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Forest harvesting and land-use conversion over two decades in Massachusetts

Robert I. McDonald [a,*], Glenn Motzkin [a], Michael S. Bank [a], David B. Kittredge [b], John Burk [a], David R. Foster [a]

[a] Harvard Forest, Harvard University, Petersham, MA 01366-0068, United States
[b] Department of Natural Resources Conservation, University of Massachusetts, Amherst, MA 01003, United States

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Abstract

Forest harvesting is an important, ongoing disturbance that affects the composition, structure, and ecological function of the majority of the world's forests. However, few studies have examined the interaction between land-use conversion and harvesting. We utilize a unique, spatially explicit database of all cutting events ($n > 13{,}000$) and land-cover conversions for Massachusetts over the past 20 years to characterize the interactions between land-use conversion and harvesting, and their relationship to physical, social, and economic factors. We examined three key variables: the proportion of forest harvested within an ecoregion (%), the mean harvest intensity ($m^3\ ha^{-1}$), and the mean harvest event area (ha). The mean harvest intensity (43 $m^3\ ha^{-1}$), mean harvest area (15 ha), and average species composition of harvests were remarkably constant over time. However, the proportion of forest harvested varied widely across the state, ranging from 0.01 to 1.48% annually. Harvesting activity ceases near the far outer suburbs of major metropolitan areas, as well as along the coast. There is a strong negative correlation ($r = -0.89$) between the proportion of forest lost to land-use conversion and the proportion of forest harvested. CART analysis shows that road density is the most important overall predictor of probability of forest harvest, with median house price also an important predictor. Harvest intensity, in contrast, appears related to ownership type, with state-owned lands having more intensive harvests (53 $m^3\ ha^{-1}$). Our results suggest that current forest management regimes are determined largely by the economic influence of nearby urban centers.
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Keywords: Harvest intensity; Forest fragmentation; Forest management; Massachusetts; New England; Non-industrial private forests

1. Introduction

Forested landscapes in the eastern United States have been dramatically transformed over the last 300 years, as forests were widely cleared for agriculture through the mid 19th century and farmland was subsequently abandoned and allowed to become reforested through natural successional processes (Cronon, 1983; Foster et al., 1998; Foster, 2000). Modern forests continue to be dramatically altered by two major anthropogenic disturbances: timber harvesting (Kittredge et al., 2003) and permanent conversion due to land-use change (Riitters et al., 2002). However, few studies have examined the interaction between these two dominant land uses (viz., Wear et al., 1999). As harvesting is common across the eastern US (Kittredge, 1996), understanding both land conversion and harvesting patterns has implications for many ecological processes, such as invasive species spread (cf., Lundgren et al., 2004) and wildlife habitat (DeStefano and DeGraaf, 2003). In this paper, we examine the spatial and temporal variability of harvesting patterns across the state of Massachusetts and model the interaction between harvesting and land-use change, particularly the expansion of suburban and exurban settlement into previously rural timber-producing areas.

We utilize a unique database of all cutting events conducted in Massachusetts over a 20-year period (1984–2003) to quantify the spatial patterns of harvesting in a region characterized by low to moderate intensity harvests, primarily on non-industrial private forest lands. This database has two advantages over other databases of timber harvesting. First, it is spatially explicit, allowing for detailed analysis of causes, patterns, and consequences of forest harvesting. Second, previous studies of forest harvesting patterns have focused primarily on public or large industrial lands, as reliable spatial information on forest harvesting is often lacking for private ownerships (Spies and

* Corresponding author. Tel.: +1 978 724 3302; fax: +1 978 724 3595.
E-mail address: rimcdon@fas.harvard.edu (R.I. McDonald).

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Turner, 1999). This is particularly true for forests in the eastern US where most land is in small parcels owned by private landowners (Kittredge et al., 2003). Our dataset overcomes these restrictions and allows a full examination of non-industrial forest logging patterns.

Furthermore, there have been only a few studies on how land-use change (Houghton, 1994), and specifically suburban and exurban development (cf., Theobald, 2001), affect forest harvesting patterns across a broader region. Several studies have suggested that logging ceases above a threshold population density (Wear et al., 1999). Recent work by Liu et al. (2003) suggests that household density might be a more proximate predictor in such cases, as it is more directly related to many important land-development processes. In a related vein, Kittredge (1996) and Kittredge et al. (2003) have suggested that parcel size is an important determinant of rates of logging, as it directly relates to the scale at which forest harvesting may be economically feasible. Lacking information on parcel boundaries for the entire state, we examine forest patch size and local road density as proxy variables for this parcel size effect. As the Massachusetts landscape has a relatively dense network of roads compared with more rural areas, we do not believe road density is indicative of ease of access, as almost all forests in Massachusetts are within 2 km of a road (cf., Riitters and Wickham, 2003), and we thus use road density simply as a correlate of parcel size. Finally, some economists have suggested that land price (cf., Lambin et al., 2001) will influence the cost–benefit analysis of the decision to harvest a forest. It has proven difficult to separate these factors, as few studies have spatially explicit forest harvesting data at scales that correspond with the scale at which harvesting decisions are made. Moreover, to some extent these factors are correlated spatially. For example, development scenarios that increase housing density in a region will likely increase road density, decrease forest patch size, and raise local land prices. Nevertheless, this correlation will not be perfect, and potentially different factors could be important in different regions.

The specific objectives of this investigation are to:

- quantify and evaluate spatial patterns of forest harvesting from 1984 to 2003;
- identify spatial and temporal variation in species composition of forest harvesting;
- evaluate trends in forest harvesting with respect to ownership type and landscape characteristics;
- model the effect of suburban and exurban development on forest harvesting rates.

