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Understanding the Spatial Pattern and Driving Factors Associated with Timberland Ownership Change in the Northern United States

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Abstract

This study analyzes changes in timberland ownership from 2003 to 2012 across the northern United States based on Forest Inventory and Analysis data identified according to five ownership categories. A total of 26,940 FIA plots that were remeasured between selected years were used for the analysis. Publicly available corporate ownership data were investigated and used to differentiate industrial and institutional (timber investment management organizations [TIMO] and real estate investment trusts [REIT]) ownership. Kernel density, Ripley's K-function, and multinomial logistic regression (MLR) methods were used to study spatial patterns of timberland ownership and to explore statistical relationships. Among FIA plots showing ownership changes, the largest observed shift was from industrial to institutional ownership, with a 45% increase in the number of plots, equivalent to almost 1.4 million acres of timberland area. Bivariate Ripley's K-function showed significant clustering for shifts between industrial and institutional ownership. A MLR model identified forest type as a significant factor associated with the transition of industrial timberlands to either institutional or family forest ownership. In addition, shifts from industrial to institutional ownership were related to road access and population density.

Study Implications: For the past few decades, we have seen an unprecedented trend of change in timberland ownership in the United States, particularly the divesture and change of traditional vertically integrated forest product companies into institutional ownership, i.e., timber investment management organizations (TIMOs) and real estate investment trusts (REITs). In this situation, key research questions to ask are where are these changes taking place in spatial terms and what are their possible linkages with different socio-economic and forest related factors. Such knowledge will help devise policy strategies to monitor and understand the affects of changing timberland ownership on future forest resources.

Keywords: FIA, multinomial logistic regression, timberland ownership, TIMO, REIT, Ripley's K-function, kernel density estimation

Approximately 58% of the 766 million acres of forest land in the United States is under private ownership, with the remaining 42% under various types of public ownership (Oswalt et al. 2019). Private timberlands provide most of the forest products in the United States to meet national and global market demands and annually contribute $102 billion dollars to the nation's gross domestic product (Wan and Fiery 2013). About two-thirds of the private ownership is noncorporate, which includes individuals, nongovernmental organizations, clubs, trusts, and other unincorporated groups. The remaining one-third of the private ownership is corporate, which includes vertically integrated forest product companies (VIFPCs), TIMOs, REITs, and other companies (Sun 2011, Butler 2016, Oswalt et al. 2019). The Northern Forest region has an even higher percentage of private timberland ownership, with 9% corporate owners and 67% family forest owners (USDA Forest Service 2001). Forest ownership plays a vital role in the management of forest resources, because ultimately it is the landowners who make decisions about parcelization and fragmentation, harvests, access to recreation, and other activities related to forests (Butler 2016).

Forest ownership patterns in the United States have changed dramatically over the past couple of decades. The biggest change in timberland ownership has been the accelerating trend of VIFPCs selling their properties to TIMOs and REITs (hereafter referred to as 'institutional' owners) (Block and Sample 2001, Zhang et al. 2012). Reasons for this change are numerous and include the generally weak financial performance of the forest products industry, growth in low-cost international fiber supply resulting in large firms consolidating followed by strategic restructuring away from timber supply, accounting principles that undervalue timberland under industrial ownership, and favorable tax policies under institutional ownership that disfavor industrial ownership (Block and Sample 2001, Clutter et al. 2005, Zhang et al. 2012, Butler and Wear 2013).

The impact of this trend is that millions of acres of forest land have shifted ownership from the forest industry to TIMOs, REITs, and others (Butler 2016). Across the country, timberlands owned by VIFPCs have decreased from 95% to 32% within the corporate category, whereas financial investors (equivalent to TIMOs and REITs together) increased from 5% to about 63% from 1996 to 2009 (Campbell Group LLC 2010). Multiple studies have identified that the potential impacts of the shifts in timberland ownership could range from minimum to substantial depending on the locations and the actors involved (Hagan et al. 2005, Randle et al. 2015). Some studies have suggested that there could be changes in forest management in terms of increased management intensity, shorter rotations, and increased harvest-to-growth ratio (Jin and Sader 2006, Hatcher et al. 2012, Gunnoe et al. 2018). Others have also hinted toward possible ecological impacts such as shifts in species composition, timberland fragmentation, land-use change, and reduction in biodiversity (Clutter et al. 2005, Hagan et al. 2005, Fernholz et al. 2007, Bliss et al. 2010, Gunnoe and Gellert 2011). Following the trends in pine plantations in the Southeast and conifer plantations in the Pacific Northwest, mixed softwood-hardwood holdings in the Northeast region have also been influenced by increasing institutional ownership (Block and Sample 2001, Dedam and Zwick 2006). Studies in Northern Maine and the Upper Peninsula region of Michigan have documented divestures and transactions of industrial forests to institutional ownership (Jin and Sader 2006, Froese et al. 2007). However, there is a gap in knowledge regarding the spatial pattern of change in ownership across the whole Northern region and among all categories of private ownership.

The main objectives of this study are to explore the spatial pattern of change in timberland ownership from 2003 to 2012 and to model the changes based on several driving factors. Specifically, we tried to quantify the changes in timberland ownership, explore spatial patterns of distribution and changes in ownership, and relate the changes to selected socio-economic and forest related factors.

Data and Methods

Study Area

The study covers 20 northern states comprising the area covered by the Northern Research Station of the USDA Forest Service (hereafter referred to as USFS-NRS), Forest Inventory and Analysis (FIA) work unit (Figure 1). It goes as far as Minnesota in the west and Missouri in the south, lying under an approximate geographical region of 36°00' N to 49°23' N latitude and 66°53' W to 97°14' W longitude. The North is the most heavily forested region in the United States, with 42% of its land area covered by forest (Shifley et al. 2012).

Inventory Data

Forest inventory data from permanent FIA plots were used for the analysis. FIA plots are centered on sample points randomly located within hexagonal grid cells established across the United States with approximately one sample plot for every 6,000 acres. Each plot is remeasured approximately every 5–7 years in the Northern Forest Region (USDA Forest Service 2007). Even though the trend of ownership change was evident from more than two decades ago, we could not incorporate FIA data from periodic inventories because of the lack of evenly distributed sample points and the inconsistencies in inventory methods used prior to annual inventories. Moreover, we were constrained by the availability of propriety data of the owners for older data, which would be needed to categorize corporate ownership. We selected our time frame from 2003 to 2012 based on the availability of data for all the states within the study area such that they were measured at least twice. Variables used in this research included approximate plot coordinates, slope, aspect, elevation, site index, stand age, ownership category, and forest type. These variables were derived from Tree, Plot, and Condition tables in the FIA database (Woudenberg et al. 2010). For the plots with more than one condition, information from the condition occupying much of the plot area was used. Additional data required to identify timberland

