

Interpolating Resident Attitudes Toward Exurban Roadside Forest Management

Steven DiFalco

University of Connecticut

Anita Morzillo (✉ anita.morzillo@uconn.edu)

University of Connecticut

Debarchana Ghosh

University of Connecticut

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Abstract

Context: Knowledge about spatial patterns of human dimensions data within landscape ecology is nascent despite its importance in natural resources management decision-making. We explored this topic within the context of utility roadside forest vegetation management, a complex situation involving ecological, cultural, and aesthetic aspects of forests and reliable power.

Objectives We applied spatial interpolation to investigate patterns of human attitudes toward exurban roadside vegetation management data across an exurban landscape.

Methods Mail surveys ($n = 1962$) were used to collect social science data from residents in four areas of Connecticut, USA. For each area, three attitudes variables were evaluated for spatial autocorrelation using Moran's I statistic. Based on identified autocorrelation distance or scale, attitudes were interpolated using inverse distance weighting. Model validation of interpolated surfaces was completed using root mean square error.

Results: Statistically significant spatial autocorrelation was present for five of 12 study area-attitude pairings at variable distances. Accuracy of interpolations also varied among study areas, suggesting that the choice of spatial scale of analysis influenced model results.

Conclusions: Social processes within the exurban landscape were spatially heterogeneous and multi-scalar for the same variables in different locations, exemplifying the complexity of social processes within exurban land use. Interpolation assumptions often applied toward ecological studies did not work well for social processes studied in this analysis. Results demonstrated the importance of understanding spatial dimensions at which social processes operate and, therefore, may influence ecological outcomes of the roadside forest within the context of state-level natural resources management and policy.

Introduction

Natural resource patterns and processes occur across multiple scales, cross administrative boundaries and ecological gradients (Turner et al. 2001; Ohmann et al. 2011; Wu 2013), and affect and are affected by socioecological processes occurring across landscapes (Johnson et al. 2019). Vast knowledge exists about spatial factors influencing ecological phenomena, such as landscape connectivity (An et al. 2020), community composition gradients (Ohmann et al. 2011), and disturbance interactions (Loehman et al. 2017). However, much less is known about the spatial patterns and processes of social science phenomena as they influence ecological processes (Robinson et al. 2019) despite its importance in natural resource planning and management. Social factors affect landscape processes such as forest vegetation management (Wyatt et al. 2011; Conway et al. 2011), distribution of wildfire occurrence (Vogt et al. 2005; Oliveira et al. 2012), and decision-making within watersheds (Andrews et al. 2018). Therefore, understanding the spatial dimensions at which social processes operate directly addresses the “what” and “where” aspects of social factors affecting ecological outcomes of natural resource issues (Bennett et al. 2017).

Natural resource decision-making at the landscape level often requires spatially explicit empirical data, which can be expensive and time-intensive to obtain (Ohmann and Gregory 2002; Bell et al. 2015). For social science, incomplete coverage, lack of longitudinal data, uncertainty of scale, and inconsistent data quality create additional challenges for integrating social science data within broader landscape analyses (e.g., Redman et al. 2002; Collins et al. 2011; Rounsevell et al. 2012; Bowen et al. 2016; Elsayah et al. 2020). When empirical data are lacking, tools and techniques such as spatial interpolation allow managers to construct inferences for sample-based data (Azpurua and Ramos 2010); biophysical examples include predicting forest composition across regions (Ohmann and Gregory 2002), interpreting changes in seasonal rain patterns (Camera et al. 2014), and assessing distribution of groundwater contamination (Gong et al. 2014) and temperature gradients across regions (Kim et al. 2010). The few applications of such tools and techniques to explore social science connections to ecological processes at the landscape level include assessing where human-perceived and physically measured ecological values overlap in socioecological hotspots (Alessa et al. 2008), and understanding visitor movement for improving park and protected area management (Beeco and Brown 2013). Despite this knowledge gap, such examples demonstrate potential for addressing social data challenges to strengthen bidirectional linkages between social science and landscape ecology. In this study, we focused on the context of utility vegetation management to explore spatial characteristics of human dimensions of roadside forest management at the landscape level.

Fallen roadside trees cause a majority of storm-related power outages (Campbell 2012; Parent et al. 2019), particularly during storm events, from which impacts are unevenly and unpredictably distributed across the landscape. Utilities implement roadside vegetation management, including tree trimming and tree removal, in attempt to mitigate power outages. In 2011 and 2012, Tropical Storm Irene, Storm Alfred [the October snowstorm], and Hurricane Sandy caused extensive damage across the eastern United States (US; Narayan et al. 2017). In response to widespread power outages after these storms, state governments throughout the northeastern US increased the aggressiveness of roadside vegetation management programs at the state level in order to mitigate future risks (McGee et al. 2012). However, decision-making about tree trimming and tree removal at multiple scales can hinder enumerative state-scale vegetation management mitigation efforts (Hale and Morzillo 2020; DiFalco and Morzillo 2021; Kloster et al. 2021). Given that public relations is the most challenging aspect of vegetation management (Johnson 2008), such strategies and policies create a complex situation involving a multitude of stakeholders with varying perspectives and opinions about associated tradeoffs among ecological, and social aspects of forests and reliable power (Hale and Morzillo 2020), and the aesthetic and cultural importance of roadside forests (DiFalco and Morzillo 2021).

