Response to comments from Referee #2

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Thank you for your review and valuable comments. Our responses and revisions, which we believe will further enhance the quality of the paper, are presented below. The comments from Referee #2 are provided in black, our responses appear in brown, and the revised or newly added text in the manuscript is shown in *italics*.

This manuscript shows different options for calibration of LCS, in particular O3 and PM2.5. The goal is to show a tradeoff between the model accuracy based on an initial training with a dataset (in terms of duration) and recurrent recalibrations.

The discussion is interesting, and it is an open question. Notice that about this topic there are many issues to be considered for this problem, with regard to the initial dataset (in terms of quality, range, duration, sampling frequency, locations for deployments), models used for calibration (statistical ones or based on AI (machine learning, deep learning)), sensor types and features (gas, cross sensitivity, fabrication (Electrochemical, Metal OXide (MOX) sensor, NDIR and/or optical, aging effect) to name a few. Nevertheless, the authors focus on sensors O3 (Alphasense Ox-B431) and PM2.5 (Sensirion AG SPS30) and using 4 different models (MLR, RR, RF, XGB) for calibration.

Thank you for emphasizing the common issues and challenges that need to be considered in low-cost sensor (LCS) calibration, many of which we aim to address through recurrent calibration and, consequently, through continuous data quality assurance.

To clarify why we focused only on these two sensor technologies (electrochemical gas sensors and optical particle sensors): In our initial work (Gäbel et al., 2022), we tested LCSs based on different technologies to identify the most suitable ones for developing our own low-cost air pollution monitoring system. Based on the raw data quality and calibration results using the common multiple linear regression (MLR) method, we found that electrochemical sensors provided the most promising results for the measurement of ozone (O_3), while the Sensirion SPS30 (optical particle sensor) stood out in terms of performance compared to the other LCSs we investigated. Therefore, we decided to focus on these two sensor technologies. In the case of the SPS30, we did not explore other optical particle sensor candidates for the measurement of $PM_{2.5}$, as its performance was satisfactory, and we retained it for the latest, more advanced version of the Atmospheric Exposure Low-Cost Monitoring (AELCM) box.

In the present paper we investigated gas sensors from another manufacturer (Alphasense), which are based on electrochemical gas sensor technology, as a consequence of our findings (Gäbel et al., 2022) and other literature about Alphasense sensors. We applied additional calibration models, but our main focus was on recurrent calibration and its impact on performance. The study considers the recommendations of the U.S. EPA (United States Environmental Protection Agency) and European technical specifications (CEN/TSs) approved by CEN (European Committee for Standardization) for LCSs providing a novel perspective on sensor calibration design by using both as guidance to evaluate overall sensor performance and to investigate the suitability of the introduced LCS as supplemental tools for air quality monitoring.

Next, you have the suggested Comments (C) to improve your manuscript:

C1.- The title should be clearer and more specific including key words such as tradeoff, O3 and PM2.5

We would use tradeoff as one of the keywords for this study, but we would not include it directly in the title.

We suggest the following title change:

"Recalibration of low-cost O_3 and $PM_{2.5}$ sensors: Is it worth it?"

C2.-The study is carried out with 2 sensos O3 (Alphasense Ox-B431) and PM2.5 (Sensirion AG SPS30). The selection should be justified and motivated: why these ones? are these the more common, more reliable, price vs quality ratio, etc.? The authors should provide a survey (a study of state of art) about this. This information is very useful for the reader.

In addition, in Section 2.1, the name of the sensors for O3 and PM2.5 and their abbreviations (AS-B431, SAG-SPS30) as well as their features should be placed in a table to ease reading.

Thank you for the suggestions. We added more information and a new table based on the Reviewers input.

Line 122 – 125:

