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RESEARCH ARTICLE

Landscape characteristics and social factors influencing attitudes toward roadside vegetation management

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Abstract
Context For the roadside forest, utility vegetation management is a driver of landscape change involving tradeoffs between reliable electric power and preservation of trees. However, little is known about public perceptions of vegetation management in the landscape context.
Objectives Our objective was to evaluate social and residential context characteristics associated with resident attitudes toward roadside utility vegetation management across Connecticut.
Methods We used a mail survey to collect social science data from residents in two study areas in Connecticut. We measured landscape characteristics associated with tree cover and development density at multiple scales around each respondent household. Random forest predictive models were used to assess attitudes toward vegetation management as explained by social and residential context variables.
Results Respondents generally had positive attitudes toward vegetation management, agreeing that it improves public safety and minimizes power outages. Social variables revealed that residents were more likely to have favorable attitudes if they had greater knowledge about trees, believed that trees should be used for human benefits, prioritized reduced power outages over forest aesthetics, and considered changes in the roadside forest to be acceptable. Residential context variables were not as strongly associated with attitudes as social variables, but did rank as important for two out of three attitudes variables.
Conclusions Attitudes toward vegetation management may be influenced by residential context, yet likely are formed independently of it. Spatial heterogeneity of exurban land use and social characteristics suggest encompassing variability in approaches to roadside forest management policy.

Keywords Attitudes · Human dimensions · Landscape ecology · Random forest · Roadside forest management · Vegetation management

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Introduction

The roadside forest, described as all trees and vegetation along all types of roads, on all types of land ownership, across the urban–rural gradient, spans from the road to the distance at which a mature tree could fall and affect the road or utilities (Hammerling 2012). Given time spent travelling on roads (Weber et al. 2014), in forested regions the roadside forest is an important interface at which humans perceive and experience nature (Akbar et al. 2003). Past research on the roadside forest has suggested that roads affect ecological patterns and processes, attributing to increased wildlife mortality, decreased habitat connectivity, and altered water and nutrient flow (Forman and Alexander 1998; Spooner 2015). Roadside trees positively influence public perceptions and visual preferences (Hull et al. 1987; Garre et al. 2009), and provide ecosystem services such as climate and air quality regulation, aesthetic and cultural values, and economic benefits (Silvera Seamans 2013; Salmond et al. 2016). Roadside trees also may contribute to a reduction in traffic safety on rural or high-speed roads, yet an increase in traffic safety and walkability in urban areas (Wolf and Bratton 2006; Mok et al. 2006). However, less is known about perceived tradeoffs of roadside trees regarding both benefits (e.g., community character, ecosystem services) and risks (e.g., to public safety and infrastructure). Yet, understanding such tradeoffs is integral to successful roadside forest management in response to public concerns.

Utility vegetation management, defined as the pruning or removal of trees, shrubs, and other vegetation that pose a risk to the reliability of utility infrastructure, and the retention of compatible trees and shrubs (State of Connecticut 2014), is a major driver of roadside forest structure and dynamics. The goal of utility vegetation management is to prevent power outages caused by tree contact with power lines—the leading cause of outages—particularly during extreme weather events (Campbell 2012; Cieslewicz and Novembri 2004). Tree-trimming crews perform vegetation management along power lines, typically in 4–5 year cycles (e.g., Eversource 2016). Utility companies must balance risk of tree-related power outages and tree loss (Schroeder 1989; Cieslewicz and Novembri 2004), as stakeholder preferences for tree retention may conflict with utility goals of reliable power (Dixon and Wolf 2007). Although public relations has been reported as the most challenging aspect of the vegetation management process (Johnson 2008), limited knowledge exists about public attitudes toward vegetation management.

Social-psychological theory suggests that attitudes, associations between an object and an evaluation of favor or disfavor, are one construct within a cognitive hierarchy ranging from values to behaviors (Fulton et al. 1996). Combined with external situational factors (e.g., Andrade et al. 2019; Keener-Eck et al. 2020), such constructs act within complex multi-scalar relationships between people and residential landscapes (Cook et al. 2012). For example, Morzillo et al. (2016) observed possible influence of environmental worldview and value orientations on affinity for residential proximity to natural amenities, including trees, across multiple scales. Elsewhere, perceptions of wildlife, sociodemographics, and characteristics of neighboring yards influenced decisions about residential landscape vegetation (Belaire et al. 2016). Related to our study, attitudes toward and preferences for the roadside forest and vegetation management may vary by socio-psychological constructs, such as knowledge about trees and tree maintenance (Andrew and Slater 2014; Davis and Jones 2014; Conway 2016), perceived aesthetic effects of forest treatments (Tahvanainen et al. 2001), and motives for planting (e.g., beauty, habitat) or removing trees (e.g., poor tree health, litter; Kirkpatrick et al. 2012; Guo et al. 2019), as well as residential context factors including urban versus rural location of residence (Racevskis and Lupi 2006), and presence of trees near the home (Davis and Jones 2014; Suppakittpaisarn et al. 2019). In the context of utility vegetation management, past research has suggested public preferences for tall trees (Schroeder 1989), perception that utility pruning harms aesthetics (Kuhns and Reiter 2007), and support for replacing tall trees with shorter trees to decrease potential for powerline obstruction (Flowers and Gerhold 2000). To our knowledge, however, no studies have examined how factors influencing such preferences and associated attitudes play out at the landscape level, information which may help navigate potential conflicts and facilitate adoption of vegetation management policy (Skahill 2014; Eversource 2016).

