



HHS Public Access

Author manuscript

J Expo Sci Environ Epidemiol. Author manuscript; available in PMC 2024 October 03.

Published in final edited form as:

J Expo Sci Environ Epidemiol. 2024 September ; 34(5): 802–813. doi:10.1038/s41370-023-00606-1.

Geospatial determinants of maternal and child exposure to fine particulate matter in Kintampo, Ghana: Levels within the household and community, by surrounding building density and near roadways

Danielle N Medgyesi¹, Mohammed Nuhu Mujtaba², Qiang Yang^{3,4}, Sulemana Watara Abubakari², Alison G Lee⁵, Jeremy Porter^{1,6}, Steven N Chillrud³, Seyram Kaali², Darby W Jack¹, Kwaku Poku Asante²

¹Department of Environmental Health Sciences, Mailman School of Public Health, Columbia University, New York, NY, USA

²Kintampo Health Research Centre, Research and Development Division, Ghana Health Service, Kintampo North Municipality, Ghana

³Lamont-Doherty Earth Observatory, Columbia University, Palisades, NY, USA

⁴Elsevier Global STM Journals, New York, NY, USA

⁵Division of Pulmonary, Critical Care and Sleep Medicine, Icahn School of Medicine at Mount Sinai, New York, NY, USA

⁶Department of Sociology, School of Humanities and Social Sciences, Brooklyn College, Brooklyn, NY, USA

Abstract

Background.—Personal exposure to fine particulate matter (PM_{2.5}) from household air pollution is well-documented in sub-Saharan Africa, but spatiotemporal patterns of exposure are poorly characterized.

Objective.—We used paired GPS and personal PM_{2.5} data to evaluate changes in exposure across location-time environments (e.g., household and community, during cooking and non-cooking hours), building density and proximity to roadways.

Methods.—Our study included 259 sessions of geolocated, gravimetrically-calibrated one-minute personal PM_{2.5} measurements from participants in the GRAPHs Child Lung Function

Corresponding author: Danielle Medgyesi, MS, Predoctoral Fellow, Columbia University Mailman School of Public Health, Department of Environmental Health Sciences, 722 West 168th St., New York, NY 10032, dm3688@cumc.columbia.edu.

AUTHOR CONTRIBUTIONS: KPA, DNM, DWJ and SNC conceived of the work. MNM, SK, DWJ and SNC led the exposure assessment work. QY processed the data used in this analysis. All authors contributed to the design of the study. JP provided spatial analysis advice. DNM completed the analysis and drafted the manuscript. All authors contributed to the interpretation of results and revision of the manuscript.

COMPETING INTERESTS: The authors declare no competing interests.

ETHICAL APPROVAL: The protocol for this study was approved by the Kintampo Health Research Center Institutional Ethics Committee, and the Institutional Review Board for Human Subjects Research at Columbia University Medical Center and Mount Sinai.

Study. The household vicinity was defined using a 50-meter buffer around participants' homes. Community boundaries were developed using a spatial clustering algorithm applied to an open-source dataset of building footprints in Africa. For each GPS location, we estimated building density (500m buffer) and proximity to roadways (100m buffer). We estimated changes in PM_{2.5} exposure by location (household, community), time of day (morning/evening cooking hours, night), building density, and proximity to roadways using linear mixed effect models.

Results.—Relative to nighttime household exposure, PM_{2.5} exposure during evening cooking hours was 2.84 (95%CI=2.70–2.98) and 1.80 (95%CI=1.54–2.10) times higher in the household and community, respectively. Exposures were elevated in areas with the highest versus lowest quartile of building density (Factor_{Q1vsQ4}=1.60, 95%CI=1.42–1.80). The effect of building density was strongest during evening cooking hours, and influenced levels in both the household and community (31% and 65% relative increase from Q1 to Q4, respectively). Being proximal to a trunk, tertiary or track roadway increased exposure by a factor of 1.16 (95%CI=1.07–1.25), 1.68 (95%CI=1.45–1.95) and 1.27 (95%CI=1.06–1.53), respectively.

Significance.—Our findings suggest that community-wide solid fuel use for household cooking contributes to personal PM_{2.5} exposure. Building density may exacerbate community exposures when multiple households are cooking simultaneously. Proximity to large roadways (trunk) and unpaved roadways (tertiary, track) increase PM_{2.5} exposure.

Keywords

Geospatial Analyses; Particulate Matter; Personal Exposure; Child Exposure/Health; Vulnerable Populations; Sustainable Development

INTRODUCTION

The combustion of solid fuels for domestic cooking is the primary source of household air pollution in low-and-middle income countries (LMICs). Sub-Saharan Africa continues to suffer the highest rate of age-adjusted disease due to household air pollution¹. Among environmental risk factors, household air pollution is the second largest contributor to the global burden of disease, while ambient air pollution is the top contributor². In regions like Africa where over 80% of the population relies on solid fuels, household air pollution may contribute significantly to ambient air pollution³.

Few studies have evaluated the relationship between levels of air pollution in the household and the community in LMICs. A modeling analysis conducted in Ghana as part of the Climate Pollutant Action Plan reported an estimated 64% of anthropogenic emissions of fine particulate matter (PM_{2.5}; 2.5 µg/m³ aerodynamic diameter) were attributed to residential emissions³. A monitoring campaign in Nepal found PM_{2.5} levels were 37% higher in rural sites during times of cooking relative to a background site⁴. A study in rural China reported ambient levels of black carbon in villages were moderately correlated with levels in the household (r=0.49)⁵.

There is also a limited understanding of the influence of geographic features, e.g., building density and roadways, on air pollution in rural LMIC communities. A study in Bangladesh demonstrated that a household's use of solid fuels for cooking increased PM_{2.5} and carbon

monoxide levels outdoors, as well as in other neighboring homes that used cleaner fuels (i.e., gas, electric)⁶. Outdoor levels of air pollution may be elevated in areas with a high density of households that use solid fuels, especially during typical hours of cooking. Roadways, a well-recognized source of air pollution in urban, developed settings^{7–9}, are gaining recognition as an important contributor to exposure in rural settings, in tandem with solid fuel use^{10–14}. In rural China, a PM_{2.5} source apportionment analysis reported that outdoor sources, including vehicles, may contribute 10–20% of household exposures¹⁴. In rural Ghana, a greater proportion of PM_{2.5} was attributed to black carbon in personal samples relative to stationary samples in the kitchen, highlighting the need to further investigate roadways as an important exposure source¹³.

Community sources – including neighbors' cooking – may partially explain why some improved cookstove trials have found less-than-expected reductions in personal PM_{2.5} exposure. In the Ghana Randomized Air Pollution and Health Study (GRAPHS), modest reductions in 48-hour PM_{2.5} exposure were observed among pregnant women who used an LPG cookstove (–35%; 95% confidence interval= –26, –38%) relative to those who used traditional cookstoves fueled by wood or charcoal^{15, 16}. Despite using an LPG cookstove, 67% of these women experienced exposure levels that exceeded WHO interim guidelines (35µg/m³). These findings emphasize the need to identify sources beyond the household and evaluate patterns of exposure throughout the day. This has important implications for energy policy. If neighbors' emissions contribute meaningfully to an individual's exposure, then household-level clean energy interventions that only reach a portion of households in a community (as often is the case with commercial distribution that disproportionately reach richer households¹⁷) may underdeliver on health benefits.

Our study leveraged GPS-tracked personal PM_{2.5} measurements collected from mothers and children living in rural Ghana who are participants of the Child Lung Function Study, a cohort extension of GRAPHS. We aimed to compare exposure levels across location-time environments (e.g., household and community, during cooking and non-cooking hours), as well as by surrounding building density and proximity to roadways. Several previous studies from this cohort have demonstrated maternal exposure to PM_{2.5} is associated with higher blood pressure and impaired infant lung function and growth trajectories^{18–21}. This study is the first to assess how personal exposure varies across location, time and sources outside of the household. Our findings will help to identify environmental conditions that increase air pollution exposure, which could lead to improved characterization of personal exposures in epidemiologic analyses²². This study also has implications in informing the design of policies aimed at reducing the burden of disease due to household and ambient air pollution.

METHODS

Study population

The Child Lung Function Study cohort includes non-smoking women and their children originally enrolled in GRAPHS, described elsewhere²³. Briefly, a total of 1,414 pregnant women were recruited from 35 community clusters (2013–2016) in the now Bono East Region of Ghana. Following the randomized trial in which cleaner cookstoves were provided and used by participants for a duration of approximately two years²⁴, mother-

child dyads have continued to participate in several follow-up sessions that have collected personal measurements of air pollutants^{15, 25} and health outcomes including maternal blood pressure^{19, 20}, child growth trajectories²¹ and lung function^{18, 26}.

