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Developing high-resolution urban scale heavy-duty truck emission inventory using the data-driven truck activity model output

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HIGHLIGHTS

- Application of data-driven, spatial regression and output optimization truck model (SPARE-Truck model).
- The bottom-up approach is used to calculate link level emissions.
- Useful to prepare truck category specific high-resolution emission inventory.

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ABSTRACT

Air quality modelers often rely on regional travel demand models to estimate the vehicle activity data for emission models, however, most of the current travel demand models can only output reliable person travel activity rather than goods/service specific travel activity. This paper presents the successful application of data-driven, Spatial Regression and output optimization Truck model (SPARE-Truck) to develop truck-related activity inputs for the mobile emission model, and eventually to produce truck specific gridded emissions. To validate the proposed methodology, the Cincinnati metropolitan area in United States was selected as a case study site. From the results, it is found that the truck miles traveled predicted using traditional methods tend to underestimate — overall 32% less than proposed model— truck miles traveled. The coefficient of determination values for different truck types range between 0.82 and 0.97, except the motor homes which showed least model fit with 0.51. Consequently, the emission inventories calculated from the traditional methods were also underestimated i.e. −37% for NO_x, −35% for SO_2, -43% for VOC, −43% for BC, −47% for OC and - 49% for $PM_{2.5}$. Further, the proposed method also predicted within ~7% of the national emission inventory for all pollutants. The bottom-up gridding methodology used in this paper could allocate the emissions to grid cell where more truck activity is expected, and it is verified against regional land-use data. Most importantly, using proposed method it is easy to segregate gridded emission inventory by truck type, which is of particular interest for decision makers, since currently there is no reliable method to test different truck-category specific travel-demand management strategies for air pollution control.

1. Introduction

Urban-scale air quality models require on-road gridded emission inventories and these accurate vehicle type-specific, high-resolution emission inventories would be very critical for regulation and sensitivity analyses (Bastien et al., 2015; McDonald and McBride, 2014; Wang et al., 2009; Waygood et al., 2013). Developing the spatio-temporal, on-road emission inventory is a multistep, data and resource-intensive process as explained in Fig. 1. The process starts from the activity data estimation and collection of other relevant inputs for emission model, and then based on level of detail in activity data, proceeds towards selection of appropriate method of processing. Finally, the gridded, temporally allocated and speciated emission inventories are created after suitable factors are applied (Bai et al., 2007; Boriboonsomsin et al., 2011; Enrique and Allende, 2015; Ireson, 2004; Niemeier et al., 1999, 2004). As also shown in Fig. 1, there are two different methods to process gridded inventory i.e. the top-down approach and the bottom-up approach (D'Angiola et al., 2010; Enrique and Allende, 2015; Hatzopoulou and Miller, 2010; Hicks and Niemeier,

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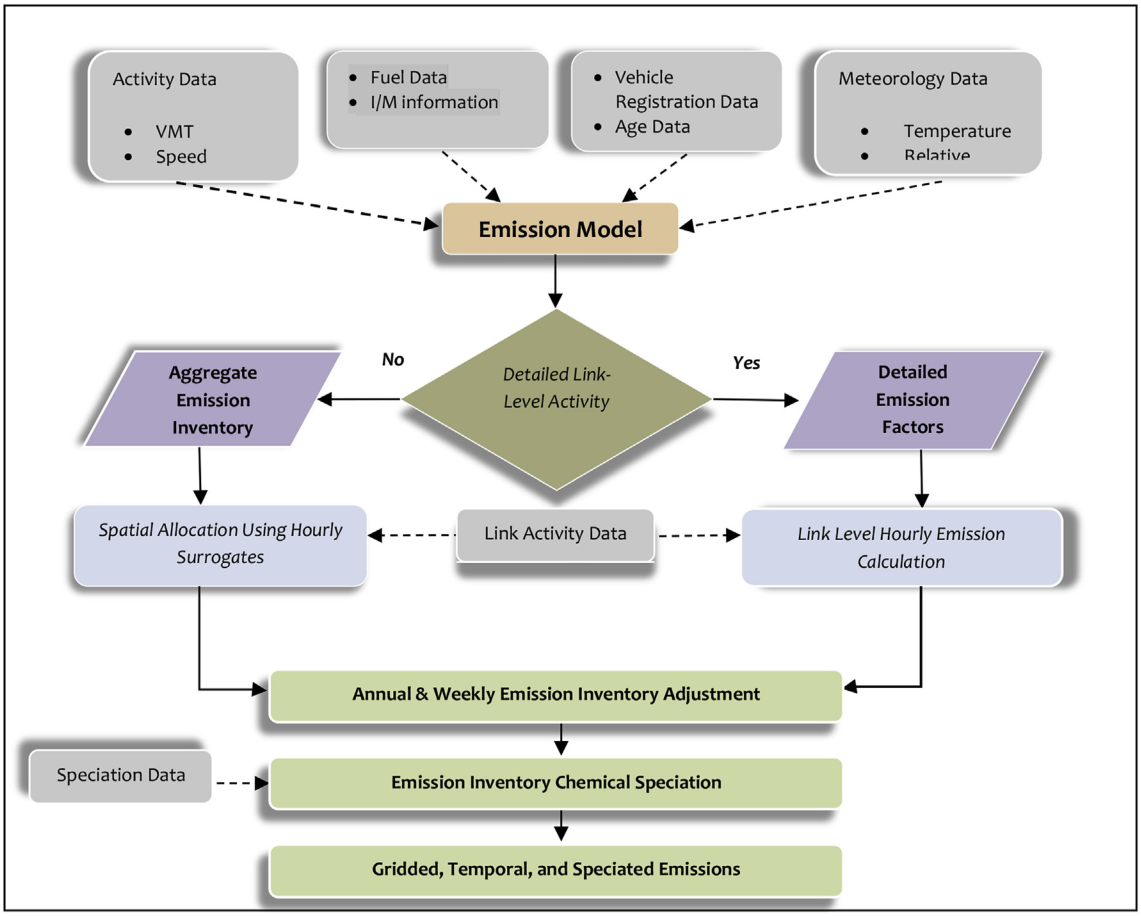

Fig. 1. Schematic diagram of gridded on-road emission inventory preparation process.

2001; Hou et al., 2015). A comparison between these two approaches showed that the bottom-up approach is more representative of reality compared to top-down approach, as later one uses spatial surrogates that may not be directly related to the emissions (Hatzopoulou and Miller, 2010; Hicks and Niemeier, 2001; Lindhjem et al., 2010; Niemeier et al., 1999, 2004; Puliafito et al., 2015; Sierra Research, 2007). Even though, the bottom-up approach requires very detailed activity data, it is often preferred for its accuracy (Brondfield et al., 2012; Cook et al., 2006; Sanna et al., 2014).

The heavy-duty trucks account for 60% of NOx and 40% of $PM_{2.5}$ emissions from mobile sources and their corresponding emission rates are tens of times higher than light duty vehicles (Milando et al., 2016; Vijayaraghavan et al., 2012). Accordingly, the accurate heavy-duty truck activity is very critical to estimate the heavy-duty truck emission inventory more precisely (Brown-Steiner et al., 2016; Kanaroglou and Buliung, 2008; Liu et al., 2014; Perugu et al., 2016; Sandhu et al., 2016; Sierra Research, 2007; U.S. EPA, 2012; Yoon et al., 2015). Air quality modelers often rely on regional travel demand models for the vehicle activity, however, most of the current travel demand models can output the person-travel activity more reliably rather than goods/service-travel activity for the emission models (Lin, 1998; Liu et al., 2014; U.S. EPA, 2012). In the current practice, modelers estimate the local truck activity fractioning the total vehicle activity obtained from the travel demand models. Developing truck activity at same reliability level as personal travel activity is very difficult task and it requires lot of survey data (Borrego et al., 2016; Di et al., 2016). For example, Kanaroglou and Buliung, 2008 had used large number of truck survey/other data samples to estimate the contribution of trucks urban emissions, unfortunately, those surveys are very expensive (Kanaroglou and Buliung, 2008). In United States, other data sources like Freight Analysis Framework (FAF) data are potential alternatives for truck demand estimation, however those may not be best suited for urban scale since their primary purpose of development is not air quality modeling. Further, it would be difficult to estimate different weight-based truck volumes for emission models from previously mentioned data sources (Cambridge Systematics, 2013; McDonald and McBride, 2014; Perugu et al., 2012).

The appropriate choice between top-down or bottom-up emission gridding methods is dependent on reliability of vehicle or truck activity data. For bottom-up approach, there are some readily available models like Direct Travel Impact Model, however, they need accurate, detailed, reliable activity data (Niemeier et al., 1999, 2004; Wang et al., 2009). To overcome this limitation, researchers recommended application of statistical models that are developed using observed count data (Hicks and Niemeier, 2001). For example, a multivariate multiple regression model was proposed by Liu et al. to predict traffic counts for on-road gridding (Liu et al., 2014). Nevertheless, application of statistical models alone is partially beneficial due to inherent problems associated with those models such as instability associated with regression etc. In addition to that, the truck-specific gridded emission inventory preparation using such statistical models can be unreliable as those models cannot distinguish among different truck types (Milando et al., 2016; Shah et al., 2006; Sierra Research, 2007). As a result, in order to prepare high-quality on-road gridded emission

Table 1
Truck classification used in current modeling approach.

Truck type	Description
Refuse Truck	Trucks primarily used to haul refuse to a central location.
Single Unit Short-haul Truck	Single unit trucks with more than four tires with a range of operation of up to 200 miles.
Single Unit Long-haul Truck	Single unit trucks with more than four tires with a range of operation of over 200 miles.
Motor Home	Trucks whose primary functional design is to provide sleeping quarters.
Combination Short-haul Truck	Combination tractor/trailer trucks with more than four tires with a range of operation of up to 200 miles.
Combination Long-haul Truck	Combination tractor/trailer trucks with more than four tires with a range of operation of over 200 miles.

inventory from trucks alone, the truck-type based activity models must be estimated empirically and should be coupled with traditional travel demand modeling techniques (Perugu et al., 2012).

Our main motivation for this research is, to develop a reliable methodology for preparing truck-related gridded emission inventory for photochemical models. To achieve this goal, we designed multiple research objectives in the process and which are: (a) Developing a model to predict daily truck volumes by different truck types (b) Estimating link level emissions and converting them into grid level emissions and (c) Evaluating the emissions model results. As mentioned earlier, to improve the reliability of truck activity, we have used bi-level modeling approach in terms of combining statistical model with traditional travel modeling approach. In the first level, the spatial regression estimates truck volumes using limited number of samples and then in the optimization level recalculates the output with the help of gravity model. We named this model as SPARE-Truck (**Spa**tial **Re**gression and Output Optimization **Truck**) model as the spatial regression output is optimized for better truck volume prediction (Perugu et al., 2016, 2012). In this research, we used following truck classification as shown in Table 1 this truck classification is very specific to the research's emission modeling needs as recommended by US-EPA (U.S. EPA, 2010). Since, US-EPA regards motor home as a type of truck, we followed the same definition.

This paper is organized as follows. The details of the proposed methodology including SPARE-Truck development, emission model and emission gridding process are described in the methods section. In the case study section, we have described the data details and application of series of models. The results and relevant analysis of results are presented in results section. The final section concludes the paper with impact of proposed model and future research direction.

2. Methods

Except CO other criteria pollutants like NO_x, $PM_{2.5}$, SO_2, VOC emission rates are very sensitive to truck activity, especially the truck miles traveled mix. Using the spatial panel regression methodology, we have proposed a model that can estimate the standard six types of truck daily volumes for all links in the modeling domain. The detailed specifications of spatial panel regression, optimization and assignment models are explained next in this section. As a next step, we adjust/optimize the truck travel demand calculated from earlier step as it improves the overall truck volume prediction. In this model, traffic data categorized by vehicle types is used as input. To calibrate and validate the overall truck volumes, an independent freight data source was used.

