ASSESSING NEAR-FIELD BLACK CARBON VARIABILITY DUE TO WOOD
BURNING AND EVALUTING REGRESSION MODELS AND
ISC DISPERSION MODELING

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COMMITTEE MEMBERSHIP

TITLE: ASSESSING BLACK CARBON VARIABILITY DUE TO NEAR-
FIELD WOOD BURNING AND EVALUATING REGRESSION
MODELS AND ISC DISPERSION MODELING

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ABSTRACT

Assessing black carbon variability due to near-field wood burning and evaluating regression models and ISC dispersion modeling

Stella Hing Tan

PM_{2.5} variability within the neighborhood scale has not been thoroughly studied for wood burning communities. High variability in near-field PM_{2.5} concentration may lead to harmful public exposure since monitoring does not occur on that scale. This study measures near-field PM_{2.5} variability by measuring black carbon (BC), a component of PM_{2.5}, in a 1 km² area located in Cambria, California. BC and meteorological data (when meteorological instruments were available) were measured over thirteen 12-hour intensive operation periods (IOPs) occurring over the winters of 2009 and 2010. Near-field BC variability was measured to understand the type of exposures found in communities where many homes are burning wood simultaneously within a small area. In addition, relationships between meteorological, geographical, and burning source characteristics and BC were observed as tools for understanding BC concentration. The computer air dispersion modeling programs, ISC-PRIME and ISCST3, were also evaluated for applicability to the near field.

BC concentrations were measured using 1- to 2-minute resolution aethalometers and 12 hour resolution Personal Environmental Monitors (PEMs). On average, over all IOPs and sites, aethalometer and PEM BC averages were very similar, ranging between 200 and 250 ng/m³, or 4 and 5 µg/m³ for PM_{2.5}, and standard deviations were often high. Averaging all BC measurements, aethalometer BC standard deviation values were 360

percent of the average BC concentration and PEM BC standard deviations were 120 percent the average BC concentration. The average standard deviation detected during each IOP was 190 percent of the average BC concentration for aethalometers and 79 percent of the average BC concentration for PEMs. The average standard deviation detected at each site was 220 percent of the average BC concentration for aethalometers and 76 percent of the average BC concentration for PEMs. The larger standard deviations measured by higher resolution aethalometers demonstrated that low resolution instruments, such as PEMs, are unable to detect high concentrations that may occur.

In addition to examining BC variability, multiple linear regression analyses were conducted to determine the impact of meteorological variables and geographic and burning source characteristics on BC concentration and a weighted BC deviation function (BC standard deviation divided by average BC concentration). Time impacts, humidity, and wind speed, accounted for about 50 percent of variability in aethalometer average BC and BC deviation. However, because all model assumptions were not satisfied, improvements are needed. Regression models based on PEM BC found wind speed and direction to account for about 80 percent of average PEM BC variability and number of burning sources to account for about 30 percent of PEM BC deviation. Although PEM BC models accounted for a high percentage of BC variability, few data points were available for the PEM analyses and more IOPs are needed to determine their accuracy.

When evaluating correlations between geographic and burning source characteristics and PEM BC concentrations, specific IOP and PEM sampling location explained almost 70

percent of variability in BC concentration, though model residuals suggested model bias. IOP likely explained variation in burning patterns and meteorology over each night while sampling location was likely a proxy for housing density, tree coverage, and/or elevation. Because all regression model assumptions could not be satisfied, the predictors were also observed graphically. Plotting BC concentration versus the number of burning sources suggested that number of burning sources may affect BC concentration in areas of low tree coverage and high housing density and in the case that the level of surrounding vegetation and structures are minimal. More data points will be needed to determine whether or not these relationships are significant.

ISC-PRIME and ISCST3 modeling overall tended to under predict BC concentrations with average modeled-to-measured ratios averaging 0.25 and 0.15, for ISC-PRIME and ISCST3, respectively. Correction factors of 9.75 and 18.2 for ISC-PRIME and ISCST3, respectively, were determined to bring modeled BC concentrations closer to unity, but the range of ratios was still high. Both programs were unable to consistently capture BC variability in the area and more investigation will be needed to improve models.

The results of the study indicate high BC variability exists on the near-field scale, but that the variability is not clearly explained by existing regression and air dispersion models. To prevent public exposure to harmful concentrations, more investigation will be needed to determine factors that largely influence pollutant variability on the neighborhood scale.

Keywords: black carbon, PM_{2.5}, near-field, multiple regression, ISCST3, ISC-PRIME

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Chapter 1. Introduction

Wood burning fireplaces and stoves, while less common throughout the United States than in previous decades, remain common in many communities. The use of wood for heating and as a fuel has been widely popular for reasons ranging from wood being an inexpensive fuel in highly forested areas to wood burning providing desired aesthetic qualities. Despite these benefits, in areas where meteorology and terrain encourage trapping of atmospheric pollutants, the prevalence of wood burning may lead to high pollutant exposures for surrounding populations inside and outside of homes (Branis et al., 2000; Turpin et al., 2007).

Incomplete wood combustion has been found to include a variety of harmful byproducts including particulate matter less than 2.5 μm ($\text{PM}_{2.5}$), carbon monoxide, polycyclic aromatic hydrocarbons (PAHs), and nitrogen oxides (NO_x) (which are a precursor to secondary $\text{PM}_{2.5}$). This study focuses on black carbon (BC) emissions as an extension of $\text{PM}_{2.5}$, which has been a major constituent of health concerns. Its incredibly small size makes $\text{PM}_{2.5}$ capable of evading the lungs' defense mechanisms and penetrating deep into the lungs. Several studies have linked $\text{PM}_{2.5}$ to respiratory and pulmonary symptoms and illnesses, and in some cases even death. In children, $\text{PM}_{2.5}$ had been shown to hinder respiratory growth in addition to causing wheezing, coughing, and asthma (Gauderman et al., 2004; Honicky et al., 1985). In adults, inflammation of the respiratory and pulmonary tract has caused tissue damage and dramatically increased the chance of death in those with pre-existing illnesses (Barregard et al., 2006; Barregard et al., 2007; Pope et al., 2002).

To protect the public from high concentrations of detrimental wood smoke byproducts such as PM_{2.5}, it is important to understand, monitor and limit public exposure.

Currently, air monitoring occurs on the regional scale and is intended to capture overall exposure concentrations. However, regional monitoring often fails to provide the high spatial resolution needed to understand local exposures on the neighborhood or near-field scale. Existing studies that attempt to bridge the gap between regional and near-field scales have been limited to observing near-field PM_{2.5} variability in areas where traffic emissions are abundant, and exposure in wood burning communities remain largely misunderstood. Studies observing wood smoke contributions to ambient pollutants focus mainly on source apportionment instead of spatial variability (Branis et al., 2000).

Ward (2009) and Malejan's (2009) parallel studies taking place in a 1 km² area in Cambria, California appear to be the only study that has evaluated near-field spatial variability for areas containing many wood burning sources. Notable conclusions from their study include the demonstration of high spatial variability and large similarity in indoor to outdoor exposures. Ward (2009) found average evening PM_{2.5} concentrations in the area to vary widely with the largest difference in PM_{2.5} concentrations over an IOP estimated between 54.5 and 81.8 µg/m³. Malejan (2009) found indoor to outdoor ratios to average about 75 percent. Additionally, available studies observing small scale variability in traffic sources indicate high variability in PM concentrations over distances less than 10 meters, where some concentrations are higher than those measured by a central monitoring station (Gulliver and Briggs, 2004; Nerriere et al., 2005). These

results suggest that locally measured PM_{2.5} concentrations resulting from high density wood burning have potential to be similarly higher than concentrations represented regionally.

Because local monitoring may not be economical, other means of determining pollutant concentrations have been used. Tools designed to represent pollutant exposures include meteorology based statistical regression models and air dispersion models. By using weather characteristics including wind speed, temperature, humidity, and precipitation, correlation-based multiple linear regression analyses have been found to explain between about 20 to 80 percent of the variability in PM_{2.5} concentrations in locations throughout the world (detailed in Section 2.2.2.1.1). Air dispersion modeling programs such as Industrial Source Complex (ISC) and American Meteorological Society/U.S. Environmental Protection Agency Regulatory Modeling System (AERMOD) have also been commonly used in regulatory applications due to their ability to determine the highest ground level pollutant concentrations. This is accomplished often by simulating site conditions based on inputs of meteorology and source characteristics. When used in optimum scenarios, both ISC and AERMOD programs can predict concentrations within a factor of 2 of the measured values. Statistical regression and air dispersion models are both relatively economical analytical methods that have high potential to help improve understanding of pollutant concentrations and variability within the neighborhood scale provided the availability of detailed inputs.

This study was conducted as a segment of a larger study whose goal was to contribute to the understanding of near-source variability for primary air pollutants generated within a residential area. The larger study focused on wood smoke particulate matter generated within a residential area in a region where residential wood burning is the primary source of particles. The research addressed four primary questions:

- What is the concentration variability associated with wood smoke burning within a residential neighborhood?
- Can near source contributions be properly estimated based on information on burning patterns, meteorology, and regional monitoring site data?
- Does indoor exposure to outdoor wood smoke sources correlate with expected values based on simple indoor-outdoor models?
- How does the near source contribution affect intake fraction calculations for wood smoke exposures?

The results of the larger study were intended to improve our understanding of the contribution of wood smoke variability to overall $PM_{2.5}$ exposure, and can be used to aid in the development of $PM_{2.5}$ source reduction prioritization, increase our understanding of the importance of variability of acute exposures, and improve the effectiveness of source control programs for reducing $PM_{2.5}$ exposures. To the extent that wood smoke behavior can be generalized to other locally distributed emission sources (such as distributed power generation) this work will aid in decision making regarding siting of sources,

improve impact calculations, and be a valuable resource for determining the potential for environmental justice concerns.

This study directly addresses the first two questions of the larger study by continuing Ward (2009) and Malejan's (2009) field study in Cambria, California and by evaluating the performance of existing regression and air dispersion modeling tools. By addressing the first two questions, the exposure and intake fractions may also be addressed, as is of interest in question four. By conducting the same air sampling procedures used in Ward (2009) and Malejan's (2009) parallel studies, the increased sample size could be used to conduct regression and modeling analyses. Goals for this study specifically include (1) further measuring pollutant variability within the near-field study area, (2) evaluating the relationship between pollutant variability and meteorology, geography, and burning sources, and (3) identifying the performance of existing dispersion models in application to the near-field based on available input variables.

Chapter 2. Background

2.1 Wood Smoke

Although the products of ideal and complete biomass combustion are carbon dioxide, steam, and heat, the composition of wood and actual combustion conditions result in products very different than the ideal. By-products including particulate matter less than $2.5\text{ }\mu\text{m}$ ($\text{PM}_{2.5}$), carbon monoxide, volatile organic compounds (sometimes including carcinogens like polycyclic aromatic hydrocarbons), and nitrogen oxides (NO_x) are also typically generated in the form of wood smoke due to complex organic molecules found in wood and non-ideal burning conditions such as low combustion temperatures. $\text{PM}_{2.5}$ may also form as secondary emissions in the atmosphere, such as when NO_x interacts with atmospheric constituents like ammonia. Many of the by-products can have negative short and/or long term effects on human health (Morandi et al, 2010).

2.1.1 Wood Smoke and $\text{PM}_{2.5}$ Impacts on Health

The health impacts of wood smoke have been demonstrated through observation of wood smoke composition and wood smoke's immediate effect on sensitive and healthy populations. Davy et al. (2007) found aerodynamic particle diameters in wood smoke from the combustion of pine and blue gum to aggregate into clumps ranging from 0.010 to 0.30 μm , much smaller than the particle diameter of $2.5\text{ }\mu\text{m}$. $\text{PM}_{2.5}$ is capable of evading our lung's natural defense mechanisms and penetrating deep into the lungs. Harmful organic compounds are often attached to carbon soot in wood smoke and have been shown to induce pulmonary reactions. Kocbach et al. (2008) found 20 times more

carcinogenic polycyclic aromatic hydrocarbons (PAHs) in wood smoke PM than in diesel PM. Kobach et al. also found the presence of organic compounds in wood smoke PM to encourage the release of inflammatory cytokines, a type of signaling protein, which may encourage tissue damage due to prolonged inflammation. Because PM_{2.5} has demonstrated negative pulmonary impacts, the US Environmental Protection Agency (EPA) established annual and 24-hour National Ambient Air Quality standards (NAAQS) for PM_{2.5} in 1997. EPA limits for PM_{2.5} are currently 15.0 µg/m³ averaged over 1-year and 35 µg/m³ for a 24 hour average (US EPA, 2010). EPA standards are meant to protect public health, including sensitive populations such as children, asthmatics, and the elderly.

Children have been an emphasis of many exposure health studies, especially due to respiratory growth concerns. In a study measuring pulmonary development of children from the age of 10 to 18 years of age in 12 communities, Gauderman et al. (2004) compared the percentage of children with low forced expiratory volume at one second (FEV₁), a measure of pulmonary function, in a community with a high level of exposure to PM_{2.5} to the percentage of children with low FEV₁ in the community with a low PM_{2.5} exposure. The percentage of children with low FEV₁ in the community exposed to the highest PM_{2.5} levels was 4.9 times (7.9 percent) the percentage of children exposed to the lowest PM_{2.5} levels (1.6 percent). Koenig et al. (1993) also found a 34 mL decline in FEV₁ for asthmatic children with each 20 µg/m³ increase in PM_{2.5} concentration and concluded that acute respiratory irritation in asthmatic elementary school children is correlated with wood burning. The use of wood burning as a home heating source in a

study amongst 62 children between the ages of 1 and 7 years in Michigan indicated a significantly higher prevalence of symptoms of acute respiratory illness (Honicky et al. 1985). Honicky et al.'s study found 77 percent of children were reported to show symptoms of wheezing with cold or having at least one attack of wheezing in the wood burning community during the winter compared to 29 percent in the non-wood-burning community. Although the study found no significant difference in the occurrence of asthma, allergies in the wood burning community occurred in 19.4 percent of the children as opposed to 3.2 percent of the children in the non-wood burning community. One study conducted on asthmatic children in Seattle, Washington found a 14 percent increase in the odds of experiencing asthma symptoms with increases in $PM_{1.0}$ (Yu et al., 2000).

Studies among the general population have also found associations between $PM_{2.5}$ and negative health impacts. Pope et al.'s (2002) study on individuals in United States metropolitan areas associated a $10 \mu g/m^3$ increase in long-term $PM_{2.5}$ concentrations with about 4, 6, and 8 percent increased risk of death from all-cause, cardiopulmonary, and lung cancer, respectively. In a study with healthy human subjects, Barregard et al. (2006, 2007) exposed 13 people to 240 through 280 micrograms per meter cubed of fine wood smoke particles, the concentration typical in a smoky indoor environment, and found wood smoke to cause inflammation and oxidative stress in the respiratory tract.

Many negative health impacts have been associated with wood smoke $PM_{2.5}$. For this reason, it is important to understand wood smoke variability within residential

neighborhoods where frequent exposure may occur in the winter time. This is especially true under meteorological conditions that may elevate exposure levels.

2.1.2 Wood Smoke PM_{2.5} Characterization

This study focuses on wood smoke PM_{2.5} because of the major health concerns associated with the fine particles. The contribution of PM_{2.5} by wood burning has often been estimated through modeling methods that separate PM_{2.5} mass produced from gasoline, diesel, and other contributors from wood smoke PM_{2.5}. These studies have found wood smoke to contribute PM_{2.5} mass ranging from 20 to 60 percent of total fine particulate mass during the wintertime and 10 to 30 percent of total annual PM_{2.5} (Schauer & Cass, 2000; Favez et al., 2009; Wu et al., 2007; Aarhus University NERI, 2010; Zhang et al. 2010; Bari et al., 2010).

PM_{2.5} has been found to be composed of 63 through 96 percent elemental carbon (EC) and organic carbon (OC), with OC often being the more dominant component in conventional wood burning (Watson et al., 2001). Although the concentrations of EC and OC in a specific sample can differ by factors of 2 and 10, respectively, based only on measurement methods (Watson et al., 2005), generally accepted definitions exist. OC is commonly defined as compounds oxidized below a temperature threshold (usually ranges between 350 and 550 °C) in the absence of an oxidizing agent (Watson et al., 2005), and encompasses thousands of organic compounds. EC is usually defined as compounds oxidized above a higher temperature threshold than OC (usually ranges between 650 and 1100 °C) in the presence of an oxidizing agent, often oxygen (Watson et al., 2005), and is

characterized by having “near-elemental soot-carbon-like composition” (Andreae et al., 2006). Black carbon (BC) is often used interchangeably with EC, but differs because BC concentrations are determined optically, or based on particles’ ability to absorb light (Andreae et al., 2006). Both the “BC” and “EC” terms include similar carbon fractions, but differ slightly due to the methods used to determine their presence.

The emission of particulate matter in wood smoke can vary significantly depending on the wood type and burning conditions. Fine et al. (2001) found 6 types of hard and soft woods burned in a conventional masonry fireplace to have average fine particle emission rates ranging between 2.7 to 11.4 grams per kilogram of wood burned. Particulate matter composition can vary significantly based on burning temperature and oxygen content. Bølling et al. (2009) evaluated several studies to determine the impact of combustion temperature and oxygen content. Low temperature combustion was found to typically yield high OC to total carbon (EC plus OC) ratios, with OC comprising 89 to 99 percent of the total wood smoke carbon content. Alternately, high temperature wood combustion with limited oxygen content yields more EC than OC, with EC comprising between 50 to 75 percent of the total carbon content. In the presence of high temperature and an adequate supply of oxygen, less harmful inorganic particles are more dominantly emitted instead. These inorganic particles are primarily composed of alkali salts, sometimes with trace elements such as zinc and magnesium (Johansson et al., 2003). They can be less harmful due to their higher tendency to grow in size in the presence of high humidity (Löndahl et al, 2007). In addition, their solubility makes them less difficult for the lungs to remove than insoluble particles (Bølling et al., 2009).

Bølling et al. also found that open fireplaces, conventional wood stoves, and masonry heaters, as are more likely found in this study, tend to emit organic or elemental carbon-dominant particulate matter. Open fireplaces reviewed by Bølling et al. yielded EC/TC ratios of 0.04 through 0.46 with higher fractions of OC. Conventional wood stoves and conventional masonry heaters, however, were less consistently OC- or EC- dominant with different studies finding some emissions more OC-dominant and some emission more EC-dominant. Modern wood stoves and masonry heaters alternatively have been found to emit more inorganic ash with less than 10 percent of emissions being comprised of OC and EC (Jokiniemi et al., 2008).

Ponderosa and Slash Pines are both found in California and are both of the same genus as the Monterey Pines found in the chosen study area. When combusted in a conventional masonry fireplace, Ponderosa and Slash pines emit higher OC than EC content by mass; Fine et al. (2002) found on average 90.1 percent OC and 7.3 percent EC by mass in Ponderosa Pine wood smoke and 100.6 percent OC and 14.7 percent EC by mass in Slash Pine (Fine et al., 2002; Fine et al., 2004). Percentages greater than 100 were explained by organic gases adsorbing to the quartz fiber. These gases were considered insignificant because backup filters indicated adsorption was less than 20 percent of the measured mass. Residents within the study area also mentioned the use of oak wood in their fireplace (Leimert resident, personal communication, February 13, 2010). Fine et al. (2002) reported Midwestern White and Black oak wood smoke to contain 76.5 percent OC and 1.1 percent EC and 76.0 percent OC and 2.3 percent EC, respectively. Wood

smoke particulate matter generated during the study should demonstrate similar OC and EC fractions. Malejan (2009) and Ward's (2009) parallel studies, which this study follows upon, found EC to comprise between 4 and 8 percent in wood smoke samples.

2.1.3 Wood Smoke Identification

To attribute collected particles to wood combustion, several techniques are typically used. These methods utilize the fact that wood combustion emits a higher organic carbon fraction than most other common particle emission processes such as gasoline or diesel vehicle fuel combustion, where EC comprises closer to 50 percent of total carbon (Watson et al., 2001). The compounds present in organic fractions of wood smoke and the optical nature of organic carbon have been valuable tools for wood smoke identification.

2.1.3.1 Light Attenuation Approach

The abundance of organic compounds in wood smoke allows for its identification through light attenuation. Particle light attenuation in the UV and visible spectrum can be better understood by using Beers Law or the power law relationship of $\sigma = K\lambda^{-\alpha}$, where σ is the spectrally dependent mass adsorption efficiency proportional to light attenuation, K is a constant, λ is the wavelength in nm, and α is the adsorption Ångström exponent (AAE). Based on the power law relationship, the adsorption Ångström exponent can indicate the degree of spectral dependence on light attenuation. Kirchstetter et al. (2004) evaluated the impact of traffic and biomass combustion particles on light absorption throughout the wavelength spectrum. They found that organic

compounds typically present in biomass combustion display high spectral dependence, with high light attenuation at wavelengths less than 600 nm. Aerosols generated by motor vehicle exhaust displayed an average spectral dependence of λ^{-1} , and often range from $\lambda^{-0.9}$ to $\lambda^{-1.1}$, while aerosols contributed by biomass smoke typically had a spectral dependence of λ^{-2} . By evaluating the spectral dependence of light attenuation, there is potential to infer the contribution of BC from biomass combustion.

2.1.3.2 Detection of Organic Compounds

Because some particulate organic compounds are specific to biomass burning, they have been used to apportion atmospheric particles contributed by wood combustion. When burned, cellulose and lignins, both essential components of vegetation, are converted into cellulose-specific monosaccharides (simple sugars) such as levoglucosan and lignin-specific phenolics (derivative of an aromatic hydrocarbon with an -OH group) such as methoxyphenols. Methoxyphenols, while emitted abundantly during lignin combustion, may be a less effective tracer due to their moderately reactive characteristics (Simpson et al., 2005). Levoglucosan alternatively has been observed to be produced abundantly during wood combustion and to be stable in the atmosphere, making it suitable as a tracer for wood smoke (Locker, 1988; Fraser & Lakshmanan, 2000; Jordan et al., 2006).

Studies have found traces of levoglucosan in all wood burning samples (Simoneit et al., 1999) and low concentrations in the non-winter ambient environment, due to high temperatures of about 300°C required to generate it. Despite its abundance and stability, levoglucosan concentrations can still be difficult to use quantitatively due to wide

variations in emissions depending on combustion conditions (Hedberg et al., 2006). A recent study conducted by Hoffmann et al. (2010) has even found that levoglucosan is not as stable as previously considered. Hoffmann et al. noted that while previous studies have found no significant levoglucosan degradation for up to 8 hours under ambient conditions (Locker, 1988) and no significant hydrolysis for 10 days under acidic conditions (Fraser & Lakshmanan, 2000), degradation by free radicals from deliquescent particles was not considered. Deliquescent particles can form hydroxide (OH) radicals when dissolved into atmospheric vapors. Evaluation of levoglucosan degradation by OH radicals indicated higher winter time degradation fluxes than previously expected (around $4.7 \text{ ng m}^{-3} \text{ h}^{-1}$). Still, levoglucosan remains the best known organic tracer for wood smoke because it is highly specific to biomass burning and is typically emitted in abundance.

2.1.3.3 Thermal Optical Approach

Thermal optical methods are primarily used to determine EC and OC fractions, and thus can be used to trace the presence of wood smoke; higher OC content would suggest particles originating from biomass combustion. EC and OC content are determined by collecting samples on quartz fiber filters and heating the samples in a ramp of temperatures specific to each method. The Interagency Monitoring of Protected Visual Environments (IMPROVE), the National Institute of Occupational Safety and Health (NIOSH) 5040, and the Lawrence Berkeley National Laboratory Effluent Gas Analysis (LBNL EGA) methods utilize the thermal optical approach to determine EC and OC fractions (Chow et al., 2001; Ellis & Novakov, 1982).

IMPROVE and NIOSH methods both heat filter compounds in a step wise manner (different temperature steps are used for each method) under a oxygen-free environment for OC and a 2 percent oxygen environment for EC as evolved carbon compounds are measured at each temperature. The temperatures used for IMPROVE and NIOSH methods range from 120 to 850°C and 250 to 850°C, respectively. LBNL EGA instead uses a constant temperature increase rate of 20°C each minute from 50 to 600°C in an oxygen environment. For each method, carbon content is measured by catalyzing evolved carbon compounds into carbon dioxide on a magnesium dioxide probe. Carbon dioxide is then converted to methane and measured with a flame ionization detector (FID). FID results are correlated with light penetration to understand peaks in methane measurements and total carbon is determined through integration of peaks.

2.2 Pollutant Variation

In addition to developing NAAQS, the EPA also requires states to establish a network of air pollution monitoring. These networks are meant to: (1) include sites that represent the highest concentrations in the area, (2) measure concentrations in areas of high population density, (3) identify the impact of a significant source or sources, (4) represent background concentrations, (5) characterize regional pollutant transport, and (6) evaluate air pollution impacts on visibility (US EPA, 2008b). These network characteristics demonstrate compliance to NAAQS and help to protect public health. Although these state-wide monitoring networks have been successful in characterizing pollutant emissions in most communities, no studies have focused on near-field pollutant

variability in areas where wood burning is common in the winter time. According to the US Census estimates, approximately 2.1 million households in the United States used wood as a heating source between 2005 and 2009 (US Census Bureau, 2009). Because the impacts of wood smoke exposure are understood to have detrimental respiratory impacts, it is important to understand neighborhood scale pollutant variability with in areas where wood burning is prevalent.

2.2.1 Spatial Representation of PM

While some studies have evaluated PM variability for urban environments primarily originating from diesel or gasoline exhaust and/or industrial sources, no studies have evaluated the impact of wood burning sources on near-field PM variability. Studies demonstrating small scale variability tend to involve mobile sampling methods and tend not to use simultaneous sampling strategies. For example, Robinson et al.'s study (2007) found large differences in PM_{2.5} concentration averages over only a 41 meter distance (35 $\mu\text{g}/\text{m}^3$ and 90 $\mu\text{g}/\text{m}^3$) when sampling with a mobile nephelometer, a device measuring light scattering by particles which can then be related to PM concentrations, in Armidale, New South Wales Australia. Higher concentrations were found in areas where wood burning was prevalent. Although mobile sampling can well demonstrate differences in concentrations over short distances, changes to concentrations over time remains unaccounted for.

Studies evaluating wood smoke contributions to PM concentrations in small areas have only measured pollutant variability at one location and have had to differentiate between

PM contributors. One study evaluated both coal and wood burning contributions to winter PM₁₀ and black smoke (similar in definition to BC) in the Czech Republic within a small rural village, Žloukovice, of 300 inhabitants (Branis et al., 2000). Resident surveys for fuel type used was conducted in conjunction with air sampling and indicated that 19.2 percent of households were found to use mainly coal and 14.5 percent of households were found to use mainly wood. Winter 1997/1998 PM₁₀ concentrations were found to widely range between 9.71 and 106.4 $\mu\text{g}/\text{m}^3$ and averaged 33.6 $\mu\text{g}/\text{m}^3$. Similarly, winter 1998/1999 PM₁₀ concentrations widely ranged between 8.48 and 118.7 $\mu\text{g}/\text{m}^3$ and averaged 41.2 $\mu\text{g}/\text{m}^3$. A strong correlation between black smoke and PM₁₀ concentrations indicated that the main source of PM₁₀ was likely from household combustion processes.

In contrast to the scarcity of near-field PM variability studies, there are a larger number of reports investigating spatial variability in PM from vehicular or unspecified sources. Many of these studies evaluated PM variability within urban scales, defined as 4 through 100 km in diameter, length, or width, and neighborhood scales, defined as 500 m to 4 km in diameter, length, or width (40 CFR part 58). Although some researchers have found low variability within urban scales (Gorin et al., 2006; Goswami et al., 2002), other studies have found substantial variability on the smaller neighborhood scale.

PM concentrations have been found to vary considerably over short distances, especially in the presence of abundant pollutant emissions. Gulliver and Briggs (2004) found large standard deviations when measuring PM₁₀, PM_{2.5}, and PM₁ concentrations at 1 second

resolution over two routes comprising high traffic and low traffic areas while walking and driving. Walking through each route required 15 to 20 minutes and resulted in PM_{10} , $PM_{2.5}$, and PM_1 concentrations of $38.18 \pm 25.17 \mu\text{g}/\text{m}^3$, $15.06 \pm 16.15 \mu\text{g}/\text{m}^3$, and $7.14 \pm 9.62 \mu\text{g}/\text{m}^3$, respectively. Concentrations for PM_{10} , $PM_{2.5}$, and PM_1 detected while driving over a 6 minute period were $43.16 \pm 22.71 \mu\text{g}/\text{m}^3$, $15.54 \pm 15.92 \mu\text{g}/\text{m}^3$, and $7.03 \pm 9.67 \mu\text{g}/\text{m}^3$, respectively. Higher variability in PM has been shown to occur in the presence of numerous gasoline and diesel vehicles, while variability declines when only background PM levels are observed (Weijers et al., 2004).

In Gulliver and Briggs' (2004) study discussed above, one of the main objectives was to compare PM_{10} concentrations measured at a fixed-road monitoring location to concentrations measured using a portable monitoring device, OSIRIS, within an 8 km^2 area. PM_{10} was measured as a subject carried an OSIRIS and walked two different routes and as a vehicle carrying another OSIRIS was driven along the same routes. The routes traveled through both main and minor roads to represent areas both with and without major PM emitting sources. The fixed-road monitor was located about 10 meters from a major road on the first route. The average PM_{10} concentrations measured during walking and measured during driving were found to be 30 and 67 percent higher than the fixed monitoring site, respectively. Gulliver and Briggs also found a greater difference between PM_{10} concentrations measured at the fixed site and the second route than with the fixed site and the first route. The second route, located much further away from the monitoring location (about 1 km away) thus demonstrated a decrease in representation with an increase in distance.

A study conducted in four French metropolitan areas of contrasting urban settings and air quality also found fixed monitoring locations to under-represent individual exposure to PM_{2.5} (Nerriere et al., 2005). Three areas within each city were selected to represent locations with high traffic emission exposure, abundant influence by local industry, and urban background levels. Volunteers within each area carried personal monitoring devices, a Harvard ChemPass along with a portable pump, and comparisons were made between the individuals and fixed monitoring stations set up within each area over a period of between 24 and 48 hours. Significant wintertime average differences were found between personal and fixed station PM_{2.5} concentrations ranging between 1.77 and 26.2 µg/m³ for four cities, with all winter average concentrations reading lower at fixed stations. It is important to note that measured PM_{2.5} may have been contributed by indoor activities, rather than external sources, although volunteers were all non-smokers who had declared no exposure to environmental tobacco smoke. Several other studies have also attributed the difficulty of representing personal pollutant exposure with fixed-monitoring stations to the abundance of indoor pollutant sources (Wilson et al., 2000; Zeger et al., 2000; Turpin et al., 2007).

