UAV-based method for measuring CO_2 emissions in forest ecosystems

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Abstract

This study addresses the difficulty of accurately quantifying CO_2 emissions in forest ecosystems due to spatial heterogeneity, complex terrain, and the combined effects of horizontal and vertical transport. A UAV-based flux quantification methodology, capable of three-dimensional CO_2 emission computation, was developed, evaluated and applied to a forest ecosystem. The UAV system is integrated with a high-precision closed-path CO_2 analyzer to measure CO_2 mole fractions and a calibrated ultrasonic anemometer to measure wind vectors, together with profile measurements of temperature and pressure. Within a mass-balance framework, the UAV measurement system is flown along horizontal loops at multiple heights together with vertical ascent flight tracks, acquiring data along the flight tracks that are used to simultaneously quantify horizontal advective and vertical turbulent carbon dioxide emission components. The method was applied at a subtropical plantation forest and evaluated against fluxes derived using a nearby eddy-covariance (EC) flux tower. Validation against long-term CO_2 flux measurements from a nearby, permanently installed eddy-covariance system shows that vertical CO_2 fluxes estimated from measured vertical CO_2 concentration gradients and a turbulence-based exchange coefficient (gradient method) agree well with EC observations across seasons, with a correlation coefficient r of 0.9 (Based on 167 paired flux estimates collected between May 2023 and December 2024). Measurements collected along the horizontal box-pattern flight paths further reveal pronounced diurnal variations in local canopy-air CO_2 mass transport: lateral advection dominates in the early morning, whereas vertical uptake prevails under well-mixed midday conditions. Sensitivity analysis of emission intensities across control volumes with different horizontal dimensions (50×50, 100×100, and 150×150 m^2) and a constant vertical extent of 50 m revealed stronger scale dependence during autumn mornings, indicating significant spatial heterogeneity in CO_2 emissions. Uncertainty assessment suggests that the total relative uncertainty of UAV-derived emissions is typically ~30%, with wind-field measurement as the main error source. Overall, this UAV approach provides a flexible and reliable method for analyzing near-

surface three-dimensional CO_2 transport over structurally heterogeneous forests and complex terrain, helping to overcome the limited spatial coverage of traditional flux towers and remote sensing.

Keywords: UAV-based observations; CO_2 emissions; Mass balance; Three-dimensional flux measurement; Spatial heterogeneity

1 Introduction

Carbon dioxide (CO_2) is the dominant anthropogenic greenhouse gas in the atmosphere, contributing approximately 50–60% to the enhanced greenhouse effect excluding water vapor (WMO, 2023). The atmospheric CO_2 budget is strongly impacted by biospheric carbon cycles. Forest ecosystems, in particular, play a critical role in the terrestrial carbon cycle and are widely recognized as major carbon sinks, covering about 40% of the global land surface and representing some of the most extensive and structurally complex ecosystems on Earth (Bonan, 2008; IPCC, 2021; Pan et al., 2011). Accurate quantification of forest-atmosphere carbon exchange remains essential for constraining regional and global carbon budgets and for evaluating ecosystem feedbacks from climate change. Recent synthesis studies and observation-network analyses continue to highlight the importance of improving carbon flux measurements across heterogeneous ecosystems (Fang et al., 2024; Burman et al., 2025). However, despite decades of carbon-cycle research using a range of observational platforms, including stationary towers, satellites, and manned aircraft (Baldocchi, 2003; Gioli et al., 2004; Jung et al., 2020), commonly applied flux quantification methods often resolve only selected components of three-dimensional CO_2 transport. For example, eddy-covariance methods primarily quantify vertical turbulent exchange, whereas aircraft-based mass-balance approaches commonly emphasize horizontal advective transport. Consequently, simultaneous quantification of both horizontal and vertical CO_2 transport remains challenging (Leuning et al., 2008). In forest ecosystems, strong spatial heterogeneity, complex canopy-atmosphere interactions, and non-negligible horizontal transport processes can introduce substantial uncertainties into quantitative estimates of ecosystem-atmosphere CO_2 exchange (Baldocchi, 2008; Schimel et al., 2015). Although vertical CO_2 flux is the primary quantity used to evaluate forest-atmosphere carbon exchange, horizontal advection can influence the local CO_2 mass balance above the canopy and affect the interpretation of vertical flux measurements under spatially heterogeneous or weakly mixed conditions. Therefore, measurements that characterize lateral CO_2 transport across finite control-

volume boundaries are useful for diagnosing when the assumption of horizontal homogeneity is valid and when vertical flux measurements may be influenced by local advective convergence or divergence. As a result, flux measurement and quantification approaches capable of resolving both horizontal and vertical CO_2 transport are required.

Eddy covariance (EC) flux measurement technique is a widely used method (Aubinet et al., 2012; Baldocchi, 2003; Burman et al., 2025; Pastorello et al., 2020; Fang et al., 2024) for quantifying ecosystem-scale vertical CO_2 fluxes and has been implemented globally through networks such as the FLUXNET (Aubinet et al., 2012; Baldocchi et al., 2001; Fang et al., 2024; Pastorello et al., 2020; Wilson et al., 2002). By design, EC provides direct measurements of time-averaged vertical turbulent flux of CO_2 between the surface and the atmosphere. However, the method relies on the validity of the Monin–Obukhov Similarity Theory (MOST), which assumes a horizontally homogeneous, flat terrain and stationary turbulence (Foken, 2008; Kaimal and Finnigan, 1994; Monin and Obukhov, 1954; Stull, 1988). Over complex terrain and heterogeneous surfaces, these assumptions are often violated, calling into question the representativeness of EC flux measurement results over such ecosystems. EC flux measurements do not explicitly resolve horizontal CO_2 transport associated with advection, canopy heterogeneity, terrain-induced flows, or mesoscale circulations (Aubinet et al., 2002; Feigenwinter et al., 2004; Finnigan et al., 2003; Leuning et al., 2005). Horizontal fluxes are therefore commonly neglected or assumed to be negligible in EC flux measurements, an assumption that may not hold under weak or non-stationary turbulence conditions (Mahrt, 1998, 2010; Vickers and Mahrt, 1997). In addition, although stationary towers can support measurements at multiple levels, conventional eddy-covariance flux observations are typically obtained at one or a limited number of fixed heights. This limits their ability to characterize continuous vertical variations in CO_2 transport and to determine flux divergence through the lower atmosphere (Schmid, 2002). For large scale atmosphere-ecosystem CO_2 exchanges, satellite remote sensing offers valuable information on horizontal distributions of atmospheric pollutants (Crisp et al., 2017; Jacob et al., 2016), but it has limited

sensitivity to vertical gradients near the surface and cannot resolve canopy-scale exchange processes with the accuracy of in situ measurements (Chevallier et al., 2014). Likewise, manned fixed-wing aircraft campaigns provide regional-scale observations of pollutants distributions and enable mass-balance approaches to emission estimation (Cambaliza et al., 2014). However, fixed-wing aircraft cannot hover or perform localized, near-vertical profile measurements at a fixed horizontal position, as rotary-wing UAVs can. Because changes in altitude are accompanied by substantial horizontal displacement, resolving fine-scale vertical CO_2 gradients and deriving vertical fluxes over a specific control volume is more challenging (Gordon et al., 2015). Collectively, these limitations highlight a persistent observational gap in the characterization of CO_2 three-dimensional transport in forest ecosystems (Fang et al., 2024; Bolek et al., 2024).

