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Impacts of Sugarcane Fires on Air Quality and Public Health in South Florida

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Background: Preharvest burning of sugarcane is a common agricultural practice in Florida, which produces fine particulate matter [particulate matter (PM) with aerodynamic diameter ≤ 2.5 µm ($PM_{2.5}$)] that is associated with higher mortality.

Objectives: We estimated premature mortality associated with exposure to $PM_{2.5}$ from sugarcane burning in people age 25 y and above for 20 counties in South Florida.

Methods: We combined information from an atmospheric dispersion model, satellites, and surface measurements to quantify $PM_{2.5}$ concentrations in South Florida and the fraction of $PM_{2.5}$ from sugarcane fires. From these concentrations, estimated mortalities attributable to $PM_{2.5}$ from sugarcane fires were calculated by census tract using health impact functions derived from literature for six causes of death linked to $PM_{2.5}$. Confidence intervals (CI) are provided based on Monte Carlo simulations that propagate uncertainty in the emissions, dispersion model, health impact functions, and demographic data.

Results: Sugarcane fires emitted an amount of primary $PM_{2.5}$ similar to that of motor vehicles in Florida. $PM_{2.5}$ from sugarcane fires is estimated to contribute to mortality rates within the Florida Sugarcane Growing Region (SGR) by 0.4 death per 100,000 people per year (95% CI: 0.3, 1.6 per 100,000). These estimates imply 2.5 deaths per year across South Florida were associated with $PM_{2.5}$ from sugarcane fires (95% CI: 1.2, 6.1), with 0.16 in the SGR (95% CI: 0.09, 0.6) and 0.72 in Palm Beach County (95% CI: 0.17, 2.2).

Discussion: $PM_{2.5}$ from sugarcane fires was estimated to contribute to mortality risk across South Florida, particularly in the SGR. This is consistent with prior studies that documented impacts of sugarcane fire on air quality but did not quantify mortality. Additional health impacts of sugarcane fires, which were not quantified here, include exacerbating nonfatal health conditions such as asthma and cardiovascular problems. Harvesting sugarcane without field burning would likely reduce $PM_{2.5}$ and health burdens in this region. https://doi.org/10.1289/EHP9957

Introduction

Sugarcane fires are prominent and controversial sources of airborne particulate matter in South Florida. Each year from October to March, about 10,000 sugarcane fields covering over 400,000 acres are burned to reduce foliage before the harvest, minimize the biomass transported to mills, and streamline the sugar extraction process (Baucum and Rice 2009; Gullett et al. 2006; Hiscox et al. 2015; Le Blond et al. 2017; McCarty 2011; McCarty et al. 2009; Nowell et al. 2018). These fires are tightly clustered around the south shore of Lake Okeechobee surrounding the small cities of Belle Glade, Clewiston, and Pahokee, an area we refer to as the Sugarcane Growing Region (SGR; Figure 1A). The SGR is also 10–40 km from the densely populated coastal cities of South Florida, which are home to >6 million people (Figure 1B). Sugarcane farming and processing is the dominant economic activity in the SGR because it employs >14,000 people and generates \$800 million in revenue annually (Palm Beach County Cooperative Extension 2021). However, residents in the SGR and coastal cities complain of frequent ash fall and smoke during the burning season and have launched complaints and lawsuits to stop the burning due to concerns over the negative health impacts of exposure to the smoke (Bennett 2019; Reid 2015; Rua 2019; Sierra Club Calusa Group 2020). At the same time, Florida recently enacted legislation that, with limited exceptions, protects farmers from liability for particle emissions from farming operations (Florida Statute 823.14).

Sugarcane fires and other biomass burning fires are sources of $PM_{2.5}$, which is linked to lung and other cancers, cardiopulmonary disease such as ischemic heart disease, and premature death (e.g., Anenberg et al. 2010; Brook et al. 2010; Hoek et al. 2013; Huang et al. 2017; Krewski et al. 2000, 2009; Wettstein et al. 2018). Biomass burning smoke is also linked to serious, nonfatal respiratory and cardiovascular morbidity, including asthma, bronchitis, pneumonia, and chronic obstructive pulmonary disease, as well as low birth weight and increased COVID-19 mortality (e.g., Arbex et al. 2007; Cançado et al. 2006; Delfino et al. 2009; Hiscox et al. 2015; Holstius et al. 2012; Mazzoli-Rocha et al. 2008; Wu et al. 2020). $PM_{2.5}$ from all sources (e.g., energy generation, industry, vehicles) is associated with an estimated 46,000 to 88,000 deaths in the United States each year (Cohen et al. 2017; Lelieveld et al. 2015; McDuffie et al. 2021), but the true number could be larger after accounting for emerging information on toxicities of different $PM_{2.5}$ components and toxicity at lower exposure thresholds (Burnett et al. 2018; Domingo et al. 2021). It is estimated that agricultural field burning in the United States could account for approximately 600 of these deaths (McDuffie et al. 2021).

Among U.S. states, Florida historically has the highest $PM_{2.5}$ emissions from agricultural field burning, primarily due to sugarcane burning, with an estimated 18% of Florida's 21 million residents living in counties with significant crop burning (McCarty 2011). Previous studies of air quality at Belle Glade, Florida, a community surrounded by sugarcane fields, strongly suggested that sugarcane fires significantly degraded air quality in the SGR. In comparison with nearby Delray Beach, PM_{10} concentrations

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C.W. contributed to this work while he was a graduate student at Florida State University (FSU). Upon leaving FSU, any contributions he has made have been on his own time, outside of his regular employment. He is currently employed at SMX (formerly Smartronix) as a lead data scientist. All other authors declare they have no actual or potential competing financial interests.

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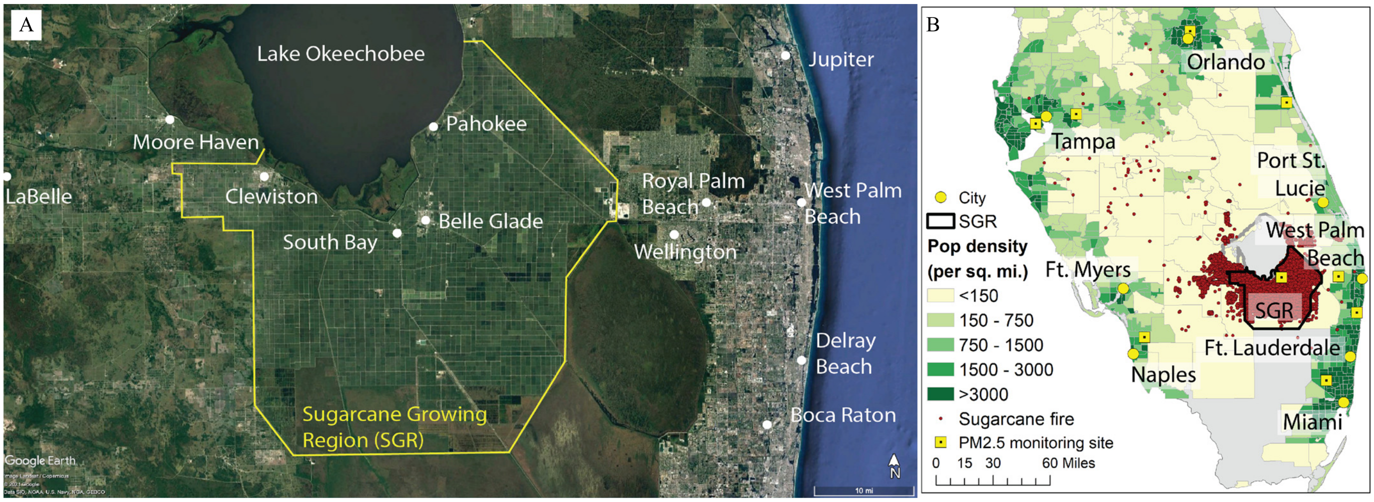

Figure 1. (A) Map of the SGR (yellow boundary) and surroundings. Background image is true-color satellite imagery from 10 and 28 January 2021 (Masek et al. 2021). Dark rectangular areas within the SGR are recently burned sugarcane fields. (B) Locations of sugarcane fires and major cities (yellow circles, labeled with names) in peninsular Florida. The SGR is shown in black and colors show population density by ZIP code. Also shown are the U.S. EPA monitoring sites used in analysis (yellow boxes with dots in the center). Note: SGR, sugarcane growing region; U.S. EPA, U.S. Environmental Protection Agency.

(PM that is 10 μm or less in aerodynamic diameter) in Belle Glade were similar outside of harvest season, but on average 50% higher during sugarcane harvest season (Sevimoğlu and Rogge 2016, 2015). Concentrations of airborne polycyclic aromatic hydrocarbons (PAH) and other chemical indicators of biomass burning were up to 15 times higher at Belle Glade during harvest than other times of the year (Afshar-Mohajer et al. 2016; Sevimoğlu and Rogge 2016, 2019).

Although past studies and public sentiment strongly suggest that sugarcane burning impacts air quality in South Florida, the geographic distribution and health consequences of the smoke have not been previously quantified. This work uses surface air quality observations, a satellite-based $PM_{2.5}$ data set, a pollutant dispersion model, and mortality records to assess the mortality impacts of $PM_{2.5}$ from sugarcane fires in South Florida at the census tract level by using dose concentration–response functions for outdoor $PM_{2.5}$ derived from previous studies. Our dispersion model includes an improved treatment of the vertical distribution of smoke due to plume rise, which has an important effect on the downwind air quality. Unlike prior national and global-scale studies, our air quality simulations use emissions computed with locally specific data coupled with a high-resolution atmospheric dispersion model, and we use a Monte Carlo approach to account for uncertainties in the concentration, health, and demographic data. Although our study is specific to sugarcane fires in South Florida, our methods can be applied to examine the mortality impacts of other biomass burning emission sources.

