



## Analysis

## A spatial-dynamic value transfer model of economic losses from a biological invasion

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## ABSTRACT

Rigorous assessments of the economic impacts of introduced species at broad spatial scales are required to provide credible information to policy makers. We propose that economic models of aggregate damages induced by biological invasions need to link microeconomic analyses of site-specific economic damages with spatial-dynamic models of value change associated with invasion spread across the macro-scale landscape. Recognizing that economic impacts of biological invasions occur where biological processes intersect the economic landscape, we define the area of economic damage (AED) as the sum of all areas on the physical landscape that sustain economic damage from a biological invasion. By subsuming fine-scale spatial dynamics in the AED measure, temporal dynamics of the AED can be estimated from an empirical distribution of the AED effective range radius over time. This methodology is illustrated using the case of a non-native forest pest, the hemlock woolly adelgid (HWA; *Adelges tsugae*). Geographic Information Systems and spatially referenced data provide the basis for statistical estimation of a spatial-dynamic value transfer model which indicates that HWA is annually causing millions of dollars of economic losses for residential property owners in the eastern United States.

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## 1. Introduction

Biological invasions by non-native forest insects and diseases currently pose a substantial, complex, and long-term threat to forest ecosystems and the services they provide to societies around the globe. For millennia, the world's biota has been separated into independently evolving ecological communities. The growth in international trade represents but a brief moment in the evolution of ecological species and yet has provided new linkages between geographically dispersed markets, and the movement of products has created new pathways for arrivals of non-native species which threaten ecological communities (Stanaway et al., 2001; Vilá and Pujadas, 2001; Levine and D'Antonio, 2003; Work et al., 2005; Caton et al., 2006; McCullough et al., 2006). Although many invasions have been inconsequential, history has shown that a few species have the potential to become major pests (Williamson and Fitter, 1996).

Forests provide suitable habitat for an assortment of invading organisms (Liebhold et al., 1995). Since the time Europeans discovered North America, more than 368 exotic phytophagous insects have become established in forests, woodlots, parks, and orchards (Mattson et al., 1994). Despite the fact that most non-native forest insects have

proven to be innocuous and cause little harm, a few — such as the European gypsy moth (*Lymantria dispar*), emerald ash borer (*Agrilus planipennis*), and hemlock woolly adelgid (*Adelges tsugae*) — have become major pests. The number of non-native tree pathogens that have become established in North America is difficult to gauge, as many microorganisms colonizing trees are innocuous and, in general, no effort is expended to document invasions by species unless they have measurable impacts. However, at least 16 pathogen species have colonized forest and urban forest trees since European settlement (Aukema et al., forthcoming), and only a few tree diseases — such as chestnut blight (*Cryphonectria parasitica*), Dutch elm disease (*Ophiostoma* spp.), and sudden oak death (*Phytophthora ramorum*) — have had substantial economic consequences.

Biological invasions of forests invoke a challenging class of problems for forest economists and policy makers for two principal reasons. First, economic losses stemming from the establishment and spread of non-native forest pests are difficult to quantify, and are therefore rarely used in decision-making (Holmes et al., 2008). This is due, in part, to the fact that economic damages resulting from biological invasions are externalities, or side effects, of other economic processes such as international and domestic trade (Perrings et al., 2002). Indeed, many of the losses in economic value induced by non-native forest pests are due to the loss of non-market economic values (Leuschner et al., 1996; Holmes et al., 2009), and creative methods are required to isolate and quantify the magnitude of economic impacts. Second, the flow of economic value in the forest economy is linked to the forest ecosystem

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by a suite of spatial–dynamic processes. The integration of spatial and temporal dynamics in a joint economic–ecological system requires creative approaches to modeling, particularly in a data poor environment (Sharov and Liebhold, 1998; Smith et al., 2009).

In this paper, we provide an economic framework designed to measure the landscape scale economic impacts of a biological invasion in forests with explicit recognition of spatial–dynamic processes. Section 2 provides an overview of the spatial dynamics of invasion spread based on the use of partial differential equations. We demonstrate in Section 3 how the temporal dynamics of the integrated area of economic damage can be directly modeled using empirical observations on the distribution of the effective range radius over time. The spread of economic damages across the landscape can then be combined with microeconomic damage models to estimate economic damages at the landscape scale. An empirical illustration of the general model is presented in Section 4 using the case of the hemlock woolly adelgid. Finally, conclusions are presented in Section 5.

## 2. Spatial-dynamic Models of Invasion Spread

Three stages of the biological invasion process are generally recognized: 1) arrival, the transport of the invading species to a new habitat; 2) establishment, the growth of the newly arrived population to a level such that extinction is no longer possible and 3) spread, the expansion of the invading species range into the geographical extent of a suitable habitat (Lockwood et al., 2007; Shigesada and Kawasaki, 1997). Most invasions are typically not even noticed until they are in the spread phase and therefore we focus here on the invasion spread. The process of invasion spread emerges from the combination of: (1) population growth, (2) dispersal of organisms, and (3) spatial geometry. The classic approach to modeling invasion spread uses a partial differential equation (PDE) which allows modelers to incorporate temporal and spatial processes simultaneously (Holmes et al., 1994). The first mathematical statements using reaction–diffusion dispersal equations to model biological invasion assumed population growth were either exponential (Skellam, 1951) or governed by density-dependent mortality (Fisher, 1937). In one spatial dimension, the partial differential equation describing logistic population growth and spread is:

$$\frac{\partial N(s, t)}{\partial t} = rN \left( 1 - \frac{N}{K} \right) + D \frac{\partial^2 N(s, t)}{\partial s^2} \quad (1)$$

where  $N(s, t)$  is the population density of the population as a function of spatial location  $s$  at time  $t$ ,  $r$  is the intrinsic (per capita) growth rate,  $K$  is the carrying capacity, and  $D$  is a measure of the mean squared displacement of individuals per unit time (measured in units of distance<sup>2</sup>/time). This simple model, which is regulated by density-dependent mortality, produces a traveling wave of invaders that moves across a homogenous landscape at a velocity that approaches the asymptotic constant rate

$$v = 2\sqrt{rD} \quad (2)$$

as the invasion unfolds. In a two-dimensional model, the asymptotic wave speed for the one-dimensional case applies, and circular waves spread outward across a homogeneous plain (Holmes et al., 1994; Shigesada and Kawasaki, 1997). The invaded area forms a disk shape with a center located at the initial point of invasion, and a linear relationship is predicted between the square root of the area invaded and time.<sup>1</sup>