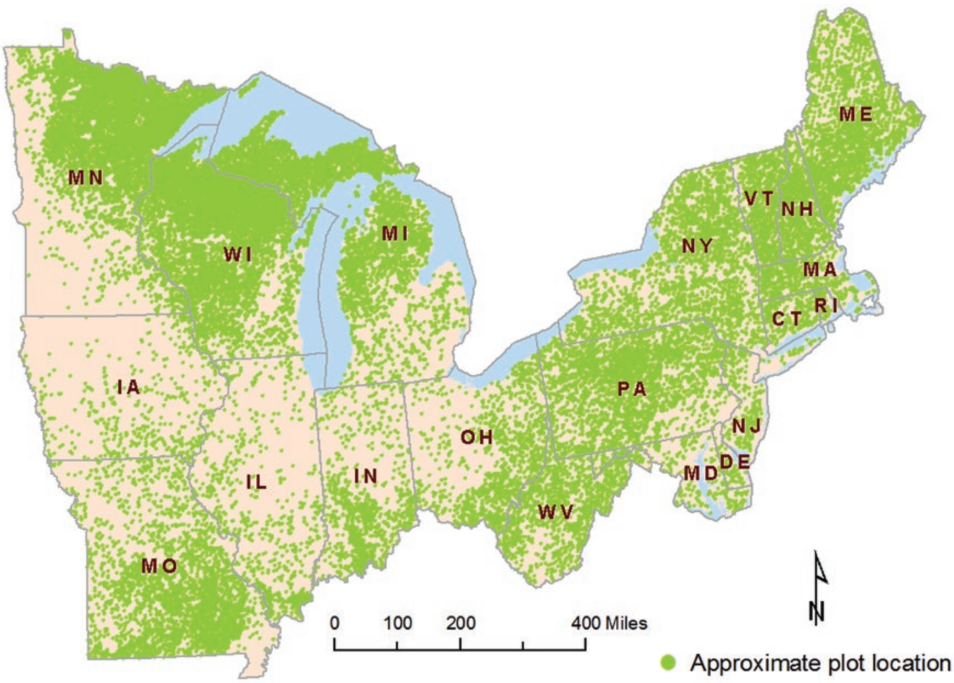

Figure 1. Study area showing 20 northern states, with green dots representing the approximate locations of forested FIA plots used in the study.

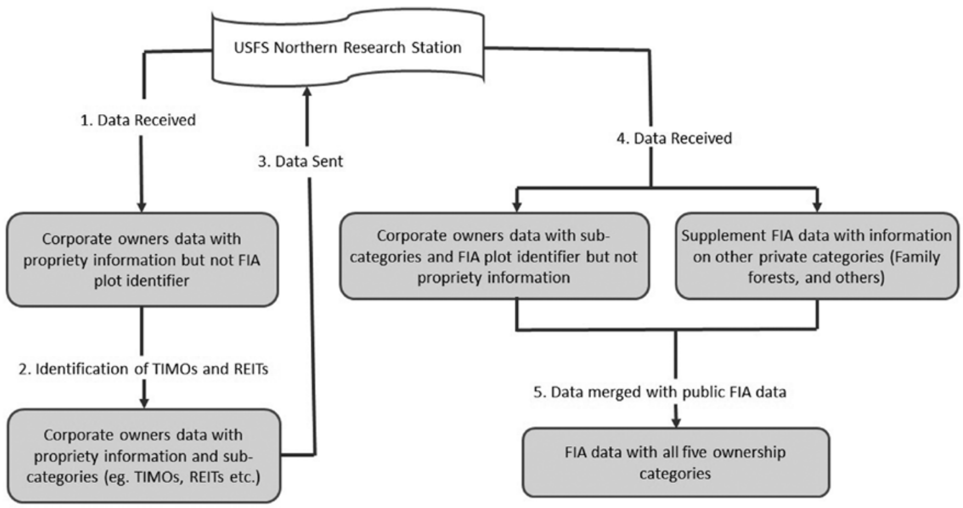

Figure 2. Steps showing data transfer and identification of five different ownership categories for the study. Numbers 1 to 5 in the figure show the sequence of events followed during the process.

ownership categories were obtained from USFS-NRS, using methodology described below (Figure 2).

Socioeconomic Data

Population density, access to roads, urban centers, and sawmills were also incorporated in the study. Spatial data for population were obtained for each census tract from 2010 (US Census Bureau 2014). Likewise, primary roads in 2010 and urban area in 2010 were obtained from the US Census Bureau (US Census Bureau 2014). Tabular data with geographical coordinates of sawmill locations in 2005 were received from USDA Forest Service (Prestemon et al. 2005).

Identifying Land Ownership Categories

We selected only those plots that were measured twice from 2003 to 2012 and had at least one forested land condition. After filtering out unwanted plots, we were left with 26,940 plots for our analysis, which is only about 32% of the total FIA plots in the study area. Each plot represents four to six years of change. First and second sets of measurements were done between 2003 to 2007 and 2008 to 2012, respectively. For this study, we categorized timberland ownership into five major categories: (1) industrial owners (traditional vertically integrated forest-based companies), (2) institutional owners (TIMOs and REITs), (3) family forest ownership (FFO), (4) public owners, and (5) other owners (Native American tribal lands, nongovernmental organizations, trusts, unincorporated groups, nonforest corporates etc.).

A critical step in data preparation was to identify the institutional owners from among other subcategories of corporate private owners (Figure 3). We received proprietary data of corporate owners from USFS-NRS that included names and addresses corresponding to each FIA plot but not the location or plot identifier information, as a matter of privacy. As a first step, we identified all TIMOs and REITs using their names and addresses. For the most part, we used lists of TIMOs and REITs from similar work done by Zhang et al. (2012) in the southern United States along with other recent online sources (Neilson 2011, FORISK 2015) and personal correspondence. Next, among the remaining data, we identified the plots of owners who had wood-processing facilities as forest industrial plots. All the remaining plots (identified as nonforest corporate, conservation organizations, or unknown groups) were then merged together into the other ownership category. We could not identify 0.38% of data (unknown category) into any of the abovementioned groups, leading to a degree of uncertainty in the analysis. The classified proprietary data were sent to the USFS-NRS and we received new set of data with corporate ownership categories and plot identification codes but without information on individual corporate owners. Plot identification codes in this data were then used to link them with the publicly available FIA data used in this analysis. Publicly available FIA data only distinguishes between private and public lands but does not provide detailed private subcategories. Detailed subcategories of private plots (corporate, individual, and others) were also obtained from the USFS-NRS office.

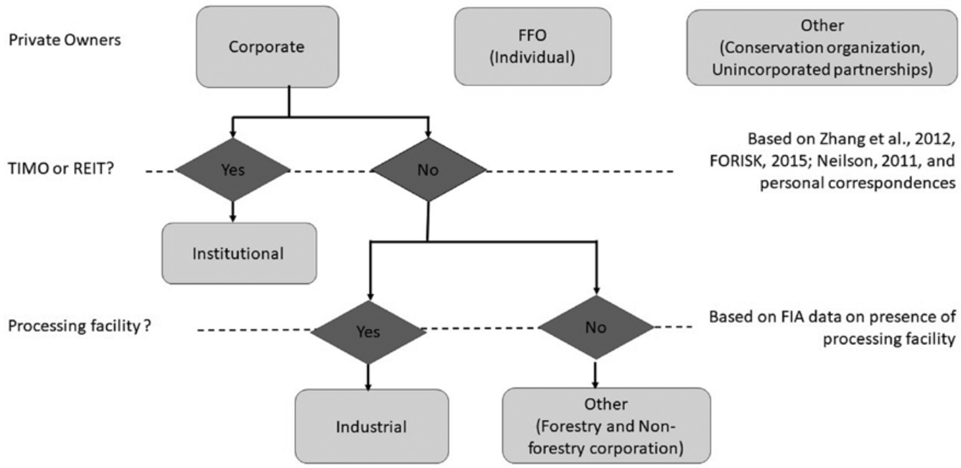

Figure 3. Process followed in identification of subcategories within corporate ownership as adapted and modified from Zhang et al. (2012). Also shown are other private ownership categories (FFO, and others).

