Emergency Mobile Monitoring for California Wildfire Smoke

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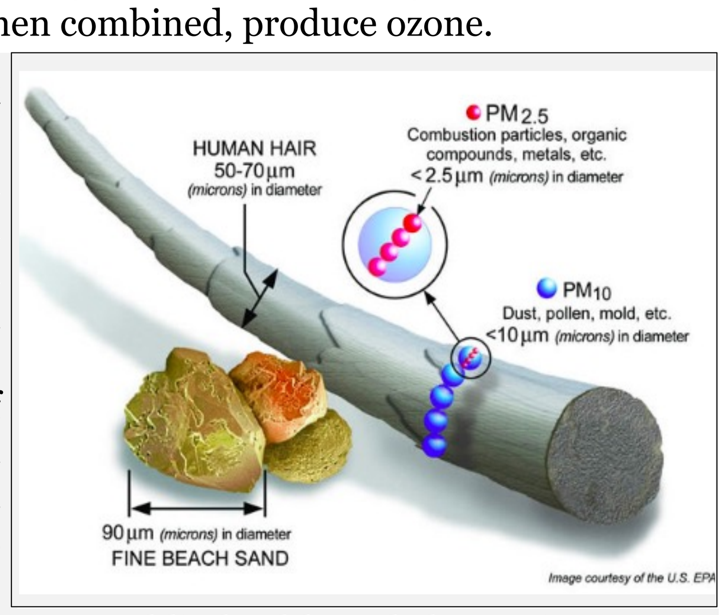
Abstract

Smoke from wildfires poses a severe threat to air quality, public health, and ecosystems across the United States, particularly in the West. Presently, air quality monitoring networks throughout California are fixed in space, which limits their ability to capture and characterize extreme pollution episodes that may be afar. To address this limitation, the California Air Resources Board (CARB) deploys emergency mobile sensors to monitor any hazardous airborne contaminants once a local agency has exhausted its resources to protect public health or the environment, most often due to wildfire smoke. However, CARB is confronted with a critical decision: how to strategically deploy emergency mobile sensors to effectively monitor human exposure to encroaching wildfires. Here we employ modal decomposition and Kalman filtering techniques to optimize the placement of CARB mobile sensors along a path that captures the spatial extent and temporal evolution of smoke exposure from 2006 to 2020. We suggest a generalized mobile path plan highlighting areas near the Northern Cascade region and the Central Valley region near the Sierra Nevada. We make performance comparisons against stationary sensors and demonstrate the cost-effective approach of mobile monitors. This sensor path planning proposal holds the potential to significantly impact CARB's resource allocation strategy, enabling them to make informed decisions.

Introduction

Primary PM2.5, or fine particulate matter with a diameter of 2.5 micrometers or smaller, is produced during wildfires when organic materials such as trees and vegetation burn. Wildfires can also lead to the secondary formation of PM2.5. The intense heat can trigger chemical reactions between gases released during the fire (such as VOCs and NOx which when combined, produce ozone.



Wildfires are significant generators of PM2.5 emissions, which can have severe impacts on the environment both near the fire zone and far beyond the source. Proper management of these wildfires and efforts to prevent and control their spread is essential to reducing PM2.5 emissions and protect public health and the environment. These tiny particles are so small that they can easily enter our respiratory system and even penetrate deep into our lungs. Once inhaled, PM2.5 can trigger a range of health problems, especially for vulnerable populations like children, the elderly, and those with respiratory conditions. Not only does PM2.5 from wildfires pose a threat to human health, but it also wreaks havoc on the environment. These minuscule particles can travel long distances, affecting air quality far away from the wildfire source.

By planning to implement mobile monitoring systems for CARB, this enables them to track PM2.5 emissions during these high pollution episodes.

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Methodology

Here modal decomposition and Kalman filtering techniques are employed to optimize the placement of CARB mobile sensors along a path that captures the spatial extent and temporal evolution of smoke exposure from 2006 to 2020.

Dynamic Mode Decomposition is a mathematical algorithm used in data analysis and modeling. It is used to extract coherent structures, patterns, or modes from high-dimensional data, typically in the form of time-series data. It essentially breaks a system down into spatio-temporal modes with time evolution associated with them. It works a little bit like a Taylor Expansion in Calculus. In the Taylor Series, you can get the key local behavior of a function from the first few terms.