Methods

Unless otherwise noted, all calculations were conducted in RStudio (version 1.2.5033; http://www.rstudio.com/) using R (version 3.6.3; https://www.r-project.org/). Additional packages used in R include plyr (Wickham 2011), dplyr (https://dplyr.tidyverse.org), raster (https://cran.r-project.org/package=raster), ncdf4 (https://cran.r-project.org/package=ncdf4), RColorBrewer (https://cran.r-project.org/package=RColorBrewer), readxl (https://readxl.tidyverse.org), tidyverse (Wickham et al. 2019), and truncnorm (https://cran.r-project.org/package=truncnorm). Nonmap figures were generated using R package ggplot2 (Wickham 2016). Map figures showing census tract–level data for the State of Florida were created using ArcGIS Desktop (version 10.7.1; https://www.esri.com/en-us/arcgis/products/arcgis-desktop/overview), including ArcMap (version 10.7.1). County and census tract boundaries are TIGER/Line shapefiles from the U.S. Census Bureau (U.S. Census Bureau 2012, 2019), and the overlay of Lake Okeechobee was from the U. S. Geological Survey's National Hydrography Dataset hosted by Esri (Esri and U.S. Geological Survey 2018).

Site Description

For our study, we focused on 20 counties in South Florida (Broward, Charlotte, Collier, Miami-Dade, DeSoto, Glades, Hardee, Hendry, Highlands, Indian River, Lee, Manatee, Martin, Monroe, Okeechobee, Osceola, Palm Beach, Polk, St. Lucie, and Sarasota) and the SGR, an area where sugarcane farms and fires are heavily concentrated (Figure 1A and 1B). Our definition of the SGR included the Everglades Agricultural Area plus adjacent parts of Hendry County around Clewiston.

Surface and Satellite Observations of $PM_{2.5}$

Figure 1B shows surface $PM_{2.5}$ measurement sites in South Florida that we used to characterize the impact of sugarcane fires on air quality from 2009 to 2018 (Table S1). These sites are part of the U.S. Environmental Protection Agency (U.S. EPA) Air Quality System and provide either hourly or daily $PM_{2.5}$ measurements using the Federal Reference Method (FRM) or Federal Equivalent Method (FEM) (https://www.epa.gov/aqs; accessed 4 November 2019). A sensor in Belle Glade, Florida, provided measurements within the SGR. A second sensor in Royal Palm Beach lies between the sugarcane fields and the densely populated Atlantic coast, but it was deactivated in October 2015. In 2019, a new sensor was established in Royal Palm Beach at a different location from the previous sensor, but this was outside our 2009–2018 study period and was not included in these analyses. We compared $PM_{2.5}$ concentrations from these two sensors against seven other monitoring sites across the Florida peninsula that are far from sugarcane burning and representative of coastal and inland sites in rural, suburban, and urban settings (Table S1). Mean concentrations were computed for harvest season (October–March) and other months of the year outside the harvest season (April–September) from the daily means. The surface data covered 10 harvest seasons and

10 outside harvest/other seasons, whose means we compared with an unpaired two-sample t-test.

We also characterized the $PM_{2.5}$ distribution between surface monitors using satellite-derived maps of $PM_{2.5}$ surface concentrations from the Atmospheric Composition Analysis Group of Washington University in St. Louis (version V4.NA.03; retrieved 1 March 2021, from https://sites.wustl.edu/acag/datasets/surface-pm2-5/#V4.NA.03). The data set provides surface $PM_{2.5}$ concentrations monthly on a 0.01° horizontal grid over North America using the methods described by van Donkelaar et al. (2019) with updated geophysical $PM_{2.5}$ from Hammer et al. (2020). These surface $PM_{2.5}$ concentrations were inferred from aerosol optical depth retrieved from multiple satellite instruments and combined with additional information from a chemical transport model and a geographically weighted regression using surface $PM_{2.5}$ measurements. The V4.NA.03 data set is statistically trained with surface $PM_{2.5}$ observations across North America and is not specifically optimized to match surface $PM_{2.5}$ measurements in South Florida. Therefore, we further localized the V4.NA.03 $PM_{2.5}$ estimates to match ground-based monitors in Florida. For each month in our study period, we computed the difference between measured surface mean $PM_{2.5}$ at nine surface sites listed in Table S1 and the satellite-derived value in the pixels containing those sites. A linear radial basis function was fit to these differences to interpolate correction factors at every point in the satellite data grid using Python 3.8 with SciPy (Virtanen et al. 2020), which were then added to the satellite estimate of $PM_{2.5}$ to create the corrected $PM_{2.5}$ map in R. An example of this correction process is given in the "Results" section titled "Monthly satellite $PM_{2.5}$ data set corrected for South Florida."

HYSPLIT Dispersion Model

Concentrations of $PM_{2.5}$ from sugarcane fires were simulated here with the Hybrid Single Particle Lagrangian Integrated Trajectory model (HYSPLIT version 4, revision 951) from 2012 to 2018 (Draxler and Hess 1998; Stein et al. 2015). Fire emissions and plume rise are described below in the "Methods" sections titled "Sugarcane fire emissions," "Sugarcane fire duration and timing," and "Sugarcane smoke plume rise and modeled uncertainty." Each simulated fire released 10,000 computational particles per hour, and their dispersion was simulated in 3D particle mode with winds and stochastic turbulence derived from the 12-km North America Mesoscale (NAM) model (NOAA Air Resources Laboratory 2020). $PM_{2.5}$ was removed from the model by dry and wet deposition at rates that depended on meteorological conditions, assuming an aerodynamic diameter of 1 μm and density of $1.3\ g/cm^3$ (Draxler and Hess 1998). In a test simulation, we found that nearly all sugarcane smoke advects away from Florida within 1 d; so, for computational expediency, particles were removed from the simulation after 24 h. The model archived hourly average $PM_{2.5}$ concentration at a height of 10 m, which represented the approximate height of the U.S. EPA $PM_{2.5}$ monitoring sensors and inhaled concentrations, over South Florida (25° to 29° N, –83° to –80°E) at 0.05° grid resolution (~5.5 km). Simulations were run for sugarcane harvest seasons, which were October through March in 2012–2018. There are very few sugarcane fires in April through September, so those months were not simulated, and the annual mean $PM_{2.5}$ concentration was assumed to be half of the simulated mean during the 6-month harvest season.

Sugarcane fire emissions. Daily sugarcane fire emissions can be derived from Open Burn Authorizations (OBA), which are required for all prescribed fires in Florida [Nowell et al. 2018; Florida Statute 590.125(3)(b)(4)]. The Florida Forest Service (FFS) provided us with anonymized OBA records for 2012–2018, each of which specifies the date, location, requested area, and type of fire (silvicultural, agricultural, or land clearing). Previous analysis of all types of OBAs found an overall error of <10% between area requested as indicated in the OBAs, with individual fires having an area difference between 20%–40% (Nowell et al. 2018). We compared fire area in a random sample of 10 sugarcane OBAs from 2019 against the sugarcane field sizes measured from satellite imagery (https://www.google.com/earth) and found a median area discrepancy of just 2.5 acres (ac) or 6% (Table S2). The OBA area for sugarcane fires was likely more accurate than for other fires because sugarcane burns are conducted in clearly demarcated rectangular fields, typically around 40 ac, with nearly homogeneous fuel (Baucum and Rice 2009).

For each sugarcane OBA, primary $PM_{2.5}$ emissions were computed from the burn area using the relationship $E = A\,F\,C\,e$ (Andreae and Merlet 2001; Seiler and Crutzen 1980). In this equation, E is the emission of $PM_{2.5}$ or another compound (g), A is the burned area [hectares (ha)], F is the fuel loading or the biomass of sugarcane per hectare (kilograms per hectare), C is the fraction of biomass consumed by the fire (unitless), and e is the emission factor (grams per kilogram), which is the mass of $PM_{2.5}$ or other compound emitted from burning a unit of biomass. Previous work estimated the fuel loading (10,648 kg/ha, range 8,967–15,692 kg/ha), combustion fraction (0.65, no error given), and the emission factor for primary $PM_{2.5}$ (4.35 g/kg; range 3.9–4.99 g/kg) for sugarcane grown in the southern United States (McCarty 2011; Pouliot et al. 2017). Using locally appropriate values is important because sugarcane fuel loads and emission factors vary widely among different sugarcane regions of the world due to the differences in crop varieties, soil, water, and fertilizer practices (McCarty 2011). In comparison with many other sugarcane growing regions, Florida sugarcane has lower combustion efficiency and higher $PM_{2.5}$ emission factors because Florida sugar crops are usually harvested while they are still green and contain more moisture (McCarty 2011).