Our objective was to understand factors that influence attitudes toward roadside vegetation management within the residential landscape context. Two hypotheses were tested based on results of the past research described above. First, we hypothesized that attitudes toward vegetation management at the landscape level would be driven by both social-psychological and residential context variables. Given their dominance in residential decision-making (see above), we also hypothesized that socio-psychological constructs would play a comparatively greater role in influencing attitudes than variables describing residential context. To pursue our objectives, we integrated social survey data, spatial analysis, and a machine-learning approach.

Methods

Study area and context

A combined high population density (ranked 6th among US states—285 people/km^2; USDC 2013), large proportion of forest cover (ranked 5th—statewide 72.6%; 1st for urban tree cover—67.4%; Nowak and Greenfield 2012) and wildland-urban interface (ranked 1st—65.7%; Martinuzzi et al. 2015), and coastal location susceptible to nor'easter storms, make Connecticut's utility infrastructure particularly vulnerable to tree-related power outages. Power is transmitted mainly through overhead powerlines; underground lines are largely infeasible due to complex regulations, rocky soil and topography, and high implementation and maintenance costs (Campbell 2012). Connecticut's roadside forest is dense and mature, averaging an estimated 100 trees per mile, the majority ($\sim$ 57%) of which are larger than 30 cm DBH, and approximately half ($\sim$ 48%) are maples (*Acer* spp.; Hammerling 2012). In 2011 and 2012, three major storms (Hurricane Irene, Storm Alfred [i.e. "the October Snowstorm"], and Hurricane Sandy) caused extensive tree damage and prolonged power outages statewide. Following these storms, increased and enhanced vegetation management efforts (described in Eversource 2016) resulted in resident concern that management was overly aggressive, resulting in new laws and regulations (PURA 2014; Skahill 2014; Dowling 2014). Local and technical decisions about roadside vegetation management also are influenced by tree number, form, and species (Appelt and Beard 2006; Hammerling 2012), and socially by local stakeholder preferences (Morzillo unpublished data). Two geographically distinct study areas in Connecticut (East and West; Fig. 1) were selected based on interviews with utility employees (n = 7; author unpublished data) and discussions with utility and project partners. Study areas contained the following characteristics: adjacent towns distributed across the urban–rural gradient, ongoing roadside utility vegetation management, and varying utility-community relationship histories and interest in integrating novel vegetation management strategies (author unpublished data).

Survey data collection

Social science data for this analysis focused on four items: (1) attitudes toward vegetation management, (2) knowledge about trees and wind resistance, (3) vegetation management preferences, and (4) background information including value orientations and socioeconomics. These data were collected using a mail survey. The sampling unit was the individual household; the sampling frame included all residential street addresses within the extents of the study areas. Street address information was purchased from Marketing Systems Group (Horsham, PA), which compiles sampling datasets from U.S. Postal Service delivery sequence files. Post office boxes, mail drops, vacant houses, and seasonal homes were excluded to focus sampling on single-family owner-occupied households (i.e., residents involved in decision-making about trees; Shakeel and Conway 2014). Based on expected response rate and desired sampling error of $\alpha = 0.05$ (95% confidence interval; Bartlett et al. 2001; Vaske 2002), 3600 surveys were mailed (East and West = 1800 each). Within each study area, our sample was divided equally between Urban and Rural strata based on the 2010 Census Urban and Rural Classification (USDC 2011). The University of Connecticut Institutional Review Board granted permission for use of human subjects (IRB # H16-007).

Surveys were mailed in winter 2017. A modified version of the Dillman Tailored Design Method (Dillman et al. 2009) was applied in an effort to increase response rates using a: (1) pre-notice postcard introducing the project, (2) survey packet including a cover letter and postage-paid reply envelope, (3) thank you/reminder postcard, and (4) second survey packet to those who had not yet responded. A short follow-up survey was sent to non-respondents of the original survey, which focused on 10 key items from the original survey (n = 2608).

Dependent variables

To assess attitudes toward roadside vegetation management, we measured participant agreement with a series of attitudes statements. Responses to each

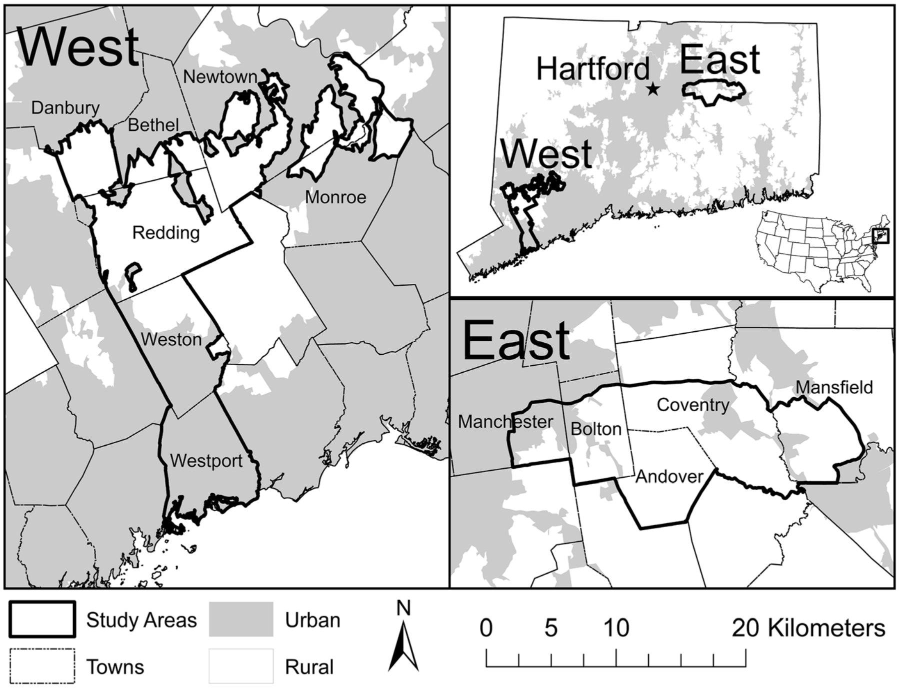

Fig. 1 Study areas in Connecticut, USA (from 2010 Census Urban and Rural Classification; USDC 2011)

