The Effect of Spatial Interpolation on the Hedonic Model: a Case of Forest Pest Damages

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Abstract:

In the hedonic model, when an investigator wishes to merge property sale data with spatial data on an environmental amenity, one problem encountered in the matching process is that the environmental data are usually limited. A challenging task is how to scale site and time specific environmental data to all property sales within a defined geographical area. Inverse distance weighting, Kriging and splines are three commonly used geo-statistical methodologies to make spatial interpolation. In this study, we investigate the effect of these spatial interpolation methods on the estimation of a hedonic model in the context of an invasive forest pest, the hemlock wooly adelgid. Our results indicate a statistically significant relationship between hemlock health and residential property values at the 0.1 km level. Comparing through different interpolation methodologies, Kriging provides the most reliable interpolation results which provides us a useful tool to scale up our analysis from specific sample sites to broad geographical area.

Key words: hemlock woolly adelgid, forest damage, spatial interpolation, hedonic model

1. Introduction

Hedonic modeling is a commonly employed method to value changes in environmental assets based on the idea that the prices of properties represents the sum of values associated with property attributes (Palmquist 1991). Recent years have seen important developments and refinements in the hedonic method, which include natural experiments to identify price effects, access to large-scale electronic data on property sale prices and characteristics, and the use of GIS (geographic information system) data to incorporate spatial dimensions of property attributes (Calhoun 2001, Parmeter and Pope 2009, Paterson and Boyle 2002).

When an investigator wishes to merge property sale data with spatial data on an environmental amenity, one problem encountered in the matching process is that the environmental data may be limited (Palmquist and Smith 2001). Although environmental data varies across broad geographical area, these data are usually measured at certain sample sites. For example, if one is interested in how air quality affects property prices, the property data may include all sales in a given area for a specified period of time while the air-quality data is collected at fixed monitoring sites[1]. The air quality data is measured continually doe discrete, but small increments in time, e.g., hourly. For other environmental media, in addition to being spatially discrete, the data may only be reported for specific points in time and the timing of measurements may vary across sites, e.g., volunteer lake water quality monitoring[2]. A challenging task is how to scale or extrapolate site and or time specific environmental data to all property sales within a defined geographical area.

Some investigators have explored this challenge in the context of air pollution using spatial extrapolation procedures such as Kriging (Beron et al. 2001). Ara et al. (2006)

[1] http://www.epa.gov/airquality/airdata/, accessed December 12, 2013.
[2] http://water.epa.gov/type/watersheds/monitoring/vol.cfm, accessed December 12, 2013

interpolated beach water quality data over space and time. Both air and water quality, within a specific area, such as an air quality basin or coastal bay might be consider ubiquitous, in that pollutants disperse out from emission sites and perhaps experience some rate of decay over distance and/or time.

In this paper we explore a different, yet important, type of data. Here we investigate the effect of spatial data extrapolation on the estimation of a hedonic model in the context of an invasive forest pest, the hemlock wooly adelgid (Brush, 1979, McClure 1991, Orwig et al., 2002). Here the data on the infestation are measure at discrete spatial locations and points in time like for the water and air quality data, but the host (hemlock trees) does not provide for continuous dispersal through space. Hemlock trees are clustered in discrete stands and, thus, the infestation must jump from stand to stand as the infestation spreads spatially through time. We investigate the effect of different methods of spatial data interpolation on the estimation of a hedonic property value model.

We investigate the use of three spatial data interpolation methods:

- inverse distance weighting (IDW),
- splines and
- Kriging.

We also consider data interpolation error across approaches and the effects on the estimated hedonic model.

It is thought that changes in climate may increase the frequency and severity of forest fires, insect and disease outbreaks, droughts and storms that can affect trees (Dale et al., 2001; Bentz, 2008; Frankel, 2008). The subsequent losses of trees can impact property values via reductions in shading to reduce heat impacts, reductions in the scenic aesthetics of an area and other consequences. Dying and dead trees can pose risks to residents and their homes. The

hemlock wooly adelgid, as an example case study, causes death of affected trees within about five years. Forward-looking communities can adapt their tree planting and protection efforts to lessen these climate-induced impacts and information on the economic value of tree canopy cover can be used to help justify such efforts. Thus, exploring the impacts of data extrapolation to investigate the economic effects of forest impacts is important to support forest and climate policy.

Our results indicate that the invasion of HWA has caused dramatic losses of healthy hemlock stands in the study area. There exist substantial accompanying losses in property value for the households nearby. Comparing through different interpolation methods, Kriging provides the most reliable interpolation results to scale up our economic hedonic analysis.

2. Literature Review

Spatial interpolation is one well developed methodology in environmental science (Burrough and McDonnell 1998, Webster and Oliver 2001). Inverse distance weighting (IDW), splines and Kriging techniques have all been widely used to predict spatial variables in a forestry context (Biondi et al. 1994; Köhl and Gertner 1997; Gunnarsson et al. 1998; Jansen et al. 2002). For example, Figueiredo-Filho et al. (1996) employed spline technique to evaluate stem diameters and volumes of trees in southern Brazil. Wulff et al. (2006) also conducted Kriging to estimate geographical distribution and dispersal of forest damage from the outbreak of *Gremmeniella* based on the National Forest Inventory dataset. Malhi et al. (2006) employs three techniques, inverse distance weighting spline and Kriging to interpolate the biomass in old-growth Amazonian forests. Their cross-validation results showed IDW is the most appropriate method although its algorithm is least sophisticated.

These spatial interpolation methods has not commonly employed in economic research expect for the evaluation analysis of air pollution. The reason is that the air pollution is only measured at several monitoring stations, while the households are located across the space. Previous researches employed spatial statistical method to interpolate the air condition measurements across study area and then match them with the household sales value based on their locations (Kim et al. 2003, Beron et al. 2004, Anselin and Lozano-Gracia 2008, Fernandez-Aviles et al. 2012).

Ara et al. (2006) has also met the same challenge when they try to evaluate the economic impact from water quality. The water quality along 18 beaches was originally measured at different place and at different time. They also employed geo-statistical method to interpolate the water quality and matched the household properties with the interpolated water quality of the nearest beach.

However, there are seldom studies which investigate how spatial interpolation will affect our hedonic economic analysis when we use prediction results rather than the true measurements in the hedonic model. Anselin and Le Gallo (2006) have compared different spatial interpolation techniques (Thiessen polygons, inverse distance weighting, Kriging and splines) when their prediction results are used as the measurement of air quality in the hedonic models. Their results showed that Kriging provides the best results for interpretation.

In our case, we try to investigate the economic losses from hemlock mortality caused by HWA infestation. Holmes et al. (2010a) found that severely-defoliated hemlocks in northern New Jersey reduced the values of residential parcels with the stricken trees and reduced the value of nearby (up to 0.5km) properties. In our study, we employ the interpolation approach (inverse distance weighting, Kriging and splines) to scale up the analysis from specific area (e.g., county)

to state level. We also investigate how different spatial interpolation methodologies would affect the hedonic model analysis.

Different with Anselin and Le Gallo (2006), we first employed cross-validation methods to compare the prediction accuracy among interpolation methods before making hedonic analysis. Because of our data structure, we can also compare the hedonic analysis results based only on sampled hemlock damage data (true measurements) with the results based on interpolated data (prediction results). These procedures would provide helpful benchmarks to check the reliability when we introduce spatial interpolation methods to scale up our hedonic analysis.