Emissions calculated above accounted for primary $PM_{2.5}$ only. Secondary $PM_{2.5}$ was also produced within the smoke plume, which also degraded air quality. Prior studies have found that total $PM_{2.5}$ is up to seven times the primary $PM_{2.5}$ in smoke from agricultural crop fires after several hours of aging (Fang et al. 2017; Liu et al. 2016; Vakkari et al. 2014) and generally 1- to 3-fold greater than primary $PM_{2.5}$ in other types of biomass burning (Ahern et al. 2019; Cubison et al. 2011; Lim et al. 2019; Vakkari et al. 2018; Yokelson et al. 2009). In our simulations, we multiplied primary $PM_{2.5}$ emissions by 2 to account for secondary chemistry that was not in the model, because this approach resulted in dispersion modeling data commensurate with surface monitor observations that included secondary $PM_{2.5}$ (see "Results" section titled "Observational Evidence of $PM_{2.5}$ from Sugarcane Fires"). Recognizing the uncertainty in the enhancement factor, we varied it from 1 (no secondary $PM_{2.5}$) to 2 in all confidence intervals (CIs) reported in the "Results" (see "Uncertainty and CIs"). Some sugarcane fires unintentionally ignite muck fires, which are fires that occur beneath the surface layer in peat soils that can smolder and emit $PM_{2.5}$ for extended periods of time after the initial fire (Sandhu et al. 2013; Watts and Kobziar 2013). Florida regulations allow these muck fires to burn for up to 72 h without penalty to landowners (Turner 2019), which could significantly add additional $PM_{2.5}$ from sugarcane fires beyond what we estimated, but their emissions were not included here because we had little information about their frequency or extent.

Sugarcane fire duration and timing. Because OBA records do not report the fire start and end times, we determined the mean diurnal cycle of sugarcane emissions from fire radiative power

(FRP) detected by the Geostationary Operational Environmental Satellite 16 (GOES-16) fire detection and characterization algorithm (GOES-R Algorithm Working Group 2018). GOES-16 better detects agricultural fires than previous satellites, due in part to its finer spatial resolution and more frequent sampling (Li et al. 2020). We analyzed the mean diurnal cycle of fire radiative power in the SGR (26.35–27°N, 80.4–81.1°W) during January 2019, based on fire detections with the highest quality data flag (see "Ground-based $PM_{2.5}$ measurements and sugarcane fire observations"). In our HYSPLIT simulations, emissions from every sugarcane fire were distributed throughout the day following this mean diurnal cycle, accounting for Daylight Saving Time (DST) [0900 hours to 1800 hours (9 A.M. to 6 P.M.) local time during DST; 0900 hours to 1700 hours (9 A.M. to 5 P.M.) otherwise].

Sugarcane smoke plume rise and modeled uncertainty. Surface $PM_{2.5}$ concentrations and air quality were sensitive to smoke plume rise or injection height (e.g., Achtemeier et al. 2011; Liu 2008; Liu et al. 2010; Mallia et al. 2018; Paugam et al. 2016; Raffuse et al. 2012; Soja et al. 2011; Val Martin et al. 2012, 2018). Plume rise methods in air quality models included both mechanistic algorithms (Achtemeier et al. 2011; Achtemeier and Adkins 1997; Briggs 1969; Freitas et al. 2007; Liu et al. 2010) and empirical distributions (Kukkonen et al. 2014; Paugam et al. 2016; Raffuse et al. 2012; Val Martin et al. 2012, 2018). HYSPLIT typically simulates buoyant plume rise using the approach of Briggs (1969), originally derived for buoyant industrial plumes. Biomass burning smoke plume heights predicted by the Briggs method, however, were consistently lower than observed plume heights and poorly correlated with them (Raffuse et al. 2012). Furthermore, HYSPLIT normally injects fire emissions at a single altitude, whereas real plumes span a range of altitudes (Achtemeier et al. 2011). More detailed dynamical models of plume rise did not always perform better mainly due to the uncertainty in input parameters including FRP measurements, presumed fire type, and local atmospheric conditions (Val Martin et al. 2012).

To improve the model, we implemented an empirical vertical distribution of smoke emissions in HYSPLIT based on the distribution of sugarcane fire plume heights determined by the multiangle imaging SpectroRadiometer (MISR) satellite instrument on board NASA's Terra satellite (Val Martin et al. 2010, 2018). Our HYSPLIT simulations stochastically distributed sugarcane fire emissions using the observed vertical distribution as a probability density function (see "Results" section, "Satellite observed plume rise for sugarcane fires and modeled uncertainty"). Because we configured each simulated fire to emit thousands of computational particles, this method emitted smoke at a realistic range of altitudes. Subsequent atmospheric turbulence mixed the smoke vertically within the boundary layer.

To quantify the uncertainty in surface $PM_{2.5}$ due to plume rise assumptions, we conducted 1-month simulations for January 2012 with four plume rise methods: our empirical distribution derived from MISR, uniform release from surface to the boundary layer, the HYSPLIT-default Briggs method, and all emissions released at the surface. Apart from the plume rise, the model settings and emissions were the same in all simulations, as described in "Methods" section "Sugarcane fire emissions." We expected surface $PM_{2.5}$ concentrations resulting from real plume rise would lie between the extreme low and high sensitivity tests. Dividing these extremes by the predicted $PM_{2.5}$ with our empirical method provided a multiplicative uncertainty estimate that we used for deriving our 95% CIs (see "Methods" section "Uncertainty and CIs"). The process was repeated for each census tract to determine the uncertainty due to plume rise in $PM_{2.5}$ concentration due to sugarcane fires.

Mortality Calculations

Mortality from sugarcane fires was assessed in a two-stage approach. First, the estimated mortality due to $PM_{2.5}$ from all sources was calculated from the corrected satellite-derived $PM_{2.5}$ concentrations using health-impact functions and demographic data described below. Second, mortality from all sources excluding sugarcane smoke was estimated by subtracting the amount of $PM_{2.5}$ from sugarcane smoke as derived from HYSPLIT from the corrected satellite-derived $PM_{2.5}$. The difference between these two mortality calculations was the estimated excess mortality burden due solely to sugarcane smoke exposure. This subtraction method was used by other studies to attribute mortality due to contributions from a given source (Kodros et al. 2016; McDuffie et al. 2021). Both stages of the analysis were computed yearly by census tract, which was our finest level of demographic mortality data. We report multiyear means as our best estimate of mortality impacts.

Epidemiological studies provided concentration–response functions (CRF) that quantify the relative risk (R) of death as a function of the annual mean concentration of $PM_{2.5}$. For our analysis, we used an updated version of the Global Exposure Mortality Model (GEMM) as the CRF (McDuffie et al. 2021). The GEMM CRFs were based on 41 studies of nonaccidental mortality and outdoor $PM_{2.5}$ using data from 16 countries (Burnett et al. 2018). Unlike some earlier CRF that included $PM_{2.5}$ mortality studies from smoking, secondhand smoke exposure, and indoor air pollution (e.g., Burnett et al. 2014), GEMM only used mortality studies based on outdoor air pollution exposure (Burnett et al. 2018). GEMM was primarily based on data from high-income countries, which was appropriate for this study of Florida, but there may be additional uncertainty in applying these CRF to low-income countries (Hystad et al. 2020; McDuffie et al. 2021). Although sugarcane fire smoke exposure is intermittent during the 6-month-long burning season, the SGR communities are repeatedly impacted throughout the burning season and year after year, making sugarcane fires more like long-term exposure than an acute short-term wildfire exposure event that may not repeat for many years. We used a compilation of R values from GEMM provided in supplemental data of McDuffie et al. (2021) for five specific mortality causes linked to $PM_{2.5}$ exposure for adults 25 y old and above: chronic obstructive pulmonary disease (COPD), diabetes mellitus type 2 (DM), lung cancer (LC), ischemic heart disease (IHD), and stroke. For IHD and stroke, R values were further broken down into 5-y age groups starting at age 25 y. We also obtained R values for a sixth mortality cause of lower respiratory infections (LRI), which includes deaths from children age 5 y and younger in addition to adults 25 y and older.

The cause-specific population attributable fractions (PAF) for each disease are given as $PAF_{age,\,disease} = 1 - \frac{1}{R_{age,\,disease,\,[PM2.5]}}$. Note that the $PM_{2.5}$ concentration used in McDuffie et al. (2021) was the population-weighted mean value. Because we were calculating impacts at the census tract level, which is the finest level of population information, we applied average $PM_{2.5}$ values across the entire census tract population. For a given cause of death and age range (only applicable to IHD and stroke), we looked up the associated R value given for our calculated $PM_{2.5}$ value from the McDuffie et al. (2021) supplemental tables. Estimated mortality linked to outdoor $PM_{2.5}$ (ΔM) is given as the disease-specific baseline mortality rate (M_0) multiplied by the PAF: $\Delta M = \sum_{disease}^{n} \sum_{age}^{m} PAF_{age,\,disease} \times M_{0,\,age,\,disease}$ (McDuffie et al. 2021) and was calculated both for total $PM_{2.5}(\Delta M_{all})$ and for $PM_{2.5}$ excluding sugarcane fires (ΔM_{no_sugar}). The overall estimated mortality attributable to the average annual $PM_{2.5}$ from sugarcane was $\Delta M_{sugar} = \Delta M_{all} - \Delta M_{no\_sugar}$.

