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AN ANALYSIS OF CONTINUOUS BLACK CARBON CONCENTRATIONS IN PROXIMITY TO AN AIRPORT AND MAJOR ROADWAYS

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Abstract

Black carbon (BC), a constituent of particulate matter, is emitted from multiple combustion sources, complicating determination of contributions from individual sources or source categories from monitoring data. In close proximity to an airport, this may include aircraft emissions, other emissions on the airport grounds, and nearby major roadways, and it would be valuable to determine the factors most strongly related to measured BC concentrations. In this study, continuous BC concentrations were measured at five monitoring sites in proximity to a small regional airport in Warwick, Rhode Island from July 2005 to August 2006. Regression was used to model the relative contributions of aircraft and related sources, using real-time flight activity (departures and arrivals) and meteorological data, including mixing height, wind speed and direction. The latter two were included as a nonparametric smooth spatial term using thin-plate splines applied to wind velocity vectors and fit in a linear mixed model framework. Standard errors were computed using a moving-block bootstrap to account for temporal autocorrelation. Results suggest significant positive associations between hourly departures and arrivals at the airport and BC concentrations within the community, with departures having a more substantial impact. Generalized Additive Models for wind speed and direction were consistent with significant contributions from the airport, major highway, and multiple local roads. Additionally, inverse mixing height, temperature, precipitation, and at one location relative humidity, were associated with BC concentrations. Median contribution estimates indicate that aircraft departures and arrivals (and other sources coincident in space and time) contribute to approximately 24 to 28% of the BC concentrations at the monitoring sites in the community. Our analysis demonstrated that a regression-based approach with detailed meteorological and source characterization can provide insights about source contributions, which
could be used to devise control strategies or to provide monitor-based comparisons with source-specific atmospheric dispersion models.

**Keywords:** generalized additive models; source apportionment; black carbon; airport; particulate matter

**Introduction**

Identifying sources of ambient pollution is necessary to most efficiently reduce environmental exposures and ultimately health effects. For a pollutant such as airborne particulate matter (PM), identification of sources is complex due to the myriad local and long-range sources, the temporal and spatial variability of these source contributions, and the heterogeneous composition of PM.

A few different approaches could be used to determine the relative contribution of various sources to ambient concentrations. One approach would be source-based, in which atmospheric dispersion models and related techniques are linked with emissions inventories to model source contributions. Accurate estimation of marginal source contributions is plausible for some pollutants and sources, but simultaneously characterizing numerous local and regional sources is challenging, and the source emission profiles may have significant uncertainties. Moreover, grid-based models with comprehensive emissions inventories (such as the Community Multiscale Air Quality model, CMAQ) cannot provide adequate spatial resolution to accurately determine source contributions at a given receptor location for pollutants with significant spatial variability (such as traffic-related primary PM) (Marshall, et al., 2008). Thus, a strictly model-based approach to source attribution may be impractical or extremely uncertain in some settings.
A second approach utilizes one of a variety of receptor-based tools (Thurston, et al., 2005). For PM, these approaches often utilize detailed particle composition data to determine relative source contributions, using techniques such as the chemical mass balance approach (CMB) or various factor analytic methods (Lall and Thurston, 2006; Pekney, et al., 2006; Qin, et al., 2006). These approaches depend on both temporally- and spatially-resolved data sets with enough density to ensure statistical power to identify associations, and are less relevant for determining relative source contributions for a specific particle constituent.

Regression-based approaches have also been used, often tied to continuous air pollution and source characterization data (deCastro, et al., 2008; LaRosa, et al., 2002; Levy, et al., 2001; Sax, et al., 2007) but also using land use regression techniques with integrated pollution measurements (Clougherty, et al., 2008; Henderson, et al., 2007; Marshall, et al., 2008; Ross, et al., 2007). The regression covariates representing source terms could in theory capture the marginal contribution of selected sources to measured concentrations, but rarely adequately capture the complexities of atmospheric dispersion or source strength variability in such a way that quantitative source contributions can be inferred. However, in settings where emissions are uncertain and atmospheric dispersion modeling of all relevant sources is challenging, regression-based approaches may be a valuable mechanism to infer source contributions.

