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Repeated assessment of $PM_{2.5}$ in Guatemalan kitchens cooking with wood: Implications for measurement strategies

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HIGHLIGHTS

- Single 24-h PM2.5 measurements do not predict longer-term averages well.
- > 48 h sampling duration substantially reduced measurement variation.
- Repeated short-term measurements led to better prediction of long-term mean.

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ABSTRACT

Household air pollution resulting from solid fuel combustion is a leading cause of global morbidity and mortality. Strategies to measure area concentrations of and exposures to $PM_{2.5}$ in rural homes focus primarily on short-term measurements, often of 24 or 48 h. Little is known about how well these short-term measurements, commonly used exposure metrics in health risk assessment of the impacts of household air pollution exposure, predict longer-term averages. In San Lorenzo District, Guatemala, we deployed the relatively low-cost University of California, Berkeley (UCB) Particle and Temperature Sensor (PATS) for 120–333 days in the kitchens of 8 homes using biomass fuels. We evaluated how well short-term measurements predicted the household-level, entire-sample average. A single 24-h measurement had between a 32% and 39% chance of being within ±25% of the household-level mean of all measurements. The Root Mean Square Error (RMSE) of a single 24-h measurement was on average 4.5 times higher than that of the mean of measurements taken once per study week. Alternate strategies – including sampling once per study week or once per study month – with this class of lower-cost sensors yield estimates which have a higher probability of being closer to the overall average value and have smaller errors relative to the overall mean. Evaluation of how well short-term measures predict longer-term averages of household air pollution at prospective study sites allows optimization of field resources to better estimate indoor concentrations and personal exposures.

1. Introduction

Nearly half of the world's population (about 3.8 billion people) are exposed to household air pollution (HAP) from burning solid fuels – including wood, dung, grass, coal, and crop residues – for cooking, heating, and other household energy needs (Health Effects Institute, 2020). The Global Burden of Disease (GBD) estimated that, in 2019, HAP resulting from the combustion of solid fuels for cooking was responsible for 2.31 million premature deaths, accounting for ~3.6% (91.5 million) of global disability-adjusted life years (DALYs) (Health Effects Institute, 2020; Murray et al., 2020). Most evidence of these health effects is from studies using either measured or modeled surrogates of individuals' typical or longer-term (months to years) exposures, often based on survey-assessed fuel type or measured kitchen particulate concentrations.

Measures of particulate matter with an aerodynamic diameter of less than 2.5 μm ($PM_{2.5}$) are central to cookstove intervention program evaluations (Balakrishnan et al., 2004; Balakrishnan and Smith, 2013;

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Chengappa et al., 2007; Dutta et al., 2007; Masera et al., 2007; Smith et al., 2007; Chen et al., 2016; Pilishvili et al., 2016) and global health assessments (Apte and Salvi, 2016; Lee et al., 2020) related to solid fuel use. Many of these studies use sampling durations of either 24 h (Balakrishnan et al., 2004; Baumgartner et al., 2011; Chowdhury et al., 2012; Sambandam et al., 2015; Sidhu et al., 2017; Ye et al., 2020) or 48 h (Alnes et al., 2014; Chengappa et al., 2007; Dutta et al., 2007; Masera et al., 2007), sometimes repeated seasonally (Baumgartner et al., 2011, 2018; Li et al., 2019), which we refer to here as short-term measures. Little work has characterized how well these short-term measures predict longer-term concentrations or exposures. Use of short-term measurements introduces classical measurement error in exposure, which attenuates estimates of the true exposure-response relationship. Lengthening the duration and/or frequency of measurements is a potential solution to this problem, but brings additional equipment and personnel costs, increases field-worker burden, and lengthens study procedures in homes, impacting participants.

As an ancillary study of the RESPIRE (Randomized Exposure Study of Pollution Indoors and Respiratory Effects) randomized control trial (Smith et al., 2010, 2011), which evaluated the impact of reduced exposure to wood smoke on childhood acute lower respiratory infections, we opportunistically placed particle monitors in homes with and without intervention chimney stoves (Fig. 1) and monitored daily $PM_{2.5}$ concentrations for, on average, 200 days per home. The current study seeks to 1) determine how accurately a single 24- or 48-h measurement predicts household-level study duration average concentrations; and 2) quantify gains in precision from alternate sampling strategies – including increased measurement duration over consecutive days and repeated 24- and 48-h sampling over time.

2. Materials and methods

Study location and population. Measurements were made between February 2004 and March 2005 in 8 households located in the western highlands of Guatemala (altitude 2200–3300 m). The region has a temperate and consistent climate (Supporting Information, Fig. S1) with three seasons: dry and cold (November through February), dry and warm (mid-February through April), and rainy and warm (May through October). The selected households in this ancillary study were a convenience sample of RESPIRE control and intervention homes, chosen in part based on location and proximity to study headquarters. Control homes cooked with a traditional open fire (n = 4); intervention homes had a chimney stove known locally as the Plancha (n = 4). All participants had relatively similar household characteristics and used wood as their primary cooking fuel. Key exposure-related characteristics of these households at baseline are summarized. RESPIRE project details – including human subjects approvals, consent, survey details, recruitment procedures, and information about the intervention, were reported previously (Smith et al., 2011).

$PM_{2.5}$ Measurements. Continuous PM measurements were made using the University of California, Berkeley Particle and Temperature Sensor (UCB-PATS, Berkeley Air Monitoring Group, USA) following standard protocols (Chowdhury et al., 2007; Smith et al., 2007). The UCB-PATS is a data-logging, battery-powered optical particle monitor created using custom microelectronics coupled with commercial smoke alarm sensing technology. Previous field validation tests have shown that UCB-PATS relates well to gravimetric $PM_{2.5}$ estimates in laboratory settings and in rural biomass-using households (Chowdhury et al., 2007); the monitor has been widely deployed for household air pollution assessments around the world (Smith, 2014). The device is powered by a 9V battery and logs photoelectric responses every minute. A total of 48 unique UCB-PATS were rotated through households during this study. All monitors were assigned the same temperature and particle coefficients used to convert raw photoelectric responses into particle concentrations in micrograms per cubic meter ($\mu g/m^3$). Masses reported by the UCB-PATS were adjusted to a pooled $PM_{2.5}$ gravimetric correction factor determined during a previous study (Chowdhury et al., 2007) amongst wood-burning households in Guatemala. Briefly, UCB-PATS were collocated with 20% duty cycle gravimetric samplers (SKC 224-PCXR8 pumps connected to BGI Triple Cyclones at a flow rate of 1.5 lpm) for 48 h in RESPIRE study households as part of field validation activities for the UCB-PATS. 50 collocated samples were collected in open fire homes and 49 were collected in chimney stove homes. Correlations were high (~0.89 between gravimetric samplers and UCB-PATS; 0.94 between duplicate UCB-PATS). Unadjusted values and gravimetric correction factors are reported in Supporting Information Table S1.

All UCB-PATS were zeroed in a resealable plastic bag for 30 min before and after deployment in the households. Monitors were placed at a height of 1.5 m from the floor of the kitchen and from windows and doors and 1 m from the combustion zone of the primary stove to approximate the breathing zone of cooks. Each monitor was placed in participating homes and run for a week. We used midnight to midnight as starting and ending points of a sampling day. Fieldworkers visited these homes weekly to swap monitors. Monitors that were removed from homes were transported to the field headquarters, where data were downloaded, and routine monitor maintenance and cleaning was performed. Logs of household visits and monitor performance were maintained.

The daily mean concentration was calculated for each household on days with less than 10% of data missing. Additionally, because we are interested in predicting longer-term daily averages, we excluded periods associated with unusual events. In one household, kitchen renovation began in January of 2005; all measurements in this home after Dec 31, 2004, were excluded. At the end of RESPIRE, all control households received the chimney stove; measurements in these four homes after introduction of the intervention were excluded. Finally, one extreme value was excluded, during which the mean concentration exceeded the next highest day by greater than 2-fold.

We used non-parametric Wilcoxon rank sum tests to evaluate differences in PM concentrations on weekdays versus weekends and by season. We used mixed models to evaluate whether the use of different

Fig. 1. The left image depicts the Plancha chimney intervention stove in San Lorenzo, Guatemala. Fuel is fed into an enclosed combustion chamber (not visible); smoke vents out through a chimney (near the rear of the stove). The right image depicts a typical open fire cookstove.

monitors impacted PM concentrations (regressing log-transformed $PM_{2.5}$ against a random effect for monitor ID) and estimated the intra-class correlation coefficient (ICC) from these models (the proportion of variability explained by monitor ID).

Quantifying the coefficient of variation (COV) with increasing measurement durations. We calculated the reduction in the coefficient of variation (the standard deviation divided by the mean) for consecutive days of measurement (Cynthia et al., 2008). We selected 10 random days as starting points from the complete pool of valid measurement days and estimated the COV for sampling periods of 1, 2, 3, 4, 5, 6, 7, 14, 21, and 28 days from the starting point. To ensure stable estimates, this process was repeated 1000 times; the average COV is reported.

Evaluating sampling strategies. To evaluate how well measures of various lengths predicted the longer-term household mean concentration, we calculated the mean of every possible set of consecutive days of measurements (of 1, 2, 3, 4, 7, 14, 21, and 28 days), the mean of a single 24-h measurement drawn once per study week and once per study month, and the mean of 48-h samples drawn once per season. For each set of measurements of varying length, we determined how many estimates fall within a given precision level – for instance, within 20% of the longer-term household mean concentration – and divided by the total number of estimates, yielding the probability (%) of a random measurement of a specific duration falling within a given range around the longer-term mean. Calculations were performed separately by household and are presented in aggregate by stove type. We additionally calculated the root mean square error (RMSE) and its standard deviation for each measure described above.

Explaining variability in $PM_{2.5}$ concentrations with mixed models. We used linear mixed effects models to partition within and between household variances. The base model took the following form:

$$Y_{ij} = \beta_0 + b_i + e_{ij} \quad (1)$$

where Y_{ij} is the jth concentration in household i, β_0 is the overall intercept, b_i is the random effect for household i, and e_{ij} is the leftover error. By comparing the base model with models of increasing complexity, we estimated how much variability in daily average $PM_{2.5}$ concentrations could be explained 1) by fixed, household-level characteristics, such as stove type, socioeconomic indicators, and home characteristics; and 2) by time-varying effects, such as day of week and season (McCracken et al., 2009). Covariates included in the models were based on previous literature and data availability. We additionally evaluated the autocorrelation between consecutive measurement days. All statistical analyses were performed in R 3.1 and 4.0 (R Foundation for Statistical Computing, Vienna, Austria).

Fieldworker time and cost. We evaluated the financial and person-time impact of the various sampling strategies described above. We reported costs of alternative sampling strategies in monetary value and percentage increase compared to a single 24-h measurement. Time requirements were estimated based on the field manager's experience with the particle monitors. Cost data was derived from study budgets.

Field workers were paid 65 Guatemalan Quetzals per day (approximately 8.45 USD in 2004–05 at the midpoint of the study) for 8 h of work, which was above the minimum wage at that time. A single monitor deployment – including launching and zeroing the device in the lab before and after sampling and traveling to and from participating households but excluding data download – required approximately 2 h of fieldworker time during this study. The data download time was estimated at 5 min per sampled day. For deployments greater than 1 week, we assumed fieldworkers would have to visit homes once per week to maintain the monitors, requiring approximately 1 h. We assumed that a deployment for a 24-h period took 2.08 h and cost 2.2 USD in 2004–05.

3. Results

$PM_{2.5}$ Measurements. Baseline characteristics of the 8 participating households are presented in Table 1. Approximately 2.4 million data points were recorded during 1634 valid measurement days. The number of days measured per home ranged from 120 to 333 days. The mean (sd) of daily concentration was 1903 (1335) $\mu g/m^3$ in open fire homes and 125 (133) $\mu g/m^3$ in chimney stove homes. Summary statistics by household are described in Table 2; time series plots by stove-type and household are presented in Fig. 2. Both the summary statistics in Table 2 and graphs in Fig. 2 indicate variability both within and between households in each group. Correlation between consecutive days of measurement is shown by household in Supplemental Fig. S2 and in aggregate in Fig. S3.

There was no significant difference in distributions of $PM_{2.5}$ concentrations on weekends and weekdays for either open fire or chimney stove homes (SI figure S6). Similarly, there was no significant seasonal difference for open fire homes; for chimney stove homes, the Warm and Dry season was significantly different from the Warm and Wet season, with a mean increase of 40 $\mu g/m^3$ in the warm, wet season. The proportion of variability explained by unique monitor ID, estimated using the intraclass correlation coefficient, was low (~0.170), indicating that monitor alone likely did not explain differences noted within and between households.

Coefficient of Variation (COV). Fig. 3 displays the change in the coefficient of variation associated with longer consecutive measurement days. Most of the reduction in COV occurs by increasing the measurement duration up to 1 week; additional reductions continue to occur, but the rate of reduction decreases.

Evaluating Sampling Strategies. Comparisons of the precision of samples of varying durations are displayed graphically in Fig. 4 for both open fires and chimney stoves. Approximately 32% of chimney and 39% of open fire 24-h samples are within 25% of the longer-term mean. Increasing the consecutive days of measurement led to increases in precision for both stove types. The magnitude of the increase varied; open fire homes saw greater increases in precision for an equivalent increase in sampling length.

Table 3 depicts the probability of falling within 50%, 25%, and 10% of the longer-term mean for each of the sampling strategies. Probabilities increase with increasing consecutive days of measurement; sampling once per study week (on average 20 times per household in the current study) or once per study month (on average 6 times per household in this study) greatly improve the probability of attaining precision goals, as does selecting 48-h samples randomly once per season. Under all scenarios, samples are less likely to fall within precision goals for the chimney stoves.

The RMSE for each sampling strategy is displayed in Fig. 5 and described in Table S2. Samples composed of a smaller number of days have more dispersed RMSEs, as indicated by the error bars representing one standard deviation above and below the central estimates. The RMSEs ranged from 27 to 110 $\mu g/m^3$ for chimney stoves (20–85% of the overall chimney stove mean) and 168–1000 $\mu g/m^3$ for open fires (10–50% of the overall open fire mean). For both stove types, the largest RMSE was for a single sampling day, while the smallest was for the mean of random days selected from each study week.

Explaining concentration variability. Mixed models evaluated during this analysis are shown in Table 4. Model (A) is the simplest model, containing no covariates; model (D) is the most complex, containing both time invariant covariates (i.e., an asset index, roof type, wall type, and kitchen volume) and time-varying covariates (i.e., daily average humidity, day of week, and season). A variable for stove type explained the majority of the between household variability; addition of other time invariant and time-varying variables explained little or no additional variability, consistent with previous modeling work in this community in Guatemala (McCracken et al., 2009). An additional model (not shown) containing a random intercept term for UCB monitor ID

Table 1
Baseline characteristics of the 8 RESPIRE households in current analysis.

	Open Fire 1	Open Fire 2	Open Fire 3	Open Fire 4	Chimney Stove 1	Chimney Stove 2	Chimney Stove 3	Chimney Stove 4
Dirt floor in main home	Y	Y	Y	Y	Y	Y	Y	Y
Electricity in main home	Y	Y	N	Y	Y	Y	Y	Y
Roof Type								
Straw	Y	Y	Y	Y		Y	Y	
Aluminum					Y			Y
Number of rooms in house	1	1	1	1	1	1	1	1
Number of people in house	8	4	5	7	6	10	7	13
Cooking area in separate closed room	Y	N	Y	Y	Y	Y	Y	Y
Leaks in roof	N	N	N	N	N	N	N	Y
Kitchen volume (m^2)	22.7	60.5	11.7	54.1	17.2	89.2	43	63
Kitchen eave spaces								
Completely closed					Y	Y		
Partly closed			Y					Y
Completely open	Y	Y		Y			Y	
Stove in same room as bed	N	Y	N	N	N	N	N	N
Smoker present in home	N	N	N	N	N	N	Y	N
Has *temazcal* wood-fired sauna bath	Y	Y	Y	Y	Y	Y	Y	Y

*Y: yes; N: no.

Table 2
Study-wide mean $PM_{2.5}$ concentrations in μg/m^3 by household and stove type.

	N	Mean	SD	Min	Median	Max	Start Date	End Date
Open Fire 1	136	2255	1068	528	2076	5987	7/7/04	12/13/04
Open Fire 2	134	1118	592	102	981	2903	7/7/04	12/12/04
Open Fire 3	120	923	494	194	863	3135	2/17/04	7/16/04
Open Fire 4	215	2717	1514	53	2476	9017	2/24/04	11/22/04
All Open Fire	605	1903	1335	53	1557	9017		
Chimney Stove 1	154	143	119	39	115	1077	7/7/04	12/31/04
Chimney Stove 2	215	147	138	41	98	1342	7/7/04	3/21/05
Chimney Stove 3	333	54	77	31	41	1122	2/17/04	3/21/05
Chimney Stove 4	327	175	149	43	128	975	2/17/04	3/21/05
All Chimney Stove	1029	125	133	31	84	1342		

Fig. 2. Daily mean $PM_{2.5}$ concentrations in μg/m^3. The top panel displays data from intervention homes. The lower panel displays data from open fire homes. The dotted lines are the study-wide means by stove type.

explained only approximately 3% of the within household variability relative to the base model. Models were fit with both a fourth order autoregressive correlation structure given the autocorrelation observed between mean concentrations over consecutive days in the data (Supporting Information Figs. S2 and S3) and with a compound symmetry correlation structure, with no substantive difference in model output.

Fieldworker time and cost. Table 5 includes cost estimates of each sampling strategy per household. Costs were driven by fieldworker time, including transportation and time in households. Sampling for consecutive days – which requires, in theory, less fieldworker intervention – was less expensive than strategies that required multiple visits to households.

4. Discussion

We report and analyze a dataset of low-cost, light-scattering based repeated measurements of $PM_{2.5}$ concentrations in households using solid fuels for cooking. By deploying real-time monitors routinely for an

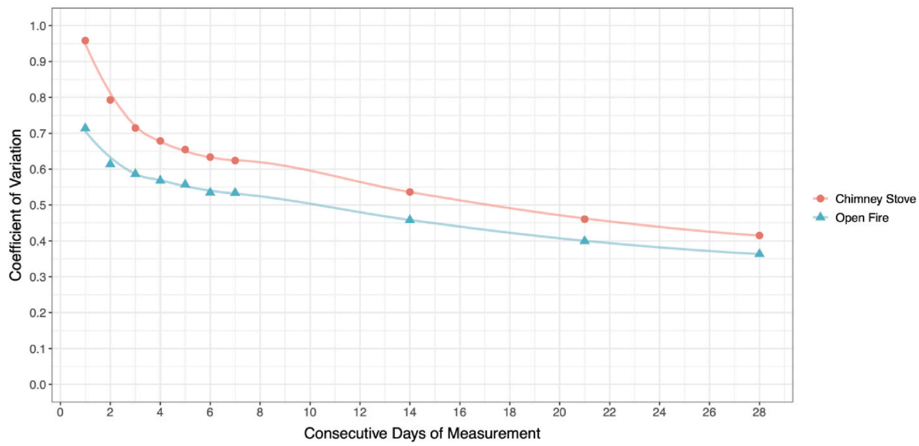

Fig. 3. The reduction in the coefficient of variation with increasing consecutive days of measurement. COVs are reported above for each measurement period of 1, 2, 3, 4, 5, 6, 7, 14, 21, and 28 consecutive days were evaluated.

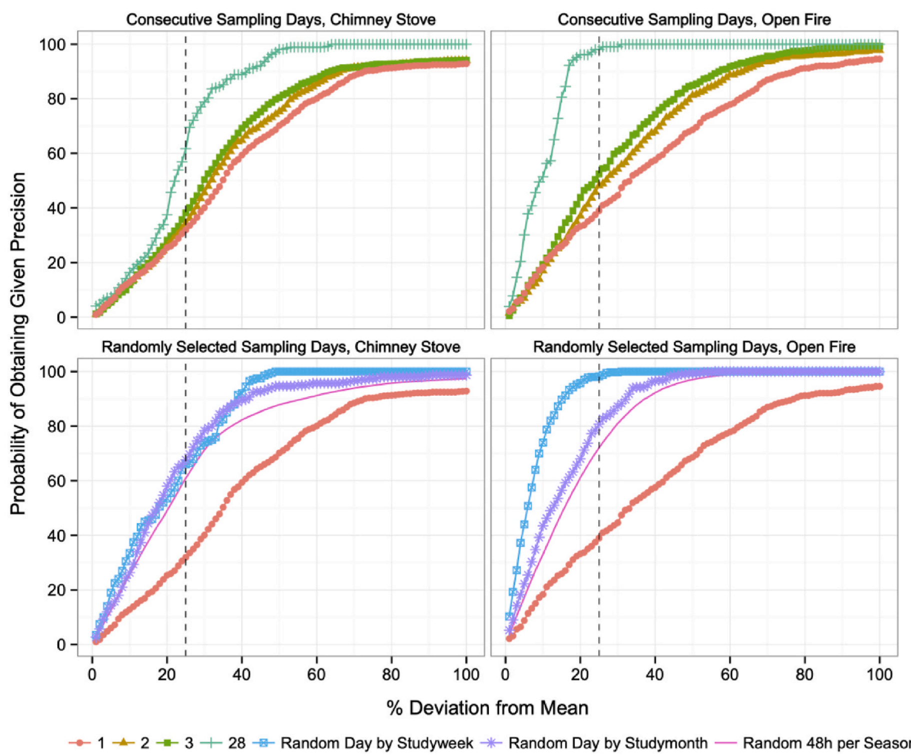

Fig. 4. Changes in precision given sampling intervals of different lengths. The x-axis represents the deviation from the longer-term mean; the y-axis is the probability of obtaining a measurement at a specific percent deviation from the longer-term mean. The top panels are for consecutively sampled days; the lower panels are for randomly selected sampling days. The stove type is specified in the panel title.

extended period of time, we were able (1) to describe the variability in $PM_{2.5}$ concentrations in rural Guatemalan homes using either an open-fire or a chimney stove, (2) to estimate how well traditionally performed short-term measures predict longer-term averages, and (3) to suggest alternative sampling approaches to better predict the longer-term mean. The sampling period allowed us to characterize 24- or 48-h measurements from midnight to midnight, which minimized the risk of capturing incomplete or inaccurate cooking episodes introduced by the timing of monitor placement (e.g., mid-day to mid-day) often seen in short-term measurements.

The convenience-based sample size of four households each in the traditional and intervention stove groups restricts the range of statistical modeling that can be applied and limits the inference derivable from this dataset. Descriptive analyses (Supporting Information, Figs. S4, S5, and S6) and distributional statistical tests indicate small differences of $PM_{2.5}$ concentrations for each stove type by season and day of the week. This is consistent with previous findings (McCracken et al., 2009; Ruiz-Mercado et al., 2013), which observed stable personal exposures to carbon monoxide throughout the year for this population. We expect more seasonal variability in kitchen $PM_{2.5}$ in regions with more varied seasons and different cooking and heating patterns. However, we could not rule out the possibility that the seasonality was not well captured in current analysis, given the small sample size. Similar analysis to the one reported here, albeit with larger sample sizes, should be repeated in other contexts to discover if a strategy that samples once for 24 h per study week or study month or once for 48 h per season could also produce better estimates of longer-term average concentrations, as reported here.

Table 3
Probability of being within 10, 25, and 50% of the longer-term, household-specific study mean by stove type and sampling strategy.

Precision Level		50% (least stringent)		25%		10% (most stringent)	
Sample	Days in sample	Open Fire	Chimney	Open Fire	Chimney	Open Fire	Chimney
Randomly selected days		Probability					
1 day	1	69%	70%	39%	32%	18%	13%
1 day per study month	6	99%	95%	81%	68%	44%	27%
1 day per study week	20	100%	100%	98%	66%	74%	34%
48-h period per season	6[a]	97%	88%	72%	61%	33%	26%
Random consecutive days		Probability					
2 days	2	81%	75%	48%	34%	17%	13%
3 days	3	85%	80%	53%	38%	19%	12%
4 days	4	89%	82%	56%	41%	24%	14%
7 days	7	96%	82%	64%	48%	24%	14%
14 days	14	99%	82%	79%	54%	36%	13%
21 days	21	100%	93%	88%	52%	47%	17%
28 days	28	100%	98%	98%	62%	51%	16%

[a] This strategy, while comprised of 6 days of measurements, requires three 48-h deployments.

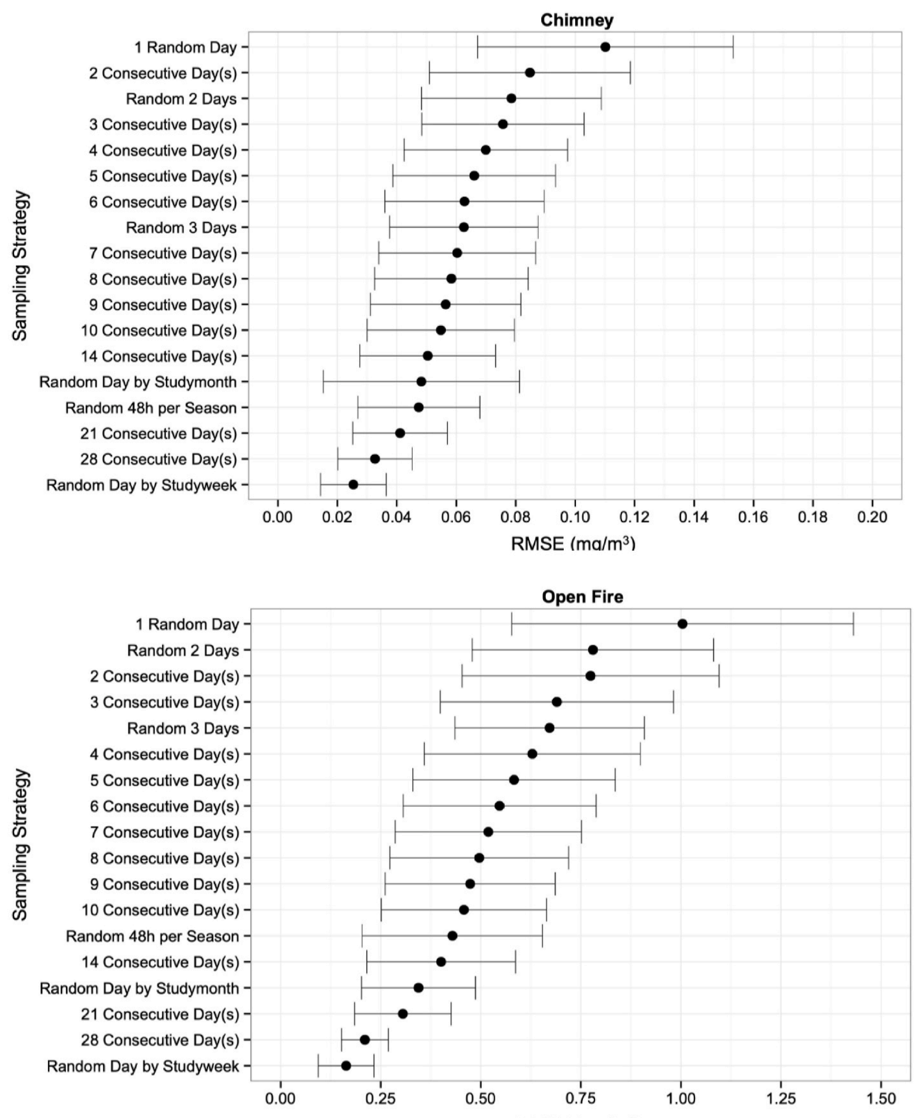

Fig. 5. Root mean square error (RMSE) comparing various sampling strategies to the longer-term mean. The x-axis is the RMSE; the y-axis is each sampling strategy. Dots indicate mean RMSE and error bars indicate one standard deviation. The top panel is for chimney stoves; the lower panel is for open fires. On average, sampling once per study week and once per study month resulted in 20 and 6 days of measurement in this study.

Table 4
Mixed-model estimates of within- and between-household components of variance for 24-h mean PM2.5 concentrations.

Model		Within-household variance	Between-household variance	R^2_{within} [a]	$R^2_{between}$ [b]
A	$Y_{ij} = \beta_0 + b_i + e_{ij}$	0.324	1.589	–	–
B	$Y_{ij} = \beta_0 + \beta_1 stove + b_i + e_{ij}$	0.324	0.262	0	0.835
C	$Y_{ij} = \beta_0 + \beta_1 stove + \beta_2 X_i + b_i + e_{ij}$	0.324	0.173	0	0.891
D	$Y_{ij} = \beta_0 + \beta_1 stove + \beta_2 X_i + \beta_3 Z_{ij} + b_i + e_{ij}$	0.318	0.160	0.02	0.899
E	$Y_{ij} = \beta_0 + \beta_1 stove + \beta_2 Z_{ij} + b_i + e_{ij}$	0.318	0.261	0.01	0.836

Model C and D contains the following time invariant variables **X**: an asset index, roof type, wall type, and kitchen volume.
Model D and E contains time varying variables ***Z:*** day of week, daily average humidity, and season.
[a] Within household variance explained by model relative to baseline model (A).
[b] Between household variance explained by model relative to baseline model (A).

Coefficient of Variation. A study in the central highlands state of Michoacán, Mexico (Cynthia et al., 2008), found that the COV was reduced from 0.68 for a single, 24-h measure to 0.48 when the sampling duration was increased to 96 h. The majority of the reduction in COV occurred by increasing the duration of sampling to 48 h. Our findings were similar; the COV was reduced from 0.96 to 0.78 for chimney stove homes and from 0.71 to 0.61 for open fire homes during the first 48 h. By 96 h, the COV in our study reduced to 0.68 and to 0.57 for chimney and open fire homes, respectively. In both Mexico and the current study, the COV decreased by 29% over the first four days. Fig. 3 indicates that the COV begins to stabilize at monitoring durations of approximately 1 week. The higher COV in chimney-stove homes may indicate occasional open fire use, a phenomenon known as stove stacking,[21,22] the well-documented practice of using multiple stoves in a home. In areas where several stoves are used, it is likely that estimation of longer-term concentrations using a single 24-h measure will be imprecise.

Sampling strategies. Short-term measurements such as 24-h or 48-h concentrations had a low probability of closely estimating the longer-term mean. Increasing the measurement duration to greater than 7 days increased the probability of falling within 25% of the longer-term mean and reduced the RMSE. Alternate sampling strategies – that focus on sampling once per study week or once per study month – improved the probability of falling within any given deviation from the longer-term mean and also reduced the RMSE. However, these strategies require additional resources and incur added costs and impositions on participating households. Increasing the measurement duration to 48 h and sampling three times offers a compromise between error and the burden imposed on households and on fieldworkers by extra measurement visits. The larger error across strategies in chimney stove households is presumably due to usage of the old stove or simultaneous use of both stoves, leading to less consistent concentrations when a small number of days are selected from the complete set of available days at random.

Work in context. Limited previous work repeatedly estimated household air pollution concentrations in the same household over many days. In Mexico, during an assessment of the Patsari cookstove, $PM_{2.5}$ kitchen concentrations were monitored for 4 days in 24 homes (Cynthia et al., 2008). Researchers observed that variability decreased as the number of sampling days increased; however, they were unable to compare this to a longer-term mean, such as an annual average concentration. In Guatemala, researchers compared single 48-h personal carbon monoxide (CO) measurements to the longer-term mean of 4 repeated measures. They found that the single measures were unreliable as a measure of longer-term exposure (McCracken et al., 2009). Lee et al. (2021) conducted a panel study among 787 Chinese adults with up to 4 days of repeated measures of $PM_{2.5}$ and black carbon (BC) and found that within-individual variances were much larger than between-individual variances. Their finding indicated that repeated measurements of daily exposure are likely needed to capture longer-term exposures, even within a single season (Lee et al., 2021). Similar findings of repeated personal exposure were also observed among women during their pregnancy by an ongoing muti-country randomized controlled trial (RCT) (Johnson et al., 2021). More recently, Keller and Clark (2022) examined different approaches to estimate long-term average HAP concentrations from repeated short-term measurements and demonstrated, based on measurements from a cookstove intervention in Honduras, that long-term average predictions using mixed models based on a small number of measurements can reduce prediction error, though with diminishing returns as the number of measurements increases.

Limitations and future work. This analysis had a number of limitations. First, the study had only 8 participating households, with some heterogeneity in household-level characteristics. The disadvantages of having only 4 households each in the chimney-stove and open-fire groups were partially alleviated by many repeated measures, though we note that a greater number of households would have aided modeling efforts.

Local cooking and heating customs, fuel types, and household

Table 5
Cost and fieldworker time commitment for various sampling strategies per household.

Sample	Sampling Days	Fieldworker time (minutes)	Data download time (minutes)	Total Time (hours)	Cost per home over sampling period ($)[a]	% Cost increase compared to a single 24-h measurement
Randomly selected days						
1 day	1	120	5	2.1	2.2	–
1 day per study month	6	720	30	12.5	13.2	500%
1 day per study week	20	2400	100	41.7	44.0	1900%
48-h period per season	6	360	30	6.5	6.9	214%
Random consecutive days						
2 days	2	120	10	2.2	2.3	5%
7 days	7	120	35	2.6	2.7	23%
14 days	14	205	70	4.6	4.9	123%
21 days	21	330	105	7.3	7.7	250%
28 days	28	435	140	9.6	10.1	359%

[a] Cost per home was calculated as the total time (in hours) divided by 8 (the number of working hours per day) times the daily wage of 8.45 USD per day.

characteristics differ amongst solid fuel using households globally. Therefore, results from current analysis may be less generalizable to other settings. Replication in additional geographies will further help determine the best approaches for optimizing sampling strategies.

Additionally, for many health outcomes associated with exposure to $PM_{2.5}$ resulting from solid fuel use for cooking, there are exposure durations of interest that are longer than the total duration measured for this study. For example, to understand effects of exposure on chronic obstructive pulmonary disease or cardiovascular disease, we would ideally measure exposure over decades. Although our study informs the viability of using short-term measure to predict annual means, it cannot address variability in exposures over these decadal timeframes. Nonetheless, our findings may help inform future exposure assessment and risk assessment studies by better informing decisions about sampling duration and frequency.

Data from the UCB monitors used during this study were not individually gravimetrically adjusted, instead relying on pooled correction factors from previous work (Chowdhury et al., 2007). As a result, the coefficients used to convert raw millivoltage from the photodetector into PM mass may misestimate the true concentration; however, we expect the relative differences between monitors remained relatively constant, based on previous field validation results (Smith et al., 2014). Furthermore, we noted a low proportion of variability explained by monitor ID in the current study. Concentrations reported in Table 1 are thus likely indicative of variability within and between homes.

The air pollution monitors used in this study are no longer commonly used and have been replaced by modern sensors, like the PATS+ (Berkeley Air Monitoring Group, Berkeley, CA), Enhanced Children's MicroPEM (ECM, RTI International, Research Triangle Park, NC), and the Ultrasonic Personal Aerosol Sampler (UPAS; Access Sensor Technologies, Fort Collins, CO). These monitors, along with commercially available sensors based like the PurpleAir (PurpleAir, Inc., Draper, Utah), can provide more highly resolved data, though many saturate at levels lower than often experienced in village kitchens. Ongoing work, including some by the authorship team, seek to understand how these modern devices can perform for even longer periods of time in similar settings where solid fuel use is prevalent.

We were unable to measure several factors that may impact kitchen $PM_{2.5}$ concentrations, including ventilation, use of multiple stoves, meteorological parameters near households, changes in household configuration, or changes in the number of people per household. Advances in the ability to monitor stove usage using small, data-logging thermometers (Stove Use Monitors – SUMs) have enabled better understanding of the variability of $PM_{2.5}$ concentrations within home, especially in homes where multiple stoves are being used. In instances where stove use is not correlated with concentrations and exposures, additional unmeasured sources should be considered. Similarly, any future studies of longer-term pollutant concentrations in biomass burning households should capture information – such as behavioral changes due to life course events, like pregnancy or delivery or changes in household structure – that may help explain the variability within and between households. These types of changes, which were not measured for this analysis, may be important for analyses looking at specific maternal and child health outcomes, and should be collected in addition to routinely collected information, including the number of household members in a home, special cooking done during monitoring periods, changes in fuel source, and stove-fuel-food combinations that may change with season.

Our simple estimate of program costs does not take into account monitor availability or pricing. Up front equipment costs can be high; the availability of monitors to perform measurements of concentration or exposure depend on program resources and vary widely. Additionally, our cost estimates may slightly underestimate the per sample fieldworker cost; although presumably, during long-data download sessions, field staff could perform other tasks, the poorer infrastructure, unforeseeable weather events, resources for keeping the field team for an extended period, and many other factors could all lead to higher per-sample costs. However, advances in monitoring technology should dramatically drive down the time required to download data and manage devices.

Under ideal circumstances, health researchers would measure personal exposure repeatedly in place of measuring kitchen concentrations as done in this study. During data collection for the current study, such ongoing monitoring was not possible due to the project cost and participant burden of personal exposure assessment. Optimizing the duration of sampling for exposure assessments is not straightforward, however. We reviewed published exposure measurements (Supporting Information Tables S3 and S4) and extracted the mean and standard deviation of exposures to estimate COVs, which varied widely depending on locale and pollutant measured. For $PM_{2.5}$ exposure measurements at our field site in Guatemala, the estimated COVs were 1.13 for open fires and 1.27 for chimney stoves (McCracken et al., 2007) – higher than the COV for a single kitchen measurement reported here (0.71 and 0.96 for open fires and chimney stoves, respectively). Contrastingly, in a Honduran community using a mixture of stoves, the COV from personal exposures to $PM_{2.5}$ was lower than that of kitchen concentrations (0.9 and 1.4, respectively) (Clark et al., 2010). In a Ghanaian community using primarily open fires, personal measurements also had a lower COV than kitchen measurements (0.61 and 0.92, respectively) (Van Vliet et al., 2013). This variability may be related to cooking styles and practices, difference among roles of household members, and other behavioral factors as well as structural differences in household environments, and indicates the need for more evaluation of personal exposure measurement duration.

As part of pilot work for future large-scale studies, investigators may wish to consider small, targeted longer-term monitoring studies along the lines of what we report here, which could leverage recent advances in particle monitors to potentially require less frequent field visits than the one-week interval we employed. These could better quantify exposure variability in different situations by monitoring household and individuals for a number of consecutive days. Such studies could greatly increase the efficiency of the sampling strategy employed in the study being planned whether to conduct exposure-response analysis of health outcomes or to assess the pollution impacts of interventions as well as help decide more mundane, but important, questions such as whether monitoring on weekends is needed.

The choice of sampling strategy is motivated by a number of competing factors, including logistical issues, such as the study budget, the cost of monitoring equipment, the availability of study staff, and the burden on participants; and analytical issues, such as whether the question of interest involves group-level estimates, which are unbiased and relatively constant, regardless of monitoring duration; or individual estimates of exposure, which are imprecise when estimated from short-term measurements of pollutant concentration. Many studies of household air pollution focus on a few measurements of either 24 or 48 h. Our findings suggest that if short measurement durations are used to link air pollutant concentrations and exposures to ill-health, the true effect size may be underestimated. Consecutive measurements for one week decrease the COV substantially relative to shorter measures; measurements for longer than one week offer little marginal improvement in COV. Measurements spread throughout the year in this study's context, however, are closer to the study-wide average and have smaller errors. Measurement durations (1) longer than 48 h or (2) consisting of repeated 24- or 48-h measurements throughout a study should be considered in future studies of household air pollution to more accurately characterize variability and to better predict longer-term concentrations.

CRediT authorship contribution statement

Ajay Pillarisetti: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Review, and Editing, Visualization. **Line W.H. Alnes:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft. **Wenlu Ye:** Methodology, Formal analysis, Writing – review & editing. **John P. McCracken:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Eduardo Canuz:** Methodology, Investigation. **Kirk R. Smith:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.atmosenv.2022.119533.

Abbreviations

CO	Carbon Monoxide
COV	Coefficient of Variation
CRA	Comparative Risk Assessment
GBD	Global Burden of Disease
HAP	Household Air Pollution
$PM_{2.5}$	Particulate Matter with an aerodynamic diameter of <2.5 μm
RESPIRE	Randomized Exposure Study of Pollution Indoors and Respiratory Effects
RMSE	Root Mean Square Error
UCB-PATS	UCB-Particle and Temperature Sensor

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