Studies focused on social dynamics of vegetation management have indicated preferences for taller street trees (Schroeder 1989), shorter trees to decrease possible powerline obstructions (Flowers and Gerhold 2000), removing trees deemed hazardous to homes (Conway 2016), and perception that utility pruning harms aesthetics of roadside trees (Kuhns and Reiter 2007). Human dimensions studies of vegetation management to the landscape context have suggested that attitudes toward vegetation management and its effects on the roadside forest were more likely to be influenced by social-

psychological variables than residential context characteristics (Hale and Morzillo 2020; Kloster et al. 2021), and that factors influencing attitudes vary across study locations (DiFalco and Morzillo 2021). Therefore, human dimensions data provide information and context for potential scalar alignment of social and ecological processes associated with vegetation management.

Our objective was to investigate spatial patterns of attitudes toward vegetation management with specific focus on spatial proximity and scale. To do this, we used spatial interpolation, a technique facilitated by spatial autocorrelation and based on the fundamental geographic principle that points, or phenomena at points, closer together are more related than those further away (Tobler 1970). Previous human dimensions research has supported this principle, such that individuals located closer together are more likely to hold more-similar attitudes regarding a natural resource issue than those located further away (Berenguer et al. 2005; Morzillo and Schwartz 2011; Carter et al. 2014; Morzillo et al. 2016; Andrade et al. 2019). Therefore, we hypothesized that spatial autocorrelation would reveal respondents with similar attitudes toward vegetation management living near each other. Similar to ecological studies (e.g. Ohmann and Gregory 2002; Camera et al. 2014; Gong et al. 2014), we also hypothesized that the scales at which spatial variation of attitudes toward vegetation management would vary for different locations. Results advance our understanding of the patterns of social processes across multiple spatial scales, and their interplay with associated short- and long-term roadside forest management planning goals.

Methods

Study context

Connecticut is a small northeastern US state (14,357 km²) that has experienced rapid population growth since the 1950s, much of which has occurred in exurban areas outside of cities (Brown et al. 2005). The integration of exurban development, extensive forest cover (72.6% of the state, Nowak and Greenfield 2012), and a dense population (285 people/km²; U.S. Census Bureau 2011) results in Connecticut having the greatest proportion of wildland-urban interface in the US (66%; Martinuzzi et al. 2015). Increased vegetation management along roadsides following the storm events of 2011 and 2012 prompted public concern about overly aggressive vegetation management protocols (Public Utilities Regulatory Authority 2014), which include tree trimming and removal as means to ensure reliable power (Eversource 2016).

Data collection

Four geographically distinct study areas in Connecticut (Northeast, Southwest, Northwest, Southeast; Fig. 1) were identified during interviews with utility employees and discussions with project partners ($n = 7$; author unpublished data). Study area extents were selected based on distribution across an urban-rural gradient and ongoing utility vegetation management along roadsides (Hale and Morzillo 2020). Data were collected from the Northeast and Southwest study areas in 2017 (Hale and Morzillo 2020), and the Northwest and Southeast study areas in 2019 (DiFalco and Morzillo 2021). Data were collected using a mail survey, which consisted of questions that addressed five main topics: experiences with power

outages, attitudes toward roadside vegetation management, roadside tree and forest management preferences, knowledge about trees and tree health, and background information including individual relationships with the environment and sociodemographic information.

<Fig. 1>

The sampling frame included a list of all residential street addresses within the four study areas, and the sampling unit was the individual household. Addresses used for mailing were purchased from Marketing Systems Group (Horsham, PA), which uses US Postal Service delivery routes to generate address lists. To focus sampling on residents most likely involved in tree management decisions at the property level, an effort was made to select single-family owner-occupied addresses. Post office boxes, seasonal homes, mail drops, and vacant homes were excluded from the sample. Based on expected response rate and a desired sampling error of $\alpha = 0.05$ (95% confidence interval; Sheskin 1985), 1800 surveys were mailed to each study area. To ensure coverage across the urban-to-rural gradient, surveys were sent to an equal number of urban and rural respondents, as determined by the 2010 Census classification of urban and rural (U.S. Census Bureau 2011).

