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Intercomparison of low-cost sensors via simultaneous atmospheric measurements: a case study

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Abstract. The adoption of low-cost sensors (LCS) is growing steadily due to their affordability, ease of use, and broad applicability. However, concerns remain regarding their reliability, prompting continued investigations into their performance and proper handling of measurements.

This study uses a three week field campaign in a urban area in central Italy carried out during the winter holiday season. Atmospheric physical and chemical parameters, temperature, relative humidity, pressure, concentration of carbon monoxide (CO), nitric oxide (NO), nitrogen dioxide (NO_2), ozone in the form of O_3 and O_X and particulate matter $PM_{2.5}$ and PM_{10}, have been measured by three different commercial LCS platform (Vaisala AQT, AirSensEUR and Libelium Smart Environment PRO) in their factory primary calibration, to assess their initial performance. The LCS have been placed in a site close to two meteorological stations hosting standard certified reference instruments, which have been used for the intercomparison process. Additionally a 2B Ozone Monitor, EPA-certified Federal Equivalent Method, has been mounted next to the LCS, to add ozone to the evaluated variables. Due to the absence of a CO reference dataset, only a comparison between LCS has been performed to asses consistency for this measurement.

Meteorological measurements showed high correlation ($R \sim 0.9$) across all LCS with the reference data, except for a discrepancy in temperature and relative humidity for AirSensEUR. The concentrations of NO and NO_2 exhibited a good correlation ($R \geq 0.75$) with reference instrument, although some discrepancies and deviations from the ideal linear relationship were observed. Differently ozone comparison had a good similarity only for Vaisala AQT ($R \sim 0.8$), while for the remaining two the differences are noticeable ($R \sim 0.5$). CO time series across the three low-cost sensors are almost the same. Finally, both PM values, available from the reference only as daily averages, showed a reasonable level of agreement with the reference instrument for AirSensEUR, albeit with greater variability.

The LCS data acquired in the atmosphere was also analysed in relation to nearby pollution sources. Workday versus holiday daily comparison and wind-pollutant correlation have been executed with the aim to evaluate the ability of these LCS to recognize daily patterns and attribute pollutant sources.

Results show the potential information-driven applications of these commercial low-cost sensors, detecting emission patterns during rush hours and holidays.

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1 Introduction

Today air pollution represents one of the most pressing challenge both for the environment and human health. It contributes to millions of premature deaths each year, exacerbating diseases such as stroke, ischaemic heart disease, chronic obstructive pulmonary disease, lung cancer, and acute respiratory infections (Harvey; Organizatioin; of Sciences et al., 2019). Fine particulates, due to their small size, can penetrate deep into the lungs and enter the bloodstream, triggering systemic inflammation, oxidative stress, immune suppression, DNA damage, and contributing to a wide range of diseases across multiple organ systems (Maji et al., 2023). Targeted restriction on pollutant sources and support from observations are necessary to effectively deal with air quality related problems (Zheng et al., 2018).

Over the past decade, low-cost sensors (LCS) have demonstrated to be an extremely efficient tool to air quality monitoring, thanks to their affordability, ease of deployment and potential for dense spatial coverage. Traditional reference-grade instruments are often highly expensive and require complex and strict routines of maintenance to ensure reliable and comparable data. Differently LCS offer a promising alternative, in particular for applications such as community-based monitoring, exposure assessments, and supplementing official monitoring networks in both urban and rural areas (Borghi et al., 2017; McKercher et al., 2017). Moreover these positive qualities can be extremely useful in solving the scarcity of in-situ monitoring stations in smaller cities, underdeveloped regions and complex territories (Vilcassim and Thurston, 2023; Martin et al., 2019).

Following their growth in popularity LCS has evolved and have been improved by manufacturers. Modern electrochemical sensors present an acceptable response speed and good sensitivity that made them fit for air quality monitoring, this while they are evolving, following a miniaturization process and wide spread application (He et al., 2023). Differently low-cost PM sensors rely on light scattering methods to execute counting of particles and separation in size (Karagulian et al., 2019).

Despite their improvement, still concerns persist across the research community regarding their accuracy, credibility of data as well as long-term stability (Morawska et al., 2018; Alfano et al., 2020). Notables differences between laboratory and field evaluation have been highlighted, due to possible technical limitations (Castell et al., 2017).

Electrochemical sensors restraint are mainly due to the oxidation or reduction reactions that happens at the surface of the sensor, which can be sensibly influenced by temperature and humidity (Stetter and Li, 2008). On the other hand, the light scattering measurement executed by low-cost PM sensors is strongly affected by refraction index and particle composition and density, between others, which are dependent on particular location and season (Karagulian et al., 2019).

Studies have show how these devices frequently suffer from cross-sensitivities and sensor drift (Spinelle et al., 2017; Baron and Saffell, 2017; Petäjä et al., 2021; Caseiro et al., 2024). A strong dependency of LCS performance to sensor type, pollutant species measured, environmental conditions, and the presence (or absence) of post-deployment calibration has been observed (Wei et al., 2018; Pichlhöfer and Korjenic, 2022).

To tackle these problems, growing researches have focused on the evaluation and calibration of LCS, both in field and laboratory settings, to determine their "fitness-for-purpose" (Morawska et al., 2018). Research on LCS is focusing on calibration strategies, field validation, and integration within multi-scale monitoring systems. Reasonably, important improvements have been seen with calibration methods that take in consideration also meteorological parameters (Karagulian et al., 2020) and

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recent approaches are increasingly looking to data-driven or hybrid calibration models that exploit machine learning combined with environmental covariates, such as temperature and humidity, to improve performances, data reliability and compensate for environmental dependencies (Schneider et al., 2023; Villarreal-Marines et al., 2024; Nowack et al., 2021).

Currently there is no universally accepted definition of a LCS and in particular of a right threshold for it to be "low-cost". In this matter, we follow the criteria proposed by Lewis et al., 2016, considering LCS systems capable of measuring multiple atmospheric parameters with a total cost of no more 10000$.

Considering one of the main aims of LCS being an increasing accessibility to air quality monitoring, with our work we intended to evaluate the quality reached by these instruments in the way they are sold. To do this we have executed a field-based evaluation of three commercial LCS platforms deploying them in factory-new state. The instrument used are the Air Quality Transmitter 530 manufactured by Vaisala Ltd (AQT), the AirSensEUR (ASE) and Smart Environment PRO manufactured by Libelium (SEP).

The acquisition campaign took place over a one-month period, including the winter holiday season, in central Italy acquiring measurements of meteorological variables and concentration of atmospheric pollutants (NO, NO_2, O_3, $PM_{2.5}$ and PM_{10}), which have been compared against reference data acquired in the vicinity of our site by a station of the regional air quality network.

Furthermore, we also examined the LCS ability to detect emission patterns by executing a workdays versus holidays daily comparison, of particular interest considering the winter holiday season, and a combined analysis of pollutant concentration with wind measurements to assess probable pollutant sources.

Our findings contribute to the growing body of evidence evaluating the utility and operational capabilities of low-cost sensors in environmental monitoring and highlight both the strengths and limitations of these technologies in real-world applications.

2 Material and methods

The monitoring campaign was carried out during the 2023 Christmas Holidays using a cluster of four low-cost air quality sensors: AQT, two SEP (with different sensor probes mounted on them) and ASE. All the LCS acquired measurements of meteorological parameters (temperature, relative humidity and pressure), concentration of CO, NO, NO_2, ozone and particulate matter (divided in bins of dimension $\leq 2.5\mu m$ and $\leq 10\mu m$).

A list of all the instruments mounted in the site is present in table 1 with relative sensors and variables measured. The ASE is an open-source platform equipped with Sensirion sensors for temperature and RH and a Bosch sensor for pressure. Electrochemical sensors from Alphasense measure CO, NO, NO_2, O_x. Particulate matter is measured using the Plantower PMS5003, which reports both raw and internally calibrated data, following a black-box model ((Yong and Haoxin, 2016),(Ma et al., 2025)).

