Environmental Research 159 (2017) 491–499

Contents lists available at ScienceDirect

Environmental Research

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

Spatial and temporal determinants of A-weighted and frequency specific sound levels—An elastic net approach

Erica D. Walker[a,*], Jaime E. Hart[a,b], Petros Koutrakis[a], Jennifer M. Cavallari[a,c], Trang VoPham[b,e], Marcos Luna[d], Francine Laden[a,b,e]

[a] Department of Environmental Health, Harvard T.H. Chan School of Public Health, Boston, MA, United States
[b] Channing Division of Network Medicine, Department of Medicine, Brigham and Women's Hospital and Harvard Medical School, Boston, MA, United States
[c] Department of Community Medicine and Health Care, UConn Health, Farmington, CT, United States
[d] Department of Geography, Salem State University, Salem, MA, United States
[e] Department of Epidemiology, Harvard T.H. Chan School of Public Health, Boston, MA, United States

ABSTRACT

Background: Urban sound levels are a ubiquitous environmental stressor and have been shown to be associated with a wide variety of health outcomes. While much is known about the predictors of A-weighted sound pressure levels in the urban environment, far less is known about other frequencies.

Objective: To develop a series of spatial-temporal sound models to predict A-weighted sound pressure levels, low, mid, and high frequency sound for Boston, Massachusetts.

Methods: Short-term sound levels were gathered at n = 400 sites from February 2015 – February 2016. Spatial and meteorological attributes at or near the sound monitoring site were obtained using publicly available data and a portable weather station. An elastic net variable selection technique was used to select predictors of A-weighted, low, mid, and high frequency sound.

Results: The final models for low, mid, high, and A-weighted sound levels explained 59 – 69% of the variability in each measure. Similar to other A-weighted models, our sound models included transportation related variables such as length of roads and bus lines in the surrounding area; distance to road and rail lines; traffic volume, vehicle mix, residential and commercial land use. However, frequency specific models highlighted additional predictors not included in the A-weighted model including temperature, vegetation, impervious surfaces, vehicle mix, and density of entertainment establishments and restaurants.

Conclusions: Building spatial temporal models to characterize sound levels across the frequency spectrum using an elastic net approach can be a promising tool for noise exposure assessments within the urban soundscape. Models of sound's character may give us additional important sound exposure metrics to be utilized in epidemiological studies.

1. Introduction

Urban environments worldwide play host to a wide variety of sounds and for many urban dwellers, the environmental soundscape has traditionally been viewed as the sacrifice they must accept in exchange for the convenience associated with living in close proximity to urban activities (Anthrop, 1970). In recent years, however, epidemiological studies have begun to shed light on the extent this sacrifice may have on human health. Exposure to urban environmental noise has been shown to be associated with a wide range of stress and cardiovascular related responses, such as elevated cortisol (Selander et al., 2009); blood pressure (Haralabidis et al., 2008); hypertension (Bluhm et al., 2007; Bodin et al., 2009; Babisch et al., 2005); myocardial infarction (Babisch et al., 2005; Selander et al., 2009); antihypertensive, anxiolytic, and antacid medication use (Floud et al., 2011); cardiovascular related hospital admissions (Hansell et al., 2013; Correia et al., 2013), and mortality (Hansell et al., 2013).

In these epidemiological studies, primarily based in Europe, sound exposure has traditionally been focused on sounds emanating from transportation sources such as road, rail, and aircraft traffic. Sound exposure levels have typically been ascertained using sound maps derived from sophisticated prediction models developed by municipal authorities or federal agencies. As data inputs needed for sound models becomes more freely available many researchers are utilizing less

* Correspondence to: Department of Environmental Health, Harvard T.H. Chan School of Public Health, 1870 Beacon Street, Apt. B1, Brookline, MA 02445, Unites States.
E-mail address: edw266@mail.harvard.edu (E.D. Walker).

http://dx.doi.org/10.1016/j.envres.2017.08.034
Received 2 July 2017; Received in revised form 15 August 2017; Accepted 17 August 2017
Available online 18 September 2017
0013-9351/

computationally and financially costly—yet powerful—methods to construct models to predict sound levels. (Gulliver et al., 2015; Torija and Ruiz, 2015; Aguilera et al., 2015; Goudreau et al., 2014; Zuo et al., 2014; Xie et al., 2011; Seto et al., 2007). Such methods show promise as they tend to correlate strongly with gold-standard propagation models, allow for variable inputs unique to a given geographical area, allow for consideration of community noise overall and not just sounds from transportation sources, and can be built to match as closely as possible to models of common confounders such as air pollution.

The typical sound exposures modeled are metrics focused on a sound's loudness, typically the A-weighted decibel (dB(A)). The A-weighting system emphasizes the frequency range where the human ear is most sensitive, while discounting both higher and lower frequencies (Alves-Pereira and Castelo Branco, 2007). However, a sound's frequency is the second component necessary to fully characterize sound. Existing epidemiological and occupational research suggests that in addition to a sound's loudness, its frequency profile is also an important characteristic to consider when assessing the relationship between noise and health outcomes (Persson Waye et al., 2003; Kumar et al., 2008; Chang et al., 2014; Walker et al., 2016).

The goal of our study was to develop spatial-temporal models across the sound spectrum for the City of Boston that may be potentially used in future epidemiologic studies. Specifically, our goal was to collect representative measurements of low, mid, and high frequency noise and A-weighted sound throughout Boston; build models to predict low frequency, mid frequency, and high frequency sound and A-weighted sound throughout the city; and compare each of the frequency-specific models to the models for the commonly used A-weighted sound.

2. Materials and methods

2.1. Study area and sampling strategy

We conducted a sound monitoring campaign between February 2015 and February 2016 throughout the city of Boston, MA. Boston occupies an area of 124 square kilometers with an estimated population of close to 700,000 individuals, making it the largest city in New England and the 23rd most populated city in the United States (United States Census Bureau, 2010). To identify potential monitoring sites, we divided the City of Boston into 500 × 500 m grid cells using ArcGIS (Redlands, CA, USA). Sites inaccessible for monitoring—e.g. sites located in the middle of a body of water or a road—were discarded. Once a list of all accessible potential sites was constructed (n = 525), 400 site locations (Fig. 1) were randomly selected for monitoring by time of day (day: 7 a.m. – 7 p.m.; rush hour (7 a.m. - to 9 a.m. and 4 p.m. to 7 p.m.) night: 7 p.m. −7 a.m.), day of week (weekday: Monday – Friday; weekend: Saturday and Sunday), and season fall (September – November), winter (December – February), spring (March – May) and summer (June – August). Convenience sampling was also conducted in certain areas of the city to ensure adequate coverage of varied land use and urban activity.

