FINAL REPORT

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Risk of pediatric asthma morbidity from multipollutant exposures.

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ABSTRACT

Background: Little is known about the impact of primary and secondary organic aerosols (POA and SOA) on risk of acute asthma morbidity among children. We evaluated whether these important characteristics of particulate matter are associated with emergency department visits and hospital admissions for asthma. We hypothesized that traffic-related concentrations of ultrafine particles near subject homes and related estimates of exposure to POA will show associations with asthma morbidity that are additive with estimates of exposure to O_3 and larger particles enriched in SOA. This addressed the multipollutant nature of human air pollution exposure. Finally, we evaluated air pollution susceptibility, including asthma recurrence, socioeconomic status, sex, age and race-ethnicity.

Methods: This is a case-crossover analysis in which subjects acted as their own control in a conditional logistic regression model adjusted for confounders. The period of exposure was the week leading up to the day each subject was seen at a hospital, and this was compared to a referent exposure period from the same days of the week and month. The hospital data included 11,390 hospital encounters (emergency department visits and hospital admissions) from 2000-2008 made by 7,954 children ages 0-18 years for a primary diagnosis of asthma in Orange County. The UC Davis/California Institute of Technology (UCD/CIT) Source Oriented Chemical Transport Model was used to output daily POA and SOA at a 4x4 km resolution from 2000-2008 for the 7,954 subject residences. POA and SOA model output included size-resolved mass, speciation, and source apportionment. We obtained ambient air pollutant and weather data from US EPA Air Quality System (AQS). Traffic-related air pollution (TRAP) was assessed using CALINE4 dispersion models at subject residential locations for ultrafine particle number concentration, $PM_{2.5}$, and NO_x averaged seasonally (warm season: May-October; cool season: November-April) and weekly. Seasonal data was used to analyze the influence of spatial exposure variation on acute ambient exposure-response relations, and weekly data for acute effects analyses.

Results: Model prediction of the UCD/CIT model showed wood smoke was the single biggest source of total organic aerosol (TOA=POA+SOA) in winter in California, and meat cooking and other anthropogenic sources (including solvent use) and mobile emissions are the most important sources in summer. Predicted SOA concentrations were low, with biogenic emissions the largest source, followed by the other anthropogenic and mobile sources. In health regression analyses we found that hospital encounters (emergency department visits and admissions) for asthma were positively associated with ambient air pollution data, including $PM_{2.5}$ and O_3 in the warm season and $PM_{2.5}$, CO, NO_2, and NO_x in the cool season. We observed that associations of daily ambient air pollution with asthma hospital morbidity are stronger among subjects living at residences with higher CALINE4-predicted air pollution from traffic, especially in the cool season. Weekly exposures to CALINE4 residential TRAP exposure were significantly associated with asthma hospital encounters in the cool season. We found no associations in the warm season with weekly exposures to UCD/CIT SOA and POA but positive associations of POA (including most specific sources) with asthma in the cool season. Results of the multipollutant models suggest that effects of warm-season ambient O_3 and $PM_{2.5}$ are largely independent of each other and not confounded by any other air pollutant. Cool-season $PM_{2.5}$ was also not confounded by any other air pollutant. We found associations with ambient $PM_{2.5}$, NO_2, and CO in the cool season were nominally stronger among Hispanics compared with non-Hispanic whites. Subjects living in neighborhoods with lower socioeconomic status were at increased risk from elevations in ambient $PM_{2.5}$. Older subjects and female subjects were at nominally increased risk from several air pollutant exposures.

Conclusions: We found consistent results that acute asthma morbidity is increased in relation to short-term elevations in various indicators of air pollution from fossil fuel combustion sources

(including traffic) during the cool season. This includes ambient gases (CO, NO_2, and NO_x), CALINE4 weekly TRAP indicators, and UCD/CIT POA (including on-road and off-road diesel plus gasoline emission sources). There were no associations with SOA in either season. We found that associations of warm-season ambient $PM_{2.5}$ with asthma hospital morbidity were additive with estimates of exposure to O_3. Associations of asthma with ambient CO, NO_2, NO_x, and $PM_{2.5}$, were enhanced among subjects living in homes near high TRAP suggesting that this is a vulnerable/susceptible population.

EXECUTIVE SUMMARY

Background: We used PM predictions generated by regional air quality models to study the relation of asthma morbidity in 7,954 children to daily exposure to primary and secondary organic aerosols (POA and SOA, respectively). We evaluated whether these important characteristics of particulate matter were associated with emergency department visits and hospital admissions for asthma. We hypothesized that traffic-related concentrations of ultrafine particles near subject homes and related estimates of exposure to POA would show associations with asthma morbidity that are additive with estimates of exposure to O_3 and larger particles enriched in SOA. This addresses the multipollutant nature of human air pollution exposure, which includes both ambient and microenvironmental particle and gas components. Finally, we evaluated air pollution susceptibility, including asthma recurrence, socioeconomic status, sex, age and race-ethnicity.

Methods: This was a case-crossover analysis in which subjects acted as their own control. The period of exposure was the week leading up to the day each subject was seen at a hospital, and this was compared to a referent exposure period from the same days of the week and month. The hospital data included 11,390 hospital encounters (emergency department visits and hospital admissions) from 2000-2008 made by 7,954 children ages 0-18 years for a primary diagnosis of asthma in Orange County. The UC Davis/California Institute of Technology (UCD/CIT) Source Oriented Chemical Transport Model was used to output daily POA and SOA at a 4x4 km resolution from 2000-2008 for the 7,954 subject residences. POA and SOA model output included size-resolved mass, speciation, and source apportionment. We obtained ambient air pollutant and weather data from US EPA AQS. Traffic-related air pollution (TRAP) was assessed using CALINE4 dispersion models at subject residential locations for ultrafine particle number concentration, $PM_{2.5}$, and NO_x averaged seasonally (warm season: May-October; cool season: November-April) and weekly. Seasonal averaged CALINE4 data was used to analyze the influence of spatial exposure variation on acute ambient exposure-response relations, and weekly averaged CALINE4 data was used alone to assess its acute effects. Land use regression (LUR) models were used to estimate more diverse sources of NO_x surrounding each subject's residence. We tested regression estimates for lag 0-6 exposure days, focusing on daily to weekly averages for ambient exposures and weekly cumulative averages of estimated particle exposures (UCD/CIT POA and SOA, CALINE4 TRAP, and LUR NO_x). Data was analyzed with conditional logistic regression adjusted for confounders. We tested effect modification of acute associations by seasonal average CALINE4 and LUR exposures stratified above and below their medians. We also tested effects modification by recurrent asthma encounters, socioeconomic status, sex, age and race-ethnicity. Multipollutant models were tested to evaluate whether associations of asthma morbidity with combustion-related air pollutants (ultrafine particles, POA, NO_x, and CO) were independent of associations with secondary air pollutants (SOA or O_3).

Results: Model prediction of the source-oriented UCD/CIT air quality model showed predicted spatial distributions of PM components were in reasonably good agreement with measurements. Better model performance with longer averaging times ≥1 month were found in the predictions. Wood smoke was found to be the single biggest source of OA in winter in California, and meat cooking and other anthropogenic sources (including solvent use) and mobile emissions are the most important sources in summer. Biogenic emissions are predicted to be the largest SOA source, followed by the other anthropogenic sources (including solvent use), and mobile sources, but predicted SOA concentrations were generally low. Concentrations of oxygenated OA were lower than measured values.

In health regression analyses we found that hospital encounters (emergency department visits and admissions) for asthma were positively associated with ambient air pollution data,

including $PM_{2.5}$ and O_3 in the warm season and $PM_{2.5}$, CO, NO_2, and NO_x in the cool season. We observed that associations of daily ambient air pollution with asthma hospital morbidity are stronger among subjects living at residences with higher CALINE4 predicted levels of air pollution from traffic. This was particularly evident for primary combustion-related air pollutants in the cooler season (CO, NO_2, and NO_x) and $PM_{2.5}$ in both seasons. Spatial differences using LUR-modeled NO_x data and CALINE4 data at a 1500 m radius were far less clear than CALINE4 data within close proximity of subject residences (500 m). In analyses of weekly exposures to CALINE4 residential TRAP we found all warm season models showed exposure-response relations that were negative but nonsignificant and all cold season models showed exposure-response relations that were positive and significant. This is consistent with findings for ambient markers of primary emission sources (NO_x and CO). Similarly, we found no associations in the warm season with weekly exposures to UCD/CIT SOA and POA but positive associations of POA (including most specific sources) with asthma in the cool season.

Results of the multipollutant models suggest that effects of warm-season ambient O_3 and $PM_{2.5}$ are largely independent of each other (both confound each other to similar small degrees in two-pollutant models, which still show associations for both air pollutants). The warm season association of asthma with ambient $PM_{2.5}$ was not confounded by CALINE4 TRAP or UCD/CIT SOA and POA. However, associations with cool-season ambient $PM_{2.5}$ may have been partly due to primary air pollutants since two-pollutant models with CALINE4 TRAP, UCD/CIT POA, or a primary gas showed both confounded each other. The warm season association of asthma with ambient O_3 was not confounded by CALINE4 TRAP, UCD/CIT SOA-POA or primary gases.

We observed limited evidence for differences in association between asthma encounters and air pollutant exposures in subjects with vs. without recurrence of hospital encounters. Some regression models did suggest increased risk among the population with repeated visits to hospital presumably by virtue of their more severe or less controlled asthma.

We found associations with ambient $PM_{2.5}$, NO_2, and CO in the cool season were nominally stronger among Hispanics compared with non-Hispanic whites. Also, subjects living in neighborhoods with lower socioeconomic status were at increased risk from elevations in ambient $PM_{2.5}$. Vulnerability due to higher exposures is supported by our findings that Hispanic and African American subjects as well as subjects without private insurance were more likely to live in residences with higher dispersion-modeled TRAP. We also observed that subjects ages ≥12 years and female subjects were at nominally increased risk from air pollutant exposures.

Conclusions: Concentrations of oxygenated OA were lower than measured values likely because of missing pathways in the model formulation. The present SOA model was identical to the SOA model used in EPA's CMAQ model (Carlton et al. ES&T 2010;44:8553-8560). Numerous studies using alternative techniques for SOA prediction are underway, but none of them to date has been able to more accurately predict OA concentrations or the C:O ratio in OA without invoking numerous unconstrained assumptions. The "SOA" predicted in the current study may be a real but incomplete subset of the oxygenated OA that exists in the atmosphere.

We found consistent results that acute asthma morbidity is increased in relation to short-term (1 to 7 days) elevations in various indicators of air pollution from fossil fuel combustion sources (including traffic), particularly during the cool seasons. This consistency was seen for ambient gases (CO, NO_2, and NO_x), CALINE4 weekly TRAP indicators, and UCD/CIT POA (including on-road and off-road diesel plus gasoline emission sources). There were no associations with SOA. We discovered that associations of asthma hospital morbidity with ambient CO, NO_2, NO_x, and $PM_{2.5}$, particularly during the colder seasonal period, are enhanced among subjects living in areas with high traffic-related air pollution near the home (≤500 m), including ultrafine and fine particles. This suggests that associations reported in the time-series

literature may underestimate effects of ambient air pollutants on morbidity for these populations as a result of acutely-increased vulnerability or chronically-increased susceptibility.

Additional studies are needed to confirm our specific novel findings using larger-scale hospital databases covering larger geographic areas to increase statistical power and generalizability. This would be particularly valuable in further evaluations of some of the suggestive findings regarding demographic and personal risk characteristics. Findings in the present study further point to the need for research that assesses the importance of air pollutant chemistry and sources in asthma exacerbations. Nevertheless, the present research findings support the growing view that many large populations are at increased vulnerability and/or susceptibility due to high exposures to traffic-related air pollution near residential locations or other microenvironments.

BODY OF REPORT

1. CHAPTER ONE: INTRODUCTION

1.1 Background

Asthma is among the most common childhood diseases, affecting 6.7 million children in the US in 2007 with major direct medical and other costs (Akinbami et al. 2009). Asthma is the most prevalent cause of disability among children, impacting their quality of life (school absences, sleep disturbance, and inability to play) and causes serious morbidity, especially among blacks and lower socioeconomic groups (Gold and Wright 2005; Wright and Subramanian 2007; Newacheck and Halfon 2000).

Asthma morbidity (including hospital admissions) has been associated with daily concentrations of ambient air pollution ($PM_{2.5}$ and O_3 in particular) in numerous studies (US EPA 2004; US EPA 2006). Studies reporting associations of ambient $PM_{2.5}$ mass with asthma outcomes have been important to the regulatory protection of susceptible populations of children. However, effect magnitudes may have been underestimated or obscured since a large fraction of the PM mass is biologically inactive while a temporally and spatially variable and often small fraction has the potential to induce oxidative stress and inflammation (Ayers et al. 2008). This is important because a major hallmark of the asthma phenotype is airway inflammation, which can be elevated in people with asthma in the presence of oxidative stress (Nadeem et al. 2008). For example, little is known about the health effects of two important classes of particles carried in $PM_{2.5}$, namely:

1) Primary organic aerosols (POA) directly emitted from combustion sources; and

2) Secondary organic aerosols (SOA), which are largely photochemically-produced.

These particle types have different spatial and temporal variability and they are thus minimally correlated in California (Delfino et al. 2009b, 2010a, 2010b). For example, we tested this in a study where SOA in $PM_{2.5}$ was represented by secondary organic carbon and POA by primary organic carbon using the EC tracer estimation method (Polidori et al. 2007), and SOA in quasi-ultrafine particles ($PM_{0.25}$) was represented by water-soluble organic carbon and organic (n-alkanoic) acids (Arhami et al. 2010). We found estimated primary organic carbon was not correlated with estimated secondary organic carbon across 300 days of measurements in the LA Basin (Spearman's $r = 0.01$, Delfino et al. 2009b). During the same study, $PM_{0.25}$ polycyclic aromatic hydrocarbons (PAH) were weakly negatively correlated with $PM_{0.25}$ organic acids ($r = -0.19$) and weakly positively correlated with $PM_{0.25}$ water-soluble organic carbon ($r = 0.39$) (Delfino et al. 2010a, 2010b). The organic component mix and size distribution differs as well, with POA being the predominant mass fraction in near-roadway UFP and SOA comprising a large part of accumulation mode particles (0.1-2.5 µm). In addition, POA components are more hydrophobic, and SOA components are more hydrophilic. These characteristics will likely determine their toxicity and differential effects in the airways.

Many studies support a role of POA chemicals from fossil fuel combustion (e.g. PAH) in increased airway inflammation through oxidative stress mechanisms (Riedl and Diaz-Sanchez 2005). SOA chemicals can also have pro-oxidant and thus pro-inflammatory effects on cells and include polar organics such as quinones (Li et al. 2003). However, there is insufficient epidemiologic data to clarify the roles of POA vs. SOA in associations of asthma morbidity with criteria air pollutants. We recently reported that the fractional concentration of exhaled NO (a biomarker of airway inflammation) was positively associated with 2-day moving average of ambient water-soluble organic carbon (a marker of SOA) in a cohort panel of 45 schoolchildren with persistent asthma (Delfino et al. 2013). Ambient $PM_{2.5}$

was not associated with exhaled NO. Dithiothreitol activity in ambient $PM_{2.5}$ (a marker of oxidative potential) was most strongly associated with exhaled NO and confounded the association with water-soluble organic carbon suggesting that the effects of SOA or other water-soluble components may have been due to the oxidative potential of PM.

Furthermore, there is a lack of data on the health-related importance of local exposure to traffic-related air pollutants, including ultrafine particles (UFP, <0.1 µm), relative to regional exposure to O_3 and $PM_{2.5}$ (that includes organic and other components). Although there is limited data in people with asthma (McCreanor et al. 2007), there is sufficient reason to believe that UFP are capable of inducing the greatest amount of airway inflammation per unit of PM mass compared with the larger particle size fractions currently regulated by the US EPA (Oberdörster et al. 2005). UFP may be more toxic than larger PM size fractions because of the number concentrations and surface areas that are magnitudes higher than larger particles (which dominate PM mass), and higher concentrations of redox active primary organic components (Ntziachristos et al. 2007).

Several epidemiologic studies have evaluated asthma severity or acute asthma outcomes and exposure to traffic using various indices and exposure markers, many showing positive associations. The incidence and prevalence of diagnosed asthma as well as asthma morbidity have also been generally associated with high traffic density near the homes or schools of the subjects (reviewed by Gowers et al. 2012; Guarnieri M, Balmes 2014; Patel and Miller, 2009; Salam et al. 2008). These findings are supported by experimental research (Guarnieri M, Balmes 2014).

Time series studies of asthma hospital encounters and ambient air pollution have infrequently focused on the influence on exposure-response relationships by potentially toxic particle components that are spatially heterogeneous. A California time series study recently evaluated associations of respiratory hospital admissions including asthma with air pollutant components and found significant associations of asthma admissions with EC, NO_3 and several elements (Ostro et al. 2009). Another study found a positive association of ambient air $PM_{2.5}$ zinc levels with hospital admissions and emergency department (ED) utilization for asthma among children in Baltimore (Hirshon et al. 2008). However, we are aware of only one case-crossover study that has evaluated asthma morbidity events in hospital and air pollution on a small (residential) spatial scale. This is a case-crossover study in France that related telephone calls to an emergency medical system for asthma exacerbations to modeled pollutant gases and PM_{10} (Laurent et al. 2008). Air pollutants were modeled for French census blocks using deterministic models including emission inventories, meteorology and background pollutant levels. Positive but nonsignificant associations were found for PM_{10}, NO_2 and SO_2, but not O_3.

In the present study we hypothesize that associations of daily hospital morbidity for asthma with daily exposure to ambient air pollution will be enhanced by higher chronic exposures to traffic-related air pollution near the homes of individual children. We expect such an effect modification because daily increases in ambient air pollution are likely to be accompanied by higher increases in traffic-related air pollution (TRAP) exposures near residences with higher traffic density. A time series study that suggested this was published 14 years ago by Norris et al. (2000). They found that increases in ambient air pollutants across the Seattle region may result from meteorological conditions of air stagnation, and likely correlated with greater concentrations of air pollutants near ground level. This phenomenon would lead to higher risks of hospital admissions for asthma, which is just what they found. Tai et al. (2010) presented evidence that homes near high traffic density can experience the greatest impact under air stagnation and other meteorological conditions (including high photochemical activity), which are often reflected by increases in ambient $PM_{2.5}$. This phenomenon would indicate that people would be more vulnerable to short-term air pollutant elevations during periods of high stagnation or high photochemical activity. In addition, chronic TRAP exposures could increase susceptibility to short-term

increases in exposures through chronic changes in a person's underlying airway inflammation (a hallmark of asthma) or other mechanisms.

In addition to differences in associations with ambient air pollutants across the spatial dimension, there remains the question of whether the associations of asthma morbidity with ambient O_3 reported in many time series studies (e.g. Stieb et al. 2009) are due at least in part to SOA in PM or other photochemically-related pollutants. For example, a Canadian study of 7 cities found positive associations of asthma ED visits with O_3 and PM. Associations with PM_{10} and $PM_{2.5}$ were considerably larger than O_3 in the warm seasons (Apr-Sep), and PM was nonsignificant for analyses that included all seasons. No multipollutant models were presented. There have been several time series studies evaluating multipollutant effects on asthma morbidity by adjusting for different pollutants in co-pollutant regression models to provide data on relative independent effects. This effort is often hindered by problems with collinearity and resultant confounding. A time series study in Atlanta found emergency department visits for asthma were positively associated with O_3 and markers of primary pollutants from traffic sources (especially CO, but also EC and NO_2). Ozone and the primary pollutant markers had largely independent effects in two-pollutant models (Strickland et al. 2010). This can be compared with another study in New York City that found significant associations of asthma hospital admissions with summertime $PM_{2.5}$ and O_3 in two-pollutant models, although the single pollutant models showed slightly stronger associations (Silverman and Ito, 2010). None of these studies were able to evaluate markers of SOA, which could explain some of the between-pollutant confounding.

Although the only photochemical oxidant regulated by the US EPA as a criteria air pollutant is O_3, it is not a substitute nor is it an adequate surrogate for SOA concentrations in urban air sheds (Wood et al. 2010). In several studies comparing O_3 with SOA markers (Delfino et al. 2009b, 2010a, 2010b; Wood et al. 2010), correlations between SOA and O_3 vary widely and are often small, possibly because they are formed from different sets of volatile organic compound (VOC) precursors (Wood et al. 2010). $PM_{2.5}$ and O_3 correlations can be highly variable as well. Therefore, it is likely that at least some part of the apparent effect of both $PM_{2.5}$ and O_3 on asthma morbidity reported in many epidemiologic studies (US EPA 2004, 2006; Stieb et al. 2009; Silverman and Ito, 2010; Strickland et al. 2010) is instead due to unmeasured SOA, which comprises a spatially and temporally variable fraction of $PM_{2.5}$.

We have preliminary data in a cohort panel of 60 elderly subjects who contributed up to 12 weekly repeated measurements of fractional exhaled NO (a biomarker of airway inflammation currently used to monitor asthma status) (Delfino et al. 2010b). At the same time, we made extensive measurements of air pollutant gases and size-fractionated particles in the outdoor environment of each subject's retirement community. As described above, SOA in $PM_{2.5}$ was represented by secondary organic carbon, (Polidori et al. 2007) and SOA in quasi-ultrafine particles ($PM_{0.25}$) was represented by water-soluble organic carbon and organic (n-alkanoic) acids (Arhami et al. 2010). We found exhaled NO was positively associated only with markers of SOA, accumulation mode particle mass (0.25-2.5 μm), and O_3. To test whether having asthma enhanced risk (most subjects did not have asthma) we tested assocaitons for among the only four subjects diagnosed with asthma. We found that associations with organic acids were strongest in this small group and still significant for repeated measures models. These exposure markers represent SOA chemicals that in large part are water soluble and highly oxygenated. Therefore, it is likely that these chemicals dissolve after being deposited on the airway epithelium and then react rapidly with extracellular macromolecules and cell constituents to induce inflammatory responses. Our findings are consistent with the experimental study by Happo et al. (2008) that showed that organic acid concentrations in urban PM were positively associated with inflammatory activity in the lungs of mice after particle instillation.

POA and other traffic-related air pollutants are also expected to be spatially and

temporally variable. Numerous experimental studies now support the hypothesis that exposure to chemicals such as polycyclic aromatic hydrocarbons from diesel and auto exhaust may play a role in the acute exacerbation of respiratory allergic diseases, including asthma. This likely occurs through oxidative stress and airway inflammation (Riedl and Diaz-Sanchez 2005). This is supported by a clinical study in adults with asthma who were alternately exposed on a roadway with diesel traffic and in a nearby park (McCreanor 2007).

Children in low income communities may be more likely to live near high density traffic, (Gunier et al. 2003; Meng et al. 2008). Although socioeconomic status (SES) could result in potential confounding of associations between asthma outcomes and air pollution, studies suggest that poverty increases asthma susceptibility to the effects of both traffic-related air pollutants (Meng et al. 2008; O'Neill et al. 2003) and ambient O_3 (Lin S et al. 2008). The direct effect of poverty on asthma severity has been attributed to many factors, including decreased access to health care, correlated risk factors such as exposure to passive smoke or indoor allergens, and psychosocial stressors (Chen et al. 2008; Clougherty et al. 2007, 2009). Therefore, results of the proposed study regarding differences between socioeconomic groups are of particular importance to the impacts of air pollutants on vulnerable populations. We assessed population susceptibility and vulnerability for asthma morbidity from exposure to air pollutants by known or suspected factors related to the severity of asthma (age, gender, race-ethnicity, health insurance, and SES). The populations discussed are likely to be most susceptible to the impacts of local and regional air pollution, and would therefore benefit from targeted interventions.

Preliminary Data

In a completed South Coast Air Quality Management District (SCAQMD)-funded study (contract no. 040623, with co-funding from NIH), we found significantly increased risk of having repeated episodes of asthma exacerbations and asthma-related lower respiratory illness requiring hospital care with chronic exposure to indices of high traffic density (Chang et al 2009). This was based on an initial analysis that involved subjects with both primary and secondary diagnoses of asthma in relation to traffic indexes, which are less quantitative than traffic dispersion-modeled air pollutant levels. Dispersion models account for wind patterns and other meteorological factors that influence the general direction and dispersion of pollutants, leading to different exposures for subjects on the upwind versus downwind side of traffic sources (Jerrett et al 2005). It was not surprising that compared with use of the indices, we found more significant associations of repeated episodes of asthma requiring hospital care with chronic exposure to residential traffic-related air pollution, which was modeled using a line source dispersion model (CALINE4 NO_2, NO_x and CO) (Delfino et al. 2009a). It is for this reason that we focus here on these more accurate assessments of traffic-related air pollution exposures as described below (Exposure Data sections). To our knowledge, the two studies discussed above (Chang et al 2009; Delfino et al. 2009a) are the only studies that have evaluated the relationship between repeated hospital encounters for individual children admitted with an asthma diagnosis and traffic-related air pollution in the outdoor home environment. This approach was applied in a different way in the present study (Task 3) by assessing effect modification of relations between hospital encounters and air pollutants by recurrence of hospital encounters.

Other evidence from our research showed that an unknown number of subjects may have been lost to follow-up, thereby making it difficult to know if subjects had been readmitted to other hospitals, or if they had moved after the first admission. For this reason, the present study developed a dataset of subjects with addresses linked to each and every admission. Therefore, the new study design was not dependent on longitudinal follow-up past any single admission or ED visit. This was done with the previous data for the years 2000-2003 used in the above published analyses (Chang 2009; Delfino 2009a), as well as adding new data for the years 2004-2008, which more than doubled the size of the dataset to over 7,000 children with asthma diagnoses living in north Orange County and accounting

for over 11,000 hospital encounters. The new dataset has visit-specific addresses linked to local traffic data.

1.2. Objectives

We used PM predictions generated by regional air quality models to study the relation of asthma morbidity in 7,954 children to daily exposure to primary and secondary organic aerosols (POA and SOA, respectively). We evaluated whether temporal and spatial variations in this important characteristic of $PM_{2.5}$ affect the relation of $PM_{2.5}$ mass concentrations to emergency department visits and hospital admissions for asthma. We hypothesized that traffic-related concentrations of ultrafine particles near subject homes and related estimates of exposure to POA would show associations with asthma morbidity that are additive with estimates of exposure to O_3 and larger particles enriched in SOA. This addresses the multipollutant nature of human exposure, which includes both ambient and microenvironmental particle and gas components. Finally, we evaluated air pollution susceptibility, including asthma recurrence, socioeconomic status and race-ethnicity.

1.3. Tasks

We hypothesize that traffic-related concentrations of ultrafine particles near subject homes and related estimates of exposure to POA will show associations with asthma morbidity that are additive with estimates of exposure to O_3 and larger particles enriched in SOA. This addresses the multipollutant nature of human exposure, which includes both ambient and microenvironmental particle and gas components. Finally, we evaluated whether associations of asthma morbidity with air pollution exposure is greater with putative susceptibility factors, including evidence asthma recurrence, low socioeconomic status, lack of private insurance, and minority race-ethnicity.

The following tasks were completed to address the above research hypothesis and research questions:

Task 1. To estimate exposures for children with asthma to primary and secondary organic aerosols.

The University of California, Davis /California Institute of Technology (UCD/CIT) Source Oriented Chemical Transport Model (coinvestigator M. Kleeman) was modified to output daily POA and SOA exposures at a 4x4 km resolution from 2000-2008 for 7954 children in Orange County. The POA and SOA model output included size-resolved mass, speciation, and source apportionment. PM variables were estimated for three particle sizes, including ultrafine, $PM_{2.5}$, and PM_{10}, along with source estimates. SOA and POA model estimations were validated using particle composition data from 3 retirement communities of a study of 45 elderly subjects. Other air pollutants estimated by the UCD/CIT model included O_3, nitrogen oxides (NO_2 and NO_x), carbon monoxide (CO).

Task 2. To assess the risk of emergency department visits and hospital admissions for asthma in children from exposure to both traffic-related particles near their homes and local ambient primary and secondary organic aerosols and O_3.

First, the new POA-SOA and other exposure data from Task 1 (across a 4x4 km grid) were combined with additional new exposure assessment work to estimate daily traffic-related air pollutant exposures (ultrafine PM, $PM_{2.5}$, NO_x, and CO) near geocoded subject residences (500 m radius buffer). This new work in Task 2 produced temporally-resolved traffic dispersion model data using real-time traffic count and speed data, Weigh-in-Motion (WIM) fleet composition data at major freeways and highways, and meteorological data from

Weather Research Forecasting (WRF) model outputs. Available data (under separate funding from SCAQMD) is less temporally resolved and includes seasonal average exposures to traffic-related air pollutant near subject residences (ultrafine PM, $PM_{2.5}$, NO_x, and CO) estimated for 6-month seasonal periods (warm season: May to October; cool season: November to April) using CALINE4 dispersion models. These available models are also based on local traffic within a 500 m radius buffer. Daily ambient air data from the SCAQMD station nearest each subject is also available.

We then evaluated the risk of both emergency department (ED) visits (N=8,227) and hospital admissions (N=3,163) from exposure to air pollution during the period of 2000-2008. Data was analyzed with case-crossover conditional logistic regression models. Multipollutant models were tested to evaluate whether associations of asthma morbidity with combustion-related air pollutants (UFP, POA, NO_x, and CO) are independent of associations with secondary air pollutants (SOA or O_3). We hypothesized that asthma morbidity would be additively associated with daily traffic-related number concentrations of UFP near subject homes (or related estimates of exposure to POA) and estimates of exposure to SOA (or O_3). We additionally evaluated whether associations of asthma morbidity with weekly average POA and SOA above differ between subjects with high seasonal exposures to traffic-related residential air pollution based on the available CALINE4 dispersion model data. This will be compared with currently funded work to estimate whether associations of asthma morbidity with daily ambient air pollution from SCAQMD sites are stronger among subjects with high seasonal exposures to traffic-related residential air pollution.

Task 3. To stratify subjects based on recurrence of hospital encounters in order to assess whether children with multiple encounters show the strongest associations with air pollutants.

We compared associations for 4,823 subjects with only one hospital encounter (ED visits or hospital admission) to associations for 1,777 subjects with more than one hospital encounter. We hypothesize that associations will be stronger for subjects with multiple hospital encounters. To reduce the likelihood of hospital usage outside of the study hospitals, subjects were selected from a 15-km catchment area (83% of the population) around the two children's hospitals that are the source of subjects in the study.

Task 4. To assess effect modification of associations by subject demographic and socioeconomic characteristics.

This evaluation focused on subject and neighborhood (Census block group) demographic factors including neighborhood SES, health insurance, race-ethnicity, sex, and age group. These factors represent potential vulnerability to the effects of air pollutants by children with asthma. It is also of interest whether traffic-related air pollutant exposures near geocoded subject residences differ by these subject characteristics and neighborhood factors.

Innovation

Previous time series studies have contributed important information about the potential health impacts of air pollution on children with asthma. However, all subjects in each targeted geographic region of the time series studies are assigned the same exposures. The health outcomes are derived from aggregate (non-individual level) daily hospital data. To our knowledge, there has not been an evaluation of the relationship between hospital data for acute asthma among individual children and daily variations in traffic-related air pollution in the immediate outdoor home environment of these children. The present study is among the first to do so. Furthermore, we estimated air pollution concentrations as the exposures of interest rather than cruder traffic indices like proximity to roadways. For this case-crossover study, we analyzed individual-level patient data for asthma ED visits and

hospital admissions as well as individual-level, local, and regional ambient exposures. This was used by us, for the first time, to combine joint effects from the temporal and spatial variation in air pollution exposure. Specifically, we estimated whether associations of asthma morbidity with daily ambient air pollution exposures from SCAQMD sites are stronger among subjects with high seasonal exposures to traffic-related residential air pollution.

We are unaware of any study evaluating the relation of asthma hospital morbidity in people to SOA exposure. There are a few studies that have linked exposure to SOA with respiratory inflammation in rodents (McDonald et al 2010; Happo et al. 2008), but most studies have relied on *in vitro* cell cultures to evaluate SOA effects (Baltensperger et al. 2008; Gaschen et al. 2010; Wilkins et al. 2001). SOA in urban air is a far more complex mixture than those typically used in these experimental studies (Robinson et al. 2007), and it is of great interest whether effects can be observed in human populations. With the exception of our preliminary results discussed above (Delfino et al. 2010b), there are no epidemiologic data to our knowledge evaluating the relation of asthma outcomes with exposure to SOA (Task 2). With the multipollutant models that we propose below, we estimated the potential magnitude of effects from SOA as compared with POA and with EPA-regulated O_3 and $PM_{2.5}$, across various potentially susceptible subpopulations (Task 4). Finally, to our knowledge only one study (our own) has related the risk of recurrent asthma hospitalization and emergency department visits with estimates of traffic-related air pollutants near the home (Delfino et al. 2009a). In Task 3, we revisited this finding in a different manner by evaluating whether case-crossover associations are stronger for subjects with multiple hospital encounters, which may be considered an indicator of greater asthma severity.

Benefits of the Project

Results of this study have the potential to help re-focus our understanding of the health effects of air pollutants. Improving air quality and public health require a systematic effort at understanding the impact of the environment on susceptible children (those with ongoing severe exacerbations of asthma). One of the most pervasive determinants of air pollution exposure affecting children living in California is residence near freeways and major surface streets. Mobile sources are also the major source of regional air pollution in California that is expected to impact concentrations of regional POA and SOA. Children in low income communities may be more likely to live near high density traffic (Gunier 2003; Meng et al 2008), which is why results regarding differences between socioeconomic groups in our study are of particular importance (Task 4).

Of considerable benefit is the ability of this study to compare estimates of associations of asthma morbidity (Task 2) with POA vs. SOA exposures from the UCD/CIT model (Task 1), ultrafine vs. larger particles from the UCD/CIT model (Task 1), and traffic dispersion-modeled air pollutants vs. measurements of air pollutants at ambient monitoring stations ($PM_{2.5}$ and criteria pollutant gases) that may represent more homogenous background exposure levels. $PM_{2.5}$ is considered a general indicator of air pollution given its diverse sources including secondary aerosol formation. The association of size-fractionated PM and organic aerosol fractions with hospital outcomes is compared here with ambient $PM_{2.5}$ associations. This is important since ambient $PM_{2.5}$ is regulated by the US EPA as a regional (ambient) air pollutant. The same importance can be ascribed to comparing associations with ambient versus traffic dispersion-modeled gaseous criteria pollutants (CO and NO_2/NO_x). Furthermore, for the first time, we estimate potential effects of air pollution on hospital morbidity by combined temporal and spatial variation in exposure. Therefore, the importance of only regulating regional pollutant concentrations to the protection of public health was an important issue addressed in this research. Findings were relevant to efforts by CARB to control $PM_{2.5}$ by assessing the important sources and components that are related to health outcomes.

The study design may be applied to other California urban regions where it has the potential to reveal the impacts of local traffic-related air pollution on asthma emergency department visits and hospital admissions, which are among the most severe health outcomes that can be experienced by children. The strength of this design is that it involves individual-level data rather than aggregate administrative data normally employed in air pollution time series studies. The present study design enables an assessment of the risk of hospital utilization from both spatial and temporal differences in air pollutant exposures. To our knowledge, this has not been evaluated in previous case-crossover studies of asthma and air pollution.

The present study also enables the assessment of susceptibility due to asthma severity as indicated by recurrent hospital encounters (one encounter vs. >1 encounter) (Task 3). To our knowledge, this indicator of severity has not been assessed in previous case-crossover studies of asthma and air pollution. Additional information regarding other determinants of hospital visits (lower socioeconomic status, lack of private health insurance, or racial-ethnic differences) was used to identify children at risk potentially because of increased local air pollutant exposures and under-treated asthma (Task 4). Ultimately, decreasing repeated utilization of hospital resources through improvements in local air quality will improve public health and preserve health care resources.

The following chapters reports on the methods, results and conclusions of each of these four tasks (Chapters 2-5). This will be followed by an overall summary and conclusions (Chapter 6), and recommendations (Chapter 7).

References

Akinbami LJ, Moorman JE, Garbe PL, Sondik EJ. 2009. Status of childhood asthma in the United States, 1980-2007. Pediatrics 123 Suppl 3:S131-45.

Arhami M, Minguillón MC, Polidori A, Schauer JJ, Delfino RJ, Sioutas C. 2010. Organic compound characterization and source apportionment of indoor and outdoor quasi-ultrafine PM in retirement homes of the Los Angeles basin. Indoor Air 20:17-30.

Ayres JG, Borm P, Cassee FR, Castranova V, Donaldson K, Ghio A, Harrison RM, Hider R, Kelly F, Kooter IM, Marano F, Maynard RL, Mudway I, Nel A, Sioutas C, Smith S, Baeza-Squiban A, Cho A, Duggan S, Froines J. 2008. Evaluating the toxicity of airborne particulate matter and nanoparticles by measuring oxidative stress potential--a workshop report and consensus statement. Inhal Toxicol 20:75-99.

Baltensperger U, Dommen J, Alfarra MR, Duplissy J, Gaeggeler K, Metzger A, Facchini MC, Decesari S, Finessi E, Reinnig C, Schott M, Warnke J, Hoffmann T, Klatzer B, Puxbaum H, Geiser M, Savi M, Lang D, Kalberer M, Geiser T. 2008. Combined determination of the chemical composition and of health effects of secondary organic aerosols: the POLYSOA project. J Aerosol Med Pulm Drug Deliv. 21:145-54.

Chang J, Delfino RJ, Gillen D, Tjoa T, Nickerson B, Cooper D. 2009. Repeated respiratory hospital encounters among children with asthma and residential proximity to traffic. Occup Environ Med 66;90-98.

Chen E, Schreier HM, Strunk RC, Brauer M. 2008. Chronic traffic-related air pollution and stress interact to predict biologic and clinical outcomes in asthma. Environ Health Perspect. 116:970-5.

Clougherty JE, Kubzansky LD. 2009. A framework for examining social stress and susceptibility to air pollution in respiratory health. Environ Health Perspect. 117:1351-8.

Clougherty JE, Levy JI, Kubzansky LD, Ryan PB, Suglia SF, Canner MJ, Wright RJ. 2007. Synergistic effects of traffic-related air pollution and exposure to violence on urban asthma etiology. Environ Health Perspect. 115:1140-6.

Delfino RJ, Chang J, Wu J, Ren C, Tjoa T, Nickerson B, Cooper D, Gillen DL. 2009a.

Repeated hospital encounters for asthma in children and exposure to traffic-related air pollution near the home. Ann Allergy Asthma Immunol 102:138-144.
Delfino RJ, Staimer N, Tjoa T, Arhami M, Polidori A, George SC, Shafer MM, Schauer JJ, Sioutas C. 2010b. Associations of primary and secondary organic aerosols with airway and systemic inflammation in an elderly panel cohort. Epidemiology 21:892-902.
Delfino RJ, Staimer N, Tjoa T, Arhami M, Polidori A, Gillen D, Kleinman MT, Schauer J, Sioutas C. 2010a. Association of biomarkers of systemic effects with organic components and source tracers in quasi-ultrafine particles. Environ Health Perspect 118:756-762.
Delfino RJ, Staimer N, Tjoa T, Gillen D, Polidori A, Arhami M, Kleinman MT, Vaziri N, Longhurst J, Sioutas C. 2009b. Air pollution exposures and circulating biomarkers of effect in a susceptible population: clues to potential causal component mixtures and mechanisms. Environ Health Perspect 117:1232–1238.
Delfino RJ, Staimer N, Tjoa T, Gillen DL, Schauer JJ, Shafer M. Airway inflammation and oxidative potential of air pollutant particles in a pediatric asthma panel. J Expo Sci Environ Epidemiol 2013;23:466-473.
Gaschen A, Lang D, Kalberer M, Savi M, Geiser T, Gazdhar A, Lehr CM, Bur M, Dommen J, Baltensperger U, Geiser M. 2010. Cellular responses after exposure of lung cell cultures to secondary organic aerosol particles. Environ Sci Technol. 44:1424-30.
Gold DR, Wright R. Population disparities in asthma. 2005. Annu Rev Public Health 26:89-113.
Gowers AM, Cullinan P, Ayres JG, Anderson HR, Strachan DP, Holgate ST, Mills IC, Maynard RL. 2012. Does outdoor air pollution induce new cases of asthma? Biological plausibility and evidence; a review. Respirology. 17:887-98.
Guarnieri M, Balmes JR. 2014. Outdoor air pollution and asthma. Lancet. 383:1581-92.
Gunier RB, Hertz A, Von Behren J, Reynolds P. 2003. Traffic density in California: socioeconomic and ethnic differences among potentially exposed children. J Expo Anal Environ Epidemiol 13:240-6.
Happo MS, Hirvonen MR, Halinen AI, Jalava PI, Pennanen AS, Sillanpaa M, Hillamo R, Salonen RO. 2008. Chemical compositions responsible for inflammation and tissue damage in the mouse lung by coarse and fine particulate samples from contrasting air pollution in Europe. Inhal Toxicol 20:1215-1231.
Hirshon JM, Shardell M, Alles S, Powell JL, Squibb K, Ondov J, Blaisdell CJ. 2008 . Elevated ambient air zinc increases pediatric asthma morbidity. Environ Health Perspect. 116:826-31.
Jerrett M, Arain A, Kanaroglou P, Beckerman B, Potoglou D, Sahsuvaroglu T, Morrison J, Giovis C. 2005. A review and evaluation of intraurban air pollution exposure models. J Expo Anal Environ Epidemiol 15:185-204.
Laurent O, Pedrono G, Segala C, Filleul L, Havard S, Deguen S, Schillinger C, Rivière E, Bard D. Air pollution, asthma attacks, and socioeconomic deprivation: a small-area case-crossover study. Am J Epidemiol 2008;168:58-65.
Li N, Hao M, Phalen RF, Hinds WC, Nel AE. 2003. Particulate air pollutants and asthma. A paradigm for the role of oxidative stress in PM-induced adverse health effects. Clin Immunol 109:250-65.
Lin S, Liu X, Le LH, Hwang SA. 2008. Chronic exposure to ambient ozone and asthma hospital admissions among children. Environ Health Perspect 116:1725-30.
McCreanor J, Cullinan P, Nieuwenhuijsen MJ, Stewart-Evans J, Malliarou E, Jarup L, Harrington R, Svartengren M, Han IK, Ohman-Strickland P, Chung KF, Zhang J. 2007. Respiratory effects of exposure to diesel traffic in persons with asthma. N Engl J Med. 357:2348-58.
McDonald JD, Doyle-Eisele M, Campen MJ, Seagrave J, Holmes T, Lund A, Surratt JD, Seinfeld JH, Rohr AC, Knipping EM. 2010. Cardiopulmonary response to inhalation of biogenic secondary organic aerosol. Inhal Toxicol. 22:253-65.
Meng YY, Wilhelm M, Rull RP, English P, Nathan S, Ritz B. 2008. Are frequent asthma symptoms among low-income individuals related to heavy traffic near homes,

vulnerabilities, or both? Ann Epidemiol. 18:343-50.
Nadeem A, Masood A, Siddiqui N. 2008. Oxidant--antioxidant imbalance in asthma: scientific evidence, epidemiological data and possible therapeutic options. Ther Adv Respir Dis. 2:215-35.
Newacheck PW, Halfon N. 2000. Prevalence, impact, and trends in childhood disability due to asthma. Arch Pediatr Adolesc Med. 154:287–293.
Norris G, Larson T, Koenig J, Claiborn C, Sheppard L, Finn D. Asthma aggravation, combustion, and stagnant air. Thorax. 2000; 55:466-470.
Ntziachristos L, Froines JR, Cho AK, Sioutas C. 2007. Relationship between redox activity and chemical speciation of size-fractionated particulate matter. Part Fibre Toxicol 4:5.
Oberdörster G, Oberdörster E, Oberdörster J. 2005. Nanotoxicology: an emerging discipline evolving from studies of ultrafine particles. Environ Health Perspect 113:823-839.
O'Neill MS, Jerrett M, Kawachi I, Levy JI, Cohen AJ, Gouveia N, Wilkinson P, Fletcher T, Cifuentes L, Schwartz J. 2003. Workshop on Air Pollution and Socioeconomic Conditions. Health, wealth, and air pollution: advancing theory and methods. Environ Health Perspect. 111:1861-70.
Ostro B, Roth L, Malig B, Marty M. 2009. The effects of fine particle components on respiratory hospital admissions in children. Environ Health Perspect 117:475-80.
Patel MM, Miller RL. 2009. Air pollution and childhood asthma: recent advances and future directions. Curr Opin Pediatr. 21:235-42.
Polidori A, Arhami M, Delfino RJ, Allen R, Sioutas C. 2007. Indoor-outdoor relationships, trends and carbonaceous content of fine particulate matter in retirement communities of the Los Angeles basin. J Air Waste Manage Assoc 57:366-379.
Riedl M, Diaz-Sanchez D. 2005. Biology of diesel exhaust effects on respiratory function. J Allergy Clin Immunol. 115:221-8.
Robinson AL, Donahue NM, Shrivastava MK, Weitkamp EA, Sage AM, Grieshop AP, Lane TE, Pierce JR, Pandis SN. 2007. Rethinking organic aerosols: semivolatile emissions and photochemical aging. Science 315:1259-62.
Salam MT, Islam T, Gilliland FD. 2008. Recent evidence for adverse effects of residential proximity to traffic sources on asthma. Curr Opin Pulm Med. 14:3-8.
Silverman RA, Ito K. 2010. Age-related association of fine particles and ozone with severe acute asthma in New York City. J Allergy Clin Immunol. 125:367-373.e5.
Stieb DM, Szyszkowicz M, Rowe BH, Leech JA. 2009. Air pollution and emergency department visits for cardiac and respiratory conditions: a multi-city time-series analysis. Environ Health. 8:25.
Strickland MJ, Darrow LA, Klein M, Flanders WD, Sarnat JA, Waller LA, Sarnat SE, Mulholland JA, Tolbert PE. 2010. Short-term associations between ambient air pollutants and pediatric asthma emergency department visits. Am J Respir Crit Care Med. 182:307-16.
Tai APK, Mickley LJ, Jacob DJ. Correlations between fine particulate matter (PM2.5) and meteorological variables in the United States: Implications for the sensitivity of PM2.5 to climate change. Atmos Environ. 2010; 44:3976-3984.
US EPA. Air quality criteria for ozone and related photochemical oxidants (final). Washington, DC: United States Environmental Protection Agency EPA/600/R-05/004aF-cF; 2006.
US EPA. Air quality criteria for particulate matter (final). Washington, DC: US Environmental Protection Agency 600/P-99/002aF-bF; 2004.
Wilkins CK, Clausen PA, Wolkoff P, Larsen ST, Hammer M, Larsen K, Hansen V, Nielsen GD. 2001. Formation of strong airway irritants in mixtures of isoprene/ozone and isoprene/ozone/nitrogen dioxide. Environ Health Perspect 109:937-41.
Wood EC, Canagaratna MR, Herndon SC, Kroll JH, Onasch TB, Kolb CE, Worsnop DR, Knighton WB, Seila R, Zavala M, Molina LT, DeCarlo PF, Jimenez JL, Weinheimer AJ, Knapp DJ, Jobson BT, Stutz J, Kuster WC, Williams EJ. 2010. Investigation of the correlation between odd oxygen and secondary organic aerosol in Mexico City and Houston. Atmos Chem Phys Discuss 10:3547–3604.

Wright RJ, Subramanian SV. 2007. Advancing a multilevel framework for epidemiologic research on asthma disparities. Chest 132(5 Suppl):757S-769S.

2. CHAPTER TWO: TASK 1

Task 1. To estimate exposures for children with asthma to primary and secondary organic aerosols. (Dr. Michael Kleeman)

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2.0 Introduction

$PM_{2.5}$ mass has been linked to severe short-term and long-term health effects such as asthma, cardio-respiratory disease, and lung cancer (see for examples (Dockery, Pope et al. 1993, Dockery and Pope 1994, Dockery 2001, Le Tertre, Medina et al. 2002, Pope, Burnett et al. 2002, Pope and Dockery 2006, Franklin, Zeka et al. 2007). Organic aerosol (OA) accounts for a large fraction of the $PM_{2.5}$ total mass at the ground level breathing zone in typical urban, suburban and rural atmospheres (Zhang, Jimenez et al. 2007). In addition to making a major contribution to $PM_{2.5}$ mass, OA contains certain organic compounds emitted/formed from specific sources that are particularly concerning due to their possible health effects (Mauderly and Chow 2008). Over 90% of the Hazardous Air Pollutants (HAPs) defined by the US EPA are classified as OA emitted directly from sources such as diesel vehicles are biomass combustion or produced through atmospheric chemical reactions. A few early studies (Mar, Norris et al. 2000, Ostro, Broadwin et al. 2006, Ostro, Lipsett et al. 2010, Cao, Xu et al. 2012, Levy, Diez et al. 2012, Krall, Anderson et al. 2013) have directly investigated the associations between exposure to OA and the observed health effects but large uncertainties still remain, partly due to the limited data available to accurately quantify exposure to different components and sources of OA.

Atmospheric OA consists of primary organic aerosol (POA) and secondary organic aerosol (SOA). POA is directly emitted to the atmosphere in particle phase while SOA is formed in the atmosphere from the oxidation of volatile or semi-volatile organic compounds (Seinfeld and Pankow 2003). Both POA and the precursors of SOA can be emitted from anthropogenic and biogenic sources (Mauderly and Chow 2008). Identifying the concentrations of POA and SOA from different sources in ambient measurements is difficult and expensive leading to limited data from monitoring networks. Epidemiological studies are likewise limited by the resulting sparseness in spatial and temporal exposure estimates.

Chemical transport models (CTMs) have recently been used as an alternative approach to fill in the spatial and temporal gaps in the exposure assessment for air pollution (Anenberg, Horowitz et al. 2010, Sarnat, Sarnat et al. 2011, Bravo, Fuentes et al. 2012, Tainio, Juda-Rezler et al. 2012) that are impractical to measure using monitoring networks. The latest generation of CTMs represents a "state-of-science" understanding of emissions, transport and atmospheric chemistry. CTM predictions provide more detailed composition information and full spatial coverage of air pollution impacts with a typical temporal resolution of 1 hour. Accurate CTMs predictions have great potential to improve exposure assessment in epidemiological studies.

Early applications of CTMs in epidemiology studies generally used relatively coarse spatial resolutions in order to reduce computational burden. Global CTMs have used horizontal resolutions of over 100 km and regional CTMs have used resolutions of 12-36 km. These resolutions are useful for large-scale exposure estimates but they cannot capture fine spatial gradients of PM concentrations, especially in areas with diverse topography and demography. Early applications of CTMs in epidemiology studies have also been limited to time periods less than one year. Recently Zhang et al. (Zhang, Chen et al. 2014) evaluated

the performance of the Community Multiscale Air Quality (CMAQ) model over a 7-year period in the Eastern United States (U.S.), but no other long-term CTMs studies for health effects analyses have been published to date. As a further limitation, previous epidemiology studies based on CTM predictions have mostly focused exclusively on $PM_{2.5}$ mass concentrations without taking full advantage of the ability to predict multiple particle size fractions, chemical components, and source contributions. To the best of the authors' knowledge, no CTMs studies in the literature have identified the concentrations and sources of POA and SOA for health effects studies.

The purpose of this chapter is to summarize the development and application of advanced source-oriented CTMs to predict the concentrations and sources of size-resolved PM for enhanced exposure assessment in epidemiological studies over a long-term period in California (Hu, Zhang et al. 2014, Hu, Zhang et al. 2014, Hu, Zhang et al. 2014). We investigate the capability of models to predict POA and SOA concentrations and source contributions. The features of the CTM POA and SOA results that could improvethe exposure assessment for epidemiological studies are identified and the limitations in modeling POA and SOA exposure for use in health effects studies are discussed.

