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Spatial and sociodemographic determinants of community loudness perception

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ABSTRACT

Urban noise is an increasingly important public health concern, but few studies have characterized drivers of community loudness perception rather than objective measures of sound, which may be an important element of the associated health effects. In this study, we used survey responses from the 2015–2016 Greater Boston Neighborhood Noise Survey (n = 898) to determine the key geospatial determinants of community loudness perception at both the street and neighborhood level. We gathered numerous land use and sociodemographic covariates and used an elastic net selection approach to determine the subset to include in final prediction models. Individual noise sensitivity and proximity to bus stops (<150 m) was associated with perceived loudness at the street and neighborhood level. In addition, at the street level, the restaurant and transportation infrastructure within close proximity (<200 m) of the residence were predictive of perceived loudness. At the neighborhood level, there was a larger and more complex set of predictors in the final prediction model, including multiple commercial/business sources at larger distances (500–1000 m buffers) from the residence. In general, these predictors overlapped with those in existing models predicting objective sound across multiple frequencies (A-weighted sound. low-frequency sound, mid-frequency sound, and high frequency sound), especially for transportation sources, although some predictors of noise perception differed from those for sound measurements. These results emphasize the importance of characterizing both perceived noise and objective sound, with the combined insights helping to develop soundscape maps and determine which urban areas require intervention to improve community public health.

1. Introduction

As a consequence of dense populations and high activity, cities are host to numerous sound sources that together create the din of city-living. While urban sound levels are traditionally viewed as a necessary sacrifice, from a public health perspective, sound exposure has been associated with a wide range of adverse health effects including annoyance [1,2], sleep disturbances [3], learning impairments [4,5], cardiovascular disease [6–9] and an increased risk of mortality [10,11].

Two main pathways exist in the development of adverse health effects resulting from environmental sounds: the direct activation of the nervous system by acoustic nerve [12], and the indirect activation through cognitive perception and emotional response [13]. Noise, defined as unwanted sound, is a more subjective exposure that elicits annoyance and is disruptive to daily life [14]. While objective sound levels are known to activate the stress mechanisms that influence health, the same level of measured sound is perceived as noise by some and not others and this disparity in experience leads to distinct levels of adverse health effects through the indirect pathway [15,16].

Understanding how noise may interfere with social interactions and activities is an important factor in noise pollution [17,18]. Noise annoyance is thought to be an effect modifier in the indirect pathway between sound levels and adverse health [19,20]. From a mental health perspective, subjectively perceived noise is an important factor in influencing psychological health [21–24]. The discomfort provoked by subjective noise is the primary pathway of triggering noise-induced illness and must be at the forefront of considerations for protecting the public health [12].

Several studies have constructed predictive models to identify key spatial and temporal determinants of environmental sound

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levels in urban environments [25–31]. However, the acoustic environment (sound pressure levels) cannot completely characterize the effects of living with those noises and should be supplemented with an understanding of the soundscape (the contextualized acoustic environment as perceived or experienced) [14,32]. Existing soundscape models have used psychoacoustic indicators such as perceived loudness [33], or a combination of psychoacoustic indicators, sound levels, environmental and contextual characteristics, sound sources, and visual sources [34–41] to predict soundscape descriptors such as sound quality, pleasantness, tranquility, and preference. The goal of this study differs from existing soundscape research as it seeks to use survey responses, digitally available spatial and sociodemographic data, and variable selection statistical methods to determine the spatial predictors of "urban loudness", a subjective soundscape indicator, rather than traditional soundscape descriptors. Loudness is the most common psychoacoustic parameter included in these models [42] and therefore results from this paper may be used to improve existing models of soundscape descriptors. These results also may determine which urban areas require intervention to improve quality of life and potential noise-related health outcomes as well as inform urban planning decision-making.

While the relationship between our environment and our perception of sound levels is complex, this paper attempts to understand and compare key spatial and sociodemographic determinants of street and neighborhood level community noise perception in Greater Boston. A community survey was collected to measure participants' location, demographics, noise sensitivity and perceived loudness of their streets and neighborhoods. Two predictive models were created to predict street and neighborhood loudness perception and selected variables were compared with predictors previously derived for sound levels in Greater Boston [43].

2. Materials and methods

2.1. Study area

The Greater Boston Neighborhood Noise Survey was conducted between March 2015 and March 2016 in the Greater Boston Area, Massachusetts. Boston occupies an area of 48 square kilometers with an estimated population of 675,647 individuals [44]. Boston along with several surrounding towns are collectively called the Greater Boston Area, though definitions of included towns and cities vary. For this study, we included several towns in the Greater Boston Area with significant ties to the city of Boston (Fig. 1).

