Environmental Pollution 171 (2012) 9–17

Contents lists available at SciVerse ScienceDirect

Environmental Pollution

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

Development of a distributed air pollutant dry deposition modeling framework

Satoshi Hirabayashi [a,*], Charles N. Kroll [b], David J. Nowak [c]

[a] The Davey Institute, The Davey Tree Expert Company, Syracuse, NY 13210, United States
[b] Department of Environmental Resources and Forest Engineering, State University of New York College of Environmental Science and Forestry, Syracuse, NY 13210, United States
[c] USDA Forest Service, Northeastern Research Station, Syracuse, NY 13210, United States

ARTICLE INFO

Article history:
Received 10 February 2012
Received in revised form
29 June 2012
Accepted 1 July 2012

Keywords:
Air pollutant
Distributed model
Dry deposition
UFORE
Geographic information system

ABSTRACT

A distributed air pollutant dry deposition modeling system was developed with a geographic information system (GIS) to enhance the functionality of i-Tree Eco (i-Tree, 2011). With the developed system, temperature, leaf area index (LAI) and air pollutant concentration in a spatially distributed form can be estimated, and based on these and other input variables, dry deposition of carbon monoxide (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and particulate matter less than 10 microns (PM10) to trees can be spatially quantified. Employing nationally available road network, traffic volume, air pollutant emission/measurement and meteorological data, the developed system provides a framework for the U.S. city managers to identify spatial patterns of urban forest and locate potential areas for future urban forest planting and protection to improve air quality. To exhibit the usability of the framework, a case study was performed for July and August of 2005 in Baltimore, MD.

1. Introduction

Air in cities may contain high levels of pollutants that cause human health problems (Mayer, 1999). In the United States, more than 3700 deaths annually are attributable to an increase in ozone levels (Bell et al., 2004). Worldwide, the World Health Organization estimated that 800 000 deaths annually could be attributed to urban air pollutants (WHO, 2002). The United Nations Population Fund predicted that the urban population worldwide would increase from 3.3 billion in 2008 to 5 billion by 2030 (UNFPA, 2007), leading to increased mortality for urban residents. Developing solutions to control air pollutants and reduce exposure risks is a goal for cities worldwide.

Air pollutant management practices often focus on controlling emission sources of air pollutants (Schnelle and Brown, 2002). These practices effectively reduce the local emission of new air pollutants, but do not address pollutants already in the air. To remove existing air pollutants, different approaches need to be employed. One such approach is the use of urban forest that can reduce air pollutants through a dry deposition process. Due to their large leaf surface areas compared to the ground on which they stand, trees can act as biological filters, removing air pollutants and hence improve air quality (Beckett et al., 1998).

For urban forest management, it is crucial to understand the effects of the existing urban forest, and plan future planting and protection to achieve air quality and other environmental goals (Dwyer et al., 2002, 2003; Luley, 2002; Nilsson et al., 2008). The United States Department of Agriculture (USDA) Forest Service's urban forest effects model (formerly called UFORE and now integrated into i-Tree Eco (i-Tree, 2011)) provides a tool to quantify urban forest structure and forest-related effects (Nowak and Crane, 2000; Nowak et al., 2008). UFORE-D is the i-Tree Eco's program that calculates hourly dry depositions of air pollutants to tree canopies based on tree cover and hourly meteorological and air pollutant concentration data. While UFORE-D is widely used to quantify dry deposition in urban areas in North America (Currie and Bass, 2008; Deutsch et al., 2005; Nowak et al., 1998, 2000, 2006; Nowak and Crane, 2000), one limitation of UFORE-D is that the spatial distribution of urban forests is not considered. As a result, pollutant removal is estimated based on average characteristics of an area; it is not possible to assess local effects of urban forests based on their spatial distribution across an area. This limitation stems from UFORE-D's lumped parameter approach. This method assumes input parameters such as meteorology and pollutant concentrations are homogeneous over an area, and quantifies dry deposition across the area as a single value. To enhance UFORE-D's spatial ability, it is desirable to employ a distributed parameter approach in which input parameters with spatial variations are employed. This approach will allow managers to better assess and visualize the local effects of urban forests and create more detailed urban tree management plans.

