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Using the Theory of Planned Behavior to Understand Family Forest Owners' Intended Responses to Invasive Forest Insects

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ABSTRACT

Private landowner participation in management initiatives can be encouraged by interventions, which must resonate with the underlying subjective motivations of the landowners. In this study, we use the Theory of Planned Behavior to gauge the relative influences of (1) attitudes; (2) subjective norms; and (3) perceived behavioral control on landowner intentions to harvest trees threatened by invasive insects. We use a survey ($n = 696$) to estimate the effects of these latent factors among family forest owners in New England. Our results suggest that, overall, normative pressures are the dominant influence on landowners' harvest intentions. However, for certain subgroups, such as those with especially high levels of knowledge and experience with forest insects, or those with forestry experience, attitudes are dominant. Perceived behavioral control was not revealed to be dominant among any of our subgroups. These findings can be used to inform landowner interventions that are differentiated by landowner type.

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Introduction

The future of the United States' forested landscape lies largely in the hands of private forest owners, who control the majority (58%) of forestland in the US. Moreover, 36% of the nation's forestland is held by over 10 million families, estates, individuals, and trusts, collectively known as family forest owners (FFOs) (Butler et al. 2016). The autonomous forest management decisions of millions of individual FFOs pose a challenge to policymakers and conservationists. Successful landscape-level management (e.g., pest management, fire control, riparian buffer maintenance, wildlife habitat enhancement) of FFO-dominated landscapes must be implemented through grass-roots mobilization of private landowners (Pradhananga, Davenport, and Olson 2015).

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Mobilizing fragmented landowners to participate in prescribed management practices can be accomplished by incentive-based (e.g., payment for services) or educational outreach programs. Successful educational outreach programs, such as extension forestry, can address landowner motivations, values, attitudes, environmental awareness, emotional involvement and loci of control, which are shown to be more effective in changing behavior than information provision alone (Kollmuss and Agyeman 2002). Much research has been dedicated to the efficacy of various modes of outreach, and the optimal method tends to be context-specific. For example, Jack, Kousky, and Sims (2008) found that payment-based methods increased private landholders' provisioning of ecosystem services including water purification, flood mitigation, and carbon sequestration. Butler et al. (2014) determined that education was more effective than cost-share or technical assistance for promoting forest stewardship. Steinmetz et al. (2016) showed that educational interventions conducted in public groups were more effective in promoting behavioral change than interventions in private settings or focusing on individuals. Careful design and administration of landowner outreach and behavioral interventions is critical because the method of delivery can have a greater impact on the outcome than the message itself (Kolehmainen and Francis 2012). Furthermore, a focus on the optimal delivery method is generally more effective than using multiple methods (Steinmetz et al. 2016).

The optimal communication method of landowner outreach efforts or behavioral interventions will vary by the nature of the desired behavior and the target audience (Butler et al. 2007; Rickenbach et al. 2017; Tyson, Broderick, and Snyder 1998; Tyson, Broderick, and Snyder 1996; Weinreich 2011). Regarding the management of nonpoint source pollution in Washington, Ryan (2009) found that riparian landowners preferred direct personal contact over brochures, advertisements, radio, internet, or television. A national survey of FFOs by the United States Department of Agriculture found that publications are preferred over other methods of communication (Butler et al. 2016). Peer-to-peer learning has been shown to be an effective technique for educating FFOs, and also for attracting inexperienced landowners to forestry (Kueper et al. 2014; Kueper, Sagor, and Becker 2013; Ma, Kittredge, and Catanzaro 2012). Community workshops, in which residents work together to discuss management practices, and lawn signs are examples of peer-oriented intervention strategies for landscape-level management (Niemiec et al. 2019).

To anticipate the behavioral intervention or outreach effort likely to be most successful in any particular case, it is helpful for policymakers to know the factors that motivate the desired behavior (Tian et al. 2015; Kusmanoff et al. 2016). For instance, a survey of landowners in Virginia found that lifestyle and amenity concerns are much more important motivations for land ownership than are timber production and economic concerns (Kendra and Hull 2005). Messaging to such "hands-off" FFOs should focus on encouraging awareness of their forestland, its potential uses and benefits, and responsibility for stewardship (Metcalf et al. 2016). "Hands-on" FFOs, on the other hand, have been shown to respond better to management advice and payment for ecosystem services (Metcalf et al. 2016). Interventions might also be differentiated by socio-demographics or ownership characteristics. For example, Tian et al. (2015) found that older and female landowners were generally more willing to manage their forests for

