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Social and biophysical variation in regional timber harvest regimes

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Abstract. In terms of adult tree mortality, harvesting is the most prevalent disturbance in northeastern United States forests. Previous studies have demonstrated that stand structure and tree species composition are important predictors of harvest. We extend this work to investigate how social factors further influence harvest regimes. By coupling the Forest Inventory and Analysis database to U.S. Census and National Woodland Owner Survey (NWOS) data, we quantify social and biophysical variation in the frequency and intensity of harvesting throughout a 20-state region in the northeastern United States. Among social factors, ownership class is most predictive of harvest frequency and intensity. The annual probability of a harvest event within privately owned forest (3%/yr) is twice as high as within publicly owned forests (1.5%/yr). Among private owner classes, the annual harvest probability on corporate-owned forests (3.6%/yr) is 25% higher than on private woodlands (2.9%/yr). Among public owner classes, the annual probability of harvest is highest on municipally owned forests (2.4%/yr), followed by state-owned forests (1.6%/yr), and is lowest on federal forests (1%/yr). In contrast, corporate, state, and municipal forests all have similar distributions of harvest intensity; the median percentage of basal area removed during harvest events is approximately 40% in these three owner groups. Federal forests are similar to private woodlands with median harvest intensities of 23% and 20%, respectively. Social context variables, including local home prices, population density and the distance to a road, help explain the intensity, but not the frequency, of harvesting. Private woodlands constitute the majority of forest area; however, demographic data about their owners (e.g., their age, educational attainment, length of land tenure, retired status) show little relationship to aggregate harvest behavior. Instead, significant predictors for harvesting on private woodlands include live-tree basal area, forest type, and distance from roads. Just as with natural disturbance regimes, harvest regimes are predictable in terms of their frequency, intensity, and dispersion; and like their natural counterparts, these variables are determined by several important dimensions of environmental context. But in contrast to natural disturbance regimes, the important dimensions of context for harvesting include a combination of social and biophysical variables.

Key words: coupled human and natural systems; disturbance ecology; Forest Inventory and Analysis Plots; land use; maximum-likelihood estimation; National Woodland Owner Survey; temperate forests; timber harvest regimes.

Introduction

The composition and structure of forest ecosystems in the United States is strongly affected by anthropogenic disturbances (Masek 2011). In the northeastern United States, harvesting is a larger cause of adult tree mortality than all other natural and anthropogenic causes combined (Canham et al. 2013). Despite its ubiquity, regional-scale ecological analyses often exclude harvests when quantifying regional patterns and consequences of tree mortality in eastern North America (Lines et al. 2010, Dietze and Moorcroft 2011, Vanderwel et al. 2013). In doing so, such analyses discount the dominant disturbance agent that, like other important causes of mortality, varies with respect to forest composition and biomass, and produces stands of varying age structure and species composition. The choice to exclude harvesting from regional disturbance analyses seems also to be motivated by an expectation that global change will alter rates and patterns of temperate tree mortality (Van Mantgem and Stephenson 2007). But this assumption fails to recognize the potential for global change to influence harvest regimes. We posit that just like "natural" disturbance regimes, harvest regimes are key drivers of meso-scale ecological dynamics and that an understanding variation in harvest regimes is critical for anticipating future forest dynamics.

Canham et al. (2013) quantifies the widespread use of partial harvesting in the northeastern United States and its important role in structuring forest ecosystems. By interpreting the statistical properties of the harvest regime, i.e., the frequency and intensity of events, the work assimilated harvesting regimes and their biophysical correlates into the framework of ecological disturbance

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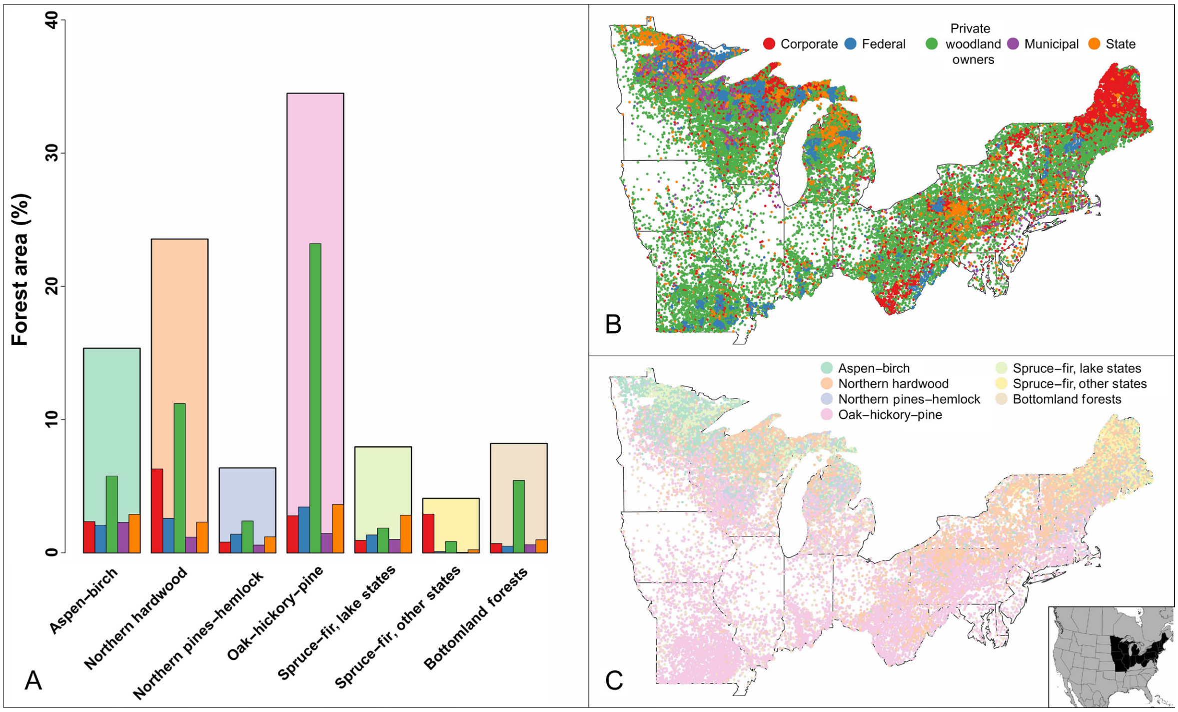

FIG. 1. (A) Distribution of U.S. Forest Service Inventory and Analysis plots color coded based on (B) owner group and (C) forest type. [Color figure can be viewed at wileyonlinelibrary.com]

theory (sensu Pickett and White 1985), which has typically been relegated to the study of natural disturbance regimes. But unlike natural disturbances, harvesting is a product of human decisions. Therefore, understanding regional variation in harvest regimes requires a full accounting of both biophysical and social influences on harvest activity. Here, we build on Canham et al. (2013) to more fully explain variation in regional harvest regimes and thereby help to fill a critical knowledge gap concerning human-induced changes in terrestrial ecosystems (Erb et al. 2016).

Across the region, a complex ownership mosaic overlays an mosaic of forest composition, which together influence attributes of the harvest regime (Jin and Sader 2006, Healey et al. 2008). Different classes of ownership (i.e., federal, state, municipal, corporate, private woodland, etc.) are constrained by different policies and normative standards and manage their forests to achieve different goals. For example, federally owned National Parks in the eastern United States prohibit timber harvesting and, as a result, have distinct forest structure and more biomass than surrounding forests (Miller 2016); similarly, public forestland across all federal agencies have higher stocks of aboveground biomass as compared to privately owned land (Zheng et al. 2010). Patterns of forest ownership vary at both coarse and fine scales in the United States (Butler et al. 2014). Eighty percent of forests in the northeastern United States are privately owned and 70% of private forests are owned by non-corporate, private, woodland owners (hereafter, private woodland owner sensu Silver et al. [2015], Fig. 1). To date, however, few studies have examined regional variation in the frequency and intensity of forest harvesting by detailed ownership classes (i.e., more resolved than public/private).