A modification of the Tailored Design Method was applied to data collection (Dillman et al. 2009). Multiple mailings were used as an effort to increase response rate, which included a: 1) pre-notice postcard to introduce the project, 2) packet containing a cover letter, survey and pre-paid return envelope, 3) reminder/thank you postcard, and 4) second survey packet to those who had not yet responded. To evaluate potential for non-response bias, non-respondents to the original survey received a short follow-up mail survey focusing on ten key items from the original survey. The University of Connecticut Institutional Review Board (IRB) granted permission for use of human subjects (IRB #H16-007).

Variables

Attitudes measure favor or disfavor toward a person, object, event, or situation (Fazio et al. 1982). Previous topics related to this study have included attitudes related to urban tree maintenance (Davis and Jones 2014), native trees (Almas and Conway 2018), and aspects of forest management (Wyatt et al. 2011; Hale and Morzillo 2020; DiFalco and Morzillo 2021). To assess attitudes toward vegetation management, we measured respondent agreement with a series of attitude statements on the survey. Responses were coded using a five-point Likert scale measuring level of agreement (5 = strongly agree; 1 = strongly disagree). Principle component analysis (PCA) with varimax rotation was used for data reduction to identify attitude statements that factored together. Cronbach's alpha (α) was used to test the internal reliability of groups of statements that factored together (Cortina 1993). Guided by Hale and Morzillo (2020) and DiFalco and Morzillo (2021), statements that factored together were summed to create scale scores, resulting in three scale-based variables: *AttProfessional*, *AttSafety*, and *AttTradeoff*.

Six attitude statements were used to construct a scale score for *AttProfessional* (2017: $\alpha = 0.880$, $n = 967$; 2019: $\alpha = 0.894$, $n = 939$), which focused on perceived professionalism of vegetation managers: (a) Those who do vegetation management care about trees; (b) Those who do vegetation management care

about minimizing outages; (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 scores indicated greater perceived accountability of vegetation management practices; possible scale scores ranged from 6-10.

Four attitude statements were used to construct a scale score for *AttSafety* (2017: $\alpha = 0.764$, $n = 967$; 2019, $\alpha = 0.759$, $n = 939$), which focused on the perceived safety of vegetation management: (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 scores indicated greater perceived safety from vegetation management; possible scale scores ranged from 4-20.

Five attitude statements were used to construct a scale score for *AttTradeoff* (2017: $\alpha = 0.758$, $n = 986$; 2019: $\alpha = 0.789$, $n = 946$), which focused on the tradeoffs between protecting trees and tree trimming to reduce power outages: (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; and (e) More intensive tree work now will require less frequent management over the long term. Greater scale scores indicate greater importance placed on power compared to trees; possible scale scores ranged from 5-25.

To describe respondents, data were collected for five sociodemographic variables (Table 1), as previous research suggested these variables may influence attitudes toward natural resources (e.g., Morzillo et al. 2010; Keener-Eck et al. 2020). Data collected for each respondent included: respondent sex (*Sex*; male or female), year they were born (*Age* in years), and length of time lived at their current address (*Tenure* in years). *Education* was represented as the highest education level selected among seven formal education levels: (a) Less than high school, (b) High school or equivalent (e.g., GED), (c) Some college, (d) Vocational or trade school, (e) College degree (2-year or certificate), (f) College degree (Bachelor's), or (g) Graduate or professional degree; *Education* was represented as the highest education level selected. For household income (*Income*), respondents selected from among five income groups ranging from <\$25,000 to \geq \$100,000.

Table 1
Sample characteristics of survey respondents for each study area location.

Variable (n)	Northeast a,b	Southwest a,b	Northwest b	Southeast ^b
<i>AttProfessional</i> (1,904; mean ± SD) ^c	21.4 ±5.0	20.5 ±4.9	20.8 ±5.2	20.3 ±5.6
<i>AttSafety</i> (1,904; mean ± SD) ^c	17.2 ±2.5	17.1 ±2.4	17.0 ±2.5	16.6 ±2.7
<i>AttTradeoff</i> (1,931; mean ± SD)	20.0 ±3.5	20.2 ±3.5	20.1 ±3.6	20.0 ±3.7
<i>Age</i> (1,812; mean age in years ± SD)	60.8 ±14.7	61.5 ±13.5	61.5 ±14.5	60.8 ±14.0
<i>Tenure</i> (1,911; mean years ± SD)	21.3 ±14.6	21.1 ±14.9	21.6 ±15.8	22.1 ±15.2
<i>Sex</i> (1,912; % female)	52.6	49.0	50.5	57.5
<i>LocReside</i> (1857, %) ^c				
Rural	32.3	18.8	27.4	32.8
Semi-rural (also referred to as exurban)	31.2	37.6	31.9	28.7
Suburban	32.5	41.9	37.3	28.9
Urban	4.0	1.7	3.4	9.6
<i>Education</i> (1,907; %) ^c				
Less than high school	0.9	0.2	0.0	0.9
High school or equivalent	9.3	3.5	7.9	12.9
Some college	13.3	7.9	10.1	13.1
Vocational or trade school	5.4	2.1	6.2	6.9
College degree (2-year or certificate)	10.9	5.6	10.1	11.1
College degree (Bachelor's)	28.3	35.9	29.8	26.4
Graduate or professional degree	31.8	45.1	36.0	28.8
<i>Income</i> (1,629; %) ^c				
Less than \$25,000	3.6	2.9	6.8	5.8
\$25,000-\$49,999	14.9	4.6	11.9	12.3
\$50,000-\$74,999	19.8	9.2	9.2	19.6
\$75,000-\$99,999	18.1	11.7	15.3	21.2
\$100,000 or more	43.6	71.6	56.9	41.1

