GeoHealth

RESEARCH ARTICLE

10.1029/2020GH000347

Key Points:

- Wildfire smoke may alter the expected intraurban gradients in black carbon concentrations and bias traffic exposure assessments
- In our simulated health effects study, bias introduced by wildfire smoke resulted in larger than expected linear regression coefficients
- Studies relying on black carbon as a marker for traffic emissions need to consider the potential for bias from other proximate BC sources

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

S. Magzamen,
sheryl.magzamen@colostate.edu

Citation:

Martenies, S. E., Hoskovec, L., Wilson, A., Allshouse, W. B., Adgate, J. L., Dabelea, D., et al. (2021). Assessing the impact of wildfires on the use of black carbon as an indicator of traffic exposures in environmental epidemiology studies. *GeoHealth*, *5*, e2020GH000347. https://doi.org/10.1029/2020GH000347

Received 5 NOV 2020
Accepted 29 JAN 2021

Assessing the Impact of Wildfires on the Use of Black Carbon as an Indicator of Traffic Exposures in Environmental Epidemiology Studies

S. E. Martenies[1,2], L. Hoskovec[3], A. Wilson[3], W. B. Allshouse[4], J. L. Adgate[4], D. Dabelea[5,6,7], S. Jathar[8], and S. Magzamen[2,5]

[1]Kinesiology and Community Healikth, University of Illinois at Urbana-Champaign, Urbana, IL, USA, [2]Environmental and Radiological Health Sciences, Colorado State University, Fort Collins, CO, USA, [3]Department of Statistics, Colorado State University, Fort Collins, CO, USA, [4]Environmental and Occupational Health, Colorado School of Public Health, University of Colorado Anschutz Medical Campus, Aurora, CO, USA, [5]Department of Epidemiology, Colorado School of Public Health, University of Colorado Anschutz Medical Campus, Aurora, CO, USA, [6]Lifecourse Epidemiology of Adiposity and Diabetes (LEAD Center), University of Colorado Anschutz Medical Campus, Aurora, CO, USA, [7]School of Medicine, Department of Pediatrics, University of Colorado Anschutz Medical Campus, Aurora, CO, USA, [8]Department of Mechanical Engineering, Colorado State University, Fort Collins, CO, USA

Abstract Epidemiological studies frequently use black carbon (BC) as a proxy for traffic-related air pollution (TRAP). However, wildfire smoke (WFS) represents an important source of BC not often considered when using BC as a proxy for TRAP. Here, we examined the potential for WFS to bias TRAP exposure assessments based on BC measurements. Weekly integrated BC samples were collected across the Denver, CO region from May to November 2018. We collected 609 filters during our sampling campaigns, 35% of which were WFS-impacted. For each filter we calculated an average BC concentration. We assessed three GIS-based indicators of TRAP for each sampling location: annual average daily traffic within a 300 m buffer, the minimum distance to a highway, and the sum of the lengths of roadways within 300 m. Median BC concentrations were 9% higher for WFS-impacted filters (median = 1.14 μg/m^3, IQR = 0.23 μg/m^3) than nonimpacted filters (median = 1.04 μg/m^3, IQR = 0.48 μg/m^3). During WFS events, BC concentrations were elevated and expected spatial gradients in BC were reduced. We conducted a simulation study to estimate TRAP exposure misclassification as the result of regional WFS. Our results suggest that linear health effect estimates were biased away from the null when WFS was present. Thus, exposure assessments relying on BC as a proxy for TRAP may be biased by wildfire events. Alternative metrics that account for the influence of "brown" carbon associated with biomass burning may better isolate the effects of traffic emissions from those of other black carbon sources.

Plain Language Summary Black carbon, a constituent of particulate matter linked to the incomplete combustion of carbonaceous fuels, has been used in an increasing number of studies as a proxy for traffic exposures. In this study, we explored the potential of large wildfire events to bias heath effect estimates relying on black carbon as a proxy measure for traffic pollutants. We found that, for Denver, CO, wildfire smoke biased traffic exposure measures in a spatially-dependent way and resulted in larger effect estimates for our simulated health outcome. Our study emphasizes the need to consider specific regional sources of traffic-related air pollutants that might bias exposure assessments.

1. Introduction

Recent evidence has indicated an expanding set of health outcomes associated with traffic-related air pollution (TRAP). For example, studies have demonstrated associations of TRAP with several important childhood health outcomes, including incident asthma, childhood overweight and obesity, autism spectrum disorder, and neurodevelopmental delays (Bowatte et al., 2015; Chiu et al., 2016; Gong et al., 2017; McConnell et al., 2016; Volk et al., 2013). Among adults, TRAP exposures have been associated with cardiovascular, pulmonary, metabolic, and neurodegenerative diseases (Alderete et al., 2018; Bowatte et al., 2018; Clifford et al., 2016; Costa et al., 2017; Howell et al., 2019; Laumbach & Kipen, 2012; Monrad et al., 2017). Due to the logistical and cost challenges associated with measuring pollutants for large study areas, TRAP exposures are often modeled using GIS-based metrics, chemical transport or dispersion models, or land use

10.1029/2020GH000347

regression models with nitrogen dioxide, carbon monoxide, or fine particulate matter as the primary indicator of exposure (Batterman et al., 2014; Howe et al., 2018; Hu et al., 2019; Khreis & Nieuwenhuijsen, 2017; Khreis et al., 2018). However, a growing number of studies are using black carbon (BC) as a source-specific indicator of traffic exposures (Caplin et al., 2019; Carlsen et al., 2018; Dons et al., 2017; Liu et al., 2017; Suglia et al., 2008). BC is an inert carbonaceous aerosol derived from fossil fuel and biomass combustion that is characterized by its absorbance of visible light, making it appear black (Petzold et al., 2013). BC typically displays sharp gradients in urban settings with the highest concentrations found near roads (Apte et al., 2017; Patton et al., 2014; Wu et al., 2015; Xing & Brimblecombe, 2018), making it a useful indicator of TRAP exposures.

In North America, roughly 70% of BC emissions are due to on-road and off-road diesel engines (Bond et al., 2013). However, biomass burning is also an important intermittent source (Briggs & Long, 2016), particularly in wildfire-prone regions such as the western United States. In the western United States, wildfires can emit significant amounts of light-absorbing carbon (LAC) particles into the atmosphere (Chow et al., 2010; Ditas et al., 2018; Mao et al., 2011). These particles typically have the same graphite core as pure BC and similarly absorb light at 880 nm (Andreae & Gelencsér, 2006; Lack et al., 2014); common optical methods using infrared (880 nm) absorption measure carbon mass but generally cannot distinguish between fossil fuel combustion or biomass burning (e.g., wildfires) as sources for LAC or BC. Thus, studies using BC measurements as a proxy for traffic may be biased by nearby or regional wildfire events or other sources of LAC.

The inability of common optical methods to distinguish LAC or BC originating from fossil fuel combustion and biomass burning may have important implications on the results of health effects studies using BC as a proxy for TRAP in wildfire-prone regions. Using BC as an indicator of traffic emissions requires the assumption that most regional BC comes from these mobile sources and that the influence from other natural or anthropogenic sources is minimal. This assumption may not hold in regions where there are seasonal variations in background BC concentrations due to wildfires or biomass burning (Dekoninck et al., 2015; Stampfer et al., 2020). Further, previous studies have suggested PM emissions from traffic sources are more strongly associated with health effects compared to those from biomass burning (Beelen et al., 2015; Ostro et al., 2015; Thurston et al., 2016). Although evidence of a causal relationship between BC and adverse health effects is growing (Janssen et al., 2011; Nichols et al., 2013), it is not yet clear if BC is the etiological agent in all cases or rather a proxy for other constituents in the PM mixture (Kirrane et al., 2019). In epidemiology studies relying on BC as a TRAP exposure metric, misclassification can result in biased effect estimates. This mischaracterization of the etiological agent can result in ineffective policies to reduce source-specific exposures.

As wildfires are expected to increase in both frequency and intensity as climate change progresses (Brey et al., 2018; Schoennagel et al., 2017; Spracklen et al., 2009), it is important to understand how wildfire BC emissions affect TRAP exposure assessments. To address this knowledge gap, we focused on two research objectives. The first was to understand how urban BC gradients (herein defined as all LAC) are altered during wildfire events and the degree to which this alteration results in TRAP exposure misclassification. The second aimed to assess the potential for exposure misclassification to bias associations between TRAP (measured as BC) and health outcomes using a simulation study. We framed our simulation study within the context of Healthy Start, an ongoing birth cohort study based in Denver, Colorado (Harrod et al., 2014). In the Denver metropolitan area, mobile sources remain the predominant intraurban air pollutant source (US Environmental Protection Agency, 2018; Vu et al., 2016). However, biomass burning represents an important intermittent source; wildfires both within the state and across western North America contribute to poor air quality in the region (Creamean et al., 2016; Val Martin et al., 2013). The ongoing Healthy Start study (5UH3OD023248; PI: Dabelea) is investigating the role of environmental and behavioral factors on childhood obesity and metabolic outcomes. Between 2009 and 2014, 1,410 pregnant mothers were enrolled into the cohort and delivered singleton births (Harrod et al., 2014). To support our ongoing research on the effects of environmental exposures on childhood health outcomes, we are actively developing retrospective models to predict prenatal and early life exposures to TRAP using BC as an exposure marker. Thus, it is important to our future work to understand the influence of wildfires on our ability to accurately characterize traffic exposures in this wildfire-prone region.

