ARTICLE IN PRESS

Atmospheric Pollution Research xxx (xxxx) xxx–xxx

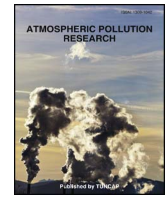
HOSTED BY

ELSEVIER

Contents lists available at ScienceDirect

Atmospheric Pollution Research

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



Comparing estimates from the R-LINE near road dispersion model using model-derived and observation-derived meteorology

Fatema Parvez, Kristina Wagstrom*

Department of Chemical and Biomolecular Engineering, University of Connecticut, 191 Auditorium Road, Unit 3222, Storrs, CT 06269-3222, USA

A R T I C L E I N F O

Keywords:
Air pollution dispersion modeling
Line source modeling
Traffic-related air pollution
Near-road air pollution

A B S T R A C T

Observed meteorological conditions, usually measured at airports or weather monitoring stations, have long provided the only source of meteorology for many Gaussian air pollution dispersion models. This introduces uncertainty and limitations in numerical model estimates, especially for locations of interest far removed from these monitoring stations. Hence, it is advantageous to employ predicted meteorology from a prognostic meteorological model as a substitute. The objective of this study was to compare estimates from the R-LINE near road dispersion model at three inland sites and one coastal site in Connecticut using observation-derived (weather station) and model-derived (Weather Research and Forecasting Model) meteorology. Both the graphical and statistical comparisons indicated less pronounced discrepancies in model estimations in the time periods generally characterized by unstable atmospheric conditions than those characterized by stable atmospheric conditions. There were also more pronounced differences at larger distances from roadways. Comparison of the estimated surface characteristic variables using both the observation-derived and model-derived meteorology displayed similar diurnal trends.

1. Introduction

The rapid growth of the world's motor vehicle fleet has led to an increased number of people living near high traffic roadways and an associated increase in adverse near road pollutant exposures (Adar and Kaufman, 2007; Salam et al., 2008). Negative outcomes associated with near road air pollution include asthma (Künzli et al., 2000; Jerrett et al., 2008; Rohr et al., 2014), respiratory impacts (Kim et al., 2015; McCreanor et al., 2007), cardiovascular impacts (Franck et al., 2011; Crouse et al., 2012; Peters et al., 2004; Riediker et al., 2004), cancer (Pearson et al., 2000; Harrison et al., 1999; Turner et al., 2011; Loomis et al., 2013), low birth weight (Wilhelm et al., 2012; Wilhelm and Ritz, 2003), and premature deaths (Pope et al., 2009; Crouse et al., 2012; Krewski et al., 2009). It is essential to quantify roadway pollutant dispersion on local scales to fully understand potential risks facing different populations.

Estimation of near road pollutant concentrations requires either extensive field measurements or dispersion modeling. As extensive monitoring is both expensive and time consuming, dispersion modeling offers a quicker, cheaper, and more spatially transferrable approach to capture the spatial and temporal variability in estimates of near road pollutant concentrations. Models such as HIWAY-2 (Petersen, 1980), UCD (Held et al., 2003), ADMS-ROADS (McHugh et al., 1997), and CALINE (Benson, 1989; 1992) all allow estimation of near road pollutant concentrations. It is computationally expensive to employ these models, especially for urban areas that contain a large number of roadways. To minimize computational burden, these models use analytical approximations to the integral associated with modeling line sources by approximating the line using multiple point sources. This approximation increases the chance of error in model predictions especially for low and variable wind speeds, wind directions near parallel to the surface, and receptors and sources at different heights (Briant and Seigneur, 2013). R-LINE (Snyder et al., 2013), a fairly new edition to this list, uses Romberg numerical integrations instead of analytical approximations, thus resolving many issues associated with the modeling framework approximations facing earlier models (Snyder et al., 2013).