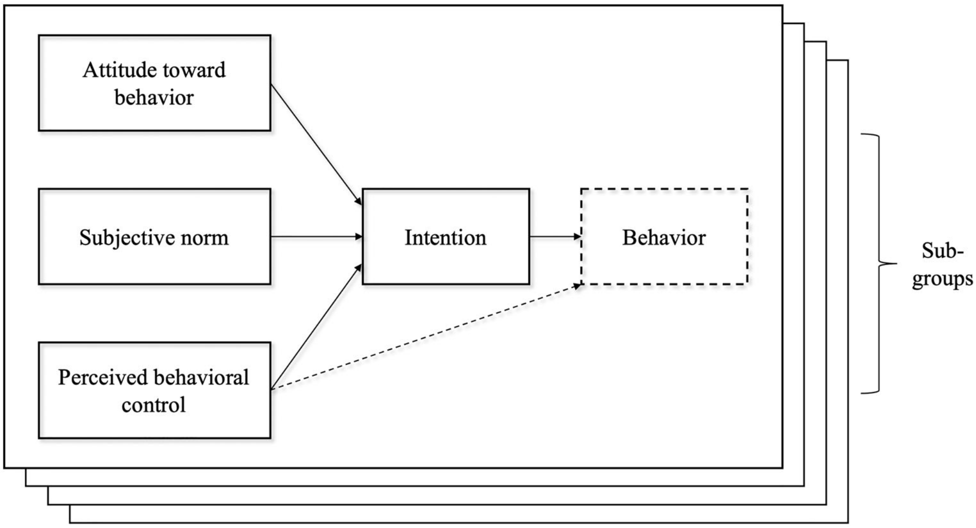

Figure 1. Theory of planned behavior model. Adapted from Icek Ajzen (1991).

ecosystem services, whereas landowners who plan to sell their forestland were not. However, in order to generalize such results and understand how to best influence future behavior, it is useful to consider the applicability and insights of a theoretical framework.

The Theory of Planned Behavior (TPB) is a model that explains how one's behavior follows from their beliefs (Ajzen 1991). Specifically, TPB assumes that actual behavior is best predicted by one's intent to perform a behavior, which in turn is based on three types of subjective beliefs: *attitude* toward the behavior, *subjective norms* (i.e., 'peer pressures') concerning the behavior, and *perceived behavioral control*. Attitude toward the behavior refers to one's opinions or perceptions of the action. Subjective norms are a combination of an individual's perception of the social pressures to perform the action and their motivation to conform. Finally, perceived behavioral control represents one's perspective on the relative ease or efficacy of performing the action, and may directly constrain actual behavior in addition to influencing intent (Figure 1). The specifics of who is the judge of the subjective norm (e.g., 'peers', 'most people'), or which parameters constitute behavioral control (e.g., 'cost', 'effort'), are left to the researcher, leaving TPB vulnerable to ambiguity (Schlüter et al. 2017). Nevertheless, TPB has been used previously to uncover the determinants of forest landowners' actual or intended behavior, including timber stand improvement (Karppinen and Berghäll 2015), sustained yield management practices (Munsell et al. 2009), forest regeneration (Pouta and Rekola 2001), riparian improvement (Corbett 2002), and flood control (Allred and Gary 2019). The insights obtained have contributed to the design and implementation of more effective communication and intervention strategies (Steinmetz et al. 2016).

In this study, we employ TPB to explore the factors influencing responses to invasive forest insects using data from a survey of FFO's in New England in order to identify potentially effective intervention strategies. The removal of infested or potentially infested timber before ('preemptive harvest'), during, or after ('salvage harvest') an insect infestation is a common response of private landowners and has the potential to intensify, broaden, and accelerate the insect's economic and ecosystem impacts (MacLean et al. 2020; Holt et al. 2020). New England hosts one of the highest diversities of invasive forest insects in North America (Liebhold et al. 2013) and over 40% of all forestland New England is controlled by FFOs (Butler et al. 2016). This makes the region especially vulnerable to pest-induced landowner harvests and highlights the need for effective outreach and education.

Our investigation is, to our knowledge, the first to apply the TPB framework to FFO responses to invasive insects. Like most other implementations of the theory (e.g., Corbett 2002; Leitch et al. 2013), our survey does not measure actual behavior, but rather intent to perform the behavior. The link between intended behavior and actual behavior is, in fact, a weakness of the TPB; while the model is quite specific on the drivers of intent (attitudes, norms, perceived behavioral control), it is less clear on the process of selecting among different intentions (Schlüter et al. 2017). Given that most FFOs in New England have not had direct experience with destructive invasive forest insects, including hemlock wooly adelgid, emerald ash borer, and Asian long-horned beetle (Simoes et al. 2019), FFO response to pests is largely hypothetical. For similar reasons, we do not incorporate past behavior into our analysis, although it has been shown to be a significant predictor for instances in which such information is available (e.g., Allred and Gary 2019; Karppinen and Berghäll 2015; Leitch et al. 2013).

TPB can be used to tailor communications and outreach based on the estimated relative influence of the three types of subjective beliefs on the intended behavior of target audiences. For instance, Klöckner (2013) showed that perceived behavioral control is at least as important as positive attitude. Thus, interventions to increase self-efficacy and efficiency are a worthwhile investment. Interventions can then be further refined if the strength of these influences can be related to other landowner characteristics. These characteristics might be incorporated into the behavioral model directly as regressors (Bagheri et al. 2019; Despotović, Rodić, and Caracciolo 2019) or indirectly as a means to partition the population before constructing TPB models for each sub-group (Figure 1). We follow this latter technique, similar to the approach of Karppinen and Berghäll (2015), however rather than segmenting the population *a priori*, we employ a clustering method to identify sub-groups empirically. After clustering FFOs, we evaluate the partitions quantitatively and qualitatively. Then, for each sub-group, we apply the TPB. Estimates of the relative influence of attitudes, normative pressures, and perceived control among the various FFO sub-groups will enable more precise, targeted interventions and outreach initiatives.

