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RESEARCH ARTICLE

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Landowner functional types to characterize response to invasive forest insects

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Abstract

1. Invasive forest insects can induce tree mortality in two ways: (a) by directly harming trees; or (b) by influencing forest owners to pre-emptively harvest threatened trees. This study investigates forest owners' intentions to harvest trees threatened by invasive insects.
2. Our first objective is to identify and characterize agent functional types (AFTs) of family forest owners in the northeastern United States using a set of contingent behaviour questions contained in a mail survey. We establish AFTs as a form of dimension reduction, effectively casting landowners into a typology in which each type (AFT) has distinct probabilities of tree harvesting in response to forest insects. Our analysis identifies three functional types of landowners: 'Cutters' (46% of respondents; high intent to harvest trees impacted by invasive forest insects), 'Responsive Cutters' (42% of respondents; intent sensitive to insect impact severity), and 'Non-cutters' (12% of respondents; low intent to cut).
3. Our second objective is to model AFT membership to predict the distribution of AFTs across the landscape. Predictors are chosen from a set of survey, geographic and demographic features. Our best AFT-prediction model has three predictor variables: parcel size (hectares of forest), geographical region, and town-level forested fraction. Application of the model provides a high-resolution probability distribution of AFTs across the landscape.
4. By coupling human and insect behaviour, our results allow for holistic assessments of how invasive forest insects disturb forests, inclusive of the management response to these pests.

KEYWORDS

agent functional types, conjoint analysis, coupled natural-human system, family forest owners, forest insect pests, forest management, survey

1 | INTRODUCTION

Invasive forest insects and pathogens are a prominent cause of forest disturbance in North America (Thorn et al., 2018). The U.S. Forest Service's National Insect and Disease Forest Risk Assessment (Krist et al., 2013) suggests that 334 million ha, or 63% of the nation's forestland, are at risk for host species mortality, and 24.8 million ha are predicted to experience more than 20% loss of host biomass by 2027. In fact, invasive insect pests are the only forest disturbance agent that has proved capable of nearly eliminating entire tree species, or in some cases entire genera, within a matter of decades (Lovett et al., 2016).

While the direct effects of invasive insects on tree mortality are relatively well understood, the indirect impacts via 'pre-emptive' or 'salvage' tree harvesting are not as well studied (Foster & Orwig, 2006). Harvesting is currently a larger cause of mature tree mortality in northeastern forests than all other causes combined (Canham, 2013); the frequency and intensity of harvests varies widely depending on both biophysical and social factors (Thompson, Canham, Morreale, Kittredge, & Butler, 2017). Past invasive pest outbreaks in northeastern forests have been accompanied by accelerated harvesting, and there are distinct ecological legacies of the interactions between these two types of biotic disturbance (Thorn et al., 2018). For example, 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, Foster, & Mausel, 2002). Since the disturbance from harvesting in response to forest insects can be more intense than that of the pest alone (Foster & Orwig, 2006), there is a need to better understand when and why landowners harvest in response to invasive insects.

Harmful insect pests present forest owners with the risk of diminished economic returns and/or woodland aesthetics (Li et al., 2014). How a landowner responds to this risk can be expected to depend on his or her objectives in owning their forest (Nordlund & Westin, 2011), as well as socioeconomic and demographic factors. The anticipated severity of the insect outbreak, the location of the woodland, and pest awareness may also be factors that influence landowners' responses (or lack thereof) to the disturbance (Boyd, Gilligan, & Godfray, 2013; Nielsen-Pincus, Ribe, & Johnson, 2015). To better understand these influences, we surveyed family forest owners (FFOs) in New England (northeastern United States) (Markowski-Lindsay et al., 2019). New England is an ideal study system because the region contains many private landowners and one of the highest diversities of invasive insect pests in North America (Liebhold et al., 2013). In New England, an estimated 41% of all forestland is controlled by FFOs (B. J. Butler et al., 2016). Thus, the response of FFOs to invasive forest insects may intensify, broaden, and potentially accelerate the ecosystem impacts associated with insects on the landscape.

Our survey contained contingent behaviour questions in a conjoint survey format to assess whether an FFO would harvest in response to different invasive insect scenarios. We used the responses to the contingent behaviour experiment to cluster individuals into agent functional types (AFTs). The idea is to group together similar 'types' of people based on common behaviour. This form of dimension-reduction leads to a functional typology which, while not describing the individual, represents archetypal patterns of behaviour that tend to repeat themselves within the community (Ficko et al., 2019). AFTs have proven to be useful for modelling human decision-making in a variety of applications, especially in the agricultural sector (Guillem, Barnes, Rounsevell, & Renwick, 2012; Karali, Brunner, Doherty, Hersperger, & Rounsevell, 2013) and in the context of large-scale socio-ecological systems (Arneth, Brown, & Rounsevell, 2014; Rounsevell, Robinson, & Murray-Rust, 2012). They have been less frequently used to represent private woodland owners (except e.g. Blanco, Brown, & Rounsevell, 2015). Further, the majority of landowner typologies have been based on objectives for ownership (Kelly, Gold, & Di Tommaso, 2017; Khanal et al., 2017; Nielsen-Pincus et al., 2015) or more nuanced criteria such as attitudes towards climate change (Khanal et al., 2016), approaches to fire management (Charnley, Kelly, & Wendel, 2017), and thoughts on pollution (Perry-Hill & Prokopy, 2014). These are all proxies for behaviour rather than explicitly functional behaviours.

In this study, we form AFTs based on landowner responses to our survey's contingent behaviour questions. In this way, the contingent *behaviours* revealed by the survey responses generate a *functional* typology. We then develop a model to predict AFTs for FFOs who did not participate in the survey, giving us a means for scaling the survey data to the entire region and yielding probability distributions for the various AFTs across the landscape. Ultimately, this AFT framework allows us to estimate the probability that any FFO in the region will harvest their trees in response to a particular invasive insect scenario. Understanding such harvest probabilities across the region provides insight into the condition in which FFO response may alter the impacts of invasive forest insects on the forests in the region.

2 | DATA AND METHODOLOGY

2.1 | Overview

To understand and describe potential landowner response to invasive forest insects, we take a three-step approach to analyse the contingent behaviour results revealed by the mail survey. First, we group respondents into AFTs based on observed patterns of contingent behaviour. We also explore patterns of responses based on forest insect attributes. Second, we characterize the AFTs in numerous ways. We compare and contrast AFTs with respect to survey-reported age, education, income, and other individual- or household-level demographics. We also characterize AFTs with respect to reported management history and objectives for forest land ownership. We use socio-demographic data from the American Community Survey (ACS; Manson, Schroeder, Van, Riper, & Ruggles, 2017) to further identify differences across AFTs based on publicly-available town-level information. Third, we develop a multinomial logistic regression model that predicts AFT membership as a function of geographic features, allowing us to map AFT probabilities across the landscape, and thereby reveal likely spatial patterns of landowner responses to invasive forest insects. A table of all datasets and their uses in this study is provided in Supporting Information A.

