Human and Ecological Risk Assessment: An International Journal

Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/bher20

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Accepted author version posted online: 05 Feb 2013.

To cite this article: Sun-Kyoung Park , Amit Marmur & Armistead G. Russell (2013) Environmental Risk Assessment: Comparison of Receptor and Air Quality Models for Source Apportionment, Human and Ecological Risk Assessment: An International Journal, 19:5, 1385-1403, DOI: 10.1080/10807039.2012.730475

To link to this article: http://dx.doi.org/10.1080/10807039.2012.730475

Human and Ecological Risk Assessment, 19: 1385–1403, 2013

ISSN: 1080-7039 print / 1549-7860 online
DOI: 10.1080/10807039.2012.730475

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ABSTRACT

Source apportionment of particulate matter has been commonly performed using receptor models, but studies suggest that the assumptions in receptor models limit the accuracy of results. An alternative approach is the use of three-dimensional source-oriented air quality models. Here, a comparison is conducted between the $PM_{2.5}$ apportioned from the Chemical Mass Balance (CMB) receptor model using organic tracers as molecular markers with those from the source-based Community Multiscale Air Quality (CMAQ) model. Source apportionment was conducted at sites in the southeastern United States for July 2001 and January 2002. $PM_{2.5}$ source apportionment results had moderate discrepancies, which originate from different spatial scales, fundamental limitations, and uncertainties of the two models. Results from CMB fluctuated temporally more than real variation due to measurement and source profile errors and uncertainties, whereas those from CMAQ could not capture daily variation well. In addition, results from CMB are mass contributions for the monitoring location, whereas those from CMAQ represent the average mass contributions of the model's grid. It is difficult to assess which approach is "better." Indeed, both models have strengths and limitations, and each model's strengths can be utilized to help overcome the other model's limitations.

Key Words: source apportionment, particulate matter, CMB, CMAQ.

INTRODUCTION

In 1997, the United States National Ambient Air Quality Standard (NAAQS) for $PM_{2.5}$ (particulate matter with aerodynamic diameter less than 2.5 micrometers) was promulgated in a response to scientific studies linking elevated fine particle concentrations with health risks (Dockery and Pope 1994; Metzger *et al.* 2004; Peel

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et al. 2002). Such environmental risks can be properly managed when appropriate models are selected for use (Wu and Olson 2010a,b). Although models help in managing and assessing environmental risks, special attention should be paid to selecting a model's parameters as well as the model itself since various models may differently estimate environmental variables (Djalalova *et al.* 2010; Kim *et al.* 2008; Manomaiphiboon *et al.* 2008; McKeen *et al.* 2009; Park *et al.* 2006b; Temiyasathit *et al.* 2009; Vautard *et al.* 2009). Hence, comparing performance of several models followed by multiple tests to identify improved parameter estimates is essential to improving risk management (Wu and Olson 2008, 2010a,b). In addition, several models can be combined together to optimize and improve risk management (Wu and Olson 2009).

The goal of this research is to compare PM2.5 source apportionment done by a receptor model with those from a source-based model, and utilize each model's strengths to help overcome the other model's limitations. Historically, source apportionment of $PM_{2.5}$ largely has been performed via several receptor-modeling techniques (Viana *et al.* 2008). In particular, one of the most widely used receptor modeling techniques is the chemical mass balance (CMB) approach (Core *et al.* 1982; Watson *et al.* 2002a). In CMB, ambient chemical concentrations are expressed as the sum of products of source profiles and source contributions. This linear system of equations is solved for source contributions by weighted least square fitting. The CMB model is based, in part, on the following six assumptions (USEPA 2004): (1) compositions of source emissions are constant over the period of ambient and source sampling; (2) chemical species do not react with each other (*i.e.*, they add linearly); (3) all sources with a potential for contributing to the receptor have been identified and have had their emissions characterized; (4) the number of sources or source categories is less than or equal to the number of species; (5) source profiles are linearly independent of each other; (6) measurement uncertainties are random, uncorrelated, and normally distributed. These six assumptions are never totally satisfied in actual practice (Watson *et al.* 2002b), and deviations from assumptions increase the uncertainty in the source contribution estimates.

The extent to which these six assumptions are violated is unknown. For example, as various source emission profiles change, such as biomass burning (*e.g.*, wildfires *vs.* burning of wood construction waste), or vehicle emissions during rush hour versus open freeways, the first assumption is violated (Brauer *et al.* 2003; Huo *et al.* 2009). Because many source profiles are often similar with each other (*e.g.*, gasoline and diesel vehicles; biomass burning, meat cooking, and vegetative detritus) the fifth assumption is also violated to some degree (Fine *et al.* 2004; Sheesley *et al.* 2007). In addition to the above assumptions, it is inappropriate to use CMB when estimating the impact of emission reductions on species that react in a significantly nonlinear fashion. Also, CMB does not link the impact of emissions to either temporal or spatial locations of the sources of $PM_{2.5}$ (Subramanian *et al.* 2006). Nevertheless, CMB has a great advantage that results provide temporal and spatial variations at the receptor in a fashion that is consistent with measured concentrations.

A bottom-up approach to source apportionment is the use of emission-based (or source-based) three-dimensional air quality models (AQMs). Such models solve the atmospheric diffusion equation, which is a statement of species conservation in a turbulent fluid. The diffusion equation describes the formation, transport, and

fate of air pollutants, including components for processing emissions, meteorology, topography, air quality observations, and chemistry (Russell and Dennis 2000). Use of air quality models in source apportionment has limitations, principally that results are dependent on the accuracy of the model's process and input data. However, such models can overcome the six assumptions of CMB. Three-dimensional models, including the Comprehensive Air Quality Model with Extensions (CAMx) and the Community Multiscale Air Quality (CMAQ) model, have been used for $PM_{2.5}$ source apportionment (Marmur *et al.* 2006).

Here, consistency and accuracy of source apportionment methods are compared by analyzing the discrepancies between CMB receptor and CMAQ models. In addition, source apportionment of $PM_{2.5}$ from the externally mixed source-oriented model was compared with that from the CMB model in the San Joaquin Valley and in the South Coast Air Basin each for three days (Held *et al.* 2005). Here, the comparison was done for two complete months (July 2001 and January 2002) over eight stations in the southeastern United States, and the reasons for discrepancy are analyzed.