2. Study area

The physiography of Massachusetts varies widely, from the sandy coastal region to upland regions of granite, schist, and gneiss, to the deep lowlands of the Connecticut and Housatonic rivers (Motts and O'Brien, 1981). Soils for much of the state are Inceptisols, with the valley floodplains and the sandy coastal region dominated by Entisols, and the western upland (between the Connecticut and Housatonic valleys—Fig. 1) being characterized by Spodisols (Brady and Weil, 2002). For the purposes of this paper, 'eastern Massachusetts' is used to refer to the southern New England Coastal Plain and points eastward, and 'western Massachusetts' refers to the regions of the state west of the coastal plain (Fig. 1). Temperature varies somewhat with distance from the ocean, from a mean high of 25.5 °C in August and a mean low of −6.1 °C in January at the coast to a mean high of 27.8 °C in August and a mean low of −10.0 °C in the Connecticut River valley (NOAA-CIRES Climatology Center). Precipitation is greatest in the western upland region (147 cm $year^{-1}$), and is lower in the Connecticut River valley (97 cm $year^{-1}$), with snowfall being more prevalent in interior regions of the state (USDA-NRCS).

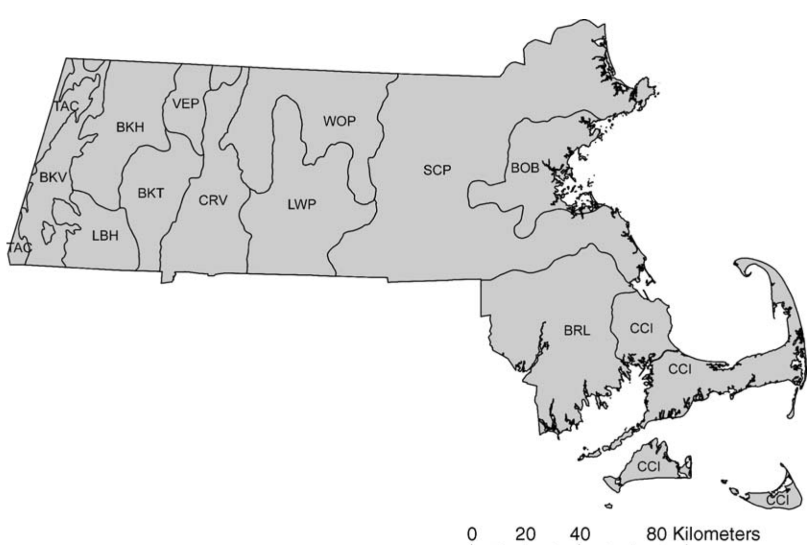

Fig. 1. Ecoregions of Masschusetts: Taconic Mountains (labeled as TAC), Berkshire Valley (BRV), Berkshire Highlands (BKH), Berkshire Transition (BKT), Vermont Piedmont (VEP), Worcester Plateau (WOP), Connecticut River Valley (CRV), Lower Worcester Plateau (LWP), Southern New England Coastal Plain (SCP), Boston Basin (BOB), Bristol Lowland (BRL), Cape Cod and the Islands (CCI), and the Lower Berkshire Hills (LBH).

When Europeans arrived in the region in the early 17th century, they found a landscape largely covered with closed-canopy forests (Foster, 1992). Witness tree data suggest that coastal areas were dominated by oak and pine. Areas east of the Connecticut River valley were dominated by a mix of oak, pine, hickory, and chestnut. Areas west of the Connecticut River valley supported a mixture of beech, birch, maple, oak, and hemlock (Cogbill et al., 2002). The majority of the landscape was extensively cleared for agriculture, with only 40–60% forest cover remaining by the mid to late 19th century, the height of agriculture. Generally, productive alluvial soils on flat land were cleared earlier, while less productive soils (e.g., sandy outwash soils) or areas with steep slopes were cleared later or not at all (Hall et al., 2002).

Widespread agricultural abandonment in the second half of the 19th century allowed the natural establishment of forests across the region, often dominated by white pine (Foster et al., 1998). Peak white pine harvesting occurred from 1900 to 1920 and had declined by the end of World War II (Kittredge et al., 2003). A major hurricane in 1938 caused widespread windthrow, particularly in the remaining pine stands (Boose et al., 2001). Since then, forest biomass has consistently increased, and harvesting levels have remained relatively steady at approximately 100 million board feet annually (Kittredge et al., 2003).

This study builds on a previous study by Kittredge et al. (2003) of the North Quabbin Region (1680 km^2) in north-central Massachusetts. There, harvesting varied by ownership, with state-owned land having more frequent and more intensive harvesting. State land is unevenly distributed across the state, concentrated predominantly around the Quabbin reservoir and in the western upland region. The vast majority of the state, however, is owned by non-industrial private forest owners (Gansner et al., 1990).

3. Methods

3.1. Harvesting data

We assembled a spatially explicit database of all (~13,000) harvest operations in Massachusetts from 1984 to 2003 (cf., Kittredge et al., 2003). Under the 1983 Massachusetts Forest Cutting Practices Act, a forest cutting plan (FCP) is required for all harvests, public and private, removing more than 87 m^3 (Kittredge, 1996). FCPs are only required for harvests on sites that will be allowed to return to forest cover; forest clearing for development is not recorded with an FCP, although the change in land-use is noticeable in our land-cover imagery (see section below on land-cover data). For the purposes of this study, we describe land as "harvested" if it had an FCP filed, while "non-harvested" forest remained in forest cover over the study period and did not have an FCP filed. Each FCP includes the spatial boundary of a cut, as drawn by the landowner's agent on topographic maps, and an estimate of the volume of timber to be removed, in aggregate and by species (although species data is occasionally not reported). Dates reported are accurate to within 2 years, as landowners have several years to implement any given FCP.

