PM$_{2.5}$ exposures increased for the majority of Indians and a third of the global population during COVID-19 lockdowns: a residential biomass burning and environmental justice perspective

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Abstract

In response to the emergence of COVID-19 during Spring 2020, many countries implemented nationwide lockdowns and mandatory stay-at-home orders, which resulted in historically clean ambient air quality. However, in many parts of the world, biomass burning for cooking is a common activity, and in India specifically, it has been implicated as the leading contributor to indoor and ambient PM$_{2.5}$, and its activity was not stopped and likely increased during lockdowns. Here, we first estimate baseline and lockdown PM$_{2.5}$ exposures specific to India using new, nationwide time-use survey data coupled with fine-scale PM$_{2.5}$ estimates within various microenvironments. We then extend this framework to estimate the population globally that will have experienced higher PM$_{2.5}$ exposures during lockdowns, due both to an increase in residential biomass burning activity as well as the entire day being spent in the more-polluted home environment for biomass fuel using households. Sixty-five percent of Indians, the percent that uses biomass fuels for cooking, were exposed to higher PM$_{2.5}$ levels during the lockdown compared to their modeled baseline exposures, with the average modeled exposure increasing by 13% (95% distribution: 8–26) from 116 (82–157) to 131 (104–170) µg m$^{-3}$. We further leverage this exposure framework to present India's most comprehensive, to date, PM$_{2.5}$ exposure disparity and environmental justice assessment; although women were still exposed to the highest levels of PM$_{2.5}$ during the lockdown (from 135 (91–191) µg m$^{-3}$ baseline to 147 (106–200) µg m$^{-3}$ during the lockdown; 8.8% (5–18) increase), the demographic groups that experienced the highest exposure increases were working-age men and school-age children, whose average modeled exposures increased by 24% (18–48) from 88 (63–118) to 108 (94–139) µg m$^{-3}$ and 18% (8–31) (from 98 (75–134) to 115 (98–145) µg m$^{-3}$), respectively. Globally, we conservatively estimate that 34.5% (21–51) of the global population observed increased PM$_{2.5}$ exposures during COVID-19 lockdowns, concentrated in low-income regions with high biomass usage. There have been a number of clean-cooking initiatives introduced in India and throughout the world to replace biomass cookstoves, but the finding that PM$_{2.5}$ exposures increased for the majority of Indians and a third of the global population—driven largely by residential biomass burning for cooking—during a period of historically clean ambient air quality, re-emphasizes the urgent need to further address clean cooking interventions to reduce PM$_{2.5}$ exposures and in turn improve health outcomes.
1. Introduction

Following the emergence of COVID-19 in early 2020, many countries ordered nationwide lockdowns and mandatory stay-at-home orders to slow its spread. In India specifically, the COVID-19 lockdown lasted from 23 March to 31 May 2020, halted industrial and commercial activities, restricted private and public transportation, and required all of its 1.33 billion residents to stay-at-home. As a result, PM$_{2.5}$ (particulate matter with aerodynamic diameter less than or equal to 2.5 micrometers) emissions and its precursors from industrial activity, commercial activity, and transportation were largely mitigated, which coupled with favorable meteorological conditions, resulted in historically improved ambient air quality [1, 2].

Exposure to high levels of ambient pollution is one of the leading causes of premature mortality worldwide leading to an estimated 6.6 million mortalities globally each year [3], and the Global Burden of Disease (GBD) estimates that 95% of all premature mortality associated with air pollution exposure is attributed to PM$_{2.5}$ [4, 5]. In India, the GBD reports exposure to ambient PM$_{2.5}$ is responsible for 0.98 million premature deaths annually, and separately estimates that household PM$_{2.5}$ exposure contributes an additional 0.61 million annual premature deaths [6]. Accurately and comprehensively assessing personal exposures has been an ongoing area of research [7], and although novel approaches to directly measure personal exposures that can capture microenvironment PM$_{2.5}$ levels have been introduced recently [8], these strategies have not yet been scalable for population-wide assessments. Thus, accurately assessing PM$_{2.5}$ exposures on population-wide scales and subsequently implementing strategies to reduce exposures can contribute to improved health outcomes.

Residential biomass burning, a common practice for cooking (and heating, lighting, and waste reduction) globally, has been implicated as the leading source contributor to indoor and ambient PM$_{2.5}$ levels in India [9–11]. During lockdowns, while emissions from the industrial, commercial, and transportation sectors were mostly mitigated, household cooking activity and subsequent emissions still occurred and likely at a larger volume as individuals whose countries imposed lockdowns were mandated to stay-at-home. In addition, considering that household air pollution levels in households that use biomass cookstoves are generally higher than ambient concentrations [11], might PM$_{2.5}$ exposures have increased for populations that utilize biomass and were mandated to stay-at-home during COVID-19 lockdowns?