There were multiple reasons for the use of Alphasense sensors. In our earlier work (Gäbel et al., 2022), we investigated the digital gas sensors DGS-NO2 and DGS-CO from SPEC Sensors, based on electrochemical (EC) gas sensor technology, as well as the MiCS-2714 (NO_2) and MiCS-4514 (CO) sensors from SGX Sensortech, based on metal oxide semiconductor (MOS) technology. Our results showed that these air sensors exhibited no satisfactory capability to capture the observed concentrations at a measurement station, according to the coefficient of determination after sensor calibration (R^2: 0.15 – 0.66). Therefore, we applied alternative LCSs to capture NO_2 and CO. Overall, the SPEC DGS-O3 units performed satisfactorily (R^2: 0.71 – 0.95) but showed high inter-sensor unit variability. For the calibrated MQ131 sensor outputs moderate to high R^2 were determined (R^2: 0.71 – 0.83). In contrast, the raw MQ131 sensor outputs showed generally poor correlation with the O_3 reference measurements. We concluded that EC gas sensor technology is suitable for detecting O_3 in an urban background environment, whereas MOS technology showed limited capability considering Winsen's MQ131 sensor. Alphasense EC gas sensors are the most used and evaluated LCSs for measuring O_3, NO_2 and CO (Karagulian et al., 2019; Kang et al., 2022) and offer a good price-to-quality ratio (see Table 2). Kang et al. (2022) reported median R^2 values of 0.70, 0.68 and 0.82, respectively, for these pollutants when measured using Alphasense EC sensors in outdoor settings, as determined by reference instrument data. In our evaluation at an urban background station (Gäbel et al., 2022), the SAG-SPS30 particulate matter sensor showed high correlative performance for calibrated data (R^2: 0.90 – 0.94). Also, other outdoor studies showed satisfactory results for the SAG-SPS30 and its measurement of $PM_{2.5}$ (R^2: 0.72 – 0.87) (Vogt et al., 2021; Roberts et al., 2022; Shittu et al., 2025).

References:

Shittu, A. I., Pringle, K. J., Arnold, S. R., Pope, R. J., Graham, A. M., Reddington, C., Rigby, R., and McQuaid, J. B.: Performance evaluation of Atmotube PRO sensors for air quality measurements in an urban location, Atmos. Meas. Tech., 18, 817–828, https://doi.org/10.5194/amt-18-817-2025, 2025.

Kang, Y., Aye, L., Ngo, T. D., & Zhou, J. (2022). Performance evaluation of low-cost air quality sensors: A review. Science of The Total Environment, 818, 151769. https://doi.org/10.1016/j.scitotenv.2021.151769

Roberts, F. A., Van Valkinburgh, K., Green, A., Post, C. J., Mikhailova, E. A., Commodore, S., Pearce, J. L., & Metcalf, A. R. (2022). Evaluation of a new low-cost particle sensor as an internet-of-things device for outdoor air quality monitoring. Journal of the Air & Waste Management Association, 72(11), 1219–1230. https://doi.org/10.1080/10962247.2022.2093293

Gäbel, P., Koller, C., & Hertig, E. (2022). Development of Air Quality Boxes Based on Low-Cost Sensor Technology for Ambient Air Quality Monitoring. Sensors, 22(10), 3830. https://doi.org/10.3390/s22103830

Vogt, M., Schneider, P., Castell, N., & Hamer, P. (2021). Assessment of Low-Cost Particulate Matter Sensor Systems against Optical and Gravimetric Methods in a Field Co-Location in Norway. *Atmosphere*, *12*(8), 961. https://doi.org/10.3390/atmos12080961

Karagulian, F., Barbiere, M., Kotsev, A., Spinelle, L., Gerboles, M., Lagler, F., Redon, N., Crunaire, S., & Borowiak, A. (2019). Review of the Performance of Low-Cost Sensors for Air Quality Monitoring. Atmosphere, 10(9), 506. https://doi.org/10.3390/atmos10090506

Table 2: Overview of the specifications of the air sensors that can be used in the AELCM unit.

Measured Variable	Sensor	Manufacturer	Abbreviation	Range	Noise [a] [Precision]	Approx. Price (Euro) 2025
$O_3 + NO_2$	OX-B431	Alphasense	AS-B431	20 ppm	15 ppb	71/84[b]
NO_2	NO2-B43F	Alphasense	AS-B43F	20 ppm	15 ppb	59/84[b]
CO	CO-B4	Alphasense	AS-B4	1000 ppm	4 ppb	56/79[b]
$PM_{2.5}$	SPS30	Sensirion AG	SAG-SPS30	1000 µg/m^3	[±10 µg/m^3 at 0 to 100 µg/m^3] [±10% at 100 to 1000 µg/m^3]	30

Tested with Alphasense ISB low noise circuit: ±2 standard deviations (ppb equivalent)[a]
Additional cost for Individual Sensor Board (ISB) low noise circuit for B sensors[b]

C3.- The references are bit confusing. Not sure if it is the proper format and they are correctly compiled (not linked with reference section). For instance, (Gäbel et al., 2022), you cannot find it directly in the reference list. Although in a double lookup you can assume that it refers to a paper in Sensors MDPI from the same authors.

Also, an update of these references is welcome, with more recent ones.

Yes, we reference Gäbel et al. (2022), which is our earlier publication about the AELCM box in Sensors MDPI.

We adjusted the output style of the references to improve readability in the section "References" (Indentation and line spaces). References in the manuscript are easier to find now in the section "References". All references in the manuscript are included in this section.