<sup>1</sup> The classic invasion model assumes that invasion occurs across a homogeneous landscape. Considering landscapes as spatially heterogeneous areas, in which the spatial distribution of habitats and populations affect the invasion process, is a key perspective in emerging models of biological invasions (Shigesada et al., 1986; With, 2002; Hastings et al., 2005; Dewhurst and Lutscher, 2009). In general, unfavorable habitats deter invasion speed.

The prediction that the square root of an invaded area is linearly related to invasion time (i.e. the range expands at a constant rate) can be tested using empirical observations and statistical methods. Despite the apparent simplicity of this model, it has been found to be reasonably congruent with many observed rates of spread of non-native organisms (Levin, 1989), including forest pests such as the gypsy moth (Liebhold et al., 1992). However, multiple modes of range expansions, such as the combination of neighborhood diffusion and long-distance dispersal, have been observed for some invading organisms (Andow et al., 1990; Shigesada et al., 1995). These organisms may exhibit non-linear relations between the square root of invaded area and time (Hastings et al., 2005). A leptokurtic, or fat-tailed, dispersal probability function, resulting from jump-dispersal facilitated by birds or other wildlife as well as human mediated transport, can generate spread rates that increase with time (Kot et al., 1996).

Mathematical models of stratified diffusion, in which organisms spread locally by Brownian diffusion and create remote colonies by a jump process, demonstrate that combined processes can greatly increase invasion rates. By creating multiple foci for range expansion, stratified diffusion induces a distribution of scattered colonies of various sizes during each time period. When the size distribution function is governed by the von Forester equation, which describes the change in the size distribution as new colonies are created and the radii of colonies expand (Trucco, 1965; Shigesada et al., 1995), the total invaded area at any moment  $t$ ,  $Area_t$ , is obtained by integrating over the area contained in every colony of each size.<sup>2</sup> If suitable data are available, the total invaded area can be measured and range-versus-time can be modeled using the effective range radius, defined as the square root of  $Area_t$  divided by the square root of  $\pi$  (Shigesada et al., 1995).

## 3. A Spatial-dynamic Model of Economic Damage

### 3.1. Temporal Dynamics of the Area of Economic Damage

The arrival and establishment of a non-native organism which impairs the flow of ecosystem services within an economic neighborhood will spread through that neighborhood according to a spatial-dynamic process (such as the progression of tree mortality with the spread of pests and pathogens).<sup>3</sup> Similarly, many new foci for the spread of economic damage across the landscape will be created as the biological organism induces economic damages in new neighborhoods. We suggest that the method of spatial aggregation via integration across colonies of all sizes (*sensu* Shigesada et al., 1995) be applied to the economic analysis where the colonies of interest are localities where economic damage occurs. Subsuming fine-scale spatial dynamics into the integrated area of economic damage (AED), defined as the sum of the area within circumscribed economic neighborhoods that sustain economic damage from a biological invasion, temporal dynamics of the AED can then be modeled by estimating range-versus-time curves. Within the forest economy, the AED occurs at the spatial intersection of forest resources with specific economic values (such as residential forests) and the presence of biophysical damage that induces a loss, or transfer, of economic value (Fig. 1).<sup>4</sup>

<sup>2</sup> Formally,  $Area_t = \int_0^\infty 2\pi r^2 u(r, t) dr$ , where  $u(r, t) dr$  represents the number of colonies with radii length between  $r$  and  $r + dr$  at time  $t$ .

<sup>3</sup> Economic damage often lags behind the general spread of an invasive organism, and may depend upon the growth rate of invasive species within infected areas. For example, it is anticipated that, in many cases, economic damage in forests results from reductions in tree growth or tree mortality, which are lagged functions of the arrival and establishment of an invasive organism.

<sup>4</sup> Biophysical damage to trees can cause wealth transfers as well as wealth losses. For example, tree mortality can induce expenditures for homeowners desiring to remove dead trees. These expenditures represent wealth transfers from homeowners to tree removal firms (Kovacs et al., 2010). The empirical example presented in Section 4 below describes a wealth loss.

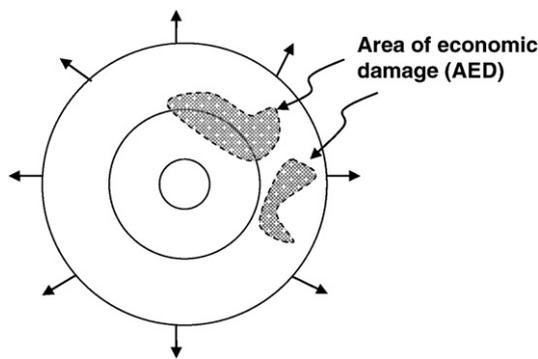


Fig. 1. Traveling waves and the area of economic damage (AED). The circles represent the range of an organism over successive periods. The shaded polygons represent the areas where economic damage occurs.

Shigesada et al. (1995) defined the effective range radius (ERR) of an area invaded by a biological organism as the square root ( $\sqrt{\cdot}$ ) of the integrated area divided by the square root of pi ( $\pi$ ). We adopt a similar approach and define the effective range radius of the AED as  $\sqrt{(AED)/\pi}$ . As described by Shigesada et al. (1995), three types of range-versus-time curves can be described: linear, biphasic, and convex. Following an initial establishment phase (during which no range expansion is discernable), an organism passes through an expansion phase, and a final saturation phase. In general, we anticipate that the AED will be observed during the expansion phase and possibly during a saturation phase in which all trees have been damaged in an economic sense. If time series or time series/cross sectional data are available for the AED, statistical methods can be used to estimate AED range-versus-time curves.