statement were coded using a five-point Likert scale measuring level of agreement (5 = strongly agree; 1 = strongly disagree). Principal component analysis (PCA) with varimax rotation (Abdi and Williams 2010) was used to reduce a large number of attitudes statements into groups of statements that factored together (e.g., Morzillo and Mertig 2011). Cronbach's alpha (α) measured internal reliability for resulting statement groups (Cortina 1993; Vaske et al. 2017). Statement groups were summed to obtain a scale score for each survey respondent.

Three dependent variables measuring resident attitudes toward vegetation management resulted from PCA. First, *AttProfessional* included six statements focused on perceived professionalism of vegetation managers ($n = 967$; 51.2% variance explained; $\alpha = 0.880$; possible and actual scale score range = 6–30): (a) Those who do vegetation management care about trees, (b) Those who do vegetation management are trained professionals, (c) Vegetation management maintains adequate power line clearance using techniques that minimize harm to trees, (d) Vegetation management is done with care for the trees, (e) Those who do vegetation management do a good job explaining the process to the public, and (f) I trust those who do vegetation management to treat the trees properly. Greater scale scores indicated greater perceived professionalism. Second, *AttSafety* included four statements focused on vegetation management in the context of safety and minimizing power outages ($n = 967$; 11.1% variance explained; $\alpha = 0.764$; possible range = 4–20; actual range = 6–20): (a) Vegetation management improves the safety of people over the long term, (b) Those who do vegetation management care about my safety, (c) Those who do vegetation management care about minimizing outages, and (d) Clearance of power lines through vegetation management minimizes power outages. Greater scale scores indicated greater perceived improved safety and welfare. Finally, *AttTradeoff* included five statements focused on the tradeoffs between protecting trees and tree trimming to reduce power outages ($n = 986$; 27.6% variance explained; $\alpha = 0.758$; possible range = 5–25; actual range = 7–25): (a) Most storm-related power outages are caused by trees or tree limbs damaging power lines, (b) Tree trimming helps to reduce the number of power outages, (c) Regardless of how it affects the trees, power line trimming must be done to keep the power on, (d) Reliable power is more important than protecting trees, (e) More intensive tree work now will require less frequent management over the long term. Greater scale scores indicated greater perceived importance of reliable power compared to trees.

Independent variables

Knowledge about trees and wind resistance

Past research suggests that residents with greater knowledge about tree care and maintenance are more likely to support urban tree protection and management (Davis and Jones 2014), and less likely to trust that tree-trimming crews treat trees properly (Kuhns and Reiter 2007). We used three variables to evaluate knowledge about trees and wind resistance. First, *KnowTree* consisted of four true belief statements focused on tree care and relationship with power outages: (a) Growth and death are natural processes for trees, (b) Most storm-related power outages are caused by trees or tree limbs damaging power lines, (c) Trimming branches off trees can be beneficial to the tree, (d) Rural trees typically live longer than urban trees. Level of agreement for each statement was coded using five-point Likert scales (5 = strongly agree; 1 = strongly disagree). Scale scores were derived for each respondent by summing responses to these statements (possible range = 4–20; actual range = 10–20); greater scale scores indicated greater knowledge. Second, for *KnowWind1* (Table 1; Supplementary Information Fig. S1), respondents selected from three illustrations of trees the tree they believed would be most resistant to damage by wind; statements were based on knowledge that trees with spreading crowns and thicker trunks are more resistant to windthrow (Bunce et al. 2019). Finally, for *KnowWind2* (Table 1), respondents indicated (yes/no/unsure) whether they considered most of the trees in their neighborhood to be wind resistant.

Preferences for vegetation management

Stakeholder attitudes toward management agencies are influenced by alignment of stakeholder and agency desired management outcomes (Smith et al. 2013). We assessed resident preferences for vegetation management outcomes using four survey questions: *Outcome*, *GreenTunnel*, *RoadForest*, and *RemoveTree* (Table 1).

Background variables

Value orientations are patterns of basic beliefs revealed through decision-making that influence attitudes and, in turn, influence behavior (Fulton et al. 1996). We assessed tree-related value orientations using six variables adapted from past research (Fulton et al. 1996; Vaske et al. 2001; Berninger and Kneeshaw 2009). Each variable was derived from a set of belief statements (Supplementary Information Table S1) coded with five-point Likert scales (5 = strongly agree; 1 = strongly disagree), and responses were summed to create scale scores. Two variables (*Abundant* and *RightToExist*) were constructed using PCA to identify statements that factored together; four variables (*Use*, *Biocentric*, *Bequest*, and *Experience*) were constructed based on past literature (Fulton et al. 1996; Vaske et al. 2001). Resulting variables (and associated themes) included: *Abundant* (importance of abundant trees); *RightToExist* (whether trees and nature have as much right to exist as humans); *Use* (philosophy regarding use of trees for human benefits; Fulton et al. 1996); *Biocentric* (natural things perceived as having inherent worth; Vaske et al. 2001); *Bequest* (importance of knowing that healthy populations of trees exist; Fulton et al. 1996); and *Experience* (importance of trees around the home; Fulton et al. 1996).