The spatial boundaries of each cut were transferred into a GIS system using on screen digitization or via a topographic base map on which FCPs could be traced (cf., Kittredge et al., 2003). All tabular data were entered into Microsoft Excel. Volume estimates were standardized for this study to m^3 (volume) and $m^3\,ha^{-1}$ (intensity). To assess the accuracy of data entry, ~5% of FCPs were redigitized by a different analyst, and the results compared. Duplicate polygons were of similar area, with a mean percent difference of 25% between the two duplicate digitizations, and spatially overlap by 65% of their area. These errors, while large, reduce dramatically in percentage terms when values are aggregated, as the difference in area varies independently among FCPs. For example, the difference in total area between the two sets of FCPs is less than 2%. For the current study, we did not assess in the field the spatial accuracy of the landowner's original delineation of the FCP, but we believe that landowner maps are rarely off by more than 100 m from the true boundary.

3.2. Land-use data

Land-cover data were obtained from MassGIS (http://www.mass.gov/mgis/), and derive from the Resource Mapping Project at the University of Massachusetts. Land-cover data were manually classified from 1:25,000 color aerial photography for 1985 and 1999. The classification scheme has 37 categories, and is similar in structure to an Anderson classification scheme (Anderson et al., 1976). To increase temporal consistence in the classification scheme, we lumped land-use data to seven classes: forest, highly developed (e.g., urban centers), lightly developed (e.g., suburban homes), agricultural, water, wetland, and non-agricultural open (e.g., lawns, power-line right of ways). Data were converted to raster format at 30 m resolution. Distance from each forested pixel to the nearest non-forest pixel was calculated (m). Forest patches were defined based on contiguous cells of forest (cell edges only), after intersection with a road layer (see below), and the size of all forest patches (ha) was calculated. Similarly, patches representing converted lands were identified by contiguous cells that had forest cover in 1985 but were not forested in 1999. For this study, "land conversion" and "deforestation" refer to this permanent removal of forest cover.

3.3. Additional GIS overlays

We re-sampled a 5 m resolution digital elevation model (DEM) from MassGIS to 30 m resolution to ease the computational burden. Slope, in degrees, was calculated using the default algorithm in ArcGIS. Beer's transformed aspect (Beers et al., 1966) was calculated for all cells, and varies from −1 on NE facing slopes receiving little incident light to 1 on SW facing slopes receiving abundant incident light. As a measure of topographically derived wetness, the topographic convergence index (TCI) was calculated for all cells (Beven and Kirkby, 1979). TCI is a transformed ratio of uphill contributing area and slope, with high values associated with floodplains and values near 0 associated with ridgetops.

Road locations were taken from TIGER line data (http://www.census.gov/geo/www/tiger/). These data were accurate as of the 2000 census, and we acknowledge that some of these roads were created since 1985, and hence were not present during some of the earlier harvesting events. We believe this to be a relatively minor issue, as there were few major roads completed during this period of time. We calculated (at 30 m resolution) the distance from every forested cell to the nearest road and the density of roads (km road per km^2 area) within 1 km of each cell. For each forested pixel, we used a map of all perennial streams and wetlands to calculate distance to water. Lastly, MassGIS coverages of surficial and bedrock geology were reclassified to a small number of classes. Surficial geology had four classes: till, sand/gravel, alluvial (i.e., floodplain soils), and fine-grained (i.e., silt-dominated). Bedrock geology had seven classes: unconsolidated sediments, granite, mafic rocks, metamorphic rocks, basin sedimentary, carbonate rocks, and calcpelite. We used these data, as well as information about slope and wetness, as measures of site conditions, and to explore ways that site factors might relate to harvesting activities.

Data on population and household density in 1990 and 2000 come from the Wildland/Urban Interface Data Release Version 2 (http://www.silvis.forest.wisc.edu/WUIRelease2.asp), which derive from US Census data and are approximately at the census block level of resolution (Radeloff et al., 2005). These data were rasterized to 30 m resolution (i.e., each forested pixel is assigned the value of the census block in which it resides), and were used to calculate changes in population and housing density between 1990 and 2000. Some FCPs occurred before 1990, but we do not believe this poses a problem as trends in these variables were very similar before 1990. Due to the high correlation between population density and housing density ($r = 0.94$), as well as their changes over time ($r = 0.82$), we limited our analyses to consideration of housing density and changes in housing density.

Data on median household income and median house price from the 2000 census (taken from MassGIS) were converted to a 30 m resolution. Data from the 1980 and 1990 censuses were not available electronically. We assumed that at a statewide level, relative differences across census blocks in household income and house prices in 2000 were likely consistent throughout the study period. Due to the strong correlation between household income and house prices ($r = 0.72$), we limited our analysis to median house price.