### 3.2. Quantile Regression

The quantile regression method was developed by econometricians (Koenker and Bassett, 1978) as an extension of the ordinary least squares model in which all parts of the distribution of a response variable can be modeled as a function of a vector of explanatory variables. It is a semiparametric method in the sense that no parametric assumptions are invoked regarding the distribution of the dependent variable in the regression. The median regression estimator minimizes the sum of absolute errors and other quantile functions are estimated by minimizing an asymmetrically weighted sum of absolute errors (Koenker and Hallock, 2001). Parameter estimates in linear quantile regression models represent the marginal change in the dependent variable with a unit change in an explanatory variable holding other explanatory variables constant.

Quantile regression has been used in ecological applications where unobserved ecological factors act as limiting constraints on organisms (Cade and Noon 2003). For example, rates of change for functions near the upper boundary of the conditional distribution of responses may be very different than mean or lower boundary responses if there are many unobserved limiting factors. Because many possible factors explaining the spread of invading organisms are unknown, such as diffusion coefficients or the impact of landscape heterogeneity, quantile regression methods appear to be well suited to estimating rates of range expansion.<sup>5</sup> In general, we suggest that the effective range radius of the AED can be estimated as a function of the time

<sup>5</sup> We note that quantile regression has been used to estimate the rate of range expansion of the hemlock woolly adelgid using observations on spread distance and time (Evans and Gregoire, 2007).

elapsed since an invading organism is first observed and a vector of other explanatory variables using quantile regression:

$$ERR_t = \frac{\sqrt{AED_t}}{\sqrt{\pi}} = \beta(\tau)X_t \quad (3)$$

where  $\beta(\tau)$  is a vector of parameter estimates for specific regression quantiles  $\tau$  (for example, the median is represented by  $\tau = 0.5$ ) and  $X_t$  is a vector of explanatory variables.<sup>6</sup> The specific  $\beta(\tau)$  parameter estimate for elapsed time is interpreted as the rate of AED range expansion conditional on the effects of other variables in the model.

### 3.3. Spatial Value Transfer

Models of economic damage from biological invasions within the AED can be estimated using micro-scale economic models. An essential first step in modeling the spatial dynamics of economic damages from an invasive species is to obtain site-specific micro-economic analysis of producer and/or consumer behavior directly impacted by a biological invasion. The behavioral economic model provides information on the economic damage per unit of invaded area.<sup>7</sup>

If economic damage sustained at sampled locations can be characterized as a function of economic units (e.g., households and firms) and landscapes (e.g., tree species impacted), then losses estimated for the sample can be transferred to the population of similar economic units at the landscape level.<sup>8</sup> Where spatial data are available depicting the location of salient economic and landscape variables characterizing the AED, GIS can be used to identify the number and location of spatial units that are damaged in the way described by the behavioral economic model. Then, the economic damage per economic unit can be multiplied by the number of economic units identified in the GIS analysis, and maps can be constructed depicting economic damages in the AED.

Unfortunately, spatial data characterizing the salient characteristics to be used for spatial value transfer are not always available for the entire area at risk of damage from a biological invasion. In these instances, it may be possible to spatially project the macro-scale economic landscape at risk using statistical or other models. Then, the spatial-dynamic model of AED growth can be linked with the projected landscape at risk to compute aggregate economic damages (Fig. 2).

### 3.4. Linking Spatial Dynamics with Value Transfer Models

The forecasted landscape at risk identified using GIS needs to be calibrated to incorporate spatial dynamic factors. In particular, it is essential to identify the date at which a non-indigenous organism begins causing economic damage within spatial units so that the temporal dynamics of economic damages within spatial units can be applied. Fortunately, data are often available listing the date at which a non-native pest was first discovered within a geographic area. These dates will typically need to be adjusted to account for the lag between the establishment of a non-native organism and the date at which it begins causing economic damage.

<sup>6</sup> Quantile functions are estimated by minimizing absolute deviations using linear programming methods (Koenker and Hallock, 2001).

<sup>7</sup> Spatial units used for analysis (trees, hectares, etc.) will depend upon the scale of analysis and the resolution of the available data.

<sup>8</sup> Value transfer methods have been developed by economists to transfer *in situ* non-market values to other, *ex situ* locations (Rosenberger and Loomis, 2003). Although most benefit transfer studies have been non-spatial, the increasing availability of, and familiarity with, Geographic Information Systems (GIS) is advancing the ability to conduct spatial value transfers (Eade and Moran, 1996; Bateman et al., 2002; Troy and Wilson, 2006).

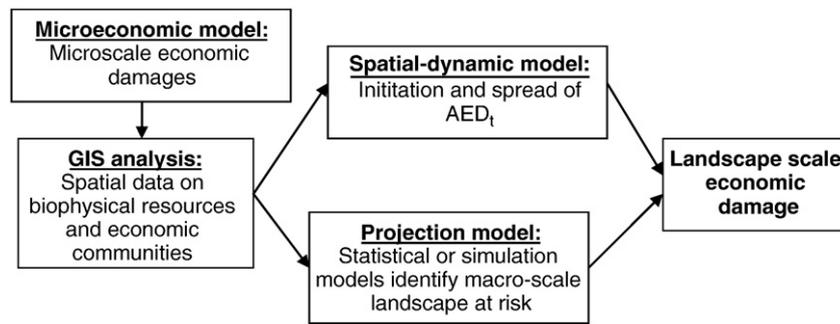


Fig. 2. General spatial-dynamic value transfer model.

Once the parameters of a spatial-dynamic model have been estimated, predictions of the incremental growth of AED can be applied to all observational units ( $i$ ). Then, the level of economic damage for each observational unit and time period can be computed:

$$D_{it} = (AED_{it} - AED_{it-1})d_{it} \quad (4)$$

where  $D_{it}$  is the aggregate economic damage across the AED in unit  $i$  at time  $t$ , and  $d_{it}$  is the economic damage per unit area within the AED. In general, unit area damages will reflect variation in economic conditions across observational units. For example, if damages accrue to residential property values, then  $d_{it}$  will reflect variations in the value of residential properties across different observational units and periods of time. The unit area damages represent the present value of all future damages that will occur in that area.

