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Property value effects of the Hemlock wooly adelgid infestation in New England, U.S.A.

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ABSTRACT

We investigate residential property-price effects of the spread of the Hemlock wooly adelgid infestation northward through central portions of Connecticut and Massachusetts, USA. We find that hemlock trees and the accompanying adelgid infestation within 0.1 km buffers of properties affect sale prices, but the results do not extend to buffers of 0.5 and 1.0 km's. Further, within the 0.1 km buffer, only the healthiest hemlock trees contribute positively to property values. We investigated the robustness of the results to three data interpolation methods, Kriging, Inverse Distance Weighting and Spline, and while there was some minor difference in outcomes the results are robust to these interpolation methods. Two property-price models were estimated, a traditional hedonic model with spatial fixed effects and a repeat sale model. The models provide substantially different property-price impacts and care needs to be taken when interpreting these estimates. Both approaches are limited but in different ways; the hedonic by potentially omitted variables and the repeat-sales by a limited number of observations. Our results provide some support for the repeat-sale model as the hedonic model with spatial fixed effects underperformed when both models were estimated using the same data.

1. Introduction

According to Lovett et al. (2016), ~2.5 non-native pests per year have been established in U.S. forests over the last 150 years and have “eliminated entire tree species or genera from United States forests within decades” (p. 1437). Such infestations that many may be aware of include, but not limited to, chestnut blight, Dutch elm disease, emerald ash borer, European gypsy moth and mountain pine beetle. Aukema et al. (2011) report that complete costs of these forest pest infestations are unknown but, in the case of three categories of forest pest, the greatest costs of the infestations are borne by homeowners. Beyond economic costs, Jones (2017) finds that the emerald ash borer significantly reduced the life satisfaction of residents of affected U.S. counties. Although Holmes and Koch (2019) also found that geographically extensive forest insect outbreaks substantially diminished life satisfaction for residents in affected areas of Colorado, they highlighted the challenges of using this modeling approach to estimate resultant changes in economic values. Given the paucity of data on the economic impacts of forest pest and evidence the impacts may be greatest for residential property owners, we investigate the property value impacts of the rapidly expanding range of the hemlock wooly adelgid (Limbu et al., 2018).

The Hemlock wooly adelgid (adelgid hereafter) is a forest pest that defoliates and ultimately kills hemlock trees within about five years (Brush, 1979; McClure, 1991; Orwig et al., 2012). First introduced into Virginia from Japan in the early 1950s, the adelgid now threatens Eastern hemlock forests in New England (McClure, 1991). The adelgid is sensitive to temperature and precipitation, and climate change is expected to have favored the northward spread of the adelgid (Orwig et al., 2012).

The Eastern hemlock (*Tsuga canadensis*) matures at a height of 40 to 70 ft with a canopy width of 25 to 35 ft. These trees can be a dominant feature in the residential landscape providing shade, a scenic resource, buffers between properties and more. On the other hand, as infested

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trees die, they can become a scenic blight and a risk to residences and people from falling limbs. Information on the effect of hemlock trees on residential property prices provides important economic information on the benefits of removing infested trees and protecting healthy trees from infestation.

Here we estimate a hedonic model to investigate the effect of declining hemlock health on residential property values. The advent and accessibility of spatial data has greatly advanced the richness of information available to explore the impacts of spatially explicit features, such as the adelgid infestation, on property sale prices (Bateman et al., 2002; Geoghegan et al., 1997; Hamilton and Morgan, 2010; Lake et al., 2000; Paterson and Boyle, 2002). We have two unique and complementary data sets that are merged with property sale data. The first is spatial data documenting 6126 hemlock stands located in central Connecticut and central Massachusetts. Second, is entomological data from sampled hemlock stands in this study area that records the damage caused by the adelgid. Spatial interpolation is used to scale the entomological sample data to all hemlock stands in the study area.

We also investigate the robustness of hedonic-coefficient estimates to three common data interpolation procedures, adelgid defoliation of hemlock stands within 0.1, 0.5 and 1.0 km of properties, and estimation using a traditional hedonic model and a repeat-sales model. Different spatial interpolation procedures use slightly different data smoothing methods (Anselin and Le Gallo, 2006; Kuntz and Helbich, 2014). With limited guidance from the literature on the best approach to use, we consider the robustness of hedonic estimates to the use of Ordinary Kriging, Inverse Distance Weighting, and Spline interpolation methods. Likewise, there is limited guidance from the literature on how close hemlock trees need to be to a property to have a price effect and we, therefore, consider hemlock stands within three buffers around sold properties. The repeat-sale model has a desirable identification property for estimating the capitalized impact of the adelgid infestation of hemlock stands on property values, yet with a much smaller number of property transactions available for estimation than with a traditional hedonic model.

We found that infested hemlock stands within the 0.1 k buffer reduced the capitalized values of single-family residences and this result was robust to data interpolation method and estimation using the traditional hedonic and repeat-sale estimation. Only hemlock stands with limited defoliation due to the adelgid (0–25%) contribute positively to property values. When we consider the capitalized depreciation of property values due to the adelgid infestation, the hedonic model reveals a modest capitalized-value reduction of 0.2% or about $650 for the average-valued property while the repeat-sale model reveals a capitalized-value decrease of 15% or about $39,600 for a comparable property. While the repeat-sale price impact may seem large, there is some statistical support for this estimate as the hedonic model underperformed when both models were estimated using the same data. Further, hemlock trees are large trees that provide shade, privacy and other amenities to property owners but can posed a significant risk to people and nearby structures from falling branches as the trees die from the adelgid infestation.

2. Previous research

We briefly discuss previous research applying hedonic models to estimate the implicit value of tree cover in residential areas. Then we move to data interpolation methods, which allow us to match adelgid, hemlock and property sales data. We close with a discussion of traditional and repeat-sale hedonic models for identifying price effects.

2.1. Previous research on tree values

Considering landscape amenities, Geoghegan et al. (1997) calculated measures of percent open space around residential properties and found that land uses surrounding a parcel have a significant influence on property prices. Cho et al. (2008) calculated the distance to nearest evergreen (conifer), deciduous and mixed forest patches for properties. They concluded that proximity to evergreen forests is valued positively in the rural–urban interface, while proximity to deciduous and mixed forest types are valued positively in the urban area. In fact, multiple papers are available in the literature that investigate the effects of trees on property values and most indicate that (healthy) trees increase property values (Mei et al., 2017; Siriwardena et al., 2016).

If trees increase property values, it is plausible that an invasive pest that degrades tree quality and ultimately kills trees will diminish property values. It has been predicted that changes in climate will increase the frequency, severity, duration and geographical extent of natural forest disturbances such as fires, insect and disease outbreaks, droughts and severe storms (Bentz, 2008; Dale et al., 2001; Frankel, 2008) and these predictions have been generally upheld (Weed et al., 2013). Advanced tree mortality can impact property values via the diminishment of ecosystem services such as the provision of shade, visual aesthetics and regulation of the hydrological cycle. Dead and dying trees also pose risks to residents and their homes. Associated property value losses have been observed for the recent mountain pine beetle infestation in the western U.S. (Cohen et al., 2016; Moeltner et al., 2017; Price et al., 2010). In an adelgid application, Holmes et al. (2010) found that severely-defoliated hemlock trees reduced the value of residential properties.

The research we report expands what is known about the effects of the adelgid on property values using site-specific measurements of the infestation at three points in time. We also cover a much larger geographic area than a single community or small region used in the studies cited above by considering the northward migration of the infestation through central portions of Connecticut and Massachusetts.

2.2. Spatial interpolation

Hedonic models typically use proximity to a property or the spatial extent within a specified buffer around a property as the environmental variables. Spatial interpolation is often used to extend known data to all property sales and various interpolation methods have been used. For example, Leggett and Bockstael (2000) used Inverse Distance Weighting, Anselin and Lozano-Gracia (2008) used Ordinary Kriging and Fernández-Avilés et al. (2012) used CoKriging. Anselin and Le Gallo (2006) compared four procedures to interpolate air quality (Inverse Distance Weighting, Ordinary Kriging, Spline and Thiessen polygons) and concluded that Ordinary Kriging worked best. Whereas, Kuntz and Helbich (2014) considered Ordinary Kriging and CoKriging and found evidence in favor of CoKriging. Such investigations of the effects of data interpolation on hedonic estimation outcomes are rare in the published literature. Anselin and Le Gallo (2006) conclude "... our findings suggest that the quality of the spatial interpolation deserves the same type of attention in the specification and estimation of hedonic house price models as more traditional concerns" (p. 50). Thus, as a robustness check, we consider three types of spatial data interpolation: Ordinary Kriging, Inverse Distance Weighting, and Spline interpolation methods.