Variable (<i>n</i>)	Northeast a,b	Southwest a,b	Northwest b	Southeast ^b
^a Adapted from Hale and Morzillo 2020 ^b Adapted from DiFalco and Morzillo 2021 ^c Significant difference among groups ($p < 0.05$): <i>AttProfessional</i> ($F_{3,1900} = 4.050, p = 0.007$) and <i>AttSafety</i> ($F_{3,1900} = 5.366, p = 0.001$); <i>LocReside</i> ($\chi^2 = 71.027, df = 9, p < 0.001$); <i>Education</i> ($\chi^2 = 85.227, df = 18, p < 0.001$); <i>Income</i> ($\chi^2 = 112.340, df = 12, p < 0.001$).				

<Table 1>

Spatial analysis

Spatial analysis was completed separately for each of the three attitudes variables, as paired with each study area (3 attitude variables x 4 study areas = 12 analyses total). For each pairing, only respondents with individual attitude scale scores were included in the analysis for each attitude variable (*AttProfessional* $n = 1904$; *AttSafety* $n = 1904$; and *AttTradeoff* $n = 1931$).

The first step of this analysis was to identify the scale or distance at which each attitude variable was spatially autocorrelated for each study area. For each of the 12 attitude-study area pairings, we performed incremental spatial autocorrelation (ISA) in ArcGIS 10.7.1 at 100 m increments, ranging from 100 m to 3000 m, to identify the distance band of maximum spatial autocorrelation (Fig. 2). ISA measured spatial autocorrelation at each distance and computed a Moran's I and z-score for each distance (Carter et al., 2014). In this analysis, we used a 95% confidence interval to identify significant spatial autocorrelation, such that z-scores > 1.96 represented clustering of attitudes, and z-score < -1.96 represented a dispersed pattern of attitudes. Only pairings for which ISA produced a spatial autocorrelation value were assessed in subsequent steps.

<Fig. 2>

For the second step of this analysis, inverse distance weighting (IDW) interpolations were completed in ArcGIS 10.7.1 using a fixed distance band for each attitude identified as having spatial autocorrelation (Table 2). The fixed distance band was equal to the distance of spatial autocorrelation for each attitude-study area pairing. Raster output was set at the 30m² cell size to match the National Land Cover Database (NLCD) cell size (Homer et al. 2020). One-fourth of the survey respondents from each paired analysis was reserved for use as an independent data set for model validation (Verbyla and Litvaitis 1989). The "Geostatistical Analysis Layer to Points" tool in ArcGIS, which extracts a predicted attitude score for each respondent in the independent dataset based on the IDW interpolation, was used to validate the interpolated surface. Model performance was measured using root mean square error (RMSE), which indicated the degree of deviation of the predicted versus the actual attitude value (from the survey), based on the following formula (adapted from Martins et al. 2019):

Table 2

Statistical results of incremental spatial autocorrelation and accuracy testing for study area-attitudes pairings with spatial autocorrelation.

Attitude	Study Area	Distance (m)	Moran's I	z-score	p-value	Test Points Included (%)	RMSE
<i>AttProfessional</i>	Northeast	2400	-0.022	-2.115	0.034	100	5.48
<i>AttSafety</i>	Northwest	200	0.310	2.259	0.024	14.7	2.66
<i>AttSafety</i>	Northeast	300	0.111	2.212	0.027	64.2	2.91
<i>AttTradeoff</i>	Southeast	600	0.103	2.020	0.043	78.1	4.53
<i>AttTradeoff</i>	Southeast	1500	0.052	2.395	0.015	98.2	3.87
<i>AttTradeoff</i>	Southwest	2200	-0.044	-2.449	0.014	100	3.88

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (p_i - a_i)^2}$$

where p_i is the predicted attitude score for the respondent at location i , a_i is the actual attitude score for the respondent at location i , and n is the number of respondents in the subset. Spatial analyses were completed using ESRI ArcGIS 10.8 and Python 2.7 (ArcPy module).