3. Modeling Framework

In the hedonic model analysis, when we value changes in environmental assets, the property value are assumed to be influenced by different attributes, house-specific characteristics Z_i, land cover characteristics L_i, and environmental characteristics E_{it}. The fixed effect panel models are commonly used to handle the problem with other spatially correlated omitted variables as Equation (1).

$$\ln P_{it} = Z_i\alpha + +L_i\beta + E_{it}\lambda + \tau_t + \omega_j + \varepsilon_{it} \quad (1)$$

Here P_{it} is the sale price for property i at time t in the semi-logarithmic function form. τ_t is the time effect, and ω_j is the spatial effect.

In the empirical analysis, we would need to match the environmental attributes with household sales. However, the measurements of environmental attributes would be limited which are usually measured at specific sites. Even if they are representative of the environmental characteristics over study area, the property sales data at these sampled sites may not be

representative of all the property values. When we only consider the impact at these specific sites, we would lose the information from property sales data over large spatial area.

For instance, in this study we assume only when the hemlock stands located within certain distance of households, they will affect the property value. Then, there are four types of locations between household properties and hemlock stands (Figure 2). In case A, the buffer only intersects with sampled hemlock stands. In case B, the buffer intersects with both the sampled and non-sampled hemlock stands. In case C, the buffer intersects only with the non-sampled hemlock stands; we do not have the hemlock damage information. In case D, the buffer does not intersect with any hemlock stands; these properties are assumed to not be affected by the HWA infestation.

Based on the sampled data, we only have the full hemlock damage information for case A. However, as the number of household properties which are only influenced by sampled hemlock stands is small, it may not be representative of the whole study area. We can also employ sampled hemlock damage information to check the impact of HWA infestation on properties in case B. However, we would miss the information of non-sampled stands which could bias our estimates.

To make the maximum use of household sale data, we would want to interpolate the environmental damage to the whole study area and match them with the sales data. In our case, using interpolated hemlock damage data, we would be able to enlarge our economic analysis to all the household sales which are influenced by HWA infestation (case A, B and C in Figure 2).

4. Description of the Study Area

In the research here, our application is to estimate the economic consequences of the spatial and temporal expansion of HWA through central Connecticut and Massachusetts. The HWA was first introduced into Virginia from Japan in the early 1950s; in the past half-century, it has spread to hemlock forests along the east coast of the U.S and became a threat to the eastern hemlock forests of New England (McClure 1991). The population growth of HWA is sensitive to temperature and precipitation, and climate change is expected to favor the spread of HWA (Orwig et al., 2002).

In an effort 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 within a 7,500 km^2 area covers central portions of Connecticut and Massachusetts (see Figure 1). In both states, all stands of eastern hemlock >1.3 ha in area were identified using high-resolution aerial photographs that were then scanned and digitally transferred into a GIS overlay. A total of 6,126 hemlock stands were identified in the study area using this method.

The field surveys were conducted at 142 hemlock stands (red dots in Figure1), and hemlock health characteristics were documented in these sampled stands. The sampled stands were distributed as evenly as possible over the study area. Hemlock vigor and live basal area are two key hemlock damage characteristics recorded in 2007, 2009, and 2011. Live basal area (m^2/ha) is the area of a given section of land that is occupied by the cross-section of tree trunks and stems at their basal. Vigor was measured on the basis of the amount of retained foliage in each stand. There are four vigor categories; 4 = 0 – 25% foliar loss, 3 = 26-50% foliar loss, 2 = 51-75% foliar loss and 1 = 76 – 99% foliar loss.

Table 1 shows the summary descriptive statistics of live basal area and frequency distribution of hemlock vigor for the sampled hemlock stands. Both the mean and maximum value of hemlock live basal area decreased between 2007 and 2011. Except for the severely damaged hemlock stands (vigor=1), the number of damaged hemlock stands (vigor=2 or vigor=3) is increasing through time while the number of healthy hemlock stands (vigor=4) is decreasing. It is likely that the number of severely damaged hemlock stands dropped in 2011 because dead trees either fell over or were removed, and were no longer included in the survey.

To investigate the effect of HWA infestation on residential property, we select three groups of household properties which are located around the hemlock stands within a distance of 0.1km, 0.5km or 1km. DataQuick provides the dataset which contains all the house attributes and sales price during the study years (2007-2011). Lot size, living area, number of bath rooms, house age and distance to highway are included as housing characteristics. We also introduce dummy variable *AC* and *fireplace* to indicate whether the house has air conditioning and fireplace.

Land cover in the neighborhood can also influence the household property value (Irwin 2002; Patterson and Boyle 2002). We constructed land cover variables based on National Land Cover Data (2006) using raster of $30m^2$ pixels. The six different types of land cover variables constructed are water, open space, high developed district, forest, agricultural land and wetland. They are calculated as the percentage of the buffer area around household property which is covered by the each land type, while the size of the buffer is respectively 0.1km, 0.5km, or 1km corresponding for each group.

In Table 2, we list the summary statistics of housing characteristic variables for properties of group <1km. We calculate summary statistics separately for the group of properties located

near the sampled stands and in the sampled years, and for the group of properties located near all the hemlock stands which were sale out from 2007 through 2011. Comparing the summary statistics, we can see the housing characteristics and land cover characteristics are similar between the two groups.

5. Spatial Interpolation

We first employ the geo-statistic interpolation methodologies to scale up our hedonic analysis and predict the spatial distribution of forest damage data; their implements are based on the assumption that the values should be more similar when the points are near to each other. Inverse distance weighting (IDW), Kriging and Spline are three interpolation methodologies commonly applied in the forestry studies; they are readily available in the geostatistical wizard of Geostatistical Analyst Tool in ARCGIS 10.1.

Inverse distance weighting (IDW) assigns values of hemlock damages to unknown points with a weighted average of the values observed at the locations in the neighbor. It gives greater weights to points closest to the prediction location, and the weights diminish as a function of distance (Shepard 1968). An interpolated value u at non-sampled point x using IDW is:

$$u(x) = \frac{\sum_i w_i(x) u_i}{\sum_i w_i(x)} \tag{2}$$

Here u_i denotes the hemlock damages at sampled point x_i, $i = 0,1, \cdots N$. $w_i = \frac{1}{{d_i}^p}$ while d_i is a given distance from the known point x_i to the unknown point x. p is the power parameter which is determined by minimizing the root mean square error calculated in the cross validation.

The Spline tool estimates values of non-sampled points using a mathematical function that minimizes overall surface curvature, resulting in a smooth surface that passes exactly through the input points (Franke 1982; Mitas and Mitasova 1988). We applied a Tension spline here as it provides the best fit based on the cross validation results. The algorithm is as following:

$$u(x) = \alpha + \sum_{i-1}^{N} \frac{\lambda_i}{2\pi\varphi^2} [\ln\left(\frac{d_i\varphi}{2}\right) + c + K_0(d_i\varphi)] \quad (3)$$

Here α and λ_i are coefficients found by the solution of a system of linear equations; c is a constant number. K_0 is the modified Bessel function. d_i is a given distance from the known point x_i to the unknown point x. φ^2 is the weight parameter which determines the smoothness of the surface. The Kernel Parameter here is calculated by minimizing the root mean square error during cross validation.

Kriging predicts the value at a non-sampled location using the weighted average of the known values of its neighbors while the weights are determined by a semivariogram model of spatial autocorrelation (Isaaks and Srivastava 1989; Cressie 1993; Goovaerts 1997; Schabenberger and Gotway 2005). The semivariogram model follows the pattern described in Figure 3 (Stein 1999). The semivariance is

$$\rho(h) = \frac{1}{2n} \sum_{i=1}^{n} (u(x_i) - u(x_i + h))^2 \quad (4)$$

where x_i represents any sampled hemlock stand, $(x_i + h)$ is a sampled stand distance h from x_i, $u(\cdot)$ is the observational value at the sampled location.