2.1. Two-step modeling approach for Spare-Truck model: regression model

The SPARE-Truck model was originally used in previous papers by same author, however, to bring completeness to the present paper it is briefly explained again (Perugu et al., 2012). Assuming that the specific type truck volume on a particular highway link $\boldsymbol{i}$ (1 to N) and for a year $\boldsymbol{t}$ (1 to T) is denoted by $\boldsymbol{y_{it}}$, it can be modeled using a set of independent variables $\boldsymbol{x_{it}}$ and the corresponding coefficients are given by β. It is also assumed that a spatial relationship exists among the variables. The spatial weighting matrix is denoted as $\mathbf{W}$, which has $\boldsymbol{N} \times \boldsymbol{N}$ dimensions and zero value diagonal elements. The spatial weights in spatial weight matrix are normalized and this matrix does not change over the time horizon. The spatial correlation among the data can be quantified by spatial autoregressive parameter ρ. The unobserved effect can be explained using the spatial weight matrix, spatial autoregressive factor, and unexplained observation specific error $\boldsymbol{\varepsilon}$. Thus, the spatial panel model for specific truck type can be represented by the following equation (Kapoor et al., 2007):

$$\boldsymbol{y_{it}} = \boldsymbol{x_{it}}\beta + \left[\boldsymbol{I_T} \otimes (\mathbf{I} - \rho\mathbf{W})^{-1}\right]\boldsymbol{\varepsilon_i} \tag{1}$$

where:

$\boldsymbol{y_{it}}$ = NT x 1 vector of observations on the time period t
$\boldsymbol{x_{it}}$ = NT x K matrix of observation on K exogenous variables.
β = NT x K matrix of coefficients
$\boldsymbol{I_T}$ = Identity matrix of size T x T
$\otimes$ = tensor multiplication operator (used in the context of vector multiplication)
$\mathbf{I}$ = Identity matrix of size $\boldsymbol{N\ x\ N}$
$\mathbf{W}$ = spatial weight matrix of size $\boldsymbol{N\ x\ N}$
ρ = spatial autocorrelation
$\boldsymbol{\varepsilon_i}$ = NT x 1 vector of unexplained observation specific error for $\boldsymbol{i}$

To estimate the parameter for the panel model, most of the previous studies used Pooled Ordinary Least Square (OLS) estimation. However, the observation-specific error induces correlation across the composite error of panel. Consequently, the Feasible Generalized Least Squares (FGLS) estimation is preferred over Ordinary Least Square (OLS) estimation. The FGLS estimation is computationally simple and much more reliable compared with OLS estimation (Kapoor et al., 2007).

2.2. Two-step modeling approach in Spare-Truck model: output optimization

Application of spatial panel model can yield link-based truck volumes by truck type. However, the volumes are insensitive to travel demand. To predict optimized truck volumes, the model needs to be calibrated thus the O-D matrices need to be estimated based on link volumes. The truck O-D matrices need to be calibrated using other independent data. We have used the derived demand optimization model to estimate truck travel demand $\boldsymbol{T_{jk}}$ between TAZs $\boldsymbol{j}$ and $\boldsymbol{k}$ (Citi Labs Inc., 2010). This model is popular in traditional travel demand modeling, and it is expressed by following equation:

$$T_{jk} = a_j\, b_k\, c_{jk}^{\alpha}\, e^{-\beta c_{jk}} \prod_L V_L \tag{2}$$

where:

a_j, b_k = Model parameters that depend on productions at TAZ j and attractions at TAZ k
c_{jk} = cost function between TAZs j and k
α, β = Generalized cost function parameters between TAZs i and j
V = estimated truck traffic volume
L = number of highway links between TAZs i and j
$\prod_L V_L$ = the product of all estimated link truck traffic volumes between TAZs i and j

In the next step, the optimized/adjusted truck matrices are re-assigned to the links using multi-class user equilibrium assignment method. Finally, the SPARE-Truck model is validated using the latest vehicle classified traffic data. To verify the reliability of results from proposed SPARE-Truck model and also evaluate the impact of new derived truck activity on truck related emissions we have carried out a case study.

2.3. Emission model

Theoretically, the truck model output could be used in any emission model as the most important inputs for emission model like speed, truck miles traveled and activity mix was outputted from the model. However, in this we chose US-EPA's MOVES model for emission estimation in this study. In United States, it is mandatory for all regional agencies outside California to use MOVES as traffic emission model for their state implementation plan and regional transportation conformity purposes (U.S. EPA, 2010). US-EPA developed this model based on "modal emission rates" approach and it uses vehicle specific power data to match those rates.

US-EPA also recommended the use of local activity related inputs for emission analysis (U.S. EPA, 2010). Applying MOVES emission rates to link-level activity data required a substantial revision to the emissions analysis approach previously used in its processor model, MOBILE, because of the new requirements and features of MOVES. For the bottom-up emission process, the emission rate mode is the most suitable format and we can look up the corresponding emission rates for each type truck activity. MOVES model generates three separate lookup tables namely "RatePerDistance," "RatePerVehicle," and "RatePerProfile." They collectively contain all the emission factors required for bottom-up link-level emission estimation process (U.S. EPA, 2010).

We apply the SPARE-Truck model to obtain the input data at required level of detail for the MOVES model. The emission rates are specific to process, road type, vehicle type, link type, average speed bin and temperature (Lindhjem et al., 2010; U.S. EPA, 2010). In addition to rates per distance (consists of running emissions), rate per vehicle (start and idling emissions) and rates per profile (consists of evaporative emissions) are also obtained from the MOVES model runs (U.S. EPA, 2010).

2.4. Emissions gridding process

Gridding is usually cumbersome as link based emissions are converted into square shaped grid cells, which involves geometric processing as link sizes may not match with grid cell size and matching activity with emission rate detail level. As the truck activity is already disaggregated to link and hour specific, the bottom-up type spatial-temporal processing of running emissions is straightforward. The links have been geo-processed such that the longer links are divided into smaller links to fit within the cell boundaries. Through this process, we have ensured that emissions are allocated where they belong. Since we have already summed up the running and start emissions at link level, another extra step of allocating starting emissions to the grid cells were not performed. The day of month and day of week factors should be applied after gridding process to get day specific gridded inventory.

2.4.1. Link level running emissions

The link-level total daily emissions are calculated using the link truck miles traveled (TMT) and corresponding emissions rates for hourly temperatures t and relative humidity h.

$$re_{vij} = TMT_{vijs}\ x\ rd_{vjsrht} \tag{3}$$

where,

re_{vij} = link level running emission in grams for truck type v, for link i and for hour j
rd_{vsjrth} = running emission rate for truck type v, for hourly speed s, for hour j, for road type r, for temperature t and for relative humidity h
TMT_{vijs} = The truck miles traveled of v type on link i during hour j with average hourly speed of s, estimated using proposed models.

2.4.2. Link level non-running emissions

Usually, non-running emissions are treated as point sources; however, this assumption complicates spatial-temporal emission processing. In this research, an alternative method was proposed to allocate start and idling emissions to links, which is re-distributing traffic analysis zone level start, idling and brake/tire wear emissions to links TMT surrogates. Since, link-level emissions include both running and non-running emissions and they are non-running emissions are assigned to surrounding links, these are more accurate compared to other methodology that allocate non-running emissions to traffic analysis zone centroids.

$$se_{vij} = \frac{TMT_{tij}}{TMT_{tj}}\left(S_j + E_j\right) \tag{4}$$

where,

se_{vij} = Non running emission inventory for link i at hour j
TMT_{vij} = vehicle miles traveled by truck type t on link i during hour j
TMT_{vj} = vehicle miles traveled by truck type t in the traffic analysis zone (TAZ) during hour j
S_j = Total start and idling emission inventory in the traffic analysis zone (TAZ) during hour j
E_j = Total brake wear and tire wear emission inventory in the traffic analysis zone (TAZ) during hour j . This quantity is zero for pollutants other than $PM_{2.5}$

To get the total link level $PM_{2.5}$ emissions e_{ij}, we add link level running and non-running emissions

$$e_{ij} = \sum_v re_{vij} + \sum_v se_{vij} \tag{5}$$

The proposed workaround not only saves the air quality model run time but also simplifies the mobile spatial temporal processing. Generally, in photochemical models the speciated criteria pollutants (i.e. NOx, SO_x, $PM_{2.5}$ and Volatile Organic Compounds) are used as input, so, in the present study we have also developed the truck related gridded inventory for criteria pollutants. According to US-EPA's NEI data, heavy-duty trucks contribute 60% of on-road NOx and PM2.5 emissions, heavy-duty diesel trucks contribute 75% SO_2 emissions (U.S. EPA, 2012). Even though, major portion of VOCs are not from tail-pipe exhaust, long idling activity causes significant emissions. The steps in developing gridded emission inventory and the detailed analysis of gridded emission inventory follows.

Multiple issues such as selecting optimum grid cell size, handling of the highway links those are curved and extended beyond the grid cell boundaries pose challenges to modelers. In this paper, all those issues were properly addressed to create the ground-truth gridded emission inventory. For country-level modeling, US-EPA uses 12kmx12 km cell size whereas for state-level modeling domain, California Air Resources Board uses 4 km × 4 km grid cell size (Sierra Research, 2007). For the regional level, it is very common to use 1 km × 1 km cell size. However, finer than 1 km grid cell size poses lot of problems in terms processing and modeling. Further, it would be ideal to have Traffic Analysis Zones (TAZ) and grid cells a comparable size for easier grid processing.

To convert link-level emissions to gridded format and also to take care earlier mentioned geometrical issues associated with gridding process, a geo-processing script has to be developed solely for this step. Using the script, the longer links are divided into smaller links to fit within the cell boundaries and at the same time the links' actual geometric lengths are recalculated. Through this process, modelers can ensure that emissions are allocated where they actually belong. Since the running and start emissions were already summed up at link level, no extra step of allocating starting emissions to the grid cells was performed. To obtain different day-specific emission inventories in the modeling time period, the day-of- week factors must be applied after gridding process.

3. Case study

3.1. Data description

To validate proposed methodology, we have applied SPARE-Truck and emission models to Cincinnati, one of major urban areas in United States. The Ohio-Kentucky-Indiana Regional Council (OKI) maintains comprehensive traffic count geo-databases for Cincinnati area for the purpose of travel-demand validation and supplying input to the Highway Performance Monitoring System. The Average Annual Daily Traffic (AADT) data in the geo-database was generated for Greater Cincinnati area using a combination of Automatic Traffic Recorder (ATR) station traffic data and the short period traffic counts. The data is classified according to Federal Highway Administration's (FHWA) 13-vehicle classes at hourly time resolution. Since the short period traffic counts are typically collected during only a single week (Monday–Thursday), the AADT values are factored through applying day-of-week, month-of-year, and other factors, developed by state department of transportation. Following Fig. 2 shows the spatial coverage of traffic counts. The rectangle designates modeling domain and the traffic data samples within the domain are used in this study.

In the current study, we have used only the traffic count data between the years 2004–2009. Moreover, not every counting site offers a complete panel of estimated AADT values for the specified time period. Even though large data sample is available, only 900 randomly selected counts are used in the analysis to test whether proposed model can reliably predict truck activity with such a limited number of counts. Socio-economic data, land-use data, and highway network data are part of different databases and, for model-estimation purposes; all these databases were geo-processed. Table 5 (annexure) provides the descriptive statistics of these traffic counts over different years, and these data are the basis for the spatial regression modeling pursued in the present study, as described in the following sections.