Each SEP unit can accommodate up to six external probes. For this study, both units measured temperature, RH, and pressure (via Bosch BME280), while CO, NO, NO_2, O_3, $PM_{2.5}$ and PM_{10} sensors where divided between the two instruments. All the concentrations were measured by Alphasense sensors. Notably, both SEP and ASE used the Alphasense $OX-A431$

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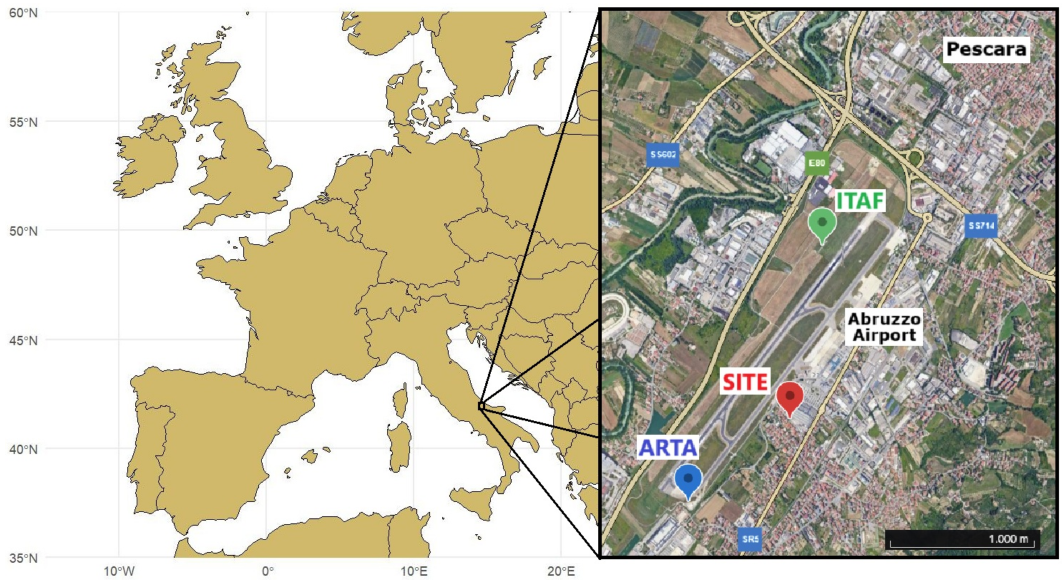

Figure 1. Location of the tree sites in the suburbs of Pescara (central Italy). In the zoom on the right can be seen the three sites: in red the site hosting our LCS and 2B ozone monitor, in green is where the Italian Air Force (ITAF) has its monitoring station and in blue is the location of the reference grade instruments used by the Regional Envi- ronmental Protection Agency (ARTA). In yellow are highlighted the major roads with their respective names (© Google Maps 2025).

sensor, but SEP firmware interprets its output directly as O_3, while ASE reports it as O_X. This distinction reflects differing calibration assumptions.

To evaluate the them, we compared our measurements with those from the Italian Air Force (ITAF) and the Regional Environmental Protection Agency (ARTA). ITAF manages a meteorological station at Abruzzo Airport, providing data in METAR format. Among the various quantities measured, values of temperature, relative humidity (obtained from dew point) and pressure have been used for comparison while wind speed and direction have been used for the source attribution analysis.

ARTA provided us hourly concentrations of NO and $NO2$ and daily averages $PM2.5$ and $PM10$ as part of a study on airport-related emissions (Bianco et al., 2024).

In addition, a model 205 Ozone Monitor (OM205) manufactured by 2B Technologies and EPA certified, has been mounted in our site so to provide reference values for ozone comparison with the LCS. Moreover, not having any reference measurements for CO concentration, an intercomparison between time series of the various LCS has been executed to evaluate consistency of measurements.

The locations of all the sites are shown in figure 1, the distance of our site with the ARTA station is $\sim 0.87km$, while with ITAF monitoring station is $\sim 1.17km$. Major pollutant sources include two main roads (SR5 and E80), the airport, and a nearby residential area. Our sensors were deployed in a private garden close to these emission sources.

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Table 1. List of all the instrument present in our site with relative variable measured and used in this work.

Instrument	Sensor Manufacturer	Sensor Model	Parameter Measured
AQM 530 (Vaisala)	Vaisala	proprietary	Temperature (°C)
			Relative Humidity (%)
			Atmospheric Pressure (hPa)
			$[CO]$ (ppm)
			$[NO]$ (ppm)
			$[NO_2]$ (ppm)
			$[O_3]$ (ppm)
			PM 2.5 ($\mu g/m^3$)
			PM 10 ($\mu g/m^3$)
AirSensEUR	Sensirion AG	SHT31	Temperature (°C)
	Sensirion AG	SHT31	Relative Humidity (%)
	Bosch Sensortech	BMP280	Atmospheric Pressure (hPa)
	\alpha Sense	CO-A4	$[CO]$ (nA)
	\alpha Sense	NO-B4	$[NO]$ (nA)
	\alpha Sense	NO2-B43F	$[NO_2]$ (nA)
	\alpha Sense	OX-A431	$[O_x]$ (nA)
	\alpha Sense	OPC-N3	PM 2.5 ($\mu g/m^3$)
	\alpha Sense	OPC-N3	PM 10 ($\mu g/m^3$)
Libelium	Bosch Sensortec	BME280	Temperature (°C)
	Bosch Sensortec	BME280	Relative Humidity (%)
	Bosch Sensortec	BME280	Atmospheric Pressure (Pa)
	\alpha Sense	CO-A4	$[CO]$ (ppm)
	\alpha Sense	NO-A4	$[NO]$ (ppm)
	\alpha Sense	NO2-A43F	$[NO_2]$ (ppm)
	\alpha Sense	OX-A431	$[O_3]$ (ppm)
	\alpha Sense	OPC-N3	PM 2.5 ($\mu g/m^3$)
	\alpha Sense	OPC-N3	PM 10 ($\mu g/m^3$)
Model 205	2B Thecnology		$[O_3]$ (ppb)

To help in asserting the various comparison made in this study, four statistical indices are used, following the work by Biancofiore et al., 2015: R factor, normalized mean squared error (NMSE), fractional bias (FB) and factor of two (FA2).

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2.1 Data Preparation

After flag-checking for potential malfunctions, all gas concentration values equal to zero were removed, and a 3-sigma filter was applied to each variable.

OM205 exhibited time misalignment related to buffering issues, which have been solved by executing a time-shift correction (section S1).

To enable comparison, our data were averaged to match the different temporal resolution of the reference dataset (1 hour and daily averaged). For the two subsequent analysis values have been averaged over 30 minutes, to match the wind data, and averaged for every 5 minutes of a day over the various days to execute the Workday vs Holiday analysis.

2.1.1 AirSensEUR Calibration

Unlike the other devices, ASE does not give output calibrated gas concentrations. Instead, it reports digital signals ("digits"), which must be converted to ppb (ppm for CO) or $\mu g/m^3$. In literature are already present various approaches to the translation of the raw digit values acquired by this instrument (Schneider et al., 2023; Karagulian et al., 2020; Pichlhöfer and Korjenic, 2022); we implemented two calibration strategies using AQT data as reference:

1. Linear regression between ASE signal and AQT values.

2. Stepwise multiple linear regression including temperature and RH as covariates, following Wei et al., 2018

The execution of the stepwise regression was done by using the *step()* function from the *stats* R package which execute a formula-based model by Akaike information criterion (R Core Team, 2023), considering the dependence of the various concentrations from the temperature and relative humidity, which can be expressed by the following the equation:

$$y = a_0 + a_1 x + a_2 T + a_3 RH \tag{1}$$

Results from both the calibration procedures are shown in figure S2 and S3, while the related statistical indices are listed in table S2 .

Both the scatter plots and the statistical indices describe a good correlation of the calibrated ASE with the reference AQT ($R > 0.84$), with an improvement obtained by switching with the stepwise regression method, which is more sensible for O_x (R goes from 0.8464 to 0.889 and bias from 12.90 to 5.628) and NO_2 (R from 0.8464 to 0.9564, bias from 3.866 to 2.295 and the slope from 0.6793 to 0.8123). This result has led to the decision of using the latter calibration method for the study.