In the "Results" section, we discuss our findings in terms of the fraction of nonaccidental estimated mortality attributable to sugarcane fires, which was $F_{A,sugar} = \Delta M_{sugar,total}/M_{0,\,total}$, where $\Delta M_{sugar,total}$ is total mortality across all six causes from sugarcane smoke exposure, and $M_{0,\,total}$ is the combined baseline mortality from the six causes of death analyzed in this study ($M_{0,total} = \sum_{disease}^{n} \sum_{age}^{m} M_{0,\,age,\,disease}$). Annual mean $PM_{2.5}$ concentrations for each census tract (all sources, sugarcane only, and all sources with sugarcane fires removed) were computed from the model and satellite data using bilinear interpolation to a high-resolution grid (0.001°), followed by averaging points within the perimeter of each tract. $PM_{2.5}$ concentrations in all South Florida census tracts exceeded commonly used lower thresholds for $PM_{2.5}$ risk (2.4–5.9 $\mu g/m^3$ Cohen et al. 2017); although the existence of those thresholds was controversial (Brook et al. 2010; Burnett et al. 2018; Forouzanfar et al. 2016), $PM_{2.5}$-attributed mortality can be expected across South Florida. For 2.4 $\mu g/m^3$ and below, the GEMM R curves assumed no additional risks and set all R values equal to 1, including the 95% uncertainty intervals (McDuffie et al. 2021).

These mortality calculations were applied to 20 counties in South Florida that are potentially impacted by sugarcane fire smoke. Mortality counts (excluding personally identifiable information) were from the Florida Department of Health, which are publicly available by request, from which we calculated aggregated mortality and mortality rates (per 100,000 people) for all six causes of COPD, DM, IHD, LC, LRI, and stroke using ICD-10 codes reported in the Global Burden of Disease study of 2017 (Institute for Health Metrics and Evaluation Global Health Data Exchange 2018) and used in the generation of the GEMM relative risk curves (McDuffie et al. 2021). Because the mortality data was anonymized and aggregated, it did not require IRB/ethics approval. Population data (P) for each census tract were from the 2013–2017 American Community Survey (ACS) (U.S. Census Bureau 2018a) and were used to calculate mortality rates per 100,000 people ($\Delta M/P \times 100{,}000$). ACS provided P broken down by age group in 5- to 10-y intervals. We calculated P of people age 25 y or older by combining all population estimates for each age group beginning at 25 y.

Uncertainty and CIs

Our best estimate of mortality attributable to $PM_{2.5}$ exposure from sugarcane fires was based on the multiyear means of variables already described: simulated $PM_{2.5}$ concentrations from sugarcane fires, satellite-derived ambient $PM_{2.5}$ concentrations, baseline mortality for six causes of death, and population at the census tract level. We derived 95% CIs for the attributable mortality using 10,000 Monte Carlo runs in which inputs to the mortality calculation were sampled over their ranges of uncertainty. The input variables included $PM_{2.5}$ emissions from sugarcane fires, smoke plume rise, secondary $PM_{2.5}$ production, ambient $PM_{2.5}$, population, baseline mortality, and R.

Relative risk and population were all drawn from normal distributions with standard deviations as follows: McDuffie et al. (2021) provides best-guess estimates and 95% uncertainty intervals for each R at a given $PM_{2.5}$ concentration. Because we assumed a normal distribution and because a 95% uncertainty interval represents the end points that are 2σ above and below the mean, the difference between the upper and lower bounds represents a spread of roughly four standard deviations (σ). For the mean, we used the best-guess estimate for each R at a given $PM_{2.5}$ concentration, with the σ being the difference between the two end points of the 95% uncertainty interval divided by four. The standard error of the 25 y and above age group was derived from the margin of error for each group following the outline from the U.S. Census Bureau (U.S. Census Bureau 2018b) and was used in our uncertainty estimates. For baseline mortality, we used the annual death counts from the examined six causes of death for each census tract from Florida Department of Health data for a random year within our study period to preserve any spatial correlation.

The remaining uncertainty variables concern the concentration of $PM_{2.5}$ and fraction of $PM_{2.5}$ from sugarcane fires. For ambient $PM_{2.5}$, we randomly selected one of the study years (2012–2018) and use the corrected satellite concentrations for that year. For the concentration of $PM_{2.5}$ from sugarcane fires (c_{sugar}) in each census tract, we use $c_{sugar} = c_{year}\alpha_F\alpha_{EF}\alpha_{plume}\alpha_{\mathrm{secondary}}$, where c_{year} is the concentration simulated by HYSPLIT in the randomly selected year, which accounts for variability in meteorology and fire locations. The other terms are multiplicative factors for uncertainty in fuel loading (α_F), emission factor (α_{EF}), plume rise (α_{plume}), and production of secondary $PM_{2.5}$ ($\alpha_{\mathrm{second}ary}$). The multiplicative factors are drawn from uniform distributions $U(a,b)$ over the interval [a, b]. Literature reviewed in "Methods" section "Sugarcane fire emissions" suggest $\alpha_F \sim U(0.8, 1.5)$, $\alpha_{EF} \sim U(0.9, 1.15)$, and $\alpha_{\mathrm{second}ary} \sim U(1, 2)$ compared to the given mean values. For plume rise, in each census tract we found the maximum and minimum $PM_{2.5}$ concentrations across the ensemble of HYSPLIT sensitivity tests with alternate plume rise assumptions and divided each end point by the estimate from our empirical method to obtain a multiplicative factor.

Demographic Data

In addition to the population information from the 2017 ACS that is used in our mortality calculations to match our study period (see the "Methods" section "Mortality Calculations") (U.S. Census Bureau 2018a), we also obtained race and household income information from the 2019 ACS, the most recent ACS at the time of analysis to capture the most current information (U.S. Census Bureau 2020a, 2020b). For our study, the percentage of nonwhite residents included all people that did not identify as "one-race" and "White" divided by the total population age 25 and above. Population was calculated both at a census tract level for mortality calculations (see the section "Mortality Calculations"), and aggregated at a regional level along with race, and median household income. These three variables were calculated at a regional level for the SGR and the rest of the 20-county area in South Florida for comparison purposes.

Results

Observational Evidence of $PM_{2.5}$ from Sugarcane Fires

Florida has $10{,}300 \pm 1{,}500$ sugarcane fires annually (mean ± interannual standard deviation) for 2004–2019, according to FFS OBA records, burning $169{,}000 \pm 26{,}000$ ha (Figure 1B). We estimated that these fires produced $(5.1 \pm 0.8) \times 10^6$ kg of primary $PM_{2.5}$ each year using mean fuel variable values outlined in the "Methods" section "Sugarcane fire emissions". According to the 2017 National Emission Inventory, on-road vehicles in Florida emitted 6.1×10^6 kg of primary $PM_{2.5}$ per year, so emissions from sugarcane fires were comparable to emissions from all vehicles in the state (U.S. EPA 2020). Although vehicle emissions are geographically widely distributed, 90% of these sugarcane fires and their emissions were concentrated in South Florida around Lake Okeechobee within 12 heavily impacted census tracts, which is the area that we refer to as the SGR (Figure 1).

Ground-based $PM_{2.5}$ measurements and sugarcane fire observations. Surface air quality measurements suggested that sugarcane fires were responsible for a hot spot of elevated $PM_{2.5}$ concentrations centered in the SGR (Figure 2). Across most of Central and South Florida (south of 29°N), $PM_{2.5}$ concentrations were higher outside of harvest than harvest/winter season on average (Figure 2A; Table S3), a pattern also seen throughout much of the southeastern United States (Chen et al. 2012; Cheng and Wang-Li 2019; Zhang et al. 2009). Only two sites in South Florida—Belle Glade and Royal Palm Beach—measured higher mean $PM_{2.5}$ in winter, which is the sugarcane harvest and prescribed fire season. At Belle Glade, the only monitoring site within the SGR, $PM_{2.5}$ was $0.7\,\mu g/m^3$ higher during the sugarcane harvest season than the rest of the year (95% CI: -0.4, $1.8\,\mu g/m^3$, $p = 0.19$, unpaired two-sample t-test; Figure 2A and Table S3). At Royal Palm Beach, the closest site outside the SGR, $PM_{2.5}$ was $0.2\,\mu g/m^3$ higher in harvest season (95% CI: –1.3, $1.7\,\mu g/m^3$, $p = 0.79$; Figure 2A and Table S3). A short-term study using 1 y of concentration measurements did not find this pattern (U.S. Sugar 2020), likely because of interannual variability in meteorology and fires (McCarty 2021), but our results using 10 y of data are more robust. In the absence of sugarcane fires, Belle Glade and Royal Palm Beach might be expected to experience a winter/harvest season $PM_{2.5}$ decrease like surrounding sites outside the SGR (0.6 to $0.8\,\mu g/m^3$ mean at Delray Beach, Palm Springs, Naples). This suggests that sugarcane harvest activities may contribute an approximate $1.4\,\mu g/m^3$ (95% CI: 0.3, $2.5\,\mu g/m^3$) to mean $PM_{2.5}$ within the SGR during harvest season and $0.9\,\mu g/m^3$ (95% CI: -0.6, $2.4\,\mu g/m^3$) in nearby surrounding areas like Royal Palm Beach. Because the harvest season is 6 months long, the contribution of sugarcane fires to the annual mean $PM_{2.5}$ is half of the contribution in harvest season.

Figure 2B (Table S4) shows week-by-week variations in sugarcane fire area and $PM_{2.5}$ at Belle Glade, which is the only location within the SGR that has a $PM_{2.5}$ monitor. The fire area abruptly rose in October and remained steady from November through March before an abrupt decline in April. The seasonal shifts in $PM_{2.5}$ concentrations followed a similar pattern. Relatively high $PM_{2.5}$ persisted from January through the end of April, at which point it dropped off with the decreased sugarcane burned area. As noted earlier, $PM_{2.5}$ concentrations at Belle Glade were generally lower in months outside of sugarcane harvest season although there were intermittent increases, some of which are likely due to wildfires. $PM_{2.5}$ rose again in the fall, coinciding with the start of sugarcane burning, although other harvest activities could potentially contribute as well.