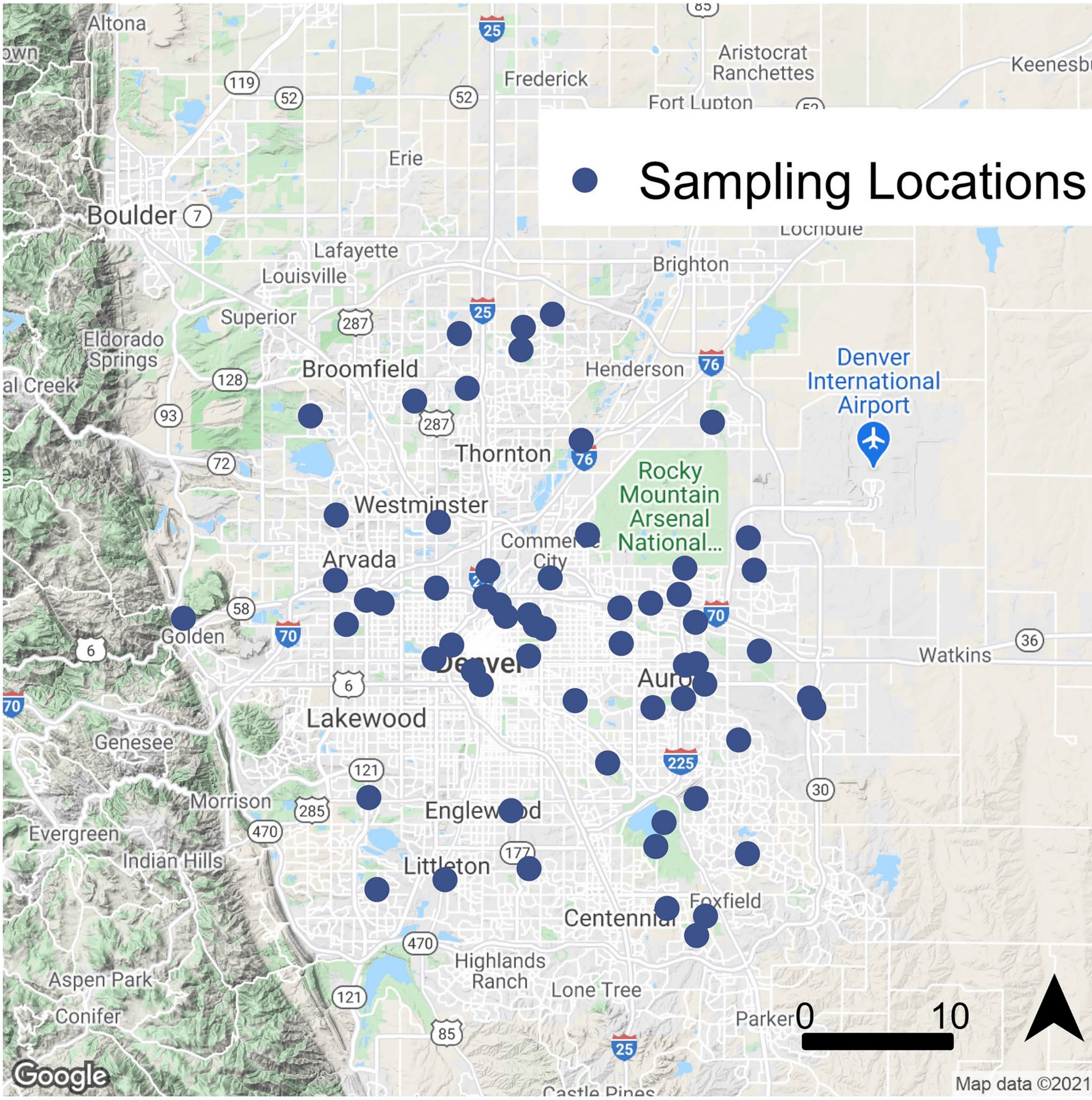

Figure 1. Sampling locations. Some locations are jittered to protect participant privacy.

2. Methods

2.1. Field Sampling Campaign

As part of the Healthy Start study (Harrod et al., 2014), we conducted a measurement campaign to develop a spatiotemporal model of BC in the Denver metropolitan area. Over the course of three sampling campaigns (Campaign 1: May 8 to July 3, 2018; Campaign 2: July 10 to August 27, 2018; Campaign 3: October 10 to November 11, 2018), we deployed between 35 and 53 low-cost monitors to locations across the study area (Figure 1). These sites were chosen to be spatially representative of the traffic exposures in the area based on the distribution of traffic in the region (US Department of Transportation, 2018). Campaigns 1 and 2 also captured BC emissions from biomass burning during the summer wildfire season, including emissions from the Spring Creek fire. The Spring Creek fire, the third-largest in Colorado history at the time, burned from June 27 to September 10, 2018 and destroyed 108,045 acres ~150 miles southwest of Denver (National Wildfire Coordinating Group, 2018).

We collected filter-based particulate matter samples using Ultrasonic Personal Air Samplers (UPAS; Access Sensor Technologies, Fort Collins, CO) (Volckens et al., 2017). Each UPAS was fitted with a size-selective cyclone inlet (2.5 μm) and housed within a custom protective case to facilitate use outdoors. Samples were collected on polytetrafluoroethylene filters (PTFE; MTL Corporation, Minneapolis, MN) using a flow rate of 1 L/min. The UPAS monitors were connected to external batteries and allowed to run at an 80% duty cycle until battery power ran out. Our target sampling period was 5 days. We collected field blanks to examine the potential for contamination in the field.

2.2. SootScan Measurements for BC

Filter-based particulate matter samples were analyzed for BC using a SootScan Model OT21 transmissometer (Magee Scientific, Berkeley, CA). Here, we use the term BC to refer to all absorbing mass in the sample at a wavelength of 880 nm. Absorbance at 880 nm was used to quantify BC using methods described by Ahmed et al. (2009). The mass absorption coefficient used to quantify BC was derived from an analysis by Presler-Jur et al. (2017). Additional details on the BC measurement methods are available in the supporting information.

2.3. Calibration of Low-Cost Monitor BC Concentrations

We calibrated our UPAS BC measurements using data from the local air quality monitoring network. The Colorado Department of Public Health and Environment (CDPHE, 2018) maintains an AE-33 aethalometer (Magee Scientific, Berkeley, CA) at a near-road monitoring site. During two of our sampling campaigns (Campaign 2 and Campaign 3), we collocated a UPAS with the AE-33 instrument. Similar to a previous study using UPAS instruments to measure BC, we used Deming regression to fit the calibration curves (Quinn et al., 2018). Additional details on the calibration methods are available in the supporting information.

2.4. Identifying Smoke-Impacted Filters

We identified wildfire smoke (WFS)-impacted filters using methods similar to those reported by Brey and Fischer (2016). First, we identified "smoke-impacted days" for each regional $PM_{2.5}$ monitor using National Oceanic and Atmospheric Administration (NOAA) and Environmental Protection Agency (US EPA) data. We obtained daily smoke plume data from NOAA's Hazard Mapping System (HMS) (National Oceanic and Atmospheric Administration, 2020). We downloaded smoke plume shapefiles for each day of our sampling campaign. Daily $PM_{2.5}$ data for monitoring locations in the study area from 2008 to 2018 were obtained from the US EPA AQS Data Mart (US Environmental Protection Agency, 2016). Long-term data for BC in the area (prior to 2016) were not available. Time series plots for each $PM_{2.5}$ monitor showed that concentrations were relatively stable over the 10-year period, with annual changes in $PM_{2.5}$ at each monitor ranging from a 0.36 $\mu g/m^3$ decrease to a 0.10 $\mu g/m^3$ increase per year (Figure S3). For each monitor, we calculated the 10-years monthly average $PM_{2.5}$ concentration. A monitor was considered "WFS-impacted" if two criteria were met: first, the daily mean $PM_{2.5}$ concentration was more than two standard deviations (SD) above the 10-years monthly mean for that monitor; and second, an HMS smoke plume was located within 50 km of the monitor (Figure S4). Due to local meteorology and time-varying fire characteristics, the location of smoke plumes can vary greatly from day-to-day (Figure S4). The original methods by Brey and Fischer used a 1-SD increase as their criterion for WFS; here we used two standard deviations as a more conservative criterion to account for typical diurnal or weekday-weekend variability in $PM_{2.5}$ concentrations. We used a 50 km buffer around the monitor location to account for portions of the smoke plume that may not be visible in satellite imagery. We assessed the second criterion using spatial intersection methods in the "sf" package in R (Pebsema, 2018). These two criteria were designed to prioritize sensitivity to WFS over spec-

10.1029/2020GH000347

ificity. Second, a filter was considered "WFS-impacted" if any EPA $PM_{2.5}$ monitor in the Denver region recorded a smoke-impacted day during the sampling period for that filter. We also considered a more stringent criterion that only evaluated smoke-impacted days at the closest or three closest monitors and found broad agreement in which filters were considered WFS-impacted (i.e., the "any area monitor" metric agreed with the closest and three closest monitors metrics for 85% and 99% of filters, respectively).

2.5. GIS-Based Indicators of Traffic Exposure and Other Land Use Characteristics

We used three GIS-based metrics for assessing traffic exposures for each filter sampling location based on existing methods commonly employed in environmental health studies (Khreis & Nieuwenhuijsen, 2017) using publicly available road network and traffic count data (CDPHE, 2018; US Department of Transportation, 2018). First, we averaged the annual average daily traffic (AADT) for all road segments within a 300 m buffer around the sampling location. Second, we measured the shortest distance between a sampling location and a major road or highway. Third, we assessed the total roadway length (major roads and highways) within a 300 m buffer around the sampling location. A 300 m buffer was selected for these metrics because prior studies indicate that BC concentrations from traffic emissions typically return to background levels at a distance farther than 300 m from roadways (Apte et al., 2017; Beckerman et al., 2008; Patton et al., 2014; Zwack et al., 2011). We also had measurements of other key land use characteristics for these filters. We summarized the percentage of land that was classified as "open space" as defined by the National Land Cover Database and the percent impervious surface for each measurement location (Multi-Resolution Land Characteristics Consortium, 2017). Impervious surfaces were intended to represent areas with more BC sources (e.g., roads, including those not considered highways or major roads) and open space was considered a measure of BC sinks (e.g., parks and vegetation). These land use characteristics were also summarized for a 300 m buffer around each sampling location.

2.6. Agreement Between GIS-Based Indicators of Traffic and BC Measurements

We assessed the level of agreement between GIS-based indicators of traffic and measurements of BC in three analyses. First, we measured correlation between BC concentrations and GIS-based traffic indicators. Second, we examined differences between measured BC at each quartile of the traffic variables for WFS-impacted and nonimpacted filters using the Kruskal-Wallis test. Third, we assessed the level of agreement between quartiles of BC concentrations and GIS-based traffic measures using Cohen's kappa statistic. The results of this third analysis are presented in the supporting information.

2.7. Simulation Study

We evaluated the potential for WFS to bias epidemiology studies using BC as a proxy for TRAP via simulation. For each of the unique sampling locations, we constructed two measures of long-term average exposure: one that was WFS-impacted and one that was nonimpacted. The WFS-impacted measure (BC_{WFS}) was the average of all BC measurements collected at the site. The nonimpacted measure ($BC_{no\ WFS}$) was the average of BC measurements collected from nonimpacted filters only. We used BC measurements only from sites with at least two WFS-impacted and two nonimpacted filters. We considered $BC_{no\ WFS}$ to be our unbiased proxy for TRAP. Although WFS has been shown to affect birth weight (Holstius et al., 2012), we assumed any effect on our outcome of interest was attributable to BC arising from TRAP alone. In total, we had estimates of BC_{WFS} and $BC_{no\ WFS}$ for 51 unique sampling locations.