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3 Results

3.1 LCS evaluation

3.1.1 Meteorological Parameters

The time series of the meteorological variables (figure 2) shows a general agreement between all the instruments in our site, in particular for the curve shape of the various time series, as it is expected.

ASE present an evident shift compared to the other instruments for the temperature and RH. The comparison between the remaining LCS (AQT and SEP) and ITAF, which is used here as reference, give sensibly better results: from table 2 and the scatter plots in figure 3 we have not only a slightly better value for R (from 0.8767 for temperature and 0.8674 for RH to an average of 0.9331 and 0.9175 respectively), but also better NMSE (from 0.1335 and 0.1215 for temperature and RH to an average of 0.03443 and 0.03063 respectively) and more noticeably better bias (for temperature from 7.315 to 1.64315 and for RH from 29.35 to 22.94) and slope (for temperature from 0.6366 to an average of 0.837 and for RH from 0.3794 to an average of 0.6176) point to a lower quality for the measurement of these quantities for the ASE. Moreover, inaccuracies in RH measurements have already been documented by Weller et al., 2018, founding an increasing in discrepancy with reference for increasing value of RH and pressure, the first of which can be seen also in figure 2 where for higher value RH it appears the higher differences.

The high value reach by the ITAF RH (100%) must surely come from its retrieval: not with a direct measurement, but a formula using the dew point value. Still the dataset has been used for reference considering also the high correlation expressed by the high values of R (between 0.8674 and 0.9276) and low values of NMSE (between 0.027 and 0.1215) in table 2. This lets us see the already mentioned higher difference with the reference for the ASE than for the remaining LCS, which happens similarly for the temperature.

The pressure presents practically identity between all the instruments from our site, which is also confirmed by the optimal indices in table 2 (the apparently high value for the bias should not concern knowing the general high value of that variable).

3.1.2 Gaseous Pollutants

The various time series acquired in our site with the reference ARTA data are shown in figure 4 for visual comparison. Examining the Pearson correlation coefficient (R) in table 3, AQT present a good correlation for all the compounds with an important dispersion of points, as distinctly visible in the scatter plots in figure 5 and in the high normalized mean squared error (NMSE). Apart from the SEP NO_2, which will be further discussed later, also the other two LCS show a good correlation in the comparison with ARTA, but retain an important scattering of values as it can be also seen from the value of the NMSE. Different situation can be seen about R for the ozone, where there is a clear discrepancy between AQT ($R = 0.8367$) and the remaining LCS ($R \sim 0.55$). Such a high value of the factor for AQT seems to be contradictory to what found by Petäjä et al., 2021, but, partially this may come from the fact that the AQT (between the three LCS) has been used for the signal recovery process of the OzM (see the Supplement for further information). Moreover all the indices for AQT describe an high similarity between

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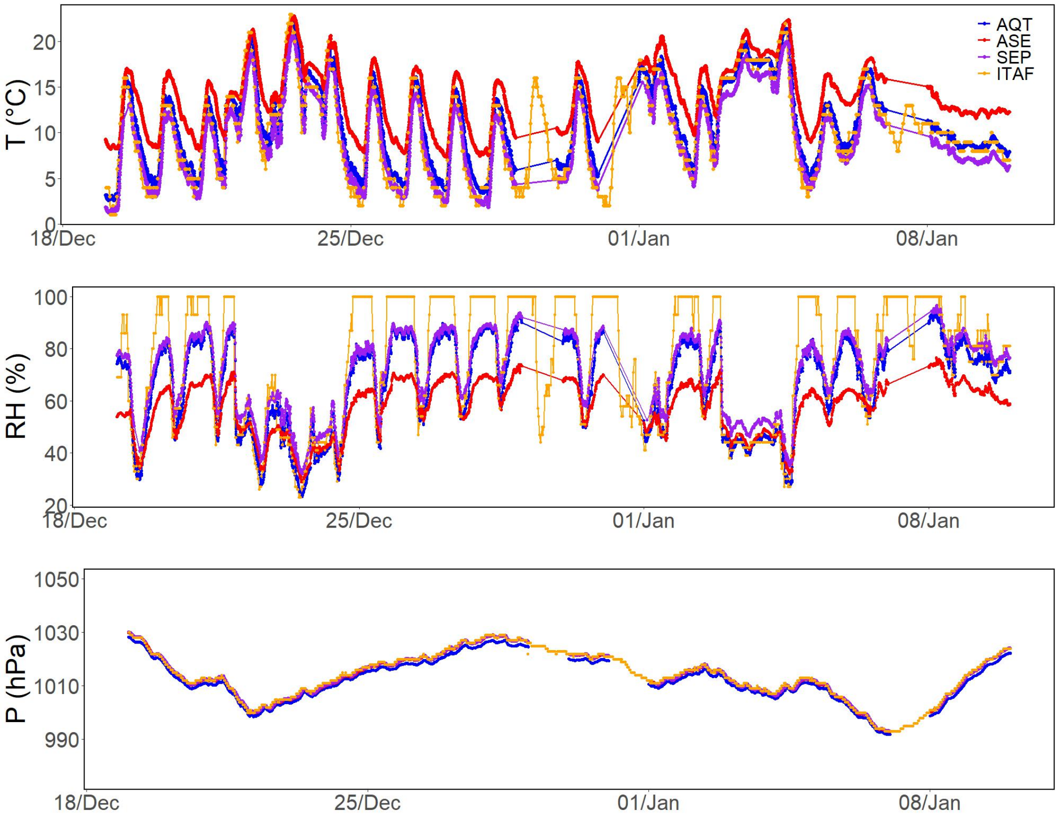

Figure 2. Time series of meteorological parameters.

the two time series, with a net improvement over what described previously in table S1, most probably due to the execution of an hourly average. Apart from the lower correlation, the remaining LCS show also a lower slope (0.5221 for ASE and 0.6387 for SEP) and way higher bias (12.86 for ASE and 106.5 for SEP), which help to depict a sensor (shared by the two instruments) with lower accuracy, as already noted by Yatkin et al., 2022.

Focusing on the various scatter plots (figure 5), NO_2 shows the lowest value of the slope of the linear regression (~ 0.3), while best values are seen for NO SEP (0.8146) and AQT ozone (1.071). The bias for AQT and ASE over the various compounds are generally low (apart from ASE O_X where it is 12.86). Differently SEP deviates strongly, showing extremely high bias values (between 64.8 and 173.1) This large bias value is particularly noteworthy considering that the SEP mounts sensors given as calibrated by the factory.

In accordance with this, the fractional bias (FB) describe the highest overestimation for SEP and in particular for the NO signal. On the other side, the highest underestimation can be seen for the two other LCS for NO_2, which however are lower in module in respect to the previously mentioned SEP.