A specific particle constituent of significant public health and source identification interest is elemental carbon/black carbon. Elemental carbon (EC) or black carbon (BC) results from combustion processes, particularly incomplete combustion processes involving organic material, and is therefore usually associated with mobile sources. EC is measured using thermal-optical techniques in which organic carbon and EC are sequentially volatilized, while BC is operationally defined and is determined by measuring visible light absorption or optical attenuation through a
filter (Hansen, et al., 1984; LaRosa, et al., 2002). The two methods have been found to be highly
correlated (Allen, et al., 1999). BC is not readily degraded in the atmosphere and may be transported
over long distances (Venkatachari, et al., 2006). It would therefore have numerous local and regional
sources, for which refined regression-based approaches could begin to determine source
contributions to monitored concentrations.

One setting in which regression-based approaches toward source identification would be of
particular interest is in close proximity to airports. Studies have shown that aircraft emit BC during
both take-off/landing and idling (Herndon, et al., 2008). The variability in source locations and
emissions contributes to uncertainties in atmospheric dispersion model outputs. While models such
as EDMS have been developed for aviation emissions and linked with CMAQ (Unal, et al., 2005) or
AERMOD (Steib, et al., 2007), significant uncertainties remain in modeling the marginal impact of
aircraft on BC concentrations at a designated receptor. However, interpretation of monitoring data is
complicated by the fact that most airports are proximate to major roadways which would include
diesel traffic, often a significant contributor to BC concentrations (Ogulei, et al., 2006; Qin, et al.,
2006; Rizzo and Scheff, 2007), and ground support equipment on airport grounds can often be
diesel-fueled (Zielinska, et al., 2004). As a result of the different sources, the concentrations of BC
will likely vary spatially and temporally across a community. While prior studies (deCastro, et al.,
2008; Levy, et al., 2001) focused on specific roadways have been able to infer BC source
contributions, more complex settings surrounding airports will require model structures that
reasonably reflect key atmospheric dispersion concepts, to allow for various sources to be separated
from one another.

Studies have shown elevated BC concentrations in proximity to airports, with some
indication of factors that contribute to elevated concentrations. For example, BC levels varied across
monitoring sites on the grounds of Los Angeles International Airport (LAX), with levels lower than those seen on one major highway and comparable to those seen on a second major highway with less truck traffic (Westerdahl, et al., 2008). Peak concentrations were qualitatively associated with flight and runway activity, but without any formal quantitative modeling or source attribution. Another study near LAX found much higher BC concentrations near a blast fence by the airport than at a reference site, with some evidence of concentrations that decrease as a function of distance from the airport, but the data were too limited in time and space to draw definitive conclusions (Fanning, et al., 2007). A recent analysis around T.F. Green Airport (PVD) in Warwick, Rhode Island found clear evidence of BC concentrations that strongly depended on wind speed, wind direction, time of day, and weekday vs. weekend, but did not formally model the joint effects of source strength and meteorology to determine relative source contributions (RI DEM, 2008). A study near LAX and Hong Kong International Airport used a nonparametric regression approach to formally evaluate the influence of wind speed and direction on concentrations, but did not consider the influence of other factors, including flight activity (Yu, et al., 2004).

In this study, our objective was to construct regression models to formally determine the contribution of the airport to measured BC concentrations in close proximity to an airport. We analyzed continuous BC data collected around PVD in 2005 and 2006, building upon previous analyses by formally modeling trends over time and across the community related to various source predictors and covariates. We developed statistical techniques to model the joint effects of wind speed and direction within the context of a regression model including source terms, and utilized these models to determine the time-varying contribution of airport activities to ambient BC concentrations.
Methods

BC data were collected as part of a larger study conducted by the Rhode Island Department of Environmental Management (RI DEM) designed to determine the levels and potential health risks of air toxics in Warwick, RI neighborhoods abutting PVD (RI DEM, 2008). PVD is a relatively small airport with, on average, 150 arrivals and 150 departures per day. Evaluation of the airport activity data reveals that approximately 86% of the activity occurs on the main runway (Runway 5-23), with the majority (63%) taking place on Runway 23 (to the southwest). The airport, surrounding roads and monitoring sites are displayed in Figure 1.

