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Potential impacts of prescribed fire smoke on public health and socially vulnerable populations in a Southeastern U.S. state

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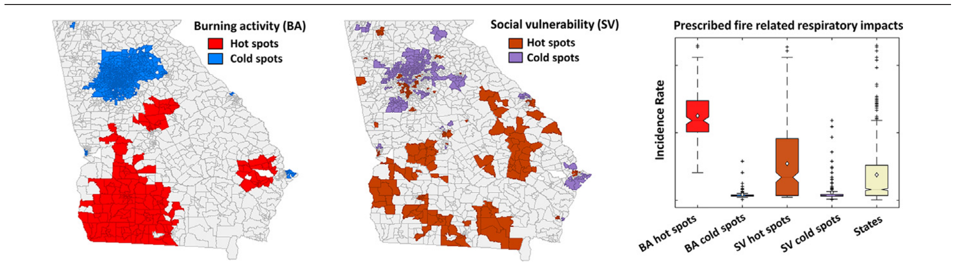
HIGHLIGHTS

- Areas with intensive prescribed burning tend to have higher socially vulnerability.
- Hundreds of morbidity and mortality cases are potentially associated with prescribed fire smoke.
- Health impacts of smoke are significantly larger in social vulnerability hot spots.
- Prescribed fire impacts in Georgia are comparable to other major emissions sources.

GRAPHICAL ABSTRACT



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ABSTRACT

Prescribed fire is an essential tool for wildfire risk mitigation and ecosystem restoration in the Southeastern United States. It is also one of the region's largest sources of atmospheric emissions. The public health impacts of prescribed fire smoke, however, remain uncertain. Here, we use digital burn permit records, reduced-complexity air quality modeling, and epidemiological associations between fine particulate matter concentrations and multiple health endpoints to assess the impacts of prescribed burning on public health across Georgia. Additionally, we examine the social vulnerability of populations near high prescribed burning activity using a demographic- and socioeconomic-based index. The analysis identifies spatial clusters of burning activity in the state and finds that areas with intense prescribed fire have levels of social vulnerability that are over 25% higher than the state average. The results also suggest that the impacts of burning in Georgia can potentially include hundreds of annual morbidity and mortality cases associated with smoke pollution. These health impacts are concentrated in areas with higher fractions of low socioeconomic status, elderly, and disabled residents, particularly vulnerable to air pollution. Estimated smoke-related health incidence rates are over 3 times larger than the state average in spatial clusters of intense burning activity, and over 40% larger in spatial clusters of high social vulnerability. Spatial clusters of low social vulnerability experience substantially lower negative health effects from prescribed burning relative to the rest of the state. The health burden of smoke from prescribed burns in the state is comparable to that estimated for other major emission sectors, such as vehicles and industrial combustion. Within spatial clusters of socially-vulnerable populations, the impacts of prescribed fire considerably outweigh those of other emission sectors. These findings call for greater attention to the air quality impacts of prescribed burning in the Southeastern U.S. and the communities most exposed to fire-related smoke.

1. Introduction

Prescribed burns, planned wildland fires conducted under controlled conditions, are used for various important land management

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objectives, including mitigation of hazardous wildfire risk and restoration of fire-dependent ecosystems (Hiers et al., 2020; Johnston, 2020; Kobziar et al., 2015). However, prescribed fires are a major source of fine particulate matter ($PM_{2.5}$) emissions in the U.S. (U.S. EPA, 2018a). Some of the largest impacts of wildland fire, which includes prescribed fires and wildfires, on ambient $PM_{2.5}$ in the country occur in the Southeastern U.S. (Fann et al., 2018; Larsen et al., 2017; Rappold et al., 2017), where prescribed fire is extensively used in land management and close to 70% of prescribed burns are conducted (Hiers et al., 2020; Kolden, 2019; Melvin, 2018; Oakman et al., 2019). In this region, prescribed fires can explain up to 50% of the variability in observed $PM_{2.5}$ concentrations (Afrin and Garcia-Menendez, 2020) and are often conducted in close proximity to communities in a wildland–urban interface with millions of residents (Radeloff et al., 2018).

Epidemiological research has identified short-term associations between wildfire or biomass burning $PM_{2.5}$ and various health outcomes. Most studies report a positive association between fire-related $PM_{2.5}$ and all-cause mortality or respiratory endpoints, and mixed evidence for cardiovascular disease (Cascio, 2018; Liu et al., 2015; Reid et al., 2016; Youssouf et al., 2014). A few studies have explored potential long-term associations with wildland fire smoke (Black et al., 2017). For example, Liu et al. (2017) investigated the long-term association between wildfire $PM_{2.5}$ and hospital admissions in urban and rural counties. Toxicological analyses suggest that fire-related $PM_{2.5}$ may cause greater inflammation and oxidative stress compared with other ambient sources since it generates more free radicals (Karthikeyan et al., 2006; Wegesser et al., 2010). Recent studies also observe larger effects of wildland fire-related $PM_{2.5}$ on respiratory health compared with those of $PM_{2.5}$ not specifically from fires (Aguilera et al., 2021; Deflorio-Barker et al., 2019; Stowell et al., 2019). Based on concentration-response functions (CRFs) derived from epidemiological evidence of the effects of general ambient $PM_{2.5}$, air pollution impact assessments have estimated public health impacts associated with fire smoke (e.g., Fann et al., 2018). Fann et al. (2018) estimated that thousands of premature deaths and illnesses in the U.S. are annually caused by wildland fire-related $PM_{2.5}$, including both wildfire and prescribed fire smoke. However, reliance on CRFs that are not fire-specific and dependence on satellite-based fire detections, unable to capture a large fraction of low-intensity fires (Huang et al., 2018; Nowell et al., 2018), suggest that the impacts associated with prescribed fires in these assessments may be underestimated. In a recent study, Huang et al. (2019) used burn permit data and an association between biomass burning $PM_{2.5}$ and respiratory health outcomes to estimate asthma-related emergency room visits in Georgia attributable to prescribed fires in the state. Still, the burden that prescribed fire smoke poses on public health is uncertain.

