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ARTICLE

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# Emerald ash borer intensifies harvest regimes on private land

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## Abstract

Invasive forest insects have significant direct impacts on forest ecosystems and they are also generating new risks, uncertainties, and opportunities for forest landowners. The growing prevalence and inexorable spread of invasive insects across the United States, combined with the fact that the majority of the nation's forests are controlled by thousands of autonomous private landowners, raises an important question: To what extent will private landowners alter their harvest practices in response to insect invasions? Using a quasi-experimental design, we conducted a causal analysis to investigate the influence of the highly impactful emerald ash borer (EAB) on (1) annual probability of harvest; (2) intensity of harvest; and (3) diameter of harvested trees, for both ash and non-ash species on private land throughout the Midwest and mid-Atlantic regions of the United States. We found that EAB detection had a negative impact on annual harvest probability and a positive impact on harvest intensity, resulting in a net increase in harvested biomass. Furthermore, our estimates suggest that EAB detection will influence private landowners to harvest greater quantities of ash, relative to non-ash species. We also found that harvested trees in EAB-infested areas had smaller diameters, on average, compared with those unaffected by EAB. These results can help policymakers, forest managers, and extension programs to anticipate and better advise landowners and managers about their options and the associated outcomes for forests.

**KEYWORDS**
causal inference, coupled human and natural systems, covariate matching, disturbance ecology, emerald ash borer, forest inventory and analysis, forest management, *Fraxinus*, harvest regimes, invasive insects, zero-inflated beta regression

## INTRODUCTION

Non-native plants, animals, and microorganisms are fundamentally altering the composition and function of ecosystems, particularly forests, whose slow growth and remoteness often hinder the timely detection of invasive species (Liebhold et al., 2017). While most non-native organisms have negligible impacts on their host environments, a selection of wood-boring beetles have established themselves as a major source of disruption to forests. Over

  

the past two centuries, wood-boring beetles have been unintentionally moved between continents in wood and wood packaging material (Brockerhoff et al., 2006), with dramatic consequences on their new habitats. For instance, tree-killing bark beetles can convert conifer-dominated stands into broad-leaved forests, effectively replacing entire swaths of trees with other, often functionally different, plant species (Edburg et al., 2012). In addition to modifying forest structure and function, bark and wood-boring insects in the United States cost hundreds of millions of dollars per year in lost timber revenue (Liebhold et al., 2017).

Invasive insects and timber harvesting represent the primary disturbance agents in eastern North American forests, and through selective mortality they substantially alter the composition and structure of the forested landscape (Canham et al., 2013; Fei et al., 2019; Liebhold et al., 2017). Synergies between invasive insects and timber harvesting pose risks and uncertainties for the future of forest management. Anticipating how landowners will respond to the presence or threat of insects is challenging and not well understood, although salvage cutting (or preemptive salvage cutting) has long been the default management choice when faced with an exogenous disturbance (Burton et al., 2008). Specific management decisions are strongly influenced by attributes of the insect (e.g., rate of spread, lethality, and host specificity), the landowner type, and the social context (Markowski-Lindsay et al., 2020). Past outbreaks in the region have been accompanied by accelerated harvesting, and there are distinct ecological legacies of the interactions between these two classes of biotic disturbance. From 1972–1986, for example, industrial timberland owners in Maine dramatically increased clear-cut salvage harvesting during an extensive spruce budworm (*Choristoneura fumiferana*) outbreak, resulting in the widespread conversion of spruce-fir forests to deciduous ones (Irland et al., 1988). Similarly, following reports that hemlock woolly adelgid (*Adelges tsugae*) had reached Connecticut in the 1980s and 1990s, many landowners harvested hemlock trees, despite their low commercial value (Orwig et al., 2002). In 2008, when Asian longhorned beetles (*Anoplophora glabripennis*) were discovered in Worcester, MA, the USDA responded by felling and chipping >35,000 trees along city streets and in urban woodlots (Dodds & Orwig, 2011). Understanding the connections and feedbacks among these drivers of change is critical for anticipating ecological impacts and developing sustainable policies.

In recent years, the phloem-feeding buprestid beetle emerald ash borer (EAB; *Agrilus planipennis*) has become the most destructive and costly forest insect to ever invade North America (Aukema et al., 2011; Lovett et al., 2016; Morin et al., 2017). The impact of EAB is so widespread and severe that American ash species (*Fraxinus* spp.) could be functionally extinct within decades (Herms & McCullough, 2014). Forest landowners and managers have been forced to adapt their decision-making to account for the presence and threat of EAB throughout range of ash in North America.

EAB, native to Asia, was first identified in the United States in 2002 near Detroit, Michigan, although it is now understood that the initial invasion occurred in the mid-1990s. Since its arrival in North America, the insect has spread to dozens of United States states and has killed millions of ash trees. The lack of resistance in North American ash hosts (Anulewicz et al., 2008) results in rapid spread of EAB, threatening the persistence of North American species in the genus *Fraxinus*. EAB dispersal is primarily a function of time (i.e., the invasion spreads across the host range until saturation occurs), although other significant correlates of EAB dispersal include human population density (+), ash and non-ash tree densities (+), and temperature (−) (Ward et al., 2020). Once EAB is established, ash species experience an increased mortality rate and corresponding decreases in volume until most live ash are killed (Klooster et al., 2018; Morin et al., 2017; Pugh et al., 2011).