To complete the comparison it is required to examine more in depth the peculiar signal of NO_2 for the SEP. SEP NO_2 and

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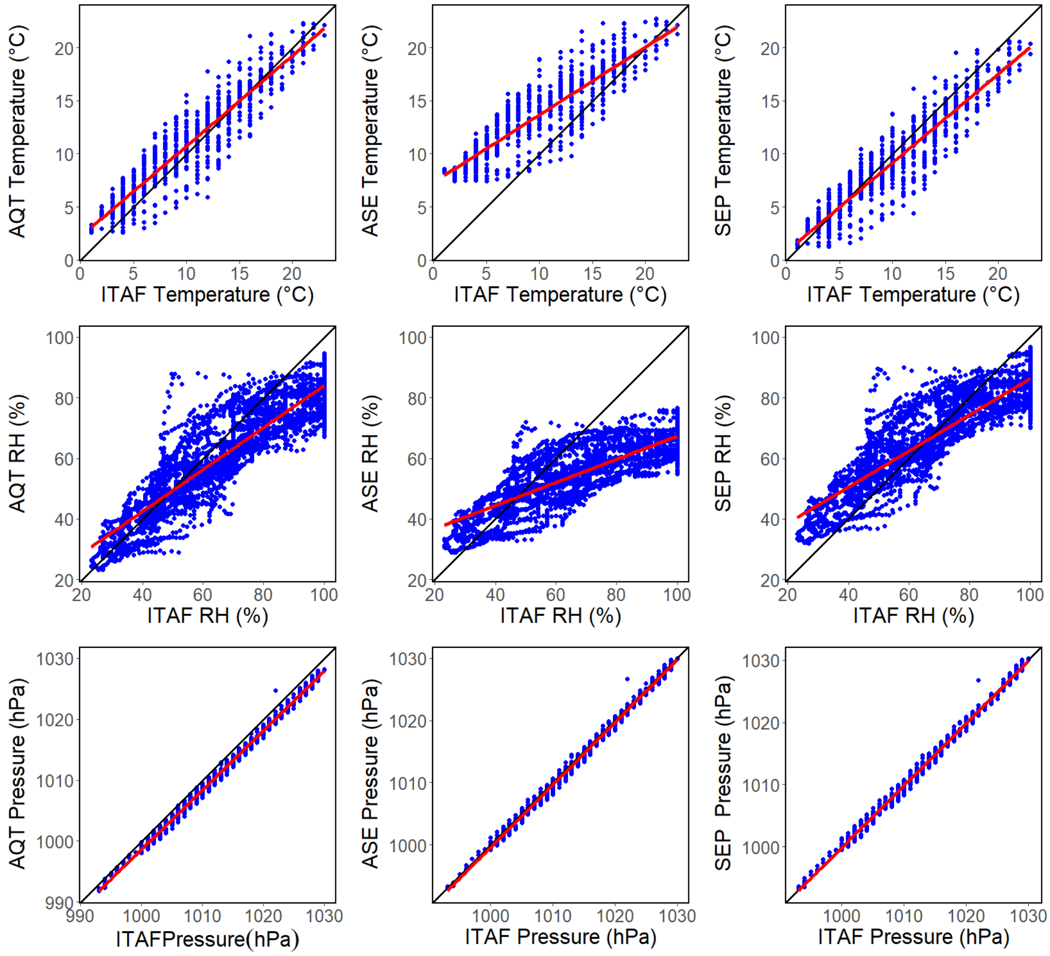

Figure 3. Scatter plots where ITAF is compared with site instruments. In red is drawn the bisector that express the wanted 1:1 relation between the two dataset, while in orange is the best fit with, in gray, the 0.95 confidence level.

RH time series show a high similarity that is confirmed by the high value of $R = 0.84$ (figure S4). This high correlation denote a strong sensitivity to humidity, not seen in the other LCS or ARTA. Considering that the sensor is a chemical sensor ($NO2 - A43F$ from Alphasense) a possible explanation is that some droplets of water could have entered in the sensor letting the electrolyte in the sensor respond mainly to the RH variation, which rends the readings unreliable. Therefore, these data were excluded from further analysis.

As previously described all the LCS were able to measure CO; not having any reference value we still opted for a inter comparison between the various LCS. The result of which is plotted in figure 6 with relative indices in table 4. It is clear the high correlation and general similarity between the various profiles, which is in agreement with what found by Papaconstantinou et al., 2024.

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Table 2. Statistical indices of the comparison between the LCS and reference for gasses compounds.

Physical Quantity	Instruments Compared	R	NMSE	FB	FA2	Bias	Slope
Temperature	ITAF vs AQT	0.9335	0.0311	-0.0606	0.9736	2.198	0.8527
	ITAF vs ASE	0.8767	0.1335	-0.2952	0.7761	7.315	0.6366
	ITAF vs SEP 1	0.9344	0.0410	0.0906	0.9765	0.7887	0.8372
	ITAF vs SEP 2	0.9314	0.0312	-0.0078	0.9767	1.941	0.8210
Relative Humidity	ITAF vs AQT	0.9276	0.0330	0.1124	1	15.21	0.6870
	ITAF vs ASE	0.8674	0.1215	0.2488	1	29.35	0.3794
	ITAF vs SEP 1	0.9140	0.0270	0.0430	1	27.08	0.5912
	ITAF vs SEP 2	0.9110	0.0319	0.0681	1	26.53	0.5746
Pressure	ITAF vs AQT	0.9964	0	0.0017	1	24.21	0.9744
	ITAF vs ASE	0.9960	0	0.0003	1	-4.75	1.004
	ITAF vs SEP 1	0.9962	0	0.0001	1	1.318	0.9986
	ITAF vs SEP 2	0.9962	0	0.0004	1	1.162	0.9993

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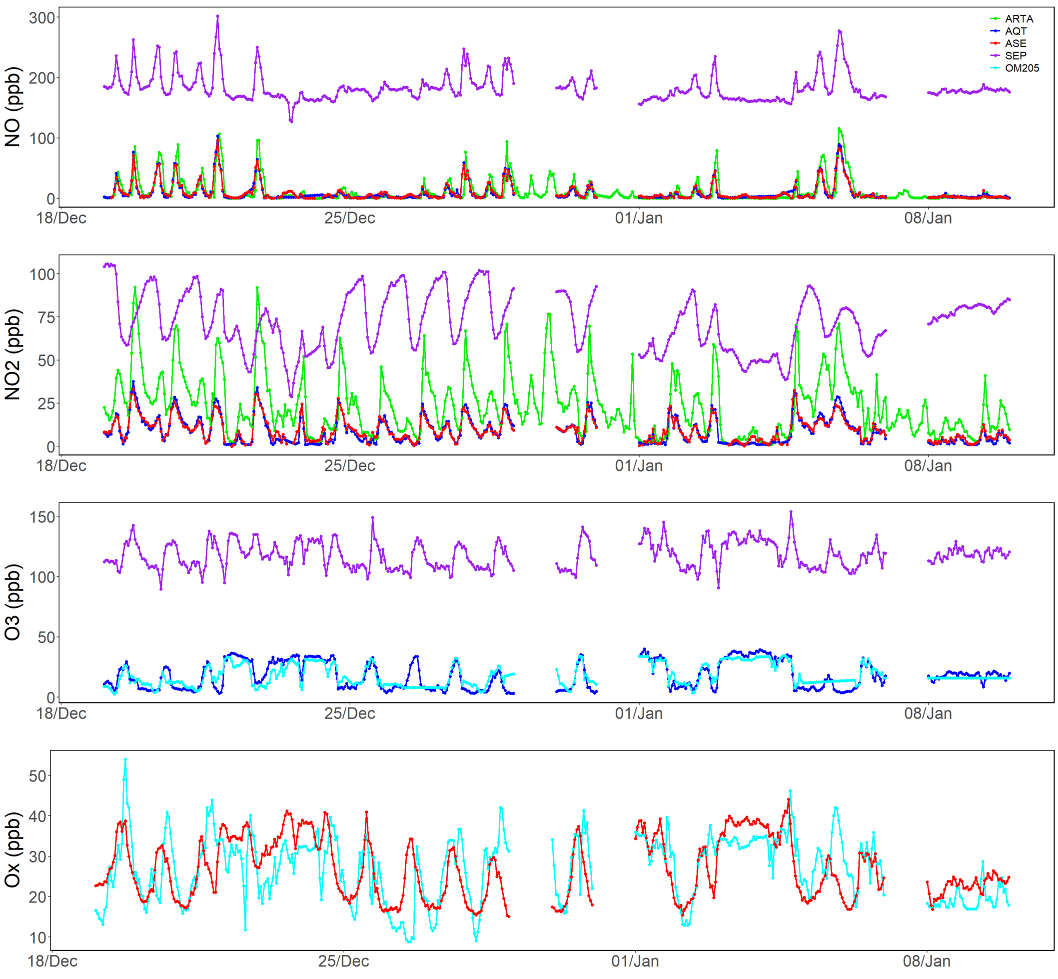

Figure 4. Time series of LCS measured gas compounds next to ARTA dataset.