The populations exposed to high levels of prescribed fire smoke remain poorly characterized as well. Unlike other major sources of air pollution, often concentrated in urban locations, prescribed fire may impact $PM_{2.5}$ concentrations more in rural areas, where air quality monitoring and management efforts are limited (Afrin and Garcia-Menendez, 2020). The demographic and social characteristics of communities in burn-intensive regions differ from those of the general population, potentially increasing their vulnerability to smoke. Socioeconomic variables have been identified as important determinants of population health (WHO, 2010). Disparities arise from unequal access to health-promoting facilities, services, and activities (Balmes, 2017; Méjean et al., 2013; Pampel et al., 2010). $PM_{2.5}$ has stronger associations with premature mortality (Wang et al., 2017), cardiovascular disease (Tibuakuu et al., 2018), and respiratory diseases (Wisnivesky et al., 2017) among lower socioeconomic status populations. For wildland fire smoke specifically, studies also suggest greater risks of adverse health effects among low-socioeconomic-status and older individuals (Cascio, 2018; Liu et al., 2015; Reid et al., 2016). Additionally, lower socioeconomic status communities in the U.S. generally experience higher air pollution (Hajat et al., 2015). Although Gaither et al. (2015) did not find higher exposures to wildland fire smoke among socially vulnerable populations in the Southern U.S., this analysis was based on satellite-derived data, which may significantly underestimate prescribed burn area (Huang et al., 2018) and cannot differentiate between wildfire and prescribed fire smoke. In a recent study, $PM_{2.5}$ concentrations associated with prescribed burning were found to be higher in areas with a higher percentage of African American population (Gaither et al., 2019). However, social disparities in exposure to air pollution from land management activities, and prescribed burning specifically, have not been carefully investigated.

Here, we assess the potential impacts of prescribed burning smoke on public health in a Southeastern U.S. state and their disparities across socially vulnerable and burn-intensive communities. The analyses rely on unique permit-based fire data set and focus on Georgia, one of the U.S. states with the most burning and best-maintained inventories of prescribed fire records and emissions. Based on this data, we identify spatial clusters of high or low burning activity and social vulnerability in the state. Using a reduced-form air quality model and epidemiologically derived CRFs, we estimate the potential effects of prescribed fire smoke on several health outcomes across Georgia. We then examine how the impacts at spatial clusters of prescribed fire and social vulnerability differ from the rest of the state. Additionally, we compare the contribution of prescribed fires to the health burden of air pollution to that of other major emissions sectors, including wildfires, vehicles, and industrial fuel combustion. To our knowledge, this study is the first to specifically evaluate potential regional-scale impacts of prescribed fire smoke on multiple health outcomes and relate them to indicators of vulnerability to external stresses on human health.

2. Methods

2.1. Spatial clusters of burning activity and social vulnerability

We use prescribed burn permits issued by the Georgia Forestry Commission (GFC) in 2016 as an indicator of prescribed fire activity (Fig. 1a). The year 2016 is considered as it is representative of burn activity across multiple years (Afrin and Garcia-Menendez, 2020) and permit-based prescribed fire emission estimates are available for this year. The open burn permits considered in the analysis are those specifically identified by the GFC as prescribed fires. The GFC considers three types of burns as prescribed fires—silvicultural (83%), agricultural (11%), and land clearing (6%) burns. The digital permit records, which include the area, date, and type of each burn, were further processed and geocoded as described in Afrin and Garcia-Menendez (2020). Annual prescribed burning activity at the census-tract level is estimated as the total permitted burn area up to 20 km away from the centroid of each tract. A 20-km radius is applied to consider short-range smoke transport from burns surrounding each tract, following Gaither et al. (2019) and based on prior research showing limited prescribed fire impacts on $PM_{2.5}$ concentration beyond a 1200 km^2 extent (Price et al., 2016).

To characterize populations near prescribed fire and potential vulnerability to smoke, we use the Centers for Disease Control and Prevention's (CDC) 2016 social vulnerability index (SVI) (Flanagan et al., 2018). The SVI includes 15 socioeconomic and demographic factors associated with increased community vulnerability to detrimental human health impacts caused by external stresses. They include variables describing a population's income, poverty level, age, fraction with disability, percentage minority, housing type, and other factors. The variables are organized into four themes: socioeconomic status; household composition; race, ethnicity, and language; and housing and transportation. For each theme, an SVI value is assigned based on the percentile ranking of underlying variables, and an overall SVI score is estimated from the percentile ranking of the theme-specific SVIs (Fig. 1b). SVI scores are available at the census-tract level and range from 0 to 1, with higher values indicating higher vulnerability. Prior studies have explored associations between the SVI and different health

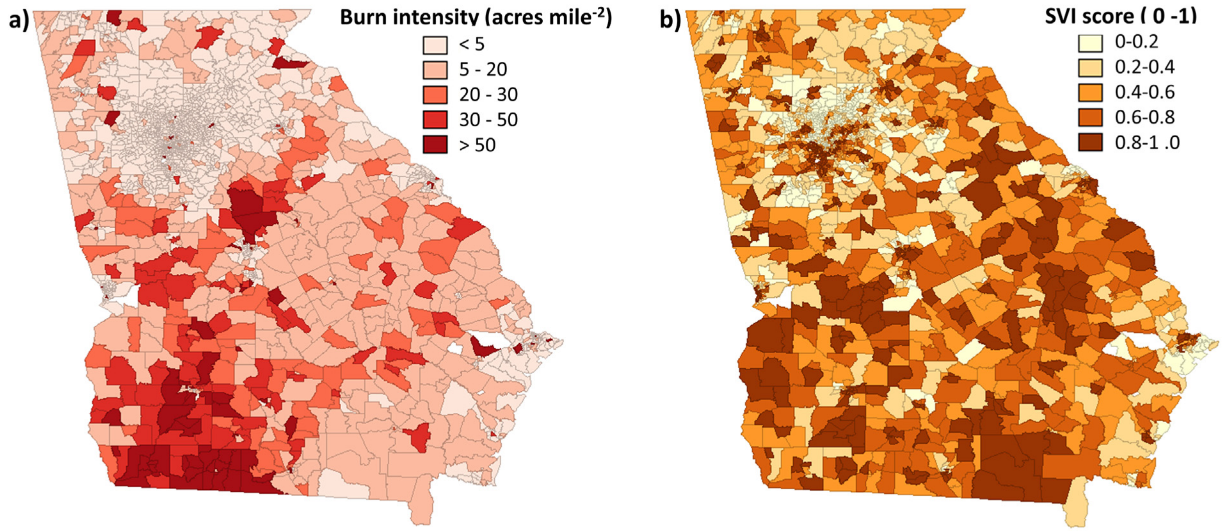

Fig. 1. Prescribed fire and social vulnerability across Georgia in 2016. (a) Census tract burn intensity, shown as permitted burn acres per area. (b) Overall social vulnerability index (SVI) for each census tract. Higher values indicate higher vulnerability.

outcomes, such as heat-related illness, physical fitness, or coronavirus disease 2019 (COVID-19) infections (Gay et al., 2016; Karaye and Horney, 2020; Lehnert et al., 2020).