2.3. Hedonic estimation

Traditional hedonic models regress sale prices of properties on property characteristics where the estimated coefficients provide the basis for computing the effects of changes in property characteristics on property prices (Taylor, 2017). This approach has been criticized because omitted relevant variables might confound the estimation of property-price effects (Bishop et al., 2020). As such, econometric and quasi-experimental approaches have been used to control for this concern so that the actual price effects can be identified.

As an econometric approach to address the potential for spatially correlated omitted variables we estimate a hedonic model with time and spatial fixed effects. The idea is that fixed effects that are matched with

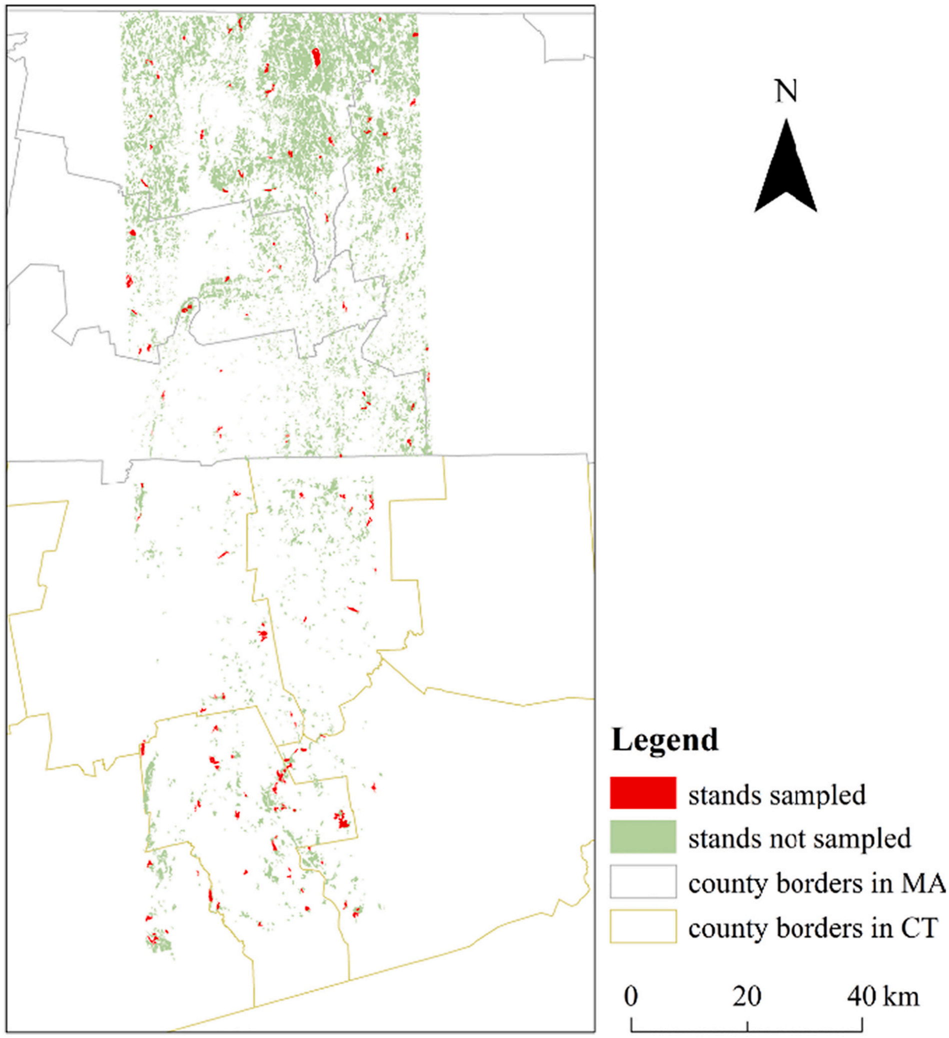

Fig. 1. Study Area Hemlock Stands.

property sale times and locations capture the influences of omitted relevant variables. While Kuminoff et al. (2010) suggest that spatial fixed effects may mitigate this concern, Abbott and Klaiber (2011) find that this may not always be the case.

Thus, we also estimate a repeat-sale model where changes in the adelgid infestation through time provide a "natural experiment" where we can observe the sale of a property at two points in time for properties that sell more than once in the study period. Thus, rather than simply regressing sale prices on the extent of the adelgid infestation, we also regress changes in sale prices on changes in the extent of the adelgid infestation. Omitted variables that are invariant through time cancel out of this model specification and thereby do not confound estimation/identification of adelgid infestation price effects. However, there are fewer observations available for estimating the repeat-sale model because most properties transact once during the study period.

Neither the traditional hedonic nor the repeat-sale hedonic are perfect. The hedonic model has the advantage of more information from more sales to use in the estimation and the repeat-sale has the advantage of the identification strategy. We apply both estimation approaches in this study.

3. Application

To understand and characterize hemlock stands at the local and landscape levels in New England, ecologists at the Harvard Forest identified, mapped and characterized hemlock stands in a 7500 km^2 transect covering central portions of Connecticut and Massachusetts (Orwig and Foster, 1998; Orwig et al., 2002). All stands of eastern hemlock with land areas greater than 1.3 ha in size were identified using high-resolution aerial photographs and digitally transferred into a GIS overlay. A total of 6126 hemlock stands were identified (see Fig. 1).

Biological sampling to document the extent of the adelgid infestation across the 6000^+ hemlock stands is expensive and logistically challenging. Consequently, 142 hemlock stands were randomly sampled within the Connecticut/Massachusetts study area and samples of hemlock health were taken within each of these stands (Gómez et al., 2015; Preisser et al., 2008). Field surveys were conducted in selected hemlock stands (red dots in Fig. 1) to document hemlock health in terms of live basal area and vigor in 2007, 2009 and 2011. Live basal area, measured as square meters per hectare at 4.5 ft above the ground, provides a systematic indication of the cross-sectional area occupied by living hemlock trees in each plot. Vigor was measured as the average amount of hemlock foliar decline in each plot. Four vigor categories were recorded: 76–99% foliar loss, 51–75% foliar loss, 26–50% foliar loss, and 0–25% foliar loss (coded as 1, 2, 3 and 4, respectively).

Both the mean and maximum value of hemlock live basal area decreased from 2007 to 2009 to 2011 (Table 1); indicating that hemlock trees were dying, or unhealthy trees were being removed during the study period. Vigor also decreased throughout the study period, indicating the adelgid infestation was increasing among the remaining

Table 1
Live Basal Area and Vigor for Sampled Hemlock Stands.

		2007	2009	2011
Live Basal Area (m^2/*ha*)	Mean	38.2	27.8	15.3
	Standard Deviation	27.6	16.3	11.9
	Min	0	0	0
	Max	125.4	73.3	54.0
	N[a]	140	138	122
			Number of Stands	
Vigor	76–99%	8	11	9
(% foliar loss)	51–75%	18	19	23
	26–50%	33	37	44
	0–25%	82	71	47
	N	141	138	123

[a] The initial number of sampling plots was 142. In 2007, data are available on live basal area for 140 of the 142 plots and vigor for 141 of the 142 plots. The sample sizes decrease over time due to some hemlock stands disappearing (trees in the stands died or unhealthy trees cut down), the land was cleared for development, or the sampling crew was not allowed follow-up access to private-land parcels.

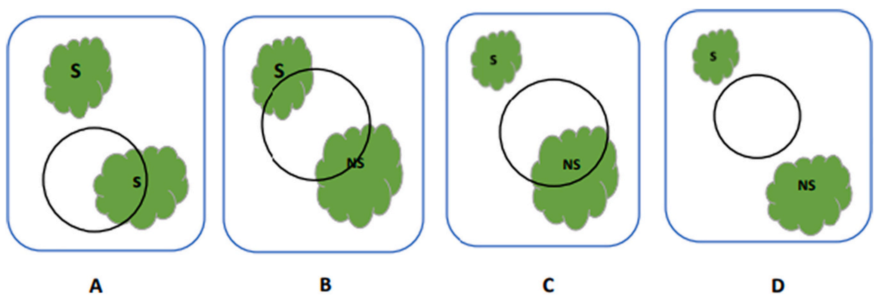

Fig. 2. Hemlock Stand Spatial Relationships to Property Buffers.
Note: S denotes a sampled hemlock stand, NS denotes a hemlock stand that was not sampled, and the black circle is the buffer around a property.

hemlock trees. The number of stands with the lowest foliar loss (0–25%) declined through time as the infestation spread. The number of severely damaged hemlock stands likely dropped in 2011 because dead trees either fell over or were removed.