The parameters of function form, range, nugget effect and sill are estimated which define the empirical semivariogram model (Cressie 1985; Chilès and Delfiner 1999). Nugget is the semivariance at distance 0 which is defined as measurement errors. Range is the distance at which the semivariance levels off, while sill is the semivariance at the distance of range.

Here the spatial correlation is assumed as isotropic over the study area, i.e. that the spatial correlation is only depending on the distance between two points but not the direction of their separation. As the infestation of HWA has the potential to move from southwest to northeast, we make trend analysis at first. A second-order polynomial trend is removed at first, while the kriging analysis is performed on the residuals. After kriging over the surface, this trend will be added back to the predicted values and create the final prediction results. As our data is highly skewed, we make normal score transformation at first; then simple Kriging is applied. It provides the best fit based on the cross validation results.

Based on the interpolation methodologies described above (IDW, Spline and Kriging), we interpolated both hemlock live basal area and vigor separately for each year. Live basal area is interpolated directly as a continuous variable. Vigor, as categorical variable, is first transformed into indicator variable. *Vigor* equals to 1 while vigor=4 (healthy stands); *Vigor* equals to 0 while vigor≤3 (damaged stands). Then we predict the probability that the hemlock stand is healthy (*PVigor*). The live basal area (or *PVigor*) in non-sampled years (2008 and 2010) is calculated as the mean of the live basal area (or *PVigor*) in the following year and the year ahead.

Cross validation is used to evaluate which model provides the best predictions. Cross validation is performed by removing one point from data set and then predicting its value using

the data at the rest locations. Comparing the predicted value to the observed value across all the points, we can obtain the measurements for evaluation. To have a good fit of the model, the mean standardized prediction error (MSE) should be close to 0, root mean square error (RMSE) should be small, and the root mean squared standardized error (RMSS) should be close to 1.

$$MSE = \frac{\sum_{i=1}^{n}(\widehat{u_i} - u_i)/\widehat{\sigma_i}}{n} \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\widehat{u_i} - u_i)^2}{n}} \tag{6}$$

6. Variable Construction of Environmental Characteristics

The hemlock damages changed the environmental attributes of residential properties which have the potential to affect property value. Live basal area (lba_{it}) and the interaction between live basal area and vigor ($lba_{it} * vigor_{it}$) are included in the model as the measurements for attributes of hemlock damage.

$$\ln P_{it} = Z_i\alpha + +L_i\beta + lba_{it}\gamma + lba_{it} * vigor_{it}\theta + \tau_t + \omega_j + \varepsilon_{it} \tag{7}$$

According the hedonic estimation result in equation (7), the marginal effect of hemlock damage on property value is

$$\frac{\partial lnp}{\partial vigor} = lba_{it}\theta \tag{8}$$

$$\frac{\partial lnp}{\partial lba} = \gamma + vigor_{it}\theta \tag{9}$$

As we are not sure how the damaged hemlocks stands would affect property value, we also need to consider about the uncertainties of variable construction. Live basal area (lba) are measured by four different indexes, ba_t , lba_w, lba_s and lba_np. lba_t represents the

percentage of the buffer area that is covered by hemlock trees (Equation 10). lba_w is the weighted average of live basal area while the weights are the intersected area of hemlock stands which intersects with the buffer (Equation 11). lba_s is also the weighted average of live basal area while the weights are the total area of hemlock stands which intersect with the buffer (equation 12). So here we assume once the hemlock stands intersect with the household buffer, the hemlocks in the whole stand area can affect the household price. lba_np is the live basal area at the nearest point. In equation (10) - (12), lba_i is the live basal area for property i; lba_{ij} is the live basal area for hemlock stand j which intersects with the buffer of property i; s_{ij} is the size of intersection area between hemlock stand j and buffer i ; B_i is the size of buffer i.

$$lba_w_i = \frac{\sum_j lba_{ij} s_{ij}}{\sum_j sij} \tag{10}$$

$$lba_t_i = \frac{\sum_j lba_{ij} s_{ij}}{B_i} \tag{11}$$

$$lba_t_i = \frac{\sum_j lba_{ij} B_i}{\sum_j Bi} \tag{12}$$

Vigor is constructed in a similar way by three indexes, $pvigor_w$, $pvigor_s$, and $pvigor_np$ from the interpolated probability of healthy hemlock stands *PVigor*. Then $pvigor_w$, $pvigor_s$, and $pvigor_np$ are transformed back into dummy variables $vigor_w$, $vigor_s$, and $vigor_np$ based on two thresholds: (1) if $pvigor_i \geq 0.5$, $vigor_i = 1$, otherwise $vigor_i = 0$; Or (2) if $pvigor_i \geq 0.75$, $vigor_i = 1$, otherwise $vigor_i = 0$ (here *i* represents index *s*, *w* or *np*). Then the interaction between live basal area and vigor are $lba * vigor_i = lba_i * vigor_i$ where *i* is index *w*, *s* or *np*; and $lba * vigor_t = lba_t * vigor_w$.

7. Results

7.1 Spatial Interpolation

Live basal area and vigor are separately interpolated over space for the sample years of 2007, 2009 and 2011. Cross validation results for interpolation methods of IDW, spline, and Kriging are listed in Table 3 which indicates relatively accurate predictions of our models. Mean prediction error (ME) and root mean square error (RMSE) are available for all three interpolation methods, while mean standardized prediction error (MSE), root mean square standardized error (RMSS), and average standard prediction error (ASE) are only available for Kriging. Based on the cross validation results of ME, spline provides the best prediction results for live basal area, while kriging provides the best prediction results for vigor. The cross validation results of RMSE are similar across interpolation methods, while different interpolation methods provide best predictions in different years. Thus, it is hard to tell which method provides better interpolation results only based on cross-validation results.

The summary descriptive statistics of interpolated live basal area and vigor for hemlock stands (n=6,126) are shown in Table 4. The data in Table 4 shows the large decrease in the size and health level of hemlocks in the study area from year 2007 to year 2011. Comparing three interpolation methods, we can see the differences of predicted values among three interpolation methods. Kriging provides the smallest standard deviation while spline provides the largest standard deviation across predicted values of all hemlock stands. The mean predicted value from Kriging is also generally smaller.

The interpolated live basal area over the study area for each year based on Kriging is shown in Figure 4. Through time we see the live basal area has decline (red areas disappear and green areas increase substantially). In year 2007, the maximum of interpolated live basal area is about 87 m^2/ha. In year 2011, the interpolated live basal area over all the study area is not larger than 40 m^2/ha.

The interpolated probability of healthy hemlock stands (2007-2011) based on Kriging is shown in Figure 5. The change of the hemlock vigor follows the same pattern as live basal area; the red area decreases substantially. Overall, the data reveals the HWA infestation in 2007 was primarily in southern Connecticut and the hemlocks in Massachusetts were generally healthy. By 2011, a period of four years, the HWA infestation had spread substantially into Massachusetts.