2.2. Sound level collection

Each sampling location was visited once and ten-minutes of measurements were collected at each location. Sound data were collected using the Cirrus Optimus Red Octave Band Analyzer CR-162C (North Yorkshire, UK), at each of the center frequencies of octave bands (31.5, 63, 125, 250, 500, 1000, 4000, 8000, and 16,000 Hz). The microphone of the CR-162C was mounted on a camera tripod such that the microphone was at a height of 1.5 m and oriented perpendicular to the nearest road. The CR-162C was calibrated before and immediately after each monitoring session. Calibrations were performed at 90 dB(A) at a frequency of 1 kHz using a Cirrus Optimus acoustic calibrator CR-514 (North Yorkshire, UK). A windscreen was used regardless of weather conditions. The geographic location of each sampling site was confirmed using a Garmin GPSMAP 60Cx global positioning system (GPS). Onsite data collection consisted of capturing meteorological conditions (temperature, wind speed, relative humidity, dew point temperature) using a Kestrel 3500 Weather Meter/Digital Psychrometer (Birmingham, MI, USA). Counts of road traffic and aircraft traffic and sound emanating from episodic events, such as barking dogs or ambulance sirens, were also collected in real time.

Spatial attributes at or near the sound monitoring site were obtained using publicly available data from the Commonwealth of Massachusetts Office of Geographic Information (MassGIS). 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 roadways, bus, train routes, hospital with emergency center, fire station, police station, and distance to the international airport (Logan International Airport), were also calculated. Road conditions including structural conditions, traffic counts, surface width, and elevation were obtained for the road closest to each sound monitoring site. Neighborhood socioeconomic factors such as mean age, population density, household income, racial composition, percentage of owner occupied units, educational attainment, marital status, unemployment, age of housing units, average tenure, and number of households with children under 18 were obtained for the Census tract where each sound monitoring site was located.

2.3. Noise measurements

The CR-162C logged data in 1s increments across the center frequencies ranging from 31.5 to 16,000 Hz resulting in 600 data points for each monitoring session. For each 1s, unweighted (decibel, dB) sound contributions from low frequency (31.5, 63, 125 Hz), mid frequency (250, 500, 1000 Hz), and high frequency (4000, 8000, and 16,000 Hz) sound was calculated by summing the appropriate center frequency decibels using the following equation given by Bell and Bell (1993):

$$L = 10log\left(\sum_{i=1}^{n} 10^{\frac{L_{p,i}}{10}}\right)\text{dB}$$

Where L is the sound pressure level (in dB), n is the time period, which, in our case is 10-min, and $L_{p,i}$ is the ith center frequency sound power level. This formula was also used to calculate the A-weighted decibel level for each 1 s interval by summing across each octave band center frequency from 31.5 to 16,000 Hz, after subtracting standard A-weighted penalties for each center frequency before summing (Bell and Bell, 1993).

Average levels for low, mid, and high frequency and A-weighted sound over the course of the 10-min monitoring session ($L_{eq,10}$) were calculated using the following formula:

$$L_{eq,10} = \frac{10log}{n}\left(\sum_{i=1}^{n} 10^{\frac{L_i}{10}}\right)\text{dB, dB(A)}$$

Where n is the 600 1 s time samples in the 10-min period and L_i is the 1 s level determined for each frequency region or for the A-weighted sound level.

2.4. Spatial-temporal modeling approach

Separate linear regression models were developed to predict low frequency, mid frequency, high frequency, and A-weighted sound. An elastic net was used to determine which of the 239 spatial, temporal, and meteorological potential predictors available for each site to include in the final prediction models. The elastic net is a hybrid variable selection technique, based on penalties from both the least absolute