Eight socioeconomic and situational background variables were included to describe respondents, as these variables have been suggested to influence attitudes toward natural resources (e.g., Morzillo et al. 2010; Kirkpatrick et al. 2012; Keener-Eck et al. 2020). Respondents indicated their residential classification (*LocReside*) by selecting from the following to best describe where they live: (a) urban, (b) suburban, (c) semi-rural (also referred to as exurban), and (d) rural. Respondents also indicated the number of individuals in their household (*HouseholdSize*), whether any household members were less than 18 years old (*Children*), their sex (*Sex*), age (*Age*), and the length of time lived at their current address (*Tenure*). For *Education*, respondents selected all that apply from seven categories (Table 2). For *Income*, respondents selected from a range of incomes grouped in \$25,000 increments from $<$ \$25,000 to $\geq$ \$100,000 (5 groups total).

Table 1 Independent variables used to measure knowledge about trees and preferences for vegetation management (non-scale score variables)

Variable	n	Question	Answer[a]	Percent (%)				
				Urban	Rural	East	West	All
KnowWind1	966	Which of the following trees do you believe would be most resistant to damage by wind?[b]	Round crown with thick trunk[c]	61.4	61.3	61.7	60.9	61.4
			Round crown with thin trunk	28.1	29.8	28.3	30.0	29.0
			Crown pruned one side; thin trunk	10.5	8.9	10.0	9.1	9.6
KnowWind2	973	Based on your response to [*KnowWind1*], would you consider most of the trees in your neighborhood wind resistant?	Yes[c]	28.9	27.4	30.0	25.7	28.1
			No	37.3	39.7	35.8	42.1	38.6
			Unsure	33.8	33.0	34.2	32.2	33.3
Outcome	967	Which of the following do you believe is most important for tree and vegetation management along roadsides in your area?	Aesthetics when finished	25.4	21.5	22.7	24.1	23.2
			Total number of trees removed	8.2	9.1	8.2	9.3	8.7
			What happens with resulting wood	0.7	1.7	1.7	0.7	1.2
			Expense to the town	2.9	1.9	2.4	2.3	2.4
			Expense to the property owner	6.0	5.8	5.8	6.1	6.0
			Reduced need for regular maintenance	9.1	8.7	10.2	7.2	8.9
			Reduced number of power outages	47.7	51.3	49.1	50.2	49.5
GreenTunnel[d]	964	In Connecticut, it is common to see a "green tunnel of trees" along roadsides. Which of the following best describes your opinion about this phenomenon?	It is important to maintain this look	34.8	31.3	29.4	37.3	32.9
			I am OK with this changing if it results in fewer outages	49.4	54.6	54.7	49.2	52.3
			I have no opinion about this	15.7	14.1	15.9	13.5	14.8
RoadForest[d]	955	Which of the following illustrations depicting roadside forest is most acceptable to you?[b]	Green tunnel of trees	8.7	8.1	6.8	10.5	8.4
			Current vegetation management	20.2	21.1	18.9	22.8	20.6
			Greater spacing of trees	71.1	70.9	74.3	66.7	71.0

Residential context variables

Context of an individual's residence within the landscape influences formation of attitudes (Berenguer et al. 2005), which we assessed using measures of tree cover and development density. Greater tree cover has been associated with greater property values (Netusil et al. 2010; Donovan and Butry 2010), neighborhood satisfaction (Lee et al. 2008a), and support for local tree protection (Davis and Jones 2014) in urban areas, whereas residents in rural areas may prefer open space and lower densities of trees (McDonald and Litton 1998; Sander and Polasky 2009; Ritter 2011). We assessed residential context using nine variables measured around each respondent's household location. Four variables were related to tree canopy cover (TCC), and five were related to development density (Table 3). Each variable was

Table 1 continued

Variable	*n*	Question	Answer[a]	Percent (%)				
				Urban	Rural	East	West	All
RemoveTree	815	In what locations would removing some trees within 100 feet of the road be acceptable to you?	On my property[d,e]	39.9	48.0	48.6	38.8	44.3
			Along streets in urban areas	57.7	52.7	52.5	58.2	55.1
			Along streets in suburban areas	62.1	58.2	57.8	62.9	60.1
			Along roads in rural areas	58.7	61.0	62.0	57.3	60.0
			Along roads in rural areas, but only on public land	41.8	44.1	40.4	46.3	42.9

[a]Respondents were instructed to "choose one" answer for all questions except *RemoveTree*, which was "choose all that apply"

[b]Visual diagrams from survey provided in supplementary information: *KnowWind1* (Fig. S1) and *RoadForest* (Fig. S2)

[c]Indicates response associated with greater knowledge in coding

[d]Significant difference between East and West strata

[e]Significant difference between Urban and Rural strata

measured at multiple scales, ranging from the parcel scale to a "macro-neighborhood" area of 2000 m radius from the household, corresponding to a 20-min walk (Lee et al. 2008b; Morzillo et al. 2016). All spatial analyses were completed using ESRI ArcGIS 10.4 and Python 2.7.10 (ArcPy module).