3.4. Descriptive analyses

Many of our analyses were stratified by US Environmental Protection Agency ecoregions, which are based on the work by Omernik (1987, 1995). These ecoregions conveniently divide Massachusetts into 13 moderately sized areas (Fig. 1). We experimented with other sets of boundaries (e.g., town boundaries) and results were similar, but we believe the ecoregion boundaries are most relevant for this study (but see McDonald et al., 2005). Within each ecoregion, we used ArcGIS 9.0 to calculate the land-use conversion rate (area permanently deforested between 1985 and 1999) and the harvesting rate (lands harvested between 1984 and 2003, but remaining in forest cover) in absolute (ha) and proportional terms (%). We repeated the analysis with data stratified by ownership type (data obtained from MassGIS), with eight ownership categories: Municipal, MA Department of Conservation and Recreation – State Parks, MA Department of Conservation and Recreation – Water Supply Protection, MA Department of Fish and Game, other MA state land, Federal, Fee-simple ownership by conservation organizations and private lands.

Temporal trends in harvesting were examined for the whole state and by ecoregion. We calculated the percent of the total volume removed by species. Practically, this proportion corrects for occasional FCPs where estimates of volume by individual landowners appear systematically high or low. Only trees logged as saw-timber had their species recorded, in one of several categories (including ''Other''). Trees cut for firewood or pulpwood are listed as softwood and hardwood, with the volume in cords. We converted this volume to m^3, and categorized firewood and pulpwood as another ''species'' in our analysis.

To better visualize the spatial pattern of harvesting based on the proportion of forest harvested, the mean harvest area and the mean harvest intensity, we conducted a series of buffer analyses in ArcGIS 9.0. The proportion of forest harvested within a 10 km moving circular buffer was calculated statewide, for every 30 m forested cell. For computational reasons, this could not be done at a 30 m resolution, but instead was done in two passes. The first pass calculated the proportion of forest harvested within a 500 m circular buffer around each 30 m cell, with the resulting output grid linearly resampled to a 500 m resolution. The second pass then calculated the proportion of forest harvested within 10 km using this smoothed 500 m grid. To calculate mean harvest area and mean harvest intensity, the underlying polygon file was converted to a point file saving the associated attributes, and the Geostatistical Analyst wizard of ArcGIS 9.0 was used to conduct a local linear interpolation of the data with a moving circular 10 km window and optimized weights. That gave us a smoothed visualization of the underlying trend in mean harvest area and intensity, where the smoothed surface did not have to pass through the observed data (as it does in kriging, for example), eliminating low frequency noise from the data.

3.5. Statistical analysis

To quantify the relationship between the potential explanatory variables and forest harvesting, we used a classification and regression tree (CART) analysis. CART is a non-parametric approach that recursively partitions a dataset into subsets that are increasingly homogeneous with regard to a response variable, based on an optimal binary split on one of a set of explanatory variables (Moore et al., 1991; Vayssieres et al., 2000). This recursive portioning means that with spatially patterned explanatory variables, CART becomes spatially heterogeneous in functional form (McDonald and Urban, 2006). In our analysis, the state of a particular 30 m cell of forest (harvested or not harvested) was estimated using a CART. All explanatory variables described above were included in the analyses, including physical variables (e.g., slope, transformed aspect, TCI, surficial geology, and bedrock geology) and key socioeconomic variables that we wished to test as potential explanatory variables (e.g., housing density, road density, forest patch size, and median house price). Ownership type was included, lumped to a four category system for adequate sample size: private, municipal, state, and federal.

Spatial autocorrelation is a potential problem in all geospatial analyses, as cells located near one another are necessarily similar (Griffith, 1992; Overmars et al., 2003). We overcame spatial autocorrelation by conducting our logistic regression with a relatively sparse sample of 11,000 pixels out of some 60 million pixels in the state. We also insured that no more than one sample cell fell within each FCP, thus avoiding having two sample cells that were influenced by the same decision to undertake forest management. Preliminary examination of joint-count statistics (cf., McDonald and Urban, 2006) suggested that this was adequate.

To avoid over-fitting the CART model (i.e., making it too sensitive to variation particular to the sample dataset), we pruned our tree to find a consistent set of rules beyond the specific sample used to create it. Based on a graphical analysis of the plot of tree size and total deviance, we settled on an eight-endnode model as the most parsimonious model that explained the majority of the deviance. After the final form of the CART model was decided, we examined surrogate variables (i.e., explanatory variables that would have reduced deviance almost as much at a given split in the tree) to gain insight into other variables that would have worked almost as well at each split. This examination is particularly important as road density, household density, and forest patch size are moderately correlated to each other ($r \sim 0.5$ in all cases).

4. Results

4.1. Temporal and spatial patterns of harvest

The spatial pattern of land-use conversion and harvesting is shown in Fig. 2. There is an apparent difference between eastern Massachusetts, where there is frequent land-use conversion but little harvesting, and western Massachusetts, where there is little land-use conversion but frequent harvesting. Ecoregions range in percent forest cover from 18% in the Boston Basin to 92% in the Taconic Mountains (Table 1). Mean forest harvest patch sizes range from 5.1 ha in the Boston Basin to 25.4 ha in the Taconic Mountains. Mean forest harvest patch size is larger than the mean land-use conversion patch size, which ranges from 1.0 ha in the Lower Berkshire Hills to 2.5 ha in the Southern NE Coastal Plain. In all ecoregions in the western portion of the state, the percent of forest harvested annually is larger than the percent of forest lost to land-use change. In contrast, ecoregions in the eastern portion of the state have a larger percentage of forest lost to land-use change annually than harvested.

Nevertheless, a strong negative correlation exists between the percent of an ecoregion's forest converted to other land-uses and the percent of the forest harvested (Fig. 3). For each increase in the annual land-use conversion rate of 0.1% there is a decrease of 0.14% in the annual harvesting rate. The strength of this relationship ($r = 0.89$) is greater than that relating harvesting to any of the socioeconomic variables, such as population density, housing density, or household income, which are also negatively correlated with harvesting rate (data not shown).