Recent advances in rotating wing unmanned aerial vehicle (UAV) platforms and lightweight sensor technologies have created new opportunities for atmospheric measurements over complex environments (Bolek et al., 2024). UAVs have emerged as practical tools for complementing existing carbon observation networks by enabling flexible, high-resolution measurements of greenhouse gases in both horizontal and vertical directions (Bolek et al., 2024; Khan et al., 2012; Villa et al., 2016). Compared with stationary towers, characterize spatial variability in CO_2 concentrations across multiple locations and altitudes within a relatively short sampling period, without relying on assumptions of horizontal homogeneity (Witte et al., 2017), enabling identification of emission or uptake hotspots that may be missed by ground-based observations (Khan et al., 2012). Nonetheless, previous UAV studies focused primarily on measurements of greenhouse-gas concentrations and generally did not demonstrate direct CO_2 flux quantification, partly because accurate wind-speed measurements from a moving rotary-wing platform can be affected by both propeller-induced airflow disturbances (Soltaninezhad et al., 2025; Thielicke et al., 2021) and rapid changes in UAV attitude during flight, including variations in pitch, roll, and yaw (Yang et al., 2024). These effects introduce additional uncertainty into flux calculations. To address these challenges, various sensors, including multi-hole probes, pitot tubes, and sonic

anemometers, have been deployed on UAVs for wind measurements and correction algorithms have been developed to mitigate measurement disturbances associated with rotor downwash, re-orientation of airflow by platform geometry, and rapid changes in UAV motion and attitude (Langelaan et al., 2011; Niedzielski et al., 2017; Nolan et al., 2018; Rogers and Finn, 2013; Soddell et al., 2004; Soltaninezhad et al., 2025; Spiess et al., 2007; Yang et al., 2024). Among these, sonic anemometers are considered particularly promising because of their high accuracy and fast response (Thielicke et al., 2021). Nevertheless, the influence of rotor-induced flow distortion, UAV attitude changes, and local turbulence on wind measurements remains non-negligible and requires dedicated calibration strategies (Soltaninezhad et al., 2025; Yang et al., 2024).

Building on our previous work on the development of an UAV platform for integrated high sensitivity, high precision, fast response measurements of greenhouse gas concentrations and three-dimensional wind speed, combined with a comprehensive wind calibration algorithm to correct for UAV motion, attitude, and rotor effects (Yang et al., 2025), we aim to improve quantification of atmospheric CO_2 transport in both horizontal and vertical directions over forest ecosystems. In the present study, we use observations collected with the UAV platform to evaluate the performance of the wind correction algorithm, assess the capability of the integrated UAV measurement system to quantify three-dimensional CO_2 transport, including canopy-scale vertical CO_2 fluxes, and characterize the robustness and uncertainty of the UAV-derived emission/uptake estimates. The evaluation is based on specifically designed flight strategies with complementary box and profile flight patterns and is conducted in field experiments at a subtropical forest site. Such flight strategies are implemented within a mass-balance framework to resolve three-dimensional CO_2 exchange in the lower atmosphere. While horizontal mass flux estimates derived from this platform have been previously evaluated and validated in field measurements (Han et al., 2024) vertical fluxes derived from such a platform have not been evaluated until now, and a critical part of the present study is to validate the UAV vertical flux measurement methodology against the collocated tower-based EC flux measurements. As presented further below,

the results demonstrate a highly versatile methodology for determining net carbon fluxes over complex ecosystem terrains that complements existing carbon flux tower measurements by providing spatially explicit information on three-dimensional CO_2 transport and, with sufficient UAV observations, an independent estimate of forest carbon fluxes.

2 Field site and platform description

2.1 Platform description

2.1.1 UAV platform

The UAV platform used in this study is a battery-powered hexacopter (KWT-X6L-15, ALLTECH, China), which provides stable flight performance and high maneuverability, including vertical take-off and landing, hovering, and controlled horizontal flight (Fig. 2b). This airframe was selected as the base platform for CO_2 measurements because of its ability to operate safely above forest canopies, its high payload capacity, and its adaptability to multiple flight strategies. The UAV has a maximum horizontal span, including the arms and rotor blades, of 2570 mm, and the height from the landing gear to the top of the main body is 565 mm, excluding the air inlet. Its maximum horizontal flight speed is 18 m s^{-1}, the maximum ascending rate is 4 m s^{-1}, and the maximum wind resistance is 14.4 m s^{-1}, all of which satisfy the requirements for atmospheric wind and CO_2 measurements in the lower boundary layer. A detailed summary of the UAV specifications is provided in Table 1.

Table 1. Specifications and capabilities of the UAV.

hover endurance	≥30 min (for 15 kg payload)
Peak flight velocity	18 m s^{-1}
Peak climb velocity	4 m s^{-1}
Control radio range	≥7 km
Operating ambient temperature	-20 ℃~55 ℃
Maximum operating altitude	≥5000 m
Wind resistance capability	14.4 m s^{-1}
Payload capacity	15 kg (without battery)
Rotor blade length	765±5 mm

Symmetric motor center-to-center length	1635±10 mm
Body stands to the body top length	565 ± 5 mm
Wing span	2570 ±10 mm
Battery capacity/unit	30000 mAh (2 units)
Battery weight/unit	6 kg ± 0.1 kg
Radio modem	902 MHz ~928 MHz
GPS accuracy	Horizontal direction: ± (8+1×$10^{-6}D$) mm; Vertical direction: ± (15+1×$10^{-6}D$) mm
Navigation	GPS (RTK system)

Note: In the GPS accuracy specification, *D* is the baseline distance between the UAV receiver and the RTK base station, expressed in kilometers.

The airframe is constructed from carbon-fiber composite materials and houses an integrated flight control system, a power supply module, and a communication unit. The flight control system includes an inertial measurement unit (IMU), accelerometers, and a global positioning system (GPS) sensor capable of real-time kinematics (RTK), and records UAV attitude and motion parameters (roll, pitch, yaw, and three-axis accelerations) which is critical for subsequent wind-speed correction. To improve positioning accuracy, the onboard RTK GPS receiver takes in real-time signals from a concurrently ground-deployed kinematic (RTK) GPS system (iRTK10, Hi-Target, China) for real time computation for centimetre- to millimetre-level accuracies in both the horizontal and vertical directions, which are particularly advantageous over a complex terrain. The power module consists of two lithium–polymer batteries connected in parallel, each with a capacity of 30,000 mAh, enabling a maximum payload of 15 kg and a typical flight endurance of approximately 30 min. The communication module operates in the 890-960 MHz frequency band, allowing reliable telemetry and control within a range of up to 10 km.

2.1.2 Scientific payloads

The integrated scientific payloads, with a total weight of 6.35 kg including the mounting chassis, were powered directly by the main UAV batteries. The payloads include a closed-path CO_2 analyzer and a 3-d ultrasonic anemometer, with their specifications summarized in Table 2. The 3-d ultrasonic anemometer (Trisonica Mini, LI-COR Environment, USA) is a compact sensor, with a measurement path of 35 mm

and a mass of 50 g, that measures three-dimensional wind speeds under its own coordinate system, air temperature, and pressure. The anemometer was mounted 70 cm above the rotor plane to minimize flow distortion caused by propeller blade downwash (Fig. 2b) (Yang et al., 2025). This configuration has been shown to achieve acceptable accuracy (±2%) in previous validation studies using reference-grade meteorological instruments (Palomaki et al., 2017; Shimura et al., 2018; Thielicke et al., 2021). The CO_2 analyzer (MIRA Ultra N_2O/ CO_2, Aeris Technologies, USA) was mounted beneath the UAV body to measure CO_2 volume mole fractions in air, with its air inlet set next to the anemometer sonic sensors to ensure spatially consistent wind and CO_2 concentration measurements. The MIRA analyzer operates in the mid-infrared (MIR) spectral range, where CO_2 absorption is substantially stronger than in the near-infrared, enabling a high sensitivity within a compact optical cell. A fixed time lag of 5 s, associated with air residence time in the sampling line, was applied to synchronize the CO_2 measurements with the wind data.