A surface map of population density was created from census blocks, and distance maps were created from road networks and urban centers in ArcGIS (ESRI 2014). Data from each of these thematic raster maps were then extracted to all the points representing FIA plots.

Kernel Density

Kernel density estimation (KDE) has often been used in studies related to forest cover change, forest fire occurrence, wildlife habitat suitability, and urban expansion (Liu et al. 2011, Long and Nelson 2012). Butler et al. (2014) applied thiessen polygons to categorize different timberland ownership categories, but we chose to use KDE because it provides an effective method of visualizing high density (hot spot) areas. We used the KDE tool in ArcGIS (ESRI 2014) to produce smoothed density raster surfaces for each ownership category using appropriate bandwidth (radius of the search window) for two separate measurement time periods and for changes in ownership categories between the two time periods.

We used approximate longitude and latitude information in the FIA data to locate the studied plots (Figure 1) for kernel density analysis. Distribution of the FIA plots was not random across the study area because of the inclusion of nonforest areas, which would falsely portray hot spots of plot density in the kernel density maps. To overcome this problem, we created a kernel density map of all studied FIA plots (all selected forested plots) to capture their distribution, ignoring ownership information, and used this layer as a common denominator to explore the relative distribution of individual ownership categories and changes in ownership categories. Based on several iterations with a range of bandwidths, we chose a bandwidth of 124 miles (200 km) for the maps, which would provide the best visual results and interpretation of our results.

Ripley's K-Function

Ripley's K-function can be used to assess the presence of clustering or regularity among points across a range of distances (bandwidths) (Baily and Gatrell 1995). Because of the presence of nonstationarity of plot distribution in the study area, we applied a bivariate K-function (Baily and Gatrell 1995), given below, instead of an individual K-function. With this method, the spatial pattern of subsample events can be explored by assessing differences in K-values between main and subsample events. For example, in terms of ownership distribution, overall FIA plot distribution would be the main event and individual ownership categories would be a subsample event. In the case of ownership shifts, total ownership shifts (e.g., from any one ownership category to any other ownership category) would be the main event and specific ownership shift (e.g., from industrial to institution) would be a subsample event. The bivariate K-function is defined as:

$$\widehat{K}_{ij}(h) = \frac{R}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} I_h(d_{ij})$$

where, $\widehat{K}_{ij}(h)$ is the K-function from one set of points to another set of points, h is the radius of the search circle, R is the area, n_1 is the number of main events, n_2 is the number of subsample events, d_{ij} is the distance between i^{th} main event and j^{th} subsample event, and I_h is an indicator function, which is 1 if $d_{ij} \leq h$ and 0 otherwise.

Under a constant intensity Poisson process, the expectation of Ripley's K-function is $K(h) = \pi h^2$. If there is clustering, $K_{12}(h)$ should be larger than what it would be under random labeling and smaller if there is dispersion (Cressie 1993). For data analysis, the variance stabilized Ripley's K-function, called the L-function, is generally used. The L-function, a square root transformation of the K-function, linearizes K, stabilizes its variance, and is approximately zero under the assumption of a Poisson process (Boyden et al. 2005).

$$\widehat{L}_{ij}(h) = \sqrt{\frac{\widehat{K}_{ij}(h)}{\pi}} - h$$

where $\widehat{L}(h)$ is the estimated L-function, π (pi) is a constant, and others are as described above. We performed 200 random labeling simulations for each experiment and reported the 95% confidence interval for the L-function to plot upper and lower confidence envelopes.

Multinomial Logistic Regression

A MLR model establishes a relationship between a dependent variable with more than two unordered categorical responses and a set of independent variables. It tests the probability of a response variable falling into a given category compared to other categories (Hosmer and Lemeshow 2000, Hilbe 2009). We applied MLR to observe the ownership shifts from industrial timberlands, as this was our major area of concern. Furthermore, we restricted the analysis only to include the shifts to institutional and FFO lands because of lack of enough data for 'public' and 'other' categories. We also excluded some underrepresented forest types from the analysis and included only the five most common ones. Out of 1,052 pieces of data, 841 (~80%) were randomly selected for training the model and the remaining 211 (~20%) were used for validation purposes. Twelve different explanatory variables (continuous and categorical) were used in the analysis (Table 1). The response variable had three possible outcomes: (1) change to institutional timberland, (2) change to FFO, and (3) no change. The 'no change' category was chosen as a reference category to compare it with the probabilities of the remaining two categories. Two logit functions were defined as follows: for change to institutional timberland,

$$ln\left(\frac{p\,(change\ to\ institutional)}{p\,(no\ change)}\right) = \beta_{01} + \beta_{11}X_{11} + \beta_{21}X_{21} + \ \ldots\ + \ \beta_{k1}X_{k1}$$

For change to FFO,

$$ln\left(\frac{p\,(change\ to\ FFO)}{p\,(no\ change)}\right) = \beta_{02} + \beta_{12}X_{12} + \beta_{22}X_{22} + \ \ldots\ + \ \beta_{k2}X_{k2}$$

where p is probability of occurrence of an event given within the parentheses, X_{i1} and X_{i2} are explanatory variable(s), βi1 and βi2 are regression coefficient(s) for respective equations, and k is the number of explanatory variables.

Table 1. Description of independent variables used for the MLR analysis.

Independent Variables	Description
Distance to road	Distance to nearest road from a plot in km
Distance to sawmill	Distance to nearest sawmill from a plot in km
Distance to urban center	Distance to nearest urban center from a plot in km
Elevation	Distance a plot is located above sea level in feet.
Forest type	Six most common forest types: i. white-red pine ii. spruce-fir iii. oak-hickory iv. elm-ash-cottonwood v. maple-beech-birch vi. aspen-birch
Population density	Interpolated value of population density at the plot location per square km
Site class	Code describing site productivity class based on the potential growth in cubic feet/acre/year. Seven classes of site productivity used in the study are: i. >84 cubic feet/acre/year ii. 50–84 cubic feet/acre/year iii. <50 cubic feet/acre/year
Site index	Average total length in feet that dominant and co-dominant trees are expected to attain in well-stocked even-aged stands at the specified base age.
Slope	Angle of slope in percent
Aspect class	i. Flat terrain (<5% slope) ii. North (0 to 45 and 315 to 360) iii. East (45 to 135) iv. South (135 to 225) v. West (225 to315)
Stand age	Age of the forest stand
Stand size class	Code indicating stand-size class based on predominant diameter class of live trees. Three classes of stand size used in the study are as follows: i. Large diameter (saw timber) - trees at least 11 inches diameter for hardwoods and at least 9 inches diameter for softwoods. ii. Medium (pole) - trees smaller than large diameter trees but at least 5 inches diameter iii. Small (sapling) - trees less than 5 inches diameter.