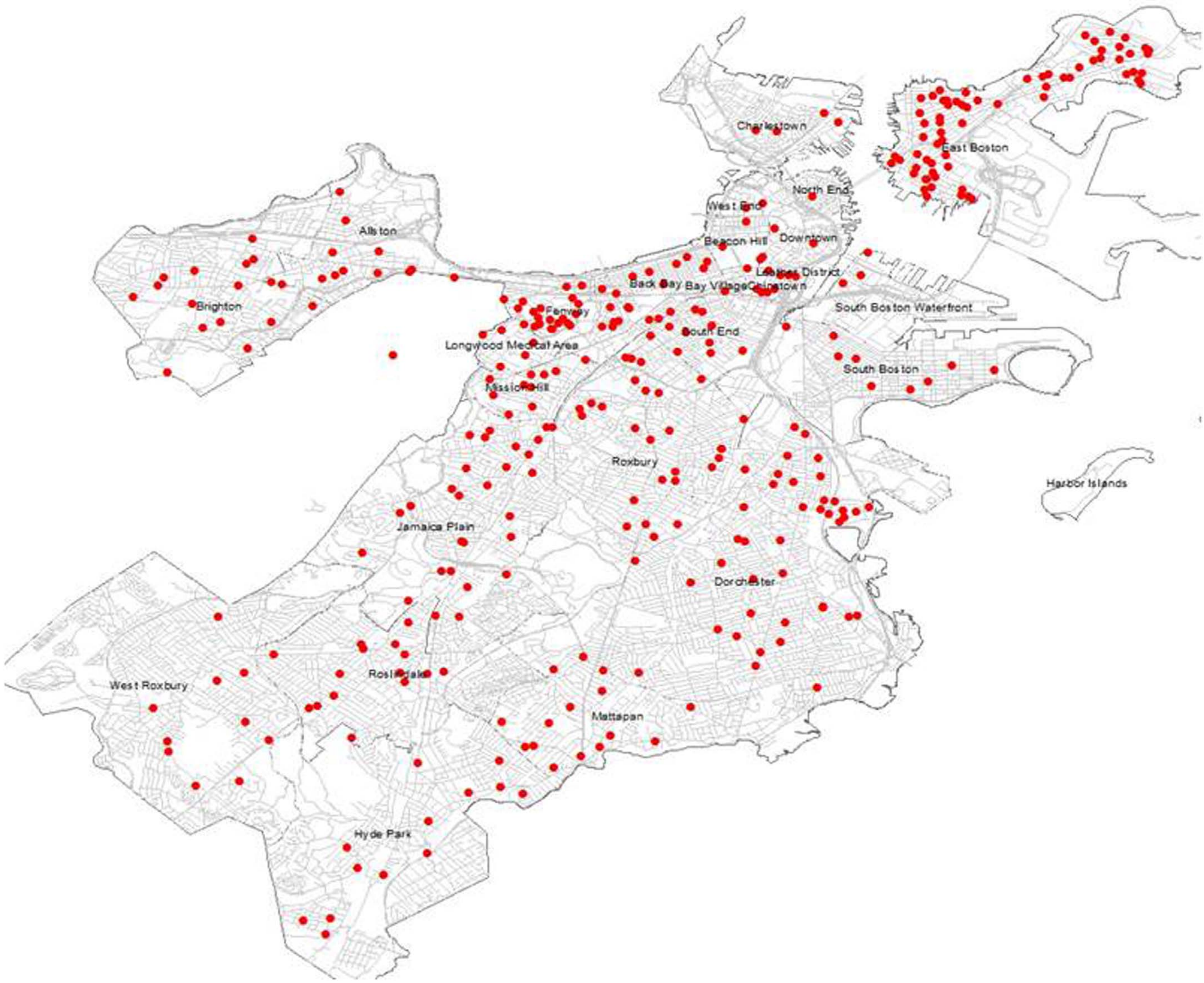

Fig. 1. Sound monitoring locations (n = 400) within the City of Boston.

shrinkage and selection operator approach (LASSO) and ridge regression variable selection approaches (Zou and Hastie, 2005). Variables are selected using the following optimization strategy:

$$\hat{\beta}_0, \hat{\beta} = argmin\left\{\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{n}\beta_j X_{ij}\right)^2 + \lambda\sum_{j=1}^{p}\left[\frac{1}{2}(1-\alpha)\beta_j^2 + \alpha\mid\beta_j\mid\right]\right\}$$

where $0 \leq \alpha \leq 1$ is a penalty weight that approaches the LASSO technique as α approaches 1 and a ridge regression when α approaches 0 (Zou and Hastie, 2005; Waldmann et al., 2013).

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 (Zou and Hastie, 2005). This variable selection technique has been used previously in genomics research but has, to our knowledge, never been used in spatial-temporal sound models (Sokolov et al., 2016; Hughey et al., 2015). To make the effect estimates comparable, each of the continuous potential predictor variables was scaled by its interquartile range (IQR). For all analyses an alpha level of 0.05 was used to determine statistical significance, and all analyses were conducted using SAS (version 9.4; SAS Institute Inc., Cary, N.C.).

2.5. Model fit and cross-validation

R^2 was used to assess the percentage of each sound metric level explained by its final prediction model. To determine the predicative accuracy of our final models, we performed cross-validation. The dataset of all sound measures and potential predictors was divided into training (90%) and validation (10%) sets. We built each of the regression models in the training dataset and then used the regression parameters from our final model to predict low frequency, mid frequency, high frequency, and A-weighted sound at the locations in the validation dataset. To assess the bias of our final models, we examined the correlation between the predicted and actual sound metric values, examined the intercepts and slopes from linear regressions of the predicted values on the measured values, and calculated the mean absolute percentage error (MAPE) (Gattorna, 1998).

$$MAPE = \frac{\sum|Predicted - Actual|}{\sum Actual}$$

Table 1
Overall descriptive statistics for sound levels in Boston, Massachusetts (Mean (SD), Median (IQR), 10th and 90th values and Spearman correlations for low frequency (25–125 Hz), mid frequency (250–1000 Hz), high frequency (2000–16,000 Hz), and A-weighted sound (n = 400 monitoring sites).

Sound Level	Mean (SD)	P50 (IQR)	P10	P90
Low Frequency (dB)	70.7 (6.8)	70.5 (10.1)	61.6	79.3
Mid Frequency (dB)	62.4 (7.6)	62.5 (11.7)	53.1	71.6
High Frequency (dB)	53.0 (8.6)	52.8 (13.7)	42.1	63.1
A-weighted (dB(A))	60.7 (7.9)	60.5 (12.6)	51.1	70.2

3. Results

Summary statistics for sound levels are found in Table 1. Overall, the highest sound levels were observed in the low frequency range, while the lowest levels were observed in the high frequency range. Although correlations were high (r = 0.82–0.98) between all the metrics, the A-weighted sound level was most highly correlated with the mid frequency range and least with the low frequency range (Table 2).

Of the 239 potential predictors considered, a total of 58 were included in at least one final prediction model. Descriptive statistics of these variables are presented as supplementary tables.

The regression coefficients and 95% confidence intervals (95%CI) for an IQR increase in each of the predictors included in the final elastic net selected models are presented in Table 3.

Commercial land use within the 25- and 150-m buffers, residential land use within a 150-buffer, traffic counts, counts of heavy vehicles, surface width of nearest road, distance to nearest road, seasonality (fall), daytime, and weekday were included in all the final elastic-net selected sound models. For land use, percentages within the 150 m buffers seemed to have the strongest influence on decibel levels. Within this buffer size, commercial land use was associated with the largest decibel increases with high frequency sound levels while residential land was associated with the largest decibel decreases with high frequency sound (β = −1.6; 95% CI: −2.4, −0.74). Across all models, traffic counts statistically significantly increased decibel levels—most notably with high frequency sound (β = 5.5; 95% CI: 4.0, 7.0). Vehicle mix—in particular, counts of heavy vehicles—was most strongly associated with low frequency sound. Characteristics of the nearest road found to be an important positive contributor to sound levels was the surface width of the nearest road. As the distance to nearest road increased, decibel levels for all sound models decreased, with the largest decreases observed with sound in the mid frequency range (β = −1.2; 95% CI: −2.0, −0.35). Temporally, the fall season was associated with statistically significantly decreased sound decibel levels as compared to the other seasons. Daytime sound measurements most prominently increased high frequency sound (β = 3.2; 95% CI: 2.1, 4.4) while with weekend sound measurements, the highest increases were observed with low frequency sound (β = 1.9; 95% CI: 0.86, 3.0).