METHODS

Source apportionment of $PM_{2.5}$ is performed using two different approaches: Chemical Mass Balance (CMB) and Community Multiscale Air Quality (CMAQ) models. CMB was applied to observations at the eight Southeastern Aerosol Research and Characterization (SEARCH) stations (Figure 1A), and CMAQ was run over the United States (Figure 1B) for July 2001 and for January 2002 corresponding to the coordinated intensive monitoring periods by the U.S. Environmental Protection Agency's (USEPA's) Eastern Supersite Program (ESP 01/02). SEARCH stations are located in North Birmingham, Alabama (BHM); Centreville, Alabama (CTR); Yorkville, Georgia (YRK); Jefferson St–Atlanta, Georgia (JST); Gulfport, Mississippi (GFP); Oak Grove, Mississippi (OAK); Outlying Landing Field #8, Florida (OLF); and Pensacola, Florida (PNS) (Figure 1A). Daily average mass contributions of $PM_{2.5}$ were compared between the two approaches for the JST station, and monthly average results were compared at all stations.

Receptor-Based $PM_{2.5}$ Apportionment Using a CMB Model

Receptor-based source apportionment of $PM_{2.5}$ is performed using CMB with organic tracers as molecular markers (CMB-MM) (Ke *et al.* 2008; Schauer *et al.* 1996; Zheng *et al.* 2007). Mass contributions are calculated for seven sources: gasoline exhaust, diesel exhaust, road dust, wood/biomass burning, meat cooking, natural gas, and power plant emissions. Historically, source profiles for the CMB application are composed of elemental species that include sulfate, nitrate, ammonium, elemental carbon, organic carbon, and trace metals. CMB has a long record of use, but the co-linearity of profiles relying solely on inorganic species proved problematic, particularly for sources that emit similar metals, but can have very different organic species concentrations. Thus, CMB-MM, which relies more on speciated organic compounds was developed (Schauer *et al.* 1996; Zheng *et al.* 2002, 2007). Source profiles are expressed as normalized values to organic carbon. Hence, CMB-MM

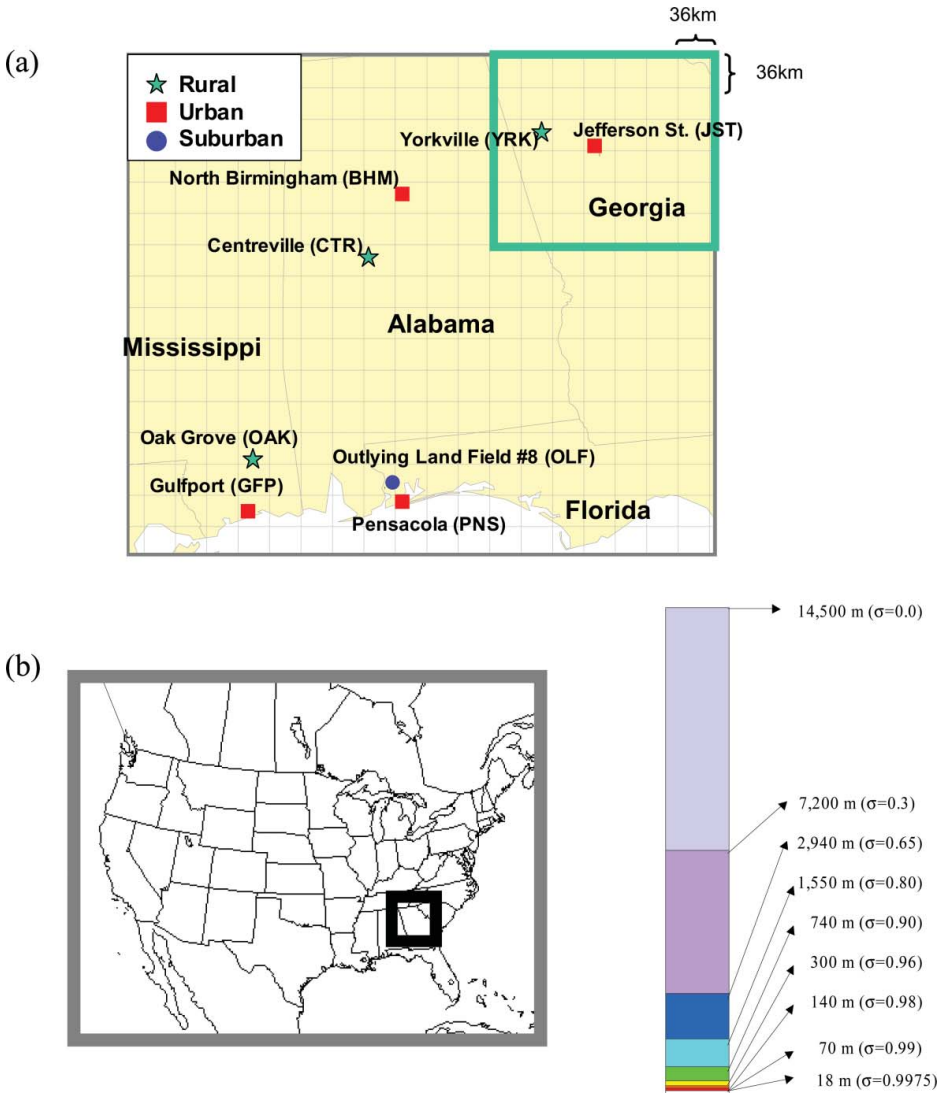

Figure 1. (A) SEARCH $PM_{2.5}$ monitors (http://www.atmospheric-research.com) over plotted by CMAQ 36-km grid. A rectangle containing YRK and JST is CMAQ 12-km domain. (B) CMAQ domain. Rectangles around the United States and over the Atlanta area are 36-km and 12-km grid domain, respectively. The number of vertical layer is nine with top pressure of 100 hPa. (Color figure available online.)

apportions mass contributions to organic carbon, then the mass contributions to $PM_{2.5}$ are calculated by dividing by the organic carbon to $PM_{2.5}$ ratio of each source.

CMB-MM requires additional effort to analyze organic compounds present in $PM_{2.5}$, but the advantage of this method over the CMB is that the relative distribution of specific organic compounds in source emissions can provide extra means to

fingerprint sources that cannot be uniquely identified by the elemental composition alone (Rogge *et al.* 1991, Rogge *et al.* 1993a,b,c,d; 1994; 1997a,b; 1998; Schauer *et al.* 1999a,b; 2001; 2002a,b). For example, cholesterol is found in the meat cooking source profile. Thus, much of the co-linearity problem of source profiles can be alleviated.