Diurnal cycles of $PM_{2.5}$ at Belle Glade, seen in Figure 2C (Table S5), were also consistent with sugarcane fires contributing significantly to $PM_{2.5}$ in the SGR. Although outside harvest season $PM_{2.5}$ concentrations had a broad maximum from 0600 hours to 1200 hours (6:00 A.M. to 12:00 P.M.), harvest season concentrations peaked sharply at 1000 hours to 1100 hours (10:00 A.M. to 11:00 A.M.). That sharp late-morning peak closely matched the predicted timing and magnitude of peak $PM_{2.5}$ contribution from sugarcane fires, shown in Figure 2D (Table S5), which follows the start of burning and observed peak fire radiative power that occurred at 0900 hours to 1000 hours (9:00 A.M. to 10:00 A.M.). Observed $PM_{2.5}$ concentrations and simulated sugarcane contribution were steady through the afternoon hours of harvest season, before dropping off after 1800 hours (6:00 P.M.), which corresponds to the required cessation of burning before sunset.

Monthly satellite $PM_{2.5}$ dataset corrected for South Florida. We used monthly corrected satellite $PM_{2.5}$ observations to get a more complete picture of $PM_{2.5}$ concentrations in South Florida. Figure 3A–C illustrate the correction process discussed in the "Methods" section "Surface and Satellite Observations of $PM_{2.5}$" for January 2016. We compared the initial satellite dataset

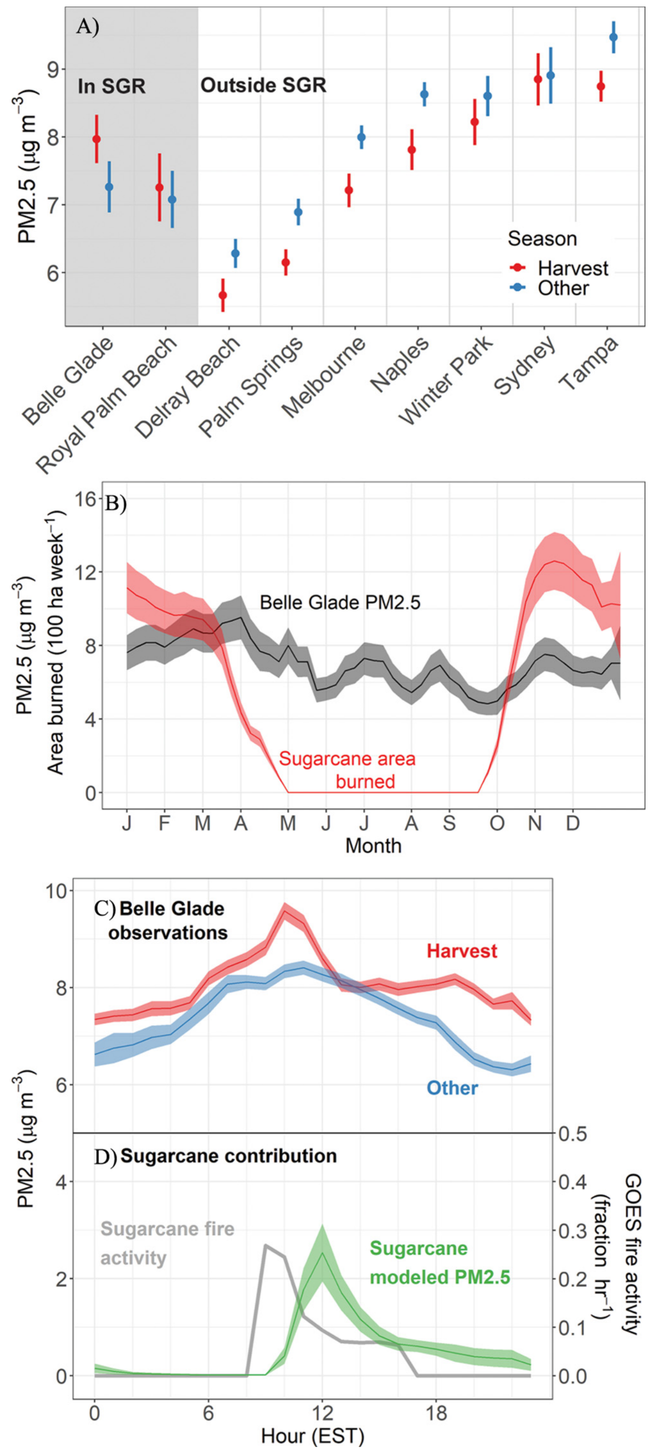

Figure 2. (A) $PM_{2.5}$ concentrations at air quality monitoring sites in Central and South Florida, showing mean concentrations during sugarcane harvest and fire season (October–March) vs. other months outside harvest (April–September). Dots and vertical lines show mean and standard error. Data are averages for 2009–2018, except for Royal Palm Beach, which stopped measurements in 2015. (B) Temporal variability of sugarcane burned area in the SGR and $PM_{2.5}$ concentrations measured in Belle Glade. Data are averaged for 2009–2019 and smoothed with a 3-wk running mean. (C) Mean diurnal cycle of $PM_{2.5}$ concentrations measured in Belle Glade from the U.S. EPA sensor from 2009–2019. (D) Simulated contribution of sugarcane fires to the mean diurnal cycle of $PM_{2.5}$ concentration in Belle Glade and mean diurnal cycle of GOES-16 FRP, which is a proxy for sugarcane fire emissions. The vertical distribution of smoke (B) and GOES-16 FRP are normalized to unit integral. Shading shows standard error of the mean. Note: FRP, fire radiative power; U.S. EPA, U.S. Environmental Protection Agency.

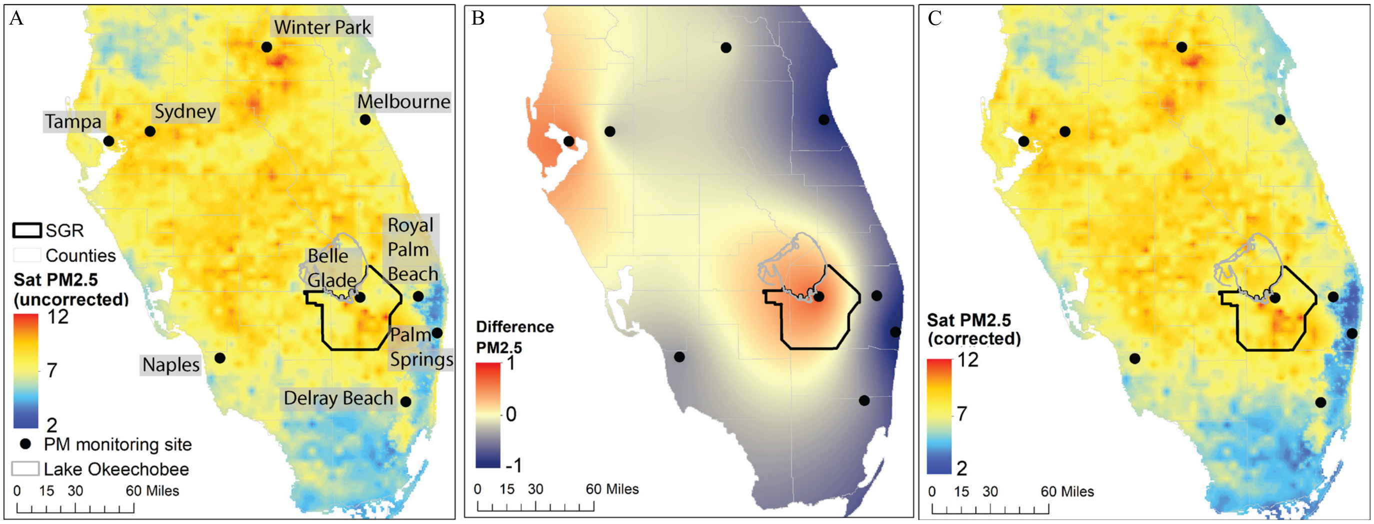

Figure 3. Example correction of satellite-derived $PM_{2.5}$ (micrograms per cubic meter) to match surface $PM_{2.5}$ concentration measurements in January 2016: (A) uncorrected satellite $PM_{2.5}$; (B) interpolated difference between uncorrected satellite $PM_{2.5}$ and surface measurements (surface minus satellite); (C) corrected satellite-derived $PM_{2.5}$ (micrograms per cubic meter). Black dots show surface measurement sites.

(Figure 3A) against the ground measurement sites at nine EPA monitoring sites (Table S1) and applied the linear radial basis function to fit differences between satellite and ground values. The interpolated differences map (Figure 3B) was added to the initial satellite map (Figure 3A) to produce a corrected satellite map specific to South Florida (Figure 3C). Figure 4A shows the multiyear mean for 2012–2018, which were the years used to estimate mortality from sugarcane smoke exposure. The differences between original satellite-derived data and measured surface values at these nine sites in Florida were $0.02 \pm 1.31\ \mu g/m^3$ [mean ± standard deviation (SD)], which is within the range of accuracy expected for this satellite-derived data (van Donkelaar et al. 2019). Although these differences were small in comparison with mean $PM_{2.5}$, we used them to spatially interpolate correction factors across South Florida so that the corrected satellite $PM_{2.5}$ data would match surface measurements in every month. Harvest and outside harvest/other season averages were computed for corrected satellite data in the same way as the surface sites, from which we computed the difference between seasons (Figure 4B).