The hemlock stands and adelgid infestation data were merged with property sale data from DataQuick, using circular buffers around the centroid of each parcel.[1] There is limited guidance from the literature on how close trees need to be to a property to have a price effect. Thus, as an additional robustness check we consider how estimation results change as the model reflects hemlock stands within 0.1, 0.5 and 1.0 km of properties. Stands within 0.1 k might be on or adjacent to a property. Stands within 0.5 k might be adjacent to a property or in a property's view shed. Stands within 1.0 k might be visible in people's daily activities leaving and returning to their properties. Larger buffer sizes were not considered because most hemlock stands in the study area are small and on private property. The study area is also heavily forested so landowners may not see or be aware of hemlock trees unless they are in relatively proximity to their home and neighborhood.

There are four potential spatial relationships between properties and hemlock stands (Fig. 2). In case A, the buffer only intersects sampled hemlock stands. In case B, the buffer intersects both sampled and non-sampled hemlock stands. In case C, the buffer only intersects non-sampled hemlock stands. In case D, the buffer does not intersect any hemlock stands.

Based on the sample data, we only have observed hemlock health information for case A and the number of properties potentially impacted by the adelgid infestation is small. To make maximum use of the Harvard Forest census of hemlock stands and our extensive property sale data, we interpolate hemlock health (live basal area and foliar loss) across the study area. Using interpolated hemlock health data, we are then able to enlarge the economic analysis to include cases A, B and C in Fig. 2, resulting in a much larger set of property sales for estimation.

Land cover in neighborhoods can also influence property values (Irwin, 2002; Paterson and Boyle, 2002). We constructed land cover variables from the National Land Cover Database (2006) using rasters of $30m^2$ pixels. The six types of land cover variables used for analysis include water, open space, developed, forest, agriculture, and wetland. Variables were calculated as the percentage of the buffer area (0.1 km, 0.5 km, 1 km) around each property covered by each land cover type.

These environmental data were merged with property sale data for the period 2007 to 2011. For years when adelgid sampling was not conducted (2008 and 2010), live basal area and vigor were calculated as the mean of the previous year and following year, 2007/2009 and 2009/2011. Land cover was assumed constant during the study period due to the available data.

4. Spatial interpolation

Spatial data interpolation is a family of methods to extend observed data spatially for locations where data are not available. Here we apply Ordinary Kriging, Inverse Distance Weighting and Spline interpolation methods (Chilès and Delfiner, 1999; Cressie, 1991; Franke, 1982; Goovaerts, 1997; Isaaks and Srivastava, 1989; Mitáš and Mitášová, 1988; Schabenberger and Gotway, 2005; Shepard, 1968; Stein, 1999). Each of these methods takes a slightly different approach to using known neighbor values to interpolate an unknown value.

Ordinary Kriging (Kriging hereafter) is used as the base interpolation method following the finding of Anselin and Le Gallo (2006) that this method worked best in their comparison study and has been used in

[1] Since properties are geolocated by parcel centroids and we do not have property boundary data, the assigned property buffers can contain hemlock trees on or adjacent to the owner's property. The property owner does not have control of trees that are not located on their property and likely cannot apply treatments to protect these hemlocks from the adelgid infestation.

Table 2
Descriptive Statistics of Hemlock Health Variables in Hedonic Model and Repeat-Sale Model Estimation (0.1 km buffers).

	Mean	SD	Min	Max
Sample Data ($n = 148$)				
lba (m^2/ha)	22.9	18.4	0	98.4
vigor	2.7	1.0	1	4.0
*lba*vigor*	65.5	55.9	0	295.3
Hedonic Model Interpolation Data ($n = 2758$)				
Kriging				
lba (m^2/ha)	30.3	12.8	5.8	79.6
vigor	3.4	0.5	1.4	4.1
*lba*vigor*	106.4	55.3	13.1	314.2
IDW				
lba (m^2/ha)	30.3	13.0	3.0	87.6
vigor	3.4	0.6	1.1	4.0
*lba*vigor*	106.4	55.4	6.0	346.1
Spline				
lba (m^2/ha)	30.5	13.2	3.8	83.4
vigor	3.4	0.6	1.1	4.6
*lba*vigor*	107.2	56.4	6.5	329.2
Repeat-Sale Model Interpolated Data ($n = 356$)				
Kriging				
lba (m^2/ha)	31.2	12.4	7.3	70.6
vigor	3.4	0.6	1.4	4.1
*lba*vigor*	111.6	53.2	13.3	283.0

other forest interpolation efforts (Freeman and Moisen, 2007; Gunnarsson et al., 1998). We apply Inverse Distance Weighting (IDW hereafter) and Spline procedures for robustness comparisons. These interpolation methods are readily available in the geo-statistical wizard of the Geostatistical Analyst Tool in ArcGIS 10.1.

Spatial interpolation methods impose the assumption that values are more similar for locations near to each other. There exists a strong south-to-north trend in the adelgid infestation. First, a second-order polynomial trend is removed, and Kriging is performed on the residuals which satisfy to the stationary assumption of ordinary Kriging. After removing the trend over space, the spatial correlation applied here is assumed to be isotropic over the study area where the correlation depends on the distance between two points but not the direction of their separation.[2] Eastern hemlocks, occur in patches across the landscape and are not contiguously dispersed through space. The adelgid infestation moves from patch to patch of hemlock, but the diffusion process is not smooth as birds, prevailing winds, and humans may carry the insects from an infested stand to healthy stands.

Values for hemlock live basal area and vigor were interpolated for all non-sampled stands in the study area for each year of the study period, 2007–2011. The interpolated hemlock variables for the 6126 hemlock stands were then extracted based on a 30 × 30 m grid to assign values for the 0.1, 0.5 and 1.0 km buffers around each property (Table 2). The first row in Table 2 shows summary statistics for the sample data on hemlock health and the other rows are summary statistics for interpolated hemlock health based on model type (*Hedonic* and *Repeat Sale*) and interpolation method. Note, while observed vigor is an integer variable ranging from 1 (lowest vigor—greatest foliar loss) to 4 (highest vigor—lowest foliar loss), the interpolation process predicts continuous values for vigor that allows for minimum vigor to be less than 1 and maximum vigor to exceed 4. This outcome is shown in Table 2 where maximum vigor is greater than 4 for all the interpolated data sets. The continuous interpolations of vigor are used in the estimation.

5. Model specification

For the traditional hedonic specification (*Hedonic Model* hereafter), a fixed-effect model is estimated:

$$lnP_{it} = Z_i\alpha + + L_i\beta + lba_{it}\gamma + (lba_{it}{*}vigor_{it})\theta + \tau_t + \omega_j + \sigma_{it} \quad (1)$$

where P_{it} is the sale price for property i at time t, Z_i is a vector of property-specific characteristics, L_i is the vector of property-specific land cover characteristics, τ_t is a vector of time fixed effects, ω_j is a vector of spatial fixed effects delineated by zip code, and σ_{it} is the random error.[3]

For the hemlock variables, *lba* is live basal area, measured as a square meter cross-section per hectare at 4.5 ft above the ground, provides a systematic indication of the cross-sectional area occupied by living hemlock trees in each plot. *Vigor* was measured as the average amount of hemlock foliar decline in each plot, ranging from 1 (lowest vigor) to 4 (highest vigor).

Property-specific characteristics include lot size, living area, number of bathrooms, number of bedrooms, house age, presence/absence of air conditioning, presence/absence of a fireplace, and distance to the nearest highway. The property-specific land cover characteristics include the percentage of buffer area covered by water, open space, development, forest, agricultural land and wetland. The hemlock variables are lba_{it} and $vigor_{it}$, and are as defined above. The time fixed effects are binary variables for each year, 2007 to 2011. Spatial fixed effects are binary variables for zip codes.[4]

[2] Kriging assumes an isotropic distributions pattern and if the adelgid was introduced in the center of the geographic extent of hemlocks in the U.S., then the spread of the infestation would be expected to be isotropic, i.e., spread equally in all direction. Due to the location where the adelgid was first introduced into the U.S., Virginia, the spread was bound on the east by the Atlantic Ocean and the spread has been in southwesterly and northeasterly directions following the geographic extent of Hemlock habitat (Limbu et al., 2018; Morin et al., 2009). Similarly, for the study area, the initial infestation was in southern Connecticut and the spread was bound to south by Long Island Sound. However, as the infestation moved inland, dispersion from an infested stand could be isotropic, spreading in any direction. Thus, in the Kriging the directional trend is removed to allow for isotropic dispersion around each location of hemlock infestation in the study area.