2. Data and methods

Here, we first model pre-COVID-19 lockdown (here-with referred as baseline exposure) and COVID-19 lockdown PM$_{2.5}$ exposures specific to each Indian state’s urban/rural populations by gender and age. To estimate baseline exposures, we combined fine-scale PM$_{2.5}$ concentration estimates in various microenvironments (household [11], ambient [12], work/school [13–15], etc) with the most-detailed time-use survey data in India (n = 445 170), specific to each state’s urban/rural populations by gender and age using a robust, Monte-Carlo exposure framework. Exposures during the COVID-19 lockdown were modeled using the same time-use survey and Monte-Carlo framework (where all time was spent in the household microenvironment) while considering an increase in home cooking activity for meals that previously were prepared and consumed outside of the house. We then extend this framework globally by combining primary cooking fuel use data [16] and lockdown status of each country to conservatively estimate the global population that experienced increased PM$_{2.5}$ exposures during lockdowns.

2.1. Estimating baseline PM$_{2.5}$ exposures for each Indian state's urban/rural populations by gender and age utilizing microenvironment PM$_{2.5}$ concentrations and time-use survey data

Household (both in the kitchen and living area) PM$_{2.5}$ concentrations were estimated using a semi-empirical modeling framework outlined in detail in Balakrishnan et al [11]. Briefly, their log-linear, India-specific model first predicts 24 h average PM$_{2.5}$ concentrations in the kitchen, K, as a function of multiple, independent, household-level variables, I, (e.g. fuel type (kerosene, dung, wood, and/or liquefied petroleum gas (LPG)), kitchen type/location (separate outdoor kitchen, indoor with partition kitchen, indoor without partition kitchen, or outdoor kitchen), ventilation status (good, moderate, or poor), hours spent cooking, and geographic region (east, west, south, or north)) as:

$$K \{ \log(\text{PM}_{2.5}) \} = \beta_0 + \beta_1 I_{\text{Kerosene}} + \beta_2 I_{\text{Dung}} + \beta_3 I_{\text{Wood}} + \beta_4 I_{\text{LPG}} + \beta_5 I_{\text{SOK}} + \beta_6 I_{\text{WFPK}} + \beta_7 I_{\text{WOK}} + \beta_8 I_{\text{VGood}} + \beta_9 I_{\text{VModerate}} + \beta_10 I_{\text{VPoor}} + \beta_11 I_{\text{Cooking hours}} + \beta_12 I_{\text{East}} + \beta_13 I_{\text{West}} + \beta_14 I_{\text{South}} + \beta_15 I_{\text{North}}$$

(1)

where the $\beta$ coefficients are fitting parameters derived in their study (listed in SI Table 1). The primary fuel...
type usage rates for each states’ urban and rural populations was retrieved from India’s Time Use Survey 2019 data (SI table 2). Fuel stacking, using a secondary fuel in addition to a primary fuel, is a common [17, 18], yet mostly unquantified practice nationwide. We utilize microdata from India’s Residential Energy Survey (2020) [19] and household expenditure survey conducted by the National Sample Survey Office (2014) [20] to quantify the frequency at which primary LPG-households use biomass as a secondary fuel (SI table 3). The National Sample Survey Office (NSSO) survey was conducted before recent LPG initiatives were introduced in Indian households that resulted in the proportion of Indian households using LPG to increase from 56% to 89% [19]. Despite the improved access to LPG, it has been previously assessed that the vast majority (~86%) of households under these schemes still use biomass fuels [21]; this penetration rate was applied to the NSSO reported fuel stacking data. Ventilation and kitchen typology data were obtained from Drinking Water, Sanitation, and Hygiene Survey (2012) [22] and Census of India (2011). Hours spent cooking were provided from Time Use Survey Data (2019) [23]. We assume all datasets that did not occur in 2020 scaled linearly from their respective base year to 2020 demographics, i.e. by population.

Balakrishnan et al [11] then modeled living area 24 h average PM$_{2.5}$ concentrations, $L$, as:

$$L = 0.147 \times K^{0.32}.$$  

Their [11] analysis of 617 households was only conducted in rural homes, but we assume the same regressions apply to urban households for this study, consistent with their nationwide household exposure approach. In addition, their regression equations estimate 24 h average PM$_{2.5}$ concentrations; the time spent in the kitchen is likely during more-polluting cooking events, suggesting our household exposure estimate used here is likely conservative.