In our simulation study, we were interested in the potential bias in a linear regression analysis (i.e., that would be used to assess relationships between TRAP and a continuous outcome like birth weight). To estimate the effect of TRAP exposure misclassification during WFS events on the estimated regression coefficients, we simulated our birthweight outcome variable as a function of TRAP not affected by WFS ($BC_{no\ WFS}$) using the following equation:

$$Y_1 = \beta_0 + \beta_1 \times \left[BC_{no\,WFS} \right] + \epsilon, \tag{1}$$

where β_0 was the intercept, β_1 was the "true" effect estimate defined a priori and ϵ was a random error term drawn from a normal distribution with a mean of 0 and a standard deviation of 1. For Equation 1, we set β_0 to 3,205 g, which was the average birth weight for Healthy Start infants. The range of our true effects estimates was based on values previously reported in the literature. For the simulated birth weight variable, we used β_1 values ranging from 0 to −50 g per 1 μg/m^3 increase in BC based on similar effect sizes reported for prenatal fine particulate matter exposures in the Healthy Start cohort (Starling et al., 2020) and elsewhere (Brauer et al., 2008; Kingsley et al., 2017). For each of the true effect estimates, we simulated 1,000 bootstrapped data sets with replacement to account for uncertainty introduced by the selection of the sampling sites across the study area. After simulating our outcome variable, we fit regression models using the true TRAP proxy measure ($BC_{no\ WFS}$) and the biased TRAP proxy measure (BC_{WFS}) as the predictors of interest. We hypothesized WFS would have widespread effects on BC measurements that would result in exposure misclassification and bias our results toward the null. We evaluated the effect of the biased proxy for TRAP (BC_{WFS}) using absolute and relative (percent) bias in the regression coefficients, the root mean squared error (RMSE) of fitted values, and interval coverage, which was defined as the percentage of β coefficients within the 95% confidence interval (CI) of the true effect estimate.

All geospatial and statistical analyses were performed in R version 3.6.1 (R Core Team, 2019). For spatial methods, we used the "sf" package (Pebsema, 2018). Geocoding was completed using the Google Geocoding API. Maps were created in R using the "ggplot2," "ggmap," and "ggsn" packages (Kahle & Wickham, 2013; Santos Baquero, 2019; Wickham, 2016).

3. Results

3.1. BC Monitoring Results

In total, we collected 609 filter-based particulate matter samples across three seasons, with 247, 249, and 113 filters collected during Campaigns 1, 2, and 3, respectively. The median number of samples collected at each location was 10 (range: 1–17 samples). The median runtime for the monitors was 5 days (range: 2–6 days) and the median volume collected was 5,715 L (range: 2,630–6,927 L).

BC concentrations varied by campaign (Table 1). Median concentrations were lowest for Campaign 1 (early summer; 0.97 μg/m^3) and highest for Campaign 3 (fall; 1.50 μg/m^3). The interquartile range (IQR) values also varied by campaign. Variability in BC concentrations was similar for Campaigns 1 (IQR = 0.15 μg/m^3) and 3 (IQR = 0.14 μg/m^3) and higher for Campaign 2 (late summer; IQR = 0.24 μg/m^3).

3.2. WFS-Impacted Filters

Of the 609 filters in our study, 239 (39%) were considered WFS-impacted. Most of these samples were collected during Campaign 2 (late summer), which coincided with the start and containment dates of the Spring Creek fire in Colorado (Figure 2). Overall, BC concentrations were lower and variability was higher for nonimpacted filters compared to WFS-impacted filters (Wilcoxon rank sum test; $p < 0.001$) (Table 2). Median (IQR) BC concentrations were 1.04 (0.48) μg/m^3 and 1.14 (0.23) μg/m^3 for nonimpacted and WFS-impacted filters, respectively.

Table 1
Summary of Calibrated Filter-Based BC Concentrations (μg/m^3) for Each Sampling Campaign

Campaign	Sampling dates	*n*	Mean (SD)	Min	25th	50th	75th	95th	Max	IQR
All		609	1.16 (0.25)	0.78	0.96	1.09	1.34	1.63	2.27	0.38
1	May 8 to July 3, 2018	247	0.99 (0.11)	0.78	0.91	0.97	1.06	1.17	1.34	0.15
2	July 10 to August 27, 2018	249	1.17 (0.22)	0.84	1.02	1.15	1.26	1.50	2.27	0.24
3	October 10 to November 11, 2018	113	1.53 (0.13)	1.35	1.44	1.50	1.58	1.79	2.08	0.14

Note: BC, black carbon; IQR, interquartile range; SD, standard deviation.

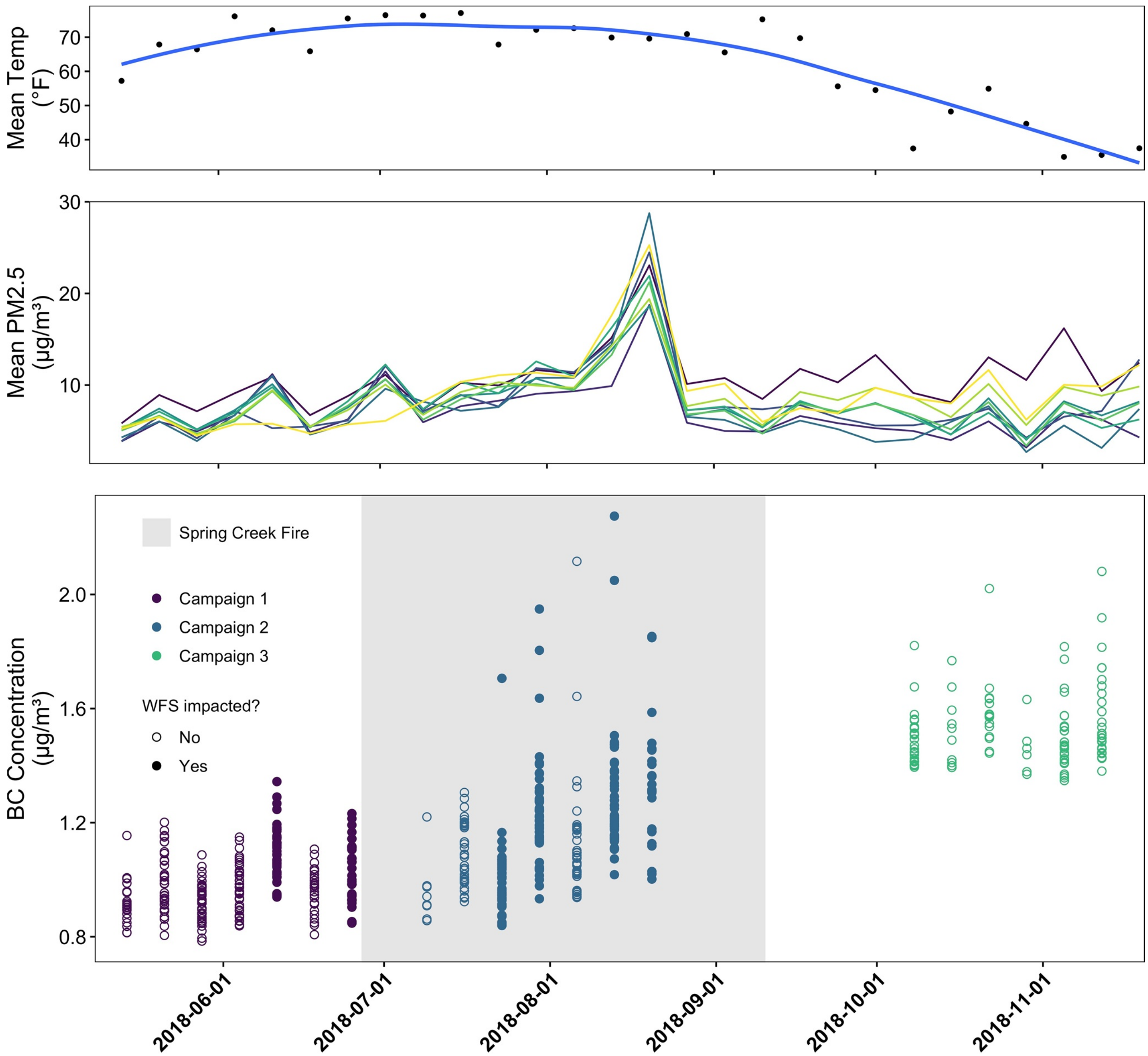

Figure 2. Time series plot of average weekly temperature (top panel), average weekly $PM_{2.5}$ concentrations for regulatory monitors in the region (second panel), and weekly black carbon concentrations collected in 2018 (third panel). The shaded area represents the start and 100% containment dates of the Spring Creek fire.

3.3. Comparisons Between GIS-Based Traffic Indicators and Filter-Based BC Concentrations

Although correlations between GIS-based traffic measures and filter-based BC measurements were generally weak (all Spearman correlation coefficients were ≤0.30), relationships were somewhat stronger for nonimpacted filters compared to WFS-impacted filters (Table S1). Across all filters, the Spearman correlation coefficient between the minimum distance to a major road (m) and BC concentrations was −0.22; correlation coefficients for nonimpacted and WFS-impacted filters were −0.30 and −0.11, respectively. Similar patterns were observed for the other GIS indicators of traffic (length of major roads and AADT in a 300 m buffer; Table S1).

Scatter plots of BC concentrations compared to the distance to highways demonstrated differences in the spatial gradients by campaign and by the presence of wildfire smoke (see supporting information). Absolute

BC concentrations were higher when WFS was present compared to when WFS was not present (Table 2). However, across all campaigns, the gradient in BC relative to distance from the nearest highway was flatter when wildfire smoke was present, suggesting wildfire smoke had a proportionally higher impact on BC concentrations measured farther from roads (Figure S5). Counter to this finding, however, the impact of WFS was less evident when considering the length of roads in a 300 m buffer (Figure S6) or average AADT in a 300 m buffer (Figure S7). For these metrics, gradients were generally unchanged for WFS-impacted and nonimpacted filters. When stratifying BC measurements by the presence of WFS and high or low percent impervious surface in a 300 m buffer, we observed the strongest BC gradients for areas with low percent impervious surface and no wildfire smoke (Figure S8). Similar results were observed when stratifying filters by the presence of WFS and high or low percent open space in a 300 m buffer (Figure S9). The presence of WFS had an appreciable effect on BC gradients when categorizing filters by quartiles of GIS-based traffic measures (Figure 3). When WFS was not present, the highest median BC concentrations were observed in the highest traffic quartiles. However, when WFS smoke was present, BC concentrations were higher for all traffic quartiles and differences in median concentrations across quartiles of GIS-based indicators of traffic were minimal. Across the two lower quartiles of GIS-based traffic indicators, concentrations were lower for nonimpacted filters compared to WFS-impacted filters (Kruskal-Wallis test, p values <0.05; Table S2). For the highest GIS-based traffic quartiles, concentrations of BC were similar for nonimpacted and WFS-impacted filters, suggesting that near major roads, traffic remained the dominant BC source even during distant wildfire events.

