Journal of Environmental Management 234 (2019) 464–475

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Forests, houses, or both? Relationships between land cover, housing characteristics, and resident socioeconomic status across ecoregions

Miranda H. Mockrin[a], Dexter H. Locke[b,*], Susan I. Stewart[c], Roger B. Hammer[d], Volker C. Radeloff[c]

[a] USDA Forest Service, Northern Research Station, 5523 Research Park Drive Suite 350, Baltimore, MD 21228 USA
[b] National Socio-Environmental Synthesis Center (SESYNC), 1 Park Place, Suite 300, Annapolis, MD 21401 USA
[c] University of Wisconsin, Department of Forest and Wildlife Ecology, 1630 Linden Dr, Madison, WI 53706 USA
[d] Oregon State University, Department of Sociology, 2251 SW Campus Way, Corvallis, OR 97331 USA

ARTICLE INFO

Keywords:
Residential development
Forest
Land cover
Housing
Sprawl

ABSTRACT

Residential development is one of the most intensive and widespread land uses in the United States, with substantial environmental impacts, including changes in forest cover. However, the relationships between forest cover and residential development are complex. Contemporary forest cover reflects multiple factors, including housing density, time since development, historical land cover, and land management since development. We investigated how forest cover varies with housing density, housing age, and household income over a range of development intensities, in six ecoregions within New York State, Wisconsin, and Colorado. We find areas with residential development do retain important forest resources: across landscapes they are typically more forested than areas that remain undeveloped. However, forest cover consistently had a negative, inverse relationship with housing density, across study areas. Relationships between forest cover and housing age and household income were less common and often restricted to only portions of a given region, according to geographically weighted regression analyses. A better understanding of how forest cover varies with residential development, outside of the typically studied urban areas, will be essential to maintaining ecosystem function and services in residential landscapes.

1. Introduction

Residential development is one of the most widespread causes of land use change in the United States (Brown et al., 2005; Pejchar et al., 2015) and globally (Alberti, 2005). In the U.S. homes are increasingly dispersed in low- and moderate-density suburbs and exurbs, consuming more land per household than urban development. In total, high-density urban land only expanded from 1% to 2% of the conterminous U.S. land area from 1950 to 2000, while exurban land expanded from 5% to 25% (Brown et al., 2005). The environmental impacts of low-density development are wide-ranging, and of particular concern when housing is built in forests or other natural vegetation (Hansen et al., 2005; Kramer, 2013). Building homes in forests removes and fragments vegetation, adds impervious surface, and introduces human residents and accompanying domestic animals and non-native plant species (Bar-Massada et al., 2014). Ecological impacts of this development are profound, including altered nutrient and biogeochemical cycles, increased pollution, and declining native and sensitive species (Alberti, 2005; Kaushal et al., 2006; McKinney, 2006).

Given the negative effects of residential development, there is a growing interest in planning and designing housing to preserve natural vegetation and ecosystem processes (Pejchar et al., 2015). Even in its most dense forms, residential development rarely leads to the complete removal of trees (Nowak et al., 1996; Nowak and Greenfield, 2012), and forests can remain extensive in areas of low-density housing (Radeloff et al., 2005b; Theobald, 2010). When forests and housing are intermingled, forests still provide important ecosystem services such as water quality, nutrient cycling, wildlife habitat and biodiversity, climate regulation, and carbon storage, as well as direct health and economic benefits to residents (as summarized by Cook et al. (2012)).

While retaining forests in developed areas is thus a land management priority, the ways in which residential development alters forest cover are not well understood. Multiple factors, from the ecoregion to the individual house, influence forest cover after development. At the broad scale, mesic ecoregions have greater forest cover in cities than arid regions (40–60% in mesic, forested ecoregions versus 15–20% in

* Corresponding author.
E-mail address: dexter.locke@gmail.com (D.H. Locke).

https://doi.org/10.1016/j.jenvman.2018.12.001
Received 6 April 2018; Received in revised form 26 November 2018; Accepted 1 December 2018
0301-4797/ Published by Elsevier Ltd.

Table 1
Study area names, state, ecoregion, and land cover/land use within study areas (from NLCD, 2006) for all PBGs except those with housing densities > 250 hu/km^2.

Study area	State	Ecoregion full name (province level)	Area (km^2)	% Forest	% Shrub, Grass, Wetlands	% Urban	% Agri-culture	% Nonveg (barren, water)
CO-Grass	Colorado	Great Plains-Palouse Dry Steppe	116,712.9	2.5	66.0	3.5	27.5	0.4
CO-Forest	Colorado	Southern Rocky Mountain Steppe-Open Woodland-Coniferous Forest-Alpine Meadow	114,235.4	53.1	38.8	1.2	3.4	3.5
NY-Adiro	New York	Adirondack-New England Mixed Forest-Coniferous Forest-Alpine Meadow	34,859.4	79.0	12.9	2.2	5.0	1.0
NY-Conti	New York	Eastern Broadleaf Forest (Continental)	20,151.0	31.1	16.6	8.1	43.3	0.9
NY-Laure	New York	Laurentian Mixed Forest	47,592.4	52.7	11.7	4.9	30.1	0.6
NY-Oceanic	New York	Eastern Broadleaf Forest (Oceanic)	18,292.3	42.9	11.9	15.6	27.8	1.8
WI-Conti	Wisconsin	Eastern Broadleaf Forest (Continental)	64,459.7	26.5	10.4	7.7	54.9	0.6
WI-Laure	Wisconsin	Laurentian Mixed Forest	77,477.1	47.0	22.3	5.1	24.9	0.7

desert or grassland ecoregions) (Nowak et al., 1996). Residential development, especially low density development, may purposefully be placed in or near forests to provide homeowners with forest amenities. As a result, low density housing may initially be associated with substantial forest cover (Brown, 2003; Turner et al., 2003; Platt et al., 2011). However, forest cover is generally inversely related to higher population and housing density (Heynen and Lindsey, 2003; Troy et al., 2007; Luck et al., 2009), and with a greater proportion of land dedicated to building footprints (i.e., bigger homes relative to parcel size) (Tratalos et al., 2007; Nielsen and Jensen, 2015; Daniel et al., 2016; Apparicio et al., 2017).

Forest cover also changes over time in response to landscape and homesite level ecological processes and management. At the homesite level, land cover changes after construction, as natural succession occurs and residents plant or remove trees (Matlack, 1993; Kim and Ellis, 2009; McWilliam et al., 2010; Nitoslawski and Duinker, 2016). In agricultural or grassland sites, residential development may lead to an increase in forest cover with tree planting and natural succession (Sharpe et al., 1986; Matlack, 1997; Brown, 2003; Berland, 2012). In such cases, the regrowth and diversity of forest may be minimal in comparison to original cover before agricultural clearing (Sharpe et al., 1986; Fahey et al., 2012). Forests will also not increase indefinitely over time: in temperate areas forests decline with development, increase with planting, and then decline with canopy maturation (Troy et al., 2007; Conway and Bourne, 2013; Grove et al., 2014; Locke et al., 2016; Pham et al., 2017).

In urban areas the amount of forest cover may also depend on past and present residents' socioeconomic status, race/ethnicity, education, and lifestyle factors (e.g., family size, marital status, occupation) (Hope et al., 2003; Grove et al. 2006, 2014; Luck et al., 2009; Boone et al., 2010; Schwarz et al., 2015; Apparicio et al., 2017). Greater forest cover in urban areas is generally associated with socioeconomic advantage as residents choose to live among more forest cover, advocate for forest cover on public land, and plant trees themselves (Grove et al., 2006; Troy et al., 2007). Both formal and informal institutions also influence residential management and forests (Martin et al., 2004; Troy et al., 2007; Boone et al., 2010; Roy Chowdhury et al., 2011; Cook et al., 2012). For example, newer neighborhoods in the southwestern U.S. have less tree cover because xeric landscaping is now common (Hope et al., 2003; Martin et al., 2004).

While understanding forest change with development is therefore complex, the relationships between forest cover and housing have been most commonly studied in urban areas, often in a single focal urban area. Emphasis is generally on understanding where forest vegetation is retained and can be augmented (Nowak et al., 1996; Locke et al., 2010). In contrast, in exurban and rural areas research focuses on documenting forest loss across landscapes (e.g., Hansen et al., 2005), with less emphasis on parcel-level management, and relationships between forest cover and socioeconomic/lifestyle factors. Forest cover over landscapes and across a range of housing densities is rarely investigated (Bar-Massada et al., 2014; Van Berkel et al., 2018).

In response to this research gap we conducted a study of forest cover and residential development across multiple ecoregions in the U.S., over a wide range of residential densities, removed from urban cores. Our first goal was to examine how forest cover varies between areas with residential development and areas without, to identify if housing is associated with more or less forest cover. We then compared forest cover in areas of recent residential development to areas that remain undeveloped. Recent development does not allow time for the effects of resident management (augmenting or removing forest) to materialize, and therefore reflects site selection and initial clearing during development, allowing us to determine if forested areas are preferred for and retained following development. We then examined how housing density, housing age, and household income combined to influence forest cover. Based on prior research, we expected forest cover to be inversely related to higher housing density, demonstrate a quadratic relationship with housing age, and be positively related to household income.

