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Capturing the spatial variability of noise levels based on a short-term monitoring campaign and comparing noise surfaces against personal exposures collected through a panel study

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ABSTRACT

Environmental noise can cause important cardiovascular effects, stress and sleep disturbance. The development of appropriate methods to estimate noise exposure within a single urban area remains a challenging task, due to the presence of various transportation noise sources (road, rail, and aircraft). In this study, we developed a land-use regression (LUR) approach using a Generalized Additive Model (GAM) for LA_{eq} (equivalent noise level) to capture the spatial variability of noise levels in Toronto, Canada. Four different model formulations were proposed based on continuous 20-min noise measurements at 92 sites and a leave one out cross-validation (LOOCV). Models where coefficients for variables considered as noise sources were forced to be positive, led to the development of more realistic exposure surfaces. Three different measures were used to assess the models; adjusted R^2 (0.44–0.64), deviance (51 − 72%) and Akaike information criterion (AIC) (469.2–434.6). When comparing exposures derived from the four approaches to personal exposures from a panel study, we observed that all approaches performed very similarly, with values for the Fractional mean bias (FB), normalized mean square error (NMSE), and normalized absolute difference (NAD) very close to 0. Finally, we compared the noise surfaces with data collected from a previous campaign consisting of 1-week measurements at 200 fixed sites in Toronto and observed that the strongest correlations occurred between our predictions and measured noise levels along major roads and highway collectors. Our validation against long-term measurements and panel data demonstrates that manual modifications brought to the models were able to reduce bias in model predictions and achieve a wider range of exposures, comparable with measurement data.

1. Introduction

Environmental noise has been associated with cardiovascular health, metabolic disorders, stress and sleep disturbance that are related to endocrine deregulation and being overweight (Christensen et al., 2016; Sørensen et al., 2013; Zijlema et al., 2016). The World Health Organization (WHO, 2011) considers transportation noise as the second most problematic nuisance to public health after air pollution. According to the World Health Organization (1999), about half of the European Union citizens live in zones which do not ensure acoustical comfort to residents. Today, more than 80% of North America's population and 73% of Europeans live in urban areas (UN, 2014). Therefore, it is essential to estimate population exposure to noise in support of epidemiological studies.

Various approaches have been developed to model noise levels in urban areas and generate exposure surfaces. Generally, these approaches include 1) models based on land use regression (LUR), which rely on spatially extensive data collection campaigns and 2) noise propagation models. The latter are typically used for special sources such as the US Federal Highways Administration (FHWA)

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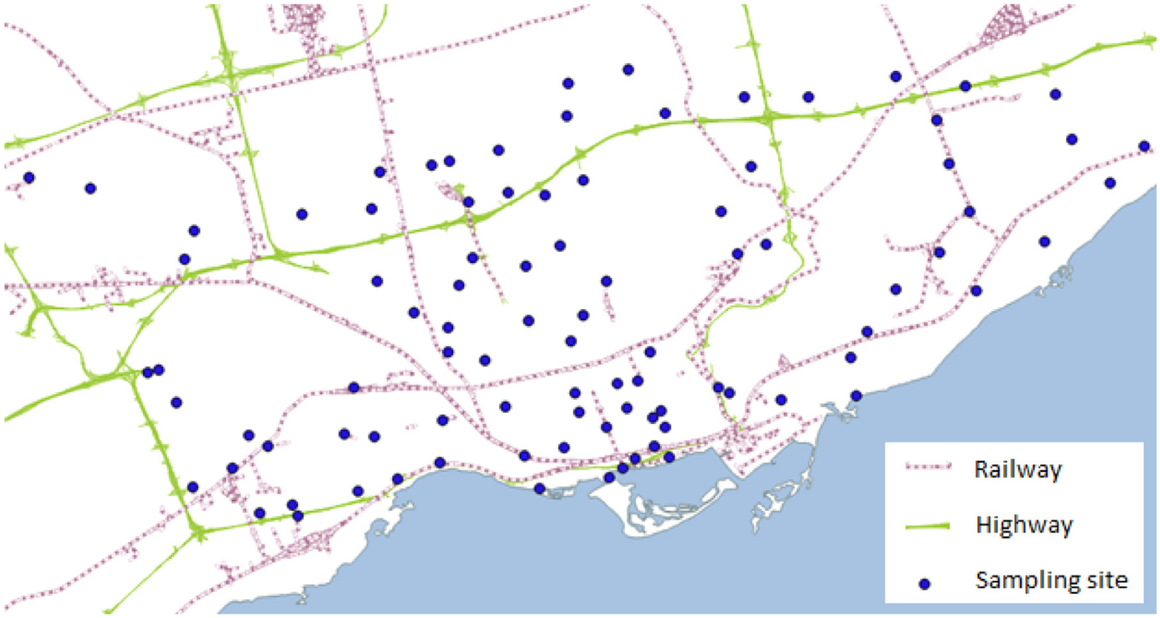

Fig. 1. Location of monitoring sites across the city of Toronto.

