The impact of wildfires on particulate carbon in the western U.S.A

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ARTICLE INFO

Keywords: Air pollution Wildfire PM\textsubscript{2.5} speciation Particulate carbon Weather

ABSTRACT

Most of the previous investigations on the relationship between PM\textsubscript{2.5} chemical characteristics and wildfire focused on the predictions of particle components concentrations or future pollution scenarios. Little research has focused on trends analyses based on large temporal datasets. Our research addresses this gap by quantifying the long-term impacts of wildfires on ambient particulate carbon levels (organic carbon - OC and elemental carbon - EC) in the western U.S. over a long of 29 years (1988–2016). We quantified the past wildfire-related increases in EC and OC concentration using Generalized Additive Models (GAMs). We used a framework that derives “penalties” (wildfire penalty, in \textmu g/m\textsuperscript{3} per year) for each season (warm and cold) by accounting for the differences of the \(\beta\) values between two models – adjusted (wildfire included as covariate in the model) and unadjusted model (wildfire is removed from the model). While the wildfire impact is incorporate into the unadjusted trends, the control by wildfire in the adjusted model removes the impact of inter-annual wildfire variation on EC and OC trends. Therefore, we considered that any differences between the unadjusted and wildfire-adjusted trends are entirely attributable to the impact of long-term wildfire changes. A positive penalty (\(\text{penalty}_{\text{unadjusted}} > \text{penalty}_{\text{adjusted}}\)) suggests that an increase in EC and OC is associated with long-term wildfire changes between 1988 and 2016. Wildfires increased in the warm season and decreased in the cold season. We estimated an annual increase of 20.106 km\textsuperscript{2} of area burned (95% CI: 20.103; 20.109) in the warm period. EC and OC concentrations increased during the warm and cold season. EC and OC concentrations had an annual decrease of 0.03\textmu g/m\textsuperscript{3} (95% CI: −0.14; 0.08) and 0.10\textmu g/m\textsuperscript{3} (95% CI: −0.21; 0.01), respectively. In the cold period, our analyses showed an increase of 0.05\textmu g/m\textsuperscript{3} (95% CI: −0.07; 0.17) and 0.07\textmu g/m\textsuperscript{3} (95% CI: −0.04; 0.19) per year for EC and OC, respectively. In the warm season, during the study period (1988–2016), the estimated total concentration change (total penalty) for EC was 0.003\textmu g/m\textsuperscript{3} (95%CI: 0.001 and 0.005) and for OC was 0.015\textmu g/m\textsuperscript{3} (95%CI: 0.008 and 0.022). In the cold season the penalties were statistically insignificant.

1. Introduction

A substantial fraction of vegetated impacted by fire worldwide every years. Mouillot and Field (2005) estimate that each year between 3 and 6 million km\textsuperscript{2} of vegetation area is burned globally. Due to the large number of factors that influence wildfires (e.g., weather, type of soil, type of vegetation, and human activity), there are different levels of fire-prone regions around the world. Africa is very fire-prone, where about 50% of west African savannas are burned each year (Liouesse et al., 2010; Tesfaye et al., 2014). In Europe, approximately 18,000 km\textsuperscript{2} are burned annually (Yousfouf et al., 2014). In the U.S., Koplitz et al. (2018) estimate 90,000 km\textsuperscript{2} of burned area per year. Approximately one-third of those areas burned in the U.S. occurs in the West. Specifically in this U.S region, previous investigations have shown that the number of large wildfires (> 4 km\textsuperscript{2}) and total area burned per year are increasing. Between 1984 and 2011, the number of large fires in the west coast of the U.S. increased at a rate of seven fires per year, and the total area burned increased at a rate of 355 km\textsuperscript{2} per year (Dennison et al., 2014).

Wildfires cause many environmental impacts including air pollution (McClure and Jaffe, 2018). Emissions from forest fires can travel over large distances, affecting air quality and human health far from the originating fires (Yousfouf et al., 2014). Fine particulate matter (PM\textsubscript{2.5}) is the major pollutant emitted by wildfires. In the U.S., according to the National Emissions Inventory (NEI), in 2014 wildfires represented more than 20% of total PM\textsubscript{2.5} emissions annually (EPA, 2014). Liu et al. (2017) reported significant risk of hospital admissions associated with smoke waves during 2004 and 2009 in the Western U.S. The authors defined smoke waves as two or more consecutive days with daily wildfire-specific PM\textsubscript{2.5} > 20\textmu g/m\textsuperscript{3}, with sensitivity analysis
considering 23, 28, and 37 μg/m³. They estimated a 7.2% increase in risk for respiratory admissions during smoke wave days with high wildfire-specific PM$_{2.5}$ (> 37 μg/m³) compared to matched non-smoke wave days.

Given the particle formation and removal mechanisms, and the diversity of particle components, estimating accurate wildfire impacts on PM$_{2.5}$ and its health implications is challenging. Therefore, some studies have defined the chemical characteristics of PM$_{2.5}$ as the outcome in the wildfire-related air pollution models (Gunsch et al., 2018; Jaffe et al., 2008; Spracklen et al., 2009). These studies have shown that the relationship between particle components and wildfire varies significantly over space and time depending on the chemical characteristics of PM$_{2.5}$ and geographical characteristics, including weather parameters (McClure and Jaffe, 2018; Spracklen et al., 2007). Among those numerous chemical components of PM$_{2.5}$ particulate carbon (including the organic and elemental carbons) have been the most indicated as an element that reflects wildfire emissions (McClure and Jaffe, 2018). Spracklen et al. (2009) estimates that changes on climate will increase organic carbon (OC) and elemental carbon (EC) concentrations by 40% and 20%, respectively, in the summer periods from 2000 to 2050 over the western U.S. Significant portion of this increase (75% and 95% for OC and EC, respectively) will be attributable to wildfire emissions.

Most of the previous investigations on the relationship between PM$_{2.5}$ chemical characteristics and wildfire focused on the predictions of particle components concentrations or future pollution scenarios. Little research has focused on trends analyses of the association between PM$_{2.5}$ constituents and wildfire based on large temporal datasets. Our research addresses this gap by quantifying the long-term impacts of wildfires on ambient particulate carbon (OC and EC) levels in the western U.S. over a long of 29 years (1988–2016).

2. Materials and methods

2.1. Study area and research design

The study was carried out in the western U.S. We selected this area because it is a region in the U.S which wildfires have been considered a critical concern for air pollution exposure (as we described in the introduction section). The west defined in our study is composed by 11 states, including Washington, Oregon, California, Idaho, Nevada, Arizona, New Mexico, Colorado, Utah, Wyoming, and Montana (Fig. 1).

This study was performed in three stages. First, we consolidated a geodatabase with three datasets - air pollution, wildfire, and weather data (covariates in the model). Each dataset has daily information for the period between 1988 and 2016. We describe each one of these datasets in the next section and in Fig. 1. In the second stage, we use Geographic Information System (GIS) techniques to summarize the amount of area burned inside buffers with 50 km (buffers around each air pollution monitoring station). Finally, in the third stage, we apply statistical analyses to estimate the past wildfire-related increases in particulate carbon levels.

2.2. Data collection

2.2.1. Air pollution data

EC and OC data were obtained from the EPA Air Data Monitoring Program - air quality data collected at outdoor monitors across the U.S. (https://www.epa.gov/outdoor-air-quality-data). The EPA air pollution monitoring data are measured by two networks, Chemical Speciation Monitoring Network (CSN) and IMPROVE. Overall, CSN sites are mainly located in urban and suburban areas, while most of the IMPROVE sites are in rural areas. These networks use different sampling methods, analytical protocols, and quality assurance (Solomon et al., 2014). Given the differences between the measurements of air pollution in CSN and IMPROVE, we adjusted the EC and OC data based on the factors reported by (Hand et al., 2011; Malm et al., 2011). In short, for CSN data, we subtracted monthly averaged blank values from the data if they were measured by Thermal Optical Reflectance (TOR) method. If the data were measured by Thermal Optical Transmittance (TOT) method, EC data was adjusted by multiplying 1.3 for compatibility with EC data from IMPROVE, whereas OC data was adjusted using the parameters recommended by Copeland et al. and Malm et al. (2011). This same adjustment for EC and OC was used recently by (Meng et al., 2018) to estimate space-time trends of PM$_{2.5}$ constituents in the U.S.

The EPA reports the concentration of each component as microgram per cubic meter (μg/m³). We accessed data constructed on a daily basis listed by year between 1988 and 2016. We considered air pollution monitoring stations with at least 10 years of year-round (January–December) data and at least 14 daily measurements each month. As result, we selected 148 EC and OC sites.

2.2.2. Wildfires data

We accessed wildfire data from the U.S. Geological Survey – USGS (https://www.usgs.gov/). The data obtained contains wildfire records (e.g., date of wildfire occurrence, geographical location, and area burned etc.) collected by Federal Land management agencies for fires that occurred in the U.S. Area burned is estimated in Km². This wildfire occurrence dataset is a collection of fire records from five federal agencies - Bureau of Indian Affairs (BIA), Bureau of Land Management (BLM), U.S. Fish and Wildlife Service (FWS), National Park Service (NPS), and U.S. Forest Service (USFS).

2.2.3. Meteorological data

Weather data was provided by the National Oceanic Atmospheric Administration’s National Climatic Data Center (ftp://ftp.ncdc.noaa.gov/pub/data/gsod/). This data contains daily information on temperature (°C), wind speed (Knots), and relative humidity. In addition to these weather parameters, the weather data includes elevation (m) information as well. We selected weather stations with the whole period (1988–2016) of year-round data and at least 21 daily measurements per month. As result, 213 stations were selected.

2.3. Consolidation of the datasets

We consolidated all the three datasets (air pollution, wildfires, and weather) using spatio-temporal matching process. Here the air pollution dataset was used as reference (wildfire and weather data were joined to air pollution data), since our aim was to investigate the impact of wildfire on air pollution concentration.

First, we merged the daily weather data with the air pollution stations. This spatio-temporal join was based on the nearest weather station’s data. We found an average distance between air pollution monitor and weather station of 18.2 km. Then we defined buffers of 50 km around each air pollution station to summarize the daily amount of area burned (Km²) within the buffers. We highlight that the air pollution sites were restricted to the study area. Wildfire and weather data were not restricted to the study area. All GIS calculations were performed in Python.

2.4. Statistical analysis

First, we applied a general linear regression model to estimate individual past changes in meteorological variables (temperature, wind speed and humidity), wildfires, and air pollution (EC and OC) per year for the period between 1988 and 2016. We stratified the analysis by two periods - cold (November–April) and warm (May–October).

Then, we quantified the past wildfire-related increases in EC and OC concentration. We used a framework proposed by Jhun et al. (2015). This framework derives “penalties” (in our study case, wildfire
penalty”) by accounting for the differences of the β values between two models – one model adjusted by the independent variable (e.g., wildfire) and one model unadjusted. Any difference of these models are attributable to the long-term impact of the independent variable (e.g., wildfire).

The framework proposed by Jhun et al. (2015) can be divided into two steps: i) central estimates, and; ii) bootstrap analysis. In the first step, we applied generalized additive models (GAMs) to estimate wildfire-associated changes in EC and OC for each season (warm and cold - the same definition as mentioned above). We used two GAM models to estimate long-term trends of daily EC and OC. The first model was adjusted for wildfire (adjusted model) and the second model the wildfire variable was excluded (unadjusted model). Both models were controlled by meteorological variables and elevation. Note that elevation was included in the model based on the literature, which suggests this variable as an important factor influencing wildfire occurrence (Maingi and Henry, 2007; Marlon et al., 2016, 2012). The adjusted and unadjusted models are described in the equations (1) and (2), respectively.

\[
Y_{i,j,p} = \alpha + \beta_{\text{adjusted}} \text{year}_{i,j,p} + \gamma \text{month}_{i,j,p} + s_{(\text{temp})} + s_{(\text{ws})} + s_{(\text{rh})} + s_{(\text{elev})} + s_{(\text{wildfire})} + e_{i,j,p} \tag{1}
\]

\[
Y_{i,j,p} = \alpha + \beta_{\text{unadjusted}} \text{year}_{i,j,p} + \gamma \text{month}_{i,j,p} + s_{(\text{temp})} + s_{(\text{ws})} + s_{(\text{rh})} + s_{(\text{elev})} + e_{i,j,p} \tag{2}
\]

where, \(Y\) is the daily concentration of the chemical specie \(p\) of PM\(_{2.5}\) (EC, OC) at site \(i\) and on date \(j\); \(\alpha\) is the regression intercept; \(\beta_{\text{adjusted}}\) and \(\beta_{\text{unadjusted}}\) are the regression coefficients representing the linear wildfire-adjusted and unadjusted pollutant trends (μg/m\(^3\) per year), respectively, in 1988–2016 for a specific season; \(\gamma\) is the vector of coefficient that represents monthly variability of specie \(p\) at site \(i\); and \(s()\) are the smoothing splice function to characterize nonlinear relationships between covariates (weather parameters, elevation, and wildfire) and daily concentration of specie \(p\). Note that this is only applied in the adjusted model (Equation (1)). The weather parameters are represented by temperature (temp), wind speed (ws), and relative humidity (rh). We highlight that, as mentioned before, wildfire is represented by total area burned (km\(^2\)) within the buffer of 50 km. This distance was selected based on the training analysis, which we observed that below 50 km there are few observations (few wildfires) to run a GAM model, and above 50 km the results were statistically insignificant. We used the software R - version 2.13.1 (R Core Team, 2013) to perform the statistical analyses.

Then we used the \(\beta_{\text{adjusted}}\) and \(\beta_{\text{unadjusted}}\) values to quantify past wildfire-related increases (“wildfire penalty”) in EC and OC. We derived the wildfire penalties (μg/m\(^3\) per year) for each season by obtaining the differences between \(\beta_{\text{adjusted}}\) and \(\beta_{\text{unadjusted}}\) (\(\beta_{\text{adjusted}} - \beta_{\text{unadjusted}}\)). While the wildfire impact is incorporated into the unadjusted trends (Equation (2)), the control by wildfire in model 1 removes the impact of interannual wildfire variation on EC and OC trends. Therefore, we considered that any differences between the unadjusted and wildfire-adjusted trends are entirely attributable to the impact of long-term

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**Fig. 1.** Air pollution sites and wildfires in western U.S. Note 1: (*) In order to keep the map more concise (clean cartographic design), we illustrate the buffer with 50 km around a single air pollution station in north California. Note 2: We illustrate here all the wildfires occurred in western U.S. between 1988 and 2016.
wildfire changes. A positive penalty ($\beta_{\text{unadjusted}} > \beta_{\text{adjusted}}$) suggests that an increase in EC and OC is associated with long-term wildfire changes between 1988 and 2016.

In the second stage, we applied a bootstrap analysis to get standard error for each coefficient ($\hat{\beta}_{\text{adjusted}}$, $\hat{\beta}_{\text{unadjusted}}$, and penalty) in the previous stage (central estimates). The bootstrap approach is recommended by the literature when the coefficients are estimated from the same input dataset and from related regression models (Härdle et al., 2003; Politis, 2003). The bootstrap was based on randomized subsets (pseudo-datasets) of the input dataset that accounted for serial correlation structures among the observations of EC and OC. We defined a block size of 20 days to create 100 pseudo-datasets for each season. Then we applied the same models described in equations (1) and (2) (adjusted and unadjusted, respectively) for each pseudo-dataset. Finally, we estimated standard error for the unadjusted trend, weather adjusted trend, and penalty by obtaining standard deviation from the 100 estimate in the bootstrap analysis.

3. Results


In Figs. 2–4 we present time series based on the yearly average with and without season stratification. We used a smoothed conditional means function based on the raw monitored values to illustrate the temporal variation for each variable (weather parameters, particulate carbon, and wildfires). Trends derived from general regression analyses are discussed in section 3.2, and section 3.3 presents the long-term impacts of wildfire on carbon particles derived from GAM models.

Yearly average temperature was slightly constant from 1988 to 2008 (Fig. 2). Between 2008 and 2016, our results showed slight increase during the warm and cold seasons. Wind speed had an increase up to 1998 in both seasons. Then, wind speed decreases substantially between during the period 1998 and 2009. Thereafter, wind speed increased (Fig. 2). Relative humidity had a very similar temporal variation during the cold and warm season and for the analysis without seasonal stratification. Our results showed an increase in relative humidity up to 1999 then showed a decrease thereafter (higher decrease in the cold season) (Fig. 2).

Over the entire study period, the EC and OC annual average concentration were 0.28 µg/m$^3$ (standard deviation: 0.18 µg/m$^3$) and 1.14 µg/m$^3$ (standard deviation: 0.26 µg/m$^3$), respectively. Yearly mean concentration time series of EC and OC is presented in Fig. 3.

Overall, EC and OC concentrations decreased from 1988 to ~1993–1998. Then, the concentrations increased substantially up to ~2004–2005 (the pick of the highest concentrations of EC and OC during our study period). Thereafter, EC and OC had a considerable decrease up to 2016. Over this period with the drastic reduction (from ~2004 to 2005 to 2016), annual average EC concentrations decreased from 0.29 µg/m$^3$ in 2005 to 0.22 µg/m$^3$ in 2016, and those for OC decreased from 1.62 µg/m$^3$ in 2004 to 1.06 µg/m$^3$ in 2016.

We estimated a total area of 16,093,059 km$^2$ of vegetation was burned in our study area between 1988 and 2016. From those, 2,161,286 km$^2$ of occurred within the 50 km buffers. As expected, most of wildfires occurred in the warm season. Mean concentration time series of wildfires is shown in Fig. 4.

3.2. Trends in weather, particulate carbon, and wildfire

In Fig. 5 we present the results of trends analysis, which illustrate the yearly changes year in weather parameters (temperature, wind speed, and relative humidity), wildfire, and particulate carbon (EC and OC). As we mentioned in the previous section, this analysis was stratified by season – cold and warm seasons.

Trends analysis of temperature shows an annual decrease of 0.0244°C (95% CI: 0.0242; 0.0246) during the warm season and 0.0145°C (95% CI: 0.0143; 0.0147) in the cold period. Wind speed decreased in both seasons, 0.0191 knots (95% CI: 0.0189; 0.0193) per year in the warm season and 0.010 knots (95% CI: 0.0099; 0.015) per year during the cold season. Slight downwards trends were observed for relative humidity in both seasons. We estimated a yearly decrease by 0.0003 (95% CI: 0.0001; 0.0006) in the warm season and 0.0008 (95% CI: 0.0003; 0.0009) during the cold season (Fig. 5).

Wildfires increased in the warm season and decreased in the cold season. We estimated an annual increase of 20.106 km$^2$ of area burned (95% CI: 20.103; 20.109) in the warm period. In the cold season, areas burned by wildfire decreased 1.187 km$^2$ (95% CI: 1.181; 1.199) per year (Fig. 5).

For particulate carbon, our results showed statistically insignificant trends. In the warm period, EC and OC concentrations had an annual decrease of 0.03 µg/m$^3$ (95% CI: −0.14; 0.08) and 0.10 µg/m$^3$ (95% CI: −0.21; 0.01), respectively. In the cold period, our analyses showed an increase of 0.05 µg/m$^3$ (95% CI: −0.07; 0.17) and 0.07 µg/m$^3$ (95% CI: −0.04; 0.19) per year for EC and OC, respectively (Fig. 5).

3.3. Impacts of wildfire on particulate carbon

The impacts of wildfires on particulate EC and OC vary across seasons. We show in Fig. 6 the unadjusted and wildfire-adjusted trends for EC and OC stratified by season. In Fig. 7, we present the penalties. Daily EC concentration had an annual variation of −0.002 µg/m$^3$ (95% CI: −0.04; 0.0002) during the warm season and −0.003 µg/m$^3$ (95% CI: −0.02; 0.003) in the cold season (unadjusted model, Fig. 6). Removing the impact of inter-annual wildfire variation on EC trends (adjusted model, Fig. 6), the trends slightly decreased in the two seasons. The annual wildfire penalty was 1.02×10$^{-4}$ µg/m$^3$ (95% CI: 3.40×10$^{-5}$; 1.70×10$^{-4}$) and 3.56×10$^{-5}$ µg/m$^3$ (95% CI: −4.55×10$^{-4}$; 5.26×10$^{-4}$) for the warm and cold seasons, respectively (Fig. 7).

OC increased in the warm period and decreased in the cold season (unadjusted model, Fig. 6). During the warm season, OC had an increase of −0.004 µg/m$^3$ (95% CI: −0.007; 0.016) per year. In the cold season, the annual variation was −0.007 µg/m$^3$ (95% CI: −0.018; 0.002). If the wildfires had not changed between 1988 and 2016, the annual variation of OC concentration would be slight lower (adjusted model, Fig. 6). This indicates an annual wildfire penalty of 0.0005 µg/m$^3$ (95% CI: 0.0003; 0.0008) in the warm season and 0.0003 µg/m$^3$ (95% CI: −0.005; 0.005) in the cold season (Fig. 7).

4. Discussion and conclusion

Our findings showed significant temporal variation in weather, particulate carbon, and wildfires in the western U.S. during the period 1988–2016. This variation was observed when we estimated the yearly average time series, the trends using linear regression model, and the trends using GAMs model to estimate the impacts of wildfire on carbon particles.

Overall, the weather trends observed in our study (Figs. 2 and 5) were in agreement with those reported in the literature including: a temperature trends study reported by the U.S. Global Change Research Program (USGCRP, 2017), wind speed trends previously estimated by Pryor et al. (2009) and Jhun et al. (2015), and relative humidity trends analysis reported Brown and Degaetano (2013).

EC and OC trends derived from regression analysis (Fig. 5) showed decreases in the warm season and increases in the cold season. These air pollution trends did not present statistical significance. A recent study by McClure and Jaffe (2018) estimated trends at monitoring location over the U.S and also observed a substantial number of air pollution monitoring stations with insignificant trends. The authors showed that most of the monitors in western U.S. presented positive trends of carbon particles for the period 1988–2016. The monitors with positive trends
presented values varying between 0.16 and 0.28 μg/m³ per year. The area in the this recent study with the highest positive trends includes the states of Idaho, south Montana, Wyoming, north Utah, and north-east Nevada (McClure and Jaffe, 2018).

We also found wildfire increases during the warm and decreases in the cold season (Figs. 4 and 5). We estimated an increase of the area burned at a rate of 20.106 km² (95% CI: 20.103; 20.109) per year during the warm season. As mentioned in the introduction section, Dennison et al. (2014) estimated an increase of 355 km² of area burned per year. This difference compared to our estimates may be explained due to the study period, study area, and the approach considered by Dennison et al. (2014). Their timeframe analysis was from 1984 to 2011, they investigated 17 western states in the U.S, and they accounted for all wildfires within those states (we only accounted for the wildfires within 50 km buffer around each air pollution station). We were unable to compare our results with studies based on the same period and area as we accounted.

Based on the penalties estimated in our analysis (Fig. 7), we can suggest that the wildfire changes between 1988 and 2016 were associated with EC and OC concentration (statistically significant only in the warm season). While the results of the unadjusted model reflect the trends from a combination of wildfire, weather and emission changes;
and the results from the adjusted model removes the influence of inter-annual changes in wildfire on EC and OC concentrations, the differences between unadjusted and adjusted models (wildfire penalties) reflect the impact of long-term wildfire changes on EC and OC levels. Note that the wildfire penalty defined in our study accounts for direct (e.g., plume dynamics, weather characteristics, type of vegetation, topography) and indirect (e.g., social dynamics, including daily commute, closure of businesses) effects of wildfire conditions.

In the warm season, during the study period (1988–2016), the estimated total concentration change (total penalty) for EC was 0.003 μg/m³ (95%CI: 0.001 and 0.005) and for OC was 0.015 μg/m³ (95%CI: 0.008 and 0.022). Over the 29 years, the total wildfire-related increase (total penalties) in daily concentration of EC in the warm season represents 2.3% of the average EC concentration in western U.S during 1988 and 2016 (average EC concentration during this period was 0.13 μg/m³) and 5% of the first quantile (first quantile of EC concentration was 0.06 μg/m³). For OC, it represents 1.8% of the average OC concentration (average OC concentration was 0.83 μg/m³) and 3% of the first quantile (first quantile of OC concentration was 0.5 μg/m³).

Since the penalties were insignificant in the cold season, the discussion of the total penalties presented here is only focused on the warm period.

The highest penalties estimated in the warm season is related to the interrelationship among carbon particle concentrations, wildfires, and weather characteristics (Liu et al., 2014). Wildfire occurrence is mostly driven by weather conditions (warm season), which reflects the association of high temperatures and low humidity (Marlon et al., 2012). During the period 1988–2016, our findings showed that the total increase of areas burned in western U.S. in the warm season was approximately 583,000 km². Therefore, this increase in wildfire in the warm season reflects the wildfire-related increase in daily concentration of EC and OC in the warm season.

Our results can also be discussed considering only the interrelationship between air pollution and weather conditions, given that our models account for the influence of inter-annual changes in temperature, wind speed, and relative humidity on EC and OC concentration. Previous investigations have found positive correlation of temperature with carbon particles - EC and OC, and negative correlation of those carbon particles with relative humidity (Tai et al., 2010). Temperature and relative humidity are suggested as the most important determinants of the EC and OC trends. Strong effect of temperature and relative humidity in determining EC and OC concentrations has been reported in the literature (Hand et al., 2013; Murphy et al., 2011; Tai et al., 2010).

Some of the limitations to our current work include the EPA measurement. During the study period the EPA changed some measurement techniques used to estimate carbon particles throughout the U.S. This
Fig. 5. Changes per year in meteorological variable, wildfire, and PM$_{2.5}$ components in 1988–2016. Note 1: Temperature (temp), wind speed (WS), and relative humidity (RH). Note 2: (units for the meteorological variables): temperature (°C/year), wind speed (knots/year).
change may have the potential to confound the interpretation of long-term trends (Hyslop et al., 2015). However, we used an adjustment function suggested by Copeland et al. (2011) and Malm et al. (2011), which presents significant accuracy. Recent studies have used the same function model PM2.5 carbon particles in the U.S (Di et al., 2016; Meng et al., 2018). Also, due to computational limitations, we estimated the amount of area burned considering a buffer with 50 km around each air pollution monitoring station. This may underestimate the impact of wildfires close (< 50 km) to the air pollution station, and this ignores the impact of wildfire at distances above 50 km. Some studies have shown that emissions from wildfire can affect air quality far away from the originating fires (Jaffe et al., 2008). In addition, due to computation limitations, we estimated trends and penalties at regional scale, rather than site-level scale. That limitation reflects on the spatial variation of our results. This is also related to the spatial distribution of the air pollution stations over western U.S., which it is not homogeneous. Another limitation is related to the weather variables included in our model. We accounted for a limited set of weather variables to maximize completeness of the weather data. After reviewing the literature, temperature, wind speed, elevation, and biomass burning are identified as significant determinants of carbon particle concentrations. Other weather parameters could have been included such as raining, snow days, cloud cover, and atmospheric mixing height. However, many of these additional weather parameters may be strongly correlated with the weather variables already included in our models. Finally, there is a limitation with wildfire data, since there is less satellite detection during the initial years of our study period (from 1988 to 2000). This may affect the measurement data of fires and burned area.

Although of the limitations, this study expands the scientific knowledge on the long-term impacts of wildfires on major components of PM$_{2.5}$, which include EC and OC. Results from this investigation can better prepare health experts and environmental scientists by supporting model predictions in an area where changes in wildfire have had significant impacts on air quality. Given that there is an interrelationship between air pollution, weather conditions, and wildfires, our approach can be of interest to policy makers to devise future strategies related to environmental health and climate change.

Fig. 6. Unadjusted and adjusted trends for EC and OC in 1988–2016 by season.
Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This work was supported by the U.S. Environmental Protection Agency (grant RD-834798 and RD-835872). The contents of this report are solely the responsibility of the grantee and do not necessarily represent the official views of the U.S Environmental Protection Agency. Further, the agency does not endorse the purchase of any commercial products or services mentioned in the publication.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.atmosenv.2019.05.054.

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