Source-Based $PM_{2.5}$ Apportionment Using the CMAQ Model

The three-dimensional air quality modeling system used for the source apportionment is USEPA Models-3, which includes the Sparse Matrix Operator Kernel Emissions (SMOKE) v1.5 for emission processing (SMOKE-Model 2012), the NCAR's 5th generation Mesoscale Model (MM5) v3.5.3 for preparing meteorological fields (Dudhia *et al*. 2005), and the CMAQ model v4.3 for air quality modeling (USEPA 1999). CMAQ was applied for July 2001 and January 2002 over the continental United States and parts of Mexico and Canada with a 36-km grid and over the Atlanta area with a 12 = km grid (Figure 1B). The projection used is the unified Regional Planning Organization (RPO) national grid, which is Lambert conformal conic projection with a central meridian of 97 W, a center of latitude of 40 N, and standard parallels of 33 N and 45 N. More information of the air quality modeling system and the model's evaluation results are available elsewhere (Park *et al.* 2006a).

Modeling with smaller spatial scale, for example 4-km grid, would be also of interest. However, the pollutant distribution is dependent on the spatial resolution of the emission inventory, and the emission inventory is often prepared with the spatial scale, larger than 4 km. Thus, the small grid size does not always produce better resolution in pollutant distribution.

Source apportionment using CMAQ can be done by direct sensitivity methods such as DDM-3D (Dunker 1981; Yang *et al.* 1997) or by Brute Force (BF) (*i.e.*, applying the model once with, then without the target source) (Park *et al.* 2005), the latter of which was applied in this study. The target emission source is removed based on the source category code (SCC) in the emission inventory. Emission sources apportioned were the same as the seven emission categories chosen in CMB for comparison purposes. CMAQ can calculate mass contributions to the secondary $PM_{2.5}$ in addition to those to the primary $PM_{2.5}$. Only mass contributions to primary $PM_{2.5}$ from CMAQ were compared with those from CMB due to the limitations of CMB.

RESULTS

Monthly $PM_{2.5}$ compositions in the southeastern United States were apportioned using CMB-MM and CMAQ (36-km grid) (Figure 2). Sulfate, nitrate, and ammonium masses are not shown to give more focus on primary $PM_{2.5}$ mass. While mass contributions calculated from CMAQ and those from CMB-MM are similar, a reasonable amount of discrepancy exists. Total primary $PM_{2.5}$ masses are different between the two methods as $PM_{2.5}$ mass from CMB-MM is the measured concentration and that from CMAQ is simulated value. Relative $PM_{2.5}$ mass and contributions from each source using CMAQ do not differ significantly between July 2001 and January 2002, whereas, those from CMB-MM vary markedly from July 2001 to January 2002.

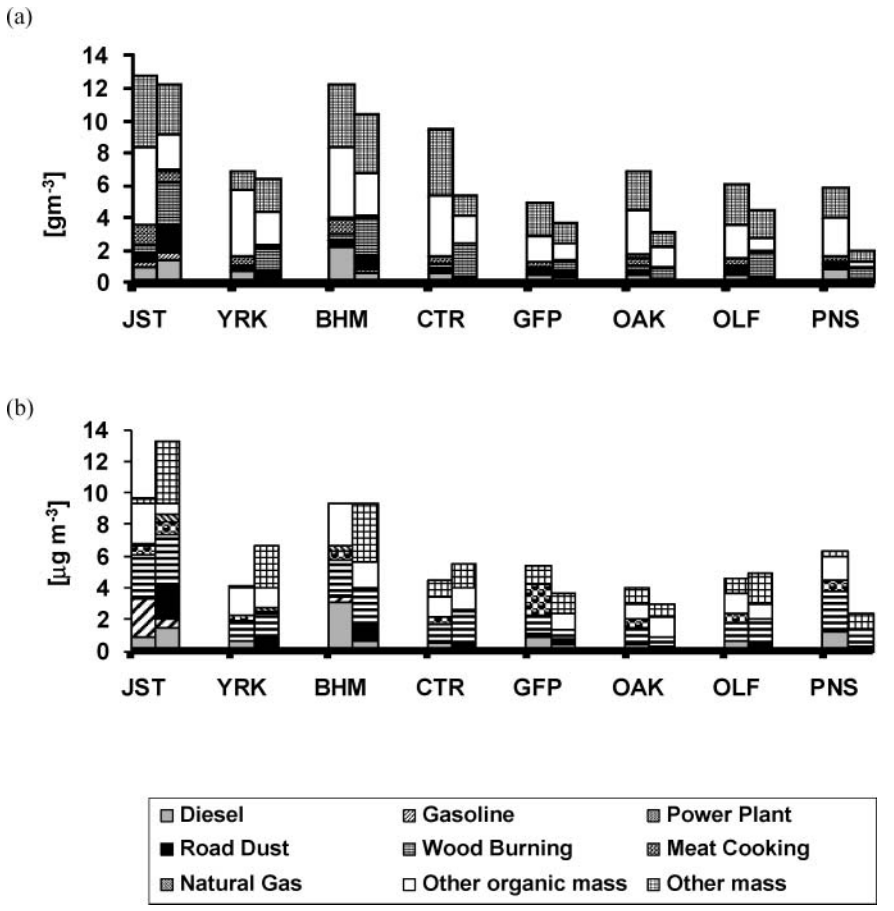

Figure 2. Monthly average mass contributions to $PM_{2.5}$ in SEARCH stations (sulfate, nitrate, and ammonium were excluded). CMB-MM, CMAQ (36 km) (left to right). (A) July 2001. (B) January 2002.

Reasons of this difference will be discussed later. Daily $PM_{2.5}$ masses at the JST station apportioned using CMB-MM and CMAQ (12 km) were compared as well (Figure 3). CMAQ mass contributions were high on some days compared with observations, and low on other days. This daily variation would not be captured if the analysis was done only for a few days, so analysis for long periods are necessary to understand the temporal trends and the robustness of the comparison over periods comparable to air quality management decision-making.