Finally, aggregate economic damage across  $j$  observational units and  $n$  time periods ( $D$ ) can be simply computed:

$$D = \sum_{i=1}^j \sum_{t=n}^t D_{it} e^{\kappa t} \quad (5)$$

where economic damages are summed over  $n$  periods, and  $\kappa$  is the economic discount rate. Economic damages for subsets of the entire aggregate area can likewise be computed by summing over the area of interest, such as states or regions.

#### 4. Empirical Application: Hemlock Woolly Adelgid in Eastern U.S. Forests

In this section, the spatial-dynamic value transfer modeling approach proposed above is presented to clarify ideas, using a case study of the hemlock woolly adelgid (*A. tsugae*, hereafter HWA). The HWA is a non-native forest pest, which was inadvertently introduced from Japan during the 1950s, is currently spreading across hemlock forests in the eastern United States, and threatens the widespread decline of eastern hemlock (*Tsuga canadensis*) and Carolina hemlock (*Tsuga caroliniana*) forests (Orwig and Foster, 1998). The spread of HWA is facilitated by wind as well as the movements of birds, mammals, and humans, and state quarantines have been established to mitigate the spread via the movement of nursery stock and hemlock logs. Roughly 25% of the 1.3 million ha of eastern hemlocks in the U.S. are currently infested with HWA and experts predict that the remaining 75% may become infested within 20 to 30 years (Morin et al., 2004; Rhea, 2004). There are no known effective native predators or parasites of this insect and eastern hemlock has shown little resistance to HWA. Mechanical control efforts have not been implemented for this species at the landscape scale, as at this time there are no known controls that can be used to slow or stop HWA spread that are cost-effective at a large scale.

Recent estimates suggest that HWA is spreading across the landscape at a rate of approximately 9–20 km/year, and that spread rates vary with environmental variables (Evans and Gregoire, 2007; Morin et al., 2009). The principal difference between these empirical models of HWA spread rates and the analysis reported here is that, in this paper, we are

interested in directly modeling changes in the area of economic damage. Economic damages lag behind the spread of HWA, and depend upon HWA population growth within invaded areas, responses by host trees, and the spatial geometry of the economic landscape.

##### 4.1. Microeconomic Losses in Residential Forests

Eastern hemlock forests provide a suite of public and private goods that have economic value, including terrestrial and aquatic wildlife habitat, aesthetic quality in residential areas, sales of nursery stock, and commercial timber (relatively low value). Although the decline of hemlock forests impacts several sectors of the forest economy, attention here is focused on the impact of HWA on private property values in residential forests.

The contribution of landscape attributes to private property values has been studied using an economic welfare-theoretic method known as the hedonic property value method. This method has been used to estimate the value that trees contribute to the sale values of homes from three perspectives: (1) yard trees contribute to property values (Morales, 1980; Anderson and Cordell, 1988; Dombrow et al., 2000), (2) forest preserves near residential neighborhoods convey value (Garrod and Willis, 1992; Tyrvaianen and Mietinnen, 2000), and (3) trees in the general forest matrix surrounding residential areas convey value (Patterson and Boyle, 2002). These studies indicate that trees contribute, roughly, from 1–5% to the property value of private residences. Consequently, we would expect that non-indigenous forest pests that cause a visible loss in forest health (Sheppard and Picard, 2006), or that ultimately cause tree mortality, would induce a loss of property values in residential areas in roughly the same proportionate value range.

A microeconomic analysis of the impact of naturally regenerated hemlock decline on residential property values in northern New Jersey indicates that the proportional loss in residential property value is generally consistent with other hedonic studies of the value of trees to private residences (Holmes et al., in press). Remote sensing data were used to identify hemlock health, measured in 5 defoliation categories (Royle and Lathrop, 1997), as well as a suite of other landscape attributes (Lathrop, 2000) thought to influence property values. Results of the micro-econometric analysis showed that severe hemlock defoliation was the principal cause of the loss of property values in the study area, and severe hemlock defoliation not only caused property value losses on the parcel where hemlock stands were located, but also caused losses on neighboring properties. Severely defoliated hemlocks within 0.1 km radius of parcel centroids reduced property values, on average, by 1% per household. This estimate represents the loss of wealth experienced by households living within the area of economic damage.<sup>9</sup>

<sup>9</sup> Chemical treatments are available to protect individual ornamental hemlock trees from HWA. Although we focus attention in this study on the aggregate economic losses to homeowners from HWA infestations in residential forests, the cost of protecting healthy hemlocks can be quite expensive. For example, the cost of foliar spray to control HWA in Maine is roughly \$260/tree/year, which can be expensive if several hemlocks are located on a landowner's property (Holmes et al., 2008).

#### 4.2. Spatial Dynamics of HWA Economic Damages

Geo-referenced data describing hemlock defoliation throughout the entire state of New Jersey (Royle and Lathrop, 1997), as used in the hedonic property value study (Holmes et al., in press), were available for each of the five time periods (1992, 1994, 1996, 1998, and 2001). For each  $30 \times 30$  m raster hemlock pixel, hemlock health was represented in one of the five categories, depicting the level of defoliation (0–20%, 21–40%, 41–60%, 61–80%, and 81–100%). These geospatial data were then combined with data delimiting residential neighborhoods in New Jersey (Lathrop, 2000). In particular, a 0.1 km buffer (consistent with the microeconomic study) was created surrounding all hemlock polygons using GIS. Then, these hemlock areas, including buffers, were intersected with residential polygons for each time step. Focusing on pixels showing severe (81–100%) hemlock defoliation, this step provided a map depicting spatially distributed neighborhoods of economic damage, consistent with the microeconomic model, for each date in the time series throughout the entire state.