Methods

Data and Variables

Our study is based on the New England Woodland Owner Survey, a mail survey that was administered in 2017 to a stratified random sample of 2000 FFOs owning $\geq$4 ha of land in the Connecticut River Watershed. We received 696 usable surveys (35% participation). The sample was stratified by six regions: Vermont (north and south), New Hampshire (north and south), Massachusetts, Connecticut; and by lot size: 4–19 ha, and $\geq$20 ha, to adequately representant parcels in the region. The survey contained several

Table 1. Theory of Planned Behavior survey instrument for intended behavioral response to a hypothetical invasive insect scenario.

Scenario

- A new woodland insect is found on your land today.
- The insect will kill 75% of your trees.
- Those trees will be killed within 10 years.
- The insect will reduce the value of your timber by 50%.

Intention/response (*select one*)

- ☐ Cut or remove trees before the insects arrive.
- ☐ Cut or remove trees after the insects have arrived.
- ☐ Cut or remove trees, but I am not sure when.
- ☐ Do not cut or remove trees.

sections, one of which was designed specifically to assess TPB. Other subsections included landowner demographics, objectives for ownership, contingent behavior questions, and familiarity with invasive forest insects. To determine the extent of nonresponse bias, we analyzed survey data in four ways: early vs late responses; ancillary data (e.g., parcel size) known for all respondents and nonrespondents; mail survey versus a phone survey of non-respondents where we attempted to reach 10% of the nonrespondent sample with follow-up telephone calls; and comparing our results to the U.S. Forest Service National Woodland Owner Survey. For each of the analyses, we found some variability but no major differences that indicate evidence of nonresponse bias. A detailed summary of the survey and additional results can be found in Markowski-Lindsay et al. (2020).

The TPB section of the survey was constructed following the guidelines of Ajzen (2002) and structured as follows: respondents were first presented with a hypothetical scenario in which insects infest trees on their forestland (Table 1). Respondents next selected one of four intended behavioral responses to the infestation, ranging from highly proactive ("Cut or remove trees before the insects arrive") to completely passive ("Do not cut or remove trees"). Two intermediate responses ("Cut or remove trees after the insects have arrived" and "Cut or remove trees, but I am not sure when") were combined into a single factor level to create a three-level ordinal categorical variable (i.e., 'proactive response', 'reactive response', 'no response'). The three-level response variable translates naturally into the forthcoming multinomial logistic regression framework. Respondents then answered a series of questions designed to measure their attitude, normative pressure, and perceived behavioral control toward insect-induced tree removal.

Respondent attitude, normative pressure, and perceived behavioral control related to insect-induced tree removal were measured with 5-point, bipolar Likert-scale questions. Two questions were asked as measures for these types of subjective beliefs. Attitudes toward cutting or removing trees infested by destructive insects were gauged by asking respondents whether they felt this behavior was (1) "a good thing to do" and (2) "improves the health of the woods." We assessed normative pressure by inquiring on opinion toward the statements (1) "I think most people who are important to me would think trees infested by these insects should be cut or removed from my woodland" and (2) "I think other landowners who I most respect would cut or remove trees infested by these insects from their woodland." The first normative statement represents an injunctive/subjective norm, whereas the second is a descriptive norm, which has been shown to have a greater impact on intended behavior; nevertheless, these two different types of norms are often combined in the TPB, and we proceed with the general label of "subjective norm" while acknowledging this limitation (Niemiec et al. 2020). Lastly, perceived behavioral control was inferred from respondents' agreement with the perception that cutting or removing trees is (1) "easy" and (2) "expensive".

Structural Equation Model

We used a structural equation model (SEM) (Bollen 2005) to cast the survey data in the framework of TPB. The general idea of an SEM is to determine whether a hypothesized theoretical model (in our case, TPB) is empirically consistent with collected data (Lei and Wu 2007). In this case, the SEM is constructed as a set of generalized linear regressions in which the stated intended behavior (cut or remove trees in response to insects) is a function of latent factors representing the three beliefs (attitude, norms, control), which in turn are each measured by the answers to two survey questions. Consistency between the theorized model and the actual data is determined by comparing the sample covariance matrix to the covariance matrix implied by the model (absolute fit) or by measuring the improvement in fit relative to a baseline model (incremental fit). Two popular absolute fit indices are the goodness-of-fit index (GFI; Jöreskog and Sörbom 1986), which is generally desired to be >0.90, and the root mean square error of approximation (RMSEA; Steiger and Lind 1980), for which an accepted value is generally <0.08. The comparative fit index (CFI; Bentler 1990) is a commonly used incremental fit index that is generally desired to be >0.90. Internal consistency within each set of latent class measurements was assessed using Cronbach's alpha.