Sampling was conducted over 17 months (May 2005 to September 2006) at five sites in Warwick; four of the sites were located in close proximity to the airport while the fifth site was located approximately 3.7 km from the airport, as shown in Figure 1. The Field View site was located less than 0.16 km west of the main taxiway for the main runway. The Lydick site was located opposite of the airport from the Field View site and was approximately 0.8 km northeast of the end of the main runway. This site may be impacted by local traffic sources as it was located near major roadways (average daily traffic (ADT) approximately 36,000) servicing the airport (RI DEM, 2008). The Fire Station site was located approximately 0.9 km north-northwest of the airport terminal building. This site may also be impacted by traffic as it is located near major roadways (ADT 30,000 and 34,000) (RI DEM, 2008). The Smith site was located in a previously residential area approximately 1 km south-southwest of the main runway. The Draper site, located approximately 3.7 km east-southeast of the airport, was selected because: 1) it was further away from airport; and 2) it may be impacted by local meteorological conditions due to the potential interaction of opposing off-shore winds and prevailing winds since it was located approximately 1 km from Narragansett Bay. It should also be noted that a major highway with approximately
170,000 vehicles per day is located to the west of the airport, approximately 2 km west of the Fire 
Station site (RI DEM, 2008).

One-minute average BC concentrations were obtained at all sites using aethalometers 
(Magee Scientific, Berkeley, CA), which estimate real-time BC concentrations using optical 
attenuation (Hansen, et al., 1984). The aethalometers were originally set-up to run in a dual-channel 
mode; however, this setting resulted in substantial noise in the concentration estimates. Therefore, 
data from May 2005 and June 2005 have been removed from the data set since they were collected 
prior to the switch to the single-channel mode (which measured at a wavelength of 880 nm). In 
addition, due to errors associated with the February 2006 data collected at the Field View site, these 
data are not included in subsequent modeling. Duplicate data from co-located aethalometers at the 
Smith site were averaged (mean precision = 8%).

In addition to BC concentration data, meteorological data and airport operations data over the 
study period were included in the data set. Hourly meteorological data including temperature, 
relative humidity, precipitation, dew point, wind speed, and wind direction were obtained from the 
National Weather Service’s airport station. Surface meteorology data file originally in the ISH 
format and upper air data file originally in the FSL format were obtained from National Oceanic and 
Atmospheric Administration (NOAA)’s National Climatic Data Center website 
(http://lwf.ncdc.noaa.gov/oa/ncdc.html) and used in estimating mixing height. Airport operations 
data were obtained from the Rhode Island Airport Corporation (RIAC). These data included arrival 
and departure times and runway usage for each individual flight throughout the study period.

All data were combined on an hourly basis. One minute BC concentration data were 
aversed using the WUAQL AethDataMasher 6.0, which processes raw input files using several 
validation steps and also corrects for non-linear loading effects (Turner, 2008; Virkkula, et al.,
Since negative concentration values were possible but would complicate log-transformation, all negative and zero values were replaced with one half of the minimum detected concentration at each site for subsequent modeling. Aircraft arrival and departure data were summed for each hour across the entire sampling period, both as total departures and arrivals at the airport and by runway. Mixing height was calculated using AERMET, which is the meteorological preprocessor for AERMOD. When both convective and mechanical mixing heights are available in AERMET, the larger of the two is used (Cimorelli, et al., 2005).