2. Materials and methods

2.1. Study areas

We analyzed forest cover and residential development in six province-level ecoregions (Bailey, 1995) in three states (New York, Wisconsin, and Colorado), forming eight unique combinations of state and ecoregion, which we termed study areas (Table 1). We refer to each study area using a combination of state abbreviation and ecoregion name. These states and their ecoregions encompass a range of land use and development histories, and include both native grasslands (eastern CO), savannas (southern WI), and forested ecosystems (western CO, NY, northern WI).

We excluded the areas with highest housing densities (≥250 housing units (hu)/km^2), found only in urban cores (Fig. 2), in order to focus on areas where development does not preclude forest cover remaining, as measured by moderate resolution remotely sensed imagery. Here, we briefly describe climate, vegetation, and land cover/land use for each ecoregion and state. We present more on housing characteristics of each study area in our results (see below).

New York State has four main ecoregions (Table 1, Fig. 1). The Laurentian Mixed Forest ecoregion is characterized by rolling hills. Average annual precipitation is moderate, and long winters and a short growing season restrict agriculture. Vegetation is transitional between boreal forest and broadleaf deciduous forest, and is composed of deciduous trees, conifers, and mixed stands (Bailey, 1995). The Eastern Broadleaf Forest (Continental) ecoregion is also characterized by deciduous broadleaf forests, rolling to flat topography, and a continental climate. Along the coast, the Eastern Broadleaf Forest (Oceanic) ecoregion is characterized by variable topography, including coastal plains, and a continental climatic regime. Vegetation includes temperate deciduous forest including northern hardwoods, Appalachian oak, and oak-pine forest. The Adirondack-New England Mixed Forest-Coniferous

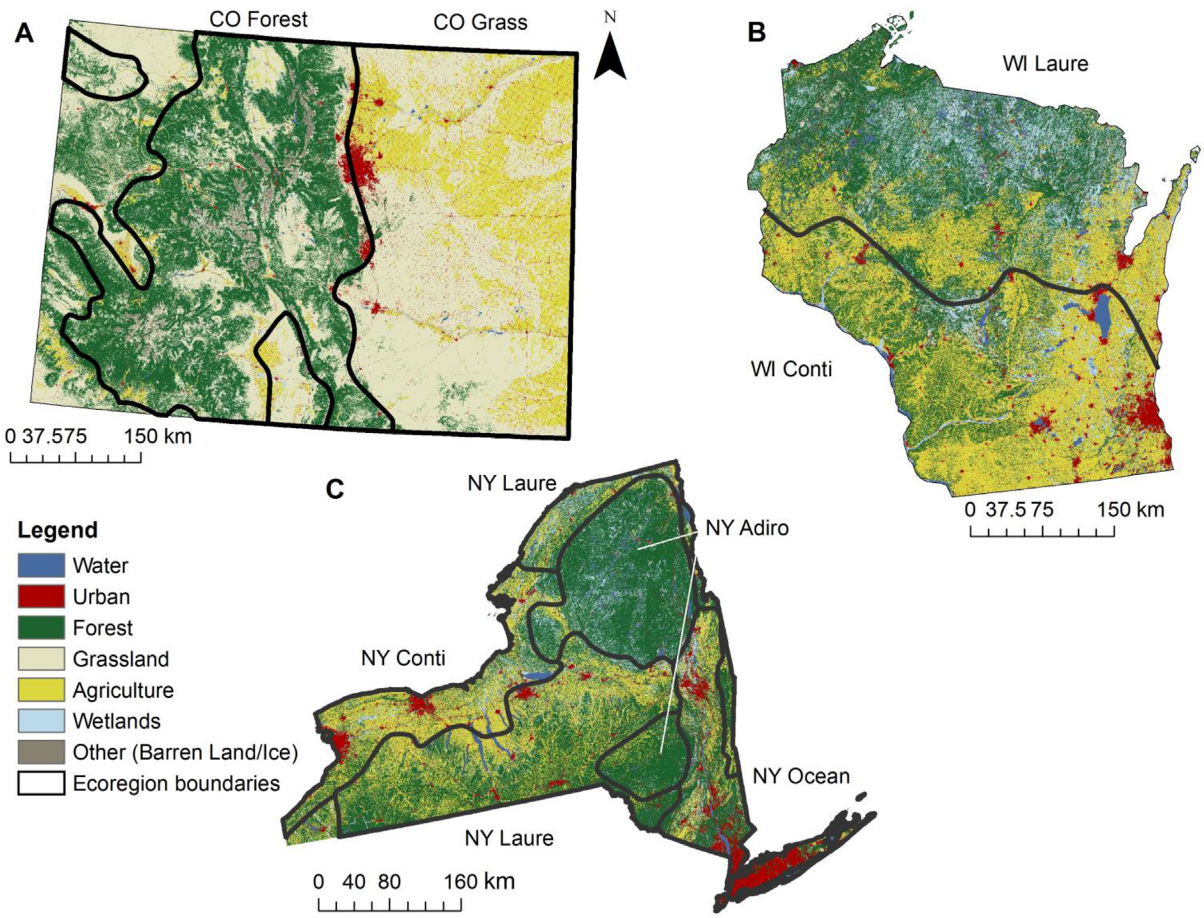

Fig. 1. NLCD land cover classes by study area for A. Colorado, B. Wisconsin, and C. New York.

Forest-Alpine Meadow ecoregion is characterized by glaciated mountains and plateaus and continental climate with year-round precipitation. Vegetation is a transition between boreal spruce-fir forest to the north and the deciduous forest to the south (Bailey, 1995). European settlement starting in the 17th century began an intense period of forest clearing for agriculture, timber harvesting, and other development, but starting in the late 1880s agriculture began to expand westward, and reforestation began (Irland, 1999). In New York today, forest cover is extensive in the NY-Adiro and NY-Laure study areas, while agriculture is widespread in the NY-Conti and NY-Laure study areas (Table 1, Fig. 1).

Wisconsin was part of the initial expansion of agriculture and timber harvesting in the Midwest. The northern part of the state falls into Laurentian Mixed forest ecoregion (WI-Laure; ecoregion described above) and was heavily logged between 1830 and 1930, after which forests began to regrow (Hammer et al., 2009). Today, forest land cover is widespread (Fig. 1). Southern Wisconsin, which falls into the Eastern Broadleaf (Continental) ecoregion (WI-Conti; ecoregion described above), was originally a mix of savanna, forest, and grasslands, but was extensively cleared for agriculture, which remains a predominant land use today (Rhemtulla et al., 2009). Among all our study areas, WI-Conti has the largest proportion of agriculture and the second lowest amount of forest cover (Table 1).

Colorado consists primarily of two ecoregions (Fig. 1). The western half of the state is forested, within the Southern Rocky Mountain Steppe-Open Woodland-Coniferous Forest-Alpine Meadow ecoregion (CO-Forest), a mountainous region with a temperate semiarid climate, but higher precipitation at higher elevations. At lower elevations pine, Douglas-fir, lodgepole pine, and aspen are common, while at higher elevations spruce and fir are common, followed by alpine tundra (Bailey, 1995). Eastern Colorado falls within the Great Plains-Palouse Dry Steppe ecoregion (CO-Grass). In the rain shadow of the Rocky Mountains, climate is semiarid continental. Vegetation is shortgrass prairie, with scattered trees and shrubs (Bailey, 1995). Similar to the other states in our study, Colorado experienced a period of extensive logging and grazing in forested areas in the mid to late 1800s (Fornwalt et al., 2009). In eastern Colorado, row crops and managed grazing largely replaced native vegetation by the 1950s (Chase et al., 1999). Today forest cover is extensive in CO-Forest, but rare in CO-Grass (Table 1, Fig. 1). In comparison to WI and NY, residential development is a newer phenomenon in CO, and has increased dramatically since the 1970s, particularly along the Colorado Front Range, where the CO Forest and CO Grass ecoregions meet (Leinwand et al., 2010).

2.2. Data sources and exploratory analyses

We used Census data from the 2000 Decennial Census to calculate housing densities (hu/km^2) and median housing age for each partial block group (PBG), for each study area. For large landscapes of interest, Census data provide the most reliable and extensive information on housing. We used year 2000 data because the long-form Census data collection from this date allowed us to calculate age of housing at the PBG level, which is a relatively fine spatial scale. PBGs represent subdivisions of block groups into smaller spatial units based on the boundaries of incorporated places, legal and census-designated county subdivisions, and rural/urban areas (Hammer et al., 2004). Using PBGs as our units of analysis maximized variations in housing density between PBGs and minimized within PBG variation (Hammer et al., 2004). We derived housing density from counts of housing units and PBG size, and calculated median housing age based on answers to the