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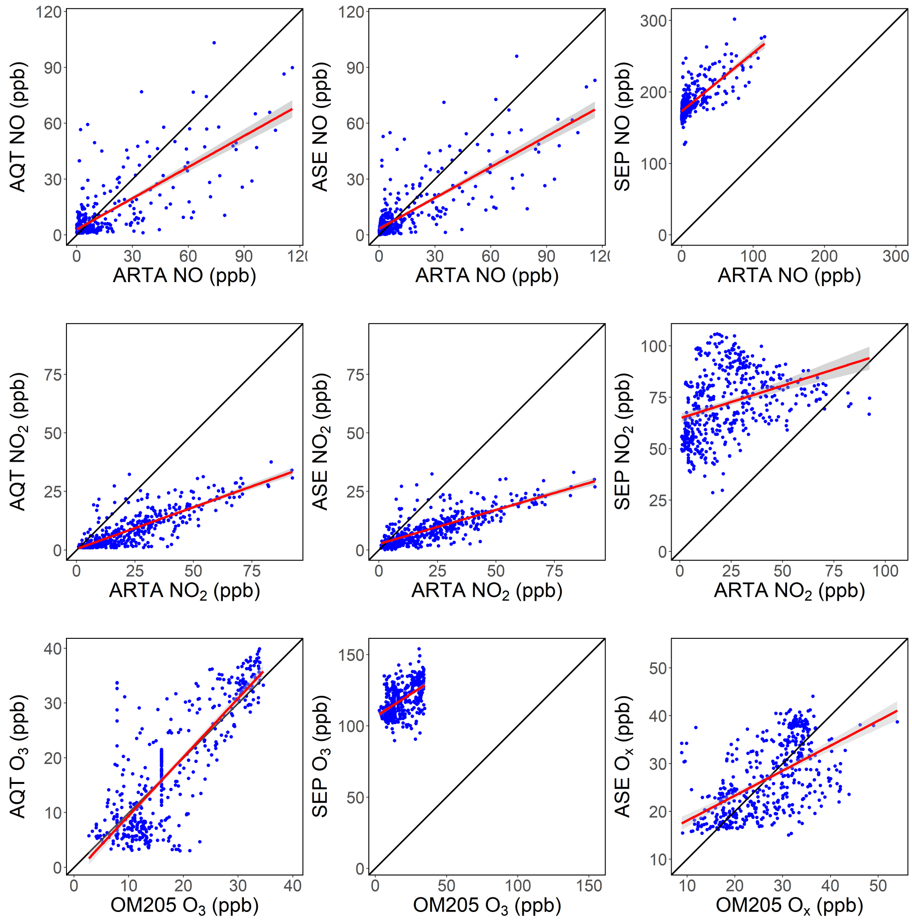

Figure 5. Scatter plot of the gas compounds that where possible to compare with ARTA. In red is drawn the bisector that express the wanted 1:1 relation between the two dataset, while in orange is the best fit with, in gray, the 0.95 confidence level.

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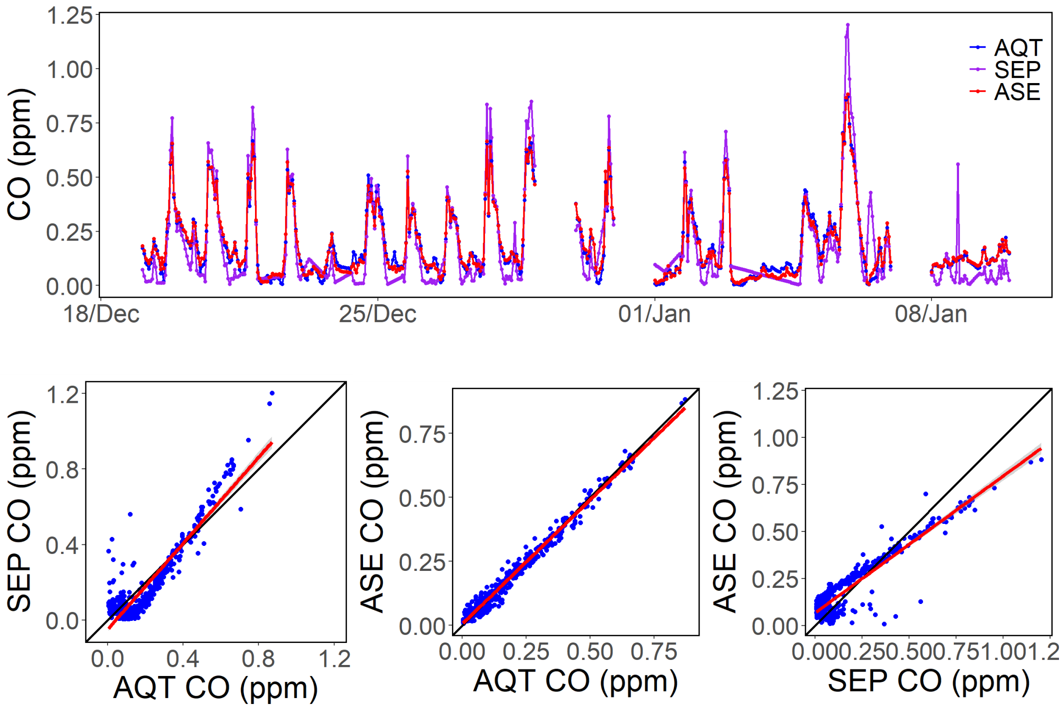

Figure 6. CO time series and In red is drawn the bisector that express the wanted 1:1 relation between the two dataset, while in orange is the best fit with, in gray, the 0.95 confidence level.

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Table 3. Statistical indices used to compare LCS measurements with reference dataset.

Physical Quantity	Instruments Compared	R	NMSE	FB	FA2	Bias	Slope
NO	ARTA vs AQT	0.7564	1.668	-0.2127	0.4198	2.949	0.5586
	ARTA vs ASE	0.7795	1.457	-0.1843	0.4537	3.390	0.5517
	ARTA vs SEP	0.7553	13.60	1.757	0	173.1	0.8146
NO_2	ARTA vs AQT	0.8250	1.783	-0.9083	0.2132	0.4366	0.3568
	ARTA vs ASE	0.7757	1.709	-0.8603	0.3014	2.595	0.2901
	ARTA vs SEP	0.3480	1.633	1.020	0.2088	64.80	0.3176
O_3	OM205 vs AQT	0.8367	0.1169	$2 \cdot 10^{-4}$	0.8396	-1.267	1.071
	OM205 vs SEP	0.5171	4.756	1.471	0	106.5	0.6387
O_x	OM205 vs ASE	0.5629	-0.0729	-0.0020	0.9802	12.86	0.5221

Table 4. Statistical indices used to compare CO LCS dataset between themselves.

Instruments Compared	R	NMSE	FB	FA2	Bias	Slope
AQT vs SEP	0.9884	0.0144	-0.0012	0.9385	0.0055	0.9697
AQT vs ASE	0.9137	0.2480	-0.1265	0.5253	-0.0488	1.139
SEP vs ASE	0.9216	0.2367	0.1254	0.5626	0.0678	0.7271

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3.1.3 Particulate Matter

The PM ARTA dataset, here used as reference for the comparison, collected as a daily average and so the measurements from our site have been average accordingly.

The daily values are shown in figure 7 as bar-plots. Here the two bars for the ASE represent the two signals given by the Plantower PMS5003 mounted in it; the one referred as "ASE Cal" is the same as the Raw one but calibrated. The process behind this calibration is done directly by the manufacturer.

Interestingly, while Kaur and Kelly, 2023 found a general underestimation and Tryner et al., 2020 a varying result depending on the particular kind of PM 2.5 take into account (e.g., wood smoke, soot), our data show a clear overestimation of the PMS5003 in comparison to the ARTA values, but always having the later inside the broad standard deviation of the PMS5003, which are generally wider than the other instruments. Moreover, the calibrated values tends to be the closest to the reference. As described by Caseiro et al., 2024, the PMS5003 do not have a heater to regulate the RH of the air parcel pumped in and, also for us, shows to be partially influenced by humidity (figure S5).