While large differences in personal and ambient concentrations have been attributed to indoor pollutant sources, it is also important to understand outdoor pollutant variability and its contribution to indoor environments. The infiltration of ambient pollutants into homes and microenvironments (such as cars and buses) has been well demonstrated and can have significant implications for public health given the large percentage of time

spent indoors. A survey funded by the California Air Resources Board from 1987 through 1988 found that on average people spend 87 percent of their time indoors (Jenkins et al., 1992).

A wide range of indoor/outdoor ratios (I/O) have been observed in several studies. Lunden et al. (2008) reported PM_{2.5} I/O ratios for the months of December and January to be 0.39 ± 0.2 and 0.38 ± 0.3 , respectively. Geller et al. (2002) found PM_{2.5} I/O ratios of 1.03 ± 0.29 and explained that outdoor concentrations accounted for 37 percent of the variation with the remaining fraction likely associated with indoor sources. Turpin et al. (2007) found outdoor PM_{2.5} to contribute 25 to 30 percent to personal exposure and 73 percent on average to indoor concentrations within residential areas located near industrial sources in Los Angeles, California, Elizabeth, New Jersey, and Houston, Texas. Allen et al. (2003) alternately found a 79 ± 17 percent contribution of outdoor PM_{2.5} to indoor PM_{2.5}. Several factors can contribute to differing outdoor pollutant contribution to indoor environments including particle properties, housing characteristics, and near-surface air flows and turbulence (Turpin et al., 2007). Infiltration of outdoor PM into indoor environments can have significant implications for public exposure, especially in locations where indoor PM concentrations are high and PM emissions are elevated due to wood burning. Because areas tend to be represented by a single monitoring station, often located relatively far from residential activity, this study was designed to contribute information on PM_{2.5} spatial variability within a small area containing multiple wood burning sources.

2.2.2 Estimation of Pollutant Variability and Concentrations

Because the number of monitoring stations used in communities may be limited by available funds, modeling methods have been developed to facilitate the prediction of pollutant concentrations in locations where monitoring does not take place. The most commonly used methods for predicting pollutant concentrations either focus on the relationship between ambient sampling data and external factors or predict pollutant concentrations based on mechanical and physical behavior (Georgopoulos et al., 2009). Both categories have their advantages and disadvantages which must be considered based on the intended use of model results. Ambient-data-based models often offer simplicity and require less detailed descriptions of environmental conditions to produce valuable information. Mechanical models, provided adequate model inputs, can offer high accuracy and high resolution. Alternatively, ambient-data-based methods sometimes fail to consider spatial and temporal variation while mechanical methods can misrepresent real conditions depending on the accuracy of assumed conditions. These two model categories are explored briefly below.

2.2.2.1 Ambient-Data-Based Models

Models based on ambient sampling data typically utilize pollutant concentrations at measured sites to interpolate concentrations at locations where sampling did not occur. The simplest of these models are mathematically linear, but more complex, non-linear models have emerged to improve predictions where linear relationships are inappropriate. An evaluation of PM₁₀ prediction methods in the large city of Greece, Thessaloniki, inhabited by 16,000 people tested the statistical performance of four methods: Multiple

Linear Regression (MLR), Classification and Regression Trees (CART), Principle Component Regression (PCR), and the Multi-Layer Perceptron type of neural network (NN) (Slini et al., 2006). Amongst these methods, MLR and PCR are linear, while NN and CART are non-linear.

MLR is a parametric method (assumes a certain probability distribution for the data) that aims to predict a desired variable Y using other predictor variables such as wind speed and temperature. In Slini et al.'s (2006) study, the PM_{10} concentration was the desired variable, Y . Each predictor variable is selected and weighted based on their ability to reduce the difference between the measured Y -value and the predicted Y -value.

The CART method is nonparametric and allows for the consideration of a pool of predictor variables that may or may not be used. The selection of predictor variables occurs through binary recursive partitioning (a continuous splitting of data into two groups) that is based on the satisfaction of conditions previously set. The conditions are modified based on what yields the most accurate predictions and based on previous knowledge about the variables.

PCR is a combination of Principle Component Analysis (PCA) and a linear regression. PCA evaluates the relationship between variables using a covariance matrix, selecting variables that are most independent (have little or no relationship to one another) and account for the most variance. Selected variables are then used in a linear regression analysis.

NN methods typically employ weights and functions in series that yield a predicted value. The major advantage to NN methods is that information about errors in predictions is used to improve the applied weights and functions through the use of algorithms.

In application of the four forecasting methods to Thessaloniki, a densely populated city with many traffic and industrial sources and complex topography, PM₁₀ and meteorological data from 1994 through 2000 was used. Slini et al.'s evaluation found NN to have the most reliable predictions containing the smallest errors in modeling performance and variables, yet NN was unable to predict peak PM₁₀ values and may sometimes underestimate concentrations. PCR and MLR, alternatively, were able to correctly predict actual episode days and did so with a low percentage of false positives. However, MLRs had the highest significant differences between predicted and observed values. The statistical evaluation of modeling methods evaluated by Slini et al. demonstrated advantages and disadvantages to each of the methods. Perez et al. (2000) also demonstrated more accurate predictions for PM_{2.5} concentrations using NN in comparison to MLR, although prediction errors were more similar for both methods than in Slini et al.'s research. Still, while NN offered the most accurate predictions, its inability to identify peak concentrations can make it less suitable for some practical purposes. Method selection should be based on the intended use of predicted values.

Although MLR may not offer the highest level of accuracy in pollutant predictions, this study will explore the method, because it is a simple linear model that is readily interpretable and operated (Pires et al., 2008), while also being relatively robust or flexible to deviations from model assumptions (Demuzere & van Lipzig, 2010). These

characteristics make MLR readily applicable and understood, in contrast to black box models such as NN that often require complex algorithms. In addition, the limited data inputs available for this study may be restrictive for more complex models. Evaluating the MLR method also expands upon Ward's (2009) research by increasing the sample size that may be used to develop a MLR model.

2.2.2.1.1 Multiple Regression Models for PM Variability

Many studies have tested the MLR's ability to explain pollutant variability, though often on a larger-than-neighborhood scale and not always with an emphasis on $PM_{2.5}$ (PM_{10} has instead been the focus of some MLR studies). These studies reveal that MLR models are site specific, though similarities between developed models offer information generally applicable to other locations. Tai et al. (2010) used the MLR to model daily $PM_{2.5}$ concentration throughout the United States using air quality and meteorological data collected from 1998 to 2008. Tai et al. found meteorological variables including surface air temperature, relative humidity, precipitation, cloud cover, geopotential height at 850 hPa, local rate of change of sea-level pressure, surface wind speed, a east-west wind direction indicator (cosine of wind direction), and a north-south wind direction indicator (sine of wind direction) to be significant predictors. These variables accounted for up to 50 percent of variability in $PM_{2.5}$ concentration. Vukovich & Sherwell (2002) also used MLR to evaluate $PM_{2.5}$ variability from 1991 through 1997 data, but on a small scale at two specific sites located in Washington, DC and Shenandoah National Park, Virginia. At the Washington, DC site, dew point accounted for the most $PM_{2.5}$ variability, 53 percent, and the addition of sky cover and SO_2 emissions increased explained variation to

77 percent. At the Shenandoah site, temperature accounted for the most variability in $PM_{2.5}$, 59 percent, and the addition of a solar radiation variable resulted in a model that accounted for 82 percent of $PM_{2.5}$ variability. A principle component analysis also demonstrated wind speed and temperature to explain similar percentages of variation in $PM_{2.5}$ concentrations at both sites.

Studies relating meteorology to PM_{10} have found similar meteorological variables to explain variation in PM_{10} concentrations. Variability in daily winter PM_{10} concentrations have been correlated to meteorological conditions using MLRs for sites within the Netherlands (Demuzere et al., 2009) and within parts of the western Alpe-Adria region in central Europe (Stadlober et al., 2008). Meteorology accounted for 23 percent of PM_{10} variability in areas within the Netherlands based on data collected between 2001 and 2006 and between 55 and 70 percent of variability within cities of the Alpe-Adria region based on data collected during different time intervals within 2001 and 2007. Wind speed and direction, maximum temperature, shortwave downward radiation, lagged wind speed and direction, lagged cloud cover, precipitation, relative humidity, and lagged precipitation were all significant predictors for Netherland sites, while Alpe-Adria region MLR models indicated lagged PM_{10} concentration, inversion, day of week and month, winds speed, and precipitation to be significant predictors.

Site specific predictors inevitably result due to differences in the location's terrain and the behavior of the location's population. Despite differences in the percentage of variability accounted for in different MLR models, relative humidity, temperature,

precipitation, and wind speed all tended to be significant predictors in many of the studies. Developing a MLR model for this study allows for the determination of variables that relate to local $\text{PM}_{2.5}$ variability. In addition to understanding the relationship between meteorological and source impacts and $\text{PM}_{2.5}$ variation at the study site, an evaluation of the MLR method on a neighborhood scale will offer information about its performance for future $\text{PM}_{2.5}$ applications. The MLR method will be discussed in greater detail in Section 4.3. In addition to the MLR method, non-linear relationships will be briefly explored as necessary to improve the developed models.

2.2.2.2 Mechanical/Physical Models

Mechanical and physical modeling methods, of which chemistry-transport models (CTM) and chemical mass balances (CMB) are common, are an alternative to ambient-data-based models. These models may rely on thorough chemical analysis of air samples, the understanding of specific source contributions, air mass behavior, and/or thermal impacts on particle chemistry (Chow & Watson, 2002; Sportisse, 2007). Although mechanical methods such as CTM and CMB can provide pollutant variability in high resolutions within small areas, they tend to require highly detailed and accurate mechanistic information that may be economically impractical (Valari & Menut, 2010).

Dispersion models belong to a category of mechanical models which does not require as much sampling and chemical analysis as CTM and CMB methods and rely instead on information more readily available in the United States, such as meteorological (i.e. wind speed and direction) and geographical (i.e. elevation) data. Dispersion models are

mathematical simulations of pollutant travel as it leaves the original source location. The use of dispersion models may allow for the determination of pollutant concentrations over differing spatial and time characteristics. Through the use of measured terrain, weather, and land use information, pollutant concentrations can be predicted at specific locations where air monitoring does not take place.

Two dispersion modeling programs were considered for use in this study, Industrial Source Complex Short Term 3 (ISCST3) and American Meteorological Society/U.S. Environmental Protection Agency Regulatory Modeling System (AERMOD). Both have been developed under the EPA's request due to regulatory need and the importance of protecting public health, and both have been thoroughly evaluated. They are discussed below.

2.2.2.2.1 AERMOD and ISCST3/ISC-PRIME

American Meteorological Society/U.S. Environmental Protection Agency Regulatory Modeling System (AERMOD) is the current EPA-preferred dispersion modeling program for near-field regulatory application (US EPA, 2008a), officially replacing its predecessor, Industrial Source Complex Short Term 3 (ISCST3), on December 9th, 2006. Under the EPA's *Guideline on Air Quality Models*, the EPA designated system is the basis of many regulatory programs and its use is required in conjunction with State Implementation Plan (SIP) development and certain instances of federal source permitting, risk assessments, and exposure analyses. Both AERMOD and ISCST3 predict the highest concentrations over a selected averaging period and specified days and

months based on source, terrain, and meteorological data input into the programs. To select the highest pollutant concentration, the two programs model all concentrations that result as the emission source constantly releases pollutants over the different meteorological conditions and as the plume interacts with the terrain.

ISCST3 was developed in 2002 by the US EPA as the third revision to the first ISCST program. Like ISCST and ISCST2, ISCST3 can evaluate plume rise and downwash for Good Engineering Practice stack heights and for shorter stacks, but it has also been refined to improve algorithms that calculate ground level pollutant concentrations at a one hour time-step or higher for area sources and for instances of dry and wet deposition. The program assumes steady-state Gaussian plume dispersion from stationary point, line, area, or volume sources and is capable of considering conditions such as complex terrain, stack tip downwash, buoyancy induced dispersion, and final plume rise. Equation 1 below shows the steady-state Gaussian dispersion model in its basic form for point sources as presented by Cooper and Alley (2002).

$$C = \frac{Q}{2\pi u \sigma_y \sigma_z} \left[\exp\left(-\frac{1}{2} \frac{(z - H)^2}{\sigma_z^2}\right) + \exp\left(-\frac{1}{2} \frac{(z + H)^2}{\sigma_z^2}\right) \right] \quad \text{Equation 1}$$

where C = steady-state concentration at a point (x,y,z), $\mu\text{g}/\text{m}^3$

Q = emissions rate, $\mu\text{g}/\text{s}$

σ_y, σ_z = horizontal and vertical spread variables, m (as functions of distance, x, and atmospheric stability)

u = average wind speed at stack height, m/s

z = vertical distance from ground level, m

H = effective stack height ($H + \Delta h$, where h = physical stack height and Δh = plume rise, m)

To calculate ground level concentrations, ISCST3 considers meteorology, including wind profiles, vertical temperature gradients, and high or calm winds (US EPA, 1995a; US EPA, 1995b).

With the help of Electric Power Research Institute (EPRI), the US EPA also developed ISC–Plume Rise Model Enhancement (ISC-PRIME), to improve predictions of building downwash where shorter stacks may cause plumes to become entrained around nearby structures. ISC-PRIME uses the same algorithms as ISCST3 with the exception of the building profile input program (BPIP), which has succeeded in improving representation of the building downwash effect (EPRI, 1997). These improvements are largely a result of considering properties and interactions such as stack location relative to the building, streamline deflection over the building, speed deficits or shear impacts on a plume in a wake, and connections between two downwash algorithms (US EPA, 2003).

While a number of options are available on ISCST3 and ISC-PRIME (ISCST3 combined with BPIP), the program has several shortcomings often resulting in an overestimation of pollutant concentrations in unstable conditions (US EPA, 2003; Trinity Consultants, 2001). The American Meteorological Society/Environmental Protection Agency Regulatory Model Improvement Committee (AERMIC) was formed in 1991 to produce a

program with more representative modeling capabilities than the US EPA's ISC programs. The result of AERMIC's work was AERMOD, designed to overcome ISCST3's weaknesses while also being suitable for complex terrain and application over distances less than 50 km (40 CFR Part 51). Although AERMOD also uses a steady-state Gaussian dispersion model, it was developed to manage deviations from Gaussian distributions, largely by considering variations in the planetary boundary layer (PBL) and through more realistic representation of meteorology and plume rise. For example, to account for vertical variations, a bi-Gaussian distribution is used in the vertical component of the convective PBL, where turbulence results due to considered characteristics such as friction and convective velocity, mechanical and convective mixing height, and sensible heat flux. In comparison to ISCST3, which considers only wind profiling, AERMOD additionally considers temperature and turbulence profiles. Changes in plume rise and dispersion are also better represented in AERMOD, because plume variables are considered in at least two locations for the plume rise and throughout the plume depth for plume dispersion. ISCST3 considers only emission variables at one point, the stack top, for plume rise and plume dispersion.

While AERMOD's modeling capabilities are often superior to ISCST3, the model type used in this study depended on the availability of meteorological data. Table 1 below summarizes the meteorological inputs required for both models.

Table 1. Required Meteorological Inputs for ISCST3 and AERMOD

ISCST3	AERMOD
Hourly Flow Vector	Hourly Flow Vector (deg.)
Hourly Wind Speed	Hourly Wind Speed (m/s)
Hourly Ambient Temperature	Hourly Ambient Temperature (K)
Hourly Stability Class	Hourly Solar Radiation
Hourly Rural Mixing Height	Hourly Cloud Cover
Hourly Urban Mixing Height	Surface characteristics
	Twice daily upper air soundings

2.2.2.2.2 Review of ISCST3/ISC-PRIME and AERMOD Performance

A quantitative evaluation between AERMOD and ISCST3 performance and differences was conducted to understand typical modeling results. Because AERMOD is the current EPA preferred model, this study included a review of AERMOD to ISCST3 ratios and AERMOD and ISCST3 performance in scenarios similar to those found in this study's evaluated site. The characteristics of focus include rural locations, complex terrain, short stacks, and cases where building downwash are significant.

Several studies and field experiments have been conducted, compiled, and reviewed to compare predictions and performance of AERMOD and ISCST3. The US EPA has been a driving force in these studies to develop a regulatory procedure intended to protect public health. Using AERMOD (version 02222), ISCST3, and ISC-PRIME, the US EPA (2003) tested a variety of scenarios in Pittsburgh, PA and Oklahoma City, OK observing the impacts of several site and source characteristics: simple and complex terrain, building downwash, rural and urban areas, and source type (point, line, area, and volume). Among the EPA evaluations, 28 cases were for complex terrain and 60 cases focused on building downwash.

The US EPA study noted ISC programs to perform less accurately for locations with complex terrain than for locations with simple and flat terrain (ISCST3) and locations where building downwash played a significant role (ISC-PRIME). When terrain was complex, ISCST3 has been seen to largely over predict concentrations and to predict concentrations much higher than AERMOD. The average AERMOD to ISCST3 ratio for short stacks over 1 hour and 3 hour averaging times was 0.26 with ratios ranging from 0.1 to 0.51. The large difference in concentrations estimated by AERMOD and ISCST3 are attributed to the COMPLEXI modeling component found in ISCST3 that was originally designed to be a conservative screening program for complex terrain (US EPA, 2003). Over all cases of complex terrain, differences between AERMOD and ISC-PRIME concentrations were also found to increase with increasing concentration averaging time.

The building downwash component of the US EPA analyses compared AERMOD (with BPIP) and ISC-PRIME results and found that AERMOD to ISC-PRIME ratios were on average close to 1, ranging from 0.87 to 1.05, including all averaging times (1 hour, 3 hour, 24 hour, annual) when building downwash was known to be significant. When including both significant and insignificant building downwash sources, the average AERMOD to ISC-PRIME ratio for all cases and all averaging times was around 1.12, though ratios ranged widely between 0.28 and 3.46. Similarities in ISC-PRIME and AERMOD with BPIP were expected to result when downwash was significant due to similarities in the PRIME algorithms used. Thus, ratios close to 1 often resulted from running both ISC-PRIME and AERMOD when building downwash was significant.

The performance of AERMOD and ISC programs was also evaluated based on 17 field studies by Perry et al. (2005) over flat and complex terrain, urban and rural conditions, different stack heights, and with and without wake effects.

Field studies evaluated by Perry et al. for complex terrain all taking place in rural locations often found AERMOD to perform more accurately than ISCST3. For example, an elevated weakly buoyant release of SF₆ in mountainous terrain in Tracy, Illinois found a predicted-to-measured concentration ratio of 1.07 for 1 hour AERMOD concentrations, while ISCST3's predicted-to-measured concentration ratio was on average about 2.81. AERMOD predicted-to-measured ratios were close to unity for 3-hour highly buoyant releases of SO₂ where building downwash was not expected, but ISCST3 predicted-to-measured ratios varied widely at 0.98 for Clifty Creek, Indiana, 8.20 for Lovett, New York, and 11 for Westvaco, Maryland. Two studies for Duane Arnold Energy Center (DAEC) and Experimental Organic Cooled Reactor (EOCR) in Idaho Falls, Idaho conducted in locations containing terrain variations, short stacks, and non-buoyant releases of SF₆, however, resulted in greater similarity between ISC-PRIME and AERMOD. In those cases, building downwash was significant and ISC-PRIME predicted-to-measured ratios were on average 0.38 and 1.69, for DAEC and EOCR, respectively, fairly similar to AERMOD predicted-to-measured ratios of 0.51 and 1.72, respectively. When ISC-PRIME was run instead of ISCST3, the degree of over prediction of concentrations was reduced, and under prediction instead occurred more often.

In comparing the accuracy of AERMOD and ISCST3 predicted ground level concentration, Perry et al., similar to the US EPA (2003) found that overall, ISCST3 tends to over predict concentrations and predicted concentrations tend to be higher than AERMOD estimates. Additionally, Perry et al. found that AERMOD and ISCST3 are capable of simulating near-field dispersion for near surface releases, but are less accurate in convective and stable conditions. Paine et al. (1998), in a study prior to Perry et al. and using one of the same field studies, also mentioned that concentrations occurring within a kilometer of the stack were under predicted, but noted predictions over longer distances to be fairly accurate. Paine et al. also recognized that under predicted near-field concentrations were small and thus modeled-to-observed concentration ratios were insignificant. Still, although AERMOD's near-field performance could use some improvement, its use of a bi-Gaussian distribution in convective conditions makes it better able to predict concentrations than ISCST3.

Venkatram et al. (2004) conducted a much smaller study to evaluate the performance of ISC-PRIME and AERMOD with and without PRIME in predicting concentrations under downwash conditions. Within a 900 m² flat parking lot area surrounded by buildings, a small line source on top of a building was simulated using a trailer and a series of tubes. SF₆ tracer was emitted and measured at 24 receptors at 2 through 5 meters and at 10 and 20 meters away from the trailer. Meteorology was also measured at one location. Although the study intended to simulate a small line source as may be found in urban

rather than rural environments, the study evaluated dispersion modeling with ISC and AERMOD over a small area similar in size to the Cambria study site.

Results from Venkatram et al.'s study indicated that both ISCST3 and AERMOD, when used in conjunction with PRIME, overestimated high concentrations and underestimated lower concentrations. This similarity between modeled ISCST3 and AERMOD concentrations run with PRIME was expected as in US EPA's (2003) study, due to the matching PRIME algorithms used. For higher observed concentrations, ISC-PRIME and AERMOD used with PRIME often predicted concentrations greater than a factor of 2 above the observed concentration. When AERMOD was used without the PRIME algorithm, modeled concentrations were higher than measured values, but typically within a factor of two.

2.3 Study Origins

Because studies contributing to the understanding of near-field spatial variability are limited, in the winter months between November 2008 and March 2009, Ward (2009) and Malejan (2009) conducted parallel studies to better understand wood smoke BC exposure within a 1 km² area in Cambria, California. Their study utilized an array of personal environmental monitors (PEMs) and aethalometers to measure BC concentrations generated by winter wood burning over several 12 hour time periods. Air samples were collected both indoors and outdoors and wood burning sources within the study area were identified using an infrared camera, which identified high chimney temperatures. Each 12-hour sampling and source identification period was identified as

an intensive operation period (IOP). Ward's analysis of the data included observation of the spatial variation of BC concentrations within the study area and determination of correlations between measured black carbon concentrations, meteorological conditions, and burning source data over six IOPs. Malejan's analysis observed the source of BC through the analysis of light attenuation over the spectrum of wavelengths and modeled BC infiltration based on indoor and outdoor aethalometer measurements during IOPs. This study aimed to expand on Ward and Malejan's study, and thus their results and conclusions are summarized below. Goals for this study include (1) further understanding pollutant variability within a near-field area in an effort to identify potential public exposure (2) further evaluating the relationship between meteorological conditions and burning source information, in addition to geographic details, and (3) identifying the performance of existing dispersion models in application to the near-field based on available input variables. In this study, the same sampling methodology as conducted in Ward and Malejan's study was used, but meteorological data was also collected at two locations where sampling took place. This is explained in detail in Chapter 3.

2.3.1 Conclusions from Ward (2009): Spatial Variation and Correlation Analysis

To characterize near-field BC variability, Ward (2009) evaluated statistics of measured BC samples (i.e. averages and standard deviations) and used statistical methods to identify variables that influence BC variability. Using the repeated measures analysis of variance (ANOVA) statistical test, Ward found statistically significant differences between BC concentrations at sampling sites within the 1 km² study area. Over a single

IOP, aethalometers detected BC concentration differences up to $3.27\mu\text{g}/\text{m}^3$. BC concentrations measured using Personal Environmental Monitors (PEMs) differed at most by $0.76\mu\text{g}/\text{m}^3$ over a single IOP. The average standard deviation and relative standard deviation of PEM BC concentrations was $0.10\mu\text{g}/\text{m}^3$ and 77.18 percent, respectively, over all IOPs. A comparison of 12 hour BC concentrations measured by co-located PEMs and aethalometers found four out of six samples to be identical. The differences between the other two samples were attributed to differences in the optical absorption cross-sectional area used.

To determine the effect of burning sources and available meteorological variables on BC concentrations, the development of multiple linear regression (MLR) analyses were attempted, but proved unsuccessful. Meteorological data was acquired from an existing Weather Underground station, Marine Terrace, located 1.89 miles south of the study area, and evaluated variables included wind speed, wind speed gust, wind direction, temperature, dew point, barometric pressure, humidity, and surface inversion conditions. The number of homes burning wood and their locations were also used to find correlations with BC concentrations. Attempts to understand BC concentrations using MLR include the reduction of BC concentration averaging time, the addition of the burning source information, and the removal of variables based on variance inflation factors (VIFs). VIFs are a statistical tool to identify correlations between variables. Correlated variables are typically removed to improve an MLR. The MLR's inability to find relationships between BC concentrations and meteorological variables even where relationships are known to exist was attributed to a shortage of available data and/or

missing variables that may contribute to BC concentration variability. In another attempt to understand the effect of meteorological variables on BC concentrations, Ward utilized a weighted function which indicated BC concentration to be proportionally related to the numbers of homes burning and inversely proportional to distance from burning sources, the sine function of the angle between the source and the wind direction, and wind speed. All tests found no suitable MLR models.

This study expands upon the aethalometer and PEM BC data set available to better identify the magnitudes of near-field BC variability in the Cambria study site. In addition, the larger sample size was used to again evaluate the relationship between meteorological and geographic predictors through statistical means, and different strategies were taken to observe predictor impacts on BC variability.

2.3.2 Conclusions from Malejan (2009): Indoor/Outdoor Infiltration and Spectral Dependence of Organic Carbon

Malejan's (2009) study, unlike Ward's (2009) study, evaluated the relationship of indoor and outdoor BC exposures and observed the spectral dependence of BC light attenuation. Based on indoor and outdoor BC concentrations measured by aethalometers, Malejan found the average indoor to outdoor (I/O) ratio was 0.75 ± 0.05 for 16 burning events. This was comparable to previous studies where observed average EC I/O ratios were 0.85 ± 0.46 (Geller et al., 2002) and BC I/O ratios were observed at 0.6 ± 0.2 (Lunden et al., 2008). In exploring infiltration models, Malejan determined a simplified version of the infiltration equation developed by the Lawrence Berkley National Laboratory (LBNL)

(Thatcher et al., 2001) to best represent measured indoor and outdoor BC concentrations (Equation 2 below).

$$\frac{\partial C_I}{\partial t} = C_0 P \lambda_V - C_1 (\lambda_V - k_{dep}) \quad \text{Equation 2}$$

where $C_I(\mu\text{g}/\text{m}^3)$ = indoor particle concentration at time t ,
 $C_0(\mu\text{g}/\text{m}^3)$ = outdoor particle concentration at time t ,
 P (dimensionless) = penetration factor,
 $\Lambda_V(\text{h}^{-1})$ = air exchange rate due to infiltration,
 $k_{dep}(\text{h}^{-1})$ = deposition loss rate

Infiltration variables including air exchange rate, deposition rate, and penetration factors were determined using SOLVER, a sum of squared difference minimizing tool, in Microsoft Excel. Under the assumptions of constant deposition rate and penetration factor and a varying infiltration rate, deposition rate was $0.10 \pm 0.02 \text{ hr}^{-1}$, penetration factor was 0.94 ± 0.03 , and air exchange rate was $0.35 \pm 0.07 \text{ hr}^{-1}$.

Using Beer's law as discussed in Section 2.1.3.1, Malejan confirmed the assumption that most BC samples collected were contributed by wood smoke. Adsorption Ångström exponents (AAE) observed by Malejan were close to the value of 2 for six out of eight PEM filter samples. The average specific attenuation coefficients at 370 and 450 nm wavelengths for the six wood smoke samples were $6.1 \pm 1.4 \text{ m}^2/\text{g}$ and $2.1 \pm 0.6 \text{ m}^2/\text{g}$, respectively. The average spectral dependence across all wavelengths between 350 and

880 nm was $\lambda^{-1.7}$ and at wavelengths less than 600 nm, spectral dependence was $\lambda^{-2.24}$ based on power law regressions.

In addition to observing spectral dependence of light attenuation to confirm that BC was of wood smoke origin, Malejan's analysis also included a comparison of measured EC and BC concentrations using the NIOSH 5040 and LBNL's thermal optical analysis (TOA) method, respectively, and observation of levoglucosan analysis (see section 2.1.3). Total carbon (TC) collected was also measured using both methods. The average ratio of LBNL TOA/NIOSH 5040 for TC was 1.44 ± 0.91 using a 95% confidence interval. The LBNL TOA EC/NIOSH 5040 BC ratio was 2.11 ± 0.67 , supporting past research that indicated large variation in EC fractions based on methods used (see section 2.1.2). A comparison of BC measured from LBNL EGA, aethalometers, and LBNL light attenuation yielded an average LBNL TOA/aethalometer ratio of 1.21 ± 0.25 and an average LBNL TOA/LBNL attenuation ratio of 1.05 ± 0.30 . Levoglucosan was found to comprise 5.9 ± 3.7 percent of total NIOSH OC and 5.4 ± 3.1 percent of NIOSH TC.

While this study does not delve into indoor BC exposure, Malejan's results draw several valuable conclusions for this study: the relationship between indoor and outdoor BC is important for understand exposure within the study area, wintertime Cambria BC originates primarily from wood smoke, and analytical methods for measuring BC may differ significantly from one another. This study expanded the sample size of observable AAE values, further demonstrating wood smoke as the principal source of BC.

Chapter 3. Materials and Methods

The BC sampling process and periods, instrument and meteorological station details, and analytical methods are summarized in this section.

3.1 Study Location

Situated off of Highway 1, a two-lane road running north and south along the California coast, Cambria lies 35 miles north of San Luis Obispo in San Luis Obispo (SLO) County, in between San Francisco and Los Angeles. The town spans about 3 km², is populated by approximately 6,500 people, and lists tourism, light industry, and agriculture as its main industrial activities (Cambria Chamber of Commerce, 2010). The 2000 US census indicated a median population age of 50.9, and 46 percent of structures (including homes) built before 1980 and 32 percent built between 1980 and 1989 (US Census Bureau, 2000).

Several characteristics combine to make Cambria a suitable location for this study. Cambria contains very little commercial diesel traffic and industrial pollution, and is located in a county noted to have some of the lowest PM_{2.5} concentrations in California (American Lung Association, 2010). Thus, for the majority of the year, Cambria experiences low PM_{2.5} concentrations. Still, a significant fraction of homes in Cambria contain chimneys and/or wood burning stoves. US Census surveys conducted between 2005 and 2009 suggest about 3.1 ± 2.5 percent of homes in Cambria use wood as a primary heating fuel (US Census Bureau, 2009). The use of wood as a heating source and the abundance of homes with chimneys and wood stoves in Cambria may be a result

of tree availability in the area in addition to the local demographic. The tree cover in the chosen 1 km² study area comprises about 60 percent based on a visual estimate from Google Earth satellite imagery. Figure 1 details an approximated estimate of tree coverage. The prevalence of trees in Cambria offers an inexpensive alternative to petroleum heating. This may be especially relevant to a population that is largely retired or approaching retirement age. Cambria's population has a median age of 55.9, and 30.6 percent of its population is above the age of 65 years (US Census Bureau, 2009). Fixed income amongst retired populations may encourage lower cost fuel sources such as wood (Tian et al., 2004).