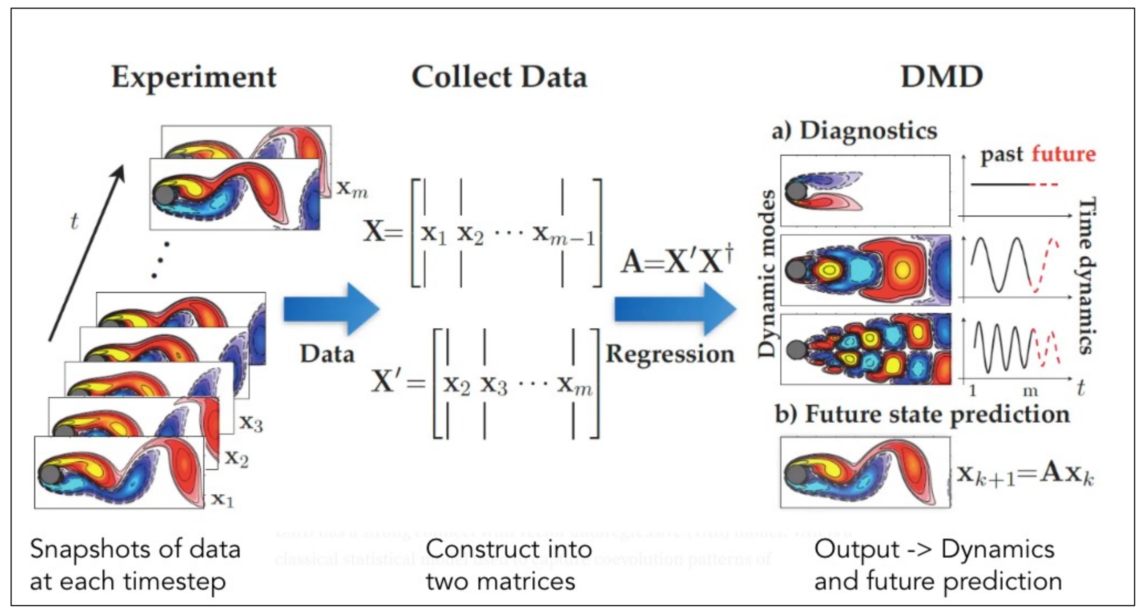

Figure 2: Dynamic Mode Decomposition from the University of Wisconsin Madison Multiphase Flow Visualization and Analysis Laboratory.

Using the prediction of future state from the DMD, we feed it into the Kalman filter to determine a best-fit path for mobile monitoring sensors to follow.

The Kalman filter is also a mathematical algorithm that is used for estimating the state of a system by combining measurements from different sources with predictions from a dynamic model. It is commonly used in various applications; however, we use it to determine a path based on data collected from sensors or measurements. By combining the dominant modes/patterns from the DMD along with our smoke data, we can utilize the Kalman Filter.