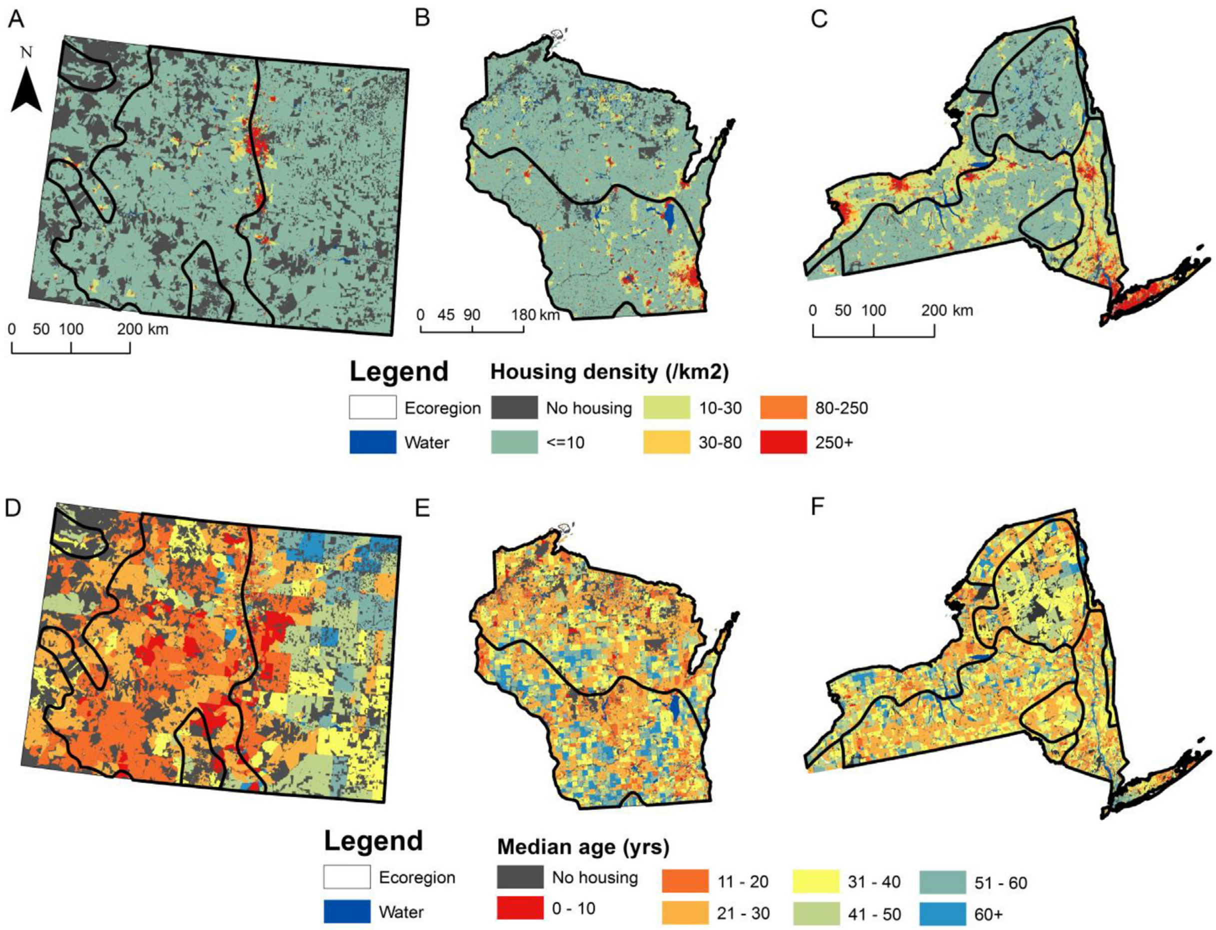

Fig. 2. Housing density per PBG for A. Colorado, B. Wisconsin, and C. New York and median housing age per PBG for D. Colorado, E. Wisconsin, and F. New York.

2000 census long-form question "In what year was this housing unit built?" (U.S. Census Bureau, 2002). Age on housing data is reported only back to 1940, so the maximum median housing age was 60 years, with earlier housing (> 60 years) coded as 61 years.

We used U.S. Department of Housing and Urban Development's calculations of percent of households with low and moderate income per PBG (data from the 2000 census) (HUD, 2013). Social characteristics influencing forest cover are varied, and extend beyond income (e.g., residents' life stage or lifestyle), but household income was the best variable available at the PBG level. Thresholds used to determine low and moderate income were calculated by HUD, and varied at the county level for the states in this study (county-level upper limits for moderate income ranged from $34,500-$51,600 in NY, $37,350-$50,050 in WI, and $36,900-$52,150 in CO) (HUD, 2007). We used the year 2006 National Land Cover Data (NLCD) from the US Geological Survey to calculate percent of each PBG that was forested (Fry et al., 2011). NLCD data are generated from 30-m x 30-m pixel Landsat satellite data. Because of their moderate resolution, NLCD tends to overestimate tree canopy in areas of low housing density, essentially missing the footprint of development, but underestimate tree canopy where residential development is high, because small patches of forest are missed (Smith et al., 2010; Gray et al., 2013). We excluded the PBGs with housing densities > 250 hu/km^2, found only in urban cores, in order to focus on areas where development does not preclude forest cover remaining (Fig. 1). Average percent forest cover for the PBGs excluded ranged from 0.1% in CO-Grass to 15.1% in NY-Adiro.

2.3. Statistical analyses

All statistical analyses were conducted separately for each study area (Table 1, Fig. 1). We used descriptive and exploratory analyses to examine univariate spatial autocorrelation in housing density, age, and forest cover (Table 2). We used Moran's I test for autocorrelation with a first-order queen-based contiguity matrix (any PBGs sharing edges or corners were defined as neighbors) (Table 2). After determining that spatial autocorrelation was present (Table 2), we used a modified *t*-test of spatial association, in the "SpatialPack" package in R (Osorio and Vallejos, 2014) to compare a) areas without residential development to areas with residential development, and b) areas without residential development to those with recent development (median housing age ≤ 20 years). Note that areas without residential development may still have 'urban' land cover (e.g., commercial development, roads).

For multivariate analyses we used regression analysis, and model-fit diagnostics to determine the most appropriate model, estimating forest cover as a function of housing density, median housing age, the quadratic form of median housing age (hereafter median housing age^2), and percent of households with low-moderate income. Each independent variable was standardized as grand mean-centered, with housing density logged first to meet normality assumptions. We first applied ordinary least squares regressions to examine initial relationships in the data, without including spatial dependence, using the *dredge()* function in the R package "MuMIn" (Bartoń, 2016) to test all possible combination of variables. We chose a best OLS model by ranking AIC scores, and examined variables retained for collinearity using variance inflation factors. We then used spatial autoregressive regression (SAR) because the Moran's I values calculated from OLS models' residuals

Table 2
Summary statistics and global Moran's I and significance for land cover, housing, and household income at the PBG level, for all PBGs with housing densities ≤250 hu/km^2 (n = 8 study areas).

		CO Forest	CO-Grass	NY Adiro	NY Conti	NY-Oceanic	NY-Laure	WI Conti	WI-Laure
n PBGs (< 250 hu/km^2)		903	784	455	1266	2024	1941	3806	2319
Size PBG (km^2)	Average	97.9	111.6	65.5	14.7	21.7	8.9	15.2	28.1
	St. dev	280.1	320.8	101.6	20.6	27.9	16.2	24.6	39.7
	CV	286.3	287.4	155.1	140.3	128.4	182.7	161.6	141.5
	Min	0.02	0.02	0.02	0.01	0.0	0.0	0.0	0.0
	Max	2669.9	3128.6	965.4	131.8	223.4	187.7	150.6	374.1
Percent forest	Average	33.1	2.4	63.9	25.9	42.8	40.1	20.5	35.3
	St. dev	31.1	8.4	24.7	17.3	23.8	23.8	18.5	24.4
	CV	93.8	355.3	38.7	66.7	55.7	59.3	90.5	69.1
	Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Max	98.4	83.8	98.3	90.7	96.8	97.1	90.1	100.0
	Moran's I*	0.6	0.6	0.6	0.6	0.5	0.5	0.6	0.7
Housing density (/km^2)	Average	63.1	54.6	38.3	72.5	53.5	93.6	46.6	29.9
	St. dev	74.2	71.7	59.6	74.1	67.1	72.5	65.5	51.5
	CV	117.5	131.3	155.5	102.3	125.5	77.5	140.7	171.9
	Min	0.0	0.0	0.2	0.7	0.3	1.0	0.3	0.1
	Max	249.6	249.9	248.6	248.3	249.5	249.8	249.8	249.7
	Moran's I* &	0.4	0.4	0.4	0.4	0.3	0.3	0.5	0.4
Median housing age (yrs)$	Average	23.7	28.8	36.8	37.8	37.9	35.1	34.6	33.1
	St. dev	14.5	17.5	13.4	14.8	14.1	13.2	16.3	14.8
	CV	61.2	60.6	36.4	39.1	37.3	37.7	47.1	44.6
	Min	5.0	5.0	8.0	5.0	5.0	5.0	5.0	5.0
	Moran's I*	0.2	0.4	0.2	0.2	0.1	0.2	0.2	0.3
Low & mod. Income percent households	Average	32.0	36.4	39.7	35.7	39.5	29.6	33.0	39.0
	St. dev	25.2	27.2	15.5	20.5	20.0	19.2	22.9	21.1
	CV	78.6	74.7	39.0	57.5	50.7	65.0	69.3	54.2
	Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Max	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	Moran's I*	0.1	0.3	0.1	0.2	0.1	0.2	0.1	0.1

* All global Moran's I significant $p < 0.0001$.
& With logged values.
$ All with the same maximum of 61 (60 + years).

showed significant spatial autocorrelation (Tables 2 and 3). All SAR models included the same final variables as the best OLS models, and we estimated them using the "spdep" package in R (Bivand et al., 2013; Bivand and Piras, 2015), with the same spatial weight matrices.