Figure 1. Approximate determination of tree coverage in study area

While wood burning households make up a small percentage of the population, the prevalence of wood burning concentrated within residential neighborhoods may lead to frequent exposure. In SLO county, residential wood combustion was estimated to constitute 26 percent of the total winter $PM_{2.5}$ in 2005 (CA ARB, 2006). Wood smoke exposure can also be enhanced by winter time coastal inversion layers in Cambria which occur due to its proximity to the ocean. Coastal inversion layers may result when air above the ocean surface is cooled by ocean upwelling and then transported to land by horizontal movement or advection. Because the transported ocean air is then situated above the land surface and is cooler than the air above it, there is no upward air movement and mixing, trapping pollutants close to human receptors. Wood smoke detected by residents has brought about health concerns, and in the winter of 2008, the San Luis Obispo Air Pollution Control District (SLO APCD) received several complaints from Cambria residents.

Several factors made Cambria an ideal location for this study. First, Cambria's typically low $PM_{2.5}$ concentrations and lack of industrial and traffic source impacts allow virtually all of the BC and $PM_{2.5}$ in the air during the winter to be attributed to wood burning. In addition, concerned residents also provide a group of participants willing to permit the placement of air sampling equipment at their residences; volunteers from Ward and Malejan's (2009) study were again happy to permit instrument placement on their property. A low average precipitation each month of about 3.3 inches during winter

months, December through March (The Weather Channel, 2010), also reduces removal of pollutants from the air, allowing for more potential sampling days during the winter.

A 1 km² area within the Leimert and Happy Hills neighborhoods as shown in Figure 2 was selected for the study. The selected neighborhoods were a suitable site, because they share similar characteristics with other Cambria neighborhoods. The area contains about 400 homes, many with constructed chimneys. The terrain is both flat and hilly at elevations between about 90 and 250 feet and all streets have only single lanes in both directions, often without sidewalks. Most homes contain front yards that separate the homes from the road. In areas of higher housing density (mostly the Happy Hills neighborhood), homes are spaced about 10 feet apart, often with the backs of two houses facing one another, and almost every house contains trees on at least two sides of the residence. In the area of lower housing density (mostly the Leimert neighborhood), homes are often spaced greater than 50 feet apart with trees surrounding the homes on all sides. Cambria's downtown is located just south of the study area comprising mostly one long street running south east from the study site. The downtown area located closest to the study site consists of restaurants, novelty shops, art galleries, hotels, a couple of gas stations, and other local businesses.

Figure 2. Map of Cambria with Study Area Selected

While Cambria provides a suitable study site for the reasons discussed above, it is important to note that pollutant variability is site specific. There is no single area that will necessarily represent all other locations where heating with wood is common. Cambria shares both geographic differences and similarities with areas where winter wood burning has contributed to high $PM_{2.5}$ levels. The Central Valley, including San Joaquin Valley, for example, has been the subject of many studies due to its failure to meet $PM_{2.5}$ National Ambient Air Quality Standards (Park et al., 2006; Chen et al., 2007;

Cahill, 2010). The Central Valley primarily experiences high pollution exposure due to the prevalence of many PM_{2.5} emitting sources and surrounding mountains. Temperature inversions that occur within or just above the valley act to trap the particles in the valley. Although Cambria may have significant sources of PM_{2.5} from wood burning during the winter, its coastal location often allows for better pollutant dispersion. Cambria's neighborhoods also differ from many Central Valley locations in its neighborhood scale topography. Although many Central Valley cities are relatively flat, Cambria neighborhoods have more hills and slopes. Central Valley cities also tend to be surrounded by agriculture fields while areas around Cambria have remained undeveloped, containing expanses of woodlands.

With the exception of topography, many homes in Central Valley cities such as Fresno, Chowchilla, Sacramento, and Clovis contain neighborhood characteristics similar to Cambria. As with the higher density Happy Hills area in the Cambria study site, these Central Valley cities have similar house spacing, homes situated back to back, and trees often line at least two sides of each home. These characteristics may result in similar pollutant transport behavior including particle deposition within trees and the generation of recirculation cavities in between homes.

3.1.1 Existing Controls and Regulations

In California, stationary air pollution sources such as wood stoves and chimneys are controlled by air pollution control districts or air quality management districts. Cambria, California falls under the jurisdiction of the San Luis Obispo Air Pollution Control

District (SLO APCD). SLO APCD Rule 504, Residential Wood Combustion, was adopted October 19, 1993 and became effective February 1, 1994. The rule regulates the purchase and sale of wood burning devices and the sale of wood, while also allowing the APCD to declare and notify residents of voluntary curtailment during poor air quality events. Once effective, only EPA-certified, Oregon-Certified, Pellet-Fueled Wood Heaters, or other district-approved devices could be purchased and sold. In addition, retailers of wood combustion devices were required to provide instructions for proper device installation and operation and inform customers about the health benefits of low-emitting devices. Rule 504 also requires that only wood with 20 percent or less moisture by weight can be advertised as “seasoned” or “dry” wood, and prohibits the burning of materials that produce noxious or toxic compounds including garbage, treated wood, plastic, rubber, petroleum products, paints, and coals in wood burning devices.

3.2 Instruments

To achieve a quantitative analysis of wood smoke concentration and the effects of meteorology on that variability, instruments were used for the purpose of measuring particles, including black carbon (BC) and PM and meteorological variables. The measurement of BC was chosen because it is a significant component of wood smoke and its concentration is determined using optical methods. These methods tend to be more economical than chemical methods that detect emitted organics like levoglucosan. The use of optical methods can also offer high resolution BC measurements while providing information about the combustion sources from which the particles originate.

Aethalometers and Personal Environmental Monitors (PEMs) were the selected sampling

instruments. Meteorological instruments were selected based on their availability in the educational and local community. A Met One Instruments, Inc. E-BAM and a Young Model 81000 Ultrasonic Anemometer were obtained for this study.

3.2.1 Aethalometers

Three to four Magee Scientific Aethalometers were used to measure BC at 1- and 2-minute resolution during the study. Aethalometers measure light attenuation (ATN) transmitted through a quartz fiber filter based on Equation 3 below

$$ATN = 100 \times \ln \left(\frac{I_0}{I} \right) \quad \text{Equation 3}$$

where I_0 is the intensity of light transmitted in the absence of filter deposit and I is the intensity of light transmitted in the presence of filter deposit. BC concentration is then determined by evaluating the change in attenuation over a select period of time (ΔATN) and measured based on Equation 4 below

$$BC = \frac{\Delta ATN A}{V \sigma_{SG}} \quad \text{Equation 4}$$

where A is the area of the filter deposit (cm^2), V is the sample volume passed through the filter (m^3), and σ_{SG} is the specific attenuation cross-section (m^2/g) (typically referred to as just σ , but the “SG” subscript was added to differentiate it from the spectrally dependent mass adsorption efficiency discussed in Section 2.1.3.1). Equation 4 assumes a constant attenuation cross-section (that particles have been deposited evenly) and a linearly proportional relationship between light attenuation and mass. As discussed by Malejan

(2009), these assumptions have been found to be false in some studies. Petzold et al. (1997) and Liousse et al. (1993) found σ_{SG} to range between 8 and 19 m²/g and 14 and 20 m²/g, respectively, and filter loading was found to affect light attenuation in Weingartner et al.'s (2003) study. Weingartner et al. observed a decrease in the optical path through the filter as filter loading increased, resulting in lower reporting of concentrations. Due to the observed impact of filter loading on concentration readings, Malejan (2009) ran aethalometers in close proximity simultaneously and compared different attenuations to their respective concentrations. No filter loading impacts were observed. The same check was conducted for this study and similarly no filter loading impacts were observed.

Of the four different Magee Scientific Aethalometers used in this study, one was multi-wavelength, measuring light attenuation at 370, 470, 520, 590, 660, 880, and 950 nm and three were dual wavelength, measuring light attenuation at 370 and 880 nm. The wavelength of 370 nm is well absorbed by EC and OC, while 880 nm is well absorbed almost exclusively by the BC component of PM. The multi-wavelength and one of the dual wavelength aethalometers were of the portable variety.

Aethalometers drew air samples at flow rates of about 4 or 7 L/min, depending on aethalometer, and BC concentration was determined based on light attenuation measured at 880 nm. Concentrations were then calculated based on the Aethalometer handbook recommendation for σ_{SG} of 16.6 m²/g (Hansen, 2005), which also falls well into previously observed ranges for σ_{SG} as discussed above. It is important to note that due to the algorithm used in the aethalometer, extremely low BC concentrations can be read as

negative values. This has been attributed to desorption of organic vapors from the filter surface as relatively clean air passes through the aethalometer. This desorption results in a decrease of UV absorbing material, which is then interpreted as a negative value in the aethalometer algorithm (Hansen, 2005). To correct for negative BC readings, the lowest detection limit (LDL) was used to replace each negative value. In accordance with the aethalometer manual, the LDL was calculated assuming 1 ng noise per 20 liters air flow (Hansen, 2005).

For this study, the aethalometers were calibrated to more precisely represent one another as done by Malejan (2009) and Ward (2009). Aethalometers were simultaneously run side-by-side over a period of 24 hours once early in the winter sampling period and then a second time after sampling was completed. The multi-wavelength aethalometer was not tested after sampling completion because the aethalometer filter tape was unexpectedly used up and changing the tape would have changed calibrated σ_{SG} values. Determined σ_{SG} values for winter 2010 demonstrated a percent difference from between 17 and 31 percent in comparison to values for winter 2009. The difference between 2009 and 2010 σ_{SG} values may be attributed to variation in flow rates and conditions for each aethalometer run.

For each side-by-side aethalometer run, the σ_{SG} values for each aethalometer was reduced or increased over one time interval of measured BC concentrations to achieve the average BC concentration of all aethalometer BC readings. The σ_{SG} values were then applied to the second time interval of BC concentrations and a statistical Analysis of Variance

(ANOVA) conducted in Minitab on the adjusted readings in the second time interval to determine whether significant differences existed between the different aethalometers. The ANOVA test evaluates whether or not significant differences exist under the assumption that the responses, or measured BC concentrations in this case, are independent from one another, are normally distributed, and that the samples from each machine have equal standard deviations. Based on probability distributions, the ANOVA test determines whether the mean response for each machine deviates enough from the mean response of all machines to be considered different. If differences were found based on the ANOVA test, σ_{SG} was adjusted until the test indicated no statistical difference between machines. σ_{SG} values were only adjusted using time segments where all machines were similar in concentration-trends. Selecting only segments displaying the same behavior eliminates influences of readings that deviated significantly from the others. BC readings were averaged over ten minutes to reduce noise in the calibration. Values for σ_{SG} determined for the two simultaneous runs were averaged and used for the study readings. Minitab analysis and graphical representation of data before and after calibration are detailed in Appendix A.

Available aethalometers were run over each 12 hour sampling period. All aethalometers were co-located with a PEM and placed outside of the homes of volunteers in locations where they would not be disturbed and where an outdoor power source was available.

3.2.2 Personal Environmental Monitors

BC was also measured using SKC Inc. Model 200 Personal Environmental Monitors (PEMs). The PEMs select for $PM_{2.5}$ and their main components include an outer-casing with inlet holes, an air outlet, where the pump is connected, an impaction ring, onto which particles larger than $2.5\ \mu m$ land and stick, and a stainless steel screen that supports a quartz fiber filter. An additional mask containing a 2 cm opening was used to decrease the deposit area and thus increase measurement sensitivity. Before each sampling period, PEMs were cleaned with methanol and allowed to dry completely to ensure all carbon particles were removed. In assembling the PEMs, filters were transferred with sanitized tweezers to minimize contamination, and a mineral oil was applied to the impaction ring to improve the capture of particles larger than $2.5\ \mu m$. A PEM assembly is shown in Figure 3. Once assembled, all PEMs were placed inside of a single plastic bag for transport.

Figure 3. PEM Assembly

Photograph was taken by Malejan (2009)

The Model 200 PEM is designed to operate at a 10 L/min flow rate. Leland Legacy flow-controlled pumps (SKC Inc.) were used to achieve the desired flow rate. The pumps

were calibrated using a Model DC-HC-1 Bios DryCal DC-2 calibrator. To protect the pumps and decrease noise, the pumps were placed inside of a plastic container surrounded by pieces of foam during sampling. A tube-sized circular opening was made in the plastic cases to allow its connection to a PEM. Figure 4 shows this configuration.

Figure 4. PEM Casing

Photograph was taken by Malejan (2009)

In preparation for each IOP, all SKC pumps were programmed to run for 12 hours either between 6 p.m. and 6 a.m. or 5 p.m. and 5 a.m. Each cleaned PEM was connected to an SKC pump at the PEM sampling location and a 12-hr integrated air sample was taken. Each aethalometer used was co-located with a PEM for comparison purposes.

After each IOP, PEM filters were placed in individual petri dishes, each petri dish was sealed with Teflon tape, all petri dishes were bundled together, wrapped in foil, and the samples were sent to Lawrence Berkeley National Laboratory (LBNL) to be analyzed. Light attenuation of filter samples over the near ultraviolet to infrared spectrum, 350 to 1000 nm, respectively, was determined using an LBNL custom built transmissometer

which uses light emitting diodes (LEDs) to send out light. To prevent high leveraging in analyses by PEM filters containing BC at concentrations lower than the detection limit, BC readings were assumed to be midway between zero and the lower detection limit (lower detection limit divided by two), 30.2 ng/m³.

3.2.3 E-BAM

A Met One Instruments, Inc. E-BAM (Beta Attenuation Monitor) 9800 Rev K borrowed from the San Luis Obispo Air Pollution Control District (SLO APCD) was used to both measure PM₁₀ and meteorological variables. Meteorological variables including wind speed, wind direction, relative humidity, and temperature were measured to better characterize the impacts of local weather patterns on pollutant dispersion. The E-BAM has been found to satisfy EPA Class III criteria for PM_{2.5} and PM₁₀, potentially making it suitable as a substitute for Federal Reference Methods (MDEQ & MCCHD, 2010).

The E-BAM measures particles by emitting beta rays onto a glass fiber filter through the decay of ¹⁴Carbon. ¹⁴Carbon is a naturally occurring radioactive isotope whose nucleus constantly emits low to medium energy electrons known as beta particles. These beta particles lose their energy when they come into contact with nearby matter and are collectively known as beta rays. As the beta rays are emitted, beta particles are first counted by a Photo Multiplier Tube (PMT) for 4 minutes on a clean glass fiber filter. The PMT then takes a second count of beta particles over another 4 minutes as air is sampled. When particles in the air are deposited on the filter, beta particles easily lose their energy to and sometimes absorb to matter from the incoming air. In the presence of

particles from the air, a reduction in beta ray intensity occurs, the PMT detects this, and the mass of absorbing matter is determined as a function of the change in beta particles detected. The difference in beta particles is used to determine the PM concentration based on Equation 5 and Equation 7. The mass density of the absorbing material is measured by solving for x in Equation 5 below:

$$I' = I_o' e^{-\mu x} \quad \text{Equation 5}$$

where I' is the beta ray intensity in counts per unit time after sampling, I_o' is the beta ray intensity in counts per unit time before sampling, μ is the absorption cross-section of the material absorbing the beta rays in cm^2/g , and x is the mass density of the absorbing material in g/cm^2 . The absorption cross-section is determined during calibration, while x is determined by Equation 6 below. Having solved for x , the collected particle concentration is calculated by multiplying x by the area and dividing by the flow rate and time as displayed in Equation 7:

$$x = \frac{1}{\mu} \ln \left(\frac{I_o'}{I'} \right) \quad \text{Equation 6}$$

$$PM_i = \frac{10^6 A}{Q \Delta t \mu} \ln \left(\frac{I_o'}{I'} \right) \quad \text{Equation 7}$$

where PM_i is the concentration of PM less than $i \mu m$ in $\mu g/m^3$ (for this study a PM_{10} Virtual Impactor inlet was used, so i is equal to 10), A is the cross sectional area of particle deposition in cm^2 , Q is the air flow rate in L/min, and Δt is the sampling time in minutes. Although Equation 5 is a simplification of the actual process, Met One Instruments, Inc. (2001) found no substantial error during operation.

Although the E-BAM can be run using a $PM_{2.5}$, PM_{10} , or TSP inlet, a PM_{10} inlet was used because a $PM_{2.5}$ inlet was unavailable. As discussed in Section 3.1, wood smoke should be the only major contributor to $PM_{2.5}$ in the study area. Additionally, PM_{10} is not expected to be present in the study area. In the absence of major traffic, industrial, and agricultural pollution sources, PM_{10} is typically found only in the form of geologic and mineral dusts. For coastal areas, sea salt can be a major contributor to PM_{10} during wind speeds higher than 4 meters per second (8.9 miles per hour) (Arasa et al., 2008). However, because sampling periods were selected to have low wind speeds, sea salt should not be a significant contributor to PM_{10} in this study. Thus, it will be assumed that $PM_{2.5}$ contributed by wood smoke is the only source of PM, and PM_{10} readings taken by the E-BAM will be considered to be equivalent to $PM_{2.5}$ concentrations.

The E-BAM uses several sensors to measure meteorological variables. Wind speed and direction are measured using a wind combination sensor Model 034B mounted on the E-BAM; the ambient temperature sensor has a range between -50 and $50^\circ C$ with an accuracy of $0.1^\circ C$; and the Model EX-593 relative humidity sensor has a range between 0 and 100 percent with an accuracy of 3 percent (Met One Instruments, Inc., 2001).

For this study, the E-BAM recorded meteorological data at the Cambria California Department of Fire (CDF) station at an elevation of 227 feet within an open field approximately 20 feet away from the closest trees and fences. Although the Met One Instruments, Inc. manual (2001) recommends placement at least 20 meters from the drip line of trees, due to particle deposition on tree surfaces, such a large amount of space was unavailable within the study area. Figure 5 shows an aerial and ground view of the EBAM site. Before operation, the E-BAM was flow and leak checked, the temperature was compared to an external thermometer, and the E-BAM was properly aligned. The E-BAM was operated using the standard PM₁₀ measurement mode, which uses a flow rate of 16.7 L/min, and PM₁₀ measurements were taken at 10 minute and 1 hour intervals. Because the E-BAM is capable of withstanding even rainy conditions, the E-BAM was left to run during and in between IOPs, starting with the third successful IOP (IOP 4b). Meteorological data was recorded by the E-BAM in seven out of nine IOPs (4b-10b), but PM₁₀ was only measured during six out of nine IOPs (4b-8b, 10b) with IOP 9b data unavailable because the filter tape ran out before the IOP began. Figure 7 on page 62 illustrates the E-BAM location within the study area, in addition to its proximity to other meteorological stations used for this study. The E-BAM station was expected to be one of the more representative meteorological stations used in this study due to its location within the study area and its relatively unobstructed placement in the fire station field.

Figure 5. Aerial (left) and ground (right) view of EBAM meteorological site located in study area

3.2.4 Ultrasonic Anemometer

A Young Model 81000 Ultrasonic Anemometer (Sonic) borrowed from the Lawrence Berkeley National Laboratory was also used to measure meteorological data within the study area. To determine 3-dimensional wind speed and direction, the sonic anemometer measures the transit time of ultrasonic acoustic signals between transducers. The capability to read 3-dimensional wind speed allows for observation of turbulence. The ultrasonic anemometer tracks temperature ranges between -50 and 50°C to correct for wake effects caused by the anemometer structure and agrees with ambient temperature within 2°C. For this reason, the anemometer temperature was used as a proxy for ambient temperature. The ultrasonic anemometer is capable of high resolution readings, up to 32 Hz and its wind speed threshold is 0.2 m/s, or 0.45 mph, (any lower wind speeds are read as 0 m/s). Wind speed accuracy between 0 and 30 m/s is ± 0.05 m/s and wind direction between 1 and 30 m/s is $\pm 2^\circ$.

In this study, the anemometer was placed in the backyard of a Cambria resident at an elevation of 207 feet approximately 5 feet away from any obstructions as shown in Figure 6. Although fewer obstructions would have been favorable, options were limited based on the configuration of the yard and availability of power. Before operation, the anemometer was aligned with true north and the temperature was compared to a thermometer. The sonic anemometer was run during three of the nine IOPs (8b-10b) taking measurements 4 times each second. Readings were recorded directly onto a Dell laptop computer using the program HyperTerminal. The ultrasonic anemometer was co-located with an aethalometer and a PEM. Figure 7 on page 62 illustrates the Ultrasonic

Anemometer location within the study area in addition to its proximity to other meteorological stations used for this study.

Figure 6. Ultrasonic anemometer set-up within study area

3.3 Additional Meteorological Data

Additional meteorological data was required for both statistical and modeling analyses. Cambria weather data was available through the Weather Underground website which provides free historical and real-time weather data in both national and international locations. In addition to providing meteorological data from its own stations, Weather Underground's Personal Weather Station (PWS) project allows any resident, organization, or business to contribute meteorological measurements in their area to the

Weather Underground website. Although PWSs are typically not certified, Weather Underground provides free meteorological archives in areas within close proximity to the Cambria study area.

Two Weather Underground PWS stations located southeast of the study site, one in the Marine Terrace (MT) neighborhood and one in the Lodge Hill neighborhood, were chosen for statistical analysis. The MT station is located about 2 miles from the study area on the roof of a home located in a residential neighborhood close to the coast. The Lodge Hill station is located at the Cambria Community Services District Fire Department (CSDF) that is 1.8 miles from the study site. The CSDF station contains trees on the west side of the fire station building, but because the meteorological instruments are located on the fire station radio tower, approximately 25 feet above the ground, there are fewer physical obstructions. Meteorological data from an additional meteorological station was available in the Lodge Hill neighborhood at Whispering Pines Bed and Breakfast about 2.8 miles from the study area, but because the station, located on the roof of the bed and breakfast house, is surrounded by woods which would act as obstructions to wind movement, the station was not used for analysis in this study. The elevations for the MT and CSDF stations are 53 and 260 ft, respectively, and meteorological readings are recorded every 10 minutes and every 30 minutes for MT and CSDF, respectively. Weather Underground stations are displayed in a Google map image in Figure 7 along with the study area, boxed in red, to demonstrate proximity and geographic characteristics. Figure 8 and Figure 9 below shows the Marine Terrace and CSDF stations, respectively.

Figure 7. Map of meteorological stations relative to study area

The study area is boxed in red, while yellow-starred locations refer to meteorological stations

Figure 8. Marine Terrace (MT) Meteorological Station
Meteorological equipment is boxed in yellow.

Figure 9. Community Services District Fire Department (CSDF) meteorological Station

Meteorological equipment is boxed in yellow.

While the CSDF station has not undergone certification similar to many other PWS stations, it has been evaluated for quality control through the National Oceanic and Atmospheric Administration (NOAA) Meteorological Assimilation Data Ingest System (MADIS) project, providing information about data accuracy. The results have been posted on the Citizen Weather Observer Program (CWOP) website and have indicated that over the largest available analysis period of the previous 52 weeks (approximately one year), pressure and wind vectors are correctly calibrated, while dew point readings and temperature readings demonstrated large errors (CWOP, 2010). For this reason,

CSDF site dew point and temperature were not used. The CSDF station was expected to be most representative of the study area among available Weather Underground stations due to its similarity to the study area in topography, terrain, and proximity to the ocean.

Because dispersion modeling requires more detailed meteorological data than available through Weather Underground and on-site measurement instruments, the San Luis Obispo Air Pollution Control District (SLO APCD) was contacted for any available data. The only meteorological data available was for the ISCST3 program for the location of Morro Bay, California, located about 20 miles south from the study site. This meteorological data was provided for the years of 1994 through 1996 by the SLO APCD.

3.4 Intensive Operation Periods

An “intensive operation period” (IOP) refers to a 12 hour air sampling period where BC was collected throughout the study area. IOPs were first chosen to occur between 6 p.m. and 6 a.m., as conducted by Ward (2009) and Malejan (2009). However, because peaks in aethalometer BC concentrations appeared to begin earlier in the evening, IOPs 4b through 7b were conducted between 5 p.m. and 5 a.m. Once daylight savings time began on March 14th, 2010, shifting time 1 hour ahead, IOPs 8b through 10b were run between 6 p.m. and 6 a.m. During each IOP, available aethalometers were co-located with a PEM as well as a meteorological instrument when available.

Each IOP required instrument and equipment preparation and placement, wood burning source identification, and equipment and instrument pickup. PEMs, aethalometers, and

meteorological instruments were placed in an array that was distributed as evenly as possible over the whole the study area. Sampling locations were restricted to volunteers' homes and locations where the PEMs would be less likely disturbed. The sample arrangement from IOP 7b is displayed in Figure 10. Table 2 below summarizes sampling period date and time, number of PEMs and aethalometers deployed, and meteorological instruments used. IOPs conducted by Ward (2009) and Malejan (2009) are also included because data from IOPs conducted during their research was included in the analysis of IOP data from this study.

Figure 10. Sample IOP arrangement from IOP 7b

Table 2. Summary of IOPs

IOP	Date	Sample Time	Number of Functioning PEMs	Number of Aethalometers	Meteorological Data (Yes=y, No=n)	
					EBAM	Ultrasonic
Winter 2009 (<i>Ward 2009 &Malejan 2009</i>)						
1a	Jan 31 - Feb 1	6 PM - 6 AM	9	2	n	n
2a	Feb 18 - Feb 19	6 PM - 6 AM	11	2	n	n
3a	Feb 26 - Feb 27	6 PM - 6 AM	8	1	n	n
4a	Feb 27 - Feb 28	6 PM - 6 AM	11	2	n	n
7a*	Mar 15 - Mar 16	6 PM - 6 AM	12	1	n	n
8a*	Mar 20 - Mar 21	6 PM - 6 AM	12	2	n	n
Winter 2010						
2b	Jan 23 - Jan 24	6 PM - 6 AM	11	3	n	n
3b	Jan 30 - Jan 31	6 PM - 6 AM	16	3	n	n
4b	Feb 13 - Feb 14	5 PM - 5 AM	15	3	y	n
5b	Feb 28- Mar 1	5 PM - 5 AM	15	4	y	n
6b	Mar 4 - Mar 5	5 PM - 5 AM	14	4	y	n
7b	Mar 11 - Mar 12	5 PM - 5 AM	15	4	y	n
8b	Mar 15 - Mar 16	6 PM - 6 AM	15	4	y	y
9b	Apr 3 - Apr 4	6 PM - 6 AM	15	4	y	y
10b	Apr 23 - Apr 24	6 PM - 6 AM	15	3	y	y

**These IOPs were not included in results and analyses due to a high prevalence of PEM BC concentrations lower than the detection limit.*

The identification of wood burning sources was conducted using a Fluke Ti25 Thermal Imager. The Fluke Ti25 can measure the temperature of objects ranging from -4°F to 662°F within accuracy of $\pm 2^{\circ}\text{C}$ or 2% and capture thermal images. To identify wood

burning sources, the Fluke Ti25 was used to determine chimney temperature. Chimney temperatures detected above 75°F were considered to be burning sources and images of burning sources were captured. A sample infrared image from IOP 3b taken on January 30th is displayed in Figure 11 below.

Figure 11. Sample Infrared Camera Image of a Chimney

At the end of each IOP, the aethalometers, PEMs, and ultrasonic anemometer were collected, while the E-BAM was left at the CDF fire station. PEM filters were then sealed and sent to LBNL for analysis as described in Section 3.2.2.

3.5 Statistical Analyses

Several statistical analyses were conducted to understand BC variability and interactions with meteorology and site characteristics. BC variability was observed through averages, medians, and standard deviations at each sampling location, between sampling locations,

between IOPs, and over all IOPs and locations. Spatial variability between meteorological data at different sites was observed through averages, medians, and standard deviations for wind speeds, wind directions, temperature, and humidity. Variability within sampling locations and between IOPs was then evaluated relative to meteorology and site characteristics through the use of multiple regression analyses. These analyses were used to determine the most representative meteorological stations and whether location relative to wind direction and burning sources was significant in the study area. Regression analyses conducted are described in detail in Section 4.3.

3.6 BC Air Dispersion Modeling

As discussed in Section 2.2.2.2, dispersion modeling can be a useful tool for understanding pollutant exposures. To identify the performance of dispersion modeling in the case where detailed data may not always be available, ISC and AERMOD were considered for application in this study. Although both programs assume steady state conditions which may not always be applicable, they have both been US EPA preferred short-distance models and are currently the best option where limited data is available. Although both programs require less data than CTM and CMB models, meteorological data obtained in this study was still insufficient for conducting model dispersion analyses. For this reason, the local air quality regulatory agencies were contacted for available meteorological data that may be applied in either program. ISCST3 was ultimately selected for this study because only data for Morro Bay, CA (located about 20 miles south from the study site) was available from the San Luis Obispo County Air Pollution Control District (SLO APCD). Morro Bay meteorological data was available for the

years, 1994, 1995, and 1996. Because AERMOD has been found to be an improvement upon ISCST3 and ISC-PRIME, a review of available literature was conducted for comparisons of ISC and AERMOD results and performance. ISC-PRIME and ISCST3 were then used to predict BC concentrations in the study area and predicted concentrations were compared to measured PEM and aethalometer BC concentrations and distributions. Dispersion modeling methods will be discussed in greater depth in Section 4.4.

Chapter 4. Results and Discussion

4.1 Identification of BC Source

To confirm that measured BC concentrations originated from wood burning sources, the adsorption Ångström exponent (AAE) was evaluated over the wave lengths of 350 nm to 700 nm as described in Section 2.1.3.1 for all PEM samples. As discussed in Section 2.1.3.1, AAE values around 1 or lower tend to be associated with BC originating from motor vehicle exhaust, while AAE values larger than 1 are found for wood smoke. For this study, AAE values greater than 1.2 were assumed to originate from wood smoke, while AAE values less than 1.2 were assumed to indicate motor vehicle exhaust. AAE values for PEM samples collected by both Ward (2009) and Malejan (2009) in the winter of 2009 and in this study during the winter of 2010 averaged 1.89, with a median value of 1.89, and a range of 0.28 to 3.98. PEM samples lower than the detection limit were excluded. A box plot detailing the distribution of AAE values is shown in Figure 12, showing the 1st quartile value of 1.6 and the 3rd quartile value of 2.2. Among all samples with BC concentrations measured above the lower detection limit, 91 percent of AAE values were associated with wood smoke while 9 percent were associated with AAE values for motor vehicle exhaust. Because Cambria, CA does not contain major sources of vehicle exhaust, it is suspected that PEM samples with AAE values less than 1.2 may have originated from an upwind source. The AAE values for all PEMs are detailed in Appendix B.

Figure 12. Box plot of all adsorption Ångström exponent (AAE) values

Box plots denote the minimum, maximum, 1st and 3rd quartile, and median value for all concentrations. The whiskers indicate the maximum and minimum values, while the top, middle, and bottom line of the box represent the 3rd quartile, median, and 1st quartile value, respectively.