2.1 Materials and Methods

2.1.1 Model Description

The host air quality model employed in the current study is based on the Eulerian source-oriented University of California-Davis/California Institute of Technology (UCD/CIT) chemical transport model (Kleeman, Cass et al. 1997, Kleeman and Cass 2001, Mysliwiec and Kleeman 2002, Held 2004, Held, Ying et al. 2005, Ying and Kleeman 2006, Kleeman, Ying et al. 2007, Ying, Fraser et al. 2007, Ying 2008, Chen, Ying et al. 2010, Hu, Ying et al. 2010, Mahmud 2010, Zhang and Ying 2010, Hu, Howard et al. 2012, Rasmussen, Hu et al. 2013). The UCD/CIT model includes a complete description of atmospheric transport, deposition, chemical reaction, and gas-particle transfer. The details of the standard algorithms used in the UCD/CIT family of models have been described in the above references and therefore are not repeated here. Only the aspects that are updated during the current study are discussed in the following section.

The photochemical mechanism used by the UCD/CIT model was updated to reflect the latest information from smog-chamber experiments. The SAPRC-11 photochemical mechanism (Carter and Heo 2012, Carter and Heo 2013) was used to describe the gas-phase chemical reactions in the atmosphere. The secondary organic aerosol (SOA) treatment was updated following the method described in Carlton et al. (Carlton, Bhave et al. 2010). Seven organic species (isoprene, monoterpenes, sesquiterpenes, long-chain alkanes, high-yield aromatics, low-yield aromatics, and benzene) are considered as precursors for SOA formation. A total of twelve semi-volatile products and seven nonvolatile products are formed from the oxidation of the precursor species. The gas-particle transfer of the semi-volatile and nonvolatile products in the UCD/CIT model is modeled as a dynamic process based on the gas vapor pressures calculated over the particle surface and the kinetic limitations to mass transfer. The explicit chemical reactions and the parameters for the thermodynamic equilibrium calculation (i.e., enthalpy of vaporization, saturation concentrations, and stoichiometric yields) are provided in Carlton et al. and references therein (Carlton, Bhave et al. 2010).

2.1.2 Source Apportionment of POA and SOA

The UCD/CIT model tracks primary particles and SOA formation from different sources separately through the calculation of all major aerosol processes such as emissions, transport, deposition, gas-to-particle conversion, and coagulation. The model tracks primary particles emitted from different sources using artificial tracers coded as additional model

species with concentrations equal to 1% of the total mass of primary PM. The small perturbation to particle mass means that particle radius and the dry deposition rates are not significantly affected. The primary PM total mass concentrations from a given source then are directly computed using 100 x artificial tracer concentrations from that source. Source-specific emission profiles are then used to estimate the POA concentrations in the primary PM total mass using the equation (1):

$$POA_{i,j} = C_{i,j} \times A_{i,j} \qquad \text{(eq. 1)}$$

where $POA_{i,j}$ and $C_{i,j}$ represent POA concentration and primary PM total mass concentration in size bin *i* from source *j*, respectively. $A_{i,j}$ represents OA fraction per unit mass of PM emitted from the *j*th emission source in size bin *i*. More details describing the POA source apportionment technique and the emission profiles are provided by (Ying, Lu et al. 2008).

SOA source apportionment is predicted by tracking the SOA precursor emissions from different sources individually through all the model processes as they are transformed by chemical reactions leading to the formation of low-volatility products that can partition to the particle phase. This approach was first developed for source apportionment of secondary inorganic aerosols, such as nitrate, sulfate, and ammonium (Mysliwiec and Kleeman 2002, Ying and Kleeman 2006) and then later applied for SOA source apportionment in California using the Caltech Atmospheric Chemistry Mechanism (Kleeman, Ying et al. 2007, Chen, Ying et al. 2010). In the current study, the SAPRC11 mechanism was expanded to track the reactions of SOA precursors emitted from different sources. Chemical reaction products leading to SOA formation are labeled with the source-identity of the reactant so that source attribution information is preserved. For the example of isoprene (ISOP) reaction with OH forming isoprene derived SOA,

ISOP + OH → SV.ISO1 + SV.ISO2 (rx. 1)
SV.ISO1 ↔ AISO1 (rx. 2)
SV.ISO2 ↔ AISO2 (rx. 3)

where SV.ISO1 and SV.ISO2 represents the two semi-volatile products that partition between gas and particle phase, and AISO1 and AISO2 represent the particle phase SOA products from SV.ISO1 and SV.ISO2, respectively. If there are two sources for isoprene, ISOP is first expanded into two species ISOP_X1 and ISOP_X2 in the model corresponding to sources X1 and X2. The above reactions (rx1 –rx3) are then expanded as:

ISOP_X1 + OH → SV.ISO1_X1 + SV.ISO2_X1 (rx. 4)
SV.ISO1_X1 ↔ AISO1_X1 (rx. 5)
SV.ISO2_X1 ↔ AISO2_X1 (rx. 6)

ISOP_X2 + OH → SV.ISO1_X2 + SV.ISO2_X2 (rx. 7)
SV.ISO1_X2 ↔ AISO1_X2 (rx. 8)
SV.ISO2_X2 ↔ AISO2_X2 (rx. 9)

Thus, the SOA products from ISOP AISO1_X1, AISO1_X2, AISO2_X1 and AISO2_X2 contain the source information so that the source contributions from each source to the SOA concentrations can be accurately calculated.

2.1.3 Model Application

2.1.3.1 Modeling Domains

The UCD/CIT model was applied to simulate the concentrations and sources of POA and SOA during ~ a decadal period (9 years from 2000 January 1st to 2008 December 31st) over California. Model simulations were configured using a one-way nesting technique with a parent domain of 24 km horizontal resolution that covered the entire state of California

(referred to as CA_24km) and two nested domains with 4 km horizontal resolution that covered the Southern California Air Basin (SoCAB) (referred to as SoCAB_4km) and San Francisco Bay Area + San Joaquin Valley (SJV) + South Sacramento Valley air basins (referred to as SJV_4km) (shown in Figure 2-1). The nested 4 km resolution domains are configured to cover the major ocean, coast, urban, and rural regions that influence California's air quality and, most importantly, to cover most of the California's population for the purpose of health effects analyses. Over 92% of California's population lives in the 4 km domains based on the most recent census information. The UCD/CIT model was configured with 16 vertical layers up to a height of 5 km above ground level in all domains, with 10 layers in the first 1 km. Particulate composition, number and mass concentrations are represented in 15 size bins, ranging from 0.01 to 10 μm in diameter. Primary particles are assumed to be internally mixed, i.e., all particles within a size bin have the same composition. Previous studies (Ying, Fraser et al. 2007) have shown that this assumption provides adequate predictions for total PM concentrations relative to source-oriented mixing treatments in California when feedbacks to meteorology are not considered (Zhang, DeNero et al. 2014).

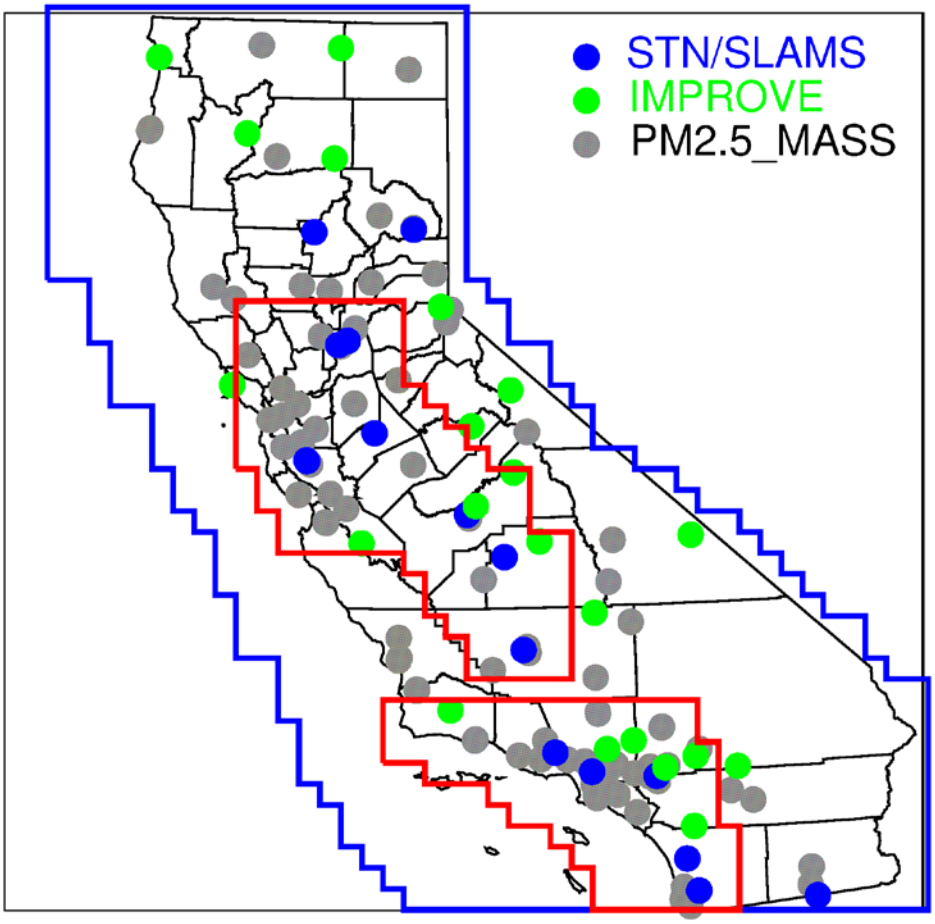


Figure 2-1. Modeling domains (blue lines outline the CA_24km domain, and red lines outline the SoCAB_4km (bottom) and SJV_4km domains (up) and PM measurement sites (dots). Blue dots represent the sites of the PM2.5 Speciation Trends Network (STN) and the State and Local Air Monitoring Stations (SLAMS), green dots represent the Interagency Monitoring of Protected Visual Environments (IMPROVE) sites, and gray dots represent the $PM_{2.5}$ Federal Reference Method (FRM) sites.

2.1.3.2 Meteorology and Emissions

Hourly meteorology inputs (wind, temperature, humidity, precipitation, radiation, air density, and mixing layer height) were generated using the Weather Research and

Forecasting model (WRF) v3.1.1 (Wei Wang January 2010, William C. Skamarock June 2008). Two-way nesting was used with the outer domain at 12 km resolution and the inner nested domain at 4 km resolution. North American Regional Reanalysis data with a 32 km resolution and a 3-hour time resolution was used as initial and boundary conditions of the coarse 12 km domain. The WRF model was configured with 31 vertical layers up to 100 hpa (around 16 km). Four-dimensional data assimilation was used. The Yonsei University (YSU) boundary layer scheme, thermal diffusion land-surface scheme, and Monin-Obukhov surface layer scheme were used based on results from a previous study in California (Mahmud 2010, Zhao, Chen et al. 2011). Surface friction velocity (u*) was increased by 50% to improve the surface wind predictions (Hu, Howard et al. 2012, Hu, Zhang et al. 2014). A sensitivity simulation conducted for the year 2000 revealed that increasing u* by 50% improved the mean wind bias from 1.15 m/s to −0.50 m/s, and lowered the root-mean-square error (RMSE) from 2.95 to 2.20 m/s. Hourly average meteorology outputs at the air quality model vertical layer heights were created. The meteorology predictions were evaluated against meteorological observations (CARB 2011). The meteorological statistical evaluation over the period 2000-2006 has been presented in a previous study (Hu, Zhang et al. 2014), and the results in the period 2007-2008 are consistent with those years. In summary, meteorology predictions of temperature and wind speed generally meet benchmarks suggested by Emery et al. (2001). Mean fractional biases (MFBs) of temperature and wind are generally within ±0.15, RMSEs of temperature are around 4 ˚C, and RMSEs of wind are generally lower than 2.0 m/s, especially in the SoCAB and SJV air basins, which are the focus of the current study. Relative humidity is under-predicted, consistent with findings in other studies in California (Bao 2008, Michelson, Djalalova et al. 2010). Wind, temperature and humidity are the major meteorological factors that influence the PM concentrations. Further discussions of the uncertainties in meteorology predictions on PM predictions are included in the Results and Discussions section.

Hourly gridded gas and particulate emissions were generated using an updated version of the emissions model described by Kleeman and Cass (Kleeman and Cass 1998). The standard emissions inventories from anthropogenic sources (i.e., point sources, stationary area sources, and mobile sources) were provided by CARB. Size and composition resolved particle emissions were specified using a library of primary particle source profiles measured during actual source tests (Taback, Brienza et al. 1979, Cooper 1989, Houck 1989, Hildemann, Markowski et al. 1991, Hildemann, Markowski et al. 1991, Harley, Hannigan et al. 1992, Kleeman, Schauer et al. 1999, Schauer, Kleeman et al. 1999, Schauer, Kleeman et al. 1999, Kleeman, Schauer et al. 2000, Schauer, Kleeman et al. 2001, Schauer, Kleeman et al. 2002, Schauer, Kleeman et al. 2002, Robert, Kleeman et al. 2007, Robert, VanBergen et al. 2007, Kleeman, Robert et al. 2008). A few studies have revealed some uncertainties associated with the standard emissions inventories. Millstein and Harley (Millstein and Harley 2009) found that PM and NOx emissions from diesel-powered construction equipment were over-estimated by a factor of 3.1 and 4.5, respectively. Countess (Countess 2003) suggested that a scaling factor of 0.33 – 0.74 should be applied to the fugitive dust emissions in the California's San Joaquin Valley. Therefore, scaling factors of 0.32 for off-road diesel sources and 0.50 for dust emissions were applied in the current study. The EMFAC 2007 model (CARB 2008) was used to scale the mobile emissions using predicted temperature and relative humidity fields through the entire nine-year modeling episode. Biogenic emissions were generated using the Biogenic Emissions Inventory System v3.14 (BEIS3.14), which includes a 1-km resolution land cover database with 230 different vegetation types (Vukovich and Pierce 2002). Sea-salt emissions were generated on-line based on the formulation described by de Leeuw et al. (de Leeuw, Neele et al. 2000) for the surf zone and the formulation described by Gong (Gong 2003) for the open ocean. Emissions from wildfires and open burning at 1 km × 1 km resolution were obtained from the Fire Inventory from NCAR (FINN) (Hodzic, Madronich et al. 2007, Wiedinmyer, Akagi et al. 2011). The FINN inventory provides SAPRC99 speciated daily emissions of gaseous and particulate emissions (EC, OC, $PM_{2.5}$ and PM_{10}) based on satellite observations of open burning events. Each open burning event is allocated to model grid

cells of each domain based on the reported longitude/latitude of the event and the area burned. The emissions were injected at the height of the planetary boundary layer (PBL). The temporal variation of wildfire emissions was obtained from the Western Regional Air Partnership report (WRAP 2005). A size distribution profile was calculated based on assumptions described in Hodzic et al. (Hodzic, Madronich et al. 2007).

Emissions of the seven SOA precursors were grouped into nine source categories: onroad gasoline engines, offroad gasoline engines, onroad diesel engines, offroad diesel engines, wood smoke, meat cooking, high sulfur fuel combustion, other anthropogenic sources, and the biogenic sources. Primary PM emissions were also grouped into these 9 source categories. Particulate composition, number and mass concentrations in the range between 0.01 and 10μm in diameter are represented in 15 size bins in the model.

2.1.3.3 Ambient Air Quality Measurements

The evaluation dataset was compiled from several measurement networks, including CARB's "2011 Air Quality Data DVD" (CARB 2011) and the database maintained by the Interagency Monitoring of Protected Visual Environments (IMPROVE). The data DVD includes daily average mass concentrations of $PM_{2.5}$, EC, OC, nitrate, sulfate, ammonium, and trace metals every 3 or 6 days at the sites of the $PM_{2.5}$ Speciation Trends Network (STN) and the State and Local Air Monitoring Stations (SLAMS). There are a total 13 $PM_{2.5}$ speciation sites included in the DVD covered in the 4 km domains during the modeling periods. The precision of STN measurements is estimated to be 3.5%, 8.6%, and 3.9% for sulfate, nitrate, and ammonium, respectively (Sickles Ii and Shadwick 2002). Measured EC concentrations at 5 sites are found to be exactly 0.5 μg/m3 on > 80% of the measurement days, suggesting corrupt or missing data at these locations. Therefore these 5 sites were excluded in the evaluation for EC, but still included in the evaluation for other PM components. The OC data were not blank corrected, resulting in a positive artifact by the NIOSH5040 method that is equivalent to approximately 1 $\mu g/m^3$. Measured OC concentrations were blank corrected in the current study by subtracting 1 $\mu g/m^3$ from all OC measurements. The IMPROVE network provides daily average mass concentrations every 3 days for $PM_{2.5}$, EC, OC, nitrate, sulfate, and soil. There are a total of 9 IMPROVE sites covered in the 4 km domains. The precision of IMPROVE measurements is estimated to be 4–6% for $PM_{2.5}$ mass, nitrate, and sulfate, and to be > 15% for EC and OC (http://vista.cira.colostate.edu/improve/Publications/OtherDocs/IMPROVEDataGuide/IMPROVEDataGuide.htm). Daily average PM_{10} mass measurements and hourly measurements of several key gaseous pollutants (ozone, CO, NO, NO_2, and SO_2) are also included in the data DVD. There are a total of 66 $PM_{2.5}$ Federal Reference Method (FRM) sites covered in the 4 km domains. Frank (Frank 2006) found that FRM $PM_{2.5}$ mass measured using STN monitors was within ± 30% of reconstructed fine mass concentrations measured using IMPROVE monitors. The site locations are shown in Figure 2-1.

2.2 Results and Discussion

2.2.1 Model Performance Evaluation

Hourly POA and SOA concentrations in multiple size fractions were calculated during the 9 year simulation period, and then averaged to daily and monthly average concentrations. The predicted total OA concentrations are validated by comparing with available ambient measured concentrations. The model predicts organic matter (OM) concentrations and ambient measurements measure organic carbon (OC) concentrations. Therefore, the OM concentrations are converted to OC concentrations by using an OM/OC ratio of 1.6 for POA (Turpin and Lim 2010) and species-specific OM/OC ratios for SOA species taken from Table 1 in Carlton et al. (Carlton, Bhave et al. 2010).

Statistical measures of MFB and mean fractional error (MFE) were calculated to evaluate the accuracy of model estimates in space and time. Boylan and Russell (Boylan

and Russell 2006) proposed concentration dependent MFB and MFE performance goals and criteria, realizing that lower concentrations are more difficult to accurately predict. The performance goals are the level of accuracy close to the best that a model can be expected to achieve, while performance criteria are the level of accuracy acceptable for standard modeling applications.

Figures 2-2 and 2-3 show the monthly MFB and MFE values, respectively, of predicted daily average EC, OC, nitrate, ammonium, sulfate and total $PM_{2.5}$ mass in the 4 km domains. Measured EC, OC, nitrate, ammonium, and total $PM_{2.5}$ mass concentrations follow similar seasonal patterns with high concentrations occurring in winters (indicated by blue colors in figures) and low concentrations occurring in summers (indicated by red colors in figures). These patterns are driven by the meteorological cycles (i.e., lower mixing layer and wind speed providing less dilution, and lower temperature encouraging partitioning of ammonium nitrate to the particle phase) and the emissions variations (i.e., additional wood burning emissions for home heating in winters). The opposite seasonal variations in sulfate concentrations are observed, due to higher oxidation rates from S(IV) to S(VI) and higher sulfur emissions from natural sources in summer (Bates, Lamb et al. 1992).

EC predictions are in excellent agreement with measurements. MFBs in all months and MFEs in 107 months out of the total 108 months are within the model performance goal. EC MFBs and MFEs show no significant difference among months/seasons, indicating consistently good EC performance during the entire 9-year modeling period. OC, nitrate, sulfate, and ammonium, the PM components that include the secondary formation pathways, meet the MFBs model performance criteria in 71%, 73%, 46%, and 92% of the simulated months, respectively. These components generally have good agreement between predictions and measurements in winter months, with only a few months not meeting the performance criteria. When analyzing by season, predicted concentrations of these species are found to be more biased in summer months, especially for sulfate and nitrate. Different factors influence the seasonal profile of each species. The more significant OC under-prediction in summertime is mainly associated with the under-prediction of SOA due to incomplete knowledge of SOA formation mechanism at the present time. Similar patterns have been reported in other modeling studies outside California (Volkamer, Jimenez et al. 2006, Matsui, Koike et al. 2009, Zhang and Ying 2011, Zhang, Chen et al. 2014). Measured nitrate concentrations in summertime (1-5 $\mu g/m^3$) are factors of 2-5 lower than concentrations in wintertime (5-12 $\mu g/m^3$). Model predictions tend to underestimate the low particle phase nitrate concentrations in summer, especially when temperatures exceed 25 °C. Model predictions for particulate nitrate are usually less than 1 $\mu g/m^3$ under these conditions, while 2-3 $\mu g/m^3$ nitrate concentrations are still observed in the ambient air. Similar under-predictions of summertime nitrate have been reported in other regional modeling studies (Yu, Dennis et al. 2005, Tesche, Morris et al. 2006, Appel, Bhave et al. 2008, Zhang, Chen et al. 2014). Model calculations reflect thermodynamics and kinetic gas-particle transfer for ammonium nitrate in mixed particles, suggesting that some other form of nitrate is present in the real atmosphere, such as organo-nitrates (Day, Liu et al. 2010). Sulfate concentrations are under-predicted because of missing emissions sources such as the sulfur emitted as dimethyl sulfide from the Pacific Ocean. Ammonium is drawn to acidic particles and so ammonium concentration predictions reflect the combined trends of nitrate and sulfate predictions. The model predictions of total mass of $PM_{2.5}$, as a summation of all components, show very good agreement with measurements, with only 3 summer months and 2 spring months (5% of all months) not meeting the performance criteria, and 78% and 75% of months within the performance goals for MFB and MFE, respectively. The largest biases in the total $PM_{2.5}$ mass occur in summer. Under-prediction in summer sulfate and OC contribute to negative biases in the total $PM_{2.5}$ mass predictions. Sulfate and OC concentrations in summer accounted for ~18% and ~37% of the total $PM_{2.5}$ mass. Therefore, sulfate and OC under-prediction contributed to a combined ~37% under-prediction of total $PM_{2.5}$ mass. However, positive biases in predicted dust concentrations rich in crustal elements such as aluminum and silica (Hu, Zhang et al. 2014) compensate for the under-predictions in carbonaceous components and water-soluble ions described above.

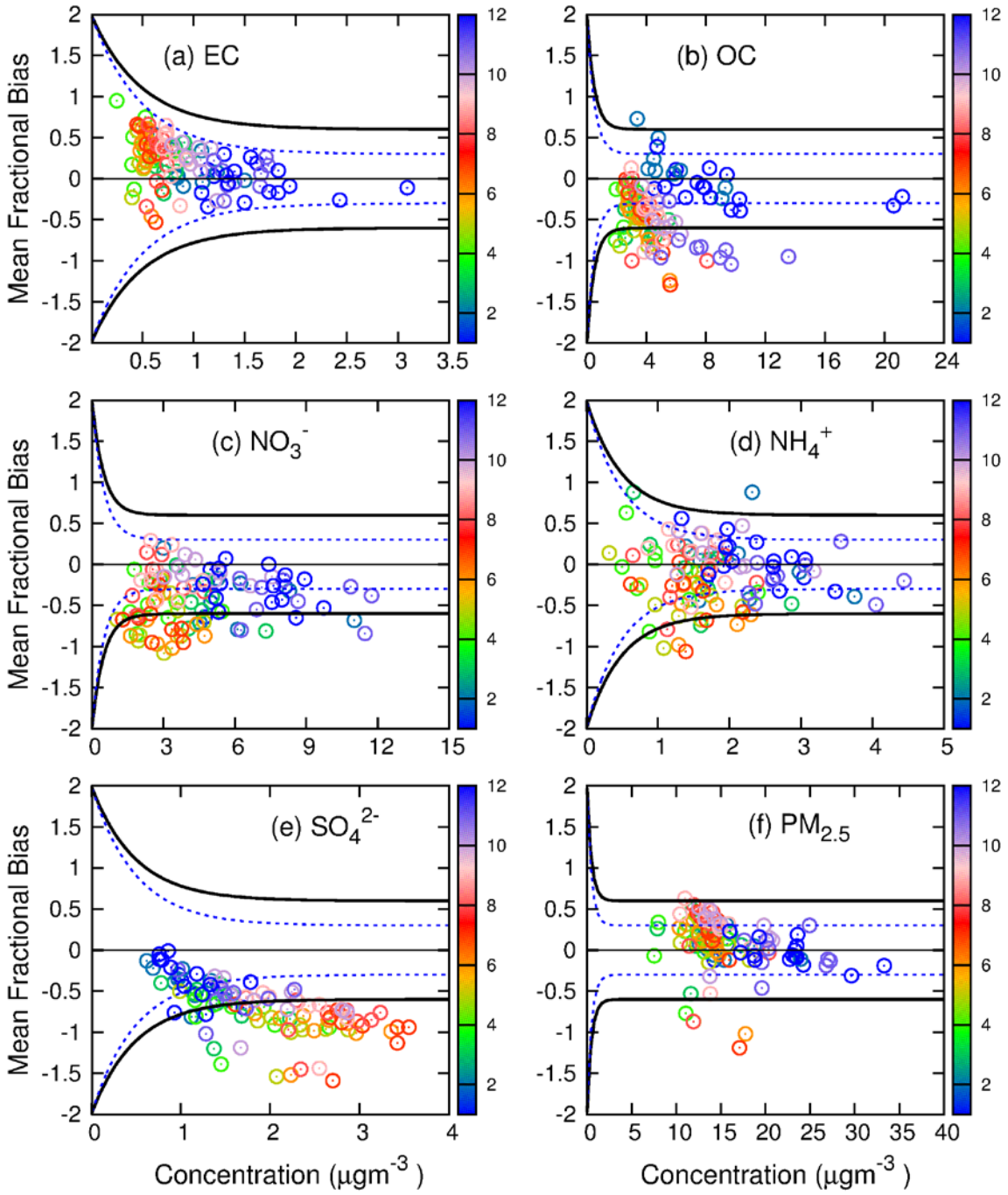


Figure 2-2. Monthly mean fractional bias (MFB) of PM2.5 EC, OC, nitrate, ammonium, sulfate, and total mass. Solid lines represent the MFB criteria, and the blue dash lines represent the MFB goals. Color scale corresponds to the month of the year.

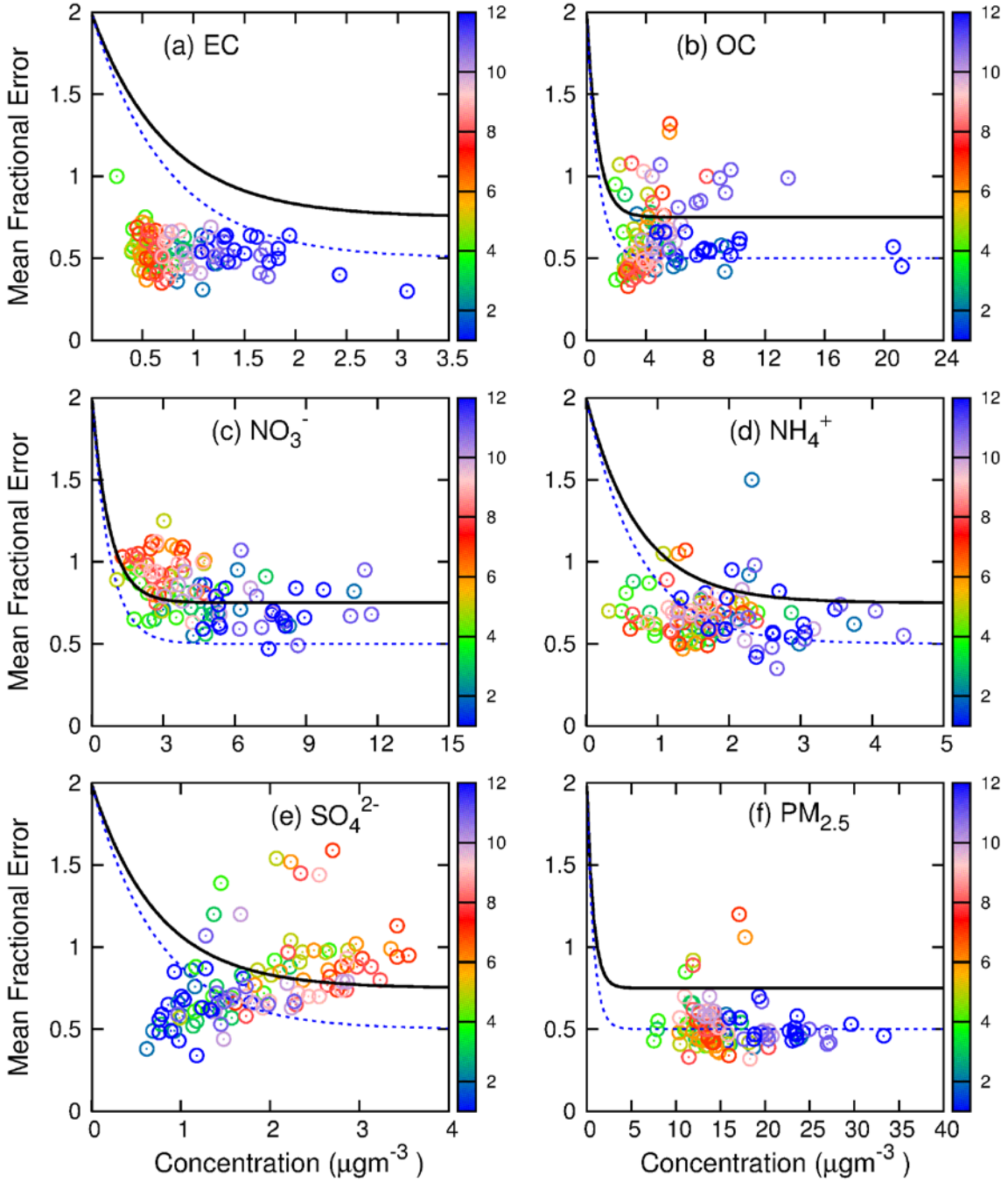


Figure 2-3. Monthly mean fractional errors (MFE) of PM2.5 EC, OC, nitrate, ammonium, sulfate, and total mass. Solid lines represent the MFE criteria, and the blue dash lines represent the MFE goals. Color scale corresponds to the month of the year.

Figure 2-4 shows the MFB and MFE values of particulate species of $PM_{2.5}$ total mass, EC, OC, nitrate, sulfate, ammonium and gaseous species of O_3, CO, NO, NO_2, SO_2 using daily averages across all measurement sites during the entire modeled 9-year period. $PM_{2.5}$ total mass, EC, OC, ammonium and gaseous species of O_3, CO, NO_2 have MFBs within ±0.3 and MFE less than 0.75, indicating general agreement between predictions and measurement for these species. Nitrate and NO have MFBs of -0.4 and -0.28, respectively, but MFEs of 0.8 and 1.07, respectively. The relatively moderate or small bias combined with relatively large error indicates that the daily predictions miss the extremely high and low concentrations. Sulfate and SO_2 have high MFBs of -0.7 and -0.5, respectively, and high MFEs of 0.8 and 0.9, respectively, indicating that these species are consistently under-predicted.

Concentrations averaged over longer times, such as 1 month or 1 year, are used in some air pollution-health effects studies. A previous examination of primary particles in California revealed that air quality model predictions are more accurate over longer averaging time because the influence of extreme events and short-term variability is reduced as the averaging period gets longer (Hu, Zhang et al. 2014). Figure 2-4 compares the MFB and MFE values for total (=primary+secondary) particulate matter and gaseous species using daily, monthly, and annual averages across all sites in the 4 km domains. The results demonstrate that longer averaging times produce better agreement between model predictions and measurements (except for sulfate, which is under-predicted due to missing emissions) because they remove the effects of random measurement errors at monitoring stations and variations in actual emissions rates that are not reflected in seasonally-averaged emissions inventories. The reduced errors associated with longer averaging times indicate that model results may be most useful in epidemiological studies that require averaging times ≥1 month. This was not possible in the present case-crossover study design that requires a sufficiently-narrow referent window (weekly time periods) to prevent bias from seasonal confounding as discussed below in Chapter 3.

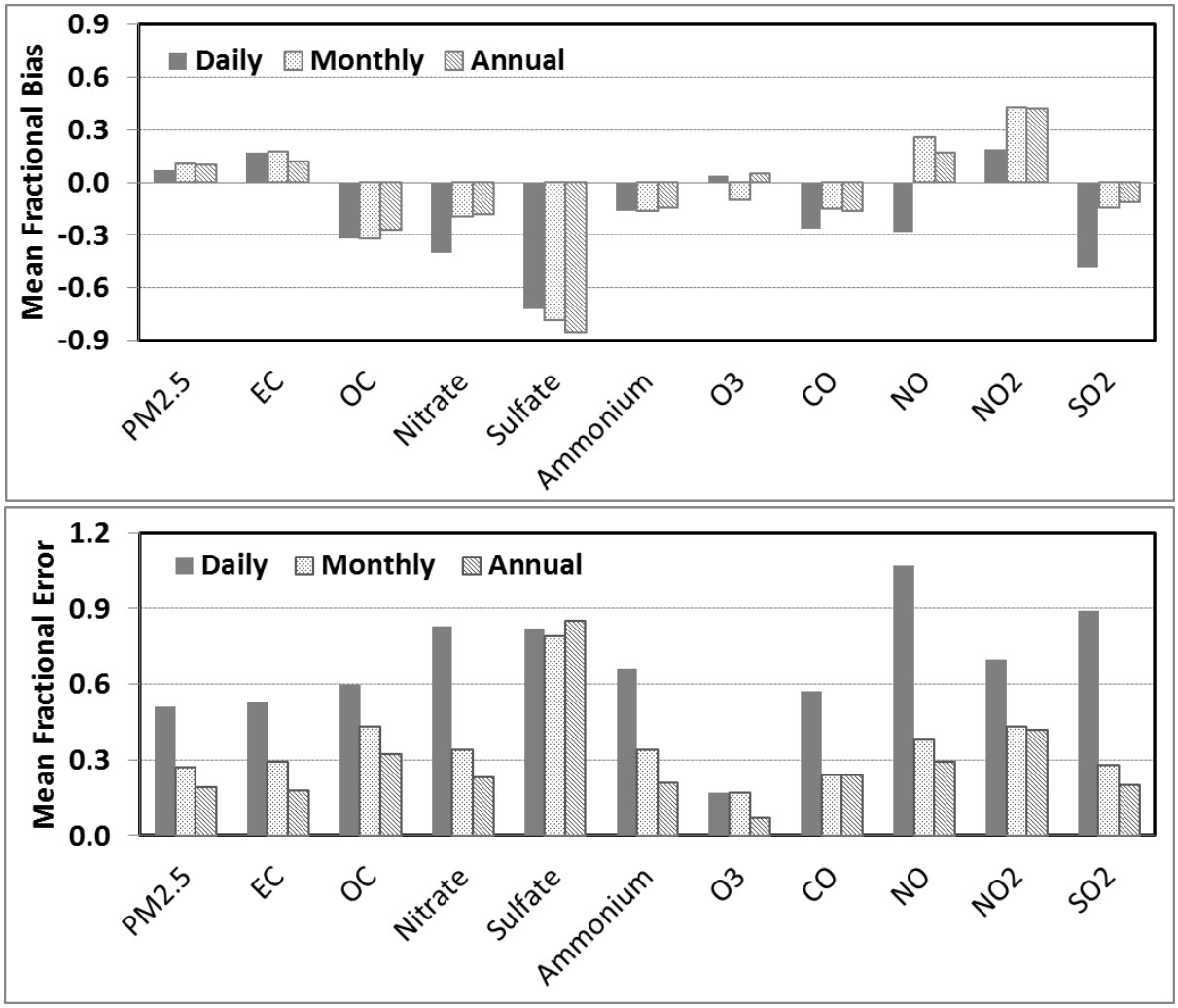


Figure 2-4. Mean fractional bias (MFB) and mean fractional errors (MFE) of PM and gaseous species when calculated using daily, monthly and annual averages.

California experiences the highest $PM_{2.5}$ concentrations in wintertime, caused by stagnant meteorological conditions characterized by low wind speed and shallow atmospheric mixing layer. The WRF model tends to over-predict wind speed during low wind speed events (≤ 2 m/s) in California. Increasing u* by 50% improves the WRF wind prediction but still over-predicts wind speed during events when measured wind speed is <1.5 m/s. A zero-order approximation of air pollutant concentration is:

$$C = \frac{E}{V} = \frac{E}{u \times \mathrm{H}}$$

where C is the pollutant concentration, E is the source pollutant emission rate, V is the air ventilation rate which is equal to (wind speed × mixing height), u and H are the horizontal wind speed and mixing height, respectively. . The concentration is linearly dependent on the inverse wind speed (1/ u). Figure 2-5 shows the MFBs of the predicted atmospheric inverse wind speed (1/ u) as a function of the observed atmospheric inverse wind speed. Also shown in Figure 2-5 are the MFBs of PM component concentrations as a function of the observed concentrations. The MFBs decrease when the inverse wind speed or concentrations increase, indicating low inverse wind speed/concentrations are over-predicted, but high inverse wind speed /concentrations are under-predicted. The trends of inverse wind speed and concentrations are well correlated, indicating that simple wind bias effects on the ventilation rates leads to bias in PM predictions, especially during the events with high PM pollution. The correlation with 1/ u MFB is stronger for primary PM component(s) than for secondary components, indicating that additional processes affect the secondary PM, such as chemistry, gas-particle partitioning, etc. Sulfate bias has the least correlation to inverse ventilation bias, because it is mainly driven by the bias in SO_2 emissions.

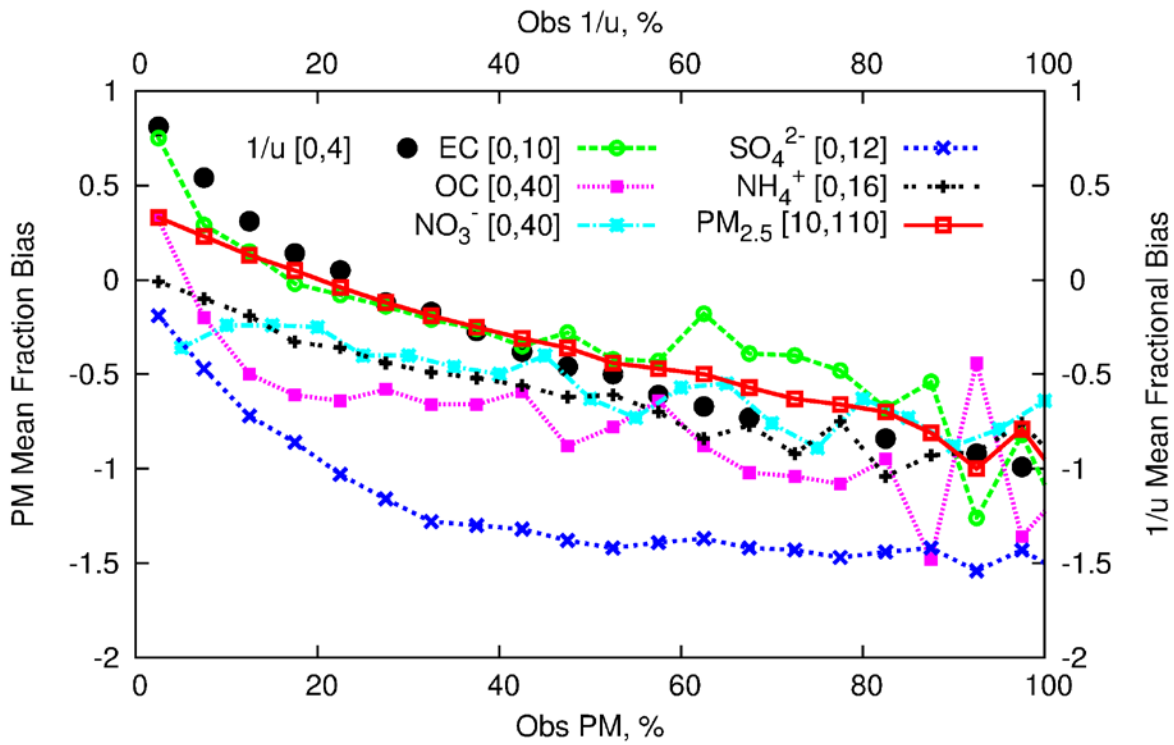


Figure 2-5. Association between predicted PM concentration bias and wind bias vs.

observed values. The observed PM concentrations and 1/u values on the x-axis are expressed in a relative scale of 0-100% of maximum range calculated as x (%) = $(C-C_{min})/(C_{max}-C_{min})*100$. Values for [$C_{min}$, C_{max}] are listed in the concentration key. Bias between predicted vs. observed values is shown on the y-axis. Ideal behavior is bias of zero at all concentrations & wind speeds.

Figure 2-6 panel (a) shows the predicted and measured monthly average concentrations of 1-h peak O_3 at 5 major urban sites (Sacramento, Fresno, Bakersfield, Los Angeles, and Riverside). Strong seasonal variations are observed in measured and predicted 1-h peak O_3. The measured 1-h peak O_3 shows seasonal variation from 100 ppb in summertime to 20 ppb in wintertime. The predicted high 1-h peak O_3 concentrations in non-winter months are in good agreement with, or slightly higher than, ambient measured concentrations at all sites. This is consistent with studies in the eastern U.S. (Zhang, Chen et al. 2014), which found similar slight over-predictions of summer O_3 concentrations. Predicted 1-h peak O_3 concentrations in cold winter months, however, are generally higher than measured values. Photochemical reaction rates in wintertime months are slow and the predicted O_3 concentration at the surface mostly reflects downward mixing of the aloft background O_3 followed by titration by surface NO emissions. The STN measurement sites in California are located in urban areas that are close to major freeways (see the site locations and nearby sources information in (Hu, Zhang et al. 2014)). The 4 km × 4 km model grid cells that contain both freeways and monitors dilute the high NO concentrations around the measurement sites leading to an under-prediction of O_3 titration and an over-prediction of O_3 concentrations. EPA recommends a threshold O_3 value of 60 ppb for model O_3 evaluations (U.S.EPA 2007), which means that wintertime O_3 concentrations at the urban sites will generally not be considered in the formal model evaluation.

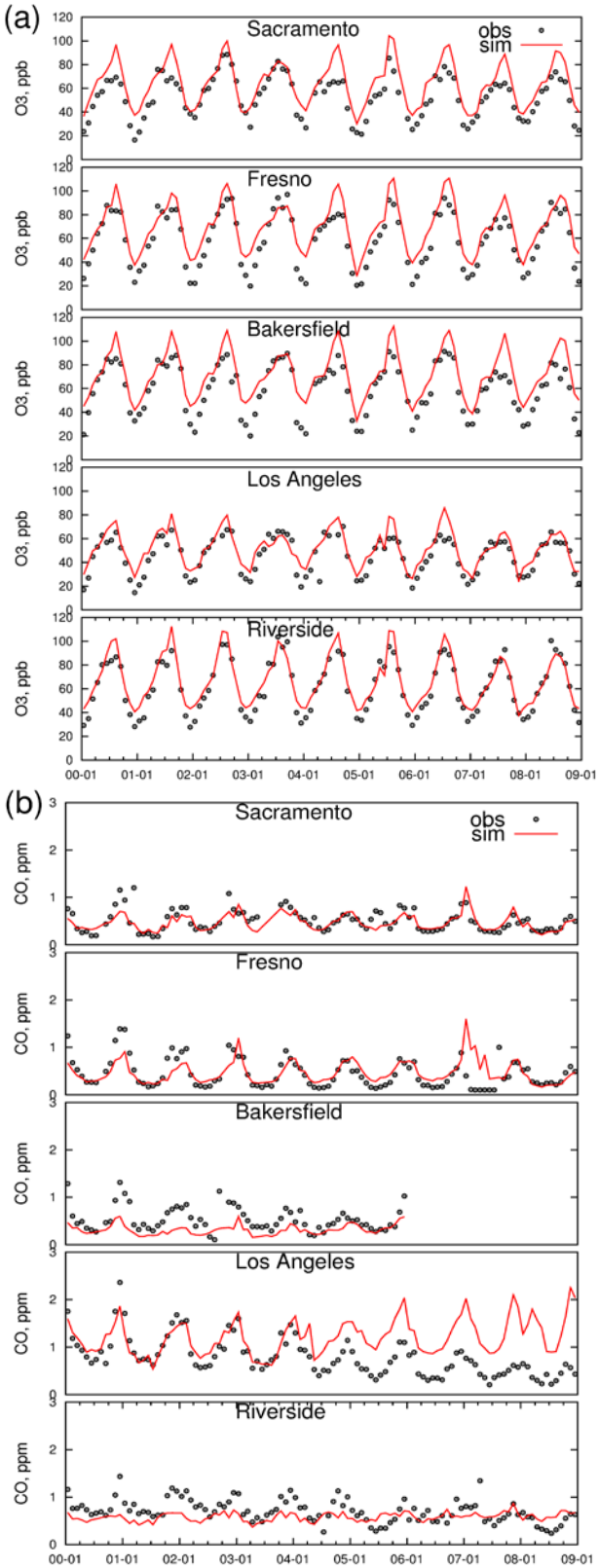
Figure 2-6 panels (b) and (c) show the predicted and measured monthly average CO and NO concentrations. Strong seasonal variations in CO and NO can be observed, with wintertime concentrations that are a factor of 3-5 higher than summertime concentrations. Model predictions generally reproduce the seasonal variations except at the Riverside site where predicted seasonal variations are weaker than measurements. The model performance varies by simulation year and location. At the Sacramento and Fresno sites , predicted CO is in good agreement with measured concentrations in all months of 2002 through 2006, but CO is under-predicted in winter months of 2000-2001 and slightly over-predicted in most months of 2007-2008. At the Bakersfield site, CO is under-predicted in 2000-2003 and in good agreement with measurements in 2004-2005 (after which further measurements are not available). At the Los Angeles site, CO is in good agreement in 2000-2003, and over-predicted in the later years. At the Riverside site, CO is under-predicted in all months of 2000-2003, under-predicted in non-summer months in 2004-2006, and in general agreement with measurements in 2007-2008. NO predictions generally agree well with measured NO concentrations in 2000-2004 at Sacramento, Fresno, Bakersfield and Los Angeles, and then are over-predicted in the later years. NO at Riverside is under-predicted in the winter months of 2000-2003, and over-predicted in the summer months of 2004-2008. Mobile emissions are the dominant sources of CO and NO in California, contributing > 80% of total anthropogenic emissions (CARB 2012). The results of the current modeling study suggest that uncertainties in the mobile emissions exist both in time and space.

Figure 2-6 panels (d) and (e) show the predicted and measured monthly average ammonium and nitrate concentrations. Ammonium nitrate is a major $PM_{2.5}$ component in California, especially in wintertime when the low temperature and high relative humidity favor partitioning to the condensed phase. The monthly average ammonium and nitrate results demonstrate similar model performance. The predicted concentrations agree reasonably well with measured ambient concentrations and seasonal variations. Model predictions are lower than measured values in the early years, especially during winter months when concentrations are highest. This pattern is very consistent with CO model performance, suggesting mobile emissions are under-estimated for the early years of the simulation period. Nitrate is formed through NO oxidation to nitric acid but NO concentrations are not

under-predicted, suggesting that the chemical conversion of NO to nitric acid is too slow. Carter and Heo (Carter and Heo 2012) suggested that SAPRC11 mechanism systematically under-predicts OH radical concentrations by ~30%, which would be consistent with the observed trends.

Figure 2-6 panel (f) shows the OC predictions and measurements. Organic aerosol in California is typically the second most abundant species, after ammonium nitrate. In the comparison, an OM/OC ratio of 1.6 (Turpin and Lim 2010) is applied to convert primary organic aerosol OM back to OC for comparison to measured concentrations. The conversion ratios for SOA species are taken from Table 1 in Carlton et al. (Carlton, Bhave et al. 2010). Predicted OC agrees reasonably well with measured concentrations, but is lower than the wintertime high concentrations in the early years, similar to other PM components. Predicted OC in summers is also in good agreement with measurements at the indicated monitoring sites. As mentioned previously, these sites are all near major freeways and therefore OC is dominated by primary organic aerosols. Larger bias is found at sites distant from local sources where SOA becomes more important. More analysis about the concentrations and sources of the OC results are included in a companion paper (Hu Manuscript in preparation).

Figure 2-6 panel (g) shows that predicted EC concentrations agree well with measured concentrations. High measured EC concentrations in a few winter months in the early years are under-predicted, but EC concentrations in the summer months are generally over-predicted. Figure 2-5 panel (h) shows that monthly average predictions for $PM_{2.5}$ mass concentrations agree well with observations, and seasonal trends are generally captured with high concentrations in winter, and low concentrations in summer. $PM_{2.5}$ is over-predicted in summer months when nitrate, sulfate, and ammonium are found to be under-predicted. These trends reflect the over-prediction of the primary components, mostly dust particles, in the model calculations (Hu, Zhang et al. 2014). This result suggests that a uniform scaling factor of 0.5 for dust emissions may not be appropriate. A smaller factor (for example, a factor of 0.25 was used in the eastern U.S. (Tesche, Morris et al. 2006)) or a spatially resolved method that accounts for the land-use types (Pace 2005) should be used for future studies in California.


