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Wildfire Pollution Exposure and Human Health: A Growing Air Quality and Public Health Issue †

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Abstract: Wildfires emit large quantities of air pollutants into the atmosphere. As wildfires increase in frequency, intensity, duration, and coverage area, such emissions have become a significant health hazard for residential populations, particularly vulnerable groups. This health hazard is exacerbated by two factors: first, wildfires are expected to increase in frequency as a result of climate change and, second, human health is adversely impacted by fine particulate matter produced from wildfires. Recent toxicological studies suggest that wildfire particulate matter may be more toxic than equal doses of ambient $PM_{2.5}$. The role of ammonia emissions from wildfires on $PM_{2.5}$ is examined. The impact of poor air quality on human health is examined and some strategies are discussed to forecast the burden of diseases associated with exposures to wildfire events, both short and long term, and help develop mitigation strategies.

Keywords: wildfires; respiratory health; deep learning; forecasting; air quality; fine particulate matter

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1. Introduction

During the last few decades, wildfire activity has been increasing. Moreover, climate change will enhance wildfire activity, resulting in increased human exposure to wildfire pollutants [1]. Acute and chronic exposures to wildfire particulate matters (PMs) are associated with premature mortalities, predominantly cardiovascular and respiratory [2]. Recent evidence suggests that $PM_{2.5}$ from wildfires causes an enhanced adverse impact on human health when compared to $PM_{2.5}$ exposure from other sources [3]. Increased daily mortality has been observed from air pollution exposure associated with dust storms and biomass burning [4,5]. Wildfire smoke contributes to high levels of air pollutants, which are risk factors for adverse cardiovascular effects, especially in vulnerable populations, and significantly contribute to morbidity and mortality in communities with health disparity, especially minority populations [6].

Research is needed for human health exposure studies from wildfire [7]. The role of climate change on human health impacts in the future needs to be examined, which will allow mitigation policies to be implemented. To improve our ability to predict the public-health burden of wildfire emissions, we need to forecast air pollutant and particulate emissions from active fires. Emissions depend on a number of variables, such as burned area, biomass, meteorology, ground conditions, soil moisture, etc. However, most of these variables are difficult to measure or even forecast for active fires.

2. Results

Pollutant emissions, e.g., NH_3 and $PM_{2.5}$ emissions, from wildfires are calculated using Equation (1) [8–11]:

$$E_i = B(x) * BA(x, t) * EF_j * FB \tag{1}$$

where:

E_i is the species' emissions (g),
$B(x)$ is the biomass loading at location x (g/m^2),
BA(x,t) is the burned area at location x and time t (m^2),
EF_j is the emission factor for species j (g species g^{-1} biomass burned), and
FB is the fraction of biomass burned.

Wiedinmyer et al. [11] published biomass loading (B(x)) values for different regions. Collection 5 MODIS Global Land Cover Type product (MCD12Q1; 500 m) Version 6 for 2018 was utilized to estimate land cover classification [12]. Burn area, (BA(x,t)), is determined using the Moderate Resolution Imaging Spectroradiometer (MODIS)/Aqua+Terra [13]). Wiedinmyer et al. [10,11] provided the fraction of biomass burned (FB). This methodology is summarized by [14,15]. The pollutant emission average emission factors (EFs), for example, $PM_{2.5}$ and $NH_{3,}$ are obtained from the literature [10,11]. The most important parameter in estimating wildfire emissions (Equation (1)) is burn area [16].

Since ammonia is a precursor in the formation of $PM_{2.5}$, we observe (Figure 1) that the emission patterns of ammonia and $PM_{2.5}$ are similar. A plot of ammonia emissions versus $PM_{2.5}$ emissions (Figure 2) in Southeast Australia provides the role of ammonia in secondary $PM_{2.5}$ formation in wildfire. The linear equation: y = 8.94 × 10^6 + 11.62x with adjusted R-squared: 0.95 further supports this conclusion. Moreover, the intercept of the linear regression provides insight into the possible background $PM_{2.5}$ emission of 8.94 × 10^6 kg per year.