4.2 Spatial Variability

The spatial variability of black carbon (BC) and meteorological data was observed to better understand near-field exposures and regional representation. Averages, medians, and standard deviations were computed for BC and meteorological data and comparisons between sites and instruments were observed.

4.2.1 Spatial Variability of BC and PM_{2.5}

BC concentrations measured throughout the study area by both aethalometers and PEMs were evaluated and are presented in this section along with a comparison between

concentrations measured by both instruments. BC concentrations were converted to PM_{2.5} based on Equation 8 below, as determined by Ward (2009) to be an approximate relationship between BC and PM_{2.5} in the study area.

$$PM_{2.5} = \frac{BC}{0.05} \quad \text{Equation 8}$$

4.2.1.1 Aethalometer Measured BC

Based on data collected every minute, BC concentrations over all IOPs ranged between lower than the detection limit and 174,000 ng/m³. The average BC concentration measured over the study area by aethalometers was 386 ng/m³, the median BC concentration was 125 ng/m³, and the standard deviation was large at 2,640 ng/m³. Because the higher standard deviation in the data is likely the result of noise in the one minute readings, statistics based on 30 minute averages were evaluated. Observing variability based on 30 minute averages reduced noise and resulted in an average BC concentration of 229 ng/m³, a median of 122 ng/m³, and a standard deviation of 827 ng/m³. The still large (though substantially smaller) standard deviation, is a testament to the large variability in BC concentrations due to factors including diurnal variations in wood burning and meteorology and differences in meteorology and burning patterns between sampling periods or IOPs.

BC variability was also observed over each IOP using all 30 minute averaged readings measured by aethalometers in operation during each IOP. Table 3 and

details the average, median, and standard deviation of 30 minute BC concentrations over each IOP. The variability within IOPs increases when high BC concentrations are detected and alternately decreases when only background concentrations are being measured. The number of aethalometers in operation may also affect the magnitude of the standard deviation since averaging BC at more sites increases the spatial variability captured by the statistic. This spatial variability can be seen in aethalometer BC concentrations versus time graphs as show in IOP 7b in Figure 14 for the different aethalometer locations. Still, an observation of IOPs 5b through 9b, all containing the same number of aethalometers, in Table 3 and Figure 13, seems to indicate that standard deviation is more highly influenced by sudden peaks in BC concentration than spatial variability alone. Spatial variability likely accounts for a smaller portion of the standard deviation, because typical differences in BC concentration between locations are much smaller than the difference between the highest BC concentrations and typical background BC concentrations measured during the study periods. Overall, the average 30 minute-based BC concentration found during an IOP was 226 ng/m^3 , or $4.5 \text{ }\mu\text{g/m}^3$ for $\text{PM}_{2.5}$, the average median value was 132 ng/m^3 , or $2.6 \text{ }\mu\text{g/m}^3$ for $\text{PM}_{2.5}$, and the average standard deviation was 438 ng/m^3 , or $8.8 \text{ }\mu\text{g/m}^3$ for $\text{PM}_{2.5}$. Detailed BC readings over time during each sampling period and at each site can be found in Appendix C.

Table 3. Aethalometer BC variability over each IOP

Statistics are based on 30 min averaged BC concentrations measured during each IOP.

IOP #	Number of Aethalometers in Operation	Average (ng/m³)	Median (ng/m³)	Max (ng/m³)	Min (ng/m³)	Standard Deviation (ng/m³)
1a	2	385	359	903	238	132
2a	2	110	69	397	32	89
3a	1	54	32	139	14	42
4a	2	137	99	883	6.9	191
2b	3	141	125	298	77	47
3b	3	184	91	1060	4.4	245
4b	3	626	237	16700	13	2000
5b	4	511	194	18200	6.9	1800
6b	4	167	78	1060	6.9	227
7b	4	151	131	896	4.4	99
8b	4	141	82	2010	6.9	252
9b	4	192	100	4100	3.6	462
10b	3	144	123	553	87	62
Average		226	132	3630	39	438

Figure 13. Aethalometer BC variability over each IOP based on 30 minute averaged BC concentrations

Capped lines represent the standard deviation. Numbers in gray boxes give the standard deviation values that lie above the axis value.

Figure 14. IOP 7b aethalometer BC concentration versus time based on 30 minute averaged BC concentrations

Locations A through D are labeled in Figure 15.

Variability over sampling sites A through E as labeled in Figure 15 was observed as displayed in Table 4, Figure 16, and Figure 17 based on aethalometer data averaged over 30 minutes. The highest BC average, median, and standard deviation was observed at site B where the highest BC concentrations were often detected. The average and median concentration over all other sites were fairly similar, with the exception of the lower median concentration at site E, which may be a result of there being fewer sampling periods available and/or the site being surrounded by many trees. Standard deviations were also fairly similar with the clear exception of site B and a slightly higher standard deviation for site A. The higher variation at site A may represent the slight shifting of the aethalometer approximately 10 feet from the original location that occurred after IOP 8b.

Thus, the increase in standard deviation may represent the change in variability due to a 10 foot location move.

Figure 15. Aethalometer sampling locations

As summarized in Table 4, the average of BC averages for all sites was 211 ng/m^3 , or $4.2 \text{ } \mu\text{g/m}^3$ for $\text{PM}_{2.5}$, the average median concentration was 111 ng/m^3 , or $2.2 \text{ } \mu\text{g/m}^3$ for $\text{PM}_{2.5}$, and the average standard deviation was 470 ng/m^3 , or $9.4 \text{ } \mu\text{g/m}^3$ for $\text{PM}_{2.5}$. To observe the impact of site B's higher BC concentrations on the overall statistics, the

average, median, and standard deviation were observed for all other sites. When excluding site B, the average BC concentration between sites was 169 ng/m^3 , the average median was 108 ng/m^3 , and the average standard deviation was 179 ng/m^3 . When site B is not considered, the average concentration is half the magnitude of the average when site B is included and standard deviation decreases substantial. Thus, BC variability increased spatially when pollutant concentrations increase. The box plots in Figure 17 demonstrate the BC concentration distribution, also illustrating the large difference between the highest and lowest concentration (greater than $174,000 \text{ ng/m}^3$, or $3,480 \text{ } \mu\text{g/m}^3$ for $\text{PM}_{2.5}$).

Table 4. Aethalometer BC variability over sites based on 30 minute averaged BC

Site	Cases	Average (ng/m^3)	Median (ng/m^3)	Std Dev
A	11	214	142	228
B	10	381	125	1632
C	6	157	112	169
D	9	175	126	168
E	3	128	50	151
Average		211	111	470

Figure 16. Aethalometer BC variability over sites based on 30 minute averaged BC
Capped lines represent the positive standard deviation. Numbers in gray boxes give the standard deviation for values that lie above the axis value.

Figure 17. Box plots comparing aethalometer BC variability between sites

Box plots denote the minimum, maximum, 1st and 3rd quartile, and median value for all concentrations. The whiskers indicate the maximum and minimum values, while the top, middle, and bottom line of the box represent the 3rd quartile, median, and 1st quartile value, respectively.

4.2.1.2 Personal Environmental Monitor Measured BC

BC concentrations analyzed from Personal Environmental Monitor (PEM) 12 hour filter sampling periods in the study area ranged from a maximum of 2,790 ng/m³, or 55.8 µg/m³ for PM_{2.5}, to a minimum below the detection limit of 60.52 ng/m³, or 1.2 µg/m³ for PM_{2.5}. The average PEM BC concentration over all locations and IOPs was 224 ng/m³,

or $4.5 \mu\text{g}/\text{m}^3$ for $\text{PM}_{2.5}$, with a median concentration of $163 \text{ ng}/\text{m}^3$, or $3.3 \mu\text{g}/\text{m}^3$ for $\text{PM}_{2.5}$, and a standard deviation of $262 \text{ ng}/\text{m}^3$, or $5.2 \mu\text{g}/\text{m}^3$ for $\text{PM}_{2.5}$. Table 5 summarizes PEM BC averages, medians, and standard deviations for each IOP. PEM BC concentrations averaged by IOP ranged between 80.5 and $441 \text{ ng}/\text{m}^3$, or 1.6 and $8.8 \mu\text{g}/\text{m}^3$ for $\text{PM}_{2.5}$, BC medians ranged between the lower detection limit and $343 \text{ ng}/\text{m}^3$, or $8.8 \mu\text{g}/\text{m}^3$ for $\text{PM}_{2.5}$, and standard deviations ranged from 31.7 to $651 \text{ ng}/\text{m}^3$, or 0.63 and $13.0 \mu\text{g}/\text{m}^3$ for $\text{PM}_{2.5}$. Higher average BC concentrations tended to have larger standard deviations and standard deviation also increased with an increase in the number of samples. Figure 18 shows box plots for each IOP, demonstrating that concentrations tended to vary widely with most concentrations much lower than the maximum concentrations for each IOP.

Table 5. PEM variability over each IOP

IOP	Number of PEMs in Operation	Average (ng/m³)	Median (ng/m³)	Standard Deviation	Number of Burning Sources
1a	9	371	343	60	5
2a	11	165	86	223	7
3a	8	82	76	32	5
4a	11	308	262	185	9
7a [*]	16	60	30	36	11
8a [*]	12	33	30	6.7	10
2b	11	82	30	86	18
3b	16	203	181	168	15
4b	15	331	281	214	7
5b	15	441	273	651	8
6b	14	220	174	183	10
7b	15	272	159	251	14
8b	15	187	154	111	7
9b	15	136	119	48	5
10b	15	81	88	47	12
Average ^{**}		221	171	174	9.4

^{*}These IOPs were not included in analyses due to a high prevalence of PEM BC concentrations lower than the detection limit. Average concentrations listed in this table assume values lower than the detection limit to be the average of a zero concentration and the detection limit (60.5 ng/m³), or 30.2 ng/m³.

^{**}IOP 7a and 8a are excluded.

Figure 18. PEM BC box plot over each IOP

Box plots denote the minimum, maximum, 1st and 3rd quartile, and median value for all concentrations. The whiskers indicate the maximum and minimum values, while the top, middle, and bottom line of the box represent the 3rd quartile, median, and 1st quartile value, respectively. IOPs 7a and 8a differ in appearance because minimum, 1st quartile, and median values are all equal to the lowest concentration (30.2 ng/m³). In addition, the 3rd quartile value is also equal to 30.2 ng/m³ for IOP 8a.

The summary table for site variability was not included in this section due to the large number of sites used for sampling. The summary table is instead included in Appendix D

under *PEM Variability* and the results are discussed here. In addition, PEM sites were simplified into three locations and the BC concentration statistics for each location was observed. Table 6 details the range and average of average BC concentrations, medians, and standard deviations observed at each PEM sampling site, and Figure 19 illustrates the average BC concentration at each site. PEM sites are labeled in Figure 20. In the case of PEM sites, variability did not tend to increase with the number of samples available. In fact, the largest standard deviation had only 3 cases (as opposed to the highest number of samples, 12). As with aethalometers, PEMs demonstrate high spatial variability with the highest and lowest BC concentrations differing by more than 2,800 ng/m³ over all IOPs and more than 2,500 ng/m³ over a single IOP.

Table 6. Summary of individual site statistics

The average, median, and standard deviation at each PEM site was determined over all IOPs and the results briefly summarized in this table. The 1st column refers to the statistic observed at each site, the 2nd column refers to the minimum value of the statistic designated in column 1, the 3rd column, refers to the maximum value of the statistic in column 1, and the 4th column refers to the average value the statistic in column 1. For example, for the row titled “Average,” the “Minimum” column refers to the smallest average BC concentration observed among all sites averaged over all IOPs.

BC Concentration for Site (ng/m ³)	Minimum	Maximum	Average
Average	LDL	520	233
Median	LDL	486	206
Standard Deviation	23.4	863	165

Figure 19. Average PEM BC concentration at each site

PEM sites are color coded based on sampling locations as shown in Figure 20. The bars represent the positive standard deviation.

Figure 20. PEM sampling locations

To evaluate spatial variation between PEM locations, the study area was divided into three locations, A, B, and C, as illustrated in Figure 21. The division was made at locations that differ in terrain, housing density, and elevation, with location A on average having the lowest housing density and highest elevations, location C on average having the highest housing density and lowest elevation, and location B on average containing

elevations in between location A and C and housing density about midway between locations A and C. Location characteristics become more important in Section 4.3.2.2 and are described in greater detail there. Table 7 and Figure 22 detail the PEM BC statistics by IOP in addition to the locations' average, median, and standard deviation over all IOPs. Observing BC concentrations during each IOP in each location, location C's average and median BC concentrations were higher than location A's average and median BC concentration. Location B, however, was less consistently comparable to location A and C. Average BC concentrations occurring in location B were highest during IOP 4b and 5b, but the lowest average PEM BC concentrations also occurred during IOPs 1a, 2a, 6b, and 9b.

Figure 21. Divided study area sections

In contrast, when averaging PEM BC concentrations over all IOPs for each location, location A had the lowest average BC concentration, followed by location B, and then location C. The difference between BC averages over each IOP and over all IOPs demonstrates that lower resolution data measured over longer time periods will tend to smooth out peaks in BC concentration. By observing the standard deviations for concentrations averaged over all IOPs for each location, the high concentrations

occurring in location B can still be observed. Standard deviation was highest at location B when compared to location A and C due to the detection of the highest concentrations in location B. Standard deviation at location A over all IOPs was the lowest, about twice as low as the standard deviation detected in location C over all IOPs. This is in turn a demonstration of the higher concentrations found in location C than in location A. The large difference between the average, median, and standard deviation of BC concentration between locations A and C was likely due to the difference in housing density and tree coverage in the locations. Because there are more homes per square area in location C, wood smoke was more concentrated, resulting in higher BC concentrations. In addition to the having lower housing density with fewer burning sources per square area, the higher number of trees found in location A also may act to slow or prevent dispersion of wood smoke into the area, contributing to lower concentrations detected in areas further away from wood burning.

Table 7. Average and median BC concentration and standard deviation for PEMs in locations, A, B, and C

	Location A			Location B			Location C		
IOP	Ave (ng/m ³)	Med (ng/m ³)	Std Dev	Ave (ng/m ³)	Med (ng/m ³)	Std Dev	Ave (ng/m ³)	Med (ng/m ³)	Std Dev
1a	355	343	34	308	308	0*	402	405	75
2a	101	81	76	69	82	34	301	171	347
3a	58	60	20	76	76	0*	116	115	7
4a	196	216	74	242	293	99	469	439	215
2b	30	30	0*	84	84	2.7	183	163	117
3b	103	78	86	206	193	27	362	451	202
4b	219	210	35	552	326	430	354	374	76
5b	246	263	47	1112	283	1451	311	294	62
6b	143	102	139	107	107	109	334	293	193
7b	135	136	29	142	142	23	475	420	306
8b	154	138	52	155	155	1.4	254	176	174
9b	119	115	19	111	111	13	173	169	69
10b	67	82	31	93	93	1.3	97	104	72
All	144	125	95	287	156	516	303	269	201

* A standard deviation value of “0” indicates that only one PEM BC value was available

Figure 22. Average PEM BC concentration based on location

Capped lines represent standard deviation as detailed in Table 7.

4.2.1.3 Aethalometer versus PEM BC Variability

A comparison of PEM and aethalometer 12 hour averaged BC concentrations was made as seen in Table 8. The average difference between all co-located aethalometer and PEM measured BC concentrations was 39 percent, with a median of 25 percent, a minimum difference of 1 percent, a maximum difference of 83 percent, and a standard deviation of 25 percent when the unusually large differences for the locations B and E was eliminated due to suspected aethalometer measurement issues. Differences between PEM and aethalometer concentrations were largely variable with aethalometer measured BC concentrations often higher than PEM BC. Percent differences between aethalometer and PEM BC concentrations were explored in correlation with wind speed and magnitude of PEM and aethalometer concentration magnitudes were evaluated, but no correlations were found. Large differences in PEM and aethalometer measurements may be attributed to the absorption of organic gases or changes in humidity. Other meteorological factors may have also resulted in differing concentrations over distances less than the distance between aethalometer and inlets.

Table 8. 12 hour averaged PEM and aethalometer (aeth) BC comparison

Aethalometer locations labeled in this table refer to sites marked in Figure 15. Aethalometer and PEM Concentrations are in ng/m³.

	Location A			Location B			Location C			Location D			Location E		
IOP	Aeth BC	PEM BC	% diff	Aeth BC	PEM BC	% diff	Aeth BC	PEM BC	% diff	Aeth BC	PEM BC	% diff	Aeth BC	PEM BC	% diff
1a	413	308	25								329		357	343	4
2a	125	30	76								32		95	75	21
3a		76		39										77	
4a		306		249	128	49					262		-662	222	134*
2b	121	82	33	89	85	4				32	30	5			
3b	198	188	5	225	237	-5				107	30	72			
4b	437	326	25	802	1048	-31				237	210	11			
5b	377	283	25	1590	265	83	280			287	270	6			
6b	186	185	1	122	30	75	160	164	-2	174	153	12			
7b	157	159	-1	115	125	-9	139	184	-33	177	115	35			
8b	125	154	-24	234	156	33	96	162	-69	88	119	-35			
9b	153	102	33	-60	120	302*	111	105	5	166	137	18			
10b	159	94	41		92		118	104	12	135	30	78			
Ave % diff	29			45			22			32			12		

**This aethalometer and PEM percent difference was excluded from averaged due to large fluctuations in aethalometer attenuation*

4.2.2 Spatial Variability of Meteorology

Because meteorological stations may often be used to represent areas greater than a few miles in diameter, meteorological variability was evaluated in this study. Figure 23 shows the distance of all meteorological stations from the EBAM station located within the study area, with the largest distance being 1.9 miles and the shortest distance being 0.1 miles. Despite the relatively short distances between stations, significant differences were found between meteorological stations. As shown in Figure 23, Table 10, and Figure 24, the Marine Terrace (MT) station wind speeds on average were almost twice as high as CSDF wind speeds, and more than three times as high as Sonic and EBAM stations. The lower EBAM and Sonic wind speeds are likely due to their placement closer to ground level, where obstructions may readily slow velocities. Table 9 details the elevation and height above ground level for the instruments from each meteorological station. A detailed summary of wind speed over time for all stations and station combinations are available in Appendix E under *Wind Speed Comparisons for All Stations*.

Table 9. Height of meteorological instrument above ground

Heights with “~” are approximate estimations of instrument height due to access limitations.

Met Station	Elevation	Instrument Height (feet)
EBAM	227	6.9
Ultrasonic Anemometer	207	6.1
CSDF	260	~25
Marine Terrace	50	~20

Figure 23. Distance between meteorological stations

Table 10. Meteorological variability over stations (IOPs 8b through 10b only)

Only IOPs 8b through 10b are detailed to allow for comparison between meteorological stations.

Station	Time Basis	Wind speed (mph)			Wind Direction		Temperature (F)			Humidity (%)		
		Average	Median	Std Dev	Average	Std Dev	Average	Median	Std Dev	Average	Median	Std Dev
MT	10 min	4.3	4.3	2.2	299	47.7	49.8	50.2	5.4	61.1	71.0	18.4
CSDf	30 min	2.4	2.0	2.4	254	49.1				77.0	88.0	21.2
EBAM	10 min	1.1	0.9	0.5	277	42.4	49.7	51.1	4.9	69.0	81.0	18.7
Sonic	10 min	0.6	0.5	0.3	89.7	78.0	49.7	50.8	5.8			

On average, wind direction did not vary widely for the MT, CSDF, and EBAM stations, but it did vary widely for the Sonic station; MT, CSDF, and EBAM wind directions varied within a 90 degree range, while Sonic wind directions varied within a 270 degree range. Observing each IOP's dominant wind direction, as shown in Appendix E under *Wind Roses for All IOPs*, for almost all cases, dominant wind directions for each station were not greater than 90 degrees from the dominant wind directions of other stations. Temperature, with measurements available at all stations except CSDF, was fairly consistent over all locations, varying about ± 5 °F over all IOPs. Relative humidity across all sites was also similar in standard deviation (about 20 percent), but differed on average at the MT, CSDF, and EBAM stations where measurements were available. The highest relative humidity was always found at the CSDF site, which is also most inland of all stations, followed by the EBAM site which is second most inland, and the MT site, which is closest to the coast and lowest in elevation, had the lowest relative humidity. Figure 24 summarizes meteorological variability for all stations over each IOP. Meteorological data is available in greater detail in Appendix D under *Meteorological Variability* and Appendix E under *Wind Roses for All IOPs*.

Figure 24. Meteorological variables compared between stations

Capped lines represent standard deviation.

4.3 Statistical Relationship of Meteorology and Source Properties with BC

Multiple linear regression (MLR) and non-linear multiple regression (NMR) analyses were used to evaluate the effect of meteorological and wood burning source variables on BC concentration. The MLR model, a first-order multiple regression model, determines the impact of explanatory, or independent, variables on a response, or dependent, variable as demonstrated in Equation 9 below for k explanatory predictors.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_k x_k + \varepsilon \quad \text{Equation 9}$$

In Equation 9, y is the response variable, x_i represents the independent variable i, β_i is a partial slope of variable i, and ε is random error. The partial slopes, β_i , represent the expected change in the response variable, y, with each change in the explanatory variables, x_i . β_0 , alternatively, is the value of y when all x_i 's are equal to zero. The random error, ε , represents variation in y that cannot be explained by the x_i 's (explanatory variables). MLR assumes that explanatory variables are linearly related to the response variable and that random error is normally distributed about zero. To minimize the sum of the squared residuals, or difference between the modeled and measured y value, the least-squares method was used. This method first examines the sum of the squared errors that result when different $\widehat{\beta}_1$ and $\widehat{\beta}_0$ values are used. The $\widehat{\beta}_1$ and $\widehat{\beta}_0$ values that result in the lowest sum of squared error are then selected for the MLR model. The NMR follows the same principles as the MLR except that the explanatory variables, x_i , and β_i are included in the model as a more complex, non-linear function such as in $\frac{1}{1+\beta_i X}$.

The 2010 version of the statistical analysis program, Minitab version 16.1.1 (Minitab Inc.) was used to determine the best regression models for this study. BC concentrations and deviations were used as response variables while meteorological data, number of sources, distance from sources, and tree coverage were tested as explanatory variables when suitable. Data from individual meteorological stations and combinations of meteorological stations were used in the analyses, where weather station groups used data that was the average of values available for the stations it combined. Weather stations were grouped based on their geographic proximity and characteristics relative to the study site. Both Weather Underground stations, Marine Terrace and CSDF were combined due to their location within Cambria but outside of the study area. The weather stations thought to be most representative of the study area, CSDF and E-BAM, were grouped. Finally, both stations located within the study area, E-BAM and Sonic, were evaluated as a combination. Meteorological variables evaluated for all sites and combinations are summarized in Table 11.

Table 11. Meteorological data available at each station

Station/ Combination	Measurement intervals	Wind Speed (mph)	sin (WD[#])	cos (WD[#])	Humidity (%)	Temp (F)	Wind Gust Speed (mph)	Vertical Wind Speed (mph)	Average Difference between Wind Direction
Marine Terrace (MT)	10 min	X	X	X	X	X	X		
CSDF	30 min	X	X	X	X		X		
E-BAM	10 min	X	X	X	X	X			
Ultrasonic Anemometer (Sonic)	< 1min	X	X	X		X		X	
MT & CSDF	30 min*	X	X	X	X		X		X
E-BAM & CSDF	30 min*	X	X	X	X				X
E-BAM & Sonic	10 min*	X	X	X		X			X

[#] WD: Wind Direction

*The measurement intervals used for combinations were based on the station with the lowest resolution. For example, for the MT and CSDF combination, meteorological data is available at 10 and 30 minute resolutions, respectively, so 30 minute intervals were used.

Meteorological data was evaluated in conjunction with both aethalometer and PEM BC, because both offered different characterizations of pollutant concentrations and variability within the study area. Because aethalometers provided BC data at high resolution during each IOP, a larger sample size is available to determine the relationship between BC concentration and weather characteristics. For this reason, it was possible to use aethalometer data to evaluate all meteorological stations and determine the meteorological station most capable of explaining variability in BC concentrations. PEM BC concentrations were also evaluated in a similar manner but for 12 hour averaged BC concentrations and deviations with 12 hour averaged meteorological data. EBAM and Sonic stations could not be evaluated for PEMs because they only operated during a subset of the IOPs and as a result contain too few data points. The differences and similarities between PEM and aethalometer relationships to weather data from different stations provided information about time averaging's impact on BC concentrations and variability.

While the time resolution of the PEMs (12 hours) was much lower than that of the aethalometers (1 minute), spatial resolution for the PEMs was higher than spatial resolution for aethalometers. Each IOP contained between 8 and 16 outdoor PEMs in different locations, while only between 1 and 4 aethalometers were operated in different outdoor locations during each IOP. PEM BC concentrations were thus used to evaluate the impact of distance from burning sources, number of burning sources, and site characteristics on BC concentration and variability.

4.3.1 Aethalometer BC and Meteorological Data

Meteorological data collected from Weather Underground and available meteorological instruments, discussed in Chapter 3, were evaluated with aethalometer results to determine the meteorological data which best accounted for variability in BC concentration and BC deviation. For the analysis of aethalometer data, two response variables were evaluated: BC concentration averaged over 30 minutes (BC_{ave}) and the weighted deviation function (BC_{dev}) described in Equation 10

$$BC_{dev} = \frac{std\ dev_t}{BC_{t,ave}} \quad \text{Equation 10}$$

where $std\ dev_t$ is equal to the standard deviation of all operating aethalometers at time t and $BC_{t,ave}$ is the average BC concentration of BC measurements from all operating aethalometers at time t . Since concentration variability is most appropriately considered as a percentage of the measurement, BC_{dev} allows for comparison of BC standard deviation over a wide range of concentrations. For instance, a standard deviation of 40 mg/m^3 implies much more variability when the average concentration is 40 ng/m^3 . The use of the weighted deviation function also reduces the bias toward high concentrations. Both averaged BC concentrations and deviations were additionally transformed as necessary to normalize residuals about zero. Normalization concentrates residuals about zero with a bell shaped frequency distribution, and was conducted by applying functions to the response variables. Because residuals are the difference between the observed response variable (in this study BC concentration or deviation) and the response variable

resulting from the regression model, residuals normalized about zero suggests that on average, the error is approximately zero.

To satisfy the independence assumption for MLR models, BC concentrations were averaged over 30 minutes to eliminate major time correlations between BC readings and a BC concentration delayed (or lagged) by one time point was included as an explanatory variable in the regression models. The presence of time correlations was evaluated using the Autocorrelation Function (ACF) and the Durbin-Watson statistic in Minitab. For the ACF, potential explanatory variables were used to develop a regression model and the residuals were stored. ACF then computes the correlation between residuals by comparing a residual at time t to the data point at time $t+k\Delta$, where Δ is 30 minutes in this study and k is any constant. Minitab produces ACF statistics and a graph that indicates whether correlations exist between the response variable at times t and $t+k\Delta$. A comparison of t and $t+1\Delta$ (where k is equal to 1) is referred to as “lag 1,” and comparing t to $t+2\Delta$ (where k is a value of 2) is called “lag 2,” and so forth. Figure 25 is a sample graph of residuals resulting from the use of the CSDF meteorological station variables in conjunction with average BC concentration. The red dotted lines indicate the 95 percent confidence intervals where time correlations are insignificant. An ACF value above the top of or below the bottom of the red dotted line indicates that correlations exist. In the case shown in Figure 25, a lag 1 correlation exists and must be accounted for in the model. Because all IOPs showed correlations with lag 1, BC concentration or deviation lagged by one time point was included as an explanatory variable. To run the ACF analysis, missing meteorological data at single time points were assumed to be the

average of the previous and following time point value. Because there were very few missing single time points, their effect on the models should be undetectable. When larger intervals of data were missing, the data set had to be excluded from the ACF analyses. Data sets where the ACF could not be conducted were assumed to be correlated at similar lags as data sets where the ACF was used. Large time intervals of missing data were rare, so their impact on all data sets should not be significant.

Figure 25. ACF Analysis Example for CSDF Meteorological Station

In developing a suitable regression model, the Durbin-Watson (DW) statistic was also evaluated. Although similar in purpose to the ACF analysis, the DW statistic checks only for correlations in the lag 1 situation and differs mathematically. Critical values developed by Durbin and Watson (1951) indicate when negative and positive correlations

exist based on the fact that squared differences in sequential residuals will be smaller for positive correlations and larger for negative correlations. A DW statistic of 2 generally indicates no serial correlation while values less than 2 and greater than 2 suggest positive and negative correlations, respectively (Ott & Longnecker, 2010). Because DW cutoffs for determining correlations are limited to sample sizes of 200 or less (Savin & White, 1977), specific DW cutoffs could not be used for this study's data sets which in most cases contained sample sizes greater than 300. For this reason, the DW statistic observed in developed aethalometer models was assumed to have no time correlations if close to the value of 2. This approximate use of the DW statistic offers additional support to the ACF conclusion – that no correlation exists at lag 1. ACF tests alone are considered to be sufficient on their own due to their ability to evaluate correlations at multiply lags instead of just one as for the Durbin Watson test.

In developing multiple regression models, suitable meteorological predictors for BC averages or deviations were determined by first including potential predictors (as listed in Table 11) for each meteorological station or combination in the regression models and then eliminating an explanatory variable that both had a p-values greater than 0.05, the significance level, and a p-value higher than the p-value of all other variables. At a significance level of 0.05, the confidence of the partial slopes can be determined using one minus the significance level, or 95 percent confidence in this case. Another regression model was then tested using all remaining explanatory variables and a second explanatory variable whose p-value was greater than the significance level and also higher than the p-value of all other independent variables was then eliminated. The same

process was then repeated until all variables with p-values higher than the significant level were removed. To account for diurnal variations in BC concentration, a predictor representing the number of time intervals passed during the sampling period was used. For example, when using 30 minute averaged BC concentrations, the first 30 minutes of the sampling period is time interval 1, the second 30 minute period is time interval 2, and so forth. A “lack of fit” test was also used to indicate whether interactions or curvature existed in the models. Minitab’s lack of fit test evaluates the applicability of the developed model for future model inputs. If interactions or curvature were found, modifications were made to account for these properties resulting in nonlinearity of the model(s).

4.3.1.1 Predictors for Aethalometer Average BC Concentration

While the relationship between BC concentrations and meteorological predictors is typically not linear, a MLR model can still be used by normalizing BC concentrations through the use of a transformative function. To normalize average BC concentrations (BC_{ave}) and residuals, a transformation that best normalize BC concentrations, raising average BC concentration to the -0.7^{th} power, was determined and used for the MLR model. Figure 26 compares the normal probability plots and histograms of average BC concentration (left) to its transformed counterpart $(BC_{ave})^{-0.7}$ (right). A straight sloping line following the blue line is needed for the normal probability plot and a bell shaped pattern is desired for the histogram. However, it is important to note that when the normalizing power was negative as shown in Figure 26, higher concentrations become the lower values of the normalized response variable.

