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Improving Estimates of Prescribed Fire Smoke: Insights From a Novel Southeastern US Burn Permit Geodatabase

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Key Points:

- Permit records show satellites undercount many small prescribed burns in the southeastern US, affecting smoke emissions and exposure
- Coupling permit data with air quality models alters fine particulate matter estimates from prescribed fires in some regions and seasons
- Exposure patterns differ by state as burn locations drive long-term averages, while population centers shape short-term smoke burdens

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract

The southeastern US accounts for over 60% of national prescribed (Rx) burning acreage and relies on Rx fire to reduce wildfire risk and sustain forest biodiversity. While ecologically beneficial, Rx fires may introduce smoke-related risks to surrounding communities. Using a burn permit geodatabase integrated with atmospheric, emissions, and chemical transport models, we estimated daily fine particulate matter ($PM_{2.5}$) attributable to the reported 2017–2019 Rx burns in Florida, Georgia, and South Carolina. Rx fires across this region contributed 1.39 ± 0.57 μg/m^3 to daily $PM_{2.5}$, increasing to 3.24 ± 1.45 μg/m^3 (37% of total $PM_{2.5}$) during the January–April high-burn season. Integrating permit data with air quality modeling improved smoke estimates relative to satellite-based inventories in some regional and seasonal comparisons. Our framework refines Rx fire smoke exposure assessment and can inform state-specific smoke management and public health planning.

Plain Language Summary

Prescribed (Rx) fire remains an indispensable conservation tool in southeastern US forests, accounting for more than 60% of US Rx burning. Accurately estimating smoke exposure from Rx burns is essential for meeting stricter air quality regulations and reducing public health impacts. This study uses a geodatabase of state burn permits to improve how Rx fire smoke is represented in air quality models. By integrating these permit records with advanced atmospheric and chemical transport models, we captured small, short-lived Rx burns often overlooked by satellites or federal fire inventories. We found that Rx fires contribute significantly to fine particle pollution across the Southeast, with Georgia experiencing the highest population exposure and over 40 smoke-impacted days annually, while Florida and South Carolina show lower and more localized impacts. State differences in smoke impacts are driven by where burns occur relative to population centers. The permit-based modeling approach reduced known errors in existing fire inventories and changed the estimated smoke exposure patterns across the region. As Rx burning expands with forest restoration efforts, this framework offers a way to balance ecosystem conservation needs and Rx fire smoke exposure.

1. Introduction

Prescribed (Rx) fire is an essential tool for forest management and conservation across the globe (Kobziar et al., 2015). Fire promotes restoration of fire-dependent ecosystems (Alexander et al., 2021; Mitchell et al., 2006), supports land-based economies like forestry and hunting (Brennan et al., 1998), and mitigates wildfire potential (Burke et al., 2021; Donovan et al., 2023; Hunter & Robles, 2020; Mitchell et al., 2014). Over time, attitudes surrounding Rx fire in the southeastern US have become more supportive and use has expanded on both public and private lands (Fowler & Konopik, 2007). However, concerns regarding smoke are projected to grow under more stringent 2024 fine particulate matter ($PM_{2.5}$) national ambient air quality standard (U.S. Environmental Protection Agency, 2024), and the Southeast has the most extensive wildland-urban interface in the country (Radeloff et al., 2018). The high frequency of Rx fire activity in the Southeast has been linked to measurable increases in air pollutant concentrations during the burn season (Zeng et al., 2008). When carefully planned under optimal smoke dispersion conditions, Rx fires typically do not transport smoke over long distances, yet they can still elevate ground-level pollutant concentrations for nearby communities (Williamson et al., 2016). Improving smoke exposure models associated with Rx fires can therefore enhance spatiotemporal $PM_{2.5}$ estimates and inform forest management while mitigating public health risks (Johnson & Garcia-Menendez, 2025).

Integrating Rx burn records into fire emissions inventories is crucial for assessing their local air quality impacts and identifying populations affected by smoke (Maji, Li, Vaidyanathan, et al., 2024, Maji, Li, Hu, et al., 2024).