Table 2
Spearman correlations between low frequency (25–125 Hz), mid frequency (250–1000 Hz), high frequency (2000–16,000 Hz), and A-weighted sound (n = 400 monitoring sites).

	Low Frequency Sound (dB)	Mid Frequency Sound (dB)	High Frequency sound (dB)	A-weighted Sound (dB(A))
Low Frequency Sound (dB)	1.0	0.86*	0.82*	0.84*
Mid Frequency Sound (dB)		1.0	0.93*	0.98*
High Frequency sound (dB)			1.0	0.97*
A-weighted Sound (dBA)				1.0

* Indicates p-value < 0.0001.

For variables not intersecting all sound models, regarding land use, increasing transportation land use within 100 m was associated with statistically significant increases in low, high, and A-weighted sound levels, with the largest increases observed with high frequency sound (β = 0.28; 95% CI: 0.15, 0.41). However, in larger buffers, these effects were mitigated, again most notably with high frequency sound. The presence of forest land use within 100 m of the monitoring site increased both high frequency and A-weighted sound levels in roughly the same fashion. While the elastic net found industrial, residential, recreational, and open land use to be important predictors for both A-weighted sound and sound across the frequency spectrum, none of these predictors had a statistically significant impact.

Lengths of bus routes, rail lines, and roads were included in final elastic net models. However, only the length of rail and road lines had statistically significant effects on sound levels—and most prominently, with high frequency sound. The length of rail lines within 1000 m was associated with an increase in high frequency sound (β = 0.89; 95% CI: 0.03, 1.8). While length of major roads within a 50 m buffer and all local roads within a 1000 m buffer both had similar impacts on increasing high frequency sound, it was the local roads that were statistically significant (β = 1.7; 95% CI: 0.54, 2.8).

Counts of buildings, bus stops, big box stores, restaurants, and entertainment establishments within radial buffers were found to be important sound level predictors. Only counts of bus stops within a 100-m buffer and counts of entertainment establishments within a 500 m buffer were statistically significant. Counts of bus stops were associated with nearly identical increases in decibel levels for mid frequency, high frequency, and A-weighted sound, with the highest effects observed with high frequency sound (β = 1.9; 95% CI: 0.72, 3.1). Counts of entertainment establishments were found to uniquely increase high frequency sound (β = 0.31; 95% CI: 0.004, 0.61).

Distances to nearest road, open space area, fire station, police station, and rail line were selected into the sound models as important contributors to sound levels. Low frequency sound was uniquely found to decrease as distance to nearest open space area increased (β = −0.76; 95% CI: −1.3, −0.18). Distance to nearest police station uniquely influenced high frequency sound (β = 1.0; 95% CI: 0.12, 2.0). As distance to nearest rail line increased was shown to decrease mid, high, and A-weighted sound levels with the largest decreases seen with mid frequency sound (β = −0.87; 95% CI: −1.5, −0.20).

Temperature was the only meteorological variable found to be an important predictor of increases in low and mid frequency sound and only in the smallest buffers (50 and 100 m). Temperature was found to most notably increase low frequency sound (β = 0.55; 95% CI: 0.14, 0.95). Vegetation and impervious surfaces were also selected as important predictors of sound levels. The largest impacts of vegetation on sound levels were observed with low frequency sound within a 25 m buffer (β = −1.1; 95% CI: −0.27). This association decreased with larger buffers with mid-frequency sound only and this effect did not remain statistically significant. For impervious surfaces, only high frequency sound increased but this effect was not statistically significant.

Model cross validation results are shown in Table 4. The proportion of variance explained by the predictors included in the model was largest for the high frequency model (R^2 = 0.69) and lowest for the mid frequency model (R^2 = 0.59). The correlations between the actual and predicted values were strong for all models (r ≥ 0.85). The intercept and slope for the regressions between actual and predicted values suggest that the models tended to predict well as the slope values were all close to 1. The MAPE values suggest that on average, all model

Table 3
Spatial –temporal models (ß, 95% CI) for predicting Low Frequency (25–125 Hz), Mid Frequency (250–1000 Hz), High Frequency (2000–16,000 Hz), and A-weighted Sound (n = 400 monitoring sites).

Determinants	Low Frequency Sound (dB)	Mid Frequency Sound (dB)	High Frequency sound (dB)	A-weighted Sound (dB(A))
Land Use				
Commercial buffers				
25 m	0.19 (−0.24, 0.61)	0.27 (−0.23, 0.76)	0.007 (−0.53, 0.55)	0.21 (−0.29. 0.730)
100 m		0.13 (0.06, 0.20)		
150 m	0.04 (−0.93, 1.00)	−0.32 (−1.40, 0.80)	2.40 (−1.10, 5.90)	1.40 (−1.70, 4.60)
200 m			−2.08 (−6.40, 0.76)	−1.30 (−4.40, 1.80)
Industrial 500 m buffer	0.28 (−0.18, 0.73)			
Transportation buffers				
50 m			−0.07 (−0.20, 0.05)	−0.09 (−0.20, 0.03)
100 m	0.06 (0.007, 0.12)		0.28 (0.15, 0.41)	0.24 (0.12, 0.37)
1000 m		−1.10 (−1.90, −0.48)	−1.6 (−2.4, −0.74)	−1.20 (−1.90, −0.40)
Residential buffers				
100 m	−0.92 (−4.80, 2.90)			
150 m	1.40 (−3.80, 6.50)	−1.30 (−2.90, 0.36)	2.30 (−2.60, 7.30)	−0.14 (−1.80, 1.50)
200 m			−2.70 (−7.03, 1.90)	
250 m	−0.45 (−2.70, 1.80)			
Recreational buffers				
100 m			0.02 (−0.05, 0.09)	
1000 m			0.37 (−0.33, 1.10)	
Open Land buffers				
25 m	−0.06 (−0.17.0.05)			
50 m			−0.04 (−0.22, 0.14)	0.02 (−0.11, 0.15)
200 m			0.34 (−0.26, 0.94)	
250 m			−0.36 (−0.97, 0.25)	
300 m	−0.02 (−0.14, 0.10)			
Forest 100 m buffer			0.09 (0.02, 0.16)	0.07 (0.01, 0.13)
Lengths				
Bus Routes buffers				
50 m	0.33 (−0.09, 0.75)			
250 m		0.30 (−0.44, 1.0)	−0.68 (−3.10, 1.70)	−0.81 (−3.10, 1.50)
300 m	0.63 (−0.01, 1.40)		1.20 (−1.40, 3.80)	1.10 (−1.40, 3.60)
500 m			−0.37 (−2.01, 1.03)	
Rail Lines buffers				
500 m	0.53 (−0.04, 1.10)		0.14 (−0.83, 1.10)	
1000 m			0.89 (0.03, 1.8)	
All Roads buffers				
25 m	−0.005 (−1.30, 1.30)			
50 m	0.42 (−0.79, 1.60)		0.002 (−1.70, 1.70)	1.00 (−0.51, 2.50)
Major Roads 50 m buffer		1.00 (−0.19, 2.30)	1.60 (−0.25. 3.50)	
Class 3 Roads 25 m buffer			0.08 (−0.005, 0.18)	
Class 5 Roads 1000 m buffer			1.70 (0.54, 2.80)	
Counts with Buffers				
Buildings				

