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Evaluation of Three Low-Cost Particulate Matter (PM2.5) Sensors for Ambient and High Exposure Conditions in Arba Minch, Ethiopia

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ABSTRACT

The burden of disease from ambient and indoor air pollution is highest in low-income countries, while their resources for monitoring air pollutants are the lowest. PM2.5 is the primary indicator of air pollution. Reference monitors of PM2.5 are expensive, but there is an increased use of low-cost sensors (LCS). Three LCS, the UCB-PATS+ (PATS), Airvisual Pro (IQAV) and Sensirion SPS30 (SPSA) are being used in Arba Minch, Ethiopia, but their quality has not yet been evaluated under circumstances common to low-income countries, and the variety of metrics used in evaluation studies make comparisons difficult. This study aims to evaluate the three LCS under circumstances encountered in Arba Minch, with metrics commonly used and officially prescribed. Measurements were conducted with the LCS at 2 ambient and 4 high exposure (kitchen) concentrations, and at four of those locations with the gravimetric reference method as well. The quality of the three LCS was evaluated *within* identical, with *reference*, and *between* different types, with commonly reported (regression slope and R^2) and officially prescribed (Pearson correlation, bias, accuracy, expanded uncertainty) metrics. The SPSA has low *within* variation in both ambient and high-exposure situations, meets official requirements compared to the *reference*, and shows a stable bias across different time and concentration levels. The IQAV and PATS *within* variations are not up to official standards but show strong linear associations. The IQAVs as a group, and PATSs individually, meet official *reference* requirements at daily level. *Between* comparison reveals that all LCS show strong linear associations even at 10-minute average level. For SPSA the association is similar across all ranges, and for the others the association is strong when different ranges are taken into account. Generally, all LCS are a good alternative for expensive reference methods. The strong linear associations suggest the possibility of correcting LCS measurement data based on other studies' results and based on other LCS, across different concentration ranges. Projects with a budget of $600 can already supply 10 measurement locations. Higher-budget projects can contribute to the quality of low-budget projects when they do not only use expensive monitors, but also LCS at the same location.

Keywords: Airvisual Pro, ambient air pollution, indoor air pollution, low-cost sensors, low- income countries, PM2.5, quality evaluation, UCB-PATS+, SPS30

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1. INTRODUCTION

Air pollution is one of the top of factors that adversely affects people's health (Babatola, 2018; Gakidou et al., 2017; Shaddick et al., 2018). An estimated 4.2 and 3.2 million premature deaths per year are attributed to ambient (outdoor) and indoor air pollution, respectively (World Health Organization, 2021b, 2022). A common proxy for air pollution, and the pollutant with most health effects, is particulate matter, specifically particles with a diameter of less than 2.5 µm (PM2.5) (World Health Organization, 2021b). The reference method for monitoring PM2.5 is filter-based gravimetry. This method typically assesses concentrations on a 24-hour average level (EPA, 2006; European Commission, 2010), and is associated with high operating costs (Sousan et al., 2021). There are various continuous monitors (monitoring concentrations at hour- or even second level) that are recognized as equivalent to the reference method. These are also expensive, as they cost $11,500-30,000 per monitor (Mooney et al., 2006). In recent years, there has been an increase in the use of low-cost sensors (LCS) (Sousan et al., 2021). This trend is of utmost importance for low-income countries, where both the burden of disease is high (World Health Organization, 2021b, 2022), and the resources for PM2.5 monitoring instruments are low.

Three PM2.5 LCS (IQAir Airvisual Pro (IQAV), UCB-PATS+ (PATS) and Sensirion SPS30 (SPSA)) have been used for published (Dingemanse et al., 2022; Dingemanse & Dingemanse-de Wit, 2022) and ongoing research projects in Arba Minch. The quality of these LCS have been the subject of different studies. For PATS, Pillarisetti et al. (2017) reported an ordinary regression result of R^2 of 0.90 (slope 1.5) in comparison with the reference method. Also, they reported an R^2 of 0.90 (slopes 1.7 – 4.8) in comparison with a continuous monitor, and an R^2 of 0.96 (slope 0.92) between two identical PATSs., At a non-smoking residence in the United States, Zamora et al. (2020) found an R^2 of 0.90 in comparison with a gravimetrically corrected continuous monitor, and an R^2 of 0.99 between two IQAV units. Under ambient conditions, Feenstra et al. (2019) reported an R^2 of 0.7 with slopes of 0.76-0.87 for the IQAV in comparison with a continuous monitor. Under laboratory conditions, Sousan et al (2021) found Pearson correlations of 0.99 between SPSA and a gravimetrically corrected continuous monitor, with slopes of 0.7 to 2 depending on the particle type, and a variation between identical sensors of 5-20%. Also under laboratory conditions, Nguyen et al. (2021) found an error of 2.7% for the SPSA in comparison with a continuous monitor at a range of 0-25 µg/m^3, and an error of 16-26% between 50-1,000 µg/m^3. Based on ambient field measurements, Falzone et al. (2020) reported expanded uncertainties lower than European requirements of 25% for the SPSA.

Quality evaluations usually include a comparison of identical LCS and/or a comparison with the reference method or a continuous monitor. The quality of LCS is evaluated with a variety of metrics. Most reported is the R^2, with corresponding slope and/or intercept from a regression (Karagulian et al., 2019). From a combination of several studies, Karagulian et al. (2019) use an R^2 of at least 0.75 together with a slope close to 1 to select the best performing LCS. While this metric indicates the strength of association between two variables, it is not necessarily the best indicator of data quality (Karagulian et al., 2019). Official guidelines for testing the equivalence of PM2.5 measurement methods have been made by the Environmental Protection Agency of the United States of America (EPA) (EPA, 2006), the National Institute for Occupational Safety and health (NIOSH) (NIOSH, 2012), and by the European Commission in the Guide to the Demonstration of Equivalence of Ambient Air Monitoring Methods (DEM) (European Commission, 2010). For identical instruments, EPA and NIOSH require a Coefficient of Variation (CV) of +- 10%, while the DEM requires an in-between sampler uncertainty of maximum 2.5 µg/m^3. For comparison with the reference method, EPA uses the Pearson correlation (r, >=0.97), a slope of 1±0.1 and an intercept of ±5 µg/m^3. The NIOSH requires an accuracy of 25% at 95% confidence level in comparison with the reference method and prescribes correction of the data if the absolute bias is >10%. Like NIOSH, the DEM has set the required uncertainty at 25%, but prescribes detailed formulas for calculating this uncertainty based on orthogonal regression and requires an evaluation of this uncertainty at a concentration level of 30 µg/m^3. Data correction is prescribed for slope and/or intercept if those are significantly different from 1 or 0, respectively.

The LCS quality evaluation can be done under various concentration levels. Typical PM2.5 concentration ranges used for ambient testing are 0-40 µg/m^3 (Falzone et al., 2020; Sousan et al., 2021). Indoor or occupational concentrations can be over 2,000 µg/m^3 (Sousan et al., 2021). EPA guidelines and the DEM are for ambient monitoring, which can be seen from the slope +- 5 µg/m^3, in-between uncertainty of 2.5 µg/m^3 and evaluation of uncertainty at concentration level of 30 µg/m^3. The requirements of NIOSH are not specific to a concentration level (both in-between sampler comparison and accuracy versus the reference method is set at a relative percentage). While a sensor preferably reacts the same under different circumstances, in reality studies find different slopes or correction factors for different concentration levels (Falzone et al., 2020; Nguyen et al., 2021) and particle types (Sousan et al., 2021).

Quality evaluation can also be done on different time periods. Both EPA and the DEM require an evaluation at 24-hour average level. This corresponds with the short-term 24-hour average air quality standard (World Health Organization, 2021a) and matches with the usual time needed to get sufficient filter load for the reference method. Continuous monitors, and LCS alike, can report concentrations at time periods of 1 second. Studies that evaluate LCS at time levels lower than 24-hour use continuous monitors calibrated by the gravimetric reference method as 'reference' (Karagulian et al., 2019), or simply use a continuous monitor as it is (Pillarisetti et al., 2017).