Across ownerships, other social factors related to the broader context of a forest or landowner may affect attributes of harvest regimes. For example, the average stumpage price (i.e., the per unit price paid for a species of tree) may affect the decision to harvest, though, in practice, typical fluctuations in stumpage, such as those seen over the past 30 yr in the northeast, are an unreliable predictor of aggregate harvest activity (Kittredge and Thompson 2016). At a broad scale, harvesting is more frequent in rural as opposed to suburban settings and, more generally, in regions with lower human population density (Wear et al. 1999, Munn et al. 2002, Kline et al. 2004, McDonald et al. 2006, Thompson et al. 2011). More locally, the distance from a harvest site to a road affects the operational logistics and costs of logging, and therefore can affect the probability that a harvest will occur and the intensity of a harvest when it does (Kline et al. 2004). A better understanding of the relationship between these and other social factors will, in turn, lead to a better understanding of the harvest patterns and the regional ecological dynamics they produce.

At the scale of individual harvest events, the social factors that affect the probability of a harvest are complex and include a mixture of economic, amenity, and policy influences (Davis et al. 2000, Beach et al. 2005). A recent review of 129 studies describing private woodland owners' attitudes toward harvesting found that parcel size, harvest revenue, and the owner's level of educational attainment are consistently and positively associated with owners' intention to harvest; absentee ownership and the age of the owner are consistently but negatively associated with the intention to harvest; the owner's income and whether or not the forest is part of a farm have been significantly correlated with harvest intentions in several studies, but the direction of the correlations has been mixed (Silver et al. 2015). This review also highlighted how few studies (<4%) measure actual harvest behavior as opposed to owners' attitudes and intentions. This is an important distinction because attitudes and intentions often do not align with planned behavior (Young and Reichenbach 1987). As such, an understanding of harvest regimes as ecological disturbances should be based on observed harvest activity, not intentions.

Our objective in this paper was to extend Canham et al. (2013) analysis of biophysical variation in regional harvest regimes by quantifying the role of the social attributes of a site and landscape in determining probability and intensity of harvesting. Using data from the U.S. Forest Service's Forest Inventory and Analysis (FIA) and its National Woodland Owner Survey (NWOS), we quantified variation in harvest frequency and intensity through the northeastern United States relative to a suite of social and biophysical variables. We examined variables that had been previously associated with harvest activity (see citations above Canham et al. 2013, Silver et al. 2015, Kline et al. 2004, Wear et al. 1999, McDonald et al. 2006) and for which there existed spatially extensive data sets that could be merged with the FIA and NWOS. Specifically, we addressed the following three questions: (1) How does the frequency and intensity of timber harvest differ on forests managed by different classes of landowners, including federal, state, municipal, corporate, and private woodland owners? (2) How does the frequency and intensity of timber harvest vary in relationship to the social setting (e.g., population density, average household income) and the biophysical setting (e.g., forest type, basal area)? (3) Is harvest frequency and intensity on private woodlands associated with personal characteristics of the forest owner (e.g., income, education level, size of property)?

Methods

We used the FIA database to analyze the regional harvest regime in two distinct phases. To question our first two research questions, we used the full FIA database to analyze harvest activity on all ownership classes within a 20-state region encompassing the northeast and several upper mid-western states (Fig. 1). To address the third question, we analyzed harvest activity on a subset of FIA plots across the same region that occur on private woodlands land and for which the NWOS data exist and describe landowner attitudes and demographics. Our analytical techniques differed between the two phases due to the differences in the data structures; we describe both below.

To address questions 1 and 2, we analyzed all forested FIA plots that had been subject to at least two measurements using the post-2000 national FIA protocol and were not in areas where logging is legally restricted ($n = 39684$). Consistent with Canham et al. (2013), we fit statistical models using two dependent variables that describe fundamental components of the harvest regime: (1) the annual probability of a harvest event occurring on the site and (2) the intensity of harvest when it occurs, measured as the fraction of live-tree basal area removed. Plots were coded as harvested when any tree >12.7 cm diameter at breast height was recorded by FIA staff as "removed," i.e., "cut and removed by direct human activity related to harvesting, silviculture, or land clearing" (Woudenberg et al. 2010) between the two most recent measurements. Note that harvesting in this context includes all types of removals, from firewood to commercial clear-cuts.

We evaluated a series of regression models characterizing the relationships between our two dependent variables and several potential independent variables based on parsimony and explanatory power. We selected a discreet number of what we term "site-level" and "context-level" independent variables that were not significantly intercorrelated ($|r| < 0.4$; [Dormann 2013,]), had been previously shown to influence harvest behavior, as reviewed in *Introduction*, and could be estimated at all FIA plot locations across the study region. We examined three site-level attributes: (1) Live-tree basal area (in m^2) measured during the initial field survey. This was the most predictive variable in the Canham et al. (2013) analysis. (2) Forest type group, which is a classification of forestland based on the tree species forming a plurality of live tree stocking (Table 1; Woudenberg et al. 2010). Note that we separated the spruce–fir forest type group into "lake states" and "other states" based the subregional differences observed in Canham et al. (2013). (3) Ownership class using the FIA program's refined private owner land codes, which are typically confidential but were made available for this study (five classes; Fig. 1; see *Acknowledgments* for FIA MOU information).

We examined three "context-level" independent variables: (1) Median household income was extracted at the plot location from the 2010 U.S. Census block group. Many studies have found an association between harvesting and landowner affluence or income (see Silver et al. [2015] for a review). Median income at the census block group (600–3000 people) offers the best seamless approximation of variation in income across the region. (2) Population density at the U.S. Census block group was extracted at the plot location to capture potential variation in harvest probability between urban, suburban, and rural landscapes, which has been identified as an important predictor of harvest activity in other studies (Wear et al. 1999, Munn et al. 2002, Kline et al. 2004, McDonald et al. 2006, Thompson et al. 2011). (3) Distance from the nearest road calculated as the minimum Euclidian distance from a public access road, which has

TABLE 1. Description of the forest groups used in this analysis.

Forest group	Description
Aspen–birch	Forests in which aspen, paper birch, or gray birch, singly or in combination, make up a plurality of the stocking; common associates include red maple, white pine, red oaks, and white ash.
Northern hardwood	Forests in which sugar maple, beech, yellow birch, black cherry, or red maple, singly or in combination, make up a plurality of the stocking; common associates include white ash, eastern hemlock, basswood, aspens, and red oak. Also called maple–beech–birch.
Northern pines–hemlock	Forests in which eastern white pine, red pine, or eastern hemlock, singly or in combination, make up the plurality of the stocking; common associates include red maple, oak, sugar maple, and aspen. Also called white–red pine.
Oak–hickory–pine	Forests in which hickory or upland oaks make up a plurality of the stocking and in which pines or eastern redcedar contribute 25–50% of the stocking. Also called oak–pine. Also forests in which upland oaks, hickory, yellow-poplar, black locust, sweetgum, or red maple, singly or in combination, make up a plurality of the stocking and in which pines or eastern redcedar make up <25% of the stocking; common associates include white ash, sugar maple, and hemlock. Also called oak–hickory.
Spruce–fir, other states	Forests outside of the lake states in which red, white, black, or Norway spruces, balsam fir, northern white-cedar, tamarack, or planted larch, singly or in combination, make up a plurality of the stocking; common associates include white pine, red maple, yellow birch, and aspens.
Spruce–fir, Lake States	As above, except within the states of Michigan, Wisconsin, or Minnesota, USA.
Bottomland forests	Bottomland forests in which tupelo, blackgum, sweetgum, oaks, or southern cypress, singly or in combination, make up a plurality of the stocking and in which pines make up <25% of the stocking; common associates include cottonwood, willow, ash, elm, hackberry, and maple. Also called oak–gum–cypress.