To weigh spatial clustering of prescribed fire, we estimate the spatial autocorrelation of census tract-level permitted burning activity using the Global and Local Moran's I statistics. Local indicators of spatial association (LISA), based on Local Moran's I (Anselin, 1995), are used to identify burn activity hot and cold spots. Following the same approach, hot and cold spots of the socially vulnerable population are identified based on overall SVI score. A LISA statistic weighs the extent of spatial clustering of similar values around each observation. Clusters of observations with higher-than-average values surrounded by neighboring elements with high values are identified as hot spots. Clusters of observations with lower-than-average values surrounded by low values are labeled as cold spots. In the spatial analyses conducted, we identify statistically significant clusters ($p < 0.05$) using a first-order contiguity-based weight matrix, which considers the values of all census tracts sharing a boundary with each tract.

2.2. Reduced-form air quality modeling

To assess source-specific impacts on $PM_{2.5}$ pollution, we apply the CO-Benefits Risk Assessment Health Impacts Screening and Mapping Tool (COBRA) managed by the U.S. Environmental Protection Agency's (U.S. EPA) Office of Atmospheric Programs (U.S. EPA, 2020a). COBRA has been used in prior studies to provide first-order estimates of the air quality and health impacts of emissions associated with different sectors and policies (e.g., Barron et al., 2018; Olawepo and Chen, 2019; Thomson et al., 2018). Given a change in sector-specific annual emissions, this reduced-complexity model (RCM) estimates consequent changes in annual county-level $PM_{2.5}$ concentrations. In COBRA, concentration fields are generated with the Climatological Regional Dispersion Model's source-receptor matrix, which relies on a simplified dispersion-transportation mechanism and representation of chemical conversions at the receptor level. The fixed transfer coefficients of the source-receptor matrix reflect the relationships between annual-average $PM_{2.5}$ at county centroids and the contributions from each source. While COBRA is designed to provide initial estimates of likely impacts of emission changes, the model has been calibrated with monitored $PM_{2.5}$ concentrations and its predictions have been found to generally agree with those of full-form dispersion simulations (U.S. EPA, 2020b).

In our analyses, we use COBRA's 2017 anthropogenic emissions inventory, a projection of U.S. EPA's 2011 Version 6.2 Air Emissions Modeling Platform which considers implemented and under-consideration federal and state measures, for emissions sources other than wildfires and prescribed fires. We update prescribed fire emissions in the simulations with estimates provided by the Environment Protection Division (EPD) of the Georgia Department of Natural Resources. EPD estimates prescribed fire emissions at county centroids based on GFC burn permits, and fuel consumption and emission factors developed for the Southeastern Modeling, Analysis, and Planning (SEMAP) project (Zeng et al., 2017). The emission factors applied by EPD are comparable to those reported by Urbanski (2014) for $PM_{2.5}$ and carbon monoxide, but lower for volatile organic compounds. Wildfire emissions are also updated with EPD's 2016 wildfire emissions estimates. These fire emissions were included in the National Emissions Inventory Collaborative's 2016 beta emissions inventories (NEIC, 2019). Sector contributions to $PM_{2.5}$ are weighed applying a brute-force zero-out approach, comparing the $PM_{2.5}$ concentrations under the base case to those estimated in the absence of each sector. Fire-related impacts are compared with those from vehicles, which here include on-road light- and heavy-duty gas and diesel vehicles, and industrial fuel combustion, defined here as fuel combustion by electric utilities and industrial facilities (e.g., industrial boilers, chemical manufacturing, and metal product fabrication), following U.S. EPA's Tier 1 emission categories (U.S. EPA, 2018a).

2.3. Health impacts assessment

We assess the health impacts of prescribed fire smoke exposure using CRFs reported by epidemiological studies linking $PM_{2.5}$ to health outcomes. In the analyses, we consider U.S.-based CRFs relating short-term increases in general and wildland fire-specific $PM_{2.5}$ to asthma emergency department visits and respiratory hospital admissions. To assess mortality impacts, we apply CRFs for both short- and long-term exposure to ambient $PM_{2.5}$. The CRFs considered are listed in Table 1. These follow a log-linear model, $\Delta Y = y_0(1 - e^{-\beta \Delta PM_{2.5}}) \times P$, where the change in health incidences (ΔY) is estimated from an effect coefficient (β) reported by each epidemiological study, baseline incidence rate (y_0), age-specific exposed population (P), and a change in $PM_{2.5}$ concentration ($\Delta PM_{2.5}$). Although COBRA includes commonly used CRFs, it does not include fire-specific functions. To apply these CRFs and others absent in the RCM, specifically those derived from

Table 1
Estimated 2016 health incidences associated with prescribed fire smoke in Georgia. For each endpoint the type of health response association, epidemiological studies on which the CRFs applied are based, and relevant age group are listed. Impacts are listed as mean incidence estimates and 95% confidence intervals.

Health endpoint	Association type	Epidemiological studies for CRFs considered	Age group	Mean estimate	95% CI
Asthma emergency department visits	ST-Ambient	Mar et al. (2010), Slaughter et al. (2005), Glad et al. (2012)	0–99	178	(−20, 348)
	ST-Fire	Borchers Arriagada et al. (2019)	0–99	264	(143, 375)
Respiratory hospital admissions	ST-Ambient	Zanobetti et al. (2009), Kloog et al. (2012)	65–99	48	(−1, 94)
	ST-Fire	Gan et al. (2017), Delfino et al. (2009)	65–99	238	(81, 375)
Mortality	ST-Ambient	Zanobetti and Schwartz (2009)	0–99	70	(54, 87)
	LT-Ambient	Lepeule et al. (2012)	25–99	920	(460, 1370)
Older adult mortality	ST-Ambient	Di et al. (2017)	65–99	51	(46, 56)
	LT-Ambient	Wang et al. (2017)	65–99	1010	(939, 1080)

LT = long-term $PM_{2.5}$ exposure; ST = short-term $PM_{2.5}$ exposure; Fire = wildland fire-specific $PM_{2.5}$; Ambient = general ambient $PM_{2.5}$.

Zanobetti and Schwartz (2009), Di et al. (2017), and Wang et al. (2017), we rely on COBRA-simulated $PM_{2.5}$ concentrations, and estimate the health impacts outside the model. Age-specific 2016 populations and baseline incidence rates for all counties are compiled from the Georgia Department of Public Health's Online Analytical Statistical Information System (OASIS, 2020).