Coefficients estimated in the model fit process represent the correlations between standardized variables (beta weights). For example, a factor loading of 1.0 indicates that a one-unit increase of the exogenous variable (survey item) corresponds to a one-unit increase in the unobserved latent factor (e.g., attitude). Covariances between the three latent factors (attitude, norms, control) are also calculated, and statistical significance for both covariances and regression coefficients are indicated by the p-value. An exogenous variable can have a statistically significant correlation with a latent factor even if the latent factor is not significantly correlated with other variables in the model.

We first fit an SEM to the entire sample of FFOs. Then, to identify partitions of FFOs between which behavioral motivations may differ, we clustered respondents into subgroups based on individual characteristics, such as management experience or exposure to invasive pests (detailed in Table 2). The clusters revealed different subgroups of landowners, each of which may be susceptible to different intervention strategies. For each subgroup, we fit a separate SEM based on the TPB framework. We considered five sets of survey items as the basis for clustering, thus generating five different partitioning schemes of respondents. For each of the five partitions, clusters were formed using hierarchical divisive clustering, also known as divisive analysis (DIANA) (Rousseeuw and Kaufman 1990). The number of clusters for each partition was determined by minimizing the within-clusters sum of squares (the "elbow method") and maximizing the average silhouette width. Two or three clusters were found for each of the five partitions.

Table 2. Summary of clustering analysis and structural equation model estimates.

			Cluster metrics	Response variable (%)				Regression coefficient			Goodness-of-fit
			Avg sil width	**don't cut**	**cut after**	**cut before**	**total**	**Attitudes**	**Norms**	**Control**	**RMSEA**
	Whole sample			14%	62%	24%	696	**0.28*****	**0.363*****	−0.02	0.03
	Sub-samples										
	Variables used to cluster	**Cluster description**									
Partition 1 (Knowledge)	• Previously had invasive pest on land (binary) • Previously cut or removed trees because of invasive insect on land (binary) • knowledge of Emerald Ash borer (Likert) • knowledge of Asian longhorned beetle (Likert) • knowledge of Hemlock wooly adelgid (Likert)	1: High knowledge of and experience with invasive insects	0.40	13%	68%	19%	95	**0.77***	−0.09	−0.05	0.04
		2: Low knowledge of and experience with invasive insects		14%	61%	24%	601	**0.21****	**0.45*****	−0.04	0.05
Partition 2 (Experience)	• Currently have a management plan (binary) • Previously cut or removed trees (binary) • Previously sought advice from a forester (binary)	1: High experience in forestry	0.52	6%	67%	26%	250	**0.48****	0.14	−0.10	0.01
		2: Low experience in forestry		19%	59%	22%	446	**0.23****	**0.42*****	−0.02	0.04
Partition 3 (Property)	• Lot size >50 ac (binary) • distance between residence and woodlands (categorical)	1: Local resident	0.30	13%	63%	24%	446	**0.28*****	**0.33*****	0.01	0.02
		2: Non-local resident with larger woodland		10%	66%	24%	153	0.57	0.18	−0.18	0.07
		3: Non-local resident with smaller woodland		24%	54%	23%	97	0.07	**0.75***	−0.19	0.00
Partition 4 (Ownership)	• tenure (categorical) • number of owners (categorical) • likelihood of selling within 5 years (Likert)	1: ≤2 owners, likely to sell in 5 years, longer tenure	0.15	15%	62%	23%	124	**0.73*****	−0.16	0.04	0.10
		2: >2 owners, unlikely to sell, shorter tenure		14%	62%	24%	572	**0.23****	**0.45*****	−0.07	0.01
Partition 5 (Demographic)	• age (categorical) • gender (categorical) • education (categorical) • income (categorical)	1: Younger women	0.22	17%	64%	20%	137	0.19	**0.50*****	0.01	0.02
		2: Older women and men		14%	62%	25%	559	**0.33*****	**0.30*****	−0.03	0.02

Avg sil width refers to the average silhouette width between clusters; greater width indicates a better fit (clusters are more distinct). RMSEA is the root mean square error of approximation; smaller error indicates a better model fit. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

We conducted our analyses using the statistical software R (R Core Team 2019). For the clustering routine we used the *cluster* package (Maechler et al. 2019); for SEM analysis we used the *lavaan* package (Rosseel 2012). Since SEM requires complete data, missing survey responses were imputed using multiple imputation via the *mice* package (van Buuren and Groothuis-Oudshoorn 2011).

Results

Landowner Responses to the Survey

Twenty-five percent of survey respondents ($n = 165$) selected the most severe response intention ("Cut or remove trees before insects arrive"), while 15% ($n = 99$) chose the least severe, no action response ("Do not cut or remove trees") to the hypothetical insect infestation scenario. The remaining 62% of respondents ($n = 432$) selected one of the two intermediate intentions: "Cut or remove trees after insects have arrived" ($n = 132$); "Cut or remove trees but unsure when" ($n = 300$).