Concentrations are compared between sites for each month using Kruskal-Wallis rank sum tests, a nonparametric test for testing the equality of population medians. Differences were then further explored using the nonparametric multiple comparisons Steel-Dwass procedure, which incorporates all pairs and uses the maximum Wilcoxon rank sum as the test statistic, from the ‘npmc’ package in R (Neuhauser and Bretz, 2001). Coefficients of divergence were used to assess the similarity between sites, with greater values representing a greater degree of divergence (Wilson, et al., 2005).

**Conditional Probability Functions**

In an attempt to determine the wind direction conditions contributing to the highest concentration levels at a given site, as a preliminary determination of major contributing sources, conditional probability functions (CPFs) were developed in a manner similar to Venkatachari et al (Venkatachari, et al., 2006). In our analysis, the CPF is defined as

\[
CPF_{\Delta\theta} = \frac{m_{\Delta\theta}}{n_{\Delta\theta}}
\]  

where \(m_{\Delta\theta}\) is the number of occurrences from wind sector \(\Delta\theta\) (22.5 degrees in this analysis) that are within the top 10% of the concentration distribution and \(n_{\Delta\theta}\) is the total number of observations from
that wind sector. Wind speeds less than 3 knots were excluded from the CPF calculations given the likelihood of plume meandering at low wind speeds, although these observations were retained in the regression modeling.

**Regression Modeling**

As discussed above, the objective of our regression modeling is to formalize the relationship between source activity and monitored concentrations, as well as the degree to which this is modified by meteorological conditions. We develop a regression modeling structure that reflects the known relationships among covariates given standard Gaussian dispersion concepts, and which utilizes statistical techniques to incorporate meteorological conditions in a more interpretable fashion than done in many previous studies.

We used statistical methods to capture the joint effects of wind speed and direction, noting that such terms are difficult to capture with individual regression covariates given the dependence between the variables and the correlation with other meteorological factors. First, vectors of wind speed in the east-west direction and north-south direction were created (Carslaw, et al., 2007; Westmoreland, et al., 2007). These vectors were then used as jointly nonparametric smooth terms in a Generalized Additive Model (GAM) predicting hourly BC concentration as a function of wind velocity and direction at each site. GAMs were implemented with linear mixed effects models (LME) using thin-plate splines for the smooth terms (Rupert, et al., 2001).

In the LME models, fixed effects related to airport operations and other meteorological data were modeled.

\[
Y_{BC} = \beta_0 + \mathbf{X}\beta + f(v_x, v_y) + \epsilon
\]  

(2)

where \( Y_{BC} \) is the log-transformed hourly mean black carbon concentration, \( \beta_0 \) is the intercept, \( \beta \) is the slope estimate for covariate \( \mathbf{X} \) (which includes inverse mixing height, temperature, relative
humidity, precipitation, and flight arrivals/departures), $\varepsilon$ is the random error term, and $f(v_x, v_y)$ is the random smoothed term as a function of the x and y components of wind speed, where

$$
\begin{align*}
v_x &= u \cos(\theta) \\
v_y &= u \sin(\theta)
\end{align*}
$$

where $u$ is the wind speed and $\theta$ is the wind direction. As the interpretation of the meteorological terms and the expected contribution of flight activity differ by monitor, we developed separate regression models for each monitor.

Since the temporal autocorrelation was rather high in our data set (one-hour lag Spearman correlation ($\rho_s$) = 0.73), it was necessary to incorporate the time aspect of the data into the regression models. Due to the large sample size, conventional repeated measures methods were not practical. Instead, a moving block bootstrap method appropriate for time-series was used in combination with the LME models (Lahiri, 2003). A moving block size of 24 hours was used for the final models. All estimates were made with 10,000 bootstrap replicates.