Figure 26. Comparison between residual charts for normalized (right) and un-normalized (left) average aethalometer BC concentration

When using meteorological variables from each station or combination to determine a model for average BC concentration, it was found that only two meteorological stations or combinations contained variables the explained variability in average BC concentration: the EBAM station and the EBAM and CSDF station combination. Table 12 summarizes the results of the Minitab analyses including the partial slopes for significant variables and the coefficients of determination (R^2) for each model. The R^2 value indicates the percent of variability in the average BC concentration accounted for by the explanatory variables included in the model. The R^2 value for the average BC concentration models ranged from 52 to 55 percent, with the EBAM and CSDF combination explaining the most variability for both linear and non-linear models. Among tested explanatory variables, relative humidity and wind speed were the only significant meteorological predictors for aethalometer BC average. Average BC

concentration lagged by one time interval (Lag 1 (BCave)^{-0.7}) and time interval, accounting for time of day, also significantly accounted for average BC concentration after transformation.

Table 12. Multiple regression models for average aethalometer BC concentrations

The table below summarizes explanatory predictors determined to be significantly correlated to aethalometer BC based on Minitab analysis.

Met Station	Model Type	Response Variable	Explanatory Variable	Coefficient ($\hat{\beta}_i$)	Std Error of Coefficient	R ² (%)
EBAM	Linear	(BCave) ^{-0.7}	Lag 1 (BCave) ^{-0.7}	5.3x10 ⁻⁰¹	6.5 x10 ⁻⁰²	52
			Time Interval	4.0 x10 ⁻⁰⁴	1.2 x10 ⁻⁰⁴	
			Humidity (%)	-2.1 x10 ⁻⁰⁴	5.8 x10 ⁻⁰⁵	
			Constant, β	2.5 x10 ⁻⁰²	5.4 x10 ⁻⁰³	
	Non-linear	(BCave) ^{-0.7}	Lag1 (BCave) ^{-0.7}	2.5 x10 ⁻⁰¹	1.4 x10 ⁻⁰¹	54
			Time Interval	-3.8 x10 ⁻⁰⁴	3.8 x10 ⁻⁰⁴	
			(Lag 1 (BCave) ^{-0.7}) *(Time Interval)	2.2 x10 ⁻⁰²	1.0 x10 ⁻⁰²	
			(Humidity %) ²	-1.4 x10 ⁻⁰⁶	4.5 x10 ⁻⁰⁷	
			Constant, β	2.8 x10 ⁻⁰²	5.1 x10 ⁻⁰³	
EBAM & LH CSDF	Linear	(BCave) ^{-0.7}	Lag 1 (BCave) ^{-0.7}	5.1 x10 ⁻⁰¹	6.5 x10 ⁻⁰²	53
			Time Interval	3.8 x10 ⁻⁰⁴	1.2 x10 ⁻⁰⁴	
			Wind Speed (mph)	2.3 x10 ⁻⁰³	9.4 x10 ⁻⁰⁴	
			Humidity (%)	-1.7 x10 ⁻⁰⁴	6.1 x10 ⁻⁰⁵	
			Constant, β	2.1 x10 ⁻⁰²	5.9 x10 ⁻⁰³	
	Non-linear	(BCave) ^{-0.7}	Lag1 (BCave) ^{-0.7}	2.5 x10 ⁻⁰¹	1.3 x10 ⁻⁰¹	55
			Time Interval	-4.5 x10 ⁻⁰⁴	3.7 x10 ⁻⁰⁴	
			(Lag 1 (BCave) ^{-0.7}) *(Time Interval)	2.3 x10 ⁻⁰²	1.0 x10 ⁻⁰²	
			Wind Speed (mph)	2.2 x10 ⁻⁰³	9.3 x10 ⁻⁰⁴	
			Log(Humidity %)	-8.3 x10 ⁻⁰³	4.0 x10 ⁻⁰³	
			Constant, β_0	5.3 x10 ⁻⁰²	1.8 x10 ⁻⁰²	

Although the model R^2 values were found to account for more than 50 percent of average BC variability, lack of fit tests conducted in conjunction with Minitab analyses suggest that the models need improvement. Lack of fit tests provide information about how well a developed model will perform for inputs independent of the variables used to develop the model. All models poorly represent average BC concentration at higher values of x_i (i.e. higher wind speeds and humidity). Additionally, all linear models were found to have potential curvature and/or interactions. Figure 27 displays plots of $(BC_{ave})^{-0.7}$ versus EBAM meteorological variables in addition to applied trend lines. Although the variables are statistically significant, the figure indicates that only a weak relationship exists between $(BC_{ave})^{-0.7}$ and the variables, time interval and relative humidity. BC concentration tends to generally decrease as time interval increases with a fairly noisy relationship. Relative humidity may potentially follow a parabolic pattern, but data between 50 and 70 percent humidity did not occur during sampling periods. The linear correlation with Lag 1 $(BC_{ave})^{-0.7}$ alternately exists because the values directly correspond to $(BC_{ave})^{-0.7}$ values. Figure 28 displays $(BC_{ave})^{-0.7}$ versus explanatory predictors for the EBAM-CSDF combination in addition to applied trend lines. The response variable, $(BC_{ave})^{-0.7}$, had similarly ambiguous relationships with relative humidity and time interval, and wind speed also seems to demonstrate a noisy distribution with a mild upward slope. This upward sloping relationship between $(BC_{ave})^{-0.7}$ and wind speed was expected since higher wind speeds tend to increase mixing and pollutant dispersion, resulting in lower BC concentrations.

Figure 27. EBAM variable plots for aethalometer average BC concentration

Note that the negative power applied to BC_{ave} inverses the correlations between average BC and the explanatory variables, time interval and relative humidity.

Figure 28. EBAM-LH CSDF combination variable plots for aethalometer average BC concentration

Note that the negative power applied to BC_{ave} inverses the correlations between average BC and the explanatory variables, wind speed (WS), time interval, and relative humidity.

The unclear relationship between the meteorological and time variables likely resulted in the detection of possible interactions and curvature by the lack of fit tests. To account for possible interactions and curvature, the models were adjusted to be non-linear. In the cases of the EBAM and EBAM-CSDF combinations, converting the linear model into a non-linear model did not improve the model's R^2 value dramatically. Mild improvements to the R^2 values may be the result of increasing the number of explanatory variables or only mildly improving the fit. The former is suspected because the standard errors for the linear models tend to be smaller than the standard deviations for the non-linear models relative to their coefficients. Smaller variations in the linear models suggest higher accuracy than non-linear models. For this reason, the linear models are likely a more suitable model for understanding average aethalometer BC concentration than the non-linear models. In future application of linear models, potential interaction detected in the Lag 1 $(BC_{ave})^{-0.7}$ predictor and possible curvature in time interval and relative humidity variables for the EBAM meteorological station should be noted. For the meteorological data combining the EBAM and CSDF stations, potential interactions in the Lag 1 $(BC_{ave})^{-0.7}$ and wind speed predictors were observed. Minitab outputs for the established models are included in their entirety in Appendix G.

While the results of the models suggest that the EBAM and CSDF combination account for more of the BC variation than the EBAM station alone, the difference is small. This may indicate that the EBAM station alone would be sufficient to represent average BC concentration when using the above models. The small improvement in R^2 values for the EBAM and CSDF combination versus EBAM alone may have resulted from the addition

of the wind speed predictor in the EBAM and CSDF combination model or because using additional information from the CSDF station helps to account for upper air meteorology (in addition to EBAM's ground level meteorology). Regardless, EBAM meteorological data alone accounted for a similar percentage of average aethalometer BC concentration.

4.3.1.2 Predictors for Aethalometer BC Deviation

BC deviation (BC_{dev}) and meteorology were evaluated to determine whether meteorology was correlated with BC standard deviation, or variance. To normalize BC deviation (BC_{dev}) as done with average BC, the best transformation was BC deviation raised to the 0.5th power. Only the CSDF meteorological station's variables were found to be suitable predictors of BC deviation. Table 13 summarizes the results of the Minitab analysis including the partial slopes for significant variables and the coefficient of determination (R^2) for the resulting linear model. The R^2 value for the CSDF model was 47 percent, with wind speed and relative humidity as significant meteorological predictors of variation in BC deviation and Lag 1 (BC_{dev})^{0.5} as a variable intended to account for time correlations. Wind speed and lagged BC deviation were positively correlated with BC deviation while relative humidity was negatively correlated.

Table 13. Multiple regression model for aethalometer BC deviation

Met Station	Model Type	Response Variable	Explanatory Variable	Coefficient ($\hat{\beta}_i$)	Std Error of Coefficient	R^2 (%)
CSDF	Linear	$(BC_{dev})^{0.5}$	Lag 1 (BC_{dev}) ^{0.5}	6.1×10^{-01}	4.5×10^{-02}	47
			Wind Speed	-2.8×10^{-02}	8.3×10^{-03}	
			Humidity	-2.4×10^{-03}	1.1×10^{-03}	
			Constant, $\hat{\beta}_0$	4.7×10^{-01}	1.1×10^{-01}	

Similar to models for average BC concentration, the BC deviation model contained possible curvature and an interaction, but larger predictor variables (i.e. high wind speed and relative humidity) were not recognized by Minitab to fit the model poorly as for BC_{ave} . Lag 1 $(BC_{dev})^{0.5}$ demonstrated potential curvature and relative humidity showed potential interactions, but attempts to account for the curvature and interaction were unsuccessful. Figure 29 shows plots of $(BC_{dev})^{0.5}$ versus CSDF wind speed, relative humidity, and Lag 1 $(BC_{dev})^{0.5}$ as well as applied trend lines. Although the Lag 1 $(BC_{dev})^{0.5}$ predictor demonstrates a general upward sloping trend, the wind speed and relative humidity relationships with BC deviation are much less apparent which is similar to the trends for the average BC concentration models. The detection of possible curvature and interactions by the lack of fit tests may have resulted from the unclear relationships between the BC deviation and the meteorological variables. Minitab outputs for the established models are included in their entirety in Appendix G.

Figure 29. CSDF variable plots for aethalometer BC deviation

4.3.2 PEM BC Relationship to Meteorology and Burning Sources

Two different MLR analyses were conducted for PEM BC data. Similar to the analyses for aethalometer BC data, the first test evaluated which meteorological data best accounted for variability in BC concentration and deviation. Each IOP's average BC concentration was determined by taking the mean of all PEM BC measured during the IOP's sampling period and the IOP's BC deviation was determined by taking the standard deviation of all PEM BC concentrations for that sampling period and then dividing by the mean BC concentration (similar to Equation 10, but where $BC_{t,ave}$ is the time integrated concentration for all operating PEMs operating over the same IOP). The second PEM BC analysis investigated the impact of wood burning sources on PEM BC concentration by focusing on geographic proximity to sources and relation to dominant wind direction.

4.3.2.1 Meteorological Representation for PEM BC

To determine which meteorological station contained variables that best explained PEM BC concentrations, a similar statistical approach was taken for PEM BC as was used for aethalometer BC in Minitab. Average PEM BC and BC deviation were used as the response variables, while meteorological characteristics were used as explanatory variables. Because PEM and aethalometer resolution differed, response and explanatory variables were used in a modified manner for the PEM analysis. Instead of using average BC concentration and weighted deviation for every 30 minutes, the 12 hour integrated BC concentration measured using each PEM was averaged with other PEMs operating during the same IOP to determine BC_{ave} . The standard deviation of those PEMs was then

divided by BC_{ave} to find the BC_{dev} value. Meteorological data (as summarized in Table 11) available at 10 and 30 minute resolution (for Marine Terrace and CSDF, respectively) were also averaged over 12 hours for use as explanatory variables in the regression analyses. Because a substantially smaller sample size was available for PEM analysis than for aethalometer analyses, EBAM and Sonic meteorological stations, which were not available for all IOPs, could not be analyzed. Additional meteorological variables, presence of inversion (yes or no) and difference in wind direction (for combined meteorological stations only), were included in the analysis. The number of wood burning sources detected on each night of sampling was also included as a predictor variable, while lagged BC concentration and deviation were not needed as in the aethalometer analysis due to the larger time spans between sampling nights. PEM BC concentrations were assumed to be independent from one another and the DW statistical cutoffs determined by Savin and White (1977) were used to confirm independence.

4.3.2.1.1 PEM Average BC Concentration

The transformation best able to normalize BC concentrations was average PEM BC concentration raised to the 0.4th power for the Marine Terrace station and the natural log of BC concentration for the CSDF station and the Marine Terrace and CSDF combination. For average PEM BC concentration, wind speed consistently accounted for variation. The sine of wind direction was found to also be a predictor for the Marine Terrace and the Marine Terrace and CSDF combination and the cosine of the wind direction was an additional predictor for the Marine Terrace station. Table 14 summarizes the results of the Minitab analysis including the partial slopes for significant

variables and the coefficient of determination (R^2) for the resulting linear model. The R^2 values for the average BC models ranged from 47 to 81 percent, with the Marine Terrace model explaining the most variability (81 percent) in average PEM BC concentration.

Figure 30, Figure 31, and Figure 32 show scatter plots and an applied trend line for the two stations and their combination and their significant variables. Minitab outputs for the average PEM BC models are included in their entirety in Appendix H.

Table 14. Linear regression models for average PEM BC concentration

Met Station	Response Variable	Explanatory Variable	Coefficient (β_i)	Std Dev of Coefficient	R^2 (%)
Marine Terrace	$(BC_{ave})^{0.4}$	Wind Speed	-2.3×10^0	4.8×10^{-01}	81
		sin(wind direction)	1.5×10^{01}	5.5×10^0	
		cos(wind direction)	1.3×10^{01}	3.3×10^0	
		Constant, β	1.8×10^{01}	1.9×10^0	
CSDF	$\ln(BC_{ave})$	Wind Speed	-7.8×10^{-01}	2.5×10^{-01}	47
		Constant, β	6.7×10^0	5.0×10^{-01}	
Marine Terrace & CSDF	$\ln(BC_{ave})$	Wind Speed	-7.3×10^{-01}	1.4×10^{-01}	74
		sin(wind direction)	2.6×10^0	1.0×10^0	
		Constant, β_0	7.3×10^0	4.1×10^{-01}	

As was expected, PEM BC concentration decreased with increasing wind speed in all models. The physical significance of sine and cosine of wind direction however is more obscure in the PEM models. The Marine Terrace model indicates that average PEM BC decreased as winds originated further northward and westward, while the Marine Terrace and CSDF combination indicated that BC concentrations decreased as winds originated further southward. The Marine Terrace station suggested wind directions may indicate that the incoming ocean breeze on the north western side of the study area contributes significantly to BC dispersion which in turn reduces BC concentration. Alternately, winds originating from the northern direction for the Marine Terrace station were

consistently higher than winds originating from the southern direction. In that case, the higher magnitude of wind speed may have been the cause of lower BC concentrations. No other wind directions and speeds for Marine Terrace and the Marine Terrace and CSDF combination demonstrated this pattern.

Figure 30. Marine Terrace variable plots for wind speed and wind direction versus PEM average BC concentration

Figure 31. CSDF variable plots for PEM average BC concentration

Figure 32. Marine Terrace and CSDF combination variable plots for PEM average BC concentration

Unlike the aethalometer models, PEM models often lacked repeated values that allow the model to account for variability within predictor variables (i.e. at one wind speed there is only one BC concentration as opposed to many different concentrations). Without repeated values, Minitab could not perform lack of fit tests. Figure 30, Figure 31, and Figure 32 demonstrate the absence of repeated values. Although the R^2 values resulting from PEM models are higher than those for aethalometer models, PEM model performance cannot be determined without the addition of repeated predictor variables.

4.3.2.1.2 PEM BC Deviation

No meteorological stations contained variables capable of explaining variation in BC deviation. However, the number of wood burning sources was found to be a suitable predictor when a natural log transformation was applied to PEM BC deviation. The number of wood burning sources alone accounted for 30 percent of the variability in PEM BC deviation, though the shortage of repeated values as discussed in Section 4.3.2.1.1 above still apply. As expected, the number of wood burning sources was positively correlated with BC concentration. When the number of burning sources increased, higher concentrations of BC were detected. As discussed in Section 4.2.1, higher detected concentrations tend to result in higher standard deviations. Table 15 and Figure 33 summarize the details of the model and plot the relationship with a trend line, respectively. Minitab outputs for the PEM BC deviation models are included in their entirety in Appendix H.

Table 15. Linear regression models for PEM BC deviation

Response Variable	Explanatory Variable	Coefficient (β_i)	Std Dev of Coefficient	R^2 (%)
$\ln(BC_{dev})$	Number of Sources	7.6×10^{-02}	3.5×10^{-02}	31
	Constant, β	-1.0×10^0	3.5×10^{-01}

Figure 33. $\ln(BC_{dev})$ versus number of wood burning sources

4.3.2.2 Directional Impacts on PEM BC

Several factors were considered in the analysis of the relationship between PEM concentrations and directional/geographic impacts. To conduct the MLR analysis and identify characteristics that have the largest effect on PEM BC, the study area was first divided into sections and labeled as shown in Figure 21, included again below for convenience. The study area divisions distinguish between differences in geographic characteristics including tree coverage, elevation, and housing density which may impact pollutant dispersion. Section A typically is higher in elevation, contains more trees surrounding homes, and contains homes that tend to be fairly separated from one another.

Section C alternately is lower in elevation, contains fewer trees than section A, and has homes in closer proximity to one another. Section B's characteristics tend to be somewhat mid-way between section A and section C in elevation, tree coverage, and housing density, though tree coverage and housing density in section B share more similarities with section C. Figure 21 demonstrates differences and similarities in tree coverage and housing density over each area. The establishment of sections allows for the MLR model to take into account sectional differences in BC dispersion and better account for variability in average BC concentrations.

Figure 21. Study area divisions used for directional regression models

Having divided the study area into sections, the number of burning sources within each location was counted to observe potential relationships with PEM BC concentrations.

The number of upwind burning sources was also considered, along with the closest distance of each sampler to any burning source and to any upwind burning source.

Impacts of wind direction were considered by including the smallest angle between each sampling location and the IOP's dominant wind direction in the model. Impacts due to

sampler site characteristics were observed through noting the sampling sites' proximity to the roads and the level of vegetation and structures surrounding the sampling instruments during operation. The level of vegetation and surrounding structures, mild, moderate, and heavy, was determined based on sampling location details. A mild level of vegetation and structures was assigned to PEM sites where surrounding vegetation was low and where virtually no structures were in close proximity. A moderate level was assigned where surrounding vegetation or structures taller than the PEM placement height were found on approximately 30 to 60 percent of the area surrounding the PEM. Lastly, a heavy level refers to PEM sites where vegetation taller than the PEM height in addition to rocks, trees, or fences were adjacent to PEM locations. The IOP during which each PEM BC concentration was sampled was also considered in the MLR to account for differences in burning behavior and site meteorology over each night.

Unlike MLRs conducted for relating BC and meteorology, the directional MLR used categorical variables (non-numerical), location (A, B, and C), IOP (4b through 10b), and level of vegetation and structures (i.e. fencing) surrounding PEMs (mild, moderate, and heavy). For categorical variables, the MLR model assumes all options of the categorical variables but one to be a dependent variable, x_i (see Equation 9 repeated below), whose value is either 1 (true) or 0 (false). The partial slope, β_i , of the included variable evaluated then represents the difference between the included option and the excluded option. For example, when considering the categorical variable, 'location,' which has three options, A, B, and C, options A and B are represented by x_i 's in the MLR model, while option C is excluded. When a PEM is located in location A, the x representing

location A is equal to 1 and the resulting partial slope is equal to the difference in BC concentration between location A and C (assuming the response variable is equal to BC concentration). The location B variable x would then be equal to 0 and would not be included for consideration in that particular sample. Categorical variables allow the MLR model to quantitatively account for differences between sampling conditions.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_k x_k + \varepsilon \quad \textbf{Equation 9}$$

Considering wind direction played an important role in the variables for the directional analyses, IOPs were only evaluated if the most representative meteorological data was available. For this reason, only IOPs 4b through 10b were evaluated since aethalometer results described in section 4.3.1.1 indicated EBAM meteorological data (measured only in IOPs 4b through 10b) to be most representative for the study area. Due to the lower time resolution of PEM data and the smaller sample size available than for aethalometer analyses, a significance level of 0.1 (90 percent confidence) was used instead of 0.05 (95 percent confidence) for previous analyses.

4.3.2.2.1 Directional MLR Modeling Results

The directional MLR was conducted by first normalizing the PEM BC data through the use of the best transformation, taking the natural logarithm of PEM BC concentration. The resulting model explained 69 percent of the variability through the two categorical variables, location and IOP, as detailed in Table 16. The final model indicates that significant differences were found between PEMs in locations A and C and over IOPs

4b,5b,7b,9b, and 10b. Significant differences between IOPs and locations indicate that 90 percent confidence intervals for BC concentration do not overlap in value for the locations and IOPs. Still, differences in concentration between locations and IOPs may be small, on average around 1 ng/m³ for each variable.

Table 16. Directional MLR model for PEM BC concentration

Response Variable	Categorical Variable	Option	Coefficient (β_i)	Std Dev of Coefficient	R ² (%)
ln(PEM BC)	Location	A	-2.6x10 ⁻⁰¹	5.7 x10 ⁻⁰²	69
		C	excluded		
	IOP	4b	4.3x10 ⁻⁰¹	1.1 x10 ⁻⁰¹	
		5b	4.5x10 ⁻⁰¹	1.1 x10 ⁻⁰¹	
		7b	2.8x10 ⁻⁰¹	1.1x10 ⁻⁰¹	
		10b	-9.7x10 ⁻⁰¹	1.1x10 ⁻⁰¹	
		9b	excluded		
	Constant, β	n/a	5.2 x10 ⁰	5.7x10 ⁻⁰²	

While the model seems to have explained a large percentage of variability, the model's residual versus fitted value plot as shown in Figure 34 does not clearly satisfy the MLR assumption of equal variance in the residuals. Residual values are often smaller at fitted values larger than 4.5, suggesting a potential non-linear relationship between the independent and dependent variables. Because the data used in the directional MLR did not clearly satisfy all MLR assumptions, even after transformation, the developed model may not be reliable and significant relationships may still exist between PEM BC concentration and other tested explanatory variables.

Figure 34. Directional MLR residuals versus fits plot

Observing variables graphically suggests a potential significance of the variables level of vegetation and structures surrounding PEMs, number of burning sources in location, and number of upwind burning sources, after sorting for location and level of vegetation and structures surrounding PEMs. As shown in Figure 35, PEM BC concentration over different locations and under differing level of vegetation and structures surrounding PEMs demonstrate that a notable relationship between PEM BC and number of burning sources in sampling location may be found. PEM BC concentrations measured in location C and at sites where vegetation and structures were minimal (“mild”) had a visible tendency to be higher as the number of burning sources in the location increased. A moderate level of vegetation and structures also seemed to have a similar pattern, though less clearly in comparison to the mild level. A similar relationship was seen for the dependent variable, number of upwind burning sources, as shown in Figure 36. Box plots showing differences in PEM BC concentrations are further detailed in Figure 37,

showing a tendency for BC concentrations to be higher in location C and in instances of mild levels of surrounding vegetation and structures.

Figure 35. PEM BC versus number of burning sources in location sorted by location and level of vegetation and structures surrounding PEM for IOPs 2b through 10b

The lnPEMBC transformation (as opposed to untransformed PEM BC concentration), makes the differences between variables more visible.

Figure 36. PEM BC versus number of upwind burning sources in location sorted by location and level of vegetation and structures surrounding PEM for IOPs 4b through 10b

The lnPEMBC transformation (as opposed to untransformed PEM BC concentration), makes the differences between variables more visible.

Figure 37. PEM BC Box Plot for Location and Degree of PEM Obstruction for IOPs 2b through 10b

Box plots denote the minimum, maximum, 1st and 3rd quartile, and median value for all concentrations. The whiskers indicate the maximum and minimum values, while the top, middle, and bottom line of the box represent the 3rd quartile, median, and 1st quartile value, respectively. Each star represents an outlier identified by Minitab. The lnPEMBC transformation (as opposed to untransformed PEM BC concentration), makes the differences between variables more visible.

4.3.3 Summary of Aethalometer and PEM BC Regression Results

Developed aethalometer and PEM regression models suggest that meteorology, time, and site characteristics can potentially account for between 47 and 81 percent of variability in BC concentration and deviation. Still, these models will need to be improved with more IOPs and samples due to detected curvature and interactions that could not be accounted for in developed models. The correlations between BC concentration and deviation and explanatory variables determined to be significant were often visually unclear with high variability in BC concentration for the same values of explanatory variables.

Between aethalometer analyses intended to indicate the more representative weather station for the study area, there was little consistency between average BC and BC deviation analyses. Although the EBAM station seemed to explain the most variability in average BC concentration, the CSDF station was more suitable for detection of BC deviation. For PEM analyses, Marine Terrace accounted for the most variability in average BC concentration (while no stations predicted PEM BC deviation well). The inconsistency in the most representative meteorological station over different analyses suggests a stochastic relationship between meteorology when an intensive grid of weather stations within the area of interest is unavailable. Still, the analyses may indicate that ground level meteorological data measured in the study area is more suitable for the prediction of higher resolution (i.e. 30 minute averaged) BC concentrations, while upper air meteorological data is more suitable for lower (i.e. 12 hour averaged) resolution BC concentrations.

PEM and aethalometer regression analyses for this study suggest that BC is significantly correlated with sampling days, time of day, BC concentrations occurring 30 minutes apart, location of BC sampling, wind speed, relative humidity, and potentially wind direction and number of burning sources. Correlations were observed as expected for some cases but not in others. The relationship between average BC concentration and sampling day and time of day was expected due to variations in residential wood burning patterns. Residential wood burning often occurs during periods of cold weather and wood burning often begins in the evening when residents return home and when temperatures drop. Likewise, BC concentrations correlated between concentrations occurring 30 minutes apart were expected because low wind speeds in the area means pollutant dispersion occurs over a longer period of time. Other expected associations include the number of wood burning sources and wind direction. The more wood burning sources present during an IOP, the more wood smoke and BC are emitted. This relationship was illustrated in Figure 33, where BC deviation increased with number of wood burning sources. Still, no correlations at 95 percent significance were found between average aethalometer BC concentration and number of burning sources, though a correlation between PEM BC deviation and number of burning sources was detected. This may indicate that number of burning sources has a larger impact on BC variability than on average BC concentration in the near-field. Correlations between average BC concentration and wind direction were also expected and were demonstrated for PEM BC as shown in Figure 30 and Figure 31 and for aethalometer BC as shown in Figure 27. Average BC concentrations are expected to decrease with increasing wind speeds because higher wind speeds increase pollutant mixing, dispersion, and dilution as

observed in studies by Chaloulaku et al. (2003), Clark (2010), Dawson et al. (2007), and Hien et al (2002). Wind directions directing wood smoke toward receptors are expected to result in higher BC concentrations, but this relationship was only detected for PEMs, likely due to the higher fluctuation of high resolution aethalometer data.

While wind speed and direction were expected to correlate with BC concentration, relative humidity was unexpectedly found to be significantly correlated with aethalometer BC. Relative humidity was found to be positively correlated to aethalometer BC average as shown in Figure 27. Although Dawson et al. (2007) and Sarotis et al. (2008) had previously found positive correlations between humidity and BC concentration, the pollutants in both studies were from traffic sources and humidity primarily played a role in encouraging the production of secondary PM_{2.5} from ammonium sulfate. Because ammonium sulfate is not typically found in wood smoke and is not expected to be significant in the study area, humidity was not anticipated to be correlated with BC. Thus, it is expected that relative humidity is representative of a meteorological characteristic that was not included in the analysis.

4.4 Dispersion Modeling

Dispersion modeling was conducted using ISC-PRIME and ISCST3 through the BEEST version 9.74 (BEE-Line Software) user interface to predict BC concentrations within the 1 km² study area. Both ISC programs are capable of computing pollutant concentrations over a specified averaging period based on source and meteorological inputs. The BEEST interface additionally produces contours based on predicted concentrations,

allowing for a visual interpretation of the results. By using both ISC-PRIME and ISCST3, the impact of building downwash may be observed; ISC-PRIME considers building downwash while ISCST3 does not. Both ISC-PRIME and ISCST3 were used to model 12 hour PEM BC concentrations over each IOP, the modeled concentrations were then compared to measured concentrations, and the results of ISC-PRIME and ISCST3 were compared to one another. The advantages and shortcoming of the two programs are discussed in Section 2.2.2.2.1, and a review of literature detailing the previously observed performance of ISCST3 and ISC-PRIME and comparisons between ISCST3, ISC-PRIME, and AERMOD performance are located in Section 2.2.2.2.2.

To conduct dispersion modeling in ISCST3 and ISC-Prime, several characteristics were categorized and assumptions were made where data was unavailable. The Cambria study area was characterized as a rural location due to the low percentage of residential land use, about 40 percent, highly forested terrain, and the combination of simple and complex terrain. Homes, instead of all being represented individually, were represented as groups when homes were located close to one another. Figure 38 illustrates the representation of homes in the BEEST interface. Structures were represented in groups rather than individually for efficiency and because a high resolution area map is fairly inconsequential without meteorological data specific to the study site.

Figure 38. Homes within study area as represented in BEEST

Because BC fireplace emission data is not readily available, BC emission rates were determined based on $PM_{2.5}$ emission data. When Purvis et al. (2000) tested standard and EPA-certified fireplace designs, they found total PM emission rates ranging between 10.3 to 58.4 grams per hr with $PM_{2.5}$ constituting about 83 percent of total PM. Thus on average, Purvis et al. found $PM_{2.5}$ emissions of 32.9 grams per hour to result from fireplace wood burning. Gullet et al. (2003) in another study testing EPA-certified

fireplaces and woodstoves found emission rates to average 23.9 grams per hour, falling into the range observed by Purvis et al. The average of Gullet et al. and Purvis et al.'s observations, a $PM_{2.5}$ emission rate of 28.4 grams per hour, was assumed in ISC-PRIME modeling. Because BC emissions were measured, a relationship between $PM_{2.5}$ and BC displayed in Equation 8 (modified to determine BC as in Equation 11) as determined by Ward (2009) for this study area was used, yielding a BC emission rate of 1.42 grams per hour per source.

$$BC = 0.05PM_{2.5} \qquad \text{Equation 11}$$

Chimneys were assumed to have an exit velocity of 9.3 feet per second, the median velocity determined in Dasch's (1982) study of fireplace emissions. On average, homes were approximately 20 feet in height, chimneys were about 25 feet tall, and chimney exit diameters were estimated to be about 7.5 inches (a compromise between the sizes of wood stoves and fireplaces). A sensitivity analysis indicated small differences in modeled concentrations between exit diameters ranging between 6 and 12 inches for ISC-PRIME, but ISCST3 concentrations differed widely. Because the "stacks" in the case of this study are chimneys located slightly above homes at heights much lower than specified for Good Engineering Practice in 40 CFR 51.100, the stacks in the study area were considered short stacks. Burning temperatures were assumed to be the maximum temperature measured by the Fluke Thermal Imager. When Fluke temperatures were unavailable, temperatures were assumed to be the average of all temperatures measured on the specific IOP.