[3] There could be concern that the hemlock variables are endogenous if, for example, owners of higher-priced properties treat hemlock trees to prevent the adelgid infestation and therefore protect property values, while owners of lower-priced properties do not take such actions. However, all property owners may treat their trees, remove infected trees, or let infected trees die in place. The latter seems unlikely because of the risk to structures and people from falling limbs. Considering treatment, a New York nursery reports costs to treat 100 in. of dbh (about four mature trees) ranges from \$80 to \$240 (http://www.whiteoaknursery.biz/Hemlock%20HWA_treatment.shtml). According to the US Forest Service, a typical 160-year-old hemlock in New York (no data for Connecticut and Massachusetts) has a dbh of 61 cm (or 24 in.) (https://www.srs.fs.usda.gov/pubs/misc/ag_654/volume_1/tsuga/canadensis.htm). Treatment of four trees likely costs less than \$250 for two to five years of protection (https://ag.umass.edu/landscape/fact-sheets/hemlock-woolly-adelgid). The median household incomes in Connecticut and Massachusetts, where the study area is located, are approximately \$79,000 and \$87,000 (https://www.statista.com/statistics/233170/median-household-income-in-the-united-states-by-state/), respectively. Thus, the treatment cost is much less than 1% of the median incomes, and these data suggest many households have the financial means to treat hemlock trees on their properties. Further, the cost to remove a mature hemlock at a height of 31 m (102 ft) can range from \$1100 to \$1800 (https://homeguide.com/costs/tree-removal-cost). Thus, for owners of lower-priced properties on a tight budget, it can be advantageous, cost wise, to treat rather than remove infested hemlock trees. To treat or remove trees is a preference choice that can apply to owners of properties at all price points. These considerations break the *prima-facia* link between higher-priced properties having higher-quality hemlock trees.

[4] The number of the spatial fixed-effect variables varies with the buffer sizes.

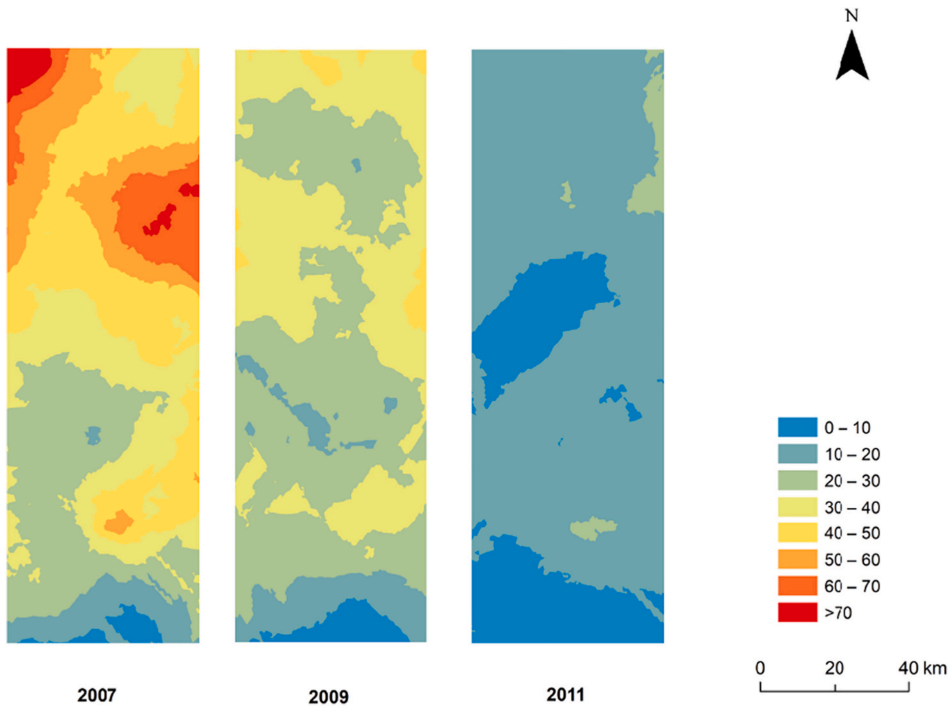

Fig. 3. Kriging Live Basal Area Interpolation (m^2/ha in study area defined in Fig. 1).

The repeat-sale specification (*Repeat-Sale Model* hereafter) is:

$$lnP_{it_r} - lnP_{it_p} = \left(lba_{it_r} - lba_{it_p}\right)\gamma^{rs} + \left(\left(lba_{it_r}*vigor_{it_r}\right) - \left(lba_{it_p}*vigor_{it_p}\right)\right)\theta^{rs} + \tau^r_{t_r} - \tau^r_{t_p} + \omega^r_j + \sigma^r_{it_{r-p}} \tag{2}$$

where r denotes the most recent sale, p denotes the previous sale of a property and ${\sigma_{it_{r-p}}}^r$ is the random error term.[5]

We differentiate between the hemlock coefficients (γ and θ versus γ^{rs} and θ^{rs}). If there is no omitted variable bias, one might expect the following relationships to hold, $E(\widehat{\gamma}) = E(\widehat{\gamma^r}) = \gamma$ and $E(\theta) = E(\widehat{\theta^r}) = \gamma$. Omitted relevant variables that would cause these relationships to not hold are variables that would be correlated with *lba* and *vigor*. For example, if property owners' response to the adelgid infestation is to remove hemlock trees and they have other species of trees removed at the same time, then the additional reduction in tree canopy would be correlated with *lba* and would be an omitted relevant variable. We do not have any evidence that such actions are occurring, and the essence of omitted relevant variables is that the investigator does not know of their existence or cannot obtain observational data. This is the reason for using quasi-experimental methods like repeat-sale modeling. While omitted relevant variables is the common explanation for the equalities above not holding, available samples for hedonic estimation are larger than for repeat-sale estimation as not all properties in an area will sell more than once. Thus, in the estimation we first estimate the *Hedonic Model* with all interpolated data and, second, using just the data included for the *Repeat-Sales Model*.

In addition to the significance and signs of the hemlock variables, the derivatives of the *Hedonic* and *Repeat-Sale Models*, respectively, can be used to evaluate the comparability of different estimation outcomes:

$$\partial lnP_{it}/\partial lba = \gamma^m + vigor_{it}\theta^m \tag{3}$$

where m denotes the model that provides the coefficient estimates, e. g., hedonic or repeat sale. Several patterns can arise for the hemlock variables. For example, if θ^m and γ^m are both significant and positive, property values increase with the size and health of hemlock stands. Alternatively, if the coefficients are significant but differ in sign, then only hemlock stands of a certain vigor will positively contribute to property values. Comparison across model estimates can become muddled when this latter condition occurs so we set the derivative equal to zero and solve for the level of vigor that defines whether hemlock stands contribute positively or negatively to property values:

$$vigor^{+/-} = \widehat{\gamma}/\widehat{\theta}. \tag{4}$$

Hemlock stands with vigor greater than *vigor*$^{+/-}$ positively contribute to property values. This provides a consistent metric to compare estimation outcomes across models.

6. Results

Summary statistics are reported in Table 2 for the hemlock variables at the 0.1 k buffer. The sample sizes are the number of property sales available for estimation with each type of data. Similar patterns of results hold for the 0.5- and 1.0-km buffers so summary statistics are not reported for these buffers here.[6]

In the econometric results reported below, we report coefficient estimates for the two hemlock variables for parsimony of exposition. Descriptive statistics for non-hemlock explanatory variables, excluding

[5] The repeat-sale specification not only removes regressors that are constant through time but removes the decisions on the functional specifications of these variables (Bishop et al., 2020; Humphreys and Nowak, 2017). The repeat-sale model is also capable of addressing endogeneity that might occur in the hedonic (Heintzelman and Tuttle, 2012; Linden and Rockoff, 2008). Suppose a property sold in 2007 with no adelgid effects and then resold in 2009 or 2011. If the property owner treated the hemlocks on the property to "preserve" the properties' value, then the model is being estimated based on between-sale comparisons and not between-property comparisons which the traditional hedonic relies on.

[6] Outliers for the property sale price were removed prior to estimation removing observations in the 0.05% and 99.95% tails of the sale-price distribution of the 1 km buffer.