Data from all scientific payloads, together with UAV attitude and flight parameters (roll, pitch, yaw, three-axis accelerations, and GPS position), were recorded by the onboard main controller via UART communication and stored on an SD card (Fig. 1). In addition, real-time telemetry, including sensor status, battery voltage, and flight parameters, was transmitted to a ground station, allowing continuous monitoring during flight operations. CO_2 sampling was performed through the analyzer's built-in sampling ports and internal pump. The CO_2 measurements were recorded at 1 Hz, while the anemometer data were recorded at 5 Hz.

Table 2. Detailed information of scientific payloads (provided by the manufacturers).

Instrument	Sample Frequency (Hz)	Weight (kg)	Measurement	Sensitivity or Accuracy
MIRA Ultra	1	6	CO_2	< 200 ppb/s (Sensitivity)
Trisonica Mini	5	0.05	Wind speed	(0 - 10 m/s): ±0.2 m/s
				(11 - 30 m/s): ±2%
			Wind direction	± 1.0°
			Temperature	± 2.0 ℃

	Pressure	± 1.0 kPa

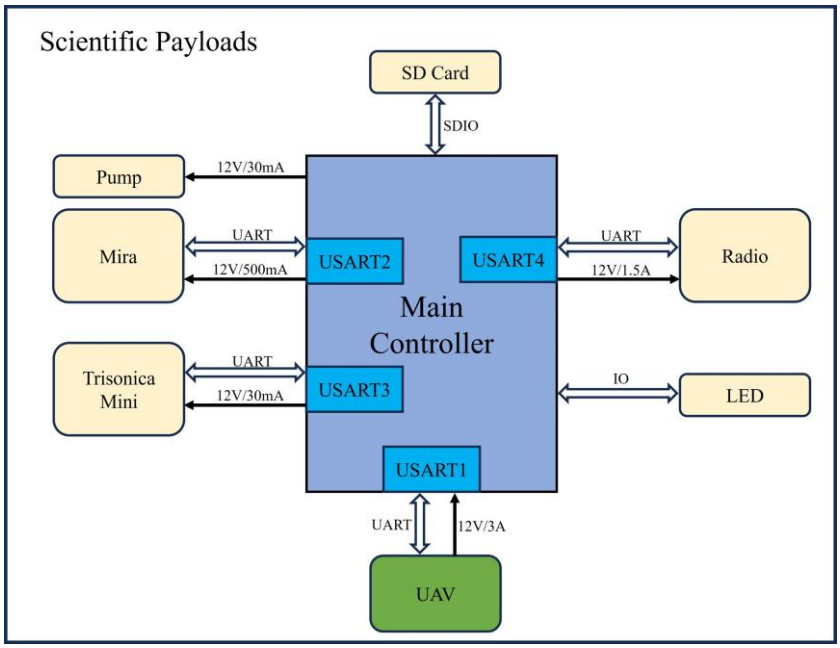


Figure 1. Diagram of the scientific payloads on the UAV-based flux measurement system. The LED is used as a status indicator to display the operating state of the UAV measurement system during flight and ground testing.

2.2 Field site description

The UAV-based field measurements were conducted at the Qianyanzhou Experimental Station (26°44′29″ N, 115°03′29″ E) located in Jiangxi Province, southern China. This station is one of the core flux observation sites of the China Flux Observation Research Network (ChinaFLUX) and is equipped with a comprehensive eddy covariance (EC) measurement system (Yu et al., 2006). The flux tower has a height of approximately 43 m above ground, with the EC system installed at 31 m above ground level, while the mean forest canopy height is about 18 m.

The long-term observation site, 1 ha in size and centred on the flux tower, is dominated by plantation forests, primarily consisting of *Pinus massoniana*, *Cunninghamia lanceolata*, and *Pinus elliottii* arranged in a strip-mixed pattern with an approximate ratio of 49:48:3, respectively (Huang et al., 2007). The region experiences a typical subtropical monsoon climate, characterized by prevailing southerly winds in summer and northerly winds in winter. The mean annual air temperature is 17.9 °C, and

the mean annual precipitation is approximately 1490 mm, with most rainfall occurring between March and June.

To evaluate the performance of the UAV platform for CO_2 vertical flux measurements, flights were conducted at Site B, approximately 160 m southeast of the flux tower at Site A, where the relatively open forest structure allowed safe UAV take-off and landing. The UAV-derived fluxes were then directly compared with tower-based measurements (Fig. 2a). The terrain within approximately 1 km^2 surrounding the flux tower is characterized by continuous low hills and gentle slopes, with slope angles of approximately 2.8°–13.5° and local relative elevation differences of approximately 10-30 m. The approximately 15 m elevation difference between Sites A and B is therefore part of the naturally undulating low-hill terrain. Owing to this topographic variability, all UAV flight altitudes reported in this study are referenced to the take-off elevation at Site B; consequently, the actual height above the local ground surface varied spatially along the flight path. Within a radius of approximately 350 m northwest of Site B, only a limited number of low-rise buildings below the forest canopy used exclusively for scientific research are present, resulting in minimal anthropogenic influence on the measured CO_2 fluxes. Such an experimental condition provides a representative forest ecosystem setting in which UAV-derived fluxes can be evaluated against flux tower observations.

From May 2023 to December 2024, a total of 209 UAV flights were conducted at the site. After quality control, including the removal of records affected by rainfall and other conditions that could compromise instrument performance, 168 flights, corresponding to approximately 70 h of cumulative flight time, were retained for analysis. These included 40 flights in spring, 55 in summer, 53 in autumn, and 20 in winter, with seasons defined according to the Northern Hemisphere meteorological seasons: March-May, June-August, September-November, and December-February, respectively.

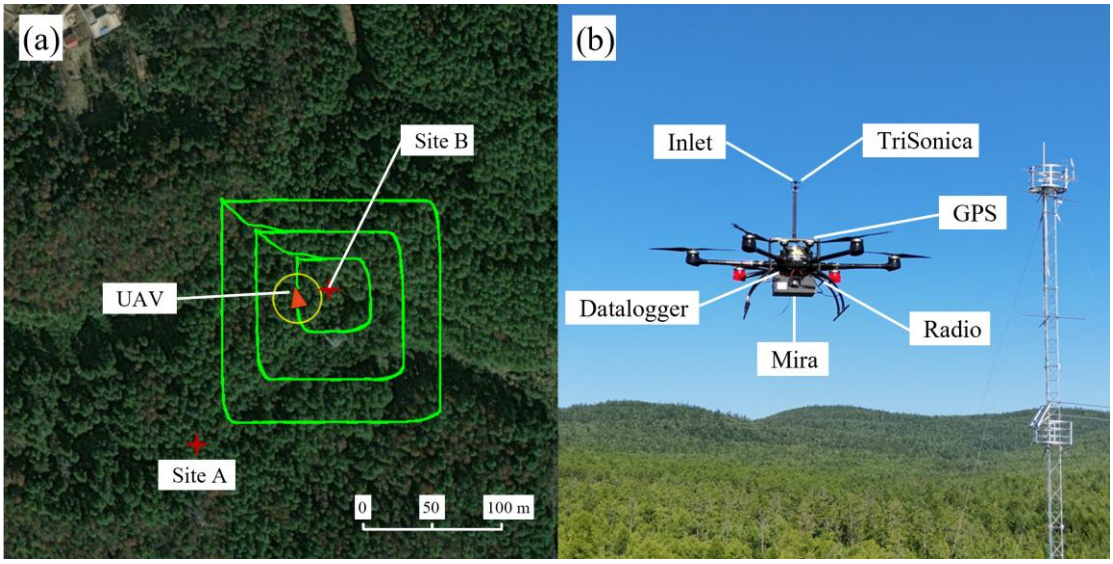


Figure 2. (a) A top-down view of the UAV's flight tracks from a representative flight. The green flight tracks represent the box pattern, categorized into three box sizes: 50×50×50 m^3, 100×100×50 m^3, and 150×150×50 m^3. Site A marks the location of the flux tower where EC measurements of vertical CO_2 fluxes are continuously carried out, while Site B denotes the take-off point for the profile pattern. The straight-line distance between the two sites is 150 m. All UAV flights were conducted following the same predefined flight routes. (b) The instrumented UAV platform; the flux tower can be seen in the background.

