

# Wildfire Pollution and Climate Change

M. Shehzaib Anjum\*, Indrila Ganguly, Swarnali Sanyal, Srijan Sengupta, and Viney P. Aneja

North Carolina State University, Raleigh, NC 27695

## Abstract

The impacts of climate change are wide ranging and still not fully understood. Increasing frequency, intensity and duration of wildfire activities in recent years are largely attributed to the rapidly changing climate. Increasing temperature and drier conditions associated with climate change, as well as improper land-use and human activities, have all enhanced the risk of wildfires. This recent increase in wildfire duration and coverage area has resulted in increased emissions of hazardous air pollutants. These wildfire emissions are significant because they contribute to a positive climate change feedback loop while also posing serious environmental health concerns for the exposed populations. Recent toxicological studies have revealed that particulate matter less than 2.5µm (PM 2.5) emissions from wildfires is likely more hazardous to human respiratory health than equal doses of ambient PM 2.5. To accurately quantify and mitigate these effects of wildfire pollution, existing measurement and wildfire prediction need to be improved. To accomplish this, we are developing a novel statistical framework that integrates physicochemical models of emissions and satellite observations to deep learning models. Our framework will improve the accuracy of forecasted pollution emissions and help mitigate the associated human health burden.

## Objective:

- Determine the concentrations of PM<sub>2.5</sub> in the Wildfire region
- Scientific modeling of wildfire emissions
- Satellite (MODIS) analysis of AOD (Aerosol Optical Depth) as a surrogate for PM<sub>2.5</sub>

## Data preparation and integration

Existing scientific models for predicting wildfire emissions rely on data collected during controlled forest burns, lab-burn experiments of vegetation, and physics-based simulation, or require constant expensive drone data collection of the area to determine fire growth in a region (Finney, 1998; Forghani et al., 2007; Lin et al., 2018). The existing commonly used models are computationally expensive to run. Physical models of wildland fire spread (Sullivan, 2009) have also been developed, but are highly complex and typically include heat transfer conservation laws, equations describing combustion chemistry, etc. Their use is generally limited to research purposes. Therefore, we propose a novel spatio-temporal forecasting model combining recurrent neural networks (RNNs) and convolutional neural networks (CNNs) (Figure 1). RNNs enable efficient modeling of time series data by propagating and updating information from previous time steps using non-linear, differentiable transformations (Boden, 2002).

On the other hand, CNNs, which are regularized versions of multilayer perceptrons, are able to capture spatial information. CNN+RNN architectures have proven to be successful in a number of similar tasks including precipitation forecasting (Shi et al., 2015), traffic prediction in transportation networks (Yu et al., 2017), music classification (Choi et al., 2017), and video frame prediction (Hosseini et al., 2019). The below figure (Figure 1) provides a schematic of the proposed forecasting model. The input variables are (i) past/ current fire perimeter, (ii) hydrological conditions, (iii) meteorological conditions, and (iv) ground conditions. This model will be combined with a statistical regression model of the form

$$E_i = f(BA),$$

where  $E_i$  is the emissions for species  $i$ , and  $BA$  is the (forecasted) burned area predicted by the deep learning model. This regression model will be trained on data generated by the physicochemical