As mentioned above, covariates such as precipitation, temperature, relative humidity, mixing height, flight arrivals and departures were considered as candidate variables in the model. Because our regression approach did not directly model temporal autocorrelation, we could not use likelihood-based model selection techniques. Instead, we used a bootstrap estimate of prediction error. For each moving-block bootstrap iteration, we used the regression coefficient estimate from the bootstrap sample to predict outcomes for the observations not selected for the bootstrap sample (roughly a third of observations), then compared prediction with observed outcome:

$$
\text{Squared Prediction Error} = (Y_{BC} - \hat{Y}_{BC})^2 = [Y_{BC} - \hat{\beta}_0^{(b)} - \hat{\beta}_1^{(b)} X - \hat{\beta}_2^{(b)} Y - \hat{f}^{(b)}(v_x, v_y)]^2
$$

(5)

where the superscript (b) indicates an estimate from a bootstrap sample. For each bootstrap iteration we computed the sum of such squared prediction errors over all unselected observations, then
computed the average of this quantity over all bootstrap iterations. This mean-squared-error (MSE) estimate was used to compare fit for candidate models. This strategy is similar to that employed by the Random Forests algorithm to compute “out-of-the-box” error estimates (Breiman, 2001). All regression modeling was done in R utilizing statistical packages ‘nlme’ and ‘mgcv.’ The MSE estimate was also used in estimating the percent of variance accounted for by the optimal model.

Results

Summary Statistics

Figure 2 presents the concentration distributions for each hour of the day across the sampling period in addition to the airport operations distributions and mixing height distributions. Note that aircraft were not scheduled to arrive or depart from the airport between 11pm and 6am. Departures began around 6am and declined into the evening, while the arrivals began later in the morning and continued until 11pm. As the airport activity began, the mixing height estimates were at their lowest and there was an apparent increase in the hourly averaged BC concentrations at all monitoring sites.

Monthly concentration distributions for each sampling location are presented in Figure 3. The concentrations measured at each of the locations shift from month to month in a similar pattern, suggesting the influence of meteorological conditions on overall concentration levels. Note that the concentrations increase slightly during the winter months, potentially due in part to lower mixing height levels during part of this time. Kruskall-Wallis tests revealed significant differences between locations within each month across the entire sampling period (p<0.05). Therefore, nonparametric multiple comparisons tests (Steel tests) were used to determine which sites were significantly different from one another within each month. Concentrations measured at the Field View site were significantly different than those at Lydick for 3 months, at Fire Station for 5 months, at Smith for 11 months, and at Draper across all months. Concentrations at Lydick were significantly different
than those at Fire Station for 8 months, at Smith for 7 months, and at Draper for 13 months. Concentrations at Fire Station were significantly different than those at Smith for 10 months and at Draper for 13 months. Concentrations at Smith were significantly different than those at Draper for 8 of the 14 months. In general, the concentrations at Draper were significantly lower than most other sites across the majority of months.

The coefficients of divergence (CODs) for pairwise comparisons are as follows, listed in order of increasing dissimilarity (increasing COD): Field View-Smith (0.18), Lydick-Smith (0.20), Field View-Lydick (0.20), Smith-Draper (0.22), Lydick-Fire Station (0.23), Lydick-Draper (0.23), Field View-Fire Station (0.24), Fire Station-Smith (0.25), Field View-Draper (0.26), and Fire Station-Draper (0.29). Concentrations at Fire Station and Draper were the most dissimilar, which was reasonable given the distance between them and their locations relative to the airport and other major sources. Concentrations at Field View and Smith were most similar, which was expected given their proximity to each other and that they are both located south and southeast of the main airport runway. Of note, most of these values fall within the range typical of metropolitan areas in eastern and central United States (0.082<max COD<0.27) (Wilson, et al., 2005).

Conditional Probability Functions

Conditional probability plots for the four locations proximate to the airport are presented in Figure 4. Approximately 33%, 42%, 43%, and 41% of the upper decile concentrations occur when the winds are calm (<3 knots) at the Field View, Lydick, Fire Station and Smith sites, respectively. Note that these values are excluded from the plots. The conditional probability functions suggest a potential impact of the airport on elevated concentrations since a greater proportion of the upper decile of the distributions occur during periods when the wind fetches over the airport grounds. However, we also note the suggested impact of traffic sources on the upper decile of the
distributions since the sites all have substantial CPFs from winds from the west that fetch over the major roadways in the area.