As with forest insects, timber harvest regimes are critical drivers of mesoscale ecological dynamics (Thompson et al., 2017). Harvest regimes are driven by physical, social, and economic factors (Thompson et al., 2017). Aboveground tree biomass, species, and diameter are correlated with the probability and intensity of harvest (Canham et al., 2013; Silver et al., 2015). The demographic attributes population density and median household income are negatively correlated with harvest intensity (Kittredge et al., 2017). Ownership type has also been shown to affect harvest regimes, with private woodland owners generally removing more trees than public entities (Thompson et al., 2017). Although timber market prices are intuitively tied to harvest patterns, Kittredge and Thompson (2016) found that fluctuations in stumpage are an unreliable predictor of aggregate harvest activity for non-industrial private landowners.

An open question is the degree to which EAB detection influences harvest regimes, an interaction that could potentially compound and modify the disturbance impact on the forested ecosystem by either broadening its impact (e.g., accelerated harvesting, transportation of infested firewood) or by limiting its spread (e.g., removal of host trees). Of particular interest is the impact of EAB detection on logging by private landowners, who autonomously make decisions that collectively affect the majority of United States forestland. A 2017 mail survey of private landowners in New England found that 84% of respondents ($n = 688$) intended to harvest, in some capacity, in response to a hypothetical tree insect invasion

(Markowski-Lindsay et al., 2020). Empirical evidence of a synergy between EAB detection and harvesting regimes, however, is lacking.

Here we determine whether EAB detection (from this point forwards "EAB") affects harvest regimes on privately owned forestland. Disturbances such as forest insect pests often prompt "salvage" harvesting, which serves to recover monetary value in affected timber or meet certain silvicultural goals (Burton et al., 2008). While salvage harvests typically occur after a disturbance such as wind or fire, "sanitation" harvests can also occur preemptively in an attempt to mitigate future damage or value loss, particularly for forest insects (Waring & O'Hara, 2005). The effects of salvage and/or sanitation harvesting can extend beyond the host species alone; for example, the spruce budworm and the hemlock woolly adelgid prompted landowners to harvest a mix of host and non-host tree species (Irland et al., 1988; Kizlinski et al., 2002). The removal of non-host tree species with the host species serves to increase the commercial value of the harvest and/or to promote a desired regeneration of species (MacLean et al., 2020). In our analysis, we examine the effects of EAB on both host (ash) and non-host (co-occurring with ash) tree species.

Using publicly available datasets, our analysis addressed the following three research questions: (1) How is the annual probability and intensity of ash species harvested impacted by EAB? (2) How is the annual probability and intensity of non-ash species harvested influenced by EAB? (3) Does the presence of EAB impact the mean diameter of harvested trees?

# MATERIALS AND METHODS

## Summary of methodology

Using data from the United States Forest Service's Forest Inventory and Analysis (FIA), the United States Department of Agriculture's Animal and Plant Health Inspection Service (APHIS), and the American Community Survey (ACS), we quantified the influence of EAB on harvest frequency, harvest intensity, and mean diameter of removed trees. We analyzed these data using a quasi-experimental statistical design to test for a causal relationship between the presence of EAB and altered harvest behavior sensu Larsen et al. (2019). Borrowing language from randomized control trials, we use "treatment" to denote EAB presence; "control" refers to no EAB; and our "response" is tree-harvesting. We first implemented a matching algorithm to ensure that "treatment" (EAB) and "control" (no EAB) observations had similar variable distributions with respect to the covariates shown by Ward et al. (2020) to impact EAB dispersal (e.g., human population density, tree density, temperature). Then, to quantify the effect of EAB on harvesting, we performed regression analysis using covariates shown by Thompson et al. (2017) to impact harvesting (e.g., volume of living trees, human population density, median household income). Finally, we compared the diameters of harvested trees on plots with and without EAB using a Student's $t$ test, with separate comparisons for ash and non-ash species.

## Data description

We obtained annual county-level EAB invasion status from the USDA APHIS for nine United States states, including parts of the Midwest and mid-Atlantic regions (Figure 1). At the county level, measurable impacts on forests generally begin to appear ~5 years after establishment and were widespread at 10 years (Morin et al., 2017). As a compromise between EAB tenure, which began in 2002 in the APHIS dataset, and number of treatment (EAB) observations, we conducted our analysis for the years 2007–2012, mirroring the second EAB "invasion cohort" described in Ward et al. (2021). Any plot in a county in which EAB was detected prior to 2007 was in the treatment group; all plots in counties that were infected after 2012 were in the control group (Figure 1). Response (harvest) data were extracted for the years 2007–2012. By omitting from our analysis counties that detected EAB between 2007–2012, we temporally separated the treatment effect from the response, which led to a more straightforward matching routine (Section 2.3).

Plot characteristics and tree data were extracted from the United States Forest Service FIA program using the *rFIA* package (Stanke et al., 2020; Stanke & Finley, 2020) for the statistical software (R Core Team, 2020). We used data from plots for which there were two censuses conducted using the contemporary plot design (1999 onwards) to allow determination of prior and subsequent plot characteristics (e.g., which trees were removed). Specifically, all prior observations were conducted between 1999 and 2006; all subsequent observations were conducted between 2007 and 2012. By comparing the initial and follow-up observations of each plot, we determined which trees were harvested as well as the species and diameter of each harvested tree. In accordance with FIA protocol, we considered harvested trees to be those that were "cut or removed by direct human activity related to harvesting, silviculture or land clearing" (Woudenberg et al., 2010). Trees with diameter < 12.7 cm (5 inches) were omitted from our analysis (including plot-level statistics) to be consistent with FIA demographic estimates.