(continued on next page)

Table 3 *(continued)*

Determinants	Low Frequency Sound (dB)	Mid Frequency Sound (dB)	High Frequency sound (dB)	A-weighted Sound (dB(A))
50 m	−0.91 (−2.60, 0.83)			
100 m	−0.46 (−2.40, 1.05)	−0.79 (−2.10, 0.50)		
150 m				−1.30 (−2.70, 0.04)
Bus Stops				
25 m				0.80 (−0.16, 1.80)
100 m		1.60 (0.18, 3.00)	1.90 (0.72, 3.10)	1.60 (0.42, 2.80)
150 m	1.00 (0.09, 2.00)	0.06 (−1.40, 1.50)		
Big Box Stores 300 m			1.20 (−0.22, 2.50)	
Entertainment Establishments 500 m			0.31 (0.004, 0.61)	
Restaurants 100 m	0.05 (−0.06, 0.16)			
Distances(in meters)				
Nearest Road	−0.64 (−1.30, 0.07)	−1.20 (−2.00, −0.35)	−0.72 (−1.60, 0.17)	−1.10 (−1.90, −0.29)
Nearest Open Space Area	−0.76 (−1.30, −0.18)			
Nearest Fire Station	−0.07 (−0.75, 0.61)	−0.23 (−1.00, 0.57)		
Nearest Police Station			1.00 (0.12, 2.00)	
Nearest Rail Line		−0.87 (−1.50, −0.20)	0.03 (−0.75, 0.82)	−0.69 (−1.40, −0.01)
Nearest Road Conditions				
Surface Width	0.93 (0.21, 1.60)	0.79 (−0.05, 1.60)	1.40 (0.53, 2.30)	1.00 (0.15, 1.90)
Terrain			−0.37 (−2.70, 1.90)	−0.96 (−3.20, 1.30)
Traffic Counts	3.10 (1.90, 4.20)	3.80 (2.40, 5.20)	5.50 (4.00, 7.00)	4.20 (2.80, 5.50)
Heavy Vehicle Counts	0.75 (0.06, 1.40)	0.69 (−0.15, 1.50)	0.39 (−0.47, 1.30)	0.55 (−0.26, 1.40)
Season				
Fall	−1.50 (−2.50, −0.55)	−1.50 (−2.70, −0.40)	−1.70 (−3.00, −0.49)	−2.10 (−3.30, −1.00)
Meteorological Conditions				
Temperature	0.55 (0.14, 0.95)	0.46 (−0.02, 0.93)		
Vegetation and Impervious Surfaces				
Vegetation Index (25 m)	−1.10 (−1.80, −0.27)			
Vegetation Index (50 m)			−0.55 (−1.70, 0.62)	
Impervious Surfaces (50 m)			0.49 (−1.00, 2.00)	
Temporality				
Day	2.30 (1.40, 3.20)	1.60 (0.51, 2.70)	3.20 (2.10, 4.40)	1.90 (0.84, 3.00)
Rush Hour			−1.40 (−3.20, 0.31)	
Weekday	1.90 (0.86, 3.00)	0.25 (−1.00, 1.50)	0.60 (−0.72, 1.90)	0.009 (−1.30, 1.30)

Table 4
Cross validation values for spatial-temporal models of low, mid, high, and A-weighted sound.

Sound Model	Elastic Net Model R^2	Correlation between actual and predicted	Intercept	Slope	MAPE*
Low Frequency	0.63	0.85	2.2	0.95	4.25
Mid Frequency	0.59	0.88	−8.9	1.1	6.50
High Frequency	0.69	0.85	2.7	0.98	9.25
A-weighted	0.64	0.86	−3.6	1.0	7.00

* Mean absolute percent error.

predictions were within approximately 9% of the measured values, with the highest accuracy in the low frequency model.

4. Discussion

We measured short-duration sound levels at 400 sites across the city of Boston and obtained, for each site, levels of low frequency, mid frequency, high frequency, and A-weighted sound. For each site, we also collected 239 potential predictors from which we built prediction models. The categories of predictors considered included spatial, temporal, and meteorological characteristics at each site directly and within buffer sizes ranging from 25 to 1000 m around each site. We used an elastic net variable selection approach to build individual statistical prediction models of the different sound metrics, across the city of Boston. These models showed strong predictive ability and accuracy.

Our A-weighted model was similar to A-weighted spatial temporal models previously constructed for other cities. Like other A-weighted models, our elastic net selected model included transportation related predictors such as length of roads and bus lines within buffers; distance to road and rail lines; traffic volume, and vehicle mix (Aguilera et al., 2015; Goudreau et al., 2014; Zuo et al., 2014; Xie et al., 2011; Seto et al., 2007). Also similar to other models, land use—in particular residential, commercial, and industrial land use percentages within buffers, were also important predictors of A-weighted sound levels (Goudreau et al., 2014; Zuo et al., 2014; Xie et al., 2011).