The OPC-N3 sensor, mounted on the SEP, showed a partial matching to the reference for the PM_{10}, while having important differences for the $PM_{2.5}$. This underestimation is in accord with what has been found by Kaur and Kelly, 2023. Finally AQT seems to underestimate to a large degree the ARTA values for both $PM_{2.5}$ and PM_{10}, in accordance with Petäjä et al., 2021.

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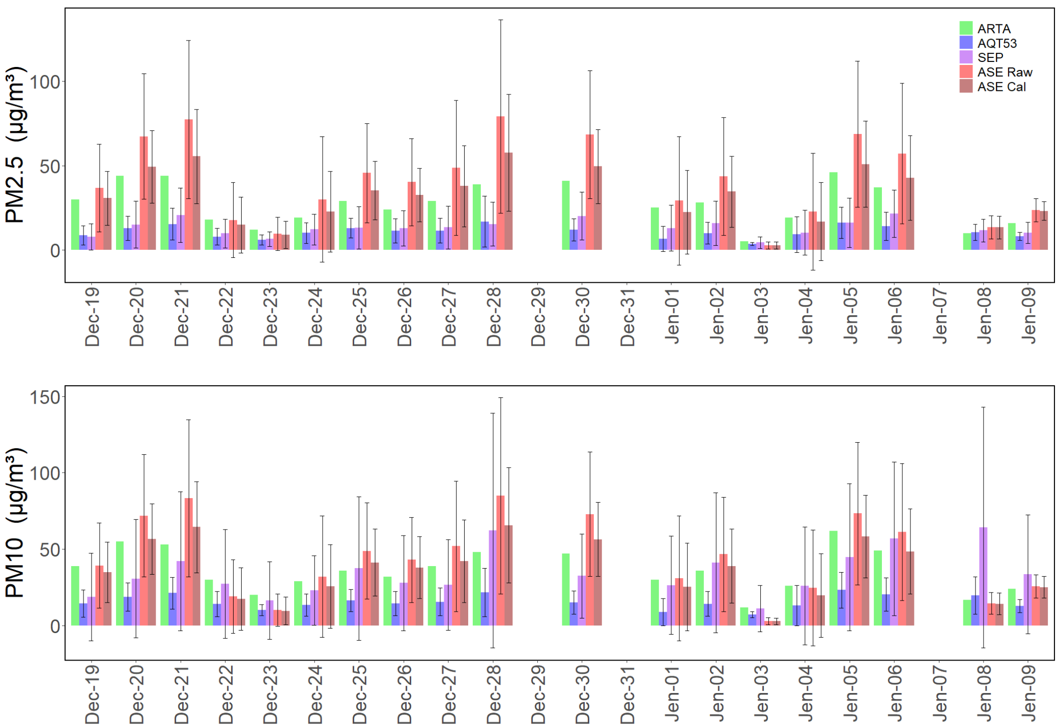

Figure 7. Daily value of PM with, in black, $\pm\,\sigma$. Absence of σ for ARTA is due to it not been given.

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3.2 Workdays vs Holidays

As already described in section 2, the observationale area hosts various and different kinds of pollution sources. This, combined with the particular time frame during which the campaign was carried out (Christmas Holidays), has led us to execute a workdays versus Holiday daily analysis, so to evaluate the possibility of obtaining relevant information from the LCS.

The LCS dataset has been averaged over 5 minutes and then over the various days distinguishing between Holidays (National festivities plus Sundays) and workdays (the remaining), which are plotted in figure 8 and 9.

The most noticeable observation is the presence of two peaks shared between almost all the plots, which could be due to the two rush hour events happening between $\sim 7\ am$ and $11\ am$ and between $\sim 5.30\ pm$ and $10\ pm$. A clear difference in the absolute value of the two peaks is clear in all the plots; a plausible explanation come from an important difference between the two rush hour events: during the evening, in particular on the E80 free-way (see figure 1, to the left of our site), long traffic jams (that starts on the E80, at the intersection with the SS714 and with queue of a few kilometers) happens almost daily and with a higher severity than during the morning rush hour. Large number of slow moving cars leads higher emission, which can, at least partially, explain the higher evening peaks. Moreover, the holidays profiles shows, in particular for NO and NO_2 (compounds strongly linked with car engine emission), a drop of the aforementioned spikes during holidays. This would validate the important contribution to the signal of the rush hours.

Observing the late evening/night it is possible to see a discrepancy between the two curves in almost all the plots. During holidays, increased domestic activities (e.g., gatherings or celebrations) typically extend late into the night, leading to higher household emission in these hours. Moreover, is evident a slightly higher standard deviation in this time frame for holidays. This may partially come from the fact that for holidays we had fewer days of measurements than for workdays, respectively 5 and 14 (considering the gap in the dataset on the 29, 31 and 07).

Focusing on CO, $PM_{2.5}$ and PM_{10} it is interesting to note how, more noticeably for holidays, the evening peak tends to split in two. The first peak happens around $6pm$ in accordance with the evening rush hour peak previously described, while the second later in the evening, around $9pm$. Considering that these compounds can be related to household emission trough wood burning and soot (Cooper, 1980; Traynor et al., 1987), a plausible source of the second peak could be fireplaces and and barbecues, used for heating and cooking. This is particularly reasonable considering the cold season and Christmas Holidays.

The ozone shows a curve that strongly differs in shapes from the other compounds, the shape is the one that is generally associated with the ozone daily cycle with low peak due to the winter season (Schanz et al., 2014). Between workday and holidays it can be noted a slightly higher value from midnight to 5 pm with an inversion between the two just after sunset. This is in line with the ozone weekend effect, for which a reduction in the ozone precursors (generally expected for the weekend, but more generally also for holidays) can led to an increase in surface O_3 as observed by Sicard et al., 2020.

It is also important to note that for ozone is present a high variability during all the day, with a slight lowering of σ only for higher values of the concentration itself (between $\sim 10am$ and $\sim 5pm$), shared by all the LCS. A possible explanation to this peculiarity can derive from the fact that local formation of ozone depends on the ratio of VOC to NO_x (Beekmann and Vautard, 2010; Markakis et al., 2014).

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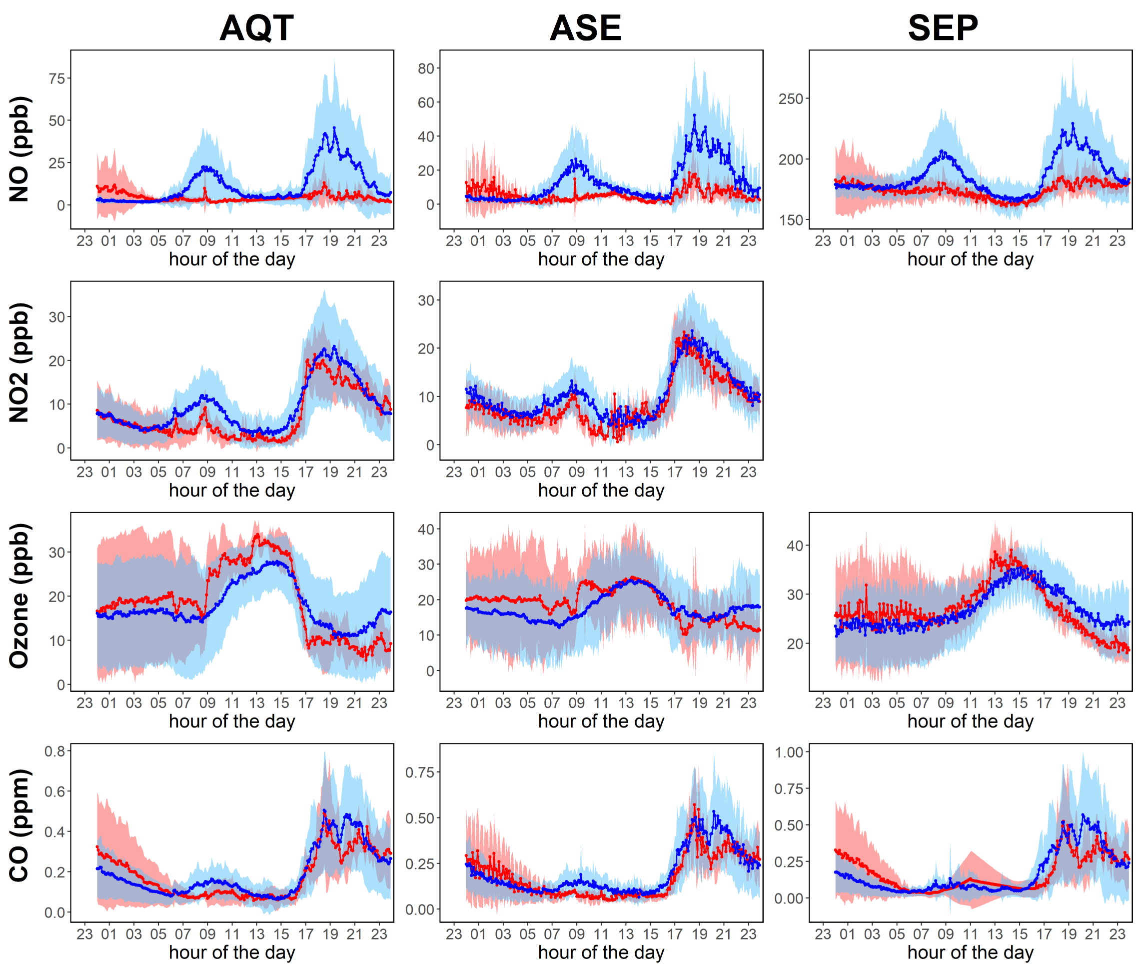