Responses to the two Likert-scaled measures of attitude were largely positive. Sixty-five percent of surveyed landowners believe that cutting or removing trees infested by insects "improves the health of the woods". Only 4% disagreed with this sentiment. Furthermore, 65% of respondents believe that cutting or removing affected trees "is a good thing to do." Four percent disagreed with this statement, including 21 of the 30 individuals who disagreed with the "health" statement. Agreement with the attitude items was positively correlated with intention to cut or remove trees. Eighty-four percent of respondents who intended to "Cut or remove trees before insects arrive" thought that cutting was healthy (90% thought cutting was good), whereas only 21% of those who selected "Do not cut or remove trees" agreed that cutting was healthy (19% thought that cutting was good) (Figure 2).

Respondents exhibited a similar level of agreement with the measures of subjective norms. Sixty-four percent expressed agreement that "most people who are important to me would think trees infested by these insects should be cut or removed from my woodland." Five percent of respondents disagreed with this statement. When asked if they think other landowners would remove infested trees from their property, 58% agreed and 3% disagreed. As with the attitude items, agreement with subjective norms was positively correlated with intention to cut. Of the respondents who indicated intention to cut before insects arrive, 86% agreed that others think they should cut (73% agreed others would cut) compared to 13% and 18% of the "do not cut" respondents agreeing that others think they should, and agreeing they think others should, respectively (Figure 2).

Respondents expressed lower levels of agreement with the measures of perceived behavioral control. Thirty-one percent of landowners agreed that "it would be easy" to remove infested trees, 41% disagreed, and 28% neither agreed nor disagreed (were "undecided"). "It would not be expensive" was agreed on by only 14% of respondents, while 55% disagreed, and 31% were unsure. Intention to cut was positively correlated with the "easy" prompt, but less so with the "not expensive" survey item (see Cronbach's alpha in Table 3). Of those who selected "do not cut," 16% thought cutting was easy and 6% thought that cutting was inexpensive. On the other hand, 41% and 16% of those who intended to cut before insects arrive agreed that cutting was easy and inexpensive, respectively (Figure 2).

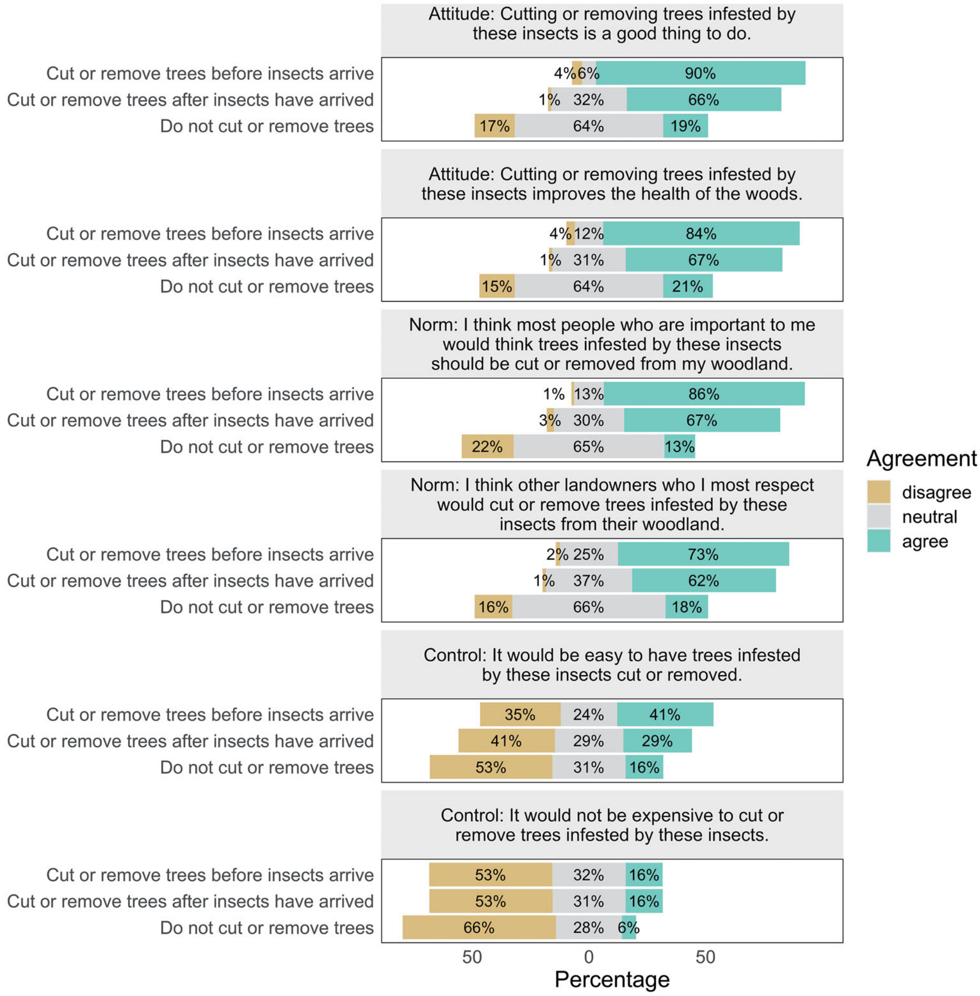

Figure 2. Agreement with Likert-type assessments of attitude, subjective norms, and perceived behavioral control. The intermediate response ("Cut or remove trees after insects have arrived") includes ("Cut or remove trees, but I am not sure when"); this lumping of response levels serves to make the variable ordinal.