Unlike previous models (Aguilera et al., 2015; Goudreau et al., 2014; Zuo et al., 2014; Xie et al., 2011; Seto et al., 2007), we considered predictors not—to our knowledge—previously examined. For land use, these included: open land use—defined as vacant land, idle agriculture, rock outcrops, and barren areas; recreational land use—defined as, ball fields, tennis courts, basketball courts, athletic tracks, ski areas, playgrounds, bike paths, swimming pools, and water parks; and forest land use. We were also able to consider the effect of spatial and meteorological variables not previously examined such as: temperature, wind speed, relative humidity, dew point temperature; distance to hospital with emergency centers, police stations, and fire stations; distance (and counts) to a finer classification of commercial land use specifically enumerating numbers of restaurants, big box stores, and entertainment establishments; impervious surfaces; and neighborhood demographics including age of residents, ethnicity, ownership status, age of housing stop, average tenure, education, and marital status. Of these variables, however, only transportation and forest land use were shown to be important statistically significant factors positively influencing A-weighted sound levels.

Also unlike previous studies, we were able to build spatial-temporal predictive models for low, mid, and high frequency sound. While most of these new variables did not predict levels of A-weighted sound, some of them were included in the elastic net frequency-specific models. Transportation land use was found to be a statistically significant predictor of both mid and high frequency sound. Industrial land use was found to uniquely influence low frequency sound. The effect estimate for temperature was strongest for low frequency sound. While not statistically significant, the percentage of impervious surfaces was positively associated with high frequency sound. Counts of restaurants within 100 m was associated with increases in low frequency sound, as was the presence of big box stores and entertainment establishments for high frequency sound. These findings support the potential importance of more finely defining commercial land use.

Comparing the modeled sound levels across the frequency spectrum to the typically modeled A-weighted sound provides us additional insight into how spatial, temporal, and meteorological variables influence not only sound levels, but contributions to that level by frequency. We observed, via our models that high frequency sound is the most sensitive frequency range to spatial and temporal predictors. Goudreau et al. (2014) in Montreal, Canada and Xie et al. (2011) in Northwest, China both saw a decrease in A-weighted sound levels in the presences of increased vegetation, which was defined using the normalized difference vegetation index (NDVI) or buffer percentages of green space. In our models, vegetation was only associated with decreases in low-frequency sound. Such a finding suggests that green space may be a useful planning tool in communities inundated with low frequency sound sources. The closest vegetation-related land use variable found to be an important contributor to A-weighted sound was the percentage of forest land use, which was found to increase A-weighted sound. Given the makeup of the city of Boston, this result is unsurprising as forest land use is also usually near rail lines.

While we are not able to compare our low, mid, and high frequency sound models with other studies due to a paucity of previous research, Ross et al. (2011) did look at the impact of traffic on sound levels across the frequency spectrum at a single high traffic location in New York City. The influence of traffic volume with high frequency sound was observed in both of our studies. More recently, the evaluation of low frequency sound from road traffic was carried out in Pisa, Italy (Ascari et al., 2015). A-weighted levels, C-weighted levels, LC-A (C-weighted levels minus A-weighted levels) and spectra were calculated using 4 prediction methods, compared, and validated against on-site simple sound measurements. While the primary aim was to compare the prediction models, comparing average levels in their study to ours, our average A-weighted sound levels tended to be lower (60.7 dB(A) vs 72.9–23.4 dB(A) for modeled and measured levels, respectively). A comparison of sound levels across the frequency spectrum in our study and this study could be ascertained only visually and suggest that our levels were, for the most part, consistent with theirs.

Some coefficients are in the opposite direction than what was originally expected. For example, as the distance from both nearest police station and rail line increased so did high frequency sound. Also, high frequency sound was found to be lower during rush hour. In the case of distance to nearest police station, a monitoring site, on average, was about 1100 m away (Supplemental Table S2). It could be argued that while distance to nearest police station is an important variable—as indicated by its inclusion in the elastic net selected high frequency sound model—it appears to be confounded by an unmeasured variable. For nearest rail line, as the distance from nearest rail line decreases mid-frequency sound and A-weighted sound behave as expected but high frequency sound does not. Finally, for rush hour, while we expected sound levels to be higher than sound levels during the day, the result that high frequency sound levels were lower agreed with our observations of mostly idling traffic, which produced more sound in the lower frequencies.

Some important limitations of this study should be considered. First, we only measured sound at each location for 10 min, which may not be representative of longer term sound levels. Prior studies have shown that 5–10-min noise samples are temporally stable and can be representative of longer term averages when variables such as time of day are considered (Allen et al., 2009; Lee et al., 2014). However, recently Ragettli et al. (2016) showed that while short-term measurements are sufficient for areas dominated by road traffic, in communities engulfed with aircraft noise, one-week measurements should be taken. As a result, shorter monitoring time periods may not adequately capture the complete impact of variables we considered that may be time dependent (restaurants and entertainment establishments). Further, while we did measure sound levels overnight (12–5 a.m.), the number measurements were far fewer in comparison to other times of day due to safety issues (Supplemental Table S3). Therefore, we did not have the power to detect differences in finer grade time scales beyond day (7 a.m.–7 p.m.) and night (7 p.m.–7 a.m.). Despite this, our A-weighted model was relatively consistent with previous models where longer sampling periods were used. Future studies should look specifically at the appropriate sampling times for each sound metric. Finally, our models were constructed in urban areas and may not reflect sound levels in less urban areas.

Our study also has considerable strengths. To our knowledge, this is the first study to build spatial-temporal statistical models for low, mid, and high frequency ranges in an urban environment in North America and the first to use the elastic net approach to do so. Many of our spatial covariates were specified for buffer sizes ranging from 25 to 1000 m, resulting in the high correlation between such variables. The elastic net approach has the advantage of performing well in such cases. Our cross-validation results do suggest that the elastic net selected linear regression models explained 59–69% of the variability associated with the linear relationship with selected predictors. This is consistent with in the predictive power of previously published models, with values ranging from 0.40 to 0.89 (Goudreau et al., 2014; Aguilera et al., 2015). Further, correlations between predicted and observed were quite high

(0.85 −0.86) and the MAPE suggested that on average, our models were off by at most 10%.

Second, this study provides important evidence concerning the relationship between sound levels across the frequency spectrum and the urban environment. These findings are important for a few reasons. First, we were able to identify potential key spatial and temporal drivers of sound frequency, which, in turn, can be used to assess if using only A-weighted measure fully captures the urban sound scape. Second, considering the frequency spectrum allows us to understand other characteristics of sound beyond its level, which may be important for determining the complete picture of how sound may be experienced by those residents exposed to it. Sound levels dominated by low frequencies are of great concern as they can may resonate with humans outside of the auditory system (Alves-Pereira and Castelo Branco, 2007).