* Corresponding author.
E-mail addresses: satoshi.hirabayashi@davey.com (S. Hirabayashi), cnkroll@esf.edu (C.N. Kroll), dnowak@fs.fed.us (D.J. Nowak).

0269-7491/$ – see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.envpol.2012.07.002

Ideally in distributed models all input parameters are available in a distributed form; however, data limitations often exist due to lack or incompleteness of measurements (Mulligan and Wainwright, 2004). As a result, most distributed models use some of their input parameters in a lumped form. This limitation exists for UFORE-D when implemented in a distributed approach. Hirabayashi et al. (2011) performed Monte Carlo with Latin hypercube sampling and Morris one-at-a-time sensitivity analyses to determine the input parameters that had the greatest impact on UFORE-D outputs. They identified temperature and leaf area index (LAI) as the most sensitive model input parameters. In addition, the amount of pollutant removed is directly dependent upon ambient pollutant concentrations. In this study, these three input parameters are distributed and employed with other lumped input parameters over the study area.

Implementing UFORE-D with a distributed approach requires dividing a study region into grid cells, applying UFORE-D within each cell, and composing a distributed result. This analysis can be streamlined by coupling UFORE-D with a geographical information system (GIS). In these circumstances, a strategy called tight coupling is often employed (Fedra, 1996). With tight coupling of a model and GIS, model functionalities are typically built within a GIS framework. Thus two originally independent systems are integrated into one system that provides a common user interface and a transparent data sharing and transfer between the model and GIS. Moreover, with functionalities offered by GIS it is possible to visualize urban forest effects on a municipal map and identify high risk areas that are potential locations for future urban forest planting and protection.

The objective of this study is to develop a distributed air pollutant dry deposition modeling framework by integrating UFORE-D into a GIS. Employing nationally available data, it provides urban forest managers in U.S. cities a framework to quantify and visualize urban forest effects for appropriate management and design plan developments. Three important input parameters for UFORE-D (i.e. temperature, LAI, and air pollutant concentration) are employed in a distributed form. Models to estimate these parameters are also integrated into the system. The model is capable of estimating concentrations and dry depositions of four criteria air pollutants (CAPs): carbon monoxide (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and particulate matter less than 10 microns (PM10). Using this framework, a case study in Baltimore, MD is performed, in which dry deposition of NO_2 for July and August in 2005 are spatially quantified, and future potential urban forest planting and protecting locations are visually identified.

2. Material and methods

2.1. Temperature calculation

Heisler et al. (2006, 2007) developed empirical models of air temperature differences between multiple weather stations in the city of Baltimore, MD and surrounding neighborhoods. On an hourly basis, Turner atmospheric stability classes are derived from the wind speed and cloud cover (Panofsky and Dutton, 1984), by which hourly meteorological data are stratified. With these explanatory variables as well as raster datasets representing elevation and upwind cover types (i.e. forest, impervious and water) from the National Land Cover Dataset (NLCD) 2001 (Homer et al., 2004), temperature differences between a reference site and grid cells in an area are estimated by regression analysis. Output variables are hourly air temperature (°C) for each cell.

2.2. LAI calculation

LAI is defined as one-sided leaf area of canopy divided by ground projected area of canopy. From field sampled data gathered in Baltimore in 2004, the maximum mid-season LAI can be estimated with UFORE-A, a sibling computer program of UFORE-D integrated in i-Tree Eco. With UFORE-A, leaf area of individual trees is estimated using regression equations for urban trees (Nowak, 1996), and the leaf area and tree cover percentage within six NLCD 2001 landcover types are estimated. Landcover types employed are developed open space, developed low intensity, developed medium intensity, developed high intensity, barren/agricultural land, and forest/wetland. LAI per unit tree cover for landcover i can be calculated as:

$$\mathrm{LAI}_i = \frac{\mathrm{LA}_i}{A_i \times \mathrm{TC}_i} \tag{1}$$

where LA_i, A_i, and TC_i are leaf area (km^2), ground area (km^2), and tree coverage (%) for landcover i, respectively.

2.3. Air pollutant concentration calculation

Air pollutant concentration is calculated based on the methods described in Morani et al. (2011). Air pollutant concentrations are modeled for two emission sources: facility stacks (point sources) and traffic on roads (line sources), and merged into one map and adjusted with monitored data in the area. This method is not designed to estimate actual air pollutant concentrations, rater the potential variabilities in concentration due to these emission sources.