We added some more recent literature, kept the relevant references and removed older references where it seemed appropriate.

C4.- Figure 1 is a bit confusing. Maybe a flow diagram of the proposal of the manuscript (the tradeoff between training duration and recalibration) should be better.

Done.

We would like to keep our original Figure 1 and present both figures side by side to make our methodological approach even clearer.

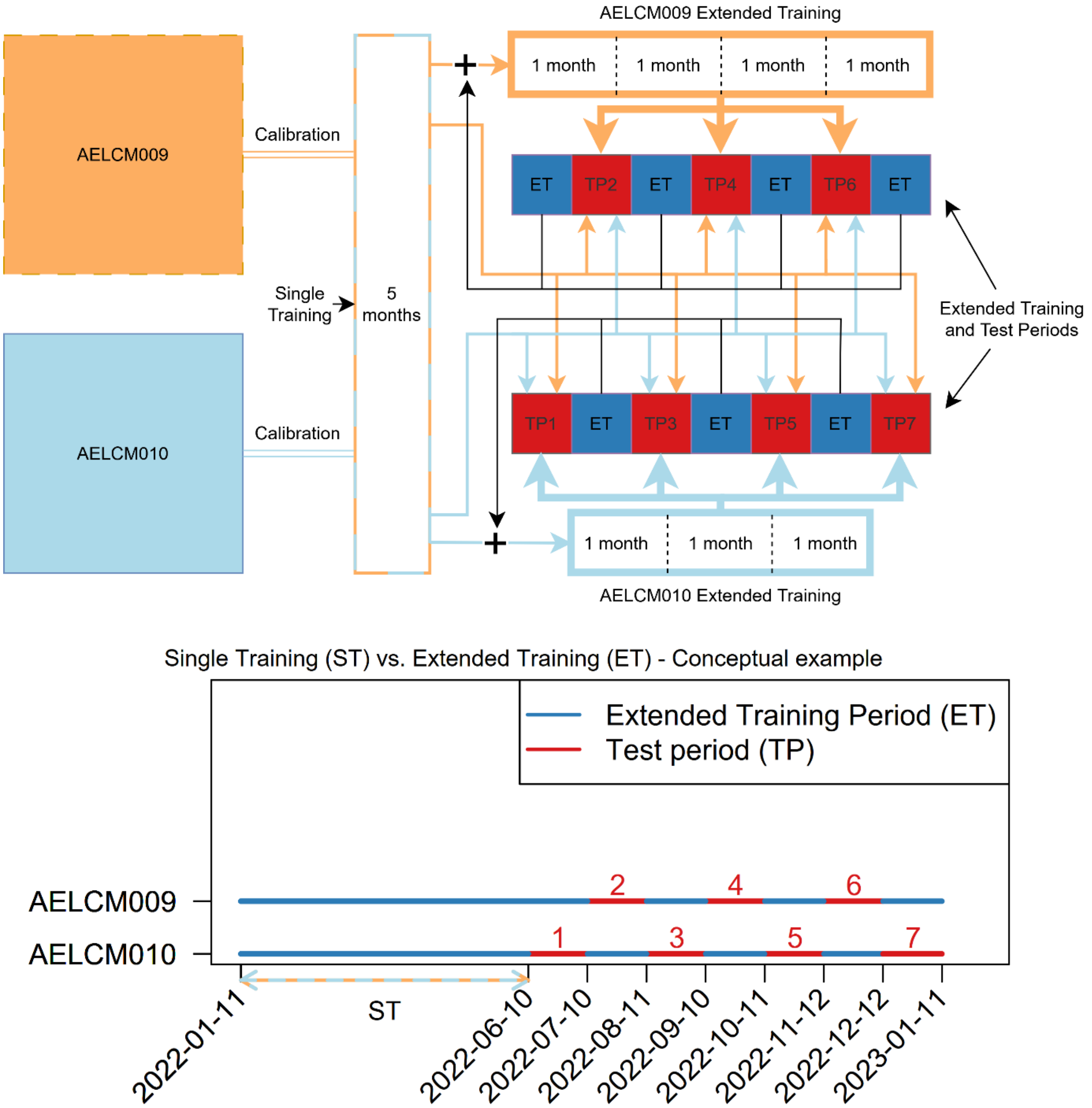

Figure 1: Schematic representation of the pairwise calibration strategy and calibration model development as a flow diagram (top) and a time series scheme (bottom) using two LCS measurement systems (AELCM009 and AELCM010) showing the single training period (ST, 11 January–10 June 2022) and the extended training period (ET) as well as the numbered one-month test periods (TP) for each LCS measurement system. The thickness of the coloured lines in the flow diagram visually represents the amount of training data used for ET of the calibration model compared to ST.