Agreement between BC quartiles and GIS-based traffic metric quartiles was poor, though agreement was generally better for nonimpacted filters compared to WFS-impacted filters Weighted Cohen's κ values ranged from 0.11 to 0.25 (Table S1). The strongest agreement between the BC measurements and the GIS-based traffic measures was for the lowest highest quartiles of exposure (Figure S10), suggesting the GIS-based indicators of traffic exposure were sufficient to broadly classify BC exposures (e.g., "low" and "high" exposure) but did not fully capture intraurban gradients in TRAP concentrations.

3.4. BC Exposure Misclassification With and Without WFS

Examining differences between BC_{noWFS} and BC_{WFS} at each sampling location demonstrated the potential for WFS to bias exposure assessments of TRAP that rely on BC concentrations as a proxy measure (Table 3). Long-term averages of $BC_{no\ WFS}$ and BC_{WFS} at each sampling location were highly correlated ($r = 0.96$). When stratified by the GIS-based traffic indicator quartiles, percent difference in the exposures was highest for the lowest traffic exposure quartiles, though differences across quartiles were not large. The effect of WFS on long-term average BC concentrations was also evident when stratifying long-term BC concentrations by distance to highway quartiles; filters impacted by WFS showed relatively flat gradients across quartiles of distance to highways (Figure S11).

3.5. Simulation Study

Counter to our original hypothesis, the results of our simulation study suggested that misclassification introduced by WFS biased regression coefficients away from the null and increased the magnitude of the effect of TRAP in our simulated linear regression (Figure 4). The effect of this bias was weakest when the true effect size is small (e.g., $\beta = -5$) and strongest when the true effect size was large (e.g., $\beta = -50$). Student's

Table 2
Summary of Filter-Based BC Concentrations (μg/m^3) for Nonimpacted and WFS-Impacted Filters

Filter type	n	Mean (SD)	Min	25th	50th	75th	95th	Max	IQR
Nonimpacted	370	1.16 (0.28)	0.78	0.94	1.04	1.42	1.65	2.12	0.48
WFS-impacted	239	1.17 (0.21)	0.84	1.02	1.14	1.26	1.48	2.27	0.23

Note: BC, black carbon; IQR, interquartile range; SD, standard deviation; WFS, wildfire smoke.

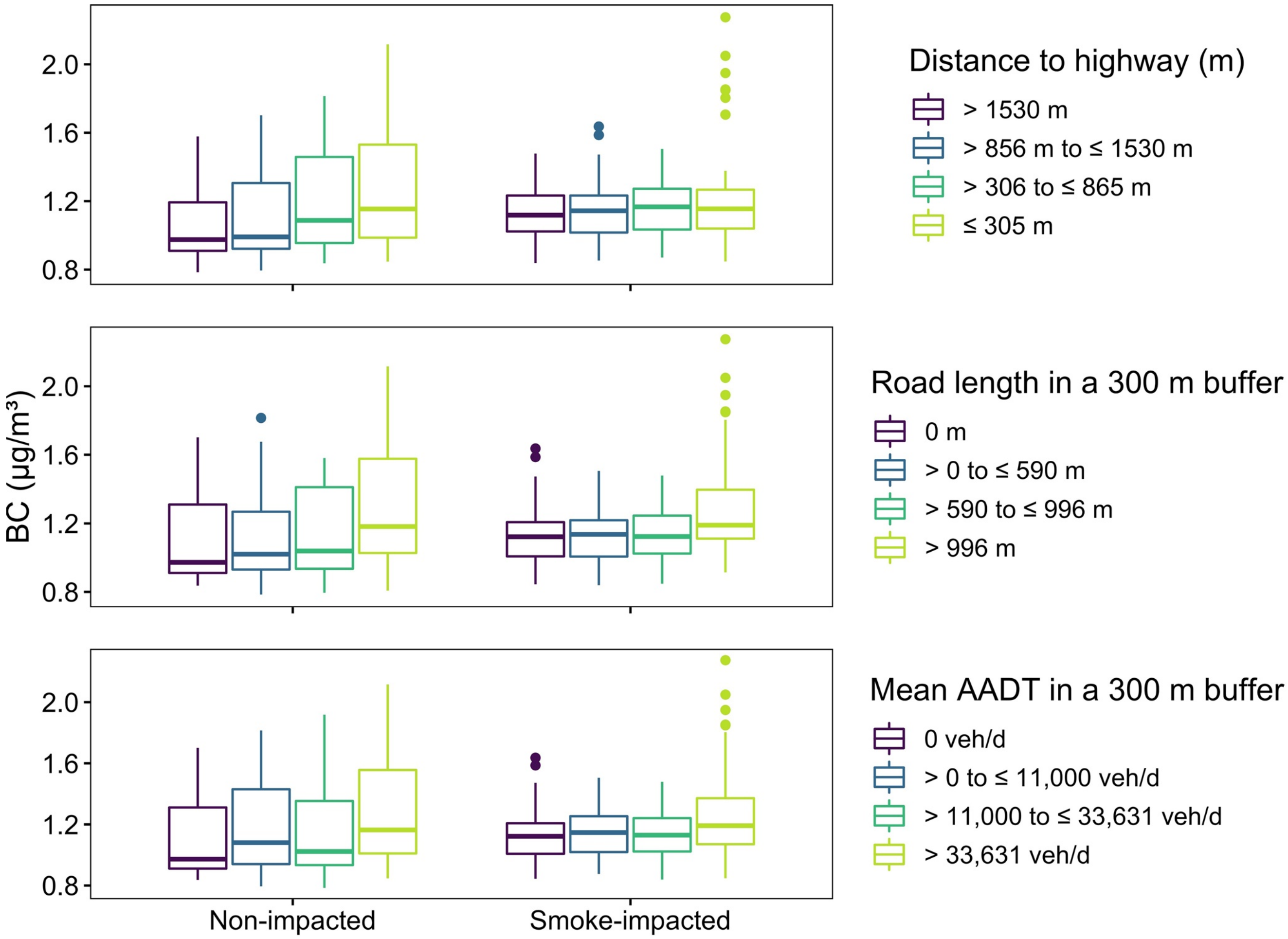

Figure 3. Boxplots of BC concentrations stratified by GIS-based traffic indicator quartile and the presence of WFS. BC, black carbon; WFS, wildfire smoke.

paired *t*-test revealed evidence of differences in the average β coefficient for $BC_{no\ WFS}$ and BC_{WFS} for all true β values except the $\beta = 0$ case (p values <0.01; Table S3).

Regression models using the unbiased $BC_{no\ WFS}$ as a proxy for TRAP exposures generally performed better compared to models using the biased BC_{WFS} measurement (Table 4). Root mean squared errors (RMSEs) were low (all RMSE = 1.0 for each true β) for models using the $BC_{no\ WFS}$ exposure estimate. Percent bias in the estimated β for each simulation was low (<0.3% for all values of true β) and interval coverage of the true effect estimate reached 94.8% on average. For models using BC_{WFS}, percent bias in the regression

Table 3
Median (IQR) Percent Difference Between the Mean $BC_{no\ WFS}$ Concentration and Mean BC_{WFS} Concentration at Each Sampling Location Stratified by GIS-Based Traffic Indicator Quartiles

	Median (IQR) percent difference in BC concentration			
GIS metric	Q1	Q2	Q3	Q4
Minimum distance to major roads (m)	4.85 (8.74)	4.30 (3.44)	−0.41 (5.68)	−0.58 (7.90)
Length of major roads in a 300 m buffer (m)	4.46 (6.04)	2.41 (6.45)	3.38 (8.10)	−0.58 (4.90)
Average AADT in a 300 m buffer (vehicles/d)	4.46 (6.04)	3.20 (6.22)	3.65 (8.62)	−0.86 (6.12)

Note: BC, black carbon; IQR, interquartile range; WFS, wildfire smoke.

10.1029/2020GH000347

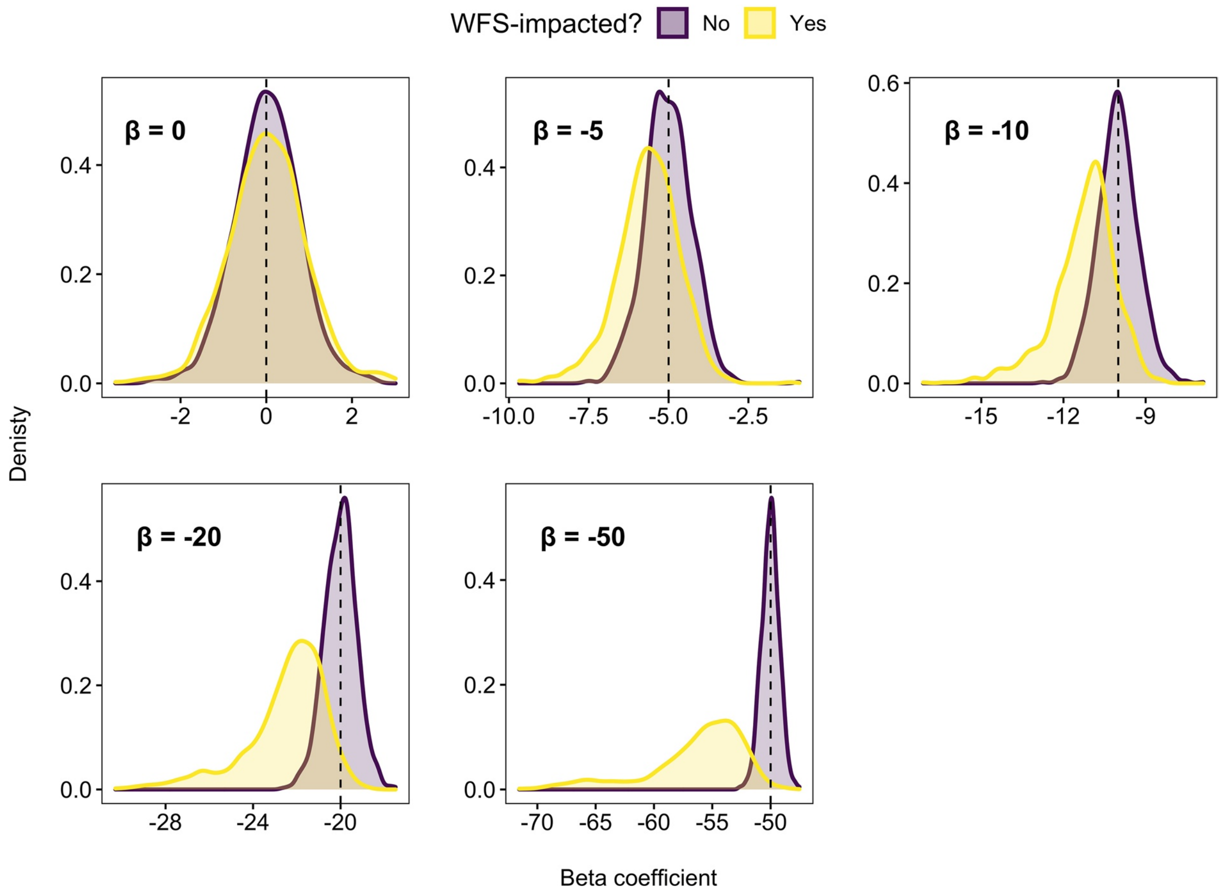

Figure 4. Distribution of β values generated from linear regression models (1,000 simulated data sets) using $BC_{no\ WFS}$ or BC_{WFS} as the exposure metric. BC, black carbon WFS, wildfire smoke.

coefficients exceeded 12%. The average RMSE ranged from 1.0 for a true β of -5 to 2.8 for a true β of -50. Interval coverage only reached 95% for the true $\beta = 0$ scenario; the interval coverage metric was generally poor (28.0–72.6%) for all other values of the true β. Low interval coverage for models using BC_{WFS} indicated a higher than acceptable Type I error rate and a greater chance for falsely detecting a positive association between TRAP and our simulated health outcome.