Satellite observations in Figure 4 complement the surface air quality sensors by providing a more complete spatial picture of the $PM_{2.5}$ distribution in South Florida. The satellite data showed that the hot spot of high $PM_{2.5}$ during harvest season, which we identified in the surface measurements, covered the entire SGR and extended slightly beyond (Figure 4B). Across this area, $PM_{2.5}$ concentrations were $0.5–1\ \mu g/m^3$ higher in harvest season than outside harvest on average. Away from the SGR, in contrast, $PM_{2.5}$ was mostly lower in winter during sugarcane harvest than other times of the year and nowhere more than $0.1\ \mu g/m^3$ higher. The close spatial correspondence of the $PM_{2.5}$ hot spot with the borders of the SGR suggested that the seasonal $PM_{2.5}$ enhancement was driven by a process unique to this area. As the dominant economic activity in the region, sugarcane agricultural practices are the most likely explanation.

Satellite observed plume rise for sugarcane fires and modeled uncertainty. Using the MISR satellite instrument from 2005 to 2009 (Val Martin et al. 2010, 2018), we identified seven smoke plumes originating in the SGR during the harvest burning, all of

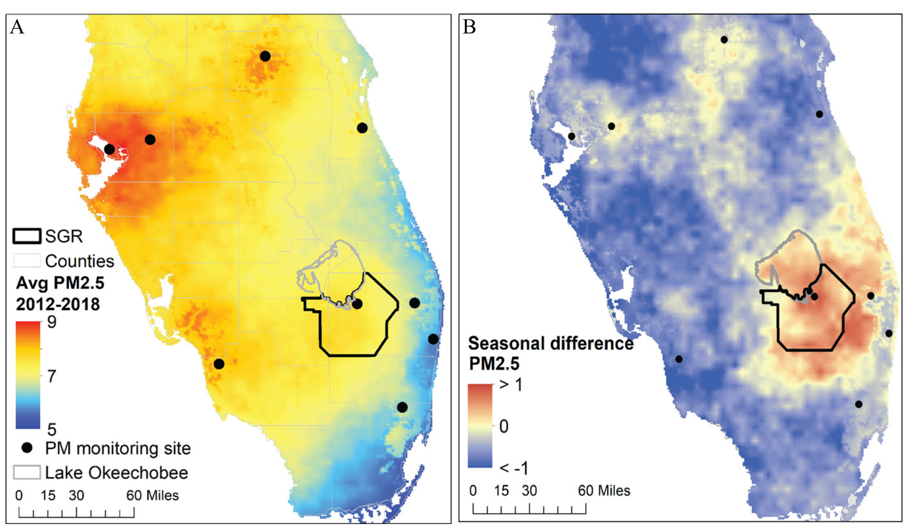

Figure 4. (A) Multiyear mean of corrected satellite derived $PM_{2.5}$ (micrograms per cubic meter) for the period 2012–2018. (B) Mean difference in surface $PM_{2.5}$ concentrations (micrograms per cubic meter) between sugarcane harvest and outside/other seasons, from corrected satellite-derived $PM_{2.5}$ data for 2009–2018. Positive values in panel B indicate harvest season has higher mean concentration. Black dots show $PM_{2.5}$ surface measurement sites used in this work.

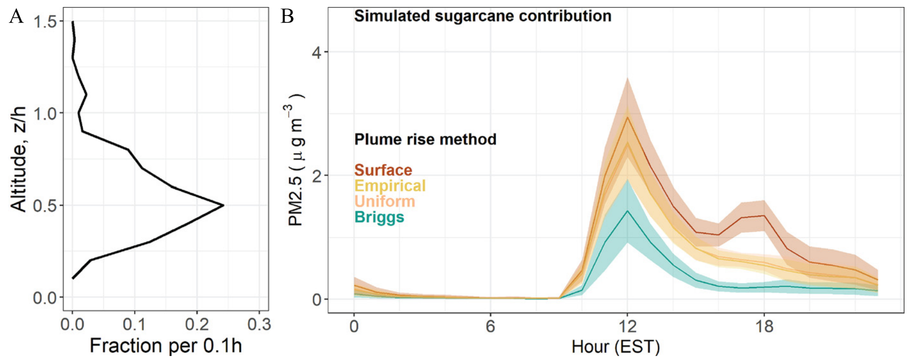

Figure 5. (A) Vertical distribution of sugarcane smoke in the SGR as a fraction of boundary layer height h, derived from MISR. (B) Mean diurnal cycle of $PM_{2.5}$ from sugarcane fires in Belle Glade simulated for January 2012 with four different plume rise methods. The empirical method is the best estimate, whereas all methods are used for constructing CIs for results. Shading shows the standard error of the mean. Note: CI, confidence interval; MISR, multi-angle imaging SpectroRadiometer; SGR, sugarcane growing region.

which originated near the locations of permitted sugarcane fires. Figure 5A (Table S6) shows the vertical distribution of smoke within these plumes (314 wind-corrected smoke points) normalized to the local boundary layer height from the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2; Gelaro et al. 2017). The MISR data showed that most smoke from sugarcane fires initially rose to the middle and upper half of the boundary layer and very little ($\sim 5\%$) escaped through the boundary layer top. This finding was consistent with field observations of sugarcane smoke plumes (Achtemeier 1996; Achtemeier and Adkins 1997). Our HYSPLIT simulations stochastically distributed sugarcane fire emissions using the observed vertical distribution (Figure 5A; Table S6) as a probability density function.

Comparing the mean diurnal cycles of our test simulations in January 2012 using our empirical method against three others (see "Methods" section "Sugarcane smoke plume rise and modeled uncertainty") at the Belle Glade sensor location, all plume rise methods had similar shapes, consisting of a sharp peak in the late morning and a decrease in the afternoon (except for a small

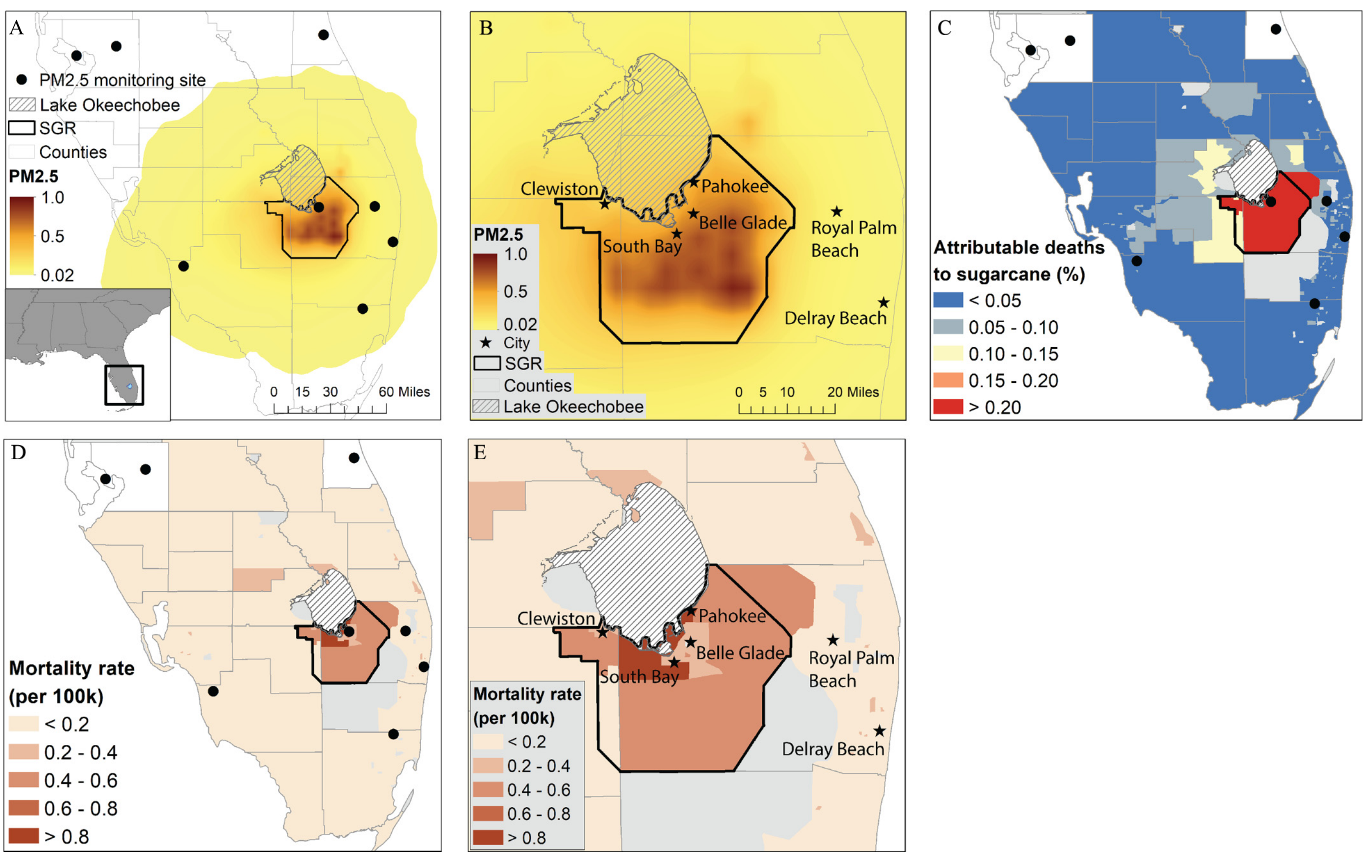

Figure 6. Estimated impacts of sugarcane fires on $PM_{2.5}$ air quality and human health: (A) simulated estimated increase in annual mean $PM_{2.5}$ concentration (micrograms per cubic meter) due to sugarcane fires in 2012–2018; (B) same as panel A with a focus on the SGR; (C) estimated fraction of mortality (six causes of death) attributable to $PM_{2.5}$ exposure from sugarcane fires; (D) estimated mortality rate per 100,000 people per year attributable to sugarcane burning; and (E) same as panel D with a focus on the SGR. Mortality and mortality rate include six causes of death associated with $PM_{2.5}$ from sugarcane fires examined in this study; see Table S9 for county-specific mortality. Light gray shading in panels C–E indicates unpopulated census tracts. Note: SGR, sugarcane growing region.

