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Air Quality Data Approach for Defining Wildfire Influence: Impacts on $PM_{2.5}$, NO_2, CO, and O_3 in Western Canadian Cities

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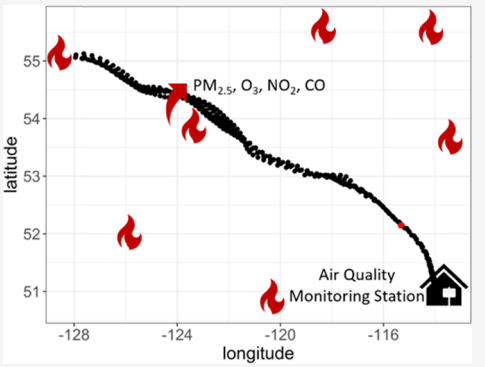
ABSTRACT: As the climate warms, it is recognized that wildfires are increasing in size and frequency. The negative effects of wildfires on air quality are well documented, especially on commonly monitored atmospheric pollutants such as $PM_{2.5}$, NO_2, CO, and O_3. However, it is not clear how frequently wildfires influence urban air quality and the size of that influence relative to traffic and industrial pollutants. To understand the impact of wildfires on air quality, we have established an automated method to identify wildfire-influenced ambient air measurements. The trajectory-fire interception method (TFIM) compares hybrid single-particle Lagrangian integrated trajectory (HYSPLIT) back-trajectories from an air quality monitoring station to satellite imagery of fire "hot-spots" to determine the number of trajectory-fire interceptions that occur. From the number of interceptions and local $PM_{2.5}$ measurements, we have defined a wildfire-influenced period to occur if the interception count is ≥20. TFIM wildfire identification compares favorably with Environment and Climate Change Canada's smoke forecast, FireWork, and with the BlueSky trajectory-based forecast. Using TFIM, we studied the impact of wildfire-influenced periods on $PM_{2.5}$, NO_2, CO, and O_3 from 2001 to 2019 in Western Canadian urban areas. We show that wildfire-influenced periods have elevated concentrations of $PM_{2.5}$, NO_2, and CO but not O_3. We show that a decreasing urban baseline of CO and NO_2 over time results in a relatively greater impact of wildfires on these pollutants, which emphasizes the changing relative importance of wildfires on air quality.



KEYWORDS: *wildfire, air quality, particulate matter, ozone, nitrogen dioxide, carbon monoxide*

INTRODUCTION

As the climate changes, it is recognized that extreme wildfire burning events will occur more frequently over larger areas.[1,2] The increase in frequency and size of wildfires has already led to negative environmental and economic effects. For example, the 2016 Horse River fire in Alberta, Canada, burned an area of 590 000 hectares in northeast Alberta.[3] The natural disaster, Canada's costliest to date, resulted in over $3.5 billion in insurance claims and in the evacuation of 88 000 people from the city of Fort McMurray.[4] Anthropogenic climate forcing effects are estimated to have increased the likelihood of extreme wildfire events in the region by 1.5−6 times relative to natural climate forcing alone.[5]

In addition to economic and environmental impacts, wildfires can also affect air quality, as occurred from the Horse River fire.[3] Primary pollutants emitted by wildfires include greenhouse gases, such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O).[6,7] Also widely studied are emissions of particulate matter, particularly $PM_{2.5}$ (defined as particulate matter <2.5 μm in diameter), and ozone (O_3) precursors such as carbon monoxide (CO), volatile organic compounds (VOCs), and nitrogen oxides (NO_x, which include NO_2 and NO). There is also evidence of wildfire influence on enhanced O_3 production.[8]

Exposure to pollutants contained in wildfire smoke has negative impacts on human health, with adverse respiratory, cardiovascular, and perinatal health outcomes that can lead to premature death.[9] In Canada, this can range from 54 to 240 deaths annually as a result of short-term exposure and 570 to 2500 annual premature mortalities from long-term exposure.[10] A recent toxicological study has suggested that $PM_{2.5}$ from wildfires is more toxic per unit mass than $PM_{2.5}$ from other sources.[11] It has become apparent that there are serious health risks from $PM_{2.5}$ and O_3 exposure below the regulatory standards, making the wildfire contributions to $PM_{2.5}$ and O_3 important to understand.[12]

Governmental agencies set air quality guidelines by recommending thresholds for selected air pollutants. In Canada, the $PM_{2.5}$ threshold as implemented by the Canadian Ambient Air Quality Standard (CAAQS) is set at an annual mean of 8.8 $\mu g/m^3$ and a 24 h mean of 27 $\mu g/m^3$.[13] The U.S.

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equivalent, the National Ambient Air Quality Standard (NAAQS), is set at an annual mean of 12.0 $\mu g/m^3$ and a 24 h average of 35 $\mu g/m^3$. These standards reflect the recommendations of air quality standards published by the World Health Organization.[14] Extreme wildfire events are considered "exceptional events" in the NAAQS and the CAAQS since they do not reflect changes in anthropogenic emissions and are removed from the data when calculating the 24 h averages and the annual mean of $PM_{2.5}$.[15] In the United States and Canada, there is no reporting standard about the impact of wildfires on air quality.