Our analysis includes GPS-tracked, one-minute personal measurements of PM_{2.5} collected from mothers and children, obtained during 48-hour logging sessions. These measurements were collected as part of a follow-up period conducted between August 2018 and July 2019, when the children in the cohort were approximately four years old. At the time of data collection, women had resumed using their traditional cookstoves. The protocol for this study was approved by the Kintampo Health Research Center Institutional Ethics Committee, Columbia University Medical Center and Mount Sinai. Women in the study provided written informed consent for the participation of themselves and their children. Analyses were conducted in R version 4.1.2. We interpreted the results using statistical measures, including a p-value threshold of <0.05 to discern statistical significance, and 95% confidence intervals to capture the range of potential values. For brevity, p-values less than 0.001 were abbreviated as 'p-value<0.001'.

Personal exposure data

Participants wore an RTI MicroPEM V3.2 monitor (Research Triangle Park, NC) in a comfortable sling with the air inlet placed near the breathing zone. The monitor is equipped with a nephelometer for real-time PM_{2.5} readings, a Teflon filter for PM_{2.5} collection, and sensors for continuous recording of relative humidity and temperature. A built-in correction factor for relative humidity was applied to continuous nephelometer readings²⁷. The methods and quality control procedures for obtaining one-minute PM_{2.5} estimates used in this study have been previously described^{15, 25}. Briefly, this included the attachment of a HEPA filter to the device for at least five minutes before and after each monitoring session to assess for drifts in the readings. This facilitated a zero-drift correction applied to continuous readings. Monitoring sessions were deemed invalid if HEPA values exceeded 20µg/m³, or if the readings exhibited step-wise patterns or improbable plateaus. Gravimetric PM_{2.5} concentrations were obtained from the filters deployed in the field, and underwent field blank correction, involving the subtraction of a median field blank mass of 5µg, prior to concentration estimation. Gravimetric corrections were carried out by multiplying each reading by the ratio of the gravimetric PM_{2.5} concentration divided by the average of nephelometer PM_{2.5} readings for the total deployment time.

A randomly selected subset of participants consented to additionally wearing a Suunto Ambit 3 GPX tracker (Amer Sports Corporation, Vantaa, Finland) placed within the sling. The tracker recorded coordinate pairs (latitude/longitude at a precision of 6 decimal degrees) and corresponding timestamps when movement was detected. Therefore, GPS records were more frequent throughout the day (median/average=every 2/19 mins) relative to the night (median/average= every 26/95 mins), when participants were less active and removed the device before sleeping. Coordinates from the tracker were joined to PM_{2.5} measurements by matching timestamps. Since there was not a GPS record for each minute, we assumed participants remained in the same area until the next GPS record. We implemented this assumption by assigning the last observed coordinate pair to subsequent one-minute PM_{2.5}

measurements until the next coordinate pair. The first coordinate pair linked to a PM_{2.5} measurement was carried upward and assigned to any preceding PM_{2.5} measurements at the beginning of the session.

Of the initial 595 GPX tracker sessions, 439 were linked to validated MicroPEM data¹⁵. We restricted to sessions in which the start time of both devices were within 2 hours (to account for set-up time) and with a total logging time of 12 or more hours after linkage (n=283). An additional 24 sessions were excluded after visual inspection of GPS trajectories revealed locations to be outside of study communities, often explained by the return of the devices to the research center in Kintampo after failed deployment, or study participants who were temporarily residing away from their home. Our final dataset included 259 sessions among 145 mothers and 114 children of GPS-tracked, one-minute PM_{2.5} measurements for a total of approximately 695k minutes.

Household boundaries

We estimated participants' home coordinates using GPS data during the nighttime (21 to 4 the next day), assuming participants would be home during this time. We evaluated GPS coordinates after linkage to continuous one-minute PM_{2.5} data; therefore, infrequent coordinates, likely recorded when the wearer removed the GPS tracker at home before bed, served to approximate participants' location for most of the night. We categorized nighttime coordinates into clusters with a 5m radius, and found similar results with a 10m radius²⁸. The centroid of the densest cluster was used to estimate the participant's home longitude and latitude. Among those who had available survey data that included field-logged GPS coordinates for participants' homes, the median distance between estimated and field-logged home coordinates was 23 meters (IQR=14–139m).

Our next step was to define a boundary around the home coordinates to account for imprecision in coordinates (e.g., satellite interference from the walls of a home) as well as activities of daily life, such as cooking, which typically occur outside but in the vicinity of the home structure¹⁵. First, we computed the average distance between unique coordinates recorded at nighttime and the estimated home centroid of each participant. The IQR of average distances ranged from 16 to 24 meters. Second, we evaluated patterns of average PM_{2.5} exposure when moving away from the home during cooking hours (Figure S1). When the household boundary was smallest (25–30m), the distribution of community exposures was higher compared to larger household buffer sizes (40–100m). This suggested that when the buffer size around the home was too small, household cooking exposures were misclassified as community exposures. Such patterns of potential misclassification diminished at buffer sizes >40m. Informed by this distribution, we defined household boundaries using a 50m radius around the home. As depicted in Figure 1, exposures occurring within a 50m buffer around the home are classified as 'household exposures'.

Community boundaries

Administrative boundaries for communities in the Bono East Region of Ghana are not publicly available (and appear not to exist in any form). Therefore, we developed a geospatial dataset of community boundaries that encompass participants' homes. We used

the “Open Buildings” public dataset of building footprints for the continent of Africa that was developed by the Google AI team in Ghana and released in August 2021^{29, 30}. Briefly, the dataset was created using a machine learning method, U-net, that classified 50-centimeter pixels of satellite imagery as ‘building’ or ‘non-building’ along with a confidence level for the classification decision. The dataset includes spatial polygons that outline the footprints of each building, as well as the building centroid and the corresponding confidence level.

We developed community boundaries using buildings that had a confidence level of 70% or greater, which represented about 77% of buildings in our study region. This decision aimed to minimize false positives (such as mistaking other geographic features for buildings) and was guided by both the developers’ recommendations³⁰ and our observations when overlaying polygons onto Google Maps satellite imagery. Communities were distinguished as groups of buildings belonging to the same cluster, identified with the spatial algorithm, DBSCAN (Density-Based Spatial Clustering of Applications with Noise)^{31–33}. The DBSCAN method provides flexibility, permitting the formation of clusters, or ‘communities’ in the context of our study, of various shapes and sizes. It also does not require prior knowledge about the number of communities in the dataset, and can disregard sparse buildings seemingly not belonging to any community (e.g., outlying or industrial buildings). The algorithm requires two parameters: epsilon (the maximum distance between a given building and its neighbors within the same community) and the minimum number of neighboring buildings required to constitute a community. Reasonable epsilon values were determined using *k*-nearest neighbor graphs (*k*-NNG), which order the smallest distance between each building in our dataset and a specified number of neighboring buildings (*k*). Epsilon values were identified at the ‘elbow’ of the *k*-NNG, where distances beyond the ‘elbow’ suggest buildings are too far apart to reasonably belong to the same community (Figure S2). These values were inputted into the clustering algorithm and further refined based on visual assessment of resulting clusters. Once community clusters were created, spatial polygons were drawn around each cluster to form community boundaries (Figure S3), allowing for concavity³⁴ and including a 50m buffer³⁵. Otherwise, boundaries would intersect the centroid of bordering buildings within the cluster. Participants were assigned to the community whose boundaries encompassed their home location. Exposures that occurred within each participant’s community but outside their household boundaries were classified as ‘community exposures’ (Figure 1). An anonymized R workflow is accessible in the GitHub repository: <https://github.com/dmedgyesi/GeospatialGhana>.

Surrounding building density

The Open Buildings dataset was also used to estimate the building density surrounding each GPS coordinate. We chose to estimate building density within a 500m buffer of each location, a distance that has been previously used to obtain land use attributes around air monitoring sites and demonstrated to be predictive of air pollutant levels^{36–38}.

The following two variables were created for each location: 1) the number of buildings within the buffer and 2) the building density, which was calculated as the sum of the area of all buildings within the buffer (m²) divided by the total area of the buffer (196,350 m²). Two

variations of these variables were created: 1) including buildings with a confidence level of at least 70% and 2) further restricting to buildings with at least 80% confidence. The number of buildings and building density at both confidence levels were correlated (Spearman's $\rho=0.97-0.98$). Variables were categorized into tertiles and quartiles to evaluate exposure in areas with low- to high- building density.

Proximity to roadways

We obtained road data for our study region from OpenStreetMap (OSM), an open-source database of geographic features worldwide³⁹. Despite the potential for crowd-sourced data like OSM to have less complete information in rural and developing regions^{40, 41}, our linkage found a diverse range of road types in our study communities ($n=35$). Trunk roads were present in 46% of communities, secondary roads in 26%, tertiary roads in 11%, unclassified roads in 80%, residential roads in 43%, service roads in 14%, track roads in 26%, and footway roads in 6% (Table S1). As detailed in Table S1, it should be noted that 'unclassified' refers to minor roads classified lower than tertiary, not roads of unknown type.

We assessed proximity to roadways within a 100m radius of each GPS coordinate, a buffer size relevant to first-order decay of air pollutants from major roadways⁷, and shown to be associated with risk of several health outcomes (e.g., premature mortality, asthma) for those living near roadways at this distance^{9, 42}. For each road type, we computed the segment length (meters) within a 100m radius of each location. The effect of nearby roadways on $PM_{2.5}$ exposure was first assessed using a binary variable indicating whether any piece of road was within 100m. We created additional variables that further categorized locations near roadways as below or at or above the median segment length.