2.2 | Landowner survey

As summarized in Markowski-Lindsay et al., 2019, we designed and administered the New England Woodland Owner Survey, which was mailed to a random sample of FFOs owning ≥ 4ha of land in the Connecticut River Watershed (Figure 1). Prior to administration, the survey content and human subjects protocol were reviewed and approved by the University of Massachusetts' Institutional Review Board in accordance with the Human Research Protection Program. The survey materials stated that participation was completely voluntary, so by returning the questionnaire participants indicated their consent. The survey sample was stratified by six regions (New Hampshire north and south, Vermont north and south, Massachusetts, and Connecticut) and also stratified by parcel size (4–19 ha and ≥20 ha) to ensure sufficient representation of larger parcels across the region. Landowner demographics, objectives for ownership, familiarity with invasive forest insects, and contingent behaviour questions were among the subsections of the survey. In 2017, 2,000 mail surveys were sent to approximately 333 FFOs per region (roughly 167 per strata). The overall participation rate was 37%, or 688 usable surveys. We detected no non-response biases based on telephone follow-up calls or early/late respondent comparisons. See Markowski-Lindsay et al., 2019 for a more in-depth discussion of the survey creation and landowner responses.

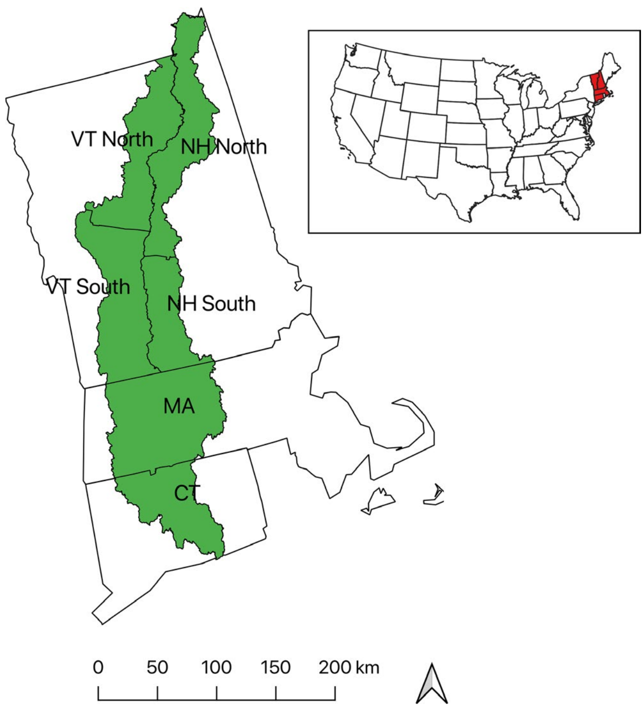

FIGURE 1 Study area. The Connecticut River Watershed (green) runs through New England (red) in the northeastern United States. The survey was stratified by the six regions shown [Colour figure can be viewed at wileyonlinelibrary.com]

The heavily wooded Connecticut River Watershed (Figure 1) lies in the heart of New England, straddling Vermont and New Hampshire to the north and then stretching south through central Massachusetts and Connecticut. Some of the most damaging tree insect species in the Connecticut River Watershed include hemlock woolly adelgid (*A. tsugae*), emerald ash borer (*Agrilus planipennis*) and European gypsy moth (*Lymantria dispar*). The scenarios presented in the survey contingent behaviour questions referenced a generic invasive insect, but the range of characteristics was chosen based on insects mentioned above.

The contingent behaviour experiment in the survey was designed to reveal FFO intended behaviour in response to different insect impact severity metrics. We presented respondents with a series of scenarios over the range of the following metrics: (a) percent of trees destroyed by the insect ('mortality percent'); (b) timber value loss due to the insect ('value loss'); (c) time from now until insect arrives ('time to arrival'); and (d) time from insect arrival until tree death ('time to mortality'). Survey respondents received one of six unique versions of the survey and were presented with five scenarios involving combinations of the four pest severity metrics (Table 1).

2.3 | Defining AFTs and exploring contingent behaviour responses

Survey respondents were grouped into AFTs based on natural clustering in the responses to the contingent behaviour questions (details in Section 3). We then fit a binary logistic regression to the responses of FFOs whose answers to the contingent behaviour questions were sensitive to the stated levels of pest impact severity metrics. The resulting model allows us to evaluate the relative importance of each of the severity metrics in determining the likelihood of harvest.

We used a Bayesian model framework, in which X, Y, Z, and Q represent the four insect impact severity metrics, i is the scenario, j is the individual, and y is the response. Random effects were permitted

TABLE 1 Contingent behaviour questions

Scenario X
• A new woodland insect will arrive on your land in Z years ($Z \in \{0,5\}$) • The insect will kill X percent of your trees ($X \in \{10,50,90\}$) • Those trees will be killed within Q years (after the insect arrives) ($Q \in \{5,15\}$) • The insect will reduce the value of your timber by Y percent ($Y \in \{10,50,90\}$)

Note: Responses to each of the five scenarios are binary: cut trees or do not cut trees.

for the intercept to account for differences across individuals. Priors on the model coefficients β were non-informative.

$$\mu_{ij} = \beta_{1j} + \beta_2 \times X_i + \beta_3 \times Y_i + \beta_4 \times Z_i + \beta_5 \times Q_i \quad (1)$$

$$p_{ij} = \text{invLogit}\left(\mu_{ij}\right) \quad (2)$$

$$y_{ij} \sim \text{Bernoulli}\left(p_{ij}\right) \quad (3)$$

The model was implemented using JAGS via the R2jags package (Su & Yajima, 2012). The model converged after 500 iterations and was run for a total of 1,000 iterations. We included survey sampling weights in the regression to generalize to the population; these weights are derived by Markowski-Lindsay et al., 2019.

2.4 | Characterizing AFTs

Survey items were used to characterize AFTs, and the ANOVA post hoc Tukey test was used to identify significant differences. Principal components analysis (PCA) was used to downscale two sets of data: (a) landowner objectives from the New England Woodland Owner Survey (Supporting Information B); and (b) socio-demographic features from the ACS dataset. The ACS dataset was extracted using the 2011–2015 five-year estimates at the town level (Manson et al., 2017). Statistical analyses were conducted in R (R Core Team, 2017).