Monthly average mass contributions of $PM_{2.5}$ from CMAQ (36 km) and that from CMB-MM at eight SEARCH stations were positively correlated, and the correlation coefficient for monthly contribution was slightly higher than that for daily mass contributions (Figures 4A and 4B). The low correlation coefficient for daily average mass contribution is partly due to zero values of mass contributions from CMB-MM

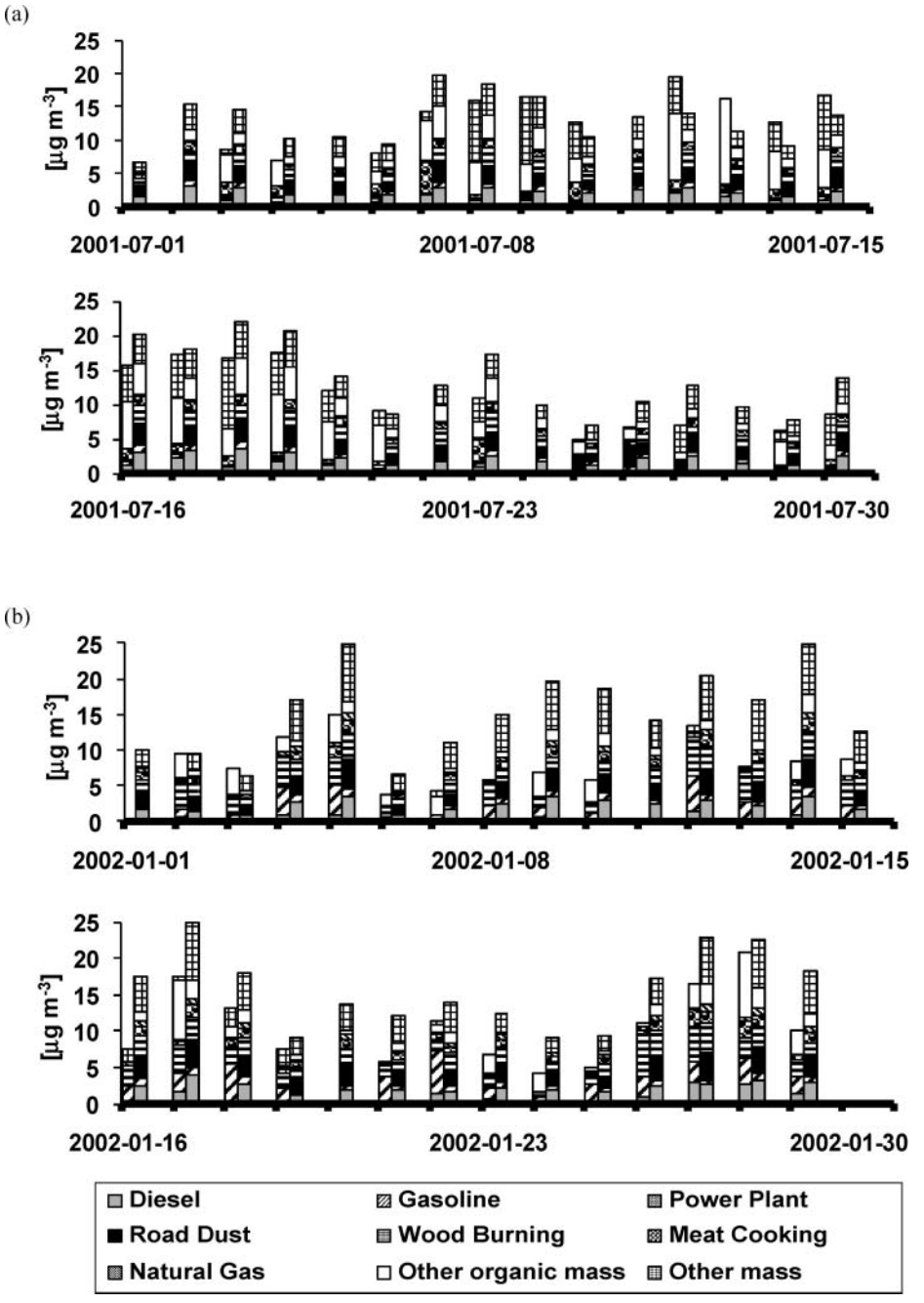

Figure 3. Daily average mass contributions to $PM_{2.5}$ in JST (sulfate, nitrate, and ammonium were excluded). CMB-MM, CMAQ (12 km) (left to right). Results of CMB-MM are not available on July 1, 2, 5, 22, 24, and 28, and on January 1, 11, and 20. (A) July 2001. (B) January 2002.

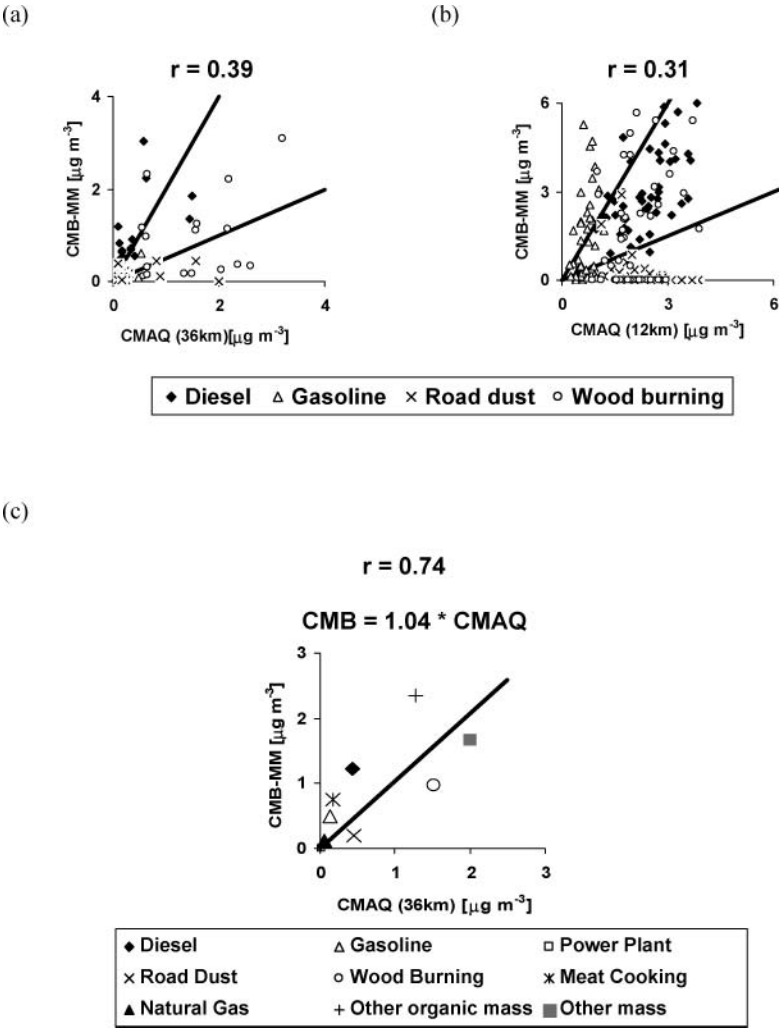

Figure 4. Scatter plot of mass contributions to $PM_{2.5}$ in July 2001 and January 2002. (A) Monthly average contributions in SEARCH stations. (B) Daily average contributions in JST. (C) Mass contributions averaged over the eight SEARCH stations for July 2001 and January 2002.