A major challenge to determining the impacts of wildfires on local air quality, and the focus of this paper, is determining when ambient air has been affected by wildfires. Overall, there is no widely accepted method to evaluate the influence of wildfires on local air quality, especially in populated regions. A combination of ground-based measurements, models, and satellite measurements has been used to make that determination, as summarized recently by Diao et al.[16] Understanding the contribution of wildfires to $PM_{2.5}$ and other pollutants has become increasingly important with the increasing frequency and severity of wildfires as the climate warms. This is especially true in urban areas given that the effort to decrease emissions from sources such as traffic and industry may be offset by increases in wildfire pollutants.[17]

Some studies have focused on individual wildfire events to understand their influence on local air quality.[18−22] Some of these studies have defined wildfire influence by setting a $PM_{2.5}$ threshold, with any measurement above that value considered to be wildfire-influenced.[23,24] This method can be delineated from background measurements by also considering the change in concentration of other biomass burning chemical tracers, with CO commonly used.[3] Other studies use back-trajectory modeling to confirm that there was a wildfire influence.[19] While these studies capture the extreme wildfire events well, they ignore the smaller contribution of pollutants from less extreme wildfires, which are more difficult to attribute relative to background pollution levels.

Trajectory/dispersion and chemical transport models used to identify wildfire influence are powerful because they can make assessments for any place or time. However, they typically rely upon wildfire emission databases, which remain quite uncertain, being very dependent on fuel type and location. Nevertheless, such models have been able to generate an analysis of the effects of wildfires on $PM_{2.5}$ concentration[25−27] and health outcomes.[10,11] These types of studies can estimate the contributions of pollutants from wildfires without interference from other sources.

To complement the use of these more detailed models, the approach developed in this work identifies wildfire influence by coupling back-trajectory analysis with publicly available fire hotspot and air quality data. This method is distinguished from models that rely on wildfire emissions databases/modules. We first use NOAAs' hybrid single-particle Lagrangian integrated trajectory (HYSPLIT) model to calculate back-trajectories from air quality monitoring stations. We then spatially and temporally overlay these trajectories with fire hotspot locations recorded in the Fire Information for Resource Management System (FIRMS) to determine if wildfires influenced the measured air quality data. One advantage of this approach is that it is driven by the actual pollutant concentrations and does not rely on emissions databases/modules. Another advantage is that this method is fully automated, so it can be applied to many stations for all time periods of interest.

Specifically, this project aims to understand the net impacts that wildfires have on air quality by (i) establishing an automated analysis method, which uses ground-based ambient air quality measurements coupled to back-trajectory analysis and satellite fire observations to determine if the air quality has been affected by wildfire smoke, (ii) comparing the measured concentrations of $PM_{2.5}$, NO_2, CO, and O_3 in urban regions with and without wildfire influence, and (iii) determining the relative impact of wildfires on human health in these locations using the Air Quality Health Index (AQHI). We use ambient air quality measurements from urban centers in Western Canada from 2001 to 2019, which are known to be prone to wildfire influence.

METHODS

Air Quality Data. Continuous air quality monitoring data ($PM_{2.5}$, O_3, NO_2, CO) were obtained from several ambient air monitoring stations in Western Canada using the National Air Pollution Surveillance (NAPS) program (https://www.canada.ca/en/environment-climate-change/services/air-pollution/monitoring-networks-data/national-air-pollution-program.html, last accessed April 2021). The station name, location, and hourly pollutant data used in this study are detailed in Table S1. Station locations are presented on a map in Figure S1.

The hourly data were averaged over 6 h using the OpenAir R package.[28] At least 75% (i.e., 5 or 6 h of data in a 6 h window) of measurements were needed to be included in our analysis, which corresponds to the CAAQS recommendation for 24 h averages. The data were further filtered for fire season, which we define here as May−September. Each year is considered a complete data set if at least 75% of the expected 6 h averages during the wildfire season were present. As a note, we describe the combined data sets of Calgary Inglewood and Calgary Central as "Calgary Center".

Back-Trajectory Analysis. We used NOAAs' hybrid single-particle Lagrangian integrated trajectory (HYSPLIT) model to track the geographic sources of air measured at each air quality monitoring station using the SplitR package. For each 6 h ambient air measurement, we ran six 72 h back-trajectories, one for each hour of measurement, with the back-trajectory originating at the location and altitude of the air monitoring station. We chose a back-trajectory length of 72 h to compliment previous studies using this method,[19] as well as the methods used by regulatory agencies when performing this type of analysis.[15,29] We ran the back-trajectories using the NARR meteorology archive, which has a resolution of 30 km.