To model air dispersion, Morro Bay meteorological data was used to represent Cambria, because mixing heights and stability classes required by the ISC programs were unavailable for Cambria. Morro Bay is a coastal community with similar climate to Cambria, located approximately 12 miles to the southeast of Cambria. Twelve hour Morro Bay meteorological data acquired from the SLO APCD was selected for each IOP based on its similarity to each IOP's meteorology. The meteorology for each sampling period as detected by the Marine Terrace station was compared to similar hours of meteorology in Morro Bay, because other Cambria meteorological stations had wind speeds that were too low to compare to Morro Bay. Days between the months of December through April where average and median wind speed and temperature were similar between Morro Bay and the Cambria Marine Terrace location were selected for use.

Once final BC concentrations were modeled by the ISCST3 and ISC-PRIME programs, BC concentrations had to be adjusted to account for the actual time period of source emissions. ISCST3 and ISC-PRIME assume each emission source to be emitting throughout the 12 hour averaging period, when in fact emissions occur over a much shorter time span. Based on aethalometer data, on average, source emissions occur over about 4.5 hours (37.5 percent) of each IOP, most often in the evening and night time. To approximately adjust BC concentrations modeled by the ISC programs to represent actual emissions, 37.5 percent of the ISC modeled concentrations were taken as the 12 hours

integrated average BC concentration in the area. It is important to note that taking a factor of the modeled concentration is an approximate method that does not account for diurnal meteorological variations. Because the ISC programs tend to choose the time interval where meteorological characteristics will yield higher concentrations (i.e. lower wind speeds and mixing height), modeled BC concentrations may be higher than would be expected in actual conditions. Modeled concentrations of zero or lower than the detection limit were assumed to be the average of zero and the lower detection limit, and were therefore set to 30.26 ng/m^3 for comparison with measured data.

4.4.1 Comparison of ISC-PRIME and ISCST3 Modeled and Measured PEM BC Concentrations

Dispersion modeling using ISC-PRIME and ISCST3 for the Cambria study area resulted in a majority of under predicted concentrations. On average, the modeled-to-measured BC concentration ratio was 0.25, ranging from 0 to 3.94, and 0.15, ranging from 0 to 1.62, for ISC-PRIME and ISCST3, respectively. Ratios of zero resulted when modeled concentrations were equal to zero. Box plots shown in Figure 39 demonstrate the distribution of ratios and the prevalence of ratios in between the 1st quartile value of 0.03 and the third quartile value of 0.24 for ISC-PRIME and the 1st quartile value of 0.02 and third quartile value of 0.15 for ISCST3. Modeled BC concentrations corresponding to each PEM measurement are included in Appendix I.

Figure 39. Box plots of modeled-to-measured BC

Box plots denote the minimum, maximum, 1st and 3rd quartile, and median value for all concentrations. The whiskers indicate the maximum and minimum values, while the top, middle, and bottom line of the box represent the 3rd quartile, median, and 1st quartile value, respectively.

While both programs tended to yield BC concentrations less than the measured BC concentrations, ISCST3 underestimated concentrations more often than ISC-PRIME.

The overall tendency to under predict concentrations was not expected for ISCST3, but has been seen to occur for ISC-PRIME as discussed in Section 2.2.2.2.2. ISCST3 was

expected to predict higher-than-measured concentrations under complex terrain as discussed by US EPA (2003) and Perry et al. (2005).

Modeled-to-measured BC ratios for ISC-PRIME were also inconsistent with the findings of Venkatram et al. (2004), who found ISC-PRIME to often over predict concentrations for high-measured concentrations and to under predict concentrations when concentrations were low. When observing the modeled-to-measured BC ratio relative to the magnitude of measured BC concentrations for ISC-PRIME as shown in Figure 40, BC concentrations over predicted by ISC-PRIME only resulted when measured concentrations were low. The same tendency was observed for ISCST3 predictions as shown in Figure 41. Figure 40 and Figure 41 also show that the highest measured BC concentrations were always under predicted by both ISC-PRIME and ISCST3. Though this study's results differ than those in Venkatram et al., it is important to point out that Venkatram et al's study took place in a flat area surrounded by buildings. Additionally, high modeled-to-measured BC ratios are less than 5 percent of all measured ratios and high measured concentrations are less than 5 percent of all measured concentrations.

Figure 40. ISC-PRIME modeled versus measured PEM BC concentration

The dashed line represents a one-to-one ratio between measured and modeled BC concentrations. The solid line is an applied trend line with equation and R^2 value shown. One outlier was removed due to evidence of direct fireplace downwash received at that point.

Figure 41. ISCST3 modeled versus measured PEM BC concentration

The dashed line represents a one-to-one ratio between measured and modeled BC concentrations. The solid line is an applied trend line with equation and R^2 value shown. One outlier was removed due to evidence of direct fireplace downwash received at that point.

The disparities between this study's results and the results of the reviewed studies were likely due to the near-field application of the ISC programs and several assumptions made in the modeling process and meteorological data used. Although emission rates and stack characteristics can vary widely, it was only within this study's means to use approximated values. Emission rates are highly variable not only amongst homes, but also amongst fireplaces and even between burning events in the same fireplace, as discussed in Section 2.1.2. In addition, all stacks were approximated to be identical, although it is likely that exit flue heights and diameters differ significantly throughout the area. The approximation of all of these characteristics reduced the accuracy of the modeled results.

In addition to model assumptions, the use of Morro Bay meteorological data likely contributed to lower modeled BC concentrations and higher BC variability in the modeled results. Although the EBAM station explained the most variability in BC concentration (Section 4.3.1.1), the Morro Bay meteorological data was selected based on similarity to the Marine Terrace data because of the availability of more data and similarity between the types of stations. However, the Marine Terrace data had average wind speeds between 3 to 5 times greater than the EBAM station. Higher wind speeds likely increased modeled BC dispersion, resulting in increased mixing and dilution of pollutants which may cause a decrease to BC concentrations determined by ISC-PRIME and ISCST3. Differences in dominant wind direction also would play a role in determining the concentration in each PEM location.

The difference between patterns observed in previous studies and observations made in this study suggest the need to improve the accuracy of model inputs used for ISCST3 and ISC-PRIME. Representative meteorology and emission and stack characteristics need to be measured within the site to produce reliable predictions of pollutant concentrations. Though dispersion modeling results may have differed significantly from previous studies, study data may still be useful if a correction factor is applied. For this reason, factors were determined for modeled BC concentrations that would bring median modeled-to-measured BC concentrations closer to unity. Concentrations that were lower than the detection limit after correction factors were applied were given the value of 30.26 ng/m³ to be consistent with measured PEM concentrations.

To find suitable correction factors, all available IOPs were split into two groups consisting of IOP 1a through 5b for the development group and IOP 6b through 10b for the test group. The development group was used to determine a correction factor that would bring the median ratio closest to unity, and the factor was then applied to the test group to determine the factor's ability to bring the latter group's median BC concentration ratios close to unity. When the development group medians were adjusted to unity, the resulting factors were 12.5 and 17.1 for ISC-PRIME and ISCST3, respectively. Application to the test group data yielded median values of 1.53 and 0.89 for ISC-PRIME and ISCST3, respectively. Because the test group median ratios were not as close to unity as desired, the correction factors were again adjusted to reduce the difference between the development and test group ratios. The final factor value for ISC-PRIME that reduced the difference between the development and test case median was

9.75, resulting in a test group ratio differing from 1 by a value of 0.20 instead of 0.53. To bring the test group median ratio closer to unity, the correction factor for ISCST3 was also adjusted. The final correction factor that reduced the difference between the development and test case median for ISCST3 was 18.2, resulting in a test group ratio differing from 1 by a value of 0.05 instead of 0.11. When correction factors were adjusted, development group median ratios also differed from unity by the same increment as the test case (about 0.2 for ISC-PRIME and about 0.05 for ISCST3).

When the factors were applied to all IOPs, the resulting median ratios were 0.94 and 1.03 for ISC-PRIME and ISCST3, respectively. The range of modeled-to measured ratios was then 0.054 to 38.4 for ISC-PRIME and 0.011 to 29.5 for ISCST3. Adjusting the modeled concentrations to approach unity allowed for more accurate prediction of a majority of the concentrations, but also dramatically resulted in over prediction of low measured concentrations. The over estimation of extremely low measured concentrations was primarily a problem where PEM concentrations were assumed to be the average of zero and the lower detection limit. These values were not excluded from the analysis, however, because low BC measurements would then be poorly represented. Figure 42 shows box plots to demonstrate the distribution of modeled-to-measured ratios after the correction factor was applied. Figure 43 shows the resulting modeled-to-measured BC concentration graphs. All corrected modeled BC concentrations for each PEM location are included in Appendix I.

Figure 42. Box plots of modeled-to-measured BC ratios after BC concentration correction factors

Box plots denote the minimum, maximum, 1st and 3rd quartile, and median value for all concentrations. The whiskers indicate the maximum and minimum values, while the top, middle, and bottom line of the box represent the 3rd quartile, median, and 1st quartile value, respectively.

Figure 43. Corrected modeled BC versus measured BC concentration

The dotted line represents a one-to-one ratio between measured and modeled BC concentrations.

4.4.2 Comparison of ISC-PRIME and ISCST3 Modeled BC Contours to Measured BC

Based on the modeled concentrations generated by ISC-PRIME and ISCST3 programs, the BEEST interface generates contours to illustrate the concentration distribution in the modeled area. Contours for all IOPs generated are included in Appendix I, but only a few will be observed in depth in this section. Although ISC-PRIME and ISCST3 modeled BC concentrations were much lower than measured BC concentrations, as demonstrated in Section 4.4.1, the contours were evaluated based on their qualitative ability to capture the concentration distribution occurring over different IOPs. To make modeled IOP data comparable to measured IOP data, different factors were applied to the modeled concentrations for each IOP and ISC program such that the average measured BC concentration was equal to the average modeled BC concentration. By using this method, it was found that ISC-PRIME and ISCST3 were only occasionally able to generate models with BC distributions similar to measured BC distributions. Figure 44 through Figure 47 illustrate dispersion contours as represented by ISC-PRIME and ISCST3 for selected IOPs. The colors of the contour show the magnitude of the modeled BC concentration with red representing the highest concentration and white representing the lowest concentration. The superimposed colored circles represent the measured BC concentrations based on the same scale as the modeled concentrations after factors were applied.

Figure 45. IOP 4b modeled contours demonstrating differences between ISC-PRIME and ISCST3

Figure 47. ISCST3 and ISC-PRIME contours demonstrating distributions differing from measured distributions

For some IOPs, both the ISCST3 and ISC-Prime models yielded contours that were similar in many details. For instance, Figure 44 shows model contours for IOP 6b, where both models yielded contour maps with similar shapes, although there is still some variability in the details. Each model predicted peak areas in similar locations and low concentrations in the northwestern portion of the study area. The measured concentrations show some features that are similar to the models, however measured concentrations tend to exhibit lower concentrations, indicating more dispersion and dilution. On the other hand, for some IOPs the two models yielded very different contours. Figure 45 shows the modeled contour maps for IOP4b. In this instance, ISC-PRIME predicts relatively consistent concentrations over much of the study area with a single peak in the southwest. However, ISCST3 predicts a concentration ridge running along the southeast border of the study area. For this IOP, ISC-PRIME appears to do a better job of representing the measured concentrations, although the model predicts low concentrations where the PEM measurements were highest, in the southwest corners of the study area. Differences between ISC-PRIME and ISCST3 BC dispersion were usually small where average wind speed was less than 3 mph (IOP 4b), but increased when average wind speeds were above 3 mph (IOP 6b). This is an indication that building downwash becomes less significant when wind speeds are low.

In general, both models were able to capture some of the features shown in the PEM measurements during some IOPs, but not during others. For instance, ISC-PRIME captured BC dispersion well for IOP 4A, but not as well for IOP 4B (Figure 46). Still, for IOP 4B, ISC-PRIME identified higher concentrations on the southwest part of the

study area and then decreasing concentrations in the northeast direction. ISC-PRIME was sometimes able to accurately predict the location where the highest BC concentration occurred, while ISCST3 was less often able to do so. Figure 47 shows two examples (IOPs 9B and 10B) where dispersion was not well modeled by both ISC programs. The locations of the highest measured BC concentrations were not identified by ISC-PRIME and ISCST3 and locations of low concentration were often identified as locations of high concentration.

When observing wind speeds for IOPs 4A, 4B, 9B, and 10B along with other IOP contours and their respective wind speeds, ISC-PRIME and ISCST3 seems to more accurately model pollutant dispersion at average wind speeds less than 3 mph. Based on the Marine Terrace meteorological station, IOPs 4A and 4B had wind speeds of 2.5 and 2.6 mph, respectively, and IOPs 9B and 10B had wind speeds of 5.6 and 3.3 mph, respectively. Unfortunately, neither model consistently provided an accurate picture of variability within the study area.

While there is potentially a relationship between wind speed and model performance, other factors may also have contributed to inaccuracy in modeled dispersion. For example, modeling may have been improved if high tree density surrounding homes could have been considered in area A. Additionally, the inability of the model to properly represent BC concentrations at receptor S1 (see Figure 20 for PEM location map) at the south most corner suggests that sources of BC may have been overlooked. The higher concentration measured at receptor CP (see Figure 20) during IOP 5B, as

shown in Figure 48, with no surrounding wood burning sources also seems to suggest that burning sources were overlooked. Burning sources may have been missed either because sources were located just outside of the study area or because wood burning began late in the night when the search for wood burning sources had already been completed. Without accurate inputs, the performance of the ISC programs is limited.

Figure 48. IOP 5B sources and receptor BC concentrations

The magnitude of receptor CP (PEM BC highlighted in orange) potentially suggests that existing burning sources went undetected.

Chapter 5. Conclusion

5.1 Overview of Results

The objectives of this study included (1) assessing BC spatial variability in the 1 km² study area containing multiple wood burning sources, (2) determining the impact of meteorology, geography, and burning source characteristics on BC concentrations and deviation through the use of regression models, and (3) evaluating the performance of ISC-PRIME and ISCST3 in application to near-field analyses where source characteristics are estimated.

The first task indicated high variability near field BC variability, with standard deviations being as high as 3 to 4 times the average BC concentration detected. Overall BC averages measured by aethalometers and PEMs tended to be fairly similar and low, but standard deviations varied considerably within IOPs, within sites, and over all IOPs and sites. Over all IOPs and sites, BC concentrations measured by aethalometers were on average 229 ng/m³, or 4.6 µg/m³ for PM_{2.5}, with a large standard deviation of 827 ng/m³ (360 percent of average), or 16.5 µg/m³ for PM_{2.5}. Similarly, between IOPs and sites, aethalometer BC averaged 226 ng/m³, or 4.5 µg/m³ for PM_{2.5}, and 211 ng/m³, or 4.2 µg/m³ for PM_{2.5}, respectively, and standard deviations between IOPs and sites were 438 ng/m³ (190 percent), or 8.8 µg/m³ for PM_{2.5}, and 470 ng/m³ (220 percent), or 9.4 µg/m³ for PM_{2.5}, respectively. Average aethalometer measured BC concentrations were fairly low relative to their standard deviation because a majority of the measured BC during each IOP consisted of background measurements. Burning typically occurred during approximately 38 percent of the IOP, and the high concentrations seen during that time

are responsible for the large standard deviation of aethalometer BC over all IOPs. Aethalometer averages between IOPs and between sites were similar, but standard deviations between IOPs and between sites were 438 ng/m^3 ($8.8 \text{ }\mu\text{g/m}^3 \text{ PM}_{2.5}$) and 470 ng/m^3 ($9.4 \text{ }\mu\text{g/m}^3 \text{ PM}_{2.5}$) on average, respectively, almost half the size of standard deviation over all IOPs and sites. Lower variability occurring between IOPs and sites than over all IOPs was expected because BC concentrations are highly specific to the burning patterns and local meteorology affecting the site during each sampling period. For instance, some IOPs experience higher concentrations on average due to the high prevalence of wood burning and lower wind speeds, while some IOPs experience only background concentrations on account of fewer burning sites and higher wind speeds. Still, though the standard deviation is lower over sites and IOPs, a standard deviation of almost $10 \text{ }\mu\text{g/m}^3 \text{ PM}_{2.5}$ may be problematic in areas that struggle to meet $\text{PM}_{2.5}$ standards.

Samples obtained from PEM measured BC concentrations averaged 224 ng/m^3 , or $4.5 \text{ }\mu\text{g/m}^3$ for $\text{PM}_{2.5}$, very similar to aethalometers, but had a lower standard deviation of 262 ng/m^3 (120 percent), or $5.2 \text{ }\mu\text{g/m}^3$ for $\text{PM}_{2.5}$. Similar to aethalometers, average BC concentrations within sites and IOPs were similar to over all IOPs and sites, but standard deviations were lower. Between IOPs and sites, PEM BC averaged 221 ng/m^3 , or $4.4 \text{ }\mu\text{g/m}^3$ for $\text{PM}_{2.5}$, and 251 ng/m^3 , or $5.0 \text{ }\mu\text{g/m}^3$ for $\text{PM}_{2.5}$, respectively, and standard deviations between IOPs and sites were 174 ng/m^3 (79 percent), or $3.5 \text{ }\mu\text{g/m}^3$ for $\text{PM}_{2.5}$, and 190 ng/m^3 , or $3.8 \text{ }\mu\text{g/m}^3$ for $\text{PM}_{2.5}$ (76 percent), respectively. The difference between aethalometer and PEM BC standard deviations reflect the higher time resolution of aethalometers, which allow them to capture peak BC concentrations. Differences in PEM

BC standard deviation between IOPs, between sites, and over all IOPs largely reflect variations in burning patterns on different sampling periods, as was the case for aethalometer BC. A lower standard deviation resulting from PEM samplings than from aethalometer samples indicate that lower resolution samples fail to capture the extent of public exposure.

Regression models in fulfillment of the second objective were conducted with two purposes in mind, determining the relationship between measured BC and meteorology and the relationship between BC and geography and burning source characteristics. The analyses indicated that meteorology accounted for only a small fraction of variability in BC concentration and that geographical and burning source impacts are difficult to identify individually.

Although multiple regression models were conducted for both PEMs and aethalometers, the larger sample size available for aethalometers make aethalometer regression models more reliable than PEM regression models for determining the meteorological station most capable of explaining variability in BC averages and deviation. Aethalometer regression models all indicated that meteorology and time dependence accounted for about 50 percent of variability in BC averages and deviation, though time of day and lagged BC concentration were more significant than meteorological variables. Among aethalometer regression models, meteorological variables significantly accounting for variability in BC were relative humidity and wind speed, but these correlations were often weak and interactions and curvature were often detected. When non-linear models

were instead used, no major improvements were seen in the model's ability to account for BC variability, so linear models were considered preferable. Among all meteorological stations evaluated, variables measured at the EBAM station proved the most suitable for explaining variability in average aethalometer BC concentration. The EBAM station's relative humidity in addition to lagged BC and time interval sufficiently accounted for variability in average BC. Although relative humidity is not physically expected to affect BC concentration directly, its significance in the regression model may suggest that changes in relative humidity take place in conjunction with another physically significant variable. Wind speed and relative humidity as measured at the CSDF station in addition to lagged BC deviation were found to be significant predictors for aethalometer BC deviation. With the exception of relative humidity, wind speed, time interval, and lagged BC were all anticipated predictors for average BC and BC deviation. BC concentration has often been observed to decrease with increasing wind speed, wood burning occurs based on a diurnal pattern, and dispersion occurring at one location may change slowly over time. In this study, aethalometer BC was found to be positively correlated with lagged BC and relative humidity, and negatively correlated with wind speed and time interval.

While less than 15 samples were available for PEM analyses, variables found to significantly explain average PEM BC concentration variability were wind speed, sine of wind direction, and cosine of wind direction. When wind speed increased, average PEM BC consistently decreased for all meteorological stations and combinations. Sine and cosine of wind direction, however, were less consistently correlated with BC

concentration. For the Marine Terrace models, winds originating from the north and west directions were correlated with lower PEM BC concentrations, whereas for the Marine Terrace and CSDF combination, BC decreased when winds originated from the south. Higher wind speeds originating from the north for the Marine Terrace station seemed to be the cause of lower BC concentrations, but this pattern was not seen for the winds of western origin or for southern winds from the Marine Terrace and CSDF combination. Number of burning sources was the only predictor to account for variability in PEM BC deviation, and was found to be positively correlated with BC deviation.

Regression models evaluating the impact of geography and burning source characteristics in connection with meteorology found only IOP and location to significantly account for variability in PEM BC concentration at a 90 percent significance level, but model residuals seemed to indicate that the model was unreliable. Significant differences between locations A and C suggest that housing density and tree coverage may play a significant role in exposure, with high housing density and lower tree coverage providing better conditions for higher BC concentrations. Because model residuals were questionable, a graphical approach to observing the impact of number of burning sources within the PEM area and number of upwind burning sources was used and potentially indicated an increase in concentration as number of sources increased. Level of surrounding vegetation and structures may also be significant. By graphically observing changes in PEM BC concentration with an increase in the number of upwind burning sources, it was seen that a positive correlation was potentially present. This trend seemed to be more apparent when the level of surrounding vegetation and structures was mild,

highlighting the impact of obstructions on BC concentration; when obstructions are minimal, dispersion patterns are more predictable, but when obstructions are more abundant, BC concentrations may be more stochastic. More samples, however, will be needed to show more definite correlations.

The third task indicated that ISC dispersion modeling in the near-field case cannot be conducted accurately when approximate inputs are used. Both programs modeled study area BC concentrations much lower than actual concentrations, with ISC-PRIME and ISCST3 modeled-to-measured ratios averaging 0.25, ranging from 0 to 3.94, and averaging 0.15, ranging from 0 to 1.62, respectively. This under prediction may be associated with application to the near-field in addition to assumptions made about burning sources and meteorological conditions where information was not available. To bring median modeled BC concentrations closer to unity, correction factors of 9.75 and 18.2 were applied to ISC-PRIME and ISCST3 values, respectively. Upon application of correction factors, median ratios were 0.94 and 1.03 for ISC-PRIME and ISCST3, respectively, and ratios ranged from 0.054 to 38.4 for ISC-PRIME and 0.011 to 29.5 for ISCST3.

Modeled PEM BC distributions were further observed through BC concentration contours generated in BEEST. ISC-PRIME typically performed better than ISCST3, especially when modeling the location of the highest measured PEM BC concentration. Still, while ISC-PRIME was sometimes able to model the location of the highest measured PEM BC concentrations and the general direction of decreasing BC

concentration, there were also many instances where the highest concentrations were modeled as the lowest concentrations and vice versa. Observed contours indicated that ISC-PRIME and ISCST3 could not consistently model BC variability within the study area.

Additionally, trends typical of other studies using ISC-PRIME and ISCST3 were not seen in this application. For example, both ISC programs typically estimated concentrations conservatively, with ISCST3 tending to be more conservative than ISC-PRIME. In this study application, ISCST3 predicted concentrations lower than ISC-PRIME 75 percent of the time. Additionally, instead of ISC-PRIME over predicting high measured concentrations and under predicting low concentrations as previously observed, this study found the programs to under predict the highest values. The inconsistencies in these results may suggest that ISC programs are not applicable to the near-field case of that more accurate burning source and local meteorological data is needed. When using estimated emission and meteorological data for the site, ISCST3 and ISC-PRIME were unable to reliably model BC concentrations. Because the ISC-PRIME and ISCST3 results were inconsistent with other studies, the developed correction factors are only applicable to this study area. To determine the applicability of ISC-PRIME and ISCST3 to near-field sites, more site specific inputs will have to be evaluated for their ability to improve dispersion modeling methods.

5.2 Future Study

This study found substantial spatial variability within the 1 km² area over each IOP. Although the average variability may not have large impacts in areas meeting PM_{2.5} standards, PM_{2.5} standard deviations of almost 10 µg/m³ or about three to four times the measured average concentration may mean harmful exposures in areas like Fresno, CA, where geographic and meteorological characteristics tend to promote high PM_{2.5} concentrations. This study aimed to better understand variables that affect BC concentrations through the use of regression models and dispersion modeling, but these methods were incapable of pinpointing any single or group of specific meteorological, , or source variables that could easily fulfill the task. The stochastic nature of meteorology and its interaction with terrain are likely the cause of these results. To better relate BC concentration to meteorology, more investigation will be needed to determine the meteorological, geographical, and source variables that better help explain pollutant variability.

Although this study found ISC air dispersion models to poorly model BC concentrations, several improvements to operating the dispersion modeling programs may still be made. For example, the acquisition of site specific meteorology, geography, and source characteristics would better assess model performance.

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Appendix A. Aethalometer Calibration

ANOVA Output for Aethalometer Calibration

Minitab output for ANOVA of segment 1 of January 19, 2010 readings with adjusted σ_{SG} to achieve a similar aethalometer data average:

General Linear Model: Calculated BC Conc (ng/m³) versus Aeth, Interval

Factor	Type	Levels	Values
Aeth	fixed	4	Aeth 1, Aeth 2, Aeth 3, Aeth 4
Interval	fixed	17	71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 97, 98, 99

Analysis of Variance for Calculated BC Conc (ng/m³), using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Aeth	3	2779	2779	926	1.03	0.387
Interval	16	1389257	1389257	86829	96.73	0.000
Error	48	43088	43088	898		
Total	67	1435124				

S = 29.9611 R-Sq = 97.00% R-Sq(adj) = 95.81%

Unusual Observations for Calculated BC Conc (ng/m³)

Obs	Calculated BC Conc (ng/m ³)	Fit	SE Fit	Residual	St Resid
16	623.803	565.012	16.249	58.790	2.34 R
50	461.255	572.913	16.249	-111.658	-4.44 R

R denotes an observation with a large standardized residual.

Tukey 95.0% Simultaneous Confidence Intervals
Response Variable Calculated BC Conc (ng/m³)
All Pairwise Comparisons among Levels of Aeth
Aeth = Aeth 1 subtracted from:

Aeth	Lower	Center	Upper
Aeth 2	-18.15	9.173	36.50
Aeth 3	-19.42	7.900	35.22
Aeth 4	-33.97	-6.643	20.68

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(-----*-----)
(-----*-----)
(-----*-----)
-----+-----+-----+-----
-25 0 25

Aeth = Aeth 2 subtracted from:

Aeth	Lower	Center	Upper
Aeth 3	-28.60	-1.27	26.05
Aeth 4	-43.14	-15.82	11.51

-----+-----+-----+-----
(-----*-----)
(-----*-----)
-----+-----+-----+-----
-25 0 25

Aeth = Aeth 3 subtracted from:

Tukey Simultaneous Tests
 Response Variable Calculated BC Conc (ng/m³)
 All Pairwise Comparisons among Levels of Aeth
 Aeth = Aeth 1 subtracted from:

Aeth	Difference of Means	SE of Difference	T-Value	Adjusted P-Value
Aeth 2	9.173	10.28	0.8926	0.8087
Aeth 3	7.900	10.28	0.7687	0.8681
Aeth 4	-6.643	10.28	-0.6464	0.9163

Aeth = Aeth 2 subtracted from:

Aeth	Difference of Means	SE of Difference	T-Value	Adjusted P-Value
Aeth 3	-1.27	10.28	-0.124	0.9993
Aeth 4	-15.82	10.28	-1.539	0.4228

Aeth = Aeth 3 subtracted from:

Aeth	Difference of Means	SE of Difference	T-Value	Adjusted P-Value
Aeth 4	-14.54	10.28	-1.415	0.4963

Residual Plots for Calculated BC Conc (ng/m³)

Graph of segment 1 of January 19, 2010 readings before adjusted σ_{SG} to achieve a similar aethalometer data average:

Graph of segment 1 of January 19, 2010 readings with adjusted σ_{SG} to achieve a similar aethalometer data average:

Minitab output for ANOVA of segment 2 of January 19, 2010 readings adjusted to have the same σ_{SG} as segment 1:

General Linear Model: Calculated BC Conc (ng/m³) versus Aeth, Interval

Factor	Type	Levels	Values
Aeth	fixed	4	Aeth 1, Aeth 2, Aeth 3, Aeth 4
Interval	fixed	19	100, 101, 102, 103, 104, 105, 106, 107, 126, 127, 128, 129, 130, 131, 132, 133, 134, 135, 136

Analysis of Variance for Calculated BC Conc (ng/m³), using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Aeth	3	957	957	319	0.49	0.691
Interval	18	2964850	2964850	164714	253.08	0.000
Error	54	35145	35145	651		
Total	75	3000951				

S = 25.5113 R-Sq = 98.83% R-Sq(adj) = 98.37%

Unusual Observations for Calculated BC Conc (ng/m³)

Obs	Calculated BC Conc (ng/m ³)	Fit	SE Fit	Residual	St Resid
1	280.832	334.097	13.726	-53.265	-2.48 R
7	552.764	496.522	13.726	56.242	2.62 R
8	685.100	636.410	13.726	48.689	2.26 R
28	648.703	576.092	13.726	72.611	3.38 R
39	384.790	325.784	13.726	59.006	2.74 R

R denotes an observation with a large standardized residual.