Table 4
Mean (SD) Diagnostic Metrics for the Simulation Study

	Unbiased TRAP exposure metric ($BC_{no\ WFS}$)				Biased TRAP exposure metric (BC_{WFS})			
True β	Bias	%Bias	RMSE	%Interval coverage	Bias	%Bias	RMSE	%Interval coverage
0	0.0 (0.8)		1.0 (0.1)	94.7 (14.7)	0.0 (0.9)		1.0 (0.1)	94.7 (15.1)
−5	0.0 (0.7)	0.3 (14.6)	1.0 (0.1)	95.5 (14.2)	−0.6 (1.0)	12.9 (19.6)	1.0 (0.1)	72.6 (11.5)
−10	0.0 (0.7)	0.1 (7.4)	1.0 (0.1)	93.8 (16.8)	−1.2 (1.2)	12.5 (11.6)	1.1 (0.1)	51.8 (9.1)
−20	0.0 (0.7)	0.0 (3.7)	1.0 (0.1)	94.6 (15.1)	−2.5 (1.8)	12.4 (9.2)	1.4 (0.1)	35.5 (8.3)
−50	0.0 (0.8)	0.0 (1.5)	1.0 (0.1)	95.3 (14.5)	−6.3 (4.1)	12.6 (8.3)	2.8 (0.3)	28.0 (6.7)

Note: BC, black carbon; RMSE, root mean square error; SD, standard deviation; TRAP, traffic-related air pollution; WFS, wildfire smoke.

4. Discussion

Due to a major wildfire event during planned exposure assessment campaigns in which we collected BC samples, we assessed whether WFS diminished the ability of BC (defined here as all LAC in a sample) to accurately reflect exposures to traffic in Denver, CO. When wildfires were not present, we observed expected gradients in BC concentrations, with the highest levels of BC measured near roadways (Xie et al., 2012). However, WFS in the region during our second sampling campaign appeared to have broad effects on BC measurements. Although all sampling locations generally experienced higher BC measurements when WFS was present, smoke from the Spring Creek fire appeared to have a stronger effect on filters farther from traffic sources, resulting in proportionally higher concentrations farther away from highways and major roads Thus, the WFS effect reduced expected BC gradients and resulted in more sampling locations with higher TRAP exposures during our simulation study. This spatially dependent effect of WFS on BC concentrations biased our results away from the null, overestimating the effect of traffic on our simulated birth weight outcome.

In wildfire-prone areas or areas where biomass burning is common, alternative indicators of biomass smoke may be helpful in disentangling the influence of these additional sources on ambient BC concentrations. For example, the Delta-C metric has been used as an indicator of wildfire smoke in previous studies (Kimbrough et al., 2016; Landis et al., 2018; Wang et al., 2010). Subtracting brown carbon mass associated with biomass burning (which has an absorbance at 375 nm) from all mass absorbing at 880 nm may better reflect BC from traffic sources. The Delta-C metric has recently been used in epidemiology studies to better differentiate the impacts of traffic and wood smoke exposures on health (Assibey-Mensah et al., 2020; Rich et al., 2018). Alternatively, specific elements (e.g., sulfur and potassium) or organic tracers such as levoglucosan may also differentiate biomass emissions from TRAP in particulate matter samples (Bhattarai et al., 2019; Chen et al., 2017; Li et al., 2003). However, routine, widespread monitoring for elements and biomass-specific organic aerosols is sparse or nonexistent in many areas and methods to collect such data can be prohibitively expensive.

The flatter gradients in BC concentrations observed for WFS-impacted filters, which primarily occurred during Campaign 2, may be due to lower traffic volumes during summer months. However, we do not believe changes in traffic patterns substantially altered the observed spatial patterns. Based on studies of other metropolitan areas, the black carbon burden in the Denver region is likely attributable to diesel emissions (McDonald et al., 2015). Diesel fuel sales in Colorado have seasonal trends, with the lowest sales occurring during the colder months (US Energy Information Administration, 2020). Importantly, these fuel sales tend to be relatively steady during the warmer summer months (April to September) when our WFS-impacted filters were identified. Additionally, we examined time trend data for carbon monoxide and elemental carbon concentrations from regional regulatory monitors collected between 2016 and 2020 (Figures S12 and S13). These two pollutants are correlated with combustion sources (i.e., traffic emissions and biomass burning) (Cyrys et al., 2003; Yoon et al., 2018; Zhang et al., 2005). In these plots, we observed the highest concentrations in the winter and relatively flat periods during the warmer months. Thus, we believe traffic volumes were not reduced substantially between the first, second, and third campaigns and that our flatter gradients were due to WFS from the Spring Creek fire.

There are some potential challenges to fully capturing the effect of a wildfire on BC measurements for TRAP exposure models. The rate of BC emissions from wildfires is governed by several factors, including the size of the fire, type of fuel, and combustion efficiency (Weise & Wright, 2014). Additionally, the spatial and temporal characteristics of wildfire smoke plumes (e.g., plume rise, dispersion) are determined by meteorology (e.g., wind speed and direction), the atmospheric chemistry of plume constituents, and the size and location of the fire, among other factors (Heilman et al., 2014; Larkin et al., 2010). Thus, the influence of local and regional wildfires on local BC concentrations does vary on relatively short time scales (e.g., hours or days). In contrast, filter-based measurements of BC require long sampling times to ensure adequate mass collection. BC concentrations in Denver over the course of our study were low (the mean across all filters was 1.15 $\mu g/m^3$); previous studies have reported modeled and measured BC concentrations across the United States ranging from <0.30 $\mu g/m^3$ to roughly 3.0 $\mu g/m^3$ (Clougherty et al., 2013; Fruin et al., 2014; Hankey & Marshall, 2015; Li et al., 2016). Aggregating daily WFS data to match the temporal scale of our BC measurements (i.e., 5-days samples) may have resulted in the misclassification of some WFS-impacted filters. Other types of nonstationary monitors, e.g., microaethalometers capable of measuring at multiple wavelengths, may be better equipped to capture the short-term influences of WFS on intraurban BC concentrations and should be considered when designing TRAP exposure assessments in wildfire-prone regions.

It is important to note that the direction of bias attributable to WFS likely depends on the characteristics of the study area. We did not observe large differences in BC concentrations in the highest traffic quartiles regardless of the presence of WFS. Because the Spring Creek fire was located ~150 miles from our study area, it is likely that there were fewer behavioral changes (i.e., changes in commuting behavior) among study area residents than would have occurred if the fire were closer to the region. Differences in fire location and intensity, meteorological conditions, or traffic density may result in different exposure misclassification scenarios. Future studies relying on absorbance at 880 nm to measure BC as a proxy for traffic will need to carefully consider the potential impacts of nontraffic BC sources on exposure assessments, especially as wildfires are projected to increase in frequency and intensity in the coming decades (Brey et al., 2018; Schoennagel et al., 2017).

Our study has some notable strengths. Our longitudinal design captured BC measurements before, during, and after a severe wildfire season in Colorado. The size and duration of the fire allowed us to identify impacts of WFS on BC measurements. The use of low-cost monitors allowed us to sample at 59 distinct locations across the Denver metropolitan area with a median 11 samples collected at each site. These locations were purposefully selected to better represent traffic exposures across the region and included both near-road and nonnear-road locations. Our study also confirms results from prior studies of the weak relationship between GIS-based traffic indicators and BC measurements. For example, Liu et al. (2017) compared BC measurements collected at sites in Detroit, MI located <150 or >300 m from a major road to GIS-based traffic and traffic density metrics (e.g., distance to major roads and major road density). This study reported correlation coefficients for BC and GIS-based indicators between 0.18 and 0.48, with the highest correlation for the heavy traffic density metric (0.48). In our study, the absolute values of the correlation coefficients ranged from 0.11 to 0.29.

There are also important limitations to note when interpreting the results of this study. First, our integrated samples did not allow us to identify specific days where wildfire smoke influenced BC concentrations. Second, there is likely some misclassification of wildfire smoke days using methods that rely on long-term monthly averages of $PM_{2.5}$ at each monitoring location. $PM_{2.5}$ concentrations fluctuate daily in ways that are likely to be unrelated to WFS (Kendrick et al., 2015; Yao et al., 2015). However, broad effects of the Spring Creek fire were emphasized by the level of agreement between the three metrics we considered for identifying WFS-impacted filters (smoke days at the nearest monitor, three closest monitors, or all area monitors). We selected a conservative approach to identifying days impacted by WFS that likely resulted in misclassification of some filters as nonimpacted. Future work should better incorporate other indicators of WFS such as brown carbon or elements associated with biomass burning when characterizing WFS-impacted samples. Third, our third campaign extended into the fall and may have been impacted by residential wood burning. Increases in BC measurements collected during the third campaign suggest residential wood burning during colder months may be an important source of BC in the region. Our measured BC concentrations were highest during Campaign 3, coinciding with pollutant-trapping temperature inversions and increases in residential wood burning (Bailey et al., 2011; Dutton et al., 2010; Vedal et al., 2009). Similar seasonal trends in BC concentrations were observed for elemental carbon and carbon monoxide (Figures S11 and S12). However, <1% of Denver-area residents report wood as their primary heating fuel (US Census Bureau, 2020), so we assumed residential wood burning to be a less important local source relative to traffic emissions during this campaign and that the effects of wood burning emissions would be widespread across the area. Other potential sources of BC during the summer months in the region include fireworks used for Independence Day celebrations. However, the sale of exploding fireworks to the general public is prohibited in Colorado (Colo. Rev. Stat. § 24-33.5-20), and due to the increased fire danger during the 2018 summer season, many counties and municipalities enacted further bans and canceled public fireworks displays (Ruble, 2018). Our first sampling campaign ended July 3, 2018 and our second campaign began July 10, 2018, therefore missing emissions from large municipal fireworks displays held on July 4th (Independence Day). Thus, we believe BC from fireworks had a minimal effect on our measurements during this time.