To estimate the dynamics of economic damage,  $AED_t$  was computed for each time period ( $t$ ) by summing the area of economic damage across all neighborhoods and for each time period.  $AED_t$  was aggregated to the county level (8 counties), resulting in a cross-section time series data set containing  $N = 40$  observations. Then, the effective range radius for each point in time ( $ERR_t$ ) was computed using the identity shown in Eq. (3). Two independent variables were used to explain the variation in  $ERR_t$ . First, data on the elapsed time since HWA was first observed in each county were available from the Northeastern Area State & Private Forestry, USDA Forest Service.<sup>10</sup> Second, Morin et al. (2009) found that the rate of spread of HWA was positively related with hemlock basal area. Geospatial data (1 km rasters) characterizing the basal area of hemlock in forest stands in the U.S. (Morin et al., 2004) were available based on spatial interpolation of permanent Forest Inventory and Analysis plot data (Hansen et al., 1993). These data, available at the minor civil division level (township), were used to compute a localized average of hemlock abundance.

The parameters for the range radius model were estimated using quantile regression as shown in Eq. (3) by setting  $\tau = 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9$ . Fig. 3 shows the data used to estimate the models as well the fitted model for the 0.1, median, and 0.9 quantiles. Overall, the linear models fit the data well, and the goodness-of-fit ( $R^1$ ) statistics ranged from 0.68 for the  $\tau = 0.1$  specification to 0.79 for the  $\tau = 0.5$  specification (for  $\tau = 0.9$ ,  $R^1 = 0.72$ ).<sup>11</sup> The linear model is consistent with the Type 1 range-versus-time curve in Shigesada et al. (1995), and linear range-versus-time curves estimated for other invasive species (Andow et al., 1990; Shigesada and Kawasaki, 1997) including the HWA (Evans and Gregoire, 2007; Morin et al., 2009). Although we are modeling the spread of severe hemlock defoliation, and not simply the presence of HWA, our results are consistent with the Shigesada et al. (1995) stratified diffusion model in which new colonies are founded by long-distance dispersal ahead of the infested population front. These colonies then expand via short-distance dispersal, coalesce, and cause severe hemlock defoliation as local HWA populations increase in number.

Quantile regression parameter estimates for AED spread as a function of the elapsed time since first infestation were generally significantly

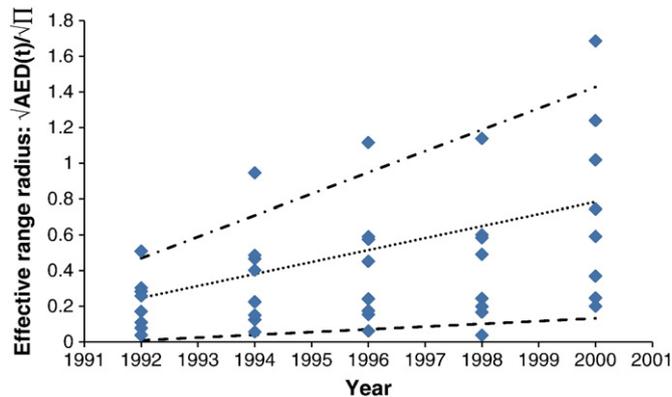


Fig. 3. Data points and range-versus-time curves for the AED with quantile regression lines shown for the 90th (upper line), median (middle line) and 10th (lower line) quantiles.

different than zero at the 0.10 level (Fig. 4).<sup>12</sup> The maximum spread rate, as represented by the 0.9 quantile parameter estimate (0.07 km/yr) was similar to the median estimate (0.063 km/yr) but more than twice as large as the parameter estimate for the 0.10 quantile (0.03 km/yr). These results suggest that unobserved factors are limiting the temporal rate of spread of severe hemlock defoliation. Less variation in the quantile regression parameters was found for hemlock basal area. Parameter estimates for AED spread as a function of hemlock basal area were significantly different than zero at the 0.01 significance level, which is consistent with results reported for HWA spread rates reported by Morin et al. (2009).

#### 4.3. Statistical Projection of Residential Hemlock Forests at Risk

At the close of 2008, HWA had been found in 15 states and in more than 300 counties (Morin et al., 2009). Because monitoring data showing the location of natural stands of hemlock, and their proximity to residential areas, are not available for most of these areas, it was necessary to develop a regression model to spatially project areas in residential hemlock forests that are likely to be similar to the area where the microeconomic analysis of HWA induced damages was undertaken.

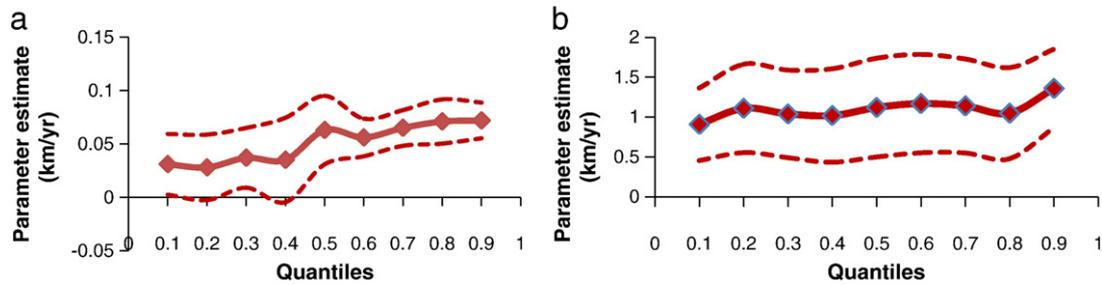
##### 4.3.1. Data

The dependent variable in the statistical projection model was designed to replicate, as closely as possible, the area of economic damage described by the microeconomic model. In particular, it was necessary to obtain data representing the area of residential, naturally regenerated hemlock forest. Two sources of data were available for this purpose. First, geospatial data for New Jersey were obtained from the Center for Remote Sensing and Spatial Analysis at Rutgers University (Royle and Lathrop, 1997; Lathrop, 2000), which included polygons for hemlock forest area and polygons for residential areas. A second data set was obtained from the Harvard Forest in Petersham, Massachusetts, which included polygons for hemlock forest area along a transect in the state of Connecticut (Orwig et al., 2002). GIS data showing the location of residential areas in Connecticut were obtained from land use-land cover maps. A 0.1 km buffer was created around natural hemlock stands in the two states with GIS tools. The intersection of these polygons with the residential polygons, also performed using GIS tools, provided information on the area in residential hemlock forests consistent with the microeconomic

<sup>10</sup> Data are available on the website: <http://na.fs.fed.us/fhp/hwa/infestations/infestations.shtm>.