When assessing impacts of long-term exposures, changes in health outcomes are estimated based on annual county-average $PM_{2.5}$ impacts predicted by COBRA and annual baseline incidence rates. For short-term health impacts, estimates of changes in health outcomes assume a constant baseline incidence rate throughout the year and are based on daily changes in $PM_{2.5}$. Daily variations in fire-related $PM_{2.5}$ are approximated by weighing simulated annual $PM_{2.5}$ impacts by daily county-level prescribed fire emissions. For other emissions sectors (wildfires, vehicles, and industrial fuel combustion), the predicted increase in annual-average concentrations is assumed to be representative of their daily contribution to $PM_{2.5}$. Except for mortality, estimates for health endpoints in which more than one CRF is considered are pooled using the random or fixed-effects weighing reported in COBRA, consistent with U.S. EPA benefits analyses (U.S. EPA, 2020b). Mortality studies are not pooled due to major differences in study design and exposed populations. Estimates of mortality impacts associated with short- or long-term exposure to $PM_{2.5}$ from prescribed fires, which should not be considered addible, are separately reported. For all health endpoints, impacts are presented as a change in number of incidences and 95th confidence intervals (95CI), estimated using the mean value of β and its 95th confidence bounds reported by each epidemiological study.

3. Results and discussion

3.1. Prescribed burning and social vulnerability spatial clusters in Georgia

Spatial autocorrelations show significant clustering of both tract-level prescribed burning and social vulnerability, with Global Moran's I values of 0.85 and 0.53, respectively. The higher value of Moran's I for burning activity reflects a stronger autocorrelation compared with that of social vulnerability. LISA statistics also identify several hot and cold spots in the state for both burning activity and social vulnerability, as shown in Fig. 2. Prescribed burning hot spots represent 20% of the area in Georgia and are largely concentrated in the Southwest, with smaller clusters in the central and eastern regions of the state. In contrast to prescribed fire, social vulnerability hot spots are dispersed across the southern portion of the state and make up 19% of its area. Approximately 25% of burn activity hot spot areas are also social vulnerability hot spots, and locations simultaneously identified as spatial clusters of high prescribed fire and social vulnerability cover close to 5% of the state. For both burning activity and social vulnerability, cold spots are largely grouped near the Atlanta metropolitan area and respectively cover 6.4% and 5.5% of the state's total area.

Distributions of the census tract-level overall and theme-specific SVI scores within the spatial clusters of prescribed fire activity and social vulnerability are shown in Fig. 3. Given that the SVI is reported as a percentile ranking of variables, the state-average score is 0.5 in all cases. As expected, overall and theme-specific mean SVI scores in social vulnerability hot spots are higher than the state average. The distributions of

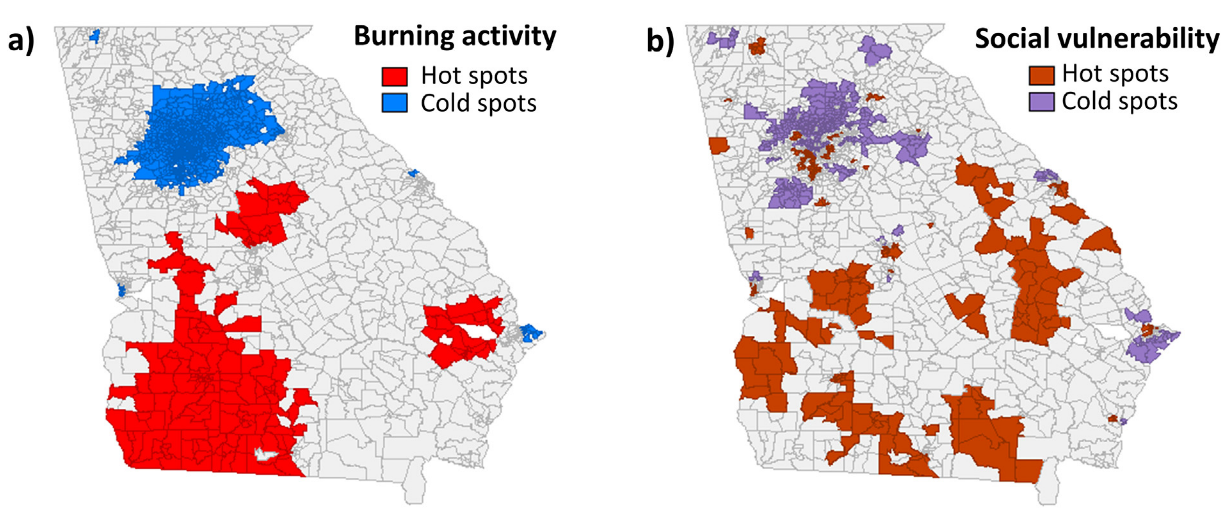

Fig. 2. Spatial clusters of prescribed fire and social vulnerability. (a) Burning activity hot spots and cold spots. Census tract-level burning activity is represented by total permitted burn area 20 km from tract centroids. (b) Social vulnerability hot spots and cold spots, based on census tract-level overall SVI score. Hots spots are comprised of census tracts with high values surrounded by others with higher values, while cold spots gather census tracts with low values surrounded by others with low values.