<Table 2>

Results

Together from both survey efforts (2017 and 2019), 1962 completed surveys were returned (Northeast $n = 555$; Southwest $n = 443$; Northwest $n = 495$; Southeast $n = 466$; Table 1). The average age across all respondents was 61.1 (± 14.2) years; 52.4% of respondents were female. On average, respondents had lived at their current address for 21.5 (± 15.1) years. For formal education completed, 29.9% of respondents indicated a Bachelor's degree, and 35.1% an advanced degree. More than half of respondents indicated a household income of \$100,000 or more (52.4%). Survey respondents were generally older with more formal education completed and greater household incomes than the overall population of the study areas (ACS 2017). Results from the non-response follow-up survey suggested that those who completed it ($n = 347$) were younger, and more likely to hold a Bachelor's degree. In general, respondents held favorable attitudes toward roadside vegetation management, with average attitude scores above the respective scale score midpoint (Table 1). Mean attitude scale score varied among study areas for *AttProfessional* ($F_{3,1900} = 4.050$, $p = 0.007$) and *AttSafety* ($F_{3,1900} = 5.366$, $p = 0.001$), but not for *AttTradeoff* (See DiFalco and Morzillo 2021 for detailed investigation of these relationships).

ISA analysis indicated the presence of spatial autocorrelation for five of the 12 attitude-study area pairings tested (Table 2). For those five pairings, distances of maximum autocorrelation varied by study area. Maximum spatial autocorrelation for *AttProfessional* was identified in the Northeast study area at 2400 m. *AttSafety* reached maximum spatial autocorrelation in the Northwest at 200 m, and in the Northeast at 300 m. ISA identified two different distances of significant spatial autocorrelation for *AttTradeoff* in the Southeast study area (600 m and 1500 m), as well as maximum spatial autocorrelation for *AttTradeoff* in the Southwest study area at 2200 m. Two of the five pairings showed negative spatial autocorrelation (i.e., dissimilar attitude scores are clustering together): *AttProfessional*-Northeast (Moran's $I = -0.022$), and *AttTradeoff*-Southwest (Moran's $I = -0.044$, Table 2).

Interpolated surfaces indicated the spatial variation of attitudes scores across study areas (Figs. 3 & 4). IDW surfaces varied in spatial coverage depending on the distance band used for interpolation. For the Northeast, maximum autocorrelation distance bands for *AttProfessional* and *AttSafety* occurred at different distances; thus, those two attitude variables had different spatial coverages for the same location (Fig. 4). At short distances (i.e., 200 m and 300 m) attitudes did not interpolate extensively across the study area extents for the Northwest and Northeast, respectively (Fig. 4).

<Fig. 3>

<Fig. 4>

Model validation indicated differences in interpolation accuracy among attitude variables and study area pairings (Table 2). Only independent data points located inside of interpolated surface were included in RMSE calculations, which varied by distance band used in the interpolation. For the Northwest, 14.7% of independent data points were included in model validation at 200 m. For both Northeast at 2400 m and Southwest at 2200 m, all 100% of independent data points were included (Table 2). RMSE scores ranged from 2.66-5.48, which also indicated variation in interpolation accuracy.

Discussion

We applied spatial interpolation to understand spatial patterns of human dimensions data, with focus on proximity and scale of attitudes metrics within the context of utility vegetation management of roadside forests. Complex levels of spatial heterogeneity existed, such that attitudes toward vegetation management varied across space, and likely are associated with location-specific characteristics. Preceding analyses suggested that respondents had generally favorable attitudes toward vegetation management across all study areas, interplay of social and landscape factors affected individual attitudes (Hale and Morzillo 2020), and variation in social variables influenced attitudes among study areas (DiFalco and Morzillo 2021). In our analysis, maximum spatial autocorrelation distances for the three attitudes variables among the four study areas supports multiscale spatial variation of people's attitudes toward vegetation management, which may hinder success of a state-level one-size-fits-all vegetation management policy. To focus the discussion, we describe two underlying social phenomena

that may contribute to the observed spatial heterogeneity among locations and offer direction for further analysis.