As mentioned earlier, to model the emission model ready truck activity, we need to process the FHWA type vehicle classifications into US-EPA's MOVES truck classification. Unfortunately, until now, we have not found relevant literature to convert FHWA classes into MOVES types. To work around this, we have used FHWA versus MOBILE and MOBILE versus MOVES crosswalk tables to come up with a crosswalk between FHWA and MOVES classifications (Perugu et al., 2012). Although both the classifications are axle based, there is no direct corresponding truck type for US-EPA's motor home type trucks in the FHWA classification. For this purpose, we have developed a corresponding fraction using MOVES default data.

After processing the traffic data, it was observed that the automobile fractional split is highest, followed by the fraction of pickups and vans. The average regional percentage of trucks is between 3 and 5 percent. However, at an individual link level, the truck percentage is as high as 26.3 percent. The percentage of observations for which the fractional mix of trucks, buses, and motorcycles is at or very close to the boundary value of zero is rather high. In particular, the truck fraction is less than 0.01 for 33 percent of observations. The single unit and combination short-haul trucks are the most prevalent truck types in the region and comprise about 60 percent of total trucks found on the highways in a day. Motor homes are the least prevalent trucks in the region and they comprise of only 2 percent of total trucks on highways.

The demographic information is developed from Public Use Micro Data Sample database and land-use data collected from different counties. As part of travel demand model maintenance, the metropolitan planning organization, OKI, also collects latest roadway attribute data. Following is the final list of predictor variables used in the spatial regression modeling with their designation name in the database in parentheses. All of the predictor variables are selected based on travel demand modeling theory and the OKI travel demand model guidelines (Ortúzar and Willumsen, 2011; Tsai, 2010).

3.1.1. Population (POPDEN)

In this study PUMS and American Community Survey data are used for population data and the data is aggregated to traffic analysis zone (TAZ) level to facilitate the trip generation in the travel demand modeling practice. During covariance analysis, we observed that the correlation between population and other important variables like employment is significant whereas the population density and employment density variables are independent. Thus, we have chosen population density as a predictor variable. The TAZ-level employment density is geo-processed so that those are joined to link-specific traffic counts.

3.1.2. Employment (EMPDEN)

Similar to population density, employment is a critical demographic variable which is directly proportional to total trips in a TAZ. The employment data also extracted from ACS and PUMS data; it is projected for future years based past trends. The population and employment in a TAZ are auto correlated, thus, we have chosen employment density as predictor variable. Further, from other regression based truck models it is evident that employment in a zone is positively correlated to the truck inflow and out flows of the zones.

3.1.3. Accessibility (ACCS)

Some of the earlier truck regression models used TAZ

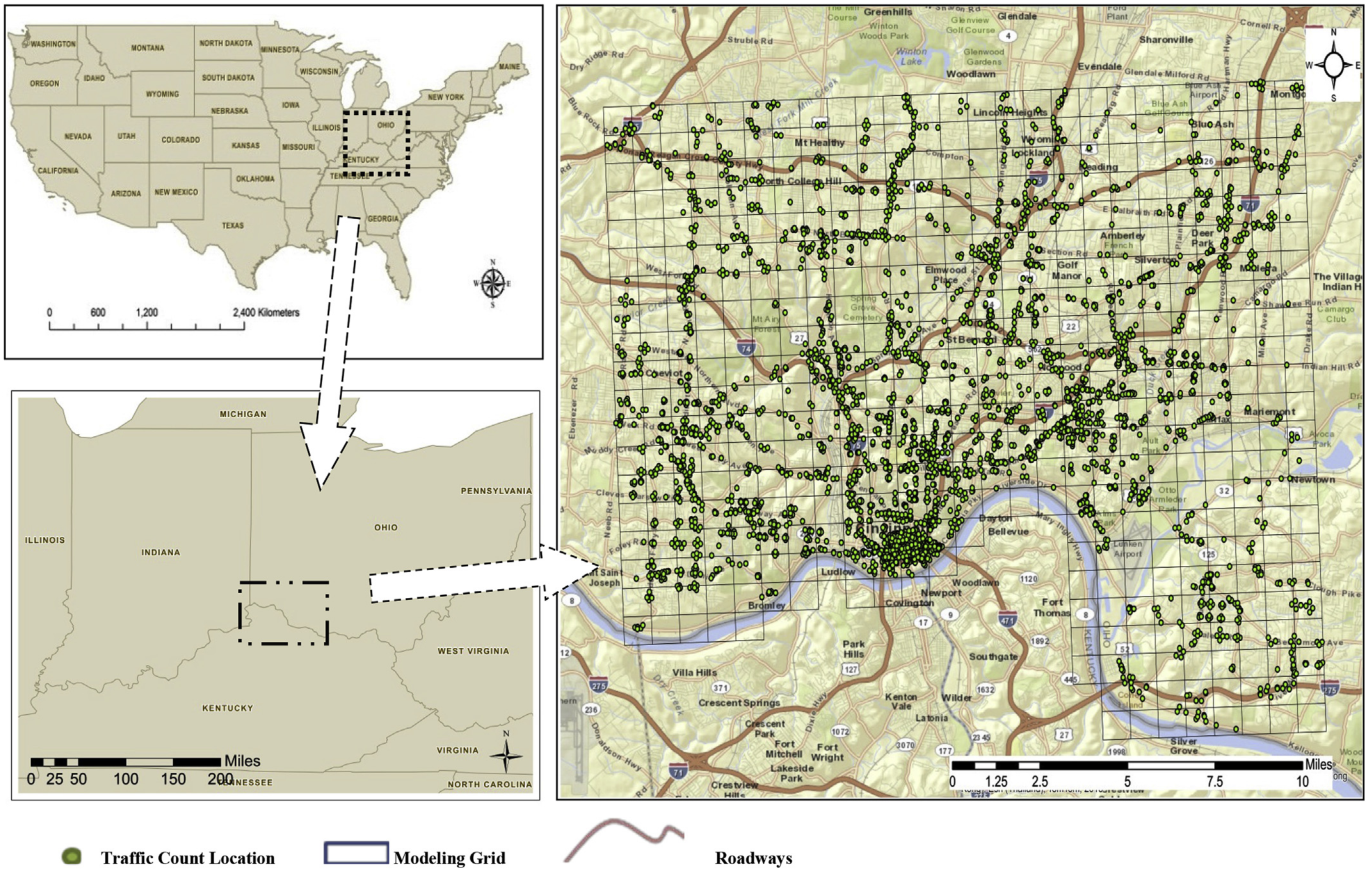

Fig. 2. Location of the case study area Cincinnati, modeling domain and the traffic count data locations used in the case study.

accessibility as a predictor variable. However, they have used nominal values for these variables. In this research, we have calculated accessibility of zone using TAZ area and total highway network length in the zone. To estimate this variable, the data from two different geo-databases were used. The first one is demographic geo-database, which provided the TAZ/zonal area, and second one is highway network geo-database, which provided highway link length in the corresponding TAZ.

3.1.4. Speed (SPD)

The posted speed limits or free flow speeds on links used for the regression modeling are extracted from the highway network geo-database. It has been observed from initial analysis that trucks use the highway facilities that have higher posted speed limits. Typically, posted speed limits in the region range between 15 mph and 70 mph. Forty percent of the total links have posted speed limits less than 35 mph At least 25 percent of links have coded speeds greater than or equal to 55 mph.

3.1.5. Capacity (CAP)

From a traffic engineering point of view, it is anticipated that trucks may be using the highway facilities with higher capacities. During covariance analysis, we also observed that there is no auto correlation between speed and capacity. This information is also

Table 2
Results from spatial regression step in SPARE-Truck model.

Variable	Truck types					
	Refuse trucks	Motor homes	Single unit short-haul trucks	Single unit long-haul trucks	Combination short-haul trucks	Combination long-haul trucks
CONSTANT	3.71e + 01	1.14e + 01	−9.10e + 01	−2.28e + 01	2.97e + 02	−1.01e + 00
LANES	6.75e + 01	7.47e + 00	1.00e + 02	5.23e + 01	6.71e + 01	3.51e + 01
CAP	1.73e − 01	1.25e − 02	6.19e − 01	8.45e − 02	4.61e − 01	3.43e − 02
SPD	−2.88e + 00	1.91e − 01	−4.11e − 01	1.38e + 00	−1.47e + 00	4.04e − 01
EMPDEN	1.95e − 04	−5.07e − 05	−1.70e − 03	−5.37e − 04	−8.80e − 04	−2.91e − 04
POPDEN	8.87e − 03	−1.19e − 03	−2.64e − 02	−5.16e − 03	−2.07e − 02	−4.28e − 03
ACCS	6.70e + 04	6.97e + 03	1.48e + 05	1.54e + 04	−1.61e + 05	3.03e + 04
RMSE	1.74	1.78	1.78	1.83	1.74	1.77
Rho	0.608	0.494	0.556	0.603	0.312	0.431
Time-specific variance	1.03e + 05	5.94e + 02	2.99e + 05	1.60e + 04	1.26e + 06	9.95e + 03
Observation-specific variance	1.47e + 05	2.49e + 03	8.00e + 05	6.66e + 04	2.61e + 06	4.23e + 04

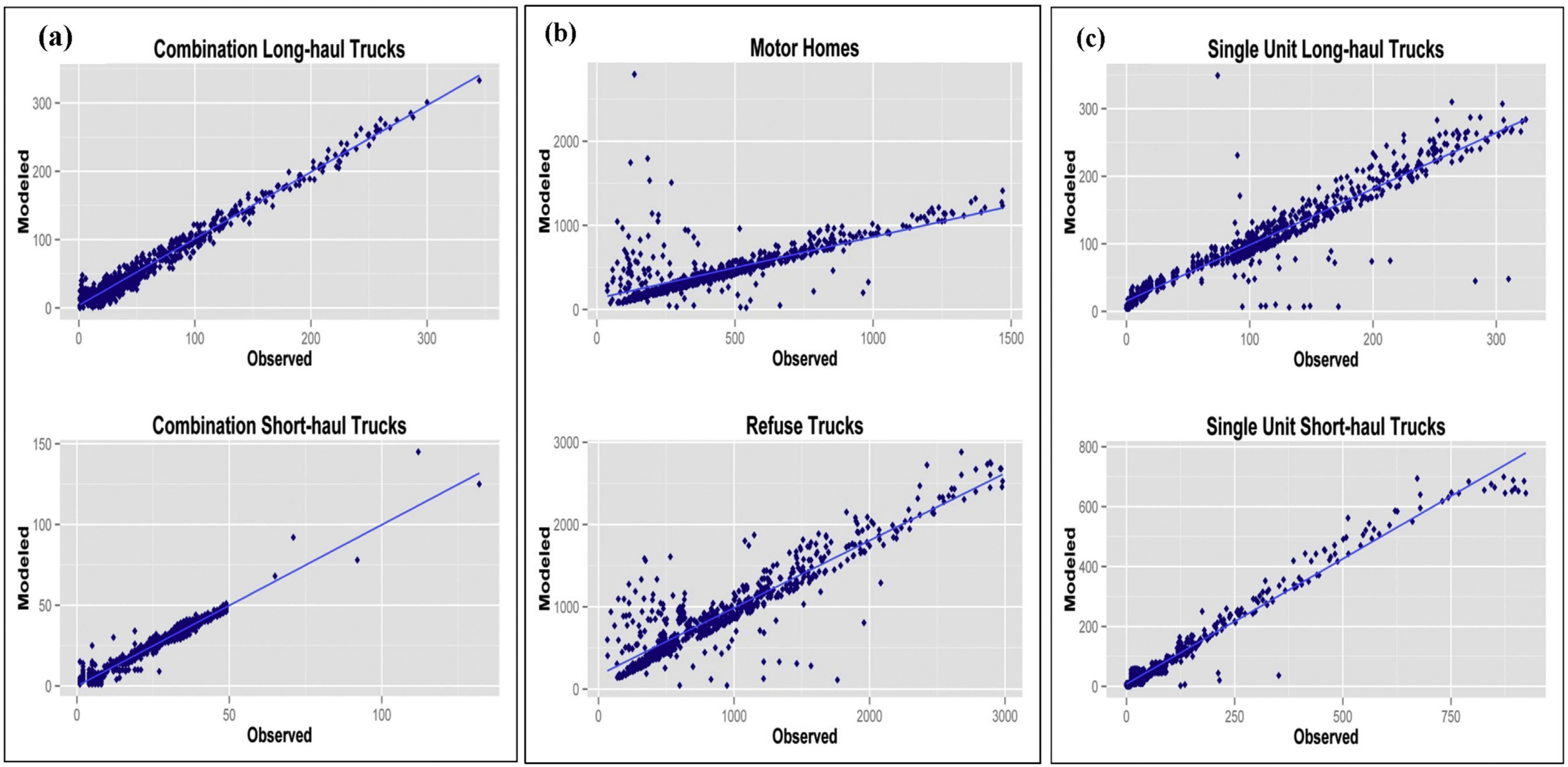

Fig. 3. Scatter plots with trend line of different truck types modeled in the current research (a) Combination Long-haul and Short-haul Trucks (b) Motor Homes and Refuse Trucks (c) Single Unit Long-haul and Short-haul Trucks.

obtained from the highway network geo-database. Link capacity is estimated based on various factors like area type, facility type, control type, lane width, etc. The capacity values for links range between 480 and 2000.