We used LaGrange spatial diagnostics, AIC scores, and likelihood ratio tests to compare different SAR models (i.e., spatial error, spatial lag, and Durbin) for all study areas (Anselin, 2005, p.198–200). Spatial error models include a spatial autoregressive error term to represent unmeasured variables that are spatially autocorrelated, while in spatial lag models the dependent variable is spatially autocorrelated. The spatial Durbin model is an extension of the lag and error models that combines a spatial error term with spatially lagged independent variables. As nested models, the Durbin models can be compared to either error or lag models using a likelihood ratio test (LeSage and Pace, 2009; Elhorst, 2010). We then calculated Moran's I for residuals of SAR models, to determine if including the spatial model had successfully accounted for spatial autocorrelation (Anselin, 2005, p. 211).

In cases where the best fitting model included the spatial lag of the dependent variable (spatial lag or Durbin models), the magnitude, direction, and significance of the model coefficients do not fully reveal variables' relationships (LeSage and Pace, 2009; Elhorst, 2010). Therefore, we used Monte Carlo simulation to obtain distributions of the direct, indirect, and total effects of change in variables, along with Z-scores and a measure of significance (p-value), through the *impacts()* function in the "spdep" package (Bivand et al., 2013; Bivand and Piras, 2015). Direct effects are those changes that occur when a change in a predictor variable in a sampling unit (in our case, PBG) corresponds to a change in the dependent variable in that unit (this also includes any feedback effects/spatial lags, when changes in the predictor variable affect neighboring observations and then the original unit). Indirect effects are a measure solely of those "spill-overs", when changes in a predictor variable of a particular unit (PBG) correspond with changes in the dependent variables of other units. The combination of both these effects is the total impact (LeSage and Pace, 2009; Elhorst, 2010).

Global spatial models—lag, error, and Durbin—do not consider spatial heterogeneity (non-stationarity). For example, the relationship between X and Y can be positive in one part of a study area and negative in another. Statistically significant Koenker (BP) statistics and spatial autocorrelation of OLS residuals led us to explore geographically weighted regression (GWR), to examine variation in the relationships between predictors and forest cover within study areas. Separate regression equations are run for each observation, using a spatial kernel that centers on a given point and weights observations subject to a distance decay function. GWR results identify areas where locally weighted regression coefficients diverge from their respective global estimates (Brunsdon et al., 1996; Fotheringham et al., 1998). We used the *gwr.sel()* and *gwr()* functions in the "spgwr" package (Bivand and Yu, 2015) to select bandwidths, and fit the GWR models, respectively. We used the adaptive kernel function with a Gaussian spatial weight kernel to search for an optimal bandwidth. Cross-validation minimization provides a way of choosing bandwidth that makes an optimal tradeoff between bias and variance (generally, more variance will lead to a smaller bandwith selected) (Cleveland and Devlin, 1988). We then mapped individual model parameters' statistical significance over each study area.

3. Results

3.1. Descriptive statistics

Study areas varied in housing characteristics and land cover (Table 1, Table 2). Average percent forest cover per PBG ranged from

Table 3
Spatial models of percent forest cover as a function of housing density, housing age, and household income at the PBG level, for study areas (n = 8). *p < 0.05; **p < 0.01; ***p < 0.001.

	CO-Forest		CO Grass		NY-Adiro		NY-Conti	
Type of model	OLS	Durbin	OLS	Lag	OLS	Durbin	OLS	Durbin
Coefficients (direct/main effects):								
Housing density (/km^2)	−12.9***	−9.9***	−0.7*	−0.3	−11.5***	−13.1***	−3.4***	−2.5***
Median housing age (yrs)			−1.2***	−0.3	35.3***	15.6***	6.7**	4.4*
Median housing age^2 (yrs)					−36.7***	−14.4***	−7.5**	−5.4**
Percent low and mod. income (household)	−3.6***	−1.7**						
Intercept	33.1***	8.0***	2.4***	0.6**	63.9***	23.1***	25.9***	7.8***
AIC	8572	7935	5551	5072	3933	3721	10,744	10,067
R^2/Pseudo-R^2	0.17	0.61	0.02	0.47	0.37	0.67	0.05	0.45
Moran's I of residuals	0.63***	−0.03	0.59***	−0.02	0.57***	0.002	0.57***	−0.04
Lambda		0.73***		0.72***		0.63***		0.69***
Lag (indirect effects):								
Housing density (/km^2)		5.1***				9.9***		0.9
Median housing age (yrs)						24.1**		−0.5
Median housing age^2 (yrs)						−27.6***		1.7
Percent low and mod. income (household)		−1.4						

	NY-Oceanic		NY Laure		WI-Conti		WI Laure	
Type of model	OLS	Durbin	OLS	Durbin	OLS	Durbin	OLS	Durbin
Coefficients (direct/main effects):								
Housing density (/km^2)	−9.9***	−7.2***	−9.5***	−9.8***	−5.4***	−2.6***	−9.5***	−4.5***
Median housing age (yrs)	8.5***	4.8**	8.0**	4.6*	1.8	2.1*	6.2**	0.4
Median housing age^2 (yrs)	−9.4***	−6.1***	−10.8***	−5.4**	−4.6***	−3.4***	−13.9***	−3.5**
Percent low and mod. income (household)	−1.5**	−0.4	−1.3**	−1.0**	0.8**	−0.3	2.9***	−0.5
Intercept	40.2***	14.8***	42.8***	12.5***	20.5***	5.7***	35.3***	37.9***
AIC	17,365	16,468	18,067	16,891	32,475	30,480	20,289	18,625
R^2/Pseudo-R^2	0.18	0.51	0.21	0.57	0.09	0.49	0.24	0.70
Moran's I of residuals	0.47***	−0.04*	0.59***	−0.05**	0.52***	−0.03**	0.63***	−0.03*
Lambda		0.62***		0.70***		0.70***		0.70***
Lag (indirect effects):								
Housing density (/km^2)		1.6*		6.7***		−0.2		0.8
Median housing age (yrs)		1.9		2.9		−2.2		2.4
Median housing age^2 (yrs)		−0.6		−3.9		0.7		−3.3
Percent low and mod. income (household)		−1.2		0.7		1.3**		3.1***

2.4% in CO-Grass to 63.9% in NY-Adiro (Table 2). Among study areas, WI-Laure and NY-Adiro had the lowest average housing densities per PBG (Table 2), and NY-Conti and NY-Oceanic the highest. Median housing ages in the study areas in New York and Wisconsin were on average a decade older or more than in Colorado (Table 2). Maps and Moran's I tests revealed that all study areas had significant positive spatial autocorrelation ($p \le 0.001$) for percent forest cover, housing density, housing age, and household income (Table 2).

3.2. Statistical analyses

Spatial t-tests demonstrated that PBGs with residential development had statistically significantly higher average percent forest cover than PBGs without residential development for most study areas (Fig. 3, Supplemental Table 1) (but not in CO-Forest and WI-Laure). We then compared areas without housing to those recently developed (median housing age ≤ 20 years). PBGs with recent development had significantly greater forest cover than areas without housing in most study areas, suggesting that forested areas were preferentially developed in recent decades (but not in NY-Adiro, CO-Forest, and WI-Laure) (Fig. 3, Supplemental Table 1). The most heavily forested study area, NY-Adiro, was the only study area where areas with housing did have greater forest cover than areas with no housing, but not for areas with recently developed housing in comparison to no housing (Fig. 3, Supplemental Table 1).

For multivariate analyses, all OLS models had significant autocorrelation in residuals and Moran's I values greater than 0.5 ($p \le 0.001$), as well as higher AIC scores than SAR models, so we restricted our interpretations to the SAR models (Tables 3 and 4). Variance inflation factors indicated that predictor variables were not significantly correlated in any study area (VIF < 2) (O'Brien, 2007), except where median housing age and median housing age^2 were retained in final models (Table 5). Although these variables are correlated by their construction, we retained both to examine the shape of the relationship between forest cover and housing age. The best-fitting SAR models were Durbin models for all study areas except CO-Grass where a spatial lag model fit best (Table 3). For the CO-Forest, CO-Grass, NY-Adiro, and NY-Conti models the SAR models successfully removed spatial autocorrelation in the residuals (Table 3). For the remaining study areas, the SAR models had small but statistically significant spatial autocorrelation in residuals (Table 3).