(Figure 4B), which was not seen in the monthly average mass contributions. The correlation for spatially and temporally averaged mass contributions was quite good (0.74), with a slope near 1, apparently hiding the real differences between CMB-MM and CMAQ results (Figure 4C). Therefore, the source of disagreement of the two models cannot be fully analyzed using averaged mass contributions (in space or in time), or results from a few sites or from a few days, and the analysis for multiple stations for long periods is necessary.

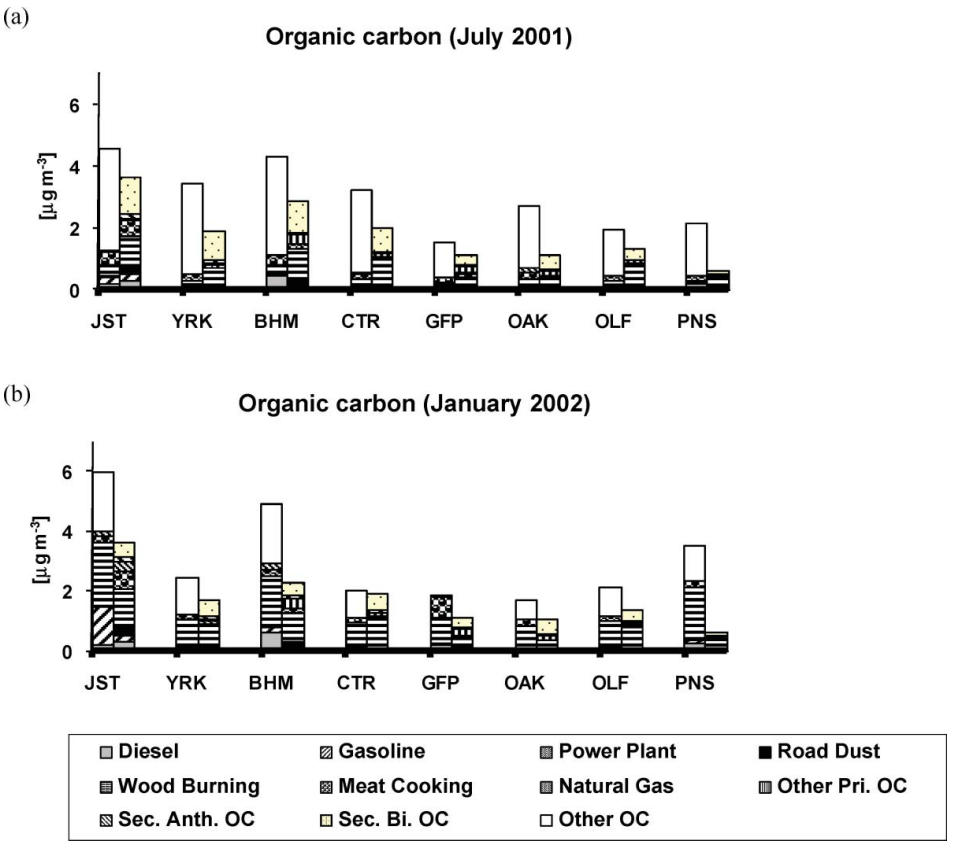

Figure 5. Monthly average mass contributions to organic carbon in SEARCH stations. CMB-MM, CMAQ (36 km) (left to right). (A) July 2001. (B) January 2002. (Color figure available online.)

DISCUSSION

Data in Figures 2, 3, and 4 suggest that the separate source apportionment techniques give comparable results on average, but differences increase when considering daily source apportionment results. Sources of disagreement include organic carbon to $PM_{2.5}$ ratio, different spatial and temporal variations of the two models, and uncertainties in the application of each model. To analyze the reasons of discrepancy is fundamental to improving the accuracy of source apportionment of $PM_{2.5}$.

Organic Carbon to $PM_{2.5}$ Ratio

The source profile used in CMB-MM is expressed as normalized values to organic carbon (OC). CMB-MM apportions mass contributions to OC, and the contributions to $PM_{2.5}$ are calculated by dividing the contributions to OC by the OC to $PM_{2.5}$ ratio (Figures 2, 5, and 6). CMAQ also uses a speciation profile, which includes the OC to $PM_{2.5}$ ratio, to differentiate $PM_{2.5}$ emissions by sub-categories. Currently, the OC

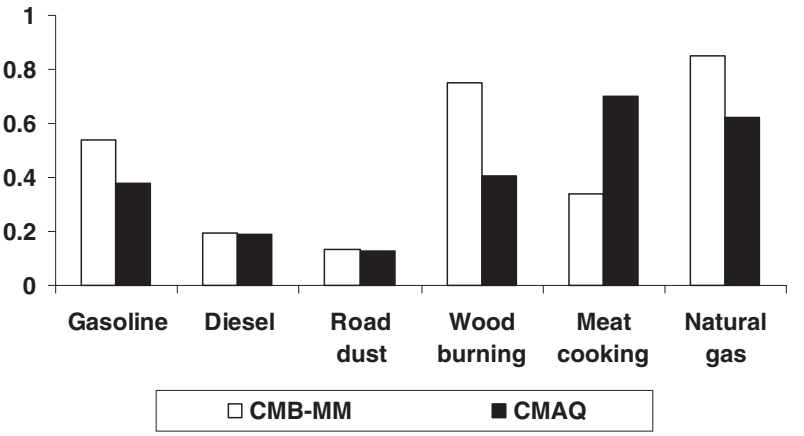

Figure 6. Organic carbon to $PM_{2.5}$ ratio.

to $PM_{2.5}$ ratios used in CMB-MM and CMAQ are different (Figure 6). Therefore, although the mass contributions to OC from CMB-MM and CMAQ are similar, the different OC to $PM_{2.5}$ ratio can cause the mass contribution to $PM_{2.5}$ of CMB-MM to be significantly different from that of CMAQ, and vice-versa. Studies showed that the ratio varies in a wide range depending on the location or experimental situation of the emission analysis (Chow *et al.* 2004; Hildemann *et al.* 1991; Javitz *et al.* 1988; Schauer *et al.* 1999a,b, 2001, 2002a,b; Watson *et al.* 2001). Currently, the same OC to $PM_{2.5}$ ratio for each source category was applied to all the monitors in the southeastern United States in the source apportionment with CMB-MM. Applying different OC to $PM_{2.5}$ ratios to different regions should be considered to improve the accuracy of CMB source apportionment.