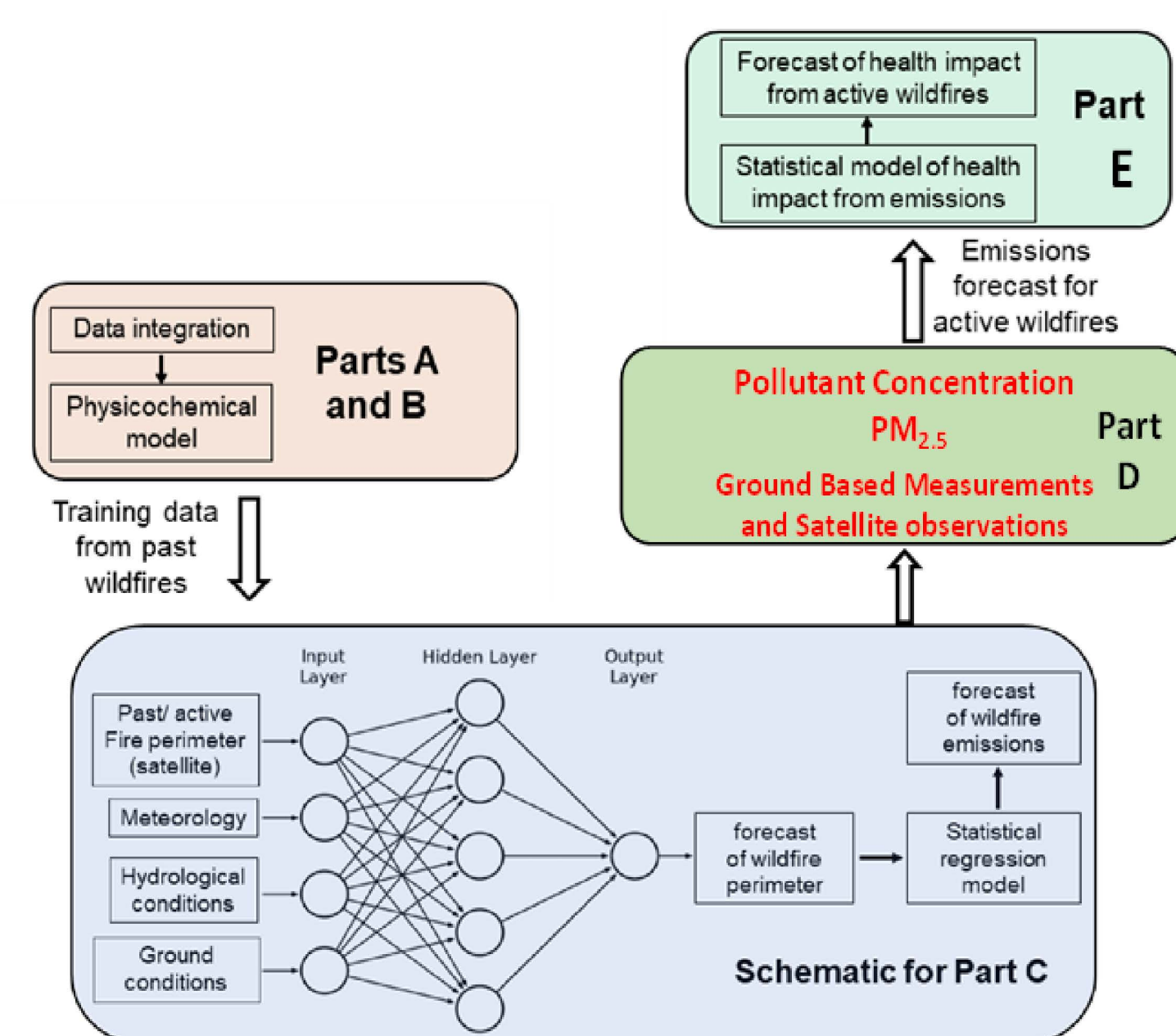


Figure 1: Schematic of the proposed forecasting model

## Results

Preliminary Results are provided for California wildfires averaged for (2015-2020). The Fire counts were observed to be the largest during the summer months (May-August), with around ~295 to ~305 fire counts per day (Figure 2). However, the size and the intensity of the wildfires are in the process being examined for a more granular analysis of the wildfires.