2.3 Flight patterns

Two complementary flight strategies were executed in this study: a box pattern and a profile pattern (Fig. 3a). The box pattern consists of a closed rectangular flight path flown above the forest canopy at multiple altitudes, enabling sampling of horizontal CO_2 transport across a defined control volume. Box flights were conducted at heights of 35, 40, 45, 50, 60, and 85 m above ground level. Using flight-path fitting and screen linear interpolation, the three-dimensional spatial distributions of CO_2 volume mole fraction, wind vectors, and air density were reconstructed within the box domain. In the present study, we reconstructed the spatial distributed data for visualization purposes only (Fig. 3b), but computed the horizontal fluxes using the original observations directly. Flight-path fitting refers to the construction of a smooth, closed loop constructed from the discrete UAV trajectories at all altitudes, thereby defining the four virtual vertical surfaces of the box. Screen linear interpolation refers to the mapping of CO_2 mole fractions and corrected wind speed measurements observed along the flight path onto a regular two-dimensional grid on the vertical surfaces for

visualization of spatial patterns.

The profile pattern was designed to capture vertical gradients of CO_2 mole fractions, wind speed, and air density from near the surface to the top measurement height. Each box-pattern flight was paired with a vertical profile, and all measurements were completed within approximately 20 min to ensure consistency of the sampled air mass in the controlled volume. Vertical CO_2 fluxes were computed from the profile data using the gradient method (Sect. 3.2.2), with the analysis height range defined by the lowest and highest box levels (35-85 m). Because the EC system is installed at 31 m, UAV-derived CO_2 vertical fluxes used data from 26 and 36 m to enable direct comparison with tower-based EC measurements.

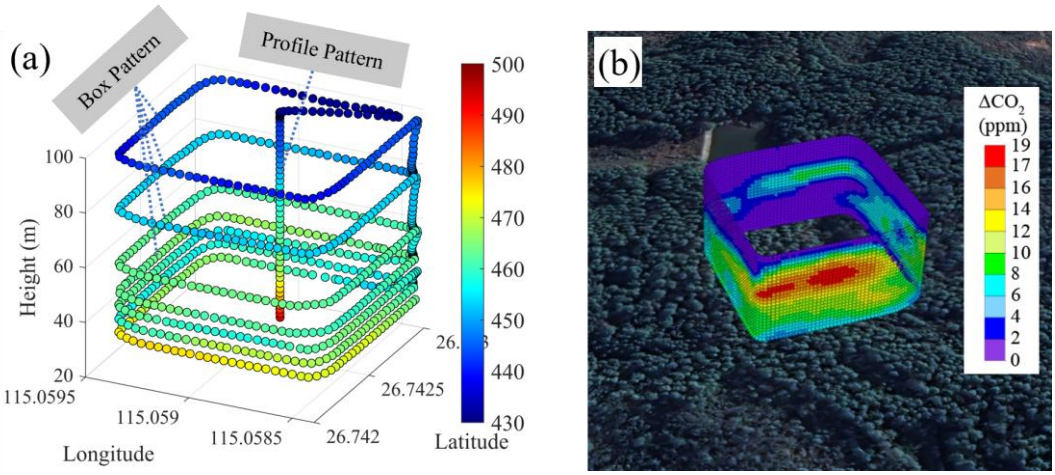


Figure 3. Overview of flight patterns. (a) Two distinct flight strategies: box pattern and the profile pattern. (b) The spatial distribution of CO_2 mole fractions obtained through flight-path fitting and screen linear interpolation for flights during 2024-08-08 7:00 - 7:30, morning.

3 Methodologies

3.1 Wind speed calibration

To obtain accurate and reliable wind speed measurements, the raw data acquired by the ultrasonic anemometer were processed using a dedicated wind speed calibration algorithm. This algorithm, developed by Yang et al. (2025), was specifically developed for the UAV platform and the mounted instrumentation used in this study, and employs computational fluid dynamics (CFD) simulations to characterize the flow-field

distortion by the UAV rotor-induced airflows. Hundreds of simulation scenarios were conducted, encompassing a wide range of flight altitudes, wind directions, and ambient wind speeds, in order to quantify the influence of rotor-induced airflow disturbances on wind measurements. The simulated disturbance fields were subsequently combined with UAV motion and attitude compensation schemes, yielding a comprehensive correction algorithm that simultaneously accounts for UAV translation, rotation, and rotor effects. The algorithm was validated with 3-D wind measurements at multiple levels on an 80-meter met tower Yang et al. (2025). All wind measurements used in this study were corrected using this algorithm, ensuring consistency and comparability with reference-grade wind observations.

3.2 CO_2 emission estimation based on UAV measurements

CO_2 emissions from within the control volume defined by the virtual box were quantified using a mass-balance framework that integrates measurements obtained from box-pattern and profile-pattern UAV flights. This approach assumes that CO_2 concentration and wind fields across the control-volume boundaries are sampled with sufficient spatial coverage and that atmospheric conditions remain steady or quasi-steady during the measurement period. Under these conditions, the net emission rate can be inferred from the fluxes crossing the boundaries of the control volume.

According to the divergence theorem, the rate of change of mass of a stable compound within a control volume equals the surface integral of the mass flux through its enclosing surfaces. Consequently, the total CO_2 emission rate within the volume equals the net outward flux integrated across all box wall surfaces, where positive flux contributions represent CO_2 mass leaving the box and negative flux contributions represent CO_2 mass entering the box. Based on the integral form of the continuity equation, the emission rate within the control volume enclosed by the box pattern can be expressed as

$$E_C = E_{C,H} + E_{C,HT} + E_{C,V} + E_{C,VT} - E_{C,M} \quad (3.1)$$

where E_C denotes the total CO_2 emission rate within the control volume, $E_{C,H}$ and $E_{C,V}$ denote the integrals of horizontal and vertical advective fluxes through the box

walls, respectively; $E_{C,HT}$ and $E_{C,VT}$ represent the integrated turbulent fluxes in the horizontal and vertical directions, and $E_{C,M}$ accounts for changes in CO_2 mass associated with air-density variations. Eq. (3.1) forms the basis of the TERRA emission inversion model (Gordon et al., 2015).

To investigate the contributions of each component to the emissions, the TERRA model was updated here, in particular the treatment of the vertical flux algorithm, to directly compute vertical turbulent fluxes based on the UAV measurements instead of relying on parametrization assuming entrainment. Here, the mean wind components ($\bar{u}$, $\bar{v}$, $\bar{w}$) were determined separately for each UAV flight using all quality-controlled observations collected during that flight. The (u) component denotes the east-west wind speed, with (u>0) indicating flow toward the east; the (v) component denotes the north-south wind speed, with (v>0) indicating flow toward the north; and (w) denotes the vertical wind-speed component, with (w>0) indicating upward flow. The corresponding turbulent fluctuations (u', v', w') were calculated by subtracting the 30 min mean value of each component from its instantaneous measurement. For the horizontal terms, the u-component was used for comparison. The mean u-component, ($\bar{u}$), was typically 2-3 m/s, whereas the 95th percentile of the corresponding turbulent fluctuation, (u'), was less than 0.1 m/s. Because the mean horizontal wind component was more than one order of magnitude larger than the turbulent fluctuation, the horizontal advective transport term ($E_{C,H}$) was much larger than the horizontal turbulent transport term ($E_{C,HT}$) under the measurement conditions in this study. For the vertical flux terms, the reverse is true; the mean vertical wind, ($\bar{w}$), was typically less than 0.02 m/s, whereas the 95th percentile of the vertical turbulent fluctuation, w', reached approximately 0.3 m/s. Thus, the vertical turbulent fluctuation was more than one order of magnitude larger than the mean vertical wind component. This scale comparison indicates that the vertical turbulent transport term, ($E_{C,VT}$), was expected to be substantially larger than the vertical advective transport term, ($E_{C,V}$), under the measurement conditions in this study. As such, vertical advection term can also be neglected from Eq. (3.1).

The density-related term ($E_{C,M}$) can be expressed as

$$E_{C,M} = M_R \iiint \chi_C \frac{d\rho_{air}}{dt} dxdydz \quad (3.2)$$

where M_R is the ratio of the molar mass of CO_2 to that of air, χ_C is the CO_2 mole fraction, ρ_{air} is the air density, t is time, and x, y, and z denote the east-west, north-south, and vertical spatial coordinates, respectively. Thus, x and y describe the horizontal directions, whereas z represents the vertical direction.

Because the maximum vertical (≈50 m), horizontal (≈150 m) extents, and duration of the UAV flights are limited, air-density variation over time $\frac{d\rho_{air}}{dt}$ within the control volume can be assumed to be negligible, and $E_{C,M}$ was therefore neglected. Accurate estimation of the remaining flux terms ($E_{C,H}$ and $E_{C,VT}$) enables computation of the net CO_2 emission rate. The reliability of the box-pattern approach for resolving CO_2 emission is further supported by Han et al. (2024), who conducted a series of controlled UAV-based CO_2 validation experiments over an industrial coking facility.

3.2.1 Computation of CO_2 horizontal emission component

The horizontal emission component was derived from box-pattern measurements by integrating the advective CO_2 flux across the four vertical walls of the virtual box. The horizontal CO_2 emission rate can be written as

$$E_{C,H} = M_R \oint\!\!\oint \chi_C(s,z)\rho_{air}(s,z)u_n(s,z)dsdz \quad (3.3)$$

where $E_{C,H}$ is the horizontal CO_2 emission, $u_n(s,z)$ is the wind speed component normal to the flight path at point (s,z). Here, the along-track coordinate (s) was defined along the horizontal flight trajectory, which formed a closed loop around the control volume. Therefore, the start and end points of (s) correspond to the same spatial location, ensuring a closed control-volume boundary and avoiding gaps in the reconstructed flux field and (s,z) indicates the point located at the path position s at flight altitude z.

For each altitude level z_i, the line flux $F(z_i)$ was first calculated from the box-pattern data as

$$F(z_i) = M_R \sum_{j=1}^{N_i} \chi_C(s_j,z_i) \cdot \rho_{air}(s_j,z_i) \cdot u_n(s_j,z_i) \cdot \Delta s_j$$

(3.4)

where j denotes the sampling point index along the flight path at altitude z_i, N_i is the total number of sampling points at altitude z_i, and Δs_j represents the along-track distance between two consecutive sampling points along the closed-loop flight trajectory.

For each UAV flight, one closed-loop transect was conducted at each measurement height, yielding one line-flux value for that height. To obtain fluxes for discrete altitude intervals, line-flux values at adjacent measurement heights were averaged in the vertical direction. The resulting layer-averaged fluxes were then used in the total horizontal CO_2 emission calculation

$$E_{C,H} = \sum_{i=1}^{n} F(z_i)\Delta z_i = M_R \sum_{i=1}^{n} \left(\sum_{j=1}^{N_i} \chi_C(s_j, z_i)\rho_{\text{air}}(s_j, z_i)u_n(s_j, z_i)\Delta s_j \right) \Delta z_i \quad (3.5)$$

where i denotes the vertical layer index from the first layer to the n-th layer, n is the total number of vertical layers, and Δz_i is the thickness of the i-th altitude interval. In this study, the first observed altitude layer z_1 corresponds to the lowest UAV sampling height (35 m above ground level).

3.2.2 Computation of CO_2 vertical emission component

The vertical CO_2 emission component was estimated from profile measurements using the gradient method, which relates turbulent scalar fluxes to vertical gradients of the scalar concentration. In practice, vertical profiling over forested terrain is operationally challenging, and UAV measurements were conducted at a single representative location. The resulting vertical fluxes were compared with eddy covariance (EC) flux tower measurements to evaluate the reliability of the UAV-derived vertical flux estimates (see Section 4.2.1). This comparison was not intended to imply that vertical fluxes alone represent the full CO_2 mass balance of the control volume. Instead, the horizontal flux terms were calculated separately to quantify lateral CO_2 transport across the control-volume boundaries, which provides information on local

453 advection and spatial heterogeneity that cannot be obtained from vertical flux
454 measurements alone.

455 The vertical CO_2 emission component was obtained from integrating the vertical
456 flux over the horizontal area enclosed by the box pattern and can be approximated by
457 the product of vertical flux and the horizontal area, expressed as

458 $$E_{C,VT} = \iint F_v dxdy = A \cdot F_v \tag{3.6}$$

459 where F_v denotes the vertical flux and A is the horizontal area of the control volume.

460 According to the flux-gradient relationship (Kaimal and Finnigan, 1994), turbulent
461 scalar fluxes are proportional to the vertical gradient of the scalar quantity:

462 $$F_v = -\rho_{air} K_C \frac{\partial \bar{c}}{\partial z} \tag{3.7}$$

463 where K_C denotes turbulent exchange coefficient, $\bar{c}$ was obtained by converting the
464 measured CO_2 mole fraction (expressed in ppm) to mass concentration (expressed in
465 mg/m^{-3}) using the concurrently measured temperature and pressure during the UAV
466 profile flight.

467 A mixing-length formulation was adopted, in which the eddy diffusivity is
468 expressed as the product of a mixing length and a velocity scale represented here by the
469 friction velocity (Lee and Mahrt, 2005)

470 $$K_M = l u_* \tag{3.8}$$

471 where l is the mixing length and K_M is the exchange coefficient for momentum.
472 Under neutral stratification conditions, K_C can be assumed to be equal to K_M, and the
473 friction velocity is defined as

474 $$u_* = l \frac{\partial \bar{u}}{\partial z} = \kappa z \frac{\partial \bar{u}}{\partial z} \tag{3.9}$$

475 where κ is the von Karman constant (κ=0.4), $\frac{\partial \bar{u}}{\partial z}$ is the vertical gradient of the mean
476 wind speed.