2.2. Greater Boston neighborhood noise Survey

The Greater Boston Neighborhood Noise Survey is a community noise survey consisting of 34 questions along the following domains: (1) Address and sociodemographic information; (2) Attitudes toward community and occupational noise; (3) Health and sleep questions; (4) Abatement strategies. This survey is available in English, Spanish, Haitian Creole, Simplified Chinese, and Vietnamese. Survey respondents were instructed to consider their community as their neighborhood and street as drawn by their city. Noise sensitivity (NS), defined as the physiological and psychological characteristic which determines the degree of reactivity to noise [45], was assessed using a visual analog scale that had been translated according to the International Organization for Standardization Technical Specification 15666 (2003). NS was self-assessed via single-item questionnaires. On an 11-point Likert scale, scores of 0 and 10 points indicated the lowest and highest sensitivity, respectively. Community loudness perception was determined using an 11-point Likert scale ranging from 0 to 10 (quiet to loud) at neighborhood and street levels. The exact wording of NS and loudness perception questions are included below:

> "In general, how SENSITIVE are you to noise? If you are not at all sensitive, choose the number zero. If you are extremely sensitive, choose the number ten. If you are somewhere in between, choose a number between zero and ten."
>
> "How loud is your STREET? If it is not loud, choose the number zero. If it is really loud, choose the number ten. If it is somewhere in between, choose a number between zero and ten."
>
> "How loud is your NEIGHBORHOOD? If it is not loud, choose the number zero. If it is really loud, choose the number ten. If it is somewhere in between, choose a number between zero and ten."

A total of 898 survey responses were obtained using convenience sampling. The survey was advertised via social media on local community group pages, posters in public community spaces, and at Boston community events.

2.3. Spatial and sociodemographic covariates

Survey respondents' addresses were geocoded. Spatial attributes of participant addresses were obtained using publicly available data from the Commonwealth of Massachusetts Office of Geographic Information (MassGIS). Counts of commercial establishments were acquired from Data Axle (Data Axle, 2015). The percentage of various land uses; building density; total counts of bus stops, entertainment establishments, "big box" stores, auto body shops, and restaurants; total length (in meters) of road networks, bus networks, and train networks were calculated within the following radial buffers: 25, 50, 100, 150, 200, 250, 300, 500, 1000 m around each sampling site. Distances to nearest interstate, major roadway, bus route, train route, school, hospital with emergency center, fire station, police station, and international airport (Logan International Airport) were also calculated based on spatial join. Road conditions including structural conditions, traffic counts, surface width, and elevation were obtained for the road closest to each participant address. Neighborhood sociodemographic factors such as mean age, population density, household income, racial composition, percentage of owner-occupied units, educational attainment, unemployment, age of housing units, average years living on street, and number of households with children under 18 were obtained for the census block group where each sound monitoring site was located [46]. These covariates were further categorized as follows: Participant Personal, Block Group Census, Commercial/Business, Entertainment/Leisure, Transportation, City Services, Built Environment, and Natural Environment (Table 1).

2.4. Statistical analysis

2.4.1. Descriptive statistics

Distributions of noise sensitivity, street loudness ratings, and neighborhood loudness ratings were calculated by participant location. We compared differences in these distributions by location and used Pearson correlations to guide the model-building process.

2.4.2. Spatial-temporal modeling approach

Separate linear regression models were developed for street and neighborhood loudness perception. To reduce overfitting of the model, for every variable with multiple buffers, only the two buffer sizes most correlated with the outcome variable were included as potential predictors. An elastic net was then used to determine which of the remaining spatial and sociodemographic

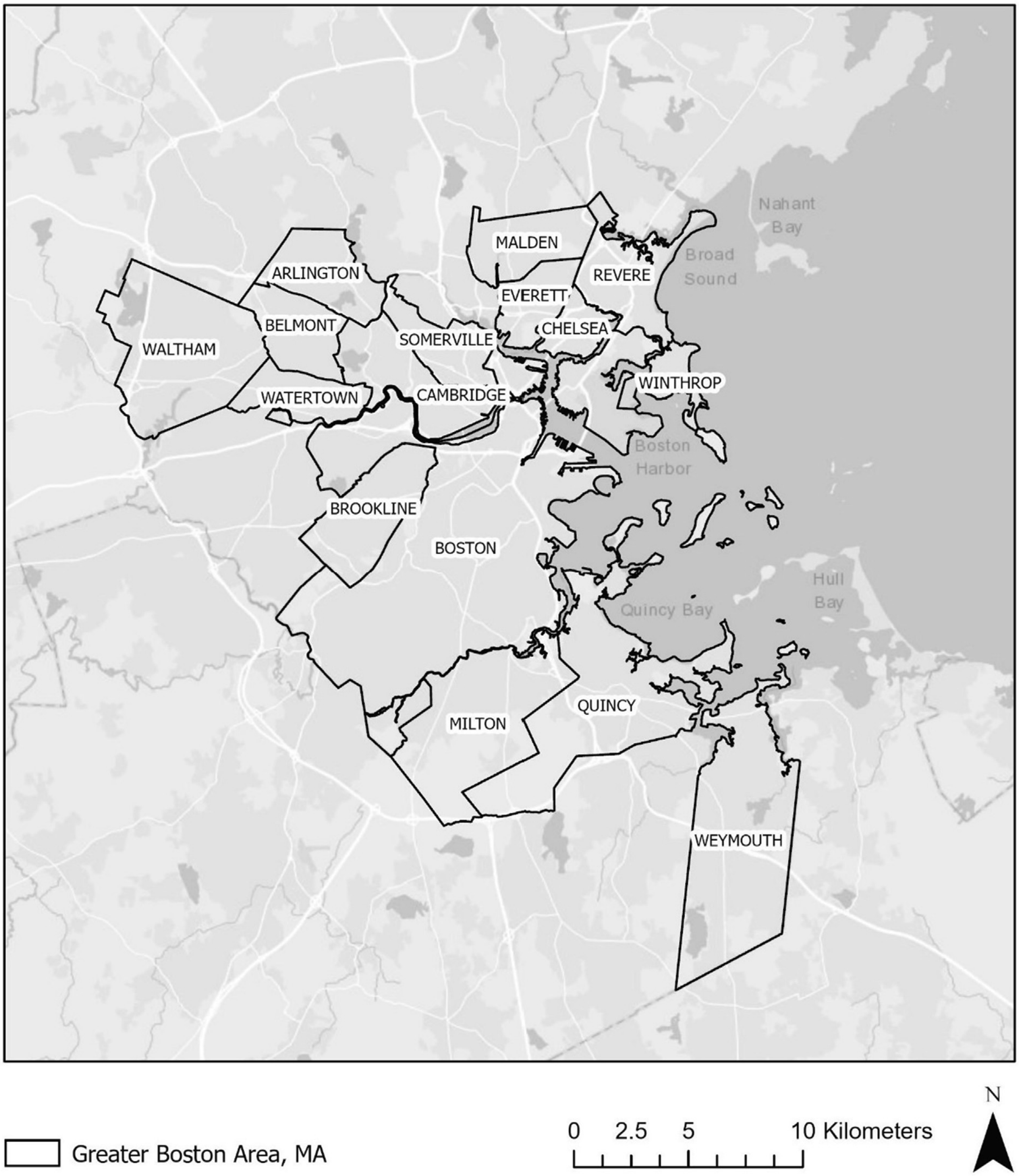

Fig. 1. Greater Boston Survey Area, Massachusetts.

candidate predictors available for each survey respondent's address to include in the final prediction models. The elastic net is a hybrid variable selection technique, based on penalties from both the least absolute shrinkage and selection operator approach (LASSO) and ridge regression variable selection approaches [47]. Variables are selected using the following optimization strategy:

$$\widehat{\beta_0}, \widehat{\beta} = argmin\left\{ \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{n} \beta_j X_{ij} \right)^2 + \lambda \sum_{j=1}^{p} \left[\frac{1}{2}(1-\alpha)\beta_j^2 + \alpha|\beta_j| \right] \right\}$$

where $0 \leq \alpha \leq 1$ is a penalty weight that approaches the LASSO technique as α approaches 1 and a ridge regression as α approaches 0 [47,48].

The elastic net approach has been shown to outperform the LASSO technique by allowing for group selection and improving a model's prediction accuracy in the presence of high correlations between predictors as is the case here since we considered spatial predictors for various nested buffer sizes [47]. For all analyses an alpha level of 0.05 was used to determine statistical significance, and all analyses were conducted using SAS (version 9.5; SAS Institute Inc., Cary, N.C.).

Table 1
A description of all candidate covariates considered for the elastic net selection process.

Categories	Variable
Participant Personal	Survey participant age
	Survey participant gender (female)
	Survey participant ethnicity (non-White minority)
	Survey participant homeownership (own)
	Survey participant household income
	Survey participant years living on current street
	Survey participant noise sensitivity (11-point Likert scale)
Block Group Census	Median age total population (estimate)
	Median household income in the past 12 months (estimate)
	Population per square kilometer
	Percentage non-White minority
	Percentage of occupied housing units occupied by owners
	Unemployment rate
	Median age of housing units
	Median years householder has lived in current housing unit
	Occupied housing units (estimate)
Commercial/ Business	Distance to nearest autobody paint or repair shop**
	Distance to nearest big box store**
	Percentage of commercial landuse*
	Number of autobody shops*
	Number of big box stores*
Entertainment/ Leisure	Distance to nearest entertainment establishment**
	Distance to nearest restaurant**
	Percentage of spectator recreation landuse*
	Percentage of participation recreation landuse*
	Number of entertainment establishments*
	Number of restaurants*
Built Environment	Percentage of residential landuse*
	Percentage of industrial landuse*
	Number of buildings*
	Percentage of area that is impervious surface*
Natural Environment	Percentage of open land landuse*
	Percentage of forest landuse*
	Average NDVI value of pixels*
	Elevation above sea level*
City Services	Distance to nearest fire department**
	Distance to nearest hosptial with an an emergency room**
	Distance to nearest open space**
	Distance to nearest police station**
	Distance to nearest school**
	Percentage of urban public/institutional landuse*
Transportation	Distance to nearest airport**
	Distance to nearest bus stop**
	Distance to nearest above ground, active rail line**
	Distance to nearest road**
	Surface width of nearest road (ft)
	Number of travel lanes of nearest road
	Speed limit of nearest road (mph)
	Structural classification of nearest road: 1 = Good. 2 = Fair. 3 = Deficient. 4 = Intolerable
	Percentage of transportation landuse*
	Cumulative length of bus routes*
	Number of bus stops*
	Cumulative length of rail lines*
	Cumulative length of roads*

*Measured within 25, 50, 100, 150, 200, 250, 300, 500, 1000 buffers (m).
**Measured as distance to nearest (m).

Table 2
Survey participant sociodemographic characteristics (n = 898).

Variable	Category	Number (n)	Percent (%)
Age	<20	1	0.11
	20–29	154	17.15
	30–39	278	30.96
	40–49	180	20.04
	50–59	119	13.25
	60–69	119	13.25
	70–79	22	2.45
	80+	3	0.33
	Unspecified	22	2.45
Gender	Female	530	59.02
	Male	360	40.09
	Unspecified	8	0.89
Household Income	Less than $10,000	13	1.45
	$10,000 to $19,999	9	1.00
	$20,000 to $29,999	22	2.45
	$30,000 to $39,999	28	3.12
	$40,000 to $49,999	44	4.90
	$50,000 to $59,999	48	5.35
	$60,000 to $69,999	50	5.57
	$70,000 to $79,999	64	7.13
	$80,000 to $89,999	65	7.24
	$90,000 to $99,999	49	5.46
	$100,000 to $149,999	214	23.83
	$150,000 or more	216	24.05
	Unspecified	76	8.46
Home Type	Apartment/condo	471	52.45
	Multi-family home	140	15.59
	Single family home	220	24.50
	Town home	39	4.34
	Unspecified	28	3.12
Ownership	Own	557	62.03
	Rent	327	36.41
	Unspecified	14	1.56
Work Type	A homemaker	12	1.34
	A student	26	2.90
	Employed	679	75.61
	Retired	62	6.90
	Self employed	89	9.91
	Unable to work	2	0.22
	Unemployed	10	1.11
	Unspecified	18	2.00
Years Living on Street	<1 year	108	12.03
	1–4 years	299	33.30
	5–9 years	190	21.16
	10 + years	295	32.85
	Unspecified	6	0.67
Education	Associate degree	26	2.90
	Bachelor's degree	321	35.75
	Doctorate	91	10.13
	High school graduate or GED	51	5.68
	Master's degree	318	35.41
	Professional degree	54	6.01
	Some high school, no diploma	1	0.11
	Trade/technical/vocational training	9	1.00
	Unspecified	27	3.01
Ethnicity	Asian or Pacific Islander	16	1.78
	Black or African American	55	6.12
	Hispanic or Latino	23	2.56
	Native American or American Indian	3	0.33
	White	749	83.41
	Other	31	3.45
	Unspecified	24	2.67

3. Results

3.1. Study population

Table 2 details the sociodemographic breakdown of our study population. The majority of our survey respondents were White (83%), women (60%), with a median household income of survey participants from $100,000 to $149,999. Most respondents (54%) live within the city of Boston. Of those that live outside of Boston, the majority (68%) live in Somerville.

3.2. Descriptive statistics

On average, street loudness was rated 5.38 ± 2.5 and neighborhood loudness was rated 5.06 ± 2.75. The average noise sensitivity rating was 6.08 ± 2.34. Fig. 2 shows the distributions of street level noise perception, neighborhood level noise perception, and noise sensitivity by major participant home location. On average, participants living in areas outside Boston report quieter streets ($p < 0.05$) and neighborhoods ($p < 0.001$), while noise sensitivity is about the same both within and outside Boston ($p = 0.22$). Street and neighborhood level noise perception are significantly correlated ($r = 0.58$), whereas noise sensitivity has a more modest correlation with each ($r = 0.16$ and 0.23, respectively), suggesting that noise sensitivity is a stable personal characteristic.

3.3. Elastic-net model results

The regression coefficients and 95% confidence intervals (CI) of each of the predictors included in the final elastic net selected models are presented in Table 3. Statistically significant predictors for both models are included in Fig. 3. Sensitivity to sound is a key predictor of perceived sound in both models, with higher noise sensitivity associated with greater perceived loudness after controlling for proximity to noise sources and other covariates. Count of bus stops also significantly increases perceived loudness of both models (100 m buffer for street and 150 m buffer for neighborhood). Overall, variables in the domains of transportation, participant's personal characteristics, and entertainment/leisure were found to be important predictors of perceived street and neighborhood loudness. Statistically significant predictors for street level loudness perception are participant-declared sensitivity to sound, number of restaurants within 100 m, number of bus stops within 100 m, cumulative length of roads within 25 m, percentage of land use within a 200 m buffer designated for transportation, and distance to nearest road. Statistically significant predictors for neighborhood level noise perception are participant-declared sensitivity to sound, gender, block group median household income, block group total occupied housing units, number of auto body shops within a 500 m buffer, number of big box stores within a 1000 m buffer, percentage land use within 100 m buffer designated for participation recreation, distance to nearest police station, bus stops within a 150 m buffer, width of nearest road, and number of travel lanes of nearest road.

Fig. 3 is a visual representation of significant variables in street and neighborhood sound level models and how they intersect. Both the street and neighborhood noise perception models are significantly influenced by participant noise sensitivity. The variable categories of transportation and of entertainment and leisure also both play a significant role in both models. The majority of the transportation variables in both models are characteristics of nearest road.

4. Discussion

In this study, we applied novel models that identified spatial and sociodemographic predictors of how individuals in the Greater Boston area rated their street and neighborhood noise. To our knowledge, this is the only study that has modeled loudness perceptions in this manner, and our findings provide valuable insights relevant to urban planning and characterization of the soundscape.

4.1. Elastic net-selected loudness predictors

Greater noise sensitivity increased loudness perception for both street and neighborhood noise. There are many studies that have measured what sounds trigger noise annoyance and stress which may act as a proxy for how sounds influence loudness judgments [49]. Out of all the individual determinants, which in the literature has included age [50], personality [51], and beliefs about the sound source [50,52], noise sensitivity has been most influential in predicting sound perception [53,54]. Noise sensitivity has been found to moderate noise annoyance and emotional reaction to noise [55,56] and is an important consideration when attempting to determine which spatial factors influence noise perception. Noise sensitivity has been found to be a better predictor for noise-related health outcomes than sound levels [57,58].

Beyond noise sensitivity, the variable groups featuring significantly in both models are entertainment/leisure and transportation. Closer proximity to and increased numbers of entertainment and leisure facilities within 100 m (restaurants in the street model, and participation recreation in the neighborhood model) and transportation within 200 m (transportation land-use, bus stops, and road length and proximity in the street model, and bus stops, surface width, and travel lanes of nearest road in the neighborhood model) both increase perceived noise. Psychoacoustic research suggests that perceived loudness is influenced by context and predicts activation of non-auditory brain regions better than objective sound levels [59]. This study does not assess soundscape quality variables, but human activity is known to influence "vibrancy" and "eventfulness" soundscape ratings [60].

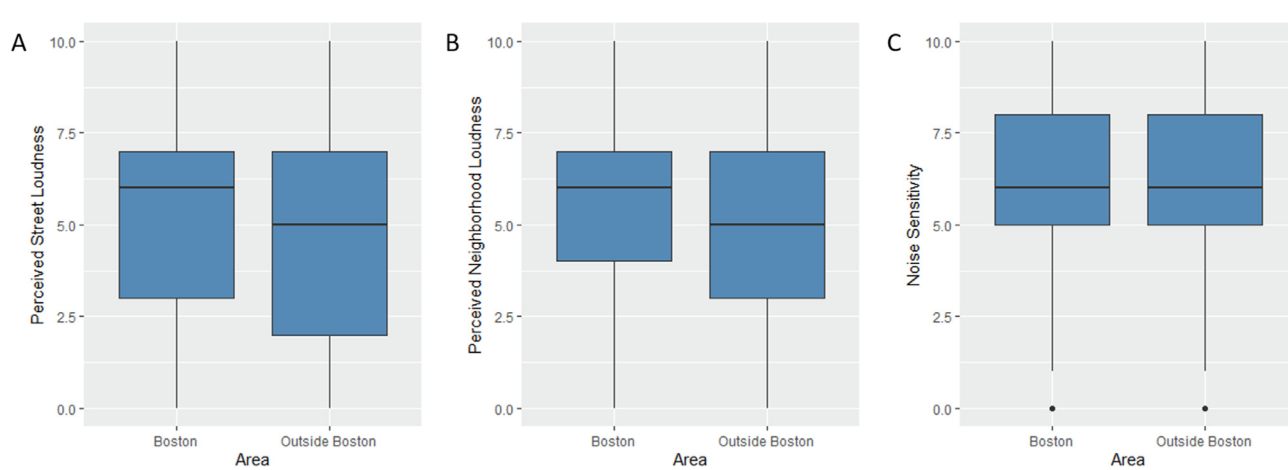

Fig. 2. Boxplots of street loudness (A), neighborhood loudness (B), and noise sensitivity (C) by participant home location. (Center line = median, limits of box = interquartile range (IQR), whiskers = smallest value greater than Q1-1.5 × IQR, largest value less than Q3 + 1.5 × IQR) (n = 898).

Table 3
Street and neighborhood perceived loudness regression models, with variables selected by elastic net (* indicates significance, $p < 0.05$).

Predictor Category	Variable	Measurement Type	Street *R-Square: 0.2018* *Adj R-Sq: 0.1916* Parameter Estimate (95% Confidence Limits)	Neighborhood *R-Square 0.2793* *Adj R-Sq 0.2284* Parameter Estimate (95% Confidence Limits)
	Intercept		4.47 (3.66, 5.28)	4.36 (1.82, 6.9)
Participant Personal	Age			0.009 (−0.007, 0.02)
	Gender (female)			−0.34 (−0.67, −0.02) *
	Home renter or owner (own)			0.16 (−0.25, 0.56)
	Income Group			0.03 (−0.22, 0.27)
	Number of years living on current street			0.14 (−0.06, 0.34)
	Noise sensitivity		0.24 (0.17, 0.31) *	0.29 (0.22, 0.36) *
Block Group Census	Median age			−0.01 (−0.05, 0.02)
	Median household income			−0.00001 (−0.00001, −0.000001) *
	Population per km^2			0.00002 (−0.00001, 0.00005)
	Percent minority			0.005 (−0.004, 0.01)
	Percent unemployed			−0.001 (−0.03, 0.03)
	Median years living in current housing unit			−0.03 (−0.09, 0.03)
	Total occupied housing units			−0.001 (−0.002, −0.0003) *
Commercial/ Business	Auto body shops	Distance to nearest (m)		−0.000051 (−0.000581, 0.00048)
		Buffer 300 (m)		0.04 (−0.07, 0.14)
		Buffer 500 (m)		0.51 (0.17, 0.85) *
	Big box stores	Buffer 1000 (m)		−0.24 (−0.43, −0.06) *
	Commercial landuse	Buffer 150 (m)		0.01 (−0.03, 0.06)
		Buffer 200 (m)		−0.01 (−0.07, 0.04)
Entertainment and Leisure	Restaurants	Buffer 100 (m)	0.09 (0.02, 0.16) *	
		Buffer 150 (m)		−0.03 (−0.14, 0.08)
		Buffer 200 (m)		0.06 (−0.008, 0.14)
		Distance to nearest (m)		−0.0001 (−0.0005, 0.0002)
	Participation recreation	Buffer 100 (m)		0.03 (0.007, 0.06) *
	Spectator recreation	Buffer 500 (m)		0.07 (−0.06, 0.2)
		Buffer 1000 (m)		0.01 (−0.16, 0.18)
	Entertainment establishment	Distance to nearest (m)		0.0003 (−0.00003, 0.0007)
Built Environment	Residential	Buffer 250 (m)		−0.001 (−0.02, 0.01)
		Buffer 1000 (m)		0.001 (−0.02, 0.02)
	Industrial	Buffer 200 (m)		0.009 (−0.02, 0.04)
	Building count	Buffer 500 (m)		−0.0002 (−0.0005, 0.0001)
		Buffer 1000 (m)		0 (−0.000075, 0.000074)
Natural Environment	Wetlands	Buffer 300 (m)		0.1 (−0.03, 0.24)
	Vegetation index	Buffer 25 (m)	−4.07 (−8.96, 0.81)	
		Buffer 300 (m)		−3.29 (−9.46, 2.87)
		Buffer 50 (m)	0.21 (−5.44, 5.85)	
		Buffer 1000 (m)		−11.78 (−33.23, 9.67)
	Open space	Distance to nearest (m)		0.001 (−0.0006, 0.003)
	Elevation	(m)		−0.004 (−0.02, 0.01)
City Services	Fire department	Distance to nearest (m)		−0.0004 (−0.001, 0.0002)
	Hospital	Distance to nearest (m)		0.00006 (−0.0002, 0.0003)
	Police station	Distance to nearest (m)		0.0005 (0.0001, 0.0008) *
	School	Distance to nearest (m)		−0.001 (−0.002, 0.00003)
Transportation	Transportation landuse	Buffer 200 (m)	0.03 (0.01, 0.06) *	
		Buffer 300 (m)		0.03 (−0.006, 0.07)
		Buffer 1000 (m)		0.006 (−0.04, 0.05)
	Bus stops	Buffer 50 (m)	0.27 (−0.13, 0.66)	
		Buffer 100 (m)	0.21 (0.005, 0.42) *	
		Buffer 150 (m)		0.17 (0.02, 0.33) *
		Buffer 200 (m)		0.09 (−0.03, 0.2)
	Cumulative length of roads (m)	Buffer 25 (m)	0.03 (0.01, 0.04) *	
		Buffer 50 (m)	−0.003 (-0.009, 0.004)	
	Cumulative length of rail (m)	Buffer 300 (m)		−0.00006 (−0.0003, 0.0002)
		Buffer 1000 (m)		−0.00002 (−0.00006, 0.00002)
	Airport	Distance to nearest (m)	−0.00006 (−0.0001, 0.00001)	−0.00001 (−0.0002, 0.0002)
	Bus stop	Distance to nearest (m)		0.001 (−0.0002, 0.003)
	Road	Distance to nearest (m)	−0.002 (−0.004, −0.0001) *	−0.0003 (−0.002, 0.002)
	Surface width of nearest road	(ft)		−0.02 (−0.04, −0.003) *
	Number of travel lanes of nearest road			0.38 (0.05, 0.71) *
	Structural classification of nearest road			0.1 (−0.18, 0.39)

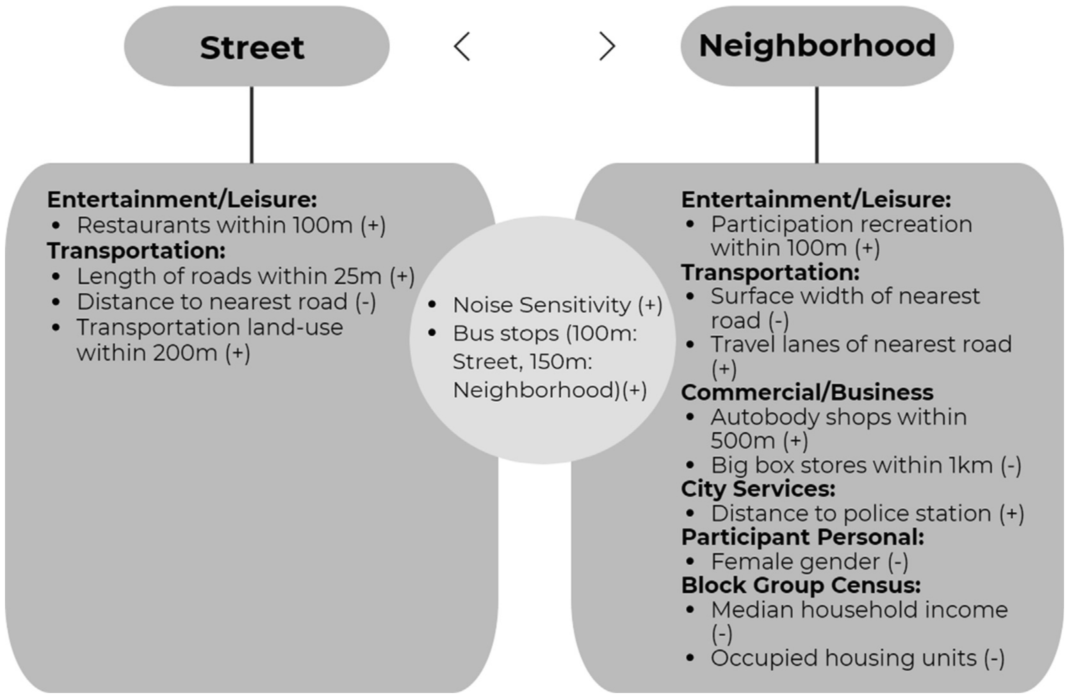

Fig. 3. Significant predictors of street noise and neighborhood perceived loudness. (+means a statistically significant increase in street or neighborhood perception while a – means a statistically significant decrease).

Entertainment and leisure may increase objective sound levels while simultaneously adding quality to the soundscape that could be perceived as positive depending on preference. In contrast, transportation sources have been commonly identified as having a negative impact on soundscape perception and on the objective sound levels of an urban environment [61,62].

In addition, in the neighborhood model, commercial/business, city services, participant personal characteristics, and block group Census characteristics all have some significance. Notably, the perception of neighborhood loudness increases as the number of auto body shops within 500 m increases, as median household income decreases, and as the number of block group occupied housing units decrease. Again, loudness perception is contextual, and these spatial predictors may add objective sound to the environment or may be inappropriate for the desired urban context.

The significant spatial predictors of perceived street noise are on a smaller scale (25–200 m) than predictors of perceived neighborhood noise (100–1000 m). Assuming that the nearest street reflects a smaller area than the neighborhood, this finding suggests that the factors influencing how street and neighborhood are perceived correspond with the street and neighborhood scale.

Some coefficients are in the opposite direction than what was hypothesized. For example, as the surface width of nearest road increases, perception of neighborhood loudness decreases. This finding appears to contradict the simultaneous finding that as travel lanes of nearest road increase, perception of neighborhood loudness increases. Surface width, especially while controlling for travel lanes, may be a proxy for narrow settings or urban canyons between buildings where noise could be amplified. In this study, surface width excludes shoulders and auxiliary lanes and only represents the characteristics of the nearest road, which may be wider in residential areas than in busy urban centers. However, we do understand that attempting to predict sound level from road surface characteristics is complex [63].

Broadly, the evaluation of identified sources is important as soundscapes are determined by urban context. Hong and Jeon [64] found that soundscape quality is related to the urban context (commercial, residential, business and recreational) as the function determines sound sources, activities, visual properties, and appropriateness of different sounds. Axelsson et al. [62] could predict pleasantness of a sound environment with perceived loudness and identification of dominant sound (technological, human, natural). By grouping personal, census, and GIS-spatial predictors in this study into categories, it helps to understand the themes predicting loudness judgements around the Boston area.

4.2. Comparison of perceived loudness and objective loudness

Objective sound and sound perception are expected to diverge due to sound source and individual noise sensitivity. In fact, in a review of the literature, Job et al. [65] found that only about 20% of noise perception can be attributed to objective sound levels. While formally incorporating objective sound levels into our regression models was not possible, we can compare our significant covariates with those in a regression model of sound measurements in a similar study area to derive insights about both similarities and differences.

Walker et al. [43] used land use and temporal predictors to create three models predicting low, mid, and high frequency sound measurements (along with A-weighted sound, which emphasizes the frequency range where the human ear is most sensitive, in order to best relate to how humans perceive loudness [66] taken in 10 min recordings around the city of Boston.

In general, the variable categories of city services and transportation appear in both perception and objective sound models. Distance to nearest police station is a positive predictor for both perceived neighborhood loudness and high frequency sound. Transportation land use is associated with both perceived loudness and objective sound, although with some differential patterns across models. For example, bus stops have a significant positive association with both perceived loudness of streets and neighborhoods and objective sound across all frequencies, whereas surface width of nearest road is a negative predictor of neighborhood perceived noise but a positive predictor of low frequency, high frequency, and A-weighted sound. The significance of transportation characteristics in predicting noise perception and sound levels is supported by numerous other studies. Transportation related predictors included in our models are comparable to those seen in other studies including length of roads and bus lines within buffers, number of bus stops within buffers, distance to road and rail lines [25–28,31,43]. Entertainment and leisure are also found to influence both urban noise perception and high frequency sound levels [43,67].

4.3. Limitations and strengths

This study does have some limitations that should be recognized. First, the relationship between an urban environment and noise perception is determined by a complex mix of various sounds with a range of intensities, durations and dispersions that makes assessment difficult [68]. Not all potential spatial and sociodemographic factors are considered, and we do not consider any temporal factors in our models.

Also, loudness and soundscape quality of an environment may be perceived differently depending on the context and function of a place, but these factors are not considered in our models [69]. This study did not take into account the residential history of participants, which may have an influence on sound expectations and subsequent noise perception ratings.

This study used convenience sampling and may not therefore directly represent the entire population of Greater Boston. The survey was available and accessible to all Boston Area residents, but those with an interest in community health or connection to the project may have been more likely to participate. Participation is also not evenly distributed around the Boston Area, with the greatest number participating from Boston (n = 487), Somerville (n = 272), and Cambridge (n = 68), and an average of 8.6 participants from each of every other participating town. Boston, Somerville, and Cambridge are also some of the most expensive places to live in Massachusetts, and the high average household income of participants in this study reflects this spatial distribution. This study population over-represents a demographic of majority White, highly educated, female, employed, high income earners. Only about 24% of participants have an average household income below the median household income of Boston, MA [44]. The loudness perceptions of this population may not reflect the loudness perception of the Boston Area.

There may also be potential bias in the definition of street and neighborhood. We instructed survey respondents to consider street and neighborhood as drawn by their city. However, participants may have used their own definitions of neighborhood or street that may have differed from these instructions. Current research suggests that definitions of community may differ [70]. Such individualized definitions may influence expectations and perception of surroundings.

We also did not consider indoor noise, which is a significant element of disruptive noise pollution. However, street and neighborhood loudness are more generalizable to the surrounding area, with greater potential for intervention from an urban planning perspective.

Despite these limitations, there are considerable strengths. We have detailed a unique method for understanding a critical soundscape indicator and community noise perception in relation to spatial and sociodemographic attributes. This provides insight on predictors of noise perception and facilitates comparison with determinants of objective sound in the same area. This comparison gives key insight into the relationships between sound sources and the perception of sound that those sources contribute to. To our knowledge, this is the first study to build spatial-temporal statistical models for loudness in an urban environment in North America and the first to use the elastic net approach to do so. This paper shows that the elastic net model selection method is helpful in distinguishing determinants of both perceived loudness and objective sound levels and the intersection of these determinants reveals what could potentially be the most problematic sound sources in the community.

5. Conclusions

Soundscape research helps to understand how people living in urban environments are affected by sound- physically, psychologically, and socially. Perception of an urban environment is the indirect link between sound pressure levels and stress responses and contributes to detrimental urban health effects. This research used sociodemographic and spatial characteristics to create a predictive model for perceived street and neighborhood loudness. Notably, noise sensitivity and variables describing greater transportation and entertainment activity significantly increase perceived loudness of Boston Area streets and neighborhoods. Perceived loudness and measured sound levels make up much of what creates an observable soundscape that may influence area desirability and health.

As urban areas continue to develop, sound reduction is necessary to create healthy acoustical environments. However, reducing sound without considering perceived noise will fail to address all the elements that make a city livable and safe. This study shows that perceived loudness is influenced by spatial and sociodemographic characteristics and that many are comparable to those that predict sound levels. The selected variables in these loudness perception models and those determinants which overlap with selected variables in similar objective sound models provide an indication of what aspects of urban streets and neighborhoods have the greatest impact on the soundscape. The use of publicly available GIS and census data as spatial and sociodemographic predictors in this study means that urban planners can easily and inexpensively predict which urban locations are at risk of loudness and associated health risks. These selected predictors can also improve existing soundscape models for a more comprehensive understanding of how we perceive our environment. By creating more systematic approaches for assessing all elements of the soundscape, application in urban planning and improvement becomes more achievable and public health can be improved.

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CRediT authorship contribution statement

Nina F. Lee: Writing – original draft, Methodology, Formal analysis, Data curation, Visualization. **Jonathan I. Levy:** Writing – review & editing. **Marcos Luna:** Resources, Data curation. **Erica D. Walker:** Conceptualization, Investigation, Methodology, Data curation, Supervision, Writing – review & editing, Project administration, Funding acquisition.

Declaration of Competing Interest

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