Note: Descriptions adapted from Northern Forest Inventory and Analysis Methodology; http://www.fs.fed.us/ne/fia/methodology/def_ah.htm

also been previously linked to harvest probability and harvest intensity (Kline et al. 2004). We included all public access roads, i.e., TIGER road levels S1200, S1400, and S1500.

We used a model comparison protocol that tested a hierarchy of models of increasing complexity using an information theoretic approach and the Akaike information criterion (AIC; sensu Burnham and Anderson 2002). We first fit a null model (i.e., a "means model"); we then compared it to models that included only site-level attributes: live BA (in m^2), forest type (five classes; Fig. 1), and ownership class (five classes); then we individually examined each of the three variables that describe the context of the site by adding to the best site-level model to see if any improved the fit to the data. If the context variables improved the model, we then fit a full model with all the explanatory variables that individually improved the site-level model.

We estimated the annual probability of harvest within each of the owner and forest type classes by fitting logistic regression models with the binomial probability estimated by likelihood methods as described below (i.e., what probability would generate the observed number of successes [harvests], given the number of trials [plots], where the model predicted annual probability of being logged, raised to the time interval between re-measurements). Following Canham et al. (2013), we used an exponential model to describe the probability of being harvested:

$$\text{Prob}(\text{logging}_i) = 1 - [ae^{-mX_i^b}]^{N_i} \tag{1}$$

where X_i is adult tree basal area (m^2/ha) at the beginning of the census interval in the *i*th plot, N_i was the census interval (in years) for that plot, and a, m, and b were estimated parameters. As a result of raising the function to the power N_i, the parameters specify the effective annual probability of harvest as a function of plot basal area. Alternate models specified the a, m, and b parameters as functions of combinations of the site and context independent variables. The likelihood function for the frequency models was

$$\text{Loglikelihood} = \sum_i \begin{cases} \log(1 - \text{Prob}(\text{logging}_i)) & \text{if plot } i \text{ was not logged} \\ \log(\text{Prob}(\text{logging}_i)) & \text{if plot } i \text{ was logged} \end{cases} \tag{2}$$

We summarized harvest intensity by owner and forest type by calculating the percentage of live BA removed from a plot within each class. When comparing models of the harvest intensity, we used the negative exponential form in Canham et al. (2013): $\text{BAR}_i = a\exp(-mX_i^b)$, where BAR is the basal area removed (in percent), X_i is adult tree basal area (m^2/ha) at the beginning of the census interval in the *i*th plot, and a, m, and b were estimated parameters. The likelihood function for the intensity models was gamma distributed. Again, alternate models specified the a, m, and b parameters as functions of combinations of the site and context independent variables. We visually examined histograms of harvest intensity by ownership classes and saw no meaningful evidence of differences in the slopes of the relationship between BA and harvest intensity. There were, however, obvious differences in the intercepts of that relationship so we focused our model comparison on models including a separate intercept term.

We solved for the maximum-likelihood values of the parameters in both sets of models using 20000 iterations of simulated annealing, a global optimization routine, in the likelihood library (Murphy 2015) for the R statistical software package (R Development Core Team 2011). We evaluated the goodness-of-fit of the models using the R^2

statistic for the intensity models and a pseudo-R^2 the frequency models. The pseudo-R^2 was calculated by fitting a line through the predicted proportion of plots as compared to the observed proportion of plots across 50 evenly spaced bins spanning from zero to the maximum predicted probability (sensu Canham and Murphy 2016). We compared the strength of evidence for alternate models based on the AIC and the Akaike weights (w_i), which are the weight of evidence in favor of model *i* being the best model, given the suite of models examined.

To address our third research question, we analyzed FIA harvest patterns in conjunction with data from the NWOS, which is the Forest Service's social science complement to their biophysical Forest Inventory and Analysis (Butler et al. 2015). NWOS instruments are sent to approximately one-third of private landowners who host one or more FIA plots on their property (though the landowners do not know the precise locations of plot(s)). The NWOS uses a self-administered mail questionnaire to solicit information on landowners' attitudes, behaviors, and demographics. Between 2011 and 2013, 5601 private woodland owners from across the study region participated in the NWOS. The overall cooperation rate across the region was 56% (Butler et al. 2015). We coupled NWOS surveys to the remeasured FIA field plots to link the characteristics of private woodlands to the probability and intensity of harvesting. Landowners frequently do not answer every question within the survey, so that the number of responses varies widely among questions. We summarized the percent of harvested plots associated with all the received responses to each of the NWOS questions. Due to the abundant and irregular pattern of missing data and the potential for false inferences associated with making multiple comparisons from the data set, we opted to present the data without estimating the statistical significance of any differences.

We then used regression tree analysis (RTA) to examine (1) the probability of a harvest event occurring between measurements and (2) the intensity of harvest when it occurred in relationship to the NWOS-derived and other variables listed above. Unlike the regression model fitting and comparison techniques used to answer the first two questions, RTA is robust to missing values. It is a nonparametric technique that recursively partitions a data set into subsets that are increasingly homogeneous with regard to the response (De'ath and Fabricius 2000). RTA results in a dendrogram that shows the hierarchical relationships among predictors and between predictors and the response. We used an implementation of RTA called conditional inference trees, which requires a significant difference ($P < 0.1$, as determined from a Monte Carlo randomization test) in order to partition the data, which minimizes bias and prevents over-fitting and the need for pruning (Hothorn et al. 2006).

Results

The average remeasurement period for the FIA plots was 4.8 yr (SD = 0.5). During this time, 12% of the plots were subject to some level of harvest. Across the 20-state study region, the annual probability of harvest was 2.6%/yr (Table 2). Northern hardwoods had the highest annual probability of harvest (3.9%/yr), followed by northern pines–hemlock (3.5%/yr). The annual probability of harvest on corporate owned land (3.6%/yr) was 25% higher than private woodlands (2.9%/yr). Privately owned lands were harvested more frequently than public, with corporate lands (3.6%/yr) harvested more than three and half times more frequently than federal lands (1%/yr). Harvest probability on municipally owned lands was an exception, in that the frequency of harvest was more similar to privately owned lands than to the other public land classes.

Based on the AIC weights, the best model describing the annualized probability of harvesting included all of the site-level variables (basal area, owner class, and forest type) but none of the context variables (Table 3). Model coefficients and two-unit support intervals for the fitted parameters are given in the Supporting Information (Appendix S1: Table S1). This model suggests that, in most forest types, corporate private woodland owners have a similar probability of harvesting and the probability increases with the amount of basal area on the site (Fig. 2; Appendix S1: Table S1). In the three most abundant forest types (i.e., northern pines–hemlock, northern hardwood, and oak–hickory–pine), state and federally owned forests have similar and markedly lower probability of harvesting than do privately or municipally owned forests, across the range of basal area.

In terms of disturbance intensity, the median percent of live basal area removed within harvest events was 40% on

Table 2. Annual probability of harvest by forest type and owner group.