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Solely satellite-based smoke products [for example, the National Oceanic and Atmospheric Administration's (NOAA) Hazard Mapping System (HMS) (NOAA, 2025)], burned area detection from satellite imagery [for example, the United States Geological Survey's (USGS) Landsat Burned Area (Hawbaker et al., 2017, 2020), and USGS and Tall Timbers's Southeast FireMap (SEFM; Tall Timbers Research Geospatial Center, 2025)], and satellite-derived fire inventories [for example, Fire INventory from the National Center for Atmospheric Research (FINN; Wiedinmyer et al., 2011, 2023), and the new Geostationary Operational Environmental Satellites Eastern US Fire Emissions inventory (GEUFE; Fite et al., 2025)] have limitations in capturing the scale, timing, and intensity of small burns. Spaceborne observations are constrained by cloud cover, canopy obstruction, sensor resolution, and satellite overpass timing (Hawbaker et al., 2017; Randerson et al., 2012; Zeng et al., 2008), so we place greater confidence in burn permit records (Huang et al., 2018; Nowell et al., 2018). Prior research has also shown that permitted Rx burn areas explain up to 50% of the daily variability in $PM_{2.5}$ concentrations at monitoring sites across the Southeast (Afrin & Garcia-Menendez, 2020). Unlike many western states, the Southeast maintains detailed state-level burn authorization records (Cummins et al., 2023). National-scale inventories such as the US Environmental Protection Agency's (EPA) National Emissions Inventory (NEI) compile fire emissions using a blend of coarse satellite detections and intermittent administrative reports (Eyth et al., 2022; U.S. Environmental Protection Agency, 2021a). Here we leveraged multi-year burn permits from Florida (FL), Georgia (GA), and South Carolina (SC) to develop a more regionally specific representation of Rx fire activity. This burn permit geodatabase provides data on burn size, type, location, and date, with particularly robust coverage across these three southeastern states (Cummins et al., 2023).

The primary goal of this study is to develop a comprehensive modeling analysis of Rx fire smoke in the Southeast that advances both methodology and understanding of $PM_{2.5}$ exposure linked to Rx burns. Among modeling approaches used to estimate smoke impacts, gridded numerical chemical transport models, such as the Community Multiscale Air Quality (CMAQ) model (Appel et al., 2017, 2021; Byun & Schere, 2006) and the Weather Research and Forecasting model with Chemistry (WRF-Chem; e.g., Grell et al., 2005, 2011), remain the gold standard for air quality simulation in this area of research. Many alternatives, including proximity-based models (Kondo et al., 2022), reduced-complexity source-receptor frameworks (Afrin & Garcia-Menendez, 2021), puff models (Huang et al., 2020), and machine learning algorithms (Liao et al., 2025), suffer from some loss of fidelity due to simplistic assumptions or empirical reliance on incomplete input data. In contrast, chemical transport models paired with fire emissions inventories explicitly account for dynamic atmospheric processes and emissions chemistry, enabling spatially and temporally resolved simulations of smoke transport and $PM_{2.5}$ exposure (Goodrick et al., 2013; Williamson et al., 2016), which is particularly important in the Southeast's humid and frequently stagnant air conditions (Achtemeier, 2006; Bartolome et al., 2019). We used CMAQ in this study as a physically consistent and policy-relevant approach to quantify air quality and public health impacts of Rx fires in the southeastern US, especially valuable in regions with limited observational coverage and nuanced smoke regimes.

By constructing a customized Rx fire emissions inventory from detailed, state-level burn permits and improving the representation of Rx fires in air quality models, we estimated short-term and long-term population exposure to Rx fire-related $PM_{2.5}$ by state. To evaluate the permit-based Rx fire emissions within the CMAQ modeling system, we used NEI as the primary benchmark because it is the conventional federal inventory and the direct baseline for our parallel CMAQ simulations. Within the broader inventory landscape, the novelty of this study lies in demonstrating the value of bottom-up records of Rx fire activity as the primary data source for burned-area analysis, emissions estimation, and modeled $PM_{2.5}$ evaluation. Our work informs forest management and public health decision-making in the Southeast, with approaches that can be extended to other fire-prone regions.

2. Methods

Our study defined Rx fires as those conducted for ecological and silvicultural benefits, explicitly excluding agricultural fires that are often unregulated and managed differently from forestry burns. Rx burn records rely on state-level permitting or voluntary notification systems; thus, uncertainties exist regarding geographic accuracy and actual burned acreage. We assumed a consistent overestimation bias of total burn extent, especially in scenarios where burns authorized by permits are later canceled by managers or when the requested area contains inherently non-flammable land cover, such as ponds or wetlands (Nowell et al., 2018). Burn permits rarely specify ignition or completion times. Estimates of burn duration were derived based on total burn area [refer to Table S1 in Li et al. (2023)]. Moreover, we assumed all Rx fires began at 11 a.m. and were extinguished by 6 p.m. local time or sooner, consistent with common daytime burning practices (Jaffe et al., 2020; Li et al., 2020).

First, we extracted a three-year (2017–2019) georeferenced and date-stamped data set of reported Rx fire activity (Figure S1 in Supporting Information S1) from the Tall Timbers burn permit geodatabase (Cummins et al., 2023). FL, GA, and SC were selected because their burn purpose information allowed separation of silvicultural and ecological burns from agricultural, pile, and invalid burns. The reclassification workflow and spatial filtering criteria are described in Text S1, Table S1, and Figure S2 in Supporting Information S1. Second, each Rx burn record's location, burned acreage, and timing served as inputs to the BlueSky Smoke Modeling Framework version 4.5 (Larkin et al., 2009), generating hourly, three-dimensional emissions profiles for use in the CMAQ model. Details about Rx fire emissions data development using BlueSky are described in Text S2 in Supporting Information S1. Finally, we integrated permit-based Rx fire inventory data with CMAQ to characterize smoke dispersion and pollution transport, with the following analyses focused on FL, GA, and SC (Figure S3 in Supporting Information S1). The meteorological fields and emissions data from other sources as well as initial and boundary conditions were obtained from EPA's Air QUAlity TimE Series (EQUATES) Project (U.S. Environmental Protection Agency, 2021b). Specifically, we coupled these EQUATES inputs and permit-based Rx fire emissions data with the CMAQ modeling system version 5.5 (U.S. Environmental Protection Agency Office of Research and Development, 2024) to simulate daily 24-hr average $PM_{2.5}$ concentrations attributable to Rx burns year-round (Text S3 in Supporting Information S1). A detailed overview of our modeling framework is available in Figure S4 in Supporting Information S1, and model configurations are shown in Table S2 in Supporting Information S1.

To quantify potential biases in Rx fire burned area and $PM_{2.5}$ emissions associated with this novel permit-based inventory, we considered several existing fire emissions inventories relevant to the southeastern US (Table S3 in Supporting Information S1). These products differ in emissions methodology, fire type attribution, spatial resolution, and temporal coverage (Text S4 in Supporting Information S1). FINN version 2.5 is useful for comparison of both burned area and emissions because it provides estimated burned area for individual fire points and daily gridded fire emissions at 1-km resolution. More recent regional products such as GEUFE include many more small, short-lived fire detections, but GEUFE is currently available only after August 2019. The Landsat-based SEFM version 2 product provides an independent reference for annual burn scars, but it does not include emissions estimates. Accordingly, we used NEI as the primary benchmark in the main text, while comparisons with FINN, SEFM, and GEUFE mainly provide broader context. Procedures used to derive Rx fire-related burned area and emissions during the high-burn season (January–April) are described in Text S4 in Supporting Information S1.

We then evaluated modeled total $PM_{2.5}$ concentrations against observations from the US EPA's Air Quality System (AQS) ground monitoring sites. To assess model performance, we calculated normalized mean bias (NMB, %), normalized mean error (NME, %), and Spearman's rank correlation coefficient (r, unitless) for daily 24-hr average $PM_{2.5}$. Performance was assessed against the recommended "goal" and broader "criteria" benchmarks (Emery et al., 2017). As a benchmark, we performed parallel CMAQ simulations using NEI-based Rx fire emissions data on the EQUATES platform (U.S. Environmental Protection Agency, 2021b; Text S5 and Table S4 in Supporting Information S1). Differences in modeled near-surface total $PM_{2.5}$ concentrations between the two inventory-based simulations were analyzed to identify systematic biases by state.

Direct validation of Rx fire-specific $PM_{2.5}$ contributions is not possible due to the lack of source-specific ground-based measurements. However, we used the approach developed by Childs et al. (2022), which estimates smoke $PM_{2.5}$ from deviations above a location- and season-specific non-smoke baseline. Though this data set includes smoke from multiple fire types, it provides a useful proxy during the high-burn season when Rx fires dominate fire activity in the Southeast.

We quantified the contribution of Rx fire smoke to population exposure using two complementary metrics: (a) the population-weighted annual average $PM_{2.5}$ concentration attributable to Rx fires; and (b) the number of person-days per year experiencing smoke-affected days with significant Rx fire contributions. Each metric captures a different temporal dimension of exposure (chronic or acute) relevant to the health domain (Casey et al., 2024). Calculation procedures are described in Text S6 in Supporting Information S1. We used gridded 1-km US population estimates for the year 2020 (Center for International Earth Science Information Network Columbia

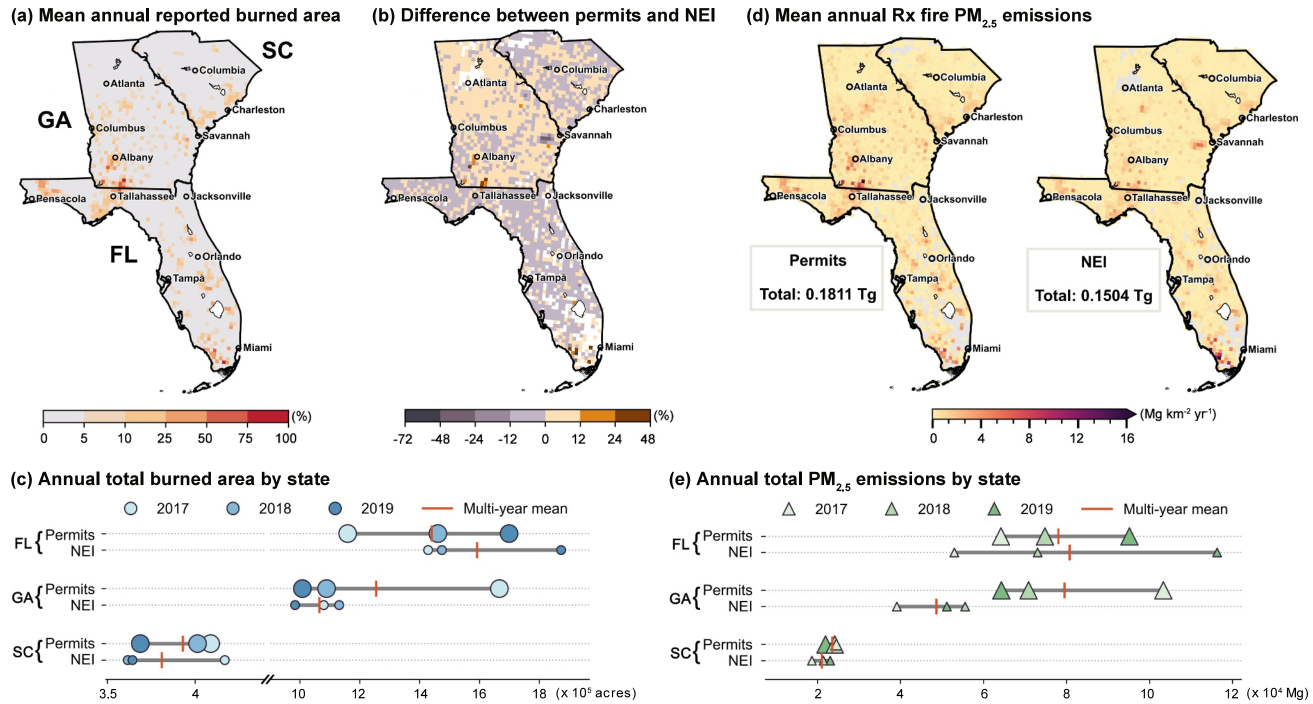

Figure 1. Spatial and temporal comparisons of Rx fire activity across Florida (FL), Georgia (GA), and South Carolina (SC) during 2017–2019. (a) Mean annual reported burned area from permit data, expressed as a percentage of each 12 km × 12 km grid cell area. (b) Percentage difference in mean annual burned area between permits and NEI; positive values indicate larger burned area in the permit-based Rx fire inventory, and negative values indicate the opposite. White areas denote grid cells with no data. (c) Annual total Rx fire burned area (in acres) by state from permits and National Emissions Inventory (NEI) with multi-year means. (d) Mean annual Rx fire $PM_{2.5}$ emissions (in Mg km^{-2} yr^{-1}) from permits and NEI, both remapped to the 12 km × 12 km Community Multiscale Air Quality domain. Inset text reports total domain-wide Rx fire $PM_{2.5}$ emissions (in Tg), and gray areas indicate grid cells with no data. (e) Annual total Rx fire $PM_{2.5}$ emissions (in Mg) by state from permits and NEI with multi-year means. Major cities are marked in (a), (b), and (d) for geographic reference.

University, 2018) to approximate exposure metrics aggregated to the CMAQ model grids using a nearest-neighbor approach.

3. Results and Discussion

3.1. Spatiotemporal Patterns in Rx Fire Activity

Rx fires were most prevalent in Northwest FL, southern GA, and the coastal plains of SC (Figure 1a), with high densities on private lands in southwestern GA and northern FL (Figure S5 in Supporting Information S1). Compared with NEI, the permit-based inventory documented generally higher Rx burned areas in GA and SC, but lower values in FL (Figures 1b and 1c). The negative permit-minus-NEI differences over eastern GA likely reflect incomplete permit records on some federal lands because federal burners were not required to obtain permits from the GA Forestry Commission (Figure 1b). Similar patterns were evident when analysis was restricted to the high-burn season (Figures S6a–S6b in Supporting Information S1). In FL, the two data sets showed similar burn-size distributions (Table S5 in Supporting Information S1), suggesting a well-integrated state–federal reporting system dominated by large agency burns. By contrast, over 60% of Rx burns in GA were smaller than 5 acres according to the permit records, whereas NEI assigned only 28%–56% to this class with greater weight in 10–50-acre ranges (Table S6 in Supporting Information S1). This discrepancy indicates that GA's permit system captured a much higher frequency of small burns than NEI, possibly due to satellite detection limits. For SC, NEI's Rx fire-size distribution was highly inconsistent over the years, while the permit data revealed a stable burn structure of small and mid-sized burns between 5 and 50 acres (Table S7 in Supporting Information S1).

Relative to other fire inventories during peak burning periods (Figures S6c–S6d in Supporting Information S1), permits often reported more burned area than SEFM, which has limited temporal sampling across the study region, whereas differences with FINN were more spatially heterogeneous. Although FINN was generally closer to permits and NEI in annual total burned area magnitude, its interannual variability differed by state (Figure S6e in Supporting Information S1). Grid-cell comparisons further showed that permit and NEI burned areas were more consistent with each other than with FINN or SEFM without explicit burn-type differentiation (Table S8 in Supporting Information S1). Overall, permit records better resolved the fine-scale structure and interannual consistency of operational Rx burning across the region.

According to permit records during 2017–2019 (Figure 1c), FL had the greatest Rx burning extent, with roughly 1.4 ± 0.3 (mean $\pm$ 1 standard deviation) million acres annually (4% of the state's total land area). Rx fires burned approximately 1.3 ± 0.4 million acres each year in GA (3% of the state's area). SC had substantially lower Rx burning activity, averaging 0.4 ± 0.02 million acres per year (2% of the state's area). FL showed a steady upward trend from 2017 to 2019, while GA reached its maximum in 2017 with over 1.6 million acres burned. In contrast, SC maintained relatively low and stable Rx burning rates over the years. Figure S7 in Supporting Information S1 shows that all three states displayed a clear seasonal cycle in permitted Rx burning with peak activity in February and March and much lower burning afterward, which was consistent with fire management strategies that avoid high-temperature or drought-prone months. FL's larger annual burned area was driven mainly by greater average burn size per event rather than clearly higher event frequency (Figure S8 in Supporting Information S1).

Estimated Rx fire emissions also varied across inventories because of differences in methodology and fire activity data sources. The permit-based inventory produced more spatially extensive and stronger Rx fire $PM_{2.5}$ emission hotspots in southwestern GA and northern FL than NEI (Figures 1d and S9a in Supporting Information S1), suggesting that it captured additional emissions not fully represented in NEI. The permit-based inventory also yielded a domain-wide total Rx fire $PM_{2.5}$ burden about 20% higher than NEI (Figures 1d and 1e). Despite that, the permit-based inventory reproduced the same broad seasonal cycle as NEI and FINN, with all three inventories showing pronounced increases and comparable monthly magnitudes during the high-burn season (Figure S9b in Supporting Information S1). Permit-based emissions exceeded NEI during 2017, particularly at the regional scale and in GA. FINN and GEUFE were generally of the same order of magnitude as permits and NEI during the months available for comparison. Statistical comparisons (Table S9 in Supporting Information S1) showed only moderate agreement between permits and NEI and poor agreement between permits and FINN, which was expected because FINN is designed for global emissions estimation, does not explicitly distinguish Rx fire from wildfire, and estimates emissions without meteorological conditions.

Our results show distinct spatiotemporal patterns of Rx burning activity across FL, GA, and SC, and reveal the importance of integrating permit-based data sets to better capture regional fire activity. The permit-based inventory captured numerous small, short-lived, and low-intensity Rx fires that were missed in NEI and traditional satellite-based inventories (Hawbaker et al., 2017; Hu et al., 2016; Randerson et al., 2012; Zeng et al., 2008). Recent studies using permit data from GA and FL also confirmed the reliability of such records by cross-referencing satellite fire counts with state and federal fire activity reports (Huang et al., 2018; Nowell et al., 2018). Incorporating these records into fire emissions inventories and modeling frameworks can provide a more regionally tailored understanding of smoke dispersion and pollutant transport, an essential advancement in the southeastern region that accounts for more than 60% of all Rx burning in the nation (Melvin, 2018, 2020). Although useful for identifying spatiotemporal patterns, in many states, satellite data sets remain the only available resource.

While offering improved coverage and granularity over earlier fire-use surveys, the use of burn permits as emissions inputs introduces some limitations, compared to NEI, that must be acknowledged. These issues present clear avenues for further development and integration with additional observational data sets, as discussed in detail below. In FL, differences between the annual permit reports and NEI estimates may result from variation in reporting periods or data sources, whereas in GA and SC, year-to-year increases in reported burn areas might reflect improved recordkeeping practices rather than actual fire activity. A phone survey in Huang et al. (2018) estimated up to 20% uncertainty in permit-reported burned area due to incomplete burns, and Nowell et al. (2018) similarly showed that actual burn sizes were often smaller than authorized. We therefore interpret permit data with these limitations in mind and encourage continued post-hoc reconciliation with other observational data sets.

3.2. State-Level Population Exposure to Rx Fire $PM_{2.5}$

Similar to the reported burned areas, Figure 2a shows that hotspots of modeled surface-level Rx fire $PM_{2.5}$ occurred in southwest GA and northwest FL. Rx fire smoke plumes were therefore more likely to affect nearby communities, and the spatial distribution of CMAQ-predicted Rx fire $PM_{2.5}$ was mostly determined by high-burn

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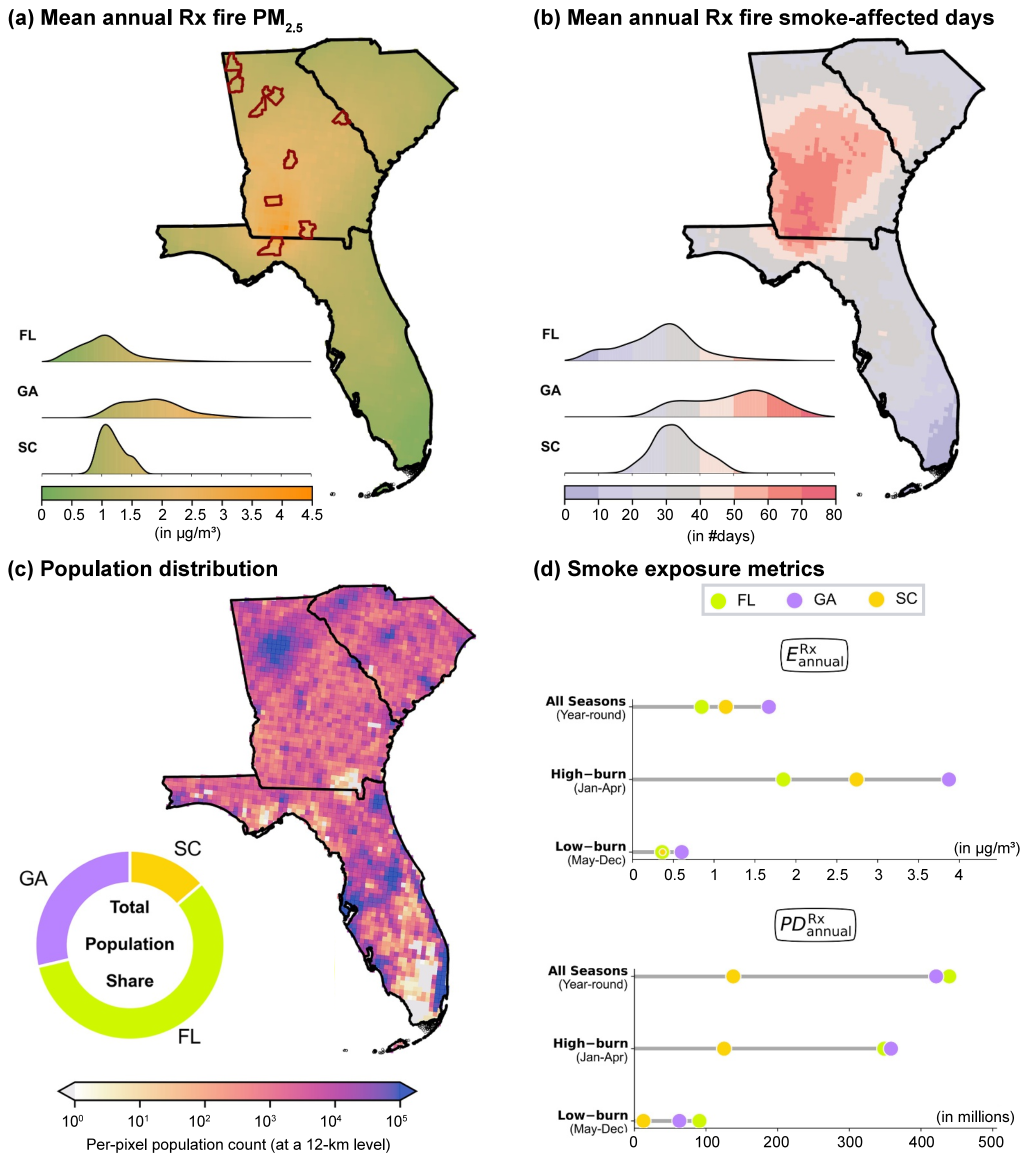

Figure 2. Spatial consideration of CMAQ-predicted Rx fire $PM_{2.5}$ (μg/m^3) and smoke-impacted days attributable to Rx burning as well as the influence of population distribution on exposure to Rx fires across Florida (FL), Georgia (GA), and South Carolina (SC) during 2017–2019. (a) Mean annual Rx fire $PM_{2.5}$ considering both high-burn (January–April) and low-burn (May–December) seasons. Eight GA counties (i.e., Dougherty, Floyd, Fulton, Gwinnett, Houston, Lowndes, Richmond, and Walker) and one FL county (i.e., Leon), identified as areas with annual average levels higher than the new $PM_{2.5}$ standard based on aggregated 2017–2019 Air Quality System monitoring data, are marked in red for reference. (b) Mean annual smoke-impacted days attributable to Rx fire, defined by CMAQ-predicted Rx fire $PM_{2.5}$ contributions. The corresponding state-level density distribution is shown along with the spatial maps in (a) and (b). Note that the *y*-axes of the density plots in (a) and (b) are individually normalized, extending to the maximum density value within each distribution. (c) Regridded population counts at a 12-km resolution. The inset ring chart displays each state's share of the total population across the three states. (d) Population-weighted annual average Rx fire $PM_{2.5}$ concentration (i.e., E^{Rx}_{annual} in μg/m^3) for each state by burning seasons, and the corresponding annual average Rx fire exposure with respect to person-days (i.e., PD^{Rx}_{annual} in millions).

season activity (Figure S10 in Supporting Information S1). Among the three states, GA exhibited the highest Rx fire-specific $PM_{2.5}$ concentrations year-round, FL displayed the broadest spatial range, and SC showed a more spatially restricted and uniformly lower range of Rx fire $PM_{2.5}$ (Figure 2a).

Across 2017–2019, Rx fire smoke contributed about 21% of daily total $PM_{2.5}$ in the region at the grid-cell level, with the highest share in GA (~25%) and the lowest in FL (~18%) (Table S10 in Supporting Information S1).

Concentrations were much higher during the high-burn season (∼3.2 μg/m^3, ∼37% of total $PM_{2.5}$) than during the low-burn season (∼0.5 μg/m^3, ∼9%) (Table S10 in Supporting Information S1). In a retrospective analysis aligned with the February 2024 update to the US EPA's annual $PM_{2.5}$ standard (U.S. Environmental Protection Agency, 2024), which lowered the limit from 12 to 9 μg/m^3, we estimated county-level annual average $PM_{2.5}$ concentration using AQS data. Eight counties in GA had estimated annual average levels above 9 μg/m^3 (Figure 2a, red-labeled counties). Although these counties did not necessarily coincide with the regions having the highest modeled Rx fire contributions, Rx fires still contributed approximately 1.5–2.0 μg/m^3 annually in several of them (Figure 2a). This spatial mismatch suggests that current monitoring networks may not adequately capture Rx fire smoke exposure hotspots and will overlook localized smoke disparities, which aligns with findings by Wang et al. (2024).

Large portions of GA experienced more than 40 smoke-impacted days annually, substantially more than FL or SC (Figure 2b). Most Rx fire smoke impacts occurred in the Moderate AQI range (12.1–35.4 μg/m^3), with 5–173 smoke-affected days per grid cell, whereas more severe categories were uncommon (Figure S11 in Supporting Information S1). Thus, population exposure to Rx fires was subject to recurrent moderate smoke days rather than rare extreme events. Figures 2c and 2d illustrate how population distribution modulated regional exposure to modeled Rx fire $PM_{2.5}$. Long-term exposure (i.e., E^{Rx}_{annual}) was driven by burn locations, but short-term cumulative exposure burden (i.e., PD^{Rx}_{annual}) was strongly associated with burn proximity to population centers. FL exhibited lower per-person exposure intensity (E^{Rx}_{annual}; Figure 2d) because major populated cities (Figure 2c) were separated from the most heavily burned regions (Figure 2a); however, its large population still resulted in a high cumulative exposure burden (PD^{Rx}_{annual}; Figure 2d). In contrast, GA recorded the highest per-person Rx fire smoke $PM_{2.5}$ concentration, reaching about twice FL levels during the high-burn season (Figure 2d). SC also showed higher population-weighted long-term exposure than FL (Figure 2d), even with smaller total burned areas (Figure 1c). When evaluated using total person-days exposed to annual average Rx fire $PM_{2.5}$, FL and GA had comparable burdens, both exceeding SC (Figure 2d).

The differences in modeled Rx fire $PM_{2.5}$ exposure among the three states depend primarily on the geographic overlap between burned areas and population centers. Simply meeting the annual average standard may not ensure equitable protection unless states also consider more localized exposure patterns. There is no known safe threshold for Rx fire $PM_{2.5}$ exposure (U.S. Environmental Protection Agency, 2020), so repeated low-level exposures common near burn sites may contribute to adverse health effects (Sacks et al., 2023).

3.3. Model Performance and Uncertainties in Simulating Total and Rx Fire-Specific $PM_{2.5}$

The permit-based CMAQ runs demonstrated robust performance in capturing yearly trends and patterns in total $PM_{2.5}$ across all three states, achieving the broader "criteria" benchmarks. Figure S12 in Supporting Information S1 presents the evaluation of modeled total $PM_{2.5}$ against US EPA AQS observations for 2017–2019 at ground-based sites across FL, GA, and SC. GA and SC also approached the more stringent "goal" thresholds. In Tables S11–S12 in Supporting Information S1, when stratified by burning seasons, permit-based modeling results across three states achieved improvement in NMB outside the high-burn window compared to NEI-based simulations. This improvement was consistent with the lower monthly Rx fire $PM_{2.5}$ emissions in the permit-based inventory during the low-burn season relative to NEI or GEUFE (Figure S9 in Supporting Information S1), supporting the interpretation that the permit-based CMAQ simulations may better capture aspects of observed total $PM_{2.5}$ magnitudes and temporal variability than the NEI-based approach during these months. However, overestimation of $PM_{2.5}$ peaks in the high-burn season led to positive bias for GA and SC in permit-based CMAQ runs (Figure S12 and Table S11 in Supporting Information S1), suggesting an issue of record verification of burned area rather than model physics. FL showed the largest seasonal adjustment: during the peak burning window, the underestimation of $PM_{2.5}$ with NEI (NMB = −20.89%) was reduced to near-neutral with permits (NMB = −0.28%) (Tables S11–S12 in Supporting Information S1). Still, the temporal correlations remained high, which indicated that reported burn timing was generally accurate in the permit-based simulations across three states (Table S11 in Supporting Information S1). Although the average model performance was within acceptable bounds of broader "criteria" at the state level, performance varied by location, especially in areas with intensive fire activity or sparse monitoring coverage.

Our comparison of CMAQ modeling results shows that substituting satellite-driven NEI Rx fire inputs with the permit-based ones can lead to measurable changes in modeled $PM_{2.5}$ by incorporating many small and short-lived burns that are not represented in the NEI-based fire inventory. The resulting performance changes are not uniform across states or seasons. Permit-based CMAQ simulations offer reasonable temporal alignment with observed $PM_{2.5}$ variability during the high-burn season and narrower regional bias during the low-burn season. The use of permit-based Rx fire emissions thus serves as a valuable tool for assessing Rx fire air quality impacts, provided that the limitations in modeling inputs are acknowledged (Text S7 in Supporting Information S1).

Ground-truthing permit-based simulations from 2017 to 2019 was difficult due to the inability of in situ air pollution monitoring networks to differentiate sources of $PM_{2.5}$. Following Childs et al. (2022), we qualitatively evaluated the temporal correlation between CMAQ-predicted Rx fire $PM_{2.5}$ and observation-estimated smoke $PM_{2.5}$, which focused on alignment in timing and magnitude of $PM_{2.5}$ spikes. As shown in Figure S13a in Supporting Information S1, we evaluated 11 AQS monitoring sites located in areas of high modeled Rx fire influence. At these high-fire-impacted sites, most locations (7 of 11) showed moderate to strong correlations ($r \geq 0.4$) between modeled Rx fire $PM_{2.5}$ and observed smoke $PM_{2.5}$ (Figure S13b in Supporting Information S1). Community Multiscale Air Quality nevertheless tended to overestimate Rx fire-only $PM_{2.5}$ magnitudes by approximately 0.3–1.6 μg m^{-3} for typical modeled concentrations of 1–3 μg m^{-3} (Figure S13c in Supporting Information S1).

In the absence of source-specific ground-based $PM_{2.5}$ measurements for Rx fires, it was necessary to compare our results both with NEI-based simulations and with smoke $PM_{2.5}$ estimates derived from observations using Childs' method. While correlations were often moderate to strong, magnitude discrepancies persisted. Some GA and SC sites likely showed low correlation because HMS plumes, used in Childs et al. (2022), missed local smoke events with lower aerosol layer altitude and thereby underestimated smoke contributions. Accordingly, these comparisons should be interpreted with caution. Even so, state-level Rx permit records added important information on thousands of low-intensity burns absent from satellite-driven NEI products, leading to improved CMAQ-based exposure estimates, especially during periods and in locations where NEI's burned area estimates are known to perform poorly.

4. Conclusions and Outlook

This study presents the value of using high-resolution, state-authorized burn permit records to quantify Rx fire smoke exposure. Compared to satellite-derived or federal inventories, the permit-based approach is effective in capturing ground-level Rx burns that are small in scale, short in duration, and low in intensity. By integrating detailed Rx fire activity records into CMAQ modeling, our methods provide a bottom-up analytical perspective for estimating population-weighted exposure and public health impacts. Our results demonstrate that permit-based CMAQ modeling provides a more source-informed framework for evaluating Rx fire smoke and exposure, rather than a uniformly superior replacement for the NEI-based approach.

Recently, Rx burning permit approvals have been increasingly influenced by air quality and public health considerations. Our modeling framework also allows simulation-based studies to test different scenarios for policy evaluation. Existing literature suggests a 25%–30% increase in $PM_{2.5}$ concentrations during burning seasons in the Southeast (El Asmar et al., 2025), but few epidemiological studies isolate health outcomes attributable to Rx fire smoke. Imprecise or inaccurate smoke $PM_{2.5}$ estimation methods can yield divergent health burden outcomes, raising concerns about the transferability of dose-response functions (Gan et al., 2017; Qiu et al., 2024). Our model can be used to improve public health impact estimations and inform land management strategies.

Uncertainties remain due to potential overreporting of authorized acreage, lack of confirmation for burn completion, and limited post-burn verification. Even so, correcting NEI's systematic underprediction is scientifically valuable. Improving exposure assessments will require cross-checking permit data with near-real-time satellite fire detections, collecting air pollution measurements, and refining smoke transport modeling techniques, which can reduce bias in estimating fire emissions without losing many small burns that NEI omits. As Rx burning expands under the combined pressures of restoration efforts, increasing wildfire risks, and extreme weather, it is critical to ensure that exposure models reflect real-world conditions, especially for local communities, so smoke management can improve without undermining the essential role of fire.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

The CMAQ v5.5 model is openly available through Zenodo (U.S. Environmental Protection Agency Office of Research and Development, 2024). EQUATES meteorology, emissions, and initial and boundary condition inputs are publicly accessible online (U.S. Environmental Protection Agency, 2021b). The southeastern US Rx fire permit database contains private landowner information and is therefore not publicly released; access may be requested directly from the Tall Timbers Research Station (kcummins@talltimbers.org). The permit-based CMAQ model outputs, along with all postprocessing and visualization codes used in this study, are archived in a public Zenodo repository (J. Huang, 2025).

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