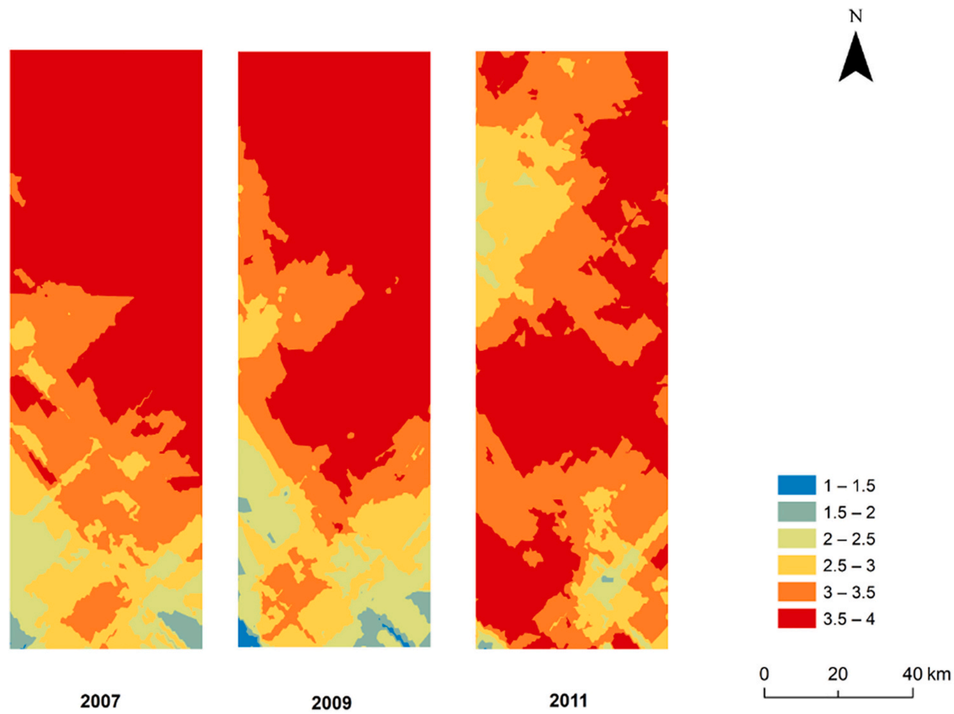

Fig. 4. Kriging Vigor Interpolation (2007–2011).

fixed effects, are reported in Appendix Table A and their respective coefficient estimates are reported in Appendix Tables B, C, D and E. Between the Hedonic and Repeat-sale data, only three of 15 characteristics show significant differences and the magnitudes of those with significant differences are so small they are inconsequential.

As a baseline for comparison, we use the traditional hedonic model applied to the observed data and the Kriged data.[7],[8] For properties that sold more than once, the most recent sales were used in the estimation to avoid correlation between multiple sales of the same property.

6.1. Spatial interpolation

In Table 2 the first three rows show summary statistics for property sales whose buffers intersect a sampled plot with a 0.1 k buffer. The next three sets of rows show summary statistics for the interpolated data to support estimation of the Hedonic Model with a 0.1 buffer. The last three rows show summary statistics for the interpolated used to estimate the Repeat-Sale Model. Sample sizes reflect the number of property sales available to estimate each model with the respective data.[9]

Live basal area and vigor were decreasing, on average, through time in the observed data and this decreasing trend is observed in the interpolated data (see Figs. 3 and 4 for the Kriging results as an example). The adelgid infestation was primarily located in southern Connecticut in 2007 and the extensive infestation progressed north into Massachusetts by 2011. The pattern of decline in hemlock vigor follows the pattern of live basal area decline.

Based on the 0.1 km buffer data used to estimate the *Hedonic Model*, mean values and standard deviations for live basal area (*lba*) and *vigor* are quite similar across Kriging, IDW and Spline interpolations (Table 2). However, the interpolation means are somewhat larger than the sample data (~30 vs. ~23 for *lba* and ~ 3.4 versus ~2.7 for *vigor*) and the comparable standard deviations are smaller (~13 vs. ~18 for *lba* and ~ 0.6 versus ~1.0 for *vigor*). For the *Repeat-Sale Model*, the Kriging summary statistics are like those for the Hedonic Model.

6.2. Hedonic regression results

To provide a baseline for comparisons, we first report estimates for the *Hedonic Model* with fixed effects (eq. 1) *using data from sampled hemlock stands* (Table 3). The model estimated for the 0.1 km buffer indicates that both hemlock variables are significant in explaining variations in housing prices and $vigor^{+/-}$ is 2.9, indicating hemlock stands positively impact property values if vigor is class 4 (25% or less foliar loss). At lower levels of vigor, hemlock stands negatively impact property values.

Increasing the size of the buffers around properties to 0.5 km and 1.0 km increases the number of potentially affected properties included in the estimation from about 500 and over 1600. The coefficients are insignificant for the 0.5 km buffer but are significant for the 1.0 km buffer. However, the interaction variable has the wrong sign; it indicates that increasing vigor reduces property values.

One might question the baseline results because the small number of sampled hemlock stands limits the numbers of property transactions in the estimation and thereby does not make use of the full spatial extent of study area information. We note that spatial interpolation allows for potential consideration of all 6126 hemlock stands in the study area and substantially increases the observations available for analysis to nearly

[7] If neighbors encourage neighbors to treat healthy hemlock trees or remove dead and dying trees, this could lead to spatial correlation of property transaction values. We ran spatial lag, spatial error and spatial auto correlation models using properties within 8 km of a subject property and that sold within one year before or after the subject property sold. All three approaches indicated a spatial effect, but the coefficient estimates were robust to the Hedonic Model using Kriged data with a 0.1 km buffer. The coefficient on *lba* ranged from −0.0064 (spatial lag and spatial auto correlation) to −0.0071 (*Hedonic Model*) and the *lba*vigor* ranged from 0.0017 (spatial lag and spatial auto correlation) to 0.0018 (*Hedonic Model* and spatial error).

[8] The estimation may be missing neighborhood variables that represent the social pressure by neighbors to protect hemlocks or remove dying and dead hemlocks. The zip-code, spatial fixed effects in our estimation follow the finding of Kuminoff et al. (2010) of removing bias.

[9] Because of the small sample of properties with buffers that include observed hemlock sample sites it is not possible to estimate the *Repeat-Sale Model* using these data.

Table 3
Hemlock Coefficient Estimates Based on Sample Data and Kriged Interpolation Data.

	Buffers		
	<0.1 km	<0.5 km	<1 km
Sample Data			
Hedonic Model			
lba (m^2/*ha*)	−0.0059**[a]	0.0017	0.0020**
	(0.0032)[b]	(0.0022)	(0.0012)
*lba*vigor*	0.0020**	−0.0005	−0.0006*
	(0.0010)	(0.0007)	(0.0004)
$vigor^{+/-}$	2.9	nc[c]	nc
N	148	484	1651
Kriging Interpolation Data			
Hedonic Model			
lba (m^2/*ha*)	−0.0071**	−0.0054***	−0.0030**
	(0.0037)	(0.0022)	(0.0016)
*lba*vigor*	0.0018**	0.0015***	0.0009**
	(0.0008)	(0.0005)	(0.0004)
$vigor^{+/-}$	3.8	3.6	3.4
N	2758	13,076	23,244
Repeat-Sale Model			
lba (m^2/*ha*)	−0.0322***	−0.0048	0.0024
	(0.0116)	(0.0066)	(0.0058)
*lba*vigor*	0.0097***	0.0007	−0.0016
	(0.0035)	(0.0017)	(0.0014)
$vigor^{+/-}$	3.3	nc	nc
N	178	816	1420
Hedonic Model with Repeat-Sale Sample[e]			
lba (m^2/*ha*)	0.0299	−0.0124*	−0.0020
	(0.0243)	(0.0077)	(0.0047)
*lba*vigor*	−0.0009	0.0032**	0.0008
	(0.0047)	(0.0016)	(0.0011)
$vigor^{+/-}$	nc	3.9	nc
N	178	816	1420

[a] Asterisks denote significance at the 1% (***), 5% (**) and 10% (*) levels for one-tailed tests.
[b] Standard errors in parentheses.
[c] Denotes no calculation because coefficient estimates are insignificant or have counterintuitive signs.

3000 with the 0.1 km buffers, about 13,000 with 0.5 km buffers, and over 23,000 with 1 km buffers.

Using the Kriged data, *lba* and *lba*vigor* are significant in the *Hedonic Model* and have plausible signs for all three buffers (Table 3).[10] The magnitudes of coefficient estimates vary across buffers, but $vigor^{+/-}$ remains relatively constant, ranging from 3.4 (in the 1 km buffer) to 3.8 (in the 0.1 km buffer), indicating that only the healthiest stands (0–25% foliar loss) contribute positively to property values (and greater foliar losses reduce property values).[11] This is a more restrictive condition than observed for the Sample Data where *vigor*+/− is 2.9. The difference is driven by the larger coefficient estimate on *lba* in the Kriged-data *Hedonic Model*.

Increasing the number of observations still leaves questions about whether the *Hedonic Model* is fully identified, and one might wonder if the fixed effects fully account for potentially correlated omitted variables. Turning to the *Repeat-Sale Model* that imposes a quasi-experimental design on the estimation, the number of observations decline to a range of a little less than 200 and a little over 1400 across the three buffers, but the advantage is that time-invariant variables that are potentially correlated with the hemlock variables cancel out of the estimation.

Only the 0.1 km buffer has significant hemlock coefficients for the *Repeat-Sale Model* (Table 3).[12] The magnitudes of the coefficient estimates are much larger in the *Repeat-Sale Model* relative to both previously discussed *Hedonic Models* (−0.0322 versus −0.0059 and − 0.0071 for *lba* and 0.0097 versus 0.0020 and 0.0018 for *lba*vigor*). It is interesting that $vigor^{+/-}$ is 3.3, splitting the difference between the *Hedonic Models* for the Sample and Kriging Data (2.9 and 3.8, respectively). This relationship occurs because only the coefficient on *lba* increased moving from the Sample-Data to Kriging Data *Hedonic Models*, while both coefficients increased in magnitude moving to the *Repeat-Sale Model*.

For the variables included in hedonic model, their descriptive statistics were not significantly different from those for the repeat-sale model sample with two exceptions, Fireplace (hedonic 48% vs. repeat-sale 41%) and Developed area (hedonic 0.08% vs. repeat-sale 0.002%) (see Appendix Table A). Thus, estimation differences between the hedonic and repeat-sales coefficient estimates may be more likely driven by the modeling approaches with the hedonic estimation potentially having omitted relevant variables that cancel out in the repeat-sale estimation.

To directly compare the *Hedonic* and *Repeat-Sale* models, we estimate the *Hedonic Model* using the same data used to estimate the *Repeat-Sale Model*.[13] The *Hedonic Model with Repeat-Sale Sample* estimation results in significant coefficients for the 0.5 km buffer and $vigor^{+/-}$ is 3.9, which is consistent with the results from the Kriged Data estimation results for the *Hedonic Model* with a 0.1 km buffer. These results suggest that the differences between the *Hedonic Model* and the *Repeat-Sale Model* arise from the different model specifications.

6.3. *Spatial interpolation robustness*

The 0.1 km buffer is used in these comparisons as it provided significant hemlock coefficient estimates for the *Hedonic* and *Repeat-Sale Models* using the Kriged data *and* was the only buffer with significant coefficients in the *Repeat-Sale Model* estimation. The Hedonic Model and Repeat-Sale Model estimation results from Table 3 based on the Kriged Data are included in first column of Table 4 to facilitate comparisons. All the hemlock coefficient estimates based the IDW and Spline data interpolations have the same signs as the Kriged interpolation estimates and all are significant except the coefficient for *lba* in the Hedonic Model using the Spline interpolation data for estimation.

Coefficient estimates based on the IDW and Spline interpolations are more like each other than they are to the Kriging interpolation. Consider, $vigor^{+/-}$ is 3.1 for IDW and Spline but 3.8 and 3.3 for the Kriging interpolation estimations, which all suggest that only the heathiest trees contribute positively to property values.

[10] Kriging results in some projections of *vigor* that are less than 1 and greater than 4. We ran the Kriged models with the <0.1 km buffer limiting *vigor* to the [1,4] interval and the estimation results were essentially identical. For the hedonic model, the coefficient estimate changes were: *lba* − 0.0071➔-0.0068 and *lba*vigor* 0.0018➔0.0018. Similarly, for the repeat-sale model: *lba* − 0.032➔0.033 and *lba*vigor* 0.0097➔0.0099).

[11] We also ran *Hedonic* and *Repeat-Sale Models* using the <0.1 km buffer where vigor was a binary variable; *lba*v1* (76–99% foliar loss), *lba*v2* (51–75% foliar loss) and *lba*v3* (26–50% foliar loss) where *v4* (0–25% foliar loss). In these models the qualitative results hold, lower vigor reduces property values. In both models, *lba* became insignificant. However, for the *Hedonic Model lba*v1* and *lba*v3* were significant and negative while *lba*v2* was insignificant. Further, the coefficient for *lba*v1* (−0.093) was larger in absolute value than the coefficient for *lba*v3* (−0.001). For the Repeat-Sale Model, there were no observations for *v1*, *lba*v2* was negative and significant (−0.01) and *lba*v3* was negative but insignificant. It is noted that the coefficients for *lba*v1* in the *Hedonic Model* and *lba*v2* in the *Repeat-Sale Model* are nearly identical.

[12] Given that our study time frame, 2007–2009 overlapped with the great recession, we also estimated a model including dummy variables to indicate the year of the second sale using the <0.1 km buffer. We found that the coefficients for *lba* and *lba*vigor* remained significant and changed very little in magnitude (−0.032➔-0.028 and 0.0097 ➔ 0.0092, respectively).

[13] We employ the most recent sale of each property in the Hedonic Model estimation.

Table 4
Hemlock Coefficient Estimates Based on Alternative Interpolation Methods (0.1 km buffers).

	Kriging	IDW	Spline
Hedonic Model (N = 2758)			
Lba (m^2/ha)	−0.0071**[a]	−0.0035*	−0.0025
	(0.0037)[b]	(0.0027)	(0.0024)
*lba*vigor*	0.0018**	0.0011*	0.0008*
	(0.0008)	(0.0007)	(0.0006)
$vigor^{+/-}$	3.8	3.3	nc[c]
Repeat-Sale Model (N = 178)			
lba (m^2/ha)	−0.0322***	−0.0245*	−0.0228**
	(0.0116)	(0.0152)	(0.0129)
*lba*vigor*	0.0097***	0.0079*	0.0075**
	(0.0035)	(0.0039)	(0.0034)
$vigor^{+/-}$	3.3	3.1	3.1

[a] Asterisks denote significance at the 1% (***), 5% (**) and 10% (*) levels for one-tailed tests.
[b] Standard errors in parentheses.
[c] Denotes no calculation because coefficient estimates are insignificant or have counterintuitive signs.

6.4. Values for improvements in Live Basal Area (lba)

Here we report values based on the 0.1 km buffer, which is the only buffer to provide consistently significant estimates with the expected coefficient signs. We consider a change moving from the 2007 level of 38 m^2/ha to the 2011 mean *lba* of 15 m^2/ha at the highest level of *vigor*, 4. This vigor level is supported by the *Hedonic Model* and the *Repeat-Sale Model* as contributing positively to property values.

As the parameter estimates in a log-linear hedonic can be used to calculate percentage changes in the dependent variable, the percentage change in housing price is computed as:

$$\begin{aligned}\%\Delta\widehat{P} &= (P_{15} - P_{38})/P_{15} \\ &= exp(\widehat{\gamma}(lba_{15} - lba_{38}) + (\widehat{\theta}(lba_{15}*vigor_4 - lba_{38}*vigor_4\ ) - 1\end{aligned} \quad (5)$$

The capitalized decrease in value for the average priced house in 2007 is then calculated by multiplying $\%\Delta\widehat{P}$ by the average sale price of \$281,358 (Kriging interpolation sample for the 1 km buffer).

The *Hedonic Model* reveals a modest capitalized-value reduction of 0.2% or about \$650 for the average-valued property. A much larger impact is found with the *Repeat-Sale* model with a capitalized-value decrease of 15% or about \$39,600. This is a dramatic difference in property value impacts and might be due to several reasons. The *Hedonic Model* estimate may be lower because there are other confounding factors that ameliorate the impact the are not captured by the fixed effects. Conversely, the restricted sample of properties that sold more than once may not be representative of all properties in the study area and the *Repeat-Sale* model provides an overestimate of the price impact.

7. Discussion

Differences in implicit prices across hedonic and repeat-sale, or other quasi-experimental, estimation is not unique to this study (e.g., Kuminoff and Pope, 2014). We found the *Repeat-Sale* coefficient estimate is more than four times larger in absolute value than the *Hedonic* estimate (4.57 = −0.032/−0.007, Kriging with 0.1-km buffer). Joshi et al. (2020) found a ratio of *Repeat-Sale* to *Hedonic* coefficient estimates of 0.57 and 0.56 for condominiums in Seattle within a 0.5-mile buffer, and 1.05 and 1.04 for condominiums within a 0.5–1-mile buffer. In comparison, Humphreys and Nowak (2017) found *Repeat-Sale* coefficient estimates for single family homes in Charlotte, NC were comparable to a *Hedonic* model with fixed effects for a 1-mile buffer (0.97 ratio) and slightly smaller for a 1–2-mile buffer (0.77 ratio).

One might expect differences between repeat-sale and hedonic estimation if there are omitted relevant variables that are time constant and cancel out in the repeat-sale estimation but not for the hedonic estimation. Differences could also be driven by the repeat-sale and hedonic samples differing in terms of the key policy variable(s) or the houses that sold twice versus once. Thus, a key insight relates to the number of observations available for estimation. Humphreys and Nowak had 12,989 observations to support their *Repeat-Sale* estimation and 41,417 for the *Hedonic* estimation, and Joshi et al. (2020) had 10,398 and 7697 for their *Repeat-Sale* estimation and 27,427 and 20,060 for the *Hedonic*. These are far more than the 178 and 2758 observations we have, respectively, for the Repeat-*Sale* and *Hedonic* estimation. These differences arise because the Humphreys and Nowak and Joshi et al. studies were conducted in urban areas, Charlotte, NC and Seattle, WA, whereas our study was conducted in largely rural areas of Connecticut and Massachusetts. Thus, the larger coefficient-estimate difference in our study may be driven by the small number of repeat-sale observations and the larger difference in repeat sales relative to single sales. Noting the summary statistics on live basal area and vigor in Table 2, which are nearly identical for the for the kriged repeat-sale and hedonic data, the larger difference observed in our study may be due to the repeat-sale sample differing from the hedonic sample in terms of properties sold in terms of features we could not control for in the hedonic. However, it is worth repeating that the hedonic and repeat-sales descriptive statistics for the variables included in the models were statistically identical with two minor differences (see Appendix Table A).

Differences might also be driven by endogeneity in the hedonic model. Heintzelman and Tuttle (2012) attributed larger effects in a hedonic model of wind farms, relative to a repeat-sale model, to the presence of endogeneity in the hedonic. Note, both models were estimated with the same number of observations. We observed the opposite relationship between the hedonic and repeat-sale estimation. While endogeneity may be a contributing factor, we suspect the observed difference are due to multiple confounding factors that include endogeneity, different samples of properties and differing sample sizes.

There are other estimation approaches that might be used in future comparisons to help explain or reduce differences in estimation outcomes between repeat-sale and hedonic estimation such as pooling single and repeat-sales data (e.g., Case and Quigley, 1991) and matching properties with differing levels of the policy variable of interest (e.g., Guntermann et al., 2016; Klaiber and Smith, 2013). Joshi et al. (2020) use one matching approach and found the ratio of repeat-sale to hedonic coefficients of about 0.70 for both their 0.5- and 0.05–1-mile buffers: reducing the difference for the smaller buffer and increasing the difference for the larger buffer.

8. Conclusions

Using spatial data interpolation allowed for the extrapolation of on-site sampling data, limited due to expense and limited access to private lands, to a large geographical area based on high resolution data on hemlock stands. This expansion of the data has important implications for the economic analysis as it allows for much larger sample sizes to support estimation of traditional hedonic models and allows for the estimation of a repeat-sale model.

Our results show that hemlock trees within 0.1 k of a property and infected by the adelgid, in central portions of Connecticut and Massachusetts, reduce property values and only the healthiest trees contribute positively to property values. This outcome is consistent with the study by (Holmes et al., 2010), conducted in New Jersey, that also found a threshold of hemlock stand health below which hemlock stands reduce property values.

The robustness analyses found that estimation results are sensitive to investigator modeling decisions. This lack of robustness is not an inherently negative outcome as important information is revealed about the extent of the adelgid's effects on property values and economic modeling choices. The results support that there is a property impact for hemlock tress located near a property (0.1 km here) but not beyond. In context, 0.1 k is 328 ft, which suggests the trees are located on subject properties or on an adjacent property; more distant trees do not have an effect.

The capitalized property value impacts are not robust between the *Hedonic* and *Repeat-Sale* models. The challenge here is that this model robustness comparisons is an imperfect investigation of convergent validity where the truth is unknown (Bishop and Boyle, 2019). The *Hedoni*c and *Repeat-Sale* models are designed to measure the same implicit price. If there are no omitted relevant variables in the *Hedonic* estimation, and this is a big if, the two estimation approaches should provide similar implicit price estimates. Even if this strict omitted-variable condition holds, one does not know which is unbiased or if both are biased. Based on theoretical considerations, the *Repeat-Sale Model* is preferred for identifying the price effect because time-invariant explanatory variables cancel out of the estimation. However, this advantage may be offset by the limited number of properties that sell more than once, which may be systematically different from all properties that sold once during the study period.

Thus, careful consideration of the empirical evidence is required. Our results provide some support for the quasi-experimental *Repeat-Sale Model* over the *Hedonic Model* with spatial fixed effects. When both models were estimated using the same data, the *Hedonic Model* underperformed.

In closing, we report losses in capitalized property values due to the adelgid infestation. However, another perspective might be how property values might recover post infestation. Our model is not equipped to answer this question in that the adelgid "rapidly" decreases hemlock health over several years while it would take hundreds of years for a replanted hemlock tree to reach maturity. Further, we do not know what action a landowner might take; nothing, planting a new hemlock, planting a different species or other. The recovery of diminished property values in the face of tree disease and pest infestation is a question that has yet to be addressed in the literature.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Appendix Table A
Descriptive Statistics of Property Characteristic Variables (0.1 km buffers).

	Hedonic Model		Repeat-Sale Model	
	Mean	Standard Deviation	Mean	Standard Deviation
	Sample Data			
Sale price ($2003)	$384,246	$250,960		
Living area (ft^2)	2289	910		
Lot size (ft^2)	86,936	133,246		
Baths	2.0	0.8		
Bedrooms	3.4	0.9		
Age (years)	42	49		
Air conditioning (%)	39	49		
Fireplace (%)	54	50		
Distance to highway (m)	937	845		
Water (%)	0.3	2.5		
Open space (%)	24	22		
Developed area (%)	0.4	3.2		
Forest (%)	52	30		
Agricultural (%)	2	9		
Wetland (%)	2	7		
N	148	148		
		Interpolation Data		
Sale price ($2003)	$311,888	$176,061	$299,834	$183,692
Living area (ft^2)	1912	840	1868	874
Lot size (ft^2)	93,253	213,342	81,288	149,281
Baths	1.8	0.8	1.8	0.7
Bedrooms	3.2	0.8	3.2	0.8
Age (years)	39	41	41	40
Air conditioning (%)	31	46	28	45
Fireplace (%)	48*[a]	50	41*	49
Distance to highway (m)	1068	1068	1016	1163
Water (%)	53	3.4	69	3.4
Open space (%)	22	20	22	18
Developed area (%)	0.1***	1.2	0.0***	0.0
Forest (%)	47	30	48	29
Agricultural (%)	5	13	5	12
Wetland (%)	3*	8	2*	6
N	2758	2758	178	178

[a] * and *** denote significant differences at the 10% and 1% levels.

Appendix Table B
Hedonic Coefficient Estimates for Different Data Sets with the 0.1 km Buffers.

Variables	Sample Data	Kriging Interpolation Data	
	Hedonic Model	*Hedonic Model*	*Repeat-Sale Model*
Living area (1000 ft2)	0.242 ***	0.242***[a]	0.207 ***
	(0.014)	(0.014)[b]	(0.046)
Lot size (1000 ft2)	1.102×10^{-3}***	1.70×10^{-4}***	-0.838×10^{-4}
	(3.04×10^{-4})	(4.24×10^{-5})	(1.731×10^{-4})
Baths	0.089	0.092***	0.104 **
	(0.059)	(0.011)	(0.049)
Bedrooms	−0.091**	0.015*	0.018
	(0.044)	(0.008)	(0.037)
Age	-1.764×10^{-3}***	−0.002***	-2.311×10^{-3} ***
	(0.621×10^{-3})	(0.0002)	(0.636×10^{-3})
Air conditioning	0.064	0.125***	0.086 *
	(0.072)	(0.013)	(0.050)
Fireplace	−0.080	0.064***	0.081
	(0.083)	(0.015)	(0.070)
Distance to highway (km)	0.082	0.010	−0.027
	(0.079)	(7.62×10^{-3})	(0.027)
Water (%)	0.017 ***	5.439×10^{-3}**	-8.054×10^{-3}
	(0.004)	(2.269×10^{-3})	(5.192×10^{-3})
Open space (%)	2.066×10^{-3}	1.642×10^{-4}	0.639×10^{-3}
	(1.257×10^{-3})	(4.389×10^{-4})	(1.825×10^{-3})
Developed area (%)	2.710×10^{-3}	-9.410×10^{-3}*	−1.406 ***
	(2.166×10^{-3})	(5.487×10^{-3})	(0.404)
Forest (%)	1.097×10^{-3}	5.320×10^{-4}*	-0.142×10^{-3}
	(1.258×10^{-3})	(2.795×10^{-4})	(0.853×10^{-3})
Agricultural (%)	2.814×10^{-3}	1.585×10^{-3}***	-0.114×10^{-3}
	(2.643×10^{-3})	(4.169×10^{-4})	(1.207×10^{-3})
Wetland (%)	−0.010**	1.445×10^{-4}	1.845×10^{-3}
	(5.144×10^{-3})	(7.211×10^{-4})	(2.037×10^{-3})
lba	−0.0059*	−0.0071*	0.0299
	(0.0032)	(0.0037)	(0.0243)
lba*Vigor	0.0020**	0.0018**	−0.0009
	(0.0010)	(0.0008)	(0.0047)
N	148	2758	178
Adjusted-R2	0.521	0.5538	0.326

[a] *** denotes significant at the 1% level, ** denotes significant at the 5% level, * denotes significant at the 10% level.
[b] Standard errors in parentheses.

Appendix Table C
Hedonic Coefficient Estimates for Different Data Sets with the 0.5 km Buffers.

