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Original article

Synergy of receptor and dispersion modelling: Quantification of PM_{10} emissions from road and soil dust not included in the inventory

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Dispersion modelling-based apportionment of emitting sources impacting the air quality depends on quality of Emission Inventory (EI) and meteorological data. The CMB (Chemical Mass Balance) receptor model and AERMOD dispersion model have been combined to identify and account for un-quantified sources of PM_{10} in EI. The speciated PM_{10} data from Baddi-Nalagarh (30.9412° N latitude, 76.78° E longitude), India was used in CMB model. The CMB analyses identified that fugitive sources, soil and road dust, contribute significantly to PM_{10} concentration; these sources were not considered in the existing EI. As a result, AERMOD significantly underestimated the PM_{10} concentration at most locations. The existing EI in each grid was improved by adjusting emission as per road lengths and deficit in measured and computed concentrations. The estimated PM_{10} road dust emission from all grids was 653 kg/d. The revised EI showed a significant improvement in AERMOD performance examined through statistical tests.

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1. Introduction

A review of air quality trends in India suggests that the levels of particulate matter (PM) exceed both 24-hr and annual standards at most locations of Indian National Air Quality Monitoring Program (CPCB, 2011a). PM levels in large cities in India on certain days could be 5–10 times higher than those in the European cities (Sharma and Maloo, 2005). These high PM levels may severely impact public health (Schwartz, 1996) and there are evidences of respiratory health problems which could be related to high pollution levels (Sharma et al., 2004; Liu et al., 2013). $PM_{2.5}$ (particulate matter of aerodynamic diameter less than or equal to 2.5 μm) is considered a better health indicator than the coarse particles, PM_{10}. (particulate matter of aerodynamic diameter less than or equal to 10 μm) (WHO, 2013). However, due to limitation on monitoring equipment, this study has focused on PM_{10}. To arrive at PM_{10} control strategies, one needs information about the sources and their relative contributions to the ambient air PM levels. Air pollution measurements are often carried out at limited locations due to resource limitations, particularly in developing countries. For example, large city like Delhi (population over 10 million and area 1500 sq km) had only nine air quality stations (CPCB, 2003). The study area (described later) for the present work had no air quality measurements done in past. The limited air quality measurements are unable to fully provide source receptor linkages to understand the causal mechanism of emissions and impacts. Validated air quality models can give a more complete description of the air quality problem including analyses of factors and causes of air pollution (Daly and Zannetti, 2007). Source apportionment using air pollution models can be classified into two categories: Receptor and Dispersion models (Haupt et al., 2006). Receptor models use data on several species present in ambient air and information about relative emissions of those species from possible sources to apportion the ambient air levels to the sources (Miller et al., 2002). Dispersion models use Emission Inventory (EI) and meteorology to trace the dispersal path of a pollutant to estimate the impact at the receptor. There has been an increased interest in receptor modelsas information on EI and meteorological data (essential for dispersion models) is not required and the model provides contribution of each source to ambient air pollution level (Callen et al., 2009). However, application of receptor model is not simple as it requires detailed information on chemical characterization (organic and inorganic composition) of PM. Receptor modelling, though costly,

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can be effective if there is a likelihood of un-quantified sources. The major limitation of receptor modelling is in its inability to predict and simulate the impact of future emissions and it is applicable only at receptor locations where extensive measurements are done. Dispersion modelling is effective both for simulation of future emissions and for estimating pollutant concentration at any desired location. The main constraints for effective dispersion modelling are incomplete EI and availability of quality meteorological data. Therefore, it is evident from the above discussion that both receptor and dispersion models have their own benefits and limitations.

Regardless of preference for receptor or dispersion model, EI, a structured collection of information about emissions of pollutants (Singh et al., 2014) is essential for post processing of modelling results to develop air pollution control strategies/action plans. Preparation of EI, in fact, is the first step in planning control of air pollution. The methods and procedures for developing EI for regular point, line and area sources are well established (Behera et al., 2011). But quantification of fugitive/non-point emission sources is challenging. Emission factors for such sources are location and process specific and cannot be applied universally. Some of the important non-point sources include dusts from road (Bhasker and Sharma, 2008), soil, pot holes etc. and these sources may be important so should be included in the EI.

Dust emissions from well-maintained paved roads are estimated by finding the silt load on the road surface and average weight of vehicles travelling on the road (USEPA, 2001). This approach is not applicable for partially paved and unpaved roads as silt load may dramatically vary within a short distance. The Indian roads in most suburban towns are poorly paved and hence silt-load based approach cannot be adopted. In India, for these sources, EI is non-existent or incomplete (Behera et al., 2011). As seen, preparation of EI is challenging, especially to capture fugitive sources in an urban mix, there is a need to explore new ways to assess fugitive component of emissions.