5. Conclusions

In a study comparing GIS-based indicators of traffic to BC measurements collected before, during, and after a major wildfire event in Denver, CO, we found that WFS had a measurable effect on our ability to use BC to represent TRAP exposure. When WFS was not present, we observed expected gradients in BC concentrations across urban sampling locations, with the highest concentrations being observed near major roads. However, when WFS was present, BC concentrations were elevated across most of the study area and spatial gradients were reduced. Proportionally higher BC concentrations measured at locations characterized as low traffic exposure areas during WFS events resulted in a misclassification of health effects attributable to TRAP. Our results suggest that the future use of BC in studies of TRAP-related health effects requires consideration of other sources in the region that may bias exposure estimates. Future epidemiological studies of traffic should consider additional exposure metrics such as Delta-C or sulfur-potassium ratios that may better isolate the effects of TRAP from other urban and nonurban sources.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The code and data used to simulate the epidemiology study are available on the primary author's GitHub page (https://github.com/smartenies/wildfire_smoke_and_traffic_BC, DOI:10.5281/zenodo.4136071).

Acknowledgments
This work was funded by grant 5UG3OD023248 from the National Institutes of Health. Thank you to Brad Rink (CDPHE) and Michael Ogletree (DDPHE) for their help in obtaining the black carbon monitoring data for the city of Denver, CO; to John Simko (NOAA/NESDIS) for his help obtaining the archived Hazard Mapping System shape files; and to Stephen Brey for his help in identifying smoke-impacted days in Denver, CO.

References

Ahmed, T., Dutkiewicz, V. A., Shareef, A., Tuncel, G., Tuncel, S., & Husain, L. (2009). Measurement of black carbon (BC) by an optical method and a thermal-optical method: Intercomparison for four sites. *Atmospheric Environment*, *43*(40), 6305–6311. https://doi.org/10.1016/j.atmosenv.2009.09.031

Alderete, T. L., Chen, Z., Toledo-Corral, C. M., Contreras, Z. A., Kim, J. S., Habre, R., et al. (2018). Ambient and traffic-related air pollution exposures as novel risk factors for metabolic dysfunction and type 2 diabetes. *Current Epidemiology Reports*, *5*(2), 79–91. https://doi.org/10.1007/s40471-018-0140-5

Andreae, M. O., & Gelencsér, A. (2006). Black carbon or brown carbon? The nature of light-absorbing carbonaceous aerosols. *Atmospheric Chemistry and Physics*, *6*(10), 3131–3148. https://doi.org/10.5194/acp-6-3131-2006

Apte, J. S., Messier, K. P., Gani, S., Brauer, M., Kirchstetter, T. W., Lunden, M. M., et al. (2017). High-resolution air pollution mapping with Google street view cars: Exploiting big data. *Environmental Science and Technology*, *51*(12), 6999–7008. https://doi.org/10.1021/acs.est.7b00891

Assibey-Mensah, V., Glantz, J. C., Hopke, P. K., Jusko, T. A., Thevenet-Morrison, K., Chalupa, D., & Rich, D. Q. (2020). Wintertime wood smoke, traffic particle pollution, and preeclampsia. *Hypertension*, *75*(3), 851–858. https://doi.org/10.1161/HYPERTENSIONAHA.119.13139

Bailey, A., Chase, T. N., Cassano, J. J., & Noone, D. (2011). Changing temperature inversion characteristics in the U.S. Southwest and relationships to large-scale atmospheric circulation. *Journal of Applied Meteorology and Climatology*, *50*(6), 1307–1323. https://doi.org/10.1175/2011JAMC2584.1

Batterman, S., Ganguly, R., Isakov, V., Burke, J., Arunachalam, S., Snyder, M., et al. (2014). Dispersion modeling of traffic-related air pollutant exposures and health effects among children with asthma in Detroit, Michigan. *Transportation Research Record*, *2452*, 105–113. https://doi.org/10.3141/2452-13

Beckerman, B., Jerrett, M., Brook, J. R., Verma, D. K., Arain, M. A., & Finkelstein, M. M. (2008). Correlation of nitrogen dioxide with other traffic pollutants near a major expressway. *Atmospheric Environment*, *42*(2), 275–290. https://doi.org/10.1016/j.atmosenv.2007.09.042

Beelen, R., Hoek, G., Raaschou-Nielsen, O., Stafoggia, M., Andersen, Z. J., Weinmayr, G., et al. (2015). Natural-cause mortality and long-term exposure to particle components: An analysis of 19 European cohorts within the multi-center ESCAPE project. *Environmental Health Perspectives*, *123*(6), 525–533. https://doi.org/10.1289/ehp.1408095

Bhattarai, H., Saikawa, E., Wan, X., Zhu, H., Ram, K., Gao, S., et al. (2019). Levoglucosan as a tracer of biomass burning: Recent progress and perspectives. *Atmospheric Research*, *220*, 20–33. https://doi.org/10.1016/j.atmosres.2019.01.004

Bond, T. C., Doherty, S. J., Fahey, D. W., Forster, P. M., Berntsen, T., DeAngelo, B. J., et al. (2013). Bounding the role of black carbon in the climate system: A scientific assessment. *Journal of Geophysical Research: Atmospheres*, *118*, 5380–5552. https://doi.org/10.1002/jgrd.50171

Bowatte, G., Lodge, C., Lowe, A. J., Erbas, B., Perret, J., Abramson, M. J., et al. (2015). The influence of childhood traffic-related air pollution exposure on asthma, allergy and sensitization: A systematic review and a meta-analysis of birth cohort studies. *Allergy*, *70*(3), 245–256. https://doi.org/10.1111/all.12561

Bowatte, G., Lodge, C. J., Knibbs, L. D., Erbas, B., Perret, J. L., Jalaludin, B., et al. (2018). Traffic related air pollution and development and persistence of asthma and low lung function. *Environment International*, *113*, 170–176. https://doi.org/10.1016/j.envint.2018.01.028

Brauer, M., Lencar, C., Tamburic, L., Koehoorn, M., Demers, P., & Karr, C. (2008). A cohort study of traffic-related air pollution impacts on birth outcomes. *Environmental Health Perspectives*, *116*(5), 680–686. https://doi.org/10.1289/ehp.10952

Brey, S. J., Barnes, E. A., Pierce, J. R., Wiedinmyer, C., & Fischer, E. V. (2018). Environmental conditions, ignition type, and air quality impacts of wildfires in the southeastern and western United States. *Earth's Future*, *6*, 1442–1456. https://doi.org/10.1029/2018EF000972

Brey, S. J., & Fischer, E. V. (2016). Smoke in the city: How often and where does smoke impact summertime ozone in the United States? *Environmental Science and Technology*, *50*(3), 1288–1294. https://doi.org/10.1021/acs.est.5b05218

Briggs, N. L., & Long, C. M. (2016). Critical review of black carbon and elemental carbon source apportionment in Europe and the United States. *Atmospheric Environment*, *144*, 409–427. https://doi.org/10.1016/j.atmosenv.2016.09.002

Caplin, A., Ghandehari, M., Lim, C., Glimcher, P., & Thurston, G. (2019). Advancing environmental exposure assessment science to benefit society. *Nature Communications*, *10*, 1236. https://doi.org/10.1038/s41467-019-09155-4

Carlsen, H. K., Nyberg, F., Segersson, D., & Olin, A.-C. (2018). Chronic exposure to black carbon particles and traffic-related particulate matter (PM) specifically from traffic are associated with reduced lung-function in a general population. *European Respiratory Journal*, *52*(Suppl. 62), OA5186. https://doi.org/10.1183/13993003.congress-2018.OA5186

Chen, J., Li, C., Ristovski, Z., Milic, A., Gu, Y., Islam, M. S., et al. (2017). A review of biomass burning: Emissions and impacts on air quality, health and climate in China. *Science of the Total Environment*, *579*, 1000–1034. https://doi.org/10.1016/j.scitotenv.2016.11.025

Chiu, Y.-H. M., Hsu, H.-H. L., Coull, B. A., Bellinger, D. C., Kloog, I., Schwartz, J., et al. (2016). Prenatal particulate air pollution and neurodevelopment in urban children: Examining sensitive windows and sex-specific associations. *Environment International*, *87*, 56–65. https://doi.org/10.1016/j.envint.2015.11.010

Chow, J. C., Watson, J. G., Lowenthal, D. H., Chen, L.-W. A., & Motallebi, N. (2010). Black and organic carbon emission inventories: Review and application to California. *Journal of the Air & Waste Management Association*, *60*(4), 497–507. https://doi.org/10.3155/1047-3289.60.4.497

Clifford, A., Lang, L., Chen, R., Anstey, K. J., & Seaton, A. (2016). Exposure to air pollution and cognitive functioning across the life course—A systematic literature review. *Environmental Research*, *147*, 383–398.