Supporting our first hypothesis that social phenomena closer together are more likely to be related than those further away, clustering of similar attitude scores existed for three of the 12 attitude-study area pairings (*AttSafety-Northwest*, *AttSafety-Northeast*, and *AttTradeoff-Southeast*). Contrasting the same hypothesis were two pairings with negative autocorrelation (*AttProfessional-Northeast*, and *AttTradeoff-Southwest*) and seven with no autocorrelation. Spatial clustering of favorable attitudes toward natural resources has been observed in other natural resources contexts. Attitudes toward tigers in Nepal were clustered based on human cultural factors, educational achievement, and experience with tiger attacks (Carter et al. 2014). Attitudes toward the desert were spatially clustered within neighborhoods of similar social and landscape characteristics; more favorable attitudes existed in high-income areas closer to preserved desert parks (Andrade et al. 2019). However, results from elsewhere in our project generally did not suggest socioeconomic factors to be strongly associated with spatial clustering of attitudes towards vegetation management (DiFalco and Morzillo 2021). Urban-rural distinctions in attitudes also may occur, such as clusters of favorable attitudes towards carnivores (e.g., wolves and black bears) more likely to be near urbanized areas (Morzillo et al. 2007; Behr et al. 2017), and rodent control behavior more likely among households closer to rather than further from natural areas (Morzillo and Schwartz 2011). However, ancillary evidence from elsewhere in our analysis (DiFalco and Morzillo 2021) did not suggest clustering based on self-selected urban-rural residential designation (*LocReside*; Table 1), or landscape characteristics surrounding respondent homes, except for *AttTradeoff-Northwest* which was positively associated with a greater percentage of tree cover (DiFalco and Morzillo 2021). Areas of negative spatial autocorrelation of attitudes demonstrates diversity of attitudes among proximate individuals, and potentially that processes observed in one area are influenced by neighboring areas (Griffith and Arbia 2010). It is possible that vegetation management actions completed by homeowners may affect and be affected by attitudes of their neighbors (e.g., Belaire et al. 2016), but support for this conclusion is beyond the scope of our data. Collectively, the mixed results from our study exemplified the heterogeneity and complexity of social processes that occur within exurban land use (e.g., Hiner 2014; Bauer et al. 2017).

Supporting our second hypothesis, varying autocorrelation distances among attitude-study location pairings illustrated that attitudes toward vegetation management existed at different spatial scales in different locations. Multi-scale governance processes may contribute to this observed heterogeneity, as observed elsewhere. For example, Morzillo et al. (2016) observed variation in resident preferences for natural resource-based amenities between two different cities, with additional inter-city differences detected at the property, neighborhood, and metropolitan scales. Although vegetation management regulations operate at the statewide level (McCarthy 2014; Public Utilities Regulatory Authority 2014), decisions about trees are influenced by individual property-scale preferences (Kloster et al. 2021) and neighborhood norms (Grove et al. 2006). Additionally, Chowdhury et al. (2011) suggested that municipal- and state-level land-use zoning affected household and neighborhood vegetation structure in the city of Baltimore, where a policy was implemented to increase urban tree canopy. Findings from that study suggested that most tree plantings would need to occur on private residential properties, thus relying on

property-scale decision-making to achieve municipal goals, and demonstrating the importance of multi-scale processes in policy outcomes (Chowdhury et al. 2011).

Besides zoning, other governance structures such as town ordinances present additional layers of complexity to governance and therefore spatial distribution of tree plantings and removals on both public and private properties (Johnson et al. 2020). Comments from our survey suggested overall confusion about jurisdictional coordination of vegetation management:

We are perplexed by the randomness of activity in roadside tree removal/trimming. Is there an overall state or town plan for a comprehensive and methodical approach?

In Connecticut, some towns have specific ordinances in place that delay or prohibit implementation of utility practices related to state vegetation management guidelines. For example in the Northeast study area, the towns of Mansfield and Coventry encourage maintaining a closed forest canopy to preserve the aesthetic quality of forested scenic roadways (Town of Mansfield 1995; Town of Coventry 1997). However, in the same study area, the adjacent towns of Bolton and Andover do not have analogous regulations. Another commonly mentioned suggestion is to bury powerlines underground, which is now required in some towns for new housing developments (e.g., Town of Avon 2007). Despite potential aesthetic benefits (Navrud et al. 2008), undergrounding utilities often are considered cost-prohibitive because of complex regulations and high implementation costs (Cieslewicz and Novembri 2004; Campbell 2012), and do not ameliorate for outages between substations and the location of underground utilities. Ultimately, inter-town differences in tree-related governance at multiple scales complicates utility ability to perform consistent vegetation management along inter-town stretches of power lines.

Diversity in respondent attitudes toward vegetation management revealed by interpolation results also may reflect differences in regional culture across the state. Others have reported direct relationships between greater household incomes and a greater likelihood to plant trees in neighborhoods that sustain greater tree cover (Conway et al. 2011; Nitoslawski et al. 2016). In our study, the distribution of incomes varied among study areas (*Income*; Table 1); tree canopy cover was numerically lowest in the Northeast (average percentage: Northeast = 47.6, Southwest = 54.0, Northwest = 55.4, and Southeast = 52.1; DiFalco and Morzillo 2021). Respondent comments on the survey alluded to linkages among where people lived, the importance of tree cover, and experiences with vegetation management:

I think where we live in _____ [Northwest study area] we have so many rural/suburban communities - all surrounded by trees, state parks trails etc. so many of us live here because nature is abundant, it surrounds us, we hike, camp, live within nature. But realistically we need to work and live safely- not have power outages for weeks where we can't live or work. We need to find balance. Nature and animal's homes are our homes.