To estimate pollutant concentrations, R-LINE requires several specific surface meteorological parameters. These include, but are not limited to, wind speed and direction at a reference height, surface friction velocity (U*), convective velocity scale (W*), and Monin-Obukhov length (L) (Snyder et al., 2013). Typical applications of R-LINE use observation-based meteorology processed by AERMET (Cimorelli et al., 2005), the meteorological processor for the AERMOD

Peer review under responsibility of Turkish National Committee for Air Pollution Research and Control.

* Corresponding author.
E-mail addresses: fatema.parvez@uconn.edu (F. Parvez), kristina.wagstrom@uconn.edu (K. Wagstrom).

https://doi.org/10.1016/j.apr.2017.10.007
Received 21 June 2017; Received in revised form 10 October 2017; Accepted 18 October 2017
1309-1042/ © 2017 Turkish National Committee for Air Pollution Research and Control. Production and hosting by Elsevier B.V. All rights reserved

Please cite this article as: Parvez, F., Atmospheric Pollution Research (2017), https://doi.org/10.1016/j.apr.2017.10.007

ARTICLE IN PRESS

dispersion model. AERMET estimates surface characteristics using weather station data including surface roughness, albedo, cloud cover, upper air temperature soundings, near surface wind speed, wind direction, and temperature (Snyder et al., 2013). This limits the use of dispersion models (including AERMOD and R-LINE) in locations lacking nearby station data. Prognostic meteorological model estimates have the potential to provide representative meteorological inputs to allow increased flexibility in dispersion modeling, particularly near road dispersion modeling. In 2012, the United States Environmental Protection Agency (EPA) released the Mesoscale Model Interface Program (MMIF) (EPA, 2015a) to prepare meteorological inputs for AERMOD using outputs from either the fifth-generation Mesoscale Model (MM5) or the Weather Research and Forecasting (WRF) model. As both R-LINE and AERMOD use the same meteorological input file structure, this opens the opportunity to use a wider selection of inputs for R-LINE.

In this study, we compare R-LINE concentration estimates using observation-derived and model-derived meteorological inputs for four different locations in Connecticut - Danbury, Windsor Locks, Windham, and New Haven. We evaluate the seasonal, temporal, and spatial differences in R-LINE estimates from these two sources of meteorological inputs. We also compare the diurnal variation in major surface characteristic variables from both input sources. Finally, we compare the impact on R-LINE's estimates at two distances from the roadway considering two different time periods (9 a.m.–5 p.m. and 6 p.m. to 8 a.m.) representing the unstable- and stable-dominant atmosphere, respectively.

2. Methods

We compare R-LINE estimates using observation-derived and model-derived meteorological inputs. For observed meteorology, we consider data from weather stations located at four major airports in Connecticut. For model-derived meteorology, we use the Weather Research and Forecasting (WRF) model predicted meteorology for the corresponding grid cell. In Section 2.1, we provide an overview of the monitoring sites and a detailed description of the meteorological data processing along with the weather prediction model specifications. We analyze R-LINE's estimates at two different time periods representing stable- and unstable-dominant atmospheric conditions for three inland sites and one coastal site in different months. We consider 9:00am-5:00pm EST/EDT as the atmospherically unstable-dominant time period and 6:00pm-8:00am EST/EDT as the atmospherically stable-dominant time period. We also compare several meteorological parameters integral to the dispersion model estimates: wind speed, wind direction, convective velocity scale, frictional velocity, and Monin-Obukhov length.

2.1. Meteorology

Meteorology is an integral input for local scale dispersion models. We use two different sources of meteorological inputs to estimate near road pollutant concentrations employing a new line source dispersion model, R-LINE. For observation-derived meteorology, we select meteorology monitoring stations at four different Connecticut airports as shown in Fig. 1: Bradley International Airport (Windsor Locks, CT), Danbury Municipal Airport (Danbury, CT), Windham Airport (Windham, CT), and Tweed New Haven (New Haven, CT). We use observation-derived meteorological data generated by the Connecticut Department of Energy and Environmental Protection (DEEP) with AERMET preprocessor (v 15 181) using 2011 data from the National Weather Service (NWS) Automated Surface Observing System (ASOS) stations (CT DEEP, 2015). We use the Mesoscale Model Interface Program (MMIFv3.2-beta) (EPA, 2015a) to process model-derived meteorology from the Weather Research and Forecasting (WRF) model (version 3.4), a mesoscale numerical weather prediction model (Skamarock et al., 2008) configured with a domain of 471 × 311 grids

