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PAPER

Can low-cost sensors (LCS) enhance air quality monitoring for personal pollution exposure assessment?

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Abstract

Laboratory and field assessments of low-cost sensors (LCS) are essential for ensuring the accuracy of $PM_{2.5}$ measurements collected by citizens in air quality campaigns. Evaluation of Sensirion SPS30 (LCS SPS30) in controlled laboratory setting showed a coefficient of determination (R^2) ranging from 0.81–0.99 and a root mean square error (RMSE) from 0.81–61.72 $\mu g\ m^{-3}$, at average concentration of 21.5 $\mu g\ m^{-3}$. In contrast, co-location assessment at an average concentration of 9 $\mu g\ m^{-3}$ resulted in R^2 of 0.5 and a RMSE of 6.82 $\mu g\ m^{-3}$. The results demonstrated that the sensor met micro-environmental monitoring standards (accuracy $< 25\%$) and United States Environmental Protection Agency's performance criteria (RMSE $\leqslant 7\ \mu g\ m^{-3}$, $R^2 > 0.7$) only at relative humidity (RH) levels below 60%, emphasising its strong sensitivity to RH and the need for RH-dependent data corrections. The observed underestimation or overestimation of $PM_{2.5}$ readings was primarily attributed to variations in particle composition and concentration. Despite accuracy variations, LCSs can effectively capture spatiotemporal urban air quality patterns and identify pollution hotspots in community monitoring, particularly in low-pollution environments. In a citizen-led $PM_{2.5}$ monitoring campaign in Maribor, Slovenia, the lowest concentrations were recorded at 15:00 (2.9 $\mu g\ m^{-3}$), while the highest occurred during the morning rush-hour (4.8 $\mu g\ m^{-3}$), likely attributed to the planetary boundary layer's impact on atmospheric particulate dispersion. Spatial analysis revealed that hotspots clustered near intersections, where vehicle waiting time is the longest.

1. Introduction

The health and environmental hazards associated with airborne fine particulate matter ($PM_{2.5}$, aerodynamic diameter $\leqslant 2.5\ \mu m$) are prevalent in many European cities, surpassing the air quality threshold levels established by the European Ambient Air Quality Directive (AQD) [1], and the interim targets defined in the World Health Organization's (WHO) air quality guidelines [2]. Exposure to even minimal $PM_{2.5}$ concentrations can increase health risks, including chronic and acute respiratory as well as cardiovascular diseases, such as stroke and lung cancer, leading to a reduced life expectancy. Therefore, systematic monitoring of these atmospheric pollutants is essential [3–6].

In urban environments, air quality monitoring stations (AQMS) continuously monitor $PM_{2.5}$ levels, adhering to standardised quality assurance and control protocols. However, the data acquired is limited and sparsely distributed across cities [7, 8]. Thus, in recent years, rapid development and deployment of light-scattering low-cost sensors (LCS) for air quality monitoring has been observed [9]. These sensors offer great health and environmental applications with several inherent advantages, including affordability, portability, improved spatial resolution and the ability to identify emission hot spots [10–12]. Various applications of these sensors have been reported, including environmental awareness activities and citizen science campaigns, monitoring both community and industrial emissions, assessment of personal indoor and outdoor exposure and data collection in remote places [13]. However, in comparison to AQMS, LCS exhibit lower levels of accuracy, sensitivity and limits of detection (LOD). Consequently, an evaluation of their dynamic response is essential before considering widespread implementation as a supplementary source of air quality data alongside AQMS [13–16]. LCS, utilising light scattering operating principle, are strongly affected by factors such as particle composition and density, hygroscopicity, refraction index, relative humidity (RH), pollutant concentration level and averaging time [17–20]. Consequently, it is imperative to evaluate these sensors using co-location field assessment methods against reference instruments such as AQMS [7, 18, 20–26] or in controlled laboratory settings [18, 20, 22, 27, 28]. Additionally, various methods, such as linear regression models [15, 29, 30], multiple linear regression [15, 29] and mechanistic models based on hygroscopic growth correction [15, 22, 29] are also employed. More recently, multimodal data fusion methods have been applied, combining ground monitoring data, satellite remote sensing data and also surveillance camera images at local, regional and global scales to enhance the spatiotemporal accuracy of air quality predictions [31, 32]. Accurately calibrated LCS offer real-time measurements at lower costs, enabling broader spatial coverage in densely populated urban areas. Unfortunately, there is still a significant gap in regulatory frameworks, accreditation, certification protocols and harmonised assessment protocols, both in laboratory and field settings, hindering the widespread implementation of these sensors [14]. A recent publication by the United States Environmental Protection Agency (US EPA) has outlined recommended target values for the performance metrics of such sensors, which marks the beginning of efforts to address the challenges of standardisation and comparability of these sensors [33].