Spatial Scale

Mass contributions calculated from CMAQ and CMB have different spatial scales. CMB calculates mass contributions of $PM_{2.5}$ at the monitoring location, whereas CMAQ simulates average concentrations of the grid, hence source contributions at the grid scale level. This different spatial scale can be a major source of the discrepancy between the two models in places where spatial gradients are relatively large. For example, primary $PM_{2.5}$ concentrations estimated from CMAQ were markedly lower than those from CMB in PNS (Figure 2). The PNS station is located near the Florida coast and the corresponding grid of CMAQ to PNS is occupied by more than 90% ocean (Figure 7). Thus, the volume-averaged concentrations are much lower than the point concentrations in PNS. Due to the large percentage of the ocean in the PNS grid, the agreement of primary $PM_{2.5}$ mass between CMAQ for the grid containing the OLF station and CMB in the PNS station is markedly better than that between CMAQ in PNS and CMB in PNS (Figure 7). An additional issue is that even a minor source very near a monitor may be responsible for a large impact at that receptor, but have a small impact over a typical grid.

The different spatial scales of the two models have an important implication for use of the results. CMB is done based on the measurement, so results are specific

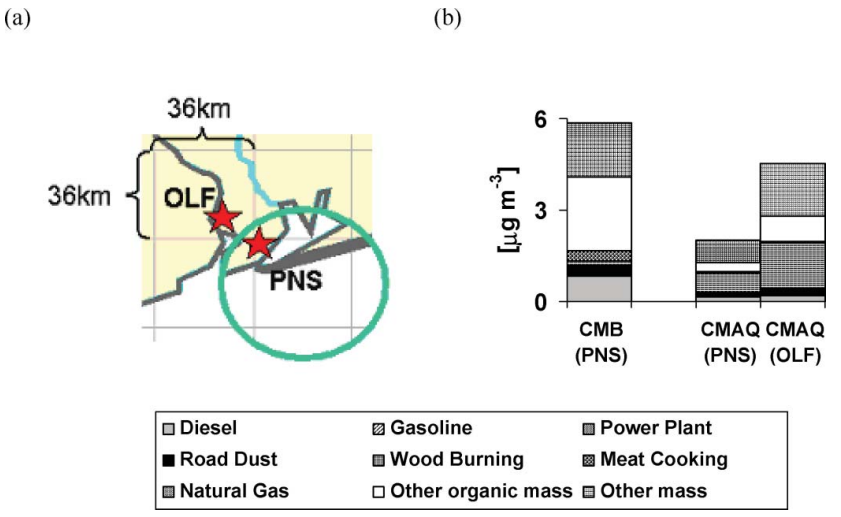

Figure 7. (A) Geographic location of the PNS and OLF sites over plotted by CMAQ 36-km grid. (B) Monthly average mass contributions to $PM_{2.5}$ in July 2001 (re-plotted using Figure 2A). (Color figure available online.)

to the monitoring location. However, mass contributions calculated from CMB may not be representative to a specific location if a strong local (spatial) concentration gradient exists. The site representativeness problem is important to epidemiological studies, because source impacts determined at the monitoring station are used to analyze the health effect of the pollutants over the area in which the monitor is located (Wade *et al.* 2004). On the other hand, CMAQ simulates average concentrations of the grid, so results are less subject to local effects. However, source-based models are sensitive to errors in emissions and meteorological fields.

To install multiple monitors in the area of interests may diminish the non-representativeness (in space) of CMB results although this approach would encounter additional costs. To decrease the grid size of the air quality model can enhance the spatial resolution of CMAQ results though model inputs have inherent spatial and temporal resolution limitations as well. The mass contributions calculated from CMAQ using different grid sizes are compared in JST and YRK (Figure 8). The JST station is located in an urban area, and the YRK station is placed in the rural area. The correlation of mass contributions from CMAQ using a different size of grid is lower in JST than in YRK because emissions are more localized in the urban area. In addition, mass contributions from the 36-km are usually higher than those from 12 km in YRK, suggesting that emission strength at the YRK station is weaker than that in the surrounding area. The Mean Fractional Error (MFE), Mean Fractional Bias (MFB), and correlation coefficient between mass contributions from CMB-MM and those from the two different grid sizes of CMAQ are compared (Table 1). The negative MFB indicates that CMAQ had lower mass contributions compared to CMB. Errors between CMB-MM and CMAQ (12 km) are not always smaller than those between CMB-MM and CMAQ (36 km). This result suggests that there are

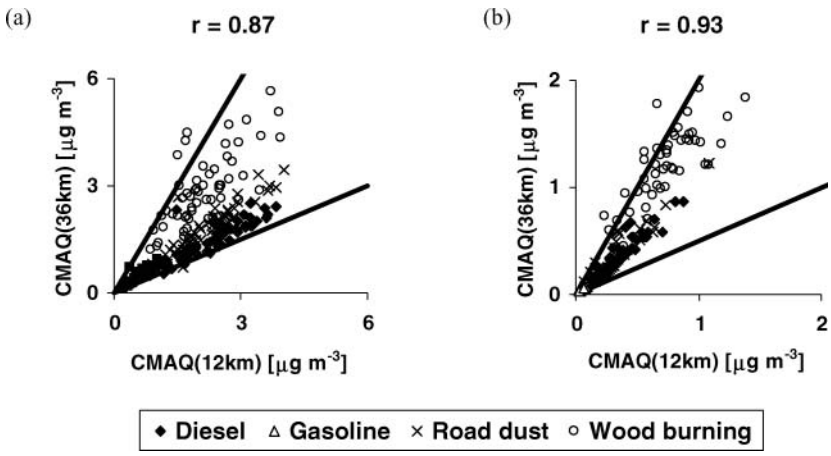

Figure 8. Scatter plot of daily average mass contributions to $PM_{2.5}$ from CMAQ in July 2001 and January 2002. (A) JST (urban area). (B) YRK (rural area).

also significant sources other than the different spatial scale that caused the results from CMB-MM and CMAQ to be different. This will be dealt with in detail.

Note that the advantage of the finer grid size only can be fully realized when the resolution of emission and meteorological inputs are also enhanced. Currently, input emissions to CMAQ were prepared for county-level data that has a spatial scale on the order of 10 km. Greater spatial detail is obtained by mapping emissions using surrogates, a process that cannot fully capture the spatio-temporal distributions. Thus, even though the size of the grid in the air quality model chosen is finer than 10 km, the spatial resolution of the sources may not lead to significant model improvement.