Table 3. Internal reliability of composite attitude, subjective norms, perceived control measures based upon Cronbach's alpha.

Composite measure	Cronbach's alpha
Attitude	0.85
Subjective norms	0.80
Perceived control	0.55

Whole-Sample SEM

The applicability of TPB to modeling the intention of FFOs to cut or remove trees infested by destructive insects was explored by fitting an SEM to the survey data from all respondents (Figure 3). The estimated model exhibited goodness-of-fit criteria well within the range of acceptability (RMSEA = 0.038, CFI = 0.998, GFI = 0.990) and

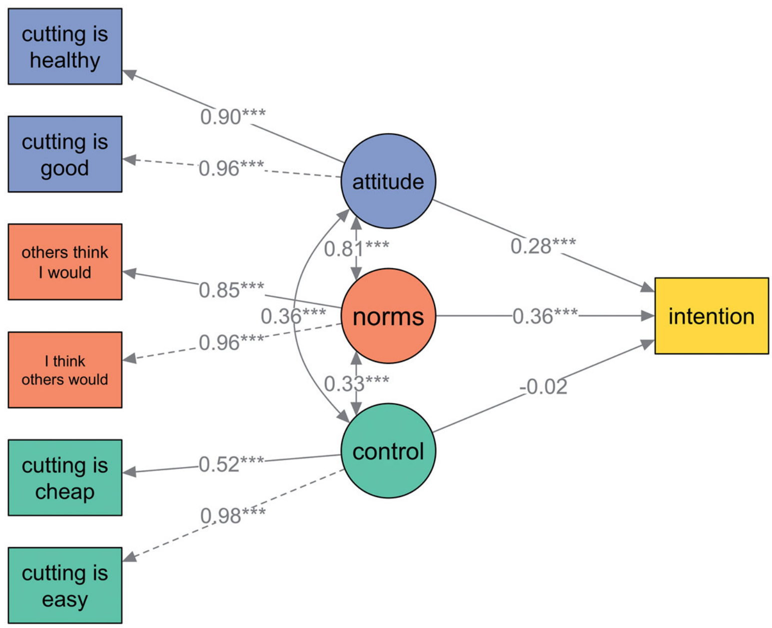

Figure 3. Whole-sample structural equation model estimates. Rectangular nodes on the left correspond to Likert-type survey measurements of the three latent factors (circular nodes). The rectangular node on the right ("intention") is the measured response variable, which is a function of the three latent factors. Unidirectional arrows represent standardized regression coefficients; bidirectional arrows are variances. Dashed lines indicate the fixed parameter for each latent factor. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

explained 37% of the variance in behavioral intention responses. Subjective norms are the most important explanatory factor, with a coefficient of 0.36, compared to attitudes (0.28), but both influences are positive and statistically significant ($p < 0.05$). Perceived behavioral control has an estimated influence close to zero and is not statistically significant ($p = 0.\ 981$).

Both indicators of each of the three latent variables are significantly positive measures of the corresponding subjective beliefs ($p < 0.05$) (Figure 3). The weakest measure was agreement with the statement that cutting or removing trees is "cheap" as an indicator of the perceived control belief (parameter estimate = 0.52). All latent belief variables are positively related to each other, especially attitude and social norms. The internal reliability for the TPB predictor measures were assessed using Cronbach's alpha. Higher Cronbach's alphas correspond to greater reliability ranging from zero to one, with Chronbach's alpha $\geq$0.5 being generally considered acceptable reliability (George and Paul 2003). Only the perceived control factor approached this minimum Cronbach's alpha threshold (Table 3).

Partitioning Respondents

We considered five different partitions of survey respondents, with each partition articulated by clustering respondents according to different survey items. SEMs were then fit to the separate subgroups (clusters) resulting from each partition based on the TPB framework. Regression coefficients for the latent variables representing beliefs (attitudes, social norms, and perceived control) for each subgroup of each partition are given in Table 2. Coefficients for survey-based measures of beliefs ("cutting is good", "cutting is healthy" etc.) do not vary appreciably between clusters and are not shown (all model estimates are available in the Supplemental Information). Furthermore, GFI and CFI are greater than 0.99 for all models, so we report RMSEA as the only goodness-of-fit index in Table 2.

Partition 1: Knowledge of Invasive Insects

Divisive hierarchical clustering of respondents based on their knowledge and experience with invasive pests yielded two distinct groups: those with high levels of knowledge and/or experience ($n = 95$) and those with low levels ($n = 601$). Almost all members (97%) of the high knowledge/experience group indicated that they had previously had one or more species of invasive insect on their land. Furthermore, approximately half of this population had previously harvested or removed trees in response to the insect. The high knowledge/experience group also scored higher on the Likert-scale, invasive forest insect familiarity questions, "How much would you say you know about the following woodland insect species?" (emerald ash borer, hemlock wooly adelgid, Asian longhorn beetle).