Tree management to reduce power outages is important to us since we are one of the last areas to have power restored [after storm events] because of our sparse population. We live in a rural setting. This management should be done in an environmentally responsible way.

Maintaining the aesthetic character of an area also was expressed by respondents as an important outcome and existed concurrently with respondent understanding of the necessity for vegetation management:

Trees are so important but tree health is just as important. The woods, land preserved and forests should remain untouched. Trees in residential areas should be maintained for health and resident safety. I would happily allow the utilities to remove the tall trees in my front yard that stand tall enough to fall on the lines but also appreciate the other trees around my property.

This parallels previous research from New England on the topic of developing strategies for maintaining the rural character of a town while balancing economic growth and development (Zabik and Prytherch 2013). Our results also suggested opportunity for integrating homeowner preferences into management plans, such as incorporating desired visual outcomes of tree trimming and potentially replace taller trees with shorter statured species less likely to interfere with powerlines, echoing findings by Flowers and Gerhold (2000).

Limitations in this study offer opportunities for better integration of social and ecological data in landscape ecology. First, the geographic assumption that points closer together are more similar (Tobler 1970; ESRI 2019) applies well to particular ecological phenomena, such as the amount of precipitation in a given location (Camera et al. 2014) or weather conditions occurring across a country (Kim et al. 2010). However, as our results demonstrated, social processes within exurban areas may not follow this assumption, as human dimensions characteristics are heterogeneous and unequally distributed. Second, distribution of different land uses varied among and within the four study areas. For example, in the Northwest study area, interspersed protected open space covers about 20% of the towns of Avon and Simsbury, but only nine percent of the adjacent town of Canton (DEEP 2010). Our analysis did not exclude areas of non-residential land use and, therefore, spatial calculations included forested public lands and protected open space, which both confine and facilitate clustering of residential development. Such patterns of interspersed are further influenced by local development planning ordinances beyond those associated with trees and vegetation management. For example, in the Southeast study area, planning regulations for the town of Montville require subdivision projects to maintain a designated amount of area as permanent open space (Town of Montville 2020). Therefore, determining the most appropriate scale to address social phenomena in such contexts requires consideration of multiple spatial scales, concurrent and competing land uses, and ecological processes simultaneously (Vogt et al. 2002).

Differences in model performance among attitude-study area pairing also alluded to opportunities to improve landscape analytics for assessing social phenomena. For example, Gong et al. (2014) found that interpolations to assess contamination of groundwater wells across Texas were more accurate when data were divided into regional districts (i.e. specific aquifers or areas of the state) rather than pooled for the whole state - i.e., adjustments made to level of analysis. Bhowmik (2012) concluded that performance between climate prediction models and actual weather conditions improved as additional meteorological

stations were added over subsequent years through increasing the number of data points. In our analysis, interpolated surfaces were more likely to predict the actual attitude score in portions of our study areas where the distance between respondents was smaller, suggesting that additional data points or oversampling among locations where households are further apart may be useful in areas of heterogeneous land use and development density, such as exurban landscapes. Future studies may also consider experimenting with mismatches between scale of data collection and social processes (Robinson et al. 2019) to better align methodological design of data collection to the spatial scale of the social process being assessed.

Results of this analysis supported the creation of multi-scalar strategies for roadside vegetation management that consider not only landscape-level decision-making but also local-level stakeholder heterogeneity. Collaborative management decisions by organizations working at different scales are critical components of such linkages, and between ecological and social components of forest management (e.g., Martins et. al 2022; Paletto et. al 2010; Madeira and Gartner 2018). In Connecticut and elsewhere this means landscape-level coordination among the forest management community, public engagement to improve awareness and understanding of the importance of the vegetation management process, recognition of general interest in maintaining the visual aesthetics of their communities, and outreach strategies and protocols that reflect and respond to both regional and local variation.

Declarations

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Ethics approval: The study was conducted according to the guidelines of the Declaration of Helsinki, and The University of Connecticut Institutional Review Board (IRB) granted permission for use of human subjects (IRB #H16-007).

Consent to participate: Informed consent was obtained from all subjects involved in the study per Institutional Review Board guidelines and protocol.

Consent for publication: All authors have read and agreed to the published version of the manuscript.

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Figures

Figure 1

Map of study areas within Connecticut. Northeast and Southwest were sampled in 2017; Northwest and Southeast sampled in 2019 (adapted from Hale and Morzillo 2020 and DiFalco and Morzillo 2021).

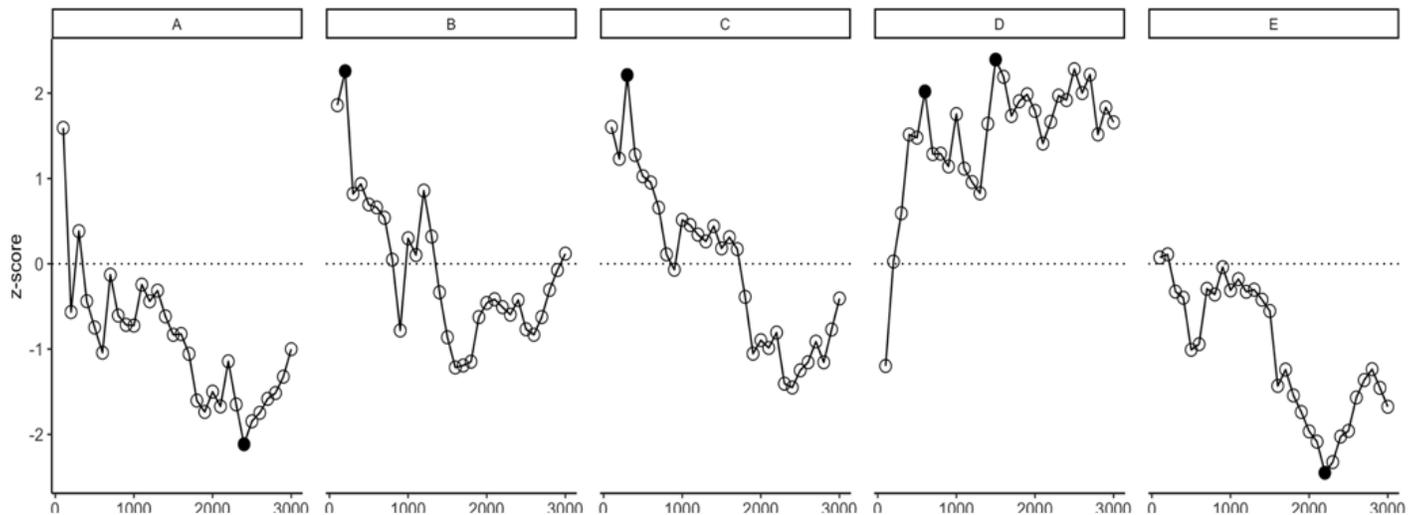


Figure 2

Output from incremental spatial autocorrelation for the five attitude-study area pairings with spatial autocorrelation: A) *AttProfessional*-Northeast, B) *AttSafety*-Northwest, C) *AttSafety*-Northeast, D) *AttTradeoff*-Southeast, and E) *AttTradeoff*-Southwest. Black circles denote distances of spatial autocorrelation determined by Moran's *I* statistic. Open circles are distances without identified spatial autocorrelation.

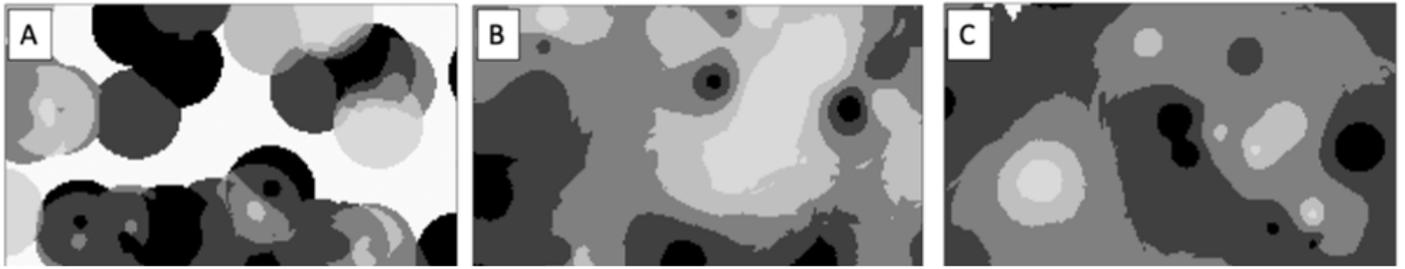


Figure 3

Example of IDW interpolated surfaces for *AttTradeoff*: a) Southeast at 600 m, b) Southeast at 1500 m, and c) Southwest at 2200 m. Darker colors indicate more favorable attitude scores. White areas are beyond interpolation extent.

Figure 4

Example of IDW interpolated surfaces for *AttSafety*: a) Northwest at 200 m, b) Northeast at 300 m, and for *AttProfessional*: c) Northeast at 2400 m. Darker colors indicate more favorable attitude scores. White areas are beyond interpolation extent.