To represent ambient PM$_{2.5}$ concentrations for each Indian state’s urban and rural populations, we used spatially-resolved (1 km $\times$ 1 km resolution), satellite-derived, surface-level PM$_{2.5}$ concentrations that were calibrated with Central Pollution Control Board monitoring sites as described further in Dey et al [12]. Here, we took the five-year average concentration between 2015 and 2019 as a baseline ambient PM$_{2.5}$ concentration (the five-year averaging time is consistent with other COVID-19-related air quality studies that assessed baseline, ambient concentrations [24–26]) for each state’s urban and rural populations, where the urban/rural grid classification was adopted from Balk et al [27] (SI figure 1 for map of urban/rural grids). The final microenvironment that was characterized was the work/school environment, where PM$_{2.5}$ concentrations were estimated using annual-average work/school to ambient PM$_{2.5}$ concentration correction factors from previous microenvironment exposure studies specific to India [13–15].

The time-use survey was a survey of 445 170 participants throughout India conducted in 2019 by the Ministry of Statistics & Programme Implementation. Survey participants documented the time they spent conducting various (out of 158) activities (e.g. cooking, eating, work/school, sleeping, commuting, etc) over a 24 h recall period. The survey was conducted in 82 897 rural and 55 902 urban households with respondents from each state’s male and female populations across age groups (we separated ages into 17 brackets (0–5, 5–10, …, 75–80, 80+; SI table 2). The 158 monitored activities were grouped as household (kitchen or living area), outdoor, or at work/school to align with microenvironments where PM$_{2.5}$ concentration estimates were available. Recall surveys have well-documented limitations associated with recall bias, particularly when assessing microenvironment exposures from solid-fuel use [18, 28]. Here, we do not directly quantify uncertainties with individual responses, but rather incorporate the distribution of responses from each state’s subpopulation groups (e.g. urban/rural, gender, age) when modeling PM$_{2.5}$ exposures, as described next.

There is uncertainty in each of the microenvironment PM$_{2.5}$ concentrations as well as with the 24 h recall surveys as applied in this exposure framework. We utilize a robust, Monte-Carlo framework ($n = 100$ 000; consistent with the number of simulations in previous PM$_{2.5}$ exposure studies [29, 30]) that incorporates uncertainties/distributions from both microenvironment PM$_{2.5}$ concentrations and the 24 h recall surveys to estimate average PM$_{2.5}$ exposures and 95% distributions for each Indian state’s subpopulation groups (e.g. urban/rural, gender, and age; see SI section 1 for a detailed example of this framework for rural Uttar Pradesh women aged 30–35). The PM$_{2.5}$ exposure approach outlined here assumes all urban or rural populations in a state have the same ambient exposure distribution for all outdoor activities, respectively, which has inherent misclassification errors, particularly considering the wide range of PM$_{2.5}$ concentrations observed in Indian cities at such fine scales [31]. Further, this approach assumes the surveyed population in a state represents the same activities conducted by other individuals within that state and subpopulation (e.g. urban/rural, gender, and age).

2.2. Increased residential biomass burning activity during the COVID-19 lockdown and subsequent PM$_{2.5}$ exposure estimates

During the COVID-19 lockdown, we assume the total number of meals consumed per person remained constant with baseline levels, but that all meals previously prepared outside the home (e.g. at a restaurant, office canteen, street vendor, etc) were
prepared inside the home, consistent with the mandatory stay-at-home guidelines. The number of meals prepared at home versus outside the home during baseline conditions for each Indian state’s urban/rural populations by gender and age was acquired from the NSSO household consumer expenditure survey [20]; the survey showed that 3.9% of urban population and 2.0% of rural population meals were prepared outside the home during baseline conditions. During the lockdown, this increased cooking activity and its associated emissions occurred at home. Using the semi-empirical approach from Balakrishnan et al [11], the increase in total household fuel consumption is modeled by an increase in time spent cooking—one of their explanatory variables—to estimate household PM$_{2.5}$ concentrations during the lockdown. To do this, we assumed the time spent cooking per amount of food prepared is constant, i.e. the amount of time spent cooking, on average, increased 3.9% and 2.0% for urban and rural populations, respectively, during the lockdown. We assume that the fraction of indoor time spent in the kitchen remained consistent with baseline time-use activity for each of the subpopulation groups (i.e. the increased cooking activity was largely conducted by women), with the remaining time of the day during the stay-at-home mandates spent in the living area. The modeling framework outlined by Balakrishnan et al [11] will have captured PM$_{2.5}$ that originated out of the household; we assume their parameterization is still applicable for the COVID-19 lockdown exposure estimate when lower ambient PM$_{2.5}$ concentrations existed.