3.1.6. Number of lanes (LANES)

Intuitively, trucks need more room for better maneuverability thus the link physical attributes like the numbers of lanes are important determinants of truck volumes on the link. The highway network database also contains the link's number of lanes data. The link information is by direction. A majority of links (54.6 percent) in the sample have two lanes; 10.2 percent of links have one lane; 24.2 percent have three lanes; and 11 percent have four lanes.

4. Results and discussion

4.1. Spatial regression results

In the first level SPARE-Truck model, six different spatial panel models were developed for six truck types using different predictor variables mentioned above. Table 2 summarizes the model estimates for all truck types. The model parameters were estimated using Stata® software through a user-developed program (Prucha, 2007). We have observed that there is strong dependency among covariates as the spatial auto-correlation parameter ranges 0.312–0.608, however due to application of FGLS method such auto-correlation is removed, thus, the model is better fitted. The present analysis also showed that the proposed FGLS estimation procedure is much better than the standard OLS estimation procedure as the latter showed lower Root Mean Square Errors (Kapoor et al., 2007). Even though, some predictor variables like "speed" and "capacity" suggest correlation, actually, they are not; as the "speed" used in this study is posted speed limit which is based on functional class of roadway, so, it may not be directly dependent on highway capacity. The table also enumerates observation-specific and time-specific variances ($\sigma_1{}^2, \sigma_v{}^2$) for different models. From the comparison of observation-specific variances ($\sigma_1{}^2$) with time-specific variances ($\sigma_v{}^2$) of different truck models, it can be concluded that these models are adjusted for time-related fixed effects as time-specific variances are quantitatively less. This adjustment would imply the model's robustness in time horizon, thus, the models are reliable for future year predictions. As discussed in methodology — to minimize if any kind of endogenous unreliability exists — the second step of optimization used.

As part of the optimization step, the model parameters are calibrated using independent data from TRANSEARCH database, which contains county-level freight flow data. Another useful feature of this database is that it also includes empty truck trips. The calibration step is an iterative procedure that starts with model parameter values of 1 and continues until the difference between consecutive demand matrices is less than a specified value of 0.1. We have used Cube Analyst® for the demand matrix estimation. We have derived six different O-D matrices based on truck types for Cincinnati area. These O-D matrices are assigned to the highway links based on multiclass equilibrium assignment (Citi Labs Inc, 2010). In this assignment procedure, it is imperative that auto trips were also used as a separate matrix.

4.2. SPARE-Truck model validation results

To validate the proposed SPARE-Truck model, we have compared the model estimated truck volumes with the traffic count data collected for the year 2010. The United States National Co-operative Highway Research Program Report No. 255 recommends comparing individual link-level assigned truck volumes to observed counts for highway assignment validation (Highway Traffic Data for Urbanized Area Project Planning and Design, 1982). This step checks the assigned volume and the corresponding traffic count's disparity for each individual link by magnitude of volume. As part of this validation step six different scatter plots for all six types of trucks were plotted as shown in Fig. 3. The modeled truck volumes are pretty well correlated with observed truck counts. However, the link-level motor home volumes are much higher compared to the number of registered motor homes in the region. This may be because of most of these vehicles pass through the region. On the contrary, the combination long-haul trucks registered in the county are much higher than average link volumes and may be due their pattern of traveling to external destinations. The comparison for different truck types shows that the model performs at a satisfactory level and all the points are falling near the trend line. The motor homes that are fewer than 250 vehicles/day are mostly under predicted with an error of 10–15 percent by the model. After threshold 250 vehicles/day, the model performed very well and consistently. We assume this discrepancy due to inconsistent conversion from FHWA class to MOVES class, however, as of now there is no proper lookup between these two types. In the case of refuse trucks, the model is consistent between 300 and 1100 values. For smaller and larger volumes, the model is pretty inconsistent. The reason for this discrepancy may be the schedule of refuse trucks, which is not taken into account in the model. Overall, the truck miles traveled, for all of the truck types except combined long-haul trucks, in the base case has been under estimated (overall 32% less than traditional model) since our new truck miles traveled mix actually matches with observed traffic counts in comparison.

The single unit long-haul trucks were predicted accurately enough by the model as the values were scattered along the trend line and as well as prediction for single unit short-haul trucks. The observed combination short-haul trucks are mostly null values for minor arterials and local streets. If we ignore zero volumes, both types of combination trucks were predicted reasonably well from the model. Based on the "Model Validation and Reasonableness Checking Manual," the data points on the regression plots should be close to the 45° line and the R^2 should be greater than 0.8. Except for motor-home- type trucks, for all other truck types the data points were close to 45° line. We have also verified the R^2 values for all types of trucks as shown in Table 3. As previously mentioned, the motor homes have the least fit and their corresponding R^2 value is 0.5103 and t-statistic is 28.475. The regression statistics showed that the model is somewhat unstable. For the rest of the models, the coefficient of determination values range between 0.82 and 0.97, which are well above the FHWA and Ohio Department of Transportation (ODOT) standards. Again, the motor homes model has the highest standard error in predicted values when compared to other models.

Highway Performance Monitoring Systems (HPMS) is a federal data management system where they collect traffic data for major highways in the nation. To get the perspective of the predicted truck volumes, we have compared them against HPMS data as shown in Fig. 4a. From the plots, it is clearly evident that the

Table 3
SPARE-Truck model validation results.

Model	R square	t-value	Standard error
Refuse Trucks	0.8197	59.46	0.01685
Single Unit Short-Haul	0.9665	149.93	0.00771
Single Unit Long-Haul	0.8732	73.19	0.01438
Motor Homes	0.5103	28.47	0.02493
Combination Unit Short-Haul	0.9281	119.31	0.008075
Combined Unit Long-Haul	0.9718	163.1	0.005938

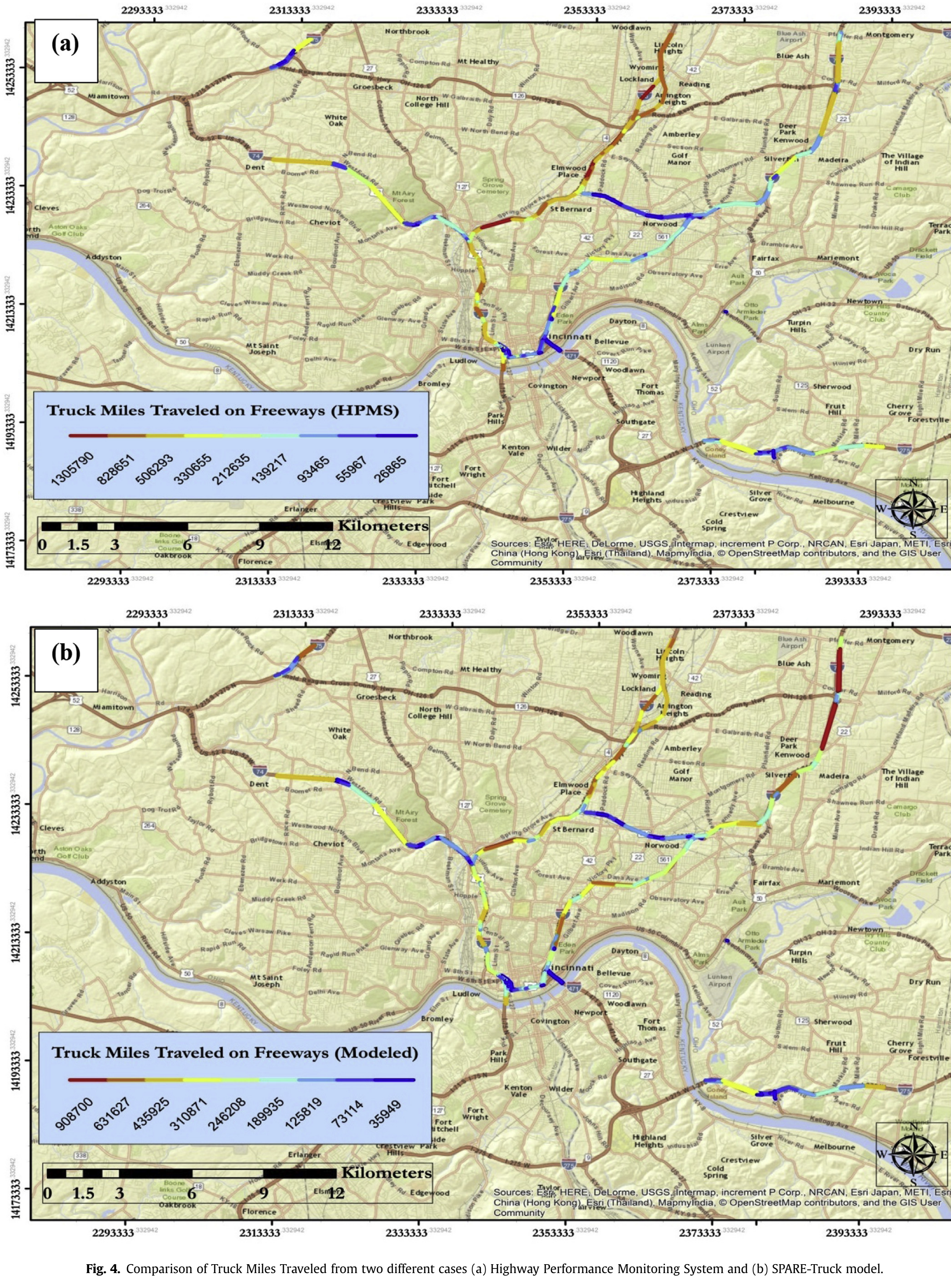

Fig. 4. Comparison of Truck Miles Traveled from two different cases (a) Highway Performance Monitoring System and (b) SPARE-Truck model.