(a)
Sacramento
obs
sim
Fresno
Bakersfield
Los Angeles
Riverside
O3, ppb
(b)
CO, ppm
00-01
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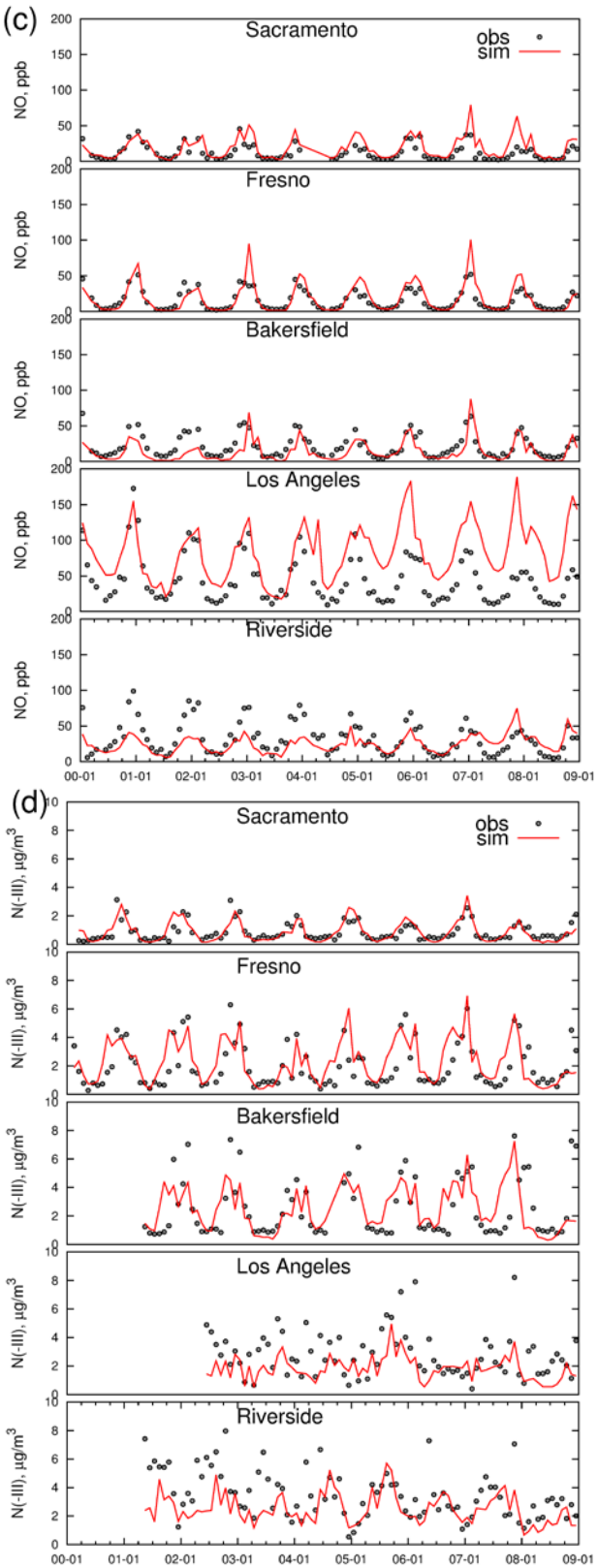
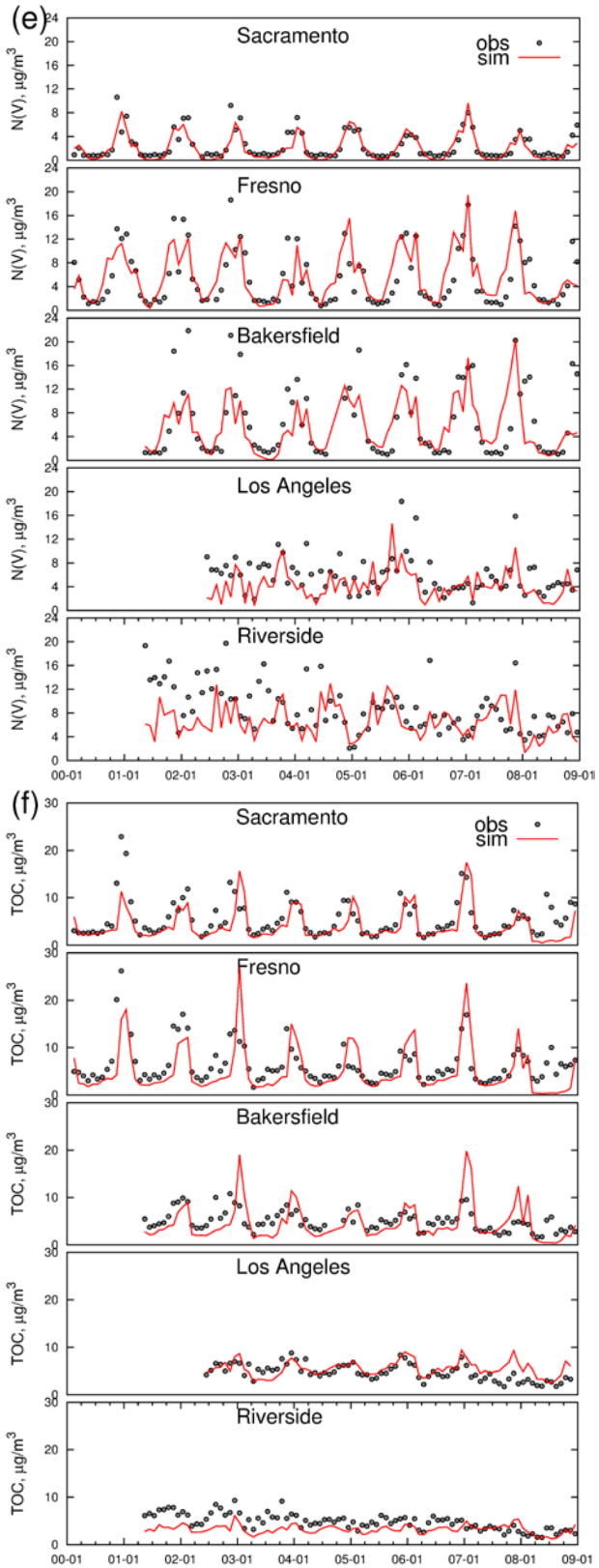


Figure 2-6. Predicted (red lines) vs. observed (dark dots) monthly average O3, CO, NO, ammonium, nitrate, OC, EC, and PM2.5 total mass at Sacramento, Fresno, Bakersfield, Los Angeles, and Riverside.


(e)
Sacramento
obs
sim
Fresno
Bakersfield
Los Angeles
Riverside
N(V), µg/m3
(f)
TOC, µg/m3
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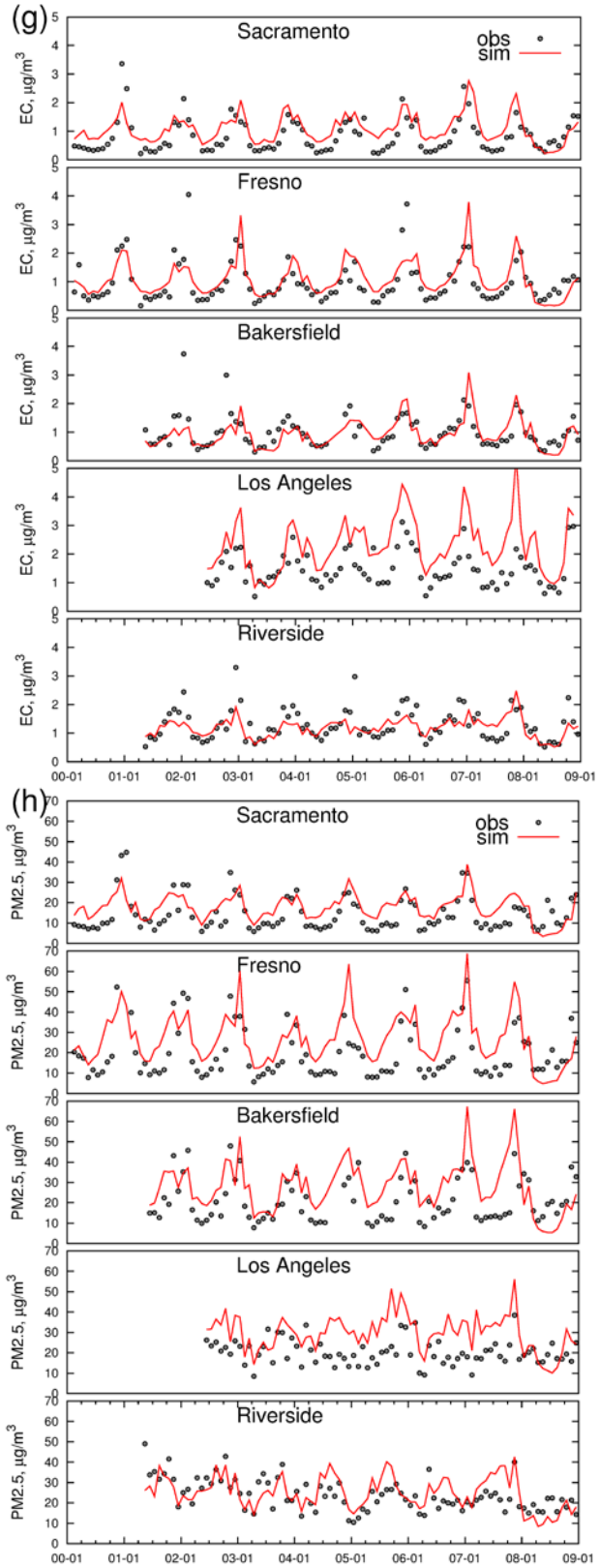


Figure 2-6 continued

2.2.2 Concentrations of POA and SOA

Figure 2-7 shows the predicted 9-year average concentrations of $PM_{2.5}$, EC, OC, nitrate, sulfate, and ammonium, compared with measured average concentrations over

California. High concentrations of all PM pollutants occur in the urban areas with large population, indicating that most of the PM is generated by anthropogenic activities. The predicted spatial distributions generally agree well with measurements, but provide much more detailed information. $PM_{2.5}$ concentrations are over-predicted in the SJV air basin due to an over-prediction of agricultural dust. High OC concentrations were measured at two sites in northern California due to intense wood burning. The two sites are in the 24 km model domain but outside the 4 km, therefore the predicted OC concentrations in the 24 km grids do not agree well with the measurements at this location. This finding confirms that 24 km resolution is probably too coarse for health effects studies and justifies the use of the 4 km grids over the majority of California's population in the current work. Background sulfate concentrations at IMPOVE sites were measured to be 0.6-1 $\mu g/m^3$ but higher concentrations of 2~3 $\mu g/m^3$ were measured in Southern California. Model calculations do not reproduce this concentration enhancement, leading to an under-prediction in the concentrations of this $PM_{2.5}$ species. In general, the reasonable agreement between model predictions and measurement builds confidence that the model predictions in locations with no available measurements likely provide a reasonable estimate of exposure fields.

Figure 2-8a shows comparisons of the average $PM_{2.5}$ OC/mass ratio estimated from ambient measurements and the UCD/CIT model predictions in the 9 year modeling period at seven representative urban locations. At each site, daily average measured concentrations of the $PM_{2.5}$ total mass and OC were obtained from the California Air Resources Board (CARB) (CARB 2011) and averaged as 9 year average observed concentrations. Predicted concentrations on the corresponding days were extracted and averaged as 9 year average predicted concentrations. The average OC/mass ratios were then calculated from the 9 year average OC and mass concentrations from measurement and predictions. The observed average OC/mass ratios vary in the range of 0.24 (at Riverside) to 0.45 (at Sacramento). The predicted average OC/mass ratios are consistently lower than observed ratios by 0.01 (3% at Los Angeles) to 0.22 (48% at Sacramento). The Predicted OC/mass ratios are in relatively good agreement with observed values at Los Angeles, Riverside, and Bakersfield (difference < 20%), but with a difference > 35% in the ratios at other sites. The model under-prediction of OC/mass ratios are attributed to the under-prediction of OC concentrations, especially the SOA concentrations (Hu, Zhang et al. 2014), and over-prediction of total mass concentrations due to over-estimated dust emissions (Hu, Zhang et al. 2014, Hu, Zhang et al. 2014). A sensitivity analysis by removing the dust concentrations from the $PM_{2.5}$ mass indicated improved agreement between predicted and observed OC/mass ratios at almost all sites except Los Angeles.

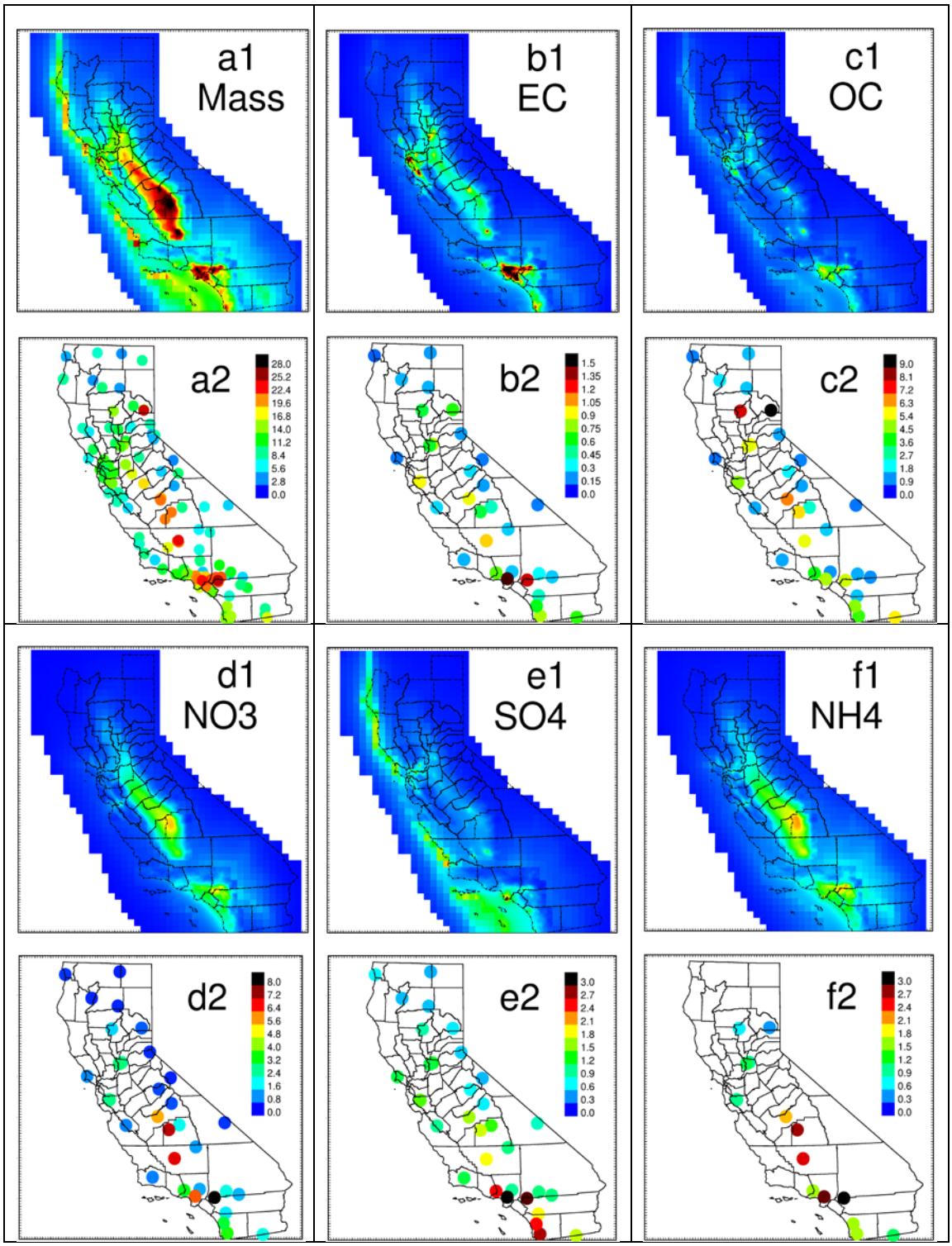


Figure 2-7. Predicted (1) vs. measured (2) 9-year average PM2.5 total mass (a), EC (b), OC (c), nitrate (d), sulfate (e), and ammonium (f) concentrations. The SoCAB_4km and SJV_4km results are overlayed on top of CA_24km results to create the model predicted spatial distributions. Predicted and measured concentrations of the same species are in the same scale shown in the panels of measurements.

Figure 2-8b compares the predicted and observed OC/mass ratios in the ultrafine ($PM_{0.1}$) or quasi-ultrafine ($PM_{0.18}$, $PM_{0.25}$) particles. The ultrafine/quasi-ultrafine

measurement data were compiled in a previous study (Hu, Zhang et al. 2014) from published literature (Kim, Shen et al. 2002, Herner, Aw et al. 2005, Sardar, Fine et al. 2005, Sardar, Fine et al. 2005, Krudysz, Froines et al. 2008). The observed OC/mass ratios in ultrafine/quasi-ultrafine size ranges are among the range of 0.43 (at Modesto) to 0.71 (at USC). The predicted ultrafine/quasi-ultrafine OC/mass ratios generally agree well with observed values at all sites. The better agreement of OC/mass ratios in the ultrafine/quasi-ultrafine than in the $PM_{2.5}$ size range reflects that contribution of SOA formation and dust emissions to ultrafine/quasi-ultrafine concentrations is limited. Condensation of SOA generally takes place in the particle accumulation mode, not in the ultrafine size range due to the increase in the saturation vapor pressure above small particles (Kelvin effect). Dust components mainly contribute to coarse and fine particles, but little to the ultrafine particles.

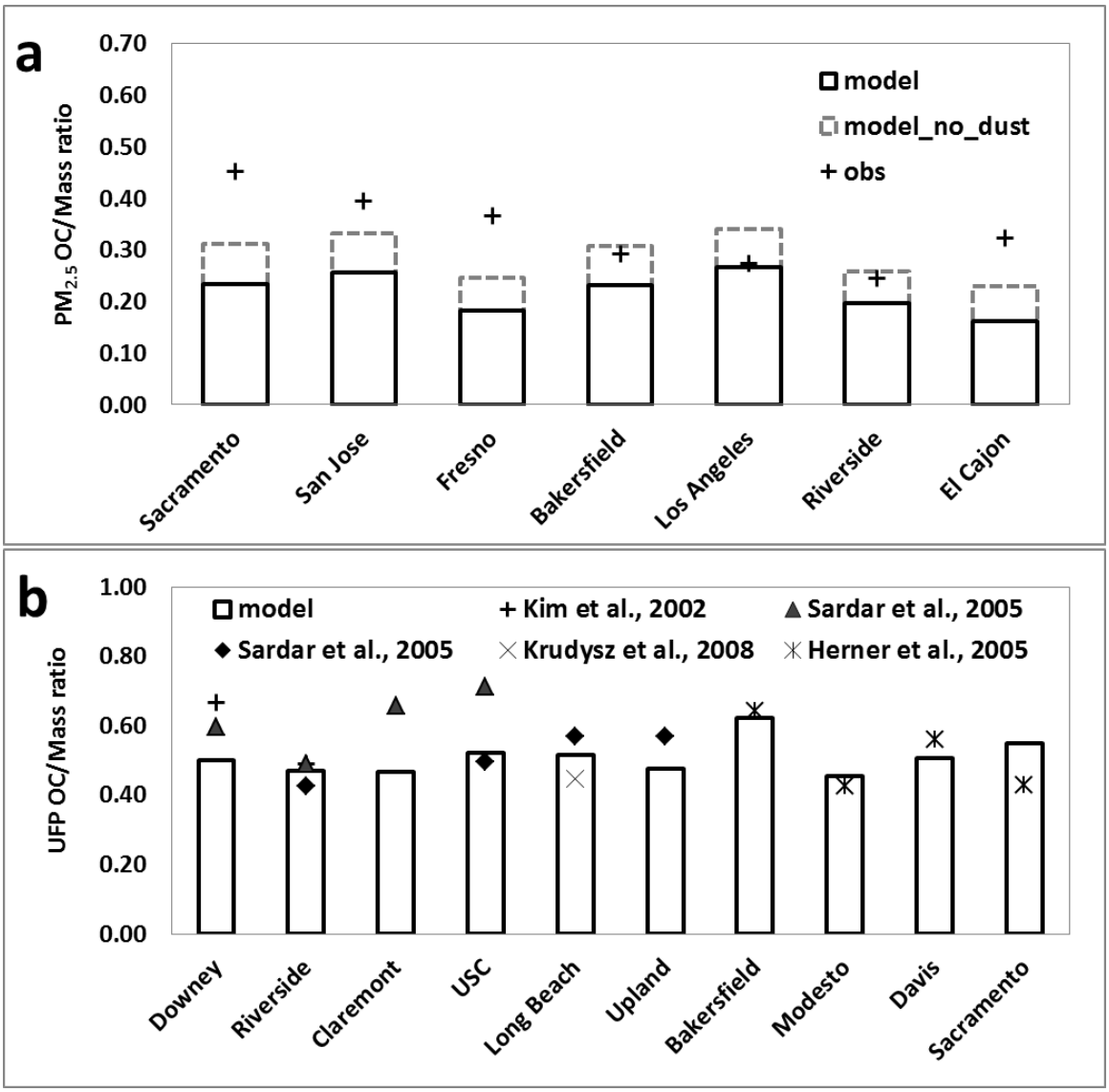


Figure 2-8. (a) Observed (obs) and predicted (model) OC/Mass ratio in PM2.5 and (b) ultrafine particles. In (a), a sensitivity analysis is conducted by removing the dust concentration from the PM2.5 total mass (model_no_dust). The ultrafine data are extracted from from published literature as indicated in the figure.

The primary and secondary fraction of total OA cannot be directly measured in ambient OA measurements. A few indirect methods have been developed to estimate the POA and SOA concentrations, such as the molecular marker-based method (Kleindienst,

Jaoui et al. 2007, Daher, Ruprecht et al. 2011, Ham and Kleeman 2011, Daher, Ruprecht et al. 2012), elemental carbon (EC) tracer method (Turpin and Huntzicker 1995, Lim, Turpin et al. 2003, Cabada, Pandis et al. 2004, Polidori, Turpin et al. 2006, Polidori, Arhami et al. 2007), water soluble organic carbon content method (Weber, Sullivan et al. 2007), aerosol mass spectrometry method (Lanz, Alfarra et al. 2007, Aiken, DeCarlo et al. 2008, Ulbrich, Canagaratna et al. 2009), and the un-explained fraction of OA by tracers for major POA categories (Schauer and Cass 2000, Chen, Ying et al. 2010). POA and SOA concentrations were estimated by the EC tracer method as described in (Polidori, Arhami et al. 2007) and by the molecular marker Chemical Mass Balance (CMB) method (only for SOA) as described in (Daher, Ruprecht et al. 2012) during sampling periods in 2005-2007 at four locations. Figure 2-9a compares the POA and SOA concentrations predicted by the UCD/CIT model (right dark columns) to the POA and SOA concentrations estimated using the EC tracer method (left gray columns). Error bars represent the standard deviation of concentrations estimated during the sampling periods by both methods. The total OA (i.e., POA + SOA) concentrations predicted by the UCD/CIT model generally agree with measured values (with fraction bias within ±35%) except at the Riverside site (with a fraction bias of -63%). But the SOA concentrations predicted by the UCD/CIT model appear to be substantially lower than the SOA concentrations estimated by the EC tracer method by up to a factor of 8.5 at the WSanG site. Figure 2-9b compares the SOA concentrations predicted by the UCD/CIT model to the SOA concentrations estimated by the molecular marker CMB method and the EC tracer method. Substantial difference is also found between the estimated SOA concentrations by the CMB and EC tracer methods, indicating the large uncertainties in the two estimation methods for SOA. The UCD/CIT predictions are consistently lower than the two methods. The finding that the UCD/CIT model generally reproduces the total OA concentrations but under-predicts the SOA fraction, or the UCD/CIT model predicts larger negative bias in the SOA than the total OA, suggests that likely some SOA precursors and pathways are missing from the current SOA mechanism, and the split of POA/SOA is likely different in the model predictions and ambient measurements. The UCD/CIT model treat the POA emissions as non-volatile, but recent studies indicates that part of POA emissions evaporates, undergoes photo-oxidation and condenses back to the particle phase (Robinson, Donahue et al. 2007). This part would be considered as SOA in ambient measurement but in the current UCD/CIT model it is still POA.

Figure 2-10 shows the 9 year average total SOA concentrations and the contributions from the 9 precursor species to the SOA concentrations. The total SOA concentration is estimated between 0.3~0.6 $\mu g/m^3$ in most California areas on a 9 year average basis. Maximum SOA concentrations are located in the southern part of the SJV. Monoterpenes, sesquiterpenes, oligomers, and long alkanes are the most important precursors, contributing over 90% of the total SOA in most areas. Other precursors (xylene, toluene, benzene, and isoprene) in total contribute maximum less than 0.1 $\mu g/m^3$ SOA concentrations. The contributions from difference precursors show substantial difference in the spatial distribution. SOA formed from long alkanes are mainly in the urban areas of Southern California and in the middle-southern part of SJV. SOA formed from isoprene, monoterpenes, and sesquiterpenes are highest at coastal and foothill locations where the biogenic emissions are greatest. Spatial distribution of oligomers of anthropogenic SOA (Oligomer_A) and biogenic SOA (Oligomer_B) reflects the spatial patterns of the long alkanes derived SOA and the total biogenic species derived SOA.

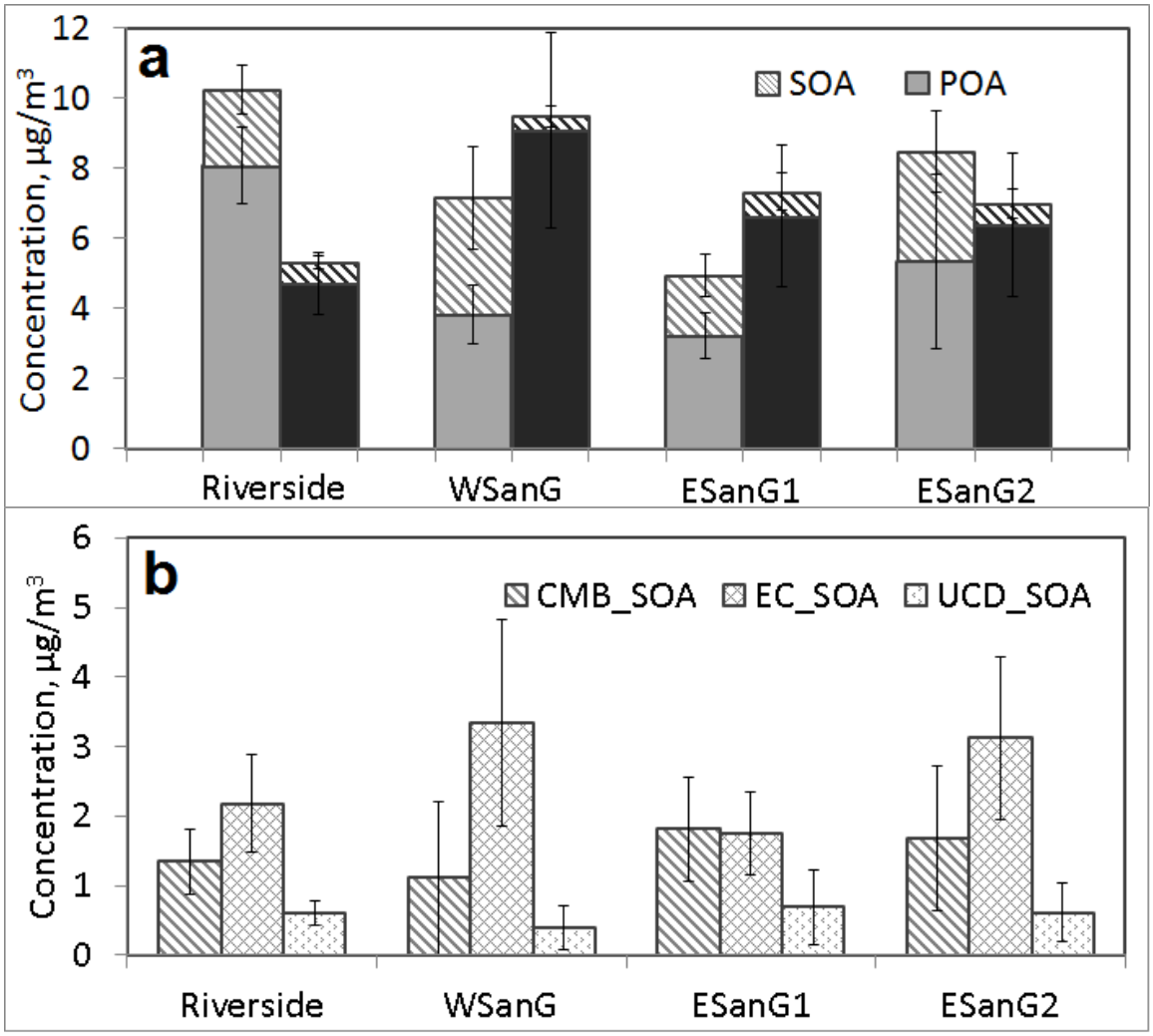


Figure 2-9. (a) POA and SOA concentrations estimated using the EC tracer method (left gray columns) and predicted by the UCD/CIT model (right dark columns). Error bars represent the standard deviation of concentrations estimated during the sampling periods by both methods. (b) SOA concentrations estimated by the molecular marker CMB method and the EC tracer method, and predicted by the UCD/CIT model. The data are for sampling periods in 2005-2007 at four sites in southern California.

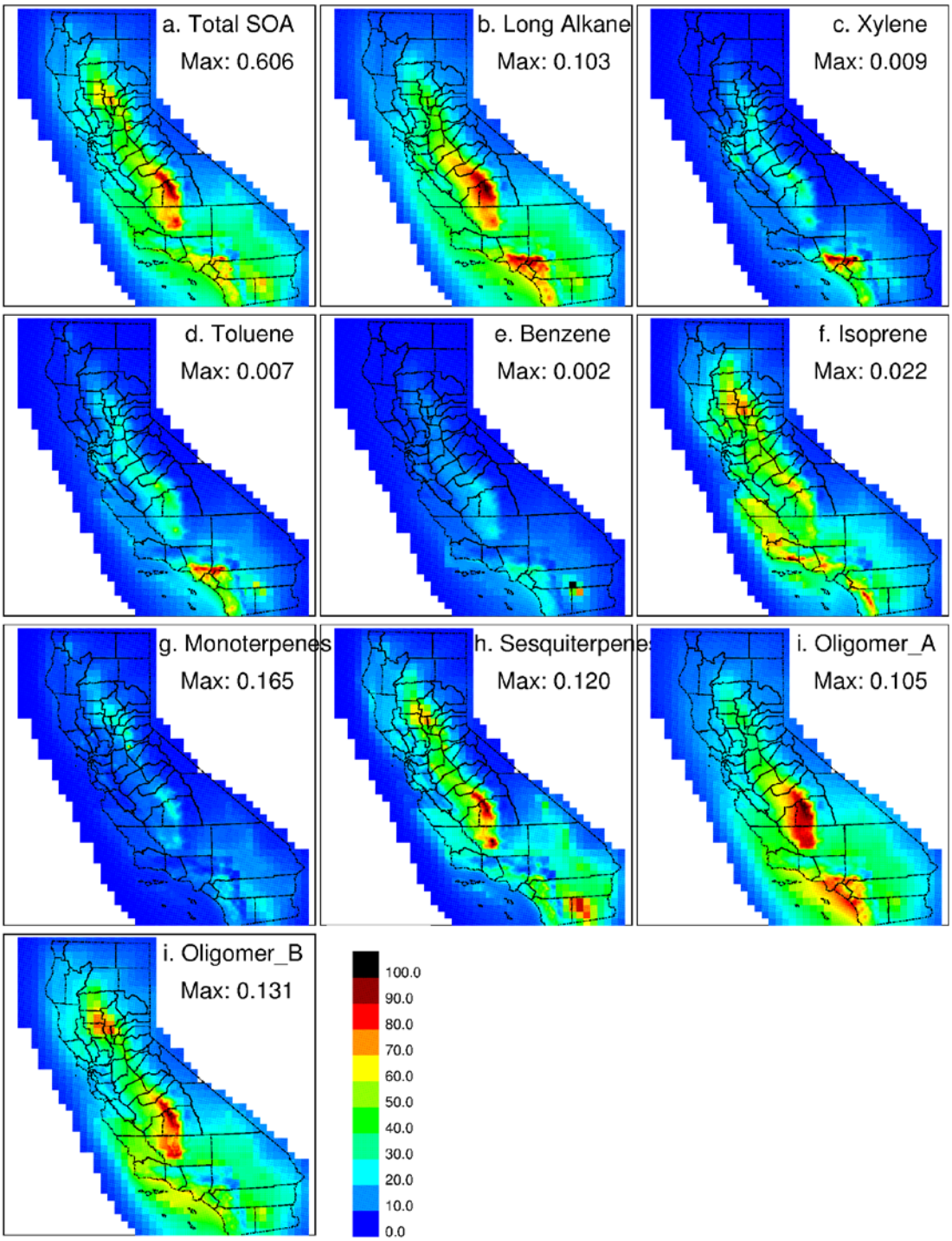


Figure 2-10. 9 year average SOA concentrations derived from (a)AALK, b) AXYL, c) ATOL, d) ABNZ, e) AISO, f) ATRP, g) ASQT, h) AOLGA, and i) AOLGB in PM2.5. The color scales (shown in the last panel in unit of %) indicate the ratio of the concentrations to the max concentration values. The maximum concentration values are shown in the panels under the names of the species, with a unit of μg/m^3.

Figure 2-11 shows the predicted total OA concentrations (Figure 2-11a) and the predicted ratios of SOA to total OA averaged over the 9 year modeling period (Figure 2-11b). High total OA concentrations with maximum concentrations > 10 μg/m^3 are located in urban areas where the POA emissions are large due to human activities. Predicted SOA generally accounts for less than 10% of total OA at urban areas, but predicted SOA contribute to 20~35% of total OA in suburban areas, and contribute to 30~50% in rural areas. Similar low SOA fractions were found in a previous study (Robinson, Donahue et al. 2007) in the eastern United States when gas-particle partitioning of POA emissions was not considered (as in the present study), but the SOA fractions were substantially increased when the POA partitioning was considered. Recent laboratory studies (Huffman, Docherty et al. 2009, May, Levin et al. 2013, May, Presto et al. 2013, May, Presto et al. 2013) revealed the volatile behavior of POA emissions from major anthropogenic sources (i.e., gasoline and diesel motor vehicles, biomass burning, meat cooking, etc.). These sources contribute the majority of total OA in the urban areas in California. Therefore, the SOA fraction in the urban areas would be greatly enhanced if the partitioning of POA was considered.

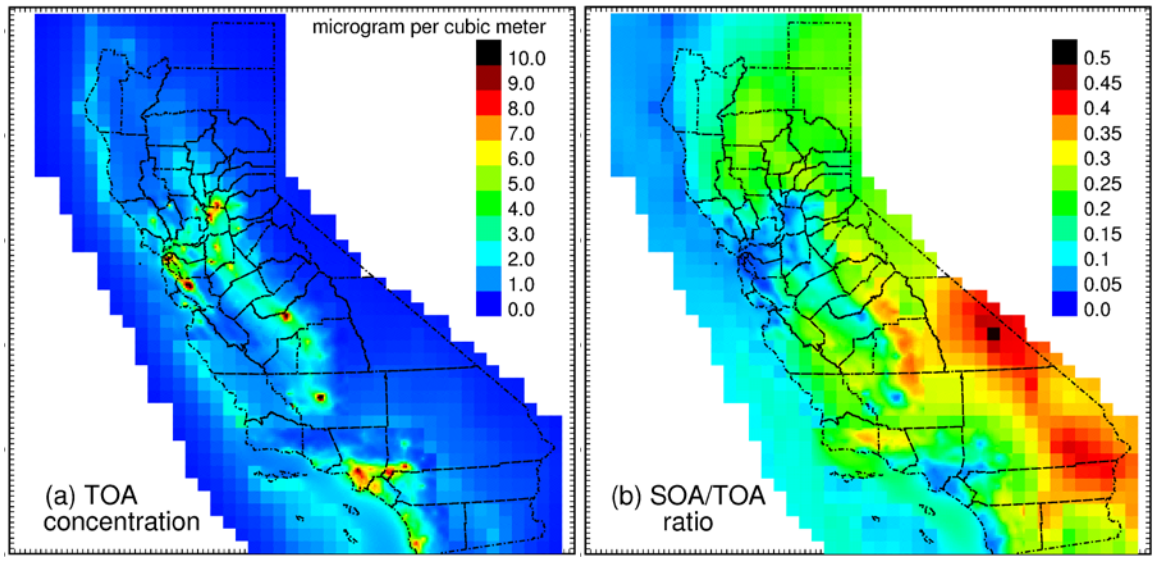


Figure 2-11. (a) Predicted 9 year average $PM_{2.5}$ Total OA (TOA) concentration in California in unit of μg/m^3. (b) Predicted 9 year average SOA/TOA ratio in California.

2.2.3 Sources of POA and SOA

Figure 2-12 shows the time series of monthly-average source contributions to total OA concentrations at six major urban locations (a) Sacramento, (b) San Jose, (c) Fresno, (d) Bakersfield, (e) Los Angeles, and (f) Riverside. The total OA concentrations were converted to OC concentrations as described in the previous section to compare with the measured total OC concentrations. Measured OC concentrations show strong seasonal variation with high concentrations in winter months and low concentrations in summer months at all sites. Predicted OC concentrations by the UCD/CIT model generally agree reasonably well with measured concentrations. At Sacramento and Fresno, the measured monthly OC concentrations frequently exceeded 10 μg/m^3 in winter and the maximum monthly OC concentrations reached or exceeded ~25 μg/m^3. Wood smoke is the dominant OC source at the two locations, contributing over 70% of the total OC concentrations on average. Wood smoke is also predicted to be the dominant OC source in winter at San Jose and Bakersfield. The model tends to over-predict the winter OC concentrations at San Jose, indicating that wood smoke emissions are likely over-estimated in this area. OC in summer is generally under-predicted and meat cooking and other anthropogenic sources are the

most important sources in summer at Sacramento, San Jose, Fresno, and Bakersfield. In total the two sources contribute to over 86% of the total OC in summer. At Los Angeles and Riverside, similar but weaker seasonal variation is observed due to smaller wood smoke contributions. Meat cooking and other anthropogenic sources are the two largest sources at the two locations. Mobile sources (gasoline and diesel engines) also contribute approximately 30% of the total OC at Los Angeles. The model tends to under-predict OC concentrations in all seasons in 2000-2006 at Riverside. Riverside is located approximately 80 km downwind of the Los Angeles urban center. Intense emissions transported from the upwind Los Angeles areas along with the meteorology and topography enhances photo-oxidation of volatile organic compounds (VOCs) and formation of SOA. A measurement study of organic aerosols at Riverside in summer indicated a high SOA fraction of the total OA with average SOA/OA ratio of 0.74 (Docherty, Stone et al. 2008). The OC under-prediction at Riverside and the general under-prediction in summer at other sites may indicate that some important precursors and pathways of SOA are missing or only partially included in the current SOA module, such as SOA formation from glyoxal and methylglyoxal (Fu, Jacob et al. 2008, Ervens and Volkamer 2010) and from aerosol aqueous phase chemistry (Volkamer, Ziemann et al. 2009).

Figure 2-13 shows the time series of monthly average SOA source contributions at the six major urban locations shown in Figure 2-1. SOA concentrations are high in summer months and low in winter, reflecting the seasonal variation in photochemistry. Predicted monthly average SOA concentrations are around 1~2 $\mu g/m^3$ in summers and 0.1~0.3 $\mu g/m^3$ in winters. SOA concentrations are higher at Fresno and Bakersfield than other sites due to larger biogenic source contributions. Biogenic emissions are the largest SOA sources across all sites, followed by the other anthropogenic sources (including solvent use). Onroad gasoline engines are an important source of SOA at Los Angeles and Riverside.

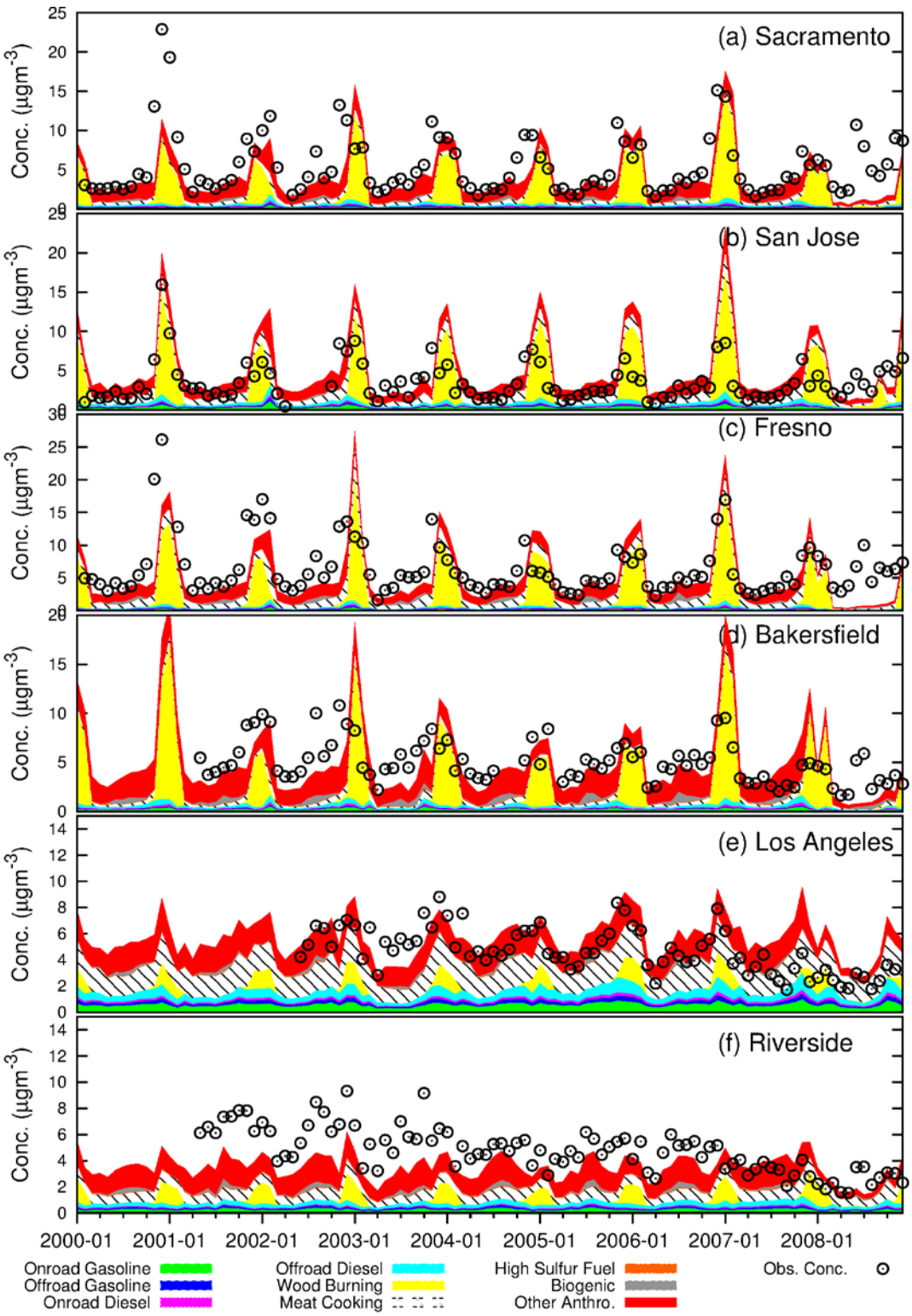


Figure 2-12. Monthly source contributions to total OC at 6 urban sites. Observed total OC concentrations are indicated by the dot-circles, and predicted OC concentrations from different sources are indicated by the colored areas.

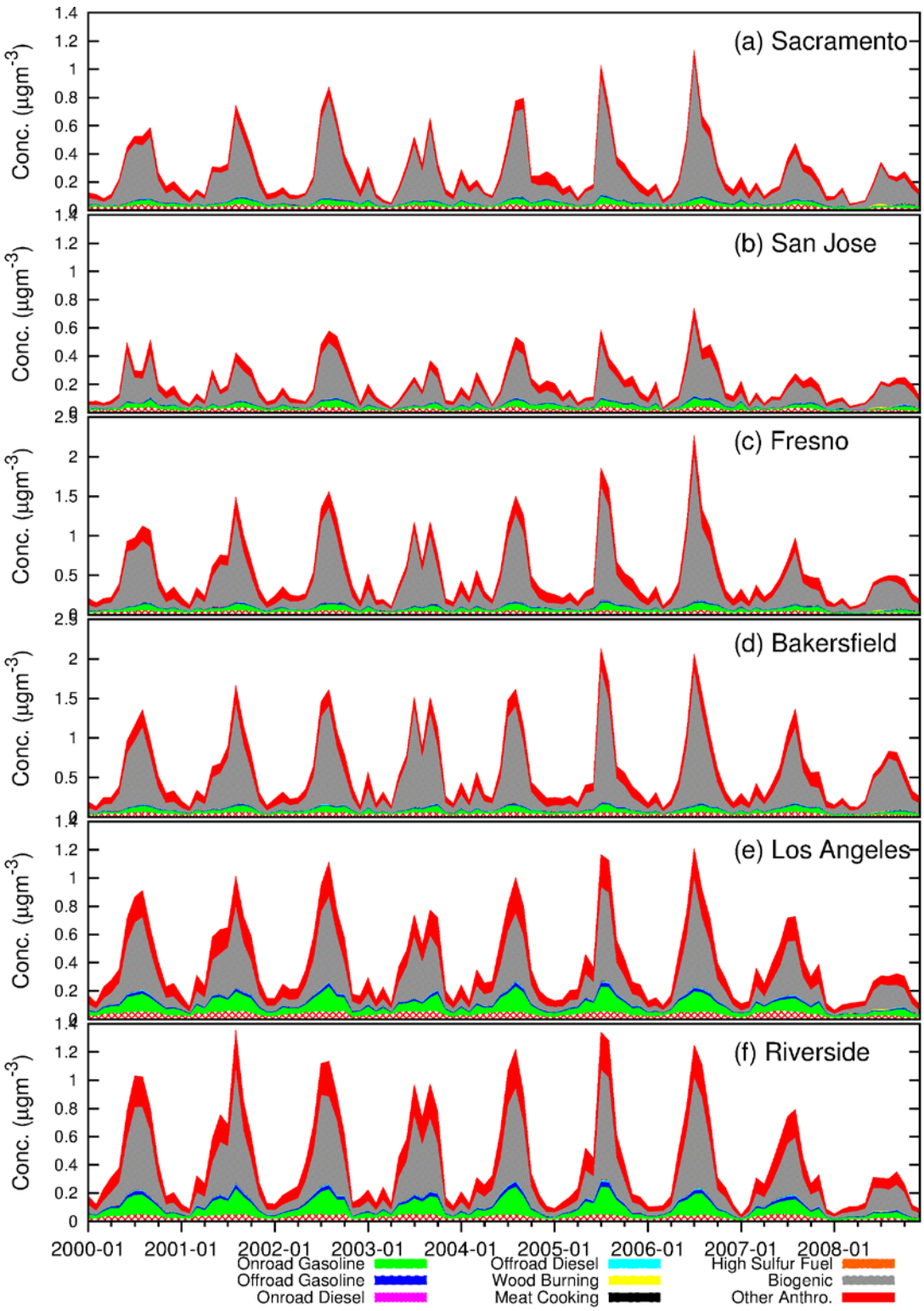


Figure 2-13. Monthly source contributions to SOA at 6 urban sites. Predicted OC concentrations from different sources are indicated by the colored areas.

Figure 2-14 shows the predicted regional source contributions of POA averaged over the 9 year modeling period. The dominant regional sources of POA are predicted to be wood smoke, meat cooking, other anthropogenic sources (including solvent use), offroad diesel and onroad gasoline. Wood smoke is the dominant POA source, especially in the northern California, with the maximum POA contribution exceeding 4 µg/m^3. Meat cooking and offroad diesel engines are dominant in urban areas, especially in metropolitan areas such as the Greater Los Angeles Area and the San Francisco Bay Area, with the maximum POA contribution exceeding 3 µg/m^3 and 1.2 µg/m^3, respectively. POA from Onroad gasoline engines contribute 0.5 ~0.8 µg/m^3 POA in the two metropolitan areas, and contribute 0.2~0.4 µg/m^3 POA along the highways in the central California. Other anthropogenic sources are dominant in the SJV and also the Los Angeles areas with the maximum POA concentrations exceeding 4 µg/m^3.

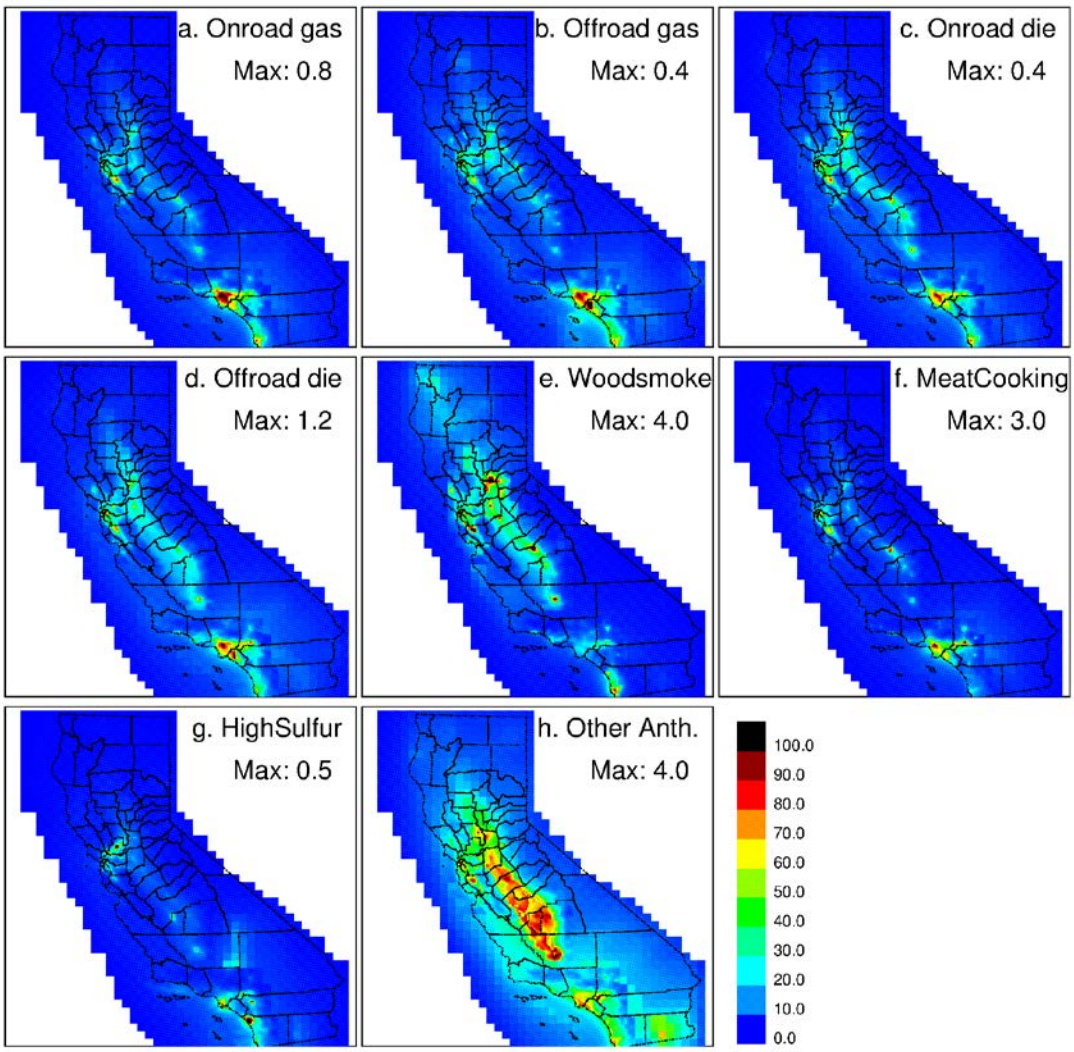


Figure 2-14. Predicted source contributions to 9 year average POA concentrations. The definition of the color scales are the same as in Figure 2-10.

Figure 2-15 shows the predicted regional source contributions of SOA averaged over the 9 year modeling period. Biogenic emission is predicted to be the single largest SOA source in the present study. The maximum SOA concentration from biogenic source is 0.48 μg/m^3 in the southern SJV. Other anthropogenic sources (including solvent use), onroad gasoline engines, and offroad gasoline engines are the dominant anthropogenic sources of SOA in California. The maximum contributions to SOA concentrations from these sources are 0.25, 0.08, and 0.02 μg/m^3, respectively. The spatial distribution of SOA concentrations from these sources are quite similar (but different from the spatial distribution of SOA from biogenic sources) with high concentrations in Southern California and the SJV. SOA formation from onroad diesel engines, offroad diesel engines, wood smoke, meat cooking and high sulfur fuel combustion are small, with maximum SOA contribution less than 0.01 μg/m^3. The SOA from diesel engines (onroad + offroad) is less than SOA from gasoline engines (onroad + offroad) and is opposite to their source contribution to POA, reflecting that total VOCs emissions from diesel engines were much lower than those from gasoline engines. A similar trend was identified in a previous winter episode study (Chen, Ying et al. 2010).