Forest type	Private woodland owners	Corporate	State	Federal	Municipal	All
Aspen–birch	0.029	0.028	0.018	0.008	0.023	0.022
Northern hardwood	0.042	0.051	0.019	0.015	0.041	0.039
Northern pines–hemlock	0.045	0.053	0.026	0.021	0.036	0.035
Oak–hickory–pine	0.028	0.029	0.014	0.010	0.025	0.024
Spruce–fir, Lake States	0.016	0.010	0.007	0.002	0.009	0.008
Spruce–fir, other states	0.037	0.029	NA	NA	NA	0.031
Bottomland forests	0.014	0.019	0.006	0.006	0.004	0.013
All	0.029	0.036	0.016	0.010	0.024	0.026

Note: NA indicates insufficient sample (<100 plots).

Table 3. Models evaluated for frequency of harvest.

Model and variables included	No. parameters	Pseudo-R^2	AIC	w_i	Rank
Null					
None, means model	1	0.206	28708.11	0.0	8
Site-level models					
Basal area	2	0.625	27562.21	0	7
Basal area, forest type	16	0.846	27142.62	0.0	6
Basal area, owner	10	0.853	26937.36	0.0	5
Basal area, owner, forest type	**70**	**0.91**	**26686.19**	**1.0**	**1**
Best site-level model + context variables					
Basal area, owner, forest type, HHMI	105	0.956	26735.65	0.0	2
Basal area, owner, forest type, population	105	0.959	26737.65	0.0	3
Basal area, owner, forest type, distance	105	0.943	26739.22	0.0	4

Notes: Boldface type highlights the best model based on the Akaike information criterion (AIC). Note that the pseudo-R^2 is based on a comparison of the predicted vs. observed proportion of plots harvested across 50 evenly spaced bins spanning zero to the maximum predicted probability of harvest. (Basal area refers to live basal area [m^2/ha] at the time of the first measurement.) HHMI, household median income; w_i, Akaike weight.

state-owned land, 40% on corporate owned land, 39% on municipal land, 23% on federal land, and 20% on private woodlands (Fig. 3). Aspen–birch was the only forest type for which high intensity harvests (i.e., >80% of the basal area removed) outnumber low-intensity harvests (i.e., <20% of the basal area removed), however, this pattern only holds when observing all owners in aggregate. The majority of aspen–birch harvests on private woodlands are low intensity. This pattern was consistent across all forest types, i.e., the majority of private woodland harvests were in the low-intensity class and the distribution follows a “reverse J” shaped curve. While corporate, state, and municipal forests tend to be harvested more intensely, they are still overwhelmingly partial harvests.

Based on the AIC weights, the best model describing the intensity of harvest included all the site variables and all the context variables (Table 4). This model includes a separate intercept term for each combination of owner by forest type. Corporate, state, and municipally owned aspen–birch forests have the highest modeled harvest intensity (Fig. 4; Appendix S1: Table S2, Table S3). Private woodland and federally owned forests had among the lowest modeled harvest intensity. Modeled harvest intensity decreased with increasing live basal area, with increasing household median income, and (less so) with increasing population density; harvest intensity increased as the distance to the nearest road increased (Fig. 4).

The NWOS data coupled to harvest data revealed few individual owner demographic characteristics associated with harvest frequency (Fig. 5). Aggregate data describing the age of landowners, their level of educational attainment, whether they are retired, their ownership size, or how long they owned their land all lack an apparent association with the frequency of harvesting. The owner’s income is one potential exception, as the probability of harvest generally declined as the owner’s income increased.

The RTA of harvest frequency identified five significant partitions using three different predictor variables, none of which came from the NWOS survey (Fig. 6). The first partition was based on whether plots had more or less than 16.9 m^2/ha of live basal area. The group with more live biomass had higher probability of harvest and was further portioned based on forest type and again on distance from road. Sites with the highest probability of harvest came from the spruce–fir, northern hardwood, aspen–birch or northern pines–hemlock and were within 131 m of a road. Overall, sites with the lowest probability of harvest were those with <4.8 m^2/ha of live basal area.

The RTA of harvest intensity using the 478 NWOS respondents for which a harvest had occurred during the previous remeasurement period identified four significant partitions, one of which, area of woodland owned, came from the NWOS (Fig. 7). The first partition was based on whether plots had more or less than 7.8 m^2/ha of live basal area. Overall, sites with the most intense harvests had >7.8 m^2/ha of live basal area, were in the aspen–birch group, and were >275 m from the nearest road. On average, harvests at these sites removed 90% of the basal area. Non-aspen–birch sites with >7.8 m^2/ha of basal area were further partitioned based on whether the landowner owned >2900 ha of forests, with the large landowners harvesting much more intensely; however, this group was represented by only seven FIA plots.

Discussion

An earlier analysis of the regional inventory data showed that forest type and basal area were important predictors of harvest frequency and intensity, and here, analyzing the same data, we show that social variables, particularly ownership class, are at least as important for characterizing regional harvest regimes. Indeed, the probability of harvest within a forest type can vary by as much as 700% depending on the owner class. Since harvest is, by far, the largest cause of tree mortality in the region, this refined understanding of the factors affecting the harvest regimes is critical for understanding regional variation in forest structure, composition, and carbon dynamics.

A significant ecological question emerges from this analysis: How do modern harvest regimes, with their mix of social and biophysical drivers, influence and interact