The assessment of LCS is therefore essential for ensuring accurate data acquisition, necessary for $PM_{2.5}$ personal exposure in citizen science campaigns. In this study, the performance of the Sensirion SPS30 (LCS SPS30) was assessed under both, controlled laboratory conditions and real-world urban environment. The research was focused on identifying the sensor's limitations under varying environmental conditions, including RH, temperature and $PM_{2.5}$ concentrations. Additionally, the study examined the comparability of LCS measurements with reference instruments and explored the potential applicability of LCS for widespread community deployment in air quality monitoring networks.

2. Methods

LCS SPS30 (CanAirIO Sensirion SPS30), real-time optical particle counter, was evaluated under laboratory-controlled conditions using the reference instrument Grimm 11d and in field settings through a co-location evaluation. The LCS SPS30 continuously measures $PM_{2.5}$ concentrations using the laser scattering technique, with results reported in $\mu g\ m^{-3}$. LCS SPS30 was introduced in 2018 and was initially calibrated by the manufacturer during the laboratory testing. They reported $PM_{2.5}$ measurement range of 0–1000 $\mu g\ m^{-3}$, concentration resolution equal to 1 $\mu g\ m^{-3}$ and particle diameter resolution equal to 0.3 μm. $PM_{2.5}$ mass concentration was calibrated to TSI Dust-TrakTM DRX 8533 Ambient Mode and $PM_{2.5}$ number concentration was calibrated to TSI OPS 3330 [34].

2.1. Laboratory assessment of LCS SPS30

The performance assessment of the LCS SPS30 under laboratory-controlled conditions (figure 1) was carried out using an environmental-pollution chamber (Envilution™) with a capacity of 125 L [35]. The chamber facilitates systematic control of specific environmental parameters, such as particulate matter emissions, RH and temperature (T) over a predetermined time period. The Envilution™ chamber features a nebulizer (utilising 0.5% Potassium Chloride [KCl] as a particulate matter emissions source), a humidifier/dehumidifier system; flow controllers for accurate pollutant emission quantification; a heat pump for T regulation and sensors to monitor the T, RH and pressure. Additionally, the chamber includes an adjustable platform for LCS evaluation, a reference instrument (Grimm 11d) for monitoring PM levels and integrated software for controlling diverse environmental conditions and recording data from reference instruments. Grimm 11d measures PM while accounting for RH. The Grimm 11d (Dust Decoder—portable aerosol spectrometer) operates on the principle of light scattering detection using a diode laser to analyse individual particles. It measures particle sizes ranging from 0.253 to 35.15 μm and dust mass concentrations from 0 $\mu g\ m^{-3}$ to 100 mg m^{-3}, with a volume flow rate of 1.2 L min^{-1}. It employs humidity compensation algorithms, heated inlets, or drying systems to reduce RH effects, ensuring accurate readings. Additionally, real-time RH monitoring and post-processing software further corrects the data. Digital Temperature and Humidity Sensor

Figure 1. Laboratory assessment of LCS SPS30.

AM2320 was additionally used to control the atmospheric conditions within the chamber. To avoid unintended reactions during assessment tests, all chamber components are made of, or coated with, polytetrafluoroethylene materials [35]. The LCS SPS30 operates within a T range of −40 to +80 °C and can accommodate RH up to 99%. In contrast, the reference instrument, Grimm 11d, functions optimally between +4 and +40 °C, with RH levels below 95%. To evaluate the comparability between both instruments, scenario's parameters corresponded to the field test under Slovenian temperate continental climate conditions, where three different scenarios were simulated. Scenario 1 maintained T between 6 and 8 °C and RH from 50 to 60%. Scenario 2 encompassed T ranging from 15 to 18 °C with RH levels ranging from 60 to 80%. In Scenario 3, T was between 18 and 22 °C with RH levels of 70 to 80%. The $PM_{2.5}$ concentrations ranged from 0 to 367 $\mu g\ m^{-3}$. To minimise the risk of condensation events and potential overestimation of particle mass concentrations [15, 22, 35–38] deliberate measures were taken to avoid extremely high RH levels and elevated T. No correction factors were applied on laboratory data assessment.