Logistic regression using PROC LOGISTIC in SAS/STAT software (SAS Institute Inc. 2016) was applied to develop the MLR model with a stepwise selection method. The selected model was then validated by assessing the classification accuracy of the predicted outcomes from validation data. As the distribution of categories of dependent variables was disproportionate, improved accuracy could be obtained when the cutoff points chosen are close to their proportion (Ohlson 1980, Palepo 1986). Some researchers have chosen cutoff points to minimize misclassification and improve accuracy in logistic regression analysis (Pereira and Itami 1991, Barniv et al. 2002). In this study, cutoff points were chosen to optimize the Kappa coefficient. To evaluate the usefulness of the model, proportion-by-chance accuracy criteria (Bayaga 2010, Monyai et al. 2016) was used, which requires model accuracy to be at least 25% more than what would be expected by chance. Proportion-by-chance accuracy was computed by squaring and summing the proportion of cases in each category.

Results

Shifts in Timberland Ownership

Across the study area, the overall net distribution of FIA plots among ownership categories did not change dramatically, with less than 1% change for any one ownership category. There were small net increases in institutional (1,187 to 1,191 plots, or 0.9%) and public ownership (10,148 to 10,255 plots, or 0.4%) from 2003 to 2012, whereas FFO and 'Other' categories showed slight decreases of –0.8% and –0.4%, respectively (Table 2). Percent change for each of these ownership categories varied spatially when summarized by states or regions (Table 3 and Figure 4).

Although net change within individual ownership categories was small, there was significant movement among ownership categories, as a total of 1,640 out of 26,940 (6%) FIA plots changed ownership category from 2003 to 2012. When comparing the number of plots within each category, institutional ownership had the largest increase with 231 (45%) more plots between successive inventories (Table 2). Most of this increase was the result of ownership shifting from industrial to institutional. FFO ownership had the largest net decrease, with 223 fewer FFO plots in the later measurements than previously. Percentage of plots changing ownership was highest for industrial lands, with 21% and 13% of plots moving to institutional and FFOs, respectively. Similarly, change was also observed in the institutional category, with about 9% and 7% of plots switching to industrial and FFO, respectively. FFO plots had the largest amount of movement, with 368 plots (2.6%) being bought by industrial owners by 2012.

Statewide percent change of timberland ownership showed different patterns for different categories (Table 3 and Figure 4). Industrial ownership showed net increases of more than 2% in eastern states, particularly Maine, New York, Pennsylvania, and West Virginia, whereas the northwestern states of Minnesota, Wisconsin, Michigan, and Indiana had net decreases. Although there was an increase in institutional plots for most of the states, a large increase was mainly observed only in Maine and Michigan. Most of the states had a net decrease in FFOs, with only major gains in New Hampshire and

Table 2. Distribution of FIA plots among ownership categories between 2003 and 2012. Values in parenthesize represent percentage relative to the totals of first measurements (2003–2007).

		2008–2012					
Ownership	Category	Industrial	Institutional	FFO	Public	Other	Total (2003–2007)
2003 - 2007	Industrial	702 (59.1%)	250 (21.1%)	150 (12.6%)	58 (4.9%)	27 (2.3%)	1187
	Institutional	45 (8.8%)	416 (81.6%)	34 (6.7%)	10 (2.0%)	5 (1.0%)	510
	FFO	368 (2.6%)	40 (0.3%)	13319 (95.3%)	115 (0.8%)	137 (1.0%)	13979
	Public	13 (0.1%)	5 (0.05%)	69 (0.7%)	10048 (99.0%)	13 (0.1%)	10148
	Other	63 (5.6%)	30 (2.7%)	184 (16.5%)	24 (2.2%)	815 (73.0%)	1116
Total (2008–2012)		1191	741	13756	10255	997	26940

Table 3. Distribution of FIA plots with at least one forested condition by state or group of states and ownership category from 2003 to 2012.

		2003–2007		2008–2012		
State	Ownership	Number	Percentage	Number	Percentage	Percent Change
ME	Industrial	113	7.4	157	10.2	+2.8
	Institutional	200	13.0	232	15.1	+2.1
	FFO	931	60.7	857	55.8	–4.9
	Public	199	13.0	203	13.2	+0.2
	Other	92	6.0	86	5.6	–0.4
	Total	1535	100.0	1535	100.0	
MI	Industrial	316	9.5	179	5.4	–4.1
	Institutional	77	2.3	214	6.5	+4.2
	FFO	1118	33.7	1119	33.8	+0.1
	Public	1710	51.6	1716	51.8	+0.2
	Other	93	2.8	86	2.6	–0.2
	Total	3314	100.0	3314	100.0	
MN	Industrial	259	5.2	203	4.1	–1.1
	Institutional	77	1.6	89	1.8	+0.2
	FFO	1557	31.5	1576	31.9	+0.4
	Public	2844	57.6	2856	57.9	+0.3
	Other	199	4.0	212	4.3	+0.3
	Total	4936	100.0	4936	100.0	
WI	Industrial	266	5.3	239	4.8	–0.5
	Institutional	137	2.7	156	3.1	+0.4
	FFO	2651	53.0	2625	52.4	–0.6
	Public	1758	35.1	1782	35.6	+0.5
	Other	194	3.9	204	4.1	+0.2
	Total	5006	100.0	5006	100.0	
DE, MD, NJ, NY, PA, and WV	Industrial	43	0.8	163	3.2	+2.4
	Institutional	5	0.1	29	0.6	+0.5
	FFO	3036	59.4	2937	57.5	–1.9
	Public	1764	34.5	1789	35.0	+0.5
	Other	263	5.1	193	3.8	–1.3
	Total	5111	100.0	5111	100.0	
VT, NH, MA, CT, and RI	Industrial	32	1.7	62	3.4	+1.7
	Institutional	11	0.6	19	1.0	+0.4
	FFO	1032	56.1	1037	56.4	+0.3
	Public	588	32.0	611	33.2	+1.2
	Other	177	9.6	111	6.0	–3.6
	Total	1840	100.0	1840	100.0	
IA, IL, ID, MS, and OH	Industrial	158	3.0	188	3.6	+0.6
	Institutional	3	0.1	2	0.04	–0.1
	FFO	3654	70.3	3605	69.4	–0.9
	Public	1285	24.7	1298	25.0	+0.3
	Other	98	1.9	105	2.0	+0.1
	Total	5198	100.0	5198	100.0	

Delaware. There were no negative changes for public ownership, with Massachusetts showing a more than 2% increase.