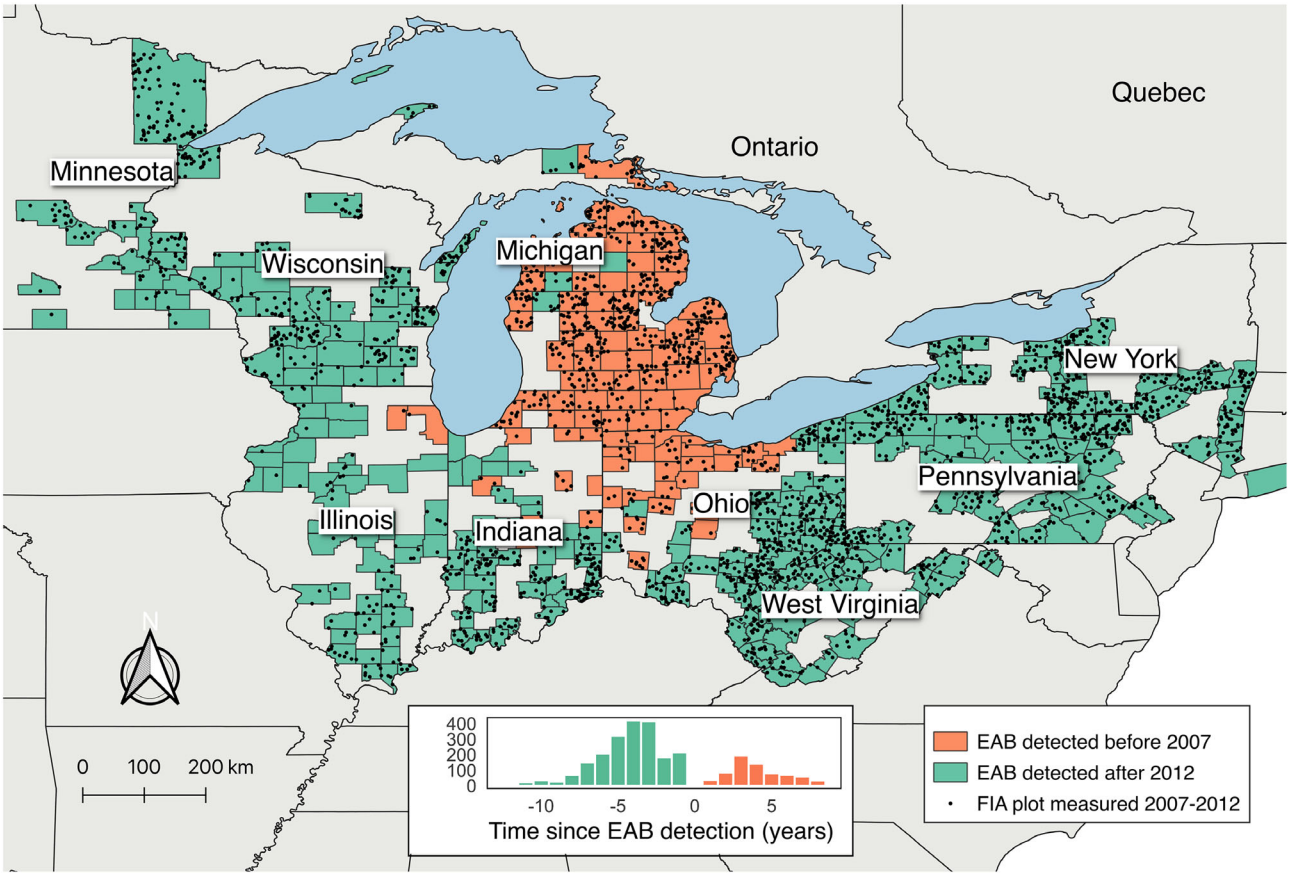


**FIGURE 1** Study area. Forest Inventory and Analysis (FIA) plots in counties where emerald ash borer (EAB) was detected before 2007 are in the treatment group; observations from counties where EAB was detected after 2012 are in the control group. Tree characteristics and harvest data were extracted from 2007–2012. Treatment observations (orange) had a range of EAB infestations from between 1 and 10 years. Negative values in the histogram indicate time to arrival for EAB

Plots that did not contain any ash trees were removed from the data as these plots were not subject to the treatment effect. In the context of this study, "ash species" includes white ash (*Fraxinus americana*), green ash (*Fraxinus pennsylvanica*), and black ash (*Fraxinus nigra*). We considered privately owned plots only (omitting federal and state plots) to contextualize our findings within the discussion of private landowner behavior (e.g., Holt et al., 2020; MacLean et al., 2020; Markowski-Lindsay et al., 2020).

Socioeconomic variables shown to be correlated with the treatment and/or response were downloaded from the ACS using the tidycensus package (Walker et al., 2020). We obtained human population density at the county level to match EAB and non-EAB counties (Ward et al., 2020). Human population density and median household income were also obtained at the census tract level to be incorporated into the finer-resolution harvest models.

Meteorological variables known to be predictive of the treatment effect were downloaded from PRISM (PRISM, 2019). We obtained climate normals (three-decade averages) for precipitation (mm), minimum temperature (°C) and maximum temperature (°C) for the period 1981–2010 at a 4 km × 4 km resolution raster. We then conducted a principal component analysis (PCA) and aggregated the rotated principal component scores to the county level by averaging values for all grid cells whose centroids occurred within a given county boundary. Minimum and maximum temperatures had high loadings on the first principal component ("PC1") whereas precipitation had high loadings on the second ("PC2"). Ward et al. (2020) identified PC1 as being correlated with the treatment effect; as such, we included PC1 as a covariate in our matching routine.

