Hazardous Air Pollutants in Wildfire Smoke across the Western U.S., 2006-2020

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1. Introduction and Background

Due in part to climate change, wildfire smoke in ambient air is an emerging public health concern. In this study, increases in Hazardous Air Pollutants (HAPs) on smoke-impacted days were analyzed for the western U.S. (Figure 1). HAPs are listed chemicals under the Clean Air Act and known to cause cancer and other serious health impacts (U.S. EPA, 2014).

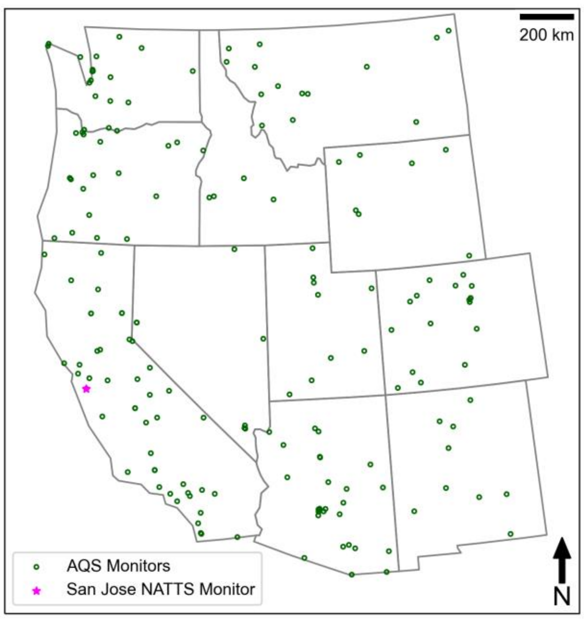

Figure 1. Map of U.S. EPA AQS monitors included in this study.

2. Data and Methods

In the primary analysis of this study, smoke-impacted days were identified across 15-years of U.S. EPA Air Quality System (AQS) daily monitoring data in western states (Figure 1) using NOAA Hazard Mapping System (HMS) remotely-sensed smoke plumes (Ruminski et al., 2006; Ruminski et al., 2007). Days were marked as smoke-impacted if an overhead smoke plume was detected at any point during that day. A permutation test (Mundry et al., 1999) was conducted on station-specific differences between smoke and non-smoke days to identify elevated HAPs both within each year and in the total 15-year period between 2006-2020.

Additionally, in a case study of measurements in San Jose, California, nonnegative matrix factorization (NMF) (Pedregosa et al., 2011) was used to separate sources of 13 HAPs at the San Jose National Air Toxics Trends Station (NATTS) monitor. Two factors were specified in the NMF model to separate temporal patterns in fire and non-fire sources. NOAA Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) (Rolph et al., 2017; Stein et al., 2015) back-trajectory modeling was used to link peak HAPs concentrations at the San Jose AQS monitor to Monitoring Trends in Burn Severity (MTBS) (Eidenshink et al., 2007) satellite-detected perimeters from major fires in 2017-2020.

3. Results

In the overall analysis, seven HAPs (**acetaldehyde, acrolein, carbon tetrachloride, chloroform, formaldehyde, manganese, and tetrachloroethylene**) were consistently higher on smoke vs. non-smoke days ($P<0.05$) over the 15-year period (Figure 2). Associations were generally stronger in 2017-2020 than in earlier years (Figure 3). In 2020, 13 of the HAPs were significantly higher ($P<0.05$) on smoke-impacted days. In the preceding 14 years, the number of HAPs higher on smoke-impacted days ranged between 2 and 10.

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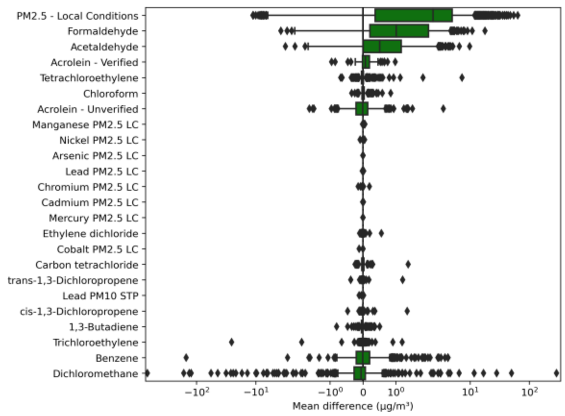

Figure 2. Distributions of year and station-specific mean differences on smoke-impacted days for each HAP and $PM_{2.5}$.