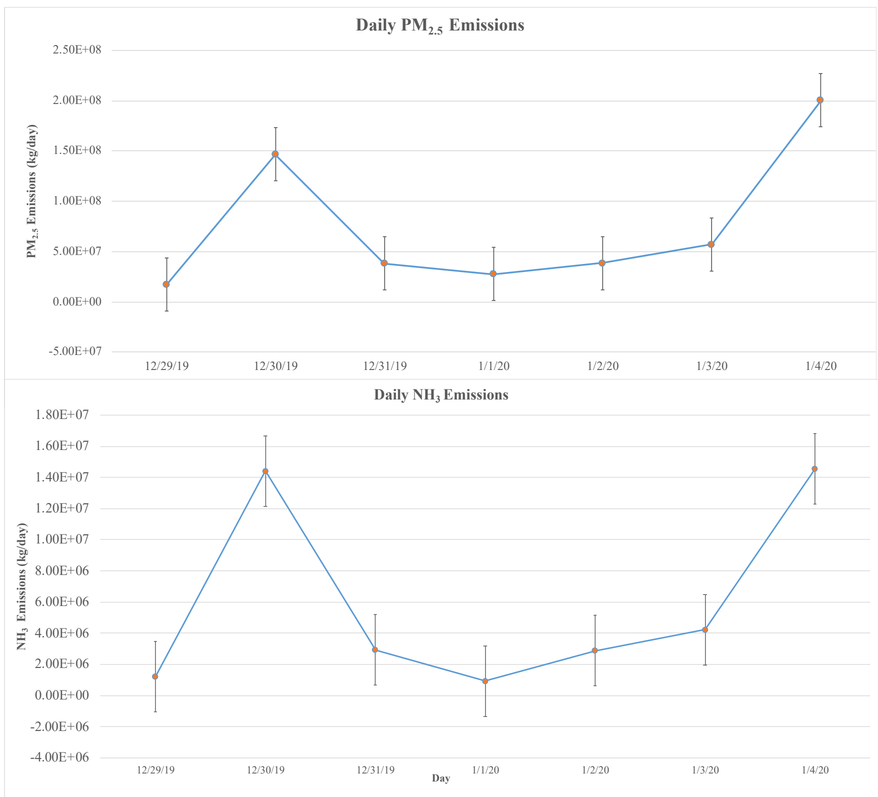

Figure 1. Daily $PM_{2.5}$ emissions and NH_3 emissions in Southeast Australia during (29 December 2019–4 January 2020). The circles represent $PM_{2.5}$ and NH_3 emissions as kg per day. The black vertical bars in the figure represent ± 1SD. (Source: [16]).

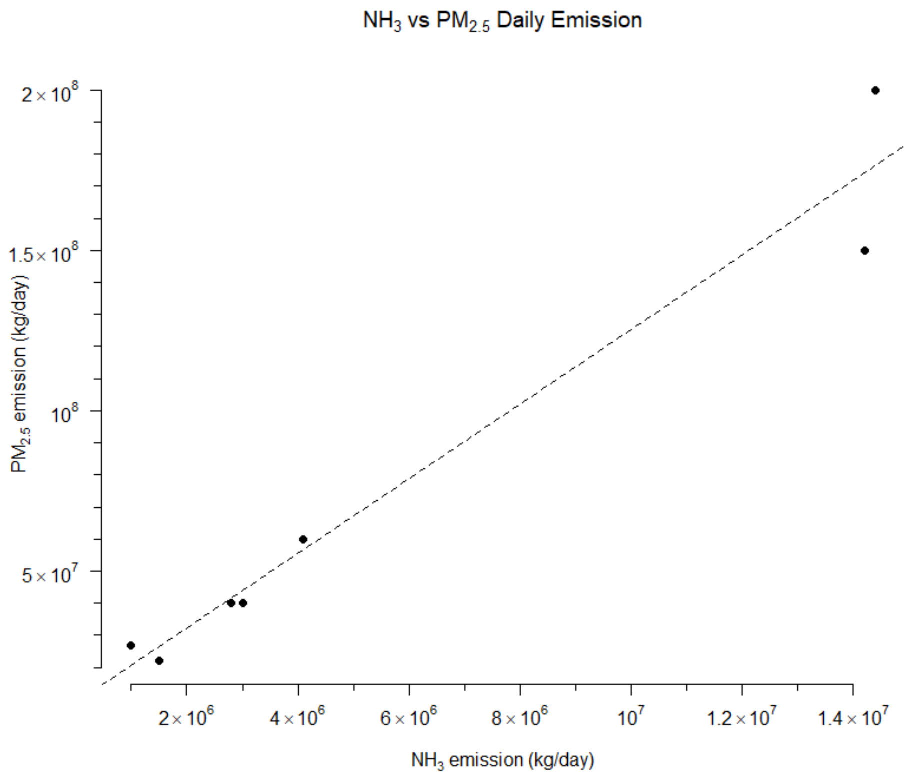

Figure 2. Daily NH_3 vs $PM_{2.5}$ emissions in Southeast Australia during the study period (source: [16]). Linear equation: y = 8.94x × 10^6 + 11.62x with Adjusted R-squared: 0.95.