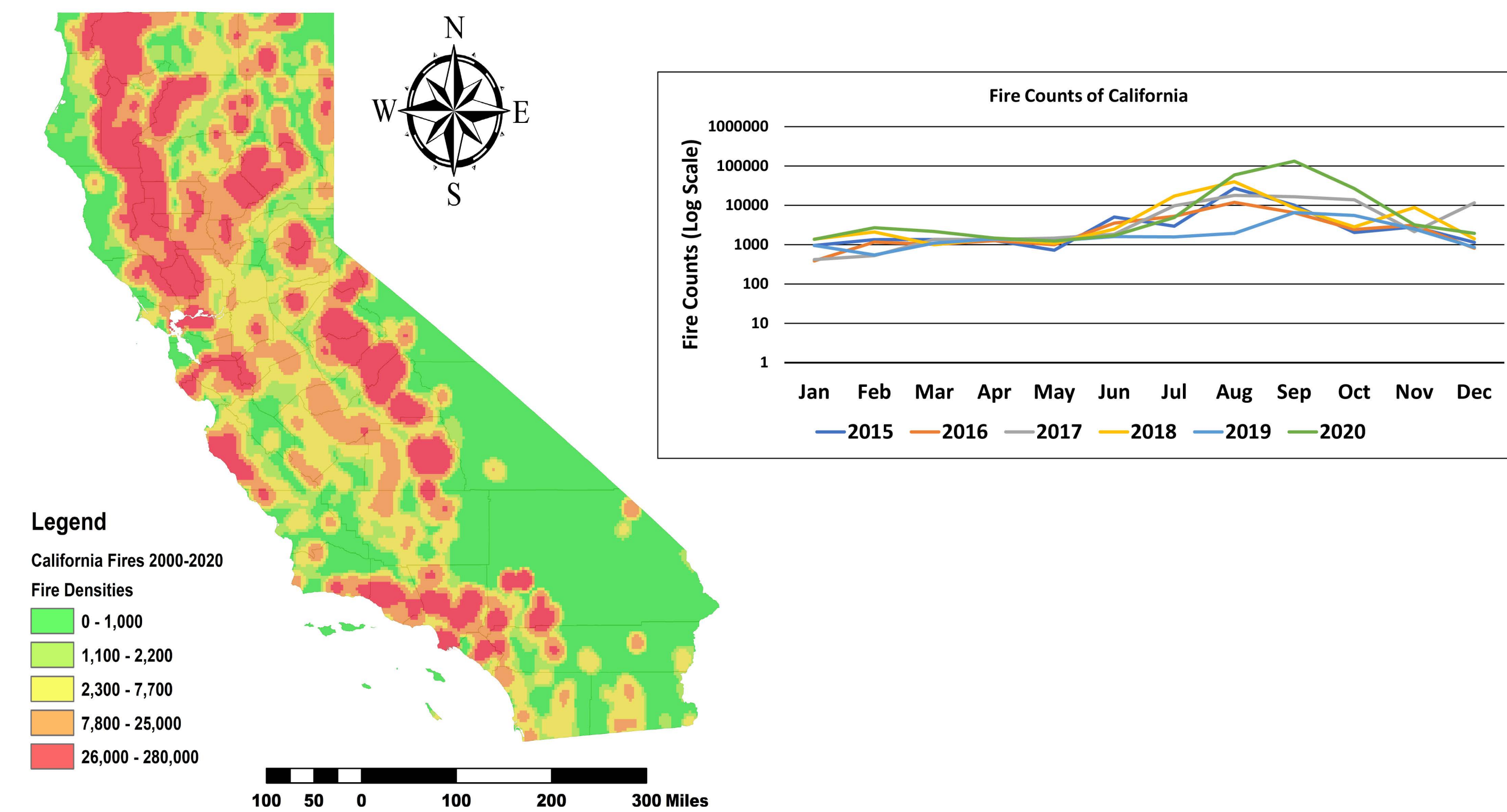


Figure 2: (a) Map Highlighting California Fire density (2000-2020); (b) Averaged (2015-2020) California Wildfires Fire Counts,