The circumstances and metrics used in LCS quality evaluations do not yet cover the situation encountered in low-income countries. The PATS shows different slopes for different situations (Pillarisetti et al., 2017), warranting its own quality evaluation. The IQAV has been validated only in high-income countries, where 'common residential sources' do not include cooking on biomass or coffee ceremony, old cars, or open waste burning. For high concentrations, the SPSA is evaluated up to 1,200 µg/m^3 PM2.5 under laboratory circumstances (Nguyen et al., 2021; Sousan et al., 2021). However, concentration levels in indoor air pollution field circumstances in low-income countries can be much higher than 1,200 µg/m^3 (Dingemanse et al., 2022). For the SPSA, under ambient concentrations, different results for two different locations in Belgium are reached (Falzone et al., 2020), and again those are not the ambient circumstances encountered in Ethiopia. Finally, the evaluations of LCS are conducted with a variety of metrics, time averaging periods and concentration ranges, which makes comparison hard. In this study, I present an evaluation of those LCS, based on data gathered in different ongoing research projects in Arba Minch, Ethiopia, with an extensive use of available metrics, time periods and concentration ranges.

The main objective of this study is to evaluate the quality of the IQAir Airvisual Pro, UCB-PATS+, and Sensirion SPS30 under field circumstances common to low-income countries, based on data gathered in ongoing research projects in Arba Minch, Ethiopia. The evaluation consists of three parts:

- A comparison of identical LCS (*within* comparison);
- A comparison of LCS with the gravimetric reference method (*reference* comparison);
- A comparison amongst different LCS (*between* comparison).

2. MATERIALS AND METHODS

2.1 Study area

Arba Minch town is the administrative center of Gamo Zone, which is one of 14 Zones in the Southern Nations, Nationalities and People's Regional State (SNNPR) of Ethiopia. Three LCS are used in (ongoing) research projects in Arba Minch, Ethiopia. Students have conducted measurements in indoor and ambient situations (Dingemanse et al., 2022; Dingemanse & Dingemanse-de Wit, 2022). At different locations, parallel measurements with multiple instruments have been conducted for quality evaluations. For this study, data from six locations was used: two ambient locations and four restaurant / kitchen locations. The two ambient locations represented low and medium ambient concentrations (in front of a residence in a low-traffic area, and at a hotel compound close to the road in the city center). The four kitchen locations represented high concentrations encountered owing to cooking or coffee preparation with biomass fuel. One location was in a small local restaurant, in a room with coffee preparation and next to a kitchen with biomass fuel cooking. Another location was in the kitchen of a small restaurant with biomass fuel cooking. The two final locations were both in a big kitchen with multiple (>5) cooking fires. While in the same kitchen, the two locations considered different. This is because the instruments were placed at separate locations in the kitchen, and cooking fires closest to those locations were used at different moments, resulting in different concentration patterns. Table 1 gives an overview of the six locations and the instruments used at those locations.

Table 1. Measurement locations, with their LCS and number of reference measurements (n_{ref}). IQAV, PATS and SPSA LCS are identified as respectively Iq_X, Pa_X and Sp_X, in which x denotes the instrument's number.

Location	ID	Air pollution sources	LCS	n_{ref}
Residence	A1	Neighborhood	Sp1, Sp2, Sp4, Iq1	
Hotel	A2	Traffic, neighborhood	Sp3, Sp5, Iq2	3
Local restaurant	K1	Cooking fires, coffee preparation	Sp2, Iq5	
Kitchen 1	K2	Cooking fires	Sp4, Iq3	3
Kitchen 2a	K3	Cooking fires	Sp6-7, Iq3-5, Pa1, Pa3-4	8
Kitchen 2b	K4	Cooking fires	Sp8-9, Iq6-8, Pa2, Pa5-6	4

2.2 Materials

2.2.1 LCS

This study evaluated three LCS: the UCB-PATS+ (PATS), the Airvisual Pro (IQAV) and the Sensirion SPS30 (SPSA). Individual LCS are coded as Pa1-Pa6, Iq1-Iq8 and Sp1-Sp5, for 6 PATSs, 8 IQAVs and 5 SPSAs, respectively. All three LCS types estimate the PM2.5 concentration based on scattering of IR light (Pillarisetti et al., 2017; Sousan et al., 2021; Zamora et al., 2020). The PATS and IQAV are commercially available 'plug-and-play'-instruments, meaning that the particle sensor is built into a case with other components for data storage and usability. The SPSA is only a particle sensor that needs to be connected to either a computer or a microprocessor together with other components for data storage and access. For this study, data collection with the SPSA was done by connecting it to an Arduino Mega microprocessor, together with a micro-SD module, a DS3231 real-time clock and a power bank. The PATS is designed for personal sampling and (high) indoor concentrations, but not for low ambient concentrations (lower detection limit is 10 µg/m^3). In this study, the PATS was not used at ambient locations A1 and A2. The IQAV is used both in ambient and indoor situations but is not meant for very high concentrations (>5,000 µg/m^3), since the highest reported value of the IQAV is set to 4,488 µg/m^3. On the SPS30, no such minimum or maximum values are set (the sensor needs to be programmed by the user), but the manufacturer specifies a range up to 1,000 µg/m^3. Table 2 gives an overview of the most important characteristics of the three LCS.

Table 2. Specifications for the LCS evaluated in this study

Parameter	PATS	IQAV	SPSA
Name	UCB-PATS+	AirVisual Pro	Sensirion SPS30
Range	10-50,0000	0-4,488	0-1,000
Logging interval	>2s	>10s	>1s
Cost ($)	500	269	30[a]
Internal storage	Yes	Yes	No [a]
Internal battery	+36 hours	2-4 hours	No [a]

a. The SPSA needs additional costs for battery and data storage. The total set-up as used in this study has a cost of approximately $60.

2.2.2 Reference instrument

Reference measurement methods for PM2.5 are based on gravimetry. As reference instrument, the Ultrasonic Personal Aerosol Sampler (UPAS) was used, as this instrument was the only available gravimetric instrument in Arba Minch, Ethiopia. The UPAS is a gravimetric instrument designed for measuring medium to high concentrations. . A filter is loaded with particles with a flowrate of 1 l/min. A cyclone ensures that only particles with a diameter smaller than 2.5 µm enter the inlet. Over ranges of 20-1,000 $\mu g/m^3$, Volckens et al. (2017) found strong correlations with the EPA federal reference method. Afshar-Mohajer et al. (2021, p. 131) found that “the UPAS may be a suitable alternative for [Respiratory Dust] mass sampling” for ranges of 100-500 $\mu g/m^3$ in occupational settings. For gravimetric analysis of the filters, a Mettler AE240 Dual Range balance was used, having a readability of 10 µg and a reproducibility of ±20 µg (IET, n.d.).

2.3 Methods

2.3.1 LCS measurements

All instruments were fixed at 1.5- 2 meters high and connected to a power source. The measurement frequency of the LCS ranged from 10 seconds to 3 minutes. For this study, all data was averaged to 10-minute time periods. Figures A1 and A2 in the Annex show the data availability for all LCS at all locations, as well as the concentration ranges encountered at those locations. At location A2, power was switched off during nighttime. As a result, there was approximately 50% data loss for Iq2 at location A2. At locations A1 and A2 (as reported by the

SPSA), daily averages ranged between 3-30 and 10-50 μg/m^3. 99%-percentile of 10-minute averages were 70 and 107 μg/m^3, respectively. At locations K1 through K4, hourly averages ranged from 2 to higher than 10,000 μg/m^3 for the SPSA. 99% percentile 10-minute averages were 30,000, 13,000, 3,000 and 1,300 μg/m^3, respectively.

2.3.2 Reference measurements

Measurements with the reference instrument were conducted 3 times 48 hours at location A2, and 24-hours (or up to a full filter) 3 times at locations K2, 4 times at K3 (2 instrument) and 4 times at K4. Table 3 shows an overview of the reference measurements.

Table 3. Details of reference measurements conducted at locations A2, K2, K3 and K4, and the LCS at those locations.

No.	Loc.	Start	Duration (hour)	Filter load (μg)	Parallel LCS
1	A2 [a]	'21-10-01 12:19	48	90	Iq1, Sp3, Sp5
2		'21-10-03 12:35	48.3	110	
3		'21-10-06 17:54	47.4	130	
4	K2	'21-10-01 11:38	20	1,460	Iq3, Sp4
5		'21-10-03 12:55	16.4	970	
6		'21-10-04 09:56	20.6	1,390	
7	K3	'22-06-08 15:15	21.3	340	Sp6, Sp7,
8		'22-06-09 13:02	22.1	210	Iq3, Iq4, Iq5,
9		'22-06-13 10:40	23.7	1,130	Pa1, Pa3, Pa4
10		'22-06-14 11:13	23.6	430	
11		'22-06-08 15:12	21.2	350	
12		'22-06-09 13:03	22.1	240	
13		'22-06-13 10:46	23.6	1,130	
14		'22-06-14 11:14	23.6	430	
15	K4	'22-06-08 15:10	21.4	500	Sp8, Sp9,
16		'22-06-09 13:22	21.9	320	Iq6, Iq7, Iq8,
17		'22-06-13 10:59	23.5	610	Pa2, Pa5, Pa6
18		'22-06-14 11:05	24.0	560	

a. Only three filter comparisons are available at A2, and these should be seen as indicative, as the instrument in combination with the available analytical scale is not designed for such low concentrations. Even with 48-hour use, the filter load is only 90-130 μg, which with a repeatability of 20 μg gives an uncertainty of 15-22% for only the gravimetric analysis.

2.4 Data corrections

Between ’21-10-05 and ’22-03-05 Sp1 at location A reported the time with a 1-to-5-hour delay. This data was shifted based on visual inspection of the daily morning and afternoon concentration peaks.

The DEM allows for removal of up to 2.5% percent of outliers based on Grubb’s outlier test at 99% level (European Commission, 2010). This outlier removal was done for Sp3 and Sp5 at location A2.

Only for purpose of the comparison with the reference method at location A2, the missing data of Iq1 was filled by data from Sp3. The slope resulting from orthogonal regression techniques as prescribed in the DEM, based on available data pairs between Sp3 and Iq1, was used to predict the missing data of Iq1 missing data based on data of Sp3.

At locations K3 and K4, there was data loss during the reference measurements. LCS results with more than 15% data loss during measurements with the reference method are not used in the reference comparison.

2.5 Quality evaluation

2.5.1 Within comparison

To compare identical samplers, the linear association was quantified with the slope (S) resulting from Ordinary Least Squares (OLS) regression without intercept, and the corresponding coefficient of determination (R^2). Furthermore, the coefficient of variation (CV) and in-between sampler uncertainty (u_{bs}) were calculated.

The **Coefficient of Variation** (CV) was calculated with equation 1 (Sousan et al., 2016):

$$CV = \frac{1}{n}\sum\frac{\sigma_i}{\mu_i} \quad (1)$$

Where, σ_i is the standard deviation and μ_i is the mean of measurements of identical LCS during time period i, and n is the number of time periods.

The **in-between sampler uncertainty** (u_{bs}) was calculated with equation 2 (European Commission, 2010):

$$u_{bs} = \sqrt{\frac{\sum(y_{i,1}-y_{i,2})^2}{2n}} \qquad (2)$$

Where, $y_{i,1}$ and $y_{i,2}$ are the results of parallel measurements for time period i, and n is the number of time periods.

2.5.2 Reference comparison

Pearson correlation coefficient (r), slope (S) and corresponding R^2 based on OLS regression without intercept, accuracy, bias and expanded uncertainty were computed to for the comparison with the reference instrument.

EPA has requirements concerning slope and intercept. In all situations, the regression of slope without intercept yielded either a higher R^2 than the R^2 for regression with intercept, or a very high R^2 (>=0.97). Therefore, for this study only results for regressions without intercept were included. The **bias** (B) was calculated with equation 3 (NIOSH, 2012):

$$B = \frac{1}{n}\sum\left(\frac{x_i}{y_i} - 1\right) \qquad (3)$$

Where, x_i is the concentration of the LCS and y_i the concentration of the reference instrument for time period i, and n is the number of time periods.

The **accuracy** (Ac) is "the theoretical maximum error of the measurement, expressed as the proportion or percentage of the amount being measured, without regard for the direction of the error, which is achieved with 0.95 probability" (NIOSH, 2012, p. 3). The accuracy should be lower than 25%. The accuracy was calculated as the upper value of the confidence interval at 90% of the relative difference between the LCS measurement reference measurement. For this, all $\frac{x_i}{y_i}$ values were calculated, and the confidence interval at 90% was calculated based on these values.

If |B| is higher than 10%, NIOSH prescribes to correct the bias in the data. Equation 4 was used for calculating corrected data x_{new} based on the old data x_{old}.

$$x_{new} = \frac{x_{old}}{B+1} \quad (4)$$

The names $Ac_{\_BC}$ and $Ac_{\_AC}$ were used to distinguish between accuracy before and after correction, respectively.

The expanded uncertainty (W_{CM}) of the LCS versus the reference instrument is calculated at a level of 30 µg/m^3, and should be maximum 25% (European Commission, 2010). A linear relationship between the LCS and reference data is assumed. For establishing this linear relationship, algorithms of orthogonal regression should be used. If slopes are significantly different from 1, and/or the intercept is significantly different from 0, the DEM prescribes to correct the data for this slope and/or intercept. Formulas are extensively shown in the DEM (DEM section 9.5 and DEM Appendix B). To distinguish between W_{CM} before and after correction, the names W_{CM_BC} and W_{CM_AC} were used, respectively. In all data comparisons conducted in this study, the slope without intercept was significant. For that reason, all reported W_{CM_AC} were based on correction for slope only.

2.5.3 Between comparison

For comparison of different LCS, accuracy and expanded uncertainty were used to quantify the degree of equivalence. W_{CM} is used at a level of 30 µg/m^3 with averages of 24-hour time-periods (European Commission, 2010). Therefore, this metric was used for comparing 24-hour averaged data of LCS at ambient locations (A1 and A2). The accuracy was used as metric for all comparisons at the high-exposure locations (K1-K4) and for all comparisons of averages over time periods smaller than 24 hours. Additionally, for comparability with other studies, R^2 for OLS regression without intercept has been calculated.

2.5.4 Quality evaluation summary

Table 4 gives a summary of the quality evaluation metrics used in this study.

Table 4. Summary of quality metrics used for evaluating LCS measurement results.

Evaluation	Metric	Locations	Reference	Score / requirement
Within LCS	S & R^2	All	Often used	R^2>0.75 at least; R^2>0.9 'very good'
	CV	All	EPA, NIOSH	<10%
	u_{bs}	A1, A2	DEM	<2.5 μg/m^3
Reference	r	All	EPA	>0.97
	S	All	EPA	1±0.1
	R^2	All	Often used	R^2>0.75 at least; R^2>0.9 'very good'
	B & Ac	All	NIOSH	Correction if |B|>10%, Ac<25%
	W_{CM}	A2	DEM	Correction for slope, W_{CM}<25%
Between LCS	S & R^2	All	Often used	R^2>0.75 at least; R^2>0.9 'very good'
	W_{CM}	A1, A2	[a]	Correction for slope, W_{CM}<25%
	B & Ac	All	[a]	Correction for B, Ac<25%

a. There is no official reference for quality metrics of LCS inter-comparison, because technically even if there is big difference, it is not known which of the LCS is right. Nevertheless, the W_{CM} and accuracy metrics of EGDE and NIOSH are used to express the agreement between two different LCS.