Statistical analyses

We described the distribution of logging time for mothers and children, as well as the percentage of total logging time by location (household vicinity, community boundaries or elsewhere) and wearing compliance during daylight hours (after 4 GMT and before 21 GMT). Wearing compliance was estimated using data from an embedded accelerometer in the MicroPEM device that indicates whether the device was worn at a given time (yes/no).

The distribution of average $PM_{2.5}$ exposure per participant is reported overall and by participant type and whether the session occurred during the Harmattan season (December-March), a dry period with high winds that increase dust levels¹⁵. We also evaluated the distribution of $PM_{2.5}$ exposure per participant averaged across categories of the following variables: time of day (morning cook hours: 5–9 GMT, evening cook hours: 16–20 GMT, nighttime: 21–4 GMT the next day, and other daytime hours), location, surrounding building density, nearby roadways and wearing compliance. Time of day and location were combined to evaluate exposure by location-time environment (e.g., community during cooking hours).

Our data follows a hierarchical structure, consisting of multiple non-independent $PM_{2.5}$ measurements for each participant, many of whom reside in the same community. To account for such dependencies, we employed linear mixed effects models that incorporated nested random effects: community and participant ID. We estimated the change in log-transformed $PM_{2.5}$ exposures by our fixed variables of interest including time of day,

location, surrounding building density and nearby roadways. Models were adjusted for additional fixed variables including whether the session occurred in the Harmattan season, participant type and wearing compliance. Estimates are expressed as a factor, calculated as the exponent of the beta coefficient [e^{β}], along with corresponding 95% confidence intervals (95% CI). Additionally, we computed the conditional R^2 for each model, which reflects the variance explained by both fixed and random effects.

Our primary models were designed to answer the three main research questions: 1) *Does exposure differ by location and time of day?*, 2) *Does exposure in the household and community vary by time of day?*, and 3) *Is exposure also influenced by surrounding building density and nearby roadways?* (Figure S4). Our first model estimated the change in exposure by time of day and location, included as separate variables. Our second model then combined these variables to evaluate exposure by location-time environment (e.g., in community during cooking periods). Building density was added to the third model, adjusting for location-time environment. Finally, all binary variables of nearby road types were added to the fourth model, adjusting for both location-time environment and building density. For road types that were associated with $PM_{2.5}$ exposure, we further explored effects when split at the median segment length. In secondary analyses, we jointly modeled location-time environment and quartiles of building density, hypothesizing that the effect of building density may be greater during cooking hours. Given the strong influence of the Harmattan season on ambient dust levels, we also conducted stratified analyses, separately modeling sessions occurring in the non-Harmattan ($n=193$) and Harmattan season ($n=66$).

We evaluated our models for residual temporal autocorrelation using ACF plots and Durbin Watson Tests (DWT). To reduce temporal autocorrelation in our models due to high correlation between one-minute $PM_{2.5}$ measurements (model series a), we also present results for 30-minute averaged data (model series b). In this approach, measurements were discarded if participants were observed in more than one location during a 30-minute window. While this resulted in data being lost for short-trips into the community, this approach has the advantage of removing brief observations on the household-boundary, likely reducing location misclassification. In addition to aggregating data to 30-minutes, we integrated a first-order autocorrelation structure within participant (model series c), which fully accounted for the dependence of lagged $PM_{2.5}$ measurements (based on non-significant DWT). We evaluated for spatial autocorrelation using Moran's I test. Before modeling, there was evidence of dependence in $PM_{2.5}$ measurements at a small distance of approximately 200 meters (Moran's $I=0.20$, $p\text{-value}<0.001$). We found limited evidence of spatial dependence in model series a-b residuals (Moran's $I=0.02\text{--}0.03$) and no significant evidence of dependence in model series c residuals (Moran's $I=0.002$), suggesting location and geographic covariates in our models accounted for spatial dependence.

RESULTS

Total logging time was similar for children and mother participants (median=48 hours); Table 1. The majority of participant logging time was spent within household boundaries (IQR=73–96% of total logging time). Most of the remaining time spent outside the household was within the community boundaries (IQR=2–13%). Time spent outside

household and community boundaries varied by participant, where 25% of participants never left the community during the exposure monitoring period and another 25% of participants spent >10% of their time elsewhere. On average, children spent 4% more of their logging time in the community compared to mothers. Mothers spent about 6% more time outside both household and community boundaries than children, likely farming. On average, devices were worn by participants for 54% of daytime logging hours; distributions of wearing compliance for children and mothers were similar.

Average participant $PM_{2.5}$ exposures ranged from a median of $78\mu\text{g}/\text{m}^3$ and IQR of $49\text{--}114\mu\text{g}/\text{m}^3$ (Table 2). Average participant exposures were greater if conducted during the Harmattan season (median= $105\mu\text{g}/\text{m}^3$) versus the non-Harmattan season (median= $72\mu\text{g}/\text{m}^3$). Exposures during the day were higher when participants were wearing their device (median= $110\mu\text{g}/\text{m}^3$) versus non-wearing periods (median= $58\mu\text{g}/\text{m}^3$). Average exposures by time of day were lowest during the night (median= $31\mu\text{g}/\text{m}^3$) and elevated during morning and evening cooking hours (median= 83 and $123\mu\text{g}/\text{m}^3$, respectively). Patterns of elevated exposures during times of cooking were observed both in the household vicinity and community. In the community, median exposure was about $20\mu\text{g}/\text{m}^3$ higher during evening cook hours relative to non-cooking daytime hours. In the household, the median difference in exposure during morning (5–9 GMT) and evening (16–20 GMT) cook hours was about 10 and $40\mu\text{g}/\text{m}^3$ greater for mothers compared to children (Table S2).

Participant average exposures were generally greater in areas with higher versus lower building density/number of buildings. We observed the greatest differences across quartiles of building density with 80%+ confidence (medians $Q1=57$, $Q2=53$, $Q3=62$ and $Q4=70\mu\text{g}/\text{m}^3$), and therefore we present this variable in our main findings (Table 2) and list other variations of surrounding buildings in supplementary information (Table S3). The distribution of average exposures in areas with the highest (Q4) versus lowest (Q1) building density, stratified by time of day, reveal differences are most pronounced during times of cooking (Figure 2).

We observed a large variation in the distribution of average exposures on/near roadways (Table 2), and no consistent patterns in exposure by roadway density (< or median segment length); Table S3. Only exposures occurring near trunk roadways were consistently greater at the mean ($154\mu\text{g}/\text{m}^3$) and median ($82\mu\text{g}/\text{m}^3$) relative to participant averages (mean= $100\mu\text{g}/\text{m}^3$; median= $78\mu\text{g}/\text{m}^3$). Average exposure near trunk roadways was greater during the nighttime but not during the daytime when other sources of air pollution, such as cookstove emissions, likely dominate (Figure S5).

Results of our linear mixed effect models for one-minute and 30-minute averaged data, with and without first-order autocorrelation structure, are presented in Table 3. Results were similar for one- versus 30-minute data, albeit autoregressive results were attenuated, particularly during cooking hours when $PM_{2.5}$ measurements are elevated and strongly correlated in time. Herein, we present results for 30-minute averaged data (model series b). Our models accounted for about 50% of the total variance in $PM_{2.5}$, with marginal improvements from Model 1 to Model 4 (conditional $R^2=0.50$ to 0.53 , respectively).

Model 1.

Exposures on average were 1.72 (95%CI=1.64–1.81) and 2.74 (95%CI=2.62–2.87) times higher during morning and evening cook hours, respectively, relative to nighttime exposure. Relative to exposure outside the community boundaries, PM_{2.5} exposure was 2.12 (95%CI=1.98–2.28) and 1.60 (95%CI=1.46–1.76) times greater in the household and community, respectively. On average, exposure was over three times higher during the Harmattan season (3.20, 95%CI=2.53–4.05). When the device was worn, exposure on average was 1.36 (95%CI=1.31–1.41) times higher. Exposure among mothers compared to children was lower (0.74, 95%CI=0.61–0.91), controlling for cooking times.

Model 2.

Modeling time and location jointly, we found exposure was greatest during evening cooking hours in respective locations (household: 2.84, 95%CI=2.70–2.98; community: 1.80, 95%CI=1.54–2.10; reference=household, nighttime). Exposure during morning cooking hours was also elevated in the household (1.69, 95%CI=1.61–1.78) and community (1.49, 95%CI=1.28–1.72). Exposure during non-cooking daytime hours was somewhat higher in the household (1.14, 95%CI=1.10–1.19) and lower in the community (0.89, 95%CI=0.82 to 0.97).

Model 3.