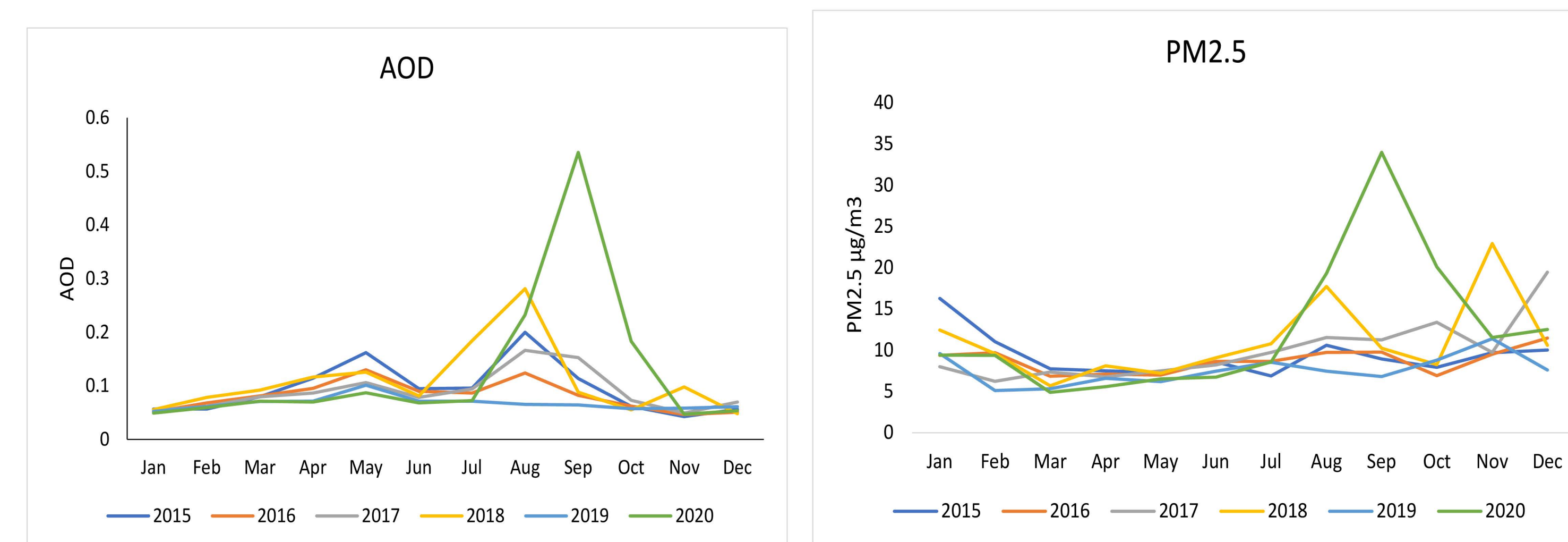


Figure 3: Averaged (2015-2020) (a) PM<sub>2.5</sub> concentration µg/m<sup>3</sup>, and (b) Satellite (MODIS) Aerosol Optical Depth (AOD)

Figure 3 provides AOD and PM<sub>2.5</sub> averaged monthly values from 2015-2020. 2018 and 2020 were intense wildfire seasons in California. Monthly Averaged Satellite AOD is used as a surrogate for PM<sub>2.5</sub>. Figure 3, suggests that AOD (Aerosol Optical Depth) during the fire season (May-August) for 2018 and 2020 were ~0.3 and ~0.53 respectively. Simultaneously the PM<sub>2.5</sub> concentrations during the same time period were ~19 (2018) and ~33 µg/m<sup>3</sup> (2020). These are monthly averaged value analysis the PM 2.5 concentration. However a more granular analysis of daily 24 hour averaged values for September 2020 (for county Mono) far exceeded (~500 to ~700 µg/m<sup>3</sup>) the US National Ambient Air Quality Standard (35µg/m<sup>3</sup>)