7.2 Hedonic Model Analysis

First, we estimate the hedonic model only based on sampled data. The estimation results including properties of case A and B in Figure 2 are listed in Table 5, while the estimation results only including properties of case A are listed in Table 6. Both tables include estimation results based on four different measurements of hemlock damages and two types of transformation with variable $vigor$. In both Table 5 and Table 6, the coefficients of variables $lba * vigor_w$, $lba * vigor_s$ and $lba * vigor_np$ are significant at 1% level only for group <0.1km. The coefficient of variable $lba * vigor_t$ shows significance at 5% level only for group <0.5km in Table 5. These results are stable across two transformation types. However, there are only about 100 observations for group <0.1km which may not be representative of the impact in the whole study area.

Then, we estimate the hedonic model based on interpolated data of hemlock damage from three interpolation methods. The estimation results of hedonic model based on interpolation method of IDW are listed in Table 7. Variables lba_t and $lba * vigor_t$ are significant at 5% level only for group <0.1km using 0.5 as the threshold in the transformation of $vigor$.

The estimation results of hedonic model based on interpolation method of spline are listed in Table 8. When we use 0.5 as the threshold in the transformation of $vigor$, variables $lba * vigor_t$, $lba * vigor_s$, and $lba * vigor_w$ are all significant at 10% level for both group

<0.1km and group <0.5km. Their coefficients for group <0.5km is smaller than the coefficients for group <0.1km. Variable lba_t is also significant at 5% level for group <0.1km. When we use 0.75 as the threshold in the transformation of $vigor$, there turns to be no strong and consistent estimation results.

The estimation results of hedonic model based on interpolation method of Kriging are listed in Table 9. When we use 0.5 as the threshold in the transformation of $vigor$, variables $lba * vigor_t$, $lba * vigor_s$, and $lba * vigor_w$ are all significant at 5% level, and variable lba_t is significant at 1% level for group <0.1km. Variables $lba * vigor_t$ and $lba * vigor_w$ are also significant at 10% level for group <0.5km. When we use 0.75 as the threshold in the transformation of $vigor$, variables $lba * vigor_t$, $lba * vigor_s$, and $lba * vigor_w$ are all significant at 1% level for group <0.1km.Variables $lba * vigor_s$, and $lba * vigor_w$ is even significant at 1% level for both group <0.5km and group <1km, however this effects may be enlarged.

Based on the estimation results of group <0.1km after Kriging, we calculate the marginal effects of lba_t and $lba * vigor_t$ while $vigor$ is transformed at the threshold of 0.5. At the mean of lba_t in 2007 which is 0.17% of the buffer area, when the healthy stands ($vigor = 1$) turns to be damaged ($vigor = 0$), the residential property value will decrease by 3.4%. When the hemlock stand is healthy ($vigor = 1$), that the hemlock live basal area increases by 0.1% of buffer area will cause the sale price to increase by 0.35%. When the hemlock stand is damaged ($vigor = 0$), that the live basal area increases by 0.1% of buffer area will cause the sale price to decrease by 1.65%.

8. Discussion

The results of this study indicate that HWA has caused dramatic damages to hemlock stands in central Connecticut and central Massachusetts during the period 2007-2011. This landscape change causes the decrease of the sales price for properties residing in the study area.

Comparing three interpolation methods, hedonic estimation results based on Kriging provides the most stable and consistent estimation results across different specifications of hemlock damage variables. IDW could not reflect the impact of hemlock damage on household properties for most of the specifications of hemlock damage variables. Spline methods can show the impact of hemlock damage on property value only when we transform $vigor$ with the threshold of 50%. Overall, Kriging technique provides the best interpolation results across different specifications of forest damage variables.

Comparing four indexes of hemlock damage variables, interpolated hemlock damage value at nearest neighbor point is not a good indicator for HWA impact, while all the other three indexes can reflect the impact of HWA on property value. lba_t can not only show the positive impact of healthy hemlock trees for group <0.5km, but also the negative impact of damaged trees which are near the household properties (group <0.1km). Generally, with the infestation of HWA, damaged hemlock trees located within 0.1km buffer of household property will lead negative impact on the property value. The reason may be the risk induced by falling trees and the fees to clean up dead trees.

According to the impact of HWA on residential property values, the aggregate economic losses have likely rapidly accelerated in the study area during the past several years. It can cause even larger damages when the infestation of HWA moves further into northern area where there are more hemlock forests. Although forest management tools are not currently available to either slow the spread or to protect naturally regenerated hemlock forests from HWA, the economic

benefits of developing such tools could be substantial. Slowing the advance of HWA into residential forests could convey substantial benefits to homeowners, and may substantially exceed the cost of such programs. Protecting or delaying the onset of HWA in such areas may be a smart investment of public and private funds.

Although Kriging provides the best interpolation results, there will still be measurement errors when we used the prediction results rather than the true value in hedonic model analysis. Figure 6 show us the cross-validation results when we use different interpolation methods, IDW, Kriging and spline. When we compare predicted and actual values for live basal area, for example, we can see there are relatively large prediction errors for stands with large live basal area, especially in 2011. That is because the distribution of sampled values is skewed with most observations for smaller live basal areas and less frequent observations for large live basal areas. This prediction error may exacerbate the computation of HWA damages in terms of maximum live basal area. Similarly for vigor, with the small frequency of observing severely damaged stands, there are relatively large prediction errors for stands with low vigor. So we should be cautious in investigating the HWA effect on property values based on these interpolated hemlock damage indicators. Here we just employed the mean of interpolation values for non-sampled hemlock stands in our hedonic estimation. We would also consider about introducing the distributions of interpolation values and measurement errors of predictions into the hedonic analysis for further investigation.

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

	Year	2007	2009	2011
Live Basal Area (m^2/ha)	Mean	38.23	27.83	15.31
	SD	27.59	16.29	11.89
	Min	0	0	0
	Max	125.45	73.34	54.04
	N[a]	140	138	122
Vigor	1	8	11	9
	2	18	19	23
	3	33	37	44
	4	82	71	47
	N	141	138	123

[a] The sample size decreased over years as some hemlock stands disappeared or were not allowed for access again.

Table 2. Descriptive Statistics of Housing Characteristics Variables

	Mean	SD	Min	Max
Sampled (N=1,680)				
House price ($2003)	336,415	253,001	38,543	5,337,336
Living Area (ft^2)	2,060	913	420	12,872
Lot size (ft^2)	63,692	129,927	0	2,400,174
Baths	1.81	0.82	0	8
Age	1957	46	1680	2011
AC	0.30	0.46	0	1
Fireplace	0.50	0.50	0	1
Distance to highway (m)	883	910	0.06	6,654
Water (%)	1.95	4.37	0	31.33
Open space (%)	12.38	8.21	1.26	46.84
Developed area (%)	0.93	2.11	0	15.16
Forest (%)	39.62	27.87	0	96.06
Agricultural (%)	5.69	8.12	0	56.18
Wetland (%)	4.19	4.98	0	35.48
Interpolated (N=24,731)				
House price ($2003)	277,616	189,890	7,517	12,364,360
Living Area (ft^2)	1,746	767	0	12,872
Lot size (ft^2)	51,204	135,630	0	7,122,060
Baths	1.63	0.72	0	9
Age	1960	39	1680	2011
AC	0.27	0.44	0	1
Fireplace	0.45	0.50	0	1
Distance to highway (m)	843	849	0	7,102
Water (%)	2.05	4.86	0	40.88
Open space (%)	13.88	8.83	0	56.78
Developed area (%)	1.46	2.72	0	31.43
Forest (%)	40.82	24.81	0.22	97.39
Agricultural (%)	5.95	8.16	0	73.58
Wetland (%)	6.08	7.18	0	54.65