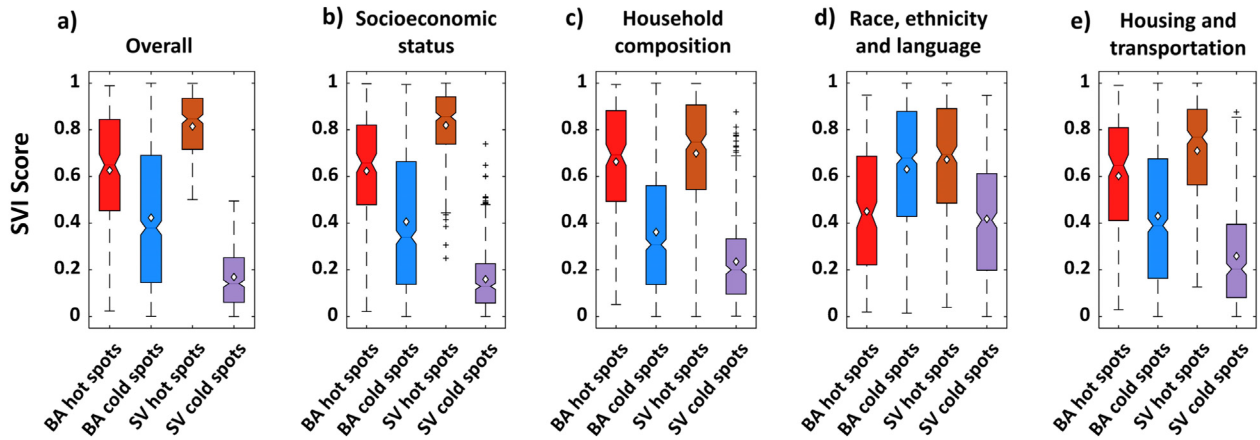

Fig. 3. SVI scores at spatial clusters of prescribed burning and social vulnerability. Boxes include SVI scores of census tracts within burning activity (BA) and social vulnerability (SV) hot and cold spots based on variables associated with: (a) all themes (overall); (b) socioeconomic status; (c) household composition; (d) race, ethnicity, and language; (e) housing and transportation. Box boundaries show interquartile range, notches and diamond markers indicate median and mean, respectively, and whiskers extend to 1.5 times the interquartile range.

SVI scores within hot spots of prescribed fire indicate that populations in burn-intensive areas tend to be more socially vulnerable than those living in areas with less prescribed fire. The mean overall SVI score in burning activity hot spots is over 25% higher than the state average. Theme-specific SVI scores are also higher in prescribed fire hot spots, except for the race, ethnicity, and language theme. The results suggest that prescribed burning smoke and its associated impacts may disproportionately affect populations with lower socioeconomic status, higher percentage of elderly individuals, larger fraction of people with disabilities, and limited access to housing and transportation. In contrast, the mean overall SVI at prescribed burning cold spots is approximately 15% lower than the state average, indicating that communities farther from concentrated burning activity are less likely to exhibit social conditions that may aggravate their human health impacts. Most theme-specific SVI scores are also lower at burning cold spots relative to the rest state average.

3.2. Prescribed fire smoke impacts on public health

The RCM simulations conducted estimate that prescribed burning in Georgia led to an average increase in annual $PM_{2.5}$ concentration of 0.9 μg m^{-3} across state census tracts in 2016 (Fig. S1). The estimated increase in concentrations is similar to the average burn-season impact on $PM_{2.5}$ at Georgia air quality monitoring sites reported by Huang et al. (2019) for 2016 (0.86 μg m^{-3}), based on a comprehensive chemical transport model simulation fused with ambient monitor observations. Prescribed burning had a larger impact on $PM_{2.5}$ in Southwest Georgia, with the largest increase in annual concentration predicted in Thomas County (5.4 μg m^{-3}). Simulated county-level total $PM_{2.5}$ concentrations are also generally consistent with annual-average observed $PM_{2.5}$, with a mean modeled county-average concentration (10.2 μg m^{-3}) comparable to the mean county-average measured $PM_{2.5}$ in 2016 (8.9 μg m^{-3}) across regulatory monitoring sites in Georgia (U.S. EPA, 2018b). Annual health incidences in Georgia associated with this fire-related $PM_{2.5}$ pollution are summarized in Table 1.

Based on the selected CRFs, prescribed fire smoke is estimated to have caused hundreds of asthma emergency department visits—264 (95CI: 143–375) based on Borchers Arriagada et al. (2019). Among older adults, prescribed fire smoke is estimated to have been associated with tens to hundreds of respiratory hospital admissions. Depending on CRF and age groups, short-term exposure to prescribed fire-related ambient $PM_{2.5}$ is estimated to have contributed to between 51 (46–56) and 70 (54–87) annual premature deaths. Long-term exposure to this level of fire-related ambient $PM_{2.5}$ is predicted to be associated with close to a thousand annual deaths across the state. Based on a CRF derived specifically from data in Southeastern U.S. states (Wang et al., 2017), 1010 (940–1080) annual deaths among older adults would be attributable to a sustained increase in ambient $PM_{2.5}$ of this magnitude. This estimate is higher than those based on other long-term adult mortality studies (e.g., 920 (460–1370) deaths based on Lepeule et al. (2012)), even though they consider a wider age range.

Recent epidemiological studies have reported associations between health endpoints and $PM_{2.5}$ specifically from wildland fires. The fire-specific CRFs considered in this analysis result in higher estimates of incidences compared with those derived from studies focused on general ambient $PM_{2.5}$ concentrations for both the asthma emergency department visits and respiratory hospital admissions, with predicted impacts that are 1.5 and 5 times larger, respectively. The magnitude of the impact on asthma emergency department visits predicted here is comparable to the estimate reported by Huang et al. (2019), which is based on regional-scale comprehensive chemical transport model simulations and a different epidemiological study (Krall et al., 2017). The estimates of smoke-related asthma incidences in Georgia in Huang et al. (2019) are also relatively consistent throughout the period analyzed by the study (2015–2018), suggesting a sustained impact of prescribed burning on $PM_{2.5}$ concentrations in the state across multiple years. An analysis of burn records and observations at regulatory air quality monitors in the Southeastern U.S. also shows a regular influence of prescribed fire on $PM_{2.5}$ in the region (Afrin and Garcia-Menendez, 2020).

Fig. 4 shows the county-level distribution of short-term health impacts attributed to prescribed fire smoke in Georgia for the health endpoints examined as incidence rates (incidences per million population at risk). The counties with higher incidence rates of smoke-related outcomes are concentrated in the southwest of the state, suggesting that those living in this region are the most affected by prescribed fire smoke. In those with the highest estimated mortality impacts, Baker and Thomas counties, incidence rates are 3 to 4 times the state average. High baseline incidence rates and comparatively high prescribed fire-related $PM_{2.5}$ can lead to a large number of smoke-related cases in southwestern locations. For example, the predicted increase in long-term mortality among older adults in Thomas County, 37 (35–39) deaths per year, is equivalent to approximately 10% of all-cause mortality in the age group. However, some of the highest estimates of total smoke-related incidences correspond to areas in the central region of the state, due to larger population and baseline incidence rates. Overall, the analysis estimates a significant impact of prescribed fire smoke on public health at multiple locations throughout Georgia.