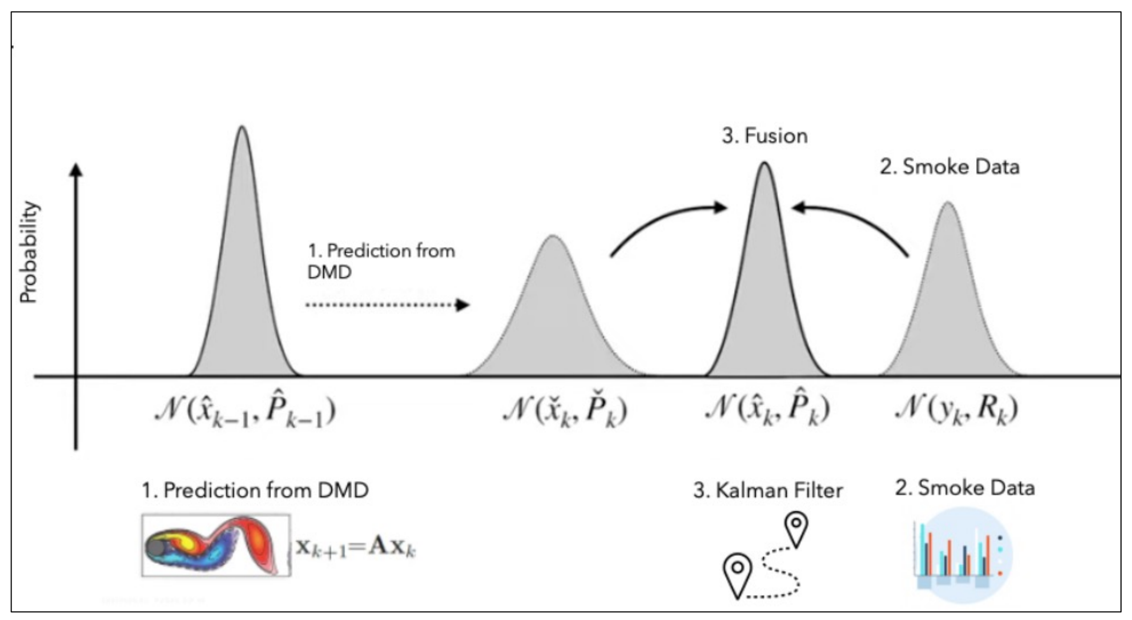

Figure 3: Kalman Filter Visualization. Using the future state prediction from the DMD, and the smoke concentration data, fuse the two using the Kalman filter, to spit out a specific path based on the data.

Results

To analyze our data which currently holds smoke concentration data for every day between 2006-2020, we only want to look at the year 2018, in which California experienced a plethora of wildfires that year during September and October.

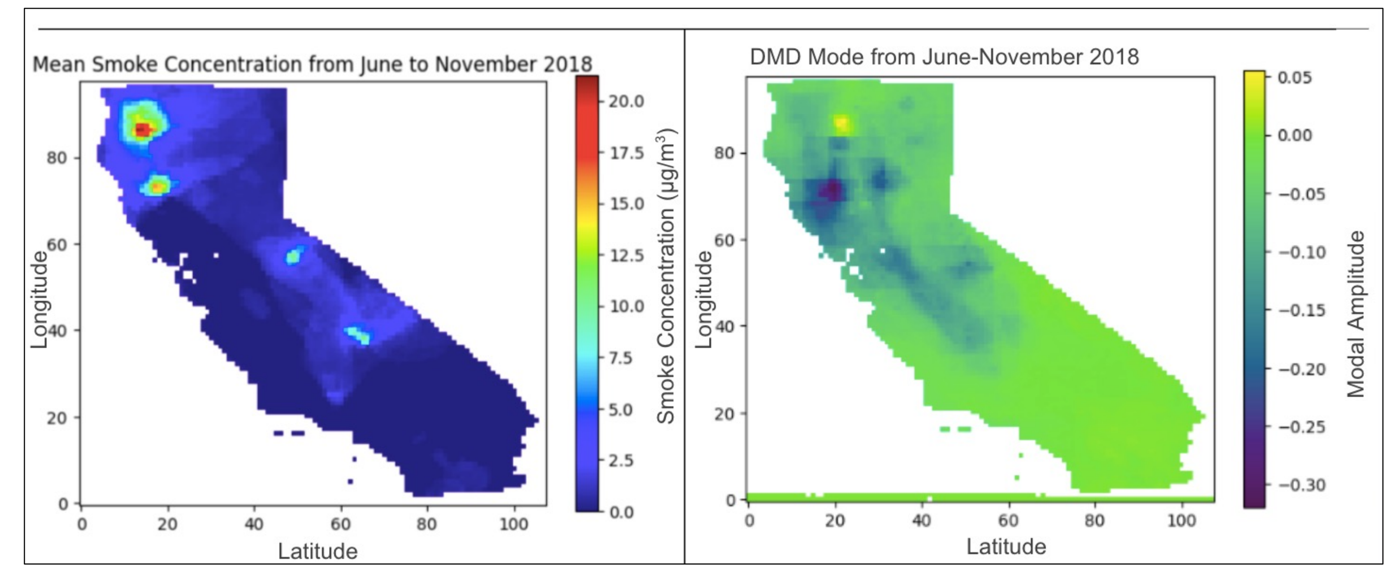

Figure 4a (left): Mean smoke concentration from June-November in the year 2018. The color bar indicates the smoke concentration measured in micrograms per meter cubed from high (red) to low (blue). Figure 4b (right): Applied DMD to extract the coherent structures and patterns from the data. The color bar indicates modal amplitude from high (purple) to low (yellow).