2.2. Air quality monitoring campaign with field co-location assessment of LCS SPS30

The $PM_{2.5}$ air quality monitoring campaign, focusing on the impact of traffic congestions on $PM_{2.5}$ concentrations in urban areas, was conducted in Maribor, Slovenia. Maribor is the second-largest city in Slovenia with 94,370 inhabitants (in 2024). The city has a humid continental climate and lies in close proximity to the Drava River. A citizen-led $PM_{2.5}$ exposure campaign was conducted between 9 and 13 October 2023, where volunteers conducted 72 bicycle trips (n = 38,803 data points) during four specific time intervals to gather $PM_{2.5}$ data: (i) 7:00–8:00, (ii) 12:00, (iii) 15:00 and (iv) 18:00–19:00. The LCS SPS30 sensors were mounted perpendicularly to the cyclists' travelling direction in order to minimise the wind effect and consequently the overestimation of the $PM_{2.5}$ concentrations (figure 2). However, since this approach was not validated, wind-induced biases during sampling might have occurred. The 10.5 km-long cycling route remained constant and was pre-determined utilising the Google Traffic feature on Google Maps. It included areas in Maribor with the highest traffic density and formed a closed loop, comprising diverse road types such as high-speed roads and 30 km h^{-1} speed roads. It passed by key locations like the main city hospital, main square and train station.

The initial co-location field assessment yielded 2,536 data points collected during four pre-determined time intervals (7:00–8:00, 12:00, 15:00, 18:00–19:00), over five consecutive days (9−13 October 2023). The assessment took place at the Slovenian Environment Agency AQMS (Maribor—Titova location; 46.558861, 15.651306) (figure 2). Continuous monitoring of $PM_{2.5}$ and PM_{10} levels at AQMS is performed using HORIBA model APDA-371 (measurement resolution of 0.1 $\mu g\ m^{-3}$; LOD < 4.8 $\mu g\ m^{-3}$; flow rate of 16.7 L min^{-1}), which automatically records hourly concentrations of airborne particulates. The instrument utilises ^{14}C (radioactivity: < 2.22 × 106 Beq, 60 ± 15 μCi, half-life of 5730 years) as a beta source using a photomultiplier tube with an organic plastic scintillator as a detector. Additionally, AQMS measurements include hourly and monthly monitoring of carbon monoxide, ozone, nitrogen dioxide and benzene.

During each cycling trip, a volunteer stopped at the AQMS to collect $PM_{2.5}$. The total co-location durations were 42 min 19 s (9 October), 54 min 28 s (10 October), 55 min 26 s (11 October), 58 min 18 s (12 October) and

Figure 2. Co-location field assessment of LCS SPS30.

37 min 35 s (13 October). The data were averaged by time interval and day, and subsequently compared with AQMS hourly data. AQMS reported valid $PM_{2.5}$ values on 9 October (15:00, 18:00–19:00), 10 October (15:00, 18:00–19:00), 11 October (7:00–8:00, 12:00, 15:00, 18:00–19:00), 13 October (12:00, 15:00, 18:00–19:00), yielding 1,543 usable data points.

2.3. Air quality monitoring campaign with field co-location assessment of LCS SPS30

LCS exhibit high sensitivity to RH levels, with numerous studies reporting that RH $>$ 85% often results in LCS overestimation of $PM_{2.5}$ concentration. This overestimation occurs due to enhanced aerosol hygroscopic growth from water vapour condensation on atmospheric particles [15, 22, 35–38]. Consequently, many studies recommend incorporating the RH into calibration equation [22, 39, 40]. Therefore, a following RH dependent correction was applied on field data, including co-location assessment:

