Ecological and Economic Determinants of Invasive Tree Species on Alabama Forestland

Anwar Hussain, Changyou Sun, Xiaoping Zhou, and Ian A. Munn

Abstract: The spread of invasive tree species has caused increasing harm to the environment. This study was motivated by the considerations that earlier studies generally ignored the role of economic factors related to the occurrence and abundance of invasive species, and empirical analyses of invasive trees on forestland have been inadequate. We assessed the impact of ecological and economic factors on the occurrence and number of invasive tree species on Alabama forestland since 1990. Count data models were used to analyze the 2004 Alabama Forest Inventory Analysis (PIA) data. The proportion of PIA plots with invasive species was 1.06% in 1990, 1.24% in 2000, and 1.35% in 2004. Occurrence of invasive trees on a plot depended on forest type (e.g., natural pines, planted pines, or oak-pines). Plots with planted pine were 171% less likely to be infested with invasive trees than otherwise similar plots. Number of invasive trees per plot was determined by a wide variety of factors, including site productivity, growing stock, stand age, ecoregion, plot proximity to metropolitan centers, ownership type, and forest management activity. The magnitude of the impact was especially large for the ownership type, with more invasive trees on private forestlands than on public lands. These findings suggest that both ecological and economic factors need to be considered in the prevention and control of invasive species invasion. FOR. SCI. 54(3):339-348.

Keywords: count data, Forest Inventory Analysis, zero-inflated negative binomial

INVASIVE PLANT SPECIES have adverse ecological and economic impacts. Although estimates of the adverse economic impacts vary, all findings reveal that losses attributable to invasive species have been well over $100 billion each year (OTA 1993, Pimentel et al. 2005). The nation's forestlands are particularly susceptible with annual losses of $2.1 billion from the decrease of forest production alone (Pimentel et al. 2001). Efforts to prevent and control the spread of invasive species have focused largely on ecological determinants even though invasions are also induced by disturbances related to socioeconomic activities (Dark 2004, Yates et al. 2004). Economic activities have fundamental impacts on the occurrence of invasive species along with landscape and species characteristics (Pimentel et al. 2005). To combat invasions effectively, management options should be identified by analyzing both ecological and socioeconomic factors that foster the occurrence (establishment) and abundance (spread) of invasive plant species. Indeed, several studies have addressed the issue from the economic perspective (Dalmazzone 2000, Eiswerth and Kooten 2002, Horan et al. 2002, Perrings et al. 2002). However, these studies are limited in that they usually covered small geographic areas, used small data sets, or just demonstrated the interaction of economic and ecological factors in abstract theoretical settings.

Forestland in the United States has been encroached by harmful invasive plant species including trees, shrubs, vines, grasses, and ferns. Only a few studies have specifically examined invasive tree species on forestland. Quigley et al. (2001) discussed how to control invasive species and improve forest health and productivity in Oregon and Washington. Hunter and Mattice (2002) documented changes in non-native woody species distribution within 30 forests of a 54-km^2 landscape in Monroe County, New York. Gray (2002) used Forest Inventory Analysis (PIA) data to advance our understanding of the invasive species phenomenon. Miller (2003) provided useful information on the identification and control of 33 invasive plant species in the 13 southern states. However, these studies have limitations in that the authors did not distinguish between factors influencing occurrence versus abundance of invasive species, and they conducted limited statistical data analyses. Therefore, there has been a need for empirical analyses to distinguishbetween factors that influence the occurrence and abundance on individual sites because these factors and their relative importance are likely to be different. To provide better information to natural resource managers, insights gained through ecological studies also need to be augmented by knowledge of economic drivers. To be cost-effective, prevention efforts must focus on where invasive species are most likely to become established. Similarly, control efforts must concentrate on infested sites in which the probability of spread is the greatest.

The rationale of this study is that ecological and socioeconomic factors determine the location of high priority sites related to invasive species. Specific objectives of the

Anwar Hussain, Department of Forestry, Mississippi State University, Mississippi State, MS 39762—Phone: (662) 325-4529; ahussain@cfr.msstate.edu. Changyou Sun (corresponding author), Department of Forestry, Mississippi State University, Mississippi State, MS 39762—Phone: (662) 325-7271; csun@cfr.msstate.edu. Xiaoping Zhou, US Forest Service, Pacific Northwest Research Station, P.O. Box 3890, Portland, OR 97205—Phone: (503) 808-2017; xzhou@fs.fed.us. Ian A. Munn, Department of Forestry, Mississippi State University, Mississippi State, MS 39762—Phone: (662) 325-7271; imunn@cfr.msstate.edu.

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study were to examine the spread patterns of these invasive tree species from 1990 to 2004 on Alabama forestland, and, furthermore, to evaluate ecological and economic factors associated with the occurrence and abundance of invasive trees on Alabama forestland. We propose that by identifying the underlying factors associated with the spread of invasive tree species, forest managers will be able to identify high priority areas on a regional scale. This study also contributes to the field of invasive species modeling by evaluating analytical techniques that are suitable for occurrence and abundance of invasive tree species.