C5.-In my opinion, the analysis of 2 different deployments (AELCM009 and AELCM010) is interesting, to see the behavior (variability) between the different sensors.

But, the content of this manuscript could improved in a more comprehensive way. It could be carried out by using the whole dataset, and running on this dataset the different variables of the tradeoff: x= duration of initial training, y=recalibration time. Based on (x,y) you can plot the different metrics (R2, RMSE, REU,…) or a cost function (this is mentioned later in C11)) as a heatmap (in 3D plots), in stead of using a fixed training of 5 months, with extended periods of 1 months, and with recalibration with different periods. A heatmap should be easier to understand and see the optimum, rather than Figures 2-4 and 5-7. Notice that these figures are ambiguous and unclear. Also, the caption is bit redundant except 1, 2 or 3 months.

Besides, it should be noted that usually, the datasets have a higher sampling frequency, usually 10 min (or even lower), rather than 1 hour. It should be explained. Even, the sampling frequency could be a new variable to be considered in the tradeoff, instead of 1 hour as default.

Carotenuto et al. (2023) provide a literature survey about the topic of low-cost air quality monitoring networks for long-term field campaigns. They highlighted that in most cases, LCS networks are still only used for test applications or specific projects, most often not even lasting one year and that there is a lack of long-term efforts aiming at routinely monitoring air quality conditions.

To help encourage such long-term initiatives and stimulate interest among potential sensor end users such as local environmental agencies that also have permanent access to calibration equipment, we deliberately incorporated the recent test protocols from the U.S. EPA and CEN into our study. By applying the recommended performance metrics and performance targets from these protocols, our aim was to support practical decision making by stakeholders considering deeper involvement in air sensor projects, rather than to conduct an in-depth statistical analysis like suggested in C5 in the second paragraph.

We also wanted to avoid obscuring our key messages for end-use communities, centered on reaching performance targets and attaining the highest possible sensor tiers. This tier-based concept is easier for end-users and stakeholders to understand, especially for those who usually have the infrastructure and resources to maintain low-cost sensor networks over the long term and who ultimately need to be convinced of their value.

In our opinion, the approach we have chosen and the form of display (2D circular bar plots and REU plots) to check the achievement of performance targets and sensor tiers are very good from an end-user and practical perspective and also for the scientific community. We work with air sensor data (O_3, $PM_{2.5}$) and performance thresholds for RMSE, R^2, Intercept and slope and the relative expanded uncertainty (REU) at the limit value of O_3 and $PM_{2.5}$ as suggested by EPA test protocols and CEN test protocols, respectively.

We are specifically highlighting in our plots (Fig. 2-4 and Fig. 5-7), when a target is fulfilled (non-hatched bars in circular bar plots) and under which circumstances (Calibration model, single training (ST), extended training (ET) variant, AELCM box). Calibration model performances are ordered from highest to lowest in each test period (TP). Because of the manifold of aspects (Calibration model, ST, ET variant, AELCM box, time periods, error metrics and so on), which should be displayed in a single plot, and the question how recurrent calibration should be designed, splitting figures by ET variants (1 month, 2 months, 3 months) is the most sensible choice in our opinion.

A further reason is, that an ET variant defines when an AELCM box needs to be exchanged with its partner AELCM box in situ. This is indicated through the curved lines in Fig. 2-4 and Fig. 5-7 (dashed: AELCM009, non-dashed: AELCM010). We also prefer 2D circular bar plots instead of 3D plots, because we can display TPs in a clocklike manner, which is an elegant way to communicate sensor performance over time in our opinion.

Our AELCM measurement systems have a sampling frequency of 4 seconds, as mentioned in line 119. We clarified it more in line 119:

The upgrades also involved the increase of the sampling frequency for each AELCM sensor from 10 seconds to every 4 seconds.

Hourly and daily means of LCS measurements were used to comply with the evaluation requirements of the CEN and EPA test protocols. We clarified that in line 164 till 168:

Gas sensor measurements were aggregated to hourly means, while $PM_{2.5}$ sensor measurements were aggregated to daily means. This was required for the performance evaluation of LCSs according to the technical specification developed by CEN (CEN/TS 17660-1:2021, 2021; CEN/TS 17660-2:2024, 2024) and the test protocol developed by EPA (Duvall et al., 2021a, Duvall et al., 2021b). As a result, gas measurements and $PM_{2.5}$ measurements given by the AEMS were aggregated to hourly and daily means, respectively.

Reference:

Carotenuto, F., Bisignano, A., Brilli, L., Gualtieri, G., & Giovannini, L. (2023). Low-cost air quality monitoring networks for long-term field campaigns: A review. Meteorological Applications, 30(6). https://doi.org/10.1002/met.2161

C6.- In Section, 2.1, it should be nice to place some pictures of the boxes and deployment, although you refer to them in your own reference ((Gäbel et al., 2022)).

(a) (b)

Figure 2. Photographs of the AEMS and AELCM units (AELCM009 and AELCM010), which are mounted on the fence next to the AEMS: (a) the stationary air and climate measurement station of the Chair for Regional Climate Change and Health, Faculty of Medicine, University of Augsburg; and (b) the housing and interior view of the engineered AELCM units.

C7.- Section 2.4 requires a better description and detail of the models used. This can be summarized in a table with a short description and reference. Additional information could be interesting such as the library used, hyperparameters used (if needed), is there overfitting in the machine learning models? etc.

In Table 1, the target (in features/target) is not necessary if it is the same name of the model (on each column). Also, it should be recommended for clarity to show only the 2 models that you are using: O3 and PM2.5.

The tuned hyperparameters of our calibration models are provided in Table S3 of our Supplement. We added additional details and descriptions of the calibration models in Table S3 for interested readers and added the used R libraries. We refer to this table in the manuscript. Furthermore, we revised line 224 as follows:

The selected and tuned model hyperparameters for RF, XGB and RR can be found in the supplement as well as more detailed information on the calibration models and used R packages (Table S3).

Furthermore, we added additional information about the purpose of the mlr3 package, as we believe the relationship between mlr3 and the R packages listed in Table S3 may not be clear to readers. The mlr3 framework enables us to use models from multiple libraries through a single, unified interface for training, testing and evaluation. We revised line 223 to clarify the role of the mlr3 package:

The mlr3 package and mlr3 ecosystem provide a framework for regression tasks and a unified interface for working with various learning algorithms, including the calibration models used in this work.

The Reviewer raised concerns about overfitting; therefore, we added additional information in line 234 to clarify how we addressed overfitting during the calibration model building process:

An out-of-sample (OOS) method following a repeated holdout strategy (Gäbel et al., 2022) was used to identify calibration models with good performance and optimally tuned hyperparameters, as estimated by their performance on the holdout data.

We revised Table 1 as suggested by the Reviewer and moved the information about the NO_2 and CO models to the Supplement.

The reason the targets were initially all placed outside the column names is that we apply a specific transformation to a target of a single calibration model. Therefore, we wanted to be consistent in our display of information. This calibration model is the MLR-based calibration model for $PM_{2.5}$ sensor measurements (last column). We removed the other targets and added an asterisk to Table 1 explaining why this one target is retained in the table.

Table 1. Model variables for the development of the calibration functions based on Multiple Linear Regression (MLR), Ridge Regression (RR), Random Forest (RF) and Extreme Gradient Boosting (XGB).

Calibration Model	**O_3 Model Features**	**$PM_{2.5}$ Model Features [Target]**
MLR	V_{OX}, V_{NO2}, V_{CO}, RH, T, V_{OX} * T	SPS30, RH, T, log(SPS30) [log($AEMS_{PM2.5}$)]*
RR	V_{OX}, V_{NO2}, V_{CO}, RH, T	SPS30, RH, T
RF	V_{OX}, V_{NO2}, V_{CO}, RH, T	SPS30, RH, T
XGB	V_{OX}, V_{NO2}, V_{CO}, RH, T	SPS30, RH, T

** This target is shown because it is transformed in the MLR calibration model configuration.*

Table S3. Description of the employed calibration models.

Calibration Model	Description	Tuned Hyperparameters	R package	Reference
Extreme Gradient Boosting	• Decision tree-based ensemble machine learning method • employs the gradient boosting framework • Boosting is the concept of producing a strong learner from weak learners • predictions are created from weak learners that continuously develop over the mistakes of the former learners	nrounds eta max_depth lambda alpha	xgboost	Mienye, I. D., & Sun, Y. (2022). A Survey of Ensemble Learning: Concepts, Algorithms, Applications, and Prospects. IEEE Access, 10, 99129–99149. https://doi.org/10.1109/access.2022.3207287 Zounemat-Kermani, M., Batelaan, O., Fadaee, M., & Hinkelmann, R. (2021). Ensemble machine learning paradigms in hydrology: A review. Journal of Hydrology, 598, 126266. https://doi.org/10.1016/j.jhydrol.2021.126266
Random Forest	• tree-based ensemble machine learning method that uses decision trees as base-learners • employs the bagging technique to build multiple decision trees using bootstrapped samples • the bagging technique generates random samples with replacements from the input data and trains the decision trees from the samples • predictions are created from the trained decision trees	mtry sample.fraction min.node.size num.trees	ranger	Mienye, I. D., & Sun, Y. (2022). A Survey of Ensemble Learning: Concepts, Algorithms, Applications, and Prospects. IEEE Access, 10, 99129–99149. https://doi.org/10.1109/access.2022.3207287 Zounemat-Kermani, M., Batelaan, O., Fadaee, M., & Hinkelmann, R. (2021). Ensemble machine learning paradigms in hydrology: A review. Journal of Hydrology, 598, 126266. https://doi.org/10.1016/j.jhydrol.2021.126266

Multiple Linear Regression	• regression method, which models linear relationships using least squares estimation
	• linear combination of features (also called independent or explanatory variables), which are weighted by coefficients, to predict the target or dependent variable
	• Assumptions:
	  ○ linear relationship between features and target
	  ○ residuals are normally distributed and independent
	  ○ constant variance of residuals (Homoscedastic)
	  ○ no outlier
	  ○ no or a lack of multicollinearity
		_	stats	Uyanık, G. K., & Güler, N. (2013). A Study on Multiple Linear Regression Analysis. Procedia - Social and Behavioral Sciences, 106, 234–240. https://doi.org/10.1016/j.sbspro.2013.12.027
				
				Wilks, D. S. (2011). Statistical methods in the atmospheric sciences (Vol. 100). Academic press.

Calibration Model	Description	Tuned Hyperparameters	R package	Reference
Ridge Regression	• linear least squares regression method augmented by L2 regularization to address the bias-variance trade-off • can be viewed as penalized regression • Multiple linear regression is the simple non-regularized case of ridge regression	s	glmnet	Wanishsakpong, W., & Notodiputro, K. A. (2024). Comparing the performance of Ridge Regression and Lasso techniques for modelling daily maximum temperatures in Utraradit Province of Thailand. Modeling Earth Systems and Environment, 10(4), 5703–5716. https://doi.org/10.1007/s40808-024-02087-z Nowack, P., Konstantinovskiy, L., Gardiner, H., & Cant, J. (2021). Machine learning calibration of low-cost NO2 and PM10 sensors: non-linear algorithms and their impact on site transferability. Atmospheric Measurement Techniques, 14(8), 5637–5655. https://doi.org/10.5194/amt-14-5637-2021 Asilevi, P. J., Dzidzorm, E. N., Boakye, P., & Quansah, E. (2025). Nitrogen dioxide (NO2) Meteorology and predictability for air quality management using TROPOMI. Npj Clean Air, 1(1). https://doi.org/10.1038/s44407-024-00003-4

C8.- Abbreviations are repeated many times. As a general rule for abbreviations, define them once and use them always, except in the abstract.

Besides, a glossary at the end of the paper should be interesting.

Done. We did adjustments to our manuscript to respect the general rule for abbreviations.

We added a list of abbreviations.

Appendix A: List of abbreviations

AELCM	Atmospheric Exposure Low-Cost Monitoring
AEMS	Atmospheric Exposure Monitoring Station
$AEMS_{XX}$	Concentration of a specific air substance measured by the AEMS
AQD	Air Quality Directive of the European Union
AS	Alphasense
AS-B431	Alphasense B-Series electrochemical sensor for O_3
AS-B43F	Alphasense B-Series electrochemical sensor for NO_2
AS-B4	Alphasense B-Series electrochemical sensor for CO
CEN	European Committee for Standardization
CET	Central European Time
CO	Carbon monoxide
DQO	Data quality objective
EC	Electrochemical
EPA	United States Environmental Protection Agency
ET	Extended training
GDE	Guide for the demonstration of equivalence
LCS	Low-cost (air) sensor
MLR	Multiple Linear Regression
MOS	Metal oxide semiconductor
NO_x	Nitrogen oxides
NSIM	Non-regulatory supplemental and informational monitoring
O_3	Ozone

OOS	Out-of-sample
$PM_{2.5}$	Particulate matter (Particles that are 2.5 microns or less in diameter)
PM_{10}	Particulate matter (Particles that are 10 microns or less in diameter)
R^2	Coefficient of determination
REU	Relative expanded uncertainty
RF	Random Forest
RH_{XX}	Relative humidity of a specific BME280 sensor in an AELCM unit
RMSE	Root-mean-squared error
RR	Ridge Regression
Rs	Spearman rank correlation
SO_2	Sulfur dioxide
SAG	Sensirion AG
SAG-SPS30	Sensirion AG optical particle sensor for PM_1 and $PM_{2.5}$
$SPS30_{XX}$	Particulate matter concentration of a specific SAG-SPS30 in an AELCM unit
ST	Single training
T_{XX}	Temperature of a specific BME280 sensor in an AELCM unit
TP	Test period
TS	Technical specification
UTC	Coordinated Universal Time
V_{XX}	Net voltage of a specific AS sensor in an AELCM unit
WHO	World Health Organization
XGB	Extreme Gradient Boosting

C9.- In addition to Table 2 (with the stats of the dataset for 1 day), why do not you plot the stats for the whole period (1 year?) and/or plot their value over the time?

Is it correct 36º in Augsburg?

Also, you can also include in Table 2 the same stats for all the features (variables) of your dataset (AEMSxx, Vxx).

These statistics are not for a single day but cover a specific timespan. For example, in the second column of the first row, you will see 11/01/22 – 11/01/23. Due to unfortunate formatting and the lack of space, this wasn't immediately clear, but all calculated statistics for the variables in column 1 are based on an entire year of data. We adjusted the table description of Table 2 and added the following to clarify:

Statistics based on the hourly means of the atmospheric variables measured by the AEMS from January 2022 to January 2023.

Plotted values over time related to Table 2 can be found in the Supplement of this work (Figure S1-S4).

According to Germany's National Meteorological Service, the Deutscher Wetterdienst (DWD), the DWD station in Augsburg recorded a daily maximum temperature of 35.9 °C on 20/07/2022, which is close to the daily maximum temperature of 35.65 °C that we measured on the same day. Therefore, the daily maximum temperature given in Table 2 appears to be correct. We obtained the station data from the DWD Climate Data Center, which provides open data: https://www.dwd.de/EN/climate_environment/cdc/cdc_node_en.html

Thank you for the suggestion to include the statistics for the raw output data in the table. We initially considered this but decided not to include it in the manuscript. In our view, presenting raw sensor signals, such as the sensors' net voltages, would not add meaningful value and would obscure the main message of Table 2. The purpose of Table 2 is to characterize the environmental conditions during the collocation period and to provide a first impression of the information content of the raw sensor signals. In our opinion, this is already achieved through the Spearman rank correlation (Rs), which illustrates the relationship between the station measurements and the raw sensor signals.

C10.- Conclusions are too long. You could simplify them add more relevant conclusions, since it is well known that with these LCS, recalibration is always required.

Besides, both in the abstract and in conclusion, you should highlight your contribution.

We shortened and simplified the section "Conclusions", focusing on the relevant conclusions. We also highlighted our own contributions in the abstract and conclusion.

Our Abstract changes to highlight our own contributions to the community:

Line 9 – 11:

In this study, we demonstrate how widely used air sensors (OX-B431 and SPS30) for the relevant air pollutants ozone (O_3) and fine particulate matter ($PM_{2.5}$) by two manufacturers (Alphasense and Sensirion) should be recalibrated for real-world monitoring applications.

Line 12 – 14:

We use multiple novel test protocols for air sensors provided by the United States Environmental Protection Agency (EPA) and the European Committee for Standardization (CEN) for evaluative guidance and to identify possible applications for OX-B431 and SPS30 sensors.

Line 21 – 24:

We investigated different recalibration cycles using a pairwise calibration strategy, which is an uncommon method for recurrent LCS calibration. Our results indicate that a regular in-season recalibration is required to obtain the highest quantitative validity and broadest range of applications for the analyzed LCSs, with monthly recalibrations appearing to be the most suitable approach.

Line 27 – 29:

Compared to one-time pre-deployment sensor calibration, in-season recalibration can broaden the scope of application for a LCS (indicative and non-regulatory supplemental measurements) *and must be considered by the end-use communities, if certain real-word applications are supposed to be performed reliably by LCSs and to achieve sufficient information content.*

Our updated and adjusted conclusions (Line 724 – 800):

In an attempt to consistently provide air sensor performance by a pair of O_3 and $PM_{2.5}$ LCSs (AS-B431 und SAG-SPS30) suitable for supplementing official air quality monitoring networks, an still uncommon approach for recurrent sensor calibration was explored during a yearlong collocation campaign at an urban background station next to the University Hospital Augsburg, Germany.

LCSs were collocated with regulatory grade air measurement instruments and were exposed to a wide range of environmental conditions, with air temperatures between -10 and 36 °C, relative air humidity between 19 and 96 % and air pressure between 937 and 983 hPa. The ambient concentration ranges were up to 83 ppb for O_3 and 153 µg m^{-3} for $PM_{2.5}$. LCS calibration models were built using linear regression techniques (MLR and RR) and machine learning (RF and XGB).

We used a pairwise (re-)calibration strategy to enable continuous in situ measurements with two alternating O_3 ($PM_{2.5}$) LCSs. The results were evaluated using novel air sensor performance targets defined by EPA test protocols and the CEN/TSs. We recommend regular in-season ET, instead of relying on a single multi-month training period. These updates to the calibration models are necessary to consistently produce data with sufficient information content (indicative and NSIM-level measurements) from AS-B431 (SAG-SPS30) units to support existing official air quality monitoring. Our findings underscore the importance of rigorous LCS data quality assurance and control for studies or LCS monitoring networks that aim to make quantitative assertions with LCSs.

Based on the EPA performance targets for O_3 (RMSE $\leq$ 5 ppb, $R^2 \geq 0.80$, Slope = 1.0 ± 0.20, Intercept (b) = $-5 \leq b \leq 5$ ppb), monthly recalibrations for AS-B431 LCSs are recommended to increase the likelihood of reliably achieving acceptable sensor bias during the O_3 season. In particular, RF and XGB calibration models benefited from the increased amount of summer training data resulting from monthly recalibrations.

We showed, that MLR and RR calibration models should be employed when ET is not an option, but a single multi-month training period is available, which accounts for seasonal variations in atmospheric conditions (meteorological and air pollution factors). If ET via monthly recalibration is feasible, RF and XGB calibration models appear to be the more sensible choice, as their quantitative performance aligns particularly well with EPA guidelines for NSIM devices targeting O_3.

The need for recurrent calibration of the SAG-SPS30 is less obvious relying on the $PM_{2.5}$ EPA performance targets (RMSE $\leq$ 7 µg m^{-3}, $R^2 \geq 0.70$, Slope = 1.0 ± 0.35, Intercept (b) = $-5 \leq b \leq$ 5 µg m^{-3}) and appears to be largely unnecessary, when a single lengthy multi-month calibration is applied. Also, a MLR calibration model for the SAG-SPS30 is adequate since no significant benefit was found by using more sophisticated ML methods as calibration tools.

The calibrated O_3 LCS and $PM_{2.5}$ LCS were able to meet the class 1 DQO (REU $\leq$ 30 % and 50 %, respectively) for different calibration models and therefore can provide indicative measurements. The REU values suggest that ET of the employed calibration models enables *the generation of a continuous LCS time series from two identical sensor model units, more consistently meeting a targeted DQO (indicative measurements). Again, extending the calibration space by ET is especially advised for tree-based ML methods to reduce the LCS measurement uncertainty with increasing pollution concentrations.*

While the performance evaluation of the SAG-SPS30 based on EPA recommendations suggests that ET is largely unnecessary and that MLR calibration is sufficient, the European standards relying on REU values tell a different story for one of the SAG-SPS30 units. The results indicate that ET is a technique that should be carried out to achieve class 1 data quality for the SAG-SPS30 deployed with AELCM009. The discrepancy between our recommendations for recurrent calibration based on the EPA test protocol performance targets (single-value performance metrics) and those based on the CEN/TS performance targets (measurement uncertainty distribution) for $PM_{2.5}$ LCSs shows that EPA test protocols and CEN/TSs should be used together as evaluative guidance to obtain a more complete understanding of an LCS's performance and to communicate to end-use communities whether specific real-world applications can be supported by LCSs.

C11.- As mentioned before in C5, if you plot heatmap find other suggestions to visualize the results:

1. **Error-vs-time curves**: plot RMSE(t) for different recalibration strategies. This shows how quickly accuracy decays and how recalibration recovers it.
2. **Heatmap**: x-axis = initial training duration (T_0), y-axis = recalibration interval (days). z = a metrics (RMSE, R2, …). This visually shows regions where short initial training + frequent recalibration ≈ long initial training + infrequent recalibration.
3. **Pareto frontier / cost-accuracy plot**: x-axis = operational/calibration cost, y-axis = long-term mean RMSE. Mark strategies on the plot.
4. **Bar chart**: number of recalibrations vs mean RMSE for each T_0.
5. **Time-to-failure distributions**: for threshold-triggered policies, plot histogram of detection delays.
6. **Uncertainty band plots** (error ± CI) to show statistical significance between strategies.

Thank you for your detailed suggestions.

We would prefer to keep our circular bar plots for the visualization of our results. The reasoning for that is explained in our response to C5.