White pine and red oak are consistently the most harvested timber species in Massachusetts, with various hardwood species cut for cordwood also forming a large component of the total volume removed (Fig. 4). Statewide, the composition

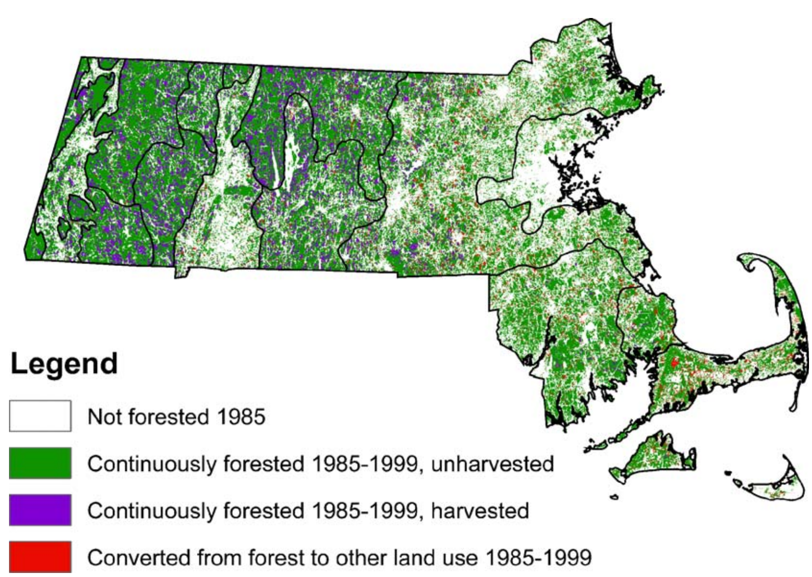

Fig. 2. Spatial distribution of forest harvest polygons and land-use change. Note that non-forested areas are shown in white and forested areas are shown in green, unless the forest was affected by land-use change (red) or harvesting (purple). Black lines are the ecoregion boundaries, defined in Fig. 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of the article.)

Table 1
Harvesting and land-use conversion summary statistics by ecoregion

Name	Forest area in 1985 (ha)	Percentage of ecoregion in forest in 1985	Mean harvest patch size (ha)	Mean harvest intensity (m^3 ha^{-1})	Harvest area (ha) from 1984 to 2003	Percentage of forest harvested per year	Mean land-use conversion patch size (ha)	Land-use conversion area (ha) from 1985 to 1999	Percentage of forest converted per year
Eastern Massachusetts									
Boston Basin	18571	18	5.11	37	41	0.01	2.07	1948	0.70
Cape Cod and Islands	97133	50	11.27	44	969	0.05	2.41	14051	0.96
Southern NE Coastal Plain	309961	52	11.59	50	27873	0.45	2.54	31615	0.68
Bristol Lowland	132215	55	10.92	41	3766	0.14	2.22	12326	0.62
Western Massachusetts									
Conn. River Valley	61310	43	12.53	39	9660	0.79	1.79	3985	0.43
Berkshire Valley	44978	51	14.60	36	7255	0.81	1.51	1429	0.21
Lower Worcester Plateau	129107	71	14.56	44	34792	1.35	1.66	5397	0.28
Vermont Piedmont	30300	77	16.47	35	8249	1.36	1.06	505	0.11
Worcester Plateau	154106	83	15.55	46	42272	1.37	1.56	4610	0.20
Berkshire Transition	77708	86	20.38	40	23622	1.52	1.16	1122	0.10
Berkshire Highlands	111296	88	20.08	43	22,532	1.01	1.27	1455	0.09
Lower Berkshire Hills	59496	88	22.81	37	17653	1.48	1.01	557	0.06
Taconic Mountains	33442	92	25.40	28	7037	1.05	1.51	207	0.04

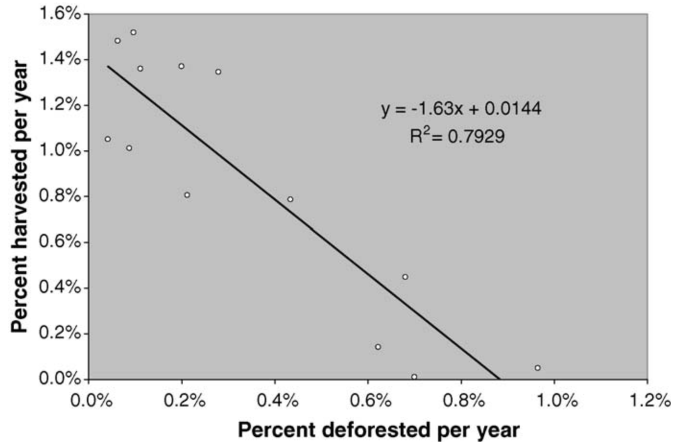

Fig. 3. Scatterplot of land-use conversion vs. land-use change for 13 ecoregions in Massachusetts.

of timber harvests in Massachusetts appears relatively constant over time. However, the species composition of harvesting varies significantly among ecoregions, with the greatest proportion of harvested volume coming from the more abundant species found in the area (Fig. 5). For example, spruce makes up a greater proportion of the total volume harvested in western Massachusetts, where it has likely long been most abundant (Hall et al., 2002).