$$C = 1 + \frac{\overline{1.65}}{-1 + \frac{1}{a_w}} \tag{1}$$

$$PM_{Corrected} = \frac{PM_{raw} \times \delta}{C} \tag{2}$$

The κ value was applied based on Köhler theory [41], where it represents the degree of particle hygroscopicity depending on particle composition. For simplification, 1.65 g cm^{-3} was used as a bulk dry particle density [22]. Previous studies observed that the dry particle mass of $PM_{2.5}$ ranged from 0.38 to 0.44 [22], with an expected range for Europe of 0.36 ± 0.16 [42], therefore, an average value of 0.41 was used as the κ constant. Water activity (a_w) was defined as RH/100, using an average relative humidity (74%) during the monitoring campaign. δ is defined as a percentage discrepancy between LCS and AQMS, and was equal to 0.37. Temperature fluctuations have negligible to no impact on LCS PM sensors [36]. The LCS SPS30 is set to record data at 5-s intervals, whereas Grimm 11d operates at 1 min intervals. Therefore, for analysis purposes, the laboratory assessment data were averaged based on 1 and 5 min averaging times, while field co-location assessment data on hourly averages. Data were statistically evaluated by analysis of variance (ANOVA), using TIBCO Statistica software [43]. Furthermore, the spatial distribution of $PM_{2.5}$ concentration was examined using QGIS software [44].

Table 1. Average (mean ± standard error) values of selected parameters within during laboratory assessment of LCS.

	LCS SPS30	Grimm 11d
$PM_{2.5}$ [$\mu g\ m^{-3}$]		
Avg.	21.5 ± 2.1	32 ± 4.8
R^2	0.83	
Slope	Grimm 11d = −8.8 + 1.9 * LCS SPS30	
RH [%]		
Avg.	61.2 ± 1.0	67.5 ± 0.8
R^2	0.92	
Slope	Grimm 11d = 17.4 + 0.8 * LCS SPS30	
T [°C]		
Avg.	12.1 ± 0.4	15.7 ± 0.5
R^2	0.98	
Slope	Grimm 11d = 2.7 + 1.1 * LCS SPS30	

3. Results and discussion

LCSs are being increasingly employed in environmental pollution campaigns to evaluate air quality in urban areas. However, they are highly susceptible to systematic biases, time-dependent drifts and aging. Therefore, it is crucial to assess them prior to the widespread use [13–16]. The AQD [1] established data quality objectives, specifying that measurement uncertainty, including coefficient of determination (R^2) and the regression slope, should primarily be used to evaluate the air quality data from monitoring methods. Nevertheless, these metrics are rarely incorporated in citizen science initiatives utilising LCSs [20]. Co-location field assessment is often used to evaluate performance of LCSs [7, 18, 20–22, 24–26], however, due to meteorological and environmental variations across the reported studies, direct comparison of LCS to reference instruments is challenging. Consequently, it is advisable to perform laboratory evaluation, which provides higher levels of reproducibility [13]. Laboratory comparability assessment ensures standardised and controlled testing conditions, enabling the simulation of environmental conditions relevant to specific environment, such as the Slovenian climate. Additionally, such assessment allows for the evaluation of unit-to-unit variability and the independent verification of the manufacturer's calibration results. Additionally, statistical indicators such as the root mean square error (RMSE), standard deviation (SD) and the intercept of the linear regression between LCS and AQMS data are commonly used. While RMSE and R^2 are considered as the most explicative measures [13, 20], factors such as averaging time and the choice of the reference instrument can also significantly affect the evaluation [19]. The US EPA publication 'Performance Testing Protocols, Metrics and Target values for Fine Particulate Matter Air Sensors' recommends specific target values for assessing the suitability of LCSs for micro-environmental air pollution monitoring campaigns. According to the publication, R^2 should remain above 0.7 and the RMSE below 7 $\mu g\ m^{-3}$ for LCSs to be considered eligible for air pollution monitoring campaigns [33].

3.1. Laboratory assessment results and comparative analysis of LCS SPS30 and reference instrument Grimm 11d

The performance of the LCS SPS30 was evaluated simultaneously with two different LCS SPS30 under different environmental conditions in relation to reference instrument Grimm 11d, corresponding to the Slovenian moderate continental climate (Tables S1–S3). The Pearson's correlation coefficients between two sensors varied 0.995–0.998. The same sensors were used in all laboratory-based scenarios. The average accuracy error was 9%, 21% and 33% for Scenario 1 Scenario 2 and Scenario 3, respectively, with R^2 values varying from 0.81–0.99. Scenario 1, with RH below 60%, was the only environmental condition in which the LCS SPS30 met the criteria for micro-environmental monitoring.

The average values presented in table 1 were used to facilitate the comparison between LCS SPS 30 and reference instrument Grimm 11d, allowing for the assessment of discrepancies across individual parameters (PM concentration, RH and T). Averaging minimises the influence of random short-term variability, thereby improving the correlation metrics. However, primarily suited for illustrating long-term trends, which are particularly relevant for personal exposure evaluation of individuals in urban environments. The average accuracy was 20.9% for $PM_{2.5}$ measurements, 8.9% for RH and 28.6% for T, with accuracy declining as RH increased.