There are a few studies (described below) which have coupled dispersion and receptor models to comprehend the source apportionment and improve model performance. Laupsa et al. (2007) studied the quality of EI for fine particulates ($PM_{2.5}$) in London using the source contributions calculated from PMF (Positive Matrix Factorization) receptor model and source apportionment using AirQUIS dispersion model. Qin and Oduyemi (2003) developed an approach using ISCST3 dispersion model to apportion missing PM_{10} emission sources, which were described in the EI, but could not be apportioned, by PMF receptor model. Loughlin et al. (2000) used Ozone Isopleth Plotting Package-Research (OZIPR) which is a trajectory box model and integrated into the genetic algorithm to represent ozone transport and chemistry in order to develop ozone control strategies. Kumar et al. (2004) used CALINE3 dispersion model to predict concentrations and applied a multiple regression model to estimate emission rates in traffic areas. The above studies (Qin and Oduyemi, 2003; Kumar et al., 2004; Laupsa et al., 2007) used PMF or FA-MR (Factor Analysis Multiple Regression) receptor model to complement the dispersion model at some point locations. Both PMF and FA-MR cannot fully account or apportion the amount of mass collected on filter paper.

The objective of the research is to first identify all the sources contributing to PM_{10} concentration using receptor modelling (as it does not require EI) and then improve the performance of dispersion modelling after updating the EI for sources identified by the receptor modelling. We have used state-of-the-art CMB (Chemical Mass Balance 8.2; USEPA, 2004) receptor model and American Meteorological Society/Environmental Protection Agency Regulatory Model (AERMOD, 2004) dispersion model having the ability to characterize the planetary boundary layer (PBL) through both surface and mixed layer scaling. This approach of identifying sources using receptor model, revising EI and improving dispersion modelling has been demonstrated for a town, Baddi – Nalagarh (30.94° N latitude, 76.78° E longitude) in the State of Himachal Pradesh, India (Fig. 1). The Baddi-Nalagarh (BN) area is the most industrialized region having a population of over 35,000. The types of industries include - pharmaceutical, textile, chemical, iron, cement, rubber, steel, spinning mills etc. The road condition in the town was quite bad as roads were broken, poorly maintained, had partially paved surfaces and this study identified these fugitive sources to be major contributor to PM_{10} concentration.

2. Methodology

Fig. 2 summarizes the stepwise methodology of this study.

2.1. GIS-based emission inventory

Various maps (roads, wards, etc) of BN were collected from different agencies (eg: Baddi Barotiwala Nalagarh Development Agency, BN Industrial map, Census of India, etc) and digitized using ArcGIS 9.2. World geodetic system (WGS) 1984 (UTM Zone 44 N) map projection system was used for digitization. These maps were used to extract desired information like city boundaries, air quality sampling locations and road lengths. All the digitized features were superimposed upon a layer of grid (1 km × 1 km; total 434 grid cells). Road lengths in each grid cell for minor (number of vehicles less than 10,000 per day) and major (number of vehicles more than 10,000 per day) roads were calculated.

2.1.1. Activity data

The broad classifications of sources are (a) industry point sources (stack height ≥20 m), (b) industry area sources (stack height <20 m), (c) line sources (vehicles), and (d) domestic sources (LPG (liquid petroleum gas), wood burning, kerosene). The details of industries (e.g. fuel uses, stack details, production etc) in all grids were collected from HPSPCB (Himachal Pradesh State Pollution Control Board, Shimla). To determine the fractions of various vehicle technology classes operating on city streets, video cameras were set up along the road side (at four locations) and traffic movement was recorded from 08:00–11:00 am and 5:00–8:00 pm. The traffic volume during lean hours was extrapolated from the collected traffic data. Parking lot survey procedure given in Singh et al. (2014) was adopted to determine fractions of various types of vehicles (e.g.: 2-wheelers, 3 wheelers, buses, trucks, year of manufacturing etc) operating in the region. Based on road length and the number of vehicles plying on roads, total vehicle kilometre travel (VKT) for each vehicle category was estimated in each grid cells.

For domestic sources, the fuel consumptions of LPG, wood, and kerosene were considered. The population per persons were estimated. Activity data (kg of fuel/person/day (for each fuel category); Census of India (2001)) multiplied by population in each panchayat provided the consumption of LPG, wood and kerosene. The category-wise domestic fuel consumption was assigned to each grid. Emission factors (CPCB, 2011b) for vehicles, domestic fuels, industrial productions and point sources were used to estimate PM_{10} emissions from each grid. The break-up of total estimated emissions of 2897 kg/d was as follows: (i) 1767 kg/d industry point sources, (ii) 107 kg/d industry area sources, (iii) 413 kg/d line sources (vehicles), and (iv) 610 kg/d domestic sources.

2.2. Air-quality monitoring and chemical analysis

Air-quality monitoring was undertaken at thirteen sampling sites (S1 to S13) (Fig. 1) to assess the air quality status and also for

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