Analytical Framework, Variables, and Data Sources

Analytical Framework

Before the spread patterns of invasive tree species on Alabama forestland is evaluated, a list of invasive tree species should be first identified and compiled from published studies and online resources. Existing lists needed to be refined for this study because definitions of invasive tree species varied widely, and different groups- and institutions had diverse and incomplete lists. Next; we used Alabama FIA data of 1990, 2000, and 2004 to assess the patterns of invasive trees on Alabama forests. For individual FIA plots in each of the three survey years, the presence of any invasive tree was noted, and, if present, the number of invasive trees was recorded. These data were compared over the three survey years to measure the spread of invasive trees over time. Paired sample proportion comparison tests were conducted to examine whether differences were statistically significant. A geographic information system (GIS) map was created to provide a visual perspective on the geographic distribution of the number of invasive trees per plot in Alabama forests. Finally, ecological and economic factors associated with the occurrence and abundance of invasive trees on Alabama forestland were analyzed. The regression analysis used the 2004 FIA database. The data for 1990 and 2000 were not included in the statistical analysis because they had limited variation from the 2004 data.

Corresponding to the occurrence and abundance of invasive trees, two characterizations of the dependent variables were used. The first one measured the occurrence of invasive tree species and was symbolized as W_i. It was a dummy variable indicating whether there was an invasive tree species on plot i in a given year. Accordingly, PIA plots were categorized into noninfested $(W_i = 1)$ versus infested (w, = 0) to create the dichotomous dependent variable. The second characterization, Y_i, measured the number of trees of all invasive species $(Y_i = 0, 1,2, \ldots, n)$ on plot i in 2004. The motivation for modeling occurrence (W_i) and abundance (Y_i) of invasive trees on a plot as distinct phenomena was to determine whether the two characterizations were influenced by a same set of ecological and economic variables, X_i, as defined below. Count data modeling techniques (Poisson model and its extensions, e.g., negative binomial, heterogeneous negative binomial, and mixture probability models) were used to analyze these data, as detailed in the next section.

Definitions of Independent Variables

Ecological variables hypothesized to influence the occurrence and abundance of invasive trees on a plot were site productivity, growing stock, site moisture, the Alabama ecoregion where the plot was located, forest type, and stand age. Economic variables influencing the occurrence and abundance of invasive trees were whether a plot was located in a metropolitan county or not, whether the type of ownership was private or public, and whether forest management activity (e.g., timber harvesting or prescribed burn) had occurred on the plot after the previous survey (i.e., 1999-2004). Although the definitions for most variables are self-evident, the construction of three variables deserves some elaboration here.

First, the PIA data have distinguished seven site productivity classes, and for the purpose of this study, they were aggregated into three classes. The PIA defines productivity based on forestland inherent capacity to grow crops of industrial wood. Potential growth is measured in cubic feet/acre/year, and the seven specific productivity classes are (1)225+, (2) 165-224, (3) 120-164, (4) 85-119, (5) 50-84, (6) 20-49, and (7) 0-19. PIA plots classified as site classes 1 and 2 were aggregated into a high-productivity site class, plots classified as site classes 3 and 4 were aggregated into a medium-productivity site class, and plots classified as site classes 5, 6, and 7 were combined into a low-productivity site class that served as the reference class in estimation. Second, on a specific plot, the PIA data distinguished five growing stock categories defined in terms of all live trees including seedlings: overstocked (100%), fully stocked (60-99%), medium stocked (35-59%), poorly stocked (10-34%), and nonstocked (0-9%) plots. To assess the impact of growing stock on invasive tree occurrence and abundance, the growing stock categories were aggregated into three groups: overstocked and fully stocked were reclassified as fully stocked; medium stocked were left as they were in the database; and poorly stocked and nonstocked were reclassified as poorly stocked. These regroupings of the FIA data were needed to reduce multicollinearity among variables.

Third, the FIA data did not explicitly report moisture levels on plots, but it was possible to combine information on site aspect and slope to generate proxies for them (Wohlgemuth 1998, Heaton and Merenlender 2000). Moisture levels serve to measure the impact of environmental factors on occurrence and abundance of invasive trees. Using data on aspect, four dummy variables were generated: dummy northeast with aspect ranging from 0-90°; dummy southeast with aspect ranging from 91-180°; dummy southwest with aspect ranging from 181-270°; and dummy northwest with aspect ranging from 271-360°. The aspect dummy variables were then interacted with slope to measure the slope-aspect orientation on each plot, resulting in four moisture level indices. These proxies for site moisture levels were designed to determine whether slope-aspect orientations affected occurrence and abundance of invasive trees.

Data Sources

In identifying the list of invasive tree species on U.S. forestland, Miller (2003) and Webster et al. (2006) served as the major sources. These studies were supplemented by information available from several Internet sources. The National Park Service (2006) has compiled the "Plant Conservation Alliance-Alien Plant Working Groups" from a wide variety of publications. The Natural Resource Conservation Service (2006) has constructed the PLANTS database, including invasive and noxious weeds. Other databases examined were compilations on invasive species by Southeast Exotic Pest Plant Council (2006) and National Invasive Species Information Center (2006). Except for data on plot proximity to metropolitan areas obtained from the US Census Bureau (2006), data on all the other variables were assembled from PIA surveys (US Forest Service 2006). These surveys provided a unique opportunity to identify critical ecological and socioeconomic factors without additional data collection.