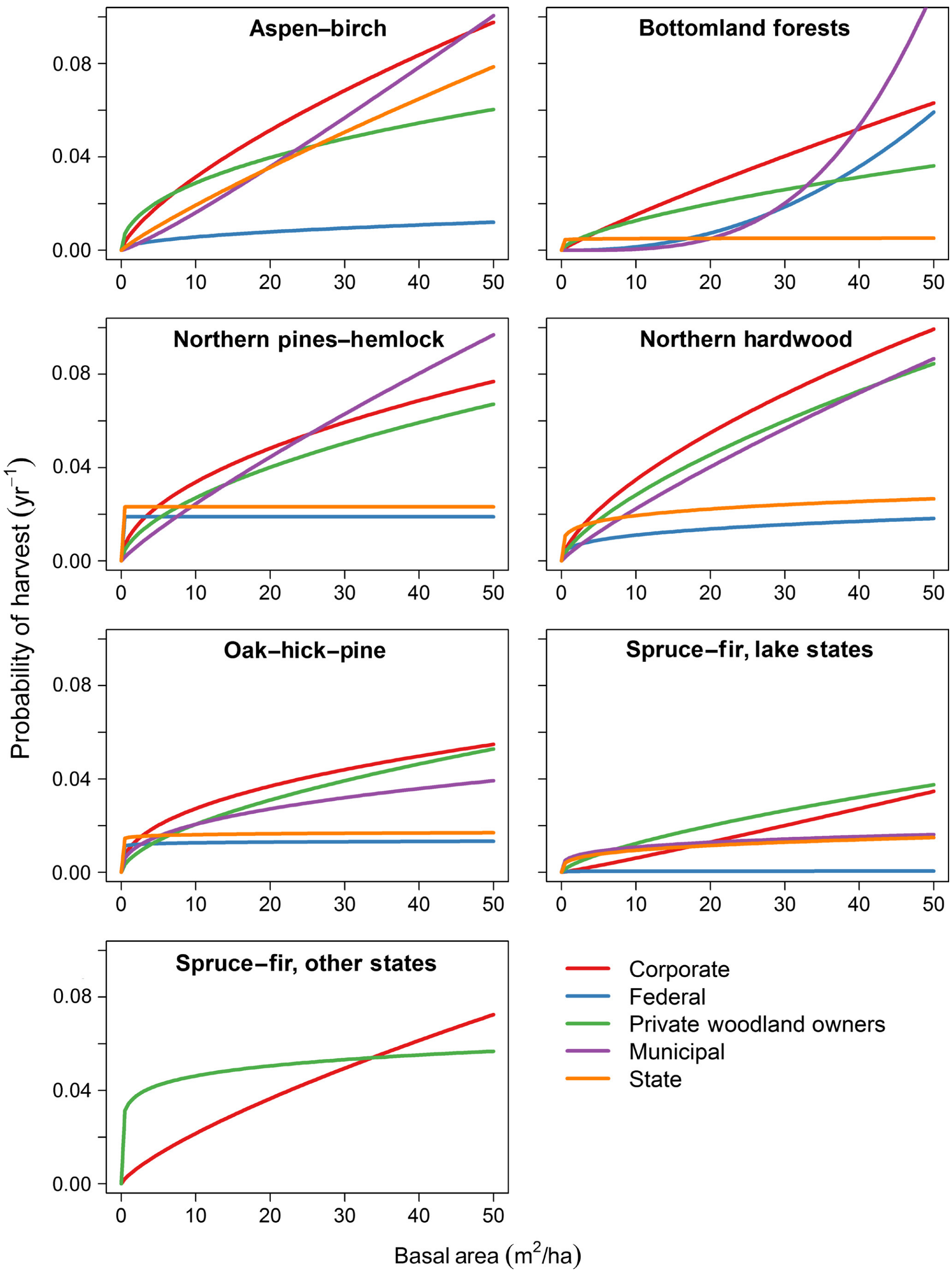

FIG. 2. Estimated annual probability that a plot is subject to harvest as a function of the live basal area at the time of the first plot measurement for seven forest types and five owner groups. Note that no line is plotted where insufficient data were available ($n < 100$). [Color figure can be viewed at wileyonlinelibrary.com]

with natural disturbances and processes? Natural disturbances are uncommon in northeastern forests, as compared to other regions in North America (Vanderwel et al. 2013). Therefore, the most important factor driving change in northeastern forests is probably the protracted recovery from colonial-era land use, when much of the region was deforested or heavily cut over. Relative to the pre-colonial period, modern forests are comparatively even aged, lacking in dead wood, and in dominance of late-successional tree species (D'Amato and Orwig 2008, Keeton et al. 2011, Runkle 2013, Thompson et al. 2013, McGarvey et al. 2015). Given this, there are a few ways in which the modern harvest regime could accelerate a trajectory toward that pre-colonial forest structure, which is often cited as a coarse filter conservation goal. Indeed, since at least the mid-1990s, many scientists and

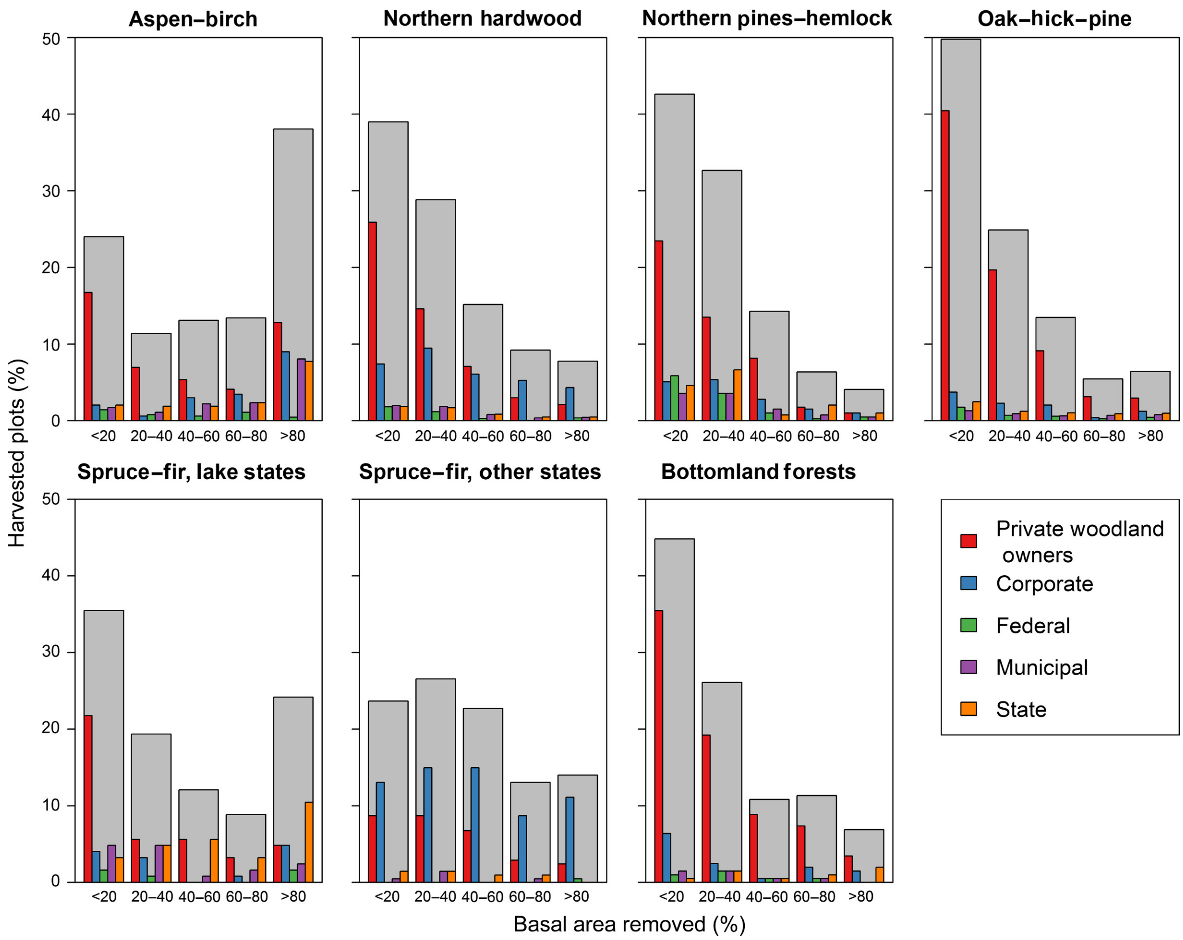

FIG. 3. Distribution of harvesting intensity (i.e., percentage of basal area removed) by forest type and land owner class. Gray bars show the percentage of basal removed across all owner classes. [Color figure can be viewed at wileyonlinelibrary.com]

foresters have argued that harvests should more closely resemble natural disturbances at stand to regional scales (Hunter 1993, Seymour et al. 2002, Thompson et al. 2006). The modern harvest regime is similar to natural disturbance regimes insomuch as it results in a spatially and temporally variable pattern of partial stand replacement, and the low-intensity partial harvests create gaps that promote vertical heterogeneity and a more

TABLE 4. Models evaluated for intensity of harvest.

Models and variables included	No. parameters	R^2	AIC	w_i	Rank
Null					
None, means model	2	0	42497.51	0.0	10
Site-level models					
Basal area	3	0.016	42440.11	0.0	9
Owner type	6	0.083	42148.09	0.0	7
Forest type	8	0.102	42210.79	0.0	8
Owner, forest types	36	0.171	41920.3	0.0	6
Best site-level model + context variables					
Distance to road, owner, and forest types	37	0.170	41903.81	0.0	5
HHMI, owner, and forest types	37	0.167	41903.45	0.0	4
Population density, owner, and forest types	37	0.172	41888.02	0.0	2
Basal area, owner, and forest types	37	0.176	41896.55	0.0	3
Full model (all context variables)					
Basal area, population density, HHMI, distance to road, owner, and forest types	**40**	**0.181**	**41841.99**	**1.0**	**1**

Notes: Boldface type highlights the best model based on AIC. Basal area refers to live basal area (m^2/ha) at the time of the first measurement. HHMI, household median income; w_i, Akaike weight.