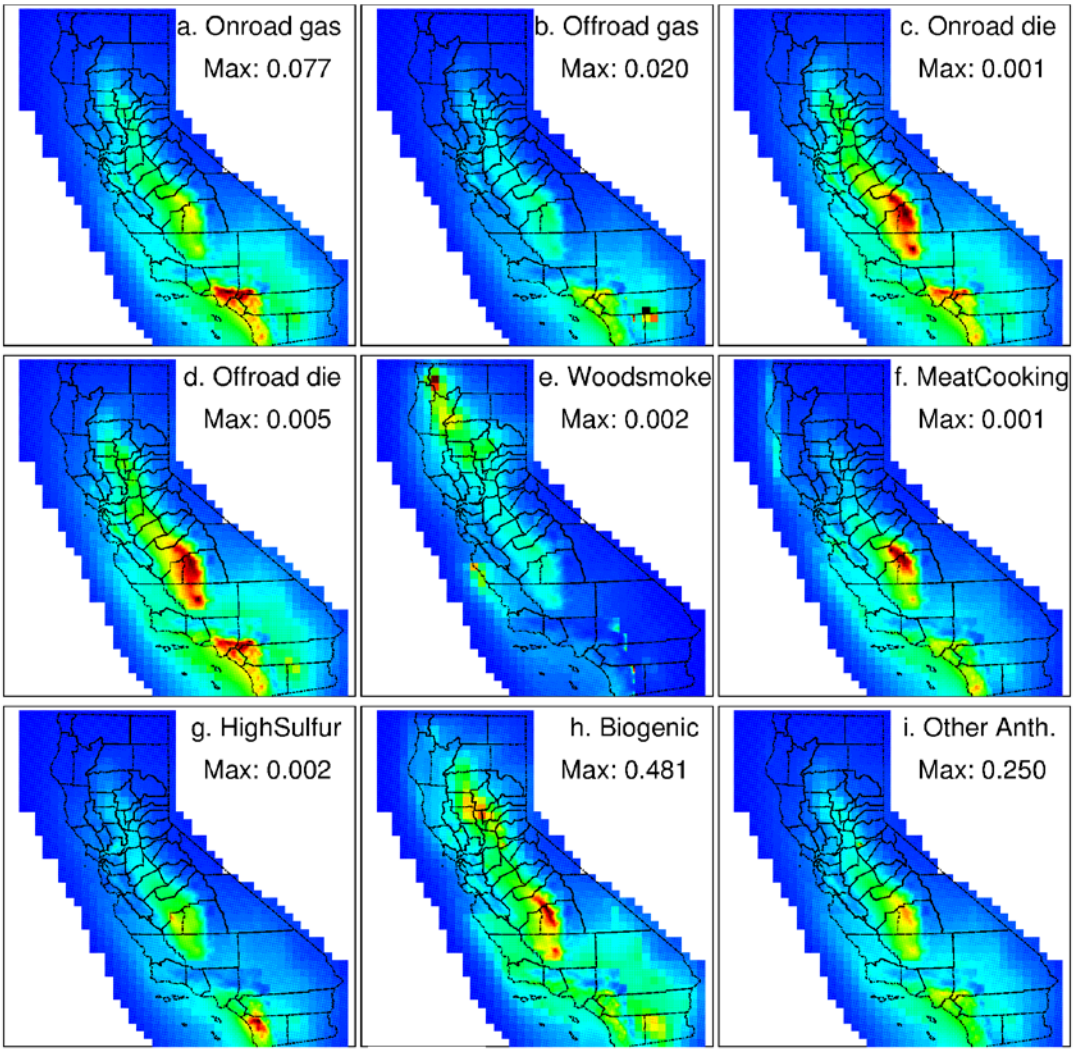


Figure 2-15. Predicted source contributions to 9 year average SOA concentrations. The definition of the color scales are the same as in Figure 2-10.

2.3 Summary and Conclusions

The source-oriented UCD/CIT model was applied to predict the concentrations and sources of POA and SOA in California for a 9 year (2000 - 2008) modeling period with 4 km horizontal resolution to provide data for the study of health effects. Model predictions were compared to measurements in order to evaluate both the spatial and temporal accuracy of the results. The performance of the source-oriented UCD/CIT air quality model is satisfactory for O_3, $PM_{2.5}$, and EC (both spatially and temporally). Predicted OC, nitrate, and ammonium are less satisfactory, but generally meet standard model performance criteria. OC bias is larger in summertime than wintertime mainly due to an incomplete understanding of SOA formation mechanisms. Bias in predicted ammonium nitrate is associated with uncertainties in emissions, the WRF predicted relative humidity fields, and the chemical mechanism. Predicted sulfate is not satisfactory due to missing sulfur sources in the emissions. Predicted spatial distributions of PM components are in reasonably good agreement with measurements. Predicted seasonal and annual variations also generally agree well with measurements. Better model performance with longer averaging time is found in the predictions, suggesting that model results with averaging times ≥1 month should be first considered in epidemiological studies. Predicted total OC concentrations (primary + secondary) and the OC/mass ratios generally agree with measured values. Compared to the POA and SOA concentrations estimated in measurements at 4 sites using the CMB method and the EC tracer method, the UCD/CIT model predicted total OA concentrations are consistent with measured values with fraction bias within ±35% except at the Riverside site, but the model predicted SOA concentrations are lower by up to a factor of 8.5. This suggests that part of POA emissions are likely semi-volatile and that the SOA model should consider its evaporation after emissions, photo-oxidation and condensation back to particle phase as SOA. In addition, SOA/OA larger bias is found in summertime than wintertime, suggesting missing pathways/precursors of SOA in the current SOA model. Wood smoke is found to be the single biggest source of OA in winter in California, and meat cooking and other anthropogenic sources (including solvent use) and mobile emissions are the most important sources in summer. Biogenic emissions are predicted to be the largest SOA source, followed by the other anthropogenic sources (including solvent use), and mobile sources, but predicted SOA concentrations are generally low, with monthly average SOA concentrations around 1~2 $\mu g/m^3$ in summers and 0.1~0.3 $\mu g/m^3$ in winters. Air pollution control programs aiming to reduce the OA concentrations to protect public health should consider controlling wood burning in winter and meat cooking/solvent use in summer in California. All model results included in the current manuscript can be downloaded free of charge at http://faculty.engineering.ucdavis.edu/kleeman/.

References

Aiken, A. C., P. F. DeCarlo, J. H. Kroll, D. R. Worsnop, J. A. Huffman, K. S. Docherty, I. M. Ulbrich, C. Mohr, J. R. Kimmel, D. Sueper, Y. Sun, Q. Zhang, A. Trimborn, M. Northway, P. J. Ziemann, M. R. Canagaratna, T. B. Onasch, M. R. Alfarra, A. S. H. Prevot, J. Dommen, J. Duplissy, A. Metzger, U. Baltensperger and J. L. Jimenez (2008). "O/C and OM/OC Ratios of Primary, Secondary, and Ambient Organic Aerosols with High-Resolution Time-of-Flight Aerosol Mass Spectrometry." Environmental Science & Technology **42**(12): 4478-4485.

Anenberg, S. C., L. W. Horowitz, D. Q. Tong and J. J. West (2010). "An Estimate of the Global Burden of Anthropogenic Ozone and Fine Particulate Matter on Premature Human Mortality Using Atmospheric Modeling." Environmental Health Perspectives

118(9): 1189-1195.
Appel, K. W., P. V. Bhave, A. B. Gilliland, G. Sarwar and S. J. Roselle (2008). "Evaluation of the community multiscale air quality (CMAQ) model version 4.5: Sensitivities impacting model performance; Part II - particulate matter." Atmospheric Environment **42**(24): 6057-6066.
Bao, J. W., Michelson, S. A., Persson, P. O. G., Djalalova, I. V., Wilczak, J. M. (2008). "Observed and WRF-simulated low-level winds in a high-ozone episode during the Central California Ozone Study." Journal of Applied Meteorology and Climatology **47**(9): 2372-2394.
Bates, T. S., B. K. Lamb, A. Guenther, J. Dignon and R. E. Stoiber (1992). "Sulfur emissions to the atmosphere from natural sourees." Journal of Atmospheric Chemistry **14**(1-4): 315-337.
Boylan, J. W. and A. G. Russell (2006). "PM and light extinction model performance metrics, goals, and criteria for three-dimensional air quality models." Atmospheric Environment **40**(26): 4946-4959.
Bravo, M. A., M. Fuentes, Y. Zhang, M. J. Burr and M. L. Bell (2012). "Comparison of exposure estimation methods for air pollutants: Ambient monitoring data and regional air quality simulation." Environmental Research **116**: 1-10.
Cabada, J. C., S. N. Pandis, R. Subramanian, A. L. Robinson, A. Polidori and B. Turpin (2004). "Estimating the secondary organic aerosol contribution to PM2.5 using the EC tracer method." Aerosol Science and Technology **38**: 140-155.
Cao, J. J., H. M. Xu, Q. Xu, B. H. Chen and H. D. Kan (2012). "Fine Particulate Matter Constituents and Cardiopulmonary Mortality in a Heavily Polluted Chinese City." Environmental Health Perspectives **120**(3): 373-378.
CARB (2008). "Calculating emission inventories for vehicles in California." User's Guide EMFAC 2007 version 2.30 **Accessed in 2010**(http://www.arb.ca.gov/msei/onroad/downloads/docs/user_guide_emfac2007.pdf).
CARB (2011). "Meteorology Data Query Tool (PST), http://www.arb.ca.gov/aqmis2/metselect.php." Accessed in 2011.
CARB (2012). "Almanac Emission Projection Data (published in 2009), http://www.arb.ca.gov/app/emsinv/emssumcat.php." Accessed in 2012.
CARB (2011). "Database: California Air Quality Data - Selected Data Available for Download <http://www.arb.ca.gov/aqd/aqdcd/aqdcddld.htm>." Accessed in 2011.
Carlton, A. G., P. V. Bhave, S. L. Napelenok, E. D. Edney, G. Sarwar, R. W. Pinder, G. A. Pouliot and M. Houyoux (2010). "Model Representation of Secondary Organic Aerosol in CMAQv4.7." Environmental Science & Technology **44**(22): 8553-8560.
Carter, W. P. L. and G. Heo (2012). "DEVELOPMENT OF REVISED SAPRC AROMATICS MECHANISMS." Final Report to California Air Resources Board Contracts No. 07-730 and 08-326.
Carter, W. P. L. and G. Heo (2012). "DEVELOPMENT OF REVISED SAPRC AROMATICS MECHANISMS." Report to the California Air Resources Board, Contract No. 07-730 and 08-326
Carter, W. P. L. and G. Heo (2013). "Development of revised SAPRC aromatics mechanisms." Atmospheric Environment **77**: 404-414.
Chen, J. J., Q. Ying and M. J. Kleeman (2010). "Source apportionment of wintertime secondary organic aerosol during the California regional PM(10)/PM(2.5) air quality study." Atmospheric Environment **44**(10): 1331-1340.
Cooper, J. A. e. a. (1989). "Dinal Appendix V-G, PM10 source composition library for the South Coast Air Basin." Technical Report, South Coast Air Quality Management District, Diamond Bar, California.
Countess, R. J. (2003). "Reconciling Fugitive Dust Emission Inventories with Ambient Measurements." 12th Annual EPA Emission Inventory Conference **San Diego, CA**(April 29 - May 1).
Daher, N., A. Ruprecht, G. Invernizzi, C. De Marco, J. Miller-Schulze, J. B. Heo, M. M. Shafer, J. J. Schauer and C. Sioutas (2011). "Chemical Characterization and Source

Apportionment of Fine and Coarse Particulate Matter Inside the Refectory of Santa Maria Delle Grazie Church, Home of Leonardo Da Vinci's "Last Supper"." Environmental Science & Technology **45**(24): 10344-10353.

Daher, N., A. Ruprecht, G. Invernizzi, C. De Marco, J. Miller-Schulze, J. B. Heo, M. M. Shafer, B. R. Shelton, J. J. Schauer and C. Sioutas (2012). "Characterization, sources and redox activity of fine and coarse particulate matter in Milan, Italy." Atmospheric Environment **49**(0): 130-141.

Day, D. A., S. Liu, L. M. Russell and P. J. Ziemann (2010). "Organonitrate group concentrations in submicron particles with high nitrate and organic fractions in coastal southern California." Atmospheric Environment **44**(16): 1970-1979.

de Leeuw, G., F. P. Neele, M. Hill, M. H. Smith and E. Vignali (2000). "Production of sea spray aerosol in the surf zone." Journal of Geophysical Research-Atmospheres **105**(D24): 29397-29409.

Docherty, K. S., E. A. Stone, I. M. Ulbrich, P. F. DeCarlo, D. C. Snyder, J. J. Schauer, R. E. Peltier, R. J. Weber, S. M. Murphy, J. H. Seinfeld, B. D. Grover, D. J. Eatough and J. L. Jimenez (2008). "Apportionment of Primary and Secondary Organic Aerosols in Southern California during the 2005 Study of Organic Aerosols in Riverside (SOAR-1)." Environmental Science & Technology **42**(20): 7655-7662.

Dockery, D. W. (2001). "Epidemiologic evidence of cardiovascular effects of particulate air pollution." Environmental Health Perspectives **109**: 483-486.

Dockery, D. W. and C. A. Pope (1994). "Acute Respiratory Effects of Particulate Air-Pollution." Annual Review of Public Health **15**: 107-132.

Dockery, D. W., C. A. Pope, X. P. Xu, J. D. Spengler, J. H. Ware, M. E. Fay, B. G. Ferris and F. E. Speizer (1993). "An Association between Air-Pollution and Mortality in 6 United-States Cities." New England Journal of Medicine **329**(24): 1753-1759.

Emery, C., E. Tai and G. Yarwood (2001). Enhanced meteorological modeling and performance evaluation for two texas episodes. p. b. E. Report to the Texas Natural Resources Conservation Commission, Internatioanl Corp. Novato, CA.

Ervens, B. and R. Volkamer (2010). "Glyoxal processing by aerosol multiphase chemistry: towards a kinetic modeling framework of secondary organic aerosol formation in aqueous particles." Atmospheric Chemistry and Physics **10**(17): 8219-8244.

Frank, N. H. (2006). "Retained nitrate, hydrated sulfates, and carbonaceous mass in Federal Reference Method fine particulate matter for six eastern US cities." Journal of the Air & Waste Management Association **56**(4): 500-511.

Franklin, M., A. Zeka and J. Schwartz (2007). "Association between PM2.5 and all-cause and specific-cause mortality in 27 US communities." Journal of Exposure Science and Environmental Epidemiology **17**(3): 279-287.

Fu, T. M., D. J. Jacob, F. Wittrock, J. P. Burrows, M. Vrekoussis and D. K. Henze (2008). "Global budgets of atmospheric glyoxal and methylglyoxal, and implications for formation of secondary organic aerosols." Journal of Geophysical Research-Atmospheres **113**(D15).

Gong, S. L. (2003). "A parameterization of sea-salt aerosol source function for sub- and super-micron particles." Global Biogeochemical Cycles **17**(4).

Ham, W. A. and M. J. Kleeman (2011). "Size-resolved source apportionment of carbonaceous particulate matter in urban and rural sites in central California." Atmospheric Environment **45**(24): 3988-3995.

Harley, R. A., M. P. Hannigan and G. R. Cass (1992). "Respeciation of Organic Gas Emissions and the Detection of Excess Unburned Gasoline in the Atmosphere." Environmental Science & Technology **26**(12): 2395-2408.

Held, T., Q. Ying, M. J. Kleeman, J. J. Schauer and M. P. Fraser (2005). "A comparison of the UCD/CIT air quality model and the CMB source-receptor model for primary airborne particulate matter." Atmospheric Environment **39**(12): 2281-2297.

Held, T., Ying, Q., Kaduwela, A., Kleeman, M. (2004). "Modeling particulate matter in the San Joaquin Valley with a source-oriented externally mixed three-dimensional photochemical grid model." Atmospheric Environment **38**(22): 3689-3711.

Herner, J. D., J. Aw, O. Gao, D. P. Chang and M. J. Kleeman (2005). "Size and composition distribution of airborne particulate matter in northern California: I-particulate mass, carbon, and water-soluble ions." Journal of the Air & Waste Management Association **55**(1): 30-51.

Hildemann, L. M., G. R. Markowski and G. R. Cass (1991). "Chemical-Composition of Emissions from Urban Sources of Fine Organic Aerosol." Environmental Science & Technology **25**(4): 744-759.

Hildemann, L. M., G. R. Markowski, M. C. Jones and G. R. Cass (1991). "Submicrometer Aerosol Mass Distributions of Emissions from Boilers, Fireplaces, Automobiles, Diesel Trucks, and Meat-Cooking Operations." Aerosol Science and Technology **14**(1): 138-152.

Hodzic, A., S. Madronich, B. Bohn, S. Massie, L. Menut and C. Wiedinmyer (2007). "Wildfire particulate matter in Europe during summer 2003: meso-scale modeling of smoke emissions, transport and radiative effects." Atmospheric Chemistry and Physics **7**(15): 4043-4064.

Houck, J. E., et al. (1989). "Determination of particle size distribution and chemical composition of particulate matter from selected sources in California." Technical Report, Contract A6-175-32, California Air Resources Board, OMNI Environment Service Incorporate, Desert Research Institute, Beaverton, Oregon.

Hu, J., C. J. Howard, F. Mitloehner, P. G. Green and M. J. Kleeman (2012). "Mobile Source and Livestock Feed Contributions to Regional Ozone Formation in Central California." Environmental Science & Technology **46**(5): 2781-2789.

Hu, J., Q. Ying, J. J. Chen, A. Mahmud, Z. Zhao, S. H. Chen and M. J. Kleeman (2010). "Particulate air quality model predictions using prognostic vs. diagnostic meteorology in central California." Atmospheric Environment **44**(2): 215-226.

Hu, J., H. Zhang, S.-H. Chen, F. Vandenberghe, Q. Ying and M. J. Kleeman (2014). "Predicting Primary PM2.5 and PM0.1 Trace Composition for Epidemiological Studies in California." Environmental Science & Technology **48**(9): 4971-4979.

Hu, J., H. Zhang, S. Chen, Q. Ying, F. Vandenberghe and M. J. Kleeman (2014). "Identifying PM2.5 and PM0.1 Sources for Epidemiological Studies in California." Environmental Science & Technology **48**(9): 4980-4990.

Hu, J., H. Zhang, Q. Ying, S. H. Chen, F. Vandenberghe and M. J. Kleeman (2014). "Long-term Particulate Matter Modeling for Health Effects Studies in California – Part I: Model Performance on Temporal and Spatial Variations." Atmospheric Chemistry and Physics Discussion, under review.

Hu, J. L., Zhang, H. L., Chen, S. H., Wiedinmyer, C., Vandenberghe, F., Ying, Q., Kleeman, M. J. (Manuscript in preparation). "Long-term Particulate Matter Modeling for Health Effects Studies in California – Part II: Concentrations and Souces of Primary and Secondary Organic Aerosols."

Huffman, J. A., K. S. Docherty, C. Mohr, M. J. Cubison, I. M. Ulbrich, P. J. Ziemann, T. B. Onasch and J. L. Jimenez (2009). "Chemically-Resolved Volatility Measurements of Organic Aerosol from Different Sources." Environmental Science & Technology **43**(14): 5351-5357.

Kim, S., S. Shen, C. Sioutas, Y. F. Zhu and W. C. Hinds (2002). "Size distribution and diurnal and seasonal trends of ultrafine particles in source and receptor sites of the Los Angeles basin." Journal of the Air & Waste Management Association **52**(3): 297-307.

Kleeman, M. J. and G. R. Cass (1998). "Source contributions to the size and composition distribution of urban particulate air pollution." Atmospheric Environment **32**(16): 2803-2816.

Kleeman, M. J. and G. R. Cass (2001). "A 3D Eulerian source-oriented model for an externally mixed aerosol." Environmental Science & Technology **35**(24): 4834-4848.

Kleeman, M. J., G. R. Cass and A. Eldering (1997). "Modeling the airborne particle complex as a source-oriented external mixture." Journal of Geophysical Research-Atmospheres **102**(D17): 21355-21372.

Kleeman, M. J., M. A. Robert, S. G. Riddle, P. M. Fine, M. D. Hays, J. J. Schauer and M. P.

Hannigan (2008). "Size distribution of trace organic species emitted from biomass combustion and meat charbroiling." Atmospheric Environment **42**(13): 3059-3075.
Kleeman, M. J., J. J. Schauer and G. R. Cass (1999). "Size and composition distribution of fine particulate matter emitted from wood burning, meat charbroiling, and cigarettes." Environmental Science & Technology **33**(20): 3516-3523.
Kleeman, M. J., J. J. Schauer and G. R. Cass (2000). "Size and composition distribution of fine particulate matter emitted from motor vehicles." Environmental Science & Technology **34**(7): 1132-1142.
Kleeman, M. J., Q. Ying, J. Lu, M. J. Mysliwiec, R. J. Griffin, J. J. Chen and S. Clegg (2007). "Source apportionment of secondary organic aerosol during a severe photochemical smog episode." Atmospheric Environment **41**(3): 576-591.
Kleindienst, T. E., M. Jaoui, M. Lewandowski, J. H. Offenberg, C. W. Lewis, P. V. Bhave and E. O. Edney (2007). "Estimates of the contributions of biogenic and anthropogenic hydrocarbons to secondary organic aerosol at a southeastern US location." Atmospheric Environment **41**(37): 8288-8300.
Krall, J. R., G. B. Anderson, F. Dominici, M. L. Bell and R. D. Peng (2013). "Short-term Exposure to Particulate Matter Constituents and Mortality in a National Study of US Urban Communities." Environmental Health Perspectives **121**(10): 1148-1153.
Krudysz, M. A., J. R. Froines, P. M. Fine and C. Sioutas (2008). "Intra-community spatial variation of size-fractionated PM mass, OC, EC, and trace elements in the Long Beach, CA area." Atmospheric Environment **42**(21): 5374-5389.
Lanz, V. A., M. R. Alfarra, U. Baltensperger, B. Buchmann, C. Hueglin, S. Szidat, M. N. Wehrli, L. Wacker, S. Weimer, A. Caseiro, H. Puxbaum and A. S. H. Prevot (2007). "Source Attribution of Submicron Organic Aerosols during Wintertime Inversions by Advanced Factor Analysis of Aerosol Mass Spectra." Environmental Science & Technology **42**(1): 214-220.
Le Tertre, A., S. Medina, E. Samoli, B. Forsberg, P. Michelozzi, A. Boumghar, J. M. Vonk, A. Bellini, R. Atkinson, J. G. Ayres, J. Sunyer, J. Schwartz and K. Katsouyanni (2002). "Short-term effects of particulate air pollution on cardiovascular diseases in eight European cities." Journal of Epidemiology and Community Health **56**(10): 773-779.
Levy, J. I., D. Diez, Y. P. Dou, C. D. Barr and F. Dominici (2012). "A Meta-Analysis and Multisite Time-Series Analysis of the Differential Toxicity of Major Fine Particulate Matter Constituents." American Journal of Epidemiology **175**(11): 1091-1099.
Lim, H. J., B. J. Turpin, L. M. Russell and T. S. Bates (2003). "Organic and elemental carbon measurements during ACE-Asia suggest a longer atmospheric lifetime for elemental carbon." Environmental Science & Technology **37**(14): 3055-3061.
Mahmud, A., Hixson, M., Hu, J., Zhao, Z., Chen, S. H., Kleeman, M. J. (2010). "Climate impact on airborne particulate matter concentrations in California using seven year analysis periods." Atmospheric Chemistry and Physics **10**(22): 11097-11114.
Mar, T. F., G. A. Norris, J. Q. Koenig and T. V. Larson (2000). "Associations between air pollution and mortality in Phoenix, 1995-1997." Environmental Health Perspectives **108**(4): 347-353.
Matsui, H., M. Koike, N. Takegawa, Y. Kondo, R. J. Griffin, Y. Miyazaki, Y. Yokouchi and T. Ohara (2009). "Secondary organic aerosol formation in urban air: Temporal variations and possible contributions from unidentified hydrocarbons." Journal of Geophysical Research: Atmospheres **114**(D4): D04201.
Mauderly, J. L. and J. C. Chow (2008). "Health effects of organic aerosols." Inhalation Toxicology **20**(3): 257-288.
May, A. A., E. J. T. Levin, C. J. Hennigan, I. Riipinen, T. Lee, J. L. Collett, J. L. Jimenez, S. M. Kreidenweis and A. L. Robinson (2013). "Gas-particle partitioning of primary organic aerosol emissions: 3. Biomass burning." Journal of Geophysical Research-Atmospheres **118**(19): 11327-11338.
May, A. A., A. A. Presto, C. J. Hennigan, N. T. Nguyen, T. D. Gordon and A. L. Robinson (2013). "Gas-particle partitioning of primary organic aerosol emissions: (1) Gasoline vehicle exhaust." Atmospheric Environment **77**: 128-139.

May, A. A., A. A. Presto, C. J. Hennigan, N. T. Nguyen, T. D. Gordon and A. L. Robinson (2013). "Gas-Particle Partitioning of Primary Organic Aerosol Emissions: (2) Diesel Vehicles." Environmental Science & Technology **47**(15): 8288-8296.

Michelson, S. A., I. V. Djalalova and J. W. Bao (2010). "Evaluation of the Summertime Low-Level Winds Simulated by MM5 in the Central Valley of California." Journal of Applied Meteorology and Climatology **49**(11): 2230-2245.

Millstein, D. E. and R. A. Harley (2009). "Revised estimates of construction activity and emissions: Effects on ozone and elemental carbon concentrations in southern California." Atmospheric Environment **43**(40): 6328-6335.

Mysliwiec, M. J. and M. J. Kleeman (2002). "Source apportionment of secondary airborne particulate matter in a polluted atmospbere." Environmental Science & Technology **36**(24): 5376-5384.

Ostro, B., R. Broadwin, S. Green, W. Y. Feng and M. Lipsett (2006). "Fine particulate air pollution and mortality in nine California counties: Results from CALFINE." Environmental Health Perspectives **114**(1): 29-33.

Ostro, B., M. Lipsett, P. Reynolds, D. Goldberg, A. Hertz, C. Garcia, K. D. Henderson and L. Bernstein (2010). "Long-Term Exposure to Constituents of Fine Particulate Air Pollution and Mortality: Results from the California Teachers Study." Environmental Health Perspectives **118**(3): 363-369.

Pace, T. G. (2005). "Methodology to Estimate the Transportable Fraction (TF) of Fugitive Dust Emissions for Regional and Urban Scale Air Quality Analyses." US EPA August 2005.

Polidori, A., M. Arhami, C. Sioutas, R. J. Delfino and R. Allen (2007). "Indoor/Outdoor Relationships, Trends, and Carbonaceous Content of Fine Particulate Matter in Retirement Homes of the Los Angeles Basin." Journal of the Air & Waste Management Association **57**(3): 366-379.

Polidori, A., B. J. Turpin, H. J. Lim, J. C. Cabada, R. Subramanian, S. N. Pandis and A. L. Robinson (2006). "Local and regional secondary organic aerosol: Insights from a year of semi-continuous carbon measurements at Pittsburgh." Aerosol Science and Technology **40**(10): 861-872.

Pope, C. A., R. T. Burnett, M. J. Thun, E. E. Calle, D. Krewski, K. Ito and G. D. Thurston (2002). "Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution." Jama-Journal of the American Medical Association **287**(9): 1132-1141.

Pope, C. A. and D. W. Dockery (2006). "Health effects of fine particulate air pollution: Lines that connect." Journal of the Air & Waste Management Association **56**(6): 709-742.

Rasmussen, D. J., J. Hu, A. Mahmud and M. J. Kleeman (2013). "The Ozone–Climate Penalty: Past, Present, and Future." Environmental Science & Technology **47**(24): 14258-14266.

Robert, M. A., M. J. Kleeman and C. A. Jakober (2007). "Size and composition distributions of particulate matter emissions: Part 2- Heavy-duty diesel vehicles." Journal of the Air & Waste Management Association **57**(12): 1429-1438.

Robert, M. A., S. VanBergen, M. J. Kleeman and C. A. Jakober (2007). "Size and composition distributions of particulate matter emissions: Part 1 - Light-duty gasoline vehicles." Journal of the Air & Waste Management Association **57**(12): 1414-1428.

Robinson, A. L., N. M. Donahue, M. K. Shrivastava, E. A. Weitkamp, A. M. Sage, A. P. Grieshop, T. E. Lane, J. R. Pierce and S. N. Pandis (2007). "Rethinking Organic Aerosols: Semivolatile Emissions and Photochemical Aging." Science **315**(5816): 1259-1262.

Sardar, S. B., P. M. Fine, P. R. Mayo and C. Sioutas (2005). "Size-fractionated measurements of ambient ultrafine particle chemical composition in Los Angeles using the NanoMOUDI." Environmental Science & Technology **39**(4): 932-944.

Sardar, S. B., P. M. Fine and C. Sioutas (2005). "Seasonal and spatial variability of the size-resolved chemical composition of particulate matter (PM10) in the Los Angeles Basin." Journal of Geophysical Research-Atmospheres **110**(D7).

Sarnat, J. A., S. E. Sarnat, J. Crooks, V. Isakov, J. Touma, H. Ozkaynak, J. Mulholland, A. Russell and P. Kewada (2011). "Associations Between Spatially Resolved Estimates of Traffic-related Pollution and Acute Morbidity: Assessing Agreement of Results Among Multiple Exposure Assignment Approaches." Epidemiology **22**(1): S31-S32.

Schauer, J. J. and G. R. Cass (2000). "Source apportionment of wintertime gas-phase and particle-phase air pollutants using organic compounds as tracers." Environmental Science & Technology **34**(9): 1821-1832.

Schauer, J. J., M. J. Kleeman, G. R. Cass and B. R. T. Simoneit (1999). "Measurement of emissions from air pollution sources. 1. C-1 through C-29 organic compounds from meat charbroiling." Environmental Science & Technology **33**(10): 1566-1577.

Schauer, J. J., M. J. Kleeman, G. R. Cass and B. R. T. Simoneit (1999). "Measurement of emissions from air pollution sources. 2. C-1 through C-30 organic compounds from medium duty diesel trucks." Environmental Science & Technology **33**(10): 1578-1587.

Schauer, J. J., M. J. Kleeman, G. R. Cass and B. R. T. Simoneit (2001). "Measurement of emissions from air pollution sources. 3. C-1-C-29 organic compounds from fireplace combustion of wood." Environmental Science & Technology **35**(9): 1716-1728.

Schauer, J. J., M. J. Kleeman, G. R. Cass and B. R. T. Simoneit (2002). "Measurement of emissions from air pollution sources. 4. C-1-C-27 organic compounds from cooking with seed oils." Environmental Science & Technology **36**(4): 567-575.

Schauer, J. J., M. J. Kleeman, G. R. Cass and B. R. T. Simoneit (2002). "Measurement of emissions from air pollution sources. 5. C-1-C-32 organic compounds from gasoline-powered motor vehicles." Environmental Science & Technology **36**(6): 1169-1180.

Seinfeld, J. H. and J. F. Pankow (2003). "Organic atmospheric particulate material." Annual Review of Physical Chemistry **54**: 121-140.

Sickles Ii, J. E. and D. S. Shadwick (2002). "Precision of atmospheric dry deposition data from the Clean Air Status and Trends Network." Atmospheric Environment **36**(36–37): 5671-5686.

Taback, H. J., A. R. Brienza, J. Macko and N. Brunetz (1979). "Fine particle emissions from stationary and miscellaneous sources in the South Coast Air Basin." Technical Report, Contract A6-191-30, California Air Resources Board, KVB Incorporate, Research-Cottrell, Tustin, California.

Tainio, M., K. Juda-Rezler, M. Reizer, A. Warchałowski, W. Trapp and K. Skotak (2012). "Future climate and adverse health effects caused by fine particulate matter air pollution: case study for Poland." Regional Environmental Change: 1-11.

Tesche, T. W., R. Morris, G. Tonnesen, D. McNally, J. Boylan and P. Brewer (2006). "CMAQ/CAMx annual 2002 performance evaluation over the eastern US." Atmospheric Environment **40**(26): 4906-4919.

Turpin, B. J. and J. J. Huntzicker (1995). "Identification of Secondary Organic Aerosol Episodes and Quantitation of Primary and Secondary Organic Aerosol Concentrations during Scaqs." Atmospheric Environment **29**(23): 3527-3544.

Turpin, B. J. and H. J. Lim (2010). "Species contributions to PM2.5 mass concentrations: revisiting common assumptions for estimating organic mass." Aerosol Science and Technology **35:1**: 602-610.

U.S.EPA (2007). Guidance on the Use of Models and Other Analyses for Demonstrating Attainment of Air Quality Goals for Ozone, PM2.5 and Regional Haze. U. S. E. P. Agency. Research Triangle Park, North Carolina.

Ulbrich, I. M., M. R. Canagaratna, Q. Zhang, D. R. Worsnop and J. L. Jimenez (2009). "Interpretation of organic components from Positive Matrix Factorization of aerosol mass spectrometric data." Atmospheric Chemistry and Physics **9**(9): 2891-2918.

Volkamer, R., J. L. Jimenez, F. San Martini, K. Dzepina, Q. Zhang, D. Salcedo, L. T. Molina, D. R. Worsnop and M. J. Molina (2006). "Secondary organic aerosol formation from anthropogenic air pollution: Rapid and higher than expected." Geophysical Research Letters **33**(17): L17811.

Volkamer, R., P. J. Ziemann and M. J. Molina (2009). "Secondary Organic Aerosol Formation from Acetylene (C2H2): seed effect on SOA yields due to organic

photochemistry in the aerosol aqueous phase." Atmos. Chem. Phys. **9**(6): 1907-1928.
Vukovich, J. M. and T. Pierce (2002). The Implementation of BEIS3 within the SMOKE modeling framework, MCNC-Environmental Modeling Center, Research Triangle Park and National Oceanic and Atmospheric Administration.
Weber, R. J., A. P. Sullivan, R. E. Peltier, A. Russell, B. Yan, M. Zheng, J. de Gouw, C. Warneke, C. Brock, J. S. Holloway, E. L. Atlas and E. Edgerton (2007). "A study of secondary organic aerosol formation in the anthropogenic-influenced southeastern United States." Journal of Geophysical Research-Atmospheres **112**(D13).
Wei Wang, C. B., Michael Duda, Jimy Dudhia, Dave Gill, Hui-Chuan Lin, John Michalakes, Syed Rizvi, and Xin Zhang (January 2010). "The Advanced Research WRF (ARW) Version 3 Modeling System User's Guide."
Wiedinmyer, C., S. K. Akagi, R. J. Yokelson, L. K. Emmons, J. A. Al-Saadi, J. J. Orlando and A. J. Soja (2011). "The Fire INventory from NCAR (FINN): a high resolution global model to estimate the emissions from open burning." Geoscientific Model Development **4**(3): 625-641.
William C. Skamarock, J. B. K., Jimy Dudhia, David O Gill, Dale M. Barker, Michael G. Duda, Xiang-Yu Huang, Wei Wang, and Jordan G. Powers (June 2008). "A Description of the Advanced Research WRF Version 3." NCAR Technical Note NCAR/TN-475+STR.
WRAP (2005). 2002 Fire Emission Inventory for the WRAP Region –Phase II, Air Sciences Inc.
Ying, Q., M. P. Fraser, R. J. Griffin, J. J. Chen and M. J. Kleeman (2007). "Verification of a source-oriented externally mixed air quality model during a severe photochemical smog episode." Atmospheric Environment **41**(7): 1521-1538.
Ying, Q. and M. J. Kleeman (2006). "Source contributions to the regional distribution of secondary particulate matter in California." Atmospheric Environment **40**(4): 736-752.
Ying, Q., J. Lu, A. Kaduwela and M. Kleeman (2008). "Modeling air quality during the California Regional PM10/PM2.5 Air Quality Study (CPRAQS) using the UCD/CIT Source Oriented Air Quality Model - Part II. Regional source apportionment of primary airborne particulate matter." Atmospheric Environment **42**(39): 8967-8978.
Ying, Q., Lu, J., Allen, P., Livingstone, P., Kaduwela, A., Kleeman, M. (2008). "Modeling air quality during the California Regional PM10/PM2.5 Air Quality Study (CRPAQS) using the UCD/CIT source-oriented air quality model - Part I. Base case model results." Atmospheric Environment **42**(39): 8954-8966.
Yu, S. C., R. Dennis, S. Roselle, A. Nenes, J. Walker, B. Eder, K. Schere, J. Swall and W. Robarge (2005). "An assessment of the ability of three-dimensional air quality models with current thermodynamic equilibrium models to predict aerosol NO3-." Journal of Geophysical Research-Atmospheres **110**(D7).
Zhang, H., G. Chen, J. Hu, S.-H. Chen, C. Wiedinmyer, M. Kleeman and Q. Ying (2014). "Evaluation of a seven-year air quality simulation using the Weather Research and Forecasting (WRF)/Community Multiscale Air Quality (CMAQ) models in the eastern United States." Science of The Total Environment **473–474**(0): 275-285.
Zhang, H., S. P. DeNero, D. K. Joe, H. H. Lee, S. H. Chen, J. Michalakes and M. J. Kleeman (2014). "Development of a source oriented version of the WRF/Chem model and its application to the California regional PM10 / PM2.5 air quality study." Atmos. Chem. Phys. **14**(1): 485-503.
Zhang, H. and Q. Ying (2011). "Secondary organic aerosol formation and source apportionment in Southeast Texas." Atmospheric Environment **45**(19): 3217-3227.
Zhang, H. L. and Q. Ying (2010). "Source apportionment of airborne particulate matter in Southeast Texas using a source-oriented 3D air quality model." Atmospheric Environment **44**(29): 3547-3557.
Zhang, Q., J. L. Jimenez, M. R. Canagaratna, J. D. Allan, H. Coe, I. Ulbrich, M. R. Alfarra, A. Takami, A. M. Middlebrook, Y. L. Sun, K. Dzepina, E. Dunlea, K. Docherty, P. F. DeCarlo, D. Salcedo, T. Onasch, J. T. Jayne, T. Miyoshi, A. Shimono, S. Hatakeyama, N. Takegawa, Y. Kondo, J. Schneider, F. Drewnick, S. Borrmann, S. Weimer, K. Demerjian, P. Williams, K. Bower, R. Bahreini, L. Cottrell, R. J. Griffin, J. Rautiainen, J.

Y. Sun, Y. M. Zhang and D. R. Worsnop (2007). "Ubiquity and dominance of oxygenated species in organic aerosols in anthropogenically-influenced Northern Hemisphere midlatitudes." Geophysical Research Letters **34**(13): L13801.

Zhao, Z., S. H. Chen, M. J. Kleeman, M. Tyree and D. Cayan (2011). "The Impact of Climate Change on Air Quality-Related Meteorological Conditions in California. Part I: Present Time Simulation Analysis." Journal of Climate **24**(13): 3344-3361.

3. CHAPTER THREE: TASK 2

Task 2: To assess the risk of emergency department visits and hospital admissions for asthma in children from exposure to both traffic-related particles near their homes and local ambient primary and secondary organic aerosols and O_3. (Dr. Ralph Delfino, Dan Gillen, Jun Wu, Bruce Nickerson).

3.0 Introduction

This is a case-crossover study to evaluate the relation between asthma morbidity and both local and regional air pollution. In the crossover design, each person acts as his or her own control such that exposures are sampled from the subject's time-varying distribution of exposure. Exposure at a time just prior to event (the case or index time, e.g. date of hospital admission) is compared to a set of control or referent times that represent the expected distribution of exposure for non-event follow-up times. All subject-specific characteristics that are time invariant over the daily periods of interest such as socioeconomic status, insurance status, or race-ethnicity are controlled for by design. Nevertheless, these characteristics are of interest as they may modify associations (Task 4). In other words, associations may be stronger in one group vs. another. We also anticipate that associations may be stronger among more severely affected children with asthma with recurrent hospital encounters (Task 3).

We used the present 2000-2008 hospital data to evaluate the relation of hospital encounters to daily ambient air pollution and dispersion-modeled seasonal air pollution near the home residence (described below). This was funded by the South Coast Air Quality Management District contract number BPG-46329 (BP West Coast Products LLC) under the settlement agreement dated March 2005, concerning past air quality rule violations at the company's Carson, California, refinery. The present study greatly enhanced the analysis of asthma morbidity and air pollution in that study by using new POA, SOA and other air pollution data produced in Task 1 along with additional exposure data in Task 2 for residential exposure to traffic-related air pollution on a finer temporal scale (daily) using improved dispersion models.

Task 1 estimated the contributions of local sources while at the same time including regional exposure levels to estimate size-fractionated organic aerosols into primary and secondary sources by particle size fraction, including ultrafine. Additional new exposure data generated as part of Task 2 included dispersion model estimates of CO, NO_x, UFP number concentration, and $PM_{2.5}$ from on-road traffic near home addresses. These estimates combined with the UCD/CIT model estimates provide important information since personal exposures to air pollutants can differ markedly from ambient monitor data due to sources near the home and to meteorologic factors.

The added health impact of local source air pollution on associations with daily regional exposures was assessed by a novel approach as presented below. This approach advances air pollution time series research, which typically relies on ambient air monitoring data, often measured at just one site per region.

3.1 Materials and Methods

3.1.1 Population

Hospital records data had been collected under separate funding for children seen from 2000 through 2008 at the Children's Hospital of Orange County (CHOC) and the University of California Irvine Medical Center (UCIMC). The two hospitals were located within 2.5 km of each other. Most of the data were collected under the health surveillance arm of the CHOC-UCI Asthma and Chronic Lung Disease Program, which was funded by The Children and Families Commission of Orange County. The aim of the surveillance

database is to assess the impact of lower respiratory disease on the health and development of preschool children, and to improve preventive care programs. To assess health impacts at later ages, we also included school children to age 18.

We extracted hospital data from billing records for children ages 0-18 years seen at CHOC and UCIMC EDs or admitted to hospital for a primary diagnosis of asthma. These are the two hospitals that primarily serve the urban core of Northern Orange County and are the same two hospitals included in the previous SCAQMD-funded study described above under Preliminary Data (Chang 2009; Delfino 2009a). We have done additional work with this data (under funding from BP Inc. through SCAQMD, contract BPG-46329) to geocode all de-identified residences and link each residence to SES data from Census block group data and to the nearest ambient air monitoring station. UC Census block group data included variables describing neighborhood socioeconomic status (SES) (for Task 4 only).

Population data for the longitudinal analysis using this dataset includes a total of 11,390 hospital encounters from 2000-2008 made by 7,954 children (both ED visits and hospital admissions) (Table 3.1). This study population includes only subject addresses at each hospital encounter that were successfully geocoded (95%) using Tele Atlas North America Inc. (Boston, MA). Some patients returned to hospital many times, thus allowing an assessment of pollution-related risk by severity. This data includes subject-specific health insurance and race-ethnicity, as well as US Census block group SES (Task 4). The Institutional Review Boards of UCI and CHOC have approved the health surveillance protocol, which includes an assessment of the effects of air pollution and socioeconomic factors.

The distribution of subject data is shown in Table 3.1. A substantial proportion of the children seen were Hispanic and had no private health insurance.

Table 3.1. Demographic characteristics of the hospital data.

Subject characteristics; %	Emergency Department visits (N = 8,088)	Hospital admissions (N = 3,089)	Total hospital encounters[a] (N =11,177)	Total unique subjects seen, (N =7,492)[b]
Male	63	61	63	62
Age (years)				
0-4	52	62	55	55
5-12	38	32	36	36
13-18	10	6	9	9
Race-ethnicity				
White non-Hispanic	36	35	36	36
White Hispanic	54	53	54	52
African American	3	4	3	3
Asian	3	4	3	4
Other/Unknown	4	4	4	5
Source of Payment				
Private Insurance[c]	36	41	37	38
Government Sponsored or Uninsured[d]	62	53	60	58
Unknown	2	6	3	4

[a] Total encounters is the sum of Emergency Department visits and hospital admissions.

[b] Total unique subjects is the subject count excluding recurrent encounters

[c] Private Insurance includes all types of private insurance such as indemnity contract & non-contracted rates, contract with outside health organizations, other sponsors, and worker's compensation.

[d] Government Sponsored and Uninsured includes Cal-Optima, Medi-Cal, county funded insurance, other government, indigent, and self pay.

3.1.2 Available Exposure Data

Overview: The case-crossover analysis (described below) evaluated the temporal relationship of hospital encounters to weekly average levels of exposures described under Task 1. In addition, under funding from BP Inc. contract no. BPG-46329 through the SCAQMD, we produced estimated residential traffic-related air pollution at each subject address using the California LINE Source Dispersion Model, version 4 (CALINE4) for 6-month seasonal periods (warm season: May-October; cool season: November-April). We also obtained ambient (background) air pollutant concentrations from EPA's Air Quality System collected at the regional air monitors operated by the SCAQMD. Each subject residential address was linked to the nearest monitor data. All $PM_{2.5}$ data is from one station (Anaheim), whereas criteria pollutant gases are from four stations (La Habra, Anaheim, Costa Mesa and Mission Viejo).

Ambient air pollution data: Missing ambient air pollutant data (0.3-7% for different pollutants) were interpolated by linear regression using data from the next nearest air monitoring station in Orange County, California (variance explained by interpolation models was $R^2 \geq 0.72$ for all pollutants and years). For $PM_{2.5}$, missing data (3%) at the Anaheim station were interpolated from the air monitoring station in Mission Viejo, CA. The Mission Viejo station was not otherwise used for $PM_{2.5}$ data because PM monitoring was not operational for the whole time period and was generally further from subjects than the Anaheim station. Criteria air pollutant gases were available from four stations in Anaheim, La Habra, Mission Viejo, and Costa Mesa, California.

CALINE4 model: California Department of Transportation traffic data for major roads and highways was linked to the home locations. We then employed a modified Gaussian line source dispersion model (CALINE4) to estimate traffic-related air pollutant gases and particles near the geocoded residences. We estimated $PM_{2.5}$, NO_x ($NO+NO_2$), and CO concentrations at each residence from local traffic emissions of both gasoline vehicles and diesel trucks within a 500 m and 1500 m radius of each residence location as previously described (Gauderman et al. 2005; Wu et al. 2009). We selected 500 m *a priori* because potentially causal pollutant components such as PAH are enriched near roadways. We performed sensitivity analyses of asthma associations using a wider 1500m buffer.

Emission factors for dispersion-modeled CO, NO_x, and $PM_{2.5}$ were obtained from the California Air Resources Board's EMFAC2007 vehicle emissions model, while emission factors for particle number were estimated based on traffic speed and fraction of diesel trucks using literature-reported values (Yuan et al. 2011). Emission factors were estimated by year and season (winter and summer). Annual average daily traffic (AADT) counts were used as traffic activity data in the dispersion model. We then scaled the estimated concentrations by applying yearly vehicle-mileage traveled information (an indicator of total traffic activity level) and a weekday/weekend and diurnal profile (24 hours) of traffic. Although the latter temporal profile of traffic was derived from summarized statistics of freeway measurements, it was applied to both freeways and surface streets in the dispersion model since no reliable data were available for the temporal profiles of traffic on surface streets.

Meteorological inputs for the CALINE4 dispersion models included hourly wind speed, direction, and temperature that were obtained from three stations of the South Coast Air Quality Management District (Figure 3.1). The average distance of assigned station closest to subjects was 7200m. We modeled 576 unique meteorological conditions that were classified by season (warm and cold), time of day (night, daytime with limited mixing, and daytime with good mixing), wind speed (six categories: ≤1, 2, 3, 4, 5.5, ≥7.5 m/s), and wind direction (16 categories: 0 to 360 degree with a 22.5 degree interval). To estimate seasonal concentrations, we scaled the model outputs by the frequency of these meteorological conditions occurring in the corresponding time periods. The season-specific CALINE4 estimates were not the same for all 9 years because 1) the meteorological data (mainly wind and temperature) were different year by year; and 2) the emission rates and

total traffic counts were somewhat different by year. However, the overall difference in concentration estimates was relatively small by year because of small differences in the yearly-changing input variables (e.g. traffic counts, emission factors, and meteorology).

For the 11,177 encounters with valid address data, dispersion-modeled exposures could not be estimated for 435 encounters located in South Orange County (3.8%) because of inadequate meteorological measurements for the hilly topography.

There is sufficient evidence in the literature to support the view that dispersion models are sufficiently accurate to predict longer-term local exposures in urban environments moderately or strongly influenced by traffic given adequate inputs of meteorological and long-term average traffic data (Jerrett et al. 2005). In this sense, the dispersion model is better in capturing spatial rather than temporal variability and more suitable for estimating longer-term exposures. Therefore, in the SCAQMD-funded study, CALINE4 estimates were limited to 6-month seasonal averages because of both resource limitations and the crude temporal resolutions of available input data (e.g. annual average daily traffic counts and seasonal mixing height data). However, as described below, in other work by Jun Wu an alternate approach was developed to enhance the temporal resolution of CALINE4 predictions for the present study.

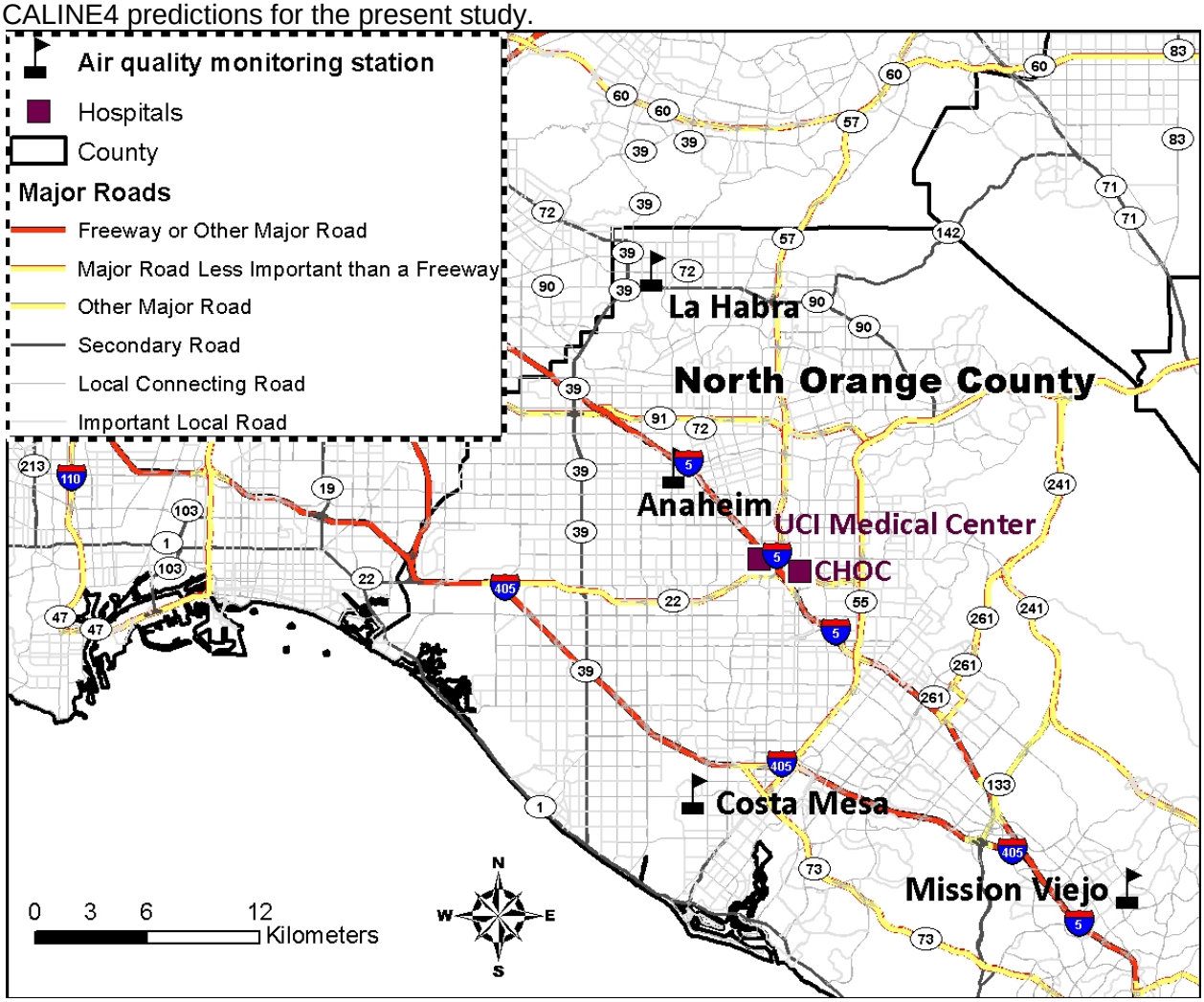


Figure 3.1. Major roadways overlaid with hospitals, air quality monitoring stations, and meteorological stations. Most air monitoring data for pollutant gases linked to subject addresses came from the three northern-most stations (La Habra, Anaheim and Costa Mesa), and $PM_{2.5}$ came from the Anaheim station.