The perception by the body outside of the auditory system varies as the sound moves across the frequency spectrum. Vestibular and tactile organs, for example, are more sensitive to low frequencies (Alves-Pereira and Castelo Branco, 2007). In occupational studies, both Chang et al. (2009) and Liu et al. (2016) found that sound frequency at 4000 Hz may have the greatest effect on hypertension while Kumer et al. (2008) found that roughly a third of workers exposed to noise frequencies ranging from 350 to 700 Hz had cardiovascular problems. In a general population study, Chang et al. (2014) observed an increasing trend in the prevalence of hypertension by exposure to ambient road traffic noise at 63, 125, and 1000 Hz. Experimentally, panel studies have found increased salivary cortisol levels and decreased heart rate variability in individuals exposed to low-frequency noise in the ranges between 31.5 and 125 Hz (Persson Waye et al., 2003; Walker et al., 2016).

Additionally, sound levels dominated by low frequencies can travel long distances without much loss of energy and can penetrate more easily through barriers, making them much more difficult to abate (Berglund et al., 1996). While we only focused on sound in the ambient environment, in areas where low frequency sound dominates, the amount of ambient-to-indoor propagation may be substantial, suggesting that in such areas, residents, even while indoors, may still suffer from levels harmful to their health.

Finally, we considered a wide range of covariates not previously examined in sound exposure models. While many of these new considered variables did not have a statistically significant impact on the sound metric estimates, we believe that this information is still useful for researchers in the field.

5. Conclusions

To our knowledge, this is the first study to build spatial-temporal statistical models for low, mid, and high frequency ranges in an urban environment in North America and the first to do so using an elastic net approach. We identified key spatial and temporal predictors for low frequency, mid frequency, high frequency, and A-weighted sound in the city of Boston, MA, using an elastic net variable selection approach. Our A-weighted models were relatively consistent with previous models, which found that transportation related predictors (length of roads and bus lines within buffers; distance to road and rail lines; traffic volume, and vehicle mix) and land use (commercial, industrial, residential) were important contributors to sound levels. However, we also considered models across the frequency spectrum, which gave us additional insight into urban environmental predictors of a sound's frequency. When taking into consideration a sound's frequency predictors such as temperature, vegetation, counts of entertainment establishments, impervious surfaces, and vehicle mix are also important predictors—especially for high frequency sound.

Further, previous epidemiological studies have traditionally used only the A-weighted sound pressure level to assess the relationship between sound levels and negative health outcomes. By constructing these predictive models for low, mid, and high frequency sound, future steps would entail using these additional metrics in epidemiological analyses to determine if consideration of a sound's character better predicts a sound's impact on human health.

Competing financial interests declaration

All authors declare that they have no competing financial interests.

Acknowledgements

Erica Walker was supported by a NIH Pre-Doctoral Environmental Epidemiology Training Grant (T32ES007069). Erica Walker and Jaime Hart were supported by the Harvard-NIEHS Center (NIH grant P30ES000002). Trang VoPham was supported by the NCI Training Program in Cancer Epidemiology (T32 CA009001).

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.envres.2017.08.034.

References

Aguilera, I., Foraster, M., Basagaña, X., Corradi, E., Deltell, A., Morelli, Slama, R., 2015. Application of land use regression modelling to assess the spatial distribution of road traffic noise in three European cities. J. Expo. Sci. Environ. Epidemiol. 25 (1), 97–105. http://dx.doi.org/10.1038/jes.2014.61.

Allen, R.W., Davies, H., Cohen, M.A., Mallach, G., Kaufman, J.D., Adar, S.D., 2009. The spatial relationship between traffic-generated air pollution and noise in 2 US cities. Environ. Res. 109 (3), 334–342. http://dx.doi.org/10.1016/j.envres.2008.12.006.

Alves-Pereira, M., Castelo Branco, N., 2007. Vibroacoustic disease: biological effects of infrasound and low-frequency noise explained by mechanotransduction cellular signaling. Progr. Biophys. Mol. Biol. 93 (1–3), 256–279. http://dx.doi.org/10.1016/j.pbiomolbio.2006.07.011.

Anthrop, D., 1970. The noise crisis. Univ. Tor. Law J. 20 (1), 1–17.

Ascari, E., Licitra, G., Teti, L., Cerchiai, M., 2015. Low frequency noise impact from road traffic according to different noise prediction methods. Sci. Total Environ. 505, 658–669.

Babisch, W., Beule, B., Schust, M., Kersten, N., Ising, H., 2005. Traffic noise and risk of myocardial infarction. Epidemiology 16 (1), 33–40. http://dx.doi.org/10.1097/01.ede.0000147104.84424.24.

Bell, L.H., Bell, D.H., 1993. Industrial Noise Control: Fundamentals and Applications. Marcel Dekker, Inc., New York City, New York.

Berglund, B., Hassmen, P., Job, R.F., 1996. Sources and effects of low-frequency noise. J. Acoust. Soc. Am. 99 (5), 2985–3002. http://dx.doi.org/10.1121/1.414863.

Bluhm, G.L., Berglind, N., Nordling, E., Rosenlund, M., 2007. Road traffic noise and hypertension. Occup. Environ. Med. 64 (2), 122–126. http://dx.doi.org/10.1136/oem.2005.025866.

Bodin, T., Albin, M., Ardo, J., Stroh, E., Ostergren, P.-O., Bjork, J., 2009. Road traffic noise and hypertension: results from a cross-sectional public health survey in southern Sweden. Environ. Health 8 (1), 38–47. http://dx.doi.org/10.1186/1476-069X-8-38.

Chang, T.-Y., Lai, Y.-A., Hsieh, H.-H., Lai, J.-S., Liu, C.S., 2009. Effects of environmental noise exposure on ambulatory blood pressure in young adults. Environ. Res. 109 (7), 900–905. http://dx.doi.org/10.1016/j.envres.2009.05.008.

Chang, T.-Y., Beelen, R., Li, S.-F., Chen, Ti, Lin, Y.-J., Bao, B.-Y., Liu, C.-S., 2014. Road traffic noise frequency and prevalent hypertension in Taichung, Taiwan: a cross-sectional study. Environ. Health 13 (37). http://dx.doi.org/10.1186/1476-069X-13-37.