## Covariate matching

When using observational data to consider a causal relationship, such as the effect of EAB on harvest regimes, one must address confoundedness, or the possibility that differences in the response variable between treatment and control groups are caused by factors that predict treatment rather than the treatment itself (Cochran & Rubin, 1973). As an example of confoundedness, ash tree

density may be a causal mechanism for both EAB invasions and ash harvesting; in this scenario, it would be impossible to identify the relationship between EAB and ash harvesting without controlling for ash tree density. Therefore, before assessing the relationship between EAB and harvest regimes, we: (1) identified variables known to be correlated with the treatment effect; and (2) ensured that the joint distributions of these variables were similar between treatment and control groups.

We matched covariates using the Genetic Matching algorithm (Diamond & Sekhon, 2013), which is a generalization of propensity score and Mahalanobis distance matching (Rosenbaum & Rubin, 1985). The algorithm is a multivariate matching method that uses an evolutionary search routine developed by Sekhon and Mebane (Sekhon & Mebane, 1998) to maximize the balance of observed covariates (i.e., the joint distribution) across treatment and control units. Human population density, ash tree density, non-ash tree density, and temperature are variables shown to be correlated with EAB invasion (Ward et al., 2020), and therefore were used as covariates for the matching algorithm. EAB spread has also been shown to be spatially and temporally autocorrelated (e.g., EAB in a county is influenced by EAB in neighboring counties). We removed spatiotemporal interactions between the treatment and response by using the following framework: All sites that first detected EAB from 2002–2006 were treatment units; sites that first detected EAB from 2013 onwards were control units; and we collected response data between 2007–2012, effectively separating the treatment effect from the response. The trade-off of this approach is that we introduce variability in the time since EAB was detected; as EAB was first detected at treatment sites anywhere between 2002–2012, the duration human knowledge of EAB in the county varied from 1 to 10 years (Figure 1, histogram).

The Genetic Matching algorithm assigns weights to control observations such that the weighted controls are similar to the unweighted treatment units. For matching numeric covariates, as in our case, the standardized difference in means can be used to diagnose balance. While there is no universally agreed upon threshold of the standardized difference in means, a difference that is near or below 0.1 has generally been taken to indicate a negligible difference in the mean covariate between treatment and control groups (Normand et al., 2001). We used the *MatchIt* package (Ho et al., 2020) to implement the Genetic Matching algorithm.

## Regression modeling

Using the matched data, our statistical model estimated two components of the harvest regime: (1) probability of being logged; and (2) percentage basal area removed if logged. Both components were modeled simultaneously, similar to Canham et al. (2013). We used a zero-inflated beta distribution for the likelihood function, since the harvest data include many zeros (unlogged plots), and the distribution of percentage basal area removed (if logged) must fall between zero and one. The zero-inflation term was modeled as a logistic regression. Both the logistic and beta components of the model varied as a function of the same four harvest covariates: aboveground biomass (*AGB*) at the previous observation, human population density (*popden*), median household income (*MHHI*), and *EAB*.

We followed a Bayesian model-fitting procedure to estimate our piecewise regression. The zero-inflation term (harvest probability) is modeled as follows, where $N$ is the number of years between plot observations and $w$ is the probability of not harvesting. By raising the inverse of harvest probability to the power $N$, we return estimates for annualized harvest probability. The regression coefficients $\beta$ have uninformative priors $\beta \sim Normal(0, 10^2)$:

$$\mu_i = \beta_0 + \beta_1 AGB_i + \beta_2 popden_i + \beta_3 MHHI_i + \beta_4 EAB_i \quad (1)$$

$$p_i = invLogit(\mu_i) \quad (2)$$

$$w_i = (1 - p_i)^N \quad (3)$$

The beta-distributed component of the model (harvest intensity) is expressed as follows, where $\gamma$ is a regression coefficient drawn from an uninformative prior $\gamma \sim Normal(0, 10^2)$; $y$ is the percent basal area harvested; and $r$ is the concentration parameter of the beta distribution, which we treat as a random variable with prior $r \sim Gamma(0.1, 0.1)$. For readability, we define the log of the beta distribution explicitly:

$$\eta_i = \gamma_0 + \gamma_1 AGB_i + \gamma_2 popden_i + \gamma_3 MHHI_i + \gamma_4 EAB_i \quad (4)$$

$$s_i = invLogit(\eta_i) \quad (5)$$

$$logBeta_i = \log(beta(y_i, rs_i, r(1 - s_i)) \quad (6)$$

Next, we define an indicator variable $z$ to denote harvested and non-harvested observations:

$$z_i = \begin{cases} 1 \, if \, y > 0 \\ 0 \, if \, y = 0 \end{cases} \quad (7)$$

Combining the zero-inflation and continuous model components, we arrive at the likelihood function.

Observe that in the absence of harvest ($z = 0$), the logistic term dominates the likelihood, whereas both the logistic and beta terms are influential when harvest is non-zero:

$$logLikelihood_i = (1 - z_i) * \log(w_i) + z_i * (\log(1 - w_i) + logBeta_i) \quad (8)$$

The model was implemented using "JAGS" via the *R2jags* package (Su & Yajima, 2012). In total, three separate models were estimated to characterize the influence of EAB on ash and non-ash harvest regimes: Model 1 (ash species only); Model 2 (non-ash species); and Model 3 (ash expressed as a fraction of total harvest).