Apply the Kalman filter based on the mean concentration smoke data, to determine a best-fit path for the mobile monitor sensors.

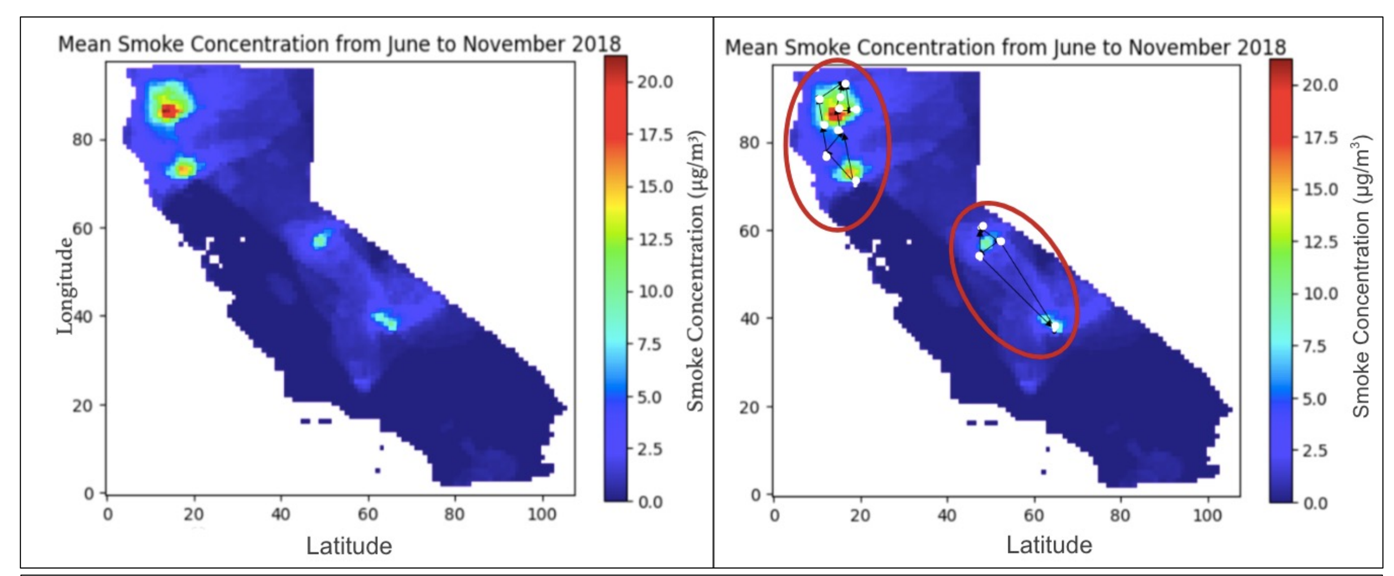

Figure 5: Kalman filter applied over DMD and placed pathways at high smoke concentrations.

Test the Kalman filter on a much larger dataset over the whole time series between 2006-2020.