2.6 Data processing software

All data processing and visualization was done with Python 3.8 (Python Core Team, 2020), with the packages Numpy (Harris et al., 2020), Pandas (The pandas development team, 2020), Matplotlib (Hunter, 2007) and Scipy (Virtanen et al., 2020). All data used and code created in this study is made available on the OSF repository, *https://doi.org/10.17605/OSF.IO/YTV79*.

3. RESULTS

3.1 Within comparison

Figure 1 shows the slopes of regressions without intercept and corresponding R^2 values for one LCS versus one or more identical LCS.

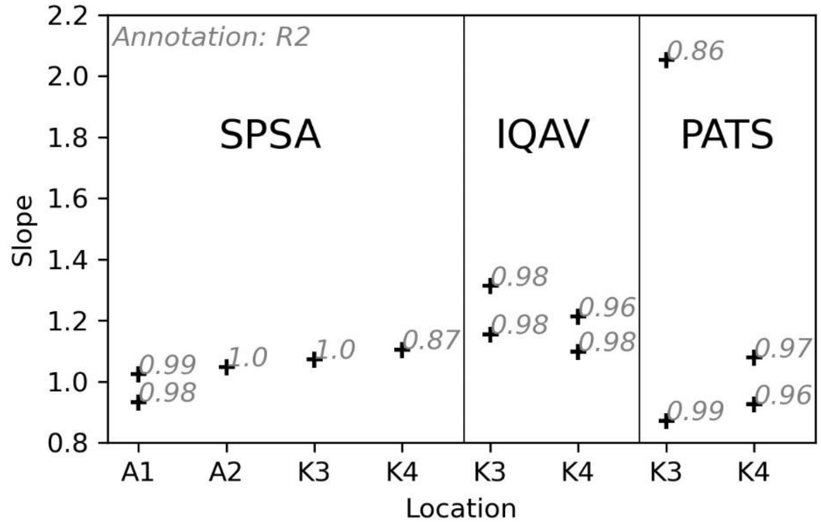

Figure 1. Slopes, annotated with corresponding R2s, between identical LCS at all measurement locations. For locations with three identical LCS, two slopes are shown (instrument 1 vs 2 and instrument 1 vs 3).

Slopes of the SPSA were close to 1, ranging from 0.93 to 1.10. This implies that the different SPSAs showed a similar signal. Identical IQAVs showed higher variation (slopes 1.10-1.31). The PATS at location K4 showed also relatively small slopes (0.93-1.08), but at K3 variation between identical PATSs was high (slopes 0.87-2.05). R^2s were generally very good, except for the SPSA at location K4 (0.87) and one PATS at K3 (0.86).

Similar results can be seen from the CV and u_{bs}. Figure 2 shows the CV for all locations, and the u_{bs} for only ambient locations.

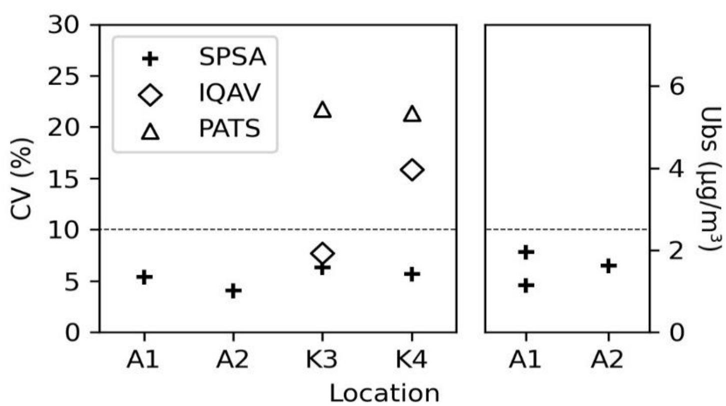

Figure 2. Coefficient of variation (CV) and in-between sampler uncertainty (ubs) for the LCS at different locations.

At all locations, the CV of the SPSA was lower than the required 10%.At the ambient locations, the u_{bs} was lower than the required 2.5 µg/m^3. The IQAV at K4 showed higher variation (CV 16%) while the PATS showed high variation at both kitchen locations (22 and 21%). This implies that those individual sensors might require separate calibrations.

3.2 Reference comparison

Figure 3 shows all filter measurement results with averages of parallel LCS measurements during the same time period.

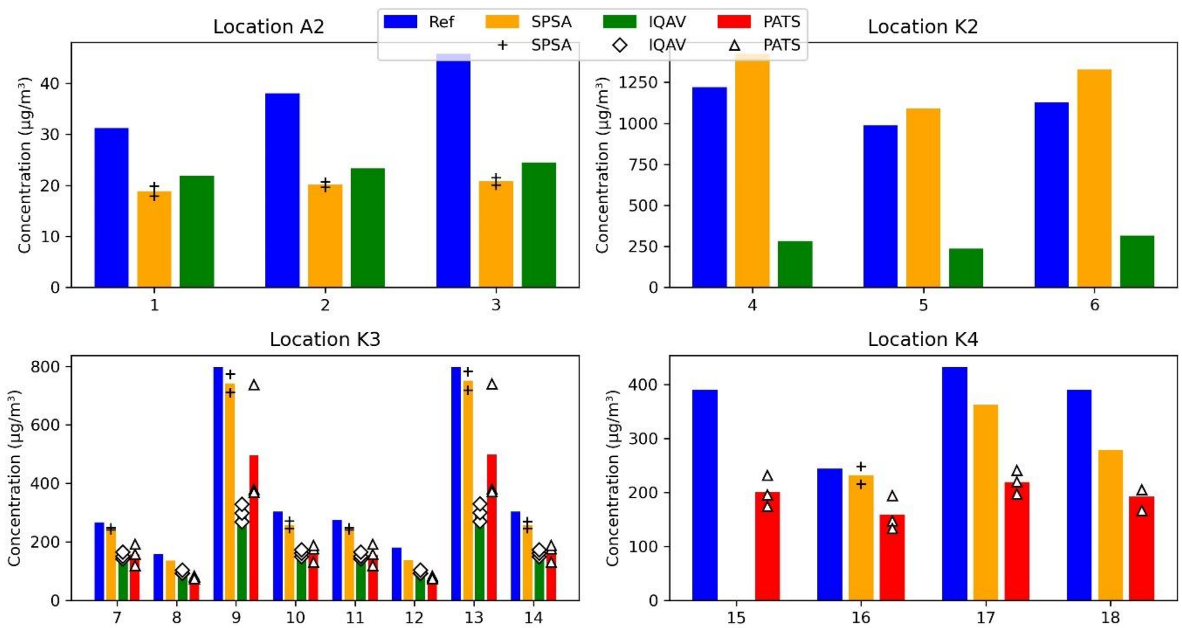

Figure 3. PM2.5 measurement results for all 18 reference measurements and parallel LCS measurements. With multiple identical LCS, results are shown with markers, and average results are shown with bar.

Filter measurement results at location A2 ranged from 31-46 µg/m^3. Filter measurements at the kitchen locations ranged from 158 to 1,220 µg/m^3. Table 5 shows the quality evaluation for individual instruments and groups of identical instruments at location A2.

Table 5. For location A2, the number of data pairs (n), and results for quality metrics in the comparison of LCS with the reference method.

LCS	n	r	S, R^2	$Acc_{\_BC}$	B	$Acc_{\_AC}$	W_{cm_BC}	W_{cm_AC}
Sp3	3	0.93	2, 0.99	60	-0.49	21	542	38
Sp5	3	1.00	1.9, 0.98	59	-0.45	24	614	42
Sp3,5	6	0.70	1.9, 0.98	53	-0.47	16	567	27
Iq1	3	0.99	1.7, 0.99	52	-0.38	22	306	37

Pearson correlations between individual LCS and the reference method were good (>0.93), but were lower when all SPSA measurements were combined (0.7). Interestingly, all R^2 values were very high (>0.98). The slopes and biases showed the need for corrections (LCS results were lower than reference results), but after bias correction, all LCS reached the required 25% accuracy (16-24%). The best accuracy was reached when all data of the SPSA were combined. This combination was also the only dataset that came close to the requirement of W_{CM} (25%).

Table 6 shows the quality evaluation at locations K2-K4. Results are shown for individual LCS, combinations of identical LCS at the same locations, and combinations of identical LCS across all kitchen locations.

Table 6. The number of data pairs (n), and results for quality metrics in the comparison of LCS with the reference method.

Location	LCS	n	r	S, R^2	$Ac_{\_BC}$	Bias	$Ac_{\_AC}$
K2	Sp4	3	0.99	0.9, 1	22	0.15	5
	Iq3	3	0.69	4, 0.99	79	-0.75	14
K3	Sp6	8	1.00	1.1, 1	18	-0.15	7
	Sp7	6	1.00	1, 1	10	-0.07	
	Sp6,7	14	1.00	1.1, 1	14	-0.12	7
	Iq3	8	0.99	2.6, 0.96	59	-0.53	22
	Iq4	8	0.99	2.4, 0.97	55	-0.50	19
	Iq5	8	0.99	2.1, 0.97	51	-0.45	19
	Iq3-5	24	0.97	2.3, 0.96	52	-0.49	17
	Pa1	8	0.99	2, 0.99	50	-0.47	12

Location	LCS	n	r	S, R^2	$Ac_{\_BC}$	Bias	$Ac_{\_AC}$
	Pa3	8	1.00	1.1, 0.98	44	-0.32	30
	Pa4	8	1.00	2.2, 1	57	-0.56	6
	Pa1,3,4	24	0.88	1.5, 0.9	50	-0.45	26
K4	Sp8	3	0.93	1.2, 0.99	34	-0.19	15
	Sp9	1					
	Sp8,9	4	0.90	1.2, 0.99	28	-0.14	20
	Pa2	4	0.96	1.8, 1	50	-0.45	11
	Pa5	4	0.96	2.2, 1	59	-0.53	15
	Pa6	4	0.73	1.7, 0.98	55	-0.39	30
	Pa2,5,6	12	0.69	1.9, 0.98	51	-0.46	19
K2-4	Sp6-9	21	0.99	1, 0.98	15	-0.08	
K2,4	Iq3-5	27	0.91	2.7, 0.92	56	-0.52	25
K3,4	Pa1-6	36	0.87	1.6, 0.92	49	-0.45	22

Pearson correlations were good (>0.9) in all cases, except for Iq3 at K2 (0.69), all PATSs combined at K3 (0.88), Pa6 at K4 (0.69) and all PATSs of all locations (0.87). The EPA requirement (>0.97) was met by multiple LCS, and most notably by the combination of all SPSA across all kitchens. This implies that the relationship between the SPSA and the reference was not location dependent. For SPSA, slopes were generally close to 1 (0.9-1.2 for individual, and 1.0 for all combined) with corresponding R^2s >0.98. IQAVs showed slopes of 2-4 while the PATSs showed slopes of 1.1-2.2. When corrected for the bias, almost all LCS reached the required accuracy of 25%. The required accuracy was not reached by Pa3 (30%), the combination of PATSs at K3 (26%) and Pa6 (30%). All SPSAs combined did not require bias correction because |B|<10% (-8%).

Generally, all LCS had a good to very good correlation with the gravimetric reference method, and with corrections requirements could be met. The SPSA needed the least correction, while the PATSs needed correction on an individual level. In other words, similar SPSA results under different circumstances can be readily compared, while PATS results need to be handled individually. Interestingly, the quality evaluation showed that the IQAV with a correction factor can give trustworthy results at a daily basis even if the IQAV is not designed for the high circumstances encountered in K2-K4 (concentrations at raw-data level often exceeded the maximum of 4,488 µg/m^3).

3.3 Between comparison

3.3.1 Ambient locations

Figure 4 shows the comparison of daily averaged concentrations between different LCS at the ambient locations, expressed in W_{CM_AC}, and R^2 of OLS regression without intercept.

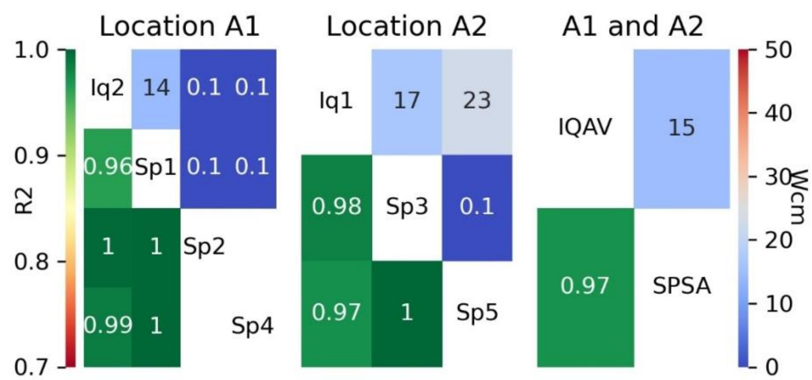

Figure 4. Comparison between individual LCS at locations A1 (left panel) and location A2 (middle panel), and all available data pairs between any IQAV and SPSA at either location (right panel). Wcm_AC and R^2 are in each panel shown respectively top right and bottom left

With R^2s of 0.96 or higher, the linear association between the SPSAs and IQAVs was strong. The comparison also met the required W_{CM_AC} of 25% both for individual LCS, and all data pairs of all LCS from the two locations combined (W_{CM_AC}=15%).

The association was also strong at lower time-averaging levels. Figure 5 shows the biases and accuracies for individual SPSAs and all SPSAs combined as X versus one IQAV as Y.

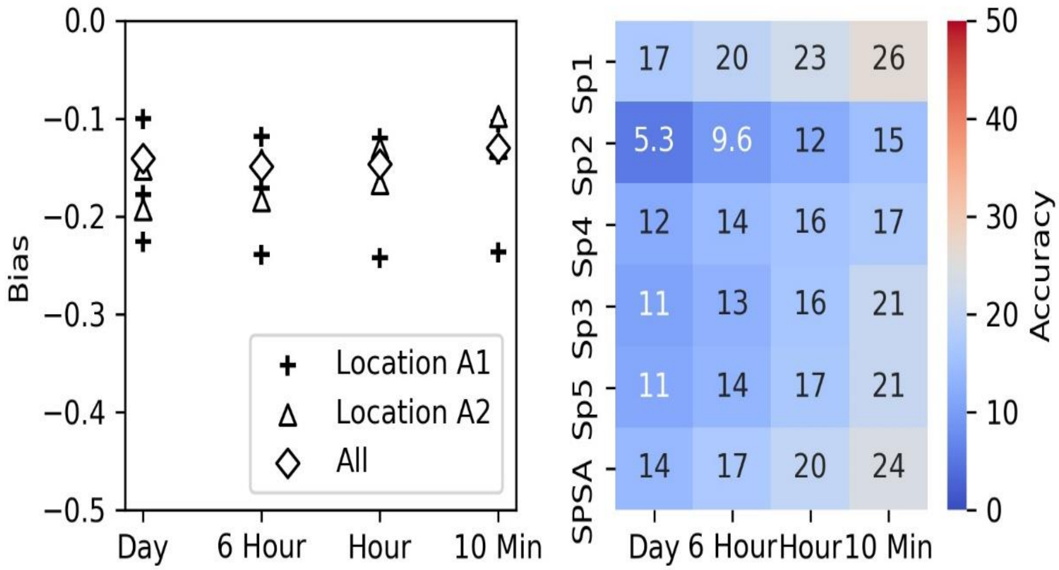

Figure 5. Biases (left panel) and Ac$_{_AC}$ (right panel), for individual SPSA and all SPSA combined compared to an IQAV, at locations A1 and A2. Results are shown for comparisons at four different time averaging periods

The negative bias of SPSA versus IQAV implies that the SPSA was measuring lower than the IQAV (see equation 3). Biases ranged from 10-25%. Corrected for this bias, accuracies ranged from 5.3 to 26%. This is far lower than up to slightly over the required 25%. Furthermore, the bias for all SPSA versus IQAV data pairs remained stable across the different time averages (between 10 and 15%), suggesting a stable relation between the SPSAs and IQAVs. In other words, the SPSA and IQAV units can be used interchangeably, and results can be compared across different ambient concentration ranges and time averaging periods, especially if data is corrected for the bias of 10-15%.

3.3.2 Kitchen locations

Figure 6 shows accuracies and R^2s for all individual LCS compared amongst each other, for daily averaged time periods.

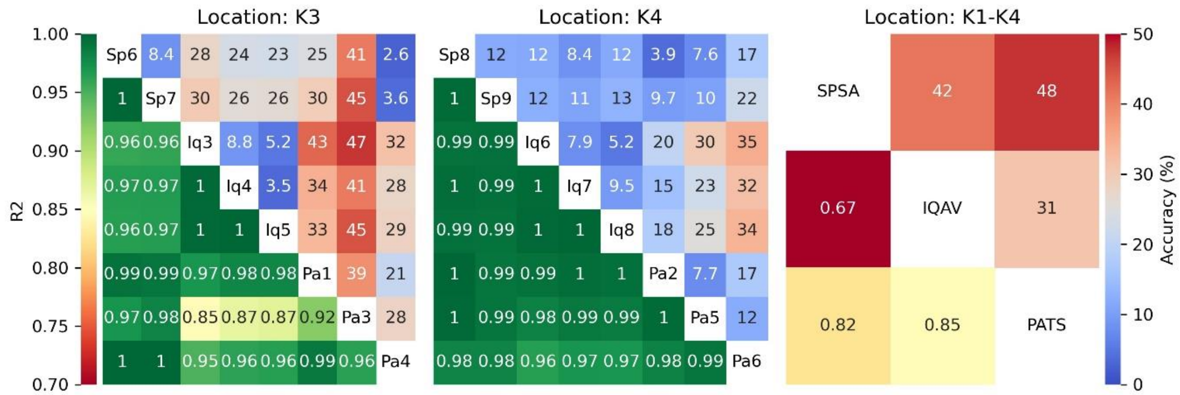

Figure 6. Comparison of daily averaged data of individual LCS at locations K3 (left panel) and location K4 (middle panel), and all available data pairs between any two different LCS at any kitchen location (right panel). $Ac_{\_AC}$ and R^2 are in each panel shown respectively top right and bottom left

Linear associations between individual LCS were very high. The R^2s between PATSs and SPSAs were >0.97, and between IQAVs and SPSAs were >0.96. Only for Pa3 in comparison with IQAVs the R^2s were lower than 0.9 (0.85-0.87). The associations were significantly lower when all data from identical LCS, from any of the kitchen locations, were combined (R^2s of 0.64-0.85). Similarly, on an individual level some instruments showed $Ac_{\_AC}$<25%, but variation for all paired combinations was higher (32-48%). This indicates that different LCS cannot be interchanged with an identical correction across different locations.

The fact that SPSA and PATS were not interchangeable without individual attention, is most likely related to the fact that the PATS sensors individually fell short as well (accuracies between Pa3 and the other two PATSs >25%). The problems of the IQAV are related to the fact that the maximum reported value is set to 4,488 µg/m^3 (while PATS and the SPSA reported raw values of over 50,000 µg/m^3).

The accuracies were worse for a 10-minute averaging level than for a daily averaging level. The underlying reason for this is that biases can be different at different concentration ranges. Concentration variations are more apparent at small time-averaging levels. Figure 7 shows the $Ac_{\_AC}$ for all LCS versus one SPSA at the same location, for different concentration ranges, at a 10-minute averaging level.

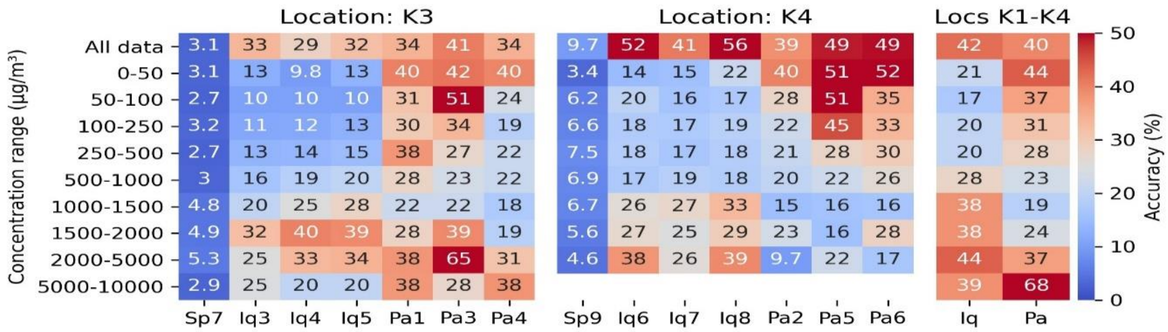

Figure 7. Comparison of daily averaged data of individual LCS versus Sp6 or Sp8 at locations K3 (left panel) and location K4 (middle panel), and all available data pairs between one SPSA and any other LCS type at any kitchen location (right panel). $Ac_{\_AC}$ is shown for different concentration ranges as measured by the SPSA. If $Ac_{\_AC}$ for LCS_i vs LCS_j is different from LCS_j vs LCS_i, the lowest of the two is taken

As expected, when taking all 10-minute averaged data, none of the accuracies of individual LCS versus one SPSA were lower than 25% (29-56%) except for the SPSA itself (3.1-9.7%). However, when looking at specific concentration ranges, there were multiple accuracies lower than 25%. Even when combining all data-pairs across all kitchens, accuracies lower than 25% could be reached for some ranges. This was the case between 0 and 500 µg/m^3 for the IQAV, and between 500 and 2,000 µg/m^3 for the PATS.

These accuracies could be low because each individual dataset was corrected for an individual bias. Figure 8 shows all biases of individual LCS versus an SPSA at the same location in locations K3 and K4.

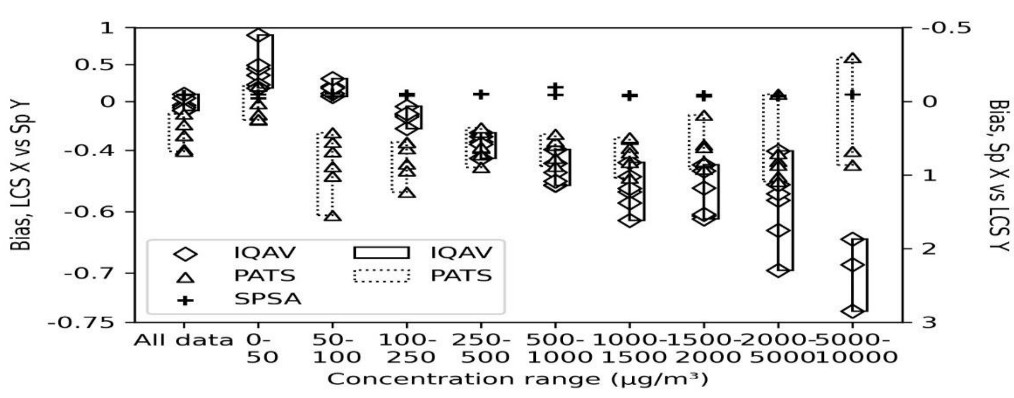

Figure 8. Biases of 10-minute averaged measurement results of individual LCS versus one SPSA, across different concentration ranges. Rectangular bars show the range of the individual biases. From equation 3 it follows that bias B=1 between i and j equals B=-0.5 between j and i. Axes are scaled such that the positive bias of LCS_i vs LCS_j (LCS_i/LCS_j-1) is equally sized to its corresponding negative bias (i.e. the positive bias of LCS_j/LCS_i-1)

The SPSA sensor compared to an identical sensor had a low bias across all concentration ranges. For the IQAV, the bias versus the SPSA sensor differed across ranges. It was close to zero at concentrations of 50-250 µg/m^3, but it increased negatively (measuring increasingly lower than the SPSA) with higher concentrations. The spread in bias for different IQAVs was small for concentration ranges up to 1,000 µg/m^3.That is to say, one correction factor can be used for all identical IQAV. The increasing underestimation with increasing concentrations is because of the IQAV reporting maximum 4,488 µg/m^3. Above the 10-minute averaged 1,000 µg/m^3, at raw-data level there are increasingly concentrations >4,488 µg/m^3, which by the IQAV are simply reported as 4,488 µg/m^3, leading to an increasing underestimation.

For the PATS, the spread of bias was relatively small for concentrations of 50-2,000 µg/m^3. For concentrations of 250-2,500 µg/m^3, the bias was in the same order of magnitude. At concentrations below 50 as well as above 2,000 µg/m^3, the spread in biases was higher. This means that identical PATS require individual attention in those concentration ranges. The overestimation versus the SPSA below 50 µg/m^3 is due to the PATS reporting minimum 10 µg/m^3, resulting in the inverse of what for the IQAV happens for high concentrations.

4. DISCUSSION

4.1 LCS under ambient conditions

The evaluation of LCS compared to the reference method under ambient conditions (n=3) was limited in comparison with other studies (Sousan et al. (2021) n=8, Falzone et al. (2020) n=24, or gravimetrically corrected continuous monitors used by Feenstra et al. (2019) and Zamora et al. (2020)). This study found high R^2s versus the reference, but the SPSA and IQAV underreported concentrations with slopes of respectively 2 and 1.6. The underreporting of the SPSA is also found by Sousan et al. (2021) for salt particles (slope 2.0). It is also found by Falzone et al. (2020) in the field (1.35-1.38). For the IQAV, however, Feenstra et al. (2019) found the IQAV measuring higher than a reference concentration, and Zamora et al. (2020) found it measuring close to a reference concentration (bias of 0.04). The difference might be due to circumstances in this study (biomass burning on the streets and in neighborhoods as a prominent source) that are different from field circumstances in studies conducted in high-income countries. The difference might also be due to the uncertainty of the reference method used in this study for ambient concentrations (see Table 3 note a). Additional comparisons with reference instruments under ambient conditions common to low-income countries are needed to gain more insight in this. This study did however show a very low variation within SPSA (much like Sousan et al. (2021) for salt particles), as well as low difference between SPSA and IQAV across different time averaging levels ($Ac_{\_AC}$<25%). The low *within* and *between* variation shown in this and other studies can be combined with other studies' promising findings in comparison with reference instruments. These low variations point to the usability of the LCS interchangeably under ambient circumstances.

4.2 LCS under high-exposure conditions

Perhaps lacking in ambient circumstances, this study on the other hand included concentration levels not encountered in other evaluation studies. 10-minute averaged concentrations in this study as reported by the LCS were >10,000 µg/m^3, while other evaluations of LCS under non-ambient conditions only went up to 1,200 µg/m^3 PM2.5 (Sousan et al., 2021). The quality of the LCS under circumstances in this study was similar to the quality level found in other studies. For SPSAs compared to a reference method, Nguyen et al. (2021) found a standard deviation (SD) of 16.6-26% (here 1-24%) while Sousan et al. (2021) reported r=0.99 (here as well), but diversity in slopes (here: close to 1). Within SPSAs, this study's CV is similar to Sousan et al. (2021) for salt particles, or, translated into absolute SD (up to 22 µg), similar to Nguyen et al. (2021) (26 µg). For the PATS, this study's R^2 >0.92 with a common slope of 1.6 is similar to that reported by Pillarisetti et al. (2017) (R^2 0.9, slope 1.5). The variation *within* PATS found in this study is not up to NIOSH standards (CV>10%), but linear association is similar to that reported by Pillarisetti et al. (2017) (R^2 0.92).

The IQAV was altogether not evaluated under high circumstances by other studies. Even despite the higher reporting limit, this study revealed a usability on a daily level ($Ac_{\_AC}$ <25%).

4.3 LCS *between* comparison

Quality evaluations *between* LCS are rare. That is understandable from a 'true quality' evaluation point of view: when comparing LCS, it is not known which of the LCS gives the true value. Nonetheless, the comparison of measurement results from different LCS is informative. In the case of a strong association (preferably the same over different instruments and concentration ranges), findings for one LCS can be extrapolated to the other. The low variance *within*, as well as the low and stable bias compared to the *reference* across different ranges for the SPSA are especially promising results. These results suggest that an instrument that needs to get more individual attention (such as the PATS), in the absence of an (expensive) reference method can be calibrated with an SPSA. Similarly, while the IQAV is not designed for high concentrations as in this study, with correction the IQAV can give trustworthy results on a daily level (in comparison with SPSA R^2s>0.96).Below 1,000 μg/m^3, the IQAV can even be reliable at a 10-minute averaged level.

6. CONCLUSIONS AND RECOMMENDATIONS

Three low-cost PM2.5 sensors were compared *within* identical sensors, with a *reference* method, and *between* each other in Arba Minch, Ethiopia, under ambient and high-exposure circumstances. Strong linear associations (R^2 mostly >0.9) were witnessed at both ambient and kitchen locations. This was the case across different time periods and across different concentration ranges. Under ambient situations, *within* SPSAs official standards were met (CV<10%, u_{bs}<2.5 μg). After bias correction, both the IQAV and the SPSA met standards for accuracy ($Ac_{\_AC}$<25%). When using these LCS in high-exposure situations, the IQAV at daily level needs a correction for a bias of -50%. It needs a similar correction at 10-minute averaging levels up to concentrations of 200 μg/m^3. At higher concentration levels, the required accuracies can be obtained by range-wise correction based on an SPSA that measures at the same location. When using the PATS, individual sensors need individual attention, but in comparison with the reference method or even by correcting with an SPSA from the same location can be upgraded to required accuracy levels. The comparability *within* SPSAs implies that findings under one circumstance, albeit distinguishing between ambient and prominently biomass-burning situations, can be applied in other circumstances.

This study shows that, when distinguishing ambient and predominantly high-exposure biomass fuel situations, LCS can be used interchangeably: either within one project or for the purpose of combining results from multiple studies in which different LCS are used. Of the three evaluated LCS, the SPSA seems to be the most flexible choice in an environment where both ambient and high-exposure situations are researched. If budget is available for quality evaluations with a reference instrument, more attention to ambient situations in low-income countries is recommended, to include situations such as busy streets and open waste burning in bigger cities. With a limited budget it is recommended to opt for a multitude of LCS rather than one or two expensive monitors.

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ANNEX

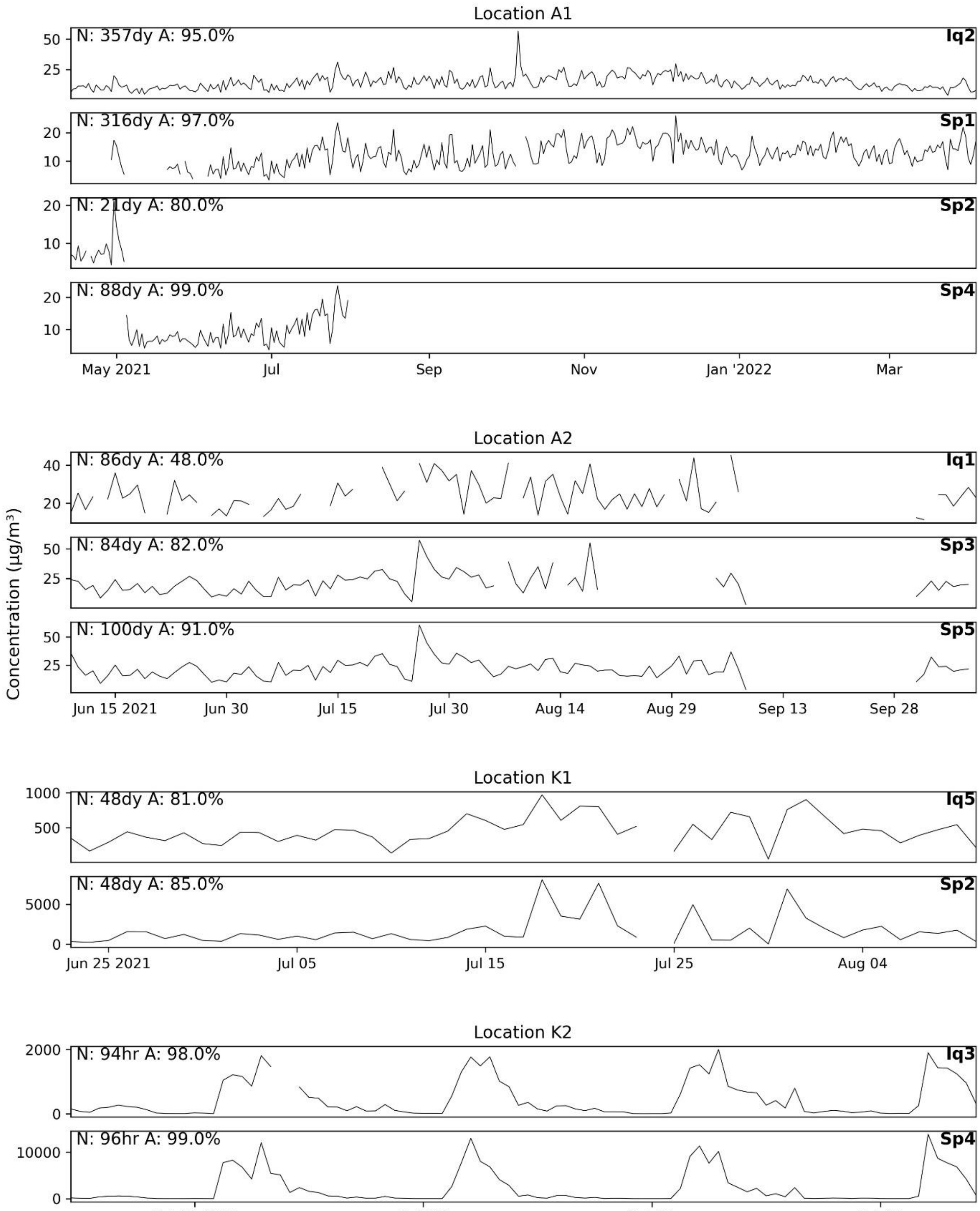

Figure A1. PM2.5 concentrations as reported by all LCS at locations A1, A2, K1 and K2, annotated with the total time period (N, in days (dy) or hours (hr)), and the percentage of available 10-minute averages (A) within that time period.

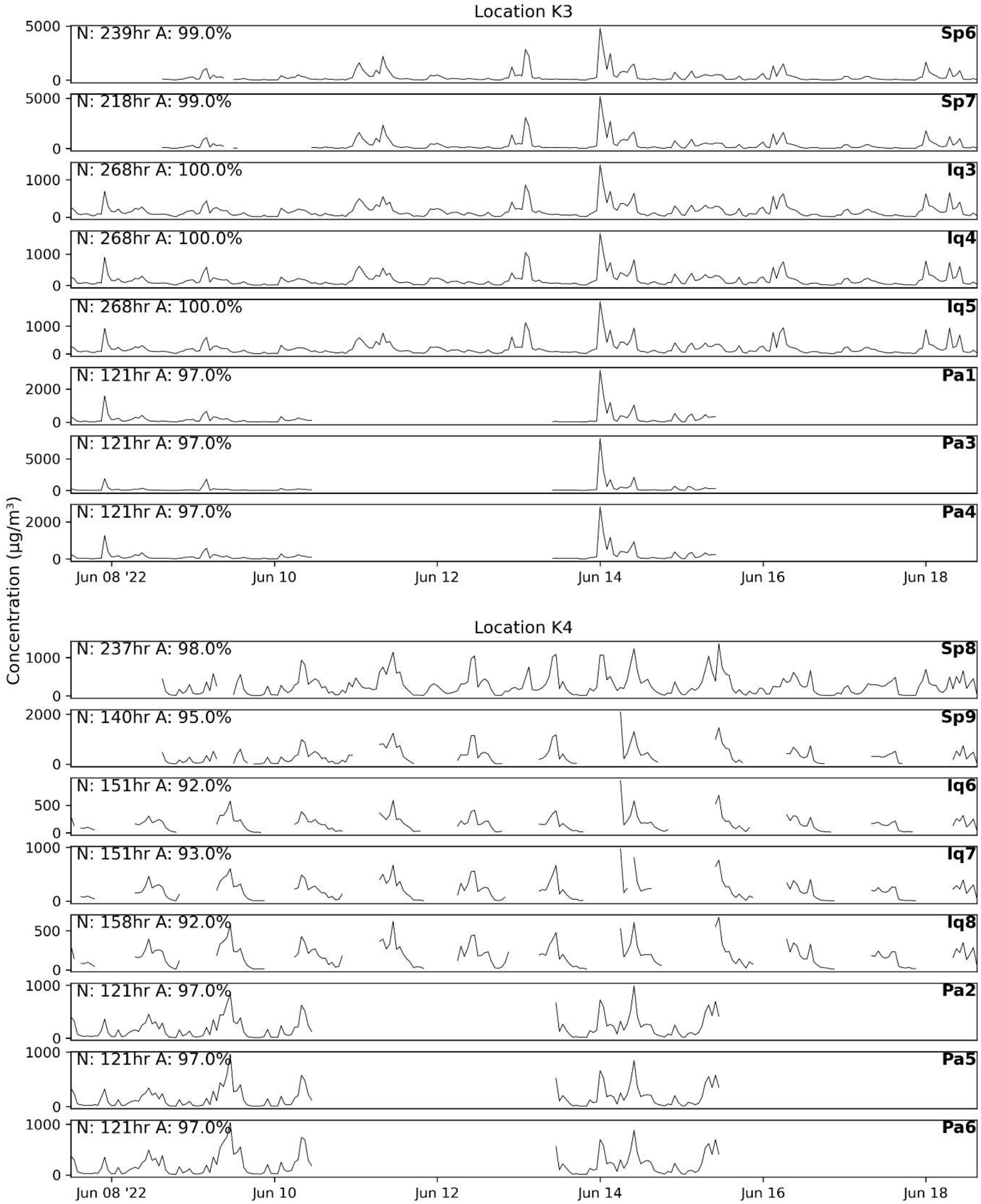

Figure A2. PM2.5 concentrations as reported by all LCS at locations K3 and K4, annotated with the total time period (N, hours (hr)), and the percentage of available 10-minute averages (A) within that time period.