Distribution of Timberland Ownership

Spatial patterns in timberland ownership distribution are clearly evident when mapped based on approximate FIA plot location (Figure 5). For the period of 2003–2007, institutional ownership is primarily located in the northern states from Minnesota to Maine. Industrial ownership is also concentrated mainly in the same states, although it is sparsely dispersed across most of the study area. Plots under FFO ownership are distributed evenly through the forest

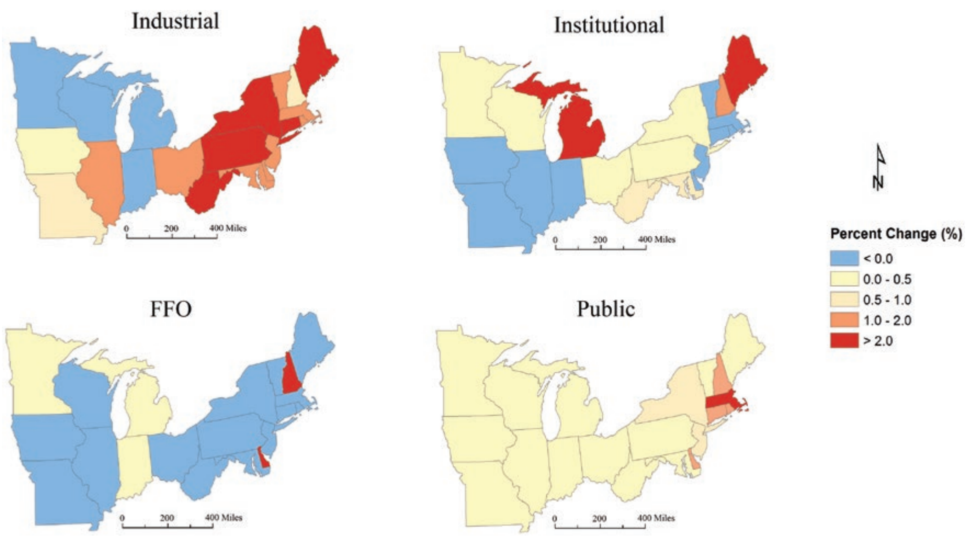

Figure 4. Statewide percent change of timberland ownership between 2003 and 2012.

area. Public ownership, mostly representing protected areas, is seen in clusters. The ownership pattern in 2008–2012 shows a similar distribution except for changes in institutional and industrial plots. An increased number of institutional ownership plots are observed in Maine and Michigan, along with some isolated patches in Maryland, New York, Pennsylvania, and West Virginia. In contrast, a reduction in number of industrial plots was obvious in Michigan.

We applied KDE and Ripley's K-functions to further explore the spatial patterns of industrial, institutional, and FFO ownership individually, as these accounted for most of the changes. KDE maps for industrial and institutional ownership showed hot spots in their distribution for both time periods (Figure 6). We observed several hot spots for industrial ownership for the 2003–2007 period, including the most significant ones in the northern areas of Maine and the Upper Peninsula of Michigan. However, these hotspots of industrial ownership were barely discernible in the second time period, except for one in Maine, which was also reduced in intensity. Results from bivariate L-function for industrial ownership (Figure 7) also captured these variations, with great reduction in clustering magnitude and narrowing down of spatial scale from about 300 miles to about 100 miles. We could say that industrial plots shifted to other categories during the later measurement and were more confined in both spatial and numerical terms.

Between 2003 and 2007, institutional ownership (Figure 6) was highly concentrated in the northern region of Maine. During 2008–2012, the intensity of institutional ownership remained strong in Maine, and it is also increased in Michigan, Minnesota, and Wisconsin. Corroborating KDE maps, results from bivariate L-function (Figure 7) showed significant clustering patterns of institutional ownership in both of these time periods. A difference was observed in the spatial scale of peak clustering for this category, which changed from about 150 miles to 300 miles. This could suggest expanding institutional ownership coverage from a highly localized pattern in 2003–2007 to a relatively wider span.

We did not observe clear hot spots for FFO maps, with relatively lower intensity of FFO ownership in areas dominated by industrial and institutional ownership. Bivariate L-function also resulted in regularity for both measurement periods (Figure 7), meaning these plots were uniformly distributed across the study area.

Spatial Distribution of Shifts in Timberland Ownership

The highest percentage change in ownership for all types of ownership change for any given 155 square-mile (400 km^2) grid cell was 28%. Hot spots were observed in several locations, particularly in Maine, New Hampshire, Vermont, Michigan, Wisconsin, West Virginia, and Maryland (Figure 8a). Ripley's L-function revealed a peak, though nonsignificant, at a spatial scale of around 300 miles, indicating some clustering (Figure 8b). At this spatial scale, the kernel density map captured localized shifts from industrial to other ownership categories, which agreed with the 300-mile clustering suggested by the L-function. For broader spatial scales,