## Harvest diameter

Using the matched dataset, we conducted a weighted Student's *t* test to compare the diameters of harvested trees (diameter ≥ 12.7 cm) in EAB and non-EAB counties. Ash and non-ash species were analyzed separately.

# RESULTS

## Matching

Before we matched the data, the treatment and control groups exhibited significant mean differences in covariates that are known to impact the probability of EAB invasion, thereby confounding causal interpretation of the results. Ash density and non-ash density both had standardized mean differences of 0.36. Population density was the most similar covariate between the two groups (0.15), whereas PC1 had the greatest contrast (0.90). The large difference in PC1, which represents temperature, can be explained by the fact that most treatment observations were located in the northern state of Michigan, whereas many of the control observations were in warmer areas of West Virginia, Indiana, and Illinois (Figure 1).

The Genetic Matching algorithm achieved negligible mean differences between treatment and control groups in ash density (0.07), non-ash density (0.01), population density (0.002) and PC1 (0.06) (Appendix S1). This balance was achieved by selecting 310 of the control observations most similar to the 691 treatment observations (2033 control observations were discarded). The 310 control units were assigned weights such that all units sum to one.

## EAB impacts on harvest probability and intensity

Ash and non-ash harvests were detected in 6% and 9% of the FIA plots, respectively. When ash was harvested, 63% of the plot's basal area ash was removed, and ash species amounted to about one-half of the total harvest, on average. Non-ash removals averaged 32% of the plot's basal area. The average time interval between subsequent measurements ($N$ in Equation 3) was 5.08 years (SD = 0.65).

Harvest probability was modeled in tandem with harvest intensity (Equation 8), in which both the probability and intensity terms varied as functions of AGB, EAB presence, human population density, and median household income (MHHI). Each model converged after 2000 iterations with a burn-in period of 200. Based on the deviance information criterion (DIC) (Spiegelhalter et al., 2002), Model 1 (ash species only) had the best fit, followed by Model 3 (ash species expressed as a fraction of total harvest) and Model 2 (non-ash species; Table 1).

Tree biomass was the strongest predictor of harvest and was a significant variable in all three models. AGB had a statistically significant positive effect on harvest probability in Model 1 (ash) and Model 2 (non-ash). AGB

**TABLE 1** Model estimates

| Model | Harvest component | AGB | | EAB | | Population Density | | MHHI | | DIC |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | SD | Mean | SD | Mean | SD | Mean | SD | |
| 1: Ash species | Probability | **0.04** | **0.01** | −0.27 | 0.27 | −0.39 | 0.29 | −0.24 | 0.17 | 187,137 |
| | Intensity | −0.01 | 0.01 | **0.91** | **0.35** | −0.18 | 0.51 | −0.14 | 0.22 | |
| 2: Non-ash species | Probability | **0.02** | **0** | **−0.54** | **0.22** | −0.28 | 0.2 | **−0.33** | **0.14** | 188,703 |
| | Intensity | **−0.01** | **0** | 0.25 | 0.25 | 0.49 | 0.27 | −0.21 | 0.16 | |
| 3: Ash as a fraction of total harvest | Probability | 0.01 | 0.01 | −0.28 | 0.28 | −0.38 | 0.29 | −0.22 | 0.17 | 187,212 |
| | Intensity | **0.02** | **0.01** | 0.55 | 0.33 | 0.24 | 0.47 | **0.75** | **0.22** | |

*Note*: Both the zero-inflation (harvest probability) and continuous (harvest intensity) components of each model vary as a function of aboveground biomass (AGB), emerald ash borer (EAB), human population density, and median household income (MHHI). Mean estimates with a non-zero 95% credible interval are in bold. Deviance information criterion (DIC) is an estimate of model error.

was also positively correlated with the intensity component of Model 3 (fraction of harvest composed of ash) (Table 1). By contrast, AGB had a negative impact on non-ash harvest intensity.

The two demographic variables, human population density and median household income, displayed limited effects in our models. MHHI was negatively correlated with the probability of non-ash harvest but had a positive influence on the intensity component of Model 3. Human population density was not estimated to be significant in any of the regressions.

EAB, our main variable of interest, had a statistically significant and negative impact on non-ash harvest probability. Our model predicts that a plot with 50 Mg/ha of non-ash biomass will experience a 0.13 reduction in annual probability of harvest due to EAB (Figure 2a). Ash harvest probability, conversely, was not sensitive to the presence of EAB within the 95% credible interval.

Harvest intensity was positively influenced by EAB, but this effect was statistically significant for ash species only (Model 1). Figure 2(b) illustrates the predicted effects of EAB on harvest intensity. The percentage of basal area removed decreases as a function of AGB, and, for ash species, EAB induces approximately 25% more basal area removal (Figure 2b).