3.2.1. Housing density

Housing density was consistently retained in SAR models, with significant, negative relationships with forest cover (Table 4), with the exception of CO-Grass study area, the only area that is not naturally forested. Total impacts are the measure of average change seen in local observations' dependent variable (percent forest cover) with a one-unit difference in the predictor variable. For study areas where total impacts were significant, a one-unit difference from the mean-centered log housing density resulted in 17.4%–5.4% difference in forest cover (Table 4). For example, in CO-Forest, with the largest total impact estimate, 90% less housing density than the mean (from 63 hu/km^2 to 6.3 hu/km^2) resulted in 17.4% more forest cover (multiplying the total impact of −17.4 by log(0.1) gave the difference in percent forest cover with a 90% decrease in housing). Conversely, a housing density 90% above the mean (from 63 hu/km^2 to 119.7 hu/km^2) resulted in −4.9% less forest cover (−17.4*log(1.9) = -4.9). For NY-Conti, the study area

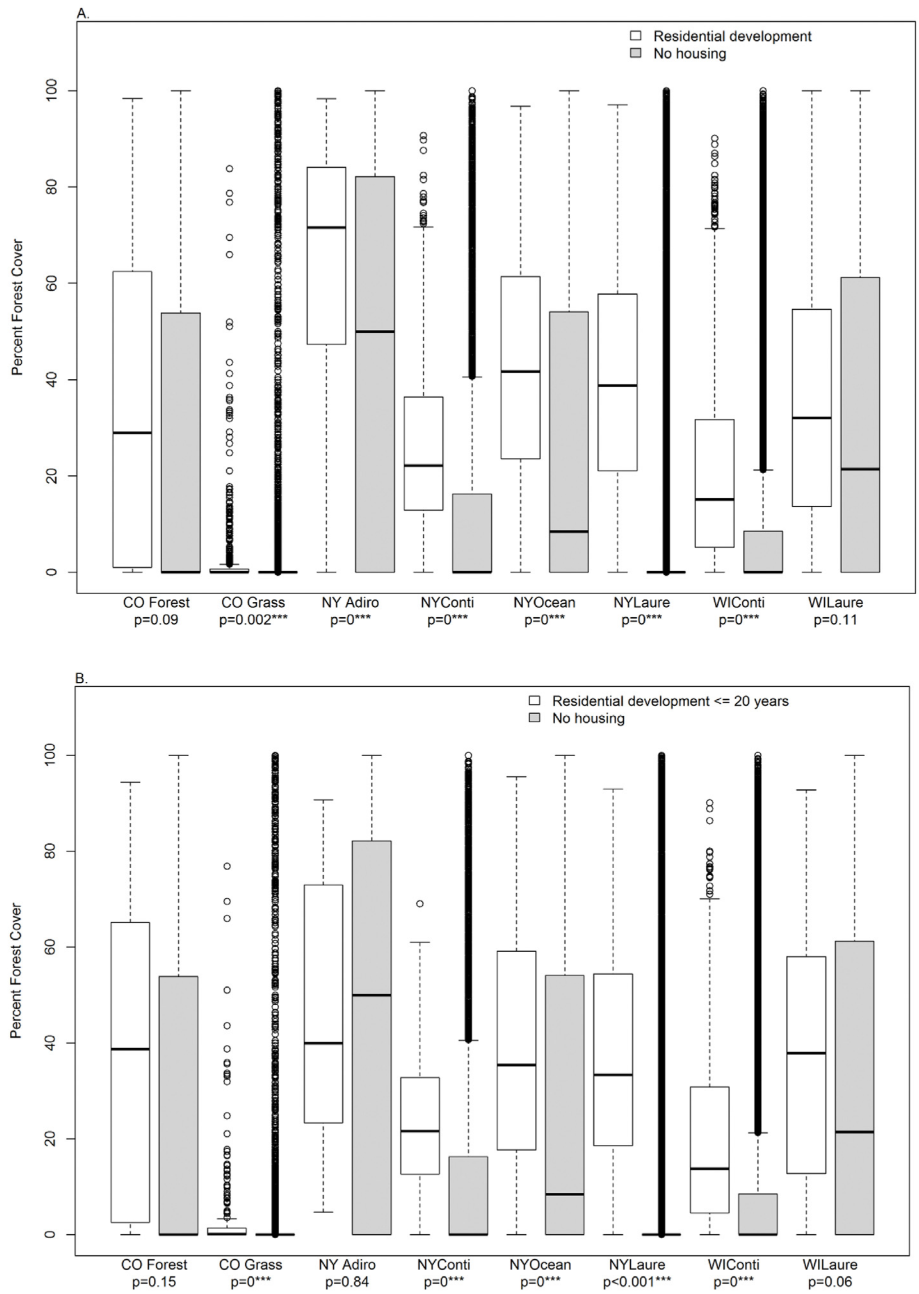

Fig. 3. Percent forest cover per PBG for A. All residential development vs. no residential development and B. Recently developed housing (< =20 years median housing age) vs. no residential development.

with the smallest total impact estimate, 90% below the mean housing density (from 72.5 hu/km^2 to 7.3 hu/km^2) resulted in 5.4% more forest cover, while housing density 90% above the mean (from 72.5 hu/km^2 to 137.8 hu/km^2) resulted in −1.5% less forest cover.

We used GWR models (Table 5) to examine local variation in regression coefficient values predicting forest cover, and where these relationships diverged from global models (Table 5, Supplemental Figs. 1–4). Negative, statistically significant relationships between forest cover and housing density were largely confirmed by GWR models: for five study areas, more than half of individual PBGs (often > 80%) fit this pattern (Table 5). No PBGs had a positive and significant relationship between housing density and forest cover (Table 5). GWR results for the CO-Grass study area also agreed with the global OLS model and SAR model results, showing minimal statistically significant relationships between housing density and forest cover.

However, for the NY-Conti and WI-Conti study areas, negative significant relationships between forest cover and housing density were not as widespread. Here, only 21% and 32% of PBGs respectively had negative, significant relationships between housing density and forest cover, while in the WI-Conti study area, 8% of PBGs had a positive, significant relationship between forest cover and housing density (Table 5). Maps of local GWR relationships can also reveal if there are spatial patterns in the distribution of such local departures from global models. In the NY-Conti study area, PBGs with a negative, significant relationship between housing density and forest cover were concentrated in the eastern and western edges of the study area, including around Buffalo (Supplemental Fig. 1). In WI-Conti, the PBGs with negative, significant relationships between housing density and forest cover were concentrated in the west, removed from the urban areas (Madison, Milwaukee) (Supplemental Fig. 1).

Table 4
Direct, indirect, and total impact estimates for spatial lag and spatial Durbin models.

	CO Forest	CO Grass	NY Adiro	NY Conti	NY Ocean	NY Laure	WI Conti	WI Laure
Direct								
Housing density (/km^2)	−10.5***	−0.4	−12.8***	−2.8***	−7.8***	−9.9***	−3.1***	−5.2***
Median housing age (yrs)		−0.4	23.2***	5.1***	5.9**	6.1**	1.9	1.1
Median housing age^2 (yrs)			−22.6***	−5.9***	−7.1***	−7.4***	−3.8***	−5.2***
Percent low-mod. income	−2.6**				−0.7	−1.0***	0.0	0.3
Indirect								
Housing density (/km^2)	−6.9**	−0.7	4.0***	−2.6	−7.1***	−0.5	−6.2***	−10.7***
Median housing age (yrs)		−0.8	83.3***	7.6	12.0*	18.6*	−2.2	10.7
Median housing age^2 (yrs)			−90.1***	−5.9	−10.7	−23.4***	−5.2	−24.5***
Percent low-mod. income	−8.9*				−3.7*	0.1	3.6***	11.0***
Total								
Housing density (/km^2)	−17.4***	−1.0	−8.7**	−5.4**	−14.9***	−10.4***	−9.3***	−15.9***
Median housing age (yrs)		−1.2	106.5***	12.6	17.9*	24.7**	−0.3	11.8
Median housing age^2 (yrs)			−112.7***	−11.8	−17.8*	−30.8***	−9.0	−29.7***
Percent low-mod. income	−11.5**				−4.4*	−0.9	3.6***	11.3***

3.2.2. Housing age

Housing age was retained in best-fitting models for all study areas except CO-Forest (Table 3), but only had significant total impacts in four study areas: NY-Conti, NY-Laure, WI-Conti, and WI-Laure (Table 4). In the WI-Laure study area, only total impacts of median housing age^2 were statistically significant and negative (Table 4). For NY-Conti, NY-Laure, and WI-Conti, both median housing age and median housing age^2 had significant total impacts (positive and negative respectively, Table 4). In each of these study areas median housing age was positively related to forest cover and median housing age^2 negatively related to forest cover, so that lower forest cover was associated with older housing (Table 4). For the study areas with statistically significant total impacts (NY-Conti, NY-Laure, WI-Conti, WI-Laure), GWR results were consistent with SAR models (significant PBGs were either positively or inversely related, the same as SAR model coefficients and total impacts) (Table 5). GWR results showed that significant relationships were limited in space, however. For example, no more than 27% of PBGs for a study area had significant local relationships between forest cover and median housing age or median housing age^2 (Table 5). There were no clear spatial patterns in the distribution of PBGs with significant relationships (Supplemental Figs. 2 and 3).

3.2.3. Household income

Household income was retained in final models for five study areas (Table 3), but had statistically significant total impacts only in four study areas (Table 4). For CO-Forest and NY-Oceanic higher percentages of households with low and moderate income were significantly negatively related to percent tree cover, suggesting that less income was associated with less forest cover (Table 4). In contrast, in the two WI study areas, there was a positive, significant relationship between percent households with low and moderate income and forest cover, so that less income was associated with greater forest cover (Table 4). GWR results revealed limited local relationships between income and forest cover. For the five study areas where income was retained in the final model only 26% or fewer of PBGs had statistically significant relationships between forest cover and income. (Table 5). For CO-Forest, the locally significant relationships revealed by GWR were primarily negative, in agreement with the global SAR model (Tables 4 and 5). In the other study areas there were both locally significant positive and negative relationships, with more PBGs with negative local relationships than positive ones. In each study area, PBGs with positive, significant relationships between forest cover and income (more forest cover associated with more households with low to moderate income) were spatially removed from urban areas, while PBGs with negative significant relationships between forest cover and income exhibited no distinctive pattern in their distribution (Supplemental Fig. 4).