Estimation Methods

Given the discrete nature of invasive species trees, count data modeling is usually the appropriate choice. To test the hypothesis that occurrence and abundance were distinct phenomena and possibly influenced differently by the same set of covariates, mixture probability distribution models were used in this study. These models are advantageous because they predict the probability of occurrence of invasive species, and, conditional on occurrence, predict the probability of abundance as a function of the same or a different set of covariates simultaneously. Conceptually, mixture probability models extend the baseline Poisson model to account for excess zeros in count data (excess in the sense that a Poisson distribution with a given mean cannot explain them). These models include the zero-inflated Poisson (ZIP) model, the Poisson hurdle (PH) model, and their generalizations, the zero-inflated negative binomial (ZINB) model, and the negative binomial hurdle (NBH) model. A given mixture probability model has two components whereby the first component examines a binary data process (with a logit or complementary log-log model), and the second explains the count data process (with a Poisson, negative binomial, or truncated negative binomial model). Two sets of parameters can be estimated on the basis of the maximum likelihood estimation of a joint log-likelihood function. Before the presentation of mixture probability models, the baseline Poisson model is described first.

Baseline Poisson Model

The Poisson regression (PR) model is the foundation of a variety of models for count data analysis. As defined earlier, let Y_i represent the number of invasive trees on plot i. In the PR model (Long 1997, Greene 2003), the dependent variable Y_i has a Poisson distribution with a conditional mean that depends on a set of covariates x_i as follows:

$$\Pr(y_i|x) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!}, \quad \mu_i = e^{x_i\beta}, \tag{1}$$

where μ_i is a distribution parameter. Taking the exponential of $(x_i\beta)$ forces μ_i to be positive, which is required for the Poisson distribution. As a unique feature of the Poisson distribution, its conditional mean is equal to its conditional variance (also known as equidispersion), and mathematically it is expressed as

$$\mathrm{E}(y_i|x) = \mathrm{Var}(y_i|x) = e^{s_i\beta} = \mu_i. \tag{2}$$

In practice, the PR model has rarely been used directly because the assumption of equidispersion generally cannot be met. The conditional variance is usually greater than the conditional mean so overdispersion is quite common. If that is the case, the standard errors from the PR model are biased downward. As a result, an array of models has been constructed to accommodate overdispersion (Hardin and Hilbe 2007, p. 223). The most common of these models is the negative binomial (NB) model, and it allows the mean of the dependent variable to differ from its variance as follows (Long 1997):

$$\mathrm{E}(y_i|x) = e^{x_i\beta} = \mu_i$$

$$\mathrm{Var}(y_i|x) = \mu_i\left(1 + \frac{\mu_i}{v_i}\right) = \mu_i + \alpha\mu_i^2, \tag{3}$$

where ex $= 1/v_i$. ex is known as the dispersion parameter because a larger ex increases the conditional variance of y. When $a = 0$, the conditional variance is equal to the conditional mean so the NB model reduces to the PR model. In practice, if H_0: ex $= 0$ is rejected, the NB model should be used. As an extension, the heterogeneous negative binomial (HNB) model further extends the NB model by parameterizing the dispersion parameter a as a function of another set of factors (z):

$$\ln \alpha_i = z\gamma, \tag{4}$$

where y is the coefficient vector. In this study, the same set of covariates hypothesized to influence occurrence and abundance was used to parameterize the dispersion parameter. As the PR, NB, and HNB models are nested, the validity of respective pairs of models can be examined using likelihood ratio test.

Mixture Probability Models

The ZIP and PH models differ from each other essentially in terms of the assumptions about the zero values taken by the response variable. The ZIP model (Lambert 1992) classifies zero responses into structural zeros because the response variable is unable to take values other than zero and sampling or incidental zeros that are the result of sampling variability consistent with some count data distribution (Poisson or NB). The PH model (Mullahy 1986) postulates that the response variable continues to assume a zero value until some latent variable related to the response variable crosses a threshold and then starts to assume values 1, 2, 3, ... , following a truncated-at-zero count data distribution (the truncation point can be other than zero, though, depending on the context). Whereas both models pair a binary probability model (e.g., logit or complementary log-log) with a count data model (e.g., Poisson or NB), the ZIP model allows zeros as outcomes in the second part of the process, whereas the PH model does not. The binary component of the ZIP model estimates the probability of being zero, and the binary component of the PH model estimates the probability of crossing a threshold or hurdle. From a computational point of view, this involves estimation of two equations (two sets of parameters) corresponding to the binary and count processes.

Let the probability of observing noninfestation on a plot (i.e., $W_i = 1$ or $Y_i = 0$) be written as P_i and the probability of observing infestation on a plot (i.e., $w_i = 0$ or $Y_i > 0$) be $1 - P_i$. When the count process follows the Poisson process, the ZIP model implies (Long 1997)

$$P(y_i|x) = \begin{cases} p_i + (1 - p_i)e^{-\mu_i} & y_i = 0 \\ (1 - p_i)\dfrac{e^{-\mu_i}\mu_i^{y_i}}{y_i!} & y_i > 0. \end{cases} \quad (5)$$

Assuming the binary component (known as the inflation equation) is logit, Pi is estimated according to $p_i(y_i = 0|x) = e^{x_i\beta}/(1 + e^{x_i\beta})$ The likelihood ratio test can be used to test the validity of ZIP count process against the ZINB model.