Finally, EAB had a positive impact on the ash fraction of harvest (Model 3, intensity component), although this estimate is statistically significant only at the 90% credible interval. Figure 3 portrays the predicted probabilities of harvesting ash (Figure 3a) and, if ash is harvested, the fraction of the total harvest comprised of ash (Figure 3b), as a function of the ash fraction of available AGB. For an FIA plot with 50%

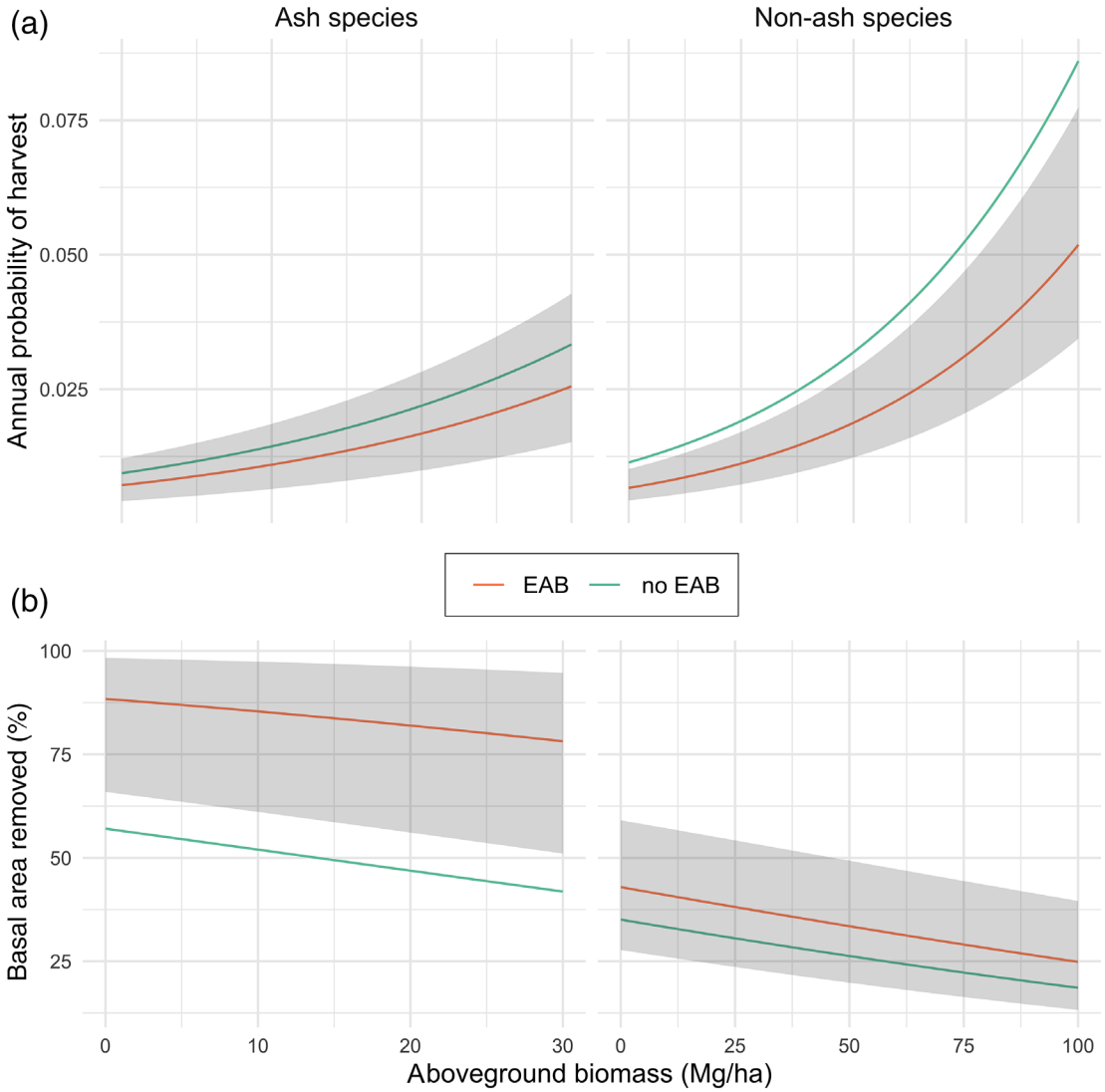


**FIGURE 2** Model predictions for Model 1 (ash species) and Model 2 (non-ash species). Annual probability of harvest follows a logistic distribution (a); intensity of harvest (percentage basal area removed) follows a beta distribution (b). Gray shading indicates the 95% credible interval for the estimated effect of emerald ash borer (EAB)