Exposures were greater in areas with higher building density, although the second quartile was somewhat lower in reference to the first quartile (Q2=0.90, 95%CI=0.80–1.02; Q3=1.47, 95%CI=1.31–1.65, and Q4=1.60, 95%CI=1.42–1.80); $p_{trend}<0.001$. When modeling location-time environment and quartiles of building density jointly, the effect of building density was strongest during cooking hours in both the household and community (Figure 3). For example, the relative percentage increase from Q1 to Q4 during evening cooking hours was 31% and 65% in the household and community, respectively.

Model 4.

Exposures were significantly higher by a factor of 1.16, 1.68 and 1.27 when near a trunk, tertiary or track road, respectively; exposures were somewhat lower when near a secondary, residential or footway road. We observed further increases in exposure when near a higher density (median segment length) of trunk (1.19, 95%CI=1.08–1.31), tertiary (1.83, 95%CI=1.54–2.19) or track (1.77, 95%CI=1.37–2.28) road.

In our analysis stratified by the Harmattan season, we found the change in PM_{2.5} exposure during cooking times was more pronounced among sessions conducted outside the Harmattan season (Table S4). Likewise, the effect of being proximal to a road was more pronounced during the non-Harmattan versus Harmattan season (trunk=1.10 versus 1.07, tertiary=1.88 versus 1.27, track=1.20 versus 1.14, respectively). However, the effect of building density was stronger during the Harmattan season (Factor_{Q1vsQ4}=2.23, 95%CI=1.80–2.75) versus non-Harmattan season (Factor_{Q1vsQ4}=1.28, 95%CI=1.09–1.49).

DISCUSSION

Our study described patterns of personal exposure to PM_{2.5} among mothers and children living in rural Ghana by location, time of day, as well as geographic features including building density and nearby roadways. We found that PM_{2.5} exposure was elevated in the morning and evening cooking hours. Exposure during cooking times was elevated both within the household and community. We found higher building density was associated with higher exposure, and that the effect was strongest during typical cooking hours. Finally, we report that PM_{2.5} exposure is greater when proximal to roadways.

To our knowledge, this is the first study to describe both spatial and temporal patterns of personal exposure to PM_{2.5} in communities that primarily rely on solid fuels for domestic cooking and energy. We demonstrated that exposures in the community follow patterns observed in the household during typical hours of cooking. Few studies have reported that air pollution levels in the community are influenced by solid fuel use in households⁴⁻⁶. A comparison of ambient PM_{2.5} measurements collected at the center of two rural communities in Nepal found community levels were 37% higher during hours of cooking relative to a background site (i.e., forest region)⁴. In comparison to exposure in the household at nighttime, we report exposures were 49–80% greater (Factor=1.49–1.80) in the community during cooking hours.

We found exposures were greater in areas with higher building density, and that this effect was strongest during typical cooking hours. Further, we found building density influenced both levels within the household vicinity (50m buffer) and the community during hours of cooking. This provides evidence that neighboring home activities not only contribute to outdoor PM_{2.5} levels, but could also influence levels in other households especially in more densely populated communities. This aligns with a study conducted in Bangladesh, which found that when a household used solid fuels for cooking, PM_{2.5} levels increased in both the surrounding outdoor environment, as well as within neighboring households that used cleaner fuels⁶.

We observed exposures were higher at the fourth quartile of building density when including buildings with 80%+ detection confidence (median/average= 70/148 µg/m³) versus 70%+ confidence (median/average= 63/133 µg/m³). Buildings detected with a higher degree of confidence tend to be larger in size, which may imply a greater presence of multi-family compounds in our defined 80%+ confidence range. Multi-family compounds are common in our study region and often feature shared courtyards typically used for simultaneous cooking activities, which may significantly contribute to nearby PM_{2.5} exposure. While definitively distinguishing multi-family homes is challenging due to a lack of detailed building information (e.g., number of rooms), future work to enhance our dataset by describing building contour and size could enable us to differentiate multi-family compounds and further understand their impact on PM_{2.5} exposure in communities.

We found evidence that PM_{2.5} exposure is greater when near a trunk, tertiary or track road. This highlights that traffic-related exposures, in addition to solid fuel use, may be an important contributor to personal exposure in rural settings¹⁰⁻¹⁴. The Techiman-Tamale Rd

(N-10), extending north to south from the city center of Kintampo, is the primary trunk road in our study region and is likely an important source of vehicle exhaust⁴³. Proximity to a trunk road increased PM_{2.5} exposure by a factor of 1.16. Being near a tertiary road had a greater impact on exposure (Factor=1.68). The tertiary roads within our study region are typically smaller, unpaved roads leading to communities and may be an important source of resuspended dust⁴⁴. Likewise, track roads, which are often unpaved and used for agricultural activities, increased exposure by a factor of 1.27. Our findings align with a study in Bogotá, Colombia, which found unpaved roads emitted about five times more PM₁₀ and twice as much PM_{2.5} per kilometer compared to paved roads⁴⁵. However, proximity to other road types (e.g., secondary, residential, unclassified, service and footway) did not increase exposure and may be due to characteristics not captured by our approach, such as traffic volume.

Exposures were more than three times greater during the Harmattan season, underscoring the need to account for seasonality differences. When restricting to sessions in the non-Harmattan season, the impact of cooking periods and proximity to roadways on exposure was more pronounced. Dust during the Harmattan season is an important source of air pollution, and therefore higher background levels may diminish the relative changes due to other sources. On the contrary, the influence of building density on exposure was more marked during the Harmattan season. Although we can only speculate, regions with greater building density may experience higher PM_{2.5} levels during the Harmattan season due to altered pollutant dispersion, lower vegetation or other community-wide burning activities, like trash burning or bush burning.

Our findings have important implications for the design of policies that aim to reduce the burden of disease from household and outdoor air pollution. Our findings underscore the importance of prioritizing community-wide transitions to cleaner fuel use in the household. This includes community-wide initiatives to reduce inequities in access to clean fuels, often driven by education, employment and income¹⁷. Otherwise, even if wealthier households switch to cleaner cookstoves, they and the rest of the community remain at risk of unsafe exposure levels if other households continue to use solid fuels. Our observations of increased exposure near roadways and in areas with high building density highlight the potential benefits of development initiatives such as road surfacing and sustainable urban planning (e.g., incorporation of greenspaces and greenways)^{46–49}. However, the successful implementation of these initiatives depends on an understanding of the local context and residents' needs, effective public education and policy advocacy, and the strengthening of institutional capacities^{47–49}. It should also be noted that the generalizability of our findings may be somewhat limited by the specific characteristics of our study communities. These communities, while rural and small, feature closely spaced households which may not be representative of other rural settings. In addition, household cooking often occurs outside near the house, which may not be representative of other communities that use solid fuels for cooking.

The use of personal measurements provided a more accurate assessment of exposure levels near the breathing zone, but is dependent upon wearer compliance and is subject to exposure measurement and location error. Our study evaluated patterns of personal exposure to

PM_{2.5} at a fine temporal and spatial resolution. Geolocated exposure data at a one-minute resolution allowed us to quantify geographic features within small spatial scales, such as roadways within 100m, a distance that is relevant to the decay of vehicle emissions. However, the fine resolution of our data also introduced spatial and temporal autocorrelation in our models of PM_{2.5} exposure. Spatial dependency, observed at a small distance of 200 meters, was mostly explained by our covariates of interest. We reduced temporal autocorrelation by aggregating data to 30-minutes. A first-order autoregressive model fully resolved temporal autocorrelation, but likely underestimated the change in exposure during cooking hours when lagged PM_{2.5} measurements are strongly correlated.

While we defined the household vicinity based on patterns of PM_{2.5} exposure near the home in an effort to account for outside cooking activities, the size of each household's vicinity is likely to vary and could result in misclassification when evaluating household versus community exposures. We quantified roadway and building density using buffer sizes around each GPS location based on previous literature^{7, 9, 36–38, 42}, but exploration of various buffer sizes may provide insight into PM_{2.5} dispersion. While not readily available, the integration of meteorological variables, such as precipitation, wind speed and direction, could improve the precision of our effect estimates and overall model performance. Wind speed and direction, in particular, play a significant role in pollutant dispersion, and their integration could provide a more nuanced understanding of the influence of roadways on personal PM_{2.5} exposure. Our models demonstrated moderate explanatory power, ranging from a conditional R² of 0.38 to 0.53, which would likely improve with the addition of meteorological conditions.

In our geospatial analysis of personal PM_{2.5} exposure among mothers and children in rural Ghana, we found that exposure was elevated within the household vicinity and the community during the morning and evening hours when solid fuels are typically used for cooking. Additionally, exposures on average were greater in areas with the highest versus lowest building density, and the effect of building density on PM_{2.5} exposure was pronounced during hours of cooking. We report that roadways also contribute to elevated PM_{2.5} exposure, particularly main and unpaved roads leading to rural communities. Our study provides evidence that, in some settings at least, policies intended to promote cleaner fuel use will be most effective at reducing household and ambient air pollution if implemented at the community-level. Future work should consider the role of solid fuel use in the household on air pollution levels in the community, and investigate other community-wide burning activities, such as trash burning and bush burning during the dry season.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

ACKNOWLEDGEMENTS:

The authors are grateful to the mothers and their children who participated in the study. The authors would also like to thank the community leaders in the study area for their support.