According to the PH model, the probability of observing noninfestation on a plot (i.e., $w_i = 1$ or $Y_i = 0$) is P_i and the probability that plot is infested (i.e., $w_i = 0$ or $Y_i > 0$) is $1 - P_i$. Assuming the response variable Y is a Poisson random variable, the PH model can be expressed as (Cunningham and Lindenmayer 2005)

$$P(y_i|x) = \begin{cases} p_i & y_i = 0 \\ (1 - p_i)\dfrac{e^{-\mu_i}\mu_i^{y_i}}{(1 - e^{-\mu_i})y_i!} & y_i > 0. \end{cases} \quad (6)$$

Assuming the binary component is logit, Pi is estimated as $p_i(y_i = 0|x) = e^{x_i\beta}/(1 + e^{x_i\beta})$. To test the validity of the PH model versus NBH model, the likelihood ratio test can be used. Comparisons of ZIP versus PH and, similarly, ZINB versus NBH, can be made using the Akaike information criterion (AIC) statistic because the respective pairs of models are not nested.

Empirical Results

Invasive Tree Species and Their Spread Patterns on Alabama Forests

In total, 16 invasive tree species were identified for the southern United States from the literature and online databases. Several characteristics were reported for each of them: common name, scientific name, year introduced, and native range (Table 1). For example, Chinese tallow tree *(Triadica sebifera)* was introduced from China to the United States around the 1700s and currently has a wide distribution in the southern United States. Overall, these invasive tree species have been introduced to the United States in a variety of ways over time and are widely distributed in the U.S. South.

To assess the spread patterns of invasive trees on Alabama forests, the listed invasive tree species were compared to the tree species contained in the Alabama PIA data. All 16 listed invasive tree species have appeared on Alabama forests at the time of this study. Several patterns emerged from the statistical analysis and comparison of the FIA data in 1990, 2000, and 2004 (Table 2). The proportion of plots with invasive species over the total PIA plots was relatively low: 1.06% in 1990, 1.24% in 2000, and 1.35% in 2004. The increases in invasive species from 1990 to 2000, 1990 to 2004, or 2000 to 2004 were not statistically significant at the conventional level of significance. A possible explanation for the lack of a significant increase might be that because different sampling designs were used in the

Table 1. Names, years introduced, and origination of selected invasive tree species in US southern forests

No.	Common name	Scientific name	Year introduced/native range
1	Australian pine	*Casuarina equisetifolia*	Late 1800/Malaysia, southern Asia, Oceania, and Australia
2	Norway maple	*Acer platanoides*	Late 1700s/continental Europe and western Asia.
3	Tree-of-heaven	*Ailanthus altissima*	1784/Central China
4	Mimosa/silktree	*Albizia julibrissin*	1745/Iran to Japan
5	European alder	*Alnus glutinosa*	Europe and western Asia
6	White mulberry	*Morus alba*	1827/China
7	Princesstree/paulownia	*Paulownia tomentosa*	1840/China
8	Silver (white) poplar	*Populus alba*	1748/Central and southern Europe to western Siberia and central Asia
9	European mountain ash	*Sorbus aucuparia*	1900s/Northern Europe and Asia
10	Siberian elm	*Ulmus pumila*	1860/northern China, eastern Siberia, Manchuria, and Korea
11	Salt cedar	*Tamarix chinensis*	1800/Eurasia and Africa
12	Melaleuca, paperbark tree	*Melaleuca quinquenervia*	1900/Australia, New Guinea, and New Caledonia
13	Chinaberry tree	*Melia azedarach*	Mid-1800s/China
14	Tallowtree	*Triadica sebifera*	1700s/China
15	Tung-oil-tree	*Aleurite fordii*	1900s/Central and western China
16	Russian olive	*Elaeagnus angustifolia*	1900s/Southeastern Europe and western Asia

Sources: USDA/APHIS 2001; Miller 2003; Webster et al. 2006; National Park Service 2006; National Invasive Species Information Center 2006; Natural Resource Conservation Service 2006; Southeast Exotic Pest Plant Council 2006.

Table 2. Number of invasive trees on Alabama FIA plots, average number of invasive trees per plot, and proportion of plots invaded by year

Items	1990	2000	2004
Number of invasive trees per plot*			
<15	5	25	25
16–30	5	5	5
31–50	1	1	1
51–100	17	19	10
101–200	10	15	5
201–500	2	3	4
>500	0	0	3
Total number of FIA plots	3,771	5,477	3,923
Total number of plots with invasive species	40	68	53
Proportion of invaded FIA plots (%)	1.06	1.24	1.35†
Average number of invasive trees per plot	1.07	0.85	1.34

* All 16 invasive tree species listed in Table 2 on Alabama forests.
† Based on a two-sample proportion comparison test, the proportions of invaded plots between 1990 and 2000, 1990 and 2004, and 2000 and 2004 were not significantly different at the conventional levels of significance.