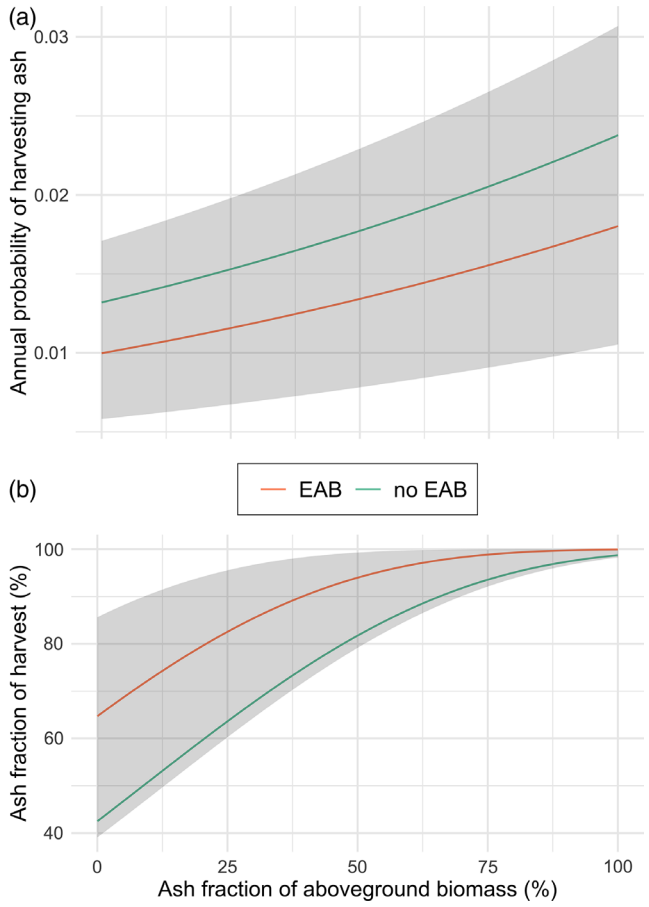


**FIGURE 3** Model predictions for the probability (a) and intensity (b) components of Model 3 (ash as a fraction of total harvest). The gray shading indicates the 95% credible interval for the effect of emerald ash borer (EAB) on the probability of harvesting ash (a) and, if ash is harvested, the fraction of the total harvest comprised of ash (b)

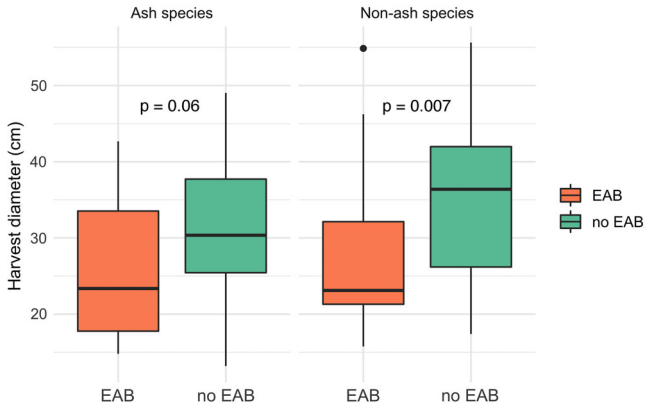


**FIGURE 4** Boxplots comparing the mean plot diameters of harvested trees in counties with and without emerald ash borer (EAB). *p*-values of the weighted Student's *t* test are printed in the center of each panel

aboveground ash biomass, EAB is estimated to increase the ash composition of harvest by ~15% (Figure 3b).

## Harvest diameter

A weighted Student's *t* test indicated that trees harvested in EAB counties were smaller than those in non-EAB counties, for both ash and non-ash species. The mean diameter of harvested ash trees in EAB counties was 25.1 cm, compared with 31.9 cm in counties without EAB ($p = 0.06$). Harvested trees of non-ash species had a mean diameter of 27.2 cm in EAB counties, compared with 36.7 cm in non-EAB counties ($p = 0.007$) (Figure 4).

# DISCUSSION

The inevitable spread of EAB throughout much of the United States poses an interesting question: To what degree will EAB influence harvest regimes? And, if harvest regimes are altered by EAB, what is the significance of those shifts? Using publicly available data, we combined covariate matching and regression analysis to uncover causal relationships between EAB and several aspects of private forest owner harvest regimes. Our results demonstrated that EAB increased the amount of harvested biomass, and that EAB-induced harvests contained greater quantities of ash, relative to non-ash species. We also find that harvested trees in EAB-infested areas had smaller diameters, on average, compared with those unaffected by EAB.

The positive effects of EAB on (1) ash harvest intensity and (2) the fraction of the overall harvest composed of ash suggest that a wave of ash removals will follow the spread of EAB across the landscape. This synchronized harvest behavior by private woodland owners is in contrast with the general characterization of private landowners as exhibiting unpredictable harvest behavior. Kittredge (2004) presented a decision cycle for private woodland owners, whereby the individual does not engage in harvesting until an exogenous personal event (e.g., medical expenses, college tuition, etc.) occurs that incentivizes a timber sell-off. However, the detection (or impending detection) of EAB could serve to upend this variability and harmonize harvest patterns of private forest owners. This opportunistic harmonization of logging has the potential to alter forest development trajectories and change structural legacies, with consequences for ecosystem services and biodiversity (Leverkus et al., 2018). Species that co-occur with ash, and particularly those that are preferred species for harvest, are the most likely to be removed and are the most vulnerable to EAB-induced harvests (MacLean et al., 2020).

The increased intensity of ash removals in response to EAB supports the survey results of Markowski-Lindsay et al. (2020), which found that that private landowners in the northeastern United States overwhelmingly intended

to harvest in response to invasive insects (including EAB, hemlock woolly adelgid, and/or Asian longhorn beetle). In fact, ash removal was encouraged in the early years of EAB detection as a means to contain the invasion (McCullough & Siegert, 2007). Somewhat surprising, however, is the estimated negative effect of EAB on harvest probability, a reduction that was statistically significant for non-ash species but not for ash. This negative effect could be due to sanitation logging that occurred prior to the timeframe of our analysis. In other words, while we estimated the effects of EAB within the first 10 years of detection, it is likely that EAB-induced harvesting occurred prior to this time, either due to undocumented EAB cases or to the foresight of proactive landowners. Savvy forest owners in the control group might also have preemptively harvested trees prior to the official EAB detection date, which would weaken the observed effect of EAB on harvest probability. The lower annual probability of harvest on EAB plots could also be due to the fact that more of these plots are located in colder regions where trees experience slower growth rates, compared with non-EAB plots. It is important to note that, despite the negative effect of EAB on harvest *probability*, the positive effect of EAB on harvest *intensity* dominated our statistical model and yields a predicted net increase in harvested basal area.