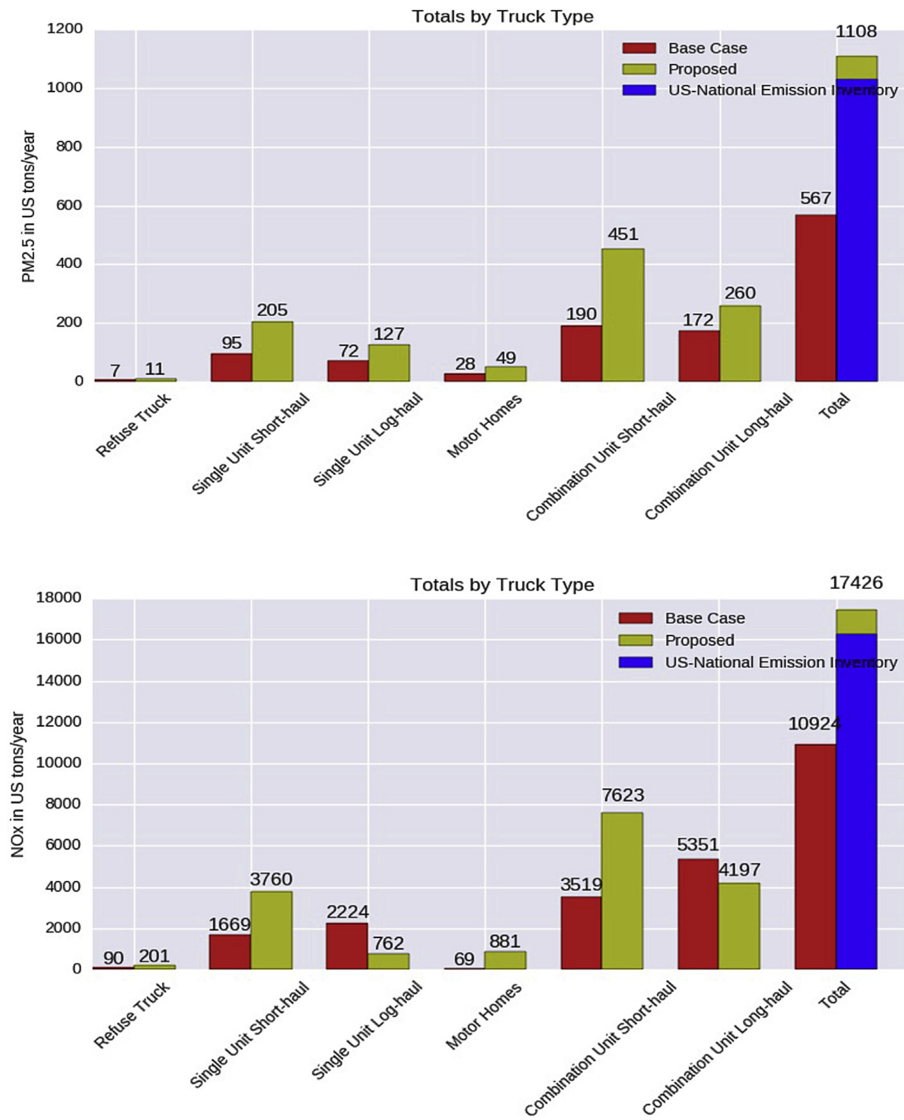

Fig. 5. Regional Heavy Duty Truck $PM_{2.5}$ and NO_x emission totals from two different sets of truck activity inputs compared with US-EPA's National Emission Inventory data.

Table 4
Emission model inputs and how they were obtained.

Inputs	Details
Daily Truck Miles Traveled	The activity is obtained from SPARE-Truck model which takes traffic counts, socio-economic data and highway network data as inputs
Speed Distribution	Using the SPARE-Truck we have obtained average link-level truck speeds which are processed and then aggregated into 13 different speed bins.
Road type distribution	Using the SPARE-Truck model truck miles traveled and corresponding road type information, the road type distribution is developed.
Fuel Mix/Fuel Usage	The Ohio State Environmental Protection Agency has provided us the county specific fuel mix information
Truck Age Distribution	We have obtained Vehicle Identification Number data with year and make information from Ohio Department of Motor Vehicles. The data is processed to make age distribution factors for all six types of trucks.
Temperature/Relative Humidity	The meteorology data collected at Lunken Airport in Cincinnati is obtained from airport authorities.

proposed method predicted more truck movement along Interstate 75 which is similar to HPMS data that represents reality (see Fig. 4b).

As part of this case study, we have analyzed emission output at different levels and compared with the output at same level of details produced using the local default output. The details of emission results are discussed in next part of this section (see Fig. 5).

4.3. Emission model results

To generate emission rates for the modeling domain, the US-EPA MOVES model was used. The model requires lot of different input data. The detail description of each input data items and how it was generated/processed was explained in the following Table 4. As mentioned in the methodology section, emission quantities are

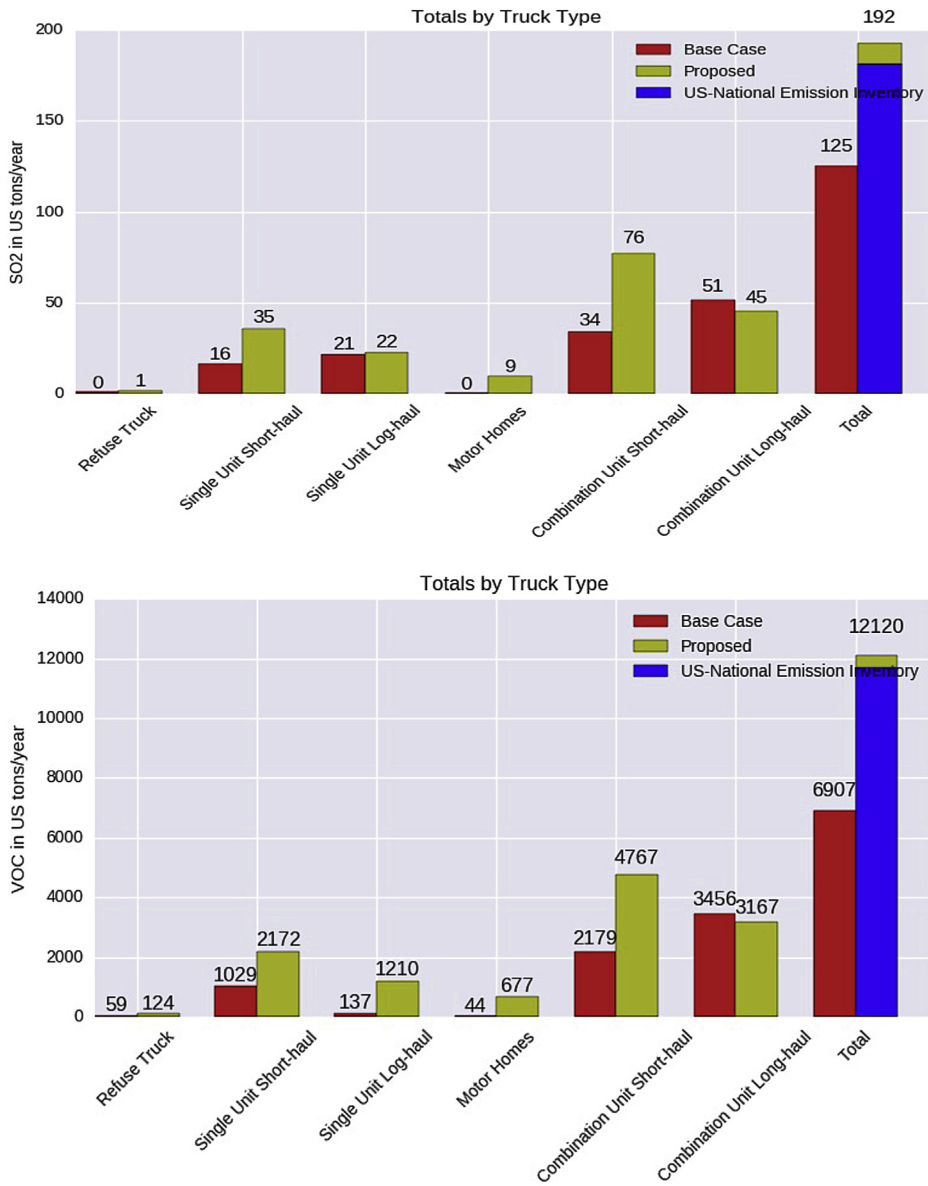

Fig. 6. Regional Heavy Duty Truck SO_2 and VOC emission totals from two different sets of truck activity inputs compared with US-EPA's National Emission Inventory data.

obtained using emission rates and corresponding emission activity.

Even though, applying corresponding emission rates to activity data is straightforward it requires a little bit of care since the emission rates are by bins. The individual link activity cannot be directly related to that bin as it has range and for more accurate emission estimation, we need to perform appropriate interpolation as rates applied. For example, to calculate the total emissions from 100 truck miles/hr. with an average speed of 37 mph, a simplistic approach would be to multiply all of the activity (i.e. 100 truck miles) with the emission rate for speed bin 7 (32.5 mph–37.5 mph). However, this approach is too sensitive to even small changes in speed. To reduce these boundary issues, instead interpolate emission rates between speed bins (in this example, between the rates for speed bin 7 (32.5 mph–37.5 mph) and speed bin 8 (37.5 mph–42.5 mph)). After the link level emissions are calculated, we have aggregated the entire link-level $PM_{2.5}$ running and non-running emission inventories for the whole study area using a set of MySQL queries. Figs. 6–8 contains the daily aggregated emission quantities generated using the default inputs used in the regional transportation conformity analysis and the new input data prepared using proposed models in the MOVES model; the table also shows US-EPA's National Emission Inventory (NEI) totals for the region. Overall, the emission quantities estimated for those truck types were also under estimated and the annual total discrepancies as following: 37% for NOx, 35% for SO_2, 43% for VOC, −43% for BC, −47% for OC and 49% for $PM_{2.5}$. Further, the proposed method also predicted within ~7% of national emission inventory for all pollutants.

Using different truck volumes estimated from SPARE-Truck model and link lengths, we were able to calculate truck VMT mix for each link in the modeling domain. Typically, the current emission models also need hourly distribution factors as separate input since they use them for diurnal vehicle activity disaggregation and adjusting proportions of vehicle starts during a typical day for emission rate calculation. We have estimated emission inventory for the modeling domain keeping all auto and transit-related activity inputs the same and using newly developed truck activity input in the MOVES model. Application of default input has yielded fewer daily emission totals for most source use types, since the