2.5 | Predicting AFTs across the landscape

We obtained land cover data from the National Land Cover Database (NLCD) 2011 (Homer et al., 2015). NLCD land cover classes were consolidated into the following four classes: 'forest' (deciduous forest + evergreen forest + mixed forest + shrub scrub + woody wetlands); 'agriculture' (crops + pasture/hay); 'low density development' (low intensity development + medium intensity development + open space); and 'high density development' (high intensity development). Each of the four land cover classes were converted to town-level percentages using city boundaries (U.S. Census Bureau, n.d.). In order to map our predicted probabilities across the landscape, we obtained parcel shapefiles from each individual state and town. Massachusetts was the only state in the region offering a complete parcel dataset. Connecticut, New Hampshire and Vermont had some missing town parcel data that were filled using towns with similar attributes (size and developed area) from within the study area.

To predict the spatial distribution of AFTs across the landscape, we developed a multinomial logistic regression model from available spatial data. The full feature set included: survey strata; parcel-scale total area and forested fraction; town-scale land cover; and town-scale socio-demographic features. Model selection proceeded in steps: First, we sought to uncover nonlinear spatial predictors of AFTs. To that end, we constructed a classification and regression tree (CART) (Breiman, 1984) with AFT as the response and all spatial parcel data (e.g. total area, survey strata) as predictors. Detected patterns were compiled into a new spatial categorical variable (see Supporting Information C for more information). We then constructed a multinomial logistic regression model, considering the full feature set, including interaction terms with newly formed spatial categorical variable. We used a stepwise Akaike information criterion (AIC) procedure (forwards and backwards) to select the best model. The multinomial logistic regression model was then used to predict the probability of each of the AFTs for ~90,000 FFO land parcels throughout the Connecticut River Watershed. Modelling was conducted in an R environment using the nnet and rpart packages (Ripley & Venables, 2011; Therneau, Atkinson, & Ripley, 2010).

3 | RESULTS

3.1 | Defining AFTs and exploring contingent behaviour responses

Responses to the contingent behaviour questions in the survey revealed a natural clustering among respondents. Twelve percent of respondents answered 'No' (they did not intend to cut) to all invasive insect scenarios provided, while 46% of respondents selected 'Yes' (they intended to cut) for all provided scenarios. The remaining 42% of respondents revealed sensitivity in their contingent cutting behaviour to variation in the four pest impact severity measures. We could thus immediately identify two AFTs: 'Cutters' – those FFOs who stated their intention to harvest in response to invasive forest insects – and 'Non-cutters' – those who stated their intention never to harvest in response to invasive forest insects. The remainder of respondents who we call 'Responsive Cutters', are evaluated for further sub-categorization based on the results of the logistic regression analysis.

Our logistic regression model for the 285 Responsive Cutters reveals that 'mortality percent' (percent of trees killed by an insect) and 'time to mortality' (time from insect arrival until tree death) are important predictors of harvest response (Figure 2). The 95% credible interval for the coefficient on 'mortality percent' is entirely positive, indicating that landowners are more likely to harvest trees as the severity of infestation increases. The 95% credible interval for the coefficient on 'time to mortality' is entirely negative, indicating that FFOs are more inclined to harvest when the threat of tree death is more imminent. The mean coefficient estimates for 'value loss' (timber value loss due to the insect) and 'time to arrival' (time from now until the insect arrives) are negative, although the 95% credible intervals for these covariates include zero, thus we do not interpret these effects as being statistically significant.

We attempted to identify additional AFTs from among the group of Responsive Cutters by performing cluster analysis on the intercepts estimated for each respondent. We also fit logistic regression models in which the coefficients on insect impact severity were allowed to vary by individual and attempted to find natural groupings

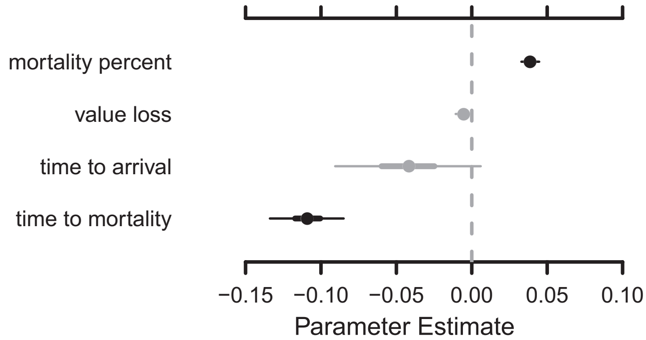

FIGURE 2 Parameter estimates for a binary logistic regression model fitted to data from the 285 'Responsive Cutters'. Thicker and thinner lines represent 68 and 95% credible intervals, respectively, with grey lines indicating 95% credible intervals that contain zero

TABLE 2 Number and percentage of FFOs, log-transformed hectares of woodland, age, tenure, and number of owners by AFT

Item	Agent functional type					
	Cutter[a]		Responsive[b]		Non-cutter[c]	
Respondents (n)	317		285		83	
% of respondents	46		42		12	
	M	SD	M	SD	M	SD
Log-transformed hectares of woodland	3.32[b,c]	1.15	3.05[a,c]	1.01	2.69[a,b]	1.09
Age of oldest owner (years)	66.7	13.2	65.1[c]	12.2	68.9[b]	10.3
Age of youngest owner (years)	59.8[c]	14.8	57.2[c]	15.8	64.8[a,b]	12.0
Tenure (years)	25.6[b]	16.7	21.9[a,c]	13.7	27.4[b]	15.1

Note: Superscript denotes statistical significance between (a) Cutters, (b) Responsive Cutters, and (c) Non-cutters in ANOVA post hoc Tukey significance test at the α = 0.05 level. All distributions are unimodal.
Abbreviations: AFT, agent functional type; FFOs, family forest owners.

in these values. While we found that there was some potential variation among the Responsive Cutters in their baseline tendency to cut (i.e. intercept) and in their sensitivity to intensity measures (i.e. coefficients), clusters that might suggest the need for functional types were not apparent. We therefore proceeded with a total of three AFTs for further characterization.

3.2 | Characterizing AFTs

Cutters, the most numerous of the three identified AFTs, on average own more area of woodland (3.32 ± 0.065 log ha) compared to the Responsive Cutters (3.05 ± 0.060 log ha) or Non-cutters (2.69 ± 0.121 log ha) (Table 2). We found that the age of respondents in the Non-cutter AFT were greatest and in the Responsive Cutter AFT were lowest, as measured by the age of the oldest and youngest of joint family owners. This was also reflected in ownership tenure (as of 2017), with

TABLE 3 Characteristics of AFTs across gender, education and household income

Attributes	Agent functional type (%) Cutter	Responsive	Non-cutter	χ^2	p Value
Respondents (n)	317	285	83		
Gender				16.74	<.001
Male	0.72	0.74	0.51		
Female	0.28	0.25	0.49		
Education				13.25	.10
<High school	0.02	0.01	0.01		
High school	0.33	0.22	0.32		
Bachelor's degree	0.26	0.29	0.27		
Advanced degree	0.29	0.35	0.33		
Household income				15.37	.05
<$25,000	0.10	0.05	0.03		
$25,000–$49,000	0.16	0.16	0.28		
$50,000–$99,000	0.34	0.33	0.25		
$100,000–$199,000	0.25	0.24	0.25		
≥$200,000	0.15	0.22	0.19		

Abbreviation: AFT, agent functional type.

the Non-cutters having the longest (27.4 ± 1.70 years) and Responsive Cutters having the shortest (21.9 ± 0.83 years) tenures.