Correia, A.W., Peters, J.L., Levy, J.I., Melly, S., Dominici, F., 2013. Residential exposure to aircraft noise and hospital admissions for cardiovascular diseases: multi-airport retrospective study. Br. Med. J. 347, f5561. http://dx.doi.org/10.1136/bmj.f5561.

Floud, S., Vigna-Taglianti, F., Hansell, A., Blangiardo, M., Houthuijs, D., Breugelmans, O., Jarup, L., 2011. Medication use in relation to noise from aircraft and road traffic in six European countries: results of the HYENA study. Occup. Environ. Med. 68 (7), 518–524. http://dx.doi.org/10.1136/oem.2010.058586.

Gattorna, J.L., 1998. Strategic Supply Chain Alignment: Best Practice in Supply Chain Management. Gower, Hampshire, England.

Goudreau, S., Plante, C., Fournier, M., Brand, A., Roche, Y., Smargiassi, A., 2014. Estimation of spatial variations in urban noise levels with a land use regression model. Environ. Pollut. 3 (4), 48–58. http://dx.doi.org/10.5539/ep.v3n4p48.

Gulliver, J., Morley, D., Vienneau, D., Fabbri, F., Bell, M., Goodman, P., Fecht, D., 2015. Development of an open-source road traffic noise model for exposure assessment. Environ. Model. Softw. 74, 183–193.

Hansell, A.L., Blangiardo, M., Fortunato, L., Floud, S., de Hoogh, K., Fecht, D., Beale, L., 2013. Aircraft noise and cardiovascular disease near Heathrow airport in London: small area study. Br. Med. J. 347. http://dx.doi.org/10.1136/bmj.f5432.

Haralabidis, A.S., Dimakopoulou, K., Vigna-Taglianti, F., Giampaolo, M., Borgini, A., Dudley, M.-L., Jarup, L., 2008. Acute effects of night-time noise exposure on blood

pressure in populations living near airports. Eur. Heart J. 29 (5), 658–664. http://dx.doi.org/10.1093/eurheartj/ehn013.
Hughey, J.J., Butte, A.J., 2015. Robust meta-analysis of gene expression using the elastic net. Nucleic Acids Res. 43 (12) (e79-e79).
Kumar, G.V.P., Dewangan, K.N., Sarkar, A., 2008. Noise exposure in oil mills. Indian J. Occup. Environ. Med. 12 (1), 23. http://dx.doi.org/10.4103/0019-5278.40812.
Lee, E.Y., Jerrett, M., Ross, Z., Coogan, P.F., Seto, E.Y.W., 2014. Assessment of traffic-related noise in three cities in the United States. Environ. Res. 0, 182–189. http://dx.doi.org/10.1016/j.envres.2014.03.005.
Liu, Jing, et al., 2016. Prevalence of hypertension and noise-induced hearing loss in Chinese coal miners. J. Thorac. Dis. 8. 3 422. http://dx.doi.org/10.21037/jtd.2016.02.59.
Persson Waye, K.P., Clow, A., Edwards, S., Hucklebridge, F., Rylander, R., 2003. Effects of nighttime low frequency noise on the cortisol response to awakening and subjective sleep quality. Life Sci. 72 (8), 863–875. http://dx.doi.org/10.1016/S0024-3205(02)02336-6.
Ragettli, M.S., Goudreau, S., Plante, C., Fournier, M., Hatzopoulou, M., Perron, S., Smargiassi, A., 2016. Statistical modeling of the spatial variability of environmental noise levels in Montreal, Canada, using noise measurements and land use characteristics. J. Expo. Sci. Environ. Epidemiol. http://dx.doi.org/10.1038/jes.2015.82.
Ross, Z., Kheirbek, I., Clougherty, J.E., Ito, K., Matte, T., Markowitz, S., Eisl, H., 2011. Noise, air pollutants, and traffic: continuous measurement and correlation at a high traffic location in New York City. Environ. Res. 111 (8), 1054–1063. http://dx.doi.org/10.1016/j.envres.2011.09.004.
Selander, J., Bluhm, G., Theorell, T., Pershagen, G., Babisch, W., Seiffert, I., Järup, L., 2009. Saliva cortisol and exposure to aircraft noise in six European countries. Environ. Health Perspect. 117 (11), 1713–1717. http://dx.doi.org/10.1289/ehp.0900933.
Seto, E.Y.W., Holt, A., Rivard, T., Bhatia, R., 2007. Spatial distribution of traffic induced noise exposures in a US city: an analytic tool for assessing the health impacts of urban planning decisions. Int. J. Health Geogr. 6 (1), 1. http://dx.doi.org/10.1186/1476-072X-6-24.
Sokolov, A., Carlin, D.E., Paull, E.O., Baertsch, R., Stuart, J.M., 2016. Pathway-based genomics prediction using generalized elastic net. PLoS Comput. Biol. 12 (3), e1004790.
Torija, A.J., Ruiz, D.P., 2015. A general procedure to generate models for urban environmental-noise pollution using feature selection and machine learning methods. Sci. Total Environ. 505, 680–693.
Waldmann, P., Mészáros, G., Gredler, B., Fuerst, C., Sölkner, J., 2013. Evaluation of the lasso and the elastic net in genome-wide association studies. Front. Genet.
Walker, E.D., Brammer, A., Cherniack, M.G., Laden, F., Cavallari, J.M., 2016. Cardiovascular and stress responses to short-term noise exposures—A panel study in healthy males. Environ. Res. 150, 391–397. http://dx.doi.org/10.1016/j.envres.2016.06.016.
Xie, D., Liu, Y., Chen, J., 2011. Mapping urban environmental noise: a land use regression method. Environ. Sci. Technol. 45, 7358–7364.
Zou, H., Hastie, T., 2005. Regularization and variable selection via the elastic net. J. R. Stat. Soc.: Ser. B (Stat. Methodol.) 67 (2), 301–320.
Zuo, F., Li, Y., Johnson, S., Johnson, J., Varughese, S., Copes, R., Liu, F., Wu, H.J., Hou, R., Chen, H., 2014. Temporal and spatial variability of traffic-related noise in the City of Toronto, Canada. Sci. Total Environ. 472, 1100.