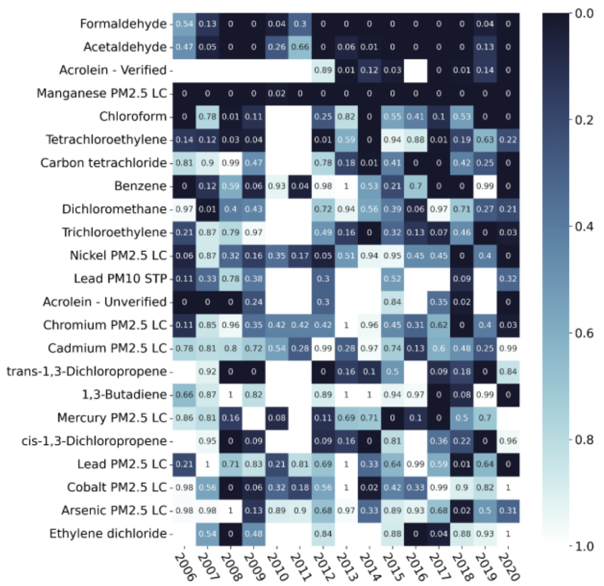

Figure 3. Annual P-values for each HAP resulting from a permutation test of the station-specific mean differences in HAP concentrations on days impacted by smoke. Darker color denotes lower P values.

Using HYSPLIT, air mass back-trajectories from days of elevated HAP concentrations were linked to the burn scars of four wildfire events near the AQS monitor in San Jose, California (Figure 4). NMF was used to separate the 13 included pollutants into two factors. Factor 1 of the NMF model, representing **1,3-butadiene, acetaldehyde, benzene, chloroform, and formaldehyde**, was elevated during wildfire events. HAPs scoring highest for factor 2 include carbon tetrachloride, dichloromethane, ethylene dichloride, tetrachlorethylene, and trichloroethylene. Minimums in Factor 1 were reduced in 2017-2020 compared to prior years of the study (Figure 5).

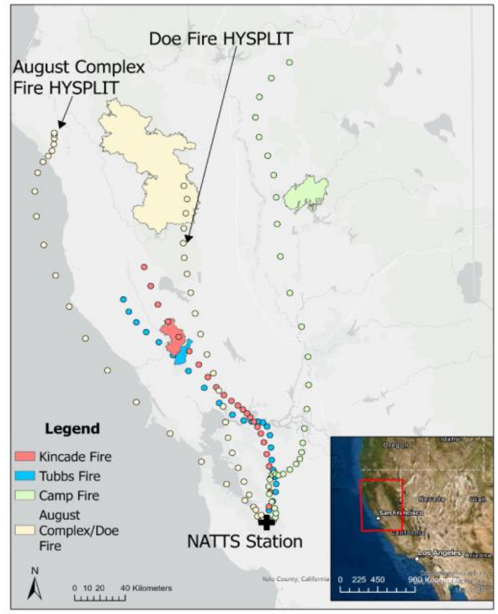

Figure 4. HYSPLIT back-trajectories attributing air measurements in San Jose to major wildfires in 2017-2020. Burn scar perimeters were obtained from MTBS.

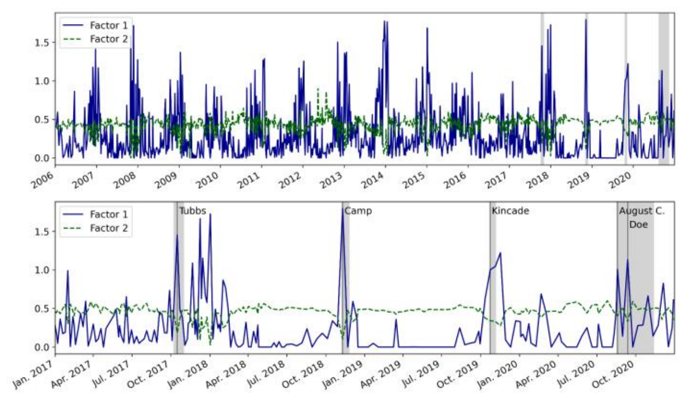

Figure 5. Temporal trends of the two factors identified in the NMF source separation analysis of 13 HAPs at the San Jose AQS monitor. Light gray shading represents duration of wildfire events, and dark gray lines indicate HYSPLIT modeling days mapped in Figure 4.

4. Conclusions and Next Steps

HAPs from wildfire smoke are an emerging risk to human health in western U.S. ambient air. **Acetaldehyde**, **chloroform**, and **formaldehyde** were identified as wildfire-associated in both the overall and case study analyses. In 2018 and

2020, more HAPs were identified as elevated than in other years in the study period. The case study of San Jose suggests that HAPs from industrial facilities in this area are declining, while those attributed to wildfire events are increasing.

Next steps include investigating the correlation between HAPs and $PM_{2.5}$ and comparing observed concentrations with U.S. EPA human health reference values. Additionally, we will explore trends in individual HAPs in San Jose and include additional case studies.

5. References

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