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A modeling framework for characterizing near-road air pollutant concentration at community scales

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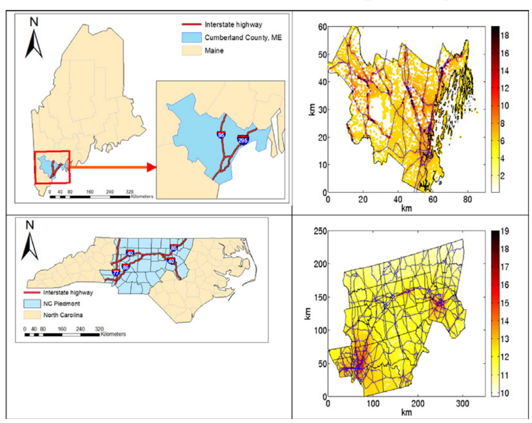
HIGHLIGHTS

- New framework provides high resolved spatial fields of traffic-related air pollutants.
- Framework rapidly captures spatial concentration gradients in near-road environment.
- Concentration reduction due to distance from roadways varies by pollutant and region.
- HDDV contributes over 55% to NOx and $PM_{2.5}$ while LDGV contributes >50% to Benzene.
- METARE approach reduces computational burden by 88-fold to obtain annual averages.

GRAPHICAL ABSTRACT

Spatial maps of modeled $PM_{2.5}$ concentrations in Cumberland County, ME (top) and the North Carolina Piedmont region (bottom) for 2010. The color bar represents pollutant concentration in μg/m^3.



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ABSTRACT

In this study, we combine information from transportation network, traffic emissions, and dispersion model to develop a framework to inform exposure estimates for traffic-related air pollutants (TRAPs) with a high spatial resolution. A Research LINE source dispersion model (R-LINE) is used to model multiple TRAPs from roadways at Census-block level for two U.S. regions. We used a novel Space/Time Ordinary Kriging (STOK) approach that uses data from monitoring networks to provide urban background concentrations. To reduce the computational burden, we developed and applied the METeorologically-weighted Averaging for Risk and Exposure (METARE) approach with R-LINE, where a set of selected meteorological data and annual average daily traffic (AADT) are used to obtain annual averages. Compared with explicit modeling, using METARE reduces CPU-time by 88-fold (46.8 h versus 32 min), while still retaining accuracy of exposure estimates. We show two examples in the Piedmont region in North Carolina (~105,000 receptors) and Portland, Maine (~7000 receptors) to characterize near-road air quality. Concentrations for NO_x, $PM_{2.5}$, and benzene in Portland drop by over 40% within 200 m away from the roadway. The concentration drop in North Carolina is less than that in Portland, as previously shown in an observation-based study, showing the robustness of our approach. Heavy-duty diesel vehicles (HDDV)

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R-LINE
METARE
Emissions

contribute over 55% of NO_x and $PM_{2.5}$ near interstate highways, while light-duty gasoline vehicles (LDGV) contribute over 50% of benzene to urban areas where multiple roadways intersect. Normalized mean error (NME) between explicit modeling and METARE in Portland ranges from 12.6 to 14.5% and normalized mean bias (NMB) ranges from −12.9 to −11.2%. When considering a static emission rate (i.e. the emission does not have temporal variability), both NME and NMB improved (10.5% and −9.5%). Modeled concentrations in Detroit, Michigan at an array of near-road monitors are within a factor of 2 of observed values for CO but not NO_x.

1. Introduction

Transportation plays an important role in modern society, but its impact on air quality can have significant adverse effects on public health, as numerous studies have shown (Gauderman et al., 2007; Baccarelli et al., 2009; Lindgren et al., 2010; McConnell et al., 2010; Künzli, 2014; Urman et al., 2013). Because 19% of the U.S. population lives near heavy-traffic roads, and this group includes larger shares of both non-white residents and lower median household incomes (Rowangould, 2013), it is essential to characterize near-road exposure to address concerns about public health and environmental justice.

Accurate characterization of exposure to air pollution from traffic is also important for environmental epidemiologic studies (Lobdell et al., 2011; Vette et al., 2013). However, estimating near-road exposure is challenging because of dynamic traffic conditions, multiple pollutants, the need to separate near-road and regional pollution, and the spatial and temporal resolution needed to document pollutants. Traditionally, field measurements, statistical modeling, and emissions-based air quality modeling have been used to overcome the challenges and quantify the impact of transportation on air quality. Land-use regression (LUR) models have also been used to capture spatial variation of traffic-related pollutants. An example can be seen in Lindström et al. (2013) where data collected from multiple monitors and a line source dispersion model are combined using a spatio-temporal framework to estimate ambient concentration. However, conducting a sampling campaign for a large domain in support of LUR modeling would require a significant number of samplers, which would be costly and time consuming. Therefore, although field measurements and statistical models can provide concentration information with greater certainty and identify the main contributors to pollutant levels, the spatial resolution and coverage may be insufficient due to the limited number of available monitoring devices or the costs associated with them.