In contrast with the strong spatial trends in the data, there appears to be little temporal variation in the harvesting regime in Massachusetts over the past two decades. The mean area of a FCP (15 ha) is fairly constant over time, varying from a minimum of 14.8 ha in 1995 to a maximum of 18.6 ha in 1999. The mean harvest intensity (43 m^3 ha^{-1}) is also fairly constant. However, the number of FCPs filed with the state (~650 plans/year) does vary through time, from a minimum of 447 in 1984 (before the program was fully implemented) to a maximum of

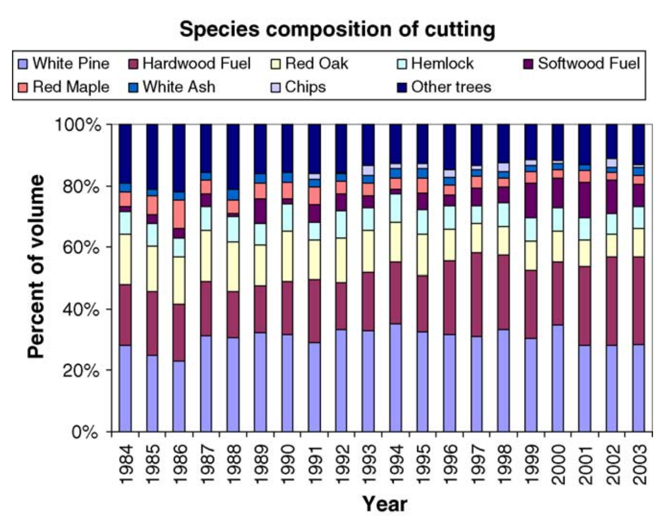

Fig. 4. Species composition of cutting in Massachusetts through time, shown as a percent of the total volume harvested. Note that white pine makes up approximately 20% of the total volume harvested, while mixed hardwoods cut as fuel wood make up approximately another 20% of the total volume harvested.

Fig. 5. Species composition of cutting in Massachusetts as a percent of the total volume harvested within each of the EPA ecoregions.

886 in 1985, with no apparent trend through time. Variation in the total volume harvested statewide (~450,000 m^3/year) thus closely tracks variation in the number of plans filed.

Generally, little or no harvesting occurs throughout much of eastern Massachusetts (Fig. 6, top). The Connecticut River Valley and the Berkshire Valley supported less harvesting than the western and central upland regions, the most heavily harvested part of the state. Mean harvest area follows a similar pattern (Fig. 6, middle). In contrast, mean harvest intensity was highest in areas near cities at the edge of the Boston metropolis such as Worcester, and in areas with a high concentration of state ownership (Fig. 6, bottom).

The proportion of forest harvested varies among ownership types, with federally owned lands having the lowest annual harvest rate (0.1%) and the MA Division of Water Supply Protection (DWSP) having the highest rate (1.4%; Table 2). The intensity of harvest is greatest for federal (68.5 $m^3\,ha^{-1}$), state water supply (63.2 $m^3\,ha^{-1}$) and state park lands (52.5 $m^3\,ha^{-1}$), and harvesting on these public lands is greater than the average rate of harvesting on private lands (40.5 $m^3\,ha^{-1}$).

4.2. Probability of harvest

The CART model highlights how road density and house prices can be used to predict harvesting patterns (Fig. 7). The first split is on road density, with cells that have a low road density (<2.47 km road per km^2) having a higher probability of being harvested (20.2% of cells harvested) than cells with a higher road density (5.7% of cells harvested). For this split, and all the others involving road density, the surrogate variables of household density and forest patch size could be substituted