Tukey 95.0% Simultaneous Confidence Intervals
Response Variable Calculated BC Conc (ng/m³)
All Pairwise Comparisons among Levels of Aeth
Aeth = Aeth 1 subtracted from:

Aeth	Lower	Center	Upper	
Aeth 2	-27.79	-5.846	16.10	(-----*-----)
Aeth 3	-30.26	-8.313	13.63	(-----*-----)
Aeth 4	-30.97	-9.027	12.92	(-----*-----)

-30 -15 0 15

Aeth = Aeth 2 subtracted from:

Aeth	Lower	Center	Upper	
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Aeth = Aeth 3 subtracted from:

Tukey Simultaneous Tests

Response Variable Calculated BC Conc (ng/m³)

All Pairwise Comparisons among Levels of Aeth

Aeth = Aeth 1 subtracted from:

Aeth	Difference of Means	SE of Difference	T-Value	Adjusted P-Value
Aeth 2	-5.846	8.277	-0.706	0.8942
Aeth 3	-8.313	8.277	-1.004	0.7475
Aeth 4	-9.027	8.277	-1.091	0.6967

Aeth = Aeth 2 subtracted from:

Aeth	Difference of Means	SE of Difference	T-Value	Adjusted P-Value
Aeth 3	-2.467	8.277	-0.2981	0.9907
Aeth 4	-3.181	8.277	-0.3843	0.9805

Aeth = Aeth 3 subtracted from:

Aeth	Difference of Means	SE of Difference	T-Value	Adjusted P-Value
Aeth 4	-0.7141	8.277	-0.08628	0.9998

Residual Plots for Calculated BC Conc (ng/m³)

Graph of segment 2 of January 19, 2010 readings before adjusted σ_{SG} from segment 1:

Graph of segment 2 of January 19, 2010 readings with adjusted σ_{SG} from segment 1:

Minitab output for ANOVA of segment 1 of June 22 -23 (2010) readings with adjusted σ_{SG} to achieve a similar aethalometer data average:

General Linear Model: P.1Calculated BC versus Aeth, Interval

Factor	Type	Levels	Values
Aeth	fixed	3	Aeth 1, Aeth 3, Aeth 4
Interval	fixed	92	46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103, 104, 105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117, 118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132, 133, 134, 135, 136, 137

Analysis of Variance for P.1Calculated BC Conc (ng/m³), using Adjusted SS for

Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Aeth	2	73	73	36	1.23	0.295
Interval	91	3808674	3808674	41854	1415.06	0.000
Error	182	5383	5383	30		
Total	275	3814130				

S = 5.43850 R-Sq = 99.86% R-Sq(adj) = 99.79%

Unusual Observations for P.1Calculated BC Conc (ng/m^3)

Obs	P.1Calculated BC Conc (ng/m^3)	Fit	SE Fit	Residual	St Resid
48	108.960	119.445	3.174	-10.486	-2.37 R
55	170.869	158.984	3.174	11.885	2.69 R
75	295.925	285.404	3.174	10.521	2.38 R
82	357.834	348.675	3.174	9.159	2.07 R
88	414.790	423.996	3.174	-9.207	-2.08 R
104	118.300	107.811	3.174	10.489	2.38 R
124	55.169	64.200	3.174	-9.031	-2.05 R
130	80.194	66.035	3.174	14.158	3.21 R
166	257.644	266.928	3.174	-9.284	-2.10 R
167	273.000	284.583	3.174	-11.583	-2.62 R
178	374.238	383.613	3.174	-9.375	-2.12 R
196	99.466	109.045	3.174	-9.580	-2.17 R
217	67.009	77.147	3.174	-10.139	-2.30 R
265	384.252	373.015	3.174	11.237	2.54 R

R denotes an observation with a large standardized residual.

Tukey 95.0% Simultaneous Confidence Intervals
Response Variable P.1Calculated BC Conc (ng/m^3)
All Pairwise Comparisons among Levels of Aeth
Aeth = Aeth 1 subtracted from:

Aeth	Lower	Center	Upper
Aeth 3	-2.714	-0.8207	1.073
Aeth 4	-1.480	0.4141	2.308

-----+-----+-----+-----
 (------*-----)
 (-----*-----)
 -----+-----+-----+-----
 -1.6 0.0 1.6

Aeth = Aeth 3 subtracted from:

Aeth	Lower	Center	Upper
Aeth 4	-0.6590	1.235	3.129

-----+-----+-----+-----
 (------*-----)
 -----+-----+-----+-----
 -1.6 0.0 1.6

Tukey Simultaneous Tests
Response Variable P.1Calculated BC Conc (ng/m^3)
All Pairwise Comparisons among Levels of Aeth
Aeth = Aeth 1 subtracted from:

Aeth	Difference of Means	SE of Difference	T-Value	Adjusted P-Value
Aeth 3	-0.8207	0.8019	-1.023	0.5630
Aeth 4	0.4141	0.8019	0.516	0.8634

Aeth = Aeth 3 subtracted from:

Aeth	Difference of Means	SE of Difference	T-Value	Adjusted P-Value
Aeth 4	1.235	0.8019	1.540	0.2748

Residual Plots for P.1Calculated BC Conc (ng/m^3)

Graph of segment 1 of June 22-23, 2010 readings before adjusted σ_{SG} to achieve a similar aethalometer data average:

Graph of segment 1 of June 22-23, 2010 readings with adjusted σ_{SG} to achieve a similar aethalometer data average:

Minitab output for ANOVA of segment 2 of June 22-23, 2010 readings adjusted to have the same σ_{SG} as segment 1:

General Linear Model: p2-aCalculated B versus Aeth, Interval

Factor	Type	Levels	Values
Aeth	fixed	3	Aeth 1, Aeth 3, Aeth 4
Interval	fixed	24	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24

Analysis of Variance for p2-aCalculated BC Conc (ng/m³), using Adjusted SS for

Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Aeth	2	1194.6	1194.6	597.3	3.98	0.025
Interval	23	186168.8	186168.8	8094.3	53.93	0.000
Error	46	6903.6	6903.6	150.1		
Total	71	194267.0

Graph of segment 2 of June 22-23, 2010 readings before adjusted σ_{SG} to achieve a similar aethalometer data average:

Graph of segment 2 of June 22-23, 2010 readings with adjusted σ_{SG} to achieve a similar aethalometer data average:

Summary of final σ_{SG} values:

Aeth	σ_{SG} (m ² /g)		
	19-Jan	22-Jun	Average
1	19	18.31	18.66
2	16.225	-	16.23
3	23.035	19.98	21.51
4	23	21.92	22.46

Appendix B. Adsorption Ångström exponent (AAE) for all PEMs

	AAE 700-350nm				AAE 700-360nm								
Location	1A	2A	3A	4A	2B	3B	4B	5B	6B	7B	8B	9B	10B
A						1.70	1.94	2.48	3.28	2.57	3.37	1.94	1.55
AW						2.36	2.18	1.39	1.75	1.39	1.70	2.74	
B1						1.27	2.02	1.58	1.29	1.59	1.00	1.86	
B2						1.59	1.98	1.42		1.60	0.99	1.99	2.10
B3	1.77		1.95	1.71			2.13	1.80	2.21		0.95	2.19	
B4						1.61	1.97			1.59	1.19	2.21	
B65	1.90	1.55		1.44									
BC						1.62	2.28	1.60	1.18	1.59	0.95	2.08	2.19
C	2.13		1.86	1.60		2.23	2.78	1.65	1.47	1.53	0.88	1.99	2.08
C2		2.23		1.58									
COW	1.85												
CP							1.95	1.22	1.36	1.41	0.94	2.00	2.20
CP1													
CPK		1.99		1.94									
CS		2.08		1.58									
D						1.36	2.31	2.78	2.62	1.12			
E1					2.13	1.93	2.49						
E2			0.28	2.35		2.35	1.88	1.24		1.79	1.04	1.89	1.99
E44		2.33											
EK							2.58	1.34	1.53	1.89	0.92	1.88	2.18
FS								1.74	2.61	1.87	2.36	2.01	1.93
K							2.16	1.47		1.76	0.94	1.83	2.23
K64	1.85	1.59											
MO	1.77	2.18	1.76	2.09									
S1					2.17	2.23	2.04	2.05	2.33	2.39			
W						2.71	2.52	1.76	2.84	1.60	2.31	1.84	
W35		2.75											
W48	1.82	3.91	1.99	2.28									
W55	1.81	2.28	2.35	1.44									
WA1					2.07								
WS	1.71												

Appendix C. Aethalometer BC Measurements over Time

The figures below illustrate 30 minute averaged BC concentration over time during each IOP at each operating aethalometer location. Negative values have been assumed to be half of the lower detection limit (the average of 0 and the lower detection limit), 30.2 ng/m^3 .

Appendix D. Spatial Variability

Aethalometer Variability

The first table below summarizes aethalometer variability for 30 minute averaged BC concentrations. BC concentrations are in nanograms per meters cubed. The second table details the minimum and maximum concentrations measured during each IOP.

Location	A - 6255 Charring St.			B - 432 Exeter Lane			C - 6126 Coventry Lane (FS)			D - 6380 Buckley Drive			E - 6475 Buckley (MO)			Average 12-hr BC conc all Locations (ng/m ³)		
IOP #	Conc	Median	std dev	Conc	Median	std dev	Conc	Median	std dev	Conc	Median	std dev	Conc	Median	std dev	Conc	Median	std dev
1a	413	364	155										357	343	100	385	359	132
2a	125	69	104										95	65	70	110	69	89
3a				54	32	42										54	32	42
4a				249	134	215							25	7	45	137	99	191
2b	159	157	38	128	104	56				135	121	42				141	125	47
3b	220	73	302	156	85	223				175	101	207				184	91	245
4b	437	310	366	1203	199	3408				237	211	115				626	237	1996
5b	377	218	301	1100	250	3643	280	165	260	287	162	333				511	194	1843
6b	186	69	271	149	79	229	160	75	196	174	90	220				167	78	227
7b	162	122	173	127	126	60	139	117	56	177	166	48				151	131	99
8b	125	103	88	234	78	451	116	80	189	88	75	54				141	82	252
9b	153	131	74	336	54	909	111	83	68	166	118	109				192	100	461
10b	159	157	38				148	116	91	135	122	41				144	123	62
All IOPs	30 min basis	214	143	228	381	125	1632	157	112	169	175	126	168	128	49	151		
	12 hr basis	229	162	119	373	195	418	159	143	62	175	174	58	159	95	28		

1 minute BC Concentration (µg/m ³)														
IOP	1a	2a	3a	4a	2b	3b	4b	5b	6b	7b	8b	9b	10b	All
Max	2	1	0.3	174	0.5	3	56	85	15	83	21	70	19	174
Min	0.067	0.067	0.13	0.067	0.067	0.070	0.067	0.067	0.070	0.070	0.067	0.067	0.067	0.067

PEM Variability

The table below summarizes PEM variability for BC concentrations. BC concentrations are in nanograms per meters cubed.

Label	Location	12 hr BC Conc (ng/m ³)												
		1a	2a	3a	4a	2b	3b	4b	5b	6b	7b	8b	9b	10b
MO	A	343	75	77	222									
B65	A	405	210	35	210									
W55	C	376	813	123	349									
WS	C	313												
K64	A	343												
W48	C	434	47	115	744									
COW	C	486												
CS	C		156		256									
CPK	A		86	48	90									
E44	B		94											
W35	C			110	528									
A	C						174	268	286	370	270	561	119	203
AW	C						451	285	308	693	453	176	280	30
B1	A					30	239					158	119	30
B2	A						125	293	191	123	145	137	112	101
B3	A	329	32		262	30	30	210	270	153	115	119	137	30
B4	A						137	222	273	30	136	277	92	30
BC	A					30	202	197	216	413	146	139	100	83
C	B	308	30	76	306	82	188	326	283	185	159	154	102	94
C2	B		82		293									
CP	A							221	318		188	130	110	81
CP1	A					30	30							
D	C						542	374	294	339	1051			
E1	B						193	281						
E2	B				128	85	237	1048	2787	30	125	156	120	92
EK	A					30	30	198	265	81	101	120	133	94
K	A					30	30	189	194	59	115	149	148	88
S1	C					309	525	448	416	247	386	229	192	117
W	C		187			78	116	396	252	192	503	142	169	30
FS	C								263	164	184	162	105	104
WA1	C					163								

Meteorological Variability

The tables below summarize meteorological variability for each meteorological station.

Location	Marine Terrace (10 min basis)											LH CSDF (30 min basis)								
	Wind speed (mph)			Wind Direction		Temperature (F)			Humidity (%)			Wind speed (mph)			Wind Direction		Humidity (%)			
IOP	Average	Median	Std Dev	Average	Std Dev	Average	Median	Std Dev	Average	Median	Std Dev	Average	Median	Std Dev	Average	Std Dev	Average	Median	Std Dev	
1a	2	2	1	214	44	51	51	2	77	77	3	2	1	2	250	51	85	86	8	
2a	4	5	1	298	45	46	46	3	75	77	6	2	2	1	125	40	88	90	7	
3a	5	4	3	339	42	51	52	4	84	85	3	2	2	2	117	47	97	98	1	
4a	3	2	1	212	45	52	51	2	71	71	3	1	1	2	347	56	78	78	7	
2b	5	5	1	-63	42	43	42	3	81	83	4	2	3	1	242	42	95	96	3	
3b	3	4	1	137	44	46	45	2	78	79	2	1	1	1	301	46	92	91	4	
4b	3	2	2	137	42	49	49	2	83	83	2	1	1	1	288	56	96	97	3	
5b	3	3	2	92	42	50	49	2	80	81	3	2	2	2	12	46	96	97	2	
6b	6	5	2	84	46	44	43	4	75	77	5	2	2	3	338	53	88	89	4	
7b	3	3	1	242	45	46	46	3	65	65	3	2	1	2	163	46	82	83	7	
8b	4	4	1	-57	47	53	51	5	40	44	7	3	4	2	280	46	54	60	13	
9b	6	5	3	-42	49	44	45	4	75	74	5	3	2	4	232	53	91	93	7	
10b	3	3	2	249	48	51	51	2	76	77	4	2	1	2	92	49	94	95	3	
All IOPs	4	4	2	264	45	48	48	4	74	77	12	2	2	2	292	47	87	93	14	

Location	EBAM (10 min basis)											Sonic (10 min basis)								
	Wind speed (mph)			Wind Direction		Temperature (F)			Humidity (%)			Wind speed (mph)			Wind Direction		Temperature (F)			
IOP	Average	Median	Std Dev	Average	Std Dev	Average	Median	Std Dev	Average	Median	Std Dev	Average	Median	Std Dev	Average	Std Dev	Average	Median	Std Dev	
1a																				
2a																				
3a																				
4a																				
2b																				
3b																				
4b	0.8	0.7	0.2	68	44	49	49	3	87	88	4									
5b	1.0	0.9	0.4	-84	44	51	50	2	86	87	3									
6b	0.9	0.7	0.2	158	48	46	44	4	79	82	6									
7b	1.0	0.9	0.4	110	46	47	46	3	71	71	5									
8b	1.0	0.9	0.4	-66	42	54	53	3	43	44	4	0.6	0.6	0.2	138	43	54	52	4	
9b	1.5	1.6	0.5	243	44	44	42	3	81	82	4	0.6	0.5	0.3	89	70	44	42	4	
10b	0.9	0.7	0.4	-63	44	52	51	1	83	84	4	0.6	0.6	0.3	90	74	52	51	4	
All IOPs	1.0	0.9	0.4	257	45	49	49	4	76	82	15	0.6	0.5	0.3	90	78	50	51	6	

Location	EBAM (10 min basis)											Sonic (10 min basis)								
	Wind speed (mph)			Wind Direction		Temperature (F)			Humidity (%)			Wind speed (mph)			Wind Direction		Temperature (F)			
IOP	Average	Median	Std Dev	Average	Std Dev	Average	Median	Std Dev	Average	Median	Std Dev	Average	Median	Std Dev	Average	Std Dev	Average	Median	Std Dev	
1a																				
2a																				
3a																				
4a																				
2b																				
3b																				
4b	0.8	0.7	0.2	68	44	49	49	3	87	88	4									
5b	1.0	0.9	0.4	-84	44	51	50	2	86	87	3									
6b	0.9	0.7	0.2	158	48	46	44	4	79	82	6									
7b	1.0	0.9	0.4	110	46	47	46	3	71	71	5									
8b	1.0	0.9	0.4	-66	42	54	53	3	43	44	4	0.6	0.6	0.2	138	43	54	52	4	
9b	1.5	1.6	0.5	243	44	44	42	3	81	82	4	0.6	0.5	0.3	89	70	44	42	4	
10b	0.9	0.7	0.4	-63	44	52	51	1	83	84	4	0.6	0.6	0.3	90	74	52	51	4	
All IOPs	1.0	0.9	0.4	257	45	49	49	4	76	82	15	0.6	0.5	0.3	90	78	50	51	6	

Appendix E. Summary of IOP Wind Speeds and Direction

Wind Speed Comparisons for All Stations

The graphs below detail wind speed over time during each sampling period at each meteorological station and combination used for analysis. The wind speeds are presented here (as opposed to another meteorological variable) to offer a comparison of a meteorological characteristic that often has a large impact on pollutant dispersion and that can vary largely in small areas.

Wind Roses for all IOPs

IOP 1a: January 31, 2009

IOP 2a: February 18, 2009

IOP 3a: February 26, 2009

IOP 4a: February 27, 2009

IOP 2b: January 23, 2010

IOP 3b: January 30, 2010

IOP 4b: February 13, 2010 –AM inversions

IOP 5b: February 28, 2010

IOP 6b: March 4, 2010

:

IOP 7b: March 11, 2010 – mostly AM inversions

IOP 8b: March 15, 2010

IOP 9b: April 3, 2010

IOP 10b: April 23, 2010

Temperature Profiles

IOP 1a

IOP 2a

IOP 3a

IOP 4a

ESRL Physical Sciences Division Wind Profiling Radar

IOP 2b

IOP 3b

IOP4b

IOP 5b

ESRL Physical Sciences Division Wind Profiling Radar

IOP 6b

IOP 7b

IOP 8b

IOP 9b

Appendix F. Graphic Summary for all IOPs

All IOPs are summarized here to include PEM and aethalometer locations, concentrations, and spectral dependence, in addition to average wind speed, dominant wind direction, and burning source locations. PEM concentration boxes colored brown indicate an AAE value greater than 1.2 (wood smoke), colored purple indicate an AAE of less than 1.2 (traffic exhaust), and colored pink and labeled LOD indicate limit of detection.

IOP 1a: January 31, 2009

IOP 2a: February 18, 2009

IOP 4a: February 27, 2009

IOP 7a: March 15, 2009

IOP 8a: March 20, 2009

IOP 2b: January 23, 2010

IOP 3b: January 30, 2010

IOP 4b: February 13, 2010 –AM inversions

IOP 5b: February 28, 2010

IOP 6b: March 4, 2010

IOP 7b: March 11, 2010 – mostly AM inversions

IOP 8b: March 15, 2010

IOP 9b: April 3, 2010

IOP 10b: April 23, 2010

Appendix G. Aethalometer BC Regression Models

Minitab output for average aethalometer BC concentration regression models.

Average BC Concentration

Linear EBAM Model

Regression Analysis: BCave^{-.7} versus lagged1_BCav, Time Interval, ...

The regression equation is
 BCave^{-.7} = 0.0255 + 0.527 lagged1_BCave^{-.7} + 0.000396 Time Interval
 - 0.000206 EB Hum (%)

161 cases used, 151 cases contain missing values

Predictor	Coef	SE Coef	T	P	VIF
Constant	0.025475	0.005374	4.74	0.000	
lagged1_BCave ^{-.7}	0.52663	0.06491	8.11	0.000	1.398
Time Interval	0.0003957	0.0001205	3.28	0.001	1.186
EB Hum (%)	-0.00020593	0.00005784	-3.56	0.000	1.292

S = 0.00931338 R-Sq = 51.9% R-Sq(adj) = 51.0%

PRESS = 0.0146199 R-Sq(pred) = 48.39%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	3	0.0147084	0.0049028	56.52	0.000
Residual Error	157	0.0136180	0.0000867		
Total	160	0.0283265			

There are no replicates.
 Minitab cannot do the lack of fit test based on pure error.

Source	DF	Seq SS
lagged1_BCave ^{-.7}	1	0.0131082
Time Interval	1	0.0005008
EB Hum (%)	1	0.0010994

Unusual Observations

Obs	lagged1_BCave ^{-.7}	BCave ^{-.7}	Fit	SE Fit	Residual	St Resid
173	0.039	0.002716	0.030489	0.001672	-0.027773	-3.03R
194	0.032	0.052949	0.028949	0.001479	0.024000	2.61R
197	0.033	0.053407	0.029419	0.001250	0.023988	2.60R
198	0.053	0.018032	0.039706	0.002116	-0.021674	-2.39R
246	0.025	0.011498	0.031962	0.002173	-0.020464	-2.26R
247	0.011	0.011542	0.025171	0.002642	-0.013629	-1.53 X
248	0.012	0.016412	0.025178	0.002556	-0.008766	-0.98 X
266	0.059	0.011739	0.042235	0.002655	-0.030496	-3.42RX
267	0.012	0.051999	0.016988	0.001562	0.035011	3.81R
269	0.045	0.006936	0.034580	0.001780	-0.027644	-3.02R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Durbin-Watson statistic = 2.18182

Lack of fit test

Possible interaction in variable lagged1_ (P-Value = 0.001)

Possible curvature in variable Time Int (P-Value = 0.027)

Possible curvature in variable EB Hum ((P-Value = 0.015)

Possible lack of fit at outer X-values (P-Value = 0.000)

Overall lack of fit test is significant at P = 0.000

Residual Plots for BCave^{-0.7}

Non-linear EBAM Model

Regression Analysis: BCave^{-0.7} versus lagged1_BCav, lag1^{-0.7}*ti, ...

The regression equation is

$$\text{BCave}^{-0.7} = 0.0275 + 0.250 \text{ lagged1_BCave}^{-0.7} + 0.0225 \text{ lag1}^{-0.7} \cdot \text{timeint} - 0.000387 \text{ Time Interval} - 0.000001 (\text{E Hum}^2)$$

161 cases used, 151 cases contain missing values

Predictor	Coef	SE Coef	T	P	VIF
Constant	0.027504	0.005091	5.40	0.000	
lagged1_BCave ^{-0.7}	0.2497	0.1354	1.84	0.067	6.281
lag1 ^{-0.7} *timeint	0.02248	0.01008	2.23	0.027	21.395
Time Interval	-0.0003867	0.0003786	-1.02	0.309	12.093
(E Hum ²)	-0.00000143	0.00000045	-3.16	0.002	1.409

S = 0.00916219 R-Sq = 53.8% R-Sq(adj) = 52.6%

PRESS = 0.0144940 R-Sq(pred) = 48.83%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	4	0.0152309	0.0038077	45.36	0.000
Residual Error	156	0.0130955	0.0000839		
Total	160	0.0283265			

There are no replicates.

Minitab cannot do the lack of fit test based on pure error.

Source	DF	Seq SS
lagged1_BCave ^{-0.7}	1	0.0131082
lag1 ^{-0.7} *timeint	1	0.0009059
Time Interval	1	0.0003777
(E Hum ²)	1	0.0008391

Unusual Observations

Obs	lagged1_BCave ^{-.7}	BCave ^{-.7}	Fit	SE Fit	Residual	St Resid
173	0.039	0.002716	0.029336	0.001718	-0.026621	-2.96R
194	0.032	0.052949	0.029438	0.001468	0.023511	2.60R
195	0.053	0.037601	0.035706	0.002818	0.001895	0.22 X
197	0.033	0.053407	0.029403	0.001220	0.024004	2.64R
198	0.053	0.018032	0.036778	0.002420	-0.018745	-2.12R
246	0.025	0.011498	0.032012	0.002089	-0.020515	-2.30R
261	0.062	0.041991	0.060947	0.002782	-0.018956	-2.17R
263	0.062	0.043976	0.063062	0.003254	-0.019086	-2.23RX
266	0.059	0.011739	0.036343	0.003684	-0.024604	-2.93RX
267	0.012	0.051999	0.021567	0.002446	0.030432	3.45R
269	0.045	0.006936	0.032624	0.001930	-0.025688	-2.87R
288	0.047	0.026760	0.045982	0.002003	-0.019222	-2.15R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Durbin-Watson statistic = 2.11275

Lack of fit test

Possible curvature in variable lagged1_ (P-Value = 0.019)

Possible curvature in variable lag1^{-0.} (P-Value = 0.008)

Possible curvature in variable Time Int (P-Value = 0.003)

Possible interaction in variable Time Int (P-Value = 0.012)

Possible lack of fit at outer X-values (P-Value = 0.000)

Overall lack of fit test is significant at P = 0.000

Residual Plots for BCave^{-.7}

Linear EBAM & CSDF Combination

Regression Analysis: BCave^{-.7} versus lagged1_BCav, Time Interval, ...

The regression equation is

$$\text{BCave}^{-.7} = 0.0207 + 0.514 \text{ lagged1_BCave}^{-.7} + 0.000377 \text{ Time Interval} \\ + 0.00231 \text{ E\&C WS (mph)} - 0.000165 \text{ E\&C Hum (\%)}$$

161 cases used, 151 cases contain missing values

Predictor	Coef	SE Coef	T	P	VIF
Constant	0.020747	0.005936	3.50	0.001	
lagged1_BCave ^{-.7}	0.51367	0.06454	7.96	0.000	1.414
Time Interval	0.0003771	0.0001220	3.09	0.002	1.243
E&C WS (mph)	0.0023149	0.0009436	2.45	0.015	1.148
E&C Hum (%)	-0.00016510	0.00006055	-2.73	0.007	1.382

S = 0.00920878 R-Sq = 53.3% R-Sq(adj) = 52.1%

PRESS = 0.0144017 R-Sq(pred) = 49.16%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	4	0.0150974	0.0037744	44.51	0.000
Residual Error	156	0.0132290	0.0000848		
Total	160	0.0283265			

There are no replicates.

Minitab cannot do the lack of fit test based on pure error.

Source	DF	Seq SS
lagged1_BCave ^{-.7}	1	0.0131082
Time Interval	1	0.0005008
E&C WS (mph)	1	0.0008579
E&C Hum (%)	1	0.0006304

Unusual Observations

Obs	lagged1_BCave ^{-.7}	BCave ^{-.7}	Fit	SE Fit	Residual	St Resid
173	0.039	0.002716	0.028667	0.001845	-0.025951	-2.88R
194	0.032	0.052949	0.028999	0.001479	0.023950	2.63R
197	0.033	0.053407	0.030773	0.001368	0.022634	2.49R
198	0.053	0.018032	0.039666	0.002118	-0.021634	-2.41R
242	0.036	0.033654	0.035567	0.003136	-0.001913	-0.22 X
246	0.025	0.011498	0.031982	0.002184	-0.020484	-2.29R
247	0.011	0.011542	0.028367	0.003042	-0.016825	-1.94 X
266	0.059	0.011739	0.042312	0.002570	-0.030573	-3.46R
267	0.012	0.051999	0.016922	0.001618	0.035077	3.87R
269	0.045	0.006936	0.032902	0.001918	-0.025966	-2.88R

R denotes an observation with a large standardized residual.

X denotes an observation whose X value gives it large leverage.

Durbin-Watson statistic = 2.18730

Lack of fit test
Possible interaction in variable lagged1_ (P-Value = 0.001)

Possible interaction in variable E&C WS ((P-Value = 0.013)

Possible lack of fit at outer X-values (P-Value = 0.000)

Overall lack of fit test is significant at P = 0.000

Residual Plots for BCave^{-0.7}

Non-linear EBAM & CSDF Combination

Regression Analysis: BCave^{-0.7} versus lagged1_BCav, Time Interva, ...

The regression equation is

BCave^{^-0.7} = 0.0526 + 0.253 lagged1_BCave^{^-0.7} - 0.000449 Time Interval
+ 0.0229 lag1^{^-0.7*timeint} + 0.00223 E&C WS (mph)
- 0.00826 log(E&C Hum)

161 cases used, 151 cases contain missing values

Predictor	Coef	SE Coef	T	P	VIF
Constant	0.05261	0.01783	2.95	0.004	
lagged1_BCave ^{^-0.7}	0.2531	0.1348	1.88	0.062	6.283
Time Interval	-0.0004485	0.0003731	-1.20	0.231	11.847
lag1 ^{^-0.7*timeint}	0.022853	0.009983	2.29	0.023	21.169
E&C WS (mph)	0.0022274	0.0009341	2.38	0.018	1.146
log(E&C Hum)	-0.008265	0.003972	-2.08	0.039	1.361

S = 0.00912289 R-Sq = 54.5% R-Sq(adj) = 53.0%

PRESS = 0.0144751 R-Sq(pred) = 48.90%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	5	0.0154263	0.0030853	37.07	0.000
Residual Error	155	0.0129002	0.0000832		
Total	160	0.0283265			

There are no replicates.

Minitab cannot do the lack of fit test based on pure error.

Source	DF	Seq SS
lagged1_BCave ^{^-0.7}	1	0.0131082
Time Interval	1	0.0005008
lag1 ^{^-0.7*timeint}	1	0.0007828
E&C WS (mph)	1	0.0006741
log(E&C Hum)	1	0.0003603

Unusual Observations

Obs	lagged1_BCave ^{^-0.7}	BCave ^{^-0.7}	Fit	SE Fit	Residual	St Resid
173	0.039	0.002716	0.028297	0.001829	-0.025581	-2.86R
194	0.032	0.052949	0.028940	0.001478	0.024009	2.67R
197	0.033	0.053407	0.030474	0.001378	0.022932	2.54R
198	0.053	0.018032	0.037113	0.002433	-0.019080	-2.17R
242	0.036	0.033654	0.034717	0.003740	-0.001064	-0.13 X
243	0.034	0.041760	0.033859	0.003135	0.007900	0.92 X
246	0.025	0.011498	0.031610	0.002171	-0.020113	-2.27R
247	0.011	0.011542	0.028999	0.003077	-0.017457	-2.03RX
261	0.062	0.041991	0.057077	0.003328	-0.015086	-1.78 X
263	0.062	0.043976	0.062065	0.003274	-0.018090	-2.12RX
266	0.059	0.011739	0.036338	0.003667	-0.024599	-2.94RX
267	0.012	0.051999	0.020798	0.002469	0.031201	3.55R
269	0.045	0.006936	0.031255	0.002055	-0.024319	-2.74R
288	0.047	0.026760	0.047748	0.002081	-0.020988	-2.36R

R denotes an observation with a large standardized residual.

X denotes an observation whose X value gives it large leverage.

Durbin-Watson statistic = 2.14577

Lack of fit test

Possible curvature in variable lagged1_ (P-Value = 0.017)

Possible curvature in variable Time Int (P-Value = 0.023)

Possible interaction in variable Time Int (P-Value = 0.032)

Possible curvature in variable lag1^-0. (P-Value = 0.013)

Possible interaction in variable E&C WS ((P-Value = 0.003)

Possible lack of fit at outer X-values (P-Value = 0.000)

Overall lack of fit test is significant at P = 0.000

Residual Plots for BCave^{-.7}

BC Deviation

Linear CSDF Model

Regression Analysis: BCdev^0.5 versus lagged1_BCde, CSDF WS (mph,

...

The regression equation is

$$\text{BCdev}^{0.5} = 0.471 + 0.611 \text{ lagged1_BCdev}^{0.5} - 0.0283 \text{ CSDF WS (mph)} \\ - 0.00235 \text{ CSDF Hum(\%)}$$

286 cases used, 26 cases contain missing values

Predictor	Coef	SE Coef	T	P	VIF
Constant	0.4709	0.1091	4.32	0.000	
lagged1_BCdev^0.5	0.61138	0.04513	13.55	0.000	1.104
CSDF WS (mph)	-0.028313	0.008305	-3.41	0.001	1.069
CSDF Hum(%)	-0.002348	0.001089	-2.16	0.032	1.063

S = 0.216478 R-Sq = 47.3% R-Sq(adj) = 46.7%

PRESS = 13.6276 R-Sq(pred) = 45.63%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	3	11.8485	3.9495	84.28	0.000
Residual Error	282	13.2153	0.0469		
Total	285	25.0638			

There are no replicates.

Minitab cannot do the lack of fit test based on pure error.