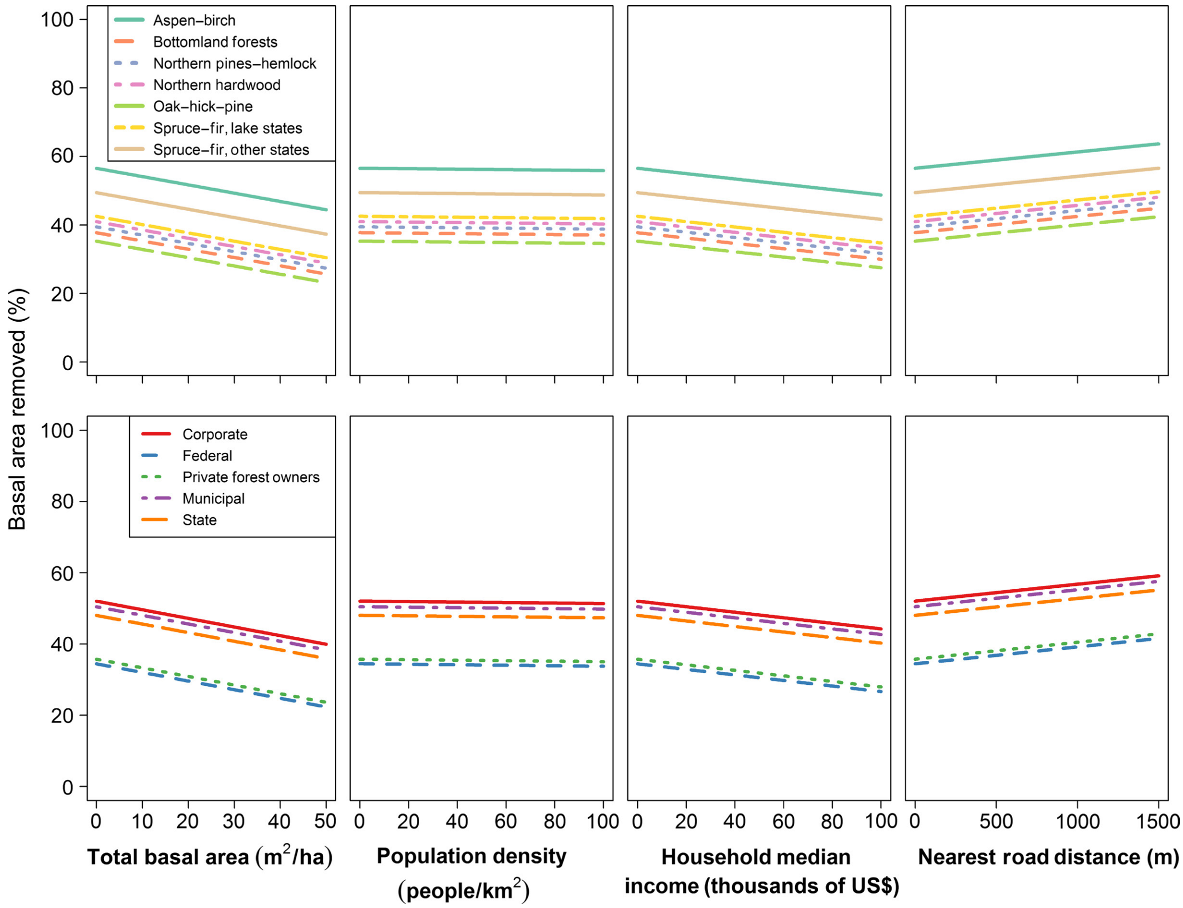

Fig. 4. Estimated intensity of harvesting on plots as a function of social and biophysical predictors based on the full model detailed in Table 3. Note that separate intercept terms were fit for each combination of owner and forest type but, to ease interpretation, a weighted mean intercept for each owner and forest type is shown. Please see Appendix S1: Table S2 for the full list of 35 intercept terms. [Color figure can be viewed at wileyonlinelibrary.com]

complex age structure. On corporate-owned aspen and spruce forests, where the harvest regimes are more intense, the natural disturbance regimes (fire and budworm) are also more intense (Fig. 3), which may lessen the difference between harvesting and natural disturbance. Comparing our analysis to Vanderwel et al. (2013), who quantified mortality rates due to natural disturbances, suggests that the rates of partial harvest exceed rates of tree mortality caused by wind and ice by a factor of 2–10 depending on ownership and forest type.

In many other ways, however, the modern harvest regime is diverting the forests' trajectories away from the historical condition, particularly through the removal of large trees and dead wood, which were abundant in pre-colonial forests. Compositionally, harvesting is somewhat neutral in its effects on restoring the historical species mix due to its focus on a suite of merchantable species that happen to be characteristic of early to mid-succession forests (with the important exception of sugar maple; Canham et al. 2013). Species that are underrepresented in the region relative to pre-colonial forests, such as shade-tolerant hemlocks and beech, are not preferentially harvested (Canham et al. 2013). Ongoing research is quantifying how social attributes influence the composition (species and size) of what is removed and what is left on site and, in turn, how this affects continued forest recovery dynamics.

Unlike the biophysical factors, social factors affecting harvest regimes lack analogs in natural disturbances. The owner mosaic, the road networks, and human demographical variability do not vary spatially along ecologically meaningful contours. This may be problematic for forest managers or policy-makers hoping to mitigate potential ecological impacts of harvesting by emulating natural disturbances. Alternatively, there may be ways to use the socially driven variability in harvesting to achieve regional-scale ecological objectives. For example, forest practice policies may need to look across ownerships and rely on public lands to provide areas with lower levels of disturbance and older forest while looking to private lands to provide early seral habitat conditions, as has been done in the Pacific Northwest (e.g., Thompson et al. 2009). Of course, this may be impossible where there is little owner-class diversity within a forest type, as is the case for the oak–hickory–pine