Cutters and Responsive Cutters were overwhelmingly male, whereas Non-cutters were almost evenly split on gender (49% female compared to 51% male; different at a significance level of $p < .001$) (Table 3). Differences in educational achievement ($p < .1$) were greatest between Cutters and Responsive Cutters; the Cutter group had larger percentages of high school or lower education, and smaller percentages of bachelor's degrees or advanced degrees, compared to the Responsive group. The educational achievement of the Non-cutter group fell in the middle of the Cutters and Responsive Cutters. Annual earnings had a similar pattern between the Cutter and Responsive groups; the Cutters had a greater proportion of low earners (<$25,000) and a smaller proportion of high earners (≥$200,000) compared to the Responsive Cutters ($p < .05$). Meanwhile, the Non-cutters had the smallest percentage of low earners (<$25,000) but the highest percentage of earners in the $25,000–$49,000 range.

Cutters, Responsive Cutters, and Non-cutters differed in management history, which built confidence in our functional typology (Figure 3). Cutters had higher frequencies of indicating that they had cut trees previously, sought advice from a forester, and had a management plan than the Responsive or Non-cutters. Furthermore, the Responsive group fell between the Cutters and Non-cutters in all three questions.

The diversity of stated landowner objectives for ownership was simplified using PCA (Table 4), wherein the first four principal components captured approximately 70% of the variance. Component 1 is strongly associated with beauty, nature, and wilderness, which we label as 'scenery'. Component 2 is associated with firewood, timber products, forest products and hunting, which we call 'utility'.

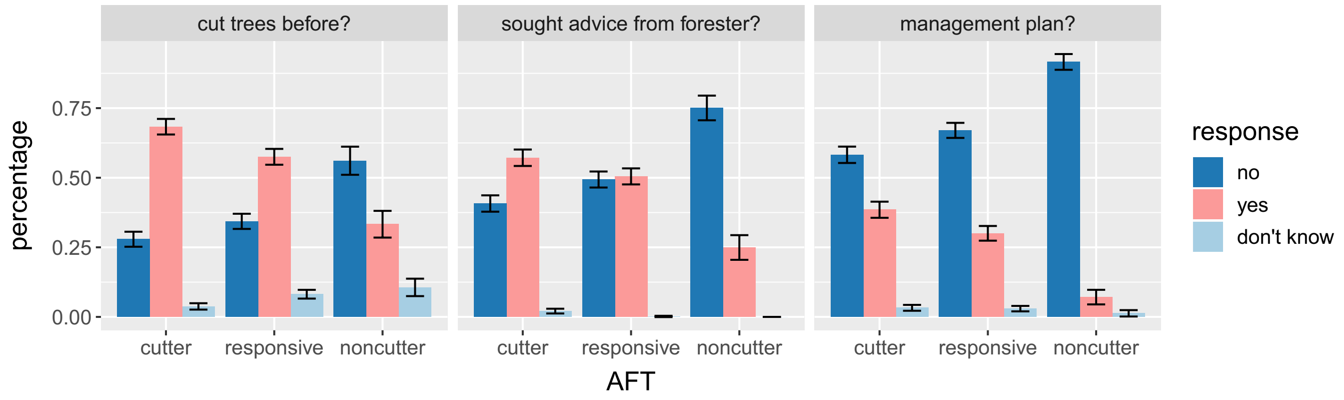

FIGURE 3 Proportion of each AFT with previous forest management experience. Error bars represent the standard errors of the estimated population mean. Abbreviation: AFT, agent functional type [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 4 PCA loadings of landowner objectives, as indicated in the New England Woodland Owner Survey

	Rotated principal component scores			
Landowner objective	PC1: 'scenery'	PC2: 'utility'	PC3: 'investment'	PC4: 'privacy'
Beauty	**0.43**	−0.27	0.05	0.07
Nature	**0.44**	−0.29	−0.01	**−0.37**
Wilderness	**0.45**	−0.22	0.01	**−0.39**
Investment	0.03	0.19	**0.88**	−0.10
Privacy	0.29	−0.15	**0.32**	**0.64**
Heirs	0.21	0.18	−0.08	0.28
Firewood	0.24	**0.42**	−0.02	0.09
Timber	0.15	**0.47**	0.14	**−0.38**
Products	0.25	**0.38**	−0.19	−0.01
Hunting	0.19	**0.39**	−0.20	0.07
Recreation	**0.35**	0.01	−0.15	0.24

Note: Rotated component scores of the first four principal components > 0.30 are in bold.
Abbreviation: PCA, principal components analysis.

Components 1 and 2 reflect the cluster analysis of Majumdar, Teeter, and Butler (2008), whose first two clusters were (a) 'multiple-objective' and (b) 'timber'. Components 3 and 4 are best represented by 'investment' and 'privacy' respectively.

AFTs exhibit statistically significant differences across principal Components 1 (scenery), 2 (utility) and 4 (privacy) ($p < .001$) (Figure 4) by the post hoc pairwise comparison test. For both the scenery and utility scores, Cutters had the highest values, followed by Responsive Cutters, then Non-cutters. The privacy scores, on the other hand, were highest for the Non-cutters and lowest for the Cutters.

The many available town-level socio-demographic variables were also simplified using PCA. The first two principal components of the town-level socio-economic variables explain approximately 60% of the variance and can be identified as (a) 'wealth' and (b) 'seniority' dimensions (Table 5). AFTs exhibit statistically significant differences across both ($p < .001$) (Figure 5) by the post hoc pairwise comparison test. Both Cutters and Responsive Cutters' scores were lower than Non-cutters on the wealth principal component, indicating that landowners inclined to harvest trees live in towns that are poorer on average (higher fraction of town in poverty, lower median household income). In addition, Cutters and Responsive Cutters' scores were higher than Non-cutters on the seniority principal component (higher median age, and higher social security and retirement income). It should be noted that FFOs are older on average than the general population (B. J. Butler et al., 2016), however the findings in Figure 5 provide an interesting juxtaposition to those in Table 2; while Non-cutters are older on average than the other two groups, Non-cutters tend to live in towns that are on average younger than the other two groups.

3.3 | Predicting AFTs across the landscape

A CART model fitting AFT to the survey stratification factors (Supporting Information C) reveals a non-monotonic spatial trend in the distribution of AFTs. Small parcels (<20 ha) in all regions except those in New Hampshire exhibit a significantly different distribution of AFTs than large parcels (≥20 ha) or those located in regions in New Hampshire (Figure 6). Put differently, this implies that FFOs in New Hampshire, regardless of their parcel size, display similar pest-induced harvesting tendencies to FFOs owning ≥20 ha in Vermont, Massachusetts, and Connecticut. To incorporate this pattern into our modelling scheme, we constructed a new two-level factor variable from the 12 original survey strata: (factor level A) parcels ≥20 ha plus all parcels in New Hampshire (north and south); (factor level B) parcels <20 ha in Vermont north and south, Massachusetts, and Connecticut.

We next fit a multinomial logistic regression model to predict AFT from our two-level spatial factor variable (Figure 6) as well as parcel- and town-scale geographic and demographic predictors. Stepwise AIC model selection reveals that the best model includes the following three predictors: our spatial factor variable, town-level forested fraction, and parcel-level area of woodland (Figure 6). We also included an interaction term between the spatial factor variable and the two continuous features (town-level

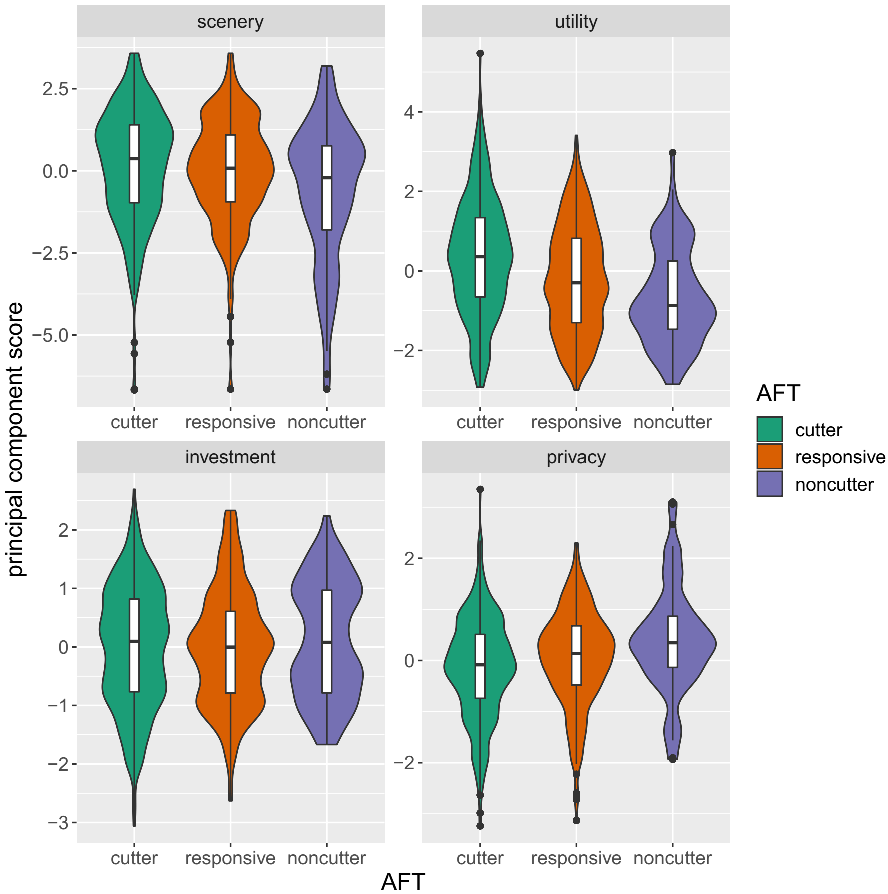

FIGURE 4 Violin plots showing the distribution of landowner objective principal component scores by AFT. One or more AFTs are significantly different from the others across principal Components 1 (scenery), 2 (utility) and 4 (privacy). Abbreviation: AFT, agent functional type [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 5 PCA scores of town socio-demographics

ACS feature	Rotated component scores PC1: 'wealth'	PC2: 'seniority'
Income from agriculture	−0.22	0.19
Income from self-employment	0.08	0.28
Income from hourly wages	**0.31**	**−0.40**
Income from social security	−0.22	**0.45**
Income from retirement	0.16	**0.34**
Income from supplemental sources	**−0.38**	−0.15
Income from public assistance	**−0.36**	−0.10
Median household income	**0.47**	−0.07
Fraction of town in poverty	**−0.44**	−0.05
GINI index of income inequality	−0.12	0.14
Median age	0.06	**0.47**

Note: Rotated principal component scores > 0.30 are in bold.
Abbreviations: ACS, American Community Survey; PCA, principal components analysis.

forested fraction and area of woodland). The interaction term revealed that town-level forested fraction is significant with respect to spatial factor level B (parcels < 20 ha), but not with factor level A (larger parcels + NH).

The model suggests that with increasing area of woodland owned, a respondent has an increasing probability of being a Cutter or Responsive Cutter, and lower probability of being a Non-cutter (Figure 7). As forest fraction increases in a town, we anticipate an increase in the probability of Cutters and a decrease in the probability of Responsive Cutters and Non-cutters. The McFadden's pseudo R^2 of this model is 0.29. Model coefficients and standard errors are reported in Supporting Information D.

Using the multinomial logistic regression (Figure 7), AFTs were predicted for all parcels in the Connecticut River Watershed, including those not owned by survey respondents (Figure 8). The Cutter and Non-cutter probabilities exhibit distinct north–south trends, with notably more Cutters in the north, whereas the Responsive Cutters are relatively evenly distributed throughout the study region. The Responsive Cutter group also has the highest average probability. Predicted AFTs (Figure 8) compared favourably against historical forest change in the same parcels over the years 2000–2018 (Hansen et al., 2013) as shown in Supporting Information E.

4 | DISCUSSION

As invasive forest insects continue to spread in New England and disturb the forested landscape, an important question emerges: how will human behaviour in response to invasive insects interact with

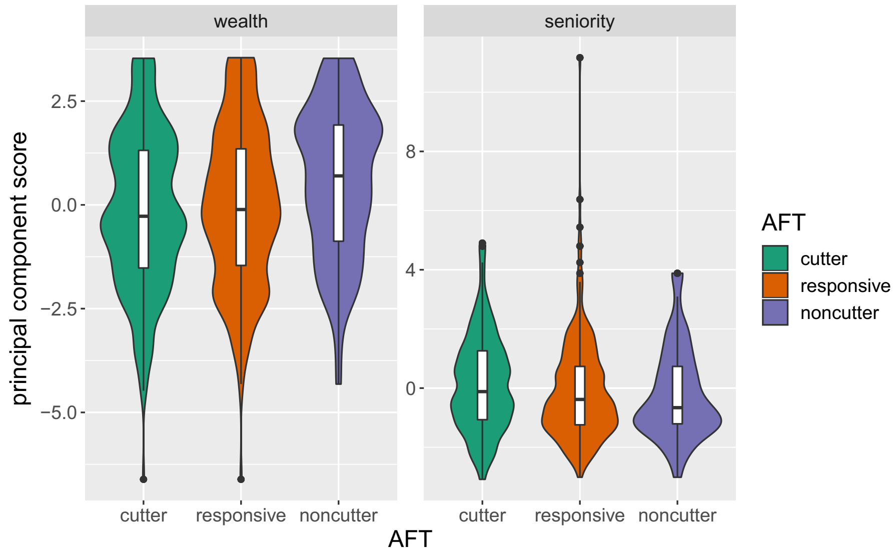

FIGURE 5 Violin plots showing the distribution of socio-demographic principal component scores by AFT. 'Wealth' (left) and 'seniority' (right) correspond to principal Components 1 and 2, respectively, from the PCA of town-averaged socio-demographic features (Table 5). One or more AFTs are significantly different from the others across both 'wealth' and 'seniority' ($p < .001$). Abbreviation: AFT, agent functional type [Colour figure can be viewed at wileyonlinelibrary.com]

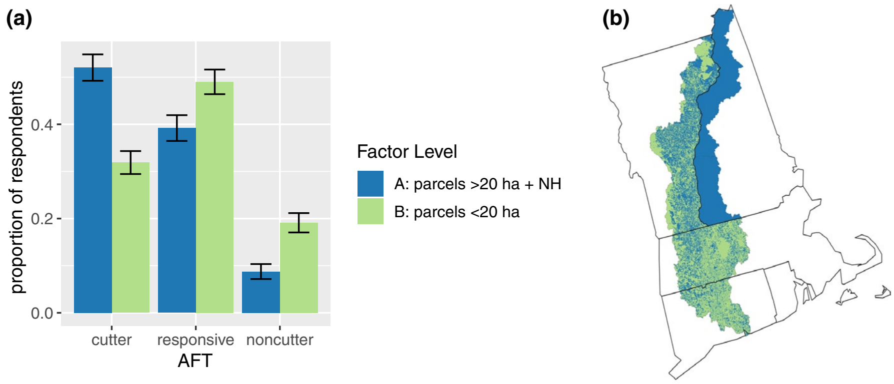

FIGURE 6 Our constructed two-level spatial factor variable. (a) Distribution of AFTs according to factor level. Parcels ≥ 20 ha and all parcels in New Hampshire (factor level A, blue) are predominantly Cutters, whereas the remaining strata are predominantly Responsive Cutters (factor level B, green). Error bars indicate the standard errors of the estimated population mean; (b) mapping of the two factor levels. Abbreviation: AFT, agent functional type [Colour figure can be viewed at wileyonlinelibrary.com]

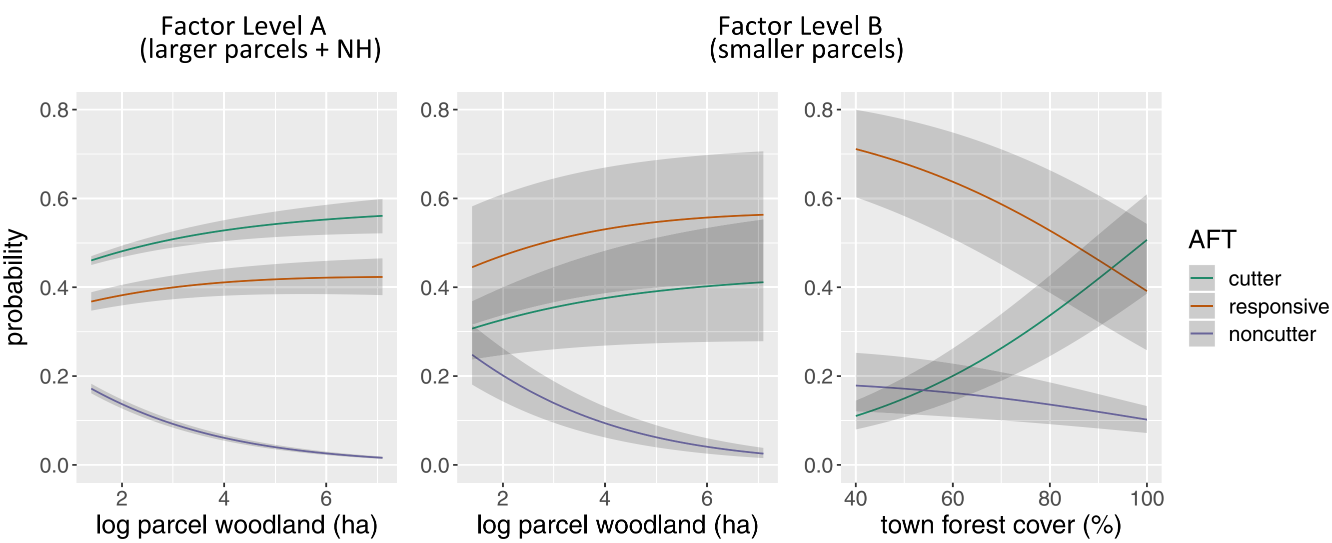

FIGURE 7 Summary of multinomial logistic regression results, with AFT probability expressed as a function of model predictors for each of the two spatial factor levels (Figure 6). In each panel, variables not indicated on the horizontal axis were held at their mean value. Shading indicates 95% predictive intervals. Abbreviation: AFT, agent functional type [Colour figure can be viewed at wileyonlinelibrary.com]

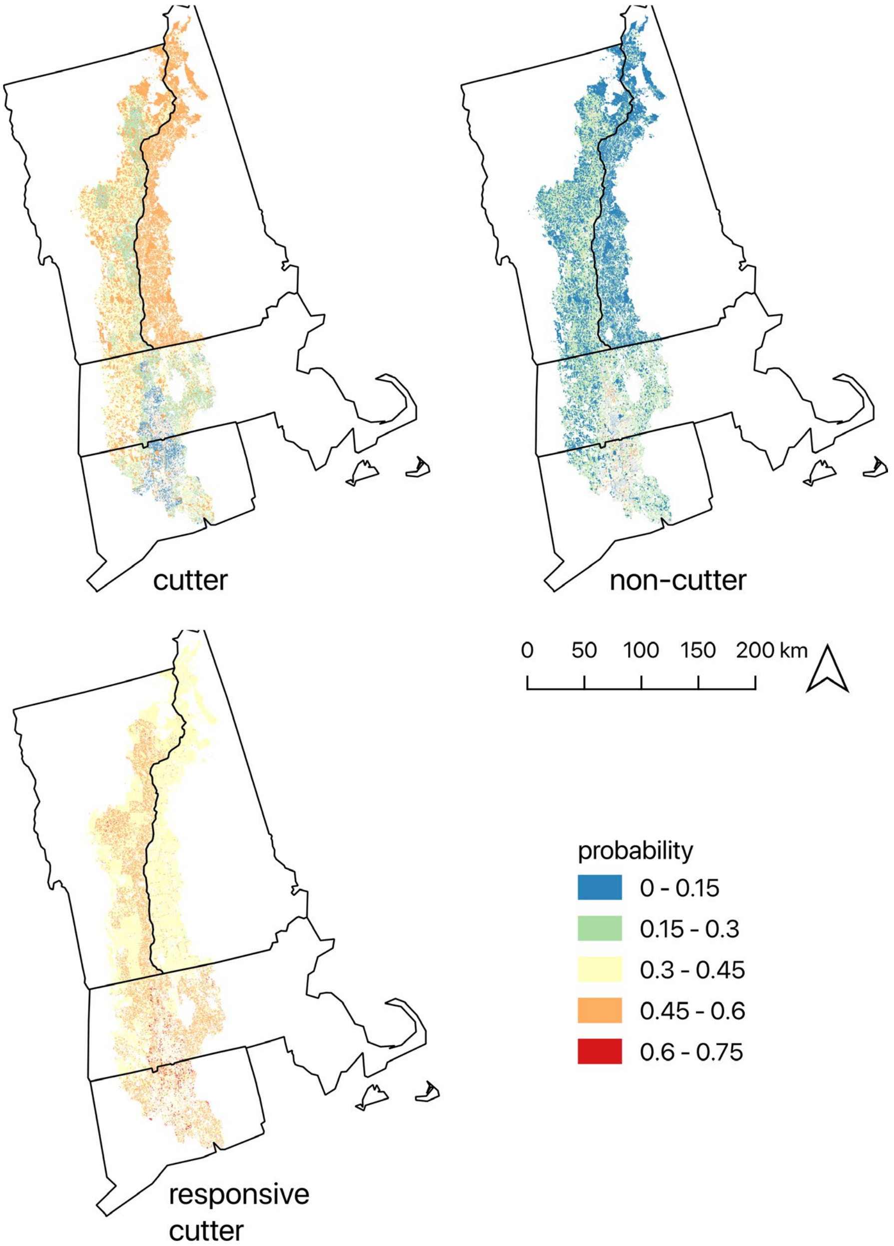

FIGURE 8 Predicted AFT probability throughout the Connecticut River Watershed, calculated from a multinomial logistic regression model based on a constructed spatial factor variable, parcel-level hectares of woodland, and town-level forested fraction. Abbreviation: AFT, agent functional type [Colour figure can be viewed at wileyonlinelibrary.com]

the disturbance created by these pests? In our survey, over 80% of respondents indicated that they would consider harvesting in response to at least one of the invasive tree insect scenarios presented to them, depending on the severity of the infestation. Just over half of the landowners reported having harvested their land before, indicating that invasive forest insects may incite harvest on more parcels than would normally be harvested during routine forest management in the Connecticut River Watershed. Indeed, with our new knowledge regarding the behaviours of these different groups of landowners and our ability to predict AFTs and AFT behaviour across the landscape, we may now be able to more holistically look at how invasive forest insects disturb forests, inclusive of the management response to these pests. Coupling human and insect behaviour is essential for modelling the ecological and economic impacts of invasive insects, particularly in New England, where there are > 200,000 forest landowners and among the highest numbers of invasive tree pests in the U.S.

Clustering landowners based on behaviour is useful because the AFTs translate naturally to models of landscape change in which human decisions are simulated alongside ecological processes (Arneth et al., 2014). While other studies have also clustered private landowners based on survey data (e.g. Khanal et al., 2017), our approach is novel for its use of empirical information collected through contingent behaviour questions. Our clusters are *AFTs* because they represent patterns of contingent *behaviour*. Because we clustered based on contingent behaviour alone (omitting objectives, management style, and demographics), our typology does not fall along clean lines of landowner objectives and motivations, suggesting that (a) tree cutting can be affected by a variety of motivations and (b) clustering on the basis of cutting behaviour alone does not capture the range of landowner intentions. However, we chose to prioritize contingent behaviour over descriptive characteristics because, in our case, understanding the behavioural response of landowners to invasive forest insects is our end-goal. This AFT modelling framework can be directly applied to compute parcel-level probability of harvest under different insect scenarios.

4.1 | Cutters

In the survey, 73% of our Cutter AFT indicated that they had previously cut trees on their property, and 45% indicated that they had a management plan – the highest in both categories of any AFT– as we would expect. The Cutters own the largest FFO fraction of the watershed (59.9%), and also own more woodland on average, suggesting that larger parcels provide more opportunity for sustaining economically viable timber harvests. Furthermore, this group exhibits the highest score on the 'utility' principal component (firewood, timber, non-timber products, and hunting) as well as the 'scenery' principal component (beauty, nature, wilderness, and recreation), indicating that landowner motivations to cut may span multiple landowner objectives. Town-level ACS data suggest that while the Cutters are not the oldest individuals, they are more likely to live in towns with older average populations, and also in towns with lower median incomes. Furthermore, our multinomial logistic regression model predicts higher Cutter probability as the town forest cover increases. These trends could be due in part to the fact that areas containing older, lower wage-earners and more forested regions of New England are more likely to contain sawmills, which is a critical factor influencing harvest. The Cutters themselves are also more likely to earn <$25,000 and less likely to earn >$200,000 compared to the other groups. Cutters have the greatest potential to affect the impact of invasive forest insects on the landscape, as 46% of the respondents were grouped into this AFT, are always predicted to cut in response to invasive tree pests, and generally own the largest parcels.

4.2 | Responsive cutters

The Responsive Cutter AFT was sensitive to variation in the parameters of the contingent behaviour questions. Responsive cutter coefficient estimates on percent tree mortality and duration to tree mortality follow intuition: The greater the tree mortality percent (i.e. severity) resulting from the insect infestation, the more likely these FFOs are to cut their trees. Additionally, the greater the time to tree mortality (i.e. delay of damage), the less likely these FFOs are to remove timber. It is unclear whether the Responsive Cutter decisions are driven primarily by financial (i.e. pre-emptive or salvage logging) or other (i.e. safety, aesthetic) motivations. However, survey results indicate that Responsive Cutters are less likely to have cut previously, are less likely to have a management plan, and have a higher likelihood of owning their land for privacy, compared to Cutters. Furthermore, Responsive Cutters exhibit higher likelihoods of earning larger incomes and obtaining advanced college degrees. Therefore, we hypothesize that Responsive Cutters have different motivations for cutting compared to Cutters, and this group's lower ranking on the 'utility' principal component perhaps suggests that Responsive Cutters are less financially-driven relative to Cutters. Spatially, FFOs living outside of New Hampshire and owning parcels < 20 ha are more likely to be Responsive Cutters compared to Cutters or Non-cutters. We frame the typical Responsive Cutter as a relatively young landowner with little past management experience who is willing to harvest infested trees, but unsure of the degree to which he or she will commit to doing so. Approximately 44% of the surveyed woodland is controlled by the Responsive Cutters, who make up 42% of the respondents. This group owns on average the second-largest parcels (after the Cutters), and will, on occasion, harvest in response to invasive forest insects, moderately affecting the impact of tree pests on the landscape.

4.3 | Non-cutters

Non-cutters are our smallest group, encompassing only 12% of the survey respondents. They own the smallest area of forest, have the longest land tenure, and are the oldest on average. Non-cutters are just as likely to be female as male, in stark contrast to the other two groups, which are predominantly male. This gender disparity reflects the global trend of lower rates of forest management among women, compared to male landowners (S. M. Butler, Huff, Snyder, Butler, & Tyrrell, 2017). The Non-cutters are the least experienced in forest management activities, and also score the lowest on the 'utility' objective principal component. Furthermore, the Non-cutters score the highest on the 'privacy' component, indicating that the landowners in this AFT value their land as a retreat rather than a source of revenue. While the Non-cutters are the oldest individuals, they live in towns that are younger and wealthier on average, perhaps due to the fact they own smaller parcels, which can be found in less remote areas. This demographic group is more inclined to let nature take its course through passive amenity appreciation and the least likely to harvest in response to invasive forest insects.

4.4 | Implications of accelerated tree mortality for nature

The coordinated actions of invasive tree insects, Cutters, Responsive Cutters, and Non-cutters are expected to reduce the biomass of host tree species in New England. Trees provide important ecosystem services, including protecting watersheds, maintaining biodiversity, and sequestering carbon (FAO, 2009), all of which are threatened by the current and impending spread of tree insect pests. Reducing ecosystem services will accelerate positive feedback loops that degrade watersheds, endanger threatened species, and contribute to climate change. In urban or peri-urban areas, ecosystem services provided by trees also include shading and mitigating storm water runoff (USDA, n.d.). These risks to the natural landscape are exacerbated by the phenomenon of 'by-catch', which describes the removal of species that co-occur with the host in order to enhances the commercial viability of the harvest, or to achieve another silvicultural objective (e.g. regeneration of a different species). By-catch furthers the ecological impacts of insect-induced tree mortality by reducing species richness, which serves as a foundation for maintaining ecosystem biodiversity.

4.5 | Limitations and future research

Cutters and Non-cutters by definition each exhibited uniformity in their responses to the contingent behaviour questions, although it is important to consider these results only within the range of values presented to them. It is entirely possible that a cutter would choose not to cut under less severe circumstances than those presented in the survey, and that a Non-cutter would respond differently under more dire conditions. Nevertheless, the range of values in the contingent behaviour questions are reflective of realistic conditions. Furthermore, the AFTs themselves were derived solely based on responses to the contingent behaviour questions; so, while we characterize AFTs using landowner age, objectives, etc., it is important to remember that such qualities are variable within the AFTs.

Still missing from this puzzle of how FFOs will influence the total disturbance initiated by invasive forest insects is the distribution and type of insect causing the response, specific types of harvests applied in response to the insects, and forest types affected by both the insects and harvests in response to (or in anticipation of) the disturbance. Our typology provides a basis for FFO response scenarios, although more research is needed to obtain finer insight into the attributes and impacts of insect-induced harvests. As alluded to in Section 4.4, it is important to account for 'by-catch' (harvesting of non-host species along with host species) because this practice could significantly increase the total disturbance initiated by insects. Another open question is how the forest product market would respond to a sudden influx of salvage-infected timber (and by-catch). Furthermore, it is possible that state-imposed quarantines could further suppress the ability of owners to profitably harvest their trees. Our AFT modelling scheme might also benefit from the consideration of sawmill location data, since the proximity of a parcel to a mill would presumably impact a landowner's willingness to cut.

Another important question is, how will the actions of FFOs feedback on the spread of invasive forest insects? Addressing this question requires a coupled natural-human systems-based perspective (Field, Dayer, & Elphick, 2017; Knight, Cowling, Difford, & Campbell, 2010) because, while pest infestations induce human impacts on the natural system, the natural system, in turn, then evolves from the human-impacted natural system (Meurisse, Rassati, Hurley, Brockerhoff, & Haack, 2018). Our typology lends itself naturally to coupled human-tree-insect modelling, which is the next stage of our team's research. Such models could be used to reveal optimal management strategies for particular pest species. Future modelling within this AFT framework will also depend on the evolution of AFTs over time. Changing landscape conditions (e.g. forest loss to development) and ownership characteristics (e.g. shifts in parcel size) will add nuance to anticipated human–pest interactions. The goal is to support land management professionals in exploring alternative future scenarios with respect to forest stocks and insect spread.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHORS' CONTRIBUTIONS

J.R.H. and M.E.B. conceived the essential questions and methodology of this paper. J.R.H. led the writing of the manuscript. M.M.-L. and B.J.B. designed and administered the New England Woodland Owner Survey. D.L. collected and processed geographic and demographic data. M.G.M. and M.E.B. provided statistical expertise with respect to the binomial and multinomial logistic regressions. D.B.K. and D.O. contributed to the discussion of the impacts of forest invasive pests on family forest owners in New England. J.R.T. conceived the original idea for the study. All authors contributed critically to the drafts and gave final approval for publication.

DATA AVAILABILITY STATEMENT

The data used in this analysis were collected from the following sources: (a) New England Woodland Owner Survey (Markowski-Lindsay et al., 2019); (b) The American Community Survey 2011–2015 five-year estimates (Manson et al., 2017); (c) The National Land Cover Database 2011 (Homer et al., 2015); (d) City boundaries (U.S. Census Bureau, n.d.); and (e) Parcel shapefiles (obtained from each individual state and town). The full dataset is archived at the Harvard Forest Data Archive: http://harvardforest.fas.harvard.edu:8080/exist/apps/datasets/showData.html?xml:id=hf326 (Markowski-Lindsay et al., 2019. Survey of Family Forest Owners Regarding Invasive Insects in the Connecticut River Watershed 2017. Harvard Forest Data Archive: HF326).

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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