The estimated health impacts of prescribed fire smoke are considerably higher in burning activity and social vulnerability hot spots (Fig. 5 and Table S1). As expected, the effects are larger within spatial clusters of intense burning, with smoke-related mean incidence rates over 3 times higher than the state average. For all health endpoints considered,

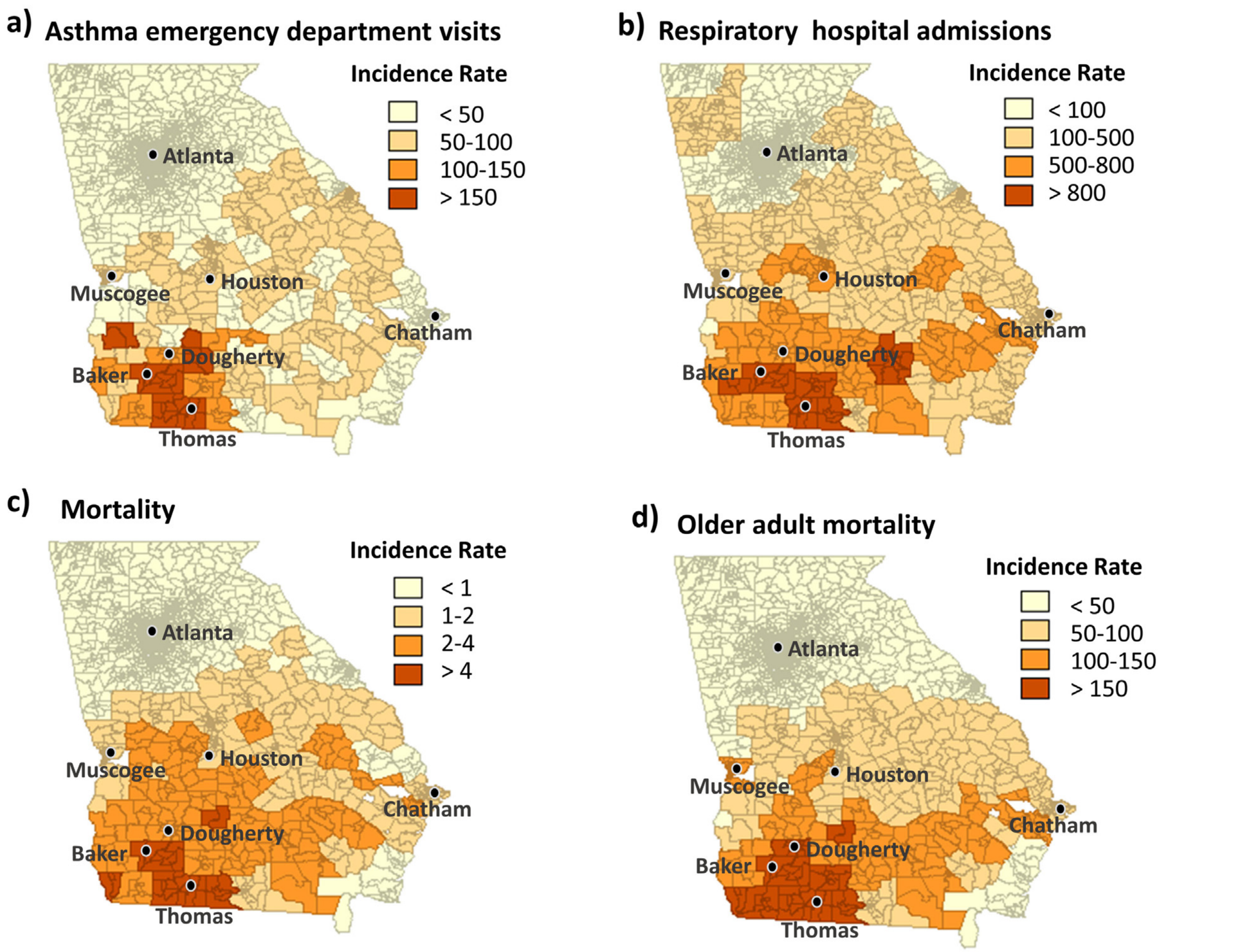

Fig. 4. Health impacts of prescribed fire smoke in 2016. Annual incidence rates estimated from the reported epidemiological associations between endpoints and short-term exposure to $PM_{2.5}$ are presented as census tract-level fire-related incidences per million age-specific population for: (a) asthma emergency room visits based on Borchers Arriagada et al. (2019); (b) respiratory hospital admissions based on Gan et al. (2017) and Delfino et al. (2009); (c) mortality based on Zanobetti and Schwartz (2009); and (d) older adult mortality based on Di et al. (2017).

the impacts of prescribed fire smoke are also significantly larger in social vulnerability hot spots relative to the rest of the state. In the spatial clusters with more socially vulnerable population, mean predicted smoke-related tract-level incidence rates are over 40% higher than the state average and over 4 times higher than in social vulnerability cold spots. Large impacts are projected in several social vulnerability hot spots, driven by smoke pollution and higher baseline incidence rates (Fig. S1). In contrast, vulnerability cold spots are predicted to experience smoke-related incidence rates that are 65% to 70% lower than the state average for the health outcomes explored. The results suggest that socially vulnerable population in the state, already more susceptible to health stressors, also experience greater adverse impacts from prescribed fire smoke relative to others.

The health impacts of prescribed fire smoke estimated in Georgia are comparable to those predicted by RCM simulations for other major emissions sectors, including wildfire, vehicles, and industrial fuel combustion, as shown in Fig. 6. In burning hot spots, prescribed fire smoke has a dominating effect compared with other emission sources and is responsible for approximately 90% of the combined impacts of the four sectors examined for all the health outcomes considered. The adverse health effects of prescribed fire in social vulnerability hot spots are also significantly larger, representing close to 1.5 times the combined impact of the other sectors across the morbidity and mortality endpoints examined. At social vulnerability cold spots, however, the health impacts of prescribed fire smoke are largely diminished and lower than those estimated for vehicles and industrial fuel combustion. Compared with prescribed fire, the impacts of wildfires across the state are minor. It is important to note that severe wildfires do not regularly occur in Georgia largely due to widespread prescribed fire use. Simulated wildfire smoke impacts in 2016 were lower in prescribed burning hot spots compared with the rest of the state. Overall, the simulated increases in negative health incidence rates attributable to prescribed fire in Georgia are nearly equal to the summed impacts predicted for vehicles, industrial combustion, and wildfires. Unlike other emission sectors, prescribed fire impacts are concentrated in the burning activity hot spots and disproportionately affect populations with higher levels of social vulnerability.