In addition, the absolute difference between LCS SPS30 and Grimm 11d was 8% for $PM_{2.5}$ concentrations up to 50 $\mu g\ m^{-3}$, 32% for concentrations between 50 in 100 $\mu g\ m^{-3}$ and 142% for very high concentrations

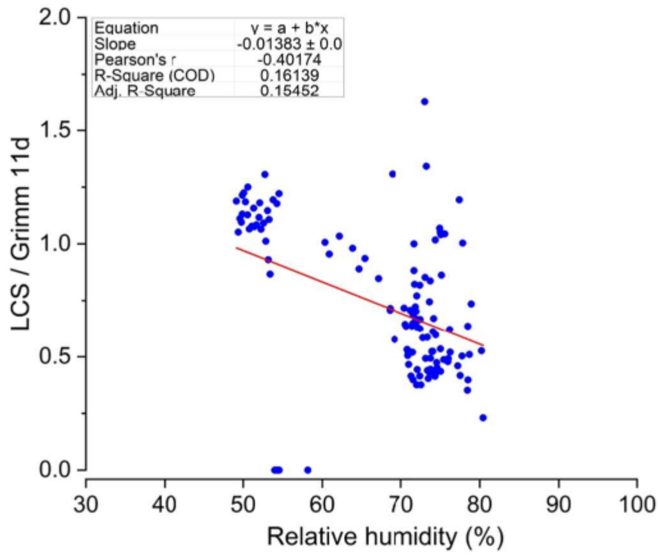

Figure 3. Susceptibility of laboratory-assessed $PM_{2.5}$ concentrations (LCS/AQMS) relative to RH variations.

above 100 μg m^{-3}. These results suggest that LCS SPS3 is not recommended for precise quantification in highly polluted environments, likely due to photodetector oversaturation causing a non-linear response. However, the sensor can still serve as a useful indicator of hazardous conditions, providing practical value for protecting exposed populations.

LCS SPS30 demonstrated an enhanced performance at longer averaging times, as evidenced by progressively higher R^2 values and lower RMSE at a 5 min averaging time compared to 1 min averaging times in all selected scenarios. Similar observations were found in the study, where both instrument and sampling uncertainty with respect to the reference method decreased with increased averaging time [45]. Longer averaging intervals (e.g., 1 h, 8 h, and 24 h) are primarily used for comparisons of LCS data to air quality standard criteria; however, shorter timeframes of 1 min can be indicative for short-term emission spikes related to specific local air pollution events [13].

3.2. Field co-location assessment results and comparative analysis of LCS SPS30 and reference instrument HORIBA model APDA-371

In total, 1543 data points within pre-determined timeframes during 5 consecutive days (9—13 October 2023) were used to assess the co-location field evaluation correspondence between LCS SPS30 and Slovenian Environment Agency AQMS Maribor—Titova HORIBA model APDA-371 (Table S4). The same sensors used in the laboratory assessment were also employed in the field co-location tests. The co-location assessment was carried out in stable atmospheric conditions without rain and at low wind speeds (<5 km h^{-1}), at the fixed placement and negligible external influences. During each cycling lap, cyclists stopped at the AQMS to perform co-location assessment. As Slovenian Environment Agency only reports hourly $PM_{2.5}$ values, LCS SPS30 values were averaged for comparison. Due to AQMS missing data for specific time intervals, some co-located LCS data were excluded from further analysis. Ratio between LCS SPS30 and AQMS varied between 0.4 and 0.8, with an average 0.6.

3.3. RH influence on $PM_{2.5}$ concentrations

The sensitivity of both laboratory- and field-based assessment protocols for $PM_{2.5}$ assessment depends on RH variations. In the controlled laboratory environment, $PM_{2.5}$ concentrations exhibited downward trend relative to RH (figure 3), indicating an underestimation of particle concentrations.