Clougherty, J. E., Kheirbek, I., Eisl, H. M., Ross, Z., Pezeshki, G., Gorczynski, J. E., et al. (2013). Intra-urban spatial variability in wintertime street-level concentrations of multiple combustion-related air pollutants: The New York City Community Air Survey (NYCCAS). *Journal of Exposure Science and Environmental Epidemiology*, *23*(3), 232–240. https://doi.org/10.1038/jes.2012.125

Colorado Department of Public Health and Environment (CDPHE). (2018). *Maps and GIS for health and environment*. Retrieved from https://www.colorado.gov/pacific/cdphe/maps-and-spatial-data

Costa, L. G., Cole, T. B., Coburn, J., Chang, Y.-C., Dao, K., & Roqué, P. J. (2017). Neurotoxicity of traffic-related air pollution. *Neurotoxicology*, *59*, 133–139. https://doi.org/10.1016/j.neuro.2015.11.008

Creamean, J. M., Neiman, P. J., Coleman, T., Senff, C. J., Kirgis, G., Alvarez, R. J., & Yamamoto, A. (2016). Colorado air quality impacted by long-range-transported aerosol: A set of case studies during the 2015 Pacific Northwest fires. *Atmospheric Chemistry and Physics*, *16*(18), 12329–12345. https://doi.org/10.5194/acp-16-12329-2016

Cyrys, J., Heinrich, J., Hoek, G., Meliefste, K., Lewné, M., Gehring, U., et al. (2003). Comparison between different traffic-related particle indicators: Elemental carbon (EC), PM2.5 mass, and absorbance. *Journal of Exposure Analysis and Environmental Epidemiology*, *13*(2), 134–143. https://doi.org/10.1038/sj.jea.7500262

Dekoninck, L., Botteldooren, D., & Int Panis, L. (2015). Using city-wide mobile noise assessments to estimate bicycle trip annual exposure to Black Carbon. *Environment International*, *83*, 192–201. https://doi.org/10.1016/j.envint.2015.07.001

Ditas, J., Ma, N., Zhang, Y., Assmann, D., Neumaier, M., Riede, H., et al. (2018). Strong impact of wildfires on the abundance and aging of black carbon in the lowermost stratosphere. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(50), E11595–E11603. https://doi.org/10.1073/pnas.1806868115

Dons, E., Laeremans, M., Orjuela, J. P., Avila-Palencia, I., Carrasco-Turigas, G., Cole-Hunter, T., et al. (2017). Wearable sensors for personal monitoring and estimation of inhaled traffic-related air pollution: Evaluation of methods. *Environmental Science and Technology*, *51*(3), 1859–1867. https://doi.org/10.1021/acs.est.6b05782

Dutton, S. J., Rajagopalan, B., Vedal, S., & Hannigan, M. P. (2010). Temporal patterns in daily measurements of inorganic and organic speciated PM2.5 in Denver. *Atmospheric Environment*, *44*(7), 987–998. https://doi.org/10.1016/j.atmosenv.2009.06.006

Fruin, S., Urman, R., Lurmann, F., McConnell, R., Gauderman, J., Rappaport, E., et al. (2014). *Spatial variation in particulate matter components over a large urban area*. (Vol. 83, pp. 211–219). Oxford, England: Atmospheric Environment. https://doi.org/10.1016/j.atmosenv.2013.10.063

Gong, T., Dalman, C., Wicks, S., Dal, H., Magnusson, C., Lundholm, C., et al. (2017). Perinatal exposure to traffic-related air pollution and autism spectrum disorders. *Environmental Health Perspectives*, *125*(1), 119–126. https://doi.org/10.1289/EHP118

Hankey, S., & Marshall, J. D. (2015). Land use regression models of on-road particulate air pollution (particle number, black carbon, PM2.5, particle size) using mobile monitoring. *Environmental Science and Technology*, *49*(15), 9194–9202. https://doi.org/10.1021/acs.est.5b01209

Harrod, C. S., Chasan-Taber, L., Reynolds, R. M., Fingerlin, T. E., Glueck, D. H., Brinton, J. T., & Dabelea, D. (2014). Physical activity in pregnancy and neonatal body composition: The Healthy Start study. *Obstetrics and Gynecology*, *124*(2 Pt 1), 257–264. https://doi.org/10.1097/AOG.0000000000000373

Heilman, W. E., Liu, Y., Urbanski, S., Kovalev, V., & Mickler, R. (2014). Wildland fire emissions, carbon, and climate: Plume rise, atmospheric transport, and chemistry processes. *Forest Ecology and Management*, *317*, 70–79. https://doi.org/10.1016/j.foreco.2013.02.001

Holstius, D. M., Reid, C. E., Jesdale, B. M., & Morello-Frosch, R. (2012). Birth weight following pregnancy during the 2003 southern California wildfires. *Environmental Health Perspectives*, *120*(9), 1340–1345. https://doi.org/10.1289/ehp.1104515

Howe, C. G., Eckel, S. P., Habre, R., Girguis, M. S., Gao, L., Lurmann, F. W., et al. (2018). Association of prenatal exposure to ambient and traffic-related air pollution with newborn thyroid function: Findings from the children's health study. *JAMA Network Open*, *1*(5), e182172. https://doi.org/10.1001/jamanetworkopen.2018.2172

Howell, N. A., Tu, J. V., Moineddin, R., Chen, H., Chu, A., Hystad, P., & Booth, G. L. (2019). The probability of diabetes and hypertension by levels of neighborhood walkability and traffic-related air pollution across 15 municipalities in southern Ontario, Canada: A dataset derived from 2,496,458 community dwelling-adults. *Data in Brief*, *27*, 104439. https://doi.org/10.1016/j.dib.2019.104439

Hu, J., Ostro, B., Zhang, H., Ying, Q., & Kleeman, M. J. (2019). Using chemical transport model predictions to improve exposure assessment of PM2.5 constituents. *Environmental Science and Technology Letters*, *6*(8), 456–461. https://doi.org/10.1021/acs.estlett.9b00396

Janssen, N. A. H., Hoek, G., Simic-Lawson, M., Fischer, P., van Bree, L., ten Brink, H., et al. (2011). Black carbon as an additional indicator of the adverse health effects of airborne particles compared with PM10 and PM2.5. *Environmental Health Perspectives*, *119*(12), 1691–1699. https://doi.org/10.1289/ehp.1003369

Kahle, D., & Wickham, H. (2013). ggmap: Spatial visualization with ggplot2. *The R Journal*, *5*(1), 144–161.

Kendrick, C. M., Koonce, P., & George, L. A. (2015). Diurnal and seasonal variations of NO, NO2 and PM2.5 mass as a function of traffic volumes alongside an urban arterial. *Atmospheric Environment*, *122*, 133–141. https://doi.org/10.1016/j.atmosenv.2015.09.019

Khreis, H., de Hoogh, K., & Nieuwenhuijsen, M. J. (2018). Full-chain health impact assessment of traffic-related air pollution and childhood asthma. *Environment International*, *114*, 365–375. https://doi.org/10.1016/j.envint.2018.03.008

Khreis, H., & Nieuwenhuijsen, M. J. (2017). Traffic-related air pollution and childhood asthma: Recent advances and remaining gaps in the exposure assessment methods. *International Journal of Environmental Research and Public Health*, *14*(3), 312. https://doi.org/10.3390/ijerph14030312

Kimbrough, S., Hays, M., Preston, B., Vallero, D. A., & Hagler, G. S. W. (2016). Episodic impacts from California wildfires identified in Las Vegas near-road air quality monitoring. *Environmental Science and Technology*, *50*(1), 18–24. https://doi.org/10.1021/acs.est.5b05038

Kingsley, S. L., Eliot, M. N., Glazer, K., Awad, Y. A., Schwartz, J. D., Savitz, D. A., et al. (2017). Maternal ambient air pollution, preterm birth and markers of fetal growth in Rhode Island: Results of a hospital-based linkage study. *Journal of Epidemiology and Community Health*, *71*(12), 1131–1136. https://doi.org/10.1136/jech-2017-208963

Kirrane, E. F., Luben, T. J., Benson, A., Owens, E. O., Sacks, J. D., Dutton, S. J., et al. (2019). A systematic review of cardiovascular responses associated with ambient black carbon and fine particulate matter. *Environment International*, *127*, 305–316. https://doi.org/10.1016/j.envint.2019.02.027

Lack, D. A., Moosmüller, H., McMeeking, G. R., Chakrabarty, R. K., & Baumgardner, D. (2014). Characterizing elemental, equivalent black, and refractory black carbon aerosol particles: A review of techniques, their limitations and uncertainties. *Analytical and Bioanalytical Chemistry*, *406*(1), 99–122. https://doi.org/10.1007/s00216-013-7402-3

Landis, M. S., Edgerton, E. S., White, E. M., Wentworth, G. R., Sullivan, A. P., & Dillner, A. M. (2018). The impact of the 2016 Fort McMurray Horse river wildfire on ambient air pollution levels in the Athabasca Oil Sands region, Alberta, Canada. *The Science of the Total Environment*, *618*, 1665–1676. https://doi.org/10.1016/j.scitotenv.2017.10.008

Larkin, N. K., O'Neill, S. M., Solomon, R., Raffuse, S., Strand, T., Sullivan, D. C., et al. (2010). The BlueSky smoke modeling framework. *International Journal of Wildland Fire*, *18*(8), 906–920. https://doi.org/10.1071/WF07086

Laumbach, R. J., & Kipen, H. M. (2012). Respiratory health effects of air pollution: Update on biomass smoke and traffic pollution. *Journal of Allergy and Clinical Immunology*, *129*(1), 3–11. https://doi.org/10.1016/j.jaci.2011.11.021

Li, J., Pósfai, M., Hobbs, P. V., & Buseck, P. R. (2003). Individual aerosol particles from biomass burning in southern Africa: 2. Compositions and aging of inorganic particles. *Journal of Geophysical Research*, *108*(D13), 8484. https://doi.org/10.1029/2002JD002310

Li, Y., Henze, D. K., Jack, D., Henderson, B. H., & Kinney, P. L. (2016). Assessing public health burden associated with exposure to ambient black carbon in the United States. *Science of the Total Environment*, *539*, 515–525. https://doi.org/10.1016/j.scitotenv.2015.08.129

Liu, S. V., Chen, F.-L., & Xue, J. (2017). Evaluation of traffic density parameters as an indicator of vehicle emission-related near-road air pollution: A case study with NEXUS measurement data on black carbon. *International Journal of Environmental Research and Public Health*, *14*(12), 1581. https://doi.org/10.3390/ijerph14121581

Mao, Y. H., Li, Q. B., Zhang, L., Chen, Y., Randerson, J. T., Chen, D., & Liou, K. N. (2011). Biomass burning contribution to black carbon in the Western United States Mountain Ranges. *Atmospheric Chemistry and Physics*, *11*(21), 11253–11266. https://doi.org/10.5194/acp-11-11253-2011

McConnell, R., Gilliland, F. D., Goran, M., Allayee, H., Hricko, A., & Mittelman, S. (2016). Does near-roadway air pollution contribute to childhood obesity? *Pediatric Obesity*, *11*(1), 1–3. https://doi.org/10.1111/ijpo.12016

McDonald, B. C., Goldstein, A. H., & Harley, R. A. (2015). Long-term trends in California mobile source emissions and ambient concentrations of black carbon and organic aerosol. *Environmental Science and Technology*, *49*(8), 5178–5188. https://doi.org/10.1021/es505912b

Monrad, M., Sajadieh, A., Christensen, J. S., Ketzel, M., Raaschou-Nielsen, O., Tjønneland, A., et al. (2017). Long-term exposure to traffic-related air pollution and risk of incident Atrial Fibrillation: A cohort study. *Environmental Health Perspectives*, *125*(3), 422–427. https://doi.org/10.1289/EHP392