4. Conclusions

Prescribed burning is extensively practiced in the Southeastern U.S. and its use as a land management tool throughout the country is expected to grow. However, the extent to which prescribed fire smoke affects public health remains unknown. This analysis, based on modeled data and several assumptions, suggests that in the state of Georgia the health impacts of prescribed fire-related air pollution can be significant, potentially including hundreds of associated morbidity and mortality outcomes. These impacts can be substantially larger than those estimated for other major emission sectors. In Georgia, the air pollution and health burden of prescribed fire smoke are concentrated in burning hot spots covering a fifth of the state. The social determinants of health of the population in these burn-intensive areas indicate higher levels of

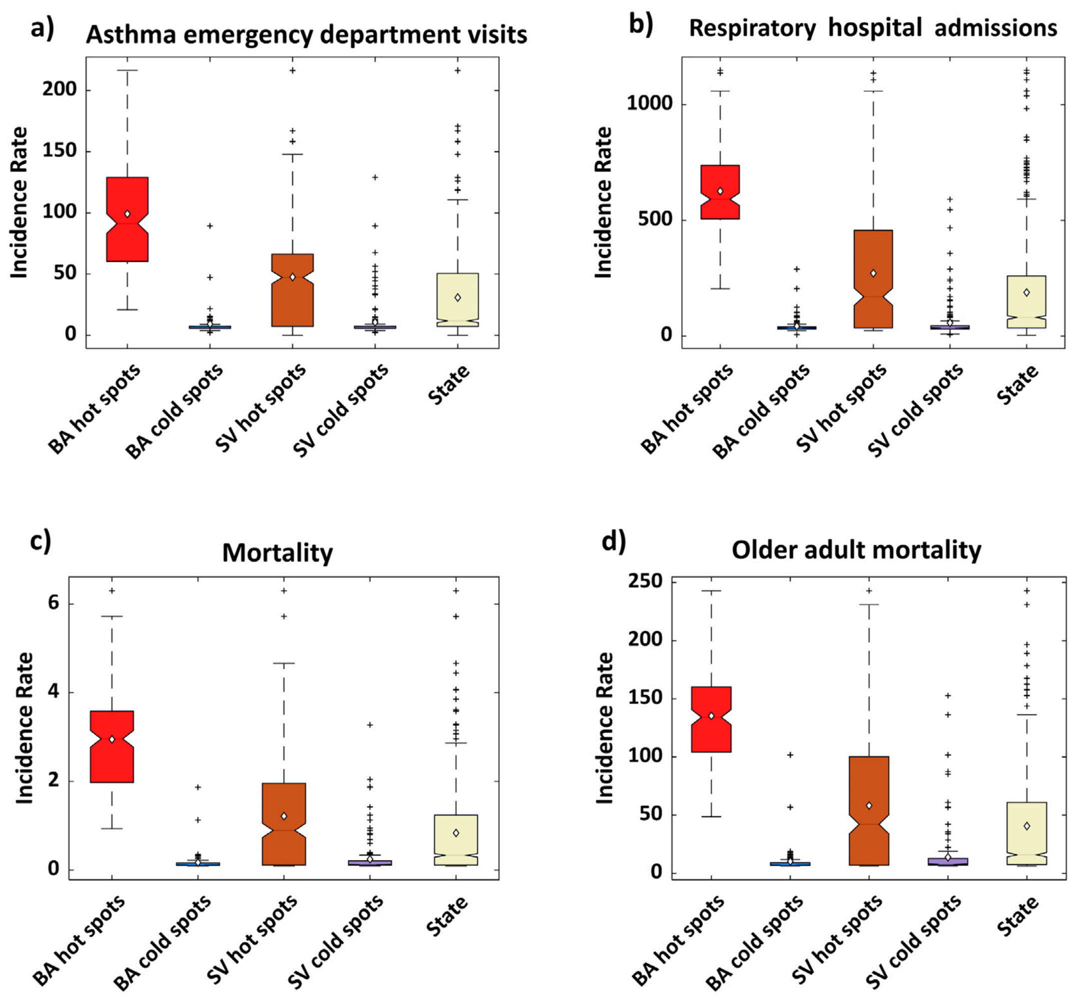

Fig. 5. Prescribed fire smoke-related health impacts at spatial clusters of burning activity and social vulnerability in Georgia. Boxes include estimated 2016 annual incidence rates (incidences per million of age-specific population) of census tracts within burning activity (BA) and social vulnerability (SV) hot spots and cold spots, and full state. Health outcomes and epidemiological studies included are: (a) asthma emergency room visits based on Borchers Arriagada et al. (2019); (b) respiratory hospital admissions based on Gan et al. (2017) and Delfino et al. (2009); (c) short-term mortality based on Zanobetti and Schwartz (2009); and (d) short-term older adult mortality based on Di et al. (2017). Box boundaries show interquartile range, notches and diamond markers indicate median and mean, respectively, and whiskers extend to 1.5 times the interquartile range.

social vulnerability, suggesting that those living in the areas with most burning activity are also more susceptible to its detrimental health effects. In particular, communities in prescribed fire hot spots have lower socioeconomic status and include a larger fraction of elderly and disabled residents, while social vulnerability in burning cold spots is significantly lower compared with the rest of the state. Our modeling results suggest that spatial clusters of socially vulnerable population across Georgia experience greater health effects associated with