Another approach to characterize traffic-related air pollutants is using emissions-based air quality models. These models can predict pollutant concentrations over a larger domain with arbitrary spatial resolution by combining emissions data and current knowledge about physical and chemical processes in the atmosphere. These models can be categorized as chemical-transport models (Caiazzo et al., 2013), dispersion models (Lobscheid et al., 2012; Venkatram et al., 2007), and hybrid models (Isakov et al., 2009; Stein et al., 2007). Compared with measurement approaches, emissions-based modeling has a greater capability to connect emissions from on-road activity to resultant pollutant level because of its ability to distinguish between source types during the modeling process. This is critical for implementing mitigation strategies. In the U.S., Fann et al. (2013), and Caiazzo et al. (2013) used detailed chemistry transport models and estimated that mobile sources are either the second largest sector to cause ozone- and $PM_{2.5}$-related premature deaths (~29,000 per year) or the largest sector causing premature deaths due to $PM_{2.5}$ (53,000 per year) and ozone (5000 per year). Both these studies highlight the growing importance of health risk due to mobile source emissions. Nevertheless, while these analyses were able to predict some compelling risk estimates, the relatively coarse spatial resolutions (36-km × 36-km and 12-km × 12-km) used in these studies can limit the ability to determine the locations of specific high-risk areas in population risk assessments (Arunachalam et al., 2006, 2011). To identify and quantify high-risk areas requires high-resolution and large-scale modeling, which is computationally intensive. In addition, quantifying the contribution from a single source would generally require running the model multiple times, which further increases the computational burden.

In our study, we developed a hybrid modeling approach that includes the Research LINE source dispersion model (R-LINE) (Snyder et al., 2013) for modeling traffic-related concentrations and ambient observed data as a source for regional background concentrations at fine resolution (i.e., at Census-block level) in a computationally efficient manner (i.e., within minutes). We modified the "bottom-up" strategy (Cook et al., 2008)—under which the emissions are accurately represented by each roadway's actual location—to estimate near-road exposures on a large scale while resolving near-road gradients. The approach has been evaluated with an explicit simulation (the bottom-up method) for Portland (Cumberland County), ME, and the model performance has been evaluated against a near-road monitoring study in Detroit, MI, conducted by the EPA and the Federal Highway Administration (FHWA) (Vallero et al., 2013).

The novelty of our approach, when compared to prior methods, is the combination of traffic-related contributions using R-LINE with a spatio-temporal kriging method to obtain background concentrations before implementing an approach to run only select hours of the year to compute annual averages (thus providing critical savings in computational time), while incorporating temporal variability of traffic-related emissions. We give two illustrative examples that involve applying the modeling framework in two geographical areas: Cumberland County, ME, and North Carolina's Piedmont region. Cumberland County (denoted as CCM) (Fig. 1a) was selected as representative for a midsize metropolitan area, and the Piedmont region (denoted as NCP) (Fig. 1b), as representative for a larger domain with both metropolitan and rural areas included. These two were also chosen to demonstrate contrast between two regions of the country.

2. Methods

2.1. Modeling framework

The modeling framework is composed of two major components: On-road concentration (Sections 2.2 and 2.3) and urban background concentration (Section 2.4). In this approach we assume that modeled concentrations at selected locations (i.e., Census-block centroids) can be used to estimate population exposure in support of exposure and health studies. Therefore, the concentrations from the two components are estimated at Census-block centroids and the summation of the two components is the total ambient concentration. Although concentration fields at parcel level may likely serve as better exposure metric, previous studies have shown that the difference in mean and maximum concentrations between parcel and Census block level only ranges from −2.4 to 7.1% (Wu et al., 2009; Batterman et al., 2014). The EPA is currently utilizing Census-block centroids as health risk estimation points in its residual risk program (U.S. Environmental Protection Agency, 2009), which allows continuity between studies.

We employed R-LINE (Snyder et al., 2013) to estimate near-road concentrations, because this model treats roads as line sources and applies new formulations for horizontal and vertical plume spread (Venkatram et al., 2013). The transportation data required to estimate emission includes road networks (individual road segment locations), traffic activity (number of vehicles for each road segment over a period