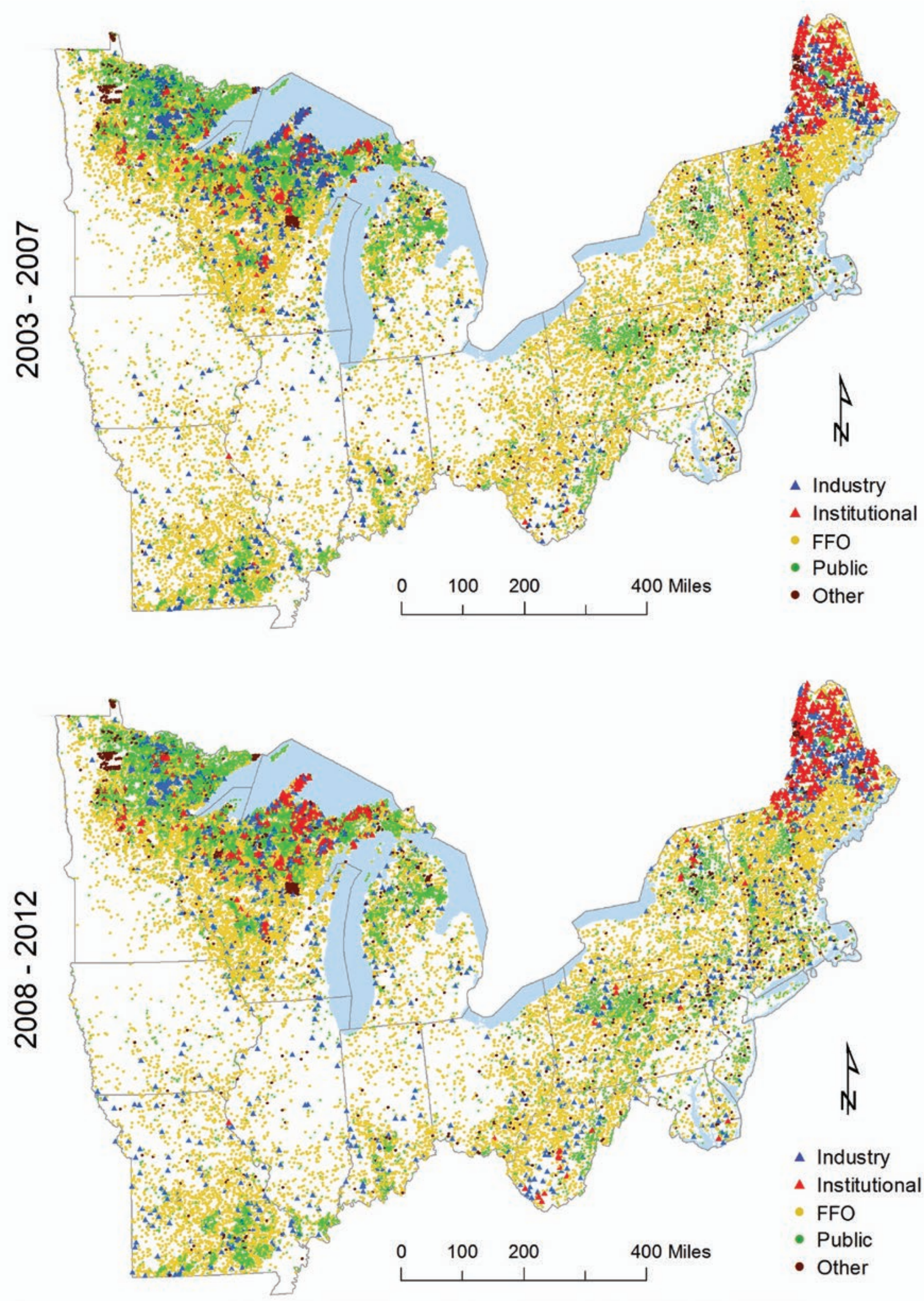

Figure 5. FIA plots with at least 50% area within forested condition by timberland ownership categories at two subsequent inventories, during 2003–2007 (a) and 2008–2012 (b).

shifts in ownership were largely dominated by FFO (about 50% of shifts are from FFO), which are uniformly distributed across the study area, thus producing significant regularity in the L-function.

The bivariate L-function analysis revealed statistically significant spatial patterns of ownership change among three different categories (Figure 9). A significant clustering pattern is observed for changes from industrial to institutional ownership. Peak clustering was observed at the spatial scale of around 300 miles. In other words, we would expect maximum clustering of these plots within a circular area with a radius of 300 miles from a given plot. We observed a dispersion pattern of plots that switched from industrial ownership to FFO, with the peak of these dispersions ranging from a scale of about 100

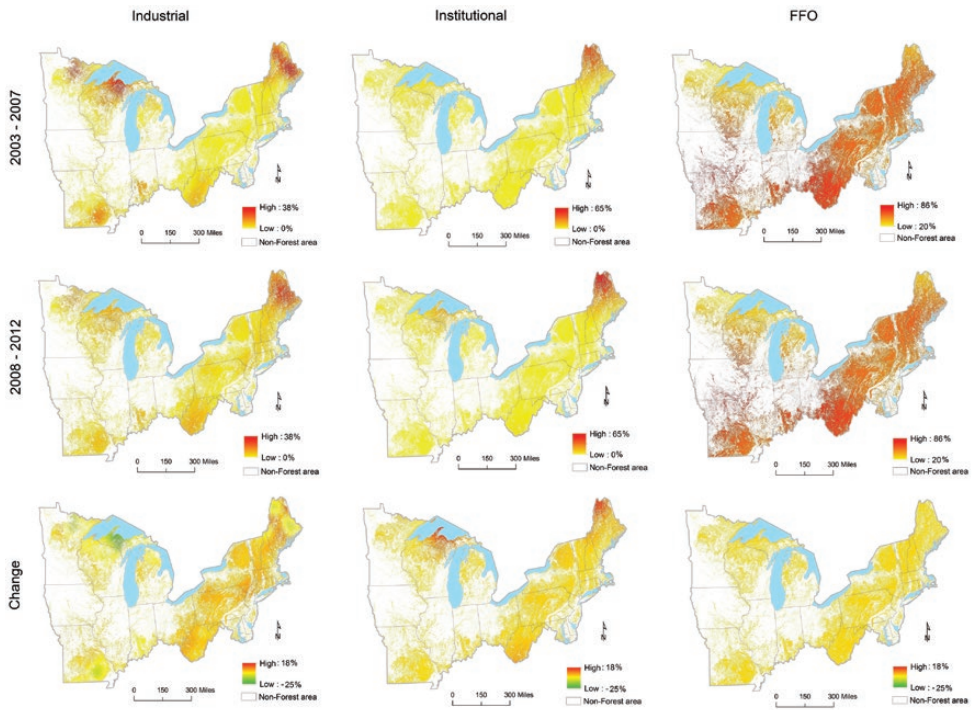

Figure 6. Kernel density maps for industrial, institutional, and FFO ownership using FIA plots for two consecutive inventories between 2003 and 2012.

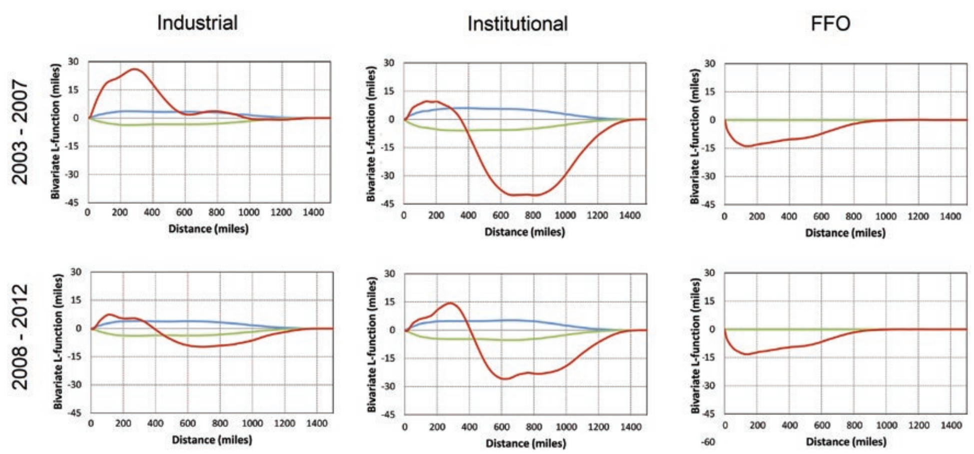

Figure 7. Bivariate L-function showing spatial pattern of industrial, institutional, and FFO ownership in two inventories. Red lines represent estimated L-function, blue and green lines represent upper and lower 95% confidence intervals, respectively.

miles to 300 miles. There was significant evidence of clustering at around 100 miles distance for the plots changing from institutional to industrial ownership. However, a significant dispersion pattern was also observed for the plots changing from institutional to FFO, peaking at around the spatial scale of 100 miles. Plots converting from FFO to either industrial or institutional ownership also depicted a dispersion that was most evident at the spatial scale of about 600 miles.