4. Discussion

Maintaining forests along with residential development is a priority for natural resource managers and residents alike. Indeed, across most of our study areas we found that areas with residential development had greater or similar forest cover to undeveloped areas, confirming that areas with residential development retain important forest resources (Radeloff et al., 2005a; Nowak and Greenfield, 2012). However, this positive relationship can potentially result from the land cover present during housing establishment, preferential residential development in forests, natural succession, management since housing establishment, or a combination of all three factors (Brown, 2003).

Our analyses comparing recent residential development and areas that remain undeveloped offer some additional insight, as higher forest cover in areas of recent development are unlikely to have resulted from residential management over 20 years or less, but rather from purposeful selection of these forested areas for development. Indeed, five of our eight study areas conformed to this pattern, suggesting that recent development occurred preferentially within forested areas. Forests are often a valued natural amenity, along with other factors such as water, climate, and access to public lands (McGranahan, 1999; Snyder et al., 2008; Chi and Marcouiller, 2013). However, for two of our most extensively forested study areas, CO-Forest and WI-Laure, there were no significant differences in forest cover between areas with housing and undeveloped areas, nor between recent residential development and undeveloped areas. Perhaps forest cover in these study areas is widespread enough that there was no meaningful preference for development within forested areas (White and Leefers, 2007; Waltert and Schläpfer, 2010), or the forest loss that occurred due to development counteracted such preferential housing site selection. Only in NY-Adiro was there less forest cover in recently developed areas than undeveloped areas, yet more forest in all residential areas than those without housing. These differences could have arisen due to past preferences for forested areas, forest regrowth after development, variation in housing densities/age/characteristics in the different conditions, or a combination of these factors.

Our multivariate analyses allowed us to more directly examine the relative relationships between forest cover and housing and household variables (housing density, age, and household income). In our seven forested study areas the most widespread significant relationship was the anticipated negative, inverse relationship between housing density and forest cover, similar to other findings, primarily in urban areas (Cook et al., 2012). Across most of our study areas, this relationship was robust: the total effects of SAR models and significant relationships in GWR were consistent, and local relationships were spatially extensive. However, the effects of housing density changes on forest cover were relatively modest (e.g., a 50% increase in housing density over the

Table 5
Summary of GWR models, coefficient estimates, and percentage of PBGs where GWR coefficients were statistically significant.

Study area	Variables	GWR bandwidth	GWR AIC	GWR R^2	% PBGs w/GWR global R^2 > SAR value	Local coefficients, GWR			% of significant (95%) PBGs, GWR		VIF from OLS
						Min	Median	Max	%-	%+	
CO	Housing density (/km^2)					−91.2	−16.2	−0.9	82.3	0.0	1.0
Forest	Percent low mod income					−30.6	−0.1	9.2	17.4	0.6	1.0
	Intercept					−212.1	15.4	58.3	0.0	94.2	
	GWR model	16,068	17,009	0.67	6.8						
CO	Housing density (/km^2)					−199.7	0.0	30.5	2.6	2.2	1.0
Grass	Median housing age (yrs)					−70.5	0.0	49.8	1.3	5.1	1.0
	Intercept					−187.5	0.5	67.7	1.0	19.0	
	GWR model	9275	5271	0.71	30.0						
NY	Housing density (/km^2)					−25.9	−14.4	−3.5	91.6	0.0	1.2
Adiro	Median housing age (yrs)					−123.8	16.7	237.2	1.1	25.7	36.7
	Median housing age^2 (yrs)					−224.2	−15.5	130.6	19.8	1.1	37.9
	Intercept					14.8	69.9	84.3	0.0	99.1	
	GWR model	16,102	3659	0.76	48.4						
NY	Housing density (/km^2)					−15.7	−2.8	3.9	20.7	0.0	1.0
Conti	Median housing age (yrs)					−49.6	3.6	44.0	1.1	7.0	26.1
	Median housing age^2 (yrs)					−45.3	−5.1	44.9	10.2	0.9	26.1
	Intercept					9.4	23.4	54.2	0.0	54.6	
	GWR model	8683	10,105	0.59	20.7						
NY	Housing density (/km^2)					−21.3	−9.7	9.3	87.3	0.0	1.0
Ocean	Median housing age (yrs)					−43.6	5.8	100.7	3.3	15.5	20.8
	Median housing age^2 (yrs)					−94.4	−6.7	38.2	19.3	2.5	20.8
	Percent low-mod income					−11.6	−0.2	13.2	10.4	7.8	1.0
	Intercept					3.1	39.6	60.3	0.0	98.8	
	GWR model	8844	16,265	0.60	19.6						
NY	Housing density (/km^2)					−56.1	−9.7	2.2	85.2	0.0	1.1
Laure	Median housing age (yrs)					−109.0	4.0	55.1	4.1	10.6	30.5
	Median housing age 2 (yrs)					−55.9	−6.1	125.7	11.4	2.6	31.1
	Percent low-mod income					−13.4	−1.3	34.0	16.7	4.5	1.0
	Intercept					16.2	40.0	80.7	0.0	100.0	
	GWR model	11,427	16,298	0.72	44.9						
WI	Housing density (/km^2)					−24.3	−1.2	28.3	32.1	8.7	1.1
Conti	Median housing age (yrs)					−78.3	2.0	128.2	4.8	9.7	20.2
	Median housing age^2 (yrs)					−158.9	−2.8	72.4	12.7	2.7	20.2
	Percent low-mod income					−25.9	−0.5	20.8	14.4	5.8	1.1
	Intercept					2.1	16.9	62.6	0.0	95.1	
	GWR model	7506	29,118	0.71	37.3						
WI	Housing density (/km^2)					−21.3	−4.6	6.7	58.4	1.2	1.0
Laure	Median housing age (yrs)					−44.6	−0.6	52.0	6.8	5.3	19.7
	Median housing age^2 (yrs)					−51.4	−2.8	53.9	9.4	3.4	19.6
	Percent low-mod income					−12.8	−0.2	11.7	17.0	9.1	1.1
	Intercept					4.0	34.1	74.3	0.0	99.7	
	GWR model	11,674	17,960	0.81	7.8						

mean led to a maximum of 3% decline in forest cover). In addition, two study areas in the Eastern Broadleaf Forest (Continental) ecoregion, NY-Conti and WI-Conti, had more restricted local relationships, where significant, local relationships between forest cover and housing density were limited in spatial extent, and concentrated around urban areas.

Significant relationships between forest cover and housing age and household income were more limited. Housing age was significant in four study areas, all of which showed an inverse relationship with increased housing age and forest cover (even when median housing age^2 was retained in models, the size of coefficients meant this was a negative relationship between age and forest cover). However, GWR results revealed these relationships were limited in spatial extent (and without any discernible spatial pattern). This suggests that time since development is associated with less forest cover, in some areas, although the underlying reason (e.g., degradation associated with residential use or establishment, past legacies of land use) is unknown. Our study areas differed from urban areas where housing age is commonly related to forest cover through a quadratic relationship (Troy et al., 2007; Grove et al., 2014; Pham et al., 2017).

Household income similarly was significant in only three SAR global models. Our findings were as expected only in the CO-Forest and NY-Laure study areas, with lower income associated with less forest cover, but we found some evidence of an inverse relationship in the two Wisconsin study areas (WI-Conti and WI-Laure). In urban areas there are cases where lower socioeconomic status is associated with more forest cover, due to either legacy effects or time lags. For example, in Baltimore, because tree planting had a large impact on forest cover, vegetation in 2000 reflected the socioeconomic status and preferences of residents from the 1960s, not present-day residents (Boone et al., 2010). At larger scales and in less intensively developed settings, it is less clear why lower socioeconomic status would be associated with more forest cover. Residents with modest means can be dedicated and effective forest managers: for example, in a socioeconomically marginalized region of Ohio small landowners have greatly increased forest cover after industrial use and forest clearing (Law and McSweeney, 2013). We note also that, much like with housing age, the spatial extent of significant relationships between household income and forest cover was limited.

Our findings may have been constrained by a number of aspects of our modeling inputs. We were restricted to characterizing housing and households at the PBG scale and using 30-m Landsat data for vegetation. These are reasonable compromises for the landscape-level analyses we conducted but we recognize that PBGs necessarily involve aggregating data on individual homes and parcels, and that 30-m pixel data are relatively coarse when considering residential landscapes. Multivariate relationships and overall models were by far the weakest for the CO-Grass study area, perhaps because the 30-m pixel and PBG scale were not sufficient to accurately capture forest extent in a native grassland ecoregion where forest cover is largely the result of tree planting and management. In addition, the NY-Laure, NY-Oceanic, WI-Laure, and WI-Conti study areas all had small but statistically significant spatial autocorrelation in Durbin model residuals, so that models may have been compromised by missing variables and/or spatial terms may be incorporating missing variables. We were also limited to examining only one aspect of the socioeconomic status of present-day residents, absent data on other variables such as education, race, or other indicators of lifestyle, for past or present residents. In urban settings, income may be less important than other socioeconomic variables e.g. education (Daniel et al., 2016) or lifestyle (Heynen and Lindsey, 2003; Boone et al., 2010).