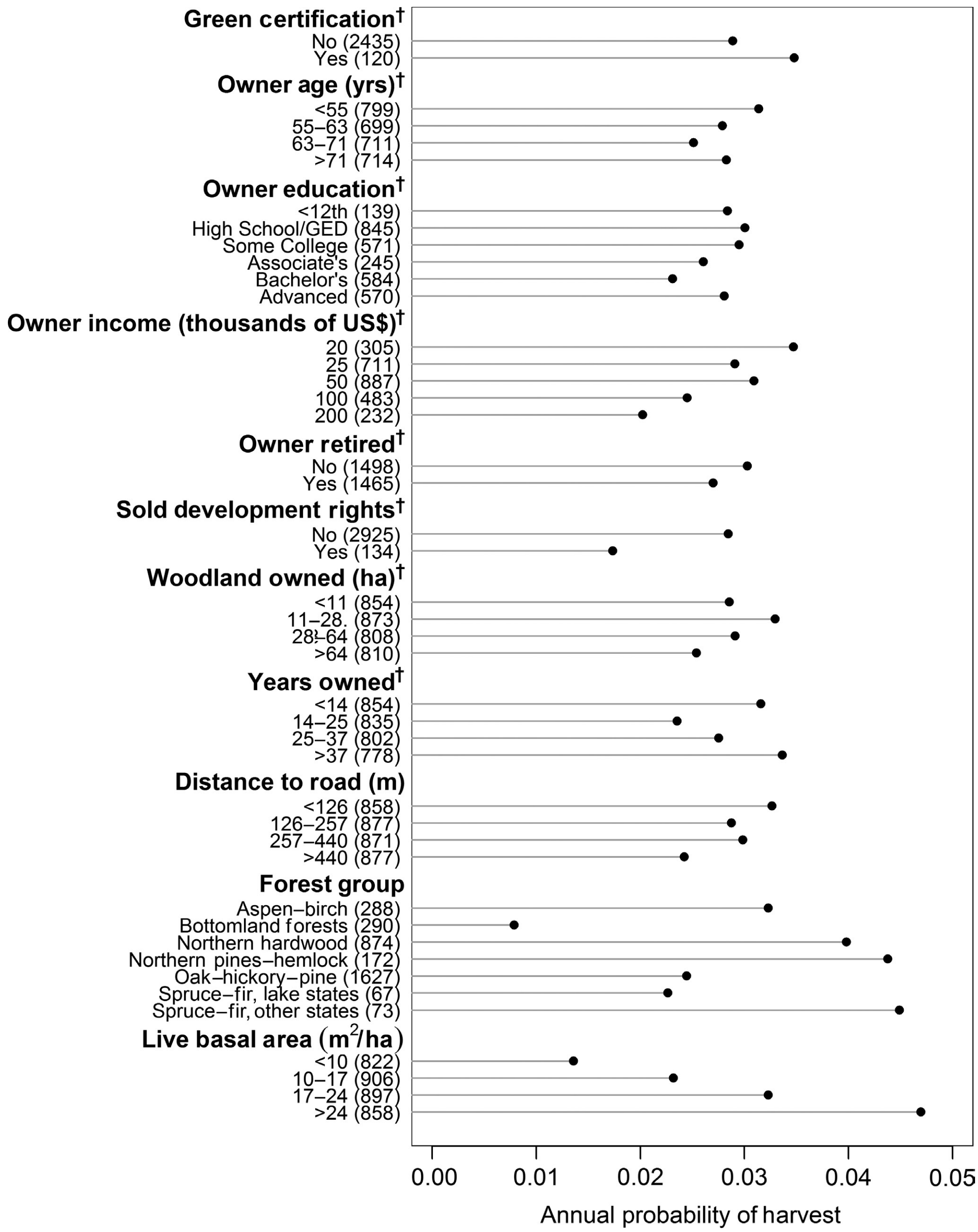

FIG. 5. Estimated annual probability of plots included within the National Woodland Owner Survey (NWOS) being subject to harvest. All plots are on privately owned woodland. All variables included above were used as potential predictors within the conditional inference tree analyses shown in Figs 6, 7. Variables with a dagger (†) are taken from the NWOS.

type, which is overwhelmingly controlled by the private woodland owner classes (Fig. 1). Beyond owner class, our analysis suggests that knowledge about the social context for harvesting would have to guide the intensity of harvests as opposed to their frequency. Indeed, all the context variables we examined—household median income, distance to nearest road, population density—were included in the best model of harvest intensity, while none were in the best model of harvest frequency.

Of the social factors considered, ownership class was the most predictive for both the frequency and the intensity of harvest regimes. But ownerships are ephemeral; so the future of the harvest regime may be strongly influenced by changes in ownership and the resulting changes in harvest behavior. Institutional forest ownership in the region has changed significantly in recent decades. For example, between 1980 and 2005 approximately 10 million hectares in Maine were divested by vertically structured timber or wood products companies selling to Timber Investment Management Organizations (TIMOs) and Real Estate Investment Trusts (REITs; Daigle et al. 2012). Whereas industrial

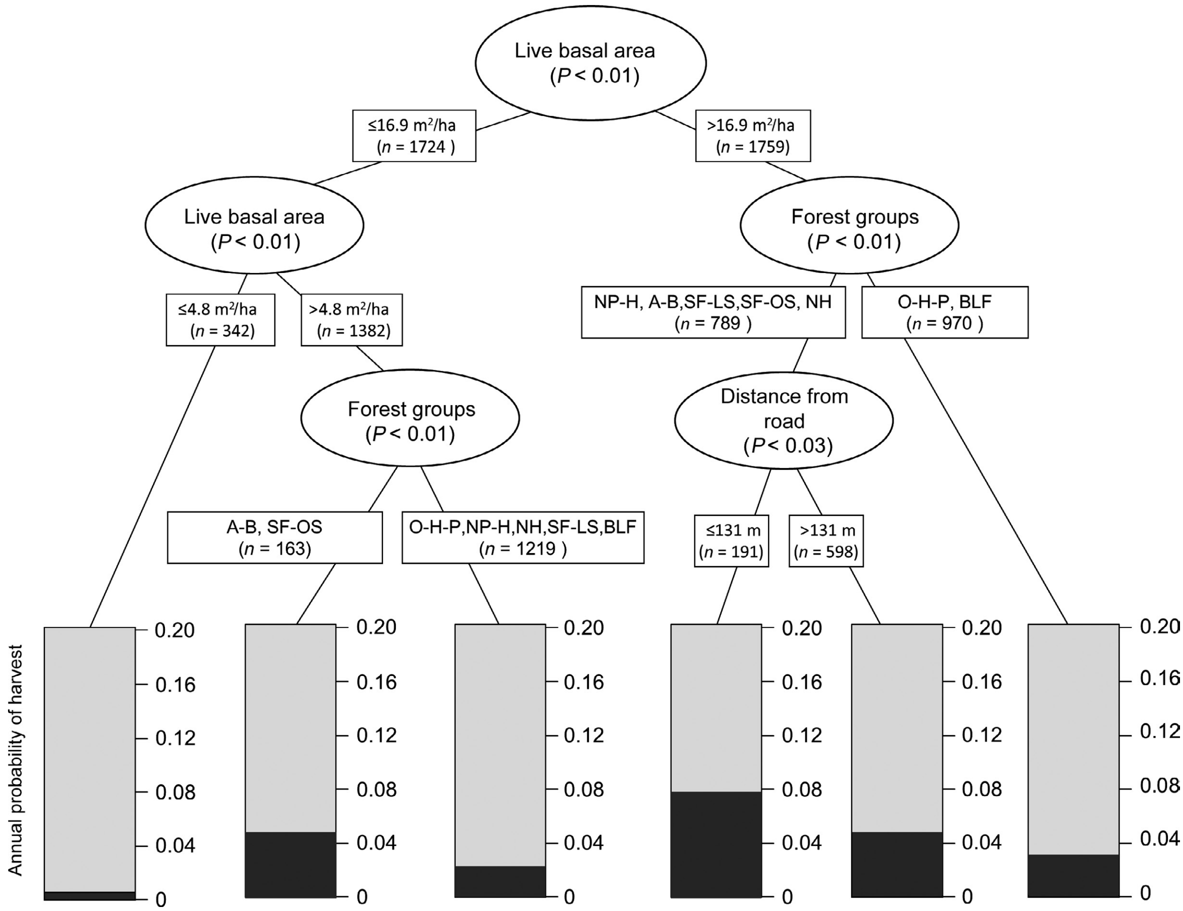

FIG. 6. Conditional inference tree showing the annual probability of National Woodland Owner Survey field plots being subject to harvest after partitioning the data using the predictors shown in Fig. 5. P values at each node are from a Monte Carlo randomization test. In order for a split to occur, the P value must be <0.05. Note that units given in the terminal nodes have been converted to annual probabilities for ease of interpretation and consistency, but the actual analyses were done based on the percentage of plots harvested within the remeasurement period. Abbreviations are NP-H, northern pines–hemlock; A-B, aspen–birch; SF-LS, spruce–fir, lake states; SF-OS, spruce–fir, other states; NH, northern hardwood; O-H-P, oak–hickory–pine; BLF, bottomland forests.

owners were motivated by the consistent production of fiber for nearby mills, harvest by investment organizations is influenced by global-scale markets and investor rate of return on short (10–15 yr) time horizons (Zhang et al. 2015). As such, there is great concern that the transfer of industrial forests to TIMOs and REITs could lead to abrupt changes in harvest regimes that could transform the structure and dynamics of the region's forests (Jin and Sader 2006, Daigle et al. 2012).