2.3. Global population estimate of PM$_{2.5}$ exposure increases during the COVID-19 lockdown

To estimate the fraction of each countries’ population that will have experienced PM$_{2.5}$ exposure increases from biomass burning activity during COVID-19 lockdowns, we combine lockdown status data for each country with primary biomass fuel use for cooking in 2020 data reported by Stoner et al [16]. The cooking fuel use data used in this study only represents primary fuel use and does not consider fuel stacking rates, outside of what we determined for India. In addition, this data only represents cooking activity and not biomass burning for heating, another common application for biomass fuel usage, suggesting these results will be a conservative estimate of the true global population that will have observed increased PM$_{2.5}$ exposures during COVID-19 lockdowns. Here, we only quantify the fraction of each countries’ population that will have experienced increased PM$_{2.5}$ exposures during lockdowns (under the guiding assumption that households that use biomass cookstoves will have observed increased exposures) and not PM$_{2.5}$ concentration increases as we do not have access to representative time-use survey data and fine-scale microenvironment PM$_{2.5}$ concentration estimates for many of those regions.

3. Results

During India’s COVID-19 lockdown, 65% of the population (the percent of the population that uses biomass as either a primary or secondary cooking fuel) experienced higher modeled PM$_{2.5}$ concentrations relative to baseline exposures, with a population-wide average increase of 13.1% (95% distribution: 8–26) (from 115.6 (82–157) to 130.8 (104–170) µg m$^{-3}$) (table 1, figure 1 and SI figure 2). The demographic groups that experienced the highest relative modeled PM$_{2.5}$ exposure increase during the lockdown were working-age (20–65 years) men and school-age (5–20 years) children, whose average exposure increased by 24.0% (18–48) (from 87.6 (63–117) to 108.3 (94–139) µg m$^{-3}$) and 18.2% (8.1–30.6) (from 97.6 (75–135) to 115.1 (98–145) µg m$^{-3}$), respectively. Although rural women, on average, had the lowest relative modeled PM$_{2.5}$ exposure increase among the various demographic groups (e.g. urban/rural, gender, age), they still had the highest exposures during the lockdown at, on average, 163.1 (117–225) µg m$^{-3}$. Geographically, the largest modeled exposure increases occurred throughout South India where baseline exposures were lowest (figure 1 and SI figure 2). Indians in the Indo-Gangetic Basin, which is known for being the most polluted airshed in India [32], had the lowest modeled PM$_{2.5}$ exposure increases during the lockdown.

During the baseline period, adult, rural females had the highest average modeled PM$_{2.5}$ exposures, which was expected considering 86% of rural households use biomass as either a primary or secondary cooking fuel (SI table 3), which results in elevated household PM$_{2.5}$ concentrations (SI table 4), and that the average adult, rural female spends 3.5 h in the kitchen environment each day, considerably higher than their male counterparts (SI table 5). By age, children <5 years old had the highest average exposures of all age groups both during the baseline and lockdown periods, which was anticipated as most of their baseline time (17.5 h) is spent at home, presumably in close proximity to their mother (kitchen area exposure). Men of all ages (except <5 years) had nearly uniform modeled average PM$_{2.5}$ exposures in both urban and rural India, respectively, during the lockdown (Urban: 93–96 µg m$^{-3}$; Rural: 115–117 µg m$^{-3}$; table 1), suggesting Indian men of all ages spent roughly the same amount of time in the kitchen and the living area during the lockdown for urban and rural populations, respectively. For Indian women, working-age ones experienced the highest modeled PM$_{2.5}$ exposures during the baseline and lockdown periods; the time-use survey data showed they are largely responsible for much of the household cooking demand during baseline periods (3.5 h, on average, compared to 0.4 h combined for all other subpopulations) and during the lockdown.
Table 1. Average Indian PM$_{2.5}$ exposures ($\mu$g m$^{-3}$) during the baseline and COVID-19 lockdown periods and PM$_{2.5}$ exposure percent change between the two periods for each subpopulation group (urban/rural, gender, age). The values in parenthesis represent 95% exposure distributions within the subpopulation group.