On a US national scale, CONUS, ammonia emissions from wildfires are estimated at approximately 5.4 × 108 ± 3.3 × 108 kg/year for 2005–2015 and the emissions of air pollutants have continued to increase. Moreover, the average annual $PM_{2.5}$ emissions (both primary and secondary) from biomass burning on a US national scale emission in 2014 is approximately 1507 × 10^6 kg per year. In general, NH_3 emissions and $PM_{2.5}$ emissions (Figure 3) reach their maxima in the summer months. Summer months, in general, are dryer and warmer and are, therefore, conducive to wildland fire activities coupled with covering a larger burn area, especially in the Western US.

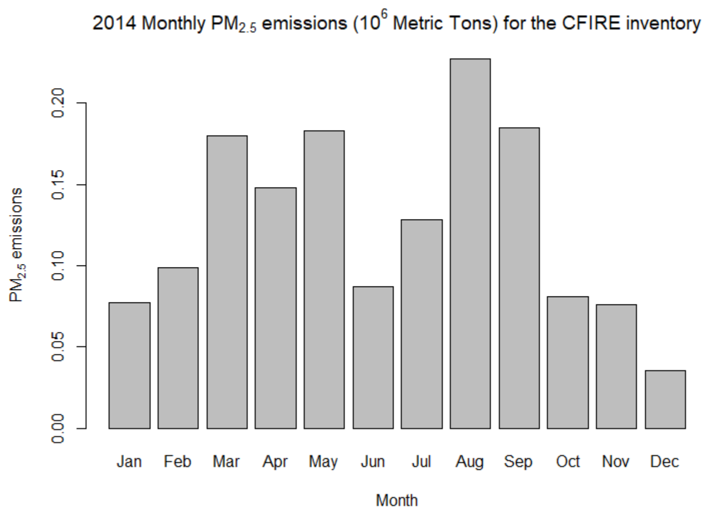

Figure 3. Monthly $PM_{2.5}$ emissions (wildfire + prescribed burn) for the CFIRE inventory (source: [17]). Total emissions in 2014 were approximately 1507 × 10^6 kg per year.

3. Discussion

Health outcomes in residential population: Wildfire emissions have impacts on human health. There needs to be statistical analysis of the patterns of mortality and morbidity for respiratory, cardiovascular, neurocognitive, chronic kidney, and other diseases in counties affected by wildfires using the Centers for Disease Control and Prevention wide-ranging online data for epidemiologic research (CDC WONDER) database and the Agency for Healthcare Research and Quality datafiles, by looking into the months/years when wildfires were the most active in respective regions. Using these results, researchers can develop a strategy on health data to be included in the forecasting model of wildfires to predict health outcomes in the most vulnerable population groups and to forecast the burden of diseases associated with exposures to wildfire events, both short and long term. This work also added significance for the eventual consideration of standards, other than the mass-based $PM_{2.5}$ NAAQS approach.

Statistical forecasting for future wildfire emissions: The physicochemical model in Equation (1) cannot be used for forecasting future emissions, as the explanatory variables cannot be measured for active wildfires. Expensive data collection procedures (e.g., using drones) are necessary for existing scientific models for predicting wildfire emissions [18–20]. Furthermore, these models do not have a mechanism to learn from past wildfire data. These issues make such models impractical for forecasting emissions in real-world scenarios. Physical models of wildland fire spread have also been developed [21]. These physical models typically include equations describing combustion chemistry as well as heat transfer conservation laws. Due to the high complexity and prohibitive computational cost of running these models, their use is generally limited to research purposes. For large wildfires that burn for a long time and over a large area, the use of such models is not practically feasible.

Instead, a promising approach is to use a deep-learning-based model for spatio-temporal forecasting of future emissions from active wildfires. This can be accomplished by merging recurrent neural networks, or RNNs, with convolutional neural networks, or CNNs. RNNs enable efficient modeling of time-series data by propagating and updating information from previous time steps, using non-linear, differentiable transformations [22]. 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 [23], traffic prediction in transportation networks [24], music classification [25], and video frame prediction [26].

4. Conclusions

The research will improve our understanding of wildland fire impacts on public and environmental health and will inform public-health strategies to reduce the associated risks. Anthropogenic emissions of NO_x and SO_2 have declined in the U. S. during the past 20 years, as a result of the Clean Air Act and its amendments, resulting in significant improvements in air quality. However, the increase in wildfire frequency and intensity threatens to reverse these achieved gains, especially in emissions of ammonia and $PM_{2.5}$. The exposure of $PM_{2.5}$ and other wildfire air contaminants associated with wildfire on respiratory, cardiovascular, and other disease-specific impacts will provide information that can be used by local healthcare and public-health specialists to target vulnerable groups.

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