1990, 2000, and 2004 FIA surveys, it was not possible for the two-sample proportion comparison test to detect the trend if, indeed, there was any. Still, considering the total forestland of 23 million acres in Alabama, the total area of forestland infested with invasive trees was 0.31 million acres (i.e., 23 X 1.35%) in 2004.

For all the PIA survey years, the majority of plots infested with invasive trees had either <30 trees/plot or 51-200 trees/plot, thus exhibiting a bimodal distribution. According to the 2004 PIA survey, the average number of invasive trees per plot was 1.34 with a SD of 25.50 so some plots had considerably higher concentrations of invasive trees than others. The accompanying GIS map (Figure 1) shed additional light on the relative concentrations of invasive trees per plot by Alabama ecoregion. There were large differences in the number of invasive trees per plot across ecoregions. In particular, the Coastal Plains and Flatwoods (ecoregion 6) had the highest dispersion in the number of invasive trees per plot. A possible explanation for this finding might be the presence of numerous water bodies and substantial economic activities within this ecoregion; the region is home to the city of Mobile, situated on Mobile Bay along the Gulf of Mexico.

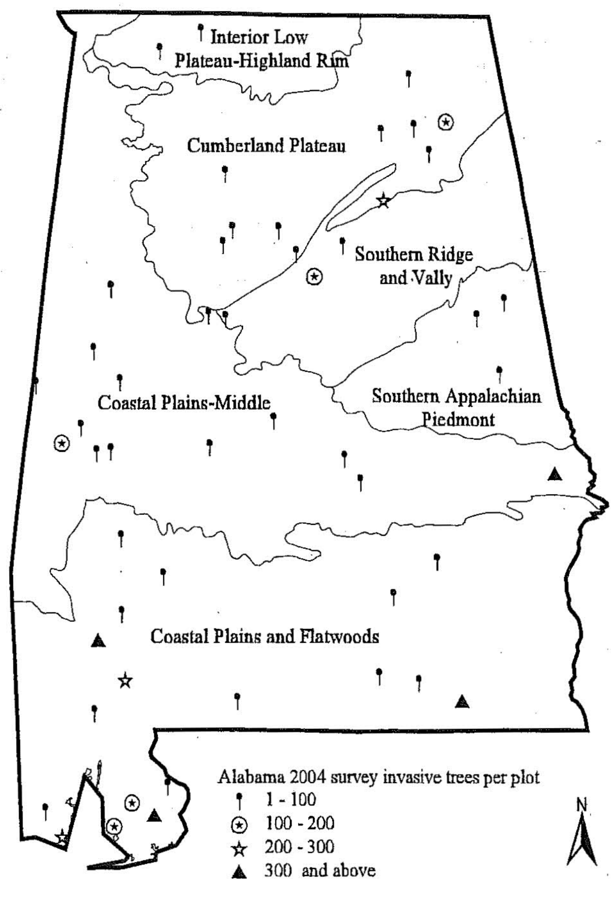

Figure 1. Number and location of invasive species trees per FIA plot and their distribution on Alabama forestland by ecoregion in 2004.

Descriptive Statistics of Covariates

The descriptive statistics of the independent variables are reported in Table 3. FIA data used were from the 2004 survey year. Plots classified as highly productive (i.e., plots corresponding to PIA site classes 1 and 2) accounted for only 6% of the total, whereas most plots were of medium (57%) and low productivity (37%). Of the plots, 31% were fully stocked, another 35% of the plots were moderately stocked, and the rest were poorly stocked plots. The slope-aspect orientation indices were designed to capture moisture levels. As these indices were constructed from the interaction of slope and aspect, it was hard to interpret their means and variances directly; only the associated regression coefficients lent themselves to interpretation. Of the six ecoregions in Alabama, the Coastal Plains-Middle (ecoregion 3) and Coastal Plains and Flatwoods (ecoregion 6) dominated the rest of the regions in the sense that these two regions alone accounted for 67% of the plots. In addition, there was a relatively balanced distribution of forestland in various forest types: natural pine at 18%, oak-pine at 13%, planted pine at 23%, upland hardwood at 31%, and lowland hardwood at 15%. Finally, statistics on the group of economic factors revealed that 28% of the plots were in metropolitan counties; a predominant proportion (i.e., 94%) of the plots were on private forestlands; and only 6% had experienced a human disturbance (e.g., timber harvesting or prescribed fire) within the previous 5 years.