In contrast, field measurements revealed an overestimation of $PM_{2.5}$ concentrations, attributed to enhanced aerosol hygroscopic growth caused by water vapour condensation on particles. The correlation between non-corrected LCS SPS30 values and the reference instrument was 0.70, which slightly improved to 0.71 following RH corrections (equations (1), (2)). Field co-located $PM_{2.5}$ concentrations relative to RH variations exhibited an upward trend (figure 4). The ratio between AQMS and LCS $PM_{2.5}$ data was 0.56 and 0.7 for corrected and not-corrected data. Applying the RH-correction (equations (1), (2)) on the field data resulted in average deviation of 24%. Across the entire sampling period, the mean $PM_{2.5}$ concentration was 9.6 μg m^{-3}

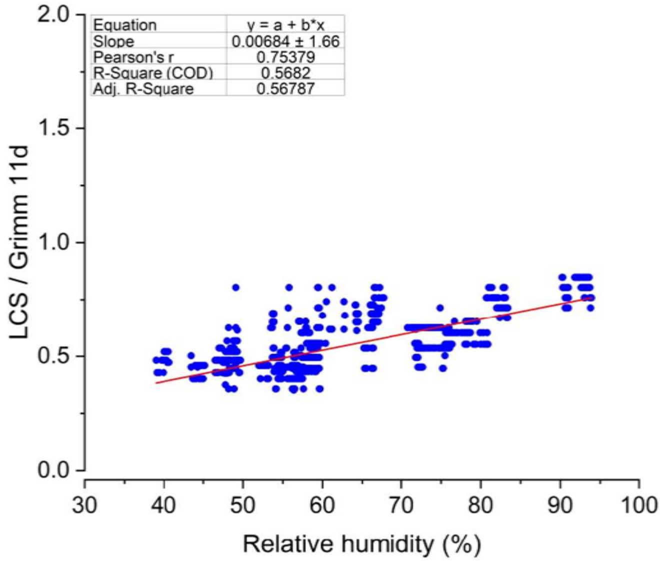

Figure 4. Susceptibility of co-located $PM_{2.5}$ concentrations (LCS/AQMS) relative to RH variations.

(range: 2–126 μg m^{-3}) for the non-corrected data and 7.7 μg m^{-3} (range 1.6–101 μg m^{-3}) for the RH-corrected data.

The discrepancy between laboratory and field co-location assessment can be explained by the differences in particle composition and environmental conditions. In the laboratory environment, solid or partially hydrated KCl particles were used, while ambient particles consist of complex mixture of volatile and hygroscopic particles whose number and composition vary more substantially. These particles absorb water and grow in size under elevated RH, leading to increased light scattering and higher $PM_{2.5}$ concentrations. In the controlled setting, particle growth is more constrained and the refractive index of the KCl particles decreases, reducing the scattering efficiency per unit mass.

3.4. Comparability of laboratory and field assessment results and micro-environmental monitoring metrics

Laboratory comparability yielded moderate to strong correlation ($0.81 < R^2 < 0.99$) between the LCS SPS30 and the Grimm 11, which was also observed by Agrawal [46], who reported R^2 values equal to 0.9. It was observed that when RH increased, it resulted in decrease of R^2. RMSE values varied between 0.81 and 61.72 μg m^{-3}, with an average RMSE of 39 μg m^{-3} at an average $PM_{2.5}$ concentration of 21.5 μg m^{-3} (LCS SPS30). The highest accuracy (8.6%), R^2 value (0.99) and lowest RMSE (0.81 μg m^{-3}) were observed under environmental conditions with a T range of 6 °C–8 °C and RH between 50% and 60%. Similar observations were also reported by [28], who reported that LCS SPS30 did not adhere to the manufacturer's specified detection ranges. They observed very low cross-unit variability, approximately 1.3% for $PM_{2.5}$, and a reported R^2 value of 0.83 [28].

In comparison, the field co-location assessment results yielded R^2 value equal to 0.50, while the RMSE was 6.82 μg m^{-3}, at an average $PM_{2.5}$ concentration 9 μg m^{-3}. Vogt *et al* [26] reported R^2 and RMSE values equal to 0.72 and 0.1–4.17 μg m^{-3}, respectively. Results obtained in this study are lower in comparison to previously reported, where RMSE was equal to 6.7 μg m^{-3} and 3.8 μg m^{-3} for non-corrected and corrected $PM_{2.5}$ values, respectively [47]. Additionally, R^2 is below the average R^2 value of 0.8 reported in various LCS performance evaluation studies [20].