<sup>11</sup> A separate goodness-of-fit value ( $R^1$ ) is computed for each value of  $\tau$  that is specified. Analogous to the standard goodness-of-fit statistic used in linear regression models ( $R^2$ ),  $R^1$  is computed as 1 minus the ratio of the appropriately weighted sum of absolute residuals for an unrestricted and restricted model, respectively (Koenker and Machado, 1999). The restricted model sets all parameter estimates on the covariates to zero, and therefore is based entirely on the intercept parameter estimate.

<sup>12</sup> Standard errors for parameter estimates were computed using the bootstrap method (Koenker and Hallock, 2001).



**Fig. 4.** Estimates of the slope parameters from the quantile regression. Slope parameters show the relationship between the rate of range expansion and (a) the elapsed time from the first infestation (left figure), and (b) hemlock basal area (right figure). The 90% confidence intervals are shown as dotted lines.

model. For purposes of the projection model, these data were aggregated to the minor civil division (township) level.

Two variables were used as explanatory variable in the projection model. First, we used geospatial data characterizing the basal area of hemlock in forest stands in the U.S. (Morin et al., 2004) as described above (Section 4.2). Second, geospatial data describing the area of forest canopy within which economic development has occurred were obtained from the National Land Cover Database (Nowak and Greenfield, 2009). Landsat images of tree canopy and impervious surface, at 30 m<sup>2</sup> resolution, were used to construct the developed canopy layer. Data were aggregated at the minor civil division (township) level.

#### 4.3.2. Tobit Model for Censored Data

Hemlock canopy in residential neighborhoods is a rare landscape feature and occurs where residential neighborhoods are built within naturally regenerated hemlock stands. Because many residential neighborhoods do not contain any natural hemlock cover, the area of natural hemlock cover is zero for a substantial number of observations. However, for neighborhoods with hemlock cover, the amount of cover may take a wide range of values. Data that display these characteristics are censored, and the censored (or Tobit) regression model can be used to obtain unbiased parameter estimates.

The Tobit model assumes that variables affecting the probability of observing a limit value (e.g., zero) also affect the size of a non-limit response (Greene, 1997). The general form of the Tobit model is defined in terms of a latent variable which, in a model used to predict residential hemlock canopy, can be thought of as the potential residential hemlock canopy cover ( $y^*$ ):

$$y_i^* = \beta'x_i + \varepsilon_i, \tag{6}$$

$$y_i = 0 \text{ if } y_i^* \leq 0,$$

$$y_i = y_i^* \text{ if } y_i^* > 0$$

where  $y^*$  is a latent variable representing potential residential hemlock canopy,  $y$  is the level of observed residential hemlock

canopy,  $\beta$  is a vector of parameters,  $x$  is a vector of explanatory variables (hemlock basal area and area of developed forest canopy), and  $i$  is the observational unit. For most purposes, an estimate of the value of the latent variable ( $\beta'x$ ) is not useful. Rather, we would like to estimate  $y$ , the level of actual residential hemlock canopy. In general, the value of  $y$ , given the data on a set of explanatory variables  $x$ , is a non-linear function:

$$E[y_i|x] = \Phi\left(\frac{\beta'x_i}{\sigma}\right) (\beta'x_i + \sigma\lambda) \tag{7}$$

where  $\lambda$  is the inverse Mill's ratio (and represents the probability that the hemlock–residential intersection occurs in each observational unit),<sup>13</sup> and  $\sigma$  is the disturbance standard deviation. Eq. (7) is the prediction equation for an observation drawn randomly from the population.

#### 4.3.3. Spatial Projection Results

All of the parameter estimates in the Tobit model have the anticipated sign and are statistically different than zero at the 0.01 level. Although goodness-of-fit is difficult to assess in a nonlinear model such as the Tobit, the goodness-of-fit statistics indicate that the explanatory variables do a satisfactory job in predicting the mean value of the dependent variable (Table 1).

Given the estimated statistical model, the residential hemlock area in each township containing hemlock forests was projected using hemlock basal area and area of developed forest canopy data. Township estimates were aggregated to the county level and a map was created showing the forecasted residential hemlock canopy (Fig. 5). According to the projection, the areas with the greatest concentration of residential hemlock forest are located in eastern New York, western and central Massachusetts, western Connecticut, and sections of Pennsylvania, New Hampshire, and Maine. These areas may be considered as the residential forest population at greatest risk of economic damages from HWA. We also note some isolated areas at risk in western New York/northwestern Pennsylvania, North and South Carolina, West Virginia, Wisconsin and Michigan.

### 4.4. Landscape Scale Economic Loss

#### 4.4.1. Computation of Economic Loss Per Unit Area

Not all of the residential forest areas at risk of damage from HWA have been infested. In order to estimate historic economic damages to residential forests, county-level records of the year in which counties were first infested by HWA were used (Morin et al., 2009). Considering these data as the base year for the establishment and spread of economic damage, the results of the spatial-dynamic model

**Table 1**

Tobit parameter estimates used to project the area of residential hemlock forest.

Variable	Coefficient
<i>Latent variable equation</i>	
Constant	−82.16*** (8.32)
Developed canopy (100 ha)	0.09*** (0.01)
Hemlock basal area (m <sup>2</sup> )	6.84*** (2.12)
<i>Disturbance standard deviation</i>	
$\sigma$	47.63*** (4.09)

Note: standard errors in parentheses. \*\*\* denotes significance at the 0.01 level. Number of observations = 585 (547 in New Jersey and 38 in Connecticut).