Four tree canopy cover (TCC) variables (*TCCRadius*, *TCCParcel*, *TCCParcelBuffer*, and *TCCRoadside*) were measured using 1-m high-resolution land cover data constructed from 2016 LiDAR and multispectral orthoimagery (Parent et al. 2015). Deciduous and coniferous vegetation classes were used to calculate TCC; open water was removed from analysis. Property parcel maps were obtained from municipalities. Road data were obtained from the State of Connecticut Department of Public Safety (Tele Atlas North America, Inc. 2010). For *TCCRoadside*, we used the "Make Service Area Layer" tool to create road networks within multiple distances (along roads) from a household. Within each road network, we computed TCC at multiple buffered distances from the road centerline, from 5 m (trees overhanging road) to 55 m (distance beyond which a tree could fall on utility infrastructure).

We also assessed five development density variables (Table 3). Impervious surface area (*ISA*) was measured from the land cover data noted above, using buildings and low impervious cover classes. Population density (*PopDensity)* and housing density (*HouseDensity*) were measured by converting block level census data (USDC 2013) to raster format, and calculating the average (population or housing) density within a given radius of each household. Distance from a household to an urban edge (*DistUrbEdge*) was measured for two urban area classes: Medium/High-Density and High-Density. These were constructed by adapting methods of Radeloff et al. (2005): for each census block, threshold TCC was $< 50\%$ TCC, and threshold housing density was > 49.4 housing units/km^2 (1 unit per 5 acres) for the Medium/High class, and > 741.3 housing units/km^2 (3 units/acre) for the High class. To ensure that urban areas were not small isolated blocks, each urban area had to be at least 1

Table 2 Descriptive statistics for background variables

Variable	*n*	Urban	Rural	East	West	All
LocReside (%)[a,b]	947					
Urban		6.1	0.2	4.0	1.7	3.0
Suburban		61.1	15.0	32.5	41.9	36.6
Semi-rural (also referred to as exurban)		21.8	44.9	31.2	37.6	34.1
Rural		11.0	39.9	32.3	18.8	26.3
HouseholdSize (mean # of individuals ± SD)[a]	984	2.6 ± 1.2	2.7 ± 1.3	2.5 ± 1.2	2.8 ± 1.3	2.6 ± 1.2
Children (% households with children)[a]	851	30.2	31.1	26.3	36.3	30.7
Sex (% female)	977	49.2	52.5	52.6	49.0	51.0
Age (mean age in years ± SD)	928	61.2 ± 14.7	60.9 ± 13.8	60.8 ± 14.7	61.5 ± 13.5	61.1 ± 14.2
Tenure (mean years in current residence ± SD)[b]	976	20.0 ± 14.2	22.3 ± 15.2	21.3 ± 14.6	21.1 ± 14.9	21.2 ± 14.8
Education (%)[a]	973					
Less than high school		0.4	0.8	0.9	0.2	0.6
High school or equivalent		6.8	6.6	9.3	3.5	6.6
Some college		10.5	11.2	13.3	7.9	10.9
Vocational or trade school		3.5	4.3	5.4	2.1	3.9
College degree (2-year or certificate)		7.7	9.3	10.9	5.6	8.5
College degree (Bachelor's)		31.2	32.1	28.3	35.9	31.7
Graduate or professional degree		39.8	35.8	31.8	45.1	37.7
Income (%)[a]	819					
Less than $25,000		3.1	3.4	3.6	2.9	3.3
$25,000–$49,999		11.7	9.4	14.9	4.6	10.5
$50,000–$74,999		16.7	14.0	19.8	9.2	15.3
$75,000–$99,999		13.8	16.8	18.1	11.7	15.4
$100,000 or more		54.7	56.3	43.6	71.6	55.6

[a]Significant difference between East and West strata

[b]Significant difference between Urban and Rural strata

km^2 after aggregating adjacent census blocks that met the TCC and housing density criteria.

Statistical analysis

Chi-square, ANOVA, Pearson's *r*, and Spearman's ρ were used to compare sample means and test bivariate relationships. Effect size (Vaske 2002) was used to assess the strength of the relationships between variables, as appropriate. All statistical analyses were conducted in either SPSS (SPSS, Inc.) or R (R Core Team; https://www.R-project.org). We defined statistical significance at the 95% confidence interval ($\alpha = 0.05$).

We used random forest (RF) regression models to evaluate association between attitudes toward roadside utility vegetation management and both social-psychological (i.e., from survey) and residential context variables. RF is a robust machine learning algorithm that uses an ensemble of decision trees to predict a dependent variable from a set of independent variables (Breiman 2001). RF accommodates categorical and continuous variables (Cutler et al. 2011), large numbers of independent variables (Strobl et al. 2008), collinear variables (Hollister et al. 2016), and unbalanced data (i.e., no data distribution assumptions; Cutler et al. 2007), achieving high predictive accuracy relative to traditional regression methods (Cutler et al. 2007). RF has been applied in numerous natural resources management contexts (e.g., Kreakie et al. 2015; Gianotti et al. 2016; Massie et al. 2016).

RF calculates the importance of each independent variable by measuring the decrease in model accuracy (i.e., increase in error) resulting from random

Table 3 Landscape variables and scales of measurement

	Variable	Description	Units	Measurement scales (m)
Tree canopy cover	*TCCRadius*	Tree cover within a radius of each household	%	250, 500, 750, 1000, 1500, 2000[a]
	TCCParcel	Tree cover within each household property parcel	%	–
	TCCParcelBuffer	Tree cover within parcel and a distance buffered outward	%	5, 15, 25, 35, 45, 55[b]
	TCCRoadside	Tree cover within a road network distance from each address point, and within a buffer distance from road center line	%	Network[c]: 50, 100, 150, 200, 250, 500, 750, 1000, 1500, 2000
				Buffer[d]: 5, 15, 25, 35, 45, 55
Development density	*ISA*	Impervious surface area within a radius of each household	%	250, 500, 750, 1000, 1500, 2000[a]
	RoadDensity	Length of roads per unit area, within a radius of each household	km/km^2	250, 500, 750, 1000, 1500, 2000[a]
	PopDensity	Population density within a radius of each household. 2010 census block data	People/km^2	250, 500, 750, 1000, 1500, 2000[a]
	HouseDensity	Housing density within a radius of each household. 2010 census block data	Housing units/km^2	250, 500, 750, 1000, 1500, 2000[a]
	DistUrbEdge	Distance to edge of urban area. Households inside urban area = 0	km	Medium/high-density, high-density