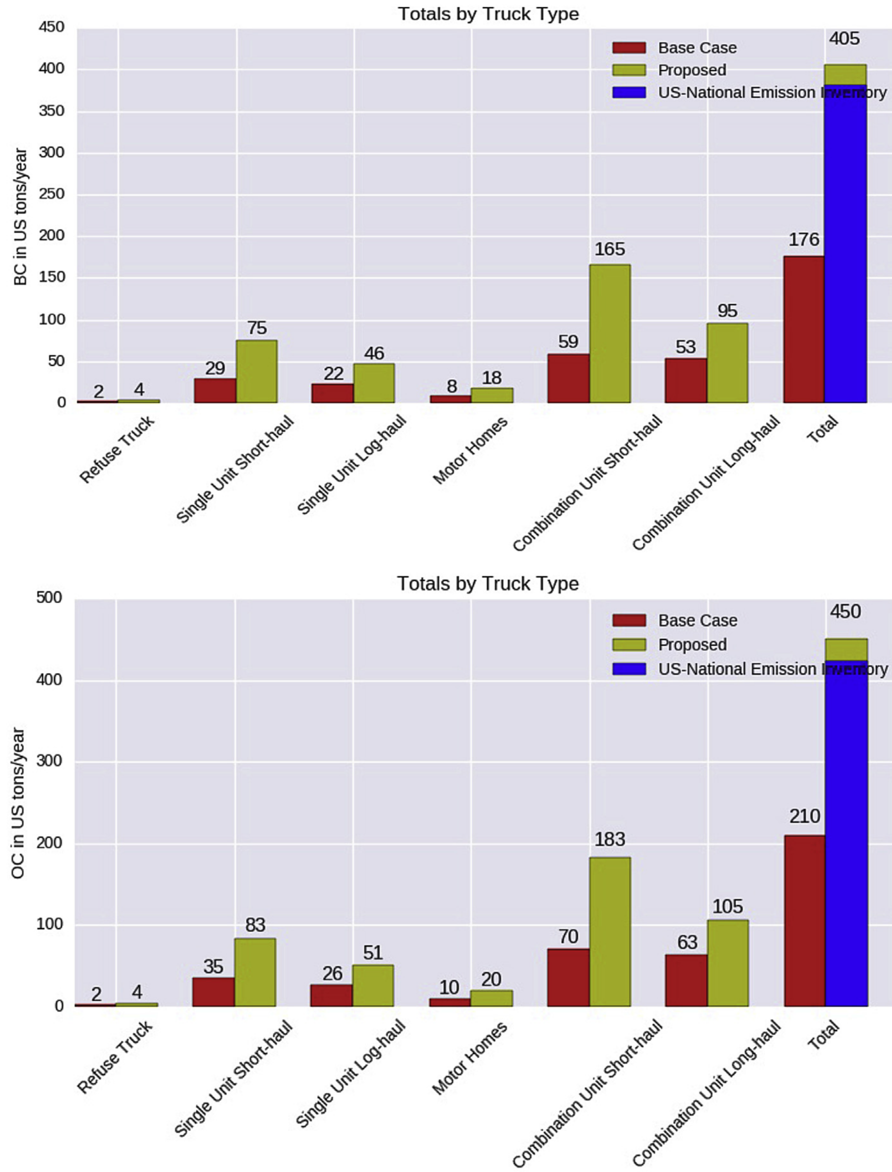

Fig. 7. Regional Heavy Duty Truck BC and OC emission totals from two different sets of truck activity inputs compared with US-EPA's National Emission Inventory data.

default truck VMT was also smaller. However, the emissions from combined long-haul trucks were estimated lower than default results and this is due to corresponding less activity.

Generally, preparing gridded emissions from link level emissions is cumbersome process as links cross grid cell boundaries and they need to be summarized. For this purpose, a geo-processing script is developed which would calculate spatial and temporal $PM_{2.5}$ emission inventory for photochemical modeling. The link-level emissions need to be summarized based on grid cell size, and care should be taken about the links that extend beyond the cell boundaries. We have geo-processed the links such that the longer links are divided into smaller links to fit within the cell boundaries. Through this process, we have ensured that emissions are allocated where they belong. Since the running and start emissions are summed up at link level already, we did not perform another extra step of allocating starting emissions to the grid cells. To process day specific gridded inventory, the day of month and day of week factors were applied after gridding process. Until now as part of the case study, the SPARE-Truck and US-EPA's MOVES model were applied sequentially to estimate link-level emissions, however, processing grid-level emission process is the last and most important step in on-road emission processing.

In the Cincinnati region, 85 percent of TAZs are about same area as 1 km $\times$ 1 km grid cell. Therefore, the 1 $\times$ 1 km grid cells are reasonable in terms of resolution, and, accordingly, emissions at this grid level are generated. In summary, the modeling domain is divided into 575 (=25 $\times$ 23) grid cells at a 1 km $\times$ 1 km resolution, in the Universal Transverse Mercator (UTM) coordinate system. The UTM coordinates of southwest corner of modeling domain, i.e. domain origin are 185,825 m east and 432,6795 m north.

To ensure the quality of gridded emission inventory, very detailed checks were carried out. As a primary step, we have extracted the peak hour emission inventory and calculated grid level proportions of truck emissions with total emissions. Since, during peak hours the highways are occupied by commuter traffic, the truck emissions were less i.e. around 15–35% as expected. As a next step, we have plotted two sets of pollutant specific daily gridded emissions (for July 17, 2010) one set using our proposed SPARE-Truck model output with MOVES emission rates another set using regional travel demand model output and truck factors with

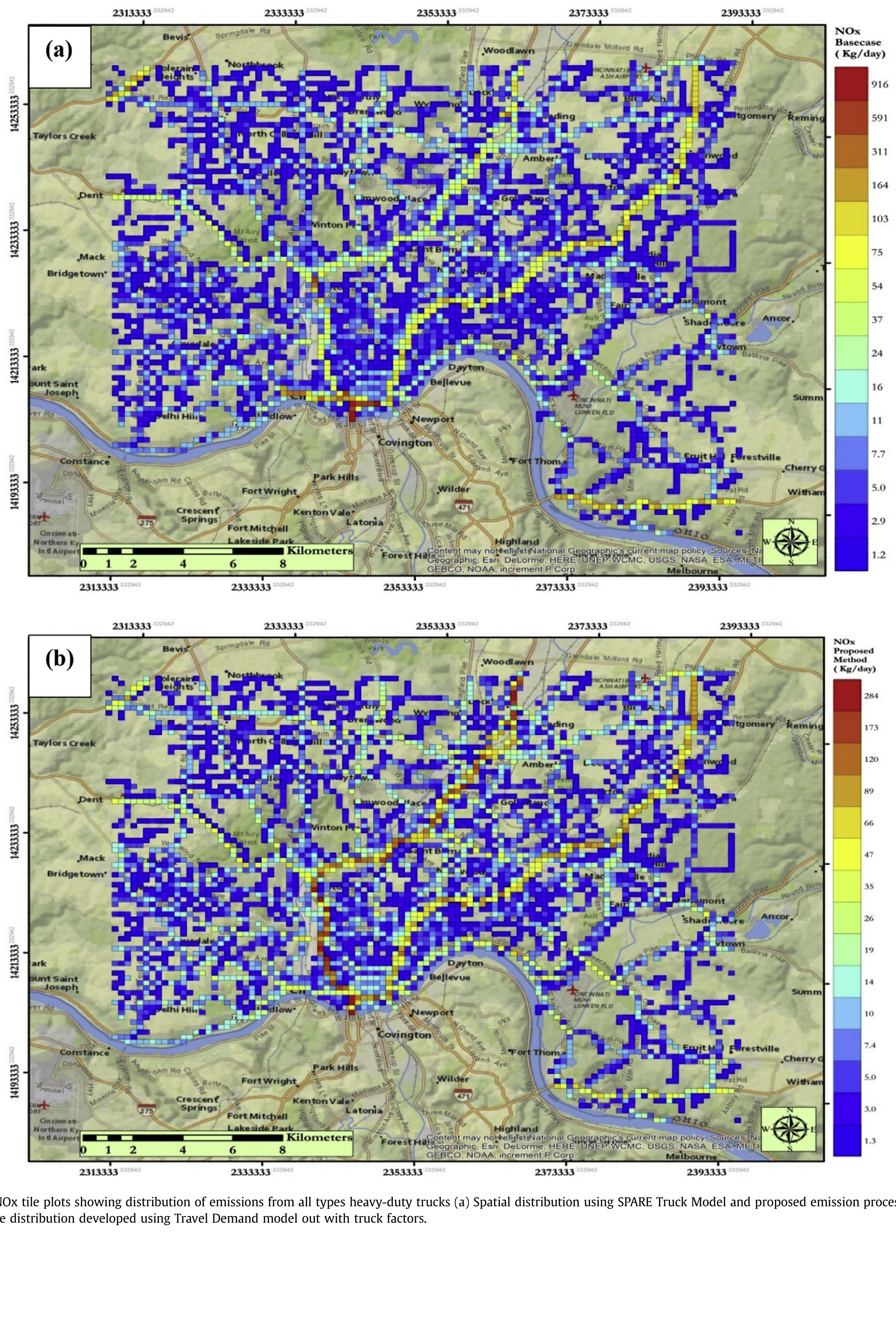

Fig. 8. NOx tile plots showing distribution of emissions from all types heavy-duty trucks (a) Spatial distribution using SPARE Truck Model and proposed emission processing (b) Base case distribution developed using Travel Demand model out with truck factors.

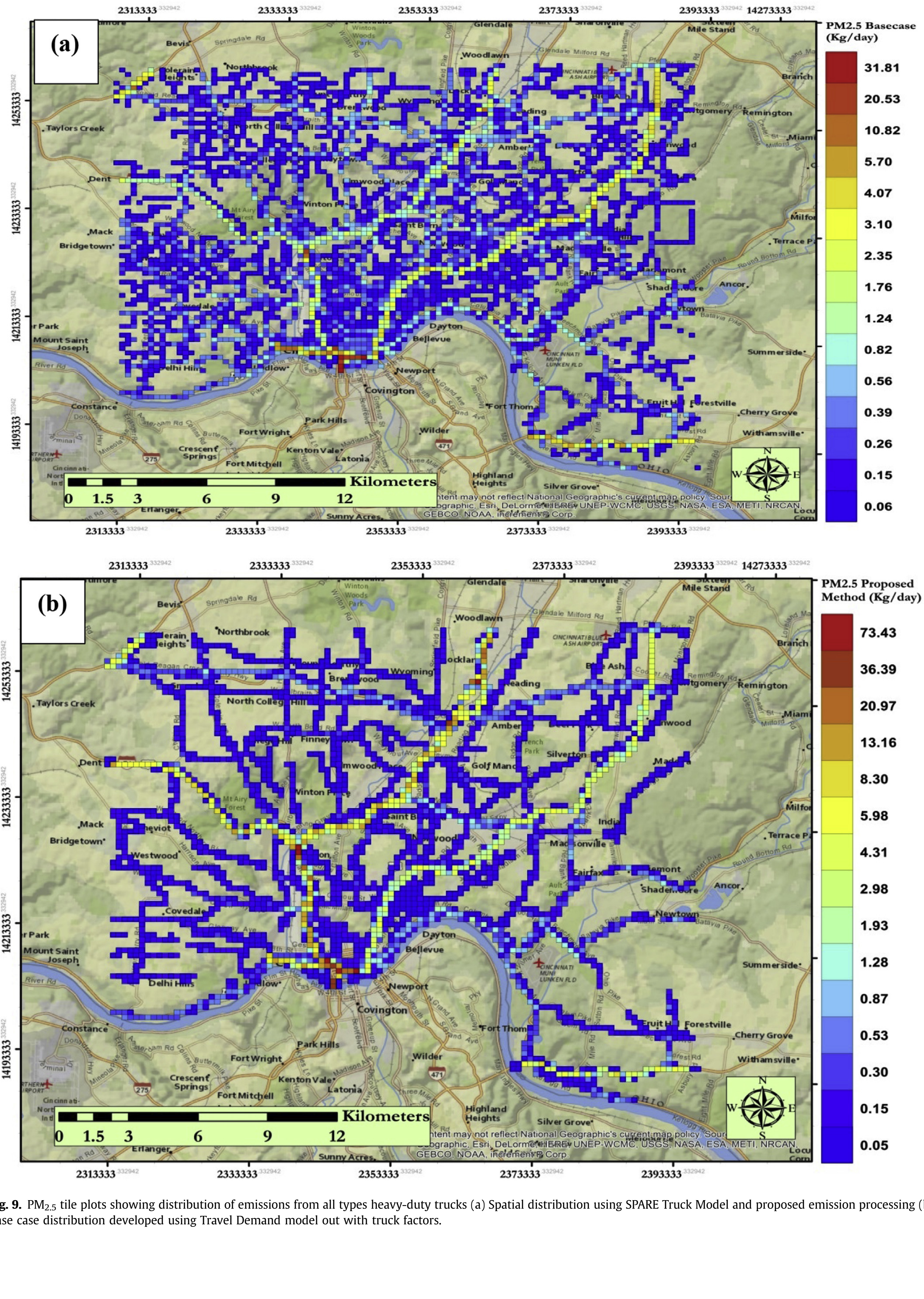

Fig. 9. $PM_{2.5}$ tile plots showing distribution of emissions from all types heavy-duty trucks (a) Spatial distribution using SPARE Truck Model and proposed emission processing (b) Base case distribution developed using Travel Demand model out with truck factors.