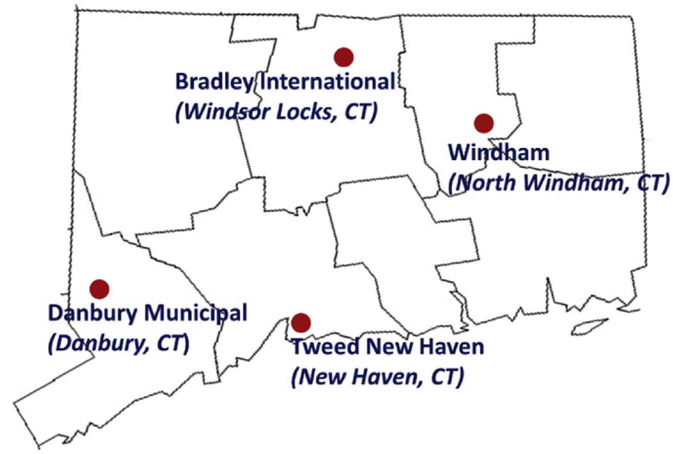


Fig. 1. Selected weather monitoring stations and resulting modeling locations used in this study. These include three inland locations (Bradley International Airport, Danbury Municipal Airport, and Windham Airport) and one coastal location (Tweed New Haven Airport).

and with a horizontal resolution of 12 × 12 km covering the United States. The vertical grid has full 35 sigma levels stretching from near surface to model top (50 hPa). Table S1 details the specific physics and schemes used in WRF. MMIF considers the height of the lowest sigma level mid-point (~10 m) in computing meteorology inputs for dispersion models.

To compare meteorology from the two input sources, we select the nearest WRF grid cell corresponding to each airport. We have included the latitude and longitude for each weather station and corresponding WRF grid cells in Table S2. We consider hourly-averaged meteorological parameters to yield hourly-averaged model predicted concentrations from R-LINE. In addition, we evaluate the diurnal variations for estimated meteorological parameters - wind speed, wind direction, convective velocity scale (W*), frictional velocity (U*), and Monin-Obukhov length (L) - processed by the two meteorology preprocessors. For comparison between model-derived and observation-derived meteorology, we estimate the standard deviation (SD), mean bias (MB), and root mean square difference (RMSD) using the following definitions:

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(P_i - \overline{P_i})^2}{n}} \tag{1}$$

$$Bias = \frac{1}{n}\sum_{i=1}^{n}\left(P_{M_i} - P_{O_i}\right) \tag{2}$$

$$RMSD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(P_{M_i} - P_{O_i}\right)^2} \tag{3}$$

P_i is the value of the specific meteorological parameter at time i. P_{Mi} and P_{Oi} are model-derived and observation-derived specific meteorological inputs, respectively, at time i. To capture the seasonal variabilities, we consider estimates in January (Winter), April (Spring), July (Summer), and October (Fall).

2.2. Description of the model and modeling domain

R-LINE is a steady state Gaussian plume dispersion model developed by the US Environmental Protection Agency (EPA) to estimate pollutant concentration from line sources, primarily roads. This model numerically integrates over multiple point sources to approximate emissions occurring along a line (Snyder et al., 2013). R-LINE (version 1.2) includes both vertical and lateral dispersion, simulates low wind meander conditions, and applies Monin-Obukhov similarity theory for vertically profiling the wind and turbulence near the surface. The Monin-

Download English Version:

https://daneshyari.com/en/article/8862633

Download Persian Version:

https://daneshyari.com/article/8862633

Daneshyari.com