[a]Radius distance from each household, based on circular buffer area

[b]Buffer distance outward from parcel boundary

[c]Distance outward from household along a network of all possible roads

[d]Buffer distance outward from road centerline

permutation of that variable's values, effectively removing the variable's effect on the model (Cutler et al. 2011). This is measured as percent increase in mean squared error (MSE); higher values indicate greater predictive power of the overall model when that variable is included. Partial dependence plots illustrate the partial relationship between individual independent variables and the dependent variable (Friedman 2001).

Applying methods from Hollister et al. (2016), we first fit a full RF model that included all independent variables and numerous trees (*ntree* = 10,000), obtaining a list of variables ranked by importance. Using this ranking, RF models were run iteratively, beginning with the top two most important variables and adding variables in each run until identification of a best-fit final model (greatest % variance explained). We ran an RF model for each of the three dependent variables (*AttProfessional, AttSafety,* and *AttTrade-off*). Independent variables included 21 social-psychological (i.e., survey) variables (Tables 1, 2, and 4), and 99 residential context variables as measured at multiple scales (Table 3). For each model, survey responses with missing data were removed; therefore, total number of respondents varied among models.

Results

Sample characteristics

We received 998 completed surveys (response rate = 27.7%; East *n* = 555; West *n* = 443; Urban *n* = 464; Rural *n* = 534; Table 2). West respondents, on average, had larger households, more households with children, more formal education completed, and greater household income than East respondents. Rural respondents generally had longer residential tenure than Urban respondents.

Table 4 Descriptive statistics (mean ± SD) for variables calculated based on scale scores

Variable	*n*	Scale	Urban	Rural	East	West	All
Attitudes toward vegetation management							
AttProfessional[a]	967	6–30	20.9 ± 5.0	21.1 ± 5.0	21.4 ± 5.0	20.5 ± 4.9	21.0 ± 5.0
AttSafety	967	4–20	17.1 ± 2.5	17.2 ± 2.4	17.2 ± 2.5	17.1 ± 2.4	17.2 ± 2.4
AttTradeoff	986	5–25	20.0 ± 3.5	20.2 ± 3.5	20.0 ± 3.5	20.2 ± 3.5	20.1 ± 3.5
Knowledge about trees							
KnowTree[a]	986	4–20	16.4 ± 1.7	16.5 ± 1.7	16.3 ± 1.7	16.7 ± 1.7	16.5 ± 1.7
Value orientations toward trees							
Abundant	938	9–45	42.3 ± 4.0	42.4 ± 4.1	42.3 ± 4.2	42.5 ± 3.8	42.4 ± 4.0
RightToExist	938	2–10	7.6 ± 2.2	7.3 ± 2.2	7.5 ± 2.2	7.3 ± 2.2	7.4 ± 2.2
Use	938	4–20	16.7 ± 2.8	16.7 ± 2.4	16.7 ± 2.6	16.7 ± 2.5	16.7 ± 2.6
Biocentric	938	3–15	12.2 ± 2.6	11.9 ± 2.6	12.1 ± 2.6	11.9 ± 2.5	12.0 ± 2.6
Bequest	938	4–20	18.6 ± 2.1	18.7 ± 2.1	18.7 ± 2.1	18.6 ± 2.1	18.7 ± 2.1
Experience[a]	938	4–20	19.0 ± 1.8	19.1 ± 19	18.9 ± 1.9	19.2 ± 1.7	19.1 ± 1.8

[a]Significant difference between East and West strata

Survey respondents (on average) were older, had completed more formal education, and had greater household income than non-response survey participants (n = 200) and census tract averages (USDC 2016). Non-response survey participants were less likely to have been in their current residence during recent major storms, less accepting of removing some trees within 100 feet of the road, and more likely to agree that some risk of power outages is acceptable in order to protect trees.

Vegetation management attitudes and preferences

Average scale scores for dependent variables (*AttProfessional*, *AttSafety*, and *AttTradeoff*) suggested favorable attitudes toward vegetation management (Table 4). Attitudes did not differ between East and West or Urban and Rural strata, with exception that *AttProfessional* scores were generally higher for the East.

Responses to vegetation management preference questions (Table 1) indicated that majorities of respondents prioritized reducing the number of power outages (*Outcome*), would accept changes to the roadside forest if it resulted in fewer power outages (*GreenTunnel*), and would accept management that resulted in greater spacing of trees (*RoadForest*). However, removing some roadside trees was least acceptable on the respondent's own property (*RemoveTree*), particularly in Urban areas and in the West study area.