Table 1. Contribution of sugarcane fires to annual mean $PM_{2.5}$ for selected cities in South Florida during the period 2012–2018, estimated from the dispersion model. Parenthetical values give 95% confidence intervals. For the cities of Belle Glade and Royal Palm Beach, the locations coincide with $PM_{2.5}$ sensors.

City	Latitude, longitude	Yearly mean with 95% CI ($\mu g/m^3$)
Belle Glade	26.725°N, −80.667°E	0.65 (0.57, 0.73)
Pahokee	26.82°N, −80.67°E	0.55 (0.43, 0.68)
Clewiston	26.75°N, −80.93°E	0.27 (0.22, 0.32)
Royal Palm Beach	26.731°N, −80.234°E	0.1 (0.07, 0.13)
West Palm Beach	26.72°N, −80.05°E	0.05 (0.03, 0.07)
Fort Myers	26.64°N, −80.87°E	0.04 (0.04, 0.05)

Note: CI, confidence interval.

secondary peak in the late afternoon with the surface method) until there was little impact from sugarcane fires at night (Figure 5B; Table S7). The peak and average concentrations, however, were more sensitive to plume rise. When averaged over the entire month (full diurnal cycle), $PM_{2.5}$ concentrations were highest in the simulation with surface release ($0.72\,\mu g/m^3$) and the lowest in the simulation with Briggs plume rise ($0.25\,\mu g/m^3$), with our empirical vertical distribution and uniform vertical distribution mean $PM_{2.5}$ values being $0.52\,\mu g/m^3$ and $0.53\,\mu g/m^3$, respectively. Dividing the extremes (all surface release and Briggs rise) by the predicted $PM_{2.5}$ with our empirical method suggested that the mean surface concentration with real plume rise would be between 0.48 to 1.38 times the level predicted by our best estimate with empirical plume rise. We performed a similar analysis for each grid cell for our sensitivity dispersion models to obtain uncertainty intervals for plume rise methods specific to the given location to inform the uncertainty in concentration due to plume rise used in the Monte Carlo analysis (see "Methods" section "Uncertainty and CIs").

$PM_{2.5}$ from Sugarcane Fires and Its Health Impacts

Smoke dispersion simulations from HYSPLIT, shown in Figure 6A for all South Florida and Figure 6B for the SGR, also suggested that sugarcane fires could explain the hot spot of $PM_{2.5}$ in the SGR that was detected in surface and satellite data (Figures 2A and 4B). The dispersion model predicted a contribution of $0.4\,\mu g/m^3$ of $PM_{2.5}$ or more over most of the SGR from sugarcane fires. This closely corresponds with the region where satellite data show higher $PM_{2.5}$ in harvest season than other times of the year (Figure 4B). At Belle Glade, the model estimated that sugarcane fires could contribute $0.65\,\mu g/m^3$ (95% CI: 0.57, $0.73\,\mu g/m^3$; Table 1) to annual mean $PM_{2.5}$, which is within range implied by surface measurements ($0.15–1.25\,\mu g/m^3$, i.e., half of the harvest-season enhancement in the "Results" section "Observational Evidence of $PM_{2.5}$ from Sugarcane Fires"). For other communities in the SGR, sugarcane fires were estimated to raise mean $PM_{2.5}$ by $0.55\,\mu g/m^3$ (95% CI: 0.43, $0.68\,\mu g/m^3$) in Pahokee and $0.27\,\mu g/m^3$ (95% CI: 0.22, $0.32\,\mu g/m^3$) in Clewiston (Table 1). At Royal Palm Beach, the predicted $0.1\,\mu g/m^3$ (95% CI: 0.07, $0.13\,\mu g/m^3$; Table 1) estimated contribution to $PM_{2.5}$ from sugarcane fires was on the low end of the range from surface observations ($0.25–0.6\,\mu g/m^3$). Outside the SGR, the model estimated that $PM_{2.5}$ from sugarcane fires dropped abruptly to the east and more slowly to the west and south, where mean estimated $PM_{2.5}$ from sugarcane fires along the Atlantic coast in West Palm Beach and the Gulf coast in Fort Myers were an estimated $0.05\,\mu g/m^3$ (95% CI: 0.03, $0.07\,\mu g/m^3$), and $0.04\,\mu g/m^3$ (95% CI: 0.04, $0.05\,\mu g/m^3$), respectively (Table 1).

This abrupt drop away from the SGR is consistent with FFS practice to deny burn permit requests under brisk westerly winds [Florida Forest Service–Everglades District (personal communication)]. The effect of this wind criteria, however, was that sugarcane smoke was preferentially directed toward smaller and less affluent inland communities (Figure S1). According to the ACS, during our study period the SGR had 62,000 residents, most of whom were non-White (57%; those who did not identify as one-race, White) with a median household income (USD \$34,000) about half of South Florida overall (Figure S1; U.S. Census Bureau 2020a, 2020b). This effect of the wind criteria could also be considered a social justice issue because the smoke from sugarcane burning appeared to have disproportionate impacts for the lower income, minority residents of the SGR.

Figures 6C,D, and E map the estimated attributable mortality and mortality rate due to $PM_{2.5}$ from sugarcane fires for six causes of death: COPD, DM, lung cancer, LRI, IHD, and stroke (95% CI shown in Figure S2; best estimate and 95% CI associated with mortality rate for all sources of $PM_{2.5}$ are given in Figure S3). Table 2 aggregates these results into geographic regions. Estimated mortality rates due to sugarcane smoke were highest in

Table 2. Estimated mortality[a] (deaths per year) and mortality rate (deaths per 100,000 people per year) due to $PM_{2.5}$ from all sources and due to $PM_{2.5}$ from sugarcane fires, along with fraction of mortality due to sugarcane fires (percentage). Parenthetical values give 95% confidence intervals.

Locations	$PM_{2.5}$ from sugarcane fires		$PM_{2.5}$ from all sources		Fraction of mortality from sugarcane fires
Region or county[b]	Mortality, ΔM_{sugar}	Mortality rate, $\Delta M_{sugar}/P$	Mortality, ΔM_{all}	Mortality rate, $\Delta M_{all}/P$	$F_{a,\,sugar}$
Sugarcane Growing Region	0.16 (0.09, 0.6)	0.4 (0.3, 1.6)	2.4 (0.3, 4.8)	6.3 (0.9, 13)	0.28 (0.16, 0.91)
Palm Beach County	0.72 (0.17, 2.2)	0.07 (0.02, 0.22)	45 (0.51, 110)	4.4 (0.05, 12)	0.04 (0.01, 0.11)
Glades County	0.013 (0.002, 0.042)	0.14 (0.02, 0.33)	0.68 (0.06, 1.5)	6.8 (0.4, 13)	0.08 (0.03, 0.15)
Hendry County	0.05 (0.02, 0.21)	0.22 (0.08, 0.72)	1.9 (0.3, 4)	7.7 (1.1, 14)	0.11 (0.06, 0.32)
Okeechobee County	0.04 (0.01, 0.09)	0.13 (0.03, 0.29)	2.3 (0.1, 4.8)	8.4 (0.3, 16)	0.05 (0.01, 0.10)
South Florida (20 counties)	2.5 (1.2, 6.1)	0.04 (0.02, 0.09)	410 (70, 830)	5.7 (1.1, 12)	0.02 (0.01, 0.05)

[a]Mortality and mortality rates are for six causes of death for people aged 25 and above, averaged over years 2012–2018, except for lower respiratory infections (LRI), which includes deaths for those age 5 y and younger. Other causes of death are chronic obstructive pulmonary disease (COPD), diabetes mellitus type 2 (DM), lung cancer (LC), ischemic heart disease (IHD), and stroke.
[b]This table includes the four most impacted counties. Results for all counties in South Florida are provided in Table S9.

the SGR where sugarcane fires were associated with the highest $PM_{2.5}$ contribution. Within the SGR, exposure to smoke from sugarcane fires was estimated to lead to 0.4 deaths per 100,000 people per year (95% CI: 0.3, 1.6 deaths per 100,000). This estimate was about 10 times higher than the estimated mortality impact of sugarcane fires in the coastal cities. Baseline mortality was no higher in the SGR than the South Florida average, so the higher $PM_{2.5}$ concentrations from sugarcane fires could be the dominant reason for the higher mortality estimate in the SGR (Figure S4A and Table S8). Although the estimated mortality rates from exposure to sugarcane smoke were highest in the SGR (Figures 6D and E), Figure 6D shows that some census tracts in coastal communities had elevated estimated mortality rates from sugarcane fires relative to their surroundings. Those tracts had higher baseline mortality rates (Figure S4A) and occurred where a high fraction of the population was elderly (Figures S4B and S4C).