<sup>13</sup> In particular,  $\lambda = \varphi(\beta'x/\sigma)/\Phi(\beta'x/\sigma)$ , where  $\varphi$  ( $\Phi$ ) is the normal probability density (cumulative distribution) function, respectively.

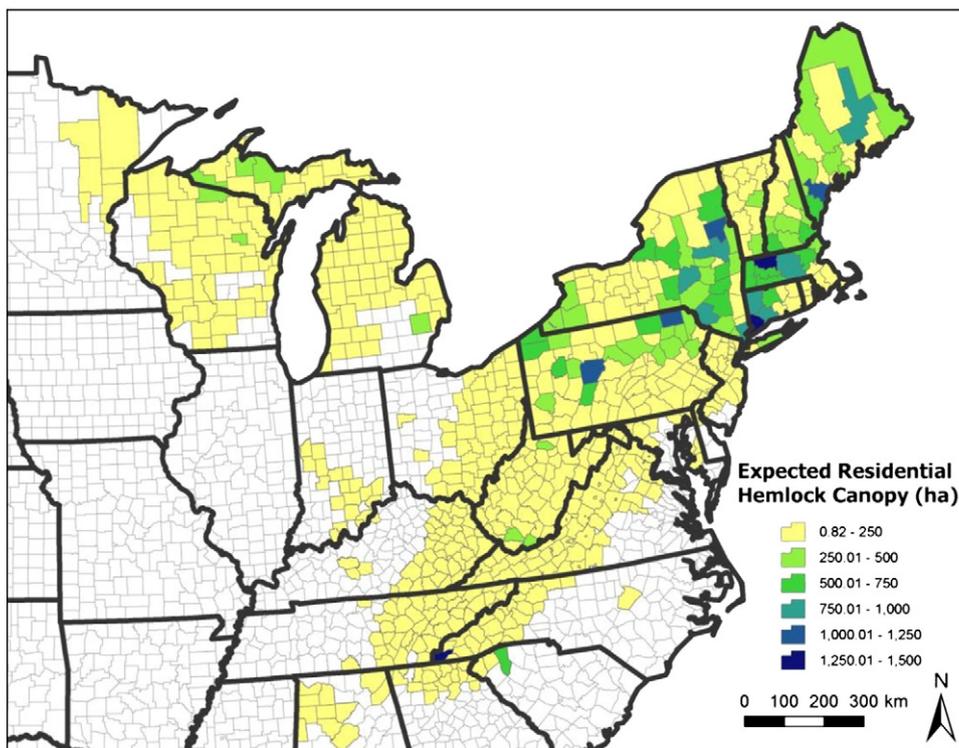


Fig. 5. Map of projected residential hemlock canopy, which is the area at risk of residential property value losses from hemlock woolly adelgid.

were combined with the spatial projection of the economic area at risk to compute  $AED_t$  for each year from 1999 to 2008. A ten-year projection period was considered to be reasonable, as the underlying spatial-dynamic model was calibrated over a ten-year period.

The loss in economic welfare for households living within the AED occurs at the point in time during which the hemlock forests are projected to first enter a severe defoliation state. The number of households impacted by a severe defoliation in year  $t$  is computed by dividing  $(AED_{it} - AED_{it-1})$  by an estimate of the average lot size within observation unit  $i$ . Because residential hemlock forests occur where residential neighborhoods occur within, and are proximate to, naturally regenerated hemlock stands, we used data on housing density within the wildland–urban interface (WUI), which includes both intermix (places where housing and vegetation intermingle) and interface (places with housing in the vicinity of continuous vegetation) communities (Radeloff et al., 2005). Estimates of average lot size, at the county level, within the WUI were computed by dividing the WUI area by the number of housing units located within the WUI.

Having estimated the number of housing units located within the AED for each county,  $d_{it}$  was computed by multiplying the number of units by the median housing price in that county, which was then multiplied by the percentage value loss due to severe hemlock defoliation<sup>14</sup>:

$$d_{it} = \frac{AED_{it} - AED_{it-1}}{\text{average lot size}} * (\text{median house price}_{it}) * (\text{degrade \%}). \quad (8)$$

Eq. (8) is based on the assumption that housing markets behave similarly in the manner by which they discount damage caused by

HWA, while reflecting variation in median housing values across different markets.<sup>15</sup>

#### 4.4.2. Sensitivity Analysis

Three scenarios used to compute landscape scale economic losses were explicitly based on the quantile regression results. In particular, high, medium, and low damage spread scenarios were constructed using parameter estimates for the 0.9, 0.5, and 0.1 quantile regressions. Data on the elapsed time since initial HWA infestation and hemlock basal area were available for all counties where residential hemlock forests were at risk of property value losses. Combining these data with the quantile regression parameter estimates and the location specific property values allowed us to compute the economic losses over the specified ten-year time period. For the sensitivity analysis, we assumed that the economic loss due to severe hemlock defoliation was equal to 1% of the property value. This percentage is in keeping with the results reported by Holmes et al. (in press).

#### 4.4.3. Results

The residential areas predicted to suffer the greatest economic losses, during the period 1999–2008, from HWA are geographically concentrated in New England (western CT, western MA, and southern NH) (Fig. 6). This spatial pattern reflects the projected presence of residential hemlock forests with high local abundance, relatively high valued residential properties, and a relatively long period of time over which these areas have been infested by HWA. Under the medium damage spread scenario, nearly 10,000 households were estimated to

<sup>14</sup> The percentage value loss due to severe hemlock defoliation is the capitalized loss of all damages to the property from hemlock defoliation.

<sup>15</sup> During the period 1999–2008, the national housing price index rose by an average annual rate of 0.048. To simplify the computational burden, it is implicitly assumed that this rate equals the discount rate. Economic values are given in 2006 dollars.