Landscape composition

Measures of tree canopy cover (TCC) were relatively high both in Urban and Rural strata (e.g., average *TCCRadius* at 1000 m radius: Urban = 57.4% ± 15.1; Rural = 74.2% ± 9.3). Overall, the East had lower development density than the West, with a smaller proportion of land area in the Urban stratum (East = 34.3 km^2 [18.2%]; West = 86.5 km^2 [31.6%]), and less impervious surface (*ISA*; East = 7.8%; West = 9.3%). More respondents in the East described their locations as rural compared to the West (*LocReside*; Table 3). However, the East, on average, had less TCC (e.g., average *TCCRadius* at 1000 m radius: East = 64.4% ± 15.2; West = 68.2% ± 14.1) and greater housing density (e.g., average *HouseDensity* at 1000 m radius: East = 176 units/km^2 ± 224; West = 120 units/km^2 ± 97) than the West.

Random forest models

The best-fit *AttProfessional* model used 868 total observations, explained 18.9% of the variance, had a mean-squared error of 19.8, and included 13 independent variables (Fig. 2). *AttSafety* used 868 total observations, explained 20.8% of variance, had a mean-squared error of 4.5, and included 12 variables.

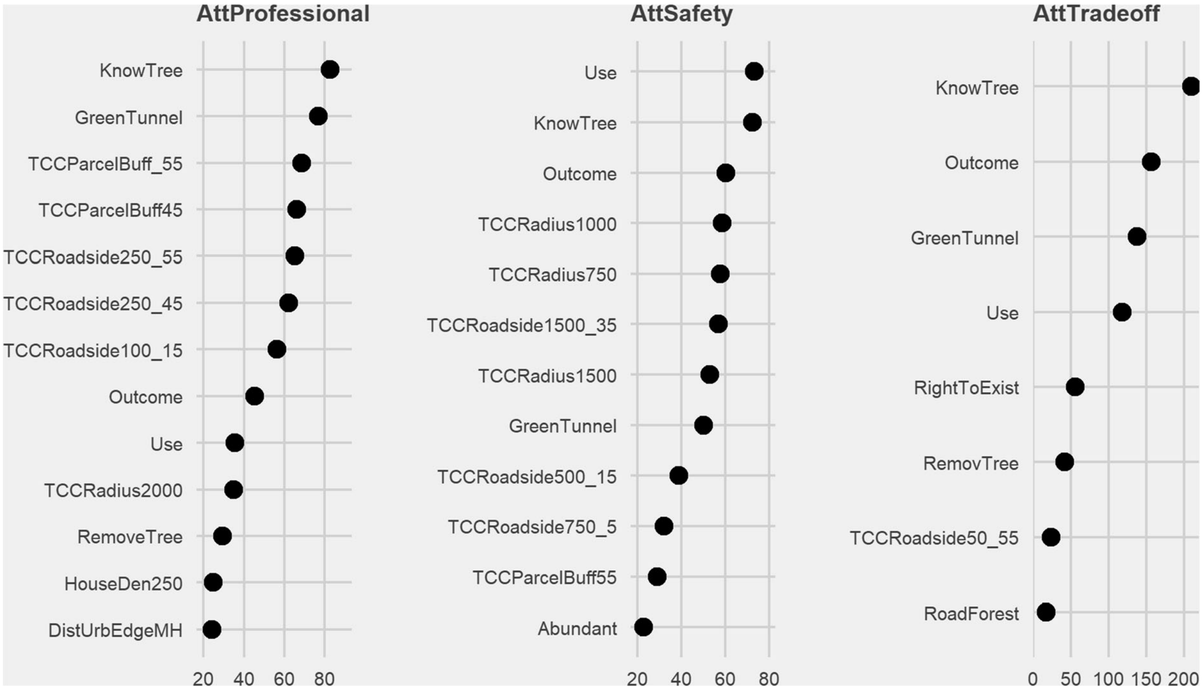

Fig. 2 Variable importance ranks for three dependent variable models (*AttProfessional*, *AttSafety*, *AttTradeoff*), measured as percent increase in mean squared error (MSE). Greater values indicate greater predictive power of the overall model when that variable is included. Landscape variable names indicate their measurement scale (meters; Table 3). *DistUrbEdgeMH* refers to medium/high-density urban areas

AttTradeoff used 865 total observations, explained 45.3% of variance, had a mean-squared error of 6.7, and included 8 variables.

Social-psychological variables were consistently ranked as more important than residential context variables across all three models (Fig. 2). In all models, *KnowTree* ranked as the first or second most important variable, and *Outcome*, *GreenTunnel*, and *Use* ranked among the top 10 (see partial dependence plots for relationships between each independent social-psychological variable and dependent variable; Supplementary Information Figs. S3–S5). Greater *KnowTree* and *Use* (anthropocentric value orientation) scale scores corresponded to greater attitude scale scores (more favorable attitudes toward vegetation management). Those who selected “Reduced number of power outages” for *Outcome* (49.5% of respondents) were more likely to have more favorable attitudes than those who selected “Aesthetics (what it looks like) when finished” (23.2%). For *GreenTunnel*, respondents who selected “I am OK with this changing if it results in fewer power outages” (52.3%) were more likely to have more favorable attitudes than those who selected “It is important to maintain this look” (32.9%).

For residential context, tree canopy cover variables were selected in all three models, whereas one development density variable was selected in one model (*AttProfessional*; *DistUrbEdge*: Medium/High-Density; n.b. correlation between *AttProfessional* and *DistUrbEdge*: Medium/High-Density was not significant [Spearman’s $\rho = -0.024$, df = 964, $p = 0.446$]). Overall, partial dependence plots for landscape variables did not reveal strong trends (Supplementary Information Figs. S3–S5). Further pairwise comparisons revealed the strongest association between dependent attitude variables and landscape variables to be between *TCCRoadside* (50 m network, 55 m buffer) and *AttTradeoff* (Spearman’s $\rho = 0.102$, df = 983, $p = 0.001$).