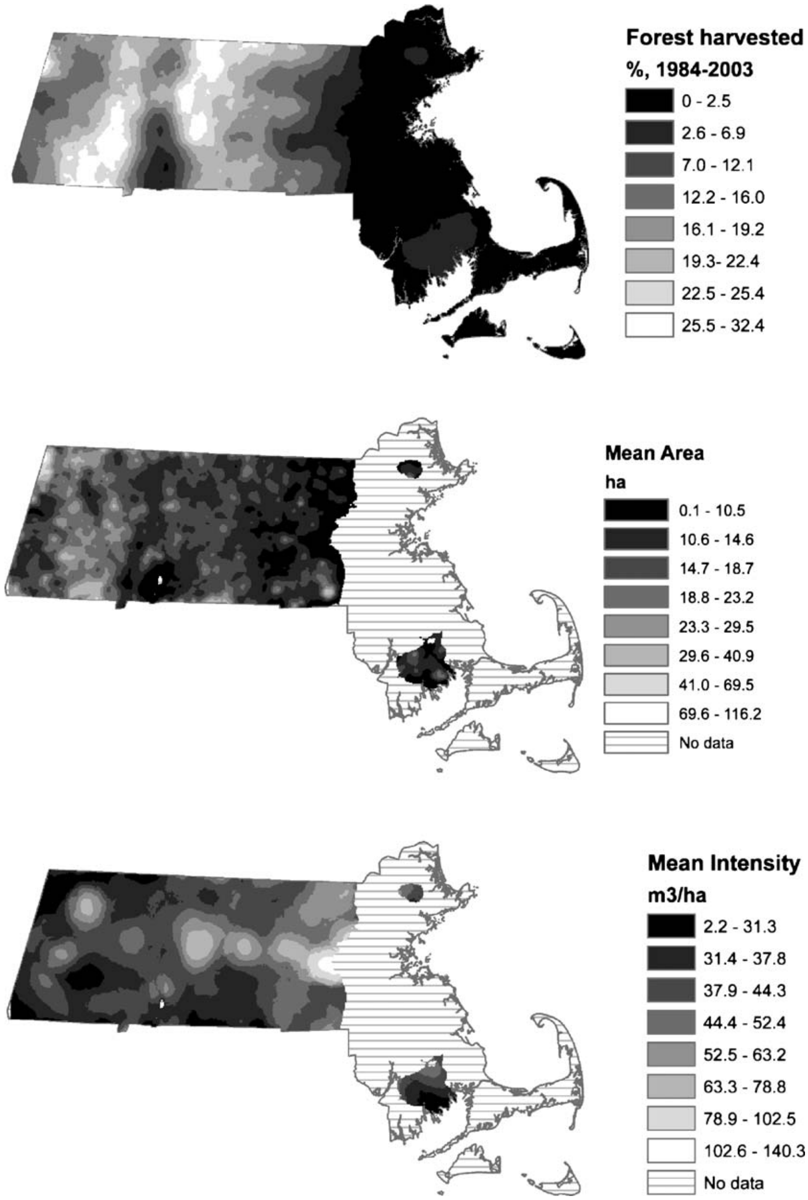

Fig. 6. Percent forest harvested (a), mean harvest patch area (b), and mean intensity of cutting (c) in Massachusetts. See text for details.

Table 2
Ownership trends

Ownership	Land area (ha)	Forest area (ha)	Percent forested	Cut area (ha)	Forest cut per year (%)	Mean intensity (m^3ha^{-1})
Municipal	133386	90422	67.8	8947	0.5	39.2
State	214800	190181	88.5	26781	0.7	52.9
DCR, State Parks	113467	103336	91.1	9831	0.5	52.5
DCR, Water Supply Protection	41688	37102	89.0	10682	1.4	63.2
DFG	52714	44237	83.9	5431	0.6	34.0
Other	6930	5505	79.4	490	0.4	44.2
Federal	25502	14406	56.5	346	0.1	68.5
Conservation lands (land trusts, etc.)	49562	33397	67.4	4387	0.7	35.6
Private lands	1670033	604784	36.2	97719	0.8	40.5
Total	2093283	1200211	57.3	186135	0.8	43.4

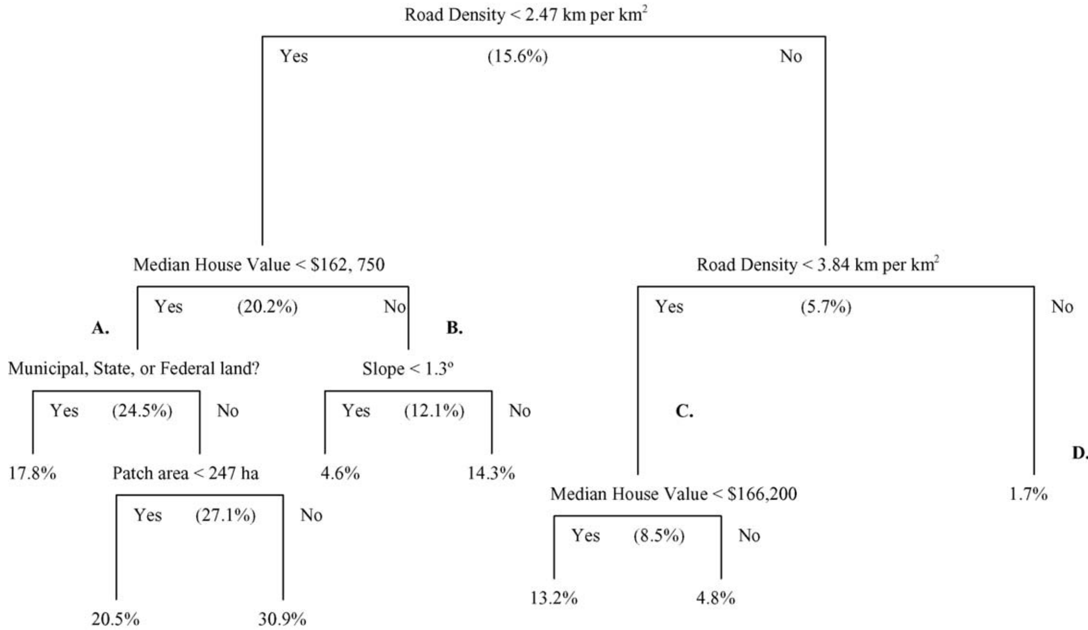

Fig. 7. Classification tree for the probability of forests being harvested. At each node, the relevant decision is shown. Percentages are the proportion of cells in the training sample that were harvested at that node. For example, a terminal node of 13.2% means that 13.2% of the cells at that node were harvested over the 20-year time period. The nodes marked A–D correspond to the nodes graphed in Fig. 8.

with only a slight reduction in deviance explained. For areas of the state with low road density, median house price is the next splitting variable, with areas with low house prices (<US$ 162,750) having a higher probability of harvest (24.5% of cells harvested) than areas with higher house prices (12.1% of cells harvested). Further down this branch of the tree, other splits utilize slope (flat areas, presumably flood plains or wetlands, have lower probability of harvest), ownership (lands in state, federal, or municipal ownership have lower probability of harvest than private lands), and forest patch area (large forest patches have higher probability of harvest). For areas of the state with higher road density (>2.47 km road per km^2), the next split is on road density again, with areas of very high road density (>3.84 km road per km^2) having a lower probability of harvest (1.7% of cells harvested) than areas with moderate (2.47–3.84 km road per km^2) road density (8.5% of cells harvested). In areas with moderate road densities, regions with more expensive housing again have lower probability of harvest. The remaining explanatory variables described in Section 3 (e.g., elevation, TCI) did not enter the CART model, and apparently are not significantly related to the probability of harvest (cf., Kittredge et al., 2003).