The recommended error threshold for accuracy in micro-environmental monitoring is 25%, as proposed by Schauer [48], and this criteria was met under both laboratory and field conditions. However, additional comparability analyses of identical sensors, based on other micro-environmental monitoring criteria defined by US EPA (R^2, RMSE) [33], indicated that the LCS SPS30 did not meet the performance thresholds, except under conditions where relative humidity (RH) was below 60%. Generally, the co-location field assessment yielded lower R^2 and RMSE in comparison to laboratory test.

Additionally, data was subset into the low concentration range of $PM_{2.5}$ from 0–29.8 μg m^{-3}, which was the maximum value observed during co-location assessment. Across all laboratory and field scenarios, low correlation values ($R^2 < 0.04$) were observed. The highest comparability was found between laboratory and

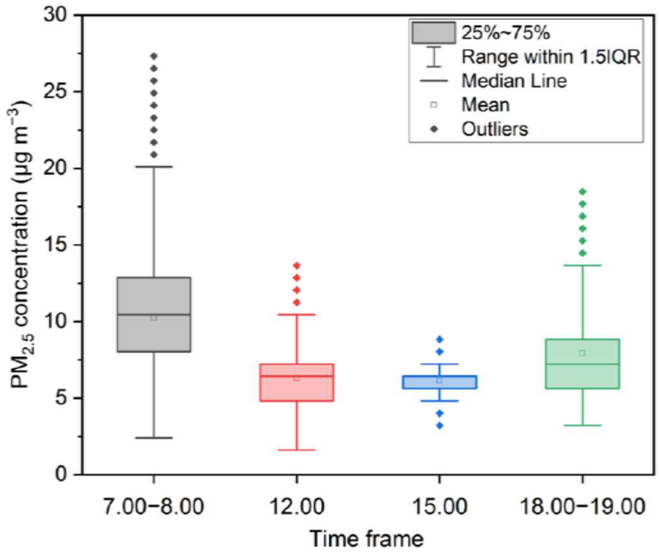

Figure 5. Temporal pattern of $PM_{2.5}$ concentrations across time intervals in Maribor, Slovenia.

Table 2. Performance overview and optimal operating conditions of the LCS SPS30.

LCS SPS30 performance overview:			
	Laboratory settings	Co-location settings	Performance criteria
Accuracy [%]	9–33	37	< 25
R^2	0.81–0.99	0.5	> 0.7
RMSE [$\mu g\ m^{-3}$]	0.81–61.72	6.82	$\leqslant 7$
LCS SPS30 optimal conditions:			
T [°C]	6–8		
RH [%]	50–60		
$PM_{2.5}$ [$\mu g\ m^{-3}$]	<50		

field values, observed under environmental conditions with T ranging from 18 to 22 °C and RH between 70% and 80%, where conditions were most similar.

Based on the laboratory and field co-location assessments, we conclude that the LCS SPS30 provides the most reliable $PM_{2.5}$ measurement under conditions of RH $< 60\%$ and in low-pollution environments ($PM_{2.5} < 50\ \mu g\ m^{-3}$) [table 2].

3.5. Citizen-led $PM_{2.5}$ monitoring campaign

During a one-week $PM_{2.5}$ monitoring campaign, a total of 72 bicycle trips were conducted in Maribor, Slovenia, resulting in 38,803 data points. After eliminating co-location data and errors, 35,642 remained (92%). All data were corrected following equations (1) and (2), using RH dependent correction. The comparative ANOVA indicated statistically significant differences at the 95% probability level between time intervals. The lowest average $PM_{2.5}$ concentrations were recorded at around 15:00 (2.9 $\mu g\ m^{-3}$), while the highest were observed during the morning rush hour between 7:00 and 8:00 (4.8 $\mu g\ m^{-3}$) (figure 5). A similar pattern was observed in Ljubljana, Slovenia, during a citizen science campaign that utilised LCS SPS30 sensors from September to December 2022 [24]. This trend can be attributed to the presence of the planetary boundary layer (PBL). The PBL, besides other factors such as meteorology, topography, demography, transportation, fuel quality, energy usage, and levels of industrialisation and urbanisation, plays an essential role in daily fluctuations of $PM_{2.5}$ concentrations. The PBL hinders the vertical mixing of air masses, limiting the dilution and dispersion of pollutants. Consequently, PBL thickness at lower T and higher RH, trapping pollutants in close proximity to the surface [49, 50]. The primary local source of $PM_{2.5}$ in Slovenia are the individual wood-burning fireplaces (74%) and traffic emissions (5%) [51].