Multi-Resolution Land Characteristics Consortium. (2017). *National land cover database*. Retrieved from https://www.mrlc.gov/

National Oceanic and Atmospheric Administration. (2020). *Hazard mapping system fire and smoke product*. Retrieved from https://www.ospo.noaa.gov/Products/land/hms.html

National Wildfire Coordinating Group. (2018). *Spring Creek fire information*. Retrieved from https://inciweb.nwcg.gov/incident/5875/

Nichols, J. L., Owens, E. O., Dutton, S. J., & Luben, T. J. (2013). Systematic review of the effects of black carbon on cardiovascular disease among individuals with pre-existing disease. *International Journal of Public Health*, *58*(5), 707–724 https://doi.org/10.1007/s00038-013-0492-z

Ostro, B., Hu, J., Goldberg, D., Reynolds, P., Hertz, A., Bernstein, L., & Kleeman, M. J. (2015). Associations of mortality with long-term exposures to fine and ultrafine particles, species and sources: Results from the California Teachers study cohort. *Environmental Health Perspectives*, *123*(6), 549–556. https://doi.org/10.1289/ehp.1408565

Patton, A. P., Perkins, J., Zamore, W., Levy, J. I., Brugge, D., & Durant, J. L. (2014). Spatial and temporal differences in traffic-related air pollution in three urban neighborhoods near an interstate highway. *Atmospheric Environment*, *99*, 309–321. https://doi.org/10.1016/j.atmosenv.2014.09.072

Pebsema, E. (2018). *sf: Simple features for R. R package version 0.6-3.* Retrieved from https://CRAN.R-project.org/package=sf

Petzold, A., Ogren, J. A., Fiebig, M., Laj, P., Li, S.-M., Baltensperger, U., et al. (2013). Recommendations for reporting "black carbon" measurements. *Atmospheric Chemistry and Physics*, *13*(16), 8365–8379. https://doi.org/10.5194/acp-13-8365-2013

Presler-Jur, P., Doraiswamy, P., Hammond, O., & Rice, J. (2017). An evaluation of mass absorption cross-section for optical carbon analysis on Teflon filter media. *Journal of the Air & Waste Management Association*, *67*(11), 1213–1228. https://doi.org/10.1080/10962247.2017.1310148

Quinn, C., Miller-Lionberg, D. D., Klunder, K. J., Kwon, J., Noth, E. M., Mehaffy, J., et al. (2018). Personal exposure to PM2.5 black carbon and aerosol oxidative potential using an automated microenvironmental aerosol sampler (AMAS). *Environmental Science and Technology*, *52*(19), 11267–11275. https://doi.org/10.1021/acs.est.8b02992

R Core Team. (2019). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from http://www.R-project.org/

Rich, D. Q., Utell, M. J., Croft, D. P., Thurston, S. W., Thevenet-Morrison, K., Evans, K. A., et al. (2018). Daily land use regression estimated woodsmoke and traffic pollution concentrations and the triggering of ST-elevation myocardial infarction: A case-crossover study. *Air Quality, Atmosphere, and Health*, *11*(2), 239–244. https://doi.org/10.1007/s11869-017-0537-1

Ruble, E. (2018). Where fireworks are and aren't allowed in metro Denver. *FOX31 Denver*. Retrieved from https://kdvr.com/news/local/where-fireworks-are-and-arent-allowed-in-metro-denver/

Santos Baquero, O. (2019). *ggsn: North symbols and scale bars for maps created with "ggplot2" or "ggmap". R package version 0.5.0*. Retrieved from http://www.R-project.org/https://CRAN.R-project.org/package=ggsn

Schoennagel, T., Balch, J. K., Brenkert-Smith, H., Dennison, P. E., Harvey, B. J., Krawchuk, M. A., et al. (2017). Adapt to more wildfire in western North American forests as climate changes. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(18), 4582–4590. https://doi.org/10.1073/pnas.1617464114

Spracklen, D. V., Mickley, L. J., Logan, J. A., Hudman, R. C., Yevich, R., Flannigan, M. D., & Westerling, A. L. (2009). Impacts of climate change from 2000 to 2050 on wildfire activity and carbonaceous aerosol concentrations in the western United States. *Journal of Geophysical Research*, *114*, D20301. https://doi.org/10.1029/2008JD010966

Stampfer, O., Austin, E., Ganuelas, T., Fiander, T., Seto, E., & Karr, C. J. (2020). Use of low-cost PM monitors and a multi-wavelength aethalometer to characterize PM2.5 in the Yakama Nation reservation. *Atmospheric Environment*, *224*, 117292. https://doi.org/10.1016/j.atmosenv.2020.117292

Starling, A. P., Moore, B. F., Thomas, D. S. K., Peel, J. L., Zhang, W., Adgate, J. L., et al. (2020). Prenatal exposure to traffic and ambient air pollution and infant weight and adiposity: The Healthy Start study. *Environmental Research*, *182*, 109130. https://doi.org/10.1016/j.envres.2020.109130

Suglia, S. F., Gryparis, A., Wright, R. O., Schwartz, J., & Wright, R. J. (2008). Association of black carbon with cognition among children in a prospective birth cohort study. *American Journal of Epidemiology*, *167*(3), 280–286. https://doi.org/10.1093/aje/kwm308

Thurston, G. D., Burnett, R. T., Turner, M. C., Shi, Y., Krewski, D., Lall, R., et al. (2016). Ischemic heart disease mortality and long-term exposure to source-related components of U.S. fine particle air pollution. *Environmental Health Perspectives*, *124*(6), 785–794. https://doi.org/10.1289/ehp.1509777

US Census Bureau. (2020). *American housing survey*. Retrieved from https://www.census.gov/programs-surveys/ahs/data/interactive/ahstablecreator.html

US Department of Transportation (US DOT). (2018). *Highway performance monitoring system*. Retrieved from https://www.fhwa.dot.gov/policyinformation/hpms.cfm

US Energy Information Administration. (2020). *Colorado No 2 distillate all sales/deliveries by prime supplier (thousand gallons per day)*. Retrieved from https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=C200040081&f=M

US Environmental Protection Agency. (2018). *2014 National emissions inventory report.* Retrieved from https://gispub.epa.gov/neireport/2014/

US Environmental Protection Agency (US EPA). (2016). *AQS data Mart*. Retrieved from https://aqs.epa.gov/api

Val Martin, M., Heald, C. L., Ford, B., Prenni, A. J., & Wiedinmyer, C. (2013). *A decadal satellite analysis of the origins and impacts of smoke in Colorado*. Copernicus GmbH. Retrieved from https://dspace.mit.edu/handle/1721.1/81308

Vedal, S., Hannigan, M. P., Dutton, S. J., Miller, S. L., Milford, J. B., Rabinovitch, N., et al. (2009). The Denver aerosol sources and health (DASH) study: Overview and early findings. *Atmospheric Environment*, *43*(9), 1666–1673. https://doi.org/10.1016/j.atmosenv.2008.12.017

Volckens, J., Quinn, C., Leith, D., Mehaffy, J., Henry, C. S., & Miller-Lionberg, D. (2017). Development and evaluation of an ultrasonic personal aerosol sampler. *Indoor Air*, *27*(2), 409–416. https://doi.org/10.1111/ina.12318

Volk, H. E., Lurmann, F., Penfold, B., Hertz-Picciotto, I., & McConnell, R. (2013). Traffic-related air pollution, particulate matter, and autism. *JAMA Psychiatry*, *70*(1), 71–77. https://doi.org/10.1001/jamapsychiatry.2013.266

Vu, K. T., Dingle, J. H., Bahreini, R., Reddy, P. J., Apel, E. C., Campos, T. L., et al. (2016). Impacts of the Denver Cyclone on regional air quality and aerosol formation in the Colorado Front Range during FRAPPE 2014. *Atmospheric Chemistry and Physics*, *16*(18), 12039–12058. https://doi.org/10.5194/acp-16-12039-2016

Wang, Y., Huang, J., Zananski, T. J., Hopke, P. K., & Holsen, T. M. (2010). Impacts of the Canadian forest fires on atmospheric mercury and carbonaceous particles in Northern New York. *Environmental Science and Technology*, *44*(22), 8435–8440. https://doi.org/10.1021/es1024806

Weise, D. R., & Wright, C. S. (2014). Wildland fire emissions, carbon and climate: Characterizing wildland fuels. *Forest Ecology and Management*, *317*, 26–40. https://doi.org/10.1016/j.foreco.2013.02.037

Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. New York, NY: Springer-Verlag.

Wu, H., Reis, S., Lin, C., Beverland, I. J., & Heal, M. R. (2015). Identifying drivers for the intra-urban spatial variability of airborne particulate matter components and their interrelationships. *Atmospheric Environment*, *112*, 306–316. https://doi.org/10.1016/j.atmosenv.2015.04.059

Xie, M., Coons, T. L., Dutton, S. J., Milford, J. B., Miller, S. L., Peel, J. L., et al. (2012). Intra-urban spatial variability of PM2.5-bound carbonaceous components. *Atmospheric Environment*, *60*, 486–494. https://doi.org/10.1016/j.atmosenv.2012.05.041

Xing, Y., & Brimblecombe, P. (2018). Dispersion of traffic derived air pollutants into urban parks. *Science of the Total Environment*, *622–623*, 576–583. https://doi.org/10.1016/j.scitotenv.2017.11.340

Yao, L., Lu, N., Yue, X., Du, J., & Yang, C. (2015). Comparison of hourly PM2.5 observations between urban and suburban areas in Beijing, China. *International Journal of Environmental Research and Public Health*, *12*(10), 12264–12276. https://doi.org/10.3390/ijerph121012264

Yoon, S., Fairley, D., Barrett, T. E., & Sheesley, R. J. (2018). Biomass and fossil fuel combustion contributions to elemental carbon across the San Francisco Bay Area. *Atmospheric Environment*, *195*, 229–242. https://doi.org/10.1016/j.atmosenv.2018.09.050

Zhang, K. M., Wexler, A. S., Niemeier, D. A., Zhu, Y. F., Hinds, W. C., & Sioutas, C. (2005). Evolution of particle number distribution near roadways. Part III: Traffic analysis and on-road size resolved particulate emission factors. *Atmospheric Environment*, *39*(22), 4155–4166. https://doi.org/10.1016/j.atmosenv.2005.04.003

Zwack, L. M., Paciorek, C. J., Spengler, J. D., & Levy, J. I. (2011). Modeling spatial patterns of traffic-related air pollutants in complex urban Terrain. *Environmental Health Perspectives*, *119*(6), 852–859. https://doi.org/10.1289/ehp.1002519