Variables	Sample Data	Kriging Interpolation Data	
	Hedonic Model	*Hedonic Model*	*Repeat-Sale Model*
Living area (1000 ft2)	0.274***	0.266 *** [a]	0.241 ***
	(0.025)	(0.007) [b]	(0.020)
Lot size (1000 ft2)	9.156×10^{-4}***	1.65×10^{-4} ***	1.42×10^{-4}
	(3.417×10^{-4})	(2.69×10^{-5})	(1.77×10^{-4})
Baths	0.010	0.073 ***	0.053 **
	(0.026)	(0.007)	(0.022)
Bedrooms	−0.022	2.816×10^{-3}	0.010
	(0.022)	(5.109×10^{-3})	(0.015)
Age	-1.535×10^{-3}**	-1.617×10^{-3} ***	-1.760×10^{-3} ***
	(0.594×10^{-3})	(1.560×10^{-4})	(2.427×10^{-4})
Air conditioning	0.098 ***	0.108 ***	0.123 ***
	(0.032)	(0.007)	(0.027)
Fireplace	0.154***	0.078 ***	0.123 ***
	(0.039)	(0.009)	(0.030)
Distance to highway (km)	0.035	0.011***	−0.008
	(0.032)	(0.007)	(0.011)
Water (%)	3.523×10^{-3}	2.891×10^{-3} ***	3.970×10^{-3}
	(3.948×10^{-3})	(0.863×10^{-3})	(2.955×10^{-3})
Open space (%)	3.192×10^{-3}***	2.584×10^{-3} ***	6.057×10^{-3} ***
	(0.790×10^{-3})	(0.566×10^{-3})	(1.383×10^{-3})
Developed area (%)	-4.509×10^{-3}	-8.596×10^{-3} ***	−0.016 ***
	(3.328×10^{-3})	(2.391×10^{-3})	(6.146×10^{-3})
Forest (%)	1.780×10^{-3}*	1.307×10^{-3} ***	3.364×10^{-3} ***
	(0.909×10^{-3})	(0.289×10^{-3})	(0.814×10^{-3})
Agricultural (%)	6.420×10^{-3} ***	2.450×10^{-3} ***	2.124×10^{-3}
	(2.198×10^{-3})	(0.431×10^{-3})	(1.572×10^{-3})
Wetland (%)	-0.660×10^{-3}	1.472×10^{-3} ***	3.090×10^{-3} *
	(3.131×10^{-3})	(0.423×10^{-3})	(1.829×10^{-3})

(*continued on next page*)

Appendix Table C (*continued*)

Variables	Sample Data	Kriging Interpolation Data	
	Hedonic Model	*Hedonic Model*	*Repeat-Sale Model*
lba	0.0017	−0.0054**	−0.0124
	(0.0022)	(0.0022)	(0.0077)
lba*Vigor	−0.0005	0.0015***	0.0032 **
	(0.0007)	(0.0005)	(0.0016)
N	484	13,076	816
Adjust-R2	0.554	0.582	0.481

[a] *** denotes significant at the 1% level, ** denotes significant at the 5% level, * denotes significant at the 10% level.
[b] Standard errors in parentheses.

Appendix Table D
Hedonic Coefficient Estimates for Different Data Sets with the 1.0 km Buffers.

Variables	Sample Data	Interpolation Data	
	Hedonic Model	*Hedonic Model*	*Repeat-Sale*
Living area (1000 ft2)	0.274	0.266 *** [a]	0.223 ***
	(0.016)	(0.007) [b]	(0.015)
Lot size (1000 ft2)	2.81×10^{-4}***	1.89×10^{-4} ***	2.94×10^{-4}*
	(1.03×10^{-4})	(3.00×10^{-5})	(1.78×10^{-4})
Baths	0.051***	0.065 ***	0.074 ***
	(0.019)	(0.006)	(0.014)
Bedrooms	−0.028**	4.082×10^{-3}	3.684×10^{-3}
	(0.011)	(4.142×10^{-3})	(1.169×10^{-2})
Age	-0.879×10^{-3}**	-1.650×10^{-3} ***	-1.760×10^{-3} ***
	(0.365×10^{-3})	(1.566×10^{-4})	(2.427×10^{-4})
Air conditioning	0.115 ***	0.109 ***	0.123 ***
	(0.018)	(0.006)	(0.022)
Fireplace	0.093***	0.077 ***	0.112 ***
	(0.015)	(0.008)	(0.024)
Distance to highway (km)	0.020	0.014***	−0.004
	(0.014)	(0.004)	(0.010)
Water (%)	0.559×10^{-4}***	2.211×10^{-3} ***	6.401×10^{-4}
	(0.157×10^{-4})	(0.854×10^{-3})	(2.491×10^{-3})
Open space (%)	0.040×10^{-3}**	3.805×10^{-3} ***	9.457×10^{-3} ***
	(0.200×10^{-4})	(0.870×10^{-3})	(2.005×10^{-3})
Developed area (%)	-0.151×10^{-3}***	-10.253×10^{-3} ***	-2.633×10^{-3}
	(0.036×10^{-3})	(2.252×10^{-3})	(4.155×10^{-3})
Forest (%)	0.265×10^{-4}***	1.556×10^{-3} ***	4.447×10^{-3} ***
	(8.65×10^{-6})	(0.351×10^{-3})	(0.851×10^{-3})
Agricultural (%)	0.729×10^{-4} ***	3.272×10^{-3} ***	5.035×10^{-3} **
	(0.136×10^{-4})	(0.535×10^{-3})	(2.053×10^{-3})
Wetland (%)	0.222×10^{-4}	1.636×10^{-3} ***	5.226×10^{-3} ***
	(0.024×10^{-3})	(0.528×10^{-3})	(1.618×10^{-3})
lba	0.0020	−0.0030*	−0.0020
	(0.0012)	(0.0016)	(0.0047)
lba*Vigor	−0.0006	0.0009**	0.0008
	(0.0004)	(0.0004)	(0.0011)
N	1651	23,244	1420
Adjust-R2	0.5406	0.5786	0.4691

[a] *** denotes significant at the 1% level, ** denotes significant at the 5% level, * denotes significant at the 10% level.
[b] Standard errors in parentheses.

Appendix Table E
Hedonic Coefficient Estimates Based on Alternative Interpolation Methods with 0.1 km Buffers.

Variables	Kriging	IDW	Spline
Living area (1000 ft^2)	0.242*** [a]	0.242***	0.242***
	(0.014) [b]	(0.014)	(0.014)
Lot size (1000 ft^2)	1.70×10^{-4}***	1.70×10^{-4}***	1.71×10^{-4}***
	(4.24×10^{-5})	(4.24×10^{-5})	(4.25×10^{-5})
Baths	0.092***	0.092***	0.092***
	(0.011)	(0.011)	(0.011)
Bedrooms	0.015*	0.015*	0.015*
	(0.008)	(0.008)	(0.008)
Age	−0.002***	−0.002***	−0.002***
	(0.0002)	(0.0002)	(0.0002)
Air conditioning	0.125***	0.125***	0.125***
	(0.013)	(0.013)	(0.013)
Fireplace	0.064***	0.063***	0.063***
	(0.015)	(0.015)	(0.015)

(*continued on next page*)

Appendix Table E (*continued*)

Variables	Kriging	IDW	Spline
Distance to highway (km)	0.010	0.010	0.010
	(7.62×10^{-3})	(7.65×10^{-3})	(7.65×10^{-3})
Water (%)	5.439×10^{-3}**	5.370×10^{-3}**	5.351×10^{-3}**
	(2.269×10^{-3})	(2.250×10^{-3})	(2.250×10^{-3})
Open space (%)	1.642×10^{-4}	1.686×10^{-4}	1.749×10^{-4}
	(4.389×10^{-4})	(4.421×10^{-4})	(4.414×10^{-4})
Developed area (%)	-9.410×10^{-3}*	-9.412×10^{-3}*	-9.345×10^{-3}*
	(5.487×10^{-3})	(5.474×10^{-3})	(5.484×10^{-3})
Forest (%)	5.320×10^{-4}*	5.460×10^{-4}*	5.507×10^{-4}*
	(2.795×10^{-4})	(2.808×10^{-4})	(2.816×10^{-4})
Agricultural (%)	1.585×10^{-3}***	1.578×10^{-3}***	1.572×10^{-3}***
	(4.169×10^{-4})	(4.161×10^{-4})	(4.167×10^{-4})
Wetland (%)	1.445×10^{-4}	1.830×10^{-4}	1.827×10^{-4}
	(7.211×10^{-4})	(7.287×10^{-4})	(7.308×10^{-4})
lba	−0.0071*	−0.0035	−0.0025
	(0.0037)	(0.0027)	(0.0024)
lba*Vigor	0.0018**	0.0011	0.0008
	(0.0008)	(0.0007)	(0.0006)
N	2758	2758	2758
Adj-R2	0.5538	0.5534	0.5533

[a] *** denotes significant at the 1% level, ** denotes significant at the 5% level, * denotes significant at the 10% level.
[b] Standard errors in parentheses.

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