The results of this CART are informative when viewed spatially (Fig. 8), with the tree pruned to the top four nodes (i.e., the top three splits). The legend is color-coded based on the proportion of forested cells in that node that was harvested. Note that the portion of the state with road density above 2.47 km road per km^2 (nodes C and D) is relatively small. However, areas with lower road densities but higher house prices (node B) encompass a large portion of the state,

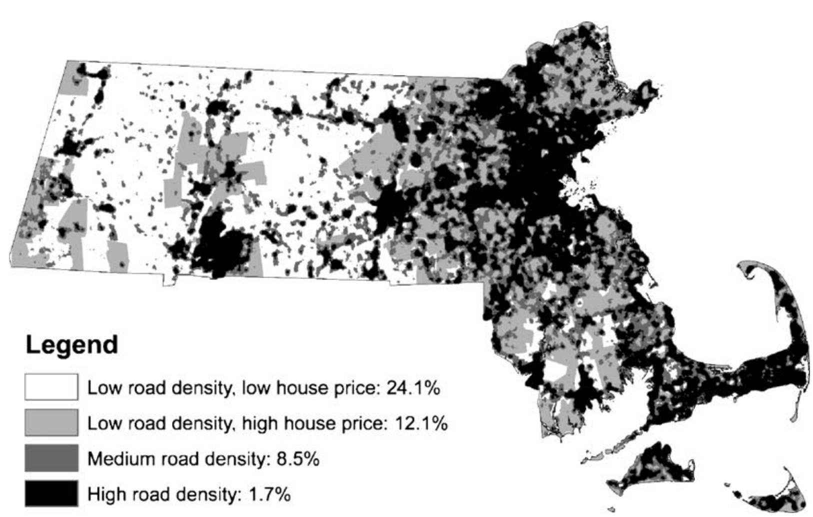

Fig. 8. Percent of forest harvested in four CART nodes. The nodes graphed correspond to those marked A–D in Fig. 7. See text for details.

including areas more than an hour drive from the city of Boston as well as resort areas in Cape Cod and the Berkshires.

5. Discussion

5.1. Harvesting patterns

There is a substantial spatial gradient in harvesting and land-use conversion, ranging from the far suburbs of Boston where there is much land-use conversion but little harvesting to the rural upland regions of the state where there is much harvesting but little land-use conversion. Our results suggest that this gradient in harvest activity is most strongly correlated with road density. Forest patch size and household density were not as strongly correlated with probability of harvest, although a successful predictive model could be built with any of these variables. We believe that road density is likely such a good predictor because it correlates with parcel size. Areas with higher road densities likely have small mean parcel sizes, and thus are less likely to be harvested (Kittredge, 1996; Kittredge et al., 2003), although comprehensive data on parcel size are not available statewide to test this hypothesis.

Our results also suggest that factors such as house prices within a region and site physiography correlate with harvesting patterns, even after controlling for road density (cf., Wear et al., 1999). The negative relationship between house price and probability of harvest suggests that something correlated with house price must affect landowner attitudes toward forest harvesting. For example, Finley and Kittredge (in press) use landowner surveys in western Massachusetts to divide landowners into different categories based on whether they value their forests for recreation, aesthetics, or harvesting income. Each landowner category has a different likelihood of harvesting their forest. If landowner category varies systematically with landowner wealth (and hence house price), then one explanation for our results is that increased wealth results in landowners being less inclined to harvest their forests. More broadly the patterns of forest harvesting in Massachusetts appear to be affected by the socioeconomic context in which these forests occur.

Statewide, the probability of harvest does not vary substantially by ownership, although ownership does appear at one place in our classification tree (Fig. 7). However, harvest intensity is affected by ownership (Table 2). State lands that are managed by DWSP for water supply are relatively intensively harvested, with a mean intensity of 63.2 $m^3\ ha^{-1}$ as compared with 40.5 $m^3\ ha^{-1}$ for private lands. These intensities represent approximately 30% and 20% of total stand volume, respectively, assuming $\sim$200 $m^3\ ha^{-1}$of total volume, and are lower than typical harvest intensities in many other forests in the United States.

5.2. Implications for other urban regions

The strong negative correlation between forest harvesting rates and rates of land-use conversion is surprising. This correlation is stronger than the correlation between forest harvesting rates and the socioeconomic variables we tested. One interpretation of this result is that in any given year a percentage of landowners want or need to generate revenue from their land. The landscape context of the landowner's property, as well as their overall socioeconomic status, influences the form (i.e., harvesting or land-use conversion) this operation will take. If one assumes that the correlation between harvesting rates and rates of land-use conversion is also indicative of a causal relationship (which may or may not be the case), our results suggest that incentives to support harvesting might reduce the amount of land-use conversion. However, in the long-term, the use-value of development is so much higher than the periodic income from forest harvesting (Lambin et al., 2001) that the effect of any such incentives may be minimal. Moreover, if the growth in affluence and rate of land-use conversion continue as at present, our results suggest that without more permanent forms of protection (i.e., fee-simple ownership by conservation agencies or conservation easements), many regions in the eastern US will go through this transition from forest harvesting to land-use conversion. This transition may be due to decreases in parcel size (i.e., increases in house density, increase in road density and decreases in forest patch size), but potentially a much larger geographic area may be affected by increases in land prices and the associated socioeconomic changes in landowner preferences.

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