Table 3. Descriptive statistics of variables used in the analysis of invasive trees on Alabama forestland in 2004

Name	Variable definition	Mean	SD
w_i	w_i = 1 if no invasive trees on a plot; 0 otherwise	0.99	—
y_i	y_i = Number of invasive trees on a plot	1.34	25.50
Site productivity			
High	Dummy = 1 for site index of 1 or 2, 0 otherwise	0.06	—
Medium	Dummy = 1 for site index of 3 or 4, 0 otherwise	0.57	—
Low	Dummy = 1 for site index of 5, 6, or 7, 0 otherwise (base)	0.37	—
Growing stock			
Fully stocked	Dummy = 1 if a plot was full or overstocked	0.31	—
Medium stocked	Dummy = 1 if a plot was medium stocked	0.35	—
Poorly stocked	Dummy = 1 if a plot was poorly stocked (base)	0.34	—
Moisture level			
Northeast	Slope (%) × aspect ranging 0–90°	7.59	20.67
Southeast	Slope (%) × aspect ranging 91–180°	22.28	51.76
Southwest	Slope (%) × aspect ranging 181–270°	39.12	86.74
Northwest	Slope (%) × aspect ranging 271–360°	55.37	120.98
Forest type			
Natural pine	Dummy = 1 if natural pine, 0 otherwise	0.18	—
Oak-pine	Dummy = 1 if oak-pine, 0 otherwise	0.13	—
Planted pine	Dummy = 1 if planted pine, 0 otherwise	0.23	—
Upland hardwood	Dummy = 1 if upland hardwood, 0 otherwise	0.31	—
Lowland hardwood	Dummy = 1 if lowland hardwood, 0 otherwise (base)	0.15	—
Forest stand age	Average age of the trees in the predominant stand-size class of the condition	33.27	22.88
Alabama ecoregion*			
Ecoregion 1	Dummy = 1 for ecoregion 1, 0 otherwise	0.02	—
Ecoregion 2	Dummy = 1 for ecoregion 2, 0 otherwise	0.08	—
Ecoregion 3	Dummy = 1 for ecoregion 3, 0 otherwise	0.30	—
Ecoregion 4	Dummy = 1 for ecoregion 4, 0 otherwise	0.14	—
Ecoregion 5	Dummy = 1 for ecoregion 5, 0 otherwise	0.08	—
Economic factors			
Proximity	Dummy = 1 if a plot was in a metropolitan county, 0 otherwise	0.28	—
Ownership	Dummy = 1 if a plot was on private land, 0 otherwise	0.94	—
Activity	Dummy = 1 if management activities within the last 5 years occurred on a plot, 0 otherwise	0.06	—

* Ecoregion 1: Interior Low Plateau-Highland Rim; ecoregion 2: Southern Appalachian Piedmont; ecoregion 3: Coastal Plains-Middle; ecoregion 4: Cumberland Plateau; ecoregion 5: Southern Ridge and Valley; ecoregion 6: Coastal Plains and Flatwoods (base).

Estimation Results of Count Data Modeling

An objective of the study was to determine whether the same set of covariates had differential impacts on occurrence and abundance. Accordingly, the same set of covariates was used in both parts of the mixture probability models. Furthermore, interactions between variables might influence occurrence and abundance, but none were included in this study because of lack of theoretical guidance.

On the basis of the likelihood ratio test, the Poisson assumption of mean-variance equality (i.e., a = 0) was rejected at the 1% level of significance, implying the NB model was favored over the PR model (Table 4). The standard NB itself was also tested against the heterogeneous NB. The associated likelihood ratio test favored the HNB model over the NB model at the 1% leveL Similarly, the ZIP versus ZINB likelihood ratio test favored ZINB; the PH versus NBR likelihood ratio tests favored NBR. The ZINB versus NBR comparison (based on AIC) favored ZINB because the AIC statistic associated with the ZINB model was about 10 points less than the AIC statistic for the NBH model, suggesting the superiority of the ZINB specification.

According to Raftery (1996), differences in AIC in excess of 6-10 are indicative of a strong preference for the model with the lesser value of this statistic. The ZINB model might thus be considered a more plausible representation of the occurrence and abundance of invasive trees on Alabama forests. Thus, the ensuing analysis of estimation results was based on the ZINB specification.

Results of the first part (i.e., the inflation component) of the ZINB model suggested that the occurrence of invasive trees species was significantly associated with forest type (Table 5). In particular, plots with planted pine were more likely to be noninfested (w_i = 1) with invasive trees than plots with lowland hardwoods (base). As revealed by the odds ratio, plots with planted pine were 171% (= $e^{0.996}$ - 1) less likely to be infested with invasive trees than otherwise similar plots.

Several variables proxying ecological conditions influenced the abundance of invasive trees. The large incidence rate ratio associated with a high productivity site class suggested that invasive trees were relatively more abundant on productive sites. Likewise, the large incidence rate ratios corresponding to fully stocked sites and moderately stocked

Table 4. Tests of Poisson equidispersion assumption and selection criteria for mixture probability models

Hypothesis	Test	p value	Decision
Poisson mean-variance equality			
PR versus NB	Likelihood ratio*	<0.000	Accept NB
NB versus HNB	Likelihood ratio	<0.000	Accept HNB
Mixture probability models			
ZIP versus ZINB	Likelihood ratio	<0.000	Accept ZINB
PH versus NBH	Likelihood ratio	<0.000	Accept NBH
ZINB versus NBH	AIC†	ZINB: 1,123.348 NBH: 1,133.237 Difference: 9.899	Accept ZINB

PR, Poisson regression; NB, negative binomial; HNB, heterogeneous negative binomial; ZIP, zero-inflated Poisson; PH, Poisson hurdle; ZINB, zero-inflated negative binomial; NBH, negative binomial hurdle.