Table 3. Cross Validation results for Live Basal Area and Vigor

		Year	ME[a]	RMSE[b]	MSE[c]	RMSS[d]	ASE[e]
IDW	live Basal Area	2007	-0.672	22.313			
		2009	0.173	14.266			
		2011	0.174	11.657			
	Vigor	2007	0.014	0.357			
		2009	0.004	0.381			
		2011	0.010	0.439			
Spline	live Basal Area	2007	-0.208	22.052			
		2009	0.039	14.392			
		2011	0.043	11.596			
	Vigor	2007	0.006	0.362			
		2009	0.002	0.366			
		2011	0.005	0.428			
Kriging	live Basal Area	2007	-0.370	22.228	-0.003	1.017	21.493
		2009	0.230	14.277	0.013	1.101	12.755
		2011	0.105	11.382	0.017	1.026	11.128
	Vigor	2007	0.002	0.364	0.004	1.016	0.364
		2009	-0.002	0.383	-0.003	1.024	0.373
		2011	-0.002	0.435	0.019	1.055	0.412

[a] ME represents mean prediction error.
[b] RMSE represents root mean square error.
[c] MSE represents mean standardized prediction error.
[d] RMSS represents root mean square standardized error.
[e] ASE represents average standard prediction error.

Table 4. Interpolated Live Basal Area and Vigor for all Stands (n=6,126)

		Year	Mean	SD	Min	Max
IDW	Live Basal Area (m^2/ha)	2007	48.919	14.059	3.486	117.288
		2009	31.581	6.183	4.337	57.980
		2011	16.487	4.567	1.804	46.987
	Vigor	2007	0.824	0.257	0	1
		2009	0.763	0.290	0.002	1
		2011	0.382	0.223	0	0.975
Spline	Live Basal Area (m^2/ha)	2007	50.342	15.163	4.023	110.439
		2009	31.521	6.209	6.424	52.124
		2011	16.641	5.059	2.376	43.598
	Vigor	2007	0.818	0.258	0	1
		2009	0.737	0.319	-0.084	1.144
		2011	0.376	0.254	0	1.038
Kriging	Live Basal Area (m^2/ha)	2007	46.899	12.808	5.537	87.250
		2009	30.668	6.100	7.082	44.364
		2011	16.228	3.453	4.167	37.181
	Vigor	2007	0.819	0.236	-0.041	1.124
		2009	0.768	0.254	-0.080	1.167
		2011	0.366	0.165	0.026	0.898

Table 5. Estimation Results of Hedonic Model Based on Sampled Data (case A and B)

	<0.1km	<0.5km	<1km
vigor=1 if P(vigor=1)>50%; otherwise vigor=0			
lba_t	-.0840	-.0545	-.0029
	(-0.79)	(-0.30)	(-0.02)
lba *vigor_t	.2180	.2245	-.3331
	(0.88)	(0.95)	(-1.17)
lba_w	-.0004	-.0011	-.0002
	(-0.29)	(-1.18)	(-0.39)
lba*vigor_w	.0059***	-.0001	-.0002
	(2.85)	(-0.11)	(-0.29)
lba_s	-.0004	-.0008	-.0001
	(-0.29)	(-0.81)	(-0.17)
lba*vigor_s	.0059***	-.0004	-.0003
	(2.85)	(-0.41)	(-0.48)
lba_np	-.0004	-.0013	.00007
	(-0.29)	(-1.43)	(0.14)
lba*vigor_np	.0059***	-.00003	-.0004
	(2.85)	(-0.03)	(-0.58)
vigor=1 if P(vigor=1)>75%; otherwise vigor=0			
lba_t	-.0840	-.0402	.0517
	(-0.79)	(-0.22)	(0.31)
lba *vigor_t	.2180	.1505	-.6105*
	(0.88)	(0.63)	(-1.89)
lba_w	-.0004	-.0010	-.0001
	(-0.29)	(-1.09)	(-0.18)
lba*vigor_w	.0059***	-.0002	-.0004
	(2.85)	(-0.22)	(-0.58)
lba_s	-.0004	-.0007	-.00004
	(-0.29)	(-0.72)	(-0.07)
lba*vigor_s	.0059***	-.0005	-.0004
	(2.85)	(-0.54)	(-0.60)
lba_np	-.0004	-.0013	.00007
	(-0.29)	(-1.43)	(0.14)
lba*vigor_np	.0059***	-.00003	-.0004
	(2.85)	(-0.03)	(-0.58)
N	143	689	1680

Note: *** denotes significant at the 1% level; ** denotes significant at the 1% level; * denotes significant at the 1% level.

Table 6. Estimation Results of Hedonic Model Based on Sampled Data (case A)

	<0.1km	<0.5km	<1km
vigor=1 if P(vigor=1)>50%; otherwise vigor=0			
lba_t	-.0615	-.2945	-.0469
	(-0.59)	(-1.48)	(-0.16)
lba *vigor_t	.3547	.5917***	-.3174
	(1.52)	(2.97)	(-0.59)
lba_w	.00005	-.0012	-.0013
	(0.03)	(-1.12)	(-1.24)
lba*vigor_w	.0087***	.0011	.0006
	(3.87)	(0.99)	(0.61)
lba_s	.00005	-.0009	-.0012
	(0.03)	(-0.84)	(-1.20)
lba*vigor_s	.0087***	.0008	.0005
	(3.87)	(0.64)	(0.46)
lba_np	.00005	-.0014	-.0012
	(0.03)	(-1.29)	(-1.20)
lba*vigor_np	.0087***	.0013	.0008
	(3.87)	(1.14)	(0.68)
vigor=1 if P(vigor=1)>75%; otherwise vigor=0			
lba_t	-.0615	-.2802	-.0453
	(-0.59)	(-1.41)	(-0.15)
lba *vigor_t	.3547	.5234**	-.3211
	(1.52)	(2.57)	(-0.60)
lba_w	.00005	-.0012	-.0012
	(0.03)	(-1.07)	(-1.23)
lba*vigor_w	.0087***	.0010	.0006
	(3.87)	(0.91)	(0.59)
lba_s	.00005	-.0009	-.0012
	(0.03)	(-0.84)	(-1.20)
lba*vigor_s	.0087***	.0008	.0005
	(3.87)	(0.64)	(0.47)
lba_np	.00005	-.0014	-.0012
	(0.03)	(-1.29)	(-1.20)
lba*vigor_np	.0087***	.0013	.0008
	(3.87)	(1.14)	(0.68)
N	125	471	1042

Note: *** denotes significant at the 1% level; ** denotes significant at the 1% level; * denotes significant at the 1% level.