In addition to changes in the probability and intensity of tree removals due to EAB, we detected differences in the average plot harvest diameter for both ash ($p = 0.06$) and non-ash ($p = 0.007$) species when comparing treatment and control groups. On the one hand, this is surprising as early efforts in Michigan were originally focused on removing only the largest ash trees to reduce the available phloem for EAB development to slow its spread (McCullough & Siegert, 2007). However, McCullough and Siegert (2007) also mention locations in MI and OH where all ash stems surrounding a focal tree in infested areas were removed. Our results are more indicative of the latter and suggest that EAB may reduce the choice of foresters, who, faced with either infected timber or the impending threat of EAB, decide to harvest more ash from a site, resulting in the harvest of smaller average trees than would normally be cut. Given that non-ash species also exhibited a difference in harvest diameter, this reduced choice appears to extend to the entire harvest. It is unclear from the data whether the increased removal of smaller non-ash trees due to EAB serves a silvicultural purpose, economic goal, or both.

Regression analysis of the matched dataset supports previous estimates of the influence of AGB on harvest probability. Similar to Canham et al. (2013) and Thompson et al. (2017), we estimated that AGB had a positive effect on harvest probability for both ash and non-ash species (Figure 2). The relationship between AGB and harvest intensity has been found to vary greatly by state and forest type, but northern hardwood forests and the Great Lakes states are known to exhibit a negative trend (Canham et al., 2013; Thompson et al., 2017), which we also observed in our estimated effect of AGB in the non-ash model (Model 2). This may be because most harvests on land owned by private owners are frequent, low intensity harvests that remove less than 20% of overstory basal area (Thompson et al., 2017).

Socioeconomic variables did not play a large role in our statistical models. We estimated no significant effect of human population density; moreover, median household income influenced only the probability of harvest for non-ash species and the intensity of ash composition of the harvest. The positive relationship between affluence and the ash composition of harvest could suggest that private landowners of lower affluence capitalize on the opportunity to harvest more tree species (in addition to ash) due to higher financial need. In general, lower-income forest owners are thought to harvest at greater intensities than their wealthier counterparts (Thompson et al., 2017).

Causal interpretation of our regression analysis was enabled by a Genetic Matching algorithm that achieved covariate balance between treatment and control units. However, this balance came at the expense of statistical power; to achieve such balance, 1723 out of 2033 control observations were discarded. This "imbalance-n" trade-off typically observed in matching routines is analogous to the well known "bias-variance" trade-off encountered in statistics and machine learning (Geman et al., 1992). Furthermore, in matching the joint distributions between treatment and control groups, we assumed that we had identified the key sources of confoundedness. Indeed, our four matching covariates (ash density, non-ash density, PC1, and human population density) are well founded correlates of EAB invasion in the literature; however, other potential influences of EAB spread exist. For instance, urban forests, which are absent from the FIA dataset, are known to play an important role in the spread of EAB by serving as the first point of contact for the pest (Colunga-Garcia et al., 2010; Paap et al., 2017). Urban trees often exist as single species plantings (Donaldson et al., 2014), and may be predisposed to infestation due to anthropogenic stress, increasing the likelihood of exotic forest pests becoming established and proliferating (Pautasso et al., 2015). Nevertheless, spatiotemporal dynamics are the primary driver of EAB invasion (Ward et al., 2020) and, in our experimental design, we remove spatiotemporal pressure as a potential confounder by separating the treatment and response in time and space (Figure 1).

Despite controlling for many potentially confounding influences, several potential sources of bias remain within our quasi-experimental design. As indicated previously, EAB detection methods were more refined for the control group compared with the treatment group. Similarly, the

control group had higher levels of knowledge of, and familiarity with, EAB. These disparities could mean that: (1) the treatment group experienced a wider range of damage due to EAB; and (2) the control group had a better opportunity to preemptively harvest healthy trees, both of which could dampen the observed effect of EAB on harvest regimes (i.e., our estimated effect may be underestimated). The evolving understanding of EAB, and the ever-changing protocols associated with its spread, make it difficult to generalize causal effects observed during any particular period of time. Another potential confounder is the implementation of quarantines (efforts to curb the transportation of infested wood), which were typically established at the county level once EAB was detected. As quarantines roughly coincide with EAB arrival, the effect of quarantines on harvest activity is a potential source of noise.

## CONCLUSION

Our study suggests that private forest owners alter their management decisions based on the presence of invasive forest insects. For the EAB in the central United States, we showed that landowners harvested more intensely and across a wider range of tree sizes when the insect was present in the county. This finding is significant because the abundance and severity of wood-boring insects in North America is projected to increase three- to four-fold by 2050 as a result of climate change and global trade (Ayres & Lombardero, 2000; Leung et al., 2014). It is particularly valuable to understand private landowner dynamics with regard to wood-boring insects, as this owner group controls a large majority of forestland in the United States and its decision-making is largely uncoordinated. Our analysis suggests that these insects will influence timber harvest regimes in novel ways with potentially significant impacts on forest and the services they provide. By understanding the relationship between insects and harvest regimes, policymakers, forest managers, and extension programs will be better equipped to advise landowners and managers about their options and the associated outcomes for forests.

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### CONFLICT OF INTEREST

The authors declare no conflict of interest.

### DATA AVAILABILITY STATEMENT

Data and code (Holt, 2021) are available through Zenodo: https://doi.org/10.5281/zenodo.5173143.

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