FUNDING:

This work was supported by the National Institute of Environmental Health Sciences (NIEHS) Grants R01 ES026991, P30 ES009089, R01 ES019547, R21 HD094229, R01 ES024489, R01 ES034433, K23 HL1353449, and T32 ES007322.

DATA AVAILABILITY STATEMENT:

The datasets generated during and/or analyzed during the current study are not publicly available because this analysis included geolocated information considered to be personally identifiable information (PII). However, the authors have created a GitHub repository demonstrating the development of community boundaries as well as estimating surrounding building density and nearby roadways using a simulated GPS trajectory [<https://github.com/dmedgyesi/GeospatialGhana>]

REFERENCES

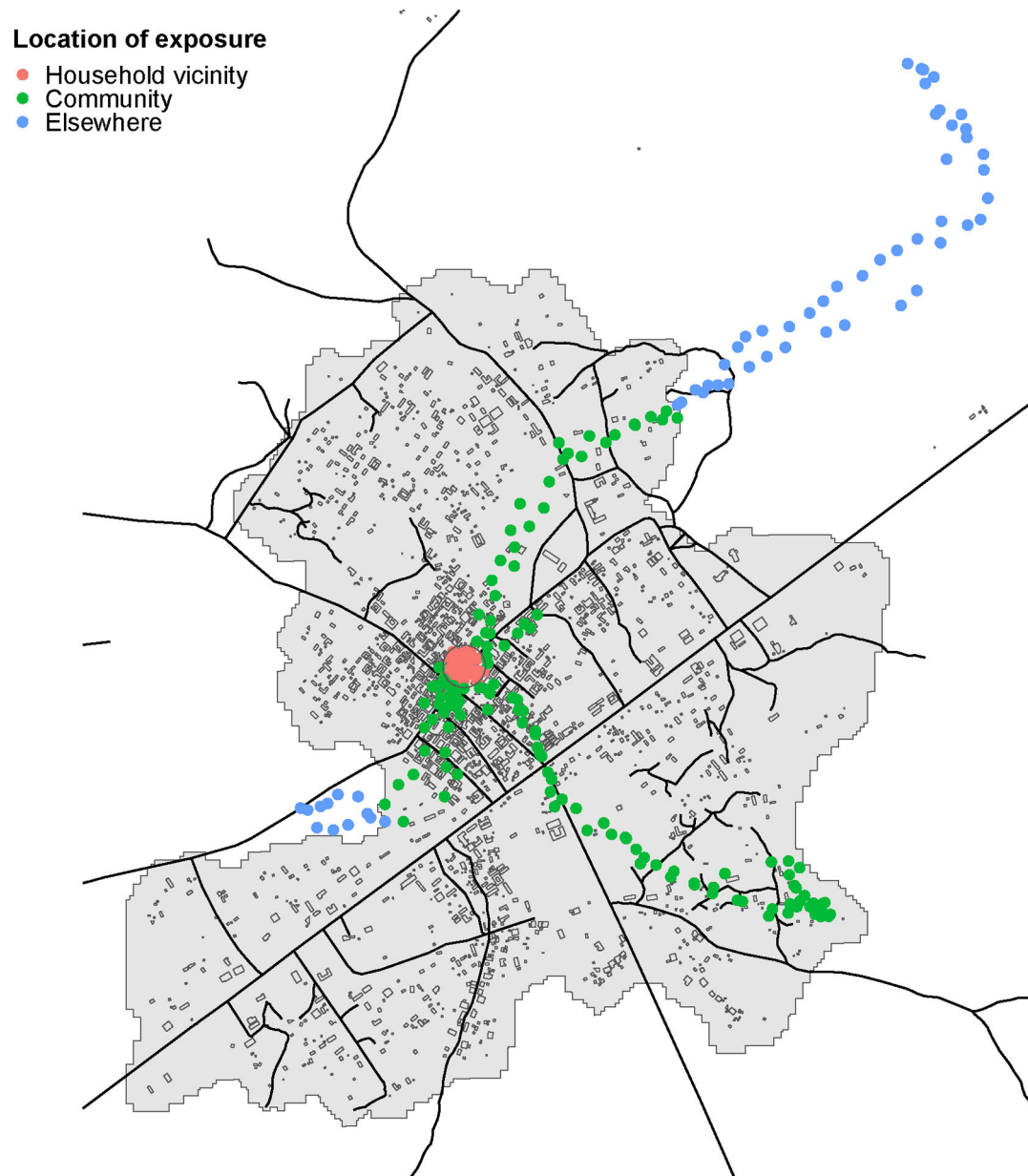
1. Bennett F, Wozniak S, Causey K, Burkart K, Brauer M Estimating disease burden attributable to household air pollution: new methods within the Global Burden of Disease Study. *The Lancet Global Health* 2021; 9.
2. Cohen AJ, Brauer M, Burnett R, Anderson HR, Frostad J, Estep K et al. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. *The Lancet* 2017; 389: 1907–1918.
3. HEI Household Air Pollution–Ghana Working Group. Contribution of Household Air Pollution to Ambient Air Pollution in Ghana. Health Effects Institute 2019; Communication 19.
4. Adhikari S, Mahapatra PS, Pokheral CP, Puppala SP Cookstove Smoke Impact on Ambient Air Quality and Probable Consequences for Human Health in Rural Locations of Southern Nepal. *Int J Environ Res Public Health* 2020; 17. [PubMed: 33375123]
5. Downward GS, Hu W, Rothman N, Reiss B, Wu G, Wei F et al. Outdoor, indoor, and personal black carbon exposure from cookstoves burning solid fuels. *Indoor Air* 2016; 26: 784–795. [PubMed: 26452237]
6. Weaver AM, Gurley ES, Crabtree-Ide C, Salje H, Yoo EH, Mu L et al. Air pollution dispersion from biomass stoves to neighboring homes in Mirpur, Dhaka, Bangladesh. *BMC Public Health* 2019; 19: 425. [PubMed: 31014315]
7. Clougherty JE, Wright RJ, Baxter LK, Levy JI Land use regression modeling of intra-urban residential variability in multiple traffic-related air pollutants. *Environmental Health* 2008; 7: 17. [PubMed: 18485201]
8. Fuks KB, Weinmayr G, Basagaña X, Gruziova O, Hampel R, Oftedal B et al. Long-term exposure to ambient air pollution and traffic noise and incident hypertension in seven cohorts of the European study of cohorts for air pollution effects (ESCAPE). *Eur Heart J* 2017; 38: 983–990. [PubMed: 28417138]
9. Requia WJ, Koutrakis P Mapping distance-decay of premature mortality attributable to PM2.5-related traffic congestion. *Environmental Pollution* 2018; 243: 9–16. [PubMed: 30170207]
10. Baumgartner J, Zhang Y, Schauer JJ, Huang W, Wang Y, Ezzati M Highway proximity and black carbon from cookstoves as a risk factor for higher blood pressure in rural China. *Proceedings of the National Academy of Sciences* 2014; 111: 13229–13234.
11. Ni K, Carter E, Schauer JJ, Ezzati M, Zhang Y, Niu H et al. Seasonal variation in outdoor, indoor, and personal air pollution exposures of women using wood stoves in the Tibetan Plateau: Baseline assessment for an energy intervention study. *Environment International* 2016; 94: 449–457. [PubMed: 27316628]
12. Carter E, Archer-Nicholls S, Ni K, Lai AM, Niu H, Secrest MH et al. Seasonal and Diurnal Air Pollution from Residential Cooking and Space Heating in the Eastern Tibetan Plateau. *Environmental Science & Technology* 2016; 50: 8353–8361. [PubMed: 27351357]