SEM coefficient estimates differed markedly between the high and low insect knowledge groups. Intended cutting behavior of the high knowledge group was explained exclusively by attitudes, whereas intended behavior of the low knowledge group was, like the sample as a whole, most influenced by attitudes and subjective norms. As with the whole-sample model, perceived behavioral control was not statistically significant.

Partition 2: Experience with Forest Management

Clustering by forest management and experience yielded the best fit of all five partitions, with a silhouette width of 0.52 (Table 2). Respondents fell into two groups regarding forest management experience. The high experience group ($n = 250$) unanimously had a written management or stewardship plan to help them meet their goals for their forestland. The majority (85%) of this cluster had previously cut or removed trees for commercial purposes. Furthermore, many of these landowners (85%) had enlisted the help of a professional forester to plan, mark, contract, or oversee the cuts. The 446 landowners in the low management experience cluster had neither drafted a management plan nor sought advice from a professional forester, although about half of this group had previously cut or removed trees for commercial sale.

The intended cutting behavior of landowner respondents with high forest management experience was influenced exclusively by attitudes, whereas that of landowners with low experience was influenced by both attitudes and social norms, similar to the whole-sample results.

Partition 3: Property Characteristics

Three clusters were identified that divide respondents according to characteristics of their forest property, including lot size and distance from one's residence. The first cluster encompasses local landowners living < 1.6 km (1 mile) from their forestland

($n = 446$). Landowners living $>=$ 1.6 km from their forestland and owning "large" lots ($\geq$ 20 ha) comprise the second group ($n = 153$). Those residing $>=$ 1.6 km away and owning "small" lots (4–19 ha) comprise the third cluster ($n = 97$).

The group of "local" landowners mirrors the whole sample in revealing both subjective norms and attitudes to have a significant influence on intended cutting behavior. The intended behavior of the group of non-local landowners owning small lots was influenced only by social norms. The remaining group–those living remotely and owning large lots–did not reveal any of the three belief variables to be statistically significant predictors of intended behavior.

Partition 4: Ownership Characteristics

Respondents clustered into two groups based on ownership tenure, number of owners, and the self-reported likelihood of selling or giving away the forestland in the next five years. The first group ($n = 124$) consists exclusively of ownership arrangements with two or fewer owners (individuals or married couples). Landowners in this cluster have generally owned their forestland for at least 15 years and most intend to sell their land within the next five years. The second cluster ($n = 572$) is characterized by the unlikelihood of selling the land in the next five years (86% selected "unlikely"). Unlike the first group, the second group includes some ownerships of >2 people (15%), and many (41%) who have owned their land for less than 15 years.

Small ownership groups ($\leq$2 owners) who have owned the property for a long time and are likely to sell within five years are, like the high knowledge and high experience groups, primarily motivated by attitudes. Those with greater numbers of owners, shorter tenures, and lower likelihoods of selling are, like the whole sample, motivated by both subjective norms and attitudes.

Partition 5: Demographics of Landowners

We identified two distinct clusters of respondents when using income, education, gender, and age as clustering variables. The first group ($n = 137$) is entirely female. The women in this group are between the ages of 25–70 and 38% have an advanced degree (master's or higher). The second cluster ($n = 559$) encompasses both men and women, although 88% of the group is male and is older than the first (38% are 70 or older) and has lower educational attainment (43% did not receive a bachelor's degree).

Fitting the TPB model to the demographic clusters, we found that the female group was, like the third cluster of partition 3, influenced primarily by norms. The older, mixed-gender cluster was influenced by both attitudes and norms, with slight preference given to attitudes, unlike any of the other groups for which both of these factors are significant.

Discussion

In our survey, 85% of landowners indicated that they would consider cutting or removing trees either before or after an insect infestation. Given that there are >200,000 forest landowners in the region and a relatively high population of invasive tree pests, this action has the potential to dramatically alter New England's forested landscape (MacLean et al. 2020). By understanding the determinants of landowner behavior vis-a-vis their response to tree pests on their forestland, policymakers, state forestry agencies, extension programs, and NGOs will be able to design and implement communications and other interventions that are most persuasive at motivating change. We combined cluster analysis and structural equation modeling with TPB to uncover the types of beliefs influencing behavior for the whole sample of survey respondents as well as for specific sub-groups. Understanding how behavioral motivations differ across transects of the population will allow interventions to be targeted more strategically.

The results suggest that the TPB model is a relevant theoretical framework for uncovering latent, subjective factors that drive FFO intentions to cut or remove insect-infested trees. Regardless of what partition we used, the SEM models fitted to the TPB framework explained our survey data very well. This is consistent with previous studies utilizing TPB to characterize the drivers of FFO intended behavior (Karppinen and Berghäll 2015; Leitch et al. 2013; Allred and Gary 2019). Our analysis does not address the link between intended behavior and actual behavior; nevertheless, intentions can provide useful insight into possible intervention strategies.