The study area (~1000 km^2) and spatial distribution of dispersion-modeled NO_x are shown in Figure 3.2. The six-month seasonal average CALINE4 data provided for an analysis of the relation between asthma morbidity and ambient air pollution stratified by

seasonal residential exposure to traffic-related air pollution (for the first time to our knowledge). This was informative because daily increases in ambient air pollution may be modified by higher exposures to traffic-related air pollutants near the home. For example, regional increases in CO or NOx may result from meteorological conditions such as air stagnation, and be correlated with increased concentrations of POA and volatile organics near ground level. Homes near busy traffic are expected to be more affected under these conditions of air stagnation, generally reflected by background increases in measured ambient air pollutant gases (CO and NO_x) as discussed in Chapter 1. Below we propose methods to improve this approach by estimating and then testing the validity of daily dispersion-modeled estimates of traffic-related air pollutants near residences.

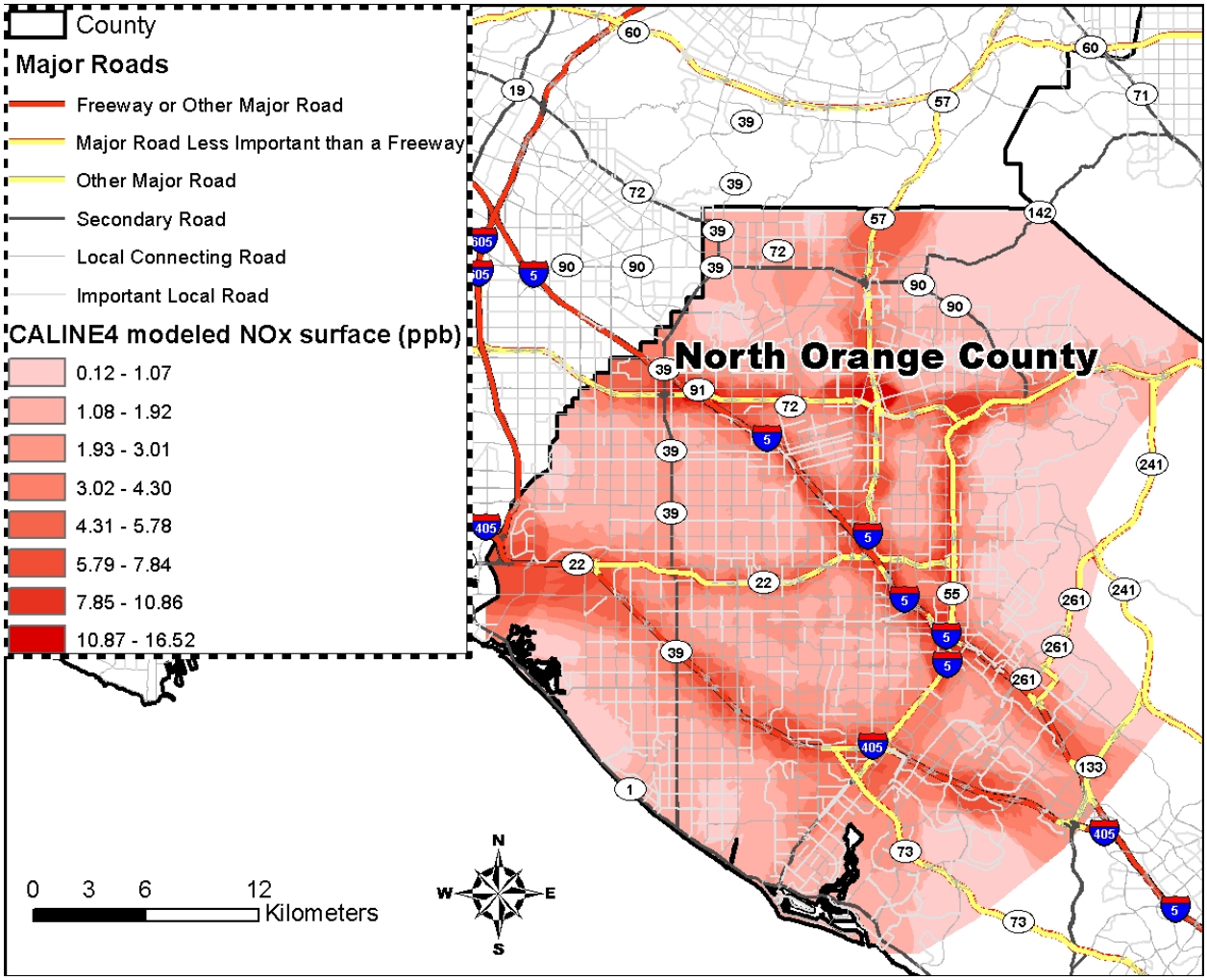


Figure 3.2. CALINE4 modeled (500 m buffer) NOx pollution surface by kriging the estimated nine-year average concentrations at the residences of the study subjects. Spearman correlation of the 6-month seasonal CALINE4 NOx with 6-month seasonal average ambient NOx at the 3 main stations in Northern Orange County (N=54) was moderately strong (r = 0.53). However, it is important that CALINE4 estimates and the NOx measurements at the stations are different in the exposure they represent – CALINE4 is only for local traffic emissions as shown on the map whereas ambient measurements are for all sources from a broad region and aged pollutants.

3.1.3 New Exposure Data

New exposure assessment work in this task was to estimate daily traffic-related air pollutant exposures (ultrafine particle number concentration, $PM_{2.5}$, NO_x, and CO) near

geocoded subject residences (500 m and 1500 m radius buffers). The new work produced temporally-resolved dispersion model data using the following model inputs. A major improvement over previous studies is that we used available real-time traffic count data on all freeways in Orange County and real-time fleet composition from Weigh-in-Motion (WIM) data at key locations on selected freeways and highways (e.g. I-405, I-5, SR-91, and SR-57 in Orange County) from the Caltrans Performance Measurement System (PeMS). These data were available from September 2001 to December 2008 and generated high temporal-resolution emission data that improved the temporal resolution of the dispersion modeling. Unfortunately, no real-time data are available on surface streets. Therefore, Caltrans annual average daily traffic counts (AADT) for surface streets and diurnal and day-of-week traffic variation profiles on nearby freeways were applied in predictions.

Meteorological data was obtained from the National Weather Service (NWS) and from the Weather Research Forecasting (WRF) model outputs that have been used in the UCD/CIT model to estimate pollutant concentration during the same study period. NWS measurements usually do not contain time-resolved upper air data (e.g. atmospheric stability class and mixing height) and also have significant gaps for calm and variable winds. However, the WRF model can alleviate the problems in measurement data by producing continuous hourly output for both surface data (e.g. wind speed/direction, temperature, humidity) and upper-air data (e.g. atmospheric stability and mixing height).

Emission factors were obtained from California Air Resources Board's EMFAC2007 (v2.3) vehicle emissions model for NO_x and CO. UFP emission factors were estimated based on previous studies (Ketzel et al. 2003; Gidhagen et al. 2004 (a,b); Gramotnev et al. 2003, 2004; Imhof et al. 2005, 2006; Kittelson et al. 2004; Morawska et al. 2005; Zhu and Hinds, 2005). For example, we developed the following regression equation to estimate UFP emission factors based on 32 observations from studies worldwide:

$$Log_{10}(EF) = 0.92 \times HDP + 0.0089 \times VS + 13.64 \qquad (r = 0.64)$$

Where, EF is emission factor of UFP particle numbers, or particle number / (vehicles · Km); HDP refers to heavy duty vehicle percentage, %; VS stands for the vehicle speed, Km/h.

The original CALINE4 model cannot be used to predict UFP because it does not account for coagulation and other aerosol mechanisms that are important in UFP dispersion. In collaboration with Dr. Yifang Zhu, co-investigator Jun Wu developed distance-dependant scaling functions (Figure 3.3) within the CALINE4 to predict UFP number concentrations near roadways (Yuan et al. 2011). The scaling functions were developed by comparing measured UFP (6-220 nm) concentrations near freeways (I-405 and I-710 in the southern California region of study and FM-973 and I-35 in Corpus Christi, Texas) and corresponding UFP concentration estimates from the original CALINE4 model with no adjustment. We then evaluated the model against additional measured data on the same freeways (I-710 and I-405) and to other roadways (SH-71 in Corpus Christi, Texas).

Validation of UFP model and Daily CALINE4 model:

Figure 3.3 shows this validation of adjusted CALINE4 UFP model with integrated distance-dependent scaling functions against other measured UFP number concentration data near I-405 and I-710 freeways in California (collected at times not used for the development of scaling functions) and against FM-973 and I-35 freeways in Texas. In all validation models, the predicted value agreed with the measured value ($R^2 > 0.85$). To further validate this model, we also evaluated prediction at four residential sites in the Los Angeles air basin using long-term data from another study (Delfino et al. 2009b). Results showed a moderately strong correlation between actual measured concentrations and CALINE4-predicted concentrations (500 m buffer) of $R^2 = 0.52$ for 357 daily particle number measurements (unpublished).

The other exposure data included daily traffic-related exposures using our updated CALINE4 model. CALINE4 model performance was assessed by comparing models for NO_x based on: 1) annual average daily traffic (AADT) on both freeway/highway and surface streets versus

2) real-time California Freeway Performance Measurement System (PeMS) traffic counts on freeway and highways, and AADT on surface streets. We modeled NOx concentrations for 17 unique sites in Los Angeles County and Orange County (see the map below, Figure 3.4). We modeled the entire year of 2002 (a total of 365 x 24 hours = 8760 hourly concentrations) at the 17 sites.

We focused on NO_x here because particle number measurements are limited in the South Coast Air Basin and previous work showed similar patterns of model performance between NOx and particle number concentrations at sites used in the Cardiovascular Health and Air Pollution Study. To enhance our assessments, we expanded the modeling sites from Orange County to both Orange and Los Angeles Counties. We also updated the method of extracting PeMS traffic counts and assigning them to the AADT roadway network (PeMS and AADT data are in different roadway systems). We extracted PeMS data, assigned them to AADT-based freeways and highways for freeway/highway modeling, and separately modeled surface streets based on AADT data. Total NO_x concentrations were estimated by adding contributions from freeway/highways (based on PeMS data) and from surface streets (based on AADT data). We used real-time (hourly) meteorological data (N=8760 hours) in

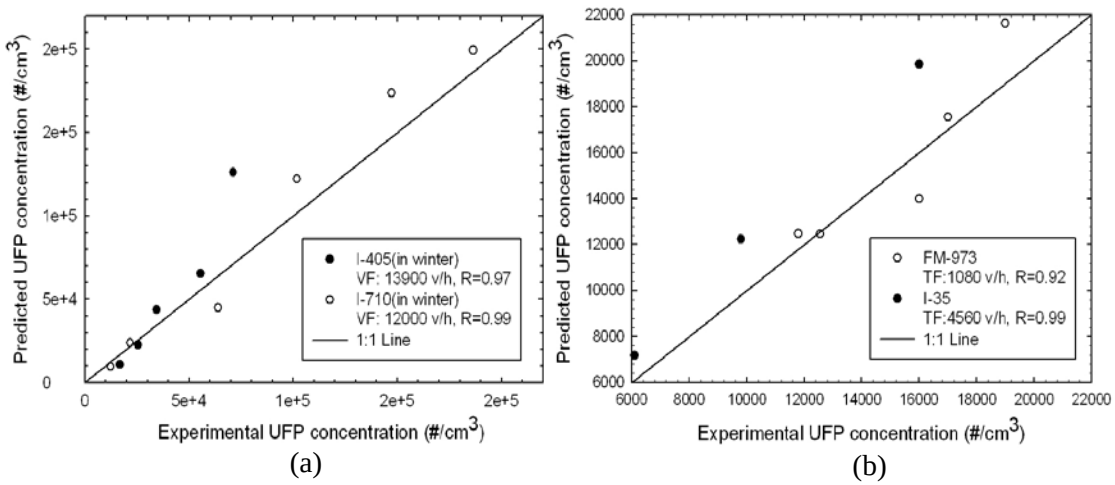


Figure 3.3. Validation of adjusted CALINE4 model using measurement data near (a) near I-405 and I-710 freeways in California; (b) FM-973 and I-35 freeways in Texas.

the dispersion modeling. If AADT data were used, we scaled AADT by weighting it with weekday/weekend and 24-hour diurnal profiles of traffic counts to convert AADT to hourly traffic counts. Using this and hourly meteorology we modeled hourly NO_x concentrations on each day and then averaged the results to get daily and monthly estimates.

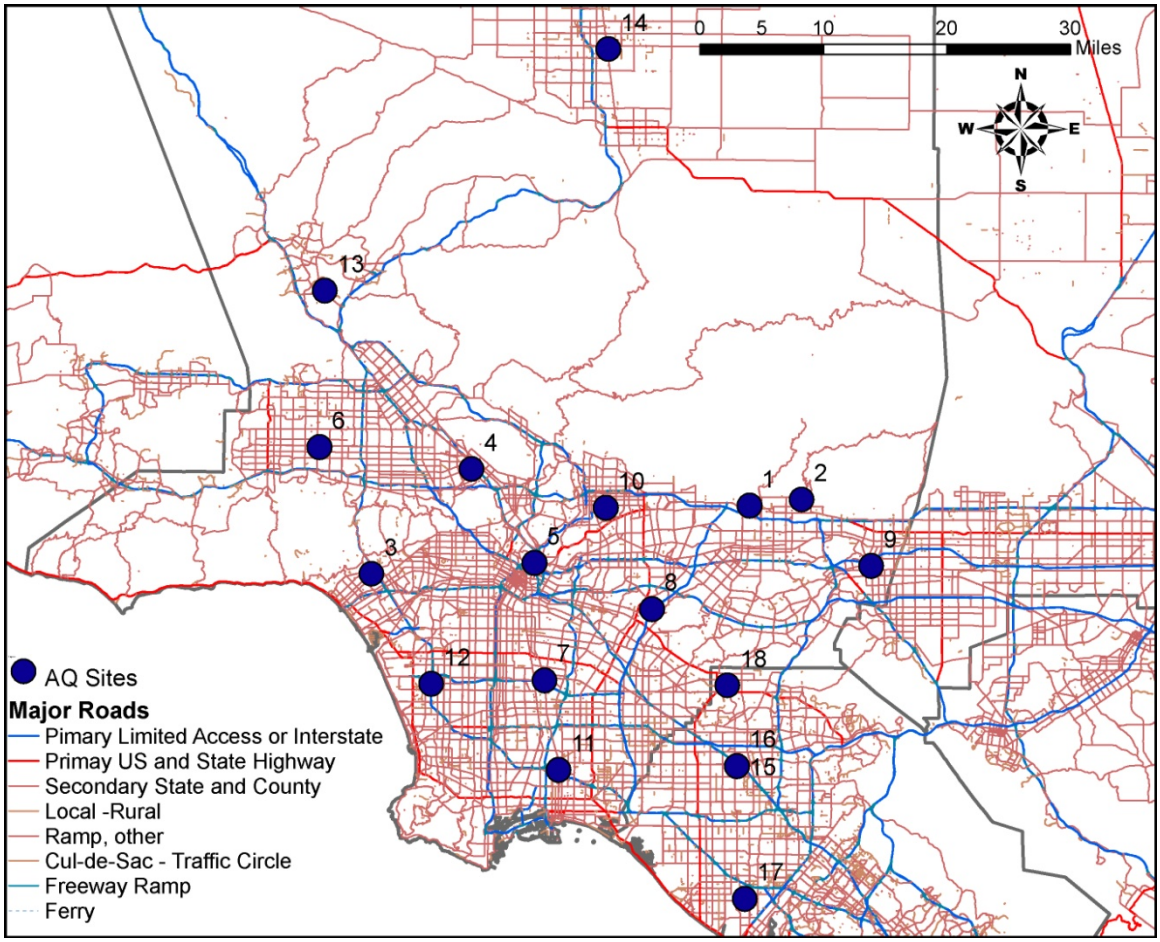


Figure 3.4. Air quality (AQ) monitoring sites in the South Coast Air Basin used in modeling 2002 NO_x concentrations.

Land-use regression models:

We estimated exposure to NO_2 and NO_x using land-use regression models as an approach to capturing diverse sources of air pollution from both traffic and non-traffic sources at distances of ≤ 15 km around the residences of each subject (Jerrett et al. 2005). These models were developed separately by season to predict season-specific concentrations based on actual measurements using Ogawa passive badge samplers at over 240 sampling locations as previously described (Li et al. 2012). The air sampling periods for NO_2 and NO_x that were used in developing the LUR models were one-week periods (maximum variability was 24 h) during September 9-22, 2006, and July 10-18 and July 24-August 1, 2009 for the warm season measurements, and February 10-23, 2007, and November 13-21 and December 4-12 for the cool season measurements. Land-use regression-estimated concentrations of NO_2 and NO_x at the over 240 sampling locations (240 locations in the summer and 251 locations in the winter, respectively) were decomposed into three components: local means, spatial residuals, and normal random residuals. Local means were modeled by generalized additive models. Spatial residuals were co-kriged with global residuals at nearby sampling locations that were spatially auto-correlated. The spatial variables we examined included roadway data, traffic counts, population density, land-use patterns, remote sensing data, and the percentage of stable atmospheric conditions during the sampling periods. We examined buffer distance from 50m to 15 km for most of the spatial variables.

To assess model predictive power, we used a cross-validation R^2 estimates for land-use regression models calculated based on the best fit line using the leave-one-out cross validation approach. This approach considers each observation from the total sample

as the validation data and the remaining observations as the training data used in the prediction model. This procedure is repeated so that every observation in the total sample is used once as the validation data. The final model predicted summer and winter NO_2 and NO_x concentration surfaces well, with cross-validation R^2 values ranging from 0.88 to 0.92. . The root mean square prediction error was 2.40 ppb and 1.67 ppb for NO_2 in the summer and winter, respectively, and 5.92 ppb and 7.83 ppb for NO_x in the summer and winter, respectively.

3.1.4 Analysis

Variables:

Dependent Variables: Events of hospital admissions and emergency department visits for asthma.

Exposure Variables: Four sources of air pollutant data were used:

1) Task 1 exposure data: UCD/CIT Source Oriented Chemical Transport Model outputs of O_3, NO_x, and PM species (namely POA and SOA) and PM source contribution (e.g. diesel, gasoline, wood smoke, etc.) in three particle size fractions, including ultrafine PM < 0.1 µm ($PM_{0.1}$), fine PM ($PM_{2.5}$), and fine plus coarse PM (PM_{10});

2) Daily concentrations of traffic dispersion-modeled CO, NO_x, O_3, UFP and $PM_{2.5}$ at subject residences to be averaged weekly for the regression analysis;

3) Six-month seasonal concentrations of traffic dispersion-modeled CO, NO_x, O_3, UFP and $PM_{2.5}$ at subject residences for use in testing the modification of effects from daily ambient air pollution exposure;

4) Nearest ambient air monitoring station measurements of US EPA-regulated CO, NO_2, NO_x, O_3, PM_{10} and $PM_{2.5}$ from EPA's Air Quality System.

Time Invariant Covariates: Subject characteristics (age, sex, race-ethnicity, health insurance status) and Census block group SES characteristics (see Task 4).

Time Varying Covariates: These include various expressions of temperature, relative humidity, and the counts of lower respiratory infections in the zip code of the subject. Day-of-week, month, and year are controlled for by the case-crossover time-stratified design described below. Nevertheless, we are interested in seasonal differences in association and so models were stratified by 6-month season (warm season: May-October; cool season: November-April).

Data Management and Descriptive Analysis: Our group has many years of experience managing large complex datasets with quality assurance of data through SAS data management programs. Descriptive analyses of exposures were used to determine the shape of the distribution (normal vs. non-normal), central tendency (mean, geometric mean, median), spatial trends (subregion/traffic density), and seasonal trends (6-month seasonal and annual trends). Cross-correlations between independent exposure variables by season were examined to determine the potential for interaction and confounding in regression models.

Regression analysis: We evaluated the association of hospital encounters for asthma with exposure to air pollution, using a case-crossover design with estimates of associations obtained with conditional logistic regression in SAS 9.2 procedure PHREG. This design makes it possible for each subject to act as his or her own control. This is because exposures are sampled from each subject's time-varying distribution of exposure. We compared exposures at time points immediately prior to the day of the hospital event (lag day 0) to a set of referent times that represent the expected exposure distribution for non-event follow-up times. Subject-specific characteristics such as socioeconomic status or

race-ethnicity are time-invariant. Therefore, they are controlled for by the case-crossover design and by using a sufficiently-narrow referent windows that also prevents bias from seasonal confounding (Janes et al. 2005a; Schwartz et al. 2003).

The case-crossover design we used is referred to as the semi-symmetric bidirectional referent selection design (Navidi and Weinhandl, 2002), with a modification proposed by Janes et al. (2005b). Air pollutant exposures of interest in the analysis are those that occur just before each subject's hospital encounter that includes the previous 7 days (the exposure period). In the model these exposures are compared with the subject's exposures at other nearby times (referent periods) when the subject was not in hospital (Figure 3.5). We did not select referent days within these seven days of exposures of interest in order to limit any serial correlation and to avoid confounding from temporally-adjacent exposures. The control (referent) days were selected from the same days of the week when subjects were not seen in hospital (8-14 days before lag day 6 or 8-14 days after lag day 0). To avoid so-called overlap bias, if another hospital encounter occurred within one of the two 7-day referent periods then we would use the other event-free referent exposure and employ an offset term ($\log_e 2$, otherwise 0) (see Janes et al. 2005b for a full discussion of this issue). We also used the offset where there was only one available referent (namely, at the beginning or end of the time series). There were 170 subjects in analyses (2%) where the offset was required, including 65 encounters (0.58%) where one referent period was missing at the beginning and end of the time series, and 111 hospital encounters (1%) where one of the two referent periods had another encounter. In a very few cases another encounter occurred in both referent periods (9 encounters, 0.1%) so that the encounter could not be analyzed. This did not alter results. For the vast majority of cases no encounter occurred in either referent period. For these encounters, one of the referents was randomly selected (Navidi and Weinhandl, 2002). As discussed by Janes et al. (2005b), by incorporating an offset term the regression yields a localizable and ignorable design such that the likelihood that incorporates the referent window selection reduces to the conditional logistic regression likelihood, yielding an unbiased estimating equation. We conducted a sensitivity analysis by testing the other localizable and ignorable design, the time-stratified method (Janes et al. 2005b). Results were qualitatively the same and conclusions were unaltered.

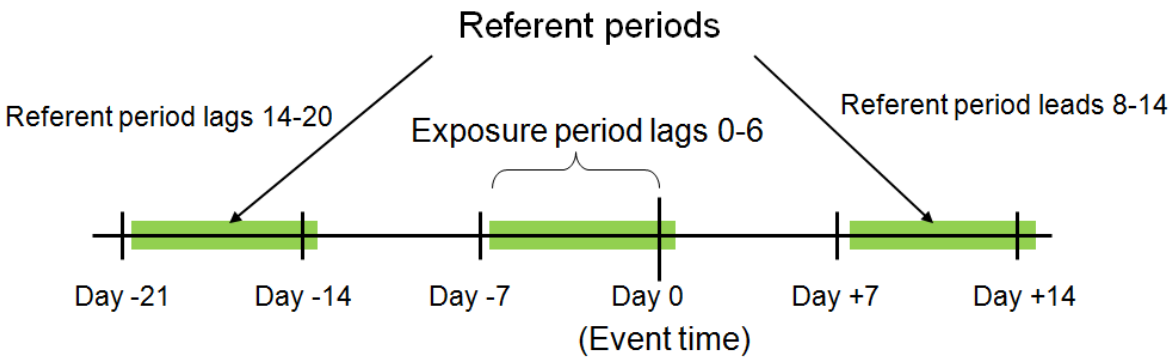


Figure 3.5. Semi-symmetric bidirectional referent selection strategy. One of the two referent periods is randomly chosen at the fixed lag or lead (future) time relative to the event, where two event-free referent periods were available, otherwise, an offset term was set to $\log_e 2$. This approach yields a localizable and ignorable design and avoids bias resulting from exposure time trends. The seven referent days are: 8-14 days before lag day 6 or 8-14 days after lag day 0. For example, the referent for a lag 0 (event) exposure would be the exposure on day -14 or day +14, and would be the same day of the week of the same 28-day period.

Given that some subjects have repeated hospital encounters, within-subject correlation was present in the data. To adjust for this, the standard error of parameter

estimates were obtained using a robust variance estimator with clustering on subject in the SAS 9.2 PHREG Procedure (Lin and Wei, 1989).

Regression estimates included current day exposures (lag 0) as well as 2-day through 7-day averages where the 6 lagged days were averaged with lag 0. This was to estimate possible cumulative acute effects of multi-day exposure. For ease of presentation we show models for lag 0 (1-day), 3-day, 5-day and 7-day averages. In each regression model we used the same averaging time for control exposure periods.

Associations of ambient air pollutants with ED visits and with hospital admissions were first tested in separate models. Results showed consistent effect estimates but with differing precision. ED visit regression coefficients had smaller standard errors, which is likely due to greater sample size. Therefore, we combined the two asthma encounter types ("asthma hospital morbidity") as previously described (Chang et al. 2009; Delfino et al. 2009a). We adjusted for 24-hr mean temperature and relative humidity of the same lag averaging time as the air pollutants. Model fit did not improve with smoothed penalized spline terms to adjust for nonlinear effects of temperature. Weather had a nominal impact on associations (≤ 7% change).

To test effect modification by 6-month seasonal average residential air pollution, subjects were stratified above and below median dispersion-modeled and land-use regression-modeled exposures to provide sufficient sample size. We hypothesized that increases in asthma morbidity from daily elevations in ambient air pollution would be enhanced by higher chronic exposures to traffic-related pollution near subject homes. Product terms of ambient pollutants with binary traffic exposure group were considered to most clearly indicate effect modification at a nominal *p*-value < 0.1. For greater interpretability, regression results were standardized to interquartile range (25th to 75th percentile) increases in each ambient air pollutant. There was little difference between estimates for ambient air pollution interactions with dispersion-modeled residential CO, NO_2 or NO_x so we present results only for dispersion-modeled NO_x, as well as for dispersion-modeled $PM_{2.5}$ and particle number.

We performed analyses within 6-month warm periods (May-Oct) and 6-month cool periods (Nov-Apr). This was done because of seasonal differences in photochemical oxidants as well as the strong seasonality of asthma exacerbations that occur in a pattern opposite to that of O_3. SOA is expected to have a similar seasonality to O_3, but different SOA chemicals may predominate in cooler vs. warmer periods, which could partly explain the low correlations of SOA markers with O_3 that we found for southern California (Delfino et al. 2010a). In addition, this seasonal analysis was performed because previous work has shown that during cooler periods of air stagnation, particle size distribution drifts toward more potentially toxic nanoparticles (Zhu et al. 2004) and there are higher concentrations of primary organic carbon, despite similar particle mass concentrations during other periods (Delfino et al. 2009b).

Comparison of Pollutant Variables: We aim here to provide new supportive data on the importance of particle size and chemistry in human responses to air pollution typically encountered in urban environments. Results for various pollutant variables were compared by their strengths of association. This was done by scaling magnitudes of association at the interquartile ranges (25th to 75th percentile) of air pollutants to allow strengths of association for different pollutants to be compared by limiting differences in units of measurement or concentration range. For example, we compared UCD/CIT modeled POA to SOA, ultrafine particle mass to $PM_{2.5}$ and PM_{10} particle mass, traffic dispersion-modeled air pollutants to measurements of air pollutants at ambient monitoring stations ($PM_{2.5}$ and criteria pollutant gases). We also compared PM associations by PM source contribution (e.g. diesel and gasoline, wood smoke, etc.).

Using the same modeling approach in SAS PHREG described above, we tested multipollutant models to evaluate whether associations of asthma morbidity with primary (combustion-related) air pollutants (ambient NO_x and CO, CALINE4 weekly TRAP, and UCD/CIT modeled POA) are independent of associations with secondary air pollutants

(UCD/CIT modeled SOA and ambient O_3). We are particularly interested in whether associations with POA and SOA are independent of each other. We are also interested in whether associations with EPA-regulated ambient $PM_{2.5}$ mass or O_3 are confounded by UCD/CIT modeled SOA, particularly during the warm seasonal period.

To conduct comparisons between different air pollutants, multipollutant models included entries for both variables. For example, if β_1 parameterizes the effect of POA and β_2 parameterizes the effect of SOA, then we tested changes in β_2 when β_1 is included and vice versa. If β_1 becomes notably smaller when β_2 is included then we concluded that SOA is a better predictor than POA. If however, both maintain similar levels of association in the model then we conclude only that SOA incorporates significant additional information beyond that contained in POA. Findings may vary by the 6-month seasonal periods. Results may also be influenced by differences in measurement error between variables and by multicollinearity, which we assessed using the variance inflation factor (VIF) statistic.

3.2. Results and Discussion

3.2.1 Available Exposure Data

Table 3.2 shows the distribution of daily ambient air pollution exposures and 6-month average CALINE4 exposures for the person-days of event observations (hospital admissions and ED visits) by 6-month season.

Table 3.3 shows the distribution of the absolute values of the exposure difference between the event days (hospital encounter) and referent days for the overall data used in the analysis, for each of the four monitoring locations (for the gases), and for results based on using the Anaheim station alone for all event and referent days. These exposure terms are relevant to the regression analyses and statistical power since comparisons in the case-crossover analysis are based on differences in concentrations on event days to referent days (Künzli and Schindler 2005). Given the relatively small region studied (~1000 km^2), as expected, there were differences by site, but they were not great. The nominal differences are clearest when comparing exposure data from all stations compared with only using the Anaheim station for the same complete set of person observations. A sensitivity analysis excluding the interpolated days in the regression analysis of asthma and air pollution showed that point estimates of associations changed by < 1% and 95% confidence limits were similarly stable.

Table 3.4 shows the Spearman rank correlation between daily ambient exposures and weather. Correlations showed moderate to strong positive correlations between the traffic-related air pollutant gases (NO_2, NO_x, and CO). Traffic-related air pollutant gases were only weakly to moderately correlated with $PM_{2.5}$, and these correlations were stronger in cool than warm seasons. O_3 in the cool seasons was negatively correlated with traffic-related gases and $PM_{2.5}$. This appears to be due to periods of air stagnation because correlations of these air pollutants with wind speed were positive with O_3 versus negative with the traffic-related gases and $PM_{2.5}$.

Table 3.2. Seasonal distribution of ambient air pollution and traffic-related air pollution exposures estimated by CALINE4 and land-use regression models.[a]

Exposure	Season	N[b]	Mean±SD	Median	Interquartile range[c]	Minimum/ Maximum
Ambient						
$PM_{2.5}$ (µg/m^3)	Cool	5755	19.0±13.8	14.5	15.4	2.54/113.9
	Warm	4421	16.0±9.5	14.1	7.77	3.09/115.5
NO_2 (ppb)	Cool	6347	26.6±12.5	25.4	15.9	1.74/84.2
	Warm	4978	16.1±10.5	13.7	13.7	1.52/67.1
NO_x (ppb)	Cool	6349	65.3±51.4	52.2	64.4	0.70/393.6
	Warm	5018	23.4±21.6	16.1	21.7	0.14/158.3
CO (ppm)	Cool	6353	0.81±0.59	0.66	0.69	0.01/4.40
	Warm	5034	0.36±0.28	0.30	0.29	0.01/2.29
O_3 (ppb)	Cool	6355	20.0±11.2	18.2	16.8	0.01/58.4
	Warm	5032	34.0±10.4	33.9	14.5	1.00/71.0
Temperature (°F)	Cool	6358	58.8±5.81	58.5	7.00	22.6/83.0
	Warm	5032	69.3±5.69	69.1	7.25	0.01/88.0
Relative humidity (%)	Cool	6287	62.7±20.9	67.3	28.6	1.92 /100.0
	Warm	5034	71.1±14.8	72.9	17.2	0.50/99.0
CALINE4[d]						
$PM_{2.5}$ (µg/m^3)	Cool	5,399	0.55±0.79	0.281	0.349	0.00/7.09
	Warm	4,222	0.55±0.84	0.269	0.355	0.00/8.07
NO_x (ppb)	Cool	5,399	1.65±2.36	0.854	1.18	0.00/18.7
	Warm	4,222	1.51±2.30	0.744	1.06	0.00/25.7
Particle Number (no./cm^3)	Cool	5,399	1,984±3,689	761	1266	0.00/34,247
	Warm	4,222	1,646±3,101	594	1041	0.00/30,647
LUR						
NO_x (ppb)	Cool	5396	53.4±11.2	57.2	12.4	1.29/71.3
	Warm	4222	19.1±6.6	18.6	9.0	0.60/44.1

Abbreviations: SD: standard deviation; ppb: parts per billion

[a] The ambient exposures are for daily 24-hr mean measurements on event days whereas the CALINE4 and LUR exposures are for 6-month seasonal averages by subject.

[b] The number of observations is based on each event of a hospital encounter in the case-crossover analysis where ambient air pollution and residential air pollution data are available.

[c] The overall across-season interquartile ranges were used in the within-season regression analyses to express magnitudes of association as follows: 11.1 µg/m^3 for $PM_{2.5}$, 18 ppb for NO_2, 52.5 ppb for NO_x, 0.55 ppm for CO, 20.2 ppb for O_3.

[d] Because CALINE4 estimates are only from local traffic within 500 m of the home (left skewed from little nearby traffic), CALINE4 pollutant concentrations are considerably lower than ambient levels and LUR-estimated NO_x.

Table 3.3. Distribution of absolute differences between hospital event and referent period exposures to ambient air pollution.[a]

Exposure	Analysis set	N[b]	Mean (SD)	Median	IQR	Minimum/ Maximum
$PM_{2.5}$ (µg/m^3)	Anaheim all subjects	9,233	10.7 (11.8)	7.0	11.1	0.0/ 99.9
NO_2 (ppb)	All stations	11,228	9.8 (8.7)	7.4	11.0	0.0/ 68.1
	Anaheim subset	6,681	10.5 (9.0)	8.2	11.3	0.0/ 68.1
	La Habra subset	350	9.7 (8.1)	7.6	10.6	0.0/ 46.9
	Costa Mesa subset	3,850	8.4 (8.0)	5.7	10.2	0.0/ 47.6
	Mission Viejo subset	347	10.2 (8.6)	8.4	11.0	0.0/ 45.8
	Anaheim all subjects	11,228	10.5 (8.9)	8.2	11.3	0.0/ 68.1
NO_x (ppb)	All stations	11,276	30.2 (35.5)	16.9	36.3	0.0/ 342.1
	Anaheim subset	6,690	32.4 (36.4)	19.3	38.1	0.0/ 342.1
	La Habra subset	354	27.4 (27.3)	18.1	31.1	0.3/ 177.0
	Costa Mesa subset	3,852	26.7 (34.4)	12.4	34.0	0.0/ 275.1
	Mission Viejo subset	380	29.1 (32.5)	17.8	37.6	0.0/ 214.4
	Anaheim all subjects	11,276	32.4 (36.1)	19.5	38.4	0.0/ 342.1
CO (ppm)	All stations	11,310	0.32 (0.37)	0.20	0.36	0.0/ 4.0
	Anaheim subset	6,718	0.33 (0.37)	0.21	0.37	0.0/ 4.0
	La Habra subset	355	0.33 (0.34)	0.21	0.41	0.0/ 2.1
	Costa Mesa subset	3,854	0.31 (0.38)	0.17	0.37	0.0/ 3.6
	Mission Viejo subset	383	0.22 (0.24)	0.14	0.24	0.0/ 1.6
	Anaheim all subjects	11,310	0.34 (0.37)	0.21	0.37	0.0/ 4.0
O_3 24-hr mean (ppb)	All stations	11,323	8.2 (6.4)	6.8	8.6	0.0/ 53.5
	Anaheim subset	6,720	7.9 (6.0)	6.7	8.3	0.0/ 41.7
	La Habra subset	355	6.4 (5.0)	5.1	7.0	0.0/ 32.7
	Costa Mesa subset	3,867	8.9 (7.0)	7.4	9.3	0.0/ 53.5
	Mission Viejo subset	381	8.8 (7.1)	7.6	8.5	0.0/ 51.0
	Anaheim all subjects	11,323	7.8 (6.0)	6.6	8.3	0.0/ 41.7

IQR: Interquartile range

[a] These differences were based on the event day exposures and referent day exposures across all measurement days used in the following analysis sets:

All stations – ambient air pollutant exposures used the regression analysis of all event and referent days as presented in the main text. For criteria pollutant gases this was based on the nearest to the subject out of four stations. $PM_{2.5}$ exposure data were only from the Anaheim station.

Anaheim subset – exposures for subjects linked to the air pollutant data measured at the Anaheim station;

La Habra subset – exposures for subjects linked to the air pollutant data measured at the Anaheim station;

Costa Mesa subset – exposures for subjects linked to the air pollutant data measured at the Anaheim station;

Anaheim all subjects – exposures used in the sensitivity analysis based on employing data from the Anaheim station only for all event and referent days.

Table 3.4. Spearman correlation matrix for daily ambient air pollutant and weather variables at the Anaheim California central air monitoring station.[a]

	Season	$PM_{2.5}$	O_3	NO_2	NO_x	CO	Temp	RH	Wind Speed
$PM_{2.5}$	Warm	1.00	0.31	0.44	0.34	0.50	0.13	0.16	-0.36
	Cool	1.00	-0.30	0.61	0.53	0.61	0.04	0.20	-0.60
O_3	Warm		1.00	-0.06	-0.10	-0.01	0.19	0.04	-0.08
	Cool		1.00	-0.57	-0.65	-0.61	0.26	0.11	0.46
NO_2	Warm			1.00	0.93	0.79	0.22	-0.22	-0.55
	Cool			1.00	0.92	0.84	0.15	-0.26	-0.62
NO_x	Warm				1.00	0.70	0.24	-0.30	-0.56
	Cool				1.00	0.86	0.02	-0.30	-0.60
CO	Warm					1.00	0.09	-0.03	-0.39
	Cool					1.00	-0.01	-0.16	-0.55
Temperature	Warm						1.00	-0.33	-0.12
	Cool						1.00	-0.26	-0.02
RH	Warm							1.00	0.14
	Cool							1.00	0.04
Wind Speed	Warm								1.00
	Cool								1.00

[a] The number of observations used in correlations is based on each event of a hospital encounter in the case-crossover analysis.

3.2.2 New Exposure Data

The following is an assessment of CALINE4 model performance by comparing models for NO_x based on: 1) annual average daily traffic (AADT) on both freeway/highway and surface streets and 2) real-time California Freeway Performance Measurement System (PeMS) traffic counts on freeway and highways, and AADT on surface streets. A total of 17 sites were used for the comparisons. Results showed a lack of improvement in the correlation between model-based NO_x and stationary measurements of NO_x for models using PeMS traffic data (hourly resolution) plus AADT over models using AADT alone. This was the case for hourly, daily and monthly predictions using 500, 1,500, and 3,000 meter radius buffers.

We observed particularly poor correlations between measured NO_x and modeled NO_x data (PeMS + AADT or AADT alone) at sites 2 and 13 ($R \leq 0.30$). These sites are located in suburban or semi-rural areas of Los Angeles. These results were likely observed because of the small traffic contribution to total NO_x levels at these sites. Results at remaining sites showed much better correlation.

Daily correlations using a 3,000 m buffer ranged from 0.41-0.80 for PeMS + AADT modeled data and 0.45-0.80 for AADT modeled data. This lack of improvement in model performance using PeMS traffic data was likely observed because the PeMS locations are not located close to the air sampling stations and they have missing data (under such conditions, we used data from remote PeMS locations to substitute missing data). The transfer of point-based PeMS data to the continuous AADT roadway network might have also led to spatial uncertainty in model calculations. Overall, we conclude that the use of current real-time PeMS data in CALINE4 modeling does not improve prediction over the sole use of AADT data.

This data was combined with the outcomes dataset for regression analyses. Descriptive statistics for daily traffic-related exposures using our updated CALINE4 model are shown in Table 3.5. We focus on 7-day averages given the observed clear improvement over daily predictions and the desire to minimize exposure error. The correlations between 7-day average CALINE4 variables and 7-day average ambient NO_x were weak with 500 m buffer CALINE4 variables (R 0.20 to 0.27) and somewhat stronger with 1500 m buffer CALINE4 variables (R 0.31 to 0.41) (not shown). Correlations of CALINE4 variables with ambient $PM_{2.5}$ were weaker (0.03 to 0.15 for 500 m, and 0.05 to 0.22 for 1500 m) (not shown).

Table 3.5.Seasonal distribution of daily traffic-related air pollution exposures estimated by dispersion (CALINE4) models.[a]

Exposure	Season	No, (missing)[b]	Mean (SD)	Median	IQR	Min	Max
CALINE4 Dispersion model (500 m buffer)							
$PM_{2.5}$ (µg/m^3)	Cool	6,050 (69)	0.83 (1.12)	0.49	0.61	0.00	12.62
	Warm	4,831 (33)	0.59 (0.86)	0.32	0.44	0.00	7.72
NO_x (ppb)	Cool	6,050 (69)	2.52 (3.44)	1.43	1.97	0.00	33.5
	Warm	4,831 (33)	1.79 (2.62)	0.97	1.36	0.00	31.70
Particle Number (no./cm^3)	Cool	6,050 (69)	2435 (4224)	1089	1912	0.00	72938
	Warm	4,831 (33)	1363 (2532)	540	1049	0.00	25122
CALINE4 Dispersion model (1500 m buffer)							
$PM_{2.5}$ (µg/m^3)	Cool	6,096 (23)	2.23 (1.89)	1.58	1.79	0.00	17.2
	Warm	4,864 (0)	1.53 (1.40)	1.03	1.24	0.00	10.2
NO_x (ppb)	Cool	6,096 (23)	6.77 (6.05)	4.79	5.61	0.00	50.9
	Warm	4,864 (0)	4.66 (4.33)	3.19	3.77	0.00	41.7
Particle Number (no./cm^3)	Cool	6,096 (23)	5805 (6202)	3641	5075	0.57	83556
	Warm	4,864 (0)	3070 (3747)	1747	2743	0.00	38665

Abbreviations: SD: standard deviation; ppb: parts per billion; IQR: interquartile range

[a] Exposure estimates are for 7-day averages of the lag 0 event days and lags 1-6 before the event days.

[b] The number of observations is based on each event of a hospital encounter in the case-crossover analysis where air pollution data are available.

Table 3.6 shows the descriptive statistics for UCD/CIT-modeled PM data based on the observations of each event of a hospital encounter in the case-crossover analysis. We used 7-day averages given the expected improvement in prediction over daily predictions. We also combined on-road gasoline with diesel sources as well as off-road gasoline with

diesel sources given their strong correlation with each other (discussed below), which is likely a reflection of the uncertainties in the estimation.

Table 3.6.Seasonal distribution of daily PM air pollution exposures estimated by UCD-CIT models.[a]

Exposure	Season	N (missing)[b]	Mean (SD)	Median	IQR	Min	Max
$PM_{0.1}$ ($\mu g/m^3$)							
$PM_{0.1}$ SOA	Cool	12,054 (184)	0.03 (0.02)	0.03	0.02	0.001	0.13
	Warm	9,614 (114)	0.07 (0.04)	0.06	0.05	0.001	0.26
$PM_{0.1}$ POA	Cool	12,054 (184)	1.14 (0.41)	1.13	0.57	0.001	2.5
	Warm	9,614 (114)	0.88 (0.35)	0.92	0.43	0.001	1.95
$PM_{0.1}$ POA from onroad gasoline & diesel	Cool	12,054 (184)	0.23 (0.08)	0.23	0.10	0.001	0.47
	Warm	9,614 (114)	0.19 (0.09)	0.21	0.09	0.001	0.45
$PM_{0.1}$ POA from offroad gasoline & diesel	Cool	12,054 (184)	0.16 (0.07)	0.17	0.09	0.001	0.46
	Warm	9,614 (114)	0.13 (0.07)	0.13	0.08	0.001	0.42
$PM_{0.1}$ POA from woodsmoke	Cool	12,054 (184)	0.16 (0.17)	0.11	0.31	0.001	0.71
	Warm	9,614 (114)	0.001 (0.001)	0.001	0.001	0.001	0.02
$PM_{0.1}$ POA from meat cooking	Cool	12,054 (184)	0.18 (0.08)	0.19	0.11	0.001	0.44
	Warm	9,614 (114)	0.17 (0.08)	0.18	0.1	0.001	0.48
$PM_{0.1}$ POA from high sulfur content fuel combustion	Cool	12,054 (184)	0.01 (0.001)	0.01	0.001	0.001	0.02
	Warm	9,614 (114)	0.01 (0.001)	0.01	0.01	0.001	0.03
$PM_{0.1}$ POA from other anthropogenic sources	Cool	12,054 (184)	0.40 (0.14)	0.39	0.19	0.001	1.02
	Warm	9,614 (114)	0.38 (0.14)	0.38	0.19	0.001	0.94
$PM_{2.5}$ ($\mu g/m^3$)							
$PM_{2.5}$ SOA	Cool	12,054 (184)	0.19 (0.11)	0.16	0.13	0.02	0.91
	Warm	9,614 (114)	0.48 (0.27)	0.44	0.36	0.03	1.66
$PM_{2.5}$ POA	Cool	12,054 (184)	6.85 (2.54)	6.58	3.45	0.68	19.91
	Warm	9,614 (114)	5.24 (1.72)	5.18	2.31	0.85	14.32
$PM_{2.5}$ POA from onroad gasoline & diesel	Cool	12,054 (184)	0.73 (0.25)	0.71	0.34	0.07	1.93
	Warm	9,614 (114)	0.56 (0.19)	0.54	0.24	0.06	1.53
$PM_{2.5}$ POA from offroad gasoline & diesel	Cool	12,054 (184)	1.51 (0.62)	1.45	0.82	0.13	4.85
	Warm	9,614 (114)	1.02 (0.44)	0.94	0.50	0.15	4.03
$PM_{2.5}$ POA from woodsmoke	Cool	12,054 (184)	0.84 (0.81)	0.71	1.49	0.001	4.29
	Warm	9,614 (114)	0.01 (0.05)	0.001	0.001	0.001	0.88
$PM_{2.5}$ POA from meat cooking	Cool	12,054 (184)	1.68 (0.67)	1.64	0.91	0.12	5.09
	Warm	9,614 (114)	1.37 (0.49)	1.33	0.6	0.21	4.25
$PM_{2.5}$ POA from high sulfur content fuel combustion	Cool	12,054 (184)	0.07 (0.03)	0.06	0.04	0.01	0.42
	Warm	9,614 (114)	0.08 (0.03)	0.08	0.04	0.01	0.24
$PM_{2.5}$ POA from other anthropogenic sources	Cool	12,054 (184)	2.02 (0.82)	1.94	1.13	0.22	5.81
	Warm	9,614 (114)	2.20 (0.87)	2.3	1.16	0.18	5.1

Table 3.6 (Cont.)

Exposure	Season	No, (missing)	Mean (SD)	Median	IQR	Min	Max
PM_{10} ($\mu g/m^3$)							
PM_{10} SOA	Cool	12,054 (184)	0.20 (0.12)	0.18	0.14	0.02	1.12
	Warm	9,614 (114)	0.50 (0.28)	0.47	0.38	0.03	1.71
PM_{10} POA	Cool	12,054 (184)	7.80 (2.91)	7.54	4.06	0.95	21.85
	Warm	9,614 (114)	5.61 (1.82)	5.41	2.3	0.99	15.59
PM_{10} POA from onroad gasoline & diesel	Cool	12,054 (184)	0.69(0.24)	0.68	0.32	0.07	1.83
	Warm	9,614 (114)	0.55(0.19)	0.53	0.24	0.06	1.47
PM_{10} POA from offroad gasoline & diesel	Cool	12,054 (184)	1.46(0.60)	1.40	0.78	0.11	4.74
	Warm	9,614 (114)	1.01(0.43)	0.93	0.50	0.15	3.97
PM_{10} POA from woodsmoke	Cool	12,054 (184)	0.80 (0.77)	0.67	1.41	0.001	4.16
	Warm	9,614 (114)	0.01 (0.06)	0.001	0.001	0.001	0.96
PM_{10} POA from meat cooking	Cool	12,054 (184)	1.61 (0.64)	1.57	0.86	0.11	4.86
	Warm	9,614 (114)	1.35 (0.48)	1.32	0.6	0.21	4.06
PM_{10} POA from high sulfur content fuel combustion	Cool	12,054 (184)	0.07 (0.03)	0.06	0.04	0.01	0.4
	Warm	9,614 (114)	0.08 (0.03)	0.08	0.04	0.01	0.22
PM_{10} POA from other anthropogenic sources	Cool	12,054 (184)	3.18 (1.16)	3.08	1.67	0.47	8.26
	Warm	9,614 (114)	2.61 (0.89)	2.58	1.09	0.35	6.52

Abbreviations: SD: standard deviation; ppb: parts per billion

[a] Exposure estimates are for 7-day averages of the lag 0 event days and lags 1-6 before the event days.

[b] The number of observations is based on each event of a hospital encounter in the case-crossover analysis where air pollution data are available.

Tables 3.7-3.9 show correlations between POA sources and SOA by particle size cut. Correlations showed that correlations between SOA and POA are low moderate in strength (around 0.4-0.5) for all size fractions, suggesting that co-regression may be possible without major problems of collinearity. In general, on-road POA sources from gasoline combustion (S1) were more strongly correlated with on-road diesel combustion sources (S3) than the off-road sources. Similarly, off-road POA sources from gasoline combustion (S2) were more strongly correlated with off-road diesel combustion sources (S4) than the on-road sources. Surprisingly, meat cooking (S6) as a source of POA was strongly correlated with both on-road and off-road POA sources. Wood-smoke (S5) as a source of POA was moderately correlated with on-road and off-road POA sources. High sulfur content fuel combustion sources (S7) was moderately correlated with on-road and off-road sources in the cool seasons and weakly correlated in the warm season. This seasonal trend was observed elsewhere and is likely a reflection of the influence of air stagnation events. Other anthropogenic sources (S9) were strongly correlated with on-road and off-road sources.

Table 3.10 shows the Spearman rank correlation between weekly average CALINE4 exposures and the UCD/CIT-modeled $PM_{0.1}$ and $PM_{2.5}$ POA variables for total POA and for all gas and diesel emissions sources. We combined gasoline and diesel sources due to the uncertainties in the estimation of diesel vehicles and the very strong correlations between the two on-road and two off-road gasoline-diesel sources (Tables 3.7-3.9) we combined them into single on-road source and single off-road source of POA. Correlations showed

strong correlations between the CALINE4-modeled variables as expected given that similar predictors are used for the traffic sources. Correlations between the CALINE4-modeled variables, ambient NO_x and CO, and the UCD/CIT variables for total POA and POA from gasoline and diesel emission sources were mostly r < 0.45. The correlation between ambient NO_x and onroad gasoline and diesel-source PM in the warm seasons was the strongest among these (r = 0.52). Correlations of ambient NO_x and CO with total POA and POA from gasoline and diesel emission sources were stronger for $PM_{2.5}$ than for $PM_{0.1}$.