Regression Modeling

Table 1 presents the final regression results for a series of models. All models include the random smoothed term for wind speed and direction, and additional terms are added sequentially, beginning with mixing height, then hourly arrivals/departures, followed by precipitation, temperature, and relative humidity. In addition, all estimates presented incorporate temporal autocorrelation. The percent of variance explained by the optimal models for Field View, Lydick, Fire Station, Smith and Draper is approximately 30, 35, 34, 31, and 26%, respectively. In the optimal multivariate models, both the number of hourly arrivals and departures has significant positive effects on BC concentrations, across all sites. The magnitude and statistical significance of the coefficients are robust to inclusion of meteorological terms.

The meteorological terms are also consistent across sampling sites and physically interpretable. Inverse mixing height has a marginally significant impact on log BC concentrations at all five sampling sites, with lower mixing heights corresponding with higher concentrations. Precipitation has a negative impact on log BC concentrations, with a consistent effect across all monitors. Concentrations are lower at higher temperatures, and the effect of relative humidity is statistically insignificant at all sites but Fire Station, where it displays a positive but modest association with concentrations.

The nonparametric effects of wind velocity are illustrated in Figure 5. The highest concentrations across all sites occur when the wind speed was low/calm. In addition, across all sites, there is a visible elevation in concentrations when the winds are coming from the west-southwest, the direction of the major highway and a variety of other upwind sources. However, each monitor
shows additional peaks that correspond with winds fetching over the airport. For example, at Field View (Figure 5a), there are peaks that correspond with winds from the north-northeast direction and the east direction, which are in the direction of various airport sources. There is an area of slightly lower concentration with winds from the east-northeast, which is a wind direction with a greater distance from a runway or taxiway. At Lydick (Figure 5b), the peak with winds from the west-southwest is more pronounced than at other monitors, and this corresponds with being downwind from both the major highway and the airport. Secondary peaks when winds are from the north and south-southeast correspond with major roadways.

The Fire Station site (Figure 5c) has its most pronounced peak with winds from the south-southeast, which captures the airport (both parking facilities and runways). Another minor peak with winds from the north is in agreement with the Lydick plot, and indicative of a traffic effect from roadways to the north of those two monitors. At the Smith site (Figure 5d), concentrations were elevated with winds from the north-northeast, which again fetches across the airport. Beyond the effect of the winds from the west-southwest, Smith also has a secondary peak with winds from the south-southeast, which appears to correspond with a major roadway. Finally, concentrations at the Draper site showed the most pronounced peak when the winds originated from the west-southwest, downwind from the airport, major highway, and other major sources. Small secondary peaks with winds from the north and southeast correspond well with traffic patterns. Thus, for all five monitors, there is indication of both effects of major roadways and effects of airport emissions, including elevated concentrations at high wind speeds when downwind from the airport.

Because of the log-linear model structure and the inclusion of a smoothed term for wind speed and direction, the marginal contributions of aircraft activities to ambient concentrations cannot be immediately inferred from the models described in Table 1. Moreover, the relative contribution of
aircraft activity would vary over time as a function of flight activity and meteorological conditions. In order to contextualize the results from the regression modeling, the contributions of arrivals and departures to predicted BC concentrations were estimated using the regression estimates from the best-fit model for each site, comparing the predicted estimate for each hour with the value setting arrivals and departures to zero. Both percent contributions (percent of total predicted BC concentration) and absolute contributions (in $\mu g/m^3$) of arrivals and departures were calculated for each site and are presented in Figure 6.