Table 7. Hedonic Estimation Results Based on IDW

	<0.1km	<0.5km	<1km
vigor=1 if P(vigor=1)>50%; otherwise vigor=0			
lba_t	-.0978**	-.0330	.0491
	(-2.15)	(-0.53)	(0.71)
lba *vigor_t	.1082**	.0683	-.0315
	(2.41)	(1.12)	(-0.45)
lba_w	0.000002	.0004	.0002
	(0.00)	(0.72)	(0.45)
lba*vigor_w	.0006	.0004	.0002
	(0.90)	(1.53)	(1.25)
lba_s	.00006	.0004	.0002
	(0.06)	(0.67)	(0.45)
lba*vigor_s	.0005	.0003	.0002
	(0.83)	(1.40)	(1.22)
lba_np	.0008	.0008	.0005
	(0.95)	(1.57)	(1.03)
lba*vigor_np	-.0005	.00004	-.00001
	(-1.01)	(0.16)	(-0.05)
vigor=1 if P(vigor=1)>75%; otherwise vigor=0			
lba_t	-.0594	-.0213	.0102
	(-1.37)	(-0.39)	(0.17)
lba *vigor_t	.0654	.06169	.0185
	(1.44)	(1.04)	(0.29)
lba_w	.0003	.0006	.0003
	(0.25)	(1.02)	(0.56)
lba*vigor_w	.0003	.0002	.0002
	(0.65)	(0.59)	(0.94)
lba_s	.0003	.0006	.0002
	(0.25)	(0.94)	(0.44)
lba*vigor_s	.0003	.0001	.0002
	(0.65)	(0.56)	(1.14)
lba_np	.0008	.0008	.0005
	(0.92)	(1.57)	(1.05)
lba*vigor_np	-.0002	.00003	-.0001
	(-0.36)	(0.13)	(-0.51)
N	2,948	13,925	24,731

Note: *** denotes significant at the 1% level; ** denotes significant at the 1% level; * denotes significant at the 1% level.

Table 8. Hedonic Estimation Results Based on Spline

	<0.1km	<0.5km	<1km
vigor=1 if P(vigor=1)>50%; otherwise vigor=0			
lba_t	-.1118**	-.0619	.0349
	(-2.43)	(-1.00)	(0.49)
lba *vigor_t	.1277***	.1060*	-.0151
	(2.91)	(1.80)	(-0.22)
lba_w	-.0006	.0001	.0001
	(-0.63)	(0.21)	(0.28)
lba*vigor_w	.0011**	.0005**	.0002
	(2.25)	(2.12)	(0.98)
lba_s	-.0006	.00004	.0001
	(-0.59)	(0.07)	(0.23)
lba*vigor_s	.0011**	.0005**	.0002
	(2.19)	(2.18)	(1.02)
lba_np	.0009	.0007	.0004
	(1.07)	(1.39)	(0.83)
lba*vigor_np	-.0006	-.00002	-.00002
	(-1.40)	(-0.09)	(-0.09)
vigor=1 if P(vigor=1)>75%; otherwise vigor=0			
lba_t	-.0710	-.0277	-.0078
	(-1.61)	(-0.52)	(-0.14)
lba *vigor_t	.0856*	.0731	.0426
	(1.90)	(1.27)	(0.68)
lba_w	.00005	.0003	-.0001
	(0.05)	(0.52)	(-0.19)
lba*vigor_w	.0005	.0003	.0005**
	(1.13)	(1.41)	(2.44)
lba_s	.00004	.0003	-.0001
	(0.03)	(0.43)	(-0.24)
lba*vigor_s	.0005	.0003	.0005**
	(1.16)	(1.38)	(2.42)
lba_np	.0008	.0007	.0004
	(1.02)	(1.36)	(0.81)
lba*vigor_np	.0001	.0001	.00004
	(0.23)	(0.52)	(0.18)
N	2,948	13,925	24,731

Note: *** denotes significant at the 1% level; ** denotes significant at the 1% level; * denotes significant at the 1% level.

Table 9. Hedonic Estimation Results Based on Kriging

	<0.1km	<0.5km	<1km
vigor=1 if P(vigor=1)>50%; otherwise vigor=0			
lba_t	-.1646***	-.0782	.0362
	(-3.33)	(-1.21)	(0.48)
lba *vigor_t	.1993***	.1253**	-.0203
	(4.23)	(1.98)	(-0.27)
lba_w	-.0010	-.0002	-.0004
	(-0.81)	(-0.33)	(-0.72)
lba*vigor_w	.0018**	.0006*	.0003
	(2.56)	(1.74)	(1.28)
lba_s	-.0010	-.0002	-.0004
	(-0.81)	(-0.24)	(-0.76)
lba*vigor_s	.0018**	.0005	.0003
	(2.55)	(1.55)	(1.22)
lba_np	.0010	.0004	-.00006
	(0.99)	(0.62)	(-0.10)
lba*vigor_np	-.0001	.00005	-.0001
	(-0.20)	(0.18)	(-0.45)
vigor=1 if P(vigor=1)>75%; otherwise vigor=0			
lba_t	-.0612	-.0394	-.0300
	(-1.39)	(-0.80)	(-0.53)
lba *vigor_t	.0801*	.0925	.0687
	(1.72)	(1.63)	(1.12)
lba_w	-.0003	-.0008	-.0011
	(-0.21)	(-0.99)	(-1.55)
lba*vigor_w	.0010*	.0010***	.00093***
	(1.68)	(3.31)	(3.48)
lba_s	-.0003	-.0008	-.0010
	(-0.21)	(-1.03)	(-1.54)
lba*vigor_s	.0010*	.0010***	.0009***
	(1.67)	(3.41)	(3.30)
lba_np	.0010	.0004	-.00005
	(0.98)	(0.61)	(-0.09)
lba*vigor_np	-.0005	.0001	0.000007
	(-1.01)	(0.36)	(-0.09)
N	2,948	13,925	24,731

Note: *** denotes significant at the 1% level; ** denotes significant at the 1% level; * denotes significant at the 1% level.

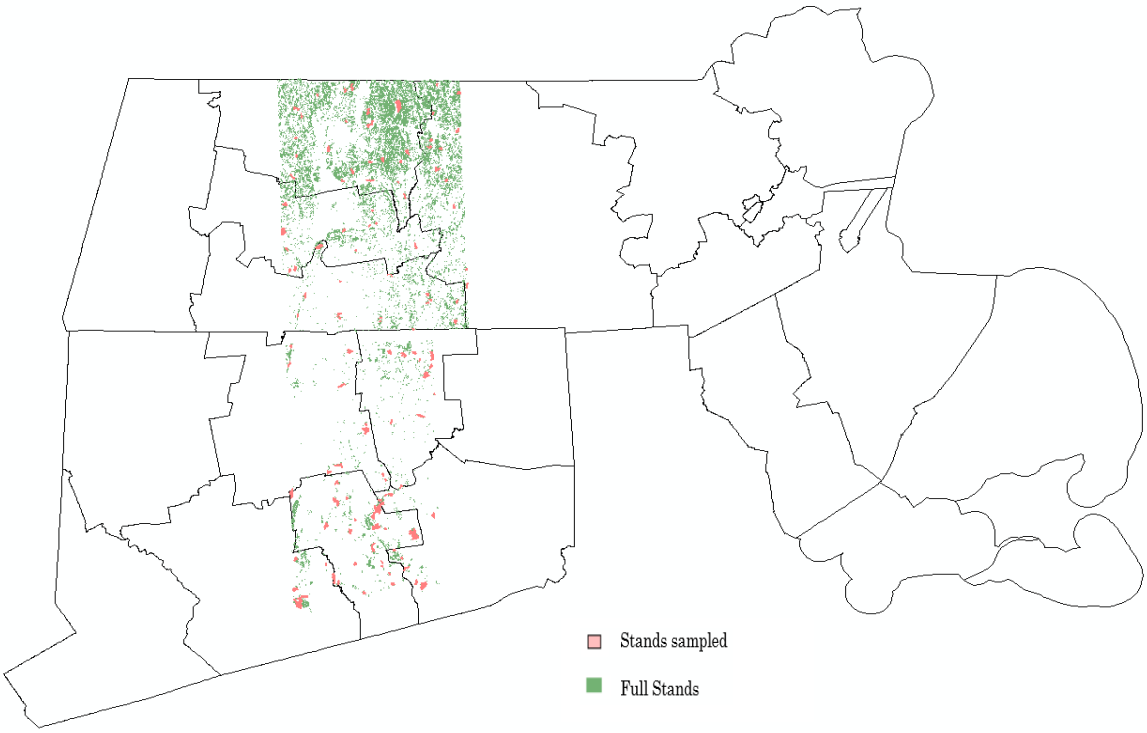


Figure 1. Hemlock Stands in the Study Area

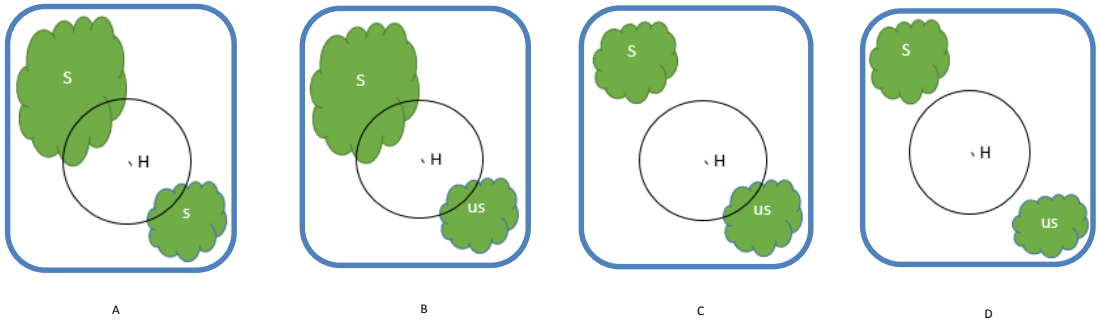


Figure 2. Locations between Household Properties and Hemlock Stands

Note: H represents household property; S represents sampled hemlock stand; US represents non-sampled hemlock stand.

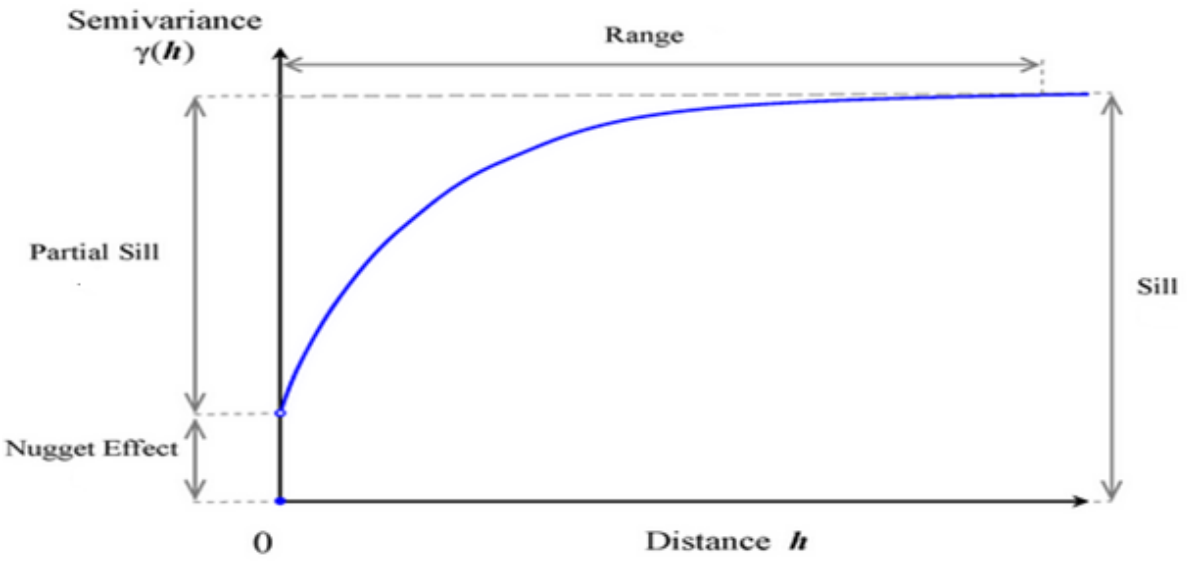


Figure 3. Semivariogram Model and the Parameters

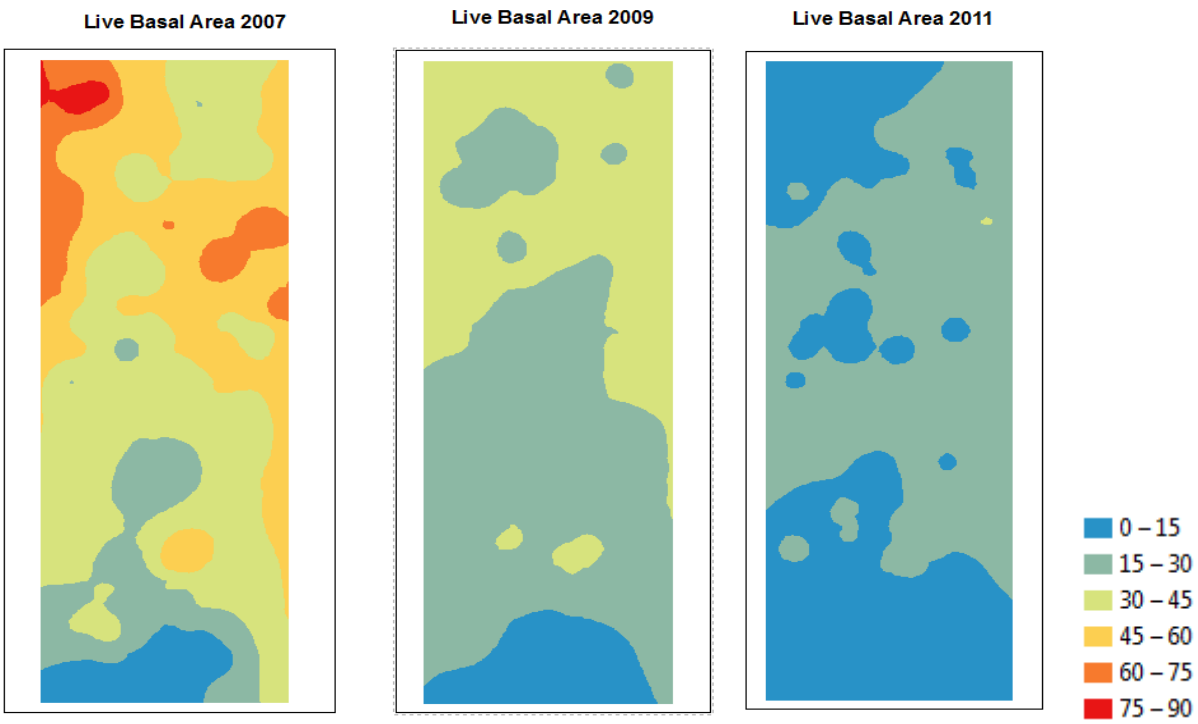


Figure 4. Interpolated live Basal Area (m^2/ha) by Kriging in the Study Area (2007-2011)

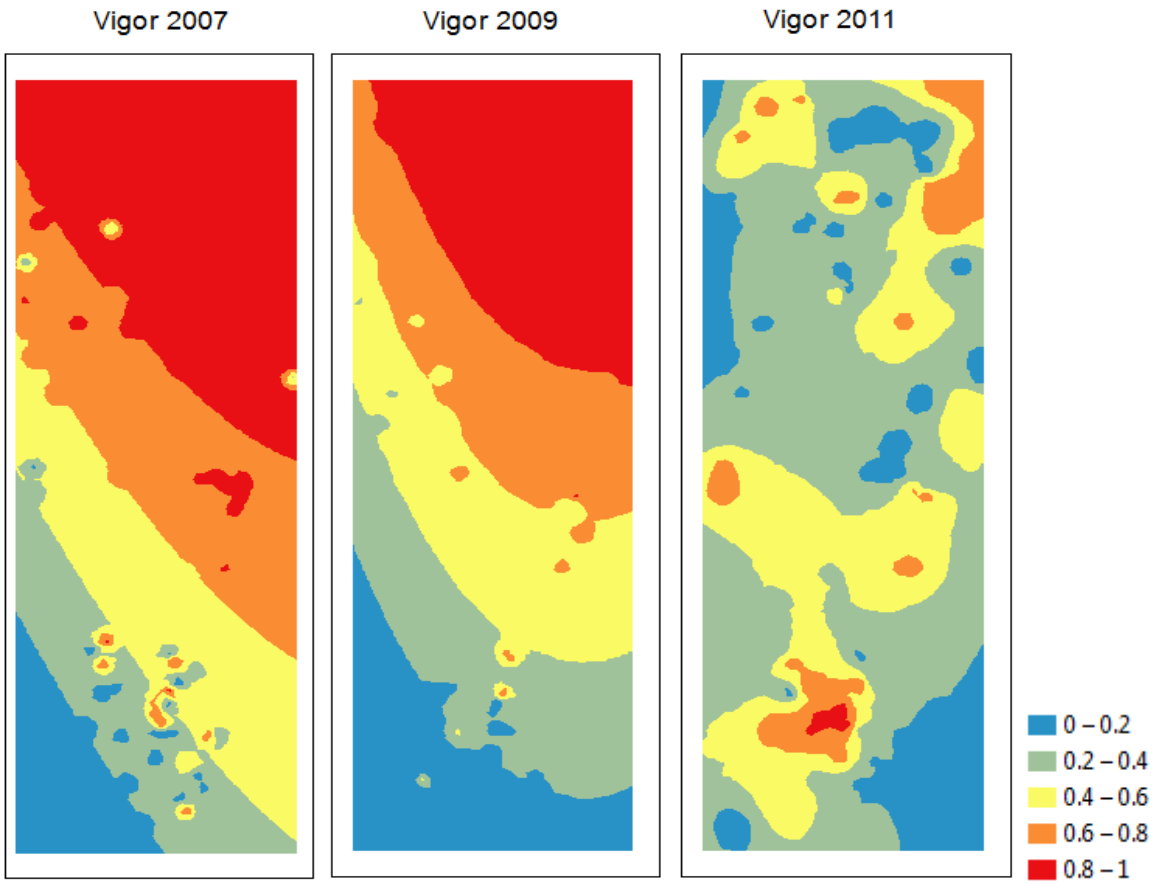
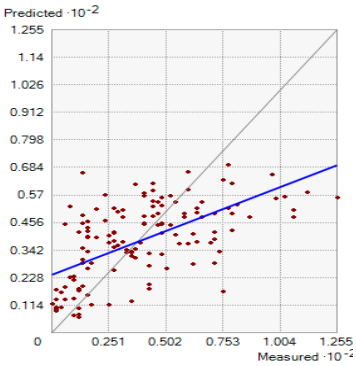
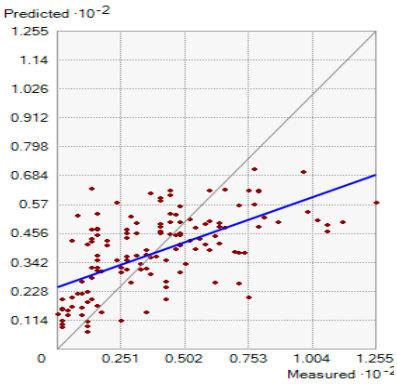


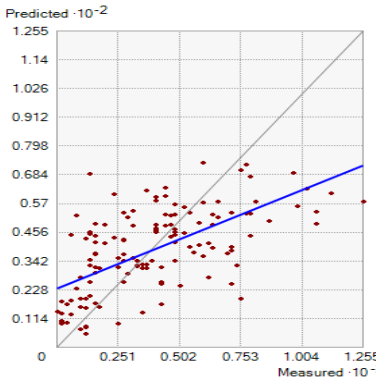
Figure 5. Interpolated Vigor (probability) by Kriging in the Study Area (2007-2011)



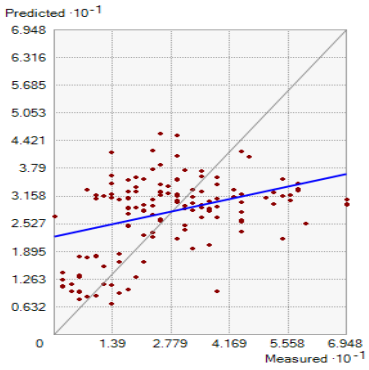
2007 IDW



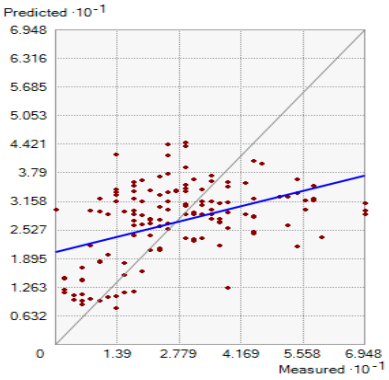
2007 Kriging



2007 Spline



2009 IDW



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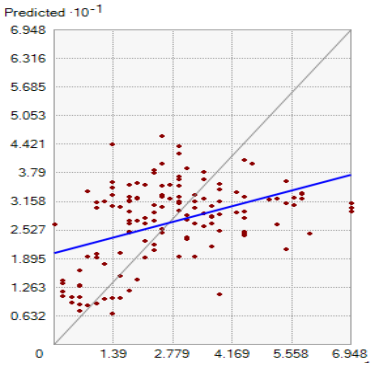

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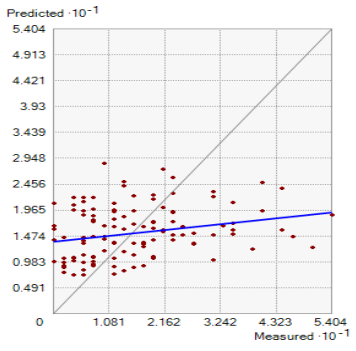

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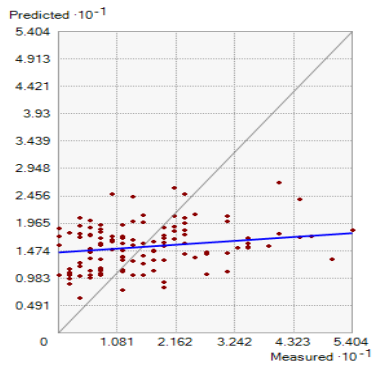
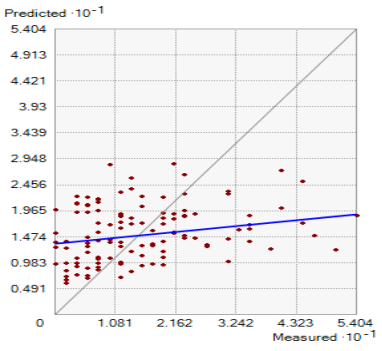


2011 Kriging



2011 Spline

Figure 6. Cross Validation Results for live Basal Area (m^2/ha) by Kriging (2007-2011)