Modeling the Shift From Industrial Ownership

In an effort to identify attributes that may be related to a higher likelihood of a plot shifting from industrial to other ownership category, MLR modeling was used. The null hypothesis—that there is no difference between a model with intercept only and a model with selected plot attributes—was rejected, indicating that there is a relationship between a plot changing ownership and plot attributes. Forest

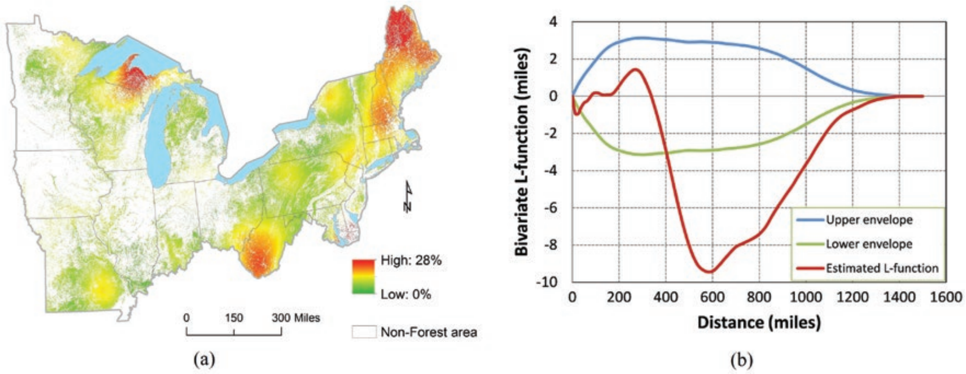

Figure 8. Spatial pattern of changes in timberland ownership, (a) as observed from kernel density function, and (b) the graphical result from bivariate L-function.

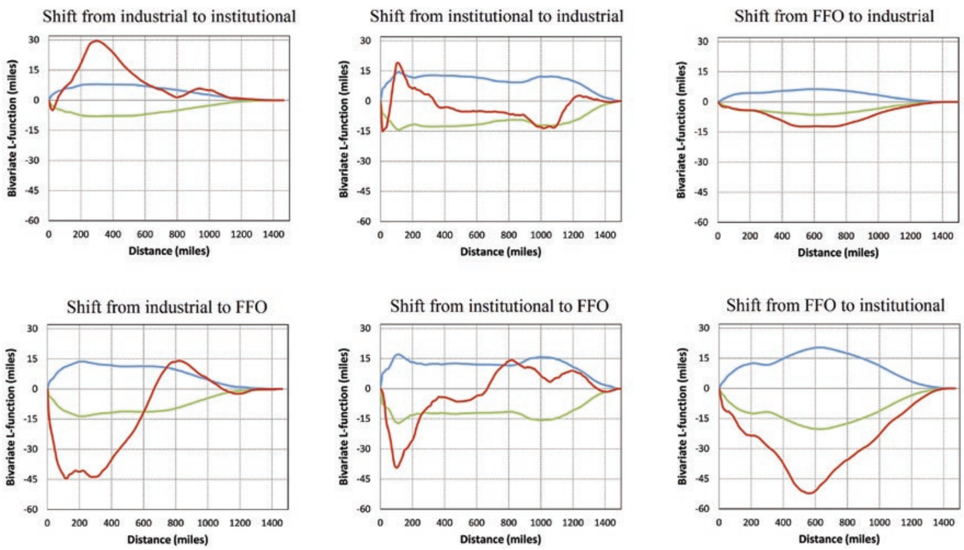

Figure 9. Bivariate L-function to observe pattern of shifts among industrial, institutional, and family forest ownership. Red lines represent estimated L, blue and green lines represent upper and lower 95% confidence intervals, respectively.

type, distance to a road, population density, and aspect class were all found to be significant ($p < 0.05$) (Table 4). The model used to evaluate change from industrial to institutional ownership found all four of these variables to be significant, whereas only forest type was significant in the model for change from industrial ownership to FFO. Values of pseudo R^2 ranged from 0.19 to 0.34, suggesting that a fair amount of variability was explained by the model.

Plot attributes that increased the odds of an industrial plot changing to institutional ownership include: spruce-fir and maple-beech-birch forests, increase in distance from a road, east-facing slopes, and lower population density in the vicinity of the plot. In contrast, oak-hickory forest plots had significantly lower odds of shifting from industrial to institutional ownership, as did north-facing slopes. For industrial plots changing to FFO ownership, oak-hickory forests and aspen-birch forests had significantly higher odds.

Model validation was done to observe the accuracy and errors associated with model predictions (Table 5). Cells along the diagonal (bold and highlighted in Table 5) represent the correct classification, whereas cells off diagonal show the incorrect classification. Industrial ownership without any change were best classified (78.2%), followed by those that changed to institutional ownership (71.4%), and the least accurate were those that converted to FFO (10.3%). Overall accuracy of the classification was 67.3%, with a Kappa value of 0.33. This overall accuracy is 58.8% higher (a minimum of 25% increase is suggested for a model to be satisfactory) than the proportion-by-chance

Table 4. Variables retained in logistic regression model and global test statistics in predicting probability of an industrial plot changing to institutional ownership within a five-year period. (* indicates *p*-value for variable < 0.05).

Variable	Change to Institutional					Change to FFO				
	β	Std. Error	Wald		Exp(β)	β	Std. Error	Wald		Exp(β)
Intercept	-1.80	0.32	31.67	*	0.17	-1.65	0.24	46.57	*	0.19
Forest Type										
Pine	Reference									
Spruce-Fir	0.63	0.28	5.18	*	1.87	-0.28	0.29	0.95		0.76
Oak-Hickory	-2.32	0.87	7.16	*	0.10	0.89	0.22	16.02	*	2.43
Elm-Ash-Cottonwood	0.01	0.43	0.00		1.01	-0.26	0.35	0.56		0.77
Maple-Beech-Birch	0.91	0.24	13.92	*	2.49	0.05	0.23	0.05		1.05
Aspen-Birch	-0.18	0.27	0.47		0.83	-0.92	0.29	10.49	*	0.40
Distance to Road (km)	0.01	0.00	44.81	*	1.01	0.00	0.00	0.64		1.00
Population density (per km2)	-0.14	0.03	17.36	*	0.87	0.00	0.00	0.21		1.00
Aspect Class										
Flat area	Reference									
North	-0.85	0.36	5.54	*	0.43	-0.19	0.43	0.20		0.83
North-East	0.02	0.35	0.00		1.02	0.32	0.34	0.90		1.38
East	0.88	0.39	5.07	*	2.41	0.53	0.42	1.61		1.69
South-East	0.33	0.38	0.75		1.40	-0.86	0.56	2.34		0.42
South	-0.33	0.41	0.65		0.72	-0.10	0.41	0.06		0.91
South-West	0.16	0.39	0.17		1.18	0.53	0.39	1.85		1.70
West	0.03	0.39	0.01		1.03	-0.41	0.51	0.64		0.67
North-West	0.20	0.44	0.21		1.22	-0.13	0.47	0.08		0.88

accuracy of 47.0% ($63.0\%^2 + 23.2\%^2 + 13.7\%^2$), suggesting that the model is useful.

