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Evaluating low-cost NDIR CO_2 for atmospheric observation in rural settings

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Abstract

Most research and monitoring activities involving low-cost atmospheric sensors (LCS) have traditionally focused on urban environments, where air quality is a pressing concern. However, an emerging area of research is their application in rural landscapes, where land use is a key determinant of climate change and net zero outcomes, directly influencing greenhouse gas emissions, carbon sequestration, and ecosystem functioning. In this study, we examine the use of LCS NDIR CO_2 sensors to monitor atmospheric concentrations in agricultural settings. We present a data analysis framework that addresses errors associated with factory auto-baseline correction and, crucially, accounts for the influence of environmental parameters such as temperature and pressure. This approach leads to improved sensor performance. Results from deployments in both rural and urban environments demonstrate strong agreement with reference-grade instruments, as shown by the root mean square error (RMSE) and coefficient of determination (R^2). Improvements of RMSE from 10 ppm to 4 ppm in winter and 5 ppm to 4 ppm in summer, with corresponding improved R^2 from 0.85 to 0.98 in winter and 0.86 to 0.97 in summer were obtained when compared to a simple scaling correction of the out-of-box data. Our study shows that corrected data not only reproduced the seasonal profile associated with rural emissions, but it also captured the diurnal variability, sometimes characterised by CO_2 change of up to 50 ppm, which is more than three times (15 ppm) the typical change in the urban environment. Overall, this study demonstrates the viability of low-cost CO_2 sensors and sensor networks for reliable long-term monitoring in rural environments. The observations obtained provide valuable inputs for developing analytical methodologies and offer actionable insights into the influence of rural land-use practices on climate.

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1. Introduction

Carbon dioxide (CO_2) is a greenhouse gas that drives the warming of Earth's climate. The United Nations Sustainable Development Goals and the Intergovernmental Panel on Climate Change (IPCC) state that CO_2 emissions must be drastically reduced by 2030 to prevent atmospheric warming above 1.5 °C (IPCC, 2018). This goal requires both international collaboration and effective monitoring technologies to collectively reduce carbon emissions. CO_2 measurements can be used to estimate emission rates (Martin et al., 2017) but have historically been limited by the high cost of necessary instrumentation.

In recent years, technological advancements in low-cost sensors (LCS) have enabled wider air quality monitoring and are increasingly being applied to greenhouse gas observations (Dubey et al., 2024). The availability of these relatively inexpensive CO_2 detectors (costing in the range of hundreds of dollars) has facilitated their integration into multispecies sensor platforms for network deployments of low-cost monitoring devices (Turner et al., 2016; Wu et al., 2016; Lopez-Coto et al., 2017). They commonly utilise a non-dispersive infrared (NDIR) detector and are typically small, portable, and require little power. These characteristics allow for the sensors' incorporation in diverse environments, as they do not require pre-existing infrastructure or costly installation campaigns.

Low-cost sensors expand access to reliable field-scale environmental data and increase the spatial coverage and resolution of CO_2 measurements (Martin et al., 2017). These sensors enable the deployment of affordable monitoring networks capable of quantifying whole-site emissions, seasonal variability, and crop-specific differences in CO_2 fluxes (Miles et al., 2021; Yang et al., 2021). By lowering financial and technical barriers, these systems extend access to actionable CO_2 data in rural, resource-limited regions, supporting emissions assessment, land-management decisions, and public health planning (Wu et al., 2016; Turner et al., 2016). These sensors also empower sustainable agriculture initiatives by enabling farmers to monitor carbon outputs at the field scale and assess crop-specific emissions, seasonal variability, and machinery-related contributions (Martin et al., 2017; Müller et al., 2020). In rural settings, CO_2 emissions are largely influenced by land use, which may range from agricultural activities (both arable and pastoral) to natural reserves, leading to spatial and temporal variation in emission profiles (Miles et al., 2021). In arable farming regions, CO_2 exchange is driven by daytime photosynthesis during the growing season and by soil and ecosystem respiration after harvest (Miles et al., 2021). Quantifying these fluxes at local scales typically relies on eddy covariance flux systems, which directly measure the net exchange of CO_2 between the land surface and the atmosphere but can be financially prohibitive for many research or management applications (Wu et al., 2016). Low-cost CO_2 sensors offer a potential solution to this challenge

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by enabling network-based deployments that, when integrated with atmospheric models, allow for enhanced field-scale emission estimation (Martin et al., 2017; Turner et al., 2016). However, the effectiveness of this approach relies on the availability of robust, high spatio-temporal datasets that accurately capture environmental and management influences on CO_2 dynamics. Previous studies have successfully deployed these sensors in urban environments for applications such as source identification and data assimilation into atmospheric models, supporting emission inventory assessments and source footprint evaluations (Delaria et al., 2021; Dubey et al., 2024; Shusterman et al., 2018). Another study evaluated several LCS brands against a reference analyser in an urban environment to verify measurement performance (Cai et al., 2025). However, the use of LCS for CO_2 monitoring in rural environments remains limited. Macagga et al. (2024) deployed these sensors in rural environments alongside higher-end reference instrumentation to assess ecosystem carbon balance and other studies have utilised low-cost sensors as components of larger devices for *in situ* soil carbon measurements (Heger et al., 2020) or chamber-based systems for citizen science projects (Sloan et al., 2025). We aim to build on these rural applications through the development of a rigorous, cross-site data-processing protocol that accounts for sensor drift over time, seasonal variability, and differences in temperature and humidity (Cai et al., 2025).

In this study, we evaluate the performance of a set of low-cost CO_2 sensors in both rural and urban environments. Specifically, we examine methods for improving raw factory-calibrated data by accounting for environmental influences and implementing best practices for quality assurance and quality control (QA/QC) to enhance data accuracy across sites.

2. Methodology

2.1 Study Locations

This study was conducted at two sites (one rural and one urban) to assess the potential of LCS CO_2 sensors in rural environments. The rural site was an arable farm in Stretham, near Ely, UK, where LCS CO_2 nodes were deployed alongside a reference-grade CO_2 analyser at a height of 1.5 m.

A similar monitoring setup was established at the urban site, located approximately 16 km away in Cambridge. The urban measurements were conducted on the rooftop of the Yusuf Hamied Department of Chemistry, University of Cambridge (52°11'52.64"N, 0°7'29.92"E) at an approximate height of 22 m. The study locations are shown in Figure 1.

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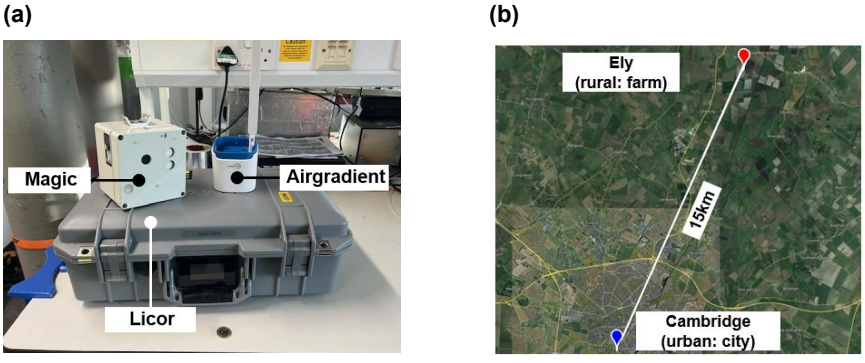

Figure 1: Instrumentation and study sites. (a) LCS CO_2 devices (Magic and AirGradient nodes) and the reference LI-COR CO_2 analyser. (b) Map showing the locations of the rural and urban study sites. Background imagery in (b) from Google Earth Pro (Imagery ©2026 Google; map data ©2026 Google).

2.2 Meteorological data and statistical analysis

The performance of the LCS data was assessed against the reference measurements using a range of statistical indicators, including root mean square error (RMSE), mean absolute error (MAE), coefficient of determination (R^2), and the slope and intercept of a least-squares linear regression fit. Overall results were consolidated using a Taylor diagram, a two-dimensional statistical visualisation that combines three key metrics: standard deviation (SD), Pearson's correlation coefficient (r), and centred root mean square error (cRMSE), which corresponds to the RMSE of bias-corrected data. This was implemented using the openair package in R (Carslaw, 2012).

Supporting meteorological data for London Heathrow airport, 51°28'39.0"N 0°27'41.0"W and Lakenheath airport, 52°25'12.0"N 0°34'00.0"E were obtained from the National Oceanic and Atmospheric Administration (NOAA) Integrated Surface Database (ISD) using the R worldmet package (Carslaw, 2020).

2.3 Low-Cost CO_2 Sensor Nodes

A bespoke portable monitoring system, known as the "Magic Box", was initially utilised for CO_2 and air quality measurements at both study locations. This device has been successfully used in previous air quality studies in urban environments (Song et al., 2018). CO_2 was monitored using the original equipment manufacturer (OEM) device Senseair K33 sensor (Senseair, K33, 2025), which operates on NDIR technology. The Automatic Baseline Correction (ABC) default setting in the K33 had been turned off, thus limiting error associated with ABC (section 2.4.2).

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A pair of the Magic boxes was collocated outdoors with a reference CO_2 monitor for a period of 12 days at the urban site (7 to 18 December 2022), nodes were then deployed at the rural site between 20 December and 22 January 2023 (~1 month) in close proximity to a rural reference monitor (< 200 m). The out-of-the-box CO_2 data were calibrated to the reference data obtained from the reference LI-COR CO_2 instrument using a 2-day period (14-15 December 2022) during the 12-day initial collocation at the urban site.

The results (see section 3.5) from those initial deployments informed the decision to incorporate an additional portable CO_2 monitoring sensor system, the AirGradient Open Air outdoor air quality monitor. This device measures particulate matter (PM), total volatile organic compounds (TVOCs), CO_2, temperature, and relative humidity. The selection of this alternative LCS device was motivated by the improved design of its weatherproof housing, which incorporates mesh openings that allow enhanced air exchange relative to the Magic box. This design reduces the likelihood of air stagnation within the enclosure and minimises internal humidity variability in response to changes in external environmental conditions. CO_2 concentrations were specifically measured using the Senseair S8 NDIR sensor (Senseair, S8, 2025). Unlike the Magic devices, the ABC setting in the AirGradient with the S8 sensor was active by default when the AirGradient units were sourced. We also assessed the viability of Senseair Sunrise sensors for rural application using a version of AirGradient that incorporated Sunrise CO_2 sensor (with the ABC off) as the main CO_2 detector. To evaluate the network applicability of LCS CO_2 in rural settings, we deployed a network (four nodes) made up of slightly modified AirGradient Open Air outdoor that used Senseair Sunrise CO_2 OEM device (Senseair, Sunrise, 2025). This modification to the CO_2 detector in the AirGradient was informed by the need to reduce power demand in the sensor system, S8 average current is orders of magnitude higher than Sunrise (18 mA compared to 1-34 µA). Although the CO_2 detectors used in the LCS devices in this study were all sourced from the same manufacturer, the analytical approach and recommendations for improved performance are generalisable and can be applied to other NDIR or LCS CO_2 sensors.

For the purposes of this study, we focus exclusively on CO_2 measurements from these sensor deployments, and not on the other measured parameters by the same sensor platforms. We used LI-COR LI-7815 CO_2/H_2O instrument co-located in the same environment as our reference grade analyser. It is based on an Optical Feedback-Cavity Enhanced Absorption Spectroscopy (OF-CEAS), with a 100 ppb resolution at 1 s averaging and response time less than 2 seconds (LI-COR, 2025). The reference data were averaged to 5-minute resolution to match the sampling rate of the AirGradient LCS CO_2 used in this study. Figure 1 (a) shows an image of the different instrumentations and Table 1 summarises the information for the various sensor platform, deployment type and duration of monitoring for our study.

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Table 1. Summary of the sensor system, CO_2 type and configuration, form and duration of deployment of study.

Sensor system	OEM CO_2	ABC Active	Deployment period	Deployment type
Magic	K33	No	December 2022-Jan 2023	Collocation (urban and rural)
AirGradient	S8	Yes	May 2023-February 2025	Collocation (urban and rural)
AirGradient	Sunrise	No	August-September 2024	Network (rural)

2.4 Sources of errors in LCS NDIR CO_2

2.4.1 Effect of OEM Automatic Baseline Correction (ABC) on CO_2 signal

Automatic Baseline Correction (ABC) is a CO_2 signal processing feature available as part of the NDIR CO_2 sensors employed in this study. Initially, the sensor manufacturer recommended enabling this function, as it is intended to correct for baseline drift over time. The ABC algorithm is activated when the measured CO_2 baseline falls below the background concentration, typically set by default at 400 ppm. The system periodically assesses whether this condition has been met over a predefined interval, usually ten days, although this period may vary. If the sensor records CO_2 concentrations below 400 ppm for the majority of that interval, the algorithm calculates the deviation and applies an automatic correction to the baseline.

Whilst we did not observe baseline drift in our study when the ABC was deactivated, long-term drift is expected to introduce error into the measurements. Users should therefore characterise this drift by detrending the data prior to applying the environmental correction framework (section 3.3) presented in this work.

2.4.2 Effect of external environmental factors on LCS CO_2 signal

Previous studies have demonstrated that LCS used for the measurement of other atmospheric species are influenced by environmental parameters, particularly temperature (Crilley et al., 2018; Di Antonio et al., 2018; Mead et al., 2013; Spinelle et al., 2017). These effects are often attributable to inherent trade-offs between portability and cost on the one hand, and instrument sensitivity and measurement resolution on the other. Another factor that suggests the possible effect of external environmental parameters on the performance of LCS under real world application is the fact that they are often calibrated under controlled environmental conditions in the lab. NDIR is a spectroscopic technique, and any external factors that might affect its optics and detectors will impact sensor performance. The extreme temperature diurnal variabilities characteristic of summertime might affect the optics and invariably sensor performance. On an extended timescale, we postulate that pressure could additionally affect

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the performance of the CO_2 sensor. The provenance of this effect can be related to the fact that the sensors OEM are calibrated at a fixed pressure and report the signal in mixing ratios (parts per million, ppm) denoted by symbol χ in Eq. (1). Number density (n) of atmospheric gas species varies with pressure as shown in the relationship in Eq. (1), since the LCS CO_2 uses information from a fixed laboratory pressure calibration (P_{lab}), a changing ambient pressure ($P_{atmosphere}$) would be expected to impact the sensor.

$$\chi_{species} = \frac{n_{species}}{n_{atmosphere}} = \frac{\left(\frac{N_{species}}{V_{atmosphere}}\right)}{\left(\frac{N_{atmosphere}}{V_{atmosphere}}\right)} = \frac{\left(\frac{N_{species}}{V_{atmosphere}}\right)}{\left(\frac{P_{atmosphere}}{kT}\right)} \quad (1)$$

Where $\chi_{species}$ represents mixing ratio of the monitored species, $N_{species}$ and $N_{ambient}$ indicates the number of moles of the species and ambient respectively, V is the volume, *k* Boltzmann's constant and T the absolute temperature. It follows that the ratio of the mixing ratios expression from Eq. (1), for a LCS calibrated at a fixed lab pressure of (P_{fixed}) relative to a reference device which has pressure compensation, is given by the expression in Eq. (2).

$$\frac{\chi_{species}^{LCS}}{\chi_{species}^{reference}} = \frac{\left(\frac{N_{species}}{V_{ambient}}\right)}{\left(\frac{P_{fixed}}{kT}\right)} * \left[\frac{\left(\frac{N_{species}}{V_{ambient}}\right)}{\left(\frac{P_{ambient}}{kT}\right)}\right]^{-1} = \frac{P_{ambient}}{P_{fixed}} \quad (2)$$

$$\chi_{species}^{LCS} = g * \left(\frac{P_{ambient}}{P_{fixed}}\right) * \chi_{species}^{reference} + offset \quad (3)$$

If we consider a LCS might have an ***offset*** and non-pressure related gain ***g***, this expression can be simplified further to show that the final pressure dependence of the mixing ratio LCS in relation to reference device mixing ratio can be reformulated as Eq. (3). An optimised version of Eq. (3) was used to generate the pressure corrected CO_2 mixing ratio as formulated in Eq. (4), where the P_{fixed} is 1012 mBar and the $P_{ambient}$ uses the hourly pressure data described in section 2.2.

$$\chi_{CO2}^{raw} = \left[\left(1.10348 * \left(\frac{P_{ambient}}{P_{fixed}}\right) - 0.218656\right) * \chi_{CO2}^{Pcorr}\right] + 52\ ppm \quad (4)$$

For the temperature correction, we found an exponential temperature dependence correction factor for the CO_2 sensor sensitivity worked best for the Sunrise S8 sensor (Eq. (5)) and a linear temperature dependence sensitivity correction for the Senseair Sunrise detector, Eq. (6).

$$\chi_{CO2}^{Pcorr} = \left[A_{S8} + \left(B_{S8} * C_{S8}^{\ sensorT}\right)\right] * \chi_{CO2}^{Tcorr} \quad (5)$$

$$\chi_{CO2}^{Pcorr} = \left[A_{Sunrise} + \left(B_{Sunrise} * sensorT\right)\right] * \chi_{CO2}^{Tcorr} \quad (6)$$

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where χ_{CO2}^{Pcorr} and χ_{CO2}^{Tcorr} represents mixing ratio for the pressure corrected and temperature corrected CO_2 respectively, $sensorT$ is the sensor temperature T expressed in Kelvin. The optimal fit parameters for the S8 sensors used in our study were $A_{S8} = 0.962$, $B_{S8} = 8.58 \times 10^{-5}$, $C_{S8} = 1.02$. Corresponding fit parameters for the CO_2 nodes used in the network deployment are presented in Table S1.

2.4.3 Effect of elevated RH on LCS CO_2 signal

An NDIR sensor measures CO_2 concentrations by comparing two infrared (IR) signals (IR-high and IR-low) from the same IR source at two distinct wavelengths, detected using a dual-bandpass filter after transmission through the air sample within an optical cavity. For CO_2 measurements, the IR-high channel is centred at approximately 3.9-4.0 μm, where CO_2 exhibits negligible absorption (reference band), while the IR-low channel is centred around 4.26 μm, corresponding to a strong CO_2 absorption band. In the presence of CO_2, the IR-low signal is attenuated, resulting in a reduced signal magnitude relative to the IR-high channel.

The presence of water vapour can influence the IR-low channel, as H_2O exhibits weak but non-zero absorption within the 3-5 μm region, potentially leading to an overestimation of CO_2 concentrations in NDIR measurements. Under conditions of extremely high relative humidity, condensation may occur on the optical cavity mirrors, causing additional signal attenuation and resulting in spurious CO_2 readings. The effect of RH and water condensation on the performance of NDIR is a well-known phenomenon (Cai et al., 2025; Martin et al., 2017; Pereira et al., 2022; Ren et al., 2025; Wu et al., 2023; Xu et al., 2024). Most LCS devices have the CO_2 sensing unit housed in a weatherproof unit and tend to rely on passive sampling to minimise power demand. In the absence of an internal heating system that helps reduce water condensation, in combination with a preference for passive sampling in LCS (to reduce power demand), there is an increased likelihood that high RH episodes would affect the CO_2 measurement. Such environmental conditions are more common in rural applications than in urban settings, where average temperatures are relatively higher (Si et al., 2024; Weng et al., 2004). We investigated the effect of RH by deploying the same pair of Magic boxes initially in the urban (December 2022) and subsequently in the rural environment (January 2023).

3. Results and Discussion

3.1. CO_2 correction for ABC

The periods during which the Automatic Baseline Correction (ABC) was triggered for the Air gradient LCS CO_2 nodes used in this study were identified by examining the scatter plots from collocation measurements with reference instruments at both the urban and rural sites. While not all nodes exhibited a significant ABC correction, instances where this occurred were clearly

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distinguishable as systematic errors, as illustrated in Figure 2. As expected, a significant improvement in agreement between the LCS and the reference instrument was observed when this correction was implemented (RMSE=4.7 ppm, R^2=0.95 compared to 19.9 ppm, R^2=0.56). Although this seems to suggest the only correction required is a simple ABC correction, it is worth noting that the data shown is for only a short period where the effects of environmental factors might be minimal if the meteorological conditions are ideal (minimal impact of temperature and pressure). For long-term (months) application, we evaluated the effects of environmental factors, as discussed in the next section.

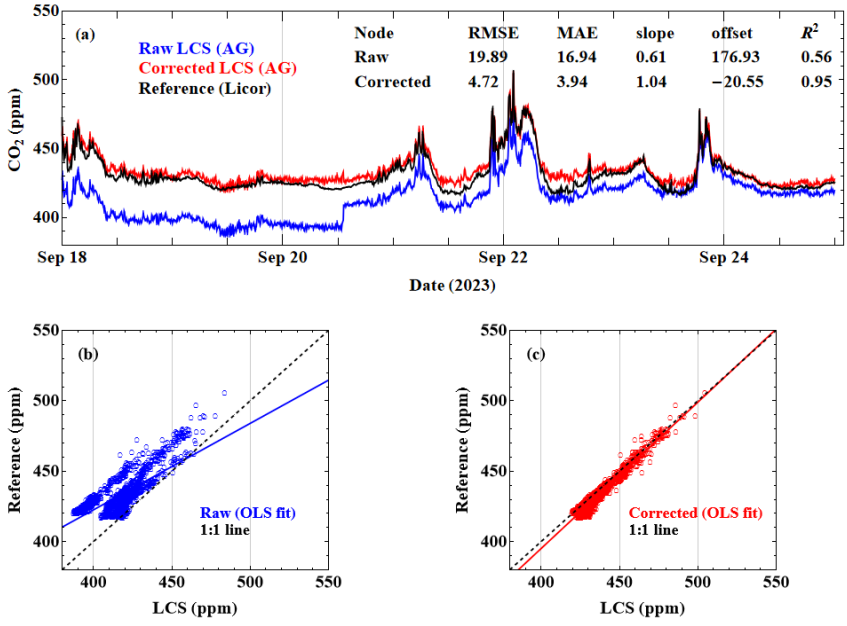

Figure 2: Comparison of LCS CO_2 against the reference. (a) Time series with associated validation metrics, (b) scatter plot for out-of-box LCS measurements relative to reference (c) scatter plot for the corrected LCS measurements (for the effect of ABC step) relative to reference. RMSE, slope and offset = 19.9 ppm, 0.6, 177 ppm (raw data) and 4.7 ppm, 1.04 and -20.6 ppm after step correction respectively.

While there is merit to using the ABC method to correct potential drifts in CO_2 readings below true hemispheric background level, the method has limitations. A temporary decrease in CO_2 concentration may result from environmental factors rather than true sensor drift, as will be discussed in the following section. Consequently, the automatic correction may introduce errors into the actual CO_2 measurements.

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3.2. Physical correction for the effect of environmental factors

We present the results (Figure 3) of the physical correction of one of the LCS sensors deployed for an extended period (a year and 7 months) from May 2023 to February 2025 in the urban study location (equivalent result for the rural location shown in Figure S1). To assess the performance of the data correction protocol, results from simple linear scaling commonly used to calibrate out-of-the-box measurements are also shown (Figure 4 (b)). An improvement in the RMSE (5.9 ppm) was observed compared to the out-of-box (44 ppm) for the collocation with the reference instrument, with a comparable improvement in the scaled correction of 8.4 ppm. A similar improvement was reported for the MAE (44 ppm to 4.1 ppm) and the coefficient of determination R^2 (0.77 to 0.89). The R^2 is particularly important because this is invariant under linear scaling (Figure 3 (a) and (b)), unlike the case with corrections that incorporate the effect of environmental parameters (temperature and pressure, Figures 3 (c) and 3 (d)). An improvement in both R^2 and RMSE (Figure 4 (c)) was observed when the CO_2 data were corrected for pressure effects (0.85 and 11.5 ppm, respectively). A substantially better performance was achieved when the combined pressure and temperature corrections were applied, R^2=0.89, RMSE=5.9 ppm, as shown in Figure 4 (d).

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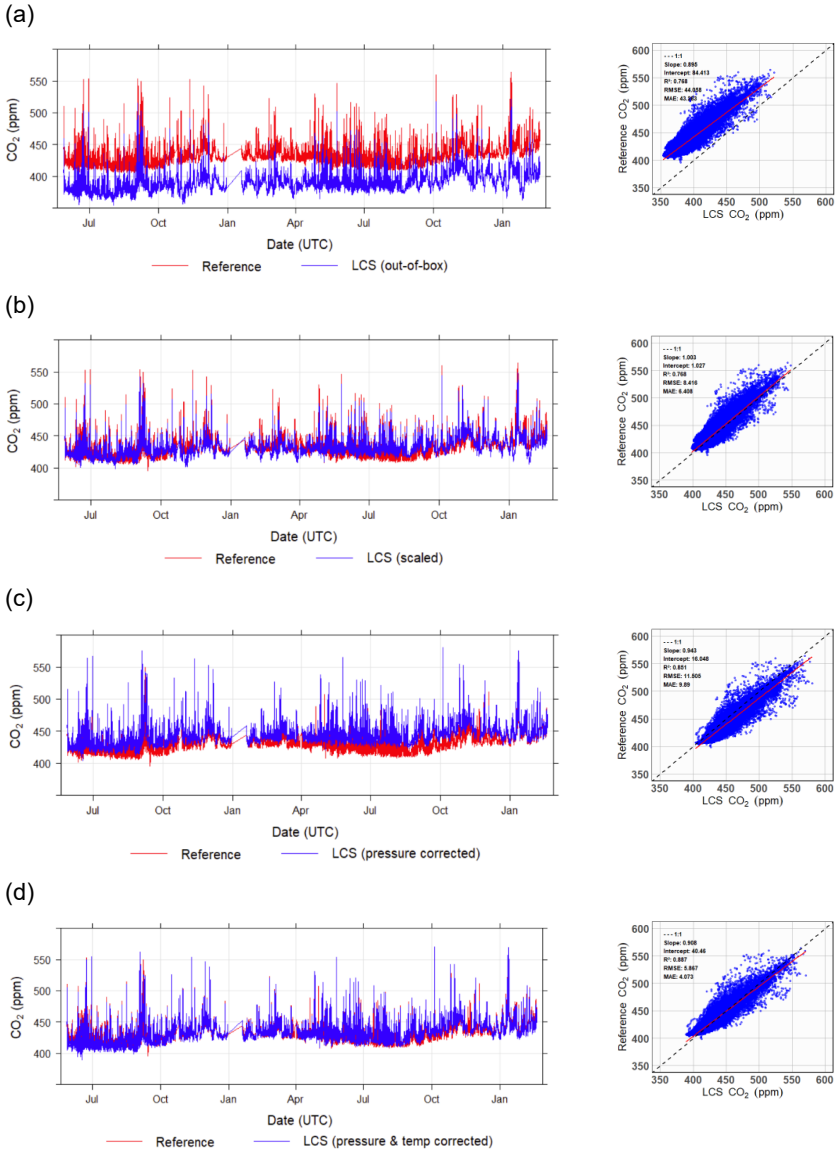

Figure 3: Results of different calibration stages of LCS CO_2 signal for the period 22 May 2023 to 18 February 2025 at the urban location. (a) Factory calibration, (b) simple linear calibration using a fixed period (1-18 August 2023), (c) pressure only correction of the out-of-box signal and (d) pressure and temperature correction of out-of-box signal.

Figures 4 and 5 present results over a shorter period, helping to highlight the effects of pressure/temperature and how the correction improves the CO_2 performance relative to the reference. Figure 4 shows an example of a 2-month period in winter when temperature effects (mean ± SD = 4.9 ± 3.27 ºC) are minimal, and the diurnal variability is small, but the pressure

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change is significant (pressure range 970-1045 mBar, average 1018.7 ± 14.70 mBar). The significant dips in the scaled LCS CO_2 readings relative to the reference before 22 December 2024, around 6 January and between 22 and 30 January 2025 in Figure 4 (a) coincide with an ambient pressure drop from around 1020 mBar to as low as 960 mBar. The pressure-temperature corrected LCS CO_2 tracks the reference data better with improved R^2 (0.98 vs. 0.85) and RMSE (4.4 ppm vs. 10.3 ppm).

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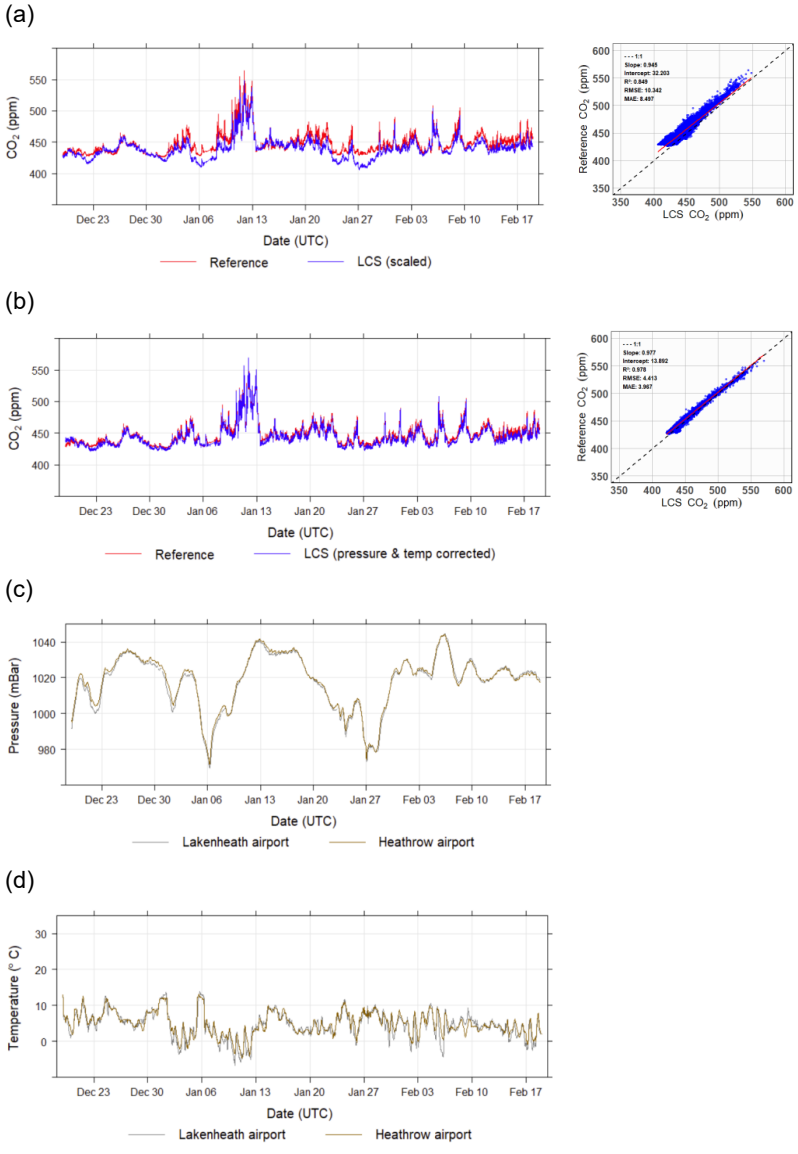

Figure 4: Comparison of two correction methodologies for the period 19 December 2024 to 18 February 2025 at the urban location. (a) simple linear scaling correction, (b)combined pressure-temperature corrected raw signal, (c) hourly pressure observation from London Heathrow and Lakenheath airport, (d) temperature readings at the airports in (c).

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In contrast, Figure 5 presents an example in summertime when the effect of temperature dominates the error on the CO_2 performance, and the pressure effect is minimal (1012.0 ± 6.82 mBar). As can be seen in Figure 5 (a) for the scaled CO_2 correction, the LCS signals show daytime overestimation, which coincides with daytime temperatures well above 10 ºC. The effect of pressure is minimal over this period except for 2-3 August, where the scaled LCS CO_2 show both daytime and nighttime dips, which is characteristic of pressure drop exemplified previously in Figure 4. An improved RMSE and R^2 values of 4.2 ppm and 0.98 compared to 5 ppm and 0.86 were observed for the pressure-temperature data corrected relative to simple scaled data.

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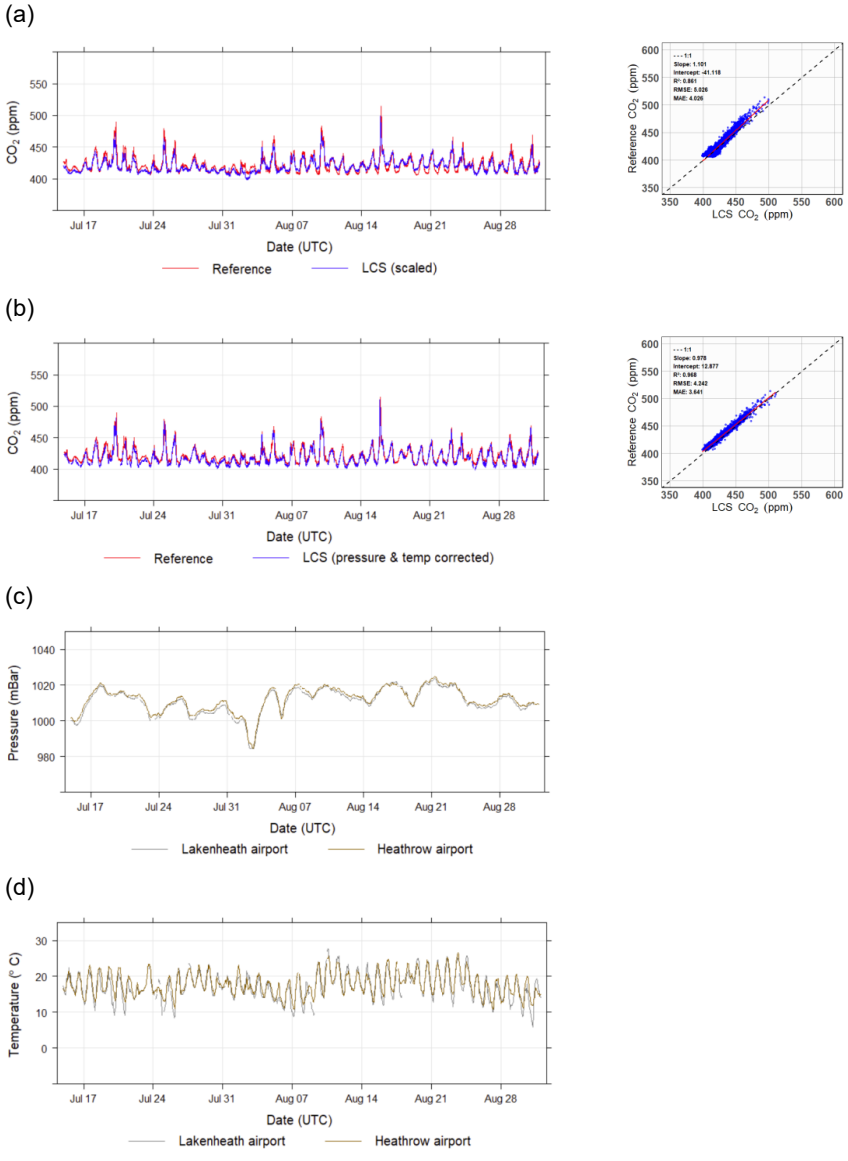

Figure 5: Comparison of two correction methodologies for the period 15 July to 31 August 2023 at the urban location. (a) simple linear scaling correction, (b) combined pressure-temperature corrected raw signal, (c) hourly pressure observation from London Heathrow and Lakenheath airport, (d) temperature readings at the airports in (c).

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3.3 Framework for LCS CO_2 data processing

Based on the known sources of errors discussed in section 2.4, and the results presented in 3.1-3.2, the following data correction protocol (Figure 6) is proposed.

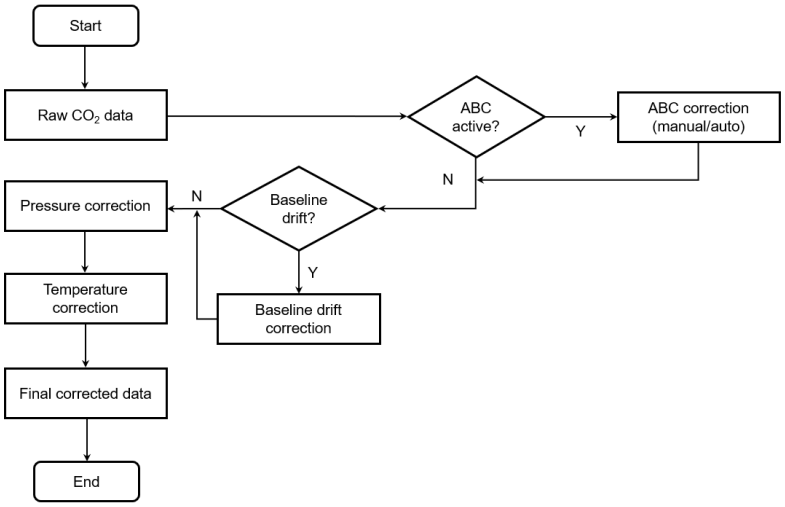

Figure 6: Framework for correction of LCS CO_2 signal.

This framework presents a logical approach for improving the precision and accuracy of LCS CO_2 for atmospheric application. We applied this data correction framework to evaluate the suitability of a network of CO_2 sensors in rural applications.

Following this framework, the performance of each data correction step-including the raw and simply scaled data relative to co-located reference measurements for the urban deployment- is summarised using a Taylor diagram (Figure 7). For the full urban dataset (Figure 7), simple scaling provides only a marginal improvement in cRMSE relative to the raw data (8.0 ppm compared with 8.2 ppm; indicated by the brown band in Figure 7), while the correlation remains unchanged (r = 0.88; grey radial scale in Figure 7). However, the scaling reduces signal variability (SD = 14.5 ppm) compared with the raw data (SD = 16.4 ppm) and the reference measurements (SD = 16.7 ppm; purple marker on the dashed black arc in Figure 7). In contrast, the correction approaches introduced in this study result in clear improvements across all three statistics. Both the pressure-corrected and pressure-temperature-corrected datasets show reduced cRMSE (6.5 ppm), improved correlation (r = 0.92), and standard deviations closer to the reference data (SD = 16.3 ppm). While the pressure correction alone improves both cRMSE and correlation relative to the raw and simply scaled data, the combined pressure-temperature correction provides the closest agreement with the reference measurements.

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Figures S2 (a) and S2 (b) present results for shorter periods in winter and summer, respectively, representing conditions dominated by pressure variability (Figure S2 (a)) and temperature variability (Figure S2 (b)) as presented in section 3.2. During the winter period, a substantial improvement is observed between the raw and pressure-corrected data, with only marginal additional improvement when temperature correction is included. This is consistent with the limited temperature variability during this period (see section 3.2). In contrast, during the summer period, when temperature variability is greater, the combined pressure-temperature correction produces a clear improvement compared with the pressure-only correction.

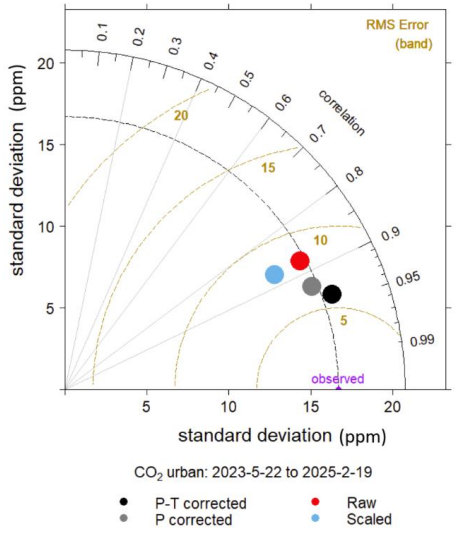

Figure 7: Taylor diagram comparing raw, scaled, pressure corrected, and pressure-temperature corrected CO_2 measurements with co-located reference observations at the urban site for 22 May 2023-18 February 2025. Data points located closer to the reference indicate better agreement with the reference measurements. Standard deviations are shown as arcs of increasing radius along the x- and y-axes, Pearson correlation coefficients are indicated by grey radial lines extending from the origin (0 on the y-axis to 1 on the x-axis), centred root mean square error (cRMSE) is represented by brown contours of increasing magnitude, referenced to the point on the x-axis.

3.4 Suitability of LCS CO_2 in rural applications

3.4.1. Collocation assessment

To assess the potential deployment of low-cost sensor (LCS) CO_2 monitoring in rural environments, we compared measurements from corrected LCS units with those obtained

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from reference-grade instruments at two locations, as outlined in Section 2. Although simple linear scaling produced similar trends to the reference data in both day-of-week diurnal and monthly plots, the LCS measurements consistently underestimated CO_2 concentrations, particularly during the winter months, at both urban and rural sites. However, as illustrated in Figure 8 (b-d), the LCS data corrected for pressure and temperature effects from the rural site show excellent agreement with the reference measurements, both in terms of absolute values and temporal trends.

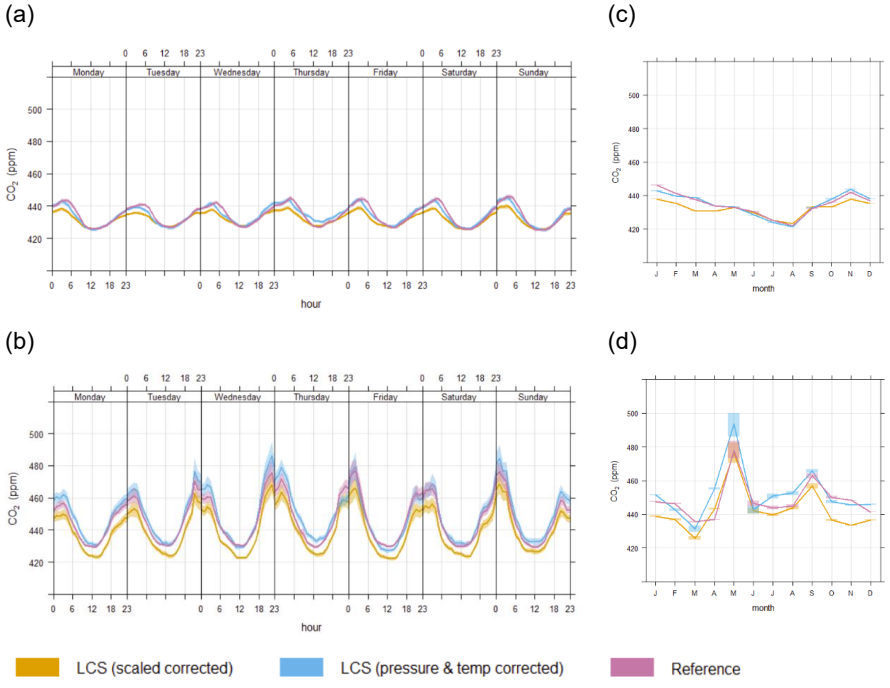

Figure 8: Comparison of rural and urban CO_2 measurements for LCS (scaled, pressure-temperature corrected) and reference device for the duration of the study. (a) Day-of-week diurnal profile at the urban site, (b) equivalent profile at the rural site, (c) monthly averages at the urban site, and (d) monthly averages at the rural site.

3.4.2. Network assessment

A direct statistical comparison with the reference measurements was not performed because the reference instrument was not collocated with any of the sensors within the network. However, because the reference instrument was deployed within the same land-use environment and at a distance of less than 1 km from each sensor, the slowly varying background CO_2 signal is expected to influence both the LCS network and the reference instrument in a similar manner. Deviations from this background signal observed by individual

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devices can therefore be attributed primarily to local sources and sinks in the immediate vicinity of each measurement location. This rural deployment consequently provides a valuable opportunity to assess the performance of LCS devices under rural environmental conditions.

The observed CO_2 concentrations were strongly influenced by local emissions associated with crop respiration, particularly during the night, when photosynthesis ceased and the planetary boundary layer was shallower (with above background CO_2 ranging periodically in excess of 200 ppm for a 5-minute averaged data). Notably, daytime errors present in the uncorrected dataset (Figure 9 (a) and (e)) were substantially reduced by applying the pressure-temperature correction approach, as demonstrated in the comparison with the reference measurement (Figure 9 (b) and (f)). In this case, the correction was primarily driven by temperature, which exhibited marked diurnal variability (Figure 9 (c) and (g)), whereas pressure changes over the one-month deployment period were comparatively minor (Figure 9 (d)). Figure 9 (f) shows that the corrected measurements exhibit a background level comparable to that of the reference data, with intermittent departures from this background. These departures, observed as short-duration enhancements (for example at P11 shortly after midnight on 27 August), indicate a stronger influence from nearby emission sources at this location compared with other sites within the network.

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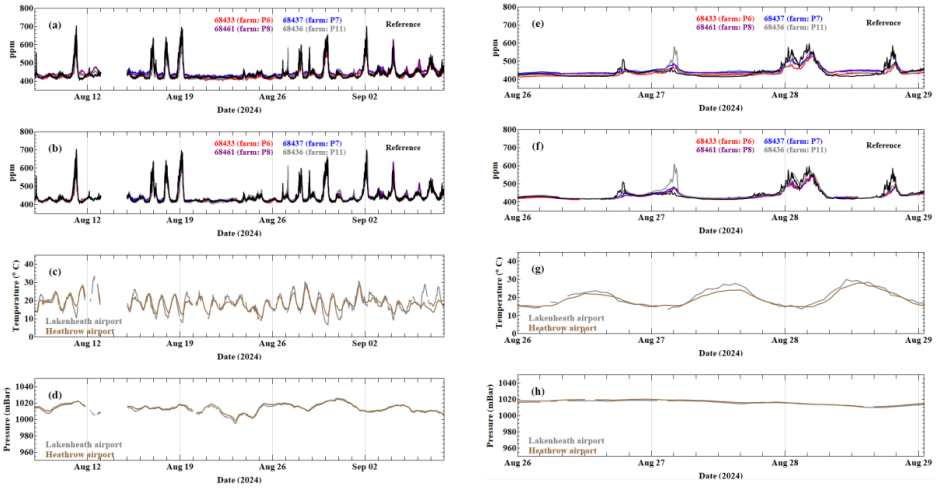

Figure 9: Comparison of two correction methodologies applied to a network of four low-cost sensor (LCS) CO_2 devices deployed at an arable farm between 8 August and 8 September 2024. Panels (a-d) show the full deployment period. (a) CO_2 concentrations corrected using a simple linear scaling approach. (b) CO_2 concentrations derived from the combined pressure-temperature correction applied to the raw sensor signal. (c) hourly surface pressure observations from London Heathrow and Lakenheath airports; and (d) corresponding air temperature observations at the airports shown in panel (c). Panels (e-h) present zoomed composite plots of panels (a-d), respectively, for a shorter period (26-28 August 2024), highlighting the impact of the correction methodologies on the LCS CO_2 network data. Missing data at the beginning of the deployment are due to cellular data transmission issues associated with the LCS network.

3.5. Additional artefacts that affect performance of LCS NDIR CO_2

Despite all the issues discussed related to environmental effect and baseline correction, poorly designed devices that utilise NDIR CO_2 sensors can still suffer from unintended artefacts related to poor air circulation that presents itself as environmental effect when there is no active sampling. Figure 10 shows that there was good agreement between the calibrated LCS CO_2 from the Magic boxes and the reference instrument (RMSE=5-7 ppm) during the deployment in the urban location, where the internal RH reading was below 80%. In contrast, the results from the calibrated Magic devices (Figure 11) in the rural environment were very poor (RMSE=35-61 ppm), as the unit only tracked the reference in the first 3-4 days. The internal RH for box Magic boxes over these periods were generally above 75%. This effect cannot be corrected empirically, as it is inherently non-systematic, unlike the temperature and pressure effects described earlier. It may, however, be mitigated by ensuring adequate air

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recirculation-such as operating the instrument within a suitably ventilated enclosure-to prevent internal RH accumulation under colder conditions, or by heating the sampled air where low-power operation is not a constraint.

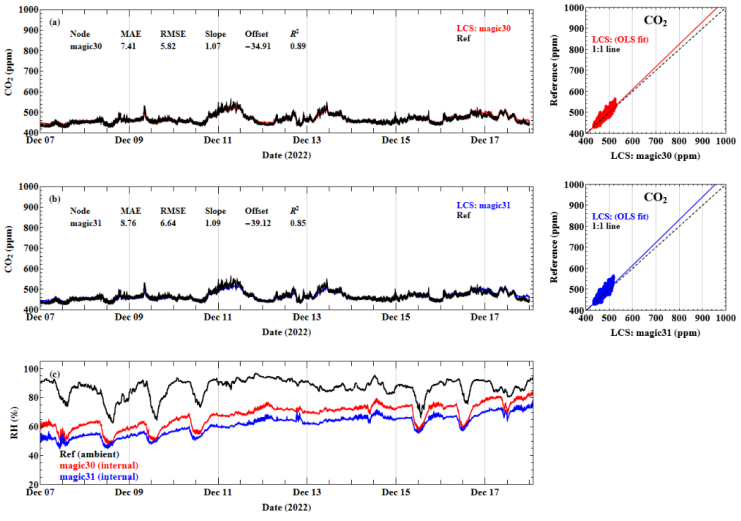

Figure 10: Comparison plots of a pair of LCS Magic units against the reference at the urban location for the period 7-18 December 2022. (a) CO_2 time series with associated validation metrics and scatter plot for Magic box 30, (b) CO_2 time series with associated validation metrics and scatter plot for Magic box 31, and (c) RH time series comparison.

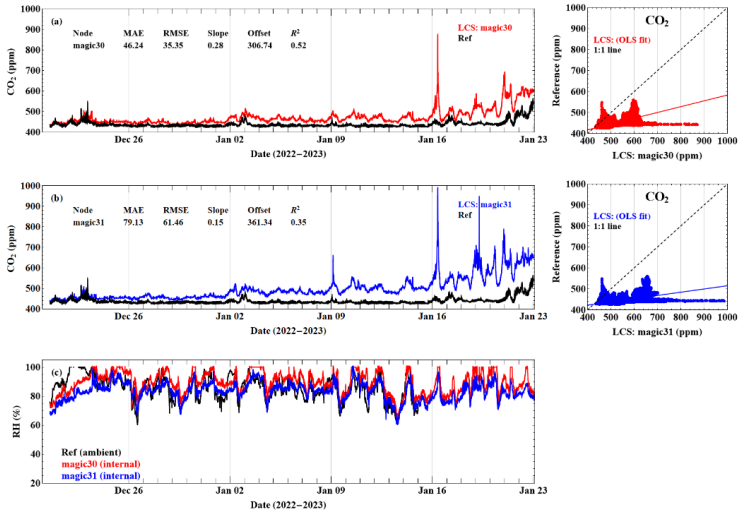

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Figure 11: Corresponding plots to those shown in Figure 10, for the same pair of sensors redeployed at the rural site, spanning the period from 20 December 2022 to 22 January 2023.

Unlike environmental factors like temperature and RH, which can vary on a microenvironmental scale (see RH readings in Figures 10 and 11), ambient pressure varies on a macroenvironmental scale, as evidenced by comparing pressure readings from two airports that are approximately 125 km apart (Figure S3). We used these secondary remote pressure readings to correct for pressure in our study.

4. Conclusions

Ambient CO_2 concentrations can be effectively monitored using LCS when environmental influences, particularly temperature and pressure, are appropriately accounted for. In our study, pressure effects were found to dominate measurement errors under colder conditions and over longer timescales associated with macro-level pressure variations. By contrast, temperature effects were more pronounced in spring and summer, varying on shorter diurnal timescales.

A notable source of measurement uncertainty in CO_2 sensors is the ABC implemented by manufacturers to adjust for sensor drift. This correction often introduces step changes in readings, thereby reducing both precision and accuracy (RMSE = 20ppm compared to 5 ppm when this is accounted for in our study). To ensure robust data processing, we recommend either disabling the ABC functionality or correcting for these step changes prior to analysis.

A comparison of sensor deployments in urban and rural environments demonstrates that, when corrected for the dominant environmental factors identified in this work, low-cost NDIR CO_2 devices are not only suitable for use in urban networks but also prove particularly valuable in rural settings, where background CO_2 levels, particularly at night, are comparatively elevated (as high as 700 ppm for 5-minute averaged data during the growing season). We observed a relatively small diurnal variability (430-445 ppm) in the urban environment compared to the rural setting (420-480 ppm). This capability enables the development of innovative approaches to greenhouse gas monitoring, particularly for agriculture and land-use climate impact assessments. Networks of these sensors when adequately configured and characterised, when combined with modelling frameworks, provide a promising and cost-effective alternative for estimating greenhouse gas fluxes in remote or otherwise under-monitored locations.

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Competing interests: The authors declare that they have no conflict of interest.

Author Contributions: OAMP and CG conceptualised the study. OAMP developed the methodology. OAMP, RF, PC, RHG, LT and KL were involved in the field deployment. OAMP and PC worked on data analysis. KL, LT, RF, RHG and OAMP worked on characterising the devices. OAMP, PC, and CG contributed to data interpretation. OAMP prepared the manuscript with contributions from all co-authors.

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