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A Low-cost UAV Coordinated Carbon Observation Network (LUCCN): an analysis of environment impact on ground base measurement node

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Abstract. Most anthropogenic carbon dioxide (CO_2) emissions originate from urban areas. To improve understandings of urban and regional emissions, we design and construct a low-cost UAV coordinated carbon observation network (LUCCN) which uses mid-accuracy (±1 ppm) CO_2 sensors. In this paper, we introduce our multi-variable non-linear regression method for calibrating the non-dispersive infrared (NDIR) CO_2 sensors for LUCCN's ground stations. We tested our calibration method with concentration data collected at the Xinglong Atmospheric Background Observatory. With comparison against data simultaneously collected by a high-accuracy cavity ring-down spectrometer, we found the maximum standard deviation of LUCCN's sensors to be 0.782 ppm in a controlled laboratory environment with a 1-second window size and 0.53 ppm in an outdoor environment with a 1-hour running average window size. As validation of LUCCN's ground measurements, we identify and present consistent trends between local CO_2 concentration variations and aerosol pollution events captured by the space-based moderate resolution imaging spectrometer (MODIS).

Keywords: CO_2 concentration, Regional emissions, Low-cost network (LUCCN), Ground base measurement

1 Introduction

Anthropogenic emission of Carbon Dioxide (CO_2) is a primary driver of climate change and global warming (Rosenzweig et al., 2010). Investigations on anthropogenic emission from fossil fuel combustion require a complete measurement system to the important sectors, e.g. energy, industry and city (Liu et al., 2014). The inventory method (bottom-up method) is the foundation to understand the condition of anthropogenic emission of each country and sector. Unfortunately, the dis-transparency and bias of inventory is a long live hot-topic to be discussed, even a standard inventory metrology has been reserved in 2006 IPCC Guidelines for National Greenhouse Gas Inventories, and refined for

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several versions (Andres et al., 2014; Bréon et al., 2015; Broquet et al., 2016). Therefore, the independent method and atmospheric inversion have been included in 2019 refinement to verify emission inventories (Maksyutov et al., 2019). State-of-art atmospheric inversion methods provide near real-time optimization of an acknowledged inventory. The improvement of inversion depended on the method and also measurement. Lack of measurement cannot effectively optimize the existing inventory (Duren et al., 2012). Unlike natural carbon emission processes e.g. ecosystem and ocean, anthropogenic emission sources are more concentrated with frequently variating emission rates (Kim et al., 2018). Therefore, monitoring anthropogenic emissions with atmospheric inversion methods requires dense and continuous measurements of CO_2 concentration variations with high quality (Broquet et al., 2016; Arzoumanian et al., 2019).

Ground-based CO_2 measurements gained significant progress in the last decade (Kort et al., 2013; Turnbull et al., 2015; Delaria et al., 2021). Systematic ground-based observations of CO_2 began in Hawaii in the 1950s, and international ground-based observation networks, such as the European Integrated Carbon Observation System (ICOS) (https://www.icos-ri.eu/, last access: 21 October 2023), the International Atmospheric Greenhouse Gas Monitoring Network (GAW) (Ries, 2013) and other greenhouse gas observation systems (Staufer et al., 2016; Delaria et al., 2021), have been gradually established to carry out continuous observations of ground-based greenhouse gases. For example, the GAW ground-based observation network has 31 global atmospheric background stations and more than 400 stations for regional GHG observations. Those international ground-based observation networks have conducted long-term, high-precision observations of ground-based greenhouse gases and are the main data sources for international scholars to monitor and assess global greenhouse gas emissions (Agustí-Panareda et al., 2022; Bao et al., 2022).

International ground-based observation networks play an important role in regional and continental scale greenhouse gas detection and assessment. Although observation networks like ICOS and GAW cover large areas, their measurements can hardly describe emissions in smaller regions, e.g. city and industry (Park et al., 2020). Therefore, we need denser networks to improve the spatial coverage and resolution on CO_2 emissions, while the new network can also contribute to the larger regional scale ground-based observation networks (Turner et al., 2016; Wu et al., 2016).

Many cities have carried out denser continuous ground-based measurements of CO_2 and other greenhouse gases. For instance, the Megacity Carbon Project and the MegaParis CO2 Project use

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high-precision in-situ measurements from cavity ring-down spectrometers (Picarro G2301 and G2401) to establish ground-based observation networks in Los Angeles and Paris (Irène et al., 2017; Verhulst et al., 2017). For both projects, the hourly measurement accuracy of CO_2 emissions observations in Paris and Los Angeles is 1 ppm, with the monthly average uncertainty of 10%. (Staufer et al., 2016; Verhulst et al., 2017). Although high-precision spectrometers can provide high-quality observations and analysis, they are expensive to manufacture and maintain (Park et al., 2020). Therefore, only a few megacities, such as Los Angeles and Paris, have established observation stations or networks, while most municipalities cannot afford the same. Nevertheless, to minimise measurement errors of urban CO2 fluxes, we need to maximise the density of ground stations.

To overcome the above limitations and to extend the observation coverages of CO_2 emissions, low-cost CO_2 ground observation sensors have been used in urban-intensive CO_2 ground observations (Liu et al., 2021). Although sensors of lower cost are usually less accurate, Broquet et al. (2016) showed that the number of instruments is more important than the accuracy of their individual sensors, and when sensors are densely deployed, the observation error could be significantly reduced (Turner et al., 2016). In short, low-cost and denser networked detection of CO_2 is more desirable.

Currently, several low-cost CO_2 ground observation networks have been established for continuous observations. For example, the Berkeley Atmospheric CO2 Observation Network (BEACO2N) has used a large number of low-cost sensors (about fifty sensors) to establish a CO_2 detection network in San Francisco, and the distance between the adjacent instruments are approximately 2 km (Broquet et al., 2016; Shusterman et al., 2018; Teige et al., 2016). In addition, Lee et al. (2017) developed a mobile CO_2 observation network in Vancouver with low-cost sensors. The network captures a CO_2 concentration map at street level that can verify city-level emission inventories. Other previous studies presented that low-cost and denser CO_2 observation networks can help to study the characteristics of urban CO_2 concentrations. In summary, lower cost ground observation network can measure concentration distribution with medium accuracy (± 1 ppm) while having greater coverages (Broquet et al., 2016; Turner et al., 2016; Arzoumanian et al., 2019).

In this article, we introduce the ground station for our novel low-cost UAV coordinated carbon observation network (LUCCN), which uses non-dispersive infrared (NDIR) CO_2 sensors. Comparing to networks using high-accuracy sensors, LUCCN's ground station is cheaper to manufacture and maintain, easier to operate and move around. Such characteristics are crucial to enable denser

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networked detections of CO_2. The rest of this article consists of four sections. Section 2 introduces the LUCCN sensors, including the principle of instrument observation and the components of the instrument. Section 2 also presents the laboratory calibration methods, results and instrument performances of LUCCN nodes. In order to further verify the observation performance of LUCCN, we present the outdoor continuous observation data calibration results in Section 3. We also compared outdoor observations against data simultaneously collected by a high-accuracy spectrometer. Finally, we prove LUCCN's effectiveness by showing consistent pollution-caused trends from satellite observations and LUCCN's measurements.

2 Ground-based node of A Low-cost UAV Coordinated Carbon observation Network (LUCCN)

2.1 Instrument

The main component of LUCCN includes a swam of ground-based nodes. In each sensor site, a series of commercial sensors are organized in a small sized newly designed weatherproof enclosure. We use a Vaisala CarboCap GMP343 for CO_2 measurement in Figure 1(b). This sensor has been introduced and well tested in Berkeley Atmospheric CO2 Observation Network (BEACO2N) studies (Delaria et al., 2021; Kim et al., 2018; Shusterman et al., 2018), which presented excellent stability in long term data collections of CO_2 concentrations.

In this study, we test the accuracy performance of GMP343 in varied measurement environment, incl. temperature, pressure and humidity. Variations of the three parameters fundamentally impact the measurement accuracy by altering infra-red light source intensity and gas molecule absorptions. Additionally, environmental impacts to accuracies vary between individual sensors due to manufacturing precisions and factory calibration methods. Beyond the CO_2 sensor, each network node contains a slot to install sensors measuring co-emitted pollutant (CO, NO_2, $PM_{2.5}$), which help us to determine source emission sectors. For example, we use AlphaSense CO and NO_2 electrochemistry sensors which are common used in GHG observation networks. However, the response time of those sensors are longer than the CO_2 NDIR sensors. The coordinate measurement is in-sufficient in a minute temporal scale. The life-age of a electrochemistry is limited as 1 year. Considering the economical efficiency and stable, the standard of LUCCN node we recommended is only contain CO_2 sensor as atmosphere composition sensor, but the measurement function in a site.

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Fig. 1. The internal structure of LUCCN and the observation field diagrams in the laboratory. (a) is the exterior diagram of LUCCN ground stations, and (b) shows the internal composition of LUCCN. (c) shows the NDIR sensors and gas conduits placed inside a cloud chamber where temperature, pressure and humidity can be adjusted according to demands. (d) shows the exterior of cloud chamber, Picarro G2301 and WMO CO_2 standard gas cylinders.

In order to correct the bias induced by measurement environment, we integrate the pressure and humidity sensors within individual nodes. Since there are pt1000 temperature sensors within all GMP343's chambers, external temperature sensors are unnecessary. For flux inversions, we integrate a Vaisala WXT-536 supersonic anemometer for measuring wind speed and directions. Finally, sensors for each node are integrated within a custom designed weatherproof enclosure. We also optimized the

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closure design for alternative mounting requirements.

To facilitate network data transmission and storage, we developed dedicated Internet of Things infrastructure and database. For data security considerations, the database software can be used for each local network without centralised storage. The total power supply requirement is less than 5 W which allows us to use solar panels instead of electric cables in extreme environments.

2.2 Performance and calibration in lab

The previous chamber tests indicate significant biases resulting from environmental parameters, including pressure, temperature, and humidity (Teige et al., 2016; Arzoumanian et al., 2019; Müller et al., 2020; Delaria et al., 2021). As a solution, we have developed a bias-correction method to reduce the environment-induced biases based on the standard manufacturer corrections. In our calibration process, each sensor has to be calibrated in an environment-controlled chamber that could adjust the temperature, pressure and humidity accurately (Figure 1c). The environment-controlled chamber used in this study is provided by Beijing Municipal Meteorological Bureau. There were seven LUCCN ground-based nodes and a Picarro G2301 involved in the calibration test at the same time. As measurement references, we connected a Picarro G2301 spectrometer to the environment-controlled chamber via an airtight tube. The Picarro G2301 was calibrated every 2 hours by WMO standard gas (402 ppm CO_2) as shown in Figure 1d to remove the drift.

Figure 2(a) shows the CO_2 dry mole fractions measured by LUCCN nodes (colored lines) and the Picarro sensor (black line). Evidently, there are notable differences between the measurements of LUCCN nodes and the Picarro sensor in Figure 2(b). In addition, LUCCN sensors' performances vary especially when there are pressure (gray dashed lines) and temperature mutations (blue dashed line) in the chamber. In the case of sudden temperature change, LUCCN # 2, LUCCN # 5, and LUCCN # 6 experience negligible variations, while values of both LUCCN # 3 and 4 noticeably increase. On the contrary, when the temperature suddenly changes, the values of LUCCN # 1 decrease significantly, while LUCCN # 7 decrease slightly. Similarly, when the pressure changes suddenly, the measurement deviations of LUCCN sensors are also slightly different. The differences in these numerical mutations are also shown in Figure 2(b). The above phenomena indicate that even in the same environment, different LUCCN sensors respond differently to environmental mutations. So it is necessary to calibrate each LUCCN sensor respectively.

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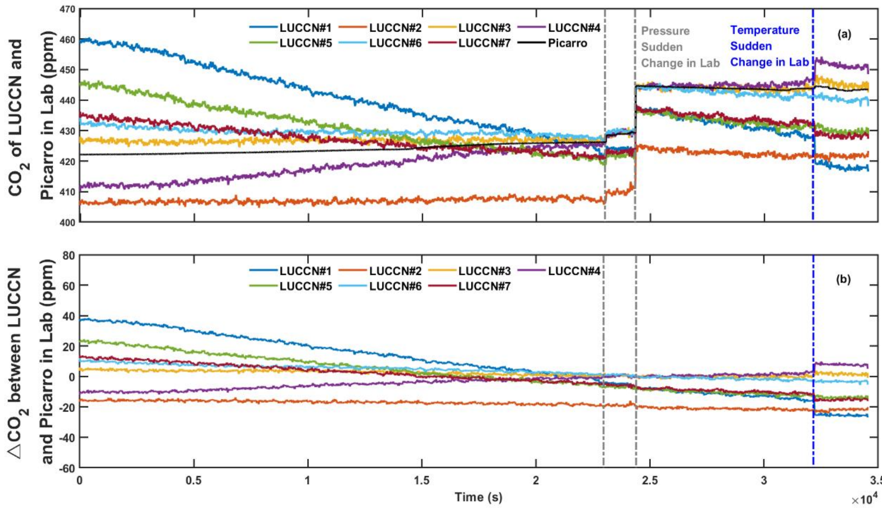

Fig. 2. (a) CO2 mole fractions measured by seven LUCCN nodes in the lab (colored lines), as well as the synchronous measurement by the Picarro sensor (black line). (b) The differences (ΔCO_2) between the measurement of LUCCN nodes and Picarro G2301 corresponding to the top image. The vertical gray dotted lines in the two figures represent the moment of sudden changes in pressure inside the cloud chamber, while the vertical blue dotted lines represent the moment of the sudden change in temperature. Among them, different LUCCN nodes exhibit the inconsistent performance during sudden environmental changes, so they need to be calibrated separately.

We employ a multi-variable non-linear regression function to establish the relation between environment parameters and the measurement bias of CO_2 concentration. In our test, we found the bias correlation changes with pressure, temperature, humidity, and CO_2 concentration itself, hence we need to calibrate sensor measurements within all possible conditions through a multi-variable function. Furthermore, we also found the correlation between biases of CO_2 concentration, and environment parameters are non-linear. Finally, the bias correction changes with sensors. Thus, we need to correct biases of individual sensors respectively.

The multi-variable non-linear regression function to correct the bias shows,

$$\Delta CO_{2,calibration} = \Sigma_n^i a_i * T^i + \Sigma_n^i b_i * P^i + \Sigma_n^i c_i * W^i + \Sigma_n^i d_i * C^i + e \tag{1}$$

In which $\Delta CO_{2,calibration}$ represents the bias ($CO_{2,LUCCN} - CO_{2,G2301}$). T, P, W and C correspond to the internal temperature, the air pressure, the water vapor pressure and CO_2 concentration. In addition, a, b, c and d are the correction coefficients of T, P, W and C respectively. e is the baseline offset.

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We applied the above correction method to a section of test data before deriving the coefficients shown in eq.(1) for calibrating the entire test dataset. Figure 3(a) shows the calibration results of LUCCN (coloured lines), and Figure 3(b) shows the differences between LUCCN and reference G2301. Overall, the corrections are sufficient to offset the biases. Compared with Figure 2(b), the differences have been reduced obviously, and the remained biases are very low. The standard deviations (SD) of $\Delta CO_{2,calibration}$ of LUCCN sensors are all less than 1 ppm, and the maximum and minimum of SD are 0.782 ppm and 0.594 ppm respectively. We also test the orders of magnitude used in this regression and find that the non-linear effect is not significant, which means lower orders, e.g. 3 order is enough even when the parameters, such as pressure and temperature, changes dramatically. It may be due to the data have been measured in the cloud chamber, so the calibration results perform better. The calibration results might be overly optimistic due to stable environmental conditions provided by the chamber, which isolate external environmental variations. Therefore, based on long-term and continuous ground observations, the accuracy, sensitivity and drift of LUCCN would be further verified in Section 3 and Section 4.

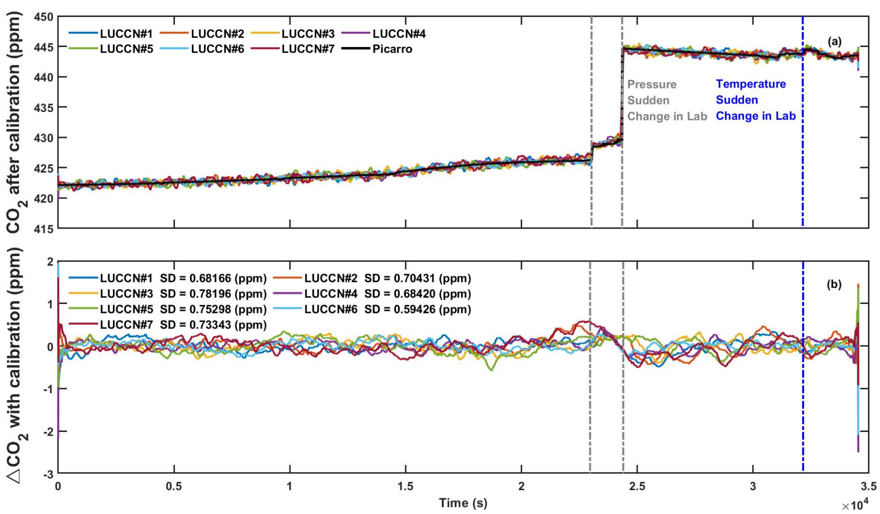

Fig. 3. (a) CO_2 mole fractions of LUCCN nodes with calibration (coloured lines) compared to the Picarro G2301 (black line); (b) The differences between the calibrated LUCCN nodes and Picarro G2301 corresponding to Figure 2(b). Compared with Figure 2(b), it can be seen that the effects of temperature and pressure fluctuations on the response of LUCCN nodes have been eliminated through the calibration. The standard deviations (SD) of LUCCN nodes with calibration are all less than 1 ppm. The gray dotted lines and blue dotted lines in the figures represent the same content as Fig. 2.

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3 Measurement

3.1 Observation site and setup

LUCCN ground base nodes have been placed at the Xinglong Atmospheric Background Observatory (Xinglong site) of the Institute of Atmospheric Physics of the Chinese Academy of Sciences. Xinglong site is located on the top of Lianzhai Mountain (40° 24'N, 117° 30'E), Xinglong County, Hebei Province, China. The site is surrounded by mountains, sparsely populated, with little human activities. The LUCCN ground base nodes have been installed very close to the Picarro G2301 tube inlet on the rooftop measurement platform building. All sensors are close to each other to ensure that the measurement targets are similar, as shown in Figure 1(a).

We collected the measurement from 27 October 2021 to 31 July 2022, with two LUCCN sensors measuring CO_2 mole fractions, temperature, pressure, relative humidity, wind direction and wind speed at the sampling frequency of 1 Hz. While the reference Picarro G2301 simultaneously measured CO_2 dry mole fractions at the sampling frequency of 0.2 Hz.

3.2 Data processing and calibration

Different from the laboratory observation, the responses of LUCCN sensors are affected by the complex variables in the outdoor ground-based observatories. Therefore, before corrections, controlling data quality is paramount for LUCCN's accuracy. Firstly, we excluded the apparent abnormal values of all observed factors. Secondly, the data points larger than three times standard deviations were also eliminated. Thirdly, it is necessary to select the synchronous observation data of LUCCN and Picarro due to minor missing records of Picarro. After calculating the CO_2 dry molar fractions of LUCCN, we interpolated the data of LUCCN and Picarro to the same sampling frequency (1 Hz).

With these data processing steps, we obtained the CO_2 dry mole fractions of one LUCCN node (bule line) and Picarro (red line) in Figure 4, and the corresponding temperature, pressure, wind speed, wind direction and relative humidity (RH) in Figure 5. There are measurements across all seasons with missing observations in May. Thus, we can observe obvious seasonal variations CO_2 dry mole fractions, temperature, pressure and RH. For example, CO_2 dry mole fractions are lower in summer and higher in winter. It should be noted that these data were averaged over 1 hour.

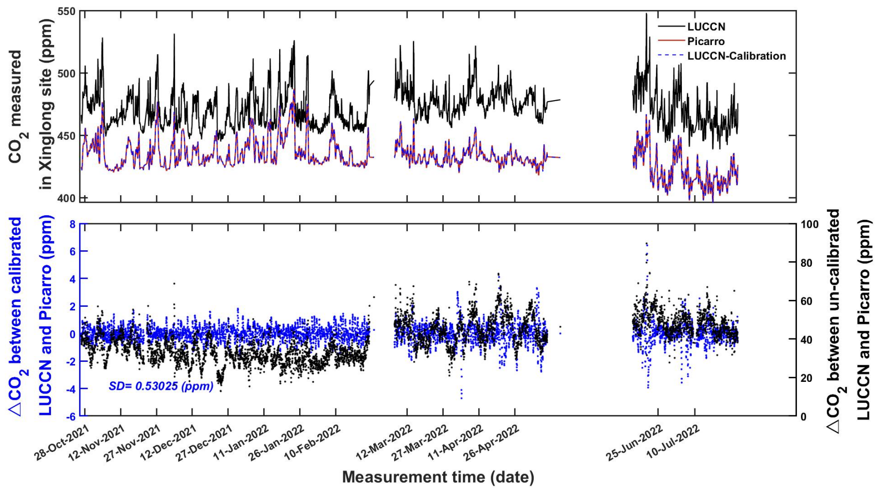

Fig. 4. (a) Time series of CO_2 dry mole fractions measured by LUCCN (black line) and Picarro (red line) at Xinglong site from 27 October 2021 to 31 July 2022. And the blue dotted line presents the calibrated CO_2 mole fractions of LUCCN. These data are averaged to 1 hour. (b) The black points present the differences between the raw of un-calibrated LUCCN and Picarro. And the blue points present the differences between the calibrated LUCCN and Picarro.

Based on the time series of LUCCN and Picarro CO_2 dry mole fractions in Figure 4(a), the differences (ΔCO_2) of these time series (black points) are not constant with time, as shown in Figure 4(b). The range of ΔCO_2 is from 4 ppm to 92 ppm. While ΔCO_2 are lower in winter, and higher in spring and highest in summer. Therefore, the responses of the LUCCN sensor can be related to the factors such as atmospheric temperature or pressure.

The last step of data processing is to reduce the influence of atmosphere on the LUCCN responses. The CO_2 dry mole fractions of LUCCN were calibrated with the bias-correction method in Section 2.2. With the calibration, CO_2 dry mole fractions of the corrected LUCCN data (bule dotted line) and Picarro data (red line) are shown in Figure 4(a). The results show that the calibration of LUCCN is highly consistent with the measurement of Picarro, and the ratios of these two sensors are close to the line $CO_{2,LUCCN} = CO_{2,Picarro}$ (eg. the line 1:1) in Figure 6. Moreover, the differences between the CO_2 dry mole fractions of LUCCN and the raw data of Picarro in Xinglong (blue points) site are significantly reduced (Figure 4(b)). The mean ΔCO_2 decreased from 39.46 ppm to 0.048 ppm at 1 hour and the SD decreases to 0.53 ppm at 1 hour. It should be noted that the SD of the LUCCN in

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Xinglong site is smaller than that of the laboratory calibration results in Figure 3(b), but this is because the Xinglong data used for calibration and calculation have been processed as 1-hour average data, while the data during laboratory test are averaged per second. The results indicate that the calibrated outdoor observation data of the LUCCN sensor can still meet the requirements of medium precision, i.e., ±1 ppm (1 SD) at 1 hour (Arzoumanian er al. 2019). In addition, SD are 0.33 ppm in autumn and 0.39 in winter, 0.65 ppm in spring, and 0.67 ppm in summer. During nearly a year of observation, the drift of LUCCN is relatively low. Based on the above analysis, we believe that LUCCN is the effective medium precision and low cost atmospheric CO_2 ground-based sensor.

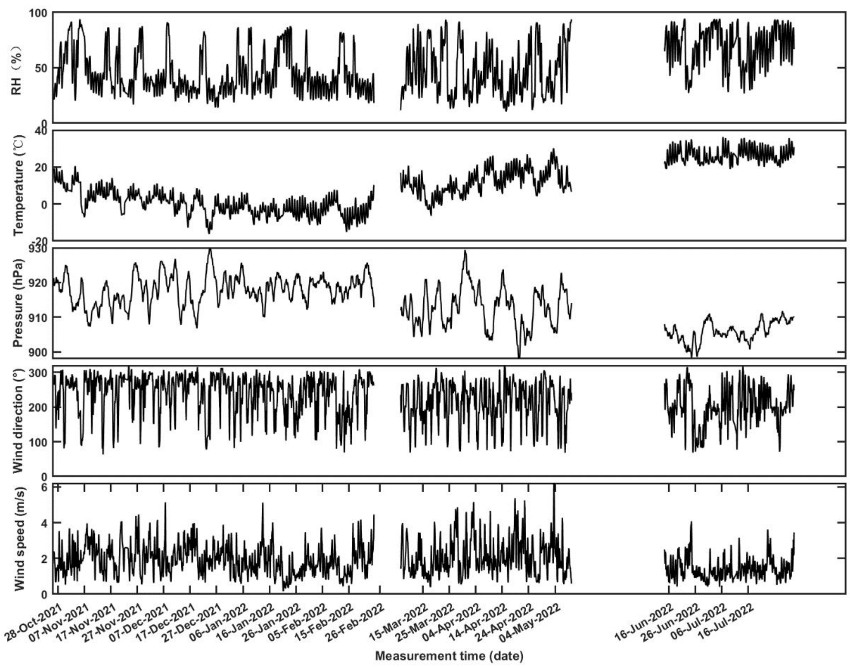

Fig. 5. Time series of observations on (a) RH, (b) temperature, (c) pressure, (d) wind direction and (e) wind speed. These meteorological factors were collected with CO_2 mole fractions of LUCCN (see the black line in Figure 4(a)) simultaneously. And these raw data are averaged to 1 hour too.

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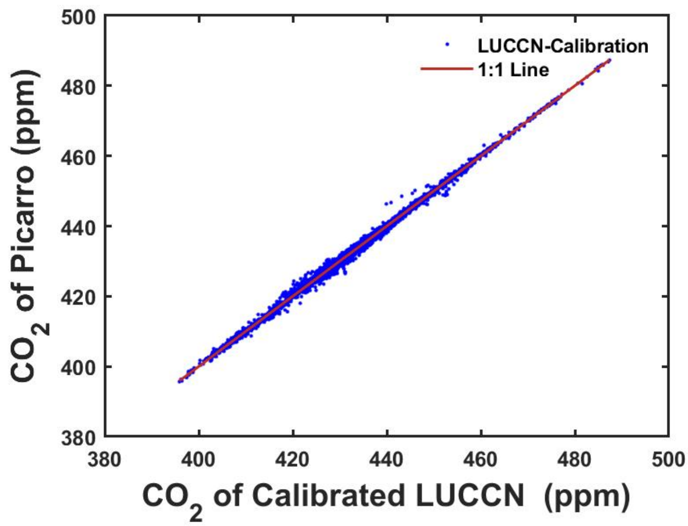

Fig. 6. The direct comparison of Picarro data and the calibrated LUCCN data at Xinglong site. The blue points are the CO_2 mole fractions with calibration of LUCCN, and the red line indicates the 1:1 line.

4 Cases study in pollution events

In order to further verify the effectiveness of the LUCCN sensor, the responses of LUCCN in pollution events were compared with the observations of the Moderate Resolution Imaging Spectroradiometer satellite (MODIS). During the measurement period of LUCCN, there were 27 pollution events in the results of MODIS. There were a few extra days when CO_2 concentrations were high while unfortunately satellite data were unavailable due to cloud coverage.

The days of these events were selected and shown in Figure 7 with red lines. During these pollution events, CO_2 dry mole fractions of these days are also higher. Such observation agreements prove that LUCCN is cable of capturing upward CO_2 concentration trends during pollution events. As for whether LUCCN can capture the pollution process, we selected three pollution cases to verify it. Figure 8 (a), (b), (c) represent the pollution process corresponding to the dashed black boxes of Figure 7. The first pollution example shows that LUCCN observed a sub-peak and a peak of CO_2 concentrations. MODIS results show that the sub-peak corresponds to the polluted weather, and the highest peak is more polluted. Before and after the peaks, the CO_2 levels observed by LUCCN were relatively lower, and the corresponding images of MODIS presented cleaner weathers, except for

November 29, 2021, when the image is obscured by clouds. The second and third examples show that the higher CO_2 concentrations observed by LUCCN corresponded to the pollution weather shown by MODIS. Moreover, when pollution levels were low before and after polluted events, the CO_2 dry mole fractions observed by LUCCN also decreased accordingly. This indicates that LUCCN is sensitive to pollution events and can capture the pollution processes effectively. Comparative analysis shows that the observation results of LUCCN and MODIS are in good agreement.

LUCCN sensors not only need to have the ability to identify pollution processes, they also need to have high sensitivity to pollution events. In view of this, we would compare the differences between LUCCN and Picarro in pollution events and non-pollution events respectively. The results show that in the pollution events, the SD of the differences between LUCCN and Picarro is 0.367 ppm. In the 27 non-pollution events randomly selected, the SD of the difference is 0.363 ppm. The results indicate that LUCCN has high sensitivity in both pollution and non-pollution events. Therefore, the LUCCN sensors are effective to measure the changes of CO_2 mole fractions.

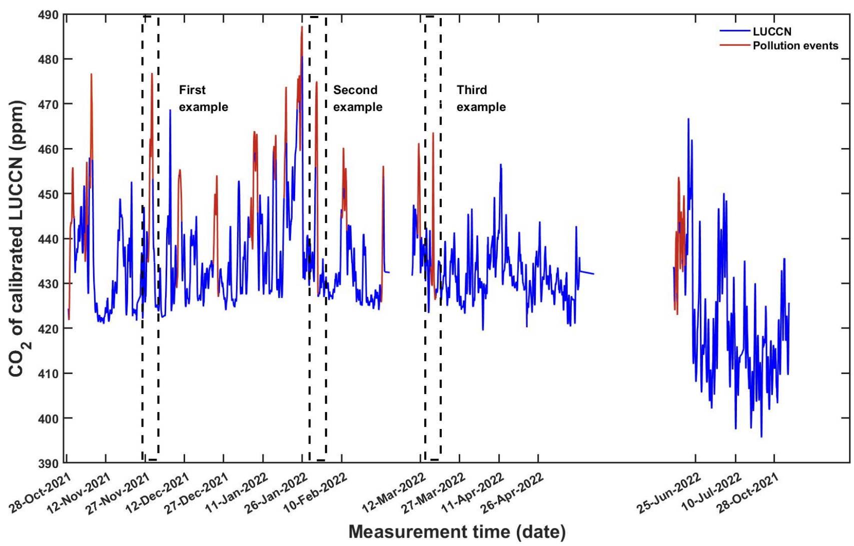

Fig. 7. The relationships between CO_2 mole fractions of LUCCN (blue lines) and the corresponding pollution events observed by the MODIS satellite (red lines) at Xinglong site. The black dashed boxes represent three examples of pollution events displayed by MODIS, which would display the measurements of LUCCN and corresponding satellite images in the following figure.

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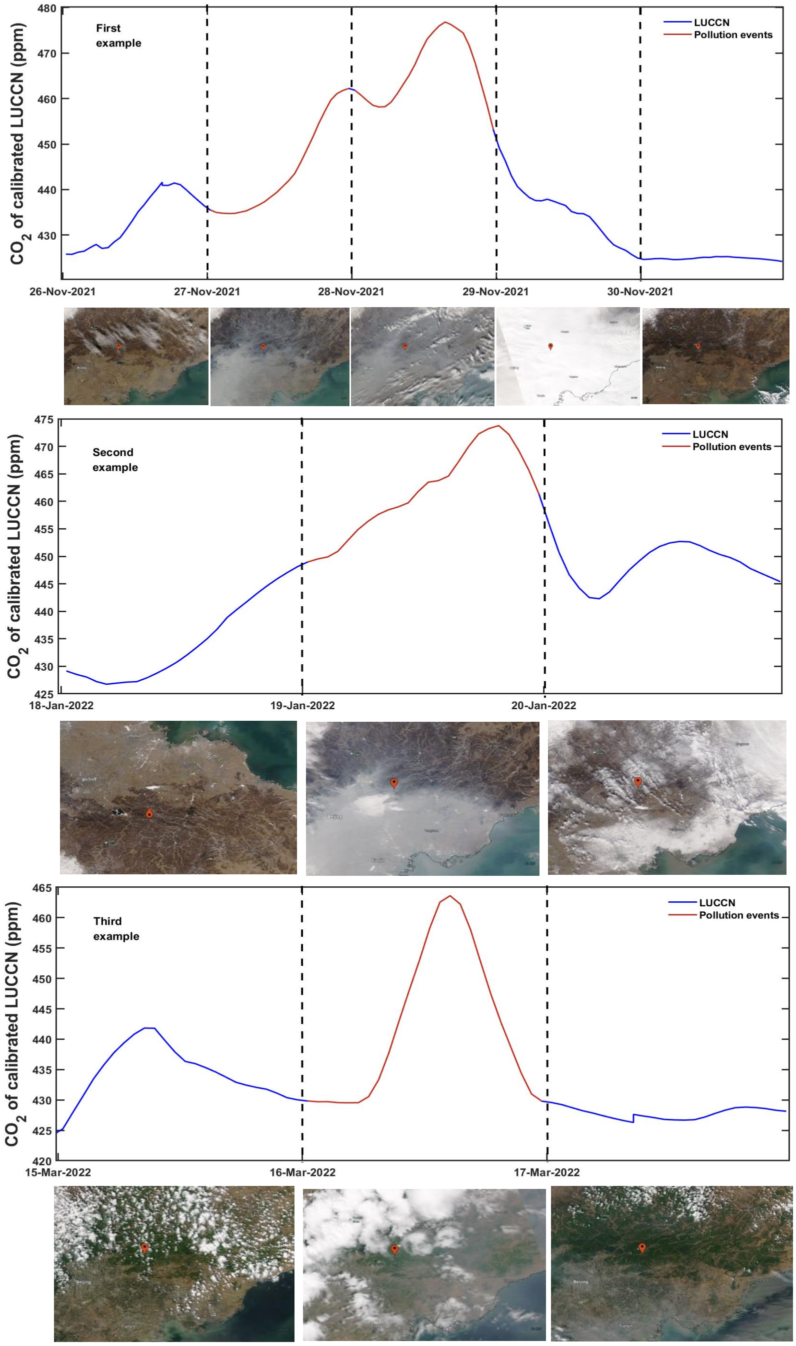

292 **Fig. 8. (a)** The first example of the pollution events in Fig.7. (b) The second example of the pollution events in
293 Fig.7. (c) The third example of the pollution events in Fig. 7. The above figures are the enlarged images of the
294 dashed boxes in Fig. 7, with the black dashed line indicating the boundary of each day. The below figures are the
295 corresponding MODIS images of each day, and the red marks indicate the location of the Xinglong site.

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5 Conclusion and outlooks

Low-cost urban CO_2 observation networks play a crucial role in monitoring urban CO_2 emissions and estimating their impacts on the environment. In this paper, we have described the composition, principle, calibration, and ground-based observations of the Low-cost UAV Coordinated Carbon Observation Network - LUCCN. At present, LUCCN nodes are capable of observing CO_2 concentration, temperature, pressure, RH, wind direction, and wind speed, and have a comprehensive design for data transmission, power supply, and equipment enclosure. Moreover, the accuracies of LUCCN have been verified through calibration experiments in the laboratory and outdoor ground observation. Because the relationships between the CO_2 measurements of LUCCN sensors and their impact factors are not completely linear, the multi-variable non-linear regression method has been adopted to calibrate the measurement data of seven LUCCN sensors in the laboratory. The calibrated results show that the differences between the measurements of LUCCN and Picarro have been significantly reduced. The SD of seven LUCCN sensors are all less than 1 ppm, where the maximum and minimum values are 0.782 ppm and 0.594 ppm respectively with 1 second averaging window size. The results show that the accuracy of the calibrated LUCCN data is higher than the medium precision requirement, i.e., ±1 ppm at 1 hour (Arzoumanian et al., 2019). This result preliminarily proves that the LUCCN can measure CO_2 concentrations effectively.

In addition to the calibration experiments in the laboratory, we completed long-term and continuous observation of LUCCN at the Xinglong Atmospheric Background Observatory from the 27th of October, 2021 to 31st of July, 2022. With the quality controlling and calibration, the 1 hour average difference values of LUCCN and Picarro decrease from 39.46 ppm to 0.048 ppm. CO_2 dry mole fractions of LUCCN and Picarro are close to 1:1. And the SD is reduced from 9.06 ppm to 0.53 ppm which is less than 1 ppm at 1 hour. That is, the accuracy of LUCCN still has reached the requirement of medium precision. Moreover, over the one-year observation period, the drift of LUCCN is small enough to be ignored. These above results further confirm that LUCCN is useful to measure the surface CO_2 concentrations.

Not only the accuracy of LUCCN has been confirmed, but also the sensitivity to the changes of CO_2 concentrations has been verified. Therefore, a comparative analysis is made with the results of the satellite observation. During the observation period, there are 27 pollution events shown by MODIS

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satellite. In the pollution events displayed by MODIS, CO_2 dry mole fractions observed by LUCCN presented higher values. Moreover, LUCCN observations also showed lower CO_2 levels in clean weathers before and after pollution events. These examples show that LUCCN can effectively measure the changes of CO_2 concentrations. And the SD between LUCCN and Picarro in pollution events and non-pollution events are 0.367 ppm and 0.363 ppm respectively. Through these analyses, LUCCN can effectively observe the fluctuations of CO_2 concentrations. Not only that, the self-adaption LUCCN system has been applied in the first integrated measurement campaign in Shenzhen, China. Through the campaign, we found that the LUCCN system is able to increase the spatial and temporal coverage of carbon emission information, especially in cases involving the detection of small, rapidly changing sources and sinks (Yang et al., 2024). To sum up, the LUCCN can realize the goal of low cost and medium precision CO_2 observation, it is also a powerful tool to achieve the ground CO_2 monitoring network.

Author contribution

Xiaoyu Ren: Data curation, Methodology, Formal analysis, Writing - original draft. Dongxu Yang: Conceptualization, Methodology, Supervision, Resources, Writing - review & editing. Yi Liu: Investigation, Supervision, Resources. Yong Wang: Resources. Ting Wang: Data curation, Software. Zhaonan Cai: Investigation, Supervision. Lu Yao: Methodology, Formal analysis. Tonghui Zhao: Writing - review & editing. Jing Wang: Methodology, Formal analysis. Zhe Jiang: Conceptualization.

Data availability

The data are accessible by contacting the authors (renxiaoyu@mail.iap.ac.cn and yangdx@mail.iap.ac.cn).

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351 **Competing Interest**

352 The authors declare that they have no conflict of interest.

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