Fire Locations. We obtained satellite data from the Fire Information for Resource Management System (FIRMS) U.S./Canada to identify the location of fires. Archived fire pixels from the moderate resolution imaging spectroradiometer (MODIS) on the Aqua and Terra satellites for Canada and the United States from 2000 to 2019 were downloaded (DOI: 10.5067/FIRMS/MODIS/MCD14DL.NRT.006, last accessed April 2021). We accessed the Standard Fire Products. The resolution of each fire pixel was 1 km × 1 km. More information about the MODIS measurements can be found in Giglio et al. and Justice et al.[30,31]

Air Quality Forecasts. Numerical model output data from Canadian wildfire forecast systems were accessed for comparison to outputs from our AQ-based retrospective

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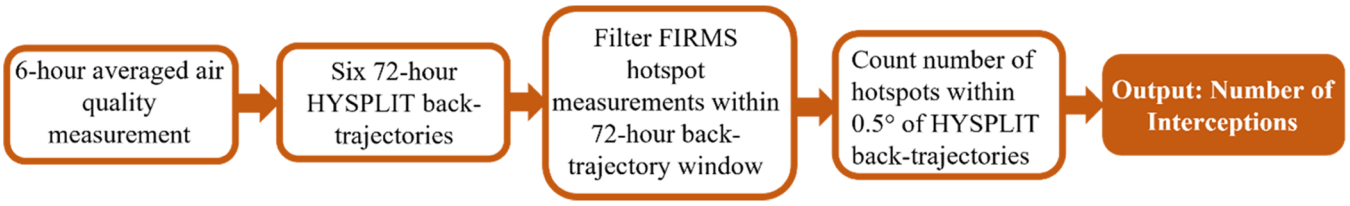

Figure 1. Stepwise workflow showing the procedural steps taken to get the number of interceptions output for our definition of wildfire influence.

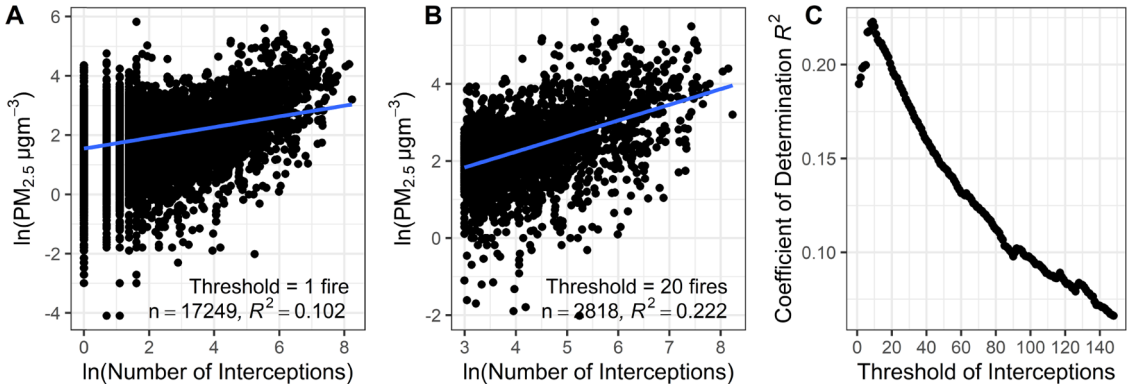

Figure 2. (A) Relationship between the number of interceptions between the back-trajectory receptor site and the fire hot-spots with the measured $PM_{2.5}$ for all of the air quality stations studied over all years. The blue line indicates the line of best fit. (B) Equivalent plot but only using data with ln(number of interceptions) > 3, showing an improved correlation to the line of best fit. (C) Coefficient of determination (R^2) as a function of the threshold of the number of interceptions included in the evaluation.

analysis approach. In particular, outputs from the Environment and Climate Change Canada's (ECCC) FireWork air quality forecast system for 2017 and 2018 were obtained for the months of June−August from Chen et al.[32] The contribution of $PM_{2.5}$ from biomass burning is determined from the difference in output between the Regional Air Quality Deterministic Prediction System (RAQDPS) and the FireWork air quality forecast. The FireWork forecast of ground-level $PM_{2.5}$ was averaged over the same 6 h period as the ambient air measurements. Briefly, FireWork integrates wildfire emissions into the Global Environmental Multi-scale-Modeling Air quality and CHemistry (GEM-MACH) chemical transport model and simulates the transport and chemistry of fire emissions over a 48 h forecast period. The model includes detailed atmospheric chemistry and meteorological parameters. More information on FireWork can be found in Chen et al. and Pavlovic et al.[32,33]

A second set of archived forecasts, from BlueSky Canada (BSC), was also downloaded (https://firesmoke.ca/forecasts/, last accessed April 5, 2021). BSC outputs four forecasts daily with a trajectory-based approach, and we compared the forecast closest in time to the 6 h ambient air quality measurement. The forecast times compared to our ambient measurement periods are presented in Table S2. The BSC forecast of ground-level $PM_{2.5}$ was averaged over the same 6 h period as the ambient air measurements. Briefly, BSC combines wildfire emissions with trajectory modeling to estimate the $PM_{2.5}$ concentration from wildfires. More information can be found in Larkin et al.[34]

Table S3 shows the area over which the $PM_{2.5}$ forecasts were averaged for each forecast model, relative to the ambient air quality monitoring station to which it was compared. FireWork data are available at a 10 km × 10 km grid resolution. BSC forecasts are available at a 4 km × 4 km grid resolution. A summary of each model is presented and discussed in the context of this project in the SI.