Finally, environmental characteristics and land use (including timber harvesting, on industrial and privately-owned lands) are also more varied across our large study areas than in relatively small urban and suburban areas. NLCD defines forest as areas where trees are generally taller than 5 m, and more than 20% of total cover, but actual forest densities and conditions are variable within this class. Our analyses examined solely forest presence but future research will require more data on forest composition, condition, and functioning, over time, in order to better understand ecosystem processes in suburban and exurban settings. For example, older residential development may contain particularly high value forests, with more mature trees and more native species than recent development (Nitoslawski and Duinker, 2016, Thomas and Gill, 2017). Without temporal data, it is challenging to understand how natural succession, tree planting, and residential management together determine forest cover within residential areas. For example, do residents continue to remove and encroach upon forests around the home (Matlack, 1993) (McWilliam et al., 2010), or augment forests by planting? Understanding this change in forest cover around homes after development in forested areas will be vital for future research. Although the negative impacts of residential development on biodiversity and ecosystem processes are widely recognized, our study and others demonstrate that areas with homes do maintain important forest resources.

5. Conclusions

Despite the limitations, our study both confirms the anticipated relationship between housing density and forest cover, while also demonstrating that relationships between forest cover and housing and household characteristics are different from those found in urban areas. The effects of housing age and income on forest cover remain unclear, in contrast to urban settings. With residential development expected to continue into the future, understanding changing forest cover across housing densities and by residential age in exurban areas, outside the typically studied urban areas, will only increase in importance. Urban areas are relatively small in the U.S. while areas with housing and forests, as well as low-density housing and forests, are extensive (Radeloff et al., 2018; Van Berkel et al., 2018). The challenge will be to recognize the forests not for the trees, but for the houses.

Acknowledgments

We thank the USDA Forest Service, including Northern Research Station and Rocky Mountain Research Station, for their financial support. This work was supported by the National Socio-Environmental Synthesis Center (SESYNC) under funding received from the National Science Foundation DBI-1639145.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2018.12.001.

References

Alberti, M., 2005. The effects of urban patterns on ecosystem function. Int. Reg. Sci. Rev. 28, 168–192.
Anselin, L., 2005. Exploring Spatial Data with GeoDaTM: a Workbook. Spatial Analysis Laboratory, Department of Agricultural and Consumer Economics. University of Illinois, pp. 244. http://www.csiss.org/clearinghouse/GeoDa/geodaworkbook.pdf.
Apparicio, P., Landry, S., Lewnard, J., 2017. Disentangling the effects of urban form and socio-demographic context on street tree cover: a multi-level analysis from Montréal. Landsc. Urban Plann. 157, 422–433.
Bailey, R., 1995. Descriptions of the Ecoregions of the United States. Miscellaneous Publication No. 1391, Map Scale 1: 7,500,000, Ogden, Utah.
Bar-Massada, A., Radeloff, V.C., Stewart, S.I., 2014. Biotic and abiotic effects of human settlements in the wildland–urban interface. BioScience 64, 429–437.
Bartoń, K., 2016. MuMIn: Multi-model Inference. R Package. https://cran.r-project.org/web/packages/MuMIn/289-290, version 1.15.6.
Berland, A., 2012. Long-term urbanization effects on tree canopy cover along an urban–rural gradient. Urban Ecosyst. 15, 721–738.
Bivand, R., Piras, G., 2015. Comparing implementations of estimation methods for spatial econometrics. J. Stat. Softw. 63, 1–36. http://www.jstatsoft.org/v63/i18/.
Bivand, R., Yu, D., 2015. Spgwr: Geographically Weighted Regression. R package version 0.6-28. http://CRAN.R-project.org/package=spgwr.
Bivand, R.S., Hauke, J., Kossowski, T., 2013. Computing the Jacobian in Gaussian spatial autoregressive models: an illustrated comparison of available methods. Geogr. Anal.