Discussion

Vegetation management within the roadside forest involves a balance between safe and reliable utility infrastructure and preserving trees (Schroeder 1989; Akbar et al. 2003; Johnson 2008). In general, our results suggested respondents to have favorable attitudes toward roadside vegetation management. Supporting our first hypothesis, attitudes were influenced by both social-psychological and residential context variables. Supporting our second hypothesis, model results suggested that knowledge about trees, basic beliefs (value orientations) about trees, and aesthetic preferences exhibited the strongest associations with all three attitudes variables. Past research suggests that familiarity with forest management is positively related to support for management practices (Hull and Robertson 2001; Abrams et al. 2005). Among limited research on utility vegetation management, Kuhns and Reiter (2007) reported that those who thought more about utility pruning were less likely to trust that tree-trimming crews treated trees properly; such attitudes became more favorable when information about the process was provided. Elsewhere, despite opposition to removing trees because of perceived harm to trees and wildlife, support existed for replacing tall trees that interfered with utility wires with short-stature trees, an action that resulted in improved perceptions of neighborhood aesthetics and the utility company (Flowers and Gerhold 2000). Comments on our survey also indicated an inverse relationship between attitudes toward vegetation management and prioritization of aesthetics:

> *I object to the hack and cut mentality of some trimming. For established neighborhoods there has to be a balance between function and aesthetics when trimming.*
>
> *Shaded two-lane roads in our state…are a delight to travel on in warm weather and that known fact should be forever preserved within your vegetation management program.*

Integrating our results, respondent knowledge about trees exists in-tandem with expressed importance of reliable power and desired balance between trimming and preservation. Therefore, opportunity exists for managers to focus communication efforts on how the vegetation management process contributes to such desired outcomes.

We offer two possibilities that may elucidate observed relationships between residential context and attitudes toward vegetation management, and associated modest performance of our models. First, the heavily forested and largely exurban land use characteristic of Connecticut (Zabik and Prytherch 2013; Martinuzzi et al. 2015) may blur variable relationships that are more distinct in predominantly urban and rural locations. Exurban, the semi-rural region beyond city suburbs with development consisting of low housing density and large lots (Theobald 2004), is the fastest growing type of land use in the US (Brown et al. 2005; Theobald 2005), and an outcome of movement of people from urban to rural areas (Egan and Luloff 2000). Migrants bring urban influences (e.g., preferences for aesthetics over traditional rural utilitarian perceptions; Jones et al. 2003; Paquette and Domon 2003), increasing both social-structural (Soini et al. 2012) and land use (Theobald 2004) heterogeneity of an area. In our study, one-third of respondents self-reported that they live in an exurban area (*LocReside*; Table 2), yet were spatially integrated among respondents within other observed and self-reported land use classifications (author unpublished data). Integration was further evidenced by socioeconomic similarity between Urban and Rural strata (Table 2), whereas urban residents generally exhibit greater levels of formal education and income than rural residents (Huddart-Kennedy et al. 2009; Parker et al. 2018). From a forest management perspective, urban–rural transition zones present unique challenges as a result of conflicting stakeholder values and goals, human activity, and limited land availability (Colgan et al. 2014). Therefore, despite willingness to forgo aesthetics for reliable power, the truly exurban context of our study areas in terms of both land use and social psychology advocates for consideration of multiple management strategies to meet diverse public expectations (Johnson 2008); as evidenced by respondent comments:

> *Tree removal for safety needs to be balanced with retention for aesthetics and micro-climate moderation—probably on a case by case basis. One answer isn't correct for all situations.*

Second, relatively small predictive power of residential context variables suggests multi-scalar complexity between attitudes toward vegetation management and resident perceptions of trees in proximity to their households. We speculated that perceptions of vegetation management also are driven by fine-scale visual (i.e., "below the canopy") and emotional factors not captured in this analysis. Past research suggests a positive but nuanced relationship between preferences for and existing tree density in the landscape (Jiang et al. 2015; Suppakittpaisarn et al. 2019). In exurban and rural areas, new residences tend to be built on large parcels and away from the road (Ryan 2002; Paquette and Domon 2003), where visual changes from roadside vegetation management may be inconspicuous. Elsewhere in this project, homeowner interviews revealed that resident decisions about vegetation management also are influenced by characteristics of and personal affinity for individual trees (Kloster 2020). Respondent comments written on our survey support fine-scale influences:

> *I might have been a little biased because I have not forgiven my town for allowing a property manager to take down _____ majestic _____ trees that were the essence of our downtown.* [detail removed for anonymity]
> *Any trees that could cause power outages belong to neighbors across the street.*

Further exploration of alignment between preferences for and measurement of trees and vegetation using methods other than remote sensing may capture the scale at which residential context influences attitudes toward vegetation management.

Together, social-psychological and residential context factors that influenced attitudes towards vegetation management provided a wide-ranging picture of resident preferences. Demographic differences between our sample, non-response survey respondents, and census data (USDC 2016) limited ability to generalize results beyond intent of our study design (Dillman et al. 2009). Despite consistency with question design elsewhere (e.g., Morzillo and Mertig 2011; Morzillo et al. 2016; Keener-Eck et al. 2020), directionality of survey question wording also may influence results. Regardless, it is apparent that the exurban landscape is heterogeneous regarding both social-psychological and residential context-based characteristics. It is unlikely that uniform vegetation management policies that assume similarity across the roadside forest are appropriate or publicly viable. Therefore, successful strategies may involve connection of information about the vegetation management process to publicly desired outcomes that can be applied in response to multiple social and residential contexts.

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