Discussion

We based our analysis of shift in timberland ownership mainly on the number of FIA plots rather than by scaling up to their corresponding land areas. Although these plots are uniformly distributed across the country within the hexagonal grids, some of the potential factors, such as inaccessibility to certain types of timberlands during field inventory and sampling bias due to the size of timberlands, could complicate such expansions (Patterson et al. 2012, Goeking and Patterson 2013). Results show that 21% of industrial timberlands changed to institutional timberlands during this period. Bliss et al. (2010) made similar findings, with forest industry being the largest seller (76% of total sales) of timberland from 1994 to 2006 across the country. One surprising result was the lack of overall change in the percentage of industrial plots across the Northern region. There were, however, regional differences. A closer examination of FIA plots by state (Figure 4) found that states with higher concentrations of corporate ownership (industrial and institutional) showed declines in industrial ownership, whereas others had an increase. One exception was Maine, where the percentage of industrial ownership actually increased from 7.4% to 10.2%, which can be largely attributed to the decrease in FFO plots. The switch of about 2.6% of overall FFO plots to industrial ownership, a large overall reduction of FFO plots and an increase in industrial plots in Maine, appears to be unusual. In general, studies have reported shifts from industrial to institutional or FFO (Block and Sample 2001, Clutter et al. 2005, Zhang et al. 2012), but because FFO is a highly dynamic category, there is a good chance that some of the midsized FFO timberlands do switch to institutional ownership or are sold for real estate (Zhang et al. 2005, Butler 2008). The change of FFOs or institutional timberlands to industrial lands also might be partly linked to misclassification of institutional ownership. Nevertheless, future studies could be designed to investigate whether large-sized FFO timberlands tend to shift to industrial ownership.

Maine, Michigan, and West Virginia showed the largest increase in institutional ownership between the two time periods of this study, where the percent of institutional plots increased by 2%, 4%, and 1%, respectively. Such a trend in institutional ownership agrees with findings from previous studies. Forest land owned by financial investors in Maine increased from around 3% to 33% and areas under REITs grew from almost nil to 8% from 1994 to 2005 (Hagan et al. 2005, Jin and Sader 2006). Lower rate of growth in institutional ownership observed in this study could be linked to a few factors. First, most of the large tracts of timberland in these states had already changed ownership before 2003. Comparative maps of Maine between 1995 and 2007 show that most of the industrial timberlands changed to institutional ownership (Mendell 2007). Similarly, in the Upper Peninsula region of Michigan, most of the VIFPCs had divested their lands to TIMOs and REITs by 2005, making them the first and the second largest holder of timberlands, respectively (Froese et al. 2007). Second, our figures are based on the number of plots rather than forest land area, and they include the effect of a disproportionately large number of FFO plots with smaller holding size compared to the industrial and institutional categories. Third, a significant percentage of institutional timberland also shifted back to industrial and FFO by about 9% and 7%, respectively. Finally, some level of uncertainty related to proper identification and classification of institutional timberlands could also have affected its percentage.

Results indicated certain influence of ownership changes to and from the FFO category towards

Table 5. Cross-validation table and accuracy assessment of MLR regression model using independent validation data for predicting whether a FIA plot will change from industrial to either institutional or FFO timberland ownership over a five year period.

	Predicted Classification Change			
Reference	No Change	Change to Institutional	Change to FFO	Percent Correct
No change	104	28	1	78.2
Change to institutional	14	35	0	71.4
Change to FFO	26	0	3	10.3
Overall percentage	68.2	29.9	1.9	67.3

industrial and institutional ownership. There is around 1% reduction in overall FFO ownership during the period. Out of the total FFO plots during 2003–2007, 2.6% and 0.3% shifted to industrial and institutional ownership, respectively, in the next inventory. Even though these transfers look small in percentage, they represent a large amount of area due to large sample size of FFO plots. This result corresponds to the trend from Maine, where 10% of FFO ownership was handed over to TIMOs from 2000 to 2004 (Jin and Sader 2006).

Industrial and institutional timberlands were mainly located in Maine, Michigan, Minnesota, and Wisconsin for both inventory years. FFO plots were found evenly dispersed across the region. Public forestlands were found clustered owing to their locations being restricted within specified areas. Distribution of corporate ownership and public ownership matched well with the areas having a high percentage (mostly above 75%) of forest land. In contrast, the distribution pattern of FFO corresponds well with the areas associated with lower percentage (mostly under 75%) of forest land (Shifley et al. 2012).

KDE maps for distribution of industrial and institutional ownership for both periods showed clear hot spots. FFO density maps did not exhibit clear hotspots. Ripley's K-function empirically confirmed what was revealed on density maps, that clustering patterns of institutional and industrial ownership were significant. A clustering pattern for institutional ownership was similar for both time points. In contrast, we observed change in clustering pattern for industrial ownership between 2003–2007 and 2008–2012, which is also visible in density maps by the reduction in hot spots.

The density map documenting changes among all ownership categories revealed hot spots in Maine, the Upper Peninsula of Michigan, and West Virginia, with smaller changes taking place in Maryland, New Hampshire, and Vermont. A significant, pronounced clustering pattern was observed for plots changing from industrial to institutional ownership. These results indicate that such transfers are taking place in clusters even after we account for the clustering pattern of industrial timberlands. This suggests that industrial owners are selling their lands as large single blocks to single or a few new institutional owners, rather than breaking up large timberland holdings into smaller ones and selling to many owners. In contrast, plots changing from industrial to FFO were observed to exhibit spatial regularity, which would imply that, unlike institutional plots, there were no certain preferences for industrial plots to switch into FFO. Moreover, this would also be an indication towards parcelization, where large industrial lands could have been divided into smaller parcels and sold to multiple FFO owners piecemeal. Institutional timberlands also showed similar patterns; a cluster pattern of plots changing to industrial and a regularity pattern for those changed to FFO. Movements from FFO to the other two categories were found to be regularly spaced across the region.

Results from multinomial logit suggested shifts from industrial to institutional ownership significantly related to more socioeconomic and forest-related variables compared with the shifts from industrial to FFO. Shifts from industrial to institutional ownership were found to be associated with road and population factors, which could explain some of the reasons behind significant clustering observed in this category of change. Although plots under industrial ownership included many forest types, those shifting to institutional ownership are more likely to be associated with spruce-fir and maple-beech-birch forests. This also explains the concentration of these shifts in Maine, Wisconsin, and Michigan, which are dominated by spruce-fir and maple-beech-birch forests. In contrast, we observed the shift from industrial to FFO ownership had a positive relationship with oak-hickory forest. Zhang et al (2005) had highlighted the importance of population density and land value to an increase in FFO ownership. Although the population density in the model itself did not appear to be significant, the higher density of oak-hickory forest along the southern belts in the study area suggest a correlation with some of the highly populated areas in the region.

Conclusions

Comparison of hot spots for industrial and institutional density maps from two different inventory periods reveals that densities of industrial ownership are decreasing while those of institutional ownership are increasing over time. Spatial pattern of overall ownership change indicated hot spots of change in Maine, Michigan, and West Virginia. Over 21% of industrial timberlands were transferred from the industrial to the institutional category, which was the largest percentage of all types of ownership transfers. Despite this, there was little net change in this category. Regional differences are evident, as in states like Michigan, Minnesota, and Wisconsin, industrial timberland is decreasing, but in other states, it is increasing. A clustering pattern was observed among plots that changed their ownership from industrial to institutional and vice versa. We also observed shifts from industrial to institutional ownership are linked with urbanization and forest types. These results are relevant as they provide evidence that there is no noticeable parcelization because of these transfers. Although the data we used for this analysis ranged from 2003 to 2012, duration between two measurements for any given individual plot was only around five years, which might not be sufficient to capture the trend precisely. Future studies with time intervals of 10 or 15 years and with an updated ownership classification method would be beneficial in exhibiting the effects more strongly.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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