Median percent contribution estimates for total airport activity (arrivals and departures) are 26, 24, 25, 24, and 28% for Field View, Lydick, Fire Station, Smith and Draper, respectively, but with significant variability across hours. The percent contribution is higher for arrivals and at the high end for departures at Draper, potentially related in part to its lower ambient concentration and greater distance from other BC sources. Fire Station on average has the lowest percent contribution for arrivals but the highest percent contribution for departures, potentially related to its location relative to Runway 16-34, which is beneath many more departures than arrivals. In terms of contributions on an absolute concentration scale, the median absolute contributions from all airport activity were 0.095, 0.085, 0.091, 0.075, and 0.079 $\mu g/m^3$ for Field View, Lydick, Fire Station, Smith, and Draper, respectively (Figure 6). The absolute contributions for arrivals are lowest at Fire Station, which can be explained by the fact that most arrivals take place on Runway 5-23. The absolute contribution at Draper, the site furthest away from the airport, could be driven by airport sources as well as local sources co-varying with airport activity. The greatest absolute BC impacts for departures occur at Fire Station and Field View.

To gain further insight about runway-specific effects and the degree to which source terms in Table 1 are causal predictors rather than proxies for other factors, we ran regression models with
runway-specific departures and arrivals, controlling for inverse mixing height (results not shown). In
the fully saturated model with covariates for arrivals and departures on runways 5, 23, 16, and 34,
departures and arrivals on the main runway (5-23) were statistically significant (p<0.05) in the
positive direction for all sites except Fire Station, which is located along the 16-34 runway. Of note,
a subset of departures and arrivals on the main runway do pass over the Draper site, making Fire
Station the only site not under these flight paths. Departures on runway 34 (in the north, north-west
direction) pass directly over the Fire Station monitor, and were a statistically significant predictor of
concentrations. Departures on runway 16, however, were not significant at Fire Station, consistent
with a proximity effect. Departures on runway 16 were significant for the Draper site.

Discussion

Our regression analyses provide both a qualitative and quantitative indication of the
contribution of aircraft emissions to BC concentrations in the community surrounding an airport.
The conditional probability plots, regression models, and smoothed functions of wind speed and
direction are suggestive of an influence of aircraft and other coincident airport activity on measured
BC concentrations, with an additional suggestion of significant contributions from a major highway
and other local roads. Further, our regression models indicate that aircraft take-off has a greater
contribution to ambient concentrations than landing, which is consistent with previous studies
characterizing BC emissions (Agrawal, et al., 2008; Herndon, et al., 2005). Our models also provide
a quantitative assessment of aircraft source contributions by hour and monitor, with a median
contribution of slightly less than 0.1 μg/m³, or approximately 25% of the observed BC
concentrations. While there are few comparable studies to ours in the literature, our findings are
broadly consistent with previous studies at LAX. Community sites surrounding LAX, a much larger
airport than PVD, had concentrations that were 0.1-1 μg/m³ greater than concentrations measured at a background site (Fanning, et al., 2007).

In spite of the interpretability of our findings, there are some clear limitations. First, regression modeling was conducted using one-hour data, both because meteorological data were only available at this time-scale and because shorter time intervals were computationally infeasible given our model structure and sample size. While a one-hour time scale partially accounts for the temporal auto-correlation seen within the data, it may obscure smaller time-scale nuances related to local sources, and does not make maximal use of the real-time flight information available. For example, peak BC concentrations within a downwind plume have been observed within minutes of nearby aircraft activity (Herndon, et al., 2008). However, use of one-hour data across 14 months of sampling allow for the characterization of larger-scale trends in air quality that may lag due to local meteorological and source conditions. For example, use of one-hour data may indirectly incorporate sources related to aircraft arrivals and departures such as taxiing and support vehicles.