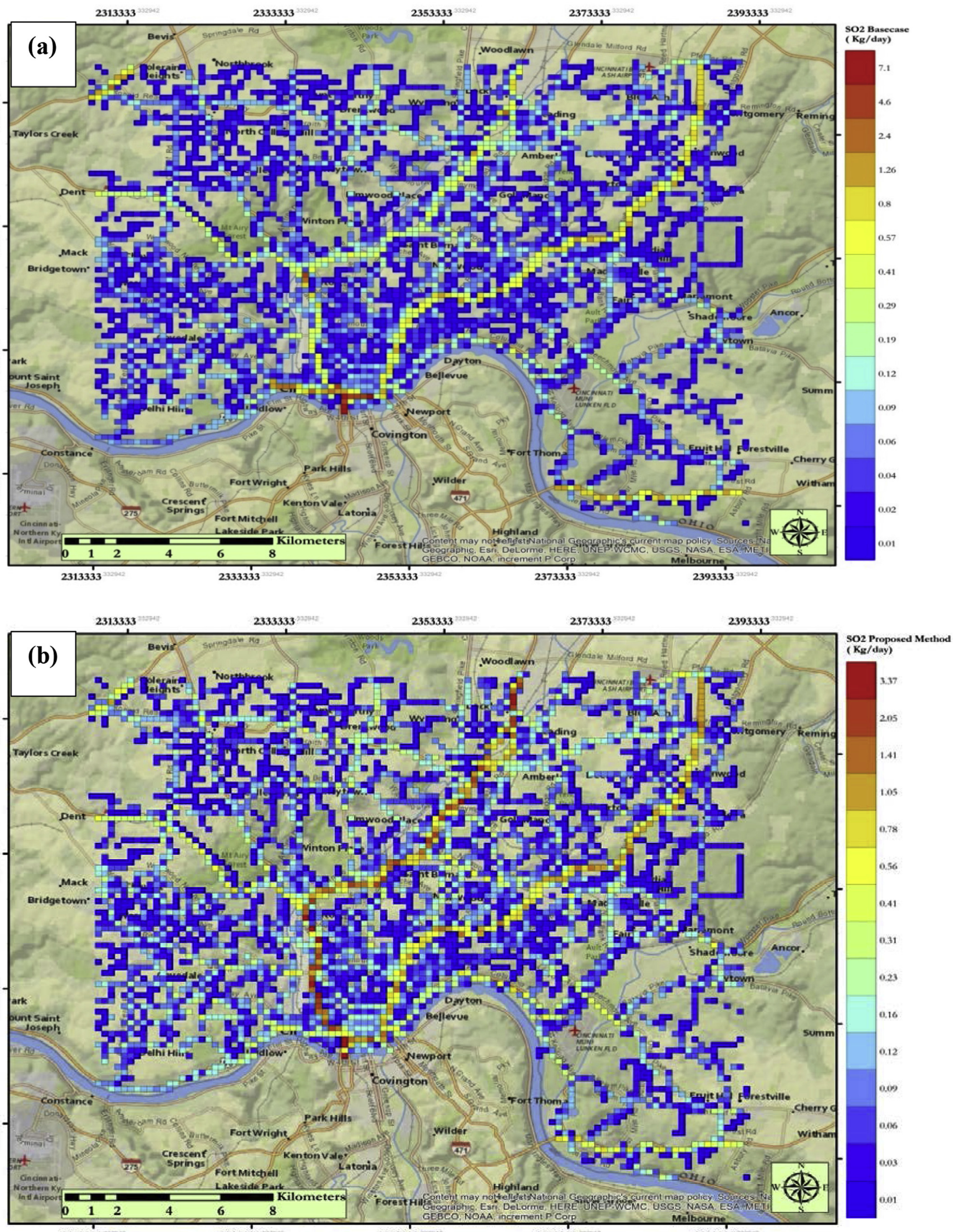

Fig. 10. SO_2 tile plots showing distribution of emissions from all types heavy-duty trucks (a) Spatial distribution using SPARE Truck Model and proposed emission processing (b) Base case distribution developed using Travel Demand model out with truck factors.

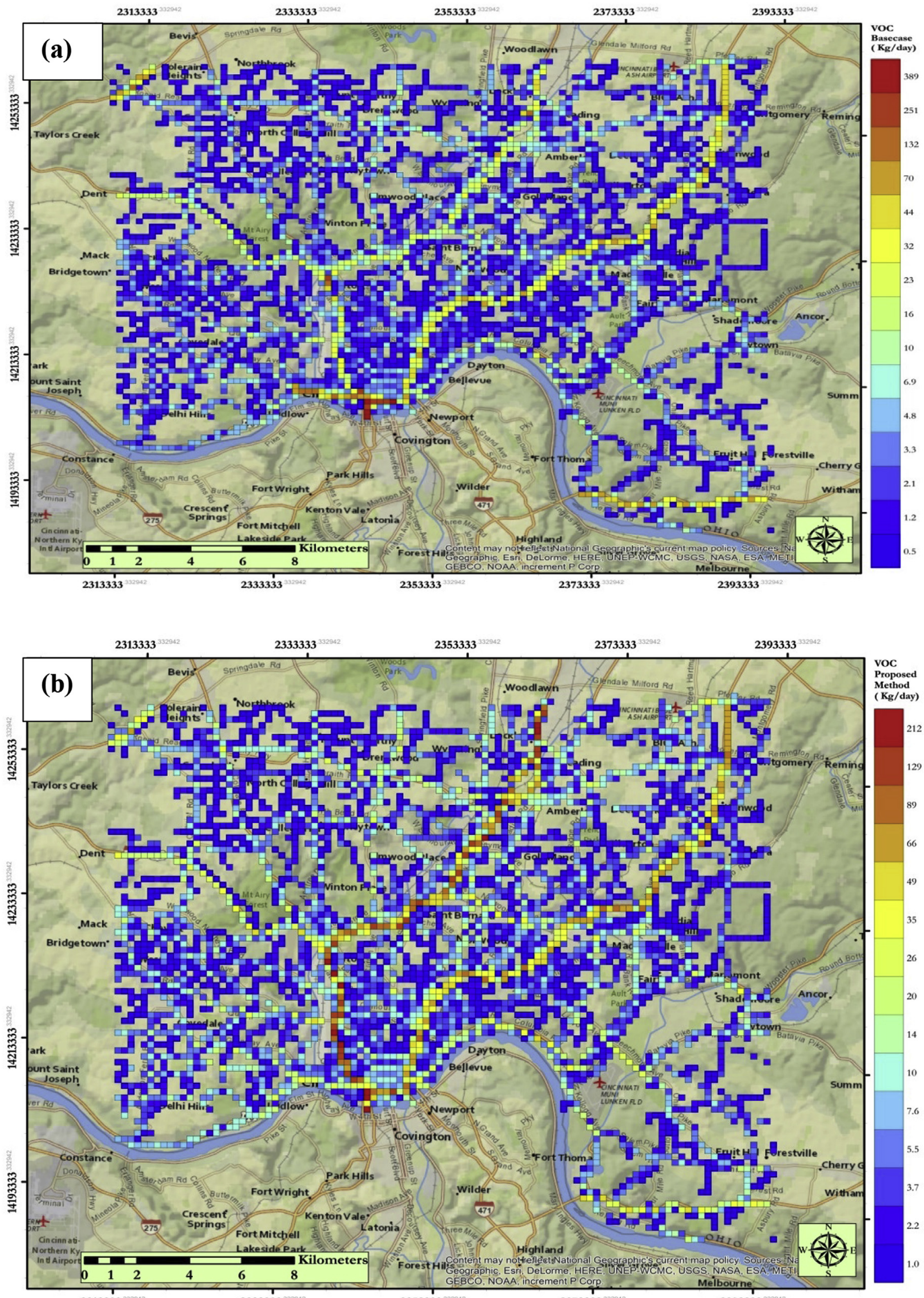

Fig. 11. VOC tile plots showing distribution of emissions from all types heavy-duty trucks (a) Spatial distribution using SPARE Truck Model and proposed emission processing (b) Base case distribution developed using Travel Demand model out with truck factors.

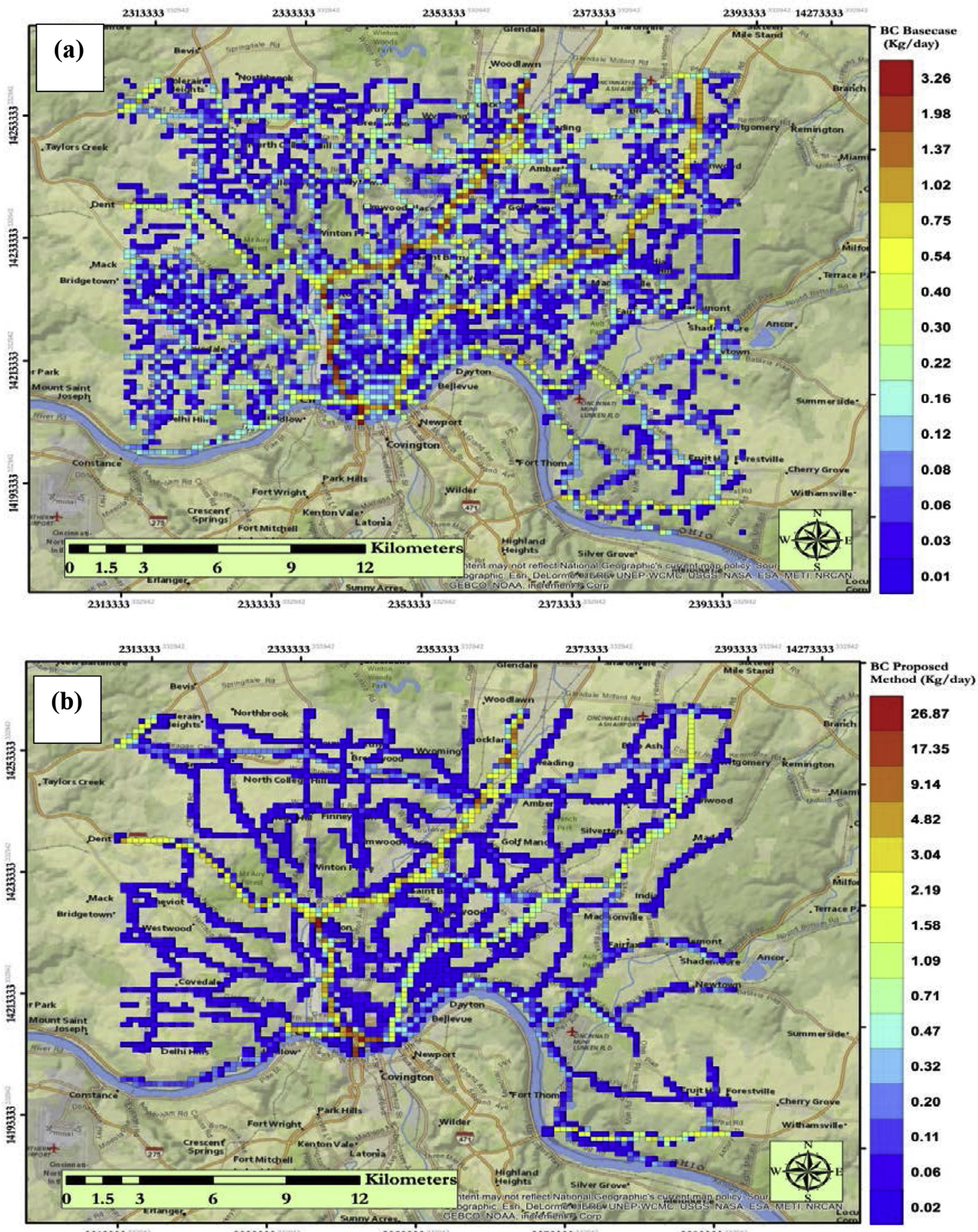

Fig. 12. BC tile plots showing distribution of emissions from all types heavy-duty trucks (a) Spatial distribution using SPARE Truck Model and proposed emission processing (b) Base case distribution developed using Travel Demand model out with truck factors.