Table 3.7. Spearman correlation matrix for weekly UCD/CIT modeled ultrafine PM variables.[a]

	Season	$PM_{0.1}$ SOA	$PM_{0.1}$ POA	$PM_{0.1}$ S1	$PM_{0.1}$ S2	$PM_{0.1}$ S3	$PM_{0.1}$ S4	$PM_{0.1}$ S5	$PM_{0.1}$ S6	$PM_{0.1}$ S7	$PM_{0.1}$ S9
$PM_{0.1}$ SOA	Warm	1	0.540	0.488	0.486	0.444	0.371	0.361	0.350	0.528	0.623
	Cool	1	0.401	0.500	0.420	0.359	0.251	-0.167	0.371	0.611	0.674
$PM_{0.1}$ POA	Warm		1	0.961	0.914	0.908	0.818	0.503	0.878	0.712	0.895
	Cool		1	0.904	0.866	0.845	0.763	0.585	0.809	0.563	0.772
$PM_{0.1}$ S1	Warm			1	0.928	0.953	0.867	0.475	0.835	0.597	0.800
	Cool			1	0.912	0.939	0.827	0.308	0.854	0.579	0.776
$PM_{0.1}$ S2	Warm				1	0.883	0.922	0.372	0.852	0.490	0.711
	Cool				1	0.855	0.893	0.299	0.879	0.447	0.675
$PM_{0.1}$ S3	Warm					1	0.875	0.443	0.831	0.572	0.717
	Cool					1	0.844	0.330	0.804	0.483	0.635
$PM_{0.1}$ S4	Warm						1	0.345	0.835	0.334	0.543
	Cool						1	0.303	0.826	0.245	0.461
$PM_{0.1}$ S5	Warm							1	0.463	0.389	0.493
	Cool							1	0.185	-0.041	0.139
$PM_{0.1}$ S6	Warm								1	0.556	0.651
	Cool								1	0.554	0.652
$PM_{0.1}$ S7	Warm									1	0.846
	Cool									1	0.831
$PM_{0.1}$ S9	Warm										1
	Cool										1

[a] The number of observations used in correlations is based on each event of a hospital encounter in the case-crossover analysis.

S1-9 refers to sources as follows: source 1: on-road gasoline; source 2: off-road gasoline; source 3: on-road diesel; source 4: off-road diesel; source 5: wood-smoke; source 6: meat cooking; source 7: high sulfur content fuel combustion; source 9: other anthropogenic sources.

Table 3.8. Spearman correlation matrix for weekly UCD/CIT modeled $PM_{2.5}$ variables.[a]

	Season	$PM_{2.5}$ SOA	$PM_{2.5}$ POA	$PM_{2.5}$ S1	$PM_{2.5}$ S2	$PM_{2.5}$ S3	$PM_{2.5}$ S4	$PM_{2.5}$ S5	$PM_{2.5}$ S6	$PM_{2.5}$ S7	$PM_{2.5}$ S9
$PM_{2.5}$ SOA	Warm	1	0.491	0.246	0.324	0.259	0.233	-0.031	0.145	0.473	0.716
	Cool	1	0.506	0.463	0.466	0.433	0.412	-0.081	0.413	0.665	0.765
$PM_{2.5}$ POA	Warm		1	0.884	0.913	0.861	0.844	0.301	0.836	0.511	0.870
	Cool		1	0.927	0.917	0.887	0.871	0.612	0.864	0.676	0.723
$PM_{2.5}$ S1	Warm			1	0.926	0.973	0.893	0.370	0.863	0.385	0.614
	Cool			1	0.928	0.963	0.897	0.498	0.891	0.613	0.583
$PM_{2.5}$ S2	Warm				1	0.881	0.929	0.261	0.826	0.337	0.673
	Cool				1	0.865	0.914	0.470	0.891	0.560	0.585
$PM_{2.5}$ S3	Warm					1	0.862	0.374	0.812	0.385	0.615
	Cool					1	0.871	0.483	0.807	0.574	0.578
$PM_{2.5}$ S4	Warm						1	0.222	0.767	0.143	0.574
	Cool						1	0.437	0.823	0.431	0.521
$PM_{2.5}$ S5	Warm							1	0.489	0.250	0.181
	Cool							1	0.350	0.193	0.158
$PM_{2.5}$ S6	Warm								1	0.458	0.548
	Cool								1	0.660	0.531
$PM_{2.5}$ S7	Warm									1	0.562
	Cool									1	0.738
$PM_{2.5}$ S9	Warm										1
	Cool										1

[a] The number of observations used in correlations is based on each event of a hospital encounter in the case-crossover analysis.

S1-9 refers to sources as follows: source 1: on-road gasoline; source 2: off-road gasoline; source 3: on-road diesel; source 4: off-road diesel; source 5: wood-smoke; source6: meat cooking; source 7: high sulfur content fuel combustion; source 9: other anthropogenic sources.

Table 3.9. Spearman correlation matrix for weekly UCD/CIT modeled PM_{10} variables.[a]

	Season	PM_{10} SOA	PM_{10} POA	PM_{10} S1	PM_{10} S2	PM_{10} S3	PM_{10} S4	PM_{10} S5	PM_{10} S6	PM_{10} S7	PM_{10} S9
PM_{10} SOA	Warm	1	0.444	0.246	0.322	0.246	0.222	-0.067	0.138	0.484	0.628
	Cool	1	0.488	0.489	0.488	0.444	0.424	-0.072	0.429	0.670	0.669
PM_{10} POA	Warm		1	0.924	0.954	0.883	0.883	0.264	0.841	0.498	0.928
	Cool		1	0.932	0.926	0.887	0.880	0.649	0.836	0.628	0.925
PM_{10} S1	Warm			1	0.926	0.974	0.891	0.363	0.864	0.392	0.771
	Cool			1	0.925	0.962	0.892	0.471	0.889	0.615	0.837
PM_{10} S2	Warm				1	0.880	0.927	0.254	0.826	0.341	0.836
	Cool				1	0.859	0.910	0.448	0.887	0.558	0.841
PM_{10} S3	Warm					1	0.861	0.370	0.811	0.386	0.737
	Cool					1	0.866	0.462	0.802	0.567	0.798
PM_{10} S4	Warm						1	0.214	0.764	0.141	0.732
	Cool						1	0.421	0.814	0.419	0.774
PM_{10} S5	Warm							1	0.483	0.260	0.133
	Cool							1	0.323	0.171	0.495
PM_{10} S6	Warm								1	0.465	0.633
	Cool								1	0.662	0.700
PM_{10} S7	Warm									1	0.553
	Cool									1	0.694
PM_{10} S9	Warm										1
	Cool										1

[a] The number of observations used in correlations is based on each event of a hospital encounter in the case-crossover analysis.

S1-9 refers to sources as follows: source 1: on-road gasoline; source 2: off-road gasoline; source 3: on-road diesel; source 4: off-road diesel; source 5: woodsmoke; source6: meat cooking; source 7: high sulfur content fuel combustion; source 9: other anthropogenic sources.

Table 3.10. Spearman correlation matrix for weekly CALINE4 (CLN4) traffic-related air pollutants (1500 m buffer) and UCD/CIT modeled POA variables for ultrafine and fine PM.[a]

	Season	CLN4 $PM_{2.5}$	CLN4 NO_x	CLN4 PN	$PM_{0.1}$ POA	$PM_{0.1}$ S1+3	$PM_{0.1}$ S2+4	$PM_{2.5}$ POA	$PM_{2.5}$ S1+3	$PM_{2.5}$ S2+4	Ambient NO_x	Ambient CO
CLN4 $PM_{2.5}$	Warm	1	0.91	0.94	0.23	0.27	0.25	0.26	0.35	0.36	0.31	0.12
	Cool	1	0.91	0.96	0.22	0.23	0.22	0.25	0.29	0.31	0.29	0.22
CLN4 NO_x	Warm		1	0.84	0.21	0.23	0.22	0.28	0.27	0.30	0.34	0.32
	Cool		1	0.87	0.18	0.16	0.13	0.25	0.24	0.24	0.38	0.40
CLN4 PN	Warm			1	0.27	0.32	0.30	0.28	0.38	0.40	0.41	0.15
	Cool			1	0.21	0.21	0.22	0.23	0.27	0.29	0.34	0.24
$PM_{0.1}$ POA	Warm				1	0.96	0.88	0.87	0.80	0.74	0.33	0.11
	Cool				1	0.90	0.83	0.83	0.78	0.75	0.31	0.25
$PM_{0.1}$ S1+3	Warm					1	0.91	0.82	0.83	0.76	0.36	0.09
	Cool					1	0.89	0.69	0.76	0.72	0.18	0.11
$PM_{0.1}$ S2+4	Warm						1	0.74	0.67	0.75	0.27	0.05
	Cool						1	0.59	0.60	0.72	0.11	0.04
$PM_{2.5}$ POA	Warm							1	0.88	0.87	0.41	0.22
	Cool							1	0.92	0.90	0.48	0.43
$PM_{2.5}$ S1+3	Warm								1	0.91	0.52	0.21
	Cool								1	0.92	0.44	0.36
$PM_{2.5}$ S2+4	Warm									1	0.48	0.19
	Cool									1	0.40	0.31
Ambient NO_x	Warm										1	0.67
	Cool										1	0.87
Ambient CO	Warm											1
	Cool											1

[a] The number of observations used in correlations is based on each event of a hospital encounter in the case-crossover analysis.
CLN4: CALINE4; PN: particle number; S1+3 = source1 (onroad gasoline) + source3 (onroad diesel); S2+4 = source2 (offroad gasoline) + source4 (offroad diesel).

3.2.3 Effect Modification of Ambient Air Pollution by Residential TRAP

Regression analysis of asthma hospital morbidity with ambient air pollution: We found many positive associations of asthma hospital morbidity with ambient air pollution (Figures 3.6-3.7, "All Subjects"). In general, associations strengthened from 1-day average to longer air pollutant averaging times. Associations with NO_2, NO_x, and CO are stronger

and 95% confidence limits tighter in cooler seasons (Figure 3.6) than in warmer seasons, whereas associations for $PM_{2.5}$ up to the 5-day average are stronger in warmer seasons (Figure 3.7). However, when using a season-specific interquartile range to express the magnitude of association with ambient air pollution, associations for $PM_{2.5}$ are stronger in cooler than warmer seasons, whereas the stronger associations in cooler seasons for NO_2, NO_x, and CO remained (Table 3.11). This may be the results of higher $PM_{2.5}$ mass concentrations in the cooler seasons being accompanied by differences in pollutant composition and toxicity (Ito et al. 2007).

Table 3.11. Associations between pediatric asthma hospital encounters and ambient air pollution: effects per seasonal interquartile range changes in air pollutant exposures.

Ambient Air Pollutant[b]	Lag-Day Average	Warm Season, % change in risk (95% CI)[a]	Cool Season, % change in risk (95% CI)
CO	1-day	3.66 (-2.89, 10.66)	-1.44 (-7.11, 4.58)
	3-day	2.38 (-5.91, 11.40)	4.57 (-2.83, 12.52)
	5-day	0.87 (-8.60, 11.33)	9.00 (-0.02, 18.83)
	7-day	-3.29 (-13.32, 7.90)	13.20 (2.88, 24.56)
NO_2	1-day	4.19 (-4.24, 13.36)	0.44 (-5.32, 6.56)
	3-day	1.89 (-8.66, 13.66)	6.38 (-1.21, 14.55)
	5-day	4.22 (-8.57, 18.80)	15.27 (5.47, 25.97)
	7-day	4.14 (-10.18, 20.75)	23.18 (11.23, 36.42)
NOx	1-day	1.43 (-4.46, 7.68)	-0.96 (-6.65, 5.09)
	3-day	0.24 (-7.43, 8.56)	4.59 (-3.03, 12.80)
	5-day	-0.60 (-9.66, 9.37)	11.47 (1.63, 22.26)
	7-day	-4.98 (-14.83, 6.01)	17.25 (5.51, 30.29)
O_3	1-day	7.38 (-0.63, 16.03)	-4.43 (-12.09, 3.90)
	3-day	20.88 (9.72, 33.17)	-11.95 (-20.75, -2.18)
	5-day	22.71 (9.74, 37.21)	-19.89 (-29.22, -9.33)
	7-day	28.78 (13.52, 46.10)	-24.16 (-33.92, -12.97)
$PM_{2.5}$	1-day	4.21 (0.20, 8.39)	1.04 (-3.90, 6.23)
	3-day	5.52 (0.85, 10.40)	4.85 (-1.07, 11.12)
	5-day	7.07 (1.18, 13.29)	9.73 (2.51, 17.46)
	7-day	7.87 (0.82, 15.41)	16.16 (7.62, 25.37)

[a] Percent change in risk of hospital encounters and 95% confidence intervals (CI) are for interquartile increases from the seasonal distribution of concentrations of air pollutants (Table 3.2). Estimates are adjusted for temperature and relative humidity of the same averaging time.

[b] All air pollutant exposures are from daily 24-hr averages.

Expected positive associations are seen with O_3 in the warm season (Figure 3.7). The standard error of estimates for 24-hr average O_3 was lower than 8-hr maximum O_3 (not shown). We observed a previously reported, but biologically implausible, inverse association with O_3 in the cool season similar to hospital time-series studies (Ito et al. 2007). This paradoxical association could be due to negative correlations of O_3 with $PM_{2.5}$, NO_2, NO_x, and CO that were positively associated with asthma morbidity. Seasonal differences in association led to weaker associations for O_3, NO_x and CO in models combining seasons (not shown). Positive associations with $PM_{2.5}$ were seen in both seasons.

Regression analysis of effect modification by CALINE4-estimated TRAP: In the following we discuss the results of the regression analysis of effect modification of the association between asthma morbidity and daily ambient pollutant exposure by spatial variability in traffic-related air pollution at subject residential locations (using the 6-month seasonal averages of CALINE4 exposure estimates). For cool season models we found that associations of asthma morbidity with daily ambient CO, NO_x, NO_2, and $PM_{2.5}$ (especially 7-day averages) were generally stronger among subjects living at residences with greater than the median level of dispersion-modeled NO_x, $PM_{2.5}$, and particle number (Figure 3.6). The main exceptions to these findings were for ambient $PM_{2.5}$ and NO_2 by dispersion-modeled NO_x and particle number strata, where there was little or no difference. Eight of 48 product terms for dispersion-modeled pollutants reached $p<0.1$ for cool-season ambient CO, NO_2, NO_x and $PM_{2.5}$ (primarily 5-day and 7-day ambient air pollution averages). The strongest effect modification was with dispersion-modeled $PM_{2.5}$, especially with ambient CO and NO_x. For example, among subjects living in the upper half of dispersion-modeled $PM_{2.5}$ during the cool season, the estimated percent change in hospital encounters in relation to an interquartile increase in 7-day average ambient NO_x (52.5 ppb) was 29% (95% confidence interval: 10, 52), compared with 5% (95% confidence interval: -6, 18) for those living in the lower half of dispersion-modeled $PM_{2.5}$, interaction p-value<0.02.

In warm seasons, associations with asthma hospital morbidity for ambient $PM_{2.5}$ tended to be stronger and with tighter 95% confidence intervals for subjects in the upper median of dispersion-modeled NO_x, $PM_{2.5}$ and particle number (Figure 3.7). There were similar differences for ambient CO, but all 95% confidence intervals included zero. Overall, seven of 48 product terms for dispersion-modeled pollutants reached $p < 0.1$ for warm-season ambient CO, NO_2, NO_x and $PM_{2.5}$. Interestingly, associations for ambient O_3 in warm seasons were more strongly positive in subjects with dispersion-modeled pollutants ≤median, although only two product terms reached $p<0.1$.

Sensitivity analysis results for dispersion-modeled data using a much wider 1500m buffer (not shown) were consistent with the above results using a 500m buffer, but differences in asthma associations above and below the median dispersion-modeled strata were smaller and 95% confidence intervals wider.

Figure 3.6. Associations between pediatric asthma hospital morbidity and ambient air pollution in the cool season: Effect modification by dispersion modeled traffic-related air pollution above and below median levels. All exposures are for the 24-hr daily average concentrations. Percent change in hospital encounters and 95% CI are for an interquartile increase in the ambient air pollutant (Table 3.2, footnote c), adjusted for temperature and relative humidity of the same averaging time.

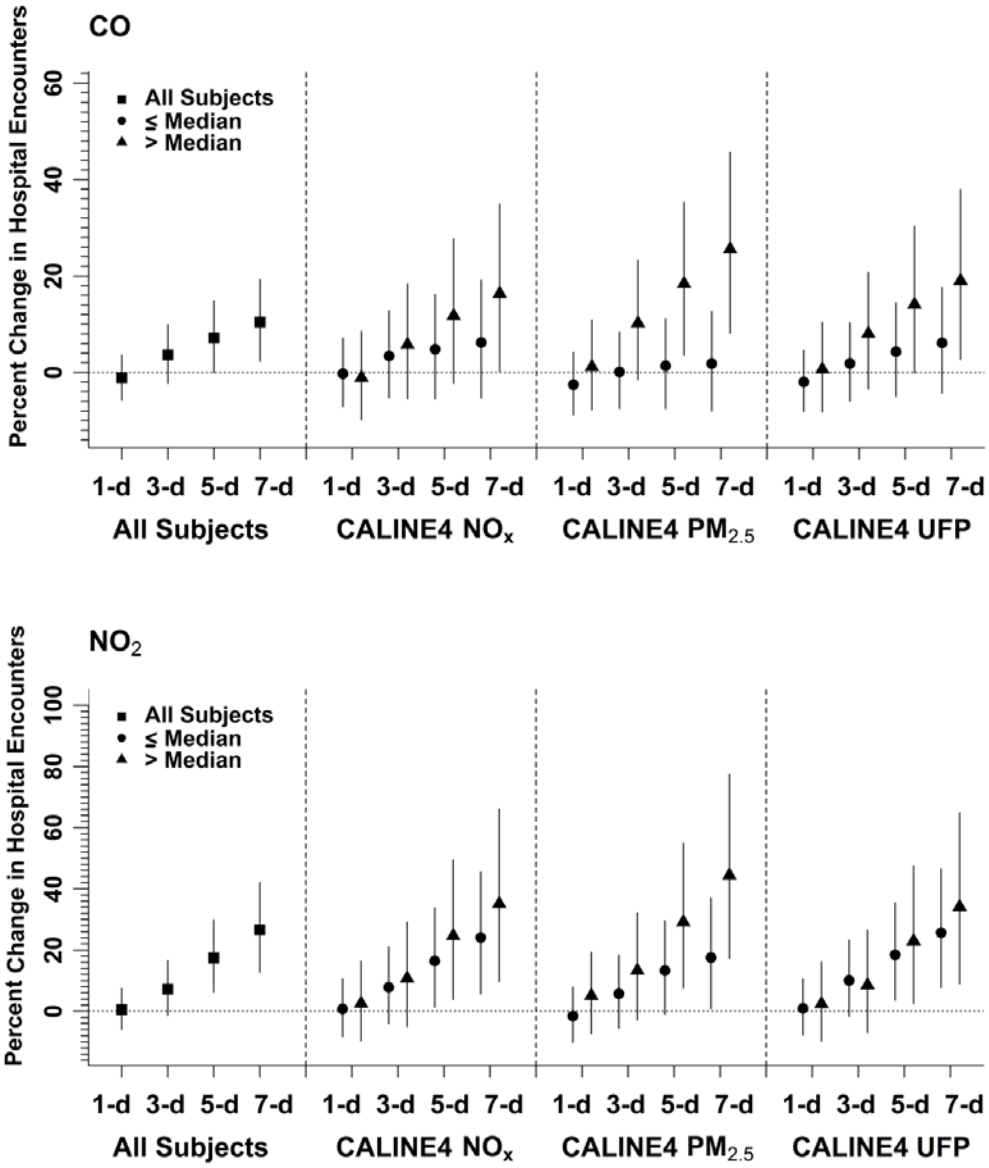


Figure 3.6 (Cont)

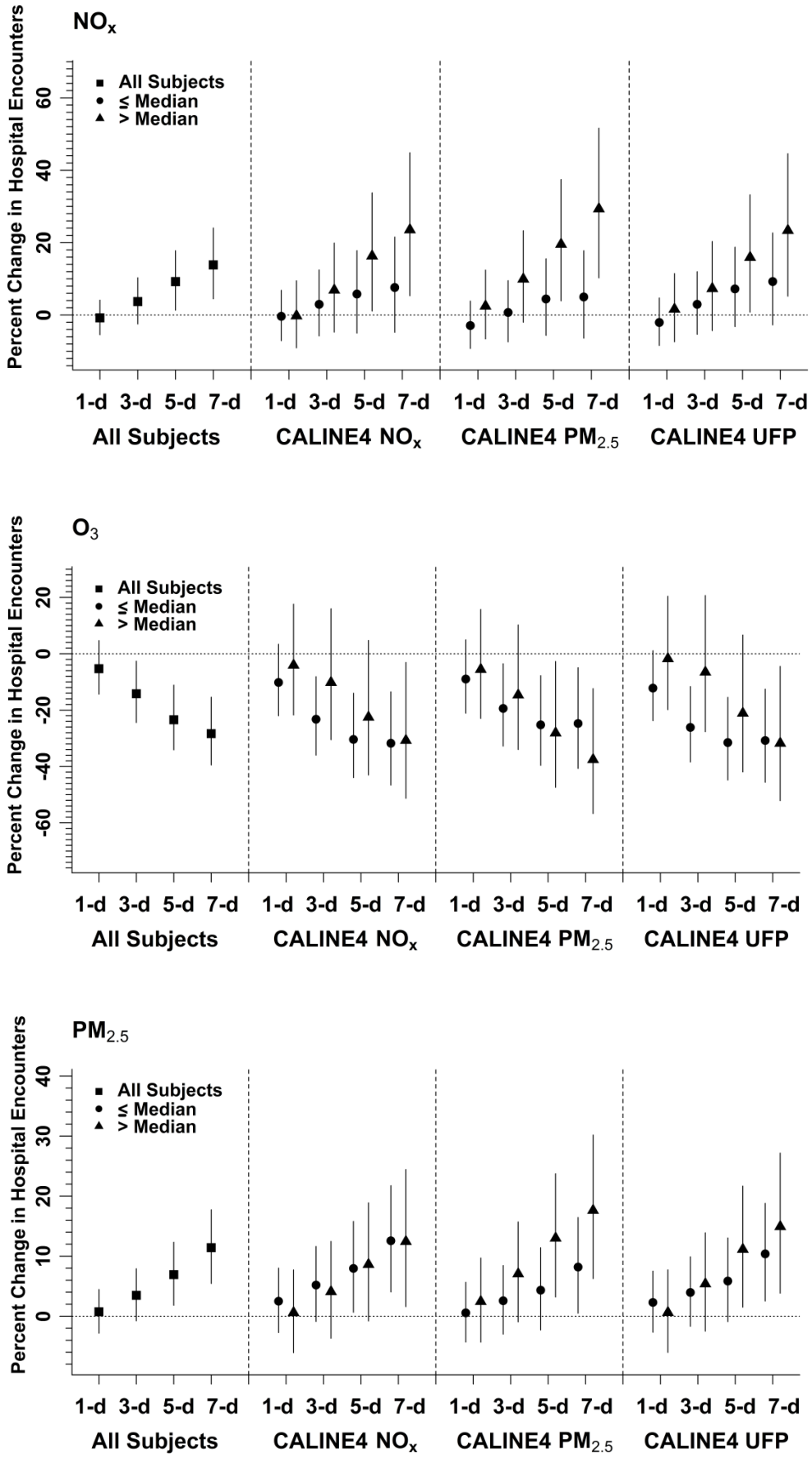


Figure 3.7. Associations between pediatric asthma hospital morbidity and ambient air pollution in the warm season: Effect modification by dispersion modeled traffic-related air pollution above and below median levels. All exposures are for the 24-hr daily average concentrations. Percent change in hospital encounters and 95% CI are for an interquartile increase in the ambient air pollutant (Table 3.2, footnote c), adjusted for temperature and relative humidity of the same averaging time.

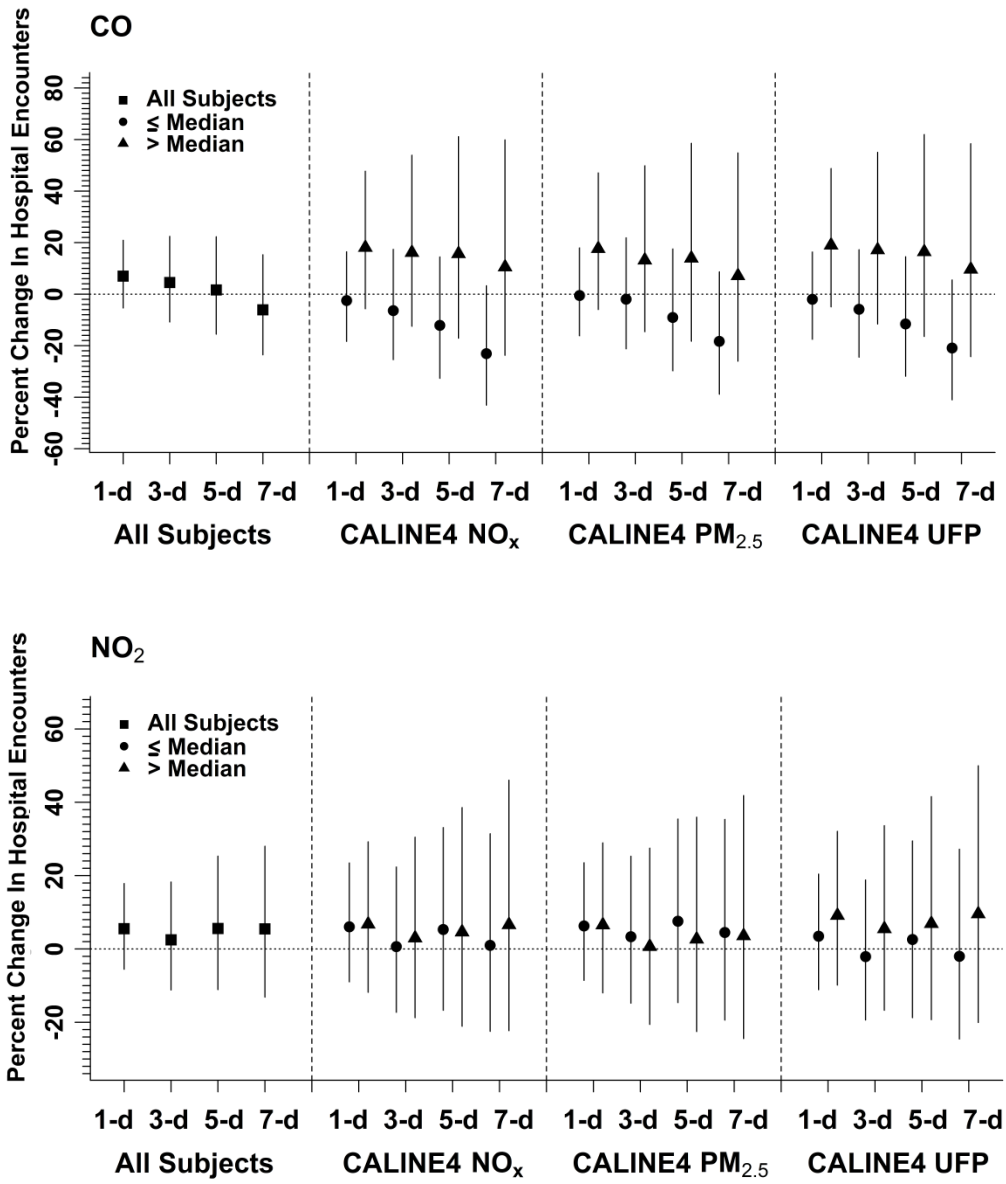
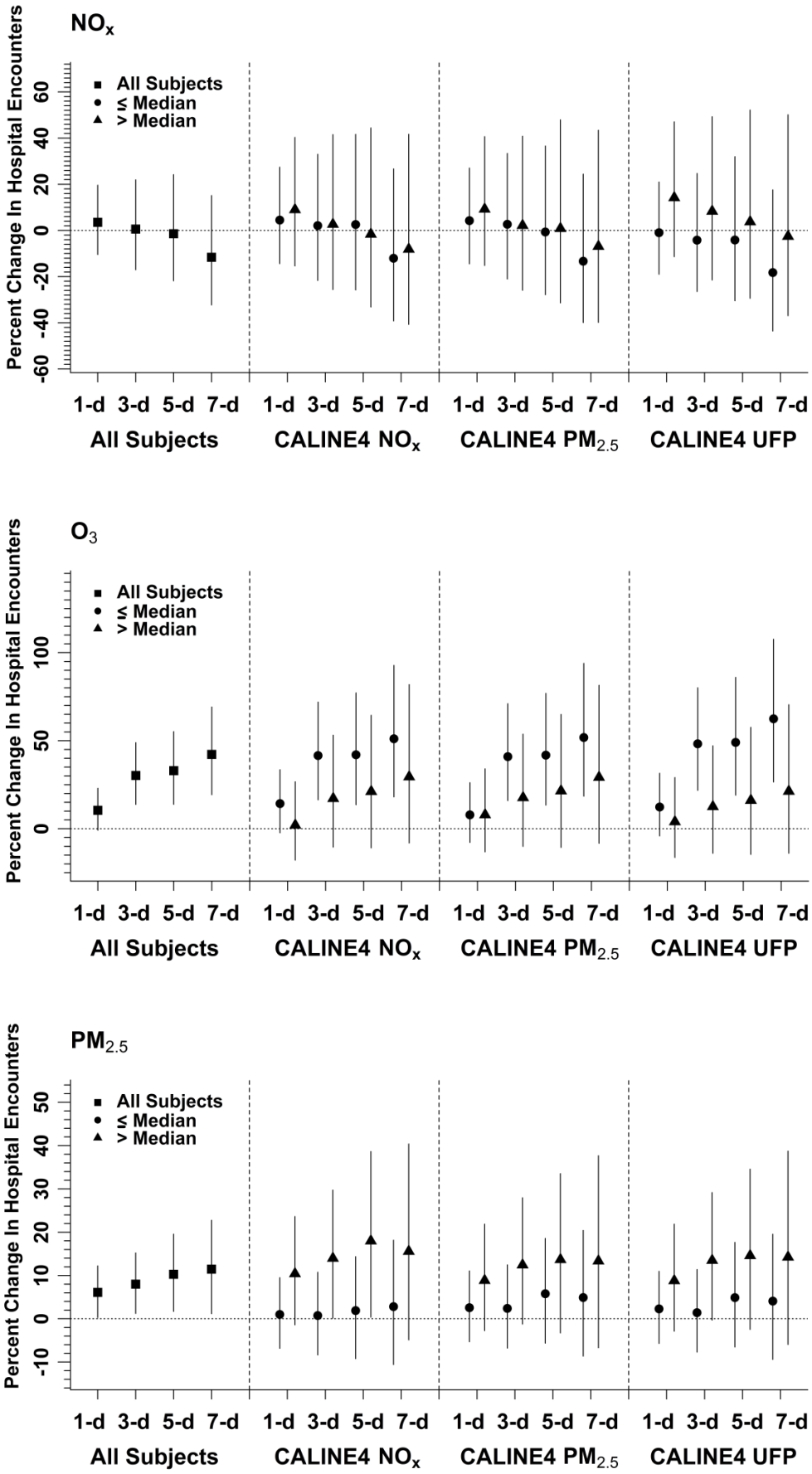


Figure 3.7 (Cont.)



Regression analysis of effect modification by LUR-estimated NO_2 /NO_x: There were no clear differences in associations above or below the median of land-use regression-estimated NO_2 (not shown). Associations with asthma hospital morbidity in the cool seasons were slightly stronger and confidence intervals narrower for 5-day and 7-day averages of ambient NO_2, NO_x, CO and $PM_{2.5}$ among subjects in the upper half of land-use regression-modeled NO_x (Table 3.12). However, confidence intervals among land-use regression estimates overlapped considerably. For land-use regression models during the warm seasons, there was less evidence of a difference in associations.

Table 3.12. Associations between pediatric asthma hospital encounters and ambient air pollution: effect modification by LUR modeled traffic-related air pollution (NO_x) above and below median levels.

Ambient exposure and averaging time	LUR NO_x % change in risk (95% CI)[a]		*p*-value for interaction[b]
	≤ median	> median	
	Cool Season		
NO_2			
24-hr	6.74 (-2.67, 17.07)	-3.40 (-14.90, 9.64)	0.122
3-day	9.02 (-2.73, 22.17)	9.63 (-5.97, 27.80)	0.943
5-day	12.89 (-1.40, 29.22)	29.56 (7.97, 55.35)	0.138
7-day	21.71 (4.28, 42.01)	38.99 (12.94, 70.77)	0.210
NO_x			
24-hr	2.32 (-4.31, 9.41)	-2.96 (-11.57, 6.49)	0.264
3-day	4.84 (-3.69, 14.12)	5.30 (-6.08, 18.07)	0.940
5-day	5.88 (-4.44, 17.30)	17.51 (2.20, 35.08)	0.143
7-day	8.81 (-3.13, 22.22)	24.02 (5.76, 45.36)	0.107
CO			
24-hr	1.49 (-5.02, 8.45)	-3.01 (-11.56, 6.38)	0.336
3-day	4.94 (-3.32, 13.92)	4.53 (-6.51, 16.87)	0.944
5-day	5.23 (-4.36, 15.79)	12.56 (-1.43, 28.52)	0.320
7-day	8.11 (-2.76, 20.19)	16.11 (0.20, 34.52)	0.342
O_3 24-hr mean			
24-hr	-16.20 (-27.83, -2.74)	1.33 (-17.39, 24.27)	0.068
3-day	-21.04 (-34.59, -4.82)	-13.36 (-33.04, 11.93)	0.478
5-day	-25.02 (-39.86, -6.82)	-28.14 (-47.40, -2.78)	0.784
7-day	-28.09 (-43.83, -8.48)	-34.15 (-53.99, -7.73)	0.612
$PM_{2.5}$			
24-hr	1.91 (-3.03, 7.10)	1.00 (-5.68, 8.16)	0.799
3-day	3.25 (-2.45, 9.27)	6.12 (-1.78, 14.66)	0.486
5-day	6.11 (-0.68, 13.36)	10.86 (1.28, 21.33)	0.343
7-day	11.37 (3.41, 19.94)	13.79 (2.84, 25.91)	0.677

Table 3.12 (cont.)

Ambient exposure and averaging time	LUR NO_x % change in risk (95% CI)		*p*-value for interaction
	≤ median	> median	
	Warm Season		
NO_2			
24-hr	2.92 (-11.96, 20.31)	9.33 (-9.77, 32.43)	0.538
3-day	-1.46 (-18.91, 19.73)	4.87 (-17.25, 32.87)	0.606
5-day	2.47 (-18.75, 29.18)	7.08 (-19.15, 41.74)	0.759
7-day	0.55 (-22.66, 30.68)	7.05 (-21.94, 46.67)	0.697
NO_x			
24-hr	2.51 (-16.47, 25.79)	10.42 (-14.39, 42.36)	0.567
3-day	-0.37 (-23.34, 29.44)	4.89 (-23.95, 44.55)	0.754
5-day	-1.14 (-28.17, 35.93)	1.24 (-31.11, 48.51)	0.903
7-day	-10.65 (-38.34, 29.01)	-9.28 (-41.56, 40.07)	0.945
CO			
24-hr	2.10 (-14.80, 22.34)	13.41 (-9.59, 42.21)	0.363
3-day	-4.87 (-23.64, 18.47)	16.14 (-12.47, 53.94)	0.167
5-day	-8.23 (-29.04, 18.59)	13.32 (-18.77, 57.88)	0.214
7-day	-18.08 (-38.93, 9.52)	6.32 (-26.81, 54.20)	0.171
O_3			
24-hr	10.75 (-4.93, 29.01)	4.86 (-15.61, 30.28)	0.622
3-day	27.67 (5.53, 54.34)	29.59 (-0.95, 69.23)	0.914
5-day	24.11 (-0.33, 54.40)	38.70 (1.97, 88.03)	0.478
7-day	32.48 (3.46, 69.35)	48.12 (5.07, 107.68)	0.523
$PM_{2.5}$			
24-hr	7.35 (-0.81, 16.19)	3.72 (-7.36, 16.12)	0.550
3-day	6.11 (-3.72, 16.94)	8.29 (-4.98, 23.41)	0.761
5-day	8.49 (-3.30, 21.71)	10.62 (-5.85, 29.96)	0.813
7-day	6.84 (-6.93, 22.64)	11.23 (-8.43, 35.06)	0.685

[a] Percent change in risk of hospital encounters and 95% confidence intervals (CI) are for interquartile increases in the air pollutant (Table 3.2, footnote c, text), adjusted for temperature and relative humidity of the same averaging time. Air pollutants are daily 24-hr averages.

[b] Stratified results and the *p*-value for interaction for land-use regression (LUR)-estimated NO_x are derived from product term models of the ambient air pollutant by LUR NO_x.

3.2.4 Associations with Modeled Weekly CALINE4 Air Pollutant Exposures

In the following we discuss the results of the regression analysis of the association between asthma morbidity and weekly average exposure to traffic-related air pollution at subject residential locations (using the daily CALINE4 exposure estimates).

Regression analyses showed positive associations with asthma morbidity that were similar to associations observed for the ambient air pollutants in the cold seasons. In the warm season, similar to ambient air pollutants, there were no associations with asthma morbidity for the primary air pollutants estimated by CALINE4 (NO_x and CO) (Table 3.13). However, unlike the ambient $PM_{2.5}$ data, there were also no associations with CALINE4

$PM_{2.5}$ in the warm season. All warm season models showed parameter estimates that were negative but nonsignificant. All cold season models showed parameter estimates that were positive and significant. Associations for CALINE4 variables using the 1500 m radius buffer are all more negative in the warm season and mode positive in the cool season than the 500 m buffer. However, the interquartile range (upon which the estimates of association are based) are greater at 1500 m (compared to 500 m) for all of the CALINE4 variables (Table 3.5), due to the higher frequency of near zero exposure for the 500 m variable. For example, we found the odds ratio for a unit change (per 1.0 ppb) in cool season NO_x estimated with a 500 m radius buffer was 1.057 versus the 1500 m variable with a odds ratio of 1.034. Therefore, the effect per ppb NO_x is actually greater for the 500 m variable.

Spearman correlations between 7-day average CALINE4 $PM_{2.5}$ and ambient $PM_{2.5}$ were weak at 0.14 in the cold seasons and 0.06 in the warm seasons (Table 3.10). This result reflects the fact that CALINE4 $PM_{2.5}$ represents primary emission sources whereas ambient $PM_{2.5}$ represents a mixture of secondary and primary sources, especially during the warmer months. The observed contrast in associations with asthma morbidity suggests that PM from primary emission sources may have less of an impact on asthma risk than exposure to secondary sources in the warm seasons. This issue is further addressed below with the use of UC Davis model data for POA and SOA.

Table 3.13. Associations between pediatric asthma hospital encounters and weekly residential traffic-related air pollution exposures estimated by dispersion (CALINE4) models.[a]

Air Pollutant[b]	**Warm Season, % change in risk (95% CI)[a]**	**Cool Season, % change in risk (95% CI)**
CALINE4 Dispersion model (500 m buffer)		
$PM_{2.5}$ (µg/m^3)	-2.88 (-14.85, 10.77)	9.38 (1.59, 17.75)
NO_x (ppb)	-0.78 (-13.26, 13.48)	9.94 (1.63, 18.93)
Particle Number (no./cm^3)	-5.94 (-14.05, 2.94)	8.75 (3.27, 14.51)
CALINE4 Dispersion model (1500 m buffer)		
$PM_{2.5}$ (µg/m^3)	-12.32 (-29.47, 8.92)	17.53 (4.57, 32.07)
NO_x (ppb)	-11.47 (-28.58, 9.68)	17.03 (4.03, 31.64)
Particle Number (no./cm^3)	-12.34 (-23.57, 0.51)	12.24 (3.80, 21.37)

[a] CALINE4 exposure estimates are for 7-day averages of the lag 0 event days and lags 1-6 before the event days.

[b] Percent change in risk of hospital encounters and 95% confidence intervals (CI) are for interquartile range increases from the annual distribution of concentrations of air pollutants as shown in Table 3.5. Estimates are adjusted for temperature and relative humidity of the same averaging time.

3.2.5 Associations with UCD/CIT-Modeled Primary & Secondary PM Exposures

No positive associations were observed for the SOA variables in both seasons and regression parameters were negative, and significantly so for $PM_{0.1}$ SOA (Table 3.14). Positive and significant associations of asthma encounters with total POA and POA source apportioned mass were observed in the cool season. This includes associations with nearly all POA sources with magnitudes of association between 12-25% increases in risk of hospital encounters for interquartile range increases in PM. Correlations are also strong with between all sources, including high sulfur content fuel combustion and other anthropogenic sources, which were also significantly associated with asthma encounters to similar

magnitudes as on-road and off-road gasoline and diesel. This makes it difficult to ascribe the contribution of each source to the health effects observed. The weakest but still significant POA source was woodsmoke, at around 4% increase in risk of hospital encounters for interquartile range increases in $PM_{2.5}$ and PM_{10} woodsmoke ($PM_{0.1}$ woodsmoke was not associated with asthma). Woodsmoke was weakly to moderately correlated to the other POA sources.

The POA associations were observed across all particle sizes with ultrafine particles showing somewhat stronger associations as expected, although confidence intervals for the various particle sizes overlapped considerably. However, in the warm season, regression parameters for the POA variables were, except for meat cooking, all nonsignificant and negative for $PM_{0.1}$, but positive for $PM_{2.5}$ and PM_{10}. This seasonal difference in associations is consistent with findings reported above for both ambient and CALINE4 NO_x and CO, which are markers of primary combustion sources as well.

Unexpectedly, positive associations for meat cooking POA were of similar magnitude to other sources, including on-road and off-road fossil fuel combustion. This is possibly due to the influence of meteorology that leads to parallel predictions in source contributions to POA from various fossil fuel combustion sources and meat cooking. This view is supported by results showing the warm and cool season correlations between total POA and meat cooking is >0.84 for all size fractions. The cool season correlation of all gasoline and diesel sources with meat cooking is > 0.8. However, it is noteworthy that meat cooking POA in $PM_{2.5}$ and PM_{10} were the only source contributions significantly associated with asthma encounters in the warm season.

We next evaluated whether associations of asthma morbidity with weekly average total POA and SOA above differ between subjects with high seasonal exposures to traffic-related residential air pollution based on the available CALINE4 dispersion model data (as presented above for daily ambient air pollution). Table 3.15 shows that there were no clear differences in association. There was nominal evidence that the negative regression parameters for SOA in the warm season were somewhat dominated by subjects living where CALINE4 $PM_{2.5}$ and UFP were higher.

Table 3.14. Associations between pediatric asthma hospital encounters and UCD/CIT-modeled primary and secondary organic aerosol.[a]

Air Pollutant[b]	Warm Season, % change in risk (95% CI)[a]	Cool Season, % change in risk (95% CI)
$PM_{0.1}$		
$PM_{0.1}$ SOA	-10.03 (-16.81, -2.70)	-3.93 (-14.28, 7.67)
$PM_{0.1}$ POA	-18.47 (-33.69, 0.10)	19.38 (7.96, 32.00)
$PM_{0.1}$ POA from on-road gasoline & diesel	-12.36 (-29.07, 8.19)	25.32 (10.50, 42.09)
$PM_{0.1}$ POA from off-road gasoline & diesel	-5.95 (-20.33, 11.02)	18.94 (7.93, 31.06)
$PM_{0.1}$ POA from woodsmoke		0.02 (-0.02, 0.05)
$PM_{0.1}$ POA from meat cooking	3.19 (-12.95, 22.32)	18.64 (5.17, 33.80)
$PM_{0.1}$ POA from high sulfur content fuel combustion	-8.35 (-19.28, 4.04)	21.56 (6.04, 39.31)
$PM_{0.1}$ POA from other anthropogenic sources	-20.59 (-32.02, -7.32)	20.29 (8.42, 33.44)
$PM_{2.5}$		
$PM_{2.5}$ SOA	-3.71 (-12.14, 5.53)	-16.80 (-29.63, -1.70)
$PM_{2.5}$ POA	2.60 (-12.01, 19.63)	14.99 (7.04, 23.53)
$PM_{2.5}$ POA from on-road gasoline & diesel	10.21 (-6.34, 29.66)	16.23 (6.41, 26.94)
$PM_{2.5}$ POA from off-road gasoline & diesel	8.39 (-4.56, 23.10)	12.39 (5.69, 19.50)
$PM_{2.5}$ POA from woodsmoke		4.21 (1.07, 7.44)
$PM_{2.5}$ POA from meat cooking	16.43 (1.75, 33.21)	13.59 (4.95, 22.94)
$PM_{2.5}$ POA from high sulfur content fuel combustion	12.81 (-2.33, 30.28)	13.53 (1.57, 26.89)
$PM_{2.5}$ POA from other anthropogenic sources	-4.08 (-17.39, 11.38)	19.38 (8.08, 31.85)
PM_{10}		
PM_{10} SOA	-1.31 (-10.11, 8.35)	-18.95 (-31.12, -4.71)
PM_{10} POA	4.59 (-10.12, 21.71)	13.98 (6.42, 22.07)
PM_{10} POA from on-road gasoline & diesel	8.63 (-7.81, 27.98)	17.48 (7.32, 28.59)
PM_{10} POA from off-road gasoline & diesel	7.43 (-5.46, 22.04)	12.85 (6.05, 20.09)
PM_{10} POA from woodsmoke		4.31 (1.15, 7.56)
PM_{10} POA from meat cooking	15.28 (0.72, 31.92)	14.45 (5.58, 24.06)
PM_{10} POA from high sulfur content fuel combustion	11.58 (-3.53, 29.03)	14.91 (2.47, 28.86)
PM_{10} POA from other anthropogenic sources	2.84 (-10.80, 18.56)	14.76 (6.29, 23.89)

[a] Percent change in risk of hospital encounters and 95% confidence intervals (CI) are for annual interquartile increases in concentrations of air pollutants. Estimates are adjusted for temperature and relative humidity of the same averaging time.

[b] UCD-CIT exposure estimates are for 7-day averages of the lag 0 event days and lags 1-6 before the event days.

Table 3.15. Associations between pediatric asthma hospital encounters and UCD/CIT-modeled primary and secondary organic aerosol: effect modification by seasonal average CALINE4-modeled traffic-related air pollution above and below median levels.

UCD/CIT exposure	All Subjects **%** change in risk (95% CI)	CALINE4 NO_x **%** change in risk (95% CI)[a]		*p*-value[b]	CALINE4 $PM_{2.5}$ **%** change in risk (95% CI)		*p*-value[b]	CALINE4 UFP **%** change in risk (95% CI)		*p*-value[b]
		≤ median	> median		≤ median	> median		≤ median	> median	
Cool Season										
$PM_{0.1}$										
$PM_{0.1}$ SOA	0.97 (0.87, 1.09)	0.98 (0.83, 1.14)	0.97 (0.78, 1.20)	0.938	0.95 (0.82, 1.11)	0.99 (0.80, 1.22)	0.717	0.97 (0.83, 1.13)	0.98 (0.79, 1.21)	0.909
$PM_{0.1}$ POA	1.22 (1.10, 1.35)	1.27 (1.10, 1.47)	1.17 (0.95, 1.43)	0.423	1.20 (1.04, 1.39)	1.23 (1.01, 1.51)	0.821	1.25 (1.08, 1.45)	1.19 (0.97, 1.46)	0.655
$PM_{2.5}$										
$PM_{2.5}$ SOA	0.86 (0.73, 1.02)	0.85 (0.68, 1.07)	0.87 (0.66, 1.14)	0.911	0.78 (0.63, 0.97)	0.95 (0.72, 1.25)	0.164	0.83 (0.67, 1.03)	0.89 (0.68, 1.17)	0.604
$PM_{2.5}$ POA	1.16 (1.08, 1.24)	1.16 (1.05, 1.27)	1.16 (1.01, 1.32)	0.979	1.11 (1.00, 1.22)	1.20 (1.06, 1.38)	0.213	1.18 (1.07, 1.30)	1.14 (1.01, 1.30)	0.612
PM_{10}										
PM_{10} SOA	0.84 (0.71, 0.99)	0.84 (0.67, 1.04)	0.85 (0.65, 1.11)	0.908	0.77 (0.62, 0.95)	0.93 (0.71, 1.21)	0.173	0.82 (0.66, 1.01)	0.87 (0.67, 1.13)	0.647
PM_{10} POA	1.15 (1.07, 1.23)	1.14 (1.04, 1.25)	1.16 (1.02, 1.31)	0.828	1.09 (0.99, 1.20)	1.20 (1.06, 1.36)	0.143	1.16 (1.06, 1.28)	1.13 (1.01, 1.28)	0.684
Warm Season										
$PM_{0.1}$										
$PM_{0.1}$ SOA	0.90 (0.83, 0.97)	0.91 (0.82, 1.02)	0.89 (0.77, 1.02)	0.689	0.95 (0.86, 1.06)	0.85 (0.74, 0.98)	0.121	0.93 (0.84, 1.04)	0.86 (0.75, 1.01)	0.274
$PM_{0.1}$ POA	0.82 (0.67, 1.02)	0.81 (0.60, 1.09)	0.84 (0.55, 1.27)	0.881	0.86 (0.64, 1.16)	0.79 (0.52, 1.20)	0.703	0.79 (0.58, 1.06)	0.86 (0.57, 1.30)	0.689
$PM_{2.5}$										
$PM_{2.5}$ SOA	0.95 (0.87, 1.04)	0.98 (0.87, 1.10)	0.92 (0.79, 1.08)	0.470	1.02 (0.90, 1.15)	0.88 (0.76, 1.03)	0.067	1.01 (0.90, 1.14)	0.89 (0.76, 1.04)	0.103
$PM_{2.5}$ POA	1.03 (0.88, 1.20)	0.99 (0.80, 1.22)	1.07 (0.79, 1.45)	0.618	1.06 (0.85, 1.32)	1.00 (0.74, 1.36)	0.742	1.01 (0.81, 1.26)	1.04 (0.77, 1.41)	0.850
PM_{10}										
PM_{10} SOA	0.97 (0.88, 1.07)	1.00 (0.88, 1.13)	0.95 (0.81, 1.11)	0.524	1.04 (0.92, 1.18)	0.90 (0.77, 1.06)	0.083	1.03 (0.91, 1.17)	0.91 (0.78, 1.07)	0.132
PM_{10} POA	1.05 (0.90, 1.22)	0.99 (0.81, 1.22)	1.12 (0.83, 1.51)	0.435	1.06 (0.85, 1.32)	1.04 (0.77, 1.40)	0.880	1.01 (0.81, 1.26)	1.08 (0.80, 1.46)	0.652

[a] Percent change in risk of hospital encounters and 95% confidence intervals (CI) are for interquartile increases in the air pollutant, adjusted for temperature and relative humidity of the same averaging time. UCD/CIT exposure estimates are for 7-day averages of the lag 0 event days and lags 1-6 before the event days.

[b] Stratified results and the *p*-value for interaction for UCD/CIT exposure estimates are derived from product term models of the UCD/CIT weekly air pollutant by the CALINE4 6-month average air pollutant estimated for a 500 m radius residential buffer.

3.2.6 Multipollutant models

We tested two-pollutant models of ambient O_3 and $PM_{2.5}$ for warm seasons given that all-subject models discussed above showed both pollutants were significantly associated with increased asthma encounters. Results are presented in Figure 3.8 for 3-day and 7-day averages of the two pollutants before the date of the asthma event using 24-hr averaging times for both. "$PM_{2.5}$ with O_3" refers to the estimate of association for PM2.5 adjusted for O_3, and "O_3 with $PM_{2.5}$" refers to the estimate of association for O_3 adjusted for $PM_{2.5}$. Results were fairly similar using the 8-hr maximum of O_3 (not shown). The results shown below suggest that effects of O_3 and $PM_{2.5}$ are somewhat independent of each other since both confound each other to similar degrees in two-pollutant models, which still show significant or nearly significant associations for both pollutants.

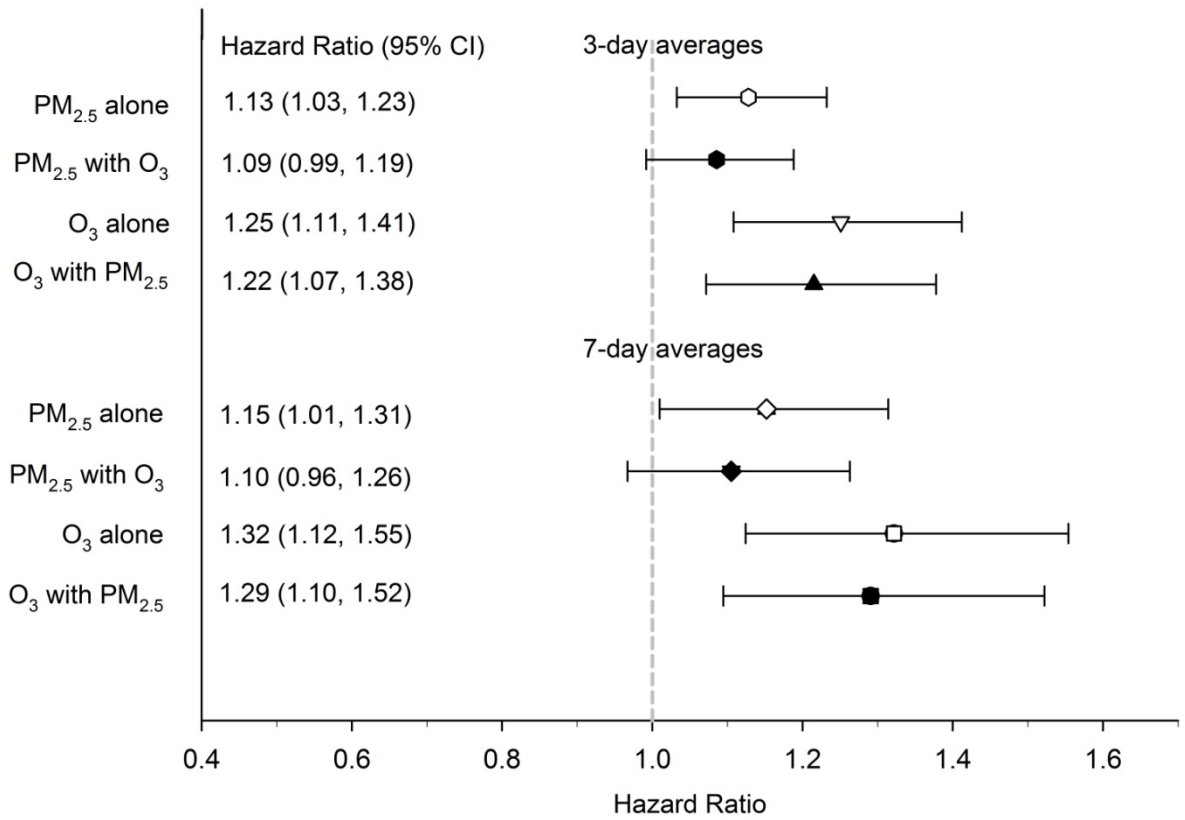


Figure 3.8. Two-pollutant models: Relation of asthma hospital encounters to an interquartile increase in 3-day and 7-day averages of 24-hr ambient $PM_{2.5}$ and 24-hr average O_3.

The cool season association of asthma encounters with 7-day average ambient $PM_{2.5}$ showed some negative confounding by exposure to 7-day average CALINE4 TRAP ($PM_{2.5}$, NO_x and CO), and UCD/CIT POA, but not UCD/CIT SOA (not shown). However, both $PM_{2.5}$ and UCD/CIT POA co-confounded each other to similar degrees in the cool season (34% and 35% decreases, respectively). Similar co-confounding in the cool season occurred in two-pollutant models of ambient $PM_{2.5}$ with CALINE4 TRAP variables and the primary gases (not shown). For example, in the two-pollutant model with $PM_{2.5}$ and NO_x, the parameter estimated for both decreased by around 35% and both were still nearly significant. The above findings suggest that part of the effect of $PM_{2.5}$ in the cool season may be due to its POA fraction or other correlated primary air pollutants. On the other hand, in the warm season the parameter estimate for ambient $PM_{2.5}$ became more positive and each of the following co-regressed variables became more negative: CALINE4 TRAP variables, and UCD/CIT SOA and POA. Similarly, the warm season association of asthma encounters with 7-day average ambient O_3 was not confounded by 7-day average exposure to CALINE4 $PM_{2.5}$, NO_x and CO, or to UCD/CIT SOA and POA (not shown). The warm season

association of asthma with ambient O_3 was not confounded by CALINE4 TRAP, by UCD/CIT SOA and POA, or by ambient primary gases (NO_2, NO_x and CO) (not shown).

Two-pollutant models of POA and SOA variables did not change the null associations of SOA with asthma morbidity or the positive associations of POA with asthma in the cool season (not shown). Similarly, two-pollutant models of POA and SOA variables did not change the null associations of both SOA and POA with asthma morbidity in the warm season (not shown).

3.3 Discussion

We found that emergency department visits and hospital admissions for asthma were positively associated with ambient air pollution data, including $PM_{2.5}$ and O_3 in the warm season and $PM_{2.5}$, CO, NO_2, and NO_x in the cool season. This is consistent with many previous epidemiologic time-series and case-crossover studies. To our knowledge, this is the first study to show that associations of daily ambient air pollution with asthma hospital morbidity are stronger among subjects living at residences with higher predicted levels of air pollution from traffic sources. We expected amplification in TRAP exposures during days with higher ambient air pollutant concentrations especially during cooler periods with lower mixing heights and air stagnation (Kim et al. 2002; Zhu et al. 2004). Traffic-related particulate matter exposures can be more pro-oxidant per unit mass than background ambient particulate matter exposures (Ntziachristos et al. 2007). This would lead to greater airway oxidative stress and inflammation (one hallmark of the asthma phenotype). All in all, our findings support our view that exposure error from the use of ambient air pollution data may be diminished using the present approach analyzing interaction between long-term spatial exposure and short-term ambient air pollution exposure. It is also possible that findings of effect modification were observed because subjects who lived near traffic had greater levels of chronic airway inflammation as a result of their persistently elevated exposures and were thus more vulnerable to short-term increases in ambient background air pollution. The strongest associations with confidence limits most often not including 0 were for 5-day and 7-day average air pollutant concentrations, likely the result of cumulative effects.

Effect modification by residential traffic-related air pollution was observed for the air pollutant gases representing pollutants from primary combustion sources (CO, NO_2, and NO_x). $PM_{2.5}$ on the other hand, represents both primary and secondary chemical constituents (from photochemical processes). It is possible that the effect modification by residential traffic-related air pollution observed for ambient $PM_{2.5}$ was from increases in primary traffic-related PM, with photochemically-generated components important as well during warmer periods (Figure 2, $PM_{2.5}$). Although the expectation was that dispersion-modeled particle number should have best represented this, dispersion-modeled $PM_{2.5}$ showed similar or stronger effect modification.

Overall, differences using land-use regression-modeled NO_x data were far less clear than traffic-related air pollution estimated by dispersion models within close proximity of subject residences (500 m). This finding is consistent with the wider 95% confidence intervals for dispersion-modeled data based on a larger 1500 m buffer. In regression models of LUR NO_x predicting CALINE4 NO_x dispersion-modeled NO_x at 500 and 1500m were not correlated with land-use regression-modeled NO_x (R^2 = 0.01 and 0.02, respectively) supporting the view that in our study region they represent different exposures (local traffic only vs. all sources, respectively). It is likely that causal pollutant components are enriched near roadways. Previous findings indicate that particle number and CO concentrations decrease in an exponential fashion by downwind distance from freeways and reach near-background levels at 200 m during daytime hours (10:00–18:00) (Zhu et al. 2002), and up to 2000 m during the pre-sunrise hours (04:00–07:30) (Hu et al. 2009). An exponential decay of NO_x is also observed that reaches near-background levels at around 500 m from a freeway (Rodes et al. 1981). Therefore, a 500 m cut-point for dispersion-modeled data likely captures the majority of primary pollutants from traffic sources near subject residences.

Ozone is an identified trigger of asthma (Trasande and Thurston, 2005). Interestingly, we found associations of asthma with ambient O_3 in warm seasons were nominally stronger among subjects with lower dispersion-modeled pollutant exposures (≤median). A possible explanation is that subjects in high traffic areas were less exposed to O_3 than subjects in low traffic areas because of the well-known reduction of O_3 by traffic-generated NO (Rodes et al. 1981). This again supports the view that exposure error is diminished with the present approach combining both spatial and temporal data.

We are aware of only one other case-crossover study that has evaluated both population-based asthma morbidity events and air pollution on a residential spatial scale (Laurent et al. 2008). This study in France examined telephone calls to an emergency medical system for asthma exacerbations. Air pollutants were modeled for census blocks using deterministic models including emission inventories, meteorology and background pollutant levels. Nominally positive associations with asthma exacerbations were found for spatially-resolved PM_{10}, NO_2 and sulfur dioxide.

In analyses of weekly exposures to CALINE4 residential TRAP exposure we found all warm season models showed parameter estimates that were negative but nonsignificant and all cold season models showed parameter estimates that were positive and significant. This is consistent with both the ambient markers of primary emission sources (NO_x and CO) as well as the UCD/CIT POA variables. The CALINE4 $PM_{2.5}$ variable was not associated with asthma encounters in the summer whereas ambient $PM_{2.5}$ was. This suggests that local traffic emission sources of $PM_{2.5}$ may not fully explain the summertime effect of $PM_{2.5}$ on asthma observed in other studies, including recent hospital time series analyses (Silverman et al. 2010; Strickland et al. 2010).

In analyses of weekly exposures to UCD/CIT local exposure to SOA and POA we found no associations in the warm season but positive associations of POA with asthma only in the cool season. This is consistent with findings for ambient NO_x and CO and with CALINE4 data. This includes associations with nearly all POA sources including on-road and off-road fossil fuel combustion, high sulfur content fuel combustion and other anthropogenic sources, likely due to high correlation from common meteorological determinants. Therefore, it is not possible to attribute more or less of an effect to one source versus another. Magnitudes of association were also similar with between 12-25% increases in risk of hospital encounters for interquartile range increases in PM. The weakest but still significant POA source was woodsmoke, at around 4% increase in risk of hospital encounters for interquartile range increases in $PM_{2.5}$ and PM_{10} woodsmoke ($PM_{0.1}$ woodsmoke was not associated with asthma). These associations were observed across all particle sizes with ultrafine particles showing somewhat stronger associations as expected, although confidence intervals overlapped considerably for the various particle sizes. Unexpectedly, positive associations for meat cooking POA were of similar magnitude to other sources, again possibly due to the influence of meteorology.

Analyses revealed that neither the SOA nor POA UCD/CIT variables explain the association of asthma encounters with ambient $PM_{2.5}$ in the warm season. Nevertheless, exposure to PM from primary emission sources may have less of an impact on asthma risk than exposure to secondary sources in the warm seasons, although the reasons are unclear.

It is conceivable that the effect of traffic-generated NO on photochemical oxidants like the reduction of O_3 in the warm season is also influencing relations with the exposure variables that reflect SOA sources. Thus, the effect of pro-inflammatory oxidants would be diminished in locations where primary combustion sources are the highest. Supporting this speculation we found evidence that the negative regression parameters for SOA in the warm season were somewhat dominated by subjects living where CALINE4 $PM_{2.5}$ and UFP were higher, although differences were largely nonsignificant. None of this explains the overall lack of association with SOA.

Results of the multipollutant models suggest that effects of ambient O_3 and $PM_{2.5}$ are somewhat independent of each other since both confound each other to similar small degrees in two-pollutant models, which still show significant or nearly significant associations for both pollutants. These results are consistent with recent findings of a large hospital time

series study of asthma during the warm seasons in New York that found very robust and persistent associations for the two pollutants when regressed together (Silverman and Ito, 2010). Our findings were also similar to another hospital time series studies of asthma in Atlanta although in that study both O_3 and $PM_{2.5}$ notably confounded each other and they had considerably widened confidence intervals in two-pollutant as opposed to single-pollutant models (Strickland et al. 2010). As discussed, the association of asthma morbidity with ambient $PM_{2.5}$ in the warm season could be due to a combination of primary and secondary particle components. However, 7-day average ambient $PM_{2.5}$ in the warm season was not negatively confounded by 7-day average exposure to CALINE4 $PM_{2.5}$, NO_x and CO, or by UCD/CIT SOA and POA. Instead, warm season NO_2, NO_x and CO positively confounded in that the association actually became stronger while the parameter estimates for these gases became more negative. However, associations with cool-season ambient $PM_{2.5}$ may have been partly due to primary air pollutants since it was negatively confounded by UCD/CIT POA, CALINE4 TRAP and the primary gases. The warm season association of asthma with ambient O_3 was not confounded by CALINE4 TRAP or UCD/CIT SOA and POA.

Limitations of the present study include the use of long-term average estimates of traffic-related air pollution (6-months) from dispersion and land-use regression models with inputs having low temporal resolution. Nevertheless, the main objective was to estimate asthma risk from daily ambient air pollution by relative spatial variability in traffic-related air pollution exposure. In addition, chronic traffic-related air pollution exposure may increase susceptibility in some fundamental way, including chronic effects on airway caliber Gauderman et al. 2007). A further limitation is that we have no direct information on the causal air pollutant constituents represented by the dispersion-modeled data. Future research is needed to address this uncertainty in pollutant variables that are likely acting as surrogates for causal components (Brauer 2010). This is reflected in an expected similar pattern of association across strata of different dispersion-modeled pollutants given their common sources and predictive inputs. Nevertheless, we did find nominal differences in traffic-related air pollution exposure classification because 79% and 77% of the subjects in the upper median of dispersion-modeled NO_x were in the upper median dispersion-modeled $PM_{2.5}$ and particle number, respectively, while 86% of the subjects in the upper median of dispersion-modeled particle number were in the upper median dispersion-modeled $PM_{2.5}$. Additional exposure error is expected since subjects spend time at unavailable non-residential locations including school. Finally, only one station was available for $PM_{2.5}$ vs. four for gases (see online supplement for sensitivity analyses).

3.4 Summary and Conclusions

We found consistent results that acute asthma morbidity is increased in relation to short-term (1 to 7 days) elevations in various indicators of air pollution from fossil fuel combustion sources (including traffic), particularly during the cool seasons. This consistency was seen for ambient gases (CO and NO_x), CALINE4 weekly TRAP indicators, and UCD/CIT total POA as well as most POA sources, including on-road and off-road diesel plus gasoline emission sources, high sulfur content fuel combustion and other anthropogenic sources. Magnitudes of association were also similarly large for most POA sources with between 12-25% increases in risk of hospital encounters for interquartile range increases in PM. This may be due to high correlations between sources resulting from the influence of common meteorological predictors. The weakest but still significant POA source was woodsmoke, at around 4% increase in risk of hospital encounters for interquartile range increases in $PM_{2.5}$ and PM_{10} woodsmoke in the cool season. These associations were observed across all particle sizes with ultrafine particles showing somewhat stronger associations as expected, although confidence intervals overlapped considerably for the various particle sizes. Unexpectedly, positive associations for meat cooking POA were of similar magnitude to other sources. However, due to the high correlation from common meteorological determinants, it is not possible to attribute more or less of an effect to one source versus another from the UCD/CIT modeled data.

The analytic results of the importance of the spatial variation in residential TRAP imply that associations of asthma hospital morbidity with ambient CO, NO_2, NO_x, and $PM_{2.5}$, particularly during the colder seasons, are enhanced among subjects living in areas with high traffic-related air pollution near the home (≤500 m), including ultrafine and fine particles. This suggests that associations reported in the time-series literature may underestimate effects of ambient air pollutants on asthma morbidity for pediatric populations so exposed as a result of acutely-increased vulnerability or chronically-increased susceptibility. Previous work has shown that during cooler periods of air stagnation, particle size distribution drifts toward higher levels of ultrafine particles (Zhu et al. 2004), and toward higher concentrations of polycyclic aromatic hydrocarbons that are not reflected by particle mass concentrations (Delfino et al. 2010). This could have greater effects per unit particle mass on asthma (Knol et al. 2009). A possible limitation to the finding of stronger cool season versis warm season associations is that seasonal differences in asthma determinants such as infectious diseases in the colder months could have affected the magnitudes of association. Findings in the present study further point to the need for research that assesses the importance of air pollutant chemistry and sources in asthma exacerbations (Brauer 2010). In addition to on-road and off-road This includes other sources of air pollution that are likely to be important to asthma morbidity as evidenced by associations with wood smoke in the cool season and other anthropogenic sources throughout the year.

References

Brauer M. 2010. How much, how long, what, and where: air pollution exposure assessment for epidemiologic studies of respiratory disease. Proc Am Thorac Soc 7:111-115.

Chang J, Delfino RJ, Gillen D, Tjoa T, Nickerson B, Cooper D. 2009. Repeated respiratory hospital encounters among children with asthma and residential proximity to traffic. Occup Environ Med 66;90-98.

Delfino RJ, Chang J, Wu J, Ren C, Tjoa T, Nickerson B, Cooper D, Gillen DL. 2009a. Repeated hospital encounters for asthma in children and exposure to traffic-related air pollution near the home. Ann Allergy Asthma Immunol 102:138-144.

Delfino RJ, Staimer N, Tjoa T, et al. 2010. Association of biomarkers of systemic effects with organic components and source tracers in quasi-ultrafine particles. Environ Health Perspect 118:756-762.

Delfino RJ, Staimer N, Tjoa T, Gillen D, Polidori A, Arhami M, Kleinman MT, Vaziri N, Longhurst J, Sioutas C. 2009b. Air pollution exposures and circulating biomarkers of effect in a susceptible population: clues to potential causal component mixtures and mechanisms. Environ Health Perspect 117:1232–1238.

Gauderman WJ, Avol E, Lurmann F, Kuenzli N, Gilliland F, Peters J, McConnell R. Childhood asthma and exposure to traffic and nitrogen dioxide. Epidemiology 2005;16:737-43.

Gauderman WJ, Vora H, McConnell R, et al. 2007. Effect of exposure to traffic on lung development from 10 to 18 years of age: a cohort study. Lancet 369:571-577.

Gidhagen, L., Johansson, C., Langner, J., Olivares, G. 2004(a). Simulation of NOx and ultrafine particles in a street canyon in Stockholm, Sweden. Atmospheric Environment, 38:2029-2044.

Gidhagen, L., Johansson, C., Omstedt, G., Langner, J., Olivares, G. 2004(b). Model simulations of NOx and ultrafine particles close to a Swedish highway. Environmental Science & Technology, 38:6730-6740.

Gramotnev, G., Brown, R., Ristovski, Z., Hitchins, J., Morawska, L. 2003. Determination of average emission factors for vehicles on a busy road. Atmospheric Environment 37:465-474.

Gramotnev, G., Ristovski, Z. 2004. Experimental investigation of ultrafine particle size distribution near a busy road. Atmospheric Environment 38:1767-1776.

Gunier RB, Hertz A, Von Behren J, Reynolds P. 2003. Traffic density in California: socioeconomic and ethnic differences among potentially exposed children. J Expo Anal Environ Epidemiol 13:240-246.
Hu SS, Fruin S, Kozawa K, Mara S, Paulson SE, Winer AM. 2009. A wide area of air pollutant impact downwind of a freeway during pre-sunrise hours. Atmos Environ 43:2541-2549.
Imhof, D., Weingartner, E., Ordonez, C., Gehrig, R., Hill, M., Buchmann, B., Baltensperger, U. 2005. Real- world emission factors of fine and ultrafine aerosol particles for different traffic situations in Switzerland. Environmental Science & Technology 39:8341-8350.
Imhof, D., Weingartner, E., Prevot, A. S. H., Ordonez, C., Kurtenbach, R., Wiesen, P., Rodler, J., Sturm, P., McCrae, I., Ekstrom, M., Baltensperger, U. 2006. Aerosol and NOx emission factors and submicron particle number size distributions in two road tunnels with different traffic regimes. Atmospheric Chemistry and Physics 6:2215-2230.
Ito K, Thurston GD, Silverman RA. 2007. Characterization of PM2.5, gaseous pollutants, and meteorological interactions in the context of time-series health effects models. J Expo Sci Environ Epidemio; 17(Suppl 2):S45-60.
Janes H, Sheppard L, Lumley T. 2005a. Case-crossover analyses of air pollution exposure data: referent selection strategies and their implications for bias. Epidemiology 16:717-726.
Janes H, Sheppard L, Lumley T. 2005b. Overlap bias in the case-crossover design, with application to air pollution exposures. Stat Med 24:285-300.
Jerrett M, Arain A, Kanaroglou P, et al. 2005. A review and evaluation of intraurban air pollution exposure models. J Expo Anal Environ Epidemiol. 15:185-204.
Ketzel, M., Wlhlin, P., Berkowicz, R., Palmgren, Finn. 2003. Particle and trace gas emissions factors under urban driving conditions in Copenhagen based on street and roof-level observations. Atmospheric Environment 37:2735-2749.
Kim S, Shen S, Zhu Y, Hinds WC, Sioutas C. 2002. Size distribution, diurnal and seasonal trends of ultrafine particles in source and receptor sites of the Los Angeles Basin. J Air Waste Manag Assoc 52:297-307.
Kittelson, D. B., Watts, W. F., Johnson, J. P. 2004. Nanoparticle emissions on Minnesota highways. Atmospheric Environment 38:9-19.
Knol AB, de Hartog JJ, Boogaard H, et al. 2009. Expert elicitation on ultrafine particles: likelihood of health effects and causal pathways. Part Fibre Toxicol 6:19.
Künzli N, Schindler C. 2005. A call for reporting the relevant exposure term in air pollution case-crossover studies. J Epidemiol Community Health 59:527-530.
Largent J, Nickerson B, Cooper D, Delfino RJ. 2012. Paediatric asthma hospital utilization varies by demographic factors and area socioeconomic status. Public Health 126:928-936.
Laurent O, Pedrono G, Segala C, et al. 2008. Air pollution, asthma attacks, and socioeconomic deprivation: a small-area case-crossover study. Am J Epidemiol 168:58-65.
Li L, Wu J, Wilhelm M, Ritz B. 2012. Use of generalized additive models and cokriging of spatial residuals to improve land-use regression estimates of nitrogen oxides in Southern California. Atmospheric Environment 55:220-228.
Lin DY, Wei LJ. 1989. The robust inference for the Cox proportional hazards model. J Am Stat Assoc 84:1074- 1078.
Morawska, L., Jamriska, M., Thomas, S., Ferreira, L., Mengersen, K., Wraith, D., Mcgregor, F. 2005. Quantification of particle number emission factors for motor vehicles from on-road measurement. Environmental Science & Technology 39:9130-9139.
Navidi W, Weinhandl E. 2002. Risk set sampling for case-crossover designs. Epidemiology 13:100-105.
Ntziachristos L, Froines JR, Cho AK, Sioutas C. 2007. Relationship between redox activity and chemical speciation of size-fractionated particulate matter. Part Fibre Toxicol 4:5.
Rodes CE, Holland DM. 1981. Variations of NO, NO2 and O3 concentrations downwind of a Los Angeles freeway. Atmos Environ 15:243-250.

Schwartz J, Zanobetti A, Bateson T. 2003. Morbidity and mortality among elderly residents in cities with daily PM measurements. In: Revised analyses of time series studies of air pollution and health. Special report. Boston, MA: Health Effect Institute pp. 25-46.
Silverman RA, Ito K. 2010. Age-related association of fine particles and ozone with severe acute asthma in New York City. J Allergy Clin Immunol. 125:367-373.e5.
Strickland MJ, Darrow LA, Klein M, Flanders WD, Sarnat JA, Waller LA, Sarnat SE, Mulholland JA, Tolbert PE. 2010. Short-term associations between ambient air pollutants and pediatric asthma emergency department visits. Am J Respir Crit Care Med. 182:307-16.
Trasande L, Thurston GD. 2005. The role of air pollution in asthma and other pediatric morbidities. J Allergy Clin Immunol 115:689-699.
Wu J, Houston D, Lurmann F, Ong P, Winer A. 2009. Exposure of PM2.5 and EC from diesel and gasoline vehicles in communities near the Ports of Los Angeles and Long Beach, California. Atmos Environ 43:1962–1971.
Yuan Y, Zhu Y, Wu J. Vehicular emitted ultrafine particle concentration and exposure spatial profile in Corpus Christi, Texas. Chemical Product and Process Modeling. 2011; 6: Article 8.
Zhu Y, Hinds WC, Kim S, Shen S, Sioutas C. 2002. Study of ultrafine particles near a major highway with heavy-duty diesel traffic. Atmos Environ 36:4323-4335.
Zhu Y, Hinds WC, Kim S, Shen S, Sioutas C. 2004. Seasonal trends of concentration and size distributions of ultrafine particles near major high in Los Angeles. Aerosol Science and Technology 38(Suppl 1):5-13.
Zhu Y, Hinds WC. 2005. Predicting particle number concentrations near a highway based on vertical concentration profile. Atmospheric Environment, 39, 1557-1556.

4. CHAPTER FOUR: TASK 3

Task 3. To stratify subjects based on recurrence of hospital encounters in order to assess whether children with multiple encounters show the strongest associations with air pollutants.

4.0 Introduction

To our knowledge only one study (our own) has related the risk of recurrent asthma hospitalization and emergency department visits with estimates of traffic-related air pollutants near the home (Delfino et al. 2009). In Delfino et al. (2009), we found significantly increased risk of repeated episodes of asthma requiring hospital care with higher chronic exposures to residential traffic-related air pollution (CALINE4 NO_2, NO_x and CO). In Task 3, we will revisit this finding in a different manner by evaluating whether case-crossover associations are stronger for subjects with multiple hospital encounters, which may be considered an indicator of greater asthma severity. This will enable the assessment of susceptibility due to asthma severity as indicated by recurrent hospital encounters (one encounter vs. >1 encounter). To our knowledge, this indicator of severity has not been assessed in previous case-crossover studies of asthma and air pollution. This is an important topic because decreasing repeated utilization of hospital resources through improvements in local air quality will improve public health and preserve health care resources.

4.1 Materials and Methods

To reduce the likelihood of hospital usage outside of the study hospitals, for Task 3 subjects were selected from a 15-km catchment area (83% of the population) around the two children's hospitals that are the source of subjects in the study. The study population of recurrent hospital encounters for the preliminary study described above for the period of 2000-2003 (Chang 2009; Delfino 2009) was determined from mapping all records and finding a high density of patients coming to CHOC and UCIMC from an approximate 15-km radius hospital catchment area. This catchment area was used again for the proposed study in Task 3. We included all subjects in the new dataset described under Task 2 who live within ~13.5 km of either of the two hospitals. This results in a total ~15 km radius since the hospitals are around 3 km apart. This includes the cities of Santa Ana, Anaheim, Garden Grove, Westminster, Fullerton, Orange, Placentia, Yorba Linda, and Tustin, among others. Out of the 7,492 total subjects, there were 6600 subjects (88.1%) within 13,500 meters (8.4 miles) of UCIMC or CHOC hospitals, including 4823 subjects with only one visit and 1777 subjects with two or more visits. There were 4847 visits among the subjects with 2 or more hospital encounters vs. 4823 visits among the subjects with only one encounter. Effect modification by whether a subject had a recurrence vs. no recurrence was tested in stratified models by these subject groups with the heterogeneity in odds ratios assessed by means of a two-sided Chi-square test.

The case-crossover analysis tested here included the modeling of recurrent versus non-recurrent encounters to generate a stratified estimation of the risk of asthma encounter for air pollution exposure. This can yield clues to possible differences in risk by an assessment of susceptibility due to asthma severity as indicated by recurrent hospital encounters (one encounter vs. >1). Due to limited sample size we did not conduct an analysis of dose-response using an ordinal recurrence variable. Results of Task 3 may be concordant with our findings for increased long-term risk of recurrent hospital encounters from seasonally averaged traffic-related air pollution exposures (Delfino 2009).

Analyses were conducted as described for Task 2, but with the addition of product terms between the air pollutant and the whether the subject was seen once or more than once as either an ED visit or hospitalization. In other words, this analysis included all subjects and all hospital encounters. We assumed that product term *p*-values <0.1 indicate potential effect modification. We assess statistical power for Task 3 below under Task 4.

We do not have access to individual level data such as medication use, indoor allergen exposure, psychosocial factors, among numerous other factors that could be related to asthma severity. This results in a lack of explanatory data that may explain differences in association by severity levels. It is also conceivable that some seasonal trend in individual factors might be related to severity and air pollution and thus confound. However, the case-cross-over analysis controls for confounding by individual factors since each subject is his or her own control and the referent exposure period is from the same month as the index exposure period.

4.2 Results

Table 4.1 shows the results of analyses of differences in asthma and air pollution associations between subjects with versus without recurrent hospital encounters for asthma. There were few Chi-square *p*-values <0.1 largely due, as can be seen, to the wide confidence intervals. For the ambient air pollution exposures in the warm season that were significant in regression models for the overall population ($PM_{2.5}$ and O_3), there was little evidence of any difference in association by recurrence status. The association with 5-day and 7-day average $PM_{2.5}$ appeared larger among subjects with vs. without recurrent hospital encounters, but the difference was not significant ($p < 0.17$ and $p < 0.22$, respectively). For the exposures in the warm season that were not significant in the regression models for overall population (NO_2, NO_x and CO) there was little evidence of any difference by recurrence status. The association with 1-day and 3-day average NO_2 and CO appeared larger among subjects without vs. with recurrent hospital encounters, but the difference was only significant for 1-day average CO ($p < 0.02$). For the ambient air pollution exposures in the cool season that were significant in regression models for the overall population ($PM_{2.5}$, NO_2, NO_x and CO), there was no discernible difference in association between the groups.

Product term models for weekly average CALINE4 or UCD/CIT POA and SOA exposures in the warm season showed no group differences in association by recurrence status. Cool season models for these exposures suggested nominally (not $p < 0.1$) stronger associations for the CALINE4 and UCDCIT $PM_{2.5}$ POA exposures among subjects with recurrent hospital encounters.

Table 4.1. Associations between pediatric asthma hospital encounters and ambient air pollution: effect modification by recurrence of encounters.

Ambient Air Pollutant	Lag-Day Average	Warm Season Odds Ratio (95% CI)[a]			Cool Season Odds Ratio (95% CI)		
		Repeated Encounters (N=2158)	No Repeated Encounters (N=2120)	Chi-square p-value[b]	Repeated Encounters (N=2689)	No Repeated Encounters (N=2703)	Chi-square p-value
$PM_{2.5}$ 24-hr average	1-day	1.08 (0.99, 1.17)	1.07 (0.99, 1.16)	0.936	1.04 (0.99 1.09)	1.03 (0.98, 1.08)	0.836
	3-day	1.10 (1.00, 1.21)	1.06 (0.98, 1.14)	0.558	1.03 (0.98 1.09)	1.04 (0.98, 1.10)	0.848
	5-day	1.14 (1.01, 1.28)	1.02 (0.92, 1.13)	0.161	1.07 (1.00 1.14)	1.06 (0.99, 1.14)	0.945
	7-day	1.14 (0.99, 1.30)	1.01 (0.90, 1.14)	0.212	1.10 (1.03 1.19)	1.10 (1.01, 1.19)	0.885
O_3 24-hr average	1-day	1.15 (0.98, 1.36)	1.11 (0.96, 1.29)	0.734	0.81 (0.70 0.94)	0.95 (0.82, 1.09)	0.140
	3-day	1.24 (1.01, 1.51)	1.22 (1.01, 1.46)	0.905	0.68 (0.57 0.82)	0.92 (0.77, 1.10)	0.023
	5-day	1.33 (1.06, 1.68)	1.22 (0.99, 1.51)	0.581	0.60 (0.48 0.74)	0.76 (0.62, 0.94)	0.116
	7-day	1.35 (1.03, 1.75)	1.32 (1.04, 1.68)	0.930	0.57 (0.45 0.72)	0.71 (0.56, 0.90)	0.191
NO_2 24-hr average	1-day	0.86 (0.72, 1.01)	1.13 (0.96, 1.33)	0.019	1.04 (0.95 1.15)	1.02 (0.93, 1.13)	0.759
	3-day	1.00 (0.81, 1.25)	1.13 (0.92, 1.39)	0.442	1.12 (0.99 1.26)	1.07 (0.94, 1.21)	0.622
	5-day	1.02 (0.78, 1.32)	1.07 (0.83, 1.38)	0.786	1.22 (1.06 1.40)	1.24 (1.06, 1.44)	0.893
	7-day	1.06 (0.79, 1.43)	1.03 (0.78, 1.37)	0.878	1.29 (1.10 1.52)	1.32 (1.11, 1.57)	0.855
NO_x 24-hr average	1-day	0.90 (0.73, 1.10)	1.02 (0.84, 1.23)	0.379	1.00 (0.94, 1.06)	1.01 (0.94, 1.08)	0.814
	3-day	1.10 (0.84, 1.44)	1.04 (0.80, 1.36)	0.790	1.06 (0.98, 1.15)	1.03 (0.95, 1.12)	0.678
	5-day	1.04 (0.76, 1.44)	0.93 (0.68, 1.28)	0.626	1.13 (1.03, 1.25)	1.09 (0.98, 1.20)	0.562
	7-day	1.01 (0.70, 1.46)	0.83 (0.58, 1.19)	0.452	1.18 (1.06, 1.32)	1.10 (0.98, 1.23)	0.381
CO 24-hr average	1-day	0.90 (0.76, 1.06)	1.20 (1.03, 1.41)	0.012	0.97 (0.92 1.03)	1.03 (0.96, 1.10)	0.230
	3-day	0.98 (0.79, 1.21)	1.22 (0.99, 1.49)	0.157	1.02 (0.95 1.09)	1.07 (0.99, 1.16)	0.338
	5-day	0.91 (0.71, 1.17)	1.12 (0.88, 1.42)	0.255	1.04 (0.96 1.14)	1.13 (1.03, 1.24)	0.225
	7-day	0.90 (0.69, 1.19)	1.00 (0.77, 1.31)	0.598	1.08 (0.98 1.18)	1.13 (1.03, 1.25)	0.453
CALINE4 $PM_{2.5}$ 1500m	7-day	0.70 (0.49, 1.01)	0.99 (0.73, 1.33)	0.153	1.25 (1.05, 1.47)	1.08 (0.91, 1.28)	0.246
CALINE4 NO_x 1500m	7-day	0.76 (0.55, 1.07)	0.96 (0.71, 1.29)	0.320	1.22 (1.03, 1.44)	1.07 (0.90, 1.27)	0.302
CALINE4 PN 1500m	7-day	0.78 (0.62, 0.98)	0.88 (0.72, 1.07)	0.433	1.18 (1.04, 1.32)	1.03 (0.92, 1.15)	0.106
UCD/CIT $PM_{2.5}$ SOA	7-day	1.00 (0.87, 1.14)	0.91 (0.79, 1.04)	0.336	0.82 (0.64, 1.06)	0.87 (0.67, 1.14)	0.730
UCDCIT $PM_{2.5}$ POA	7-day	1.09 (0.86, 1.39)	0.94 (0.75, 1.18)	0.376	1.20 (1.08, 1.34)	1.11 (1.00, 1.23)	0.295

[a] Percent change in risk of hospital encounters and 95% confidence intervals (CI) are for interquartile range increases from the annual distribution of concentrations of air pollutants as shown in Tables 3.2, 3.5 and 3.6. Estimates are adjusted for temperature and relative humidity of the same averaging time.

[b] The heterogeneity of odds ratios between groups was assessed by means of a two-sided Chi-square test.

4.3 Discussion

There was a modest trend in somewhat stronger association among subject with recurrent encounters (warm season $PM_{2.5}$, cool season CALINE4 and UCD/CIT $PM_{2.5}$ POA exposures). The association in the cool season for POA is consistent with the overall associations presented in Task 2 above. Nevertheless, very few models showed significant differences in association between subjects with vs. without recurrence in hospital encounters for asthma. This is likely due to wide 95% confidence limits that indicated a lack of precision for estimating these highly stratified association estimates. Also, although asthma associations with the traffic-related CALINE4 and UCD/CIT $PM_{2.5}$ POA appeared stronger in the recurrent group, this was not case for criteria pollutant gases that are considered markers of primary sources (NO_2, NO_x and CO). As discussed, in our previous analyses we found significantly increased risk of repeated episodes of asthma requiring hospital care with higher chronic exposures to residential CALINE4 NO_2, NO_x and CO (Delfino et al., 2009). Although this suggests that subjects with recurrent hospital encounters would be at increased risk of acute exposures, we found limited evidence for this in the present analysis.

4.4 Summary and Conclusions

We conclude that there is limited evidence for a difference in association between asthma encounters and air pollutant exposures in subjects with vs. without recurrence of hospital encounters. Some regression models did suggest increased risk among the population with repeated visits to hospital presumably by virtue of their more severe asthma. To further test this possibility, a larger sample size would be required.

References

Chang J, Delfino RJ, Gillen D, Tjoa T, Nickerson B, Cooper D. 2009. Repeated respiratory hospital encounters among children with asthma and residential proximity to traffic. Occup Environ Med 66;90-98.

Delfino RJ, Chang J, Wu J, Ren C, Tjoa T, Nickerson B, Cooper D, Gillen DL. 2009a. Repeated hospital encounters for asthma in children and exposure to traffic-related air pollution near the home. Ann Allergy Asthma Immunol 102:138-144.

1. CHAPTER FIVE: TASK 4

Task 4. To assess effect modification of associations by subject demographic and socioeconomic characteristics.

5.0 Introduction

This task focused on differences in association by race-ethnicity, sex, pediatric age group, and subject and local demographic factors. We hypothesize that associations observed in Task 2 will be strongest among subjects without health insurance or with government-sponsored insurance and among those living in Census block groups with lower SES. These factors are expected to increase risk as a result to more limited access to health care, environmental factors and psychosocial stressors in poorer communities (Chen et al. 2008; Clougherty et al. 2007, 2009). Racial-ethnic differences in association that we tested may be in part due to these differences in SES. However, although fixed subject characteristics cannot confound associations of hospital morbidity with air pollution in case-crossover models, it is possible that residential dispersion-modeled strata could function as a surrogate of demographic differences that vary with traffic. This is possible since poorer and minority children are more likely to live near higher density traffic (Gunier et al. 2003), and in the present study population, are more likely to lack private health insurance (Largent et al. 2012). Therefore, to test both the possibility if interaction and confounding we conducted a secondary analysis to assess the influence of race-ethnicity or health insurance status on differences in association by traffic-related air pollution strata. In these models, effect modification by dispersion-modeled exposures was estimated within race-ethnicity and insurance strata using multiplicative interaction models.

Sex differences are also important to evaluate because of differences in the age-dependent prevalence of asthma and phenotypic and possibly etiologic differences in asthma (Becklake and Kauffmann 1999). We are also interested in whether younger children are at greater risk.

5.1 Materials and Methods

First, we conducted unconditional logistic regression analyses of risk for being in the upper half of CALINE4 exposures among different racial-ethnic groups and health insurance types. Then, we conducted analyses of interactions between subject characteristics and air pollutants as described for Task 2 using conditional logistic regression model executed in SAS 9.2 procedure PHREG. In this analysis, we added product terms between the air pollutant and the potential effect modifier. Individual-level data was used to test for effect modification by race-ethnicity and health insurance status (categorized as private insurance vs. government or self-pay). Because of sample size limitation and the desire to compare private insurance to all other forms of insurance as a surrogate of SES, we combined Cal-Optima, Medi-Cal, county funded insurance, other government, indigent, and self-pay. We also used census-derived SES variables to create an overall Census block group SES index using the method of Yost et al. (2001). The “Yost index” or “score” was developed for California and derived from a principal components analysis from seven Census SES variables (education index, median household income, percent living 200% below poverty level, percent blue-collar workers, percent ages >16 years in workforce without job, median rent, and median house value). The Yost score thus synthesizes information about three domains of SES, namely, education, income and occupation, and region-specific cost of living. It was categorized for analysis.

We also tested stratified regression models by age group and sex. Age groups included 0-11, and ≥12 years, which are age groups with differences in the approach to treatments as outlined by the National Heart, Lung, and Blood Institute expert panel guidelines (NHLBI 2007). We used a chi-square test of heterogeneity to assess differences in associations by age group and sex.

To investigate whether the spatial estimates of traffic-related air pollution exposure (6-month average CALINE4) serves as a surrogate for race-ethnicity and/or insurance status we considered effect modification of associations of hospital morbidity with daily ambient air pollution by spatial differences in dispersion-modeled exposure (Task 2) within race-ethnicity and insurance strata using models with 3-way interaction terms for these potential surrogates in the conditional logistic regression model. Stratified results for CALINE4 residential traffic-related air pollutant exposures by demographic factors were derived from these product term models of the ambient air pollutant by CALINE4 pollutant by the demographic factor (race-ethnicity or insurance):

$$\text{logit}(p) = \log(p/(1-p)) = \beta 0 + \beta 1*(x1) + \beta 2*(x1)*(x2) + \beta 3*(x1)*(x3) + \beta 4*(x1)*(x2)*(x3),$$

where: p is the probability that the hospital morbidity event Y occurs, p(Y=1), p/(1-p) is the odds ratio, log(p/(1-p)) is the log odds ratio, or logit, β0 is the intercept, β1 is the regression coefficient for x1 (the ambient air pollutant), β2 is the regression coefficient for the interaction of x1 and x2 (the CALINE4 air pollutant binary classification), β3 is the regression coefficient for the interaction of x1 and x3 (the demographic classification of race-ethnicity or health insurance), and β4 is the regression coefficient for the 3-way interaction of x1, x2 and x3. Here the likelihood function from conditional logistic regression with matched case and referent periods is equivalent to the likelihood function of the Cox model with events and censored observations, respectively. Therefore, the hazard ratio from SAS Proc PHREG is equivalent to the odds ratio in conditional logistic regression.

5.2 Results

A substantial proportion of the children seen were Hispanic and had no private health insurance (Table 3.1, Chapter 3 above), and lived in Census block groups with low median household income (a quarter with < $36,671) and high poverty (a quarter with > 22.7% below the poverty level).

Unconditional logistic regression analyses of subject-level demographic factors showed that in both cool and warm seasons, Hispanic and African American subjects as well as subjects without private insurance were more likely to live in residences with higher dispersion-modeled traffic-related air pollution (Table 5.1).

The ratio of emergency department visits to hospital admissions was similar across racial-ethnic groups. It was 2.6 for both White non-Hispanics and Hispanics, 2.4 for African Americans, and 2.7 for Other/Unknown. The ratio was higher for subjects with government-sponsored health insurance or uninsured (3.0), than for those with private insurance (2.3).

In analyses examining effect modification of asthma-air pollution relations by subject characteristics we found that some associations with multiday-average ambient $PM_{2.5}$, NO_2, NO_x, and CO in the cool season were stronger among Hispanics compared with non-Hispanic whites; *p*-values for interaction reached $p < 0.1$ for NO_x and CO (Table 5.2). We further observed isolated stronger associations of asthma morbidity with ambient $PM_{2.5}$ in the warm season among subjects without vs. with private health insurance (Table 5.2). However, there were no other consistent differences by insurance in either season.

As discussed, we used the Yost score in an analysis testing effect modification by a neighborhood-level indicator of SES. Here, subjects with a low Yost score represents the lower half of SES (the presumed higher risk group) and subjects with a high Yost score represents the upper half (Table 5.2). We found associations of asthma with all averaging times for ambient $PM_{2.5}$ in the warm season were stronger among subjects living in neighborhoods with low Yost scores (*p*-values for interaction < 0.05). Odds ratios were also higher in the low Yost score group for warm-season NO_2 across averaging times, but none of the stratified models were significant even though two of 5 product terms for 1-day and 7-day average were significant ($p < 0.05$). Warm-season NO_x and CO were only consistent with this finding for 1-day averages. For cool season models, asthma was again more strongly associated with $PM_{2.5}$ in the low Yost score group, although product terms were less significant than in the warm season. However, there were no notable differences for the air pollutant gases.

Table 5.1. Odds ratio (OR) for being in the upper half of CALINE4 exposure among racial-ethnic groups and health insurance status.[a]

Subject Characteristic	Odds ratio for being in the upper half of CALINE4 exposure		
	CALINE4 NO_x OR (95% CI)	CALINE4 $PM_{2.5}$ OR (95% CI)	CALINE4 UFP OR (95% CI)
Race[b]		Cool Season	
White non-Hispanic	Reference level	Reference level	Reference level
White Hispanic	1.24 (1.12, 1.37)	1.60 (1.44, 1.78)	1.45 (1.30, 1.62)
African American	1.23 (0.94, 1.61)	1.50 (1.14, 1.97)	1.65 (1.26, 2.17)
Asian	0.71 (0.55, 0.92)	0.82 (0.64, 1.06)	0.81 (0.63, 1.04)
Other/Unknown	1.03 (0.84, 1.26)	1.13 (0.90, 1.41)	1.03 (0.82, 1.29)
Source of Payment			
Private Insurance	Reference level	Reference level	Reference level
Gov't Sponsored/Uninsured	1.21 (1.10, 1.32)	1.35 (1.23, 1.48)	1.34 (1.22, 1.47)
Unknown	1.71 (1.40, 2.10)	1.09 (0.87, 1.36)	1.15 (0.92, 1.44)
Race		Warm Season	
White non-Hispanic	Reference level	Reference level	Reference level
White Hispanic	1.26 (1.13, 1.39)	1.63 (1.47, 1.82)	1.52 (1.37, 1.69)
African American	1.22 (0.93, 1.60)	1.46 (1.11, 1.92)	1.53 (1.16, 2.02)
Asian	0.62 (0.48, 0.80)	0.80 (0.62, 1.03)	0.81 (0.64, 1.04)
Other/Unknown	1.17 (0.94, 1.45)	1.21 (0.97, 1.52)	1.17 (0.94, 1.46)
Source of Payment			
Private Insurance	Reference level	Reference level	Reference level
Gov't Sponsored/Uninsured	1.22 (1.12, 1.33)	1.37 (1.25, 1.50)	1.39 (1.26, 1.53)
Unknown	1.71 (1.35, 2.16)	1.11 (0.89, 1.39)	1.25 (1.01, 1.55)

[a] Subjects were seen in an emergency department and/or were admitted to hospital.
[b] This analysis was limited only to Hispanic ethnicity compared with white non-Hispanic because of the small sample size of other racial minorities (Table 3.1, Chapter 3).

In comparisons of age groups we found that warm-season associations tended to be stronger for subjects ages ≥12 years as compared with ages 0-11 years for $PM_{2.5}$, NO_2 and CO, but none of the product terms reached our a priori level of significance ($p < 0.1$) (Table 5.4). There were no differences for O_3. In cool-season models we again observed a consistent pattern for $PM_{2.5}$, NO_2 and CO, but in this case, associations with $PM_{2.5}$ were significantly stronger for subjects ages ≥12 years as compared with ages 0-11 years. None of the product terms for NO_2 or CO reached $p < 0.1$.

In analyses of effect modification by gender, warm season model suggested stronger associations in females for 5-day and 7-day average $PM_{2.5}$ and O_3, but product terms were not significant (Table 5.2). No other consistent differences were observed for the warm season. In cool-season models, associations for 1-day, 3-day and 5-day average NO_2, NO_x, and CO were stronger among females, but the product term was only significant at $p < 01$ for 1-day average NO_2.

Table 5.3 presents models evaluating effect modification of associations of hospital morbidity with daily ambient air pollution by spatial differences in dispersion-modeled exposure (Task 2) within race-ethnicity and insurance strata using models with 3-way interaction terms. The was no consistent evidence that effect modification of associations by cool or warm season TRAP differed between Hispanic plus African American subjects as compared with white non-Hispanic subjects. There was also little consistent difference in TRAP effect modification in cool or warm seasons for populations with vs. without private insurance. In most models 95% confidence limits were wide indicating a lack of precision for estimating these highly stratified association estimates.

Table 5.2.Associations between pediatric asthma hospital encounters and ambient air pollution: effect modification by subject demographic characteristics.

Ambient Air Pollutant	Lag-Day Average	Warm Season Odds Ratio (95% CI)[a]			Cool Season Odds Ratio (95% CI)		
		White non-Hispanic	Hispanic	*p*-value for interaction[b]	White non-Hispanic	Hispanic	*p*-value for interaction
$PM_{2.5}$	1-day	1.06 (0.99, 1.13)	1.06 (0.97, 1.17)	0.924	0.98 (0.90, 1.06)	1.04 (0.92, 1.17)	0.330
	2-day	1.07 (0.99, 1.16)	1.07 (0.95, 1.19)	0.956	1.00 (0.91, 1.10)	1.08 (0.94, 1.24)	0.267
	3-day	1.07 (0.99, 1.16)	1.08 (0.96, 1.20)	0.874	1.03 (0.94, 1.14)	1.09 (0.95, 1.25)	0.424
	5-day	1.10 (1.00, 1.21)	1.09 (0.95, 1.25)	0.917	1.07 (0.96, 1.20)	1.14 (0.97, 1.34)	0.481
	7-day	1.13 (1.01, 1.27)	1.05 (0.89, 1.23)	0.348	1.13 (0.99, 1.28)	1.24 (1.04, 1.49)	0.283
O_3	1-day	1.05 (0.92, 1.21)	1.09 (0.91, 1.31)	0.700	0.97 (0.84, 1.12)	0.98 (0.80, 1.19)	0.963
	2-day	1.16 (0.99, 1.35)	1.12 (0.91, 1.37)	0.731	1.01 (0.86, 1.19)	0.94 (0.76, 1.18)	0.526
	3-day	1.21 (1.03, 1.44)	1.13 (0.90, 1.42)	0.531	0.99 (0.83, 1.19)	0.91 (0.72, 1.17)	0.511
	5-day	1.21 (1.00, 1.46)	1.11 (0.86, 1.43)	0.506	0.94 (0.76, 1.15)	0.81 (0.61, 1.08)	0.320
	7-day	1.27 (1.03, 1.57)	1.11 (0.84, 1.47)	0.343	0.83 (0.66, 1.05)	0.79 (0.57, 1.10)	0.803
NO_2	1-day	1.12 (0.98, 1.29)	1.11 (0.93, 1.32)	0.901	0.97 (0.88, 1.07)	1.01 (0.88, 1.15)	0.615
	2-day	1.12 (0.96, 1.31)	1.12 (0.92, 1.37)	0.992	0.98 (0.88, 1.09)	1.03 (0.89, 1.20)	0.514
	3-day	1.10 (0.93, 1.31)	1.11 (0.89, 1.38)	0.980	0.98 (0.86, 1.10)	1.06 (0.90, 1.25)	0.327
	5-day	1.16 (0.95, 1.42)	1.17 (0.91, 1.52)	0.936	1.05 (0.91, 1.21)	1.19 (0.98, 1.45)	0.205
	7-day	1.09 (0.87, 1.35)	1.19 (0.89, 1.59)	0.545	1.12 (0.95, 1.32)	1.30 (1.04, 1.63)	0.204
NOx	1-day	1.05 (0.95,1.17)	1.10 (0.97, 1.24)	0.557	0.95 (0.87, 1.05)	1.04 (0.91, 1.20)	0.209
	2-day	1.06 (0.95,1.19)	1.10 (0.95, 1.27)	0.627	0.94 (0.84, 1.05)	1.07 (0.91, 1.25)	0.124
	3-day	1.09 (0.96,1.23)	1.08 (0.92, 1.26)	0.903	0.92 (0.82, 1.04)	1.12 (0.94, 1.33)	0.033
	5-day	1.08 (0.94,1.26)	1.07 (0.89, 1.30)	0.903	0.97 (0.84, 1.12)	1.24 (1.00, 1.53)	0.025
	7-day	0.99 (0.85,1.17)	1.06 (0.86, 1.32)	0.546	1.04 (0.88, 1.23)	1.31 (1.02, 1.67)	0.071
CO	1-day	1.09 (0.98, 1.21)	1.10 (0.95, 1.27)	0.909	0.94 (0.86, 1.04)	1.03 (0.88, 1.20)	0.268
	2-day	1.09 (0.96, 1.23)	1.11 (0.94, 1.31)	0.841	0.96 (0.86, 1.06)	1.06 (0.90, 1.26)	0.210
	3-day	1.09 (0.95, 1.25)	1.12 (0.93, 1.34)	0.800	0.95 (0.85, 1.07)	1.13 (0.93, 1.36)	0.077
	5-day	1.08 (0.92, 1.26)	1.13 (0.91, 1.40)	0.659	0.97 (0.85, 1.11)	1.26 (1.01, 1.58)	0.023
	7-day	1.00 (0.85, 1.18)	1.08 (0.85, 1.38)	0.525	1.02 (0.88, 1.19)	1.34 (1.04, 1.73)	0.040

Table 5.2 (cont.)