RESULTS AND DISCUSSION

Defining Wildfire Influence. To understand how wildfires impact air quality, we first determine if an ambient air measurement has been influenced by wildfire smoke. For each 6 h period, we ran six 72 h back-trajectories with HYSPLIT, i.e., one for each hour of the measurement period. These back-trajectories were then spatially compared to the fire hotspot data reported by FIRMS for that time. An interception was deemed to have occurred if the back-trajectory and the fire hotspot were within 0.5° of each other, which corresponds to a box of ∼30 km × 55 km in Western Canada. This process is presented visually in Figure S2. This range was chosen to be close to the 32 km resolution of the meteorological data used in HYSPLIT. If there was an interception, there was the potential for wildfire influence on the air parcel that was measured at the ambient air quality station. The stepwise procedure is outlined in Figure 1.

To test the hypothesis that interceptions indicate wildfire influence, we compared the number of interceptions along the trajectories to measured $PM_{2.5}$ values over a measurement period. It is well known that $PM_{2.5}$ is emitted by wildfires, and we further justify its choice as a wildfire tracer below. In Canada, wildfires contribute significantly to measured $PM_{2.5}$, including extreme events.[35] In particular, in Figure 2A, we show the relationship between the number of interceptions and the measured $PM_{2.5}$ for all our stations over all time periods. The correlation in the plot is not strong (R^2 = 0.102), presumably due to several factors, including the influence of nonwildfire sources affecting $PM_{2.5}$, the uncertainty in both the FIRMS measurements and the HYSPLIT back-trajectories, the variable emission intensity from individual fires, the degree of dispersion from distant wildfire sources, and scavenging of fire

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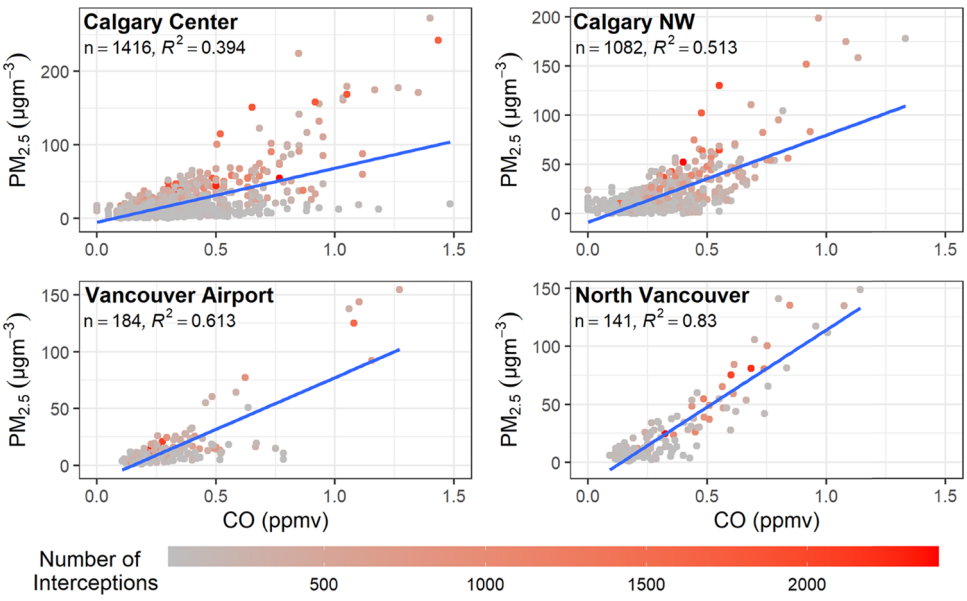

Figure 3. Plots showing the correlation between measured $PM_{2.5}$ and CO for wildfire-influenced periods at different ambient air quality monitoring stations. Blue line is the line of best fit.

emissions en route to the receptor site. Summertime weather and periods of warm, stagnant air can lead to the buildup of pollutants (like $PM_{2.5}$) at a monitoring site from anthropogenic sources, which contributes to the uncertainty in this method. We conclude from Figure 2A that identifying wildfire influence from a trajectory interception with only one fire hotspot is not effective.

Panel B shows the improvement in correlation when we set a threshold of 20 interceptions. Presumably, this improvement occurs because larger and/or more fires produce more $PM_{2.5}$, which then represents a larger fraction of the $PM_{2.5}$ measured downwind at the air quality monitoring station. In Figure 2C, we show how the coefficient for determination (R^2) value changes as the interception threshold is changed. The correlation reaches a maximum at an interception threshold value of ∼20, and so we set this threshold to indicate an ambient $PM_{2.5}$ measurement that is wildfire-influenced. We will refer to this definition of wildfire influence as the trajectory-fire interception method (TFIM) throughout the rest of this paper. This approach removes small fire hotspot counts, which are unlikely to contribute significantly to ambient pollutant concentrations, while including as many measurement periods as possible.