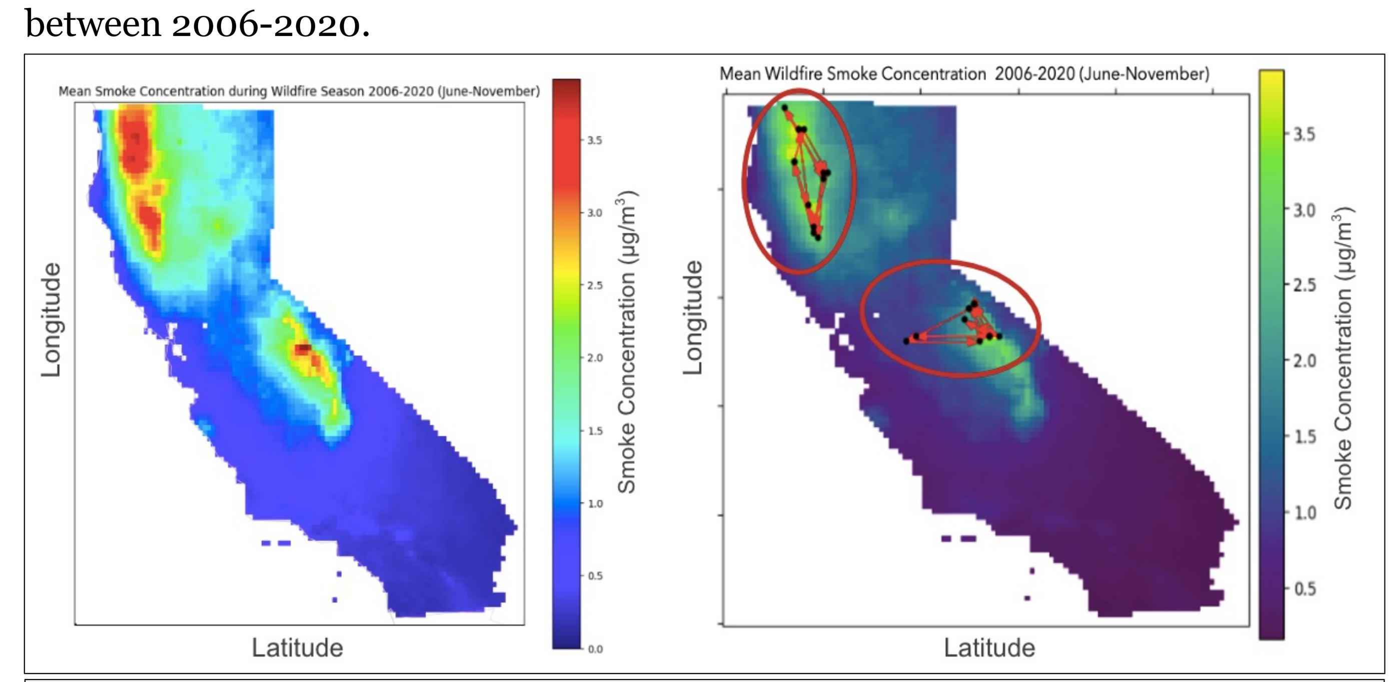

Figure 6a (left): Mean smoke concentration from June-November between the years 2006-2020. The color bar indicates the smoke concentration measured in micrograms per meter cubed from high (red) to low (blue). Figure 6b (right): Applied Kalman filter over DMD to determine a path based on the coherent structures and patterns from the data. The color bar indicates modal amplitude from low (purple) to high (yellow).

Discussion

In Figure 4a; the Northern Cascade region is lit up with smaller fires throughout the central valley, which coincides with where the wildfires occurred that year. In Figure 4b; the DMD very clearly detected smoke in similar regions. DMD not only notices the hot spot of smoke in Northern California but also highlights areas with less smoke and more variability as seen in the Central V alley. DMD is utilized because using the mean or standard deviation would not highlight these spots with higher smoke variability.

Figure 5 represents feeding the DMD data through the Kalman filter between June and November for the year 2018 to determine a best-fit line as shown by the arrows.

Figure 6a depicts the mean smoke concentration during the wildfire season between 2006-2020. The Northern Cascade region is lit up as well as the central valley area around the Sierra Nevada region. Figure 6b; the Kalman filter is applied over the mean concentration from DMD. It spits out this path throughout the areas experiencing higher than usual presence of wildfires between those years. The arrows indicate a proposed path due to the smoke data and predicted state from DMD. The Kalman filter accurately determined a path based on the DMD patterns and variability of the smoke data. The bottom path in Figure 6b diverges from the area of highest smoke to cross the central valley. This is to capture smoke variability in this region, even though it is not the smokiest during this period.

Conclusion

By successfully determining a route for mobile monitors to travel, this allows better data collection and more accurate data. By pinpointing these distinct paths, we can now switch to using more cost-effective mobile monitors as opposed to relying on fewer, pricier, and less dependable stationary monitors. This sensor path planning proposal holds the potential to significantly impact CARB's resource allocation strategy, enabling them to make informed decisions. By enhancing our path planning methodologies, we can not only advance our understanding of air quality but also make vast improvements in human health and the surrounding ecosystems that rely on it.

Acknowledgements

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