Figure 8. Daily concentration plot of different gas compounds divided in weekdays (blue) and holidays (red).

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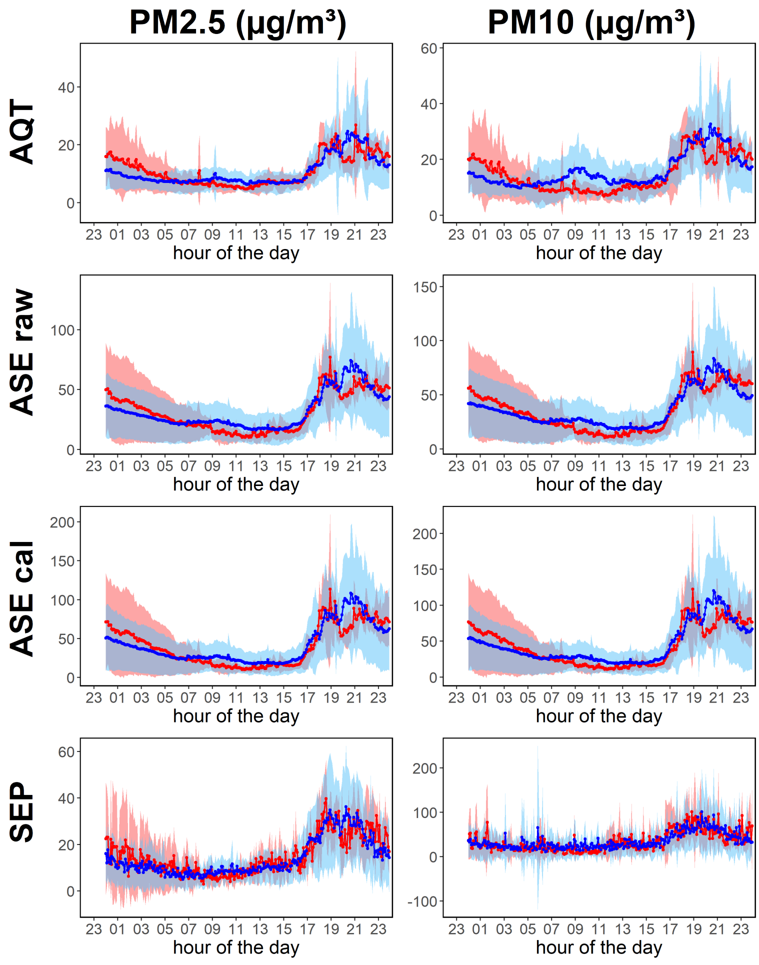

Figure 9. Daily concentration plot of different size of particulate matter divided in weekdays (blue) and holidays (red).

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3.3 Wind Analysis

Considering the presence of many interesting location source of various pollutant we tried to track them by comparing the concentrations with the wind measurements acquired by ITAF. The result is plot in figure 10 and 11, separating between day and night using a mean time frame for day time from $7.30am$ to $4.30pm$.

Considering the gaseous compounds, during night NO, NO_2 and CO the peak of concentration occurs for low speed wind with a small westerly component. Considering how this peak, as explained in 3.2, happens during the evening rush hour the westerly contribution to the wind can help in the supposition that an important contribution to the signal might be due to the almost daily traffic jams on E80 highway (west to our site, figure 1).

During daytime, following what already described in section 3.2 all the compounds (with exception for ozone) are showing a peak related to the morning rush hour and only for NO this has a height comparable to the evening one. Interestingly, all the peak seems to happen in presence of a still slow speed wind but with a south-west origin. Looking at the map in figure 1, this direction could hint at a lesser contribution from the traffic jam to the signal.

Focusing on the ozone, figure 10, the polar plots are almost the opposite in regards to the mean concentration values to the NO_2 plots. This is expected for the $NO_x/Ozone$ daily cycle.

Moving on to the PM, from figure 11 strong discrepancies appear between the instruments both for PM 2.5 and PM 10.

The ASE, which has better performed in the comparison with ARTA, maintain the same profile of the chemical compounds, while AQT and SEP still present generally higher values during night but correlated with distinctly different wind directions and speeds. Knowing the poor result in the previous comparison, these last instruments may be considered with lower regard with respect to the ASE for this last analysis.

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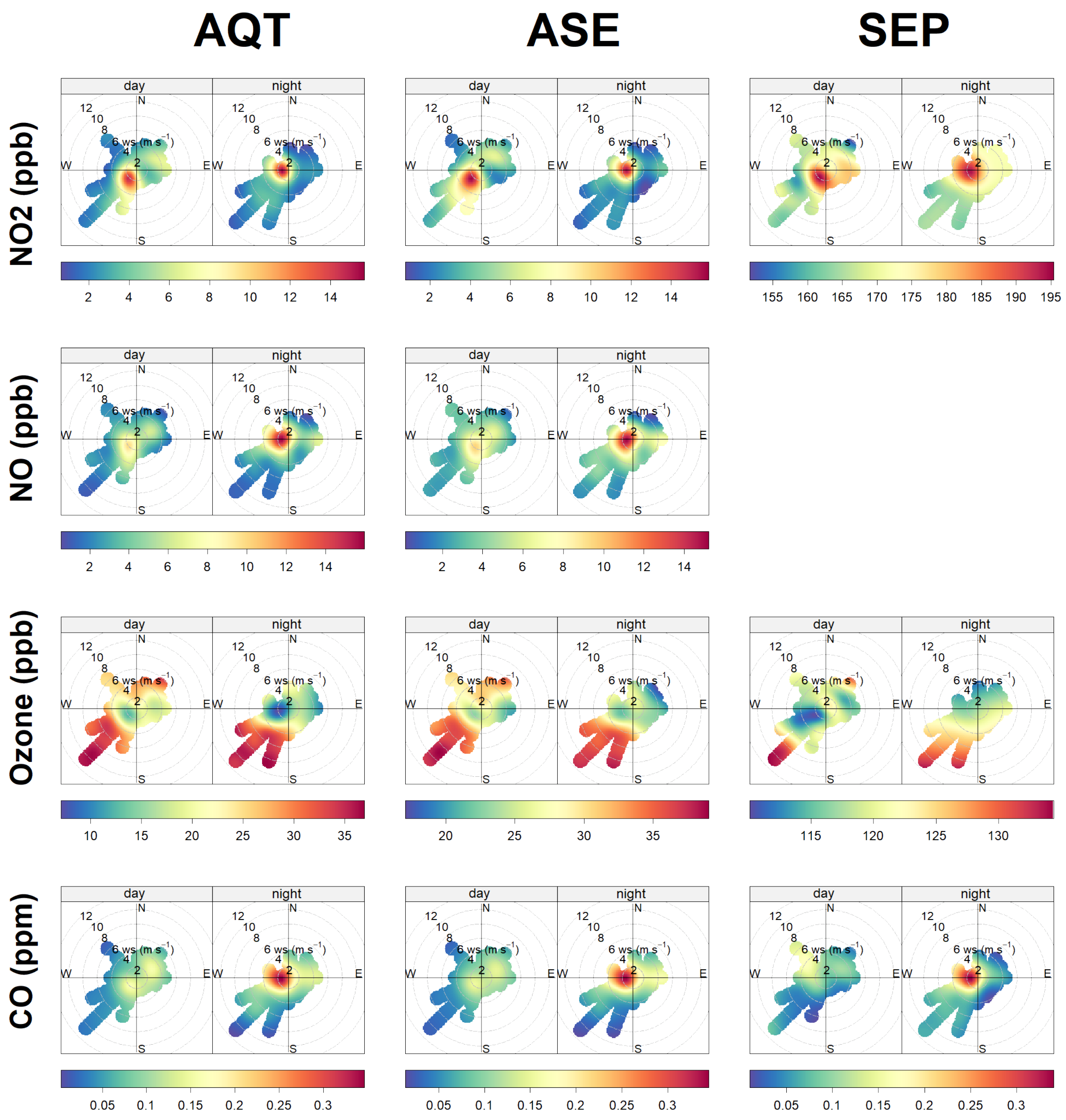

Figure 10. Wind analysis (mean speed and direction) of mean concentration of various gasses pollutant.

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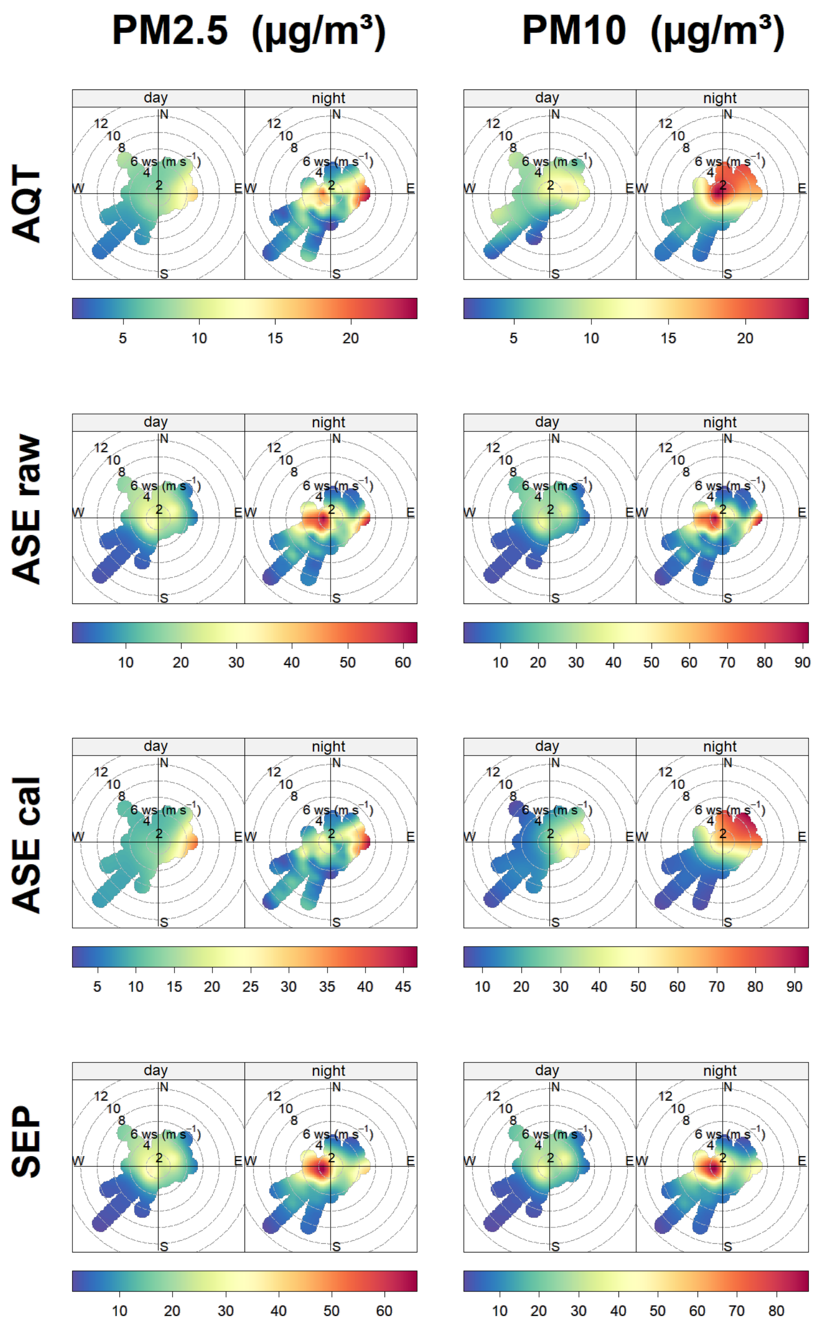

Figure 11. Wind analysis (mean speed and direction) of mean concentration of two PM sizes.

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4 Conclusions

This study presents a simultaneous field evaluation in a complex urban environment of three commercial low-cost air quality sensor platforms done by comparing their measurements with those from certified reference instruments. While numerous studies have investigated individual low-cost sensors or calibrated sensor networks, the present work uniquely assesses the performance realistically achievable by end users, without post-deployment optimization, under wintertime and high-humidity conditions.

Meteorological parameters were generally accurately captured by all sensors, with strong correlations to ITAF references, especially for pressure. Some limitations were observed in the ASE temperature and RH measurements, which showed biases under high humidity.

In terms of gaseous pollutants, CO measurements were highly consistent across the LCS devices. NO and NO_2 data showed good correlation with ARTA, with the exception of the SEP NO_2 sensor, which suffered from severe bias likely due to humidity interference. Ozone measurements had lower performance overall, with AQT performing best.

Particulate matter results revealed significant variability. ASE, particularly in its calibrated form, matched daily ARTA data relatively well. AQT consistently underestimated PM values, and SEP showed moderate agreement for PM_{10} but underestimated $PM_{2.5}$.

The result of the intercomparison with standard certified reference grade instrument demonstrate that factory calibration still do not ensure general reliability of measurements. Moreover even nominally identical sensors mounted on different platforms showed sensible differences.

Nevertheless noteworthy is how the subsequent analyses showed that limited accuracy does not necessarily imply limited information value. All platforms were able to resolve daily cycles, highlighting traffic and holiday related emission peaks, and to be use in pollutant–wind relationships analysis, the result of which was consistent with known local sources. This provides experimental evidence that low-cost sensors can support qualitative source attribution and temporal pattern analysis even when quantitative agreement with reference instruments is suboptimal.

These findings emphasize the need to distinguish between accuracy-driven and information-driven applications of low-cost sensors. While low-cost platforms cannot replace regulatory-grade instrumentation, their deployment can substantially enhance air quality monitoring by increasing spatial coverage, particularly in environments not served by official networks. Still data prove their effective use in research field requires critical validation, compound-specific interpretation, and integration with meteorological information.

Code and data availability. Code and data are available upon request, sending an email to lorenzo.gentile@iusspaiva.it

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285 *Author contributions.* PDC, PC, LG: conceptualization. LG, PG: data curation, formal analysis. PDC: funding acquisition. LG, EA, PC: methodology. PC, LG: software. AM, EA, PC, PDC: supervision. LG: visualization. LG: writing (original draft). All authors: writing (review and editing)

Competing interests. At least one of the (co-)authors is a member of the editorial board of Atmospheric Measurement Techniques.

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