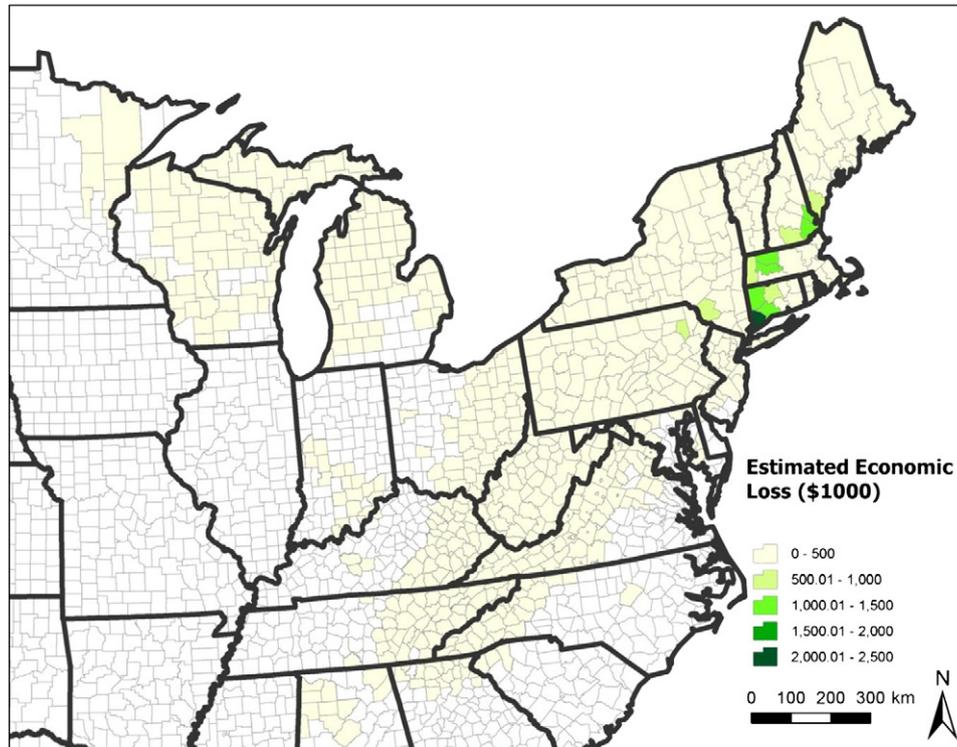


Fig. 6. Map of economic losses to residential property owners from HWA, medium damage spread scenario, 1999–2008.

have lost wealth due to severe hemlock defoliation during the study period (Table 2).

The aggregate estimate of residential property value losses, computed by summing the county-level estimates under the three different scenarios, ranged from roughly \$12.4 million in the low scenario to \$29.5 million in the high scenario. The estimated economic losses were sensitive to the parameter values used in the alternative scenarios and the medium damage spread scenario might provide the most reasonable estimate of economic losses (\$20.2 million) given available data. The states with the largest estimated economic losses are Connecticut, Massachusetts, New York, New Hampshire and Pennsylvania which account for roughly 87% of the estimated losses

across the 15 states where economic losses were estimated. The aggregate amount of residential property value loss is anticipated to increase as HWA continues to defoliate hemlocks in residential areas where it is already established, as well as by expanding its range into new residential locations.

## 5. Summary and Conclusions

Rigorous assessments of the economic impacts of introduced species, at a national scale, are needed to provide credible information to policy makers. Although the non-market economic impacts of invasive species are challenging to measure, we suspect that much of the economic damage from biological invasions of forests will be due to the loss of non-timber values. Therefore, innovative methods are needed to provide realistic estimates of aggregate non-market damages.

In this paper, we argue that economic assessments of the aggregate damages induced by biological invasions need to link microeconomic analyses of site-specific economic damages with spatial-dynamic models of value change. With this purpose in mind, the area of economic damage (AED) was defined as the sum of the areas on the landscape that sustain economic damage from a biological invasion. A method was described to model short-term (10 year) economic damage dynamics, and an empirical example was presented to demonstrate how the model could be implemented. The empirical estimates suggested that during the period 1999–2008, hemlock woolly adelgid caused tens of millions of dollars worth of economic losses to thousands of residential property owners in the eastern United States.

Other non-native forest pests, such as sudden oak death (*P. ramorum*) and the emerald ash borer (*Agrilus planipennis* Fairmaire), appear poised to cause major losses to residential property owners along the California coast and in the mid-western United States, respectively (Holmes and Smith, 2008; Kovacs et al., 2010). Additionally, the Asian long-horned beetle (*Anoplophora glabripennis*)

Table 2

Estimates of the number of households affected and the economic losses for residential property owners impacted by hemlock woolly adelgid, by state, 1999–2008.

State	Low scenario		Medium scenario		High scenario	
	Households	Value loss (\$1000)	Households	Value loss (\$1000)	Households	Value loss (\$1000)
CT	1003	3378	1597	5368	2338	7859
DE	0	0	1	2	1	3
GA	0	0	0	0	1	1
MA	1096	2510	1746	4050	2555	5913
MD	8	12	18	34	25	46
ME	242	542	373	835	549	1229
NC	69	76	116	128	168	186
NH	660	1762	1012	2704	1489	3979
NJ	103	161	349	543	464	723
NY	766	2025	1254	3423	1827	4964
PA	1251	1308	2021	2132	2951	3109
RI	1	2	5	8	7	10
TN	326	285	510	447	749	656
VA	174	278	284	475	414	687
WV	152	54	250	92	365	133
Total	5851	12,393	9536	20,241	13,903	29,498

has caused mortality of more than 20,000 trees in Worcester, Massachusetts, causing millions of dollars to be spent by local governments and the U.S. Department of Agriculture for tree removal, and undoubtedly causing a reduction in residential property values in those urban forest neighborhoods.<sup>16</sup> A full accounting of the current and imminent economic losses due to the full constellation of non-native forest pests is essential for the development of informed policy that can meaningfully address the economic and ecological threats imposed by these ongoing threats to forest health. However, the development of a full suite of economic damage models will require spatially referenced time series forest disturbance data so that the integration of economic and ecological analysis can be made in a rigorous fashion. At present, very few data are available that permit the development of integrated economic–ecological analysis of invasive species. Until relevant data become available, analysis of the economic impacts of forest invasive species will be severely limited.

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