In the current analysis we were not able to directly incorporate local traffic sources or other non-aircraft sources, given that continuous source characterization data were not available for these sources. This indicates that our regression coefficients for aircraft activity should be interpreted with caution, and also prevents us from quantifying the contributions from specific roadways. Available data suggest that local traffic patterns are generally similar to aircraft activity patterns with traffic increasing shortly after 6am and decreasing after 11pm, the flight activity hours at the airport (RI DEM, 2008). Aside from any coincidental temporal consistency, traffic related to the airport itself would closely parallel, if not slightly precede or succeed, aircraft activity patterns as airline passengers travel locally to and from the airport. For these reasons, our regression models may overstate the impact of aircraft emissions. That being said, our models do account for prevailing
winds at five monitors distributed in different directions relative to the airport, which should help to isolate the airport from major roadways far from the airport. Moreover, there is a clear indication that activity at the airport impacts concentrations, as seen in Figures 5a-e and supported by the interpretability and consistency of our models using runway-specific flight activity. The fact that our model shows fairly similar contributions from aircraft at sites within 0.2 km of the fenceline and 3.7 km from the airport grounds would seem to be further corroboration that these effects are related to aircraft in flight rather than ground-level sources on the airport grounds, and is supported by dispersion modeling studies that show BC plumes with similar concentrations over multiple kilometers (Fanning, et al., 2007). In addition, our finding of elevated concentrations at high wind speeds fetching across the airport is consistent with that reported previously and attributed to aircraft arrivals or departures (Yu, et al., 2004). However, the degree to which our findings are solely attributable to aircraft versus other airport-related sources requires further study.

The effects of wind speed and direction were incorporated into the regression modeling using smooth term estimates extracted from GAM models. This was done to capture the dynamic nature of wind speed and direction at each site across the sampling period. While this approach has its advantages and provides significant insight about multiple source contributions, a potential disadvantage is that some of the source contributions may be captured within this term, which could indicate that the covariates for flight activity would underestimate the contribution from aircraft emissions. The magnitude of this potential incorporation is uncertain.

PVD is a small regional airport with only an average of 150 departures and 150 arrivals per day. As a result, the magnitude of the source signal from the airport is not as large as it would be near other larger airports, which can hinder source characterization estimates. However, an advantage to modeling sources in proximity to a smaller airport is that other local sources often
associated with airports are also smaller. For example, the traffic load in the area near PVD is much smaller than what would be observed at other airports. In addition, the area around PVD is not dense with other industrial or mobile sources.

In spite of these limitations, our study has some important advantages. While dispersion models based on emissions estimates can similarly provide marginal contributions from defined sources, the uncertainties in estimating time-resolved BC emissions and in appropriately modeling sources that move vertically and horizontally with differential emissions over time can be large. Our methodology offers another approach by which marginal contributions from a defined mobile or area source can be characterized. At a minimum, this regression-based approach provides a mechanism to formally compare the results of dispersion models with monitoring data, which may shed some light on the strengths and weaknesses of both approaches. Our incorporation of smooth functions of wind speed and direction, along with other meteorological complexities, provides a more physically interpretable regression model structure and emphasizes that the relative contribution of a source can vary tremendously over time. The regression modeling structure we applied can be used in a variety of contexts in which continuous air pollution measurements are collected, to help determine the magnitude and variability of contributions from multiple sources.

Acknowledgements

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Monitoring Program received by the Rhode Island Department of Environmental Management. We would like to thank Ying Zhou for her assistance with the mixing height data, George Allen for his assistance with aethalometer data processing, and Steve Melly for map production.
References


Table 1. Regression models linking log(black carbon) in $\mu$g/m$^3$ with meteorological and source covariates across five monitoring sites. The best-fit models, as determined by MSE Loss comparisons, are listed in bold.

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Figure 1. T.F. Green airport, surrounding roads, and fixed monitoring sites.
Figure 2. Airport arrival and departure distributions, mixing height distributions and mean black carbon concentration (μg/m³) distributions for each hour of the day across the entire sampling period. Site-specific values represent the mean black carbon concentration for each hour.
Figure 3. Black carbon concentration distributions for each site and month across the entire sampling period.
Figure 4. Conditional probability functions showing upper 10% of the black carbon concentration distribution by wind direction. Calm winds (<3 knots) excluded.
Figure 5. Black carbon concentration intensities by wind speed and direction for Field View (a), Lydick (b), Fire Station (c), Smith (d), and Draper (e). Wind speed is measured in knots. Intensities range from red (highest concentration) to green (lowest concentrations).
Figure 6. Percent and absolute contribution estimates of arrivals and departures at the airport based on regression model estimates.
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