|                      | All Ages | 0-5 | 5-10 | 10-15 | 15-20 | 20-25 | 25-30 | 30-35 | 35-40 | 40-45 | 45-50 | 50-55 | 55-60 | 60-65 | 65-70 | 70-75 | 75-80 | 80+ |
|----------------------|----------|-----|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-----|
| **Baseline PM$_{2.5}$ Exposure (\mu g m$^{-3}$)** |          |     |      |       |       |       |       |       |       |       |       |       |       |       |       |       |      |     |
| Urban Male           | 80.6     | 124.3 | 80.4 | 79.9 | 79.4 | 77.0 | 73.3 | 72.7 | 72.3 | 72.6 | 72.9 | 74.7 | 77.4 | 83.1 | 85.7 | 87.5 | 89.1 | 90.3 |
| Rural Female         | 107.7    | 123.9 | 80.9 | 82.4 | 94.2 | 109 | 117.9 | 120.2 | 126.5 | 119.9 | 134.6 | 117.4 | 134.5 | 111.9 | 109.7 | 108.5 | 103.6 | 99.5 |
| Female               | 105.5    | 183.9 | 96.5 | 96.0 | 96.8 | 95.4 | 93.8 | 93.9 | 94.7 | 94.9 | 95.7 | 97.1 | 99.2 | 102.5 | 104.4 | 106.1 | 108.3 | 111.7 |
| Rural Male           | 149.4    | 184.0 | 97.6 | 104.4 | 139.5 | 170.3 | 177.7 | 178.5 | 174.4 | 167.0 | 160.5 | 154.3 | 159.5 | 145.7 | 140.4 | 132.2 | 127.7 | 119.9 |
| Rural Female         | 149.4    | 184.0 | 97.6 | 104.4 | 139.5 | 170.3 | 177.7 | 178.5 | 174.4 | 167.0 | 160.5 | 154.3 | 159.5 | 145.7 | 140.4 | 132.2 | 127.7 | 119.9 |
| **PM$_{2.5}$ Exposure Percent Increase during the COVID-19 Lockdown** |          |     |      |       |       |       |       |       |       |       |       |       |       |       |       |       |      |     |
| Urban Male           | 97.4     | 129.6 | 93.8 | 94.1 | 95.1 | 95.7 | 94.6 | 94.3 | 94.4 | 94.4 | 94.4 | 94.4 | 94.4 | 94.4 | 94.2 | 94.3 | 93.9 | 93.3 |
| Rural Female         | 116.6    | 195.5 | 116.3 | 116.5 | 116.8 | 116.6 | 116.2 | 116.4 | 116.6 | 116.6 | 116.8 | 116.9 | 116.9 | 117.4 | 119.9 | 119.9 | 119.9 |
| Female               | 163.1    | 195.5 | 117.0 | 124.4 | 154.1 | 180.3 | 187.7 | 191.4 | 188.5 | 181.7 | 174.3 | 167.1 | 161.7 | 157.7 | 148.2 | 137.9 | 124.2 |
| Rural Male           | 181.8    | 20.5  | 16.2 | 16.5 | 11.6 | 7.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 |
| Rural Female         | 181.8    | 20.5  | 16.2 | 16.5 | 11.6 | 7.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 |
| All Indians          | 130.8    | 176.6 | 110.2 | 122.9 | 123 | 132.2 | 135.7 | 137.1 | 131 | 134 | 132.1 | 129.7 | 127.1 | 125.7 | 123.3 | 118.4 | 115.1 | 111.5 |

The values in parenthesis represent 95% exposure distributions within the subpopulation group.
Figure 1. India-specific state-level average (left column) baseline PM$_{2.5}$ exposures ($\mu$g m$^{-3}$), (center column) COVID-19 lockdown PM$_{2.5}$ exposures ($\mu$g m$^{-3}$), and (right column) percent PM$_{2.5}$ exposure increases during the lockdown for the entire population and various subpopulation groups. The color scale for the range of PM$_{2.5}$ exposures and percent increases is the same in all panels. See SI figure 2 and SI table 4 for exact concentrations and exposure increases shown here.

Household PM$_{2.5}$ concentrations were substantially higher than ambient concentrations across most states for both urban and rural populations with rural populations having higher levels of household PM$_{2.5}$ pollution than urban households, on average (SI figure 3 and SI table 4). Household PM$_{2.5}$ concentrations modestly increased during the lockdown from baseline levels (urban kitchen area = 0.84% increase, urban living area = 0.34%, rural kitchen area = 0.73%, rural living area = 0.22%; SI table 6),
consistent with the slight 3.9% and 2.0% increase in cooking activity in urban and rural homes, respectively. The cleanest environment is the work/school environment, where school children and working-age men spend 3.9 and 4.0 h per day on average; by comparison, the time-use data found working-age women spend 1.2 h of their average day in those environments. Using time-use survey responses that provide insights on indoor and outdoor exposures, the population-weighted average PM$_{2.5}$ exposure found here is 115 (82–157) µg m$^{-3}$, ~30% higher than the 91.7 µg m$^{-3}$ ambient, home-based estimate over India reported by the GBD [6].