Four national databases are employed to calculate air pollutant maps. The Topologically Integrated Geographic Encoding and Referencing (TIGER) road network data (TIGER, 2008), the U.S. Department of Transportation's highway statistics data (U.S. DOT, 2008), hourly meteorological measurements in 2005 obtained from National Climate Data Center (NCDC) (NCDC, 2008) and the US EPA's Nation Emission Inventory (NEI) for 2002 (NEI, 2008).

Air pollutant dispersions from roads are estimated in two steps. First air pollutant emissions from automobiles are estimated based on traffic volume and emission factors (Table 1), and then air pollutant dispersion is estimated with a modified General Finite Line Source Model (GFLSM) (Luhar and Patil, 1989; McHugh and Thomson, 2003):

$$C_i = \frac{Q_i}{2\sqrt{2\pi}\sigma_z u}\exp\left[-\frac{1}{2}\left(\frac{z_\mathrm{r}-z_\mathrm{s}}{\sigma_z}\right)^2\right]\left[\mathrm{erf}\left(\frac{y_\mathrm{r}+L_i/2}{\sqrt{2}\sigma_y}\right)-\mathrm{erf}\left(\frac{y_\mathrm{r}-L_i/2}{\sqrt{2}\sigma_z}\right)\right] \tag{2}$$

where C_i (g m^{-3}) is the air pollutant concentration for road type i, Q_i (g s^{-1} m^{-1}) is the pollutant emission rate per unit length for road type i, u (m s^{-1}) is wind speed, σ_y (m) and σ_z (m) are the standard deviations of lateral and vertical concentration distributions, respectively, y_r (m) is the crosswind distance between receptor and source, L_i (m) represents in-cell road length for road type i, and z_s (=0.5 m) and z_r (=1.5 m) are height of the source and receptor, respectively. u must be larger than 0 m s^{-1} to estimate concentrations with Equation (2).

Emission of nitrogen in both highway statistics and NEI data are reported as oxides of nitrogen (NO_x). Air quality standards are expressed in terms of nitrogen dioxide (NO_2) because it is closely related to health effects. The concentration of NO_x estimated with the aforementioned models is converted to the concentration of NO_2 based on the empirical function for the ratio of NO_2 and NO_x (Derwent and Middleton, 1996).

Pollutants emitted from a point source can be approximated with the Gaussian dispersion equation expressed as (Zannetti, 1990):

$$C_i = \frac{Q}{2\pi\sigma_y\sigma_z u}\exp\left[-\frac{1}{2}\left(\frac{y_\mathrm{r}}{\sigma_y}\right)^2\right]\exp\left[-\frac{1}{2}\left(\frac{h_\mathrm{s}+\Delta h-z_\mathrm{r}}{\sigma_z}\right)^2\right] \tag{3}$$

where C (g m^{-3}) is air pollutant concentration at a receptor, Q (g s^{-1}) is pollutant emission rate from a source facility, Δh (m) is emission plume rise, and h_s (m) is height of the source (stack height).

Several assumptions are made to employ Equations (2) and (3) for estimating air pollutant concentrations (Turner, 1994). Highway and facility emission data are provided on an annual basis. These data are converted to per-second values to be incorporated in Equations (2) and (3) and assumed to be continuous over time. The mass of emitted pollutants is assumed to remain the same in the atmosphere during transport, and no pollutants are removed through chemical reactions, gravitational settling, or turbulent impaction. The meteorological conditions are assumed to remain unchanged over the time period that the emitted pollutant travels from the source to receptors. It is assumed that the time averaged concentration profiles at any distance in both the crosswind and vertical directions are well represented by

Table 1
Emission factors obtained from U.S. Environmental Protection Agency (US EPA, 1998) for CO and NO_x, and from EPA's highway vehicle particulate emission modeling software, PART5 (US EPA, 2009a) for PM10 and SO_2.

Road type	Emission factor (g miles^{-1})			
	CO	NO_x	PM10	SO_2
Interstate highway (A1)	7.40	2.58	0.096	0.113
Other freeway and expressway (A2)	10.58	2.02	0.096	0.113
Other principal arterial (A3)	10.58	2.02	0.096	0.113
Local road (A4)	20.52	2.02	0.095	0.113