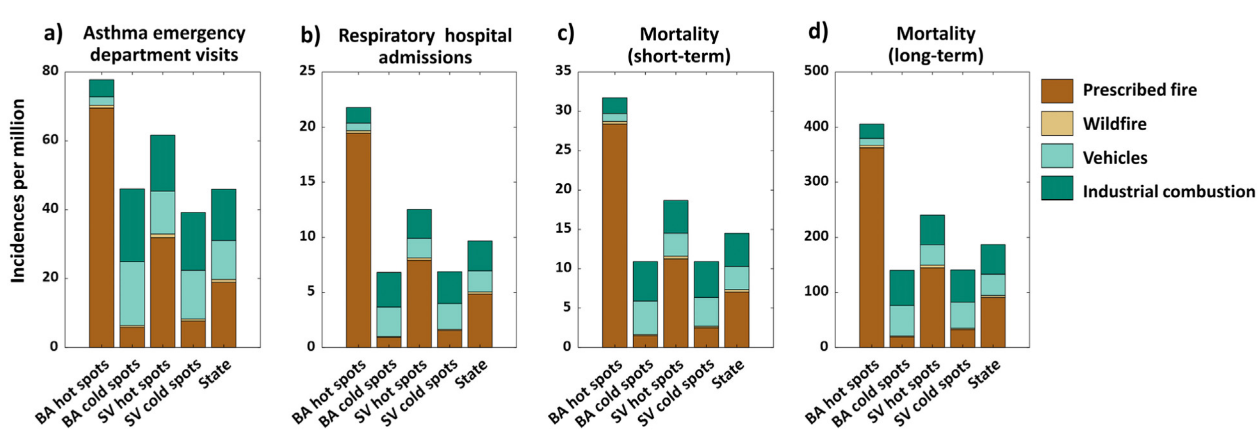

Fig. 6. Estimated health impacts of major emission sectors at spatial clusters of prescribed burning activity and social vulnerability in Georgia. Bars show mean estimates of 2016 incidences per million associated with prescribed fire, wildfires, vehicles, and industrial fuel combustion, within burning activity (BA) and social vulnerability (SV) hot spots and cold spots, and full state. Health outcomes included are: (a) asthma emergency room visits based on Mar et al. (2010), Slaughter et al. (2005), and Glad et al. (2012); (b) respiratory hospital admissions based on Zanobetti et al. (2009) and Kloog et al. (2012); (c) short-term mortality based on Zanobetti and Schwartz (2009); and (d) long-term mortality based on Lepeule et al. (2012).

prescribed fire, and in these communities smoke impacts far outweigh those associated with other emission sources that have traditionally been the focus of air pollution mitigation strategies.

This study, based on a unique permit-based fire dataset, is among the first to specifically assess public health impacts of prescribed fire and represents a step towards better understanding its role in U.S. air quality. However, the results are influenced by uncertainties associated with the data, models, and methods applied. Among them, one is the use of data on prescribed fire occurrence and magnitude, the compilation of which remains a major challenge. Satellite fire detection products fail to capture many low-intensity burns (Huang et al., 2018; Nowell et al., 2018), and prior research has shown that $PM_{2.5}$ concentrations observed at monitoring sites in Georgia have a stronger association with permitted burn areas than with satellite-derived areas (Afrin and Garcia-Menendez, 2020). In contrast, burn permit records collected by state and land management agencies, such as those used for this study, lack follow-up post-burn information, and are limited by inconsistent recordkeeping and reporting requirements. We focus on the state of Georgia, which has one of the most complete digital prescribed burn permit inventories. Still, discrepancies exist between permitted and actual burn areas, including permitted burns that were not conducted and actual burns that were not recorded. Based on a post-burn survey of landowners, the uncertainty of the burn areas in Georgia's prescribed fire permit records has been estimated at 20% (Huang et al., 2018). Bottom-up fire records for other states are commonly far less complete.

The study's analyses rely on air pollution fields simulated with an RCM. While RCMs have shown capable of providing first-order approximations of air pollution impacts (Gilmore et al., 2019), they are based on simplified-source receptor relationships. Further, to better estimate the impacts of prescribed fire smoke several assumptions were applied to COBRA's standard output. Among them, one is the approximation of daily variations in prescribed fire-related $PM_{2.5}$ based on weighing by daily prescribed fire emissions. The assumption follows prior research showing that recent nearby permitted burn areas can explain a large fraction of the variability in observed $PM_{2.5}$ concentrations (Afrin and Garcia-Menendez, 2020). An equivalent approach is not applied to other major sectors considered, as daily-resolved baseline emissions are not provided by COBRA and the associations between emissions and $PM_{2.5}$ concentrations may be different for these sources. However, we found that the estimates of annual health impacts are only marginally sensitive to daily variability in $PM_{2.5}$ impacts. While the $PM_{2.5}$ concentrations and prescribed fire impacts modeled are generally consistent with observations and the predictions of a comprehensive air quality model, the values here are slightly higher and constrained by the limitations of COBRA. Bias in modeled smoke impacts propagates to our estimates of health impacts. Atmospheric models with higher spatial resolution and more complex representations of the processes that drive transport and transformation of fire emissions can be used to simulate the effects of prescribed burning on air quality in greater detail in future research (Huang et al., 2021).

Beyond improving representations of fire-related air pollution, there is significant uncertainty in estimates of health responses to prescribed fire smoke. When comparing the impacts of different emission sectors, we rely on a common set of CRFs derived from general ambient $PM_{2.5}$ concentrations. Exposure to wildland fire smoke, however, differs significantly from exposure to pollution from other sources, potentially rendering these CRFs less capable of representing the true associations between fire-related $PM_{2.5}$ and health outcomes, compared with $PM_{2.5}$ from other emission sectors. In our analysis, predicted health impacts are considerably larger when applying fire-specific CRFs. However, epidemiological studies have only recently begun to report associations between different health endpoints and wildfire smoke. None have investigated associations with prescribed fire air pollution specifically. Additional research exploring the associations between prescribed burn smoke and reported health outcomes is needed. The use of constant baseline incidence rates across the year may affect smoke impact estimates for health outcomes with rates that are significantly different during the burning season, extending from January to April, compared with the rest of the year. For example, the death rate in Georgia during the first third of 2016 was close to 6% higher than the annual-average (Geostat, 2021), suggesting a small potential underprediction of the mortality cases associated with prescribed fire smoke.

Many Southern ecosystems depend on recurring fire (Hiers et al., 2020; Waldrop et al., 2012, 2016; Zhao et al., 2019). Prescribed burning currently plays a critical role in the management of fire-adapted landscapes, where fire suppression practices have shown to be unsustainable. A key outcome of prescribed fire treatment is lower hazardous wildfire risks. The populations most protected by these reductions in wildfire likelihood are those in burn-intensive areas, also identified by this analysis as particularly susceptible to health impacts associated with prescribed fire smoke. Further, by reducing the risk of uncontrolled wildfires prescribed burning can protect large populations from experiencing severe air pollution associated with wildfires. However, the wildfire mitigation and ecological benefits of prescribed fire come at a cost to the air quality in burn-intensive areas. Although prescribed fire air pollution is generally less intense and extends across smaller areas compared with that from wildfires (Guan et al., 2020; Williamson et al., 2016), these trade-offs must be considered in developing unique strategies to mitigate the impacts of wildland fire smoke (Altshuler et al., 2020; Johnston, 2020). In contrast to other major emissions sources, typically concentrated in urban areas, the regions with the largest prescribed fire impacts often have limited air quality monitoring and their populations are likely more vulnerable to air pollution. Better characterizing these communities and developing effective strategies that protect their residents against the negative effects of smoke must be a component of integrated fire management and air quality decision-making.

CRediT authorship contribution statement

Sadia Afrin: Conceptualization, Writing – original draft, Investigation, Formal analysis, Software, Methodology. **Fernando Garcia-Menendez:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.148712.

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