Temporal Variation

Analysis showed that daily source apportionment results from CMAQ did not agree as well with those from CMB-MM (Figures 2 and 3) as did the monthly averages. Note that the monthly average value has better agreement between CMB-MM and CMAQ. That is because temporal averaging also leads, effectively, to spatial averaging of source impact as winds change directions. CMB uses daily measurements, so results will capture the day-to-day temporal variation. However, the variation can fluctuate more than the true degree due to measurement errors and colinearity of source profiles in the CMB calculations. Mass contributions of road dust in January 2002 from CMB-MM are found for only one day, January 7, 2002 (Figure 3) because of very low levels of Al and Si in the January 2002 samples.

Conversely, CMAQ simulates pollutant concentrations based on an annual emission inventory that is then disaggregated to account for monthly, daily, and hourly variations. Continuous emissions monitors (CEMs) on major point sources add temporal accuracy, but are limited to only the largest sources of SOx and NOx. Modeled temperature somewhat corrects mobile and biogenic emissions. It is suspected that such emissions underestimate the temporal variations of source activity, because emissions are prepared by applying typical statistical trends to the annual emission

Table 1. Mean fractional error (MFE), mean fractional bias (MFB), and correlation (r) between daily average mass contributions in JST from CMB (MM), CMAQ (12 km), and CMAQ (36 km). The positive MFB indicates mass contributions from CMAQ are higher than those from CMB.

			CMB (MM) *vs.* CMAQ (12 km)	CMB (MM) *vs.* CMAQ (36 km)
		Diesel	35.8	56.9
	Jul.	Gasoline	122.1	109.1
	2001	Road dust	156.0	153.2
MFE		Wood burning	185.5	189.6
[%]		Diesel	41.9	70.0
	Jan.	Gasoline	86.4	103.0
	2002	Road dust	199.6	199.5
		Wood burning	50.3	55.9
		Diesel	−12.2	−51.6
	Jul.	Gasoline	122.1	108.8
	2001	Road dust	147.0	138.2
MFB		Wood burning	185.5	189.6
[%]		Diesel	−27.0	−67.0
	Jan.	Gasoline	−79.2	−99.6
	2002	Road dust	199.6	199.5
		Wood burning	−17.6	9.2
		Diesel	0.57	0.50
	Jul.	Gasoline	0.17	0.10
	2001	Road dust	−0.30	−0.35
r		Wood burning	−0.30	−0.16
(correl.)		Diesel	0.55	0.62
	Jan.	Gasoline	0.35	0.30
	2002	Road dust	−0.20	−0.18
		Wood burning	0.47	0.29

$MFE = \frac{1}{N}\sum_{i=1}^{N}\frac{|C_1-C_2|}{(\frac{C_1+C_2}{2})}$ $MFB = \frac{1}{N}\sum_{i=1}^{N}\frac{(C_1-C_2)}{(\frac{C_1+C_2}{2})}$

C_1 and C_2 are pollutant concentrations compared. N equals the number of C_1 and C_2 pairs drawn from all valid monitoring station data for the comparison time period of interest.

inventory. The typical trends do not include irregular events (*e.g.*, forest fires or traffic irregularities) (Figure 9). In addition, the airport emissions are much more variable than the smooth profile used for emissions inventory modeling (Unal *et al.* 2005). Thus, seasonal variations of mass contributions in addition to daily variations using CMAQ were significantly smaller than those from CMB-MM (Figures 2 and 3), and temporal variation of CMAQ is mainly driven by the variation in meteorology due to relatively constant emissions.

The influence of the meteorological fields on the CMAQ results is clear from the analysis of wind speed and pollutant concentrations. All the primary pollutant concentrations from CMAQ are negatively correlated with wind speed (Table 2),

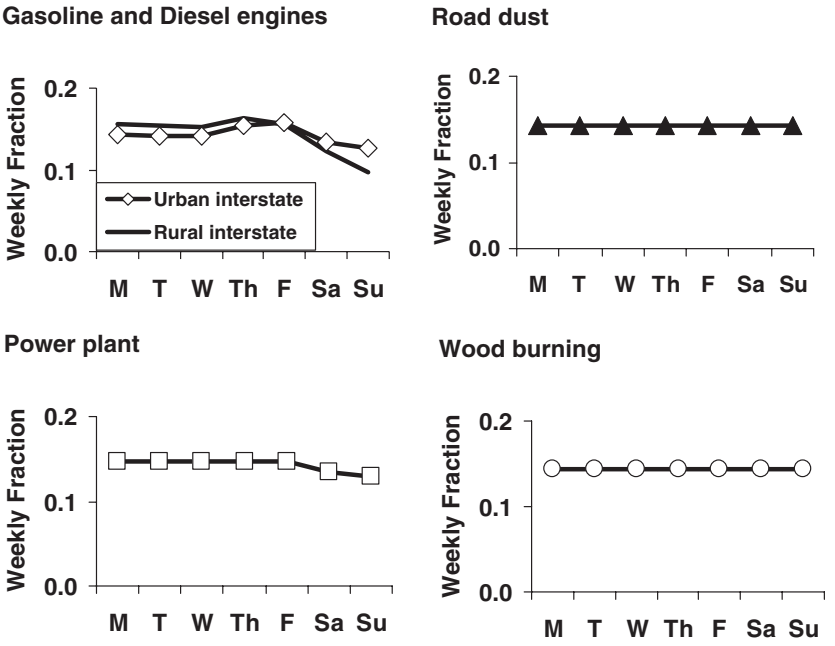

Figure 9. Daily temporal profile of emissions in CMAQ.

indicating the effect of increased dilution. The negative correlation was higher in winter than in summer because the wind speed is higher in wintertime. However, road dust in July and in January, and gasoline in July using CMB-MM are not highly correlated with wind speed (Table 2). The little correlation between emission sources and wind speed is reasonable because two opposite effects may happen; one is that more particles would be suspended and be transported more efficiently in the air when the wind is strong, and the other is the increased dilution may be happen when the wind is strong.

Uncertainty of Each Model

Another reason for disagreement between the two models includes uncertainty of the two models. Important sources of uncertainty in CMB results include source profiles. Studies show that mass contributions estimated from CMB are significantly different depending on source profiles chosen (Ke *et al.* 2008). Another source of uncertainty is that CMB apportions primary mass, which is only a fraction of total

Table 2. Correlation coefficient(r) between daily contributed mass to $PM_{2.5}$ and wind speed in JST.