Source	DF	Seq SS
lagged1_BCdev^0.5	1	11.1693
CSDF WS (mph)	1	0.4614
CSDF Hum(%)	1	0.2179

Unusual Observations

Obs	lagged1_BCdev^0.5	BCdev^0.5	Fit	SE Fit	Residual	St Resid
5	0.54	0.3654	0.4166	0.0446	-0.0512	-0.24 X
32	0.79	0.0964	0.6893	0.0163	-0.5929	-2.75R
72	0.12	0.7511	0.3180	0.0329	0.4331	2.02R
74	1.13	0.8738	0.7665	0.0514	0.1072	0.51 X
90	0.98	0.1408	0.8490	0.0261	-0.7082	-3.30R
159	1.27	0.4328	1.0183	0.0371	-0.5855	-2.74R
173	0.83	1.3952	0.7601	0.0220	0.6350	2.95R
242	0.59	0.9188	0.7699	0.0708	0.1490	0.73 X
243	0.92	0.8679	0.9481	0.0594	-0.0802	-0.39 X
244	0.87	0.4724	0.9075	0.0554	-0.4351	-2.08RX
245	0.47	0.3890	0.5408	0.0501	-0.1518	-0.72 X
247	0.95	1.2704	0.8252	0.0483	0.4452	2.11RX
248	1.27	0.9713	0.9958	0.0461	-0.0245	-0.12 X
261	0.44	0.6372	0.6116	0.0445	0.0256	0.12 X

284	0.33	0.8523	0.3908	0.0180	0.4615	2.14R
288	0.32	1.0421	0.3588	0.0201	0.6833	3.17R
290	0.96	0.2560	0.6768	0.0450	-0.4208	-1.99 X

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Durbin-Watson statistic = 2.29582

Lack of fit test

Possible curvature in variable lagged1_ (P-Value = 0.000)

Possible interaction in variable CSDF Hum (P-Value = 0.015)

Overall lack of fit test is significant at P = 0.000

Residual Plots for BCdev^{0.5}

Matrix Plot of BCdev^{0.5} vs lagged1_BCde, CSDf WS (mph, CSDf Hum(%))

Appendix H. PEM BC Linear Regression Models

Average BC Concentration

Marine Terrace Station Results

Regression Analysis: BCave^{0.4} versus MT Wind Speed, MT sin(Wind Dir , ...

The regression equation is

$$\text{BCave}^{0.4} = 17.9 - 2.34 \text{ MT Wind Speed} + 14.9 \text{ MT sin(Wind Dir)} \\ + 12.9 \text{ MT cos(Wind Dir)}$$

Predictor	Coef	SE Coef	T	P	VIF
Constant	17.935	1.924	9.32	0.000	
MT Wind Speed	-2.3439	0.4801	-4.88	0.001	2.275
MT sin(Wind Dir	14.900	5.487	2.72	0.024	3.185
MT cos(Wind Dir	12.850	3.298	3.90	0.004	1.654

S = 1.19197 R-Sq = 81.3% R-Sq(adj) = 75.1%

PRESS = 30.9167 R-Sq(pred) = 54.90%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	3	55.764	18.588	13.08	0.001
Residual Error	9	12.787	1.421		
Total	12	68.551			

There are no replicates.

Minitab cannot do the lack of fit test based on pure error.

Source	DF	Seq SS
MT Wind Speed	1	33.934
MT sin(Wind Dir	1	0.256
MT cos(Wind Dir	1	21.574

Durbin-Watson statistic = 1.95165

No evidence of lack of fit (P >= 0.1).

Residual Plots for BCave^{0.4}

CSDF Station Results

Regression Analysis: ln(BCave) versus CSDF Windspeed (mph)

The regression equation is
 $\ln(\text{BCave}) = 6.71 - 0.778 \text{ CSDF Windspeed (mph)}$

Predictor	Coef	SE Coef	T	P	VIF
Constant	6.7078	0.4957	13.53	0.000	
CSDF Windspeed (mph)	-0.7779	0.2486	-3.13	0.010	1.000

S = 0.510667 R-Sq = 47.1% R-Sq(adj) = 42.3%

PRESS = 3.66382 R-Sq(pred) = 32.44%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	1	2.5541	2.5541	9.79	0.010
Residual Error	11	2.8686	0.2608		
Total	12	5.4227			

There are no replicates.
Minitab cannot do the lack of fit test based on pure error.

Unusual Observations

CSDF						
Windspeed						
Obs	(mph)	ln(BCave)	Fit	SE Fit	Residual	St Resid
8	1.77	6.449	5.331	0.146	1.118	2.28R

R denotes an observation with a large standardized residual.

Durbin-Watson statistic = 1.57091

No evidence of lack of fit ($P \geq 0.1$).

Residual Plots for ln(BCave)

MT & CSDF Combination Results

Regression Analysis: ln(BCave) versus Wind Speed (mph), Ave sin(WD) MT+C

The regression equation is

$$\ln(\text{BCave}) = 7.25 - 0.725 \text{ Wind Speed (mph) MT+CSDF} + 2.60 \text{ Ave sin(WD) MT+CSDF}$$

Predictor	Coef	SE Coef	T	P	VIF
Constant	7.2515	0.4139	17.52	0.000	
Wind Speed (mph) MT+CSDF	-0.7253	0.1417	-5.12	0.000	1.069
Ave sin(WD) MT+CSDF	2.598	1.021	2.54	0.029	1.069

S = 0.378544 R-Sq = 73.6% R-Sq(adj) = 68.3%

PRESS = 2.32623 R-Sq(pred) = 57.10%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	2	3.9898	1.9949	13.92	0.001
Residual Error	10	1.4330	0.1433		
Total	12	5.4227			

There are no replicates.

Minitab cannot do the lack of fit test based on pure error.

Source	DF	Seq SS
Wind Speed (mph) MT+CSDF	1	3.0628
Ave sin(WD) MT+CSDF	1	0.9270

Unusual Observations

Wind Speed (mph)						
Obs	MT+CSDF	ln(BCave)	Fit	SE Fit	Residual	St Resid
8	2.48	6.449	5.745	0.163	0.704	2.06R

R denotes an observation with a large standardized residual.

Durbin-Watson statistic = 1.66475

No evidence of lack of fit ($P \geq 0.1$).

Residual Plots for ln(BCave)

BC Deviation

Impact of Number of Sources

Regression Analysis: ln(dev) versus Num Sources

The regression equation is
 $\ln(\text{dev}) = -1.02 + 0.0762 \text{ Num Sources}$

Predictor	Coef	SE Coef	T	P	VIF
Constant	-1.0245	0.3530	-2.90	0.014	
Num Sources	0.07620	0.03456	2.20	0.050	1.000

S = 0.502173 R-Sq = 30.6% R-Sq(adj) = 24.3%

PRESS = 3.64262 R-Sq(pred) = 8.92%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	1	1.2255	1.2255	4.86	0.050
Residual Error	11	2.7740	0.2522		
Lack of Fit	7	1.7770	0.2539	1.02	0.525
Pure Error	4	0.9970	0.2492		
Total	12	3.9994			

7 rows with no replicates

Durbin-Watson statistic = 1.89061

No evidence of lack of fit (P >= 0.1).

Residual Plots for ln(dev)

Directional Regression Analysis

General Linear Model: lnPEMBC versus Location, IOP

Factor	Type	Levels	Values
--------	------	--------	--------

Location	fixed	2	a, c
IOP	fixed	5	10b, 4b, 5b, 7b, 9b

Analysis of Variance for lnPEMBC, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Location	1	5.1416	3.8152	3.8152	20.90	0.000
IOP	4	17.1473	17.1473	4.2868	23.48	0.000
Error	54	9.8585	9.8585	0.1826		
Total	59	32.1474				

S = 0.427277 R-Sq = 69.33% R-Sq(adj) = 66.49%

Term	Coef	SE Coef	T	P
Constant	5.18631	0.05674	91.41	0.000
Location				
a	-0.26024	0.05693	-4.57	0.000
IOP				
10b	-0.9682	0.1105	-8.76	0.000
4b	0.4319	0.1104	3.91	0.000
5b	0.4460	0.1104	4.04	0.000
7b	0.2795	0.1104	2.53	0.014

Unusual Observations for lnPEMBC

Obs	lnPEMBC	Fit	SE Fit	Residual	St Resid
32	6.95768	5.72607	0.14009	1.23162	3.05 R
49	5.31249	4.47835	0.14483	0.83414	2.08 R
50	3.40992	4.47835	0.14483	-1.06843	-2.66 R
60	3.40992	4.47835	0.14483	-1.06843	-2.66 R

R denotes an observation with a large standardized residual.

Residual Plots for lnPEMBC

ANOVA Test for Location

One-way ANOVA: InPEMBC versus Location

Source	DF	SS	MS	F	P
Location	2	8.744	4.372	8.60	0.000
Error	101	51.334	0.508		
Total	103	60.078			

S = 0.7129 R-Sq = 14.55% R-Sq(adj) = 12.86%

Pooled StDev = 0.7129

Grouping Information Using Tukey Method

Location	N	Mean	Grouping
c	32	5.5427	A
b	21	5.2060	A B
a	51	4.8791	B

Means that do not share a letter are significantly different.

Tukey 95% Simultaneous Confidence Intervals
All Pairwise Comparisons among Levels of Location

Individual confidence level = 98.06%

Location = a subtracted from:

Location = b subtracted from:

Residual Plots for InPEMBC

ANOVA Tests for IOP

One-way ANOVA: InPEMBC versus IOP

Source	DF	SS	MS	F	P
IOP	6	24.635	4.106	11.24	0.000
Error	97	35.442	0.365		
Total	103	60.078			

S = 0.6045 R-Sq = 41.01% R-Sq(adj) = 37.36%

Pooled StDev = 0.6045

Grouping Information Using Tukey Method

IOP	N	Mean	Grouping
5b	15	5.7479	A
4b	15	5.6853	A B
7b	15	5.3457	A B C
8b	15	5.1364	A B C
6b	14	5.0373	B C
9b	15	4.8662	C D
10b	15	4.2187	D

Means that do not share a letter are significantly different.

Tukey 95% Simultaneous Confidence Intervals
All Pairwise Comparisons among Levels of IOP

Individual confidence level = 99.67%

IOP = 10b subtracted from:

IOP = 4b subtracted from:

IOP = 5b subtracted from:

IOP = 6b subtracted from:

IOP = 7b subtracted from:

IOP = 8b subtracted from:

Residual Plots for InPEMBC

Appendix I. ISC-PRIME and ISCST3 Dispersion Modeling

Summary of ISC Modeled BC concentrations and Modeled-to-Measured Ratios

The table below summarizes modeled and measured BC concentrations at each PEM location in addition to the ratio of the modeled-to-measured concentration. Ratios listed as 0 were found where modeled concentrations were measured zero and where modeled concentrations were very small. In cases where modeled concentrations are small, ratios of 0.00 mean less than 0.005.

IOP	Site Label	Measured PEM BC (ng/m ³)	ISC-PRIME		ISCST3	
			BC (ng/m ³)	modeled/measured BC	BC (ng/m ³)	modeled/measured BC
1a	W48	434	49.0	0.11	39.2	0.09
1a	W55	376	154.4	0.41	146.6	0.39
1a	K64	343	4.7	0.01	4.7	0.01
1a	MO	343	9.6	0.03	9.6	0.03
1a	B65	405	5.6	0.01	5.6	0.01
1a	COW	486	149.9	0.31	88.4	0.18
1a	C	308	24.8	0.08	24.8	0.08
1a	B3	329	17.9	0.05	17.9	0.05
1a	WS	313	64.8	0.21	64.8	0.21
2a	E44	94	2.2	0.02	2.0	0.02
2a	W48	47	9.8	0.21	10.4	0.22
2a	W55	813	9.3	0.01	108.7	0.13
2a	MO	75	4.4	0.06	4.4	0.06
2a	B65	210	76.0	0.36	2.6	0.01
2a	CPK	86	2.2	0.03	2.9	0.03
2a	CS	156	0.0	0.00	0.0	0.00
3a	B65	110	1.6	0.01	0.0	0.00
3a	CPK	115	11.1	0.10	0.1	0.00
3a	CS	123	1.1	0.01	0.0	0.00
3a	CP1	77	1.9	0.03	1.9	0.03
3a	E2	35	0.0	0.00	0.0	0.00
3a	W	48	0.0	0.00	0.0	0.00

IOP	Site Label	Measured PEM BC (ng/m ³)	ISC-PRIME		ISCST3	
			BC (ng/m ³)	modeled/measured BC	BC (ng/m ³)	modeled/measured BC
3a	C	72	0.0	0.00	0.0	0.00
4a	B65	528	21.9	0.04	13.5	0.03
4a	CPK	744	23.5	0.03	21.1	0.03
4a	CS	349	22.8	0.07	15.0	0.04
4a	CP1	222	5.8	0.03	5.7	0.03
4a	E2	210	5.8	0.03	6.0	0.03
4a	W	90	2.7	0.03	2.7	0.03
4a	S1	256	1.2	0.00	0.4	0.00
4a	C	306	12.9	0.04	10.3	0.03
4a	B3	262	12.8	0.05	12.8	0.05
4a	C2	293	10.9	0.04	12.2	0.04
4a	E2	128	2.9	0.02	2.8	0.02
2b	CP	30	6.6	0.22	7.4	0.24
2b	B3	85	29.5	0.35	11.0	0.13
2b	B1	78	53.0	0.68	6.5	0.08
2b	EK	82	57.6	0.71	29.7	0.36
2b	K	30	117.4	3.88	12.9	0.43
2b	W	30	1.9	0.06	6.8	0.22
2b	WA1	163	85.9	0.53	23.9	0.15
2b	B3	30	23.8	0.79	5.0	0.17
2b	B4	30	3.2	0.11	3.9	0.13
2b	CP1	30	0.0	0.00	0.0	0.00
2b	B1	309	10.1	0.03	6.8	0.02
3b	E2	237	34.9	0.15	8.3	0.04
3b	W	116	47.3	0.41	18.2	0.16
3b	D	542	55.3	0.10	40.3	0.07
3b	E1	193	89.8	0.47	49.6	0.26
3b	C	188	92.1	0.49	59.7	0.32
3b	B3	30	119.2	3.94	35.7	1.18

IOP	Site Label	Measured PEM BC (ng/m ³)	ISC-PRIME		ISCST3	
			BC (ng/m ³)	modeled/measured BC	BC (ng/m ³)	modeled/measured BC
3b	B4	137	81.1	0.59	46.3	0.34
3b	CP	30	26.7	0.88	32.4	1.07
3b	B1	239	34.7	0.15	83.4	0.35
3b	B2	125	11.2	0.09	11.2	0.09
3b	A	174	53.5	0.31	58.0	0.33
3b	AW	451	154.9	0.34	39.6	0.09
3b	BC	202	38.7	0.19	26.8	0.13
3b	EK	30	31.9	1.05	29.6	0.98
3b	K	30	1.7	0.06	1.8	0.06
3b	S1	525	13.7	0.03	3.4	0.01
4b	E2	1048	6.4	0.01	2.2	0.00
4b	W	396	88.6	0.22	18.7	0.05
4b	D	374	19.5	0.05	31.5	0.08
4b	E1	281	37.8	0.13	13.0	0.05
4b	C	326	19.6	0.06	18.4	0.06
4b	B3	210	22.1	0.11	22.1	0.10
4b	B4	222	21.5	0.10	27.7	0.12
4b	CP	221	14.8	0.07	14.8	0.07
4b	B2	293	8.4	0.03	8.4	0.03
4b	A	268	20.9	0.08	21.8	0.08
4b	AW	285	12.5	0.04	14.8	0.05
4b	BC	197	21.8	0.11	18.1	0.09
4b	EK	198	16.1	0.08	10.1	0.05
4b	K	189	6.1	0.03	6.1	0.03
4b	S1	448	1.4	0.00	0.8	0.00
5b	E2	2788	37.6	0.01	0.1	0.00
5b	W	252	60.0	0.24	30.9	0.12
5b	D	294	27.3	0.09	38.6	0.13
5b	C	283	27.4	0.10	24.5	0.09

IOP	Site Label	Measured PEM BC (ng/m ³)	ISC-PRIME		ISCST3	
			BC (ng/m ³)	modeled/measured BC	BC (ng/m ³)	modeled/measured BC
5b	B3	273	5.8	0.02	5.8	0.02
5b	CP	318	5.1	0.02	5.2	0.02
5b	B1	191	14.6	0.08	14.6	0.08
5b	B2	270	0.0	0.00	0.0	0.00
5b	A	286	35.5	0.12	12.9	0.05
5b	AW	308	81.5	0.26	24.1	0.08
5b	BC	216	16.3	0.08	16.2	0.08
5b	FS	263	20.8	0.08	17.9	0.07
5b	EK	265	6.2	0.02	6.2	0.02
5b	K	194	0.0	0.00	0.0	0.00
5b	S1	415	4.7	0.01	1.6	0.00
6b	E2	30	3.7	0.12	3.5	0.12
6b	W	192	55.8	0.29	8.2	0.04
6b	D	339	13.7	0.04	13.1	0.04
6b	C	185	22.7	0.12	17.9	0.10
6b	B3	153	13.7	0.09	12.1	0.08
6b	B4	30	60.5	2.00	49.1	1.62
6b	B1	123	1.4	0.01	1.4	0.01
6b	A	370	20.2	0.05	19.6	0.05
6b	AW	693	85.1	0.12	49.2	0.07
6b	BC	413	11.9	0.03	7.8	0.02
6b	FS	164	42.0	0.26	48.8	0.30
6b	EK	81	5.4	0.07	5.7	0.07
6b	K	59	2.6	0.04	2.7	0.05
6b	S1	247	2.4	0.01	0.7	0.00
7b	E2	125	22.8	0.18	7.3	0.06
7b	W	503	70.3	0.14	20.9	0.04
7b	D	1051	81.0	0.08	19.7	0.02
7b	C	159	41.5	0.26	29.8	0.19

IOP	Site Label	Measured PEM BC (ng/m ³)	ISC-PRIME		ISCST3	
			BC (ng/m ³)	modeled/measured BC	BC (ng/m ³)	modeled/measured BC
7b	B4	136	4.5	0.03	4.5	0.03
7b	CP	188	6.6	0.04	6.6	0.04
7b	B1	145	3.4	0.02	3.4	0.02
7b	B2	115	0.0	0.00	0.0	0.00
7b	A	270	54.9	0.20	104.0	0.39
7b	AW	453	93.9	0.21	178.7	0.39
7b	BC	146	3.6	0.02	7.6	0.05
7b	FS	184	27.4	0.15	25.9	0.14
7b	EK	101	1.5	0.01	1.5	0.01
7b	K	115	0.0	0.00	0.0	0.00
7b	S1	386	4.5	0.01	2.1	0.01
8b	E2	156	1.7	0.01	1.6	0.01
8b	W	142	21.6	0.15	5.0	0.04
8b	C	154	4.8	0.03	4.8	0.03
8b	B3	119	15.0	0.13	16.5	0.14
8b	B4	277	29.7	0.11	29.7	0.11
8b	CP	130	13.2	0.10	13.8	0.11
8b	B1	158	0.0	0.00	0.0	0.00
8b	B2	137	42.8	0.31	133.5	0.97
8b	A	561	2.4	0.00	0.0	0.00
8b	AW	176	86.7	0.49	44.8	0.25
8b	BC	139	0.0	0.00	0.0	0.00
8b	FS	162	32.9	0.20	33.3	0.21
8b	EK	120	0.3	0.00	0.3	0.00
8b	K	149	5.0	0.03	5.8	0.04
8b	S1	229	0.5	0.00	0.1	0.00
9b	E2	120	27.9	0.23	0.4	0.00
9b	W	169	28.4	0.17	0.0	0.00
9b	C	102	39.7	0.39	10.7	0.10

IOP	Site Label	Measured PEM BC (ng/m ³)	ISC-PRIME		ISCST3	
			BC (ng/m ³)	modeled/measured BC	BC (ng/m ³)	modeled/measured BC
9b	B3	137	69.0	0.50	2.4	0.02
9b	B4	92	54.3	0.59	25.6	0.28
9b	CP	110	15.8	0.14	3.6	0.03
9b	B1	119	5.5	0.05	3.7	0.03
9b	B2	112	11.3	0.10	9.9	0.09
9b	A	119	11.5	0.10	19.5	0.16
9b	AW	280	91.3	0.33	4.6	0.02
9b	BC	100	6.0	0.06	1.6	0.02
9b	FS	105	17.1	0.16	4.4	0.04
9b	EK	133	3.3	0.03	3.6	0.03
9b	K	148	4.9	0.03	0.5	0.00
9b	S1	192	1.5	0.01	0.5	0.00
10b	E2	92	31.1	0.34	10.2	0.11
10b	W	30	31.7	1.05	10.8	0.36
10b	C	94	30.2	0.32	23.5	0.25
10b	B3	30	63.6	2.10	27.4	0.91
10b	B4	30	59.6	1.97	27.1	0.90
10b	CP	81	36.5	0.45	39.2	0.48
10b	B1	30	20.9	0.69	7.5	0.25
10b	B2	101	51.9	0.51	137.0	1.36
10b	A	203	25.3	0.12	24.8	0.12
10b	AW	30	27.8	0.92	23.3	0.77
10b	BC	83	41.5	0.50	56.9	0.69

IOP	Site Label	Measured PEM BC (ng/m ³)	ISC-PRIME		ISCST3	
			BC (ng/m ³)	modeled/measured BC	BC (ng/m ³)	modeled/measured BC
10b	FS	104	40.0	0.38	34.7	0.33
10b	EK	94	18.8	0.20	31.8	0.34
10b	K	88	20.3	0.23	33.4	0.38
10b	S1	117	6.4	0.05	4.2	0.04

Graphical Summary of ISCST3 and ISC-PRIME Modeled Results

The modeled concentrations are displayed in the images below along with contours of the concentrations. The concentrations in red text are the highest modeled concentration in that specific case. Concentrations displayed have not been adjusted to account for the 37.5% burning time over the sampling period (as opposed to 100%).

ISC-PRIME

ISCST3

IOP 4B ISCST3

IOP5b ISCST3

Summary of Corrected ISC Modeled BC concentrations and Modeled-to-Measured Ratios

The table below summarizes the corrected modeled and measured BC concentrations at each PEM location in addition to the ratio of the modeled-to-measured concentration. Numbers listed as “0” are less than 0.005.

IOP	Site Label	Measured PEM BC (ng/m ³)	ISC-PRIME		ISCST3	
			BC (ng/m ³)	modeled/measured BC	BC (ng/m ³)	modeled/measured BC
1a	W48	434	478	1.10	714	1.6
1a	W55	376	1506	4.01	2668	7.1
1a	K64	343	46	0.13	86	0.3
1a	MO	343	93	0.27	174	0.5
1a	B65	405	55	0.14	102	0.3
1a	COW	486	1462	3.01	1609	3.3
1a	C	308	242	0.79	452	1.5
1a	B3	329	174	0.53	325	1.0
1a	WS	313	632	2.02	1180	3.8
2a	E44	94	30	0.32	36	0.4
2a	W48	47	96	2.06	189	4.1
2a	W55	813	91	0.11	1979	2.4
2a	MO	75	43	0.57	80	1.1
2a	B65	210	741	3.53	47	0.2
2a	CPK	86	30	0.35	53	0.6
2a	CS	156	30	0.19	30	0.2
3a	W35	110	30	0.28	30	0.3
3a	W48	115	108	0.94	30	0.3
3a	W55	123	30	0.25	30	0.2
3a	MO	77	30	0.39	35	0.5
3a	B65	35	30	0.86	30	0.9
3a	CPK	48	30	0.63	30	0.6
3a	B3	72	30	0.42	30	0.4
4a	W35	528	213	0.40	245	0.5
4a	W48	744	229	0.31	384	0.5
4a	W55	349	222	0.64	273	0.8
4a	MO	222	56	0.25	105	0.5
4a	B65	210	56	0.27	110	0.5
4a	CPK	90	30	0.34	49	0.5
4a	CS	256	30	0.12	30	0.1
4a	C	222	56	0.25	105	0.5
4a	B3	210	56	0.27	110	0.5
4a	C2	90	30	0.34	49	0.5
4a	E2	256	30	0.12	30	0.1
2b	CP1	30	64	2.11	135	4.5
2b	E2	85	288	3.37	200	2.3
2b	W	78	517	6.66	118	1.5
2b	C	82	562	6.89	541	6.6
2b	B3	30	1144	37.81	234	7.7
2b	B1	30	30	1.00	123	4.1
2b	WA1	163	838	5.15	435	2.7
2b	BC	30	232	7.68	92	3.0

IOP	Site Label	Measured PEM BC (ng/m ³)	ISC-PRIME		ISCST3	
			BC (ng/m ³)	modeled/measured BC	BC (ng/m ³)	modeled/measured BC
2b	EK	30	31	1.04	70	2.3
2b	K	30	30	1.00	30	1.0
2b	S1	309	99	0.32	123	0.4
3b	E2	237	340	1.43	152	0.6
3b	W	116	461	3.96	331	2.8
3b	D	542	539	0.99	734	1.4
3b	E1	193	876	4.54	903	4.7
3b	C	188	898	4.78	1087	5.8
3b	B3	30	1162	38.41	650	21.5
3b	B4	137	790	5.76	842	6.1
3b	CP1	30	260	8.60	589	19.5
3b	B1	239	338	1.42	1517	6.3
3b	B2	125	109	0.87	204	1.6
3b	A	174	521	3.00	1056	6.1
3b	AW	451	1510	3.35	721	1.6
3b	BC	202	377	1.87	488	2.4
3b	EK	30	311	10.28	539	17.8
3b	K	30	30	1.00	32	1.1
3b	S1	525	134	0.26	62	0.1
4b	E2	1048	63	0.06	40	0.0
4b	W	396	863	2.18	340	0.9
4b	D	374	190	0.51	574	1.5
4b	E1	281	369	1.31	237	0.8
4b	C	326	191	0.59	335	1.0
4b	B3	210	215	1.02	401	1.9
4b	B4	222	209	0.94	504	2.3
4b	CP	221	145	0.66	270	1.2
4b	B2	293	82	0.28	152	0.5
4b	A	268	204	0.76	397	1.5
4b	AW	285	122	0.43	269	0.9
4b	BC	197	212	1.08	329	1.7
4b	EK	198	157	0.79	183	0.9
4b	K	189	60	0.32	111	0.6
4b	S1	448	30	0.07	30	0.1
5b	E2	2788	367	0.13	30	0.0
5b	W	252	585	2.32	562	2.2
5b	D	294	266	0.91	703	2.4
5b	C	283	267	0.94	445	1.6
5b	B3	273	57	0.21	106	0.4
5b	CP	318	50	0.16	94	0.3
5b	B1	191	143	0.75	266	1.4
5b	B2	270	30	0.11	30	0.1
5b	A	286	346	1.21	234	0.8
5b	AW	308	795	2.58	439	1.4
5b	BC	216	158	0.73	296	1.4
5b	FS	263	203	0.77	326	1.2
5b	EK	265	61	0.23	113	0.4
5b	K	194	30	0.16	30	0.2
5b	S1	415	46	0.11	30	0.1

IOP	Site Label	Measured PEM BC (ng/m ³)	ISC-PRIME		ISCST3	
			BC (ng/m ³)	modeled/measured BC	BC (ng/m ³)	modeled/measured BC
6b	E2	30	36	1.18	63	2.1
6b	W	192	544	2.83	148	0.8
6b	D	339	133	0.39	238	0.7
6b	C	185	222	1.20	326	1.8
6b	B3	153	134	0.88	220	1.4
6b	B4	30	589	19.48	894	29.5
6b	B1	123	30	0.25	30	0.2
6b	A	370	197	0.53	357	1.0
6b	AW	693	830	1.20	895	1.3
6b	BC	413	116	0.28	142	0.3
6b	FS	164	410	2.50	888	5.4
6b	EK	81	53	0.65	105	1.3
6b	K	59	30	0.51	50	0.9
6b	S1	247	30	0.12	30	0.1
7b	E2	125	222	1.77	134	1.1
7b	W	503	686	1.36	380	0.8
7b	D	1051	789	0.75	359	0.3
7b	C	159	405	2.55	543	3.4
7b	B4	136	44	0.32	82	0.6
7b	CP	188	65	0.34	121	0.6
7b	B1	145	33	0.22	61	0.4
7b	B2	115	30	0.26	30	0.3
7b	A	270	535	1.98	1893	7.0
7b	AW	453	916	2.02	3252	7.2
7b	BC	146	35	0.24	138	0.9
7b	FS	184	267	1.45	471	2.6
7b	EK	101	30	0.30	30	0.3
7b	K	115	30	0.26	30	0.3
7b	S1	386	44	0.11	38	0.1
8b	E2	156	30	0.19	30	0.2
8b	W	142	211	1.48	92	0.6
8b	C	154	47	0.31	88	0.6
8b	B3	119	147	1.23	301	2.5
8b	B4	277	290	1.04	540	1.9
8b	CP	130	129	0.99	250	1.9
8b	B1	158	30	0.19	30	0.2
8b	B2	137	418	3.05	2429	17.7
8b	A	561	30	0.05	30	0.1
8b	AW	176	845	4.81	816	4.6
8b	BC	139	30	0.22	30	0.2
8b	FS	162	320	1.97	606	3.7
8b	EK	120	30	0.25	30	0.3
8b	K	149	49	0.33	106	0.7
8b	S1	229	30	0.13	30	0.1
9b	E2	120	272	2.26	30	0.3
9b	W	169	276	1.64	30	0.2
9b	C	102	387	3.80	195	1.9
9b	B3	137	673	4.92	44	0.3
9b	B4	92	529	5.75	466	5.1

IOP	Site Label	Measured PEM BC (ng/m ³)	ISC-PRIME		ISCST3	
			BC (ng/m ³)	modeled/measured BC	BC (ng/m ³)	modeled/measured BC
9b	CP	110	154	1.40	66	0.6
9b	B1	119	53	0.45	67	0.6
9b	B2	112	110	0.98	181	1.6
9b	A	119	112	0.94	355	3.0
9b	AW	280	890	3.18	84	0.3
9b	BC	100	58	0.58	30	0.3
9b	FS	105	167	1.58	80	0.8
9b	EK	133	33	0.24	65	0.5
9b	K	148	48	0.32	30	0.2
9b	S1	192	30	0.16	30	0.2
10b	E2	92	303	3.30	186	2.0
10b	W	30	309	10.22	197	6.5
10b	C	94	295	3.15	427	4.6
10b	B3	30	620	20.49	499	16.5
10b	B4	30	581	19.20	493	16.3
10b	CP	81	356	4.37	714	8.8
10b	B1	30	204	6.73	136	4.5
10b	B2	101	506	5.02	2494	24.7
10b	A	203	246	1.21	451	2.2
10b	AW	30	271	8.95	423	14.0
10b	BC	83	405	4.88	1035	12.5
10b	FS	104	390	3.75	631	6.1
10b	EK	94	184	1.96	579	6.2
10b	K	88	198	2.26	608	6.9
10b	S1	117	62	0.53	76	0.6