Transportation Noise Model (TNM) typically used for highway traffic noise prediction (Boeker et al., 2008), or the Integrated Noise Model (INM) for Aircraft and train noise (Lui et al., 2006). Other propagation approaches include multisource models such as CadnaA® (DataKustik and GmbH) and SoundPlan® (Braunstein + Berndt GmbH and Germany). The computational requirements of numerical models are greater than LUR models for metropolitan areas. Aguilera et al. (2015) applied LUR modelling to assess the spatial variability of road noise in three European cities (Barcelona, Basel and Grenoble) and found no significant difference between noise levels estimated by road-traffic noise LUR models, and noise propagation models.

LUR techniques are generally used for deriving exposure levels in epidemiologic studies of air pollution (Weichenthal et al., 2016). Nevertheless, a few LUR models have been recently developed to capture the spatial variability in noise levels (Aguilera et al., 2015; Xie et al., 2011; Ryu et al., 2017; Alam et al., 2017; Goudreau et al., 2014; Ragettli et al., 2016; Wang et al., 2016). Xie et al. (2011) developed LUR linear and nonlinear models considering six land use variables and road, highway and rail length in the Dalian Municipality, Northwest China. Ryu et al. (2017) used an ordinary least squares (OLS) model, and spatial statistics approaches (spatial autoregressive model (SAR) and the spatial error model (SEM)), including variables for population, building densities, transportation, and land use in the city of Cheongju, South Korea. Alam et al. (2017) developed LUR models at three temporal resolutions (monthly, daily and hourly) in Dublin, Ireland. Goudreau et al. (2014) and Ragettli et al. (2016) developed LUR models using a Generalized Additive Model (GAM) (Hastie and Tibshirani, 1990) to estimate the spatial variation of noise levels in Montreal, Canada. Wang et al. (2016) developed LUR models for four different seasons in metropolitan Taichung, Taiwan.

Most previous studies determined the LUR equation without constraining the signs of the coefficients in the model, which may lead to bias in model predictions. The objective of this study is to develop a LUR model for the city of Toronto, Canada and demonstrate an effective method to select the variables. In addition, the impact of manual adjustments to improve model predictions are examined. These modifications could include replacing a buffer size or distance so that the coefficient exhibits a sign and magnitude that intuitively makes sense or converting non-linear to linear coefficients when the non-linear effect seems like an over fitting. Our study focuses on the spatial variability of noise levels in the city of Toronto, considering various transportation noise sources (road, rail, and aircraft). We also compare the predictions of the LUR models against data collected in the context of a panel study conducted during the same time period and therefore capturing personal exposures for a sample of individuals within the same city. Using only the outdoor exposures of individuals in the panel study, we ask the question of whether exposure surfaces representing temporally averaged noise levels can capture the distributions of exposures experienced by panel participants. In addition, our surface predictions were compared against noise data collected during a long-term campaign, based on which, various noise averaging measures were extracted. With advances in sensor technology and community-driven urban sampling projects, we expect a rise in short-term participatory sampling. In this study, we evaluate the value of short-term sampling campaigns in capturing the spatial distribution of noise levels.

2. Methodology

Our study is set in the city of Toronto, Canada's largest city, home to a diverse population of about 2.8 million residents. Toronto covers an area of 641 km^2 and stretches 43 km from east to west and 21 km from north to south at its longest points.

2.1. Data collection and processing

Noise measurements were performed at 92 near-road sampling locations spread around the city and equally distributed between intersections and mid-blocks. These locations were chosen to cover the various land-uses within the city and a range of noise levels associated with the following transportation sources: road-traffic, railway activities, and airplane movements (Fig. 1). The objective of data collection was to optimise the temporal coverage of a 7 a.m. to 7 p.m. day. This time range was chosen to represent the period of day with the highest traffic density. Each visit to a fixed point consisted of a 20-min sampling duration. Each day was divided into three time blocks of 4 h each. Block 1 ranged from 7 a.m. to 11 a.m., Block 2 from 11 a.m. to 3 p.m., and Block 3 from 3 p.m. to 7 p.m. Measurements were conducted at least once per time block for a minimum of five or six repetitions.

Personal noise dosimeters Type 4448 made by Brüel & Kjaer (GmbH) were used to collect noise levels in units of LA_{eq}. This term is the equivalent continuous sound level, which explains the same sound energy as noise varying over time; 20 min in this study.