45, 150–179.
Boone, C.G., Cadenasso, M.L., Grove, J.M., Schwarz, K., Buckley, G.L., 2010. Landscape, vegetation characteristics, and group identity in an urban and suburban watershed: why the 60s matter. Urban Ecosyst. 13, 255–271.
Brown, D.G., 2003. Land use and forest cover on private parcels in the Upper Midwest USA, 1970 to 1990. Landsc. Ecol. 18, 777–790.
Brown, D.G., Johnson, K.M., Loveland, T.R., Theobald, D.M., 2005. Rural land-use trends in the conterminous United States, 1950–2000. Ecol. Appl. 15, 1851–1863.
Brunsdon, C., Fotheringham, A.S., Charlton, M.E., 1996. Geographically weighted regression: a method for exploring spatial nonstationarity. Geogr. Anal. 28, 281–298.
Chase, T.N., Pielke, R.A., Kittel, T.G., Baron, J.S., Stohlgren, T.J., 1999. Potential impacts on Colorado Rocky Mountain weather due to land use changes on the adjacent Great Plains. J. Geophys. Res. Atmos. 104, 16673–16690.
Chi, G., Marcouiller, D.W., 2013. In-migration to remote rural regions: the relative impacts of natural amenities and land developability. Landsc. Urban Plann. 117, 22–31.
Cleveland, W.S., Devlin, S.J., 1988. Locally weighted regression: an approach to regression analysis by local fitting. J. Am. Stat. Assoc. 83, 596–610.
Conway, T.M., Bourne, K.S., 2013. A comparison of neighborhood characteristics related to canopy cover, stem density and species richness in an urban forest. Landsc. Urban Plann. 113, 10–18.
Cook, E.M., Hall, S.J., Larson, K.L., 2012. Residential Landscapes as Social-ecological Systems: a Synthesis of Multi-scalar Interactions between People and Their Home Environment. Urban Ecosystems.
Daniel, C., Morrison, T.H., Phinn, S., 2016. The governance of private residential land in cities and spatial effects on tree cover. Environ. Sci. Pol. 62, 79–89.
Elhorst, J.P., 2010. Applied spatial econometrics: raising the bar. Spatial Econ. Anal. 5, 9–28.
Fahey, R.T., Bowles, M.L., McBride, J.L., 2012. Origins of the Chicago urban forest: composition and structure in relation to presettlement vegetation and modern land use. Arboric. Urban For. 38, 181–193.
Fornwalt, P.J., Kaufmann, M.R., Huckaby, L.S., Stohlgren, T.J., 2009. Effects of past logging and grazing on understory plant communities in a montane Colorado forest. Plant Ecol. 203, 99–109.
Fotheringham, A.S., Charlton, M.E., Brunsdon, C., 1998. Geographically weighted regression: a natural evolution of the expansion method for spatial data analysis. Environ. Plann. A 30, 1905–1927.
Fry, J.A., Xian, G., Jin, S., Dewitz, J.A., Homer, C.G., Limin, Y., Barnes, C.A., Herold, N.D., Wickham, J.D., 2011. Completion of the 2006 national land cover database for the conterminous United States. Photogramm. Eng. Rem. Sens. 77, 858–864.
Gray, A.N., Azuma, D.L., Lettman, G.J., Thompson, J.L., McKay, N., 2013. Changes in Land Use and Housing on Resource Lands in Washington State, 1976-2006. US Department of Agriculture, Forest Service, Pacific Northwest Research Station.
Grove, J.M., Locke, D.H., O'Neil-Dunne, J.P., 2014. An ecology of prestige in New York City: examining the relationships among population density, socio-economic status, group identity, and residential canopy cover. Environ. Manag. 54, 402–419.
Grove, J.M., Troy, A.R., O'Neil-Dunne, J.P.M., Burch, W.R., Cadenasso, M.L., Pickett, S.T.A., 2006. Characterization of households and its implications for the vegetation of urban ecosystems. Ecosystems 9, 578–597.
Hammer, R.B., Stewart, S.I., Hawbaker, T.J., Radeloff, V.C., 2009. Housing growth, forests, and public lands in Northern Wisconsin from 1940 to 2000. J. Environ. Manag. 90, 2690–2698.
Hammer, R.B., Stewart, S.I., Winkler, R.L., Radeloff, V.C., Voss, P.R., 2004. Characterizing dynamic spatial and temporal residential density patterns from 1940–1990 across the North Central United States. Landsc. Urban Plann. 69, 183–199.
Hansen, A.J., Knight, R.L., Marzluff, J.M., Powell, S., Brown, K., Gude, P.H., Jones, K., 2005. Effects of exurban development on biodiversity: patterns, mechanisms, and research needs. Ecol. Appl. 15, 1893–1905.
Heynen, N.C., Lindsey, G., 2003. Correlates of urban forest canopy cover. Publ. Works Manag. Pol. 8, 33.
Hope, D., Gries, C., Zhu, W., Fagan, W.F., Redman, C.L., Grimm, N.B., Nelson, A.L., Martin, C., Kinzig, A., 2003. Socioeconomics drive urban plant diversity. Proc. Natl. Acad. Sci. 100, 8788.
HUD, 2007. In: Overview of the Calculation Process for the Moderate Income Level. U.S. Department of Housing and Urban Development, Washington D.C. https://www.hudexchange.info/programs/census/low-mod-income-summary-data/calculation/.
HUD, 2013. In: Census 2000 Low and Moderate Income Summary Data. U.S. Department of Housing and Urban Development, Washington D.C. https://www.hudexchange.info/programs/census/low-mod-income-summary-data/#overall.
Irland, L.C., 1999. Northeast's Changing Forests. Distributed by Harvard University Press for Harvard Forest, Petersham, MA.
Kaushal, S.S., Lewis, W.M., McCutchan, J.H., 2006. Land use change and nitrogen enrichment of a Rocky Mountain watershed. Ecol. Appl. 16, 299–312.
Kim, J., Ellis, C.D., 2009. Determining the effects of local development regulations on landscape structure: comparison of the Woodlands and North Houston, TX. Landsc. Urban Plann. 92, 293–303.
Kramer, M., 2013. Our built and Natural Environments: a technical review of the interactions among land use, transportation, and environmental quality. In: Environment Protection Agency, Smart Growth Program, Washington, D.C.: U.S. Government.
Law, J., McSweeney, K., 2013. Looking under the canopy: rural smallholders and forest recovery in Appalachian Ohio. Geoforum 44, 182–192.
Leinwand, I.I., Theobald, D.M., Mitchell, J., Knight, R.L., 2010. Landscape dynamics at the public–private interface: a case study in Colorado. Landsc. Urban Plann. 97, 182–193.
LeSage, J.P., Pace, R.K., 2009. Introduction to Spatial Econometrics (Statistics, Textbooks and Monographs). CRC Press.
Locke, D.H., Grove, J.M., Lu, J.W., Troy, A., O'Neil-Dunne, J.P., Beck, B.D., 2010. Prioritizing preferable locations for increasing urban tree canopy in New York City. Cities Environ. (CATE) 3, 4.
Locke, D.H., Landry, S.M., Grove, J.M., Roy Chowdhury, R., 2016. What's scale got to do with it? Models for urban tree canopy. J. Urban Ecol. 2 juw006.
Luck, G.W., Smallbone, L.T., O'Brien, R., 2009. Socio-economics and vegetation change in urban ecosystems: patterns in space and time. Ecosystems 12, 604–620.
Martin, C.A., Warren, P.S., Kinzig, A.P., 2004. Neighborhood socioeconomic status is a useful predictor of perennial landscape vegetation in residential neighborhoods and embedded small parks of Phoenix, AZ. Landsc. Urban Plann. 69, 355–368.
Matlack, G., 1997. Land use and forest habitat distribution in the hinterland of (r) a large city. J. Biogeogr. 24, 297–307.
Matlack, G.R., 1993. Sociological edge effects: spatial distribution of human impact in suburban forest fragments. Environ. Manag. 17, 829–835.
McGranahan, D.A., 1999. Natural Amenities Drive Rural Population Change. Agricultural Economic Report No. 781. US Department of Agriculture, Economic Research Service, Washington DC.
McKinney, M.L., 2006. Urbanization as a major cause of biotic homogenization. Biol. Conserv. 127, 247–260.
McWilliam, W., Eagles, P., Seasons, M., Brown, R., 2010. The housing-forest interface: testing structural approaches for protecting suburban natural systems following development. Urban For. Urban Green. 9, 149–159.
Nielsen, M.B., Jensen, M.B., 2015. Land cover in single-family housing areas and how it correlates with urban form. Urban Ecosyst. 18, 1103–1123.
Nitoslawski, S.A., Duinker, P.N., 2016. Managing tree diversity: a comparison of suburban development in two Canadian cities. Forests 7, 119.
Nowak, D.J., Greenfield, E.J., 2012. Tree and impervious cover in the United States. Landsc. Urban Plann. 107, 21–30.
Nowak, D.J., Rowntree, R.A., McPherson, E.G., Sisinni, S.M., Kerkmann, E.R., Stevens, J.C., 1996. Measuring and analyzing urban tree cover. Landsc. Urban Plann. 36, 49–57.
O'Brien, R.M., 2007. A caution regarding rules of thumb for variance inflation factors. Qual. Quantity 41, 673–690.
Osorio, F., Vallejos, R., 2014. SpatialPack: Package for Analysis of Spatial Data. R package version 0.2-3. http://cran.r-project.org/package=SpatialPack.
Pejchar, L., Reed, S.E., Bixler, P., Ex, L., Mockrin, M.H., 2015. Consequences of residential development for biodiversity and human well-being. Front. Ecol. Environ. 13, 146–153.
Pham, T.-T.-H., Apparicio, P., Landry, S., Lewnard, J., 2017. Disentangling the effects of urban form and socio-demographic context on street tree cover: a multi-level analysis from Montréal. Landsc. Urban Plann. 157, 422–433.
Platt, R.V., Schoennagel, T., Veblen, T.T., Sherriff, R.L., 2011. Modeling wildfire potential in residential parcels: a case study of the north-central Colorado Front Range. Landsc. Urban Plann. 102 (2), 117–126.
Radeloff, V.C., Hammer, R.B., Stewart, S.I., 2005a. Rural and suburban sprawl in the US Midwest from 1940 to 2000 and its relation to forest fragmentation. Conserv. Biol. 19, 793–805.
Radeloff, V.C., Hammer, R.B., Stewart, S.I., Fried, J.S., Holcomb, S.S., McKeefry, J.F., 2005b. The wildland-urban interface in the United States. Ecol. Appl. 15, 799–805.
Radeloff, V.C., Helmers, D.P., Kramer, H.A., Mockrin, M.H., Alexandre, P.M., Bar-Massada, A., Butsic, V., Hawbaker, T.J., Martinuzzi, S., Syphard, A.D., 2018. Rapid growth of the US wildland-urban interface raises wildfire risk. Proc. Natl. Acad. Sci. 115, 3314–3319.
Rhemtulla, J.M., Mladenoff, D.J., Clayton, M.K., 2009. Legacies of historical land use on regional forest composition and structure in Wisconsin, USA (mid-1800s–1930s–2000s). Ecol. Appl. 19, 1061–1078.
Roy Chowdhury, R., Larson, K., Grove, M., Polsky, C., Cook, E., Onsted, J., Ogden, L., 2011. A multi-scalar approach to theorizing socio-ecological dynamics of urban residential landscapes. Cities Environ. (CATE) 4, 6.
Schwarz, K., Fragkias, M., Boone, C.G., Zhou, W., McHale, M., Grove, J.M., O'Neil-Dunne, J., McFadden, J.P., Buckley, G.L., Childers, D., Ogden, L., Pincetl, S., Pataki, D., Whitmer, A., Cadenasso, M.L., 2015. Trees grow on money: urban tree canopy cover and environmental justice. PLoS One 10, e0122051.
Sharpe, D.M., Stearns, F., Leitner, L.A., Dorney, J.R., 1986. Fate of natural vegetation during urban development of rural landscapes in southeastern Wisconsin. Urban Ecol. 9, 267–287.
Smith, M.L., Zhou, W., Cadenasso, M., Grove, M., Band, L.E., 2010. Evaluation of the national land cover database for hydrologic applications in urban and suburban Baltimore, Maryland. J. Am. Water Resour. Assoc. 46 (2), 429–442.
Snyder, S.A., Kilgore, M.A., Hudson, R., Donnay, J., 2008. Influence of purchaser perceptions and intentions on price for forest land parcels: a hedonic pricing approach. J. For. Econ. 14, 47–72.
Theobald, D.M., 2010. Estimating natural landscape changes from 1992 to 2030 in the conterminous US. Landsc. Ecol. 25, 999–1011.
Thomas, A., Gill, R.A., 2017. Patterns of urban forest composition in Utah's growing mountain communities. Urban forestry & urban greening 23, 104–112.
Tratalos, J., Fuller, R.A., Warren, P.H., Davies, R.G., Gaston, K.J., 2007. Urban form, biodiversity potential and ecosystem services. Landsc. Urban Plann. 83, 308–317.
Troy, A.R., Grove, J.M., O'Neil-Dunne, J.P.M., Pickett, S.T.A., Cadenasso, M.L., 2007. Predicting opportunities for greening and patterns of vegetation on private urban lands. Environ. Manag. 40, 394–412.
Turner, M.G., Pearson, S.M., Bolstad, P., Wear, D.N., 2003. Effects of land-cover change on spatial pattern of forest communities in the Southern Appalachian Mountains (USA). Landsc. Ecol. 18, 449–464.
U.S. Census Bureau, 2002. Technical Documentation: Census 2000 Summary File 3. Technical Documentation Prepared by the U.S. Census Bureau. U.S. Census Bureau,

Washington, D.C.
Van Berkel, D.B., Rayfield, B., Martinuzzi, S., Lechowicz, M.J., White, E., Bell, K.P., Colocousis, C.R., Kovacs, K.F., Morzillo, A.T., Munroe, D.K., 2018. Recognizing the 'sparsely settled forest': multi-decade socioecological change dynamics and community exemplars. Landsc. Urban Plann. 170, 177–186.
Waltert, F., Schläpfer, F., 2010. Landscape amenities and local development: a review of migration, regional economic and hedonic pricing studies. Ecol. Econ. 70, 141–152.
White, E.M., Leefers, L.A., 2007. Influence of natural amenities on residential property values in a rural setting. Soc. Nat. Resour. 20, 659–667.