Extending this framework globally, where households that use biomass fuels for cooking will have experienced increased PM$_{2.5}$ exposures during lockdowns due to increased cooking activity and more time spent indoors, we conservatively estimate that 34.5% (21–51) of the global population experienced increased PM$_{2.5}$ exposures during lockdowns, largely confined to developing regions with high biomass for cooking utilization rates (figure 2).

4. Discussion

The COVID-19 lockdowns, which were observed by most countries around the world, offered a unique natural experiment to assess air quality impacts from a near-entire mitigation of emissions from the industrial, commercial, and transportation sectors. Despite the resulting historic improvements in ambient air quality, PM$_{2.5}$ exposures increased for the majority of Indians and a third of the global population, attributed largely to biomass burning as fuel for cooking. Given that residential biomass burning has also been implicated as the leading source contributor to ambient PM$_{2.5}$ in India, where air quality standards exist, the Indian government has introduced various initiatives to promote clean cooking (e.g. Pradhan Mantri Ujjwala Yojana (PMUY) and Unnat Chulha Abhiyan (UCA)). These initiatives, which have targeted low-income, rural households, have had tangible success in some areas, but require better strategies to achieve the widespread clean cooking adoption that was desired, including addressing shortcomings associated with inadequate infrastructure, user hesitancy, dropout, unreliable LPG supply/refills, etc [21, 33].

In addition, residential biomass burning for cooking and heating has exacerbated PM$_{2.5}$ exposure disparities in non-lockdown times throughout India [31, 34]—with most of the burden on women and rural populations that use biomass as cooking fuel. Surprisingly, during the COVID-19 lockdown when families of similar strata were confined to presumably similar indoor environments, exposure disparities persisted, both in terms of actual PM$_{2.5}$ exposures as well as increases from baseline exposures. During India’s lockdown, women were still responsible for meal preparation, resulting in 3.0 h, on average, more in the kitchen environment compared to men (SI table 5), which explains their 24.3% (6–35), on average, higher modeled PM$_{2.5}$ exposure compared to men (table 1). Working-age men and school-age children experienced the highest exposure increase during the lockdown despite a lower overall exposures compared to other subpopulations. During the baseline period, these groups spent more time in the work/school and ambient environments (SI table 5), which are much less polluted than household concentrations, on average (SI table 4).
Baseline PM$_{2.5}$ exposures, as assessed here, provides the first-of-its kind, nationwide exposure estimate for India that incorporates detailed time-use data in various microenvironments among subpopulations. As a result, the exposure estimates found in this study cannot explicitly be evaluated; however, the indoor modeling framework utilized here was built on real-time measurements in Indian homes and the ambient satellite data was rigorously calibrated and fused with India-specific observational data. Recent research in India has determined ambient PM$_{2.5}$ concentrations are similar in urban and rural areas [12, 35], but by utilizing time-use data, we find PM$_{2.5}$ exposures are higher in rural (127 (91–173) µg m$^{-3}$) compared to urban (93.7 (66–125) µg m$^{-3}$) populations, again driven largely by higher rates of residential biomass burning in rural households (86% of rural households use biomass as either a primary or secondary fuel compared to 23% of urban homes), which cannot be explicitly accounted for in ambient-only exposure studies. In addition, we find that none of any Indian state’s subpopulation group’s average PM$_{2.5}$ exposure meets the 40 µg m$^{-3}$ annual national ambient air quality standard (the lowest exposure group is urban A&N Islands men aged 35–40 at 51.3 (26–69) µg m$^{-3}$; the lowest mainland exposure group is urban Tamil Nadu men aged 25–30 at 59.5 (43–81) µg m$^{-3}$).