13. Van Vliet ED, Asante K, Jack DW, Kinney PL, Whyatt RM, Chillrud SN et al. Personal exposures to fine particulate matter and black carbon in households cooking with biomass fuels in rural Ghana. *Environ Res* 2013; 127: 40–48. [PubMed: 24176411]
14. Lai AM, Clark S, Carter E, Shan M, Ni K, Yang X et al. Impacts of stove/fuel use and outdoor air pollution on chemical composition of household particulate matter. *Indoor Air* 2020; 30: 294–305. [PubMed: 31880849]
15. Chillrud SN, Ae-Ngibise KA, Gould CF, Owusu-Agyei S, Mujtaba M, Manu G et al. The effect of clean cooking interventions on mother and child personal exposure to air pollution: results from the Ghana Randomized Air Pollution and Health Study (GRAPHS). *Journal of Exposure Science & Environmental Epidemiology* 2021; 31: 683–698. [PubMed: 33654272]
16. Jack DW, Ae-Ngibise KA, Gould CF, Boamah-Kaali E, Lee AG, Mujtaba MN et al. A cluster randomised trial of cookstove interventions to improve infant health in Ghana. *BMJ Global Health* 2021; 6: e005599.
17. Bofah RO, Appiah-Konadu P, Ngwu FN Transition to cleaner cooking energy in Ghana. *Clean Energy* 2022; 6: 957–966.
18. Lee AG, Kaali S, Quinn A, Delimini R, Burkart K, Opoku-Mensah J et al. Prenatal Household Air Pollution Is Associated with Impaired Infant Lung Function with Sex-Specific Effects. Evidence from GRAPHS, a Cluster Randomized Cookstove Intervention Trial. *American Journal of Respiratory and Critical Care Medicine* 2018; 199: 738–746.
19. Quinn AK, Ae-Ngibise KA, Jack DW, Boamah EA, Enuameh Y, Mujtaba MN et al. Association of Carbon Monoxide exposure with blood pressure among pregnant women in rural Ghana: Evidence from GRAPHS. *Int J Hyg Environ Health* 2016; 219: 176–183. [PubMed: 26614250]
20. Quinn AK, Ae-Ngibise KA, Kinney PL, Kaali S, Wylie BJ, Boamah E et al. Ambulatory monitoring demonstrates an acute association between cookstove-related carbon monoxide and blood pressure in a Ghanaian cohort. *Environ Health* 2017; 16: 76. [PubMed: 28732501]
21. Boamah-Kaali E, Jack DW, Ae-Ngibise KA, Quinn A, Kaali S, Dubowski K et al. Prenatal and Postnatal Household Air Pollution Exposure and Infant Growth Trajectories: Evidence from a Rural Ghanaian Pregnancy Cohort. *Environmental Health Perspectives*; 129: 117009.
22. Adams C, Riggs P, Volckens J Development of a method for personal, spatiotemporal exposure assessment. *J Environ Monit* 2009; 11: 1331–1339. [PubMed: 20449221]
23. Jack DW, Asante KP, Wylie BJ, Chillrud SN, Whyatt RM, Ae-Ngibise KA et al. Ghana randomized air pollution and health study (GRAPHS): study protocol for a randomized controlled trial. *Trials* 2015; 16: 420. [PubMed: 26395578]
24. Carrión D, Prah R, Gould CF, Agbokey F, Mujtaba M, Pillarisetti A et al. Using longitudinal survey and sensor data to understand the social and ecological determinants of clean fuels use and discontinuance in rural Ghana. *Environ Res Commun* 2020; 2.
25. Daouda M, Mujtaba MN, Yang Q, Seyram K, Lee AG, Tawiah T et al. Prediction of personal exposure to PM_{2.5} in mother-child pairs in rural Ghana. *Journal of Exposure Science & Environmental Epidemiology* 2022; doi 10.1038/s41370-022-00420-1.
26. Kaali S, Jack DW, Prah R, Chillrud SN, Mujtaba MN, Kinney PL et al. Poor early childhood growth is associated with impaired lung function: Evidence from a Ghanaian pregnancy cohort. *Pediatr Pulmonol* 2022; 57: 2136–2146. [PubMed: 35614550]
27. Chakrabarti B, Fine PM, Delfino R, Sioutas C Performance evaluation of the active-flow personal DataRAM PM_{2.5} mass monitor (Thermo Anderson pDR-1200) designed for continuous personal exposure measurements. *Atmospheric Environment* 2004; 38: 3329–3340.
28. Arnold TB. leaderCluster: Leader Clustering Algorithm. In: R package version 1.2., 2014.
29. Sirko W, Kashubin S, Ritter M, Annkah A, Bouchareb YSE, Dauphin Y et al. Continental-scale building detection from high resolution satellite imagery. *arXiv* 2021; <https://arxiv.org/abs/2107.12283>.
30. Open Buildings A dataset of building footprints to support social good applications. Google Research, Ghana 2021; <https://sites.research.google/open-buildings/>.
31. Density-Based Clustering Based on Hierarchical Density Estimates. Berlin, Heidelberg. Springer Berlin Heidelberg, 2013.

32. Ester M, Kriegel H-P, Sander J, Xu X. A density-based algorithm for discovering clusters in large spatial databases with noise. In: Proceedings of the Second International Conference on Knowledge Discovery and Data Mining. Portland, Oregon: AAAI Press, 1996. pp 226–231.
33. Hahsler M, Piekenbrock M, Doran D dbSCAN: Fast Density-Based Clustering with R. *Journal of Statistical Software* 2019; 91: 1 – 30.
34. Gombin J, Vaidyanathan R, Agafonkin V. concaveman: A Very Fast 2D Concave Hull Algorithm. In: R package version 1.1.0., 2020.
35. Pebesma E Simple Features for R: Standardized Support for Spatial Vector Data. *The R Journal* 2018; 10: 439–446.
36. Poplawski K, Gould T, Setton E, Allen R, Su J, Larson T et al. Intercity transferability of land use regression models for estimating ambient concentrations of nitrogen dioxide. *Journal of Exposure Science & Environmental Epidemiology* 2009; 19: 107–117. [PubMed: 18398445]
37. Amini H, Taghavi M, Naddafi K, Nabizadeh R, Yunesian M Correlation of air pollutants with land use and traffic measures in Tehran, Iran: A preliminary statistical analysis for land use regression modeling. *Journal of Advances in Environmental Health Research* 2013; 1: 1–8.
38. Coker ES, Amegah AK, Mwebaze E, Ssematimba J, Bainomugisha EA land use regression model using machine learning and locally developed low cost particulate matter sensors in Uganda. *Environ Res* 2021; 199: 111352. [PubMed: 34043968]
39. Padgham M, Rudis B, Lovelace R, Salmon M osmdata. *Journal of Open Source Software* 2017; 2.
40. Kim-Blanco P, Cîrlugea B-M, de Sherbinin A. Quality assessment of crowd-sourced data: OpenStreetMap roads validation in the developing countries of West Africa. 2018.
41. Herfort B, Lautenbach S, Porto de Albuquerque J, Anderson J, Zipf A The evolution of humanitarian mapping within the OpenStreetMap community. *Scientific Reports* 2021; 11: 3037. [PubMed: 33542423]
42. Baumann LM, Robinson CL, Combe JM, Gomez A, Romero K, Gilman RH et al. Effects of distance from a heavily transited avenue on asthma and atopy in a periurban shantytown in Lima, Peru. *J Allergy Clin Immunol* 2011; 127: 875–882. [PubMed: 21237505]
43. Brugge D, Durant JL, Rioux C Near-highway pollutants in motor vehicle exhaust: A review of epidemiologic evidence of cardiac and pulmonary health risks. *Environmental Health* 2007; 6: 23. [PubMed: 17688699]
44. Samiksha S, Sunder Raman R, Nirmalkar J, Kumar S, Sirvaiya R PM10 and PM2.5 chemical source profiles with optical attenuation and health risk indicators of paved and unpaved road dust in Bhopal, India. *Environmental Pollution* 2017; 222: 477–485. [PubMed: 28089210]
45. Pachón JE, Galvis B, Lombana O, Carmona LG, Fajardo S, Rincón A et al. Development and Evaluation of a Comprehensive Atmospheric Emission Inventory for Air Quality Modeling in the Megacity of Bogotá. *Atmosphere* 2018; 9: 49.
46. Mikou M, Rozenberg J, Koks EE, Fox CJE, Peralta Quiros T Assessing rural accessibility and rural roads investment needs using open source data. *World Bank Policy Research Working Paper* 2019.
47. Takyi E, Mensah H, Aazore FK, Nalumu DJ, Abu JJ Understanding the Urban Planning-Green Space Depletion Nexus: Insights from the Kwabre East Municipality, Ghana. *Urban Forum* 2022; doi 10.1007/s12132-022-09471-x.
48. Diko SK, Hollstein LM Towards an alternative interpretation of the socio-cultural dimensions of urban greenspace planning in the Global South: Evidence from the Kumasi Metropolis of Ghana. *Journal of Urban Affairs* 2023; 45: 522–545.
49. Abass K, Appiah DO, Afriyie K Does green space matter? Public knowledge and attitude towards urban greenery in Ghana. *Urban Forestry & Urban Greening* 2019; 46: 126462.

IMPACT STATEMENT

Household air pollution from cooking with solid fuels in sub-Saharan Africa is a major environmental concern for maternal and child health. Our study advances previous knowledge by quantifying the impact of household cooking activities on air pollution levels in the community, and identifying two geographic features, building density and roadways, that contribute to maternal and child daily exposure. Household cooking contributes to higher air pollution levels in the community especially in areas with greater building density. Findings underscore the need for equitable clean household energy transitions that reach entire communities to reduce health risks from household and outdoor air pollution.



For illustrative purposes only.

Community and geographic features have been modified and selected from a region outside our study.

Figure 1.

Example of a GPS trajectory throughout a session. GPS points are color-coded as being within the vicinity of the household (50m buffer), community boundaries or elsewhere. Outlines of arbitrary shapes represent buildings in the area and lines represent roadways.