		Diesel	Gasoline	Road dust	Wood burning
July 2001	CMB(MM)	−0.57	−0.07	0.34	−0.30
	CMAQ	−0.48	−0.35	−0.57	−0.10
January 2002	CMB(MM)	−0.70	−0.69	0.01	−0.40
	CMAQ	−0.72	−0.71	−0.83	−0.73

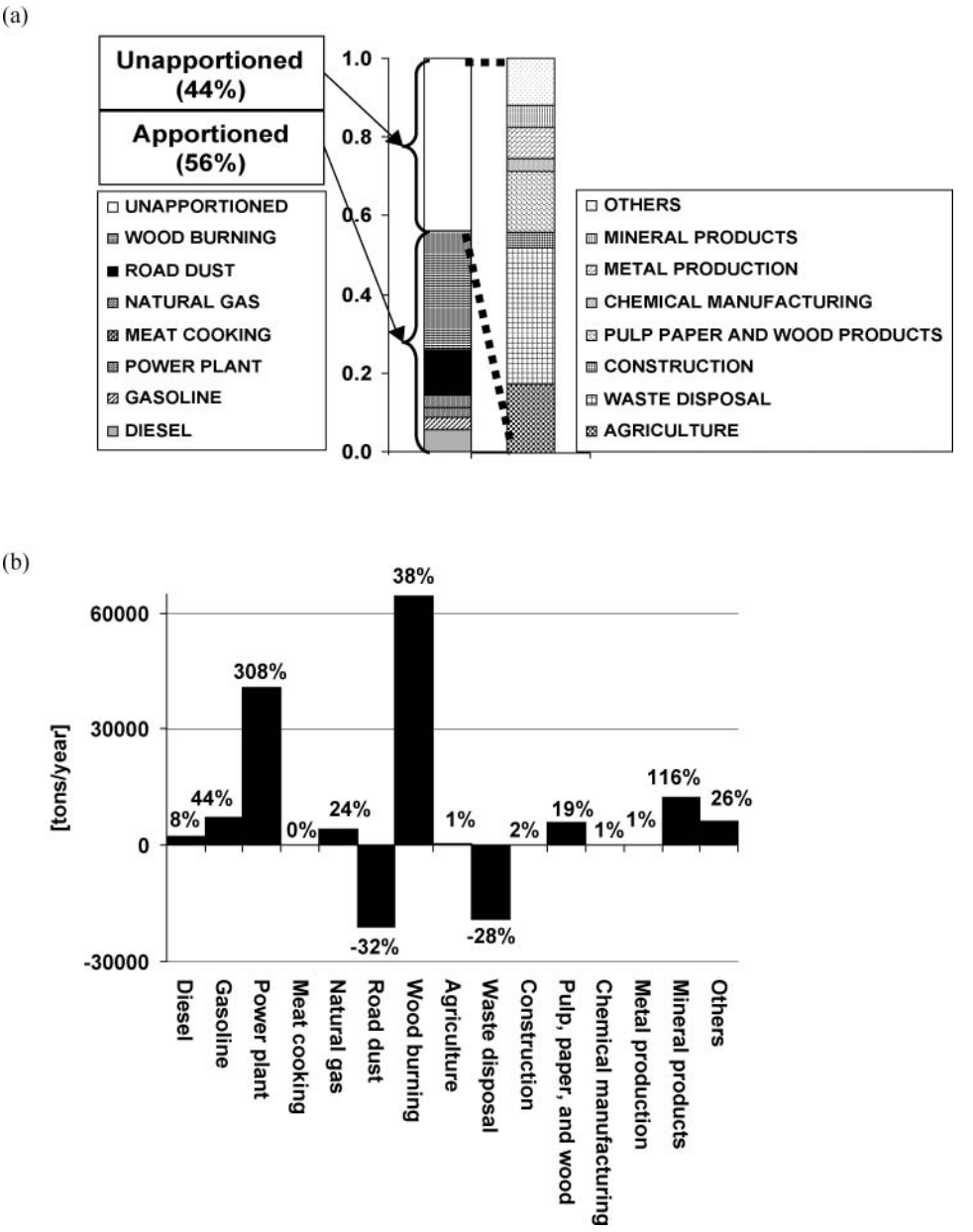

Figure 10. (A) $PM_{2.5}$ emissions in the southeastern United States (AL, GA, FL, and MS) in 2001 based on 1999 National Emission Inventory (NEI 99) ($5.7E + 5$ tons year^{-1}). (B) Difference of 2001 $PM_{2.5}$ emissions in the southeastern United States between emissions based on NEI 99 and those based on USEPA Platform 2001 (USEPA 2001-NEI 99). The normalized difference is expressed as a percentage.

$PM_{2.5}$ mass (Figures 2 and 3). Unknown sources are important not only because they occupy a large parts of $PM_{2.5}$ mass, but also because unknown sources can affect estimating known sources in CMB (Christensen 2004). According to 1999 National Emission Inventory (1999 NEI), major $PM_{2.5}$ sources that did not have profiles for use here include agriculture, waste disposal, and wood products (Figure 10).

Major sources of uncertainty in CMAQ results include the emission inventory, speciation profiles, and meteorological inputs (Placet *et al.* 2000). Currently, the emission inventory is known to be one of the more uncertain inputs (Abdel-Aziz and Frey 2004; Gilliland *et al.* 2003; Hogrefe *et al.* 2003; Mannschreck *et al.* 2002; Mendoza-Dominguez and Russell 2001; Placet *et al.* 2000; Taghavi *et al.* 2005; Vautard *et al.* 2003). Two recent year 2001 emission inventories over the southeastern United States are significantly different (Figure 10). Depending on sources, up to 300% of difference was observed. One method to improve the accuracy of emissions would be to calculate scaling factors of emissions via inverse modeling by incorporating measured concentrations. Indeed, both models have strengths and limitations, and each model's strength can be utilized to overcome the other model's limitations.

ACKNOWLEDGMENTS

This research was supported by the U.S. Environmental Protection Agency under Agreements RD82897602, RD83107601, RD83096001, and RD83479901. We thank John Jansen of the Southern Company, Eric Edgerton in the Atmospheric Research & Analysis, Inc., and researchers involved in ASACA, USEPA-STN, IMPROVE, and SEARCH projects for their assistance and hard work developing the data used. We also appreciate comments from Sergey Napelenok.

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