477 To account for atmospheric stratification, a stability correction (Budyko et al.,
478 1962) was introduced as

479 $$l = m\kappa z \tag{3.10}$$

480 where m is the stratification correction parameter, determined as a function of the

gradient Richardson number (R_i) according to Budyko's study

$$m = (1 - R_i)^{1/2} \tag{3.11}$$

Under neutral stratification conditions ($R_i = 0$), m = 1. For computational convenience, the gradient Richardson number R_i is approximated by the bulk Richardson number R_B in finite-difference form

$$R_i \approx R_B = \frac{\frac{g\Delta\bar{\theta}}{\bar{\theta}\Delta z}}{\left(\frac{\Delta\bar{u}}{\Delta z}\right)^2} = \frac{g}{\overline{\theta_1}+\overline{\theta_2}} \frac{(\overline{\theta_2}-\overline{\theta_1})(z_2-z_1)}{(\overline{u_2}-\overline{u_1})^2} \tag{3.12}$$

where g is the gravitational acceleration constant; $\Delta\bar{\theta}$ and $\Delta\bar{u}$ represent the changes in the temperature and wind-speed magnitude between the layers (Δz), after smoothing with a seven-point moving window. In applying Eq. (3.12), the smoothed $\bar{\theta}$ and $\bar{u}$ vertical profiles are directly used to compute R_B, taking respective data points from two adjacent heights, z_1 and z_2, using the smoothed temperature and wind speed profiles at the two heights for $\overline{u_1}$, $\overline{u_2}$, $\overline{\theta_1}$, and $\overline{\theta_2}$. When applying the gradient method to estimate the flux, the vertical separation, $\Delta z = z_2 - z_1$, is typically chosen within a range of 1-10 m (Meredith et al., 2014). In this study, $\overline{u_1}$, $\overline{u_2}$ and $\overline{\theta_1}$, $\overline{\theta_2}$ were taken 5 m below and 5 m above any target height ($\Delta z = 10$ m), respectively, during the UAV ascent in the vertical profile measurements.

Because forest canopies represent aerodynamically rough and structurally complex surfaces, wind profiles above the canopy may deviate from the ideal logarithmic form. Following the neutral logarithmic wind-profile formulation from Monin–Obukhov similarity theory (Raupach, 1994), the vertical profile of the mean wind-speed magnitude ($\bar{u}$) was expressed as

$$\bar{u} = \frac{u_*}{\kappa} ln \frac{z-d}{z_0} \tag{3.13}$$

where d is the zero-plane displacement height, which for this type of forest is typically taken as 70%-80% of the vegetation height, and z_0 is the surface roughness length.

Assuming neutral atmospheric stratification and treating u_*, d, and z_0 as constants over the same time period, u_* can be derived from wind measurements at two heights thereby eliminating z_0 from Eq. (3.13) and rearranging the equation so that

$$u_* = \frac{\kappa(\overline{u_2}-\overline{u_1})}{\ln[(z_2-d)/(z_1-d)]} \quad (3.14)$$

Substituting Eq. (3.10), Eq. (3.11) and Eq. (3.14) into Eq. (3.8) yields

$$K_c = \kappa^2(1-R_i)^{1/2}\frac{(\overline{u_2}-\overline{u_1})}{\ln[(z_2-d)/(z_1-d)]}(z-d) \quad (3.15)$$

Further substituting Eq. (3.15) into Eq. (3.7) and integrating the latter result in the vertical flux

$$F_v = \rho_{air}\kappa^2(1-R_i)^{1/2}\frac{(\overline{u_2}-\overline{u_1})(\overline{c_1}-\overline{c_2})}{\{\ln[(z_2-d)/(z_1-d)]\}^2} \quad (3.16)$$

where $\overline{c_1}$ and $\overline{c_2}$ represent the mean concentrations of CO_2 at heights z_1 and z_2, respectively, converted from measured CO_2 mole fractions at using the measured temperature and pressure at both heights. In this study, z_1 and z_2 correspond to 5 m below and 5 m above the target height, respectively, during the UAV ascent.

The vertical CO_2 emission ($E_{C,VT}$) is finally expressed as

$$E_{C,VT} = A\rho_{air}\kappa^2(1-R_i)^{1/2}\frac{(\overline{u_2}-\overline{u_1})(\overline{c_1}-\overline{c_2})}{\{\ln[(z_2-d)/(z_1-d)]\}^2} \quad (3.17)$$

For each UAV flight, $E_{C,VT}$ was calculated from the vertical profile measurements rather than from the box-pattern measurements. The CO_2 gradient between (z_1 = 26) m and (z_2 = 36) m was used to estimate the vertical flux, and the resulting flux was assigned to the midpoint height of approximately 31 m. This height was selected because it corresponds to the EC flux measurement height of the nearby flux tower. In contrast, $E_{C,H}$ was calculated from the box-pattern observations along the lateral boundaries of each UAV-defined control volume.

In summary, horizontal CO_2 emission components were derived from box-pattern measurements using the divergence theorem, whereas vertical emission components were obtained from profile-pattern measurements using the gradient method. Finally, the three-dimensional net CO_2 emission was obtained using the original observations. The reliability of the vertical flux estimates, computed using Eq (3.16), was evaluated through direct comparisons with results from flux tower observations (see Section 4.2.1).

3.3 Stationary tower-based data processing

The EC system installed at the flux tower consists of a three-dimensional ultrasonic anemometer (CSAT3, Campbell Scientific, USA), an open-path CO_2/H_2O analyzer (LI-7500, LI-COR Biosciences, USA), and a datalogger (CR3000, Campbell Scientific, USA). Raw data are acquired at a sampling frequency of 10 Hz. In the present study, concurrent EC data from tower were processed during which the time lag between wind and gas measurements was corrected following the method of Sahlée et al. (2007), and standard quality-control procedures were applied to the turbulence data (*SI Appendix*, S1).

Fluxes were computed over 30 min averaging intervals, and coordinate rotation, virtual temperature correction, and frequency-response correction were applied to ensure high-quality vertical flux estimates. Following standard eddy covariance formulations (Webb et al., 1980; Baldocchi, 2003), the friction velocity (u_*) and scalar fluxes (F_v) were computed as

$$u_* = (-\overline{u'w'})^{1/2} \tag{3.18}$$

$$F_v = \rho_{air}\overline{w'c'} \tag{3.19}$$

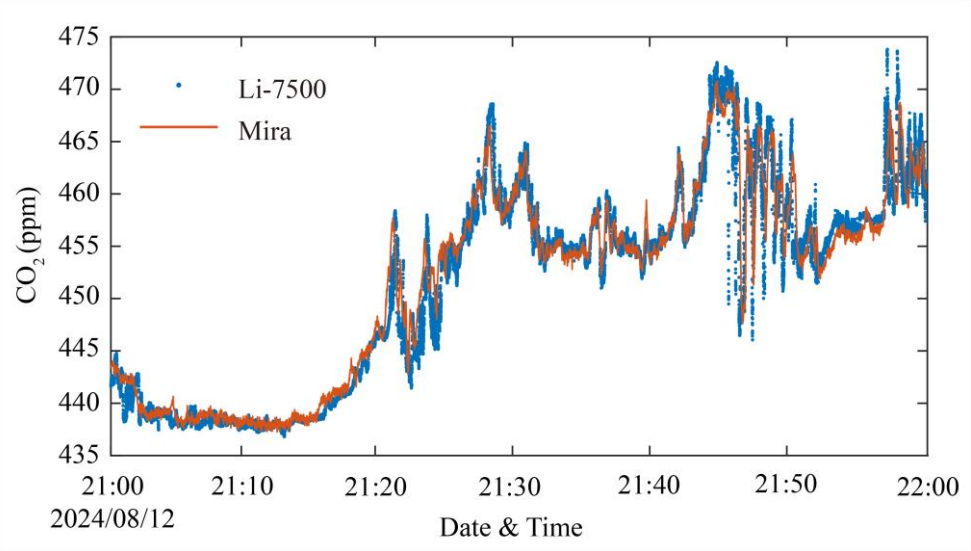
where the primes denote turbulent fluctuations of the corresponding variables.

4 Results and discussion

4.1 Gas analyzer comparison test

To evaluate the consistency between different CO_2 analyzers, ground-based intercomparison experiments were conducted using an open-path CO_2/H_2O gas analyzer (LI-7500), which was part of the eddy covariance system, and the closed-path analyzer (MIRA) used on the UAV. The experiment was performed from 21:00 to 22:00 local time on 12 August 2024 (Fig. 4). The air inlets of the two analyzers were positioned at the same height to ensure sampling of the same air mass, with the LI-7500 operating at 10 Hz and the MIRA analyzer at 1 Hz. A fixed time lag of 5 s, associated with air flow through the sampling line, was applied to synchronize the MIRA

563 measurements with the LI-7500 data.



564

565 **Figure 4.** The comparative chart of CO_2 mole fraction measured by the LI-7500 and Mira.

566

567 As shown in Fig. 4, the CO_2 mole fractions measured by the two instruments
568 exhibit highly consistent temporal variabilities, although small differences in absolute
569 values and short-term fluctuations are present. Both datasets show a pronounced
570 increase in CO_2 mole fraction during the initial phase of the experiment, followed by
571 enhanced variability with multiple peaks, and sustained elevated concentrations during
572 the later period. The overall temporal coherence between the two datasets is strong,
573 indicating that both instruments capture the same underlying CO_2 fluctuation dynamics.
574 The MIRA measurements, with an average value of approximately 451.7 ppm, tended
575 to report slightly lower CO_2 mole fractions than the LI-7500 measurements, which had
576 an average value of approximately 451.8 ppm. This attenuation is primarily attributed
577 to high-frequency losses associated with the closed-path sampling system, including
578 viscous damping and signal smoothing during sample transport through the 1/8-inch
579 outer-diameter polytetrafluoroethylene (PTFE) sampling tube. Because the sampling
580 tube used in this study was relatively short (approximately 0.5 m) and the sample
581 residence time inside the tube was 0.5 s, its influence on CO_2 measurements is expected
582 to be limited. Such attenuation is a well-documented characteristic of closed-path
583 systems and does not compromise the ability of the analyzer to resolve mean

concentration levels and mesoscale variability (Burba et al., 2012; Metzger et al., 2016). In summary, despite minor attenuations at high frequencies, the closed-path MIRA analyzer demonstrates a strong agreement with the EC-based LI-7500 measurements, supporting its suitability for CO_2 measurements from the UAV-based platform.

Further, the scatterplot of the CO_2 measurement results from both instruments, shown in Fig. 5, reveals a strong linear relationship. The data are closely distributed around a narrow band of the fitted linear regression line, with a correlation coefficient of r = 0.986. Because both analyzers are subject to measurement uncertainties, reduced major axis (RMA) regression was applied. The RMA regression yielded a slope of 0.966 and an intercept of 1.64 ppm. The close clustering of the data points around the fitted line indicates low random error and high precision between the two instruments. This regression result indicates that the UAV observations were able to capture temporal variability in CO_2 in the real atmosphere, such as minute-scale increases, decreases, and multi-peak structures. In addition, the calculations of the horizontal line flux divergence and the vertical flux both require subtraction of the background CO_2 concentration and estimation of the CO_2 gradient, respectively. Therefore, the systematic bias between the two instruments is expected to have a negligible impact on the flux calculations.

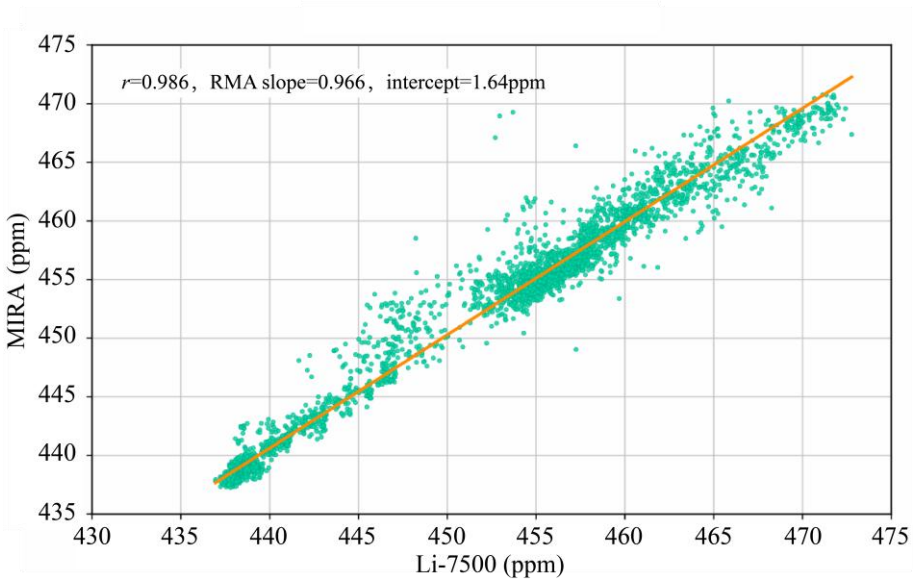


Figure 5. Scatterplot comparison of CO_2 mole fractions measured by the UAV-mounted MIRA analyzer and the flux-tower LI-7500 analyzer. The orange line denotes the reduced major

axis (RMA) regression. The regression yielded a slope of 0.966 and an intercept of 1.64 ppm, with a correlation coefficient of $r = 0.986$, indicating strong agreement between the two instruments under field conditions.

4.2 In-flight comparison test

4.2.1 Seasonal variability of vertical fluxes

A key part of the present study is to determine reliable vertical flux measurements using the UAV platform over a forest ecosystem on complex terrains. To quantitatively evaluate the agreement between UAV-based profile retrievals and flux tower measurements, the UAV-derived vertical CO_2 flux (F_v) and friction velocity (u_*) are compared against their EC counterparts (Fig. 6). Because both datasets contain measurement uncertainties, the Reduced Major Axis (RMA) regression (Smith, 2009; Warton et al., 2006) was used, which is more appropriate than ordinary least squares when neither datasets can be treated as error-free. The season-specific RMA slope, intercept, and Pearson correlation coefficient (r) are summarized in Table 3. For the comparison with the EC system installed at 31 m above ground, the UAV-derived vertical flux was calculated using vertical profile sampling data collected during the UAV flights at z_1=26 m and z_2=36 m.

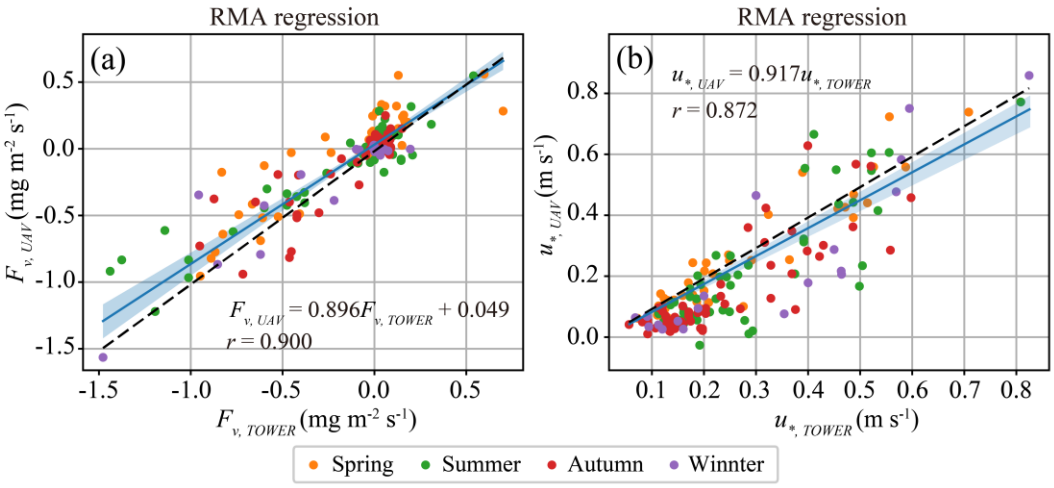


Figure 6. Reduced major axis (RMA) regressions comparing UAV-based measurements with flux tower observations across all seasons. Panel (a) shows CO_2 flux (F_v) and panel (b) shows friction velocity (u_*). In both panels, the x axis represents the flux tower measurements and the y axis

represents the UAV-based measurements. Points are colored by season (Spring, Summer, Autumn, Winter). The solid blue line denotes the RMA fit, the shaded band indicates the 95% confidence interval (CI) of the regression line, and the dashed black line represents the 1:1 reference. The regression equations are expressed using the corresponding physical variables in each panel, and the Pearson correlation coefficient (r) is also reported.

Table 3. Seasonal reduced major axis (RMA) regression results comparing UAV-derived measurements with flux tower observations for CO_2 flux (F_v) and friction velocity (u_*). Seasons are defined according to the three-month meteorological seasons: spring (March-May), summer (June-August), autumn (September-November), and winter (December-February). For each season, the table reports the sample size of the number of retained UAV flights (n), correlation coefficient (r), RMA slope and its 95% confidence interval (CI), and the intercept. The u_* regressions are constrained to pass through the origin (intercept fixed at 0).

Variables	Season	n	r	Slope	95% CI of Slope	Intercept
F_v	Spring	40	0.890	0.928	[0.777, 1.074]	0.127
	Summer	52	0.938	0.801	[0.694, 0.929]	0.034
	Autumn	55	0.863	0.997	[0.771, 1.281]	0.022
	Winter	20	0.917	0.940	[0.551, 1.079]	0.013
u_*	Spring	40	0.942	1.012	[0.926, 1.093]	0
	Summer	52	0.845	0.915	[0.790, 1.021]	0
	Autumn	55	0.843	0.819	[0.679, 0.951]	0
	Winter	20	0.884	0.914	[0.677, 1.059]	0

As shown in Fig. 6a, UAV-derived $F_{v,UAV}$ exhibits a clear linear relationship with EC $F_{v,TOWER}$, with points generally distributed around the 1:1 line, indicating that the UAV approach captures the temporal variability of canopy-scale vertical CO_2 exchange. Table 3 further demonstrates consistently strong coefficients of determination across seasons (r=0.863-0.938). The slope, slightly lower than unity, suggests a modest "range compression" in the UAV-derived fluxes, meaning that the magnitudes tend to be slightly attenuated under strong emission or strong uptake conditions (large positive/negative fluxes). In spring, the slope is 0.928 (95% CI: [0.777, 1.074], r=0.890), and in autumn the slope is 0.997 (95% CI: [0.771, 1.281], r=0.863); both are close to unity and their confidence intervals encompass 1, suggesting good

consistency in flux magnitude. In summer, the slope decreases to 0.801 (95% CI: [0.694, 0.929], r=0.938), and the confidence interval does not include 1, indicating a smaller flux magnitude during periods of stronger exchange. Hence the slightly lower $F_{v,UAV}$ than $F_{v,Tower}$ likely reflects enhanced nonstationarity and rapid scalar fluctuations during peak growing season, which increase sensitivity to sampling height from ground and platform-related perturbations. In winter, the slope is 0.940 (95% CI: [0.551, 1.079], r=0.917), showing strong correlation but larger uncertainty due to the smaller sample size (n=20).

Figure 6b shows a clear linear relationship between friction velocity $u_{*,UAV}$ and $u_{*,TOWER}$. Because u_* should physically approach zero under very weak turbulence, an origin-constrained regression (intercept fixed at 0) was used to avoid non-physical extrapolation from a free intercept. The full-sample RMA regression is:

$$u_{*,UAV}=0.917(\pm 0.063)u_{*,TOWER},\ r=0.872 \quad (4.1)$$

This result indicates that the UAV platform captures the variations in turbulent intensity well (r=0.872), while the slope below unity suggests a slight multiplicative underestimation of u_* relative to tower observations. Regressions for different seasons (Table 3) further indicate that the best agreement occurs in spring, with a slope of 1.012 (95% CI: [0.926, 1.093], r=0.942). In contrast, $u_{*,UAV}$ shows a slight underestimation relative to $u_{*,TOWER}$ in summer, autumn, and winter, respectively, with a slope of 0.915, 0.819, 0.914.

Taken together, Fig. 6 and Table 3 demonstrate that the fluxes and turbulence metrics derived from the UAV measurements reproduce well the tower-observed variability of both canopy-scale CO_2 exchange and key turbulence characteristics across all seasons (r=0.9 for F_v and r=0.872 for u_*), supporting the feasibility and robustness of such UAV profile measurements for monitoring above-canopy exchange. Nevertheless, two systematic features warrant attention: (i) F_v magnitudes tend to be slightly underestimated in summer (slope significantly < 1), and (ii) u_* shows a slight overall underestimation under the origin-constrained regression.

4.2.2 Diurnal variability of vertical fluxes

To further evaluate the applicability and consistency of the UAV-based profiling method under different diurnal conditions, the UAV-derived F_v estimates were grouped and compared with results from EC observations in three time periods: early morning (06:00-08:00 LST), noon (13:00-15:00 LST), and evening (19:00-21:00 LST). Reduced Major Axis (RMA) regression was applied to both the vertical CO_2 flux (F_v) and the friction velocity (u_*) for each time period (Fig. 7), with the corresponding statistical results summarized in Table 4.

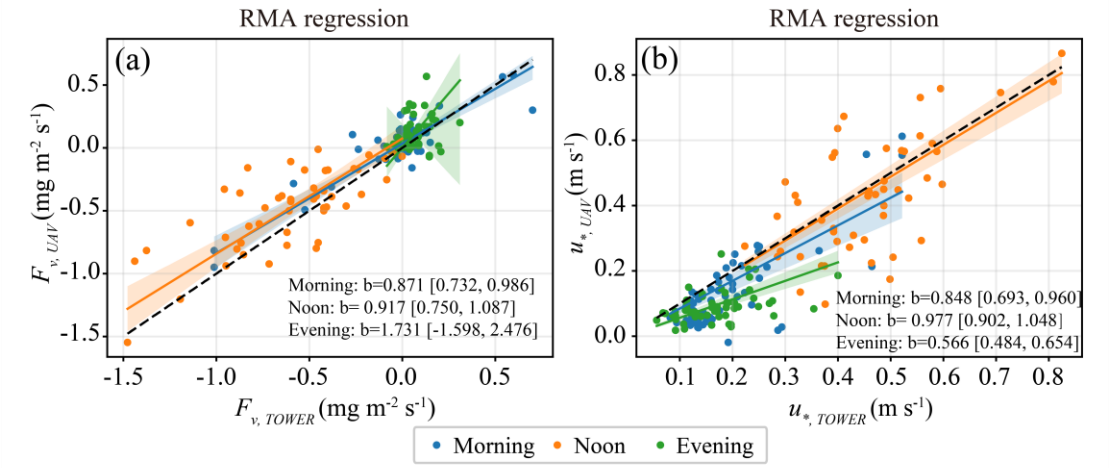


Figure 7. Reduced major axis (RMA) regressions comparing UAV-based measurements with flux tower observations for (a) CO_2 flux (F_v) and (b) friction velocity (u_*) grouped by time of day. In both panels, the x axis represents the flux tower measurements and the y axis represents the UAV-based measurements. Data are separated into morning (06:00-08:00 LST), noon (13:00-15:00 LST), and evening (19:00-21:00 LST) and shown with different colors. Solid colored lines represent the RMA fits for each time period, and the shaded bands indicate the 95% confidence intervals. The dashed black line denotes the 1:1 reference. Reported in each panel are the RMA slopes and their 95% confidence intervals; the u_* regressions