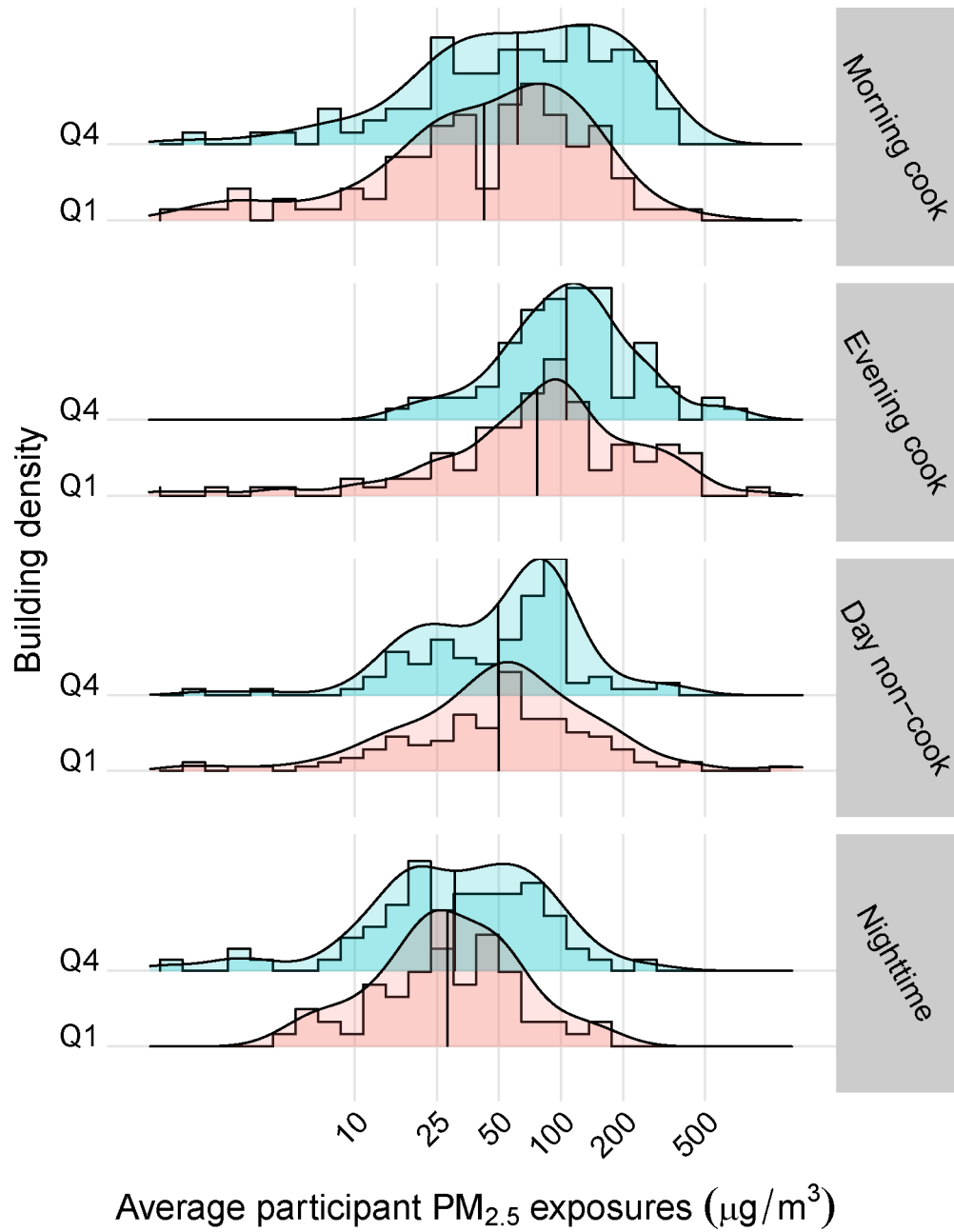


Figure 2. Distribution of average participant PM_{2.5} exposures (µg/m³) for the fourth versus first quartile (Q4 vs. Q1) of surrounding building density (80%+ confidence) by time of day. The intersecting black vertical line in each histogram represents the mean value.

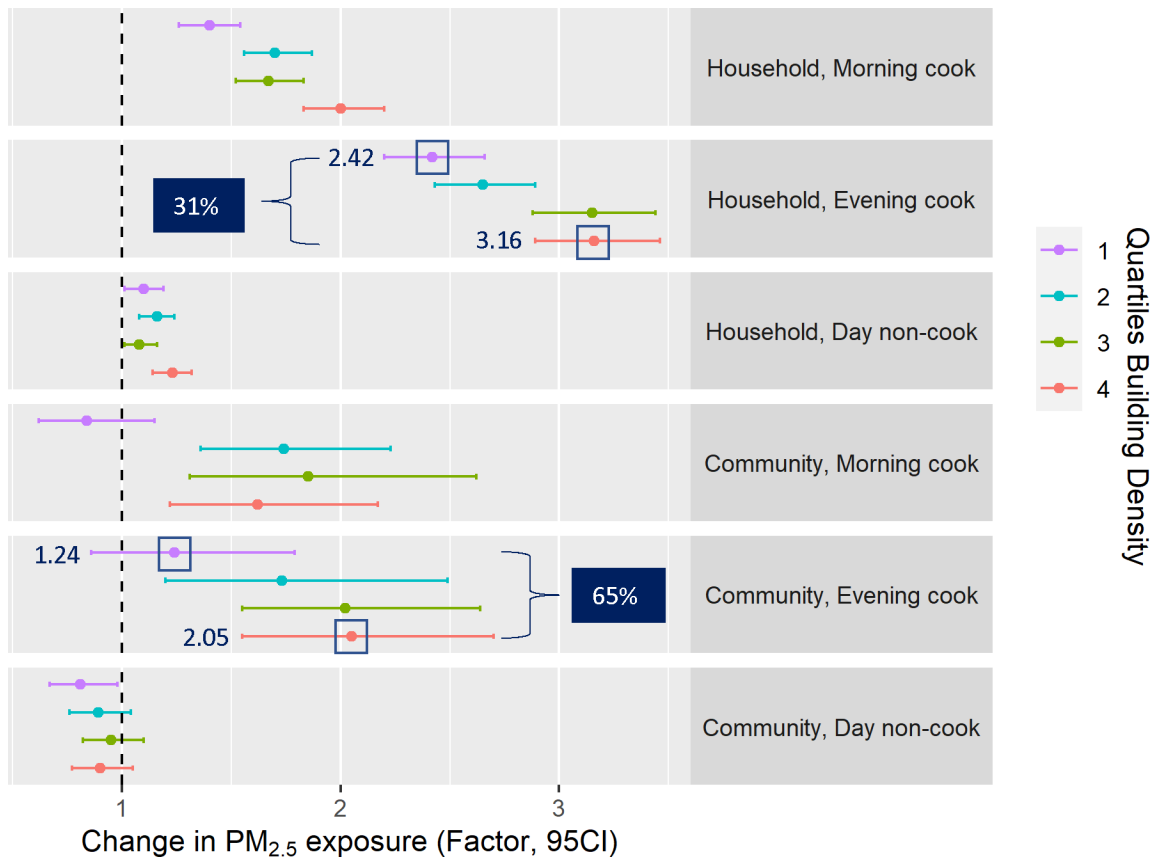


Figure 3.

Factor change in 30-minute average log-transformed $PM_{2.5}$ exposure ($\mu g/m^3$) and 95% confidence intervals for location-time environments modeled jointly with quartiles of surrounding building density. Reference is exposures during nighttime in the household. Model adjusted for nested random effects community and participant ID and fixed effects Harmattan season, participant type (child or mother) and wearing compliance. Dark blue box shows the relative percentage increase from Q1 to Q4.

Distribution of total logging time (hours) for sessions with geolocated one-minute PM_{2.5} measurements, and the percentage of total logging time (%) by location and wearing compliance for children and mother participants in the Child Lung Function Study

Table 1.

	N sessions	Mean	Median	Perc. 25 th	Perc. 75 th
Total logging time (hours)					
All participants	259	45	48	46	49
<i>Children participants</i>	114	43	48	40	49
<i>Mother participants</i>	145	46	48	47	49
Percentage of total logging time by location (%)					
All participants					
Household vicinity	259	84	87	73	96
Community boundaries	259	10	6	2	13
Outside both boundaries (elsewhere)	259	7	1	0	11
<i>Children participants</i>					
Household vicinity	114	85	89	75	96
Community boundaries	114	12	7	3	17
Outside both boundaries (elsewhere)	114	3	0	0	2
<i>Mother participants</i>					
Household vicinity	145	83	83	72	96
Community boundaries	145	8	5	2	12
Outside both boundaries (elsewhere)	145	9	3	0	17
Percentage wearing compliance (%)[†]					
All participants	254	54	56	38	71
<i>Children participants</i>	109	54	58	40	71
<i>Mother participants</i>	145	53	54	37	71

[†] Accelerometer data from the MicroPEM device was not available for 5 participants. During daytime hours after 4 GMT to before 21 GMT

Distribution of personal exposures to PM_{2.5} (µg/m³) among children and mothers in the Child Lung Function Study. For each participant, exposure was averaged for the duration of their session and reported overall, by participant type (child or mother) and by Harmattan season (December-March). Participant exposures were also averaged across categories of wearing compliance, time of day, location, surrounding building density and nearby roadways.