Overall, these results suggest that $PM_{2.5}$ from sugarcane burning can lead to an estimated 2.5 deaths annually across South Florida (95% CI: 1.2, 6.1 deaths), which is 0.04 deaths per 100,000 people per year (95% CI: 0.02, 0.09 per 100,000), whereas all sources of $PM_{2.5}$ are associated with an estimated 410 deaths annually (95% CI: 70, 830 deaths) for the six causes (Table 2). We estimated 0.16 deaths per year within the SGR were due to $PM_{2.5}$ from sugarcane fires (95% CI: 0.09, 0.6 deaths) (Table 2). Although sugarcane smoke had the biggest impact on estimated mortality rate within the SGR, where $PM_{2.5}$ from the fires is concentrated, most of the estimated deaths occurred in more populous areas outside the SGR. Estimated mortality in highly impacted counties is shown in Table 2 and for all South Florida counties in Table S9. Palm Beach County, which contains most of the SGR, had the most estimated deaths attributable to sugarcane fires (0.72 per year; 95% CI: 0.17, 2.2), due to its large population, whereas Hendry County, which contains the western part of the SGR, had the highest estimated mortality rate from the fires (0.22 per 100,000, 95% CI: 0.08, 0.72 per 100,000). Nearby Glades and Okeechobee Counties were also noticeably impacted by sugarcane smoke and had mortality rates of 0.14 per 100,000 (95% CI: 0.02, 0.33 per 100,000) and 0.13 per 100,000 (95% CI: 0.03, 0.29 per 100,000), respectively. Mortality and mortality rates separated by each of the six causes of death are provided in Table S10, with attributable fraction of deaths due to sugarcane fire emissions (Figure 6C), and health and demographic data (Figure 4) by census tract available in a supplemental spreadsheet (Excel Table S1).

Discussion

We estimated the contribution of burning of sugarcane fields to $PM_{2.5}$ concentrations in South Florida using surface and satellite observations and an atmospheric dispersion model. Although our results focus on one type of agricultural burning over a regional area, our approach is applicable to quantifying the impacts of other burning sources on air quality and public health. Similar empirical treatment of emissions and plume rise can be implemented in the HYSPLIT dispersion model for other fire types, and the Monte Carlo framework can be adapted to other vegetation fuels and demographic data.

Ground-based sensors showed that $PM_{2.5}$ is 0.5–1.1 $\mu g/m^3$ higher during sugarcane harvest season than during the rest of the year in the SGR at Belle Glade and 0.3 $\mu g/m^3$ higher just outside the SGR at Royal Palm Beach. This finding was the opposite of the other locations in Central and South Florida, which had higher mean $PM_{2.5}$ outside sugarcane harvest season. Satellite data showed that the region with higher $PM_{2.5}$ during sugarcane harvest season closely coincided with the boundaries of the SGR, implying that the source and pattern of high $PM_{2.5}$ during the period October–March was particular to that region. As most locations outside the SGR were 0.6 $\mu g/m^3$ lower outside of harvest, sugarcane burning could add an estimated 0.3 to 2.5 $\mu g/m^3$ $PM_{2.5}$ to the average at Belle Glade during sugarcane harvest season and, equivalently, add 0.15–1.25 $\mu g/m^3$ to the annual mean. The degraded air quality of the local region was consistent with previous studies of PM_{10} and hazardous air pollutants in and around the SGR (Sevimoğlu and Rogge 2016, 2015) and with degraded air quality reported in literature from other sugarcane burning regions of the world (Hiscox et al. 2015; Le Blond et al. 2017). From our HYSPLIT dispersion simulations, which included a new stochastic empirical plume height algorithm based on satellite measurements of sugarcane smoke plumes, we estimated that sugarcane fires contributed up to 1.0 $\mu g/m^3$ to annual mean $PM_{2.5}$ concentrations in the SGR, 0.65 $\mu g/m^3$ in Belle Glade, and very little (0.04 $\mu g/m^3$) in coastal Palm Beach County. The magnitude and spatial extent of predicted $PM_{2.5}$ enhancement in the dispersion model corresponded with the observed area of elevated $PM_{2.5}$ in and around the SGR in the harvest season. This correspondence strongly suggests that sugarcane fires were responsible for the hot spot and that the dispersion model reasonably represented the impact of sugarcane fires on $PM_{2.5}$ air quality.

Mortality from the $PM_{2.5}$ produced by sugarcane fires across a 20-county area in South Florida was estimated to be 2.5 deaths per year (95% CI: 1.2, 6.1 deaths), with 0.16 (95% CI: 0.09, 0.6) deaths per year in the SGR. This mortality rate is an estimated 0.4 deaths per 100,000 people per year in the SGR (95% CI: 0.3, 1.6 deaths per 100,000) in comparison with 0.04 per 100,000 per year across South Florida (95% CI: 0.02, 0.09 deaths per 100,000; Table 2; see Table S8 for baseline mean annual deaths for all six causes in South Florida and the SGR). Sugarcane fires, therefore, are expected to have 10 times greater mortality impact on SGR residents, who were predominantly non-White and lower income (57% non-White, $34,000 median household income), than wealthier residents of coastal Palm Beach County (23% non-White, USD $71,000 median household income) or South Florida in general (23% non-White, USD $62,000 median household income) (U.S. Census Bureau 2020b). Hendry County had the highest estimated mortality rate from sugarcane smoke exposure at 0.22 deaths per 100,000 per year (95% CI: 0.08, 0.72 per 100,000), and Palm Beach County had the highest number of estimated deaths at 0.72 per year (95% CI: 0.17, 2.2). These mortality estimates are calculated in such a way that they also represent the number of deaths that could be avoided by halting sugarcane burning while all other $PM_{2.5}$ sources remained constant.

Our 95% CI mortality estimates accounted for uncertainty in sugarcane emissions, demographic data, and relative risk functions. Additional factors that we were not able to quantify could contribute to higher, or possibly lower, mortality impacts. Mortality in people under age 25 has not been included (except for LRI) due to lack of widely accepted relative risk functions. Any contribution of outdoor $PM_{2.5}$ to other causes of death beyond the six causes considered here would also create larger impacts. Mortality in agricultural workers, who can be exposed to very high $PM_{2.5}$ concentrations during field-burning operations, is also not included (Le Blond et al. 2017). Like many studies, ours also assumed that all $PM_{2.5}$ components and sources are equally toxic, but biomass burning smoke may be more toxic than implied by the $PM_{2.5}$ impact functions used here, which are based on populations that were primarily exposed to urban aerosols from industrial, commercial, and vehicular sources, rather than biomass burning (Kelly and Fussell 2020; Park et al. 2018; Wegesser et al. 2009). Several studies suggest that biomass burning smoke can be up to 10 times more toxic than urban aerosol for some health outcomes such as hospitalizations (Aguilera et al. 2021), and toxicity may greatly increase when accounting for ammonia and hazardous air pollutants (Domingo et al. 2021). If future studies continue to support the differential toxicity of biomass burning smoke, then the mortality from sugarcane fires could perhaps be several times greater than we have estimated, although lower estimates are possible. Chronic exposure to biomass burning, including sugarcane smoke, also has serious nonfatal consequences, including asthma, bronchitis, missed work and school days, and impacts on pregnancy and child development (Arbex et al. 2007; Boopathy et al. 2002; Cançado et al. 2006; Holstius et al. 2012; Mnatzaganian et al. 2015).

Prescribed fire is not only applied to preharvest sugarcane and other postharvest agricultural fields but is also commonly used in Florida's forests and wildlands as shown by the FFS burn authorizations (Nowell et al. 2018). According to FFS records, the vast majority of prescribed burning within the SGR occurs on sugarcane fields. Outside the SGR in the rest of Florida, most of the prescribed burning is conducted for the purposes of wildfire mitigation and habitat management (Nowell et al. 2018). Although all types of prescribed wildland fires impact air quality, fires set with the express purposes of wildfire mitigation and wildlife habitat management benefit ecosystems and surrounding communities by reducing wildfire risk, maintaining wildlife habitat, and increasing biodiversity (Fernandes and Botelho 2003; Hiers et al. 2020; Navarro et al. 2018; Schweizer et al. 2019; Schweizer and Cisneros 2017; Waldrop and Goodrick 2012). Prescribed sugarcane fires do not have these community benefits. There are alternatives to the preharvest sugarcane burning, however. In green harvesting, leaves can be left in the field as mulch (Sandhu et al. 2013) or transported with the stalk to a processing plant where biomass can be used for fuel, bioethanol, or other products (Carlucci et al. 2021; Cavalett et al. 2011; Fedenko et al. 2013; Renouf et al. 2008). Such green harvesting methods are already widely used in other major SGRs, such as Brazil and Australia (da Silva et al. 2021; Sandhu et al. 2017). Nevertheless, Florida growers have concerns about how green harvesting affects profits, crop yield, and crop management (Ma et al. 2014; Sandhu et al. 2013, 2017). New legislation limiting the liability of sugarcane growers for particle emissions (Florida Statute 823.14) will certainly affect debate and decisions about field burning vs. green harvesting, but the adoption of green harvesting methods could reduce the premature mortality in South Florida, with particular benefits for minority, low-income communities within the SGR.

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