of open space on residential property values. *Land Econ.* 78(4):465–480.

KUMINOFF, N.V., C.F. PARMETER, AND J.C. POPE. 2009. *Averting hidden danger: Developing hedonic specifications that mitigate omitted variable bias.* Working Paper, Applied Economics, Virginia Tech, Blacksburg, VA.

LATHROP, R.G. 2000. *New Jersey land cover change analysis project.* Center for Remote Sensing and Spatial Analysis, Cook College, Rutgers University, New Brunswick, NJ. 34 p.

LEVINE, J.M., AND C.M. D'ANTONIO. 2003. Forecasting biological invasions with increasing international trade. *Conserv. Biol.* 17(1):322–326.

LIEBHOLD, A.M., W.L. MACDONALD, D. BERGDAHL, AND V.C. MASTRO. 1995. Invasion by exotic forest pests: A threat to forest ecosystems. *For. Sci. Mon.* 30:1–49.

MATTSON, W.J., P. NIEMELA, I. MILLERS, AND Y. INGUANZO. 1994. *Immigrant phytophagous insects on woody plants in the United States and Canada: An annotated list.* US For. Serv. Gen. Tech. Rep. NC-GTR-169. 27 p.

MCCULLOUGH, D.G., T.T. WORK., J.F. CAVEY, A.M. LIEBHOLD, AND D. MARSHALL. 2006. Interceptions of nonindigenous plant pests at US ports of entry and border crossings over a 17-year period. *Biol. Invasions.* 8(4):611–630.

MORALES, D., B.N. BOYCE, AND R.J. FAVRETTI. 1976. The contribution of trees to residential property values: Manchester, Connecticut. *Valuation* Oct/Nov:26–43.

MUMFORD, J.D. 2002. Economic issues related to quarantine in international trade. *Eur. Rev. Agric. Econ.* 29(2):329–348.

PALMQUIST, R.B. 1991. Hedonic methods. P. 77–120 in *Measuring the demand for environmental quality*, Braden, J. B. and D.D. Kolstad (eds.). Elsevier, New York, NY.

PATTERSON, R.W., AND K.J. BOYLE. 2002. Out of sight, out of mind? Using GIS to incorporate visibility in hedonic property value models. *Land Econ.* 78(3):417–425.

PAYNE, B.R., W.B. WHITE, R.E. MCCAY, AND R.R. MCNICHOLS. 1973. *Economic analysis of the Gypsy Moth problem in the Northeast: II. Applied to residential property.* US For. Serv. Res. Paper NE-285. 6 p.

PERRINGS, C., E.B. BARBIER, M. WILLIAMSON, D. DELFINO, S. DALMAZZONE, J. SHOGREN, P. SIMMONS, AND A. WATKINSON. 2002. Biological invasion risks and the public good: An economic perspective. *Conserv. Ecol.* 6(1):1.

PIEL, F., M. GILBERT, C. DE CANNIÈRE, AND J.-C. GRÉGOIRE. 2008. Coniferous round wood imports from Russia and Baltic countries to Belgium. A pathway analysis for assessing risks of

exotic pest insect introductions. *Divers. Distrib.* 14(2): 318–328.
PIMENTEL, D., L. LACH, R. ZUNIGA, AND D. MORRISON. 2000. Environmental and economic costs of nonindigenous species in the United States. *Bioscience* 50(1):53–65.
POPE, J.C. 2008. Do seller disclosures affect property values? Buyer information and the hedonic model. *Land Econ.* 84(4):551–572.
POWE, N.A., GARROD, G.D., AND WILLIS, K.G. 1995. Valuation of urban amenities using an hedonic price model. *J. Property Res.* 12(1):137–147.
ROYLE, D.D., AND R.G. LATHROP. 1997. Monitoring hemlock forest health in New Jersey using Landsat TM data and change detection techniques. *For. Sci.* 4(3) 3:327–335.
ROYLE, D.D., AND R.G. LATHROP. 2002. Discriminating *Tsuga canadensis* hemlock forest defoliation using remotely sensed change detection. *J. Nematol.* 34(2):213–221.
SNYDER, S.A., M.A. KILGORE, R. HUDSON, AND J. DONNAY. 2007. Determinants of forest land prices in Northern Minnesota: A hedonic pricing approach. *For. Sci.* 53(1):25–36.
TAYLOR, L.O. 2003. The hedonic method. P. 331–394 in *A primer on nonmarket valuation*, Champ, P. A., Boyle, K. J. and T.C. Brown (eds.). Kluwer Academic Publishers, Dordrecht, The Netherlands.
THORSNES, P. 2002. The value of a suburban forest preserve: Estimates from sales of vacant residential building lots. *Land Econ.* 78(3):426–441.
TYRVÄINEN, L., AND A. MIETTENEN. 2000. Property prices and urban forest amenities. *J. Environ. Econ. Manag.* 39(2): 205–223.
WORK, T.T., D.G. MCCULLOUGH, J.F. CAVEY, AND R. KOMSA. 2005. Arrival rate of nonindigenous insect species into the United States through foreign trade. *Biol. Invasions.* 7(2): 323–332.