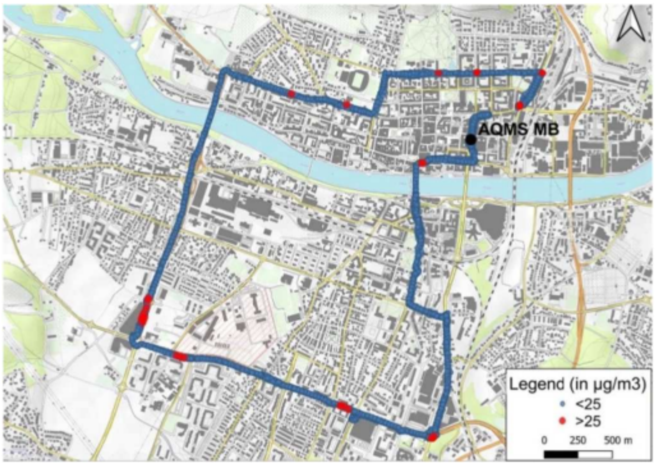

Figure 6. Spatial distribution of $PM_{2.5}$ in Maribor, Slovenia.

Furthermore, the urban layout and proximity to pollution sources can significantly influence air pollution levels, as revealed through the spatial analysis of $PM_{2.5}$. Air pollution hot spots, represented by darker red colour (figure 6), were predominantly concentrated around major intersections near highway entry points, shopping malls and bus station. These areas experience heavier traffic and prolonged vehicle idling, particularly during peak commute hours. Cyclists face higher risks of exposure at congested intersections, underpasses, and roundabouts relative to well-ventilated open bike lanes and street intersections [8, 52, 53].

The corrected $PM_{2.5}$ values were subsequently compared to the threshold value (25 μg m^{-3}) outlined in the AQD [1] which serves as a regulatory framework for managing ambient air quality across Europe Union. AQD only sets annual threshold targets, therefore lacks effective criteria for evaluating short-term $PM_{2.5}$ pollution. Analysis of the $PM_{2.5}$ data collected by LCS SPS30 revealed that the threshold value was surpassed in 0.15% of all cases. In a similar study conducted in Ljubljana, Slovenia [24], 21.2% of all data surpassed this limit, indicating on a better air quality status in Maribor.

4. Conclusions

LCSs offer valuable insights into commuter's personal air pollution exposure but are sensitive to humidity, affecting $PM_{2.5}$ accuracy. Without standardised calibration methods, data comparison across different LCSs and monitoring campaigns is difficult. This study assessed the performance of the Sensirion SPS30 under controlled laboratory and real-world urban conditions to evaluate its potential for widespread community deployment.

The results showed that the sensor met micro-environmental monitoring standards and US EPA performance criteria (R^2, RMSE) only at RH levels below 60% and in low-pollution environments. A strong humidity dependence was observed in both laboratory and field conditions, with the LCS SPS30 exhibiting underestimation or overestimation of $PM_{2.5}$ readings, respectively. These discrepancies are mainly attributed to differences in particle composition and concentration. In ambient air, more hygroscopic and volatile particles absorb water and grow at higher RH levels, increasing light scattering and $PM_{2.5}$ reading. In contrast, controlled settings limit particle growth and reduce refracting index lowering scattering efficiency per unit mass.

Despite inconsistencies in sensor accuracy, LCSs can effectively capture spatiotemporal variations in urban air quality and identify pollution hotspots in community-based monitoring campaign. However, RH dependent correction remains essential for reliable interpretation of $PM_{2.5}$ measurements. In this study, LCS SPS30 were deployed by citizens during an air quality campaign in Maribor, Slovenia. Results indicated that $PM_{2.5}$ hotspots were clustered near intersections, where vehicle waiting times were longest. Elevated $PM_{2.5}$ concentrations were observed during the morning rush hour, corresponding to peak traffic density and the lowest levels of planetary boundary layer, limiting effective pollutant dispersion.

LCS SP30 sensors can serve as valuable supplementary tools for increasing public awareness or air pollution challenges; however their absolute $PM_{2.5}$ measurements should be interpreted with caution. Future work should focus on evaluating the long-term stability of these sensors under both laboratory and field conditions, assessing their performance in highly polluted environments and developing standardised assessment protocols. Such efforts will improve cross-study comparability and support the use of LCSs as reliable and cost-effective tool exposure assessment.

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Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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