Ambient Air Pollutant	Lag-Day Average	Warm Season Odds Ratio (95% CI) Private Insurance	Warm Season Odds Ratio (95% CI) Uninsured or Gov't-sponsored	*p*-value for interaction	Cool Season Odds Ratio (95% CI) Insured	Cool Season Odds Ratio (95% CI) Uninsured or Gov't-sponsored	*p*-value for interaction
$PM_{2.5}$	1-day	1.01 (0.93,1.09)	1.06 (1.00, 1.12)	0.205	1.01 (0.92, 1.11)	1.02 (0.95, 1.08)	0.872
	2-day	1.00 (0.91,1.10)	1.09 (1.03, 1.16)	0.079	1.06 (0.95, 1.19)	1.05 (0.97, 1.13)	0.800
	3-day	0.99 (0.90,1.09)	1.09 (1.03, 1.16)	0.042	1.08 (0.97, 1.20)	1.04 (0.96, 1.12)	0.505
	5-day	0.97 (0.87,1.09)	1.13 (1.05, 1.21)	0.013	1.09 (0.96, 1.24)	1.11 (1.02, 1.21)	0.783
	7-day	0.97 (0.84,1.11)	1.14 (1.05, 1.25)	0.018	1.14 (0.99, 1.32)	1.18 (1.07, 1.31)	0.630
O_3	1-day	1.04 (0.88,1.22)	1.10 (1.00, 1.22)	0.457	0.86 (0.72, 1.02)	1.02 (0.92, 1.14)	0.046
	2-day	1.12 (0.93,1.34)	1.16 (1.04, 1.30)	0.675	0.82 (0.68, 1.00)	0.99 (0.88, 1.12)	0.067
	3-day	1.19 (0.98,1.46)	1.21 (1.07, 1.37)	0.880	0.79 (0.64, 0.99)	0.93 (0.82, 1.07)	0.145
	5-day	1.18 (0.94,1.48)	1.23 (1.06, 1.41)	0.755	0.74 (0.57, 0.96)	0.83 (0.71, 0.97)	0.401
	7-day	1.31 (1.02,1.69)	1.26 (1.07, 1.48)	0.749	0.71 (0.54, 0.95)	0.77 (0.64, 0.92)	0.607
NO_2	1-day	1.07 (0.92,1.24)	1.03 (0.93, 1.14)	0.639	1.07 (0.95, 1.20)	0.97 (0.90, 1.04)	0.081
	2-day	1.03 (0.87,1.22)	1.04 (0.92, 1.17)	0.898	1.11 (0.98, 1.26)	1.00 (0.92, 1.08)	0.096
	3-day	0.98 (0.81,1.18)	1.04 (0.91, 1.18)	0.529	1.11 (0.97, 1.28)	1.04 (0.95, 1.14)	0.329
	5-day	0.97 (0.78,1.21)	1.06 (0.91, 1.25)	0.429	1.16 (0.98, 1.36)	1.16 (1.04, 1.30)	0.935
	7-day	0.94 (0.74,1.20)	1.07 (0.89, 1.28)	0.310	1.21 (1.01, 1.46)	1.27 (1.11, 1.44)	0.637
NO_x	1-day	1.03 (0.92, 1.15)	1.01 (0.94, 1.09)	0.730	1.02 (0.90, 1.14)	0.97 (0.90, 1.05)	0.458
	2-day	1.02 (0.90, 1.15)	1.00 (0.92, 1.09)	0.808	1.06 (0.93, 1.21)	0.99 (0.91, 1.08)	0.284
	3-day	1.01 (0.88, 1.15)	0.99 (0.90, 1.09)	0.819	1.09 (0.95, 1.26)	1.02 (0.93, 1.12)	0.358
	5-day	1.02 (0.87, 1.20)	0.97 (0.86, 1.09)	0.510	1.13 (0.95, 1.35)	1.11 (0.98, 1.25)	0.796
	7-day	0.95 (0.79, 1.14)	0.92 (0.80, 1.05)	0.737	1.18 (0.96, 1.43)	1.19 (1.04, 1.36)	0.925
CO	1-day	1.04 (0.92,1.17)	1.04 (0.96, 1.13)	0.924	1.04 (0.93, 1.17)	0.95 (0.88, 1.03)	0.122
	2-day	1.03 (0.90,1.19)	1.04 (0.95, 1.15)	0.861	1.09 (0.95, 1.24)	0.98 (0.90, 1.07)	0.132
	3-day	1.01 (0.86,1.18)	1.04 (0.94, 1.15)	0.717	1.09 (0.95, 1.26)	1.02 (0.93, 1.12)	0.354
	5-day	1.00 (0.83,1.20)	1.02 (0.91, 1.16)	0.814	1.10 (0.93, 1.30)	1.09 (0.97, 1.22)	0.940
	7-day	0.95 (0.78,1.17)	0.98 (0.85, 1.12)	0.821	1.12 (0.93, 1.35)	1.15 (1.02, 1.30)	0.787

Table 5.2 (cont.)

Ambient Air Pollutant	Lag-Day Average	Warm Season Odds Ratio (95% CI) Low Yost Score	Warm Season Odds Ratio (95% CI) High Yost Score	*p*-value for interaction	Cool Season Odds Ratio (95% CI) Low Yost Score	Cool Season Odds Ratio (95% CI) High Yost Score	*p*-value for interaction
$PM_{2.5}$	1-day	1.19 (1.02, 1.39)	0.99 (0.89, 1.11)	0.017	1.05 (0.95, 1.15)	0.98 (0.91, 1.04)	0.139
	2-day	1.27 (1.05, 1.53)	0.97 (0.84, 1.11)	0.004	1.10 (0.99, 1.22)	0.99 (0.91, 1.07)	0.055
	3-day	1.25 (1.05, 1.50)	1.00 (0.88, 1.13)	0.011	1.10 (0.99, 1.22)	1.00 (0.93, 1.08)	0.090
	5-day	1.34 (1.07, 1.68)	1.00 (0.86, 1.16)	0.009	1.16 (1.02, 1.31)	1.05 (0.96, 1.15)	0.116
	7-day	1.37 (1.06, 1.78)	0.99 (0.82, 1.19)	0.014	1.22 (1.06, 1.40)	1.12 (1.01, 1.23)	0.214
O_3	1-day	1.08 (0.90, 1.28)	1.10 (0.96, 1.25)	0.839	1.01 (0.85, 1.19)	0.90 (0.80, 1.02)	0.215
	2-day	1.18 (0.97, 1.44)	1.16 (1.00, 1.34)	0.873	0.96 (0.80, 1.16)	0.89 (0.78, 1.02)	0.426
	3-day	1.23 (0.99, 1.53)	1.26 (1.07, 1.48)	0.860	0.90 (0.73, 1.11)	0.86 (0.74, 1.00)	0.647
	5-day	1.24 (0.97, 1.60)	1.29 (1.08, 1.55)	0.761	0.79 (0.62, 1.01)	0.81 (0.68, 0.97)	0.842
	7-day	1.25 (0.94, 1.65)	1.45 (1.18, 1.77)	0.297	0.76 (0.57, 0.99)	0.76 (0.63, 0.92)	0.961
NO_2	1-day	1.15 (0.97, 1.36)	0.97 (0.85, 1.10)	0.043	0.99 (0.89, 1.11)	1.02 (0.94, 1.10)	0.667
	2-day	1.11 (0.92, 1.34)	0.99 (0.86, 1.14)	0.212	1.03 (0.91, 1.17)	1.03 (0.95, 1.13)	0.979
	3-day	1.07 (0.87, 1.31)	0.99 (0.84, 1.15)	0.441	1.08 (0.94, 1.23)	1.05 (0.95, 1.16)	0.715
	5-day	1.15 (0.90, 1.47)	0.98 (0.81, 1.18)	0.180	1.19 (1.02, 1.40)	1.12 (0.99, 1.25)	0.410
	7-day	1.23 (0.94, 1.61)	0.93 (0.75, 1.14)	0.043	1.27 (1.06, 1.52)	1.20 (1.05, 1.37)	0.572
NO_x	1-day	1.16 (0.86, 1.57)	0.95 (0.75, 1.19)	0.186	0.97 (0.87, 1.08)	1.01 (0.93, 1.09)	0.466
	2-day	1.06 (0.75, 1.49)	1.00 (0.77, 1.30)	0.775	1.00 (0.88, 1.13)	1.03 (0.94, 1.12)	0.658
	3-day	0.98 (0.67, 1.45)	1.03 (0.77, 1.37)	0.827	1.05 (0.92, 1.21)	1.04 (0.94, 1.15)	0.876
	5-day	1.01 (0.64, 1.59)	0.97 (0.68, 1.36)	0.864	1.15 (0.97, 1.36)	1.08 (0.96, 1.22)	0.491
	7-day	0.97 (0.58, 1.63)	0.79 (0.53, 1.16)	0.418	1.23 (1.02, 1.49)	1.12 (0.98, 1.29)	0.337
CO	1-day	1.19 (0.90, 1.56)	0.99 (0.81, 1.22)	0.199	0.97 (0.87, 1.09)	1.00 (0.92, 1.08)	0.706
	2-day	1.12 (0.82, 1.53)	1.05 (0.83, 1.32)	0.695	1.02 (0.90, 1.15)	1.02 (0.93, 1.11)	0.975
	3-day	1.06 (0.75, 1.49)	1.06 (0.82, 1.36)	0.987	1.05 (0.92, 1.21)	1.04 (0.94, 1.15)	0.807
	5-day	1.05 (0.70, 1.57)	1.00 (0.74, 1.34)	0.818	1.12 (0.96, 1.32)	1.06 (0.94, 1.19)	0.454
	7-day	0.99 (0.63, 1.56)	0.87 (0.63, 1.21)	0.578	1.17 (0.98, 1.40)	1.10 (0.96, 1.25)	0.471

Table 5.2 (cont.)

Ambient Air Pollutant	Lag-Day Average	Warm Season Odds Ratio (95% CI) Ages 0-11	Warm Season Odds Ratio (95% CI) Ages 12-18	*p*-value for interaction	Cool Season Odds Ratio (95% CI) Ages 0-11	Cool Season Odds Ratio (95% CI) Ages 12-18	*p*-value for interaction
$PM_{2.5}$	1-day	1.06 (0.98, 1.16)	1.22 (0.96 1.55)	0.268	0.99 (0.94 1.04)	1.13 (0.99 1.29)	0.057
	2-day	1.09 (0.98, 1.20)	1.32 (1.00 1.75)	0.164	1.01 (0.95 1.08)	1.21 (1.04 1.42)	0.025
	3-day	1.09 (0.99, 1.20)	1.29 (1.00 1.68)	0.193	1.02 (0.95 1.08)	1.24 (1.07 1.44)	0.009
	5-day	1.11 (0.98, 1.25)	1.38 (1.00 1.89)	0.185	1.06 (0.99 1.14)	1.31 (1.10 1.56)	0.021
	7-day	1.13 (0.97, 1.30)	1.39 (0.97 2.02)	0.254	1.12 (1.04 1.22)	1.38 (1.14 1.68)	0.035
O_3	1-day	1.10 (1.00, 1.21)	1.02 (0.80 1.30)	0.554	0.95 (0.87 1.04)	0.97 (0.77 1.22)	0.892
	2-day	1.17 (1.05, 1.31)	1.16 (0.88 1.52)	0.927	0.93 (0.84 1.02)	0.94 (0.72 1.23)	0.907
	3-day	1.24 (1.10, 1.40)	1.28 (0.94 1.73)	0.859	0.88 (0.79 0.99)	0.86 (0.64 1.17)	0.887
	5-day	1.26 (1.10, 1.45)	1.30 (0.91 1.85)	0.875	0.80 (0.70 0.91)	0.83 (0.58 1.18)	0.835
	7-day	1.34 (1.15, 1.57)	1.33 (0.90 1.98)	0.967	0.75 (0.65 0.87)	0.80 (0.54 1.19)	0.752
NO_2	1-day	1.02 (0.92, 1.14)	1.20 (0.96 1.51)	0.165	0.99 (0.93 1.06)	1.08 (0.93 1.27)	0.254
	2-day	1.02 (0.90, 1.15)	1.17 (0.90 1.52)	0.305	1.02 (0.95 1.10)	1.10 (0.93 1.31)	0.380
	3-day	1.00 (0.87, 1.14)	1.14 (0.86 1.51)	0.344	1.05 (0.97 1.14)	1.15 (0.95 1.39)	0.341
	5-day	1.02 (0.87, 1.20)	1.20 (0.86 1.66)	0.351	1.14 (1.04 1.26)	1.21 (0.97 1.52)	0.592
	7-day	1.01 (0.84, 1.21)	1.28 (0.88 1.86)	0.220	1.22 (1.10 1.36)	1.29 (1.00 1.67)	0.672
NO_x	1-day	1.03 (0.85, 1.24)	1.13 (0.75 1.71)	0.647	0.97 (0.91 1.04)	1.11 (0.95 1.30)	0.101
	2-day	1.03 (0.83, 1.29)	1.00 (0.61 1.63)	0.898	1.00 (0.93 1.08)	1.09 (0.91 1.30)	0.367
	3-day	1.03 (0.80, 1.33)	0.90 (0.53 1.53)	0.624	1.03 (0.95 1.12)	1.12 (0.92 1.36)	0.412
	5-day	0.98 (0.73, 1.33)	0.98 (0.52 1.85)	0.996	1.12 (1.01 1.23)	1.11 (0.87 1.40)	0.952
	7-day	0.84 (0.60, 1.18)	0.99 (0.48 2.02)	0.657	1.18 (1.05 1.32)	1.13 (0.86 1.48)	0.766
CO	1-day	1.05 (0.90, 1.24)	1.33 (0.90 1.97)	0.244	0.96 (0.90 1.02)	1.15 (0.98 1.35)	0.031
	2-day	1.06 (0.98, 1.16)	1.39 (0.88 2.20)	0.211	1.00 (0.93 1.07)	1.12 (0.94 1.34)	0.221
	3-day	1.09 (0.98, 1.20)	1.36 (0.83 2.23)	0.243	1.03 (0.95 1.11)	1.17 (0.96 1.42)	0.211
	5-day	1.09 (0.99, 1.20)	1.49 (0.84 2.66)	0.129	1.08 (0.98 1.18)	1.16 (0.91 1.46)	0.566
	7-day	1.11 (0.98, 1.25)	1.49 (0.79 2.81)	0.084	1.12 (1.01 1.24)	1.20 (0.92 1.56)	0.609

Table 5.2 (cont.)

Ambient Air Pollutant	Lag-Day Average	Warm Season Odds Ratio (95% CI) Male	Warm Season Odds Ratio (95% CI) Female	*p*-value for interaction	Cool Season Odds Ratio (95% CI) Male	Cool Season Odds Ratio (95% CI) Female	*p*-value for interaction
$PM_{2.5}$	1-day	1.13 (0.97, 1.32)	1.02 (0.90, 1.15)	0.174	1.02 (0.93 1.12)	1.00 (0.92 1.07)	0.611
	2-day	1.15 (0.94, 1.39)	1.07 (0.91, 1.25)	0.467	1.05 (0.94 1.17)	1.03 (0.94 1.12)	0.668
	3-day	1.12 (0.94, 1.34)	1.10 (0.95, 1.27)	0.839	1.04 (0.93 1.16)	1.06 (0.97 1.16)	0.707
	5-day	1.10 (0.88, 1.39)	1.23 (1.02, 1.49)	0.344	1.09 (0.96 1.23)	1.11 (1.01 1.23)	0.723
	7-day	1.10 (0.84, 1.44)	1.29 (1.04, 1.61)	0.233	1.15 (1.00 1.33)	1.17 (1.05 1.31)	0.820
O_3	1-day	1.09 (0.91, 1.31)	1.08 (0.93, 1.25)	0.934	1.01 (0.85 1.21)	0.86 (0.75 0.99)	0.064
	2-day	1.16 (0.95, 1.43)	1.18 (1.00, 1.39)	0.878	0.98 (0.81 1.20)	0.84 (0.72 0.98)	0.113
	3-day	1.18 (0.94, 1.47)	1.37 (1.15, 1.65)	0.174	0.94 (0.76 1.17)	0.79 (0.66 0.93)	0.099
	5-day	1.20 (0.93, 1.56)	1.40 (1.13, 1.72)	0.250	0.84 (0.65 1.08)	0.74 (0.61 0.90)	0.315
	7-day	1.25 (0.93, 1.67)	1.53 (1.21, 1.94)	0.171	0.78 (0.59 1.04)	0.72 (0.58 0.90)	0.556
NO_2	1-day	1.04 (0.87, 1.23)	1.07 (0.92, 1.24)	0.728	0.97 (0.87 1.08)	1.07 (0.97 1.17)	0.091
	2-day	1.03 (0.85, 1.25)	1.06 (0.90, 1.25)	0.772	1.00 (0.88 1.13)	1.09 (0.99 1.21)	0.143
	3-day	1.03 (0.83, 1.27)	1.01 (0.84, 1.21)	0.846	1.02 (0.89 1.17)	1.14 (1.02 1.27)	0.109
	5-day	1.05 (0.82, 1.34)	1.05 (0.84, 1.31)	0.966	1.11 (0.95 1.31)	1.22 (1.07 1.39)	0.278
	7-day	1.06 (0.80, 1.41)	1.02 (0.80, 1.31)	0.764	1.22 (1.01 1.46)	1.26 (1.08 1.46)	0.736
NO_x	1-day	1.00 (0.73, 1.37)	1.13 (0.86, 1.48)	0.455	0.97 (0.86 1.09)	1.03 (0.94 1.13)	0.318
	2-day	0.97 (0.68, 1.39)	1.13 (0.83, 1.55)	0.393	0.98 (0.87 1.12)	1.07 (0.96 1.18)	0.214
	3-day	0.98 (0.66, 1.46)	1.05 (0.74, 1.49)	0.743	0.99 (0.86 1.14)	1.13 (1.01 1.26)	0.083
	5-day	0.96 (0.60, 1.54)	1.03 (0.68, 1.56)	0.768	1.07 (0.90 1.27)	1.19 (1.03 1.36)	0.249
	7-day	0.88 (0.52, 1.51)	0.82 (0.51, 1.31)	0.767	1.17 (0.96 1.42)	1.18 (1.01 1.38)	0.898
CO	1-day	1.02 (0.77, 1.36)	1.22 (0.96, 1.55)	0.221	0.96 (0.86 1.08)	1.02 (0.93 1.12)	0.323
	2-day	1.03 (0.75, 1.42)	1.18 (0.90, 1.54)	0.414	0.99 (0.87 1.13)	1.05 (0.95 1.16)	0.365
	3-day	1.03 (0.72, 1.47)	1.11 (0.82, 1.50)	0.672	1.01 (0.88 1.16)	1.10 (0.99 1.23)	0.208
	5-day	0.98 (0.64, 1.49)	1.11 (0.78, 1.58)	0.550	1.06 (0.90 1.25)	1.14 (1.00 1.29)	0.414
	7-day	0.90 (0.56, 1.44)	0.97 (0.65, 1.44)	0.761	1.13 (0.94 1.36)	1.14 (0.98 1.31)	0.957

[a] Percent change in risk of hospital encounters and 95% confidence intervals (CI) are for seasonal interquartile increases in the air pollutant (Table 3.2, Chapter 3), adjusted for temperature and relative humidity of the same averaging time. Air pollutants are daily 24-hr averages.

[b] Stratified results and the *p*-value for interaction for Hispanic ethnicity or having private insurance are derived from product term models of the ambient air pollutant by the demographic factor.

Table 5.3. Associations between pediatric asthma hospital encounters and ambient air pollution by different demographic strata: Effect modification by CALINE4 dispersion modeled traffic-related air pollution above and below median levels.

Ambient exposure, 7-day ave.	Subject demographic strata[c]	CALINE4 NO_x Odds Ratio (95% CI)[a]		*p-value for interaction*[b]	CALINE4 $PM_{2.5}$ Odds Ratio (95% CI)		*p-value for interaction*	CALINE4 UFP Odds Ratio (95% CI)		*p-value for interaction*
		≤ median	> median		≤ median	> median		≤ median	> median	
					Cool Season					
	White non-Hispanic									
NO_2		1.06 (0.86, 1.30)	1.25 (0.94, 1.67)	0.254	1.05 (0.87, 1.28)	1.29 (0.96, 1.74)	0.178	1.13 (0.93, 1.37)	1.17 (0.87, 1.57)	0.802
NO_x		0.93 (0.75, 1.16)	1.30 (0.95, 1.76)	0.036	0.95 (0.78, 1.16)	1.34 (0.98, 1.83)	0.034	1.01 (0.83, 1.23)	1.23 (0.90, 1.67)	0.217
CO		0.97 (0.79, 1.19)	1.15 (0.87, 1.51)	0.234	0.99 (0.82, 1.18)	1.18 (0.89, 1.57)	0.210	1.03 (0.86, 1.24)	1.09 (0.83, 1.45)	0.693
O_3		0.87 (0.64, 1.20)	0.57 (0.35, 0.90)	0.070	0.85 (0.63, 1.16)	0.56 (0.35, 0.89)	0.076	0.73 (0.54, 1.00)	0.69 (0.43, 1.11)	0.815
$PM_{2.5}$		1.11 (0.95, 1.30)	1.09 (0.88, 1.35)	0.887	1.09 (0.95, 1.26)	1.12 (0.90, 1.39)	0.804	1.12 (0.98, 1.29)	1.07 (0.86, 1.33)	0.655
	White Hispanic and African American									
NO_2		1.37 (1.04, 1.81)	1.29 (0.88, 1.90)	0.239	1.26 (0.96, 1.64)	1.39 (0.94, 2.05)	0.597	1.33 (1.02, 1.73)	1.33 (0.90, 1.96)	0.850
NO_x		1.31 (0.97, 1.76)	1.25 (0.83, 1.90)	0.079	1.20 (0.90, 1.59)	1.34 (0.89, 2.04)	0.292	1.24 (0.93, 1.65)	1.30 (0.86, 1.97)	0.483
CO		1.20 (0.89, 1.60)	1.22 (0.83, 1.80)	0.449	1.05 (0.81, 1.36)	1.37 (0.93, 2.03)	0.678	1.11 (0.86, 1.45)	1.30 (0.88, 1.91)	0.625
O_3		0.65 (0.43, 0.98)	0.80 (0.44, 1.45)	0.034	0.74 (0.49, 1.11)	0.71 (0.39, 1.29)	0.206	0.73 (0.48, 1.09)	0.72 (0.39, 1.30)	0.898
$PM_{2.5}$		1.26 (1.02, 1.56)	1.22 (0.91, 1.63)	0.911	1.16 (0.94, 1.41)	1.31 (0.97, 1.76)	0.524	1.18 (0.96, 1.44)	1.29 (0.96, 1.73)	0.356
	Private Insurance									
NO_2		1.14 (0.92, 1.41)	1.29 (0.96, 1.73)	0.414	1.16 (0.95, 1.43)	1.27 (0.95, 1.72)	0.551	1.22 (1.00, 1.50)	1.19 (0.89, 1.61)	0.865
NO_x		1.02 (0.81, 1.27)	1.40 (1.02, 1.92)	0.044	1.07 (0.87, 1.33)	1.37 (1.00, 1.89)	0.129	1.11 (0.90, 1.38)	1.30 (0.95, 1.78)	0.338
CO		1.04 (0.84, 1.30)	1.22 (0.91, 1.64)	0.291	1.04 (0.86, 1.26)	1.30 (0.96, 1.75)	0.148	1.07 (0.88, 1.30)	1.24 (0.92, 1.68)	0.318
O_3		0.72 (0.53, 0.99)	0.65 (0.41, 1.03)	0.643	0.72 (0.53, 0.97)	0.65 (0.41, 1.04)	0.705	0.68 (0.50, 0.92)	0.70 (0.44, 1.11)	0.868
$PM_{2.5}$		1.21 (1.02, 1.44)	1.12 (0.89, 1.40)	0.462	1.17 (1.00, 1.36)	1.15 (0.92, 1.44)	0.925	1.18 (1.01, 1.38)	1.13 (0.90, 1.42)	0.694
	Government Sponsored or Uninsured									
NO_2		1.29 (0.99, 1.69)	1.34 (0.91, 1.96)	0.646	1.17 (0.90, 1.52)	1.49 (1.02, 2.19)	0.431	1.27 (0.97, 1.65)	1.37 (0.94, 2.01)	0.585
NO_x		1.20 (0.89, 1.60)	1.24 (0.83, 1.87)	0.171	1.07 (0.81, 1.41)	1.39 (0.92, 2.10)	0.931	1.16 (0.88, 1.53)	1.29 (0.86, 1.94)	0.831
CO		1.14 (0.86, 1.51)	1.20 (0.82, 1.77)	0.589	1.03 (0.80, 1.32)	1.36 (0.92, 2.01)	0.772	1.12 (0.87, 1.45)	1.24 (0.84, 1.82)	0.788
O_3		0.71 (0.47, 1.06)	0.78 (0.43, 1.39)	0.507	0.83 (0.56, 1.24)	0.67 (0.37, 1.20)	0.661	0.75 (0.50, 1.12)	0.74 (0.41, 1.32)	0.842
$PM_{2.5}$		1.18 (0.95, 1.46)	1.22 (0.91, 1.63)	0.432	1.11 (0.91, 1.35)	1.31 (0.98, 1.76)	0.229	1.15 (0.94, 1.41)	1.25 (0.94, 1.68)	0.382

Table 5.3 (cont.)

Ambient exposure, 7-day ave.	Subject demographic strata	CALINE4 NO_x Odds Ratio (95% CI) ≤ median	CALINE4 NO_x Odds Ratio (95% CI) > median	*p-value for interaction*	CALINE4 $PM_{2.5}$ Odds Ratio (95% CI) ≤ median	CALINE4 $PM_{2.5}$ Odds Ratio (95% CI) > median	*p-value for interaction*	CALINE4 UFP Odds Ratio (95% CI) ≤ median	CALINE4 UFP Odds Ratio (95% CI) > median	*p-value for interaction*
					Warm Season					
	White non-Hispanic									
NO_2		1.01 (0.76, 1.34)	1.01 (0.69, 1.46)	0.992	1.01 (0.78, 1.32)	1.01 (0.69, 1.47)	0.984	0.97 (0.75, 1.27)	1.06 (0.73, 1.54)	0.677
NO_x		0.95 (0.77, 1.17)	0.91 (0.69, 1.21)	0.804	0.93 (0.76, 1.13)	0.93 (0.70, 1.23)	0.996	0.90 (0.74, 1.10)	0.96 (0.73, 1.27)	0.644
CO		0.86 (0.68, 1.07)	1.00 (0.74, 1.36)	0.310	0.90 (0.73, 1.11)	0.97 (0.71, 1.32)	0.617	0.87 (0.70, 1.07)	1.01 (0.74, 1.37)	0.351
O_3		1.49 (1.12, 2.00)	1.42 (0.93, 2.16)	0.814	1.49 (1.12, 1.99)	1.42 (0.93, 2.16)	0.811	1.60 (1.21, 2.13)	1.29 (0.85, 1.97)	0.318
$PM_{2.5}$		0.94 (0.81, 1.09)	1.15 (0.92, 1.43)	0.072	0.94 (0.81, 1.09)	1.17 (0.93, 1.46)	0.057	0.97 (0.83, 1.12)	1.11 (0.90, 1.39)	0.211
	White Hispanic and African American									
NO_2		1.11 (0.77, 1.60)	1.14 (0.69, 1.88)	0.914	1.16 (0.81, 1.67)	1.10 (0.66, 1.83)	0.844	1.07 (0.75, 1.54)	1.16 (0.70, 1.93)	0.990
NO_x		1.02 (0.77, 1.34)	1.02 (0.70, 1.48)	0.862	1.01 (0.77, 1.32)	1.02 (0.70, 1.49)	0.946	0.99 (0.75, 1.30)	1.04 (0.71, 1.51)	0.939
CO		0.98 (0.72, 1.32)	1.10 (0.73, 1.66)	0.854	0.99 (0.74, 1.33)	1.09 (0.72, 1.64)	0.966	0.97 (0.72, 1.30)	1.10 (0.73, 1.67)	0.934
O_3		1.22 (0.84, 1.76)	1.04 (0.62, 1.77)	0.703	1.22 (0.84, 1.76)	1.05 (0.62, 1.79)	0.730	1.24 (0.86, 1.79)	1.04 (0.61, 1.77)	0.881
$PM_{2.5}$		1.10 (0.90, 1.35)	1.09 (0.82, 1.45)	0.141	1.14 (0.94, 1.40)	1.06 (0.79, 1.41)	0.045	1.08 (0.88, 1.32)	1.11 (0.83, 1.48)	0.444
	Private Insurance									
NO_2		0.85 (0.64, 1.13)	1.03 (0.70, 1.52)	0.336	0.80 (0.61, 1.06)	1.13 (0.77, 1.66)	0.086	0.79 (0.60, 1.05)	1.13 (0.77, 1.66)	0.073
NO_x		0.86 (0.70, 1.06)	1.08 (0.82, 1.43)	0.117	0.84 (0.68, 1.03)	1.14 (0.86, 1.51)	0.030	0.83 (0.67, 1.02)	1.13 (0.86, 1.50)	0.028
CO		0.79 (0.63, 0.99)	1.18 (0.86, 1.62)	0.013	0.80 (0.64, 1.00)	1.20 (0.87, 1.65)	0.014	0.83 (0.66, 1.04)	1.13 (0.82, 1.55)	0.053
O_3		1.53 (1.16, 2.02)	1.00 (0.67, 1.51)	0.041	1.59 (1.21, 2.09)	0.94 (0.62, 1.41)	0.011	1.61 (1.22, 2.12)	0.94 (0.62, 1.41)	0.009
$PM_{2.5}$		0.93 (0.80, 1.08)	0.98 (0.78, 1.24)	0.663	0.92 (0.79, 1.06)	1.01 (0.80, 1.28)	0.416	0.94 (0.81, 1.09)	0.97 (0.77, 1.22)	0.802
	Government Sponsored or Uninsured									
NO_2		1.08 (0.75, 1.55)	1.03 (0.62, 1.70)	0.357	1.16 (0.81, 1.65)	0.97 (0.59, 1.61)	0.046	1.08 (0.75, 1.55)	1.02 (0.62, 1.69)	0.112
NO_x		0.98 (0.74, 1.28)	0.89 (0.61, 1.29)	0.090	0.98 (0.75, 1.29)	0.88 (0.61, 1.29)	0.029	0.95 (0.72, 1.25)	0.90 (0.62, 1.32)	0.058
CO		0.93 (0.69, 1.25)	1.00 (0.66, 1.52)	0.128	0.96 (0.72, 1.29)	0.98 (0.65, 1.49)	0.076	0.90 (0.67, 1.22)	1.03 (0.68, 1.56)	0.389
O_3		1.21 (0.85, 1.74)	1.29 (0.77, 2.16)	0.069	1.17 (0.82, 1.68)	1.32 (0.78, 2.22)	0.016	1.27 (0.88, 1.82)	1.24 (0.73, 2.09)	0.051
$PM_{2.5}$		1.07 (0.88, 1.30)	1.16 (0.87, 1.56)	0.817	1.11 (0.91, 1.35)	1.13 (0.84, 1.51)	0.598	1.07 (0.88, 1.31)	1.16 (0.86, 1.55)	0.772

[a] Percent change in risk of hospital encounters and 95% confidence intervals (CI) are for interquartile increases in the air pollutant (Table 3.2, Chapter 3), adjusted for temperature and relative humidity of the same averaging time.

[b] The *p*-value for interaction is testing the null hypothesis that effect modification by CALINE4 classification is the same across demographic strata (Hispanics and African Americans versus whites, or subjects with no private insurance versus those with private insurance). Rejection of this hypothesis implies that the differential effect of a pollutant by CALINE4 classification varies by the corresponding demographic strata.

[c] Stratified results for CALINE4 residential traffic-related air pollutant exposures by demographic factors are derived from three-way product term models of the ambient air pollutant by CALINE4 pollutant by the demographic factor (race-ethnicity or insurance):
$\text{logit}(p) = \log(p/(1-p)) = \beta_0 + \beta_1*(x_1) + \beta_2*(x_1)*(x_2) + \beta_3*(x_1)*(x_3) + \beta_4*(x_1)*(x_2)*(x_3)$,
where x_1 is the ambient air pollutant, x_2 is the CALINE4 air pollutant binary classification, and x_3 is the demographic classification (race-ethnicity or health insurance).

5.3 Discussion

Analyses showed associations with ambient $PM_{2.5}$, NO_2, and CO in the cool season were nominally stronger among Hispanics compared with non-Hispanic whites, but there were no consistent differences for health insurance status. We did find some evidence of effect modification by a neighborhood-level indicator of SES (Yost score) suggesting that lower SES neighborhoods are at increased risk from elevation in ambient $PM_{2.5}$ during both the warm and cool seasons. This was also possibly the case for warm-season NO_2, although the stratified models were nonsignificant. These finding are consistent with studies showing that poverty increases the susceptibility of adverse outcome among subjects with with exposure to traffic-related air pollutants (Meng et al. 2008; O'Neill et al. 2003). The susceptibility may be due to a myriad of factors including limited access to health care, indoor environments, and psychosocial stressors in poorer communities. Another important contributor is likely to be vulnerability due to higher exposures. This is supported by our findings that Hispanic and African American subjects as well as subjects without private insurance were more likely to live in residences with higher dispersion-modeled traffic-related air pollution. This last finding is consistent with another study (Gunier et al. 2003).

Associations were stronger for subjects ages ≥12 years as compared with ages 0-11 years for $PM_{2.5}$, NO_2 and CO in both seasons, but this reached a statistically significant difference (product term at $p < 0.1$) only in the cool season for $PM_{2.5}$. Several air pollutants were more strongly associated with asthma among females, but the difference was rarely statistically significant. We previously reported that associations between repeated hospital encounters and residence near heavy traffic were stronger in girls than in boys with primary or secondary diagnoses of asthma (Chang et al. 2009). The underlying reason for the increased susceptibility observed is unclear as discussed in that study. There are many biological and clinical differences in asthma between the sexes that could be behind this finding, including reproductive factors, airway structure and function, lung function growth rates, atopic status, and symptom perception (Becklake and Kauffmann, 1999; Clougherty 2010; Gold et al. 1994). A recent review of this issue with a focus on $PM_{2.5}$ and NO_2 only found that pediatric studies generally showed stronger associations in boys in early life and in girls in later childhood (Clougherty 2010). This, combined with the suggestive findings for age strata, prompted us to explore this issue further with an analysis stratifying by the two selected age groups and then retesting the interaction of air pollution by sex. Results follow.

We found few product terms were significant beyond that expected by chance. Nevertheless, some interesting patterns emerged in this exploratory analysis (not shown). In the warm season, among subjects ages 12-18 years associations were stronger in females for $PM_{2.5}$ but the reverse was true for O_3. However, only one of 10 product terms was significant (1-day average $PM_{2.5}$). In the warm season, among subjects less than 12 years old, the opposite pattern was observed, i.e., $PM_{2.5}$ was stronger in males and O_3 stronger in females (three of 10 product terms was significant, 1-day average $PM_{2.5}$, and 3-day and 7-day O_3). Also, in the warm season, older males showed stronger associations with primary gases (NO_2, NO_x and CO), but none of the of 15 product terms was significant. In the cool season, among subjects ages 12-18 years associations were stronger in males for primary gases (NO_2, NO_x and CO) (none of the product terms were significant). In the cool season, among subjects less than 12 years old, the opposite pattern was observed with associations being stronger in females for primary gases (five out of 15 product terms were significant). Therefore, our data are not consistent with the review by Clougherty (2010) and sex differences in these highly stratified models show no clear pattern.

Three-way product term models (ambient air pollutant by high vs. low CALINE4 variables by subject characteristic) did not suggest that dispersion-modeled traffic-related air pollution strata are acting as surrogates of racial-ethnic or health insurance differences. However, this analysis was limited by the fact that the only individual-level socioeconomic data we had was health insurance status. Unmeasured demographic and socioeconomic

factors may confound the observed effect modification, but the current study was unable to fully account for this after stratification by race-ethnicity and insurance status.

As with any stratified analysis, the smaller sample sizes of these different subgroups likely limited the statistical power to detect potential interactions and confounding. Assuming there are underlying differences in risk, this likely explains our inability to detect differences in association.

5.4 Summary and Conclusions

Analyses showed associations with ambient $PM_{2.5}$, NO_2, and CO in the cool season were nominally stronger among Hispanics compared with non-Hispanic whites. Also, subjects living in lower SES neighborhoods as assessed with the Yost score are at increased risk from elevations in ambient $PM_{2.5}$. Vulnerability due to higher exposures is supported by our findings that Hispanic and African American subjects as well as subjects without private insurance were more likely to live in residences with higher dispersion-modeled traffic-related air pollution.

Also, older subjects and female subjects were at nominally increased risk for several air pollutant exposures. We speculate that the age finding may be partly due to differences in outdoor exposures with older children spending more time outdoors than younger children. As such, ambient data would be subject to less exposure error. Biological and clinical differences across age groups and the sexes are likely key (Becklake and Kauffmann, 1999; Clougherty 2010; Gold et al. 1994). The apparent higher risk among females is intriguing. The literature shows this risk difference is observed primarily in adolescence (Clougherty 2010). However, we found a mixed picture of sex differences by age group, although few of these highly stratified estimates were significant.

Comparing Hispanic plus African American subjects with white non-Hispanic subjects, there was no consistent evidence of effect modification of associations of asthma with ambient daily air pollution by cool or warm season residential TRAP (6-month average CALINE4 exposures). There was also little consistent difference in TRAP effect modification in cool or warm seasons for populations with vs. without private insurance. In most models 95% confidence limits were wide indicating a lack of precision for estimating these highly stratified association estimates.

References

Becklake MR, Kauffmann F. 1999. Gender differences in airway behaviour over the human life span. Thorax 54:1119-1138.

Chen E, Schreier HM, Strunk RC, Brauer M. 2008. Chronic traffic-related air pollution and stress interact to predict biologic and clinical outcomes in asthma. Environ Health Perspect. 116:970-5.

Clougherty JE. 2010. A growing role for gender analysis in air pollution epidemiology. Environ Health Perspect 118:167-76.

Clougherty JE, Kubzansky LD. 2009. A framework for examining social stress and susceptibility to air pollution in respiratory health. Environ Health Perspect. 117:1351-8.

Clougherty JE, Levy JI, Kubzansky LD, Ryan PB, Suglia SF, Canner MJ, Wright RJ. 2007. Synergistic effects of traffic-related air pollution and exposure to violence on urban asthma etiology. Environ Health Perspect. 115:1140-6.

Gold DR, Wypij D, Wang X, Speizer FE, Pugh M, Ware JH, Ferris BG Jr, Dockery DW. 1994. Gender- and race-specific effects of asthma and wheeze on level and growth of lung function in children in six U.S. cities. Am J Respir Crit Care Med 149:1198-208.

Gunier RB, Hertz A, Von Behren J, Reynolds P. 2003. Traffic density in California: socioeconomic and ethnic differences among potentially exposed children. J Expo Anal Environ Epidemiol 13:240-246.

Largent J, Nickerson B, Cooper D, Delfino RJ. 2012. Paediatric asthma hospital utilization varies by demographic factors and area socioeconomic status. Public Health 126:928-936.

Meng YY, Wilhelm M, Rull RP, English P, Nathan S, Ritz B. 2008. Are frequent asthma symptoms among low-income individuals related to heavy traffic near homes, vulnerabilities, or both? Ann Epidemiol. 18:343-50.

National Heart, Lung, and Blood Institute (NHLBI). 2007. The Expert Panel Report 3: Guidelines for the Diagnosis and Management of Asthma. Bethesda MD: NHLBI, National Institutes of Health, Pub no 08-4051.

O'Neill MS, Jerrett M, Kawachi I, Levy JI, Cohen AJ, Gouveia N, Wilkinson P, Fletcher T, Cifuentes L, Schwartz J. 2003. Workshop on Air Pollution and Socioeconomic Conditions. Health, wealth, and air pollution: advancing theory and methods. Environ Health Perspect. 111:1861-70.

Yost K, Perkins C, Cohen R, Morris C, Wright W. 2001. Socioeconomic status and breast cancer incidence in California for different race/ethnic groups. Cancer Causes Control 12:703-11.

6. CHAPTER 6. OVERALL SUMMARY AND CONCLUSIONS

The source-oriented UCD/CIT model was applied in Task 1 to predict the concentrations and sources of POA and SOA in California for a 9 year (2000 - 2008) modeling period with 4 km horizontal resolution to provide data for the present study of health effects. Model prediction of the source-oriented UCD/CIT air quality model showed OC bias is larger in summertime than wintertime mainly due to an incomplete understanding of SOA formation mechanisms. Predicted spatial distributions of PM components were in reasonably good agreement with measurements. Predicted seasonal and annual variations also generally agree well with measurements. Better model performance with longer averaging time is found in the predictions, suggesting that model results with averaging times ≥1 month should be first considered in epidemiological studies. Predicted total OC concentrations (primary + secondary) and the OC/mass ratios generally agree with measured values. Compared to the POA and SOA concentrations estimated in measurements at 4 sites using the CMB method and the EC tracer method, the UCD/CIT model predicted total OA concentrations are consistent with measured values with fraction bias within ±35% except at Riverside site, but the model predicted SOA concentrations are lower by up to a factor of 8.5. This suggests that part of POA emissions are likely semi-volatile and the SOA model should consider its evaporation after emissions, photo-oxidation and condensation back to particle phase as SOA. Concentrations of oxygenated OA were thus lower than measured values likely because of missing pathways in the model formulation. The SOA model used in the current study was identical to the SOA model used in EPA's CMAQ model (Carlton et al. 2010). Numerous studies using alternative techniques for SOA prediction are underway, but none of them to date has been able to more accurately predict OA concentrations or the C:O ratio in OA without invoking numerous unconstrained assumptions. It is likely that the "SOA" predicted in the current study is a real but incomplete subset of the oxygenated OA that exists in the atmosphere.

Wood smoke is found to be the single biggest source of OA in winter in California, and meat cooking and other anthropogenic sources (including solvent use) and mobile emissions are the most important sources in summer. Biogenic emissions are predicted to be the largest SOA source, followed by the other anthropogenic sources (including solvent use), and mobile sources, but predicted SOA concentrations are generally low, with monthly average SOA concentrations around 1~2 $\mu g/m^3$ in summers and 0.1~0.3 $\mu g/m^3$ in winters.

In Task 2 we found consistent results that acute asthma morbidity is increased in relation to short-term (1 to 7 days) elevations in various indicators of air pollution from fossil fuel combustion sources (including traffic), particularly during the cool seasons. This consistency was seen for short-term changes in ambient gases (CO and NO_x), CALINE4 weekly TRAP indicators, and UCD/CIT total POA as well as most POA sources, including on-road and off-road diesel plus gasoline emission sources, high sulfur content fuel combustion and other anthropogenic sources. Magnitudes of association were also similarly large for most POA sources with between 12-25% increases in risk of hospital encounters for interquartile range increases in PM. This may be due to high correlations between sources resulting from the influence of common meteorological predictors. The weakest but still significant POA source was wood smoke, at around 4% increase in risk of hospital encounters for interquartile range increases in $PM_{2.5}$ and PM_{10} wood smoke in the cool season. Wood smoke was weakly correlated with other POA sources, suggesting some degree of independence for this finding. These associations of asthma morbidity with POA were observed across all particle sizes with ultrafine particles showing somewhat stronger associations as expected, although confidence intervals for the various particle sizes overlapped considerably. Unexpectedly, positive associations for meat cooking POA in the cool season were of similar magnitude to other sources, again possibly due to the influence of meteorology. However, it is noteworthy though, that meat cooking POA in $PM_{2.5}$ and PM_{10} were the only POA source contributions significantly associated with asthma encounters in

the warm season. These unexpected findings for UCD/CIT POA components suggest that a combination of high correlations between predicted components due to common meteorology model inputs and exposure error make any inference based on the toxicology tenuous.

We found no evidence that asthma morbidity was associated with UCD/CIT-estimated SOA as hypothesized. A likely major contributor to this is exposure error as evidenced by the larger bias in prediction by the UCD/CIT model for SOA/OA found in summertime than in wintertime, attributed to missing pathways and precursors of SOA in the SOA model (see above). Also, given the analytic need to analyze effects of short-term (weekly average or less) exposures in the case-crossover model, the poorer performance of the UCD/CIT model for averaging times of less than one month also contributed to exposure error.

With regard to O_3, we observed in two-pollutant models that during the warm season positive associations with O_3 were largely independent of positive associations with $PM_{2.5}$ and vice versa, suggesting that effects could be additive. This is consistent with findings in other regions of the U.S.

This is the first study to our knowledge to assess joint effects from the temporal and spatial variation in air pollution exposure in an asthma cohort. Our findings revealed that long-term spatial variation in residential TRAP was important in acute air pollutant effects. Associations of asthma hospital morbidity with ambient CO, NO_2, NO_x, and $PM_{2.5}$, particularly during the colder seasons, were enhanced among subjects living in areas with high traffic-related air pollution near the home (≤ 500 m), including CALINE4-estimated residential ultrafine and fine particles. The US EPA sets National Ambient Air Quality Standards for criteria air pollutants to protect public health and the standards are informed by findings in time-series studies that have shown that increased air pollution concentrations are associated with increases in mortality, hospital admissions and emergency department visits for cardiorespiratory outcomes. These ambient air pollutant measurements are made daily at regional locations often far from where people counted in such studies live. Ours is the first study to show that associations of asthma hospital encounters with ambient air pollutants are enhanced among pediatric subjects living in areas with high traffic-related air pollution near the home. Therefore, associations in time-series studies may underestimate effects of ambient air pollutants on asthma morbidity for populations at increased vulnerability or susceptibility due to high exposures to traffic-related air pollution. The same could be true for other cardiorespiratory outcomes.

In Task 3 we observed limited evidence for differences in association between asthma encounters and air pollutant exposures in subjects with vs. without recurrence of hospital encounters. Some regression models did suggest increased risk among the population with repeated visits to hospital presumably by virtue of their more severe asthma. To further test this possibility, a larger sample size would be required.

In Task 4 we found associations with ambient $PM_{2.5}$, NO_2, and CO in the cool season were nominally stronger among Hispanics compared with non-Hispanic whites. Also, subjects living in lower SES neighborhoods as assessed with the Yost score were at increased risk from elevations in ambient $PM_{2.5}$. Vulnerability due to higher exposures is supported by our findings that Hispanic and African American subjects as well as subjects without private insurance were more likely to live in residences with higher dispersion-modeled traffic-related air pollution. We also observed that older subjects and female subjects were at nominally increased risk from several air pollutant exposures. We speculate that the age finding may be partly due to differences in outdoor exposures with older children spending more time outdoors than younger children. Biological and clinical differences across age groups and the sexes are also likely key.

7. CHAPTER 7. RECOMMENDATIONS

Additional studies are needed to confirm our specific novel findings using larger-scale hospital databases covering larger geographic areas to increase statistical power and

generalizability. This would be particularly valuable in further evaluations of some of the suggestive findings regarding demographic and personal risk characteristics. Findings in the present study further point to the need for research that assesses the importance of air pollutant chemistry and sources in asthma exacerbations. Such studies would be large undertakings given the effort required in producing fine-scaled spatial exposure data linked to subject-specific outcomes. Nevertheless, current research findings, including the present study, strongly support the view that many large populations are at an increased level of vulnerability and/or susceptibility due to high exposures to traffic-related air pollution near residential locations or other microenvironments. Mobile sources are also a major source of regional air pollution in California. One of the most pervasive determinants of air pollution exposure by children living in California is residence near freeways and major surface streets. This is especially important for potentially susceptible children (e.g., those with asthma who have severe exacerbations requiring hospital care). Our findings suggest that such populations may not be adequately protected by ambient air quality standards that center on levels of criteria air pollutants measured at regional air monitoring sites. Other sources of air pollution are likely to be important to asthma morbidity as evidenced by associations with wood smoke in the cool season and other anthropogenic sources throughout the year. Air pollution control programs aiming to reduce organic aerosol concentrations to protect public health should also consider controlling wood burning in winter and meat cooking/solvent use in summer in California.

8. Presentations and Publications

Presentations:

Delfino RJ, Wu J, Tjoa T, Gullesserian S, Nickerson B, Gillen D. Asthma Morbidity and Ambient Air Pollution: Effect Modification by Residential Traffic-related Air Pollution. Presented to: American Thoracic Society, International Conference, May 18-23, 2012, San Francisco, CA. Am J Respir Crit Care Med 185;2012:A2478..

Publications:

Delfino RJ, Wu J, Tjoa T, Gullesserian S, Nickerson B, Gillen DL. Asthma morbidity and ambient air pollution: effect modification by residential traffic-related air pollution. Epidemiol, 2014;25:48-57.

9. Abbreviations

AADT: Annual average daily traffic
CALINE4: CAlifornia LINE Source Dispersion Model, version 4
CHOC: Children's Hospital of Orange County
CI: confidence interval
CO: carbon monoxide
CMAQ: Community Multiscale Air Quality
CTMs: Chemical transport models
ED: emergency department
FINN: Fire INventory from NCAR
FRM: Federal Reference Method
IQR: interquartile range
IMPROVE: Interagency Monitoring of Protected Visual Environments

ISOP: isoprene
LUR: land-use regression
MFB: Mean fractional bias
MFE: mean fractional error
NO_x: nitrogen oxides
NWS: National Weather Service
O_3: ozone
OA: Organic aerosol
OC: organic carbon
OR: Odds ratio
PBL: planetary boundary layer
PeMS: California Freeway Performance Measurement System
PM: particulate matter
PN: particle number
POA: primary organic aerosols
ppb: parts per billion
RMSE: root-mean-square error
SCAQMD: South Coast Air Quality Management District
SD: standard deviation
SES: socioeconomic status
SJV: San Joaquin Valley
SLAMS: State and Local Air Monitoring Stations
SOA: secondary organic aerosols
SoCAB: Southern California Air Basin
STN: Speciation Trends Network
TOA: Total organic aerosol
TRAP: traffic-related air pollution
UCD/CIT: UC Davis/ California Institute of Technology
UFP: ultrafine particles, PM < 0.1 µm in aerodynamic diameter
UCIMC: University of California Irvine Medical Center
VOC: volatile organic compound
WRF: Weather Research Forecasting
WIM: Weigh-in-Motion