Table 2.

		PM _{2.5} exposure (µg/m ³)				
		N participants	Mean	Median	Perc. 25 th	Perc. 75 th
PARTICIPANT EXPOSURES AVERAGED FOR DURATION OF SESSION						
Overall		259	100	78	49	114
Children		114	102	77	47	95
Mothers		145	99	81	54	119
Harmattan season						
No		193	94	72	43	95
Yes		66	117	105	84	137
PARTICIPANT EXPOSURES AVERAGED ACROSS CATEGORIES						
Wearing compliance /						
No		254	85	58	32	94
Yes		254	146	110	71	170
Time of day						
Nighttime (21-4 GMT next day)		259	46	31	18	59
Morning cook hrs (5-9 GMT)		258	125	83	41	155
Evening cook hrs (16-20 GMT)		259	198	123	82	202
Other (non-cooking) daytime hours		259	86	64	40	98
Participant location						
Household vicinity		259	98	78	48	113
Community boundaries		254	128	66	34	112
Outside both boundaries (elsewhere)		147	61	39	18	81
Location-time environment						

	PM _{2.5} exposure (µg/m ³)				
	N participants	Mean	Median	Perc. 25 th	Perc. 75 th
Household, morning cook hrs	257	113	81	41	156
Household, evening cook hrs	258	208	132	89	203
Household, other daytime hrs	259	88	61	36	102
Household, nighttime	259	46	32	18	59
Community, morning cook hrs	217	147	48	25	137
Community, evening cook hrs	196	170	70	38	128
Community, other daytime hrs	231	97	51	25	93
Another place/time	168	56	36	16	76
Surrounding building density (500m)					
<i>Quartiles</i>					
Q1[0.000,0.011)	157	85	57	30	95
Q2[0.011,0.018)	160	87	53	19	117
Q3[0.018,0.032)	162	104	62	31	102
Q4[0.032,0.155]	109	148	70	31	106
Proximal to roadways (100m)					
Any segment length nearby, by road type					
Trunk	149	154	82	38	134
Primary	2	54	54	50	59
Secondary	82	123	68	29	125
Tertiary	50	136	45	26	94
Unclassified	155	166	57	30	91
Residential	111	86	71	35	105
Service	34	67	25	8	73
Track	38	130	67	18	133
Footway	15	45	32	5	64

¹ Accelerometer data from the MicroPEM device was not available for 5 participants. During daytime hours after 4 to before 21

Table 3.

Factor change and 95% confidence interval (95%CI) in log-transformed PM_{2.5} exposure (µg/m³) by time, location, surrounding building density and nearby roadways among children and mothers in the Child Lung Function Study¹. Estimated with linear mixed effects models with nested random effects: community and participant ID. Results for model series a) one-minute data, b) 30-minute averaged data and c) 30-minute averaged data with first-order autocorrelation structure within participant.

	a) One-minute Factor (95CI) ²	b) 30-minute Factor % (95CI)	c) 30-minute autoregressive Factor % (95CI)
MODEL 1: Time of day and location			
Time of day			
Nighttime (21–4 next day)	REF	REF	REF
Morning cook hours (5–9)	1.62 (1.6, 1.64)	1.72 (1.64, 1.81)	1.44 (1.36, 1.54)
Evening cook hours (16–20)	2.50 (2.47, 2.52)	2.74 (2.62, 2.87)	1.63 (1.54, 1.74)
Other daytime hours	1.12 (1.11, 1.13)	1.16 (1.12, 1.21)	1.18 (1.13, 1.23)
Participant location			
Outside both boundaries (elsewhere)	REF	REF	REF
Household vicinity	2.15 (2.12, 2.18)	2.12 (1.98, 2.28)	2.17 (1.99, 2.37)
Community boundaries	1.65 (1.62, 1.68)	1.60 (1.46, 1.76)	1.70 (1.54, 1.89)
Harmattan season			
No	REF	REF	REF
Yes	3.17 (2.47, 4.08)	3.20 (2.53, 4.05)	3.07 (2.44, 3.85)
Participant type			
Child	REF	REF	REF
Mother	0.68 (0.55, 0.84)	0.74 (0.61, 0.91)	0.77 (0.64, 0.94)
Wearing compliance			
No	REF	REF	REF
Yes	1.37 (1.36, 1.39)	1.36 (1.31, 1.41)	1.23 (1.19, 1.27)
Conditional R²	0.413	0.498	0.384
MODEL 2: Location-time environment ³			
Household, nighttime	REF	REF	REF
Household, morning cook hrs	1.58 (1.56, 1.6)	1.69 (1.61, 1.78)	1.44 (1.35, 1.53)
Household, evening cook hrs	2.61 (2.58, 2.63)	2.84 (2.70, 2.98)	1.71 (1.61, 1.82)
Household, other daytime hours	1.10 (1.09, 1.11)	1.14 (1.10, 1.19)	1.18 (1.13, 1.23)
Community, morning cook hrs	1.41 (1.37, 1.44)	1.49 (1.28, 1.72)	1.14 (1.00, 1.3)
Community, evening cook hrs	1.81 (1.76, 1.85)	1.80 (1.54, 2.10)	1.37 (1.20, 1.56)
Community, other daytime hours	0.85 (0.84, 0.87)	0.89 (0.82, 0.97)	0.91 (0.83, 1.00)
Another place/time	0.61 (0.60, 0.62)	0.62 (0.58, 0.67)	0.63 (0.57, 0.69)
Conditional R²	0.414	0.499	0.385

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript

		a) One-minute Factor (95CI) ²	b) 30-minute Factor % (95CI)	c) 30-minute autoregressive Factor % (95CI)
MODEL 3: Surrounding building density^{3,4}				
Quartiles building density (500m)				
	Q1[0.000,0.011)	REF	REF	REF
	Q2[0.011,0.018)	0.89 (0.86, 0.91)	0.90 (0.80, 1.02)	0.96 (0.84, 1.08)
	Q3[0.018,0.032)	1.42 (1.39, 1.46)	1.47 (1.31, 1.65)	1.28 (1.13, 1.45)
	Q4[0.032,0.155]	1.57 (1.53, 1.61)	1.60 (1.42, 1.80)	1.36 (1.19, 1.55)
	Conditional R²	0.426	0.518	0.396
MODEL 4: Proximal to roadways^{3,4,5}				
On or nearby (100m) road type?				
Trunk	No	REF	REF	REF
	Yes	1.13 (1.11, 1.14)	1.16 (1.07, 1.25)	1.23 (1.15, 1.32)
Secondary	No	REF	REF	REF
	Yes	0.93 (0.91, 0.95)	0.90 (0.81, 1.00)	1.00 (0.91, 1.11)
Tertiary	No	REF	REF	REF
	Yes	1.6 (1.55, 1.66)	1.68 (1.45, 1.95)	1.31 (1.13, 1.51)
Unclassified	No	REF	REF	REF
	Yes	0.97 (0.95, 0.99)	0.97 (0.89, 1.06)	1.02 (0.94, 1.10)
Residential	No	REF	REF	REF
	Yes	0.83 (0.81, 0.84)	0.77 (0.70, 0.85)	0.93 (0.84, 1.02)
Service	No	REF	REF	REF
	Yes	0.69 (0.65, 0.73)	1.15 (0.87, 1.52)	1.12 (0.91, 1.38)
Track	No	REF	REF	REF
	Yes	1.10 (1.05, 1.15)	1.27 (1.06, 1.53)	1.18 (1.01, 1.39)
Footway	No	REF	REF	REF
	Yes	1.28 (0.9, 1.82)	0.54 (0.27, 1.08)	0.96 (0.65, 1.41)
	Conditional R²	0.435	0.531	0.400
Model 4.1: Roadway density (100m)^{3,4,5}				
Trunk	Zero	REF	REF	REF
	<median (1, 164m)	1.07 (1.05, 1.09)	1.12 (1.03, 1.22)	1.21 (1.13, 1.31)
	median (165, 403m)	1.18 (1.16, 1.21)	1.19 (1.08, 1.31)	1.28 (1.17, 1.41)
Tertiary	Zero	REF	REF	REF
	<median (3, 168m)	1.44 (1.38, 1.50)	1.34 (1.13, 1.59)	1.21 (1.05, 1.40)
	median (169, 263m)	1.64 (1.58, 1.71)	1.83 (1.54, 2.19)	1.62 (1.33, 1.98)
Track	Zero	REF	REF	REF
	<median (0.3, 104m)	1.05 (1.00, 1.11)	1.08 (0.87, 1.34)	1.18 (0.99, 1.39)
	median (105, 344m)	1.25 (1.17, 1.33)	1.77 (1.37, 2.28)	1.31 (1.02, 1.69)
	Conditional R²	0.430	0.523	0.404

¹Includes 259 participant sessions with geo-located PM_{2.5} measurements

²Computed as the exponent of the beta coefficient [e^{β}]

³Adjusted for Harmattan season, participant type, and wearing compliance

⁴Additionally adjusted for location-time environment

⁵Additionally adjusted for building density

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript