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TECHNICAL PAPER



Comparison of black carbon measurements using filter-specific reference transmittance to those using lab blanks or an average of unloaded filters

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ABSTRACT

Filter-based optical techniques compare light transmission intensities between loaded (I) and unloaded (I₀) filters as a measure of light-absorbing mass for subsequent estimations of equivalent black carbon (eBC). We analyzed 5,379 15 mm Teflon filters from the Household Air Pollution Intervention Network (HAPIN) trial to assess the influence that different methods of I₀ estimations have on eBC measures. We compared eBC measurements using filter-specific I₀ values (Method 1) to those using three other methods of I₀ estimation: the lab blank scan from a given session (Method 2), the average of all pre-sample filter scans (Method 3), and the average of all lab blank filter scans (Method 4). We assessed the agreement between Method 1 and the alternative methods using Bland-Altman analysis. We also assessed the relationship between Method 1 and the alternative methods across the complete measurement range and after stratifying exposure data into quartiles according to Method 1 eBC exposures. The mean (SD) personal eBC exposure for Method 1 was 7.8 µg/m³ (5.9), and exposures ranged from 1.3 to 46.8 µg/m³. Compared to Method 1, eBC using Methods 2, 3, and 4 were higher by 0.7 µg/m³, 0.1 µg/m³, and 0.7 µg/m³, respectively. The performances of linear regression models between Method 1 and all other methods were moderate to strong (R² range: 0.42–0.93) in the second, third, and fourth quartiles; however, the models in the first quartile (eBC range: 1.3–2.9 µg/m³) performed poorly (R² = 0.25–0.26), with error approximately 25% of the mean. Our findings suggest that, in most instances, conventional methods for obtaining I₀ values can be used to sufficiently characterize eBC; however, analyzing filters before sampling adds appreciably to the accuracy of eBC estimations in lower concentration settings.

Implications: Filter-based optical techniques compare light transmission intensities between loaded (I) and unloaded (I₀) filters as a measure of light-absorbing mass for subsequent estimations of equivalent black carbon (eBC). To assess the influence that different methods of I₀ estimations have on eBC measures, we analyzed 5,379 15 mm Teflon filters from the Household Air Pollution Intervention Network (HAPIN) trial. Our findings suggest that, in most instances, conventional methods for obtaining I₀ values can be used to sufficiently characterize eBC; however, analyzing filters before sampling adds appreciably to the accuracy of eBC estimations in lower concentration settings.

PAPER HISTORY

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Introduction

Health-based air quality guidelines have long been established for aerosol particles primarily characterized via fine particulate matter (PM_{2.5}) measurements

(WHO 2021). The most light-absorbing fraction of these particles, black carbon (BC), is a by-product of incomplete combustion and has been gaining regulatory attention due to its detrimental impact on both climate (Bond et al. 2013) and human health (Janssen et al.

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2012). BC can be estimated directly through thermal desorption of elemental carbon (EC) or incandescence from refractory black carbon (rBC) and indirectly through the conversion of light absorption of particulate mass measurements to estimate equivalent black carbon (eBC) (Sharma et al. 2017).

The residential combustion of polluting fuels (e.g., kerosene, coal, or biomass such as wood, dung, and charcoal) contributes a substantial proportion (~35%) of global BC emissions (Xu et al. 2021). Current trends suggest that these emissions will likely increase as a result of growing rural populations in low- and middle-income countries (LMICs), where the daily use of polluting fuels for household needs is most prevalent. Field-based measures of BC concentrations and exposures in LMICs are becoming more important to fully estimate the burden of disease from residential biomass burning, the health benefits associated with switching to cleaner-burning fuel alternatives, and the contribution of this pollutant to global warming. Direct methods of BC estimation, like thermal desorption, are costly and resource-intensive, limiting the practical use of these methods in exposure studies in LMICs.

Particle light attenuation (b_{att}) measurements on polytetrafluoroethylene (PTFE, TeflonTM) filter media and EC measured on quartz filters correlate well with each other ($\rho > \sim 0.80$), demonstrating the potential for b_{att} measures to serve as a quick, efficient, and cost-effective way to indirectly measure EC (as eBC) without destroying filter media (Chow et al. 2010). Light attenuation can also be reported in attenuation of light (ATN) units at a specific wavelength, where the intensity of light through an unloaded filter (I_0) is compared to that which is attenuated through a loaded filter (I) (eq 1). The b_{att} is then estimated with the ATN, the volume of air sampled (m^3), and the sample area (m^2) on the filter (Presler-Jur et al. 2017) (eq 2). The mass concentration of eBC ($\mu g/m^3$) is then calculated by dividing b_{att} in inverse megameter (Mm^{-1}) units, by the mass absorption coefficient σ_{att} ($m^2/\mu g$), which is derived by taking the slope of the linear regression of b_{att} on EC measurements (Chow et al. 2010) (eq 3).

$$ATN = \ln\left(\frac{I_0}{I}\right) * 100 \quad (1)$$

$$b_{att}(Mm^{-1}) = \frac{Area(m^2)}{Volume(m^3)} * ATN * 10^4 \quad (2)$$

$$[eBC]\left(\frac{\mu g}{m^3}\right) = b_{att}(Mm^{-1}) / \sigma_{att}\left(\frac{m^2}{\mu g}\right) \quad (3)$$

To our knowledge, few exposure studies in LMICs have measured I_0 using pre-sampled filters (Young et al. 2022). Instead, the more conventional approach has been to measure I_0 as the average light intensity transmitted through many unloaded filters. However, the average light transmission value of unloaded filters does not likely represent an individual Teflon filter's I_0 value due to the heterogeneity of Teflon filter media. For instance, light intensities through unloaded filters can vary by as much as 60,000 units (Presler-Jur et al. 2017). For this reason, Presler-Jur et al. recommended that filter-specific I_0 measurements should be made (i.e., using the pre-sampled filter to estimate I_0) to provide a more comparable measure of light attenuated when passing through the post-sampled filter for subsequent estimations of eBC. To date, there are no field-based studies that have assessed the potential for improved accuracy of eBC measures from filter-specific I_0 values.

To address this knowledge gap, we compared personal eBC measures from the Household Air Pollution Intervention Network (HAPIN) trial, which used filter-specific I_0 values for eBC measures in Guatemala, Peru, and Rwanda, to corresponding eBC measures using other methods to estimate I_0 . The findings from this study provide information on the added benefit of using filter-specific I_0 values, as opposed to using I_0 values from blank lab filters or the average of unloaded filters, to estimate eBC.

Methods

Study setting and participants

The study design, site descriptions, and related exposures are all described in detail elsewhere (Barr et al. 2020; Clasen et al. 2020, 2022; Johnson et al. 2020, 2022; Williams et al. 2020). Briefly, we conducted a randomized controlled trial to evaluate the effectiveness of a liquefied petroleum gas (LPG) fuel and stove intervention versus the continued use of a traditional biomass cookstove (Clasen et al. 2020). The trial had study sites located in Guatemala, India, Peru, and Rwanda. In each site, ~800 households were enrolled (split equally between control and intervention arms), totaling 3,195 pregnant women. Study site selection criteria included, but were not limited to, population density, fuel use, socioeconomic status, and other sources of ambient and/or indoor air pollution.

Exposure assessment

Aerosol particles were collected onto Teflon filters using the RTI Enhanced Children's MicroPEM™ (ECM, RTI International, Research Triangle Park, U.S.A.) to measure time-weighted gravimetric $PM_{2.5}$. The ECM is small and lightweight and uses a 2.5-micron size-cut impactor at a flow rate of 0.3 L per minute for gravimetric measures. The ECM also measures real-time $PM_{2.5}$ concentrations using a nephelometer and logs temperature, relative humidity, and triaxial accelerometry. Personal exposure measures among pregnant women were collected at baseline (gestational age between 9–20 weeks) and at two follow-up periods after randomization at 24–28 (post-intervention visit 1, “P1”) and 32–36 (post-intervention visit 2, “P2”) weeks of gestation (Johnson et al. 2022). All participants were asked to wear aprons fitted with an ECM in their breathing zone. If the participants were to conduct any activities that might damage the equipment (e.g., sleeping, bathing, heavy washing), they were instructed to keep the apron with the ECM nearby but not on their person. Field blank filters were collected for approximately 3% of all samples to adjust for mass changes associated with filter handling and processing.

Light absorption measurements

We used the Magee Scientific Sootscan model OT21 transmissometer (Magee Scientific Corporation, Berkeley, CA) (Figure 1) to measure the absorbance of a sampled filter relative to an unloaded reference filter at 880 nm wavelength. The Sootscan OT21 has a filter tray with two slots. The top slot holds the adapter for the

blank reference filter, and the bottom slot holds the adapter for the sample filter. Sandwiched between either adapter is the filter on top of a diffuser. Both the filter and diffuser were made of the same filter substrate material.

Filters were analyzed at the University of Georgia (UGA, Athens, GA, U.S.A.) before deployment to the study sites in Guatemala, Peru, and Rwanda. Figure 2 shows the I_0 for all reference filter “scans.” The intensity of light transmitted through the pre-sampled filter was the filter-specific I_0 value (Method 1: gray dots). Method 1 represents our “gold standard” for I_0 estimation. After filters were returned to UGA for post-sampling, lab blank reference filter scans were used to estimate I_0 values (Method 2: black dots). We also used the average of all pre-sample (Method 3: red line) and lab blank (Method 4: blue dashed line) filter scans as estimates for I_0 . We did not calculate site-specific average I_0 values for Methods 3 and 4, since all filters were scanned before deployment with the same instrument at UGA. For all study measurements, we used a derivation of eqs 1–3 to estimate eBC exposures. First, we calculated the ATN using each method of I_0 estimation (Methods 1–4). ATN values below 1 or above 125 were removed from our analyses upon recommendation from Magee Scientific (Aerosol Magee Scientific 2025). To estimate the mass deposited on the filter (μg), we multiplied the ATN by both the effective filter area (0.000079 m^2) and the unit conversion constant (10^4), and then divided by the σ_{att} reported in Garland (2017) ($13.7 \mu g/\text{cm}^2$ or $7.6e-6 \text{ m}^2/\mu g$), as this value represents the relationship between light attenuation measurements, via Teflon filters, and EC measurements, using thermal desorption techniques, from biomass cookstove sources. Concentrations of

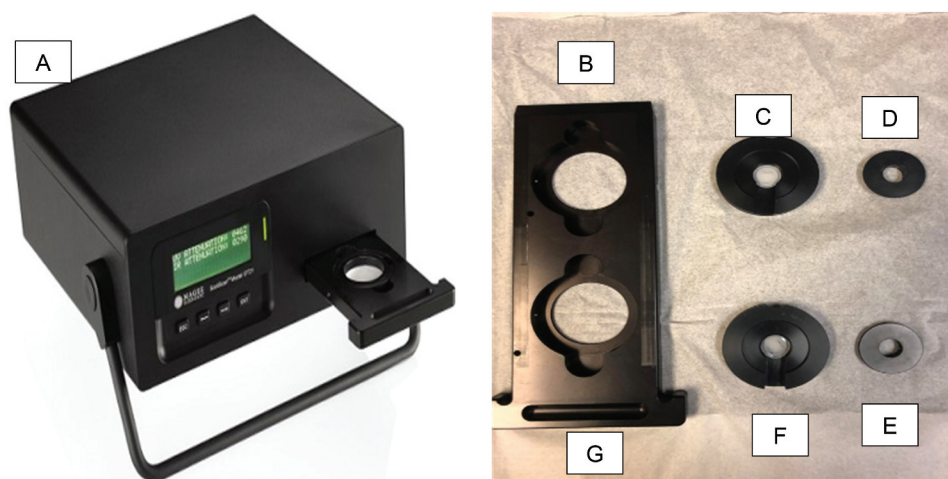


Figure 1. Magee Scientific Sootscan model OT21 transmissometer (A) (Magee Scientific corporation, Berkeley, CA) and filter tray with two slots (B & G) that hold the adapters for the lab blank or reference filter (C & D) and sample (F & E) filters. For Method 1, the reference filter scan is from the pre-analyzed sample filter as opposed to the lab blank filter.

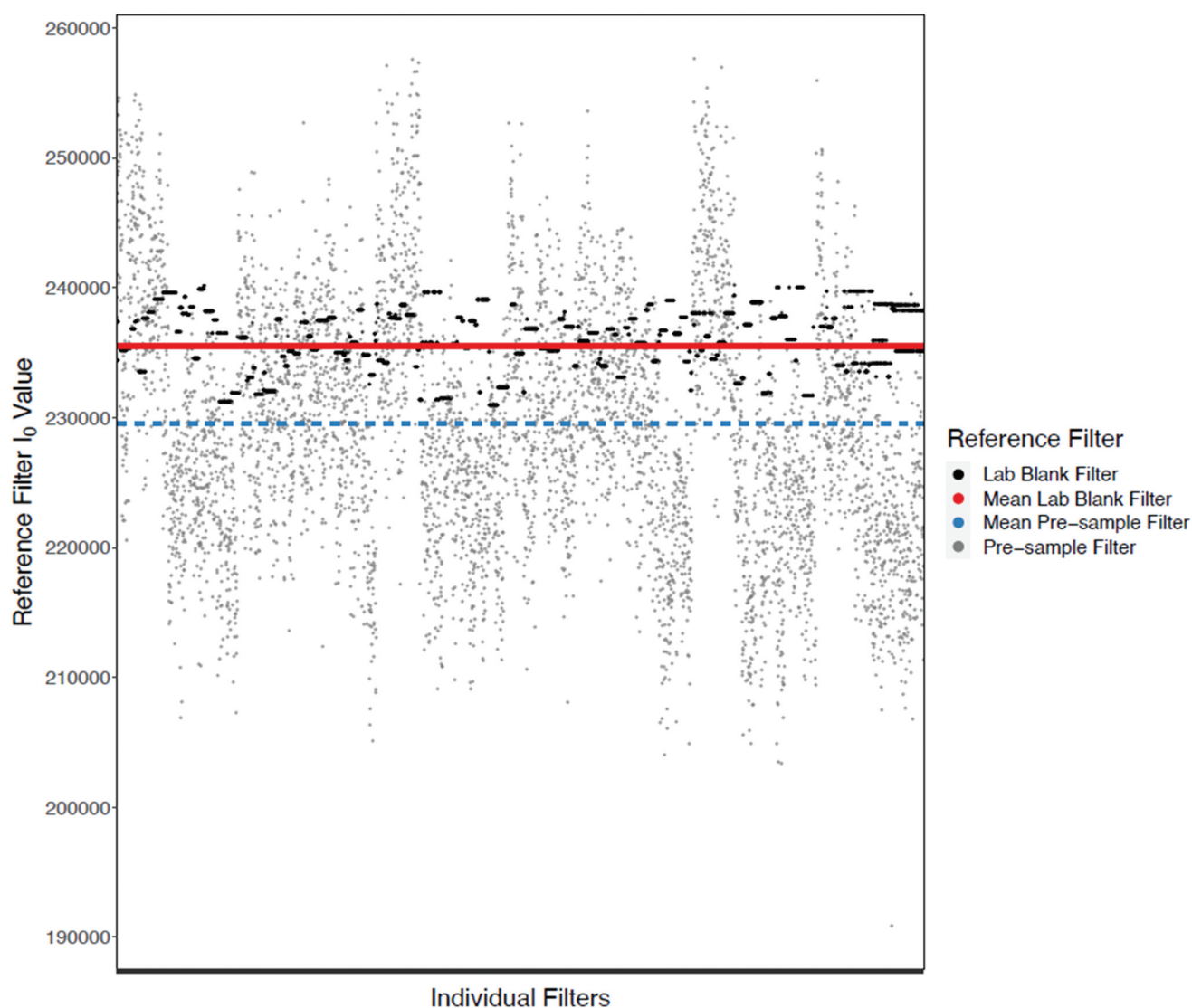


Figure 2. Reference filter I_0 values for all lab blank and pre-sample filter scans. Pre-sample and blank filter scans represent I_0 estimations using Methods 1 and 2, respectively. Methods 3 and 4 are the average I_0 values for all pre-sample ($I_0 = 229497.2$) and blank filter ($I_0 = 235510.6$) scans, respectively.

eBC ($\mu\text{g}/\text{m}^3$) were then calculated as the mass deposited on the filter (μg) divided by the total sample volume (m^3) collected over the 24-hour sampling period. Data from India were not included in this manuscript due to a slightly modified Sootscan procedure conducted at Sri Ramachandra Institute for Higher Education and Research (SRIHER, Chennai, India), which impacts the direct comparison of measures between India and the other study sites.

Statistical analysis

We applied the conventional approach for estimating site-specific limit of detections (LoDs), in μg units, as three times the standard deviation (SD) of field blank results (EPA [date unknown]). Values below the LoD

were replaced by the $\text{LoD}/\sqrt{2}$. We applied all further analyses to site-specific LoD-adjusted measures. We conducted a descriptive summary to characterize the between-method variations in eBC exposures and Bland-Altman analyses (Bland and Altman 1999; Giavarina 2015) to estimate the average differences (mean bias) and limits of agreement (LoA) between method-specific measurements. We also used the paired t -test to test the null hypothesis that the means of eBC for all alternative methods were the same as that for Method 1. Finally, we evaluated the relationship between measures using Method 1 and those using the alternative methods via linear regression analyses of non-transformed eBC exposures across the entire measurement range and after stratifying by quartile according to Method 1 eBC

exposures. Paired observations of the alternative methods were placed into Method 1 eBC exposure quartiles regardless of exposure level. We performed all analyses in R (versions 3.6 and 4.0, R Foundation for Statistical Computing, Vienna, Austria).

Results

Summary of filter I_0 values

A summary of I_0 values from all filters from the current study is provided by study site and filter type in Table 1. There is large variation in I_0 values for unloaded filters, as the SDs for all pre-sample and field blank filters were above 9,000 units, with the difference between the minimum and maximum I_0 values being upwards of ~68,000 units. The SDs of lab blank filter scans were considerably smaller than those for the other filter types because only two lab blank filters were used throughout the duration of the study period. The relatively low SDs of the lab blank filter scans suggest that the variability within filters is low.

Limit of detection analysis

Method- and site-specific LoDs (μg) are provided in Table 2. Across all study sites, we observed consistently higher LoDs for Methods 2–4, compared to those for Method 1.

Summary and agreement of method-specific eBC exposures

Method-specific personal eBC exposures and agreement between methods are provided in Table 3 and Figure 3, respectively. The overall Method 1 mean (SD) eBC exposure was $7.8 \mu\text{g}/\text{m}^3$ (5.9) with noticeably higher exposures among pregnant women in Guatemala and Rwanda compared to women in Peru. For all measures, the mean eBC exposures were higher for Methods 2–4 compared to Method 1 (all $p < 0.001$), with mean differences (limits of agreement: LoA) of $0.7 \mu\text{g}/\text{m}^3$ (–1.4–2.8), $0.1 \mu\text{g}/\text{m}^3$ (–1.9–2.1), and $0.7 \mu\text{g}/\text{m}^3$ (–1.4–2.7), respectively (Figure 3). This trend was consistent within each

Table 1. Summary of I_0 values by study site and filter type.

I_0 value summary	Pre-sample filter scans	Lab blank filter scans	Field blank filter scans
Guatemala			
N	2345	72*	215
Average (SD)	229612 (9072.5)	235552.1 (2212.3)	228829 (9705.6)
Range	204045.5–257569.5	230956–239662.5	205561–255443.5
Median (IQR)	229233.5 (223249–235579)	235570.5 (234146.1–237586.2)	229130 (221308.2–234949.2)
Peru			
N	1719	50*	275
Average (SD)	226891.5 (10006.8)	236211 (2388.8)	227837.1 (9171.8)
Range	190870.5–257629	231695.5–240202	205959–251801
Median (IQR)	225903.5 (219688–233294.2)	236301.8 (234412.9–238195.21)	226625.5 (220625.8–234191)
Rwanda			
N	2825	83*	86
Average (SD)	230180.6 (8846.2)	235758.5 (2127.4)	232780.6 (8016.5)
Range	189538–254853	231228–240208	217628.5–252389
Median (IQR)	230336 (224245–236261)	235378 (234553.2–237429.8)	232855 (227159.2–238540.6)
Overall			
N	6889	205*	576
Average (SD)	229166.3 (9319.4)	235796.4 (2226.4)	228945.4 (9350.7)
Range	189538–257629	230956–240208	205561–255443.5
Median (IQR)	228986 (222531.5–235527)	235646 (234334.5–237628)	228720.8 (221616.8–235397)

Note. *The N here represents the number of scans for the two lab blank filters used over the course of the study.

Table 2. Limit of detections (LoDs) for each method and study site combination.

Study site	N _{field blanks}	Method 1 ^a (μg)	Method 2 ^b (μg)	Method 3 ^c (μg)	Method 4 ^d (μg)
Guatemala	211	0.578	1.38	1.36	1.36
Peru	262	0.886	1.31	1.36	1.36
Rwanda	86	1.60	1.73	1.78	1.78
India ^e	121	N/A	1.03	N/A	N/A

Note. ^aMethod 1: pre-sample scan for I_0 value; ^bMethod 2: lab blank scan for I_0 value; ^cMethod 3: average pre-sample I_0 ; ^dMethod 4: average lab blank I_0 ; ^eSlightly modified Sootscan procedure at SRIHER compared to that at UGA that impacts the direct comparison of the LODs between India and the other study sites.

Table 3. Summary of mean (SD) eBC exposure measures ($\mu\text{g}/\text{m}^3$).

	N _{sample filters}	Method 1	Method 2	Method 3	Method 4
Overall	6889	7.8 (5.9)	8.5 (5.9)	7.9 (5.8)	8.5 (5.9)
Guatemala	2345	9.2 (5.7)	9.8 (5.8)	9.2 (5.7)	9.8 (5.8)
Peru	1719	5.6 (6.4)	6.5 (6.5)	6.1 (6.2)	6.5 (6.4)
Rwanda	2825	8.0 (5.3)	8.6 (5.3)	8.0 (5.2)	8.6 (5.2)

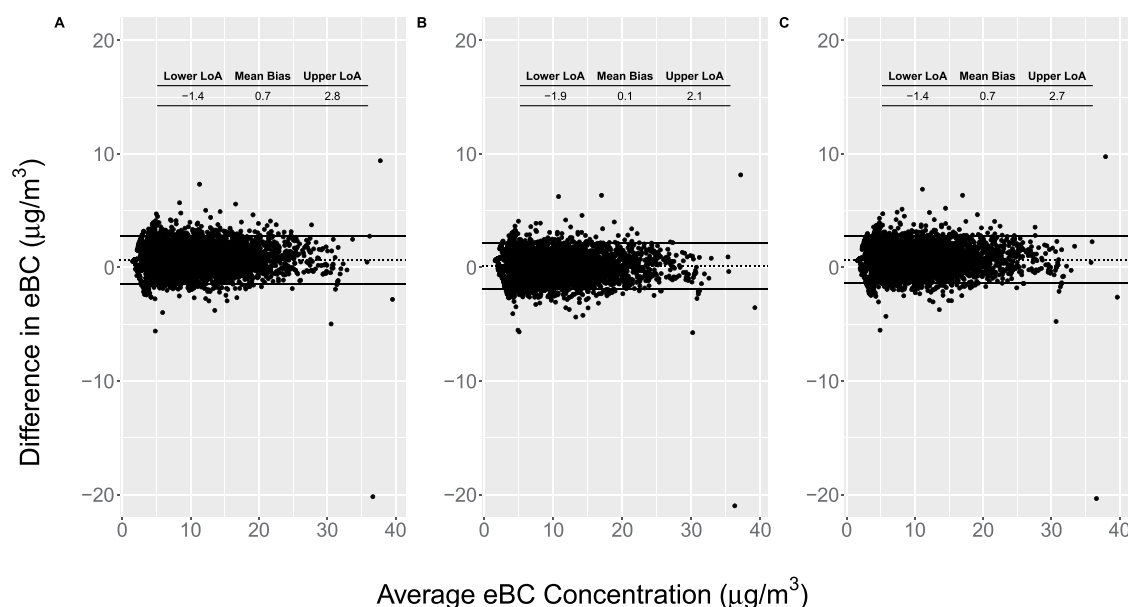


Figure 3. Bland-Altman plots comparing the agreement between Method 1 eBC measures and those from Method 2 (A: session-specific lab blank scan), Method 3 (B: average of pre-sample filter scans), and Method 4 (C: average of lab blank scan). The dashed line reports the average difference or mean bias ($\mu\text{g}/\text{m}^3$) (Method (2 or 3 or 4)–Method 1) between measures. The bold lines show the limits of agreement (LoA), where 95% of the differences lie between the upper (ULoA) and lower (LLoA) limits of agreement. Bland-Altman statistics are provided in their corresponding panels.

study site for both methods using lab blanks (Method 2 and Method 4). However, there were no significant differences in mean eBC exposures between Method 3 and Method 1 in Guatemala and Rwanda (both $p > 0.05$), while the mean exposure level for Method 3 was higher than that for Method 1 in Peru ($p < 0.001$). Visual inspection of the Bland-Altman plots shows that there is no evidence of proportional bias between methods: the average difference between methods is constant and does not change as exposures increase.

Method comparisons via linear regression

Given the systematic bias (overreporting eBC measures) associated with using lab blanks or an average of unloaded filters for I_0 estimations, compared to using filter-specific I_0 values, we assessed the linear relationship between eBC exposures from Method 1 and all other methods after stratifying the data into quartiles to gauge the relative contribution of the systematic bias to measurement error at different levels of exposure. Table 4 provides results from

the linear regression models showing the relationship between Method 1 and Methods 2–4. Overall, the linear regression models between Method 1 and all other methods fit well, as adjusted R^2 values were high (all 0.97), with RMSEs ranging from 1.0–1.1 $\mu\text{g}/\text{m}^3$. RMSEs decreased as exposures got smaller in magnitude; however, it is clear that the relative fit of the models decreased appreciably in turn, as R^2 values went from 0.91 in the fourth quartile to as low as 0.22 in the first quartile. Our results show that, in the lowest quartile of Method 1 eBC exposures (range: 1.3–2.9 $\mu\text{g}/\text{m}^3$), our models do not perform well with errors that are approximately 25% of the mean in the lowest quartile.

Discussion

Our I_0 values varied by as many as 68,000 units, which highlights the inherent variability between individual Teflon filters. The LoDs using Methods 2–4 were consistently higher than those using Method 1, reflecting the increased uncertainty of I_0

Table 4. Model performance statistics for the linear regression between Method 1 and Method 2–4 measures.

Quartile	N _{sample filters}	Method 1 eBC ($\mu\text{g}/\text{m}^3$)			Method 2		Method 3		Method 4	
		Range	Mean	Median	R ²	RMSE	R ²	RMSE	R ²	RMSE
First Quartile	1799	1.3–2.9	2.0	1.9	0.26	0.49	0.25	0.49	0.26	0.49
Second Quartile	1629	2.9–6.3	4.4	4.6	0.45	0.80	0.42	0.82	0.45	0.80
Third Quartile	1746	6.3–11.4	8.7	8.7	0.66	0.85	0.67	0.85	0.67	0.84
Fourth Quartile	1715	11.4–46.8	16.1	14.8	0.92	1.21	0.93	1.20	0.93	1.20
Overall	6889	1.3–46.8	7.8	6.3	0.97	1.06	0.97	1.04	0.97	1.05

Note. All Method 1 eBC exposures were stratified into four quartiles; corresponding data for Methods 2–4 were placed in the matching quartile regardless of concentration level.

RMSE represents the root mean square error between the averaged Method 1 and Method 2, 3, and 4 measures.

The adjusted R² values represent the percentage of the variation in Method 1 measures that is explained by Method 2–4 measures.

values estimated from session-specific lab blank filter scans or the average of unloaded filter scans (Presler-Jur et al. 2017) versus the true I_0 value estimated by scanning the filter media before sampling. Our LoD analyses suggest that there is less variance in ATN units when the field blank was compared to itself (within-filter variance) than when it was compared to lab blanks or an average of unloaded filter scans (between-filter variance). Our current findings provide further empirical evidence that conducting pre-sample analysis of filter media allows us to account for the variability in transmittance between individual Teflon filters (Presler-Jur et al. 2017), resulting in more accurate representations of I_0 values and lower LoDs. We observed consistent overreporting of eBC exposures for all alternative methods of I_0 estimation, relative to Method 1. We also observed the relationships between Method 1 and all other methods to be moderate to strong across most exposures; however, these relationships were weak in the lowest eBC exposure quartile range.

To the best of our knowledge, the current study is the first field-based study to compare eBC estimations using pre-sampled (Method 1) versus session-specific lab blanks, an average of unloaded filters, or an average of lab blanks (Methods 2–4) as a reference for the absorbance of post-sampled Teflon filters. Our findings have important implications for future studies in LMICs, like cookstove intervention trials, that may aim to accurately characterize personal BC across a wide range of exposures. In instances where intervention programs are conducted by institutions with limited resources, Methods 2–4 provide a way to employ about half the laboratory labor hours as Method 1. However, the additional step of conducting pre-sample filter scans reduces the measurement error by accounting for the inherent variability between Teflon filters, thereby providing more accurate representations of I_0 values and subsequent eBC concentrations.

The added accuracy of eBC measures using Method 1 may allow future studies to more accurately estimate coefficients of health risk associated

with exposure to BC, since exposure misclassification can bias exposure-response relationships toward the null (Armstrong 1998; Kim et al. 2011). Some exposure-response studies in high-income countries comparing the magnitude of associations for BC and $\text{PM}_{2.5}$ with various cardiovascular health endpoints (Luben et al. 2017; Kirrane et al. 2019) found no difference between the two pollutants, while others in LMICs have reported stronger associations for BC, relative to $\text{PM}_{2.5}$, with blood inflammatory markers (Fandiño-Del-Rio et al. 2021), blood pressure (Baumgartner et al. 2014), and adverse birth outcomes (Balakrishnan et al. 2023). Moreover, constituents of $\text{PM}_{2.5}$, like BC, inherently have greater measurement error than $\text{PM}_{2.5}$ itself (Clougherty et al. 2008; Mostofsky et al. 2012), which can further obscure the true relative strength of each pollutant as an indicator for health risks. Therefore, further improvements in the accuracy of eBC measurements, particularly at the lower end of exposure levels, may allow future epidemiological studies to adequately elucidate the role that co-pollutant confounding plays when comparing health risk effect estimates for BC and $\text{PM}_{2.5}$ exposures.

Study limitations

Our filter-based optical method for estimating BC assesses the presence of light-absorbing carbon particles in totality. As such, our results may be impacted by the following artifacts: light scattering from the filter substrate, as well as the filter loading effect and light scattering effect as particles are accumulated onto the sample filter. The light scattering from the filter may enhance light attenuation (i.e., overestimation of eBC) by directing light away from the sensor and increasing the optical path, and is typically a function of the instrument and filter material (Clarke 1982); Tami C. (Bond et al. 1999; Zhang et al. 2023). Thus, this artifact likely does not impact our results, as we performed a comparison of eBC measures within the same instrument.

The filter loading effect, on the other hand, may result in an underestimation of eBC that is positively correlated to the number of particles deposited onto the filter (Drinovec et al. 2015). Interestingly, comparisons of the filter loading effect models reported in the literature suggest that eBC concentrations can be underestimated by as much as 30% to 40% for ATN values up to 120 (Drinovec et al. 2015). However, findings from other studies suggest that the impacts of the filter loading effect are minimal for data restricted to $ATN < 300$ (Gundel et al. 1984; Greilinger et al. 2019). Here, we applied the manufacturer's recommendation and restricted the dataset to $ATN < 125$. Therefore, we suspect that the filter loading effect did not substantially impact our results, especially since we found major between-method differences in eBC concentrations when concentrations were in the lowest quartile range.

Furthermore, aerosol particles potentially contain non-BC substances, such as organic carbon (OC)—also referred to as brown carbon or BrC—which have light-absorbing and/or light-scattering properties that can interfere with the light-absorbing properties of BC. For instance, BrC can absorb light in the red and near-infrared spectral region (Hoffer et al. 2017), which can lead to an overestimation of BC or EC by approximately 2–3 fold using optical instruments (Tasoglou et al. 2018). However, the light-absorbing contribution of BrC is likely minimal at 880 nm (i.e., the wavelength used for the Sootscan OT21 used in the current study), as BrC particles produced a signal that was only 2% of eBC measured at 880 nm but was up to 20% of eBC measured at 370 nm (Grimes and Dickerson 2021). In addition, in the current study and for all HAPIN studies detailing BC exposures, we did not adjust for the proposed reduction in measurement sensitivity due to the light scattered by the filter-particle matrix as more particles are embedded onto the filter (Drinovec et al. 2017; Good et al. 2017). According to Zhang et al. (2023), this particle light scattering effect may be “disregarded as it is much smaller compared to biases caused by other effects” (Zhang et al. 2023, 15). Even still, special considerations should be taken when characterizing BC with optical instruments in health and climate change studies. Future studies that assess non-BC constituents in biomass cookstove emissions are needed to understand the relative contributions of both inorganic and organic carbon compounds to human health risks.

Conclusion

The study provides the first field-based comparison of eBC measures using filter-specific I_0 values versus

those using lab blanks or the average unloaded filters. Through LoD analyses, we provide evidence that the variation in light transmission between unloaded filters is greater than that within the same filter. Our results suggest that eBC measurements from archived filters are sufficient in most settings. However, the additional step of analyzing Teflon filter media before sampling adds appreciably to the accuracy of BC estimation in low-emission settings. Therefore, we recommend using filter-specific I_0 values for BC estimations, especially in studies that seek to accurately characterize exposure contrasts from cookstove interventions that aim to improve health.

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The study protocol has been reviewed and approved by institutional review boards (IRBs) or Ethics Committees at Emory University (00089799), Johns Hopkins University (00007403), Sri Ramachandra Institute of Higher Education and Research (IEC-N1/16/JUL/54/49) and the Indian Council of Medical Research – Health Ministry Screening Committee (5/8/4-30/Env)/Indo-US/2016-NCD-I), Universidad del Valle de Guatemala (146-08-2016) and Guatemalan Ministry of Health National Ethics Committee (11-2016), Asociación Beneficia PRISMA (CE2981.17), the London School of Hygiene and Tropical Medicine (11664-5) and the Rwandan National Ethics Committee (No.357/RNEC/2018), and Washington University in St. Louis (201611159). The study has been registered with ClinicalTrials.gov (Identifier NCT02944682). No authors have any competing interests to disclose.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The data that support the findings in this study will be available upon request.

Disclosure

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