Given that CO arises from incomplete combustion and has a long atmospheric lifetime, the same type of analysis could theoretically have been performed with CO measurements. To test the usefulness of using CO as a tracer for wildfire influence in Figure 3, we show the relationship between measured concentrations of $PM_{2.5}$ and CO for four different air quality stations for TFIM-defined wildfire influence periods. The relationship between $PM_{2.5}$ and CO for all time periods is presented in Figure S3. The Kamloops station is not included because of a lack of CO measurements. The plots illustrate an important point. In a more highly traffic- and industry-polluted city such as Calgary, there are many periods when CO levels are high but $PM_{2.5}$ is not. These high pollution backgrounds are problematic for assessing wildfire influence using CO measurements alone. In particular, the range in the CO concentrations is not nearly as large as it is for the $PM_{2.5}$ levels. For example, periods with high wildfire influence are characterized by $PM_{2.5}$ values of over 100 $\mu g/m^3$, in contrast to clean periods with values up to roughly 2 orders of magnitude smaller. By contrast, because of the frequent and variable CO background, the equivalent mixing ratios for CO vary only mildly from just above 1 ppm to somewhat below 0.5 ppm. The much wider prevalence of $PM_{2.5}$ measurements compared to that of CO in publicly available air quality data sets is another justification for why we use $PM_{2.5}$ as a wildfire tracer.

Another way to validate the definition of wildfire influence using the TFIM method is by comparing the enhancement ratios (ERs) of $\Delta PM_{2.5}/\Delta CO$ to other studies. The ER represents the relative increase in $PM_{2.5}$ and CO above the background concentration during a wildfire event. From the slopes of the blue linear fits of Figure 3, we calculate ERs in the range of 0.066−0.135 $\mu g\ m^{-3}\ ppbv^{-1}$. These ERs all fall in the range of those measured in urban areas in the United States of 0.057−0.228 $\mu g\ m^{-3}\ ppbv^{-1}$ during wildfire-influenced periods to provide a second validation to the TFIM method.[36] As well, we note that our results also fall near the range of values reported in a recent compilation of biomass burning emission factors for boreal forests of 0.18 ± 0.17.[7] These numbers were calculated at 298 K and 1 atm of pressure.

Although the TFIM approach is a retrospective analysis using archived air quality data, it is nevertheless interesting to compare its results to forecasts from chemical transport models, specifically FireWork. We note that Munoz-Alpizar et al. have identified a minimum threshold for wildfire influence as a 24 h $PM_{2.5}$ average of 0.2 $\mu g/m^3$ above the average without wildfires, which is the lower limit of the FireWork forecast with minimal numerical noise.[25] They also chose to examine $PM_{2.5}$ thresholds of wildfire influence of 1, 2, 5, 10, and 25 $\mu g/m^3$. This range includes values similar to the EPA's significant impact level guidance document, which specifies that changes in the 24 h average below the 1.2 $\mu g/m^3$ threshold are negligible.[36]

Figure 4 presents the level of agreement between TFIM and FireWork, where we define an agreement to occur when both

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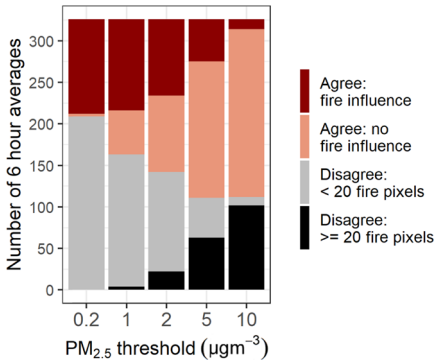

Figure 4. Number of 6 h measurement periods at Calgary Central in 2017 analyzed with the TFIM definition of wildfire influence. This definition is compared to five different wildfire influence thresholds from the FireWork forecast. Agreement indicates that both models had the same conclusion on wildfire influence, and disagreement shows that one method predicted wildfire influence when the other method did not.

approaches predict either no wildfire influence or wildfire influence. It is seen that the level of agreement increases to roughly 66% at thresholds of 5 and 10 $\mu g/m^3$. At the lowest threshold value of 0.2 $\mu g/m^3$, FireWork predicts a wildfire influence, which is not predicted by TFIM 64% of the time, which accounts for all of the disagreement. In Figure S10, we show that almost all of the disagreement arises for low concentrations of $PM_{2.5}$ that are close to background concentrations, but the models agree on wildfire influence for the high concentrations of measured $PM_{2.5}$. As well, a comparison to the BSC forecast using the same thresholds for defining wildfire influence is presented in Figure S11. The BSC definition of wildfire influence agrees with our definition ~80% of the time, regardless of the $PM_{2.5}$ threshold. The better agreement between the BSC forecast and TFIM is not surprising, given that both BSC and our method rely on back-trajectory analysis.

To compare the forecast methods with the TFIM approach, we note that the forecast models rely upon fire emissions modules, which are highly dependent on fire and fuel characteristics, and upon their representations of the physical and chemical processes that smoke emissions undergo in the atmosphere. Even direct comparisons of the two different forecasts with each other yield significant differences.[37] By contrast, the TFIM definition of wildfire influence is not subject to uncertainties in the emissions databases. However, it is a simple, data-based retrospective approach that cannot account for the impact that different fires have on the emissions or for scavenging processes along the trajectory path. As well, parameters in the model including the length of the back-trajectory and the definition of an interception will affect its output. Its key attribute is that it uses measured pollutant concentrations to assess wildfire influence.

Influence of Wildfires on Air Pollutant Concentrations and the AQHI. Figure 5 shows measurements of $PM_{2.5}$, NO_2, CO, and O_3 at Calgary Center from 2001 to 2019 (May to September) for TFIM-defined wildfire (red) and nonwildfire periods (white). The blue squares show the median, and the yellow circles represent the average for the entire wildfire season (May−September). Sample sizes and number of fires can be found in Figure 5E,F. Similar plots as in Figure 5 are shown in the SI for the other stations (Figures S3−S6). A different way of visualizing the wildfire-influenced vs nonwildfire-influenced days is presented in Figure S12, which shows a time series of $PM_{2.5}$ measurements made in Calgary Center in 2017 colored by wildfire influence. Calgary Center is discussed in detail because it has the most complete data set and the largest number of wildfire-influenced days.

Each point in Figure 6 illustrates the relationships between the average values of $PM_{2.5}$, NO_2, CO, and O_3 for wildfire-influenced periods versus nonwildfire-influenced periods at a particular station every year. Increased concentrations of $PM_{2.5}$ during wildfire-influenced periods are expected given our approach, as illustrated in Figure 6A, where most data points either lie along the black 1:1 line or above it. The degree to which the points are above the 1:1 line quantifies the wildfire influence.

Similarly, most of the median values of CO and NO_2 for periods that include wildfire influence are higher than nonwildfire days in Figure 5. Correspondingly, in Figure 6B,C, many CO and NO_2 data points fall above the 1:1 line, indicating that wildfires also influence these pollutants to a quantifiable degree. On the other hand, a consistent wildfire influence on O_3 is not demonstrated, with points roughly equally distributed above and below the 1:1 line in Figure 6D. Unlike CO, $PM_{2.5}$, and NO_2, which are the primary wildfire emissions, ozone is a secondary pollutant. NO_x-dependent, nonlinear chemistry associated with ozone production does not necessarily lead to elevated ozone mixing ratios at the measurement site since they may depend on the distance from the wildfire plume.[8] Overall, it is understood that ozone concentrations are not necessarily elevated in wildfire plumes, depending on a number of conditions including the nature of the fire, $PM_{2.5}$ level, time of day, and degree of photochemistry suppression by haze.[38−41] For example, an aircraft study of boreal forest fires showed little ozone enhancement, with occasional indications of ozone depletion in the wildfire plumes.[40] Indeed, it has been shown that with particularly high concentrations of $PM_{2.5}$, ozone concentrations can be suppressed during high $PM_{2.5}$ wildfire episodes.[42] Correspondingly, in our study (Figure S9), odd oxygen (here $O_3 + NO_2$) is shown to be, at times, both elevated and suppressed during wildfire-influenced periods. This is illustrating the complex relationship between ozone and wildfires, which is especially true in urban areas with existing pollutants. The TFIM does not address these nuances required to understand the mechanisms for changes in ozone pollution from wildfires.

The average mixing ratios of CO and NO_2 during the wildfire season (May to September) have decreased from 2001 to 2019, as illustrated by the blue rectangles in Figure 5. We attribute this to improvements in local air quality through anthropogenic emissions reductions. Interestingly, the ozone mixing ratios have not decreased with decreasing NO_2, which is indicative of the nonlinear relationship between ozone and NO_2. A similar lack of responsiveness to changing NO_x levels has been documented in other urban environments.[43−45] Figure S4E shows the average trends for odd oxygen (i.e., $O_3 + NO_2$). There is a small decrease in odd oxygen over the years from the decreasing NO_2; however, the smaller decrease indicates the nonlinearity between NO_x and O_3. With the decrease in traffic and industrial pollution levels, the pollution associated with wildfires is becoming a more important source of air pollution in a relative sense. Accordingly, wildfires in some regions could contribute to elevated $PM_{2.5}$ pollution