## Case Studies

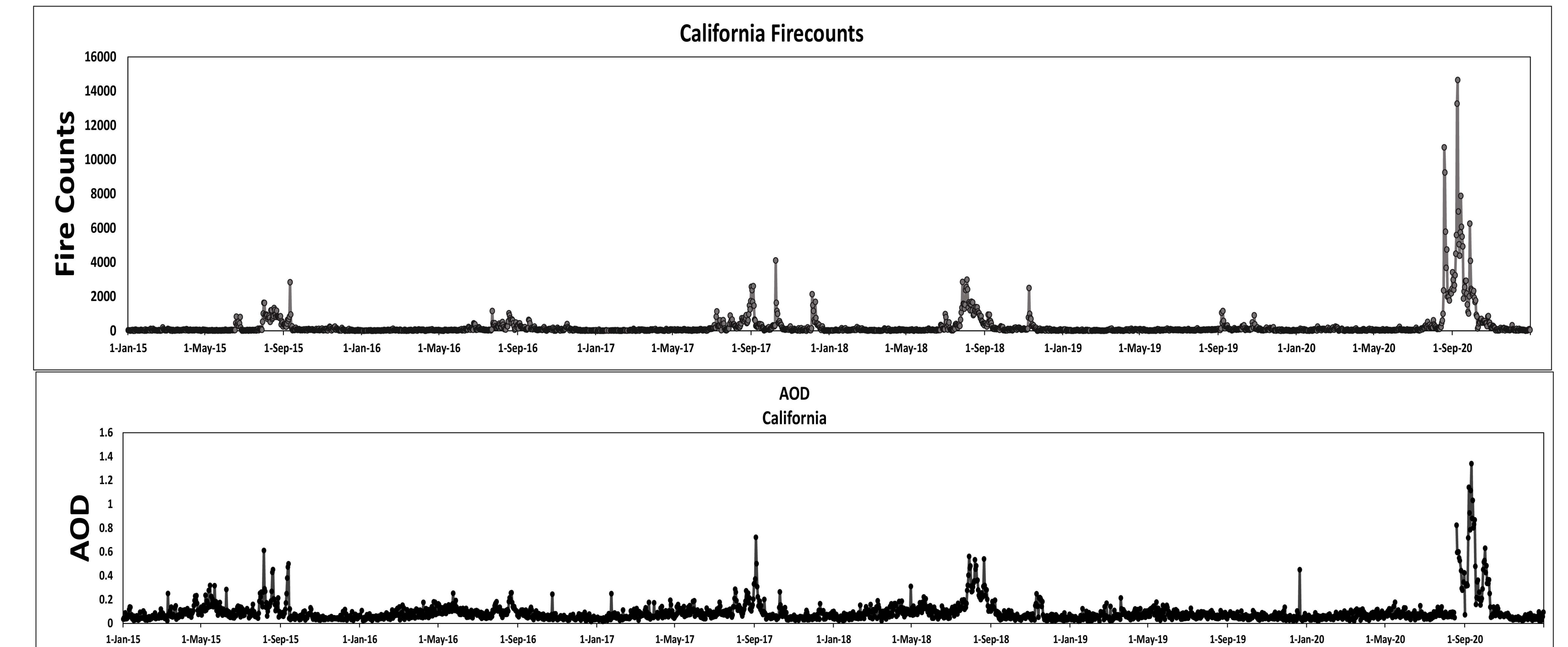


Figure 4: Daily VIIRS Fire Counts and Daily AOD values (MODIS) from 2015-2020 averaged for California and

According to this comparative analysis we can observe that during periods of intense fire activities such as during 2015, 2018 and the recent 2020 fires the AOD (Our surrogate for Air Quality) is high. This highlights the fire seasons impact on air quality and human health.

## Conclusion

- The Frequency of wildfire events have increased from 2015 to 2020
- Satellite and Ground-based measurements show agreement during intense wildfires
- The PM<sub>2.5</sub> Standard is exceeded during intense wildfires, e.g. 2020

## References

Boden, M. (2002). A guide to recurrent neural networks and backpropagation. the Dallas project, 2(2), 1-10.  
 Finney, M. A. (1998). FARSITE, Fire Area Simulator--model development and evaluation (No. 4). US Department of Agriculture, Forest Service, Rocky Mountain Research Station.  
 Forghani, A., Cechet, B., Radke, J., Finney, M., & Butler, B. (2007, July). Applying fire spread simulation over two study sites in California lessons learned and future plans. In 2007 IEEE International Geoscience and Remote Sensing Symposium (pp. 3008-3013). IEEE  
 Lin, Z., Liu, H. H., & Wotton, M. (2018). Kalman filter-based large-scale wildfire monitoring with a system of UAVs. IEEE Transactions on Industrial Electronics, 66(1), 606-615.  
 Liu, J.C., G. Pereira, S.A. Uhl, M.A. Bravo, and M.L. Bell. 2015. "A systematic review of the physical health impacts from non-occupational exposure to wildfire smoke." Environmental research 136:120-132.

## Acknowledgement

We thank CHHE for their generous Support to conduct this research  
 We thank EPA for providing the ground based PM<sub>2.5</sub> measurement data  
 We thank NASA for providing the satellite data products used in this analysis  
 We thank Fulbright Fellowship for providing financial support to MSA