Social norms were the most influential driver of intended behavior for the full-sample, followed by attitudes. These results complement Karppinen and Berghäll (2015), who found normative pressures to have the greatest impact on timber stand improvement. Studies of FFO engagement with energy and carbon markets found attitudes to be most influential (Leitch et al. 2013; Thompson 2010). The dominance of normative influences suggests that policymakers should consider intervening with social "nudges" (Thaler and Sunstein 2009), which have been found to be successful in increasing intended behavior in other environmental contexts, such as farmers' intentions to maintain participation in agri-environmental schemes (Kuhfuss et al. 2016). Social nudges can be either top-down (policymakers communicating with landowners) or lateral (landowners communicating with landowners). Top-down influences are useful in communities with low resident interaction, such as places with larger properties or few organized community events (Niemiec et al. 2016). Meanwhile, peer-to-peer nudging not only taps the social norm, but also ameliorates the issue of a centralized intervention not reaching all members of the community (e.g., not checking one's email) (Graham 2013). Our findings emphasize the work of Kueper, Sagor, and Becker (2013), who posit that peer exchange not only offers an approachable and attractive learning opportunity for FFOs, but also relieves pressure on limited professional assistance capacity.

Perceived behavioral control was not a statistically significant predictor of intended behavior for our sample, although the survey items regarding both internal control ("cutting is easy") and external control ("cutting is cheap") were statistically significant measures of the control factor. We were surprised to find that perceived control was not influential, although there is precedence for this in the literature (e.g., Allred and Gary 2019). Perceived behavioral control is the newest addition to the TPB framework, which itself is borne from the two-factor Theory of Reasoned Action (Fishbein and Ajzen 1975). Previous studies such as Dayer, Allred, and Stedman (2014) have suggested that for disengaged FFOs, financial or technical assistance was less important than learning about a new management practice. Our findings support this notion; monetary and technical empowerment could be deemphasized in favor of educational materials (attitude) or social programs (norms) regarding management of invasive tree insects. However, perceived behavioral control may become more important following an actual infestation of destructive insects, as opposed to the theoretical nature of the survey scenario. Or, at a minimum, the actual controls may mitigate landowners' behavioral intentions if the actions become too costly, too complex, or the owners cannot find the people to do the work. Notably, internal consistency for this factor was lowest of the three factors and approached the lower limit of acceptability. As with all three subjective components of the TPB, the specific verbiage of the measurement instrument (e.g., "cutting is easy", "cutting is cheap") is left to the researcher, and thus the significance (or lack thereof) of any particular factor could be attributed to theory and/or implementation.

When estimated separately for various sub-groups of the population, TPB factor values showed some differences. FFOs with high levels of knowledge about invasive insects or high levels of forestry experience were motivated only by their attitudes toward whether or not cutting or removing trees was "good" or "healthy," with no statistically significant influence of social norms or perceived control. This was also the case for ownership arrangement with two or fewer owners with a longer ownership tenure (a group which may include many of the more knowledgeable or experienced owners). These groups have greater personal experience with the management of their land, and this appears to have impacted the factors influencing their intentions. This finding supports the Elaboration Likelihood Model, which theorizes that individuals who are heavily invested in a topic are more likely to use rational thinking to process the message, while individuals who are less informed are more influenced by subtle cues about the behaviors of others (Schultz et al. 2016; Petty and Cacioppo 1984). Interventions aimed at the most experienced FFOs should prioritize factual information about the value of tree removal as a form of pest management and acknowledge and build upon the owners' personal knowledge bases. These individuals may also be effective ambassadors for sharing information with less experienced owners.

"Absentee" landowners (FFOs living primarily $>=$ 1.6 km from their forest) with lot sizes 4–19 ha, as well as female FFOs under 70, were mostly influenced by subjective norms. This finding supports Karppinen and Berghäll (2015) who also detected greater influence of subjective norms among women and forest owners with smaller forests. Interventions for these groups, therefore, should prioritize social networks, for example ensuring that the results of interventions are visible and communicated frequently through peer-to-peer programs to encourage landowners to engage in social praise of compliant landowners (Graham 2013).

An important limitation for our analysis is the distinction between preemptive and salvage cutting in the response variable, but not in the measurement of perceptual variables. Stated differently, the response variable had three levels ('cut before insects', 'cut after insects', 'don't cut'), whereas the subjective factors were measured on a bipolar Likert-type scale intended to represent inclination to harvest, generally. The question of what motivates preemptive versus salvage logging, specifically, would benefit from future research. Subsequent research could also probe the non-harvest response; for instance, the framework described here could be used to uncover the motivations for pesticide treatment.

Conclusion

Overall, our results suggest that policymakers who seek to intervene in the current state of FFO behavior regarding tree insects may be able to partition their target audience according to a variety of ownership characteristics and then design and administer intervention methods accordingly. By mobilizing the collective actions of autonomous landowner decisions in this way, they may have the potential to coordinate management at a landscape scale. Such a strategy requires identifying detailed ownership characteristics in the first place, and future work could benefit from generalizing characteristics and/or types of landowners to the town or county level. Nevertheless, our finding that subjective norms are the prevailing determinant, on average, of intended FFO behavior in response to tree insects can be used to inform large-scale interventions. Although our results are for one action–harvesting related to invasive insects–and for a single region of the U.S., the results are theoretically supported and consistent with other studies; therefore, implications can be made for other geographies and actions, although additional testing is needed to verify these assumptions and incorporate local contexts.

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