Globally, ~2.7 billion people, mostly concentrated in low-income regions, use various forms of biomass fuels (e.g. wood, charcoal, crop residue, dung, etc) for cooking [16, 36]. Emphasizing the global health burden associated with exposures to these emissions, McDuffie et al [37] found that 20% of the global mortality burden from ambient PM$_{2.5}$ exposures is attributed to solid-fuel consumption for residential cooking and heating. There have been a number of interventions, both from public and private entities, to address clean cooking (and heating) around the world, but the findings presented here (and in other regional COVID-19 PM$_{2.5}$ exposure assessments [38–42]) that PM$_{2.5}$ exposures increased despite historically clean ambient air quality during COVID-19 lockdowns, underscores the urgent need to further address clean cooking (and heating) interventions to achieve improved air quality and subsequent human health benefits.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: http://vapimodel.blogspot.com/.

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References

[1] Sharma S, Zhang M, Anshika, Gao J, Zhang H and Kota S H 2020 Effect of restricted emissions during COVID-19 on air quality in India Sci. Total Environ. 728 138878
[2] Singh R P and Chauhan A 2020 Impact of lockdown on air quality in India during COVID-19 pandemic Air Qual. Atmos. Health. 13 921–8
[3] Murray C J L et al 2020 Global burden of 87 risk factors in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019 Lancet 396 1223–49
[4] Lim S S et al 2012 A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the Global Burden of Disease Study 2010 Lancet 380 2224–60
[5] Lelieveld J, Evans J S, Fnais M, Giannadaki D and Pozzer A 2015 The contribution of outdoor air pollution sources to premature mortality on a global scale Nature 525 367–71
[6] Pandey A et al 2021 Health and economic impact of air pollution in the states of India: the Global Burden of Disease Study 2019 Lancet Planet. Health 5 e25–e38
[7] Yu X et al 2020 Quantifying the impact of daily mobility on errors in air pollution exposure estimation using mobile phone location data Environ. Int. 141 105772
[8] Do K, Yu H, Velasquez J, Grell-Brisk M, Smith H and Ivey C E 2021 A data-driven approach for characterizing community scale air pollution exposure disparities in inland Southern California J. Aerosol Sci. 152 105704
[9] Venkataraman C et al 2018 Source influence on emission pathway and ambient PM$_{2.5}$ pollution over India (2015–2050) Atmos. Chem. Phys. 18 8017–39
[10] Chowdhury S, Dey S, Guttikunda S, Pillarisetti A, Smith K R and Di Girolamo L 2019 Indian ambient air quality standard is achievable by completely mitigating emissions from household sources Proc. Natl Acad. Sci. 116 10711–6
[11] Balakrishnan K, Ghosh S, Ganguli B, Sambandam S, Bruce N, Barnes D F and Smith K R 2013 State and national household concentrations of PM$_{2.5}$ from solid cookfuel use: results from measurements and modeling in India for estimation of the global burden of disease Environ. Health 12 77
[12] Dey S et al 2020 A satellite-based high-resolution (1-km) ambient PM$_{2.5}$ database for India over two decades (2000–2019): applications for air quality management Remote Sens. 12 3872
[13] Sahu V and Gurjar B R 2020 Spatial and seasonal variation of air quality in different microenvironments of a technical university in India Build. Environ. 185 107310
[14] Datta A, Suresh R, Gupta A, Singh D and Kulshrestha P 2017 Indoor air quality of non-residential urban buildings in Delhi, India Int. J. Sustain. Built Environ. 6 412–20

[15] Mohammed M O A, Song W-W, Ma W-L, Li W-L, Ambuchi J J, Thabit M and Li Y-F 2015 Trends in indoor–outdoor PM$_{2.5}$: research: a systematic review of studies conducted during the last decade (2003–2013) Atmos. Pollut. Res. 6 893–903

[16] Stoner O, Lewis J, Martinez I L, Gumy S, Economou T and Adair-Rohani H 2021 Household cooking fuel estimates at global and country level for 1990–2030 Nat. Commun. 12 5793

[17] Ravindra K, Kaur-Sidhu M, Mor S and John S 2019 Trend in household energy consumption pattern in India: a case study on the influence of socio-cultural factors for the choice of clean fuel use J. Clean. Prod. 213 10224–34

[18] Gould C E, Hou X, Richmond J, Sharma A and Urpelainen J 2020 Jointly modeling the adoption and use of clean cooking fuels in rural India Environ. Res. Commun. 2 085004

[19] Mani S, Agrawal S, Jain A and Ganesan A 2021 State of Clean Cooking Energy Access in India: Insights from the India Residential Energy Survey (IRES 2020) (New Delhi: Council on Energy, Environment, and Water)

[20] Kumar A, Jain N, Nandraj S and Furtado K 2015 NSSO 71st round: same data, multiple interpretations Econ. Polit. Wkly. 50 46–47

[21] Mani S, Jain A, Tripathi S and Gould C F 2020 The drivers of sustained use of liquified petroleum gas in India Nat. Energy 5 450–7

[22] Government of India 2012 Key Indicators of Drinking Water, Sanitation, Hygiene and Housing Condition in India ed N T Round (New Delhi: National Sample Survey Organization)

[23] Government of India 2019 NSS Report: Time Use in India-2019

[24] He C et al 2021 Global, continental, and national variation in PM$_{2.5}$, O$_3$, and NO$_2$ concentrations during the early 2020 COVID-19 lockdown Atmos. Pollut. Res. 12 136–45

[25] Hao X, Li J, Wang H, Liao H, Yin Z, Hu J, Wei Y and Dang R 2021 Long-term health impact of PM$_{2.5}$ under whole-year COVID-19 lockdown in China Environ. Pollut. 290 118118

[26] Mishra G, Ghosh K, Dwivedi A K, Kumar M, Kumar S, Chintalapati S and Tripathi S N 2021 An application of probability density function for the analysis of PM$_{2.5}$ concentration during the COVID-19 lockdown period Sci. Total Environ. 782 146081

[27] Balk D, Montgomery M R, Engin H, Lin N, Major E and Jones B 2019 Urbanization in India: population and urban classification grids for 2011 Data 4 1

[28] Rehfuess E A, Tzala L, Best N, Briggs D J and Joffe M 2009 Solid fuel use and cooking practices as a major risk factor for ALRI mortality among African children J. Epidemiol. Community Health 63 887

[29] Milner J, Armstrong B, Davies M, Ridley L, Chalabi Z, Shrubsole C, Vardoulakis S and Wilkinson P 2017 An exposure–mortality relationship for residential indoor PM$_{2.5}$ exposure from outdoor sources Climate 5 66

[30] Cleland S E, Serre M L, Rappold A G and West J J 2021 Estimating the acute health impacts of fire-originated PM$_{2.5}$ exposure during the 2017 California wildfires: sensitivity to choices of inputs GeoHealth 5 e2021GH000414

[31] Lal R M, Nappareddy A S, Luo L, Tripathi S N, Ramaswami A, Bergin M H and Russell A G 2016 Municipal solid waste and dung cake burning: discoloring the Taj Mahal and human health impacts in Agra Environ. Res. Lett. 11 104009

[32] Das M, Das A, Ghosh S, Sarkar R and Saha S 2021 Spatio-temporal concentration of atmospheric particulate matter (PM$_{2.5}$) during pandemic: a study on most polluted cities of indo-gangetic plain Urban Clim. 35 100758

[33] Kar A, Pachauri S, Balis R and Zerriffi H 2019 Using sales data to assess cooking gas adoption and the impact of India’s Ujjwala programme in rural Karnataka Nat. Energy 4 806–14

[34] Lal R M, Tibrewal K, Venkataraman C, Tong K, Fang A, Ma Q, Wang S, Kaiser J, Ramaswami A and Russell A G 2022 Impact of circular, waste-reuse pathways on PM$_{2.5}$ air quality, CO$_2$ emissions, and human health in India: comparison with material exchange potential Environ. Sci. Technol. 56 9773–83

[35] Ravishankara A R, David L M, Pierce J R and Venkataraman C 2020 Outdoor air pollution in India is not only an urban problem Proc. Natl Acad. Sci. 117 28640

[36] International Energy Agency 2017 Energy Access Outlook 2017

[37] McDuffie E E et al 2021 Source sector and fuel contributions to ambient PM$_{2.5}$ and attributable mortality across multiple spatial scales Nat. Commun. 12 3594

[38] Chen Y, Senthilkumar N, Shen H and Shen G 2021 Environmental inequality deepened during the COVID-19 in the developing world Environ. Sci. Technol. 55 7–8

[39] Li J, Men Y, Liu X, Luo Z, Li Y, Shen H, Chen Y, Cheng H, Shen G and Tao S 2021 Field-based evidence on changes in household PM$_{2.5}$ and exposure during the 2020 national quarantine in China Environ. Res. Lett. 16

[40] Shen H et al 2021 Increased air pollution exposure among the Chinese population during the national quarantine in 2020 Nat. Hum. Behav. 5 239–46

[41] Zhang Y et al 2021 Non-negligible contributions to human health from increased household air pollution exposure during the COVID-19 lockdown in China Environ. Int. 158 106918

[42] Li X et al 2022 Field measurements of indoor and community air quality in rural Beijing before, during, and after the COVID-19 lockdown Indoor Air 32 e13095