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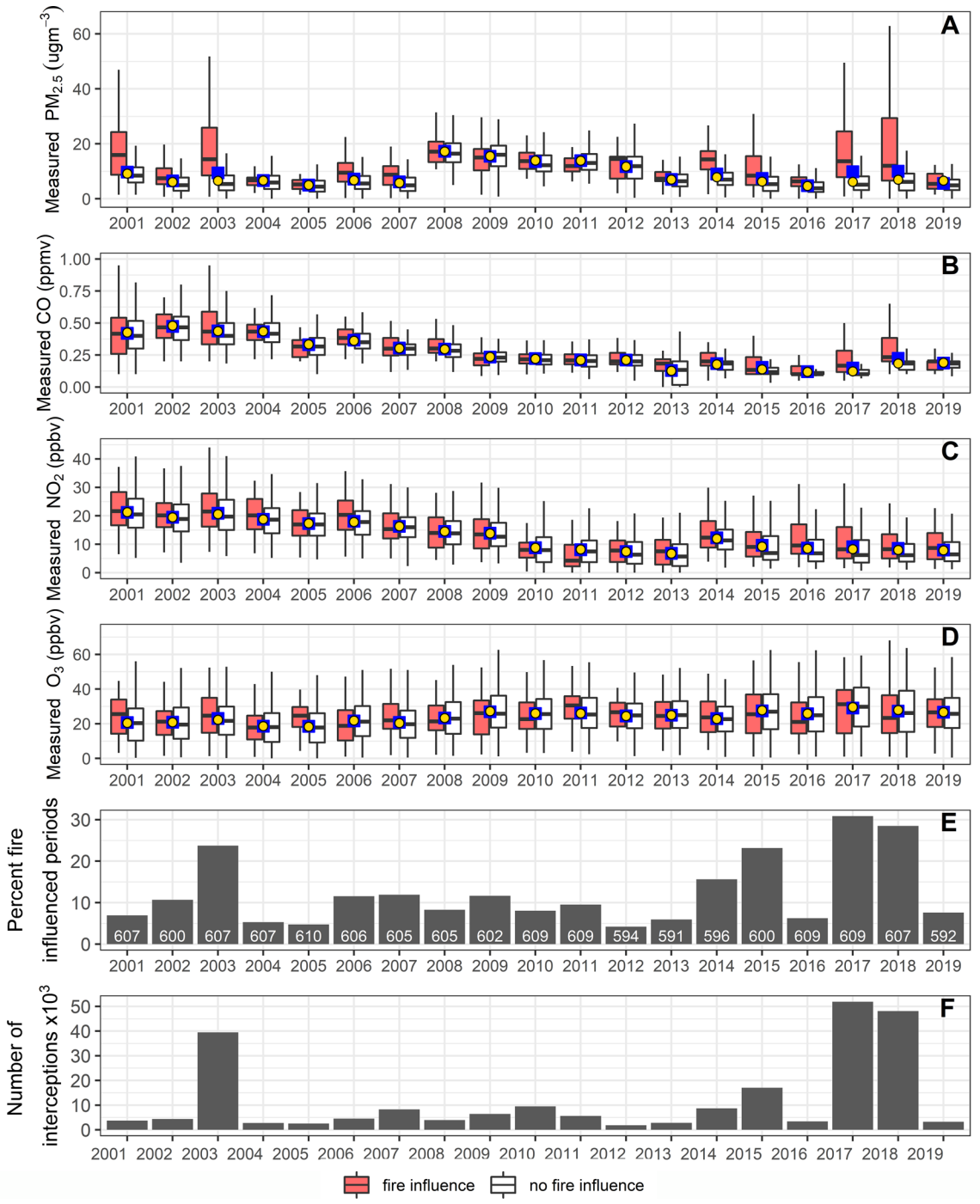

Figure 5. Boxplots showing the distribution of 6 h average measurements of (A) $PM_{2.5}$, (B) CO, (C) NO_2, and (D) O_3 for Calgary Center wildfire season (May−September). The outlier values are not included in this figure for clarity but are shown in Figure S4. The line in the boxplot represents the median, and the box represents the 25th and 75th percentile values. The blue squares represent the median value for the wildfire season, and the yellow circles represent the average value for the wildfire season. Panel (E) shows the percent of 6 h measurement periods influenced by wildfires, with the total number of 6 h measurement periods indicated by the white numbers. Panel (F) shows the total number of fires intercepted by all back-trajectories.

above the WHO guidelines of an annual average of 10 $\mu g/m^3$ even with measures to address anthropogenic pollution.[17]

The percentage changes of the average level of pollutants for wildfire-influenced periods compared to those for the non-wildfire-influenced periods are presented in Tables S4 and S5 for Calgary Center for the past two decades. The largest differences are in $PM_{2.5}$ and CO, with wildfire-influenced increases ranging from −0.1 to 95.2% for $PM_{2.5}$ and −0.5 to 26.5% for CO. The percent changes in NO_2 are also mostly positive but with a smaller range from −0.2 to 10.5%. The percent change in mixing ratios of O_3 is negligible, with no discernible trend. For CO and NO_2, the percent change becomes larger over time due to the reduction in background mixing ratios of these pollutants.

We use 2003, 2017, and 2018 to illustrate substantial wildfire influence, which resulted in large differences between wildfire-

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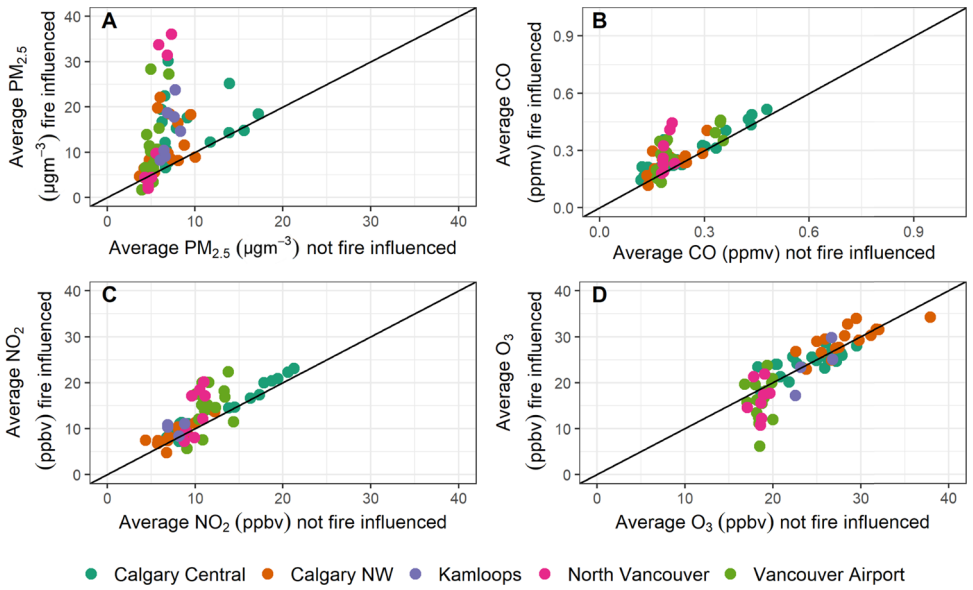

Figure 6. (A) Comparison between averages of $PM_{2.5}$ during wildfire-influenced periods vs nonwildfire-influenced periods for all locations. Points are colored by station location. (B–D) Same, but for CO, NO_2, and O_3.

and nonwildfire-influenced periods.[32,46] These years had more fire hot-spots intercepting the back-trajectories, more wildfire-influenced periods, more air quality exceedances, and the largest differences between the median values for wildfire- and nonwildfire-influenced periods (Figure 5E,F). They also have the largest percentage changes (Table S4) for $PM_{2.5}$. The percentage changes for NO_2 and CO are elevated in 2017 and 2018 but not for 2003. In 2003, elevated hemispheric CO in North America was attributed to the long-range transport of CO from Siberia, Russia, and China, which could account for the smaller percent change between wildfire-influenced and nonwildfire-influenced periods.[47]

Results from other cities (presented in Figures S3–S6) highlight the variable impacts that wildfires cause on local air quality in regions with different meteorology and baseline concentrations of pollutants. For example, with a maritime climate, Vancouver Airport and North Vancouver stations have very few wildfire-influenced periods (Figures S4 and S5). This is reflected in its low and steady baseline values of $PM_{2.5}$, CO, NO_2, and O_3. The wildfire-influenced periods increase the mixing ratio of pollutants well above the baseline mixing ratios; however, there are so few periods they do not increase the overall average significantly. In the case of Kamloops (Figure S5), the city is located near major fires in interior BC in 2017.[46] The effect from these wildfires is pronounced for $PM_{2.5}$ and NO_2 but not for O_3.

■ ENVIRONMENTAL IMPLICATIONS

Using the TFIM method, we have quantified the increase in $PM_{2.5}$, CO, and NO_2 during wildfire-influenced periods compared to that of nonwildfire-influenced periods; we saw no consistent changes in O_3. The wildfire relative contributions to NO_2 and CO levels increased with time due to a reduction in the background of these pollutants, as well as an increase in wildfire influence. This analysis highlights the need to consider the existing pollutant background when assessing air quality impacts from wildfires. Overall, the TFIM method, which uses standard air quality measurement products, provides an alternate approach to assess wildfire influence compared to more complex models that rely upon wildfire emissions estimates.

Our results can be viewed alongside the recognition that anthropogenic climate change is increasing the length of the fire season, fire intensity, and fire size, especially in Western Canada and the United States.[1,2,48−50] For example, changes in wildfire behavior have already been associated with $PM_{2.5}$ air quality in the Western US, with observations of decreased $PM_{2.5}$ concentrations except in wildfire-prone regions.[26,27] These trends emphasize the need to understand how wildfires will impact air quality in urban areas since the decrease in pollutant concentrations from traffic and industrial sources may be negated by increases in pollutant concentrations from wildfires.[17]

The identification of wildfire-influenced measurements is only triggered if there is an exceedance of the pollutant concentration above the national standards. The TFIM method explores the possibility of wildfire influence for all time periods, regardless of whether there is an exceedance. We show in Figure S13 that the number of wildfire-influenced days exceeds the number of days in which there is an exceedance in pollutant concentration, which emphasizes that wildfires can impact air quality without exceeding air quality standards. An important caveat to the calculation of ambient air quality with regard to the CAAQS and NAAQS is the treatment of exceptional events, such as wildfires. Once data have been determined to be caused by an exceptional event, they can be excluded from the CAAQS or NAAQS calculations because such events can often not be controlled and do not represent the average air quality of a certain location. With increasing wildfire prevalence, it can be argued that wildfire-influenced periods should be included in these assessments. Although challenging, some wildfires can be controlled through government policy.[51] Policy can also reduce human exposure to these pollutants with more stringent regulations of anthropogenic emissions, which would reduce the overall concentration of pollutants even during wildfire events. The method for determining wildfire influence presented in this paper presents a robust, data-based method that can be widely applied to

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Environ. Sci. Technol. 2021, 55, 13709−13717

identify such events at any location with continuous ambient air quality measurements.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.1c04042.

Details on air quality forecasts; forecast model description; air quality data for Calgary NW, Kamloops, Vancouver Airport, and North Vancouver; comparison to the BlueSky Canada forecast; and quantitative differences between wildfire- and nonwildfire-influenced periods (PDF)

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Notes

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