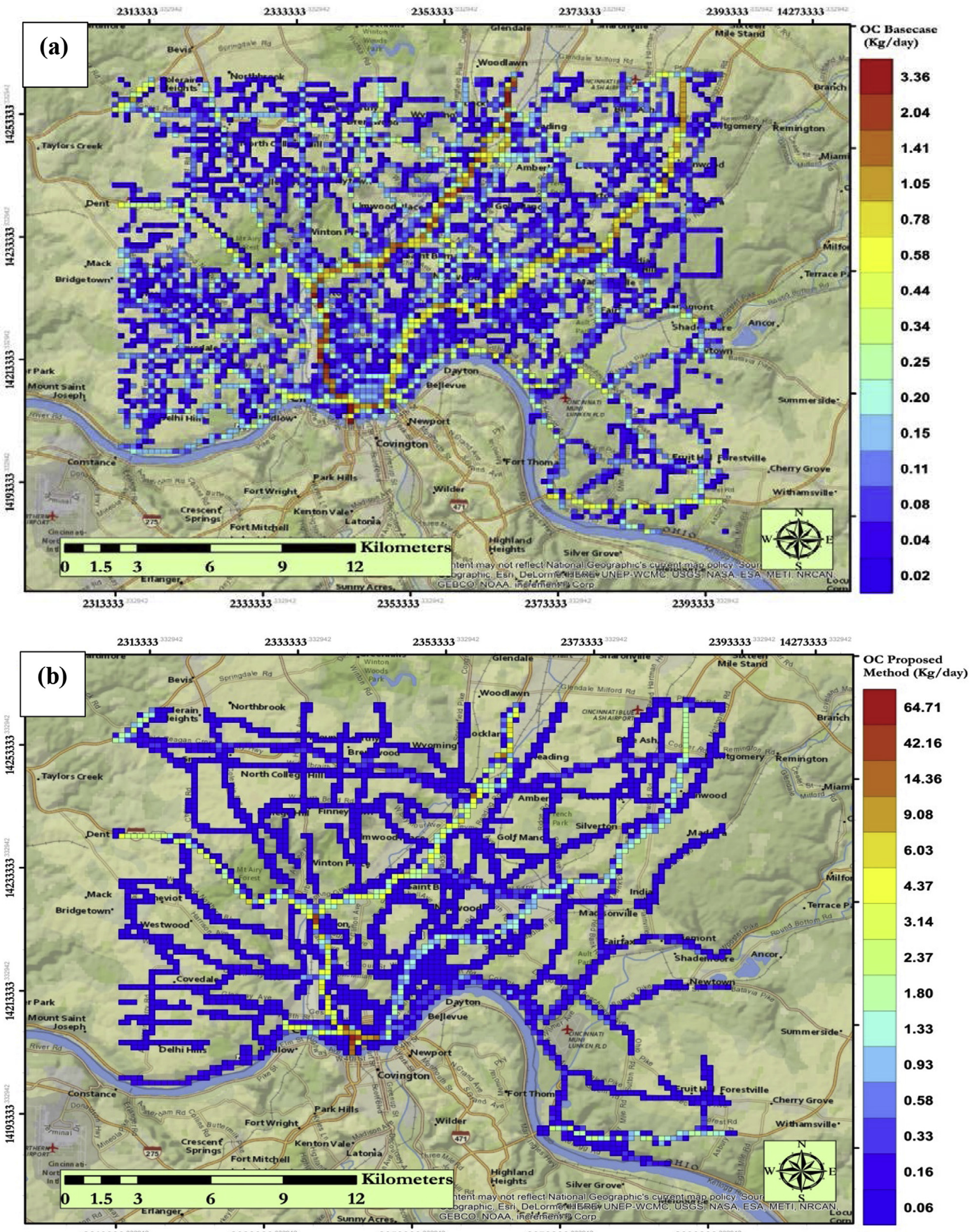

Fig. 13. OC tile plots showing distribution of emissions from all types heavy-duty trucks (a) Spatial distribution using SPARE Truck Model and proposed emission processing (b) Base case distribution developed using Travel Demand model out with truck factors.

MOVES emission rates. The patterns are consistent with the regional industrial pattern and truck transportation networks.

For example, the grids along Interstate highway 75 have the highest SO_2, NO_x, $PM_{2.5}$ emissions because of a lot of freight (combination trucks) movement through the region. As expected BC and OC distribution is very similar to $PM_{2.5}$. On the other hand, the base case plot showed more of these emissions along Interstate 71 highway, which is predominantly commuter corridor. This anomaly may be because of using factoring method used in the default methodology as it might have overestimated trucks from total vehicles output from travel demand model. Based on proposed method, the $PM_{2.5}$ emission proportion of all Interstate highway 75 grids in the region is around 55%, which is consistent with Highway Performance Monitoring Systems data, which confirms that around 45–50% of truck miles traveled are accounted for this interstate highway.

Even though very few single unit long-haul trucks are registered in the region, more emission quantities are estimated due to the external-external activity of this truck type. The combination long-haul trucks use restricted highways since they tend to haul freight longer distances compared to other types of trucks, thus the related hourly emissions are also high. All of the combination trucks are diesel fueled thus SO_2 emissions are higher (Shah et al., 2006). However, the emission output due to default hourly distribution showed that they emit the same amount of emissions on both types of roadways. Most interestingly, the default emissions were higher during evening peak hour, but the proposed model output was almost flat during midday, which is more reasonable since truck drivers try to avoid congested hours in major cities when their trips are longer (Nyhan et al., 2016).

In next level we have compared specific location level emission inventory. City of Sharonville, Ohio is part of Cincinnati urban area and it is mostly industrial land use type. In this area, major factories like GE Aerospace and other related industries generate lot of single unit truck traffic and consequently the surrounding grid cells should have more single unit truck related emissions. Single unit trucks on average emits more $PM_{2.5}$ compared to other trucks. In Fig. 8-b (proposed method) it is clearly evident Sharonville which is south of Woodlawn area has very high $PM_{2.5}$ emissions of 12.5–15.5 kg/day/km^2. Contrarily, in the base case scenario (in Fig. 8-a), those emissions were predicted around 3.6–5.8 kgs/day/km^2, that clearly shown they are under predicted.

The University of Cincinnati area has combined employment and enrollment of around 50,000, thus, generates lot of commuter traffic. Even though, the area attracts moderate truck traffic, their proportion compared to commuter traffic is feeble. As expected in the base case, this area is one of high emission concentration area. Similarly, grid cells near Rookwood and Kenwood were under allocated in the base case whereas proposed moderately allocated to those areas as they have significant truck activity due to shopping centers (See Figs. 8–11). We suspect this inconsistent allocation of emissions may be due to the drawback in truck activity prediction, which is based on auto travel activity (Milando et al., 2016). The comparative analysis of spatial distribution provided us much confidence in the proposed methodology as it predicted high emissions near truck-activity-dominant areas (see Fig. 12).

From spatial distribution of emissions plots it has been observed that there are considerable emissions in suburban areas that are away from central business district. These emissions can be attributed to the motor homes and refuse trucks activity. As mentioned emission model results, since there is some discrepancy in truck count conversion between FHWA highway axle based classification and motor homes type used in this study, motor homes have been over estimated. This may have caused some of motor home emissions in residential land use type. However, intermittent activity of refuse truck may also have caused some inconsistent emission sin these areas. Further, the NOx and $PM_{2.5}$ emissions are sensitive to grades and the proposed method predicted high emissions along Interstate highway 75 at locations at Brent Spence Bridge. Overall, the gridded emissions predicted using proposed are distributed in the areas where more truck traffic is observed. However, the spatial emission distribution is somewhat similar for all pollutants, this may be limitation to current link level processing of combing running and non-running emissions. Most importantly, using proposed method it easy to segregate gridded emission inventory by truck-type, this is of particular interest for air quality modelers, to provide reliable results to decision makers (Milando et al., 2016) (see Fig. 13).

5. Conclusions

This paper has presented the successful application of data-driven modeling methodologies to develop truck-related input for any emission model. Application of optimization/demand adjustment model as second step of SPARE-Truck model, is actually an advancement over using simple regression models, which are pretty unstable due to large unexplained effects exist in explanatory variables. The truck miles traveled, for all of the truck types except combined long-haul trucks, in the base case has been under estimated (overall 32% less than traditional model) since our new truck miles traveled mix actually matches with observed traffic counts in comparison. Thus, the emission quantities estimated for those truck types were also under estimated and the annual total discrepancies as following: 37% for NOx, 35% for SO_2, 43% for VOC, −43% for BC, −47% for OC and 49% for $PM_{2.5}$. Further, the proposed method also predicted within ~7% of national emission inventory for all pollutants.

The significant contribution of this study is that the emission inventory using proposed methodology is higher than the base case emission quantities which used default aggregated input. This is very important improvement for regional planning agencies in United States since it would affect their emission budget revisions for future years. The methodology used in the case study is easily adoptable by any other metropolitan area in the United States for updating their current inputs for US-EPA's MOVES model.

Most importantly, using proposed method it is easy to segregate gridded emission inventory by truck type, which is of particular interest for decision makers, since currently there is no reliable method to test different truck-category specific travel-demand management strategies for air pollution control. However, the proposed modeling methodology may not be appropriate if policy makers are particularly interested in curbing certain types of pollutants in the region, as from the present analysis results, it seems that the urban-scale spatial emission distribution is somewhat similar for all pollutants. This limitation is anticipated well in advance as part of proposed link based processing which combines the running and non-running emissions at highway link level, however, in reality most of the non-running emissions may not happen on links, but, rather at parking and fueling locations. The solution for this problem is going to be pursued as part of future research.

In spite of the lot of effort put in the present study, we could only improve the truck miles traveled and its mix. The other major input that would affect mobile emission output is the truck speed distribution. Using current methods, we can estimate only daily or peak time period speeds; whereas to predict accurate emission rates, we need to provide actual link level congested speed to the emission model. It would be very relevant to process the hourly truck volumes we obtained from the present model to get new congested speeds through hourly assignment. This improvement is also considered as part of future work.

Appendix

Table 5
Summary statistics of explanatory and modeling variables.

Variable	Mean	Standard deviation	Minimum	Maximum
Number of Lanes	1.66	0.8415	1	5
Capacity	876.22	276.94	480	2000
Speed	29.56	8.62	15	69
Population	7893.94	39,501.81	0	45,803
Employment	3551.98	3483.36	0	17,752
Accessibility	0.00021	0.00026	1.00E-05	0.00216
Refuse Trucks	277.21	306.57	1	966
Single Unit Short Haul Trucks	480.10	822.86	15	10,361
Single Unit Long Haul Trucks	135.32	219.31	1	2287
Motor Homes	24.45	39.65	1	377
Combination Short Haul Trucks	450.62	1357.40	1	8563
Combination Long Haul Trucks	56.88	157.85	1	2167

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