Private woodlands dominate the ownership mosaic so it is significant to learn the extent to which they differ in harvest practices from other owner-classes. Private woodland owners harvest somewhat less frequently than do corporate owners; the primary difference between these two owner-classes relates to the intensity of harvests when they occur. Private woodlands are harvested less intensely than other owner-classes in the same forest type. Indeed, in every forest type, the majority of private woodland owner harvests remove <20% of the live basal area. Beyond these higher-level comparisons between private woodland owners and other owner-classes, we found little predictive information either from the FIA, census, or NWOS data to explain harvest behavior within the private woodland owner-class. Such unpredictable harvest behavior is consistent with Kittredge (2004), who presented a decision cycle for private woodland owners (i.e., family forests owners in his parlance), whereby the owner is satisfied with the amenity benefits the land provides (e.g., privacy, beauty, recreation) until an exogenous event potentially unrelated to the land itself (e.g., medical expenses, college tuition, etc.) occurs that stimulates an interest in financial income. Faced with an unexpected expense, harvesting may generate the required income. This type of decision cycle would be undetectable by the type of demographic data collected by NWOS and speaks to the larger variation within the private woodland owner category. In light of these results, it seems that aggregate private woodland owner harvest behavior may be a source of significant

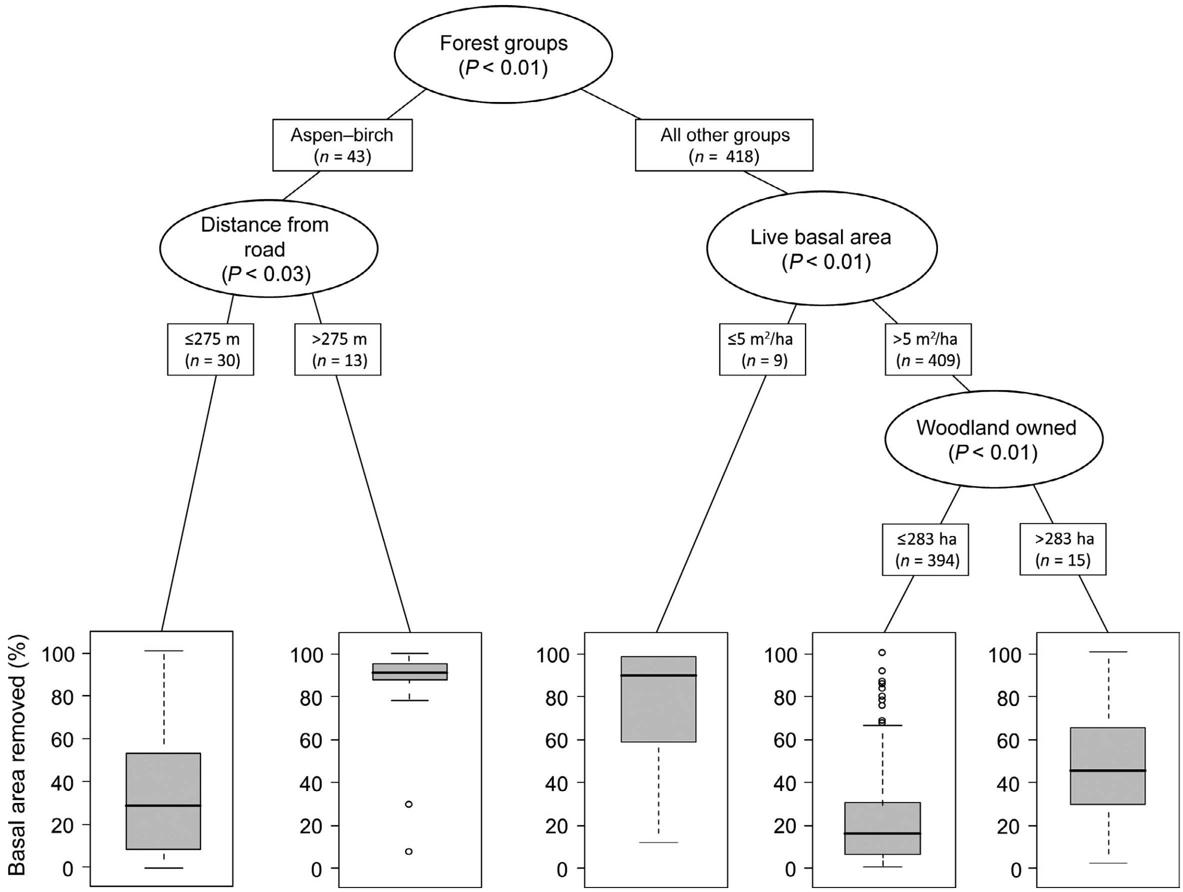

Fig. 7. Conditional inference tree showing the intensity of harvesting on National Woodland Owner Survey field plots after partitioning the data using the predictors shown in Fig. 5. P values at each node are from a Monte Carlo randomization test. In order for a split to occur, the P value must be <0.05. Plots at terminal nodes show the intensity of harvest as percent basal area removed. Boxplots are constructed such that the dark line is the median, the box is the inner quartile range, whiskers are 90th percentile, and the dots are outliers.

uncertainty in future development of stand structure. The inherent variation in the relatively large private woodland owner class, and their reactive harvest behavior due to external stimuli or unplanned financial need, confounds the ability to predict future conditions in a consistent way, relative to other owner classes. This finding has value, as one might otherwise conclude that private woodland owners behave uniformly according to their professed attitudes (e.g., consistent and prevalent ownership attitudes favoring privacy, aesthetics, and nature would suggest negligible harvest), or follow other predictable rationales (e.g., private woodland owners of lower affluence will harvest more due to higher financial need).

Conclusion

In the northeastern United States, forest harvesting is a dominant ecological disturbance, yet is often excluded from regional analyses of forest change. Based on recent forest inventory data, we estimate that 2.6% of the region's forests are subjected to some level of harvest each year, but the frequency of harvesting varies widely based on biophysical and social factors. Forest ownership type explains much of the variation; private forests are harvested twice as frequently as public forests. Harvests throughout the region are overwhelmingly partial disturbances, and many remove just a small fraction of the available biomass. Unlike harvest frequency, though, there is no clear divide between public and private forests in terms of harvest intensity. In fact, harvesting on private corporate-owned land is, on average, most intense while harvesting on private woodlands (i.e., family forests) is least intense. Public-land harvest intensities all fall in between. More than one-half of the region's forests are private woodlands. As such, a better understanding of the social attributes related to harvest behavior on these lands is necessary for developing a predictive understanding regional-scale forest dynamics. Unfortunately, the detailed demographic information regarding private woodland owners we examined offered little insight into aggregate harvest frequency or intensity. Nonetheless, our analysis shows how coupling social and biophysical variables can be used characterize variation in harvest regimes within the context and rubric of ecological disturbance theory and, thus, increase our understanding of regional-scale socioecological dynamics.

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Supporting Information

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