* Likelihood ratio test: $LR = -2(\ln L_{un} - \ln L_c)$ where $\ln L_{un}$ and $\ln L_c$, respectively, refer to log likelihood statistic for the unconstrained and constrained specifications.

† $AIC = (-2 \ln L + 2k)/N$, where $\ln L$ is the likelihood of the model, k is the number of parameters (including the constant) in the count model, and N is the sample size.

Table 5. Empirical results of invasive trees occurrence and abundance on Alabama forestland in 2004 based on zero-inflated negative binomial regression

	Occurrence				Abundance			
Variable	Coefficient	SE	OR	p value	Coefficient	SE	IRR	p value
Site productivity								
High	0.478	1.050	1.613	0.649	8.788	2.684	6,555.561	0.001
Medium	−0.196	0.351	0.822	0.577	0.375	0.633	1.456	0.553
Growing stock								
Fully stocked	−0.281	0.546	0.755	0.606	3.461	1.092	31.852	0.002
Medium stocked	−0.124	0.639	0.883	0.846	3.563	1.640	35.272	0.030
Moisture level								
Northeast	0.000	0.009	1.000	0.974	−0.017	0.017	0.983	0.305
Southeast	−0.001	0.003	0.999	0.839	0.006	0.007	1.006	0.404
Southwest	0.001	0.002	1.001	0.595	−0.001	0.004	0.999	0.881
Northwest	0.002	0.002	1.002	0.223	0.005	0.006	1.005	0.397
Forest type								
Natural pine	0.417	0.553	1.517	0.451	−0.905	0.969	0.405	0.350
Oak-pine	0.847	0.636	2.333	0.183	0.657	1.361	1.930	0.629
Planted pine	0.996	0.541	2.707	0.065	−0.768	1.079	0.464	0.476
Upland hardwood	0.990	0.704	2.692	0.160	3.300	2.227	27.100	0.139
Forest stand age	0.003	0.022	1.003	0.894	−0.136	0.071	0.873	0.053
Alabama ecoregion								
Ecoregion 1	−1.033	0.950	0.356	0.277	−1.805	1.920	0.165	0.347
Ecoregion 2	−0.405	0.887	0.667	0.648	−3.955	2.483	0.019	0.111
Ecoregion 3	−0.257	0.493	0.773	0.602	−2.849	1.338	0.058	0.033
Ecoregion 4	−0.561	0.421	0.570	0.182	0.161	0.846	1.174	0.850
Ecoregion 5	−0.071	0.790	0.931	0.928	−3.430	1.803	0.032	0.057
Economic factors								
Proximity	−0.304	0.358	0.738	0.396	1.851	0.780	6.367	0.018
Ownership	2.329	1.424	10.268	0.102	7.006	2.121	1,102.847	0.001
Activity	−2.001	1.792	0.135	0.264	−7.496	3.466	0.001	0.031
Intercept	0.977	1.693	2.656	0.564	−12.236	1.977	0.000	0.000
$\ln(\alpha)$					0.984	0.662		0.137
α					2.674	1.771		
$\Pr > \chi^2$	0.002							
AIC	1,123.348							
Observations	3,923							

OR, odds ratio; IRR, incidence rate ratio.

sites suggested that invasive trees in Alabama thrived in dense forests. Finally, the number of invasive trees significantly decreased with an increase in stand age; the size of its impact was 12.7% for each additional year. Site-slope aspect and forest type did not exhibit significant statistical association with abundance.

Regarding the abundance of invasive species trees across ecoregions, the coefficients on the variables representing the Coastal Plains-Middle (ecoregion 3) and Southern Ridge and Valley (ecoregion 5) were negative and highly significant ($p < 0.00$). Plots in these ecoregions had fewer invasive species trees than Coastal Plains and Flatwoods (ecoregion 6). The Southern Appalachian Piedmont (ecoregion 2), Cumberland Plateau (ecoregion 4), and Interior Low Plateau-Highland Rim (ecoregion 1) did not significantly differ from the Coastal Plains and Flatwoods (ecoregion #6).

All of the variables constructed to proxy the influence of economic conditions (i.e., proximity, forestland ownership type, and forest management activity) on abundance of invasive trees were significant. In terms of the direction of the impact, proximity and type of ownership had a positive impact on abundance, whereas forest management activity had a negative impact. The incidence rate ratio for type of ownership was especially large, indicating that plots on private forestlands had relatively more invasive trees than plots on public lands.

Discussion

To reduce potential damages associated with invasive tree species, various management strategies have been considered in recent years. Frequently mentioned strategies include restrictions on international trade via species screening (Keller et al. 2007), early detection and rapid response via integrated approaches to control 2000, Webster et al. 2006), and ecosystem level actions rather than species-specific control strategies (Marvier et al. 2004). To supplement these strategies, this research developed an analysis protocol identifying several ecological and economic factors that influenced the occurrence and abundance of invasive trees on Alabama forests. In designing plans to prevent and control the spread of invasive species, it will be important to differentiate between factors influencing occurrence and abundance and to augment ecological factors with economic drivers. In this regard, -the following insights from this research might prove helpful.

We found that a very small proportion of plots in Alabama forests were infested with invasive trees. This finding has implications for management and future modeling efforts. From the perspective of forest management and control options, this low occurrence suggests that targeting of high-risk sites needs to be selective. In addition, not all non-native species become invasive so the cost-minimizing approach to control and management implies targeting of specific invasive species. From a modeling perspective, this low occurrence requires analytical tools that use count data models that can manage a high proportion of zero values to understand occurrence and abundance of invasive species. The infrequent nature of invasive species translates into certain data generation processes that can be examined by tools appropriate for handling such data (Cunningham and Lindenmayer 2005).

Our estimation results based on count data analysis showed that the ecological and socioeconomic factors explaining occurrence and abundance of invasive trees were different. Although occurrence was significantly associated with forest type (particularly planted pine), abundance was influenced by a host of factors including site productivity, growing stock, stand age, ecoregion, proximity, type of ownership, and forest management activity. This finding accorded with our hypothesis that occurrence and abundance of invasive trees were distinct phenomenon and related differently to the same set of variables. This pattern of association between explanatory variable and occurrence/abundance suggested that modeling invasive trees spread poses a relatively difficult challenge. A plausible explanation consistent with Cunningham and Lindenmayer (2005) is that when data are scant, particularly in terms of a very low frequency of occurrences (e.g., <5%), numerical computation problems arise in model estimation and the data fitting. Regarding the direction of association between planted pine and occurrence, a plausible explanation might be that pines are generally planted on productive sites and landowners (public and private) remove any species from these sites that inhibit pine production.

A wide range of ecological factors showed significant impacts on the abundance of invasive tree species. Whereas some of the relationships seemed plausible, others needed more information to be interpreted. For instance, site productivity had a positive association with abundance, which is not surprising because by definition we would expect greater density of plants on productive sites than on otherwise similar sites. Likewise, the finding that abundance was negatively associated with stand age agreed with Flory and-Clay (2006). Webster and Gibson (2007) also noted that old-growth stands could substantially differ from more recently disturbed stands in species composition and might be less susceptible to invasion by exotic plant species. The positive association of abundance with fully stocked sites was, however, counterintuitive because one would expect invasive species to spread where competition was less intense. A possible explanation is that some invasive species in Alabama forests thrive in fully stocked forests, and they may be shade tolerant (Parendes and Jones 2000).

We found that plots in Alabama ecoregion 3 (Coastal Plains-Middle) and ecoregion 5 (Southern Ridge and Valley) significantly differed from plots in ecoregion 6 in terms of the number of invasive trees, and this result is consistent with the findings by Evan et al. (2006). The northern and southern ecoregions of Alabama differ greatly from the mid-regions in terms of geology, physiography, vegetation, subregional climate, soils, land use, wildlife, and hydrology. The significant relationships of abundance according to ecoregion types may reflect the influences of these factors.

Consistent with the motivation of this study, all of the variables hypothesized to proxy the role of economics-related activities in influencing invasive species abundance were significant. Proximity of plots to metropolitan centers and type of ownership had positive impacts, whereas forest management activity negatively influenced abundance. Although the specific nature of the mechanism is not clear, possible reasons for a positive association of invasive species abundance and proximity to metropolitan areas include the relatively greater degree of ecosystem fragmentation (Marvier et al. 2004, Yates et al. 2004) in these areas and more activities on those lands (e.g., illicit disposal of garden waste, seeds brought in on tires, and other issues associated with high use) (Lundgren et al. 2004). The impact of forest management activity (timber harvesting, thinning, prescribed burn, and chemical release) on invasive species abundance could be negative or positive, depending on the nature of its implementation. For instance, harvesting might introduce invasive species and abundance may increase, but chemical release would severely reduce the abundance of invasive species. Thus, a priori, there is no basis to expect a positive or negative association unless the type of management activity and its timing of implementation are controlled in some way.

In light of the above findings, future research may proceed in several directions to further improve our understanding of the occurrence and abundance of invasive trees on forestland. For instance, major invasive tree species were aggregated in this study, but that may be improved by species-specific analysis because the degree or nature of invasion among species may differ. Given that not all invasive species are equally damaging to forest health and that species-specific analysis is time-consuming, it is appropriate to focus on major invasive species. Analysis of the role of economic factors can be refined further by distinguishing private land into nonindustrial private forestland and industrial forestland. This should add additional insights because nonindustrial private forest landowners and industrial landowners generally pursue different management objectives, which in tum is likely to influence invasive species spread patterns in different ways. The management activity variable may be refined further by differentiating among types of management activities (e.g., harvesting, prescribed burn, and thinning) and their implementation timing because these are likely to have dissimilar impacts on occurrence and abundance. Future research might also benefit from a panel data modeling of invasive species, thus allowing us to understand both the spatial and temporal patterns of invasive species phenomenon. Panel data modeling would require the use of FIA data for multiple years on a reasonable number of remeasured plots. Finally, to explore the significance of riparian corridors for invasive species occurrence and abundance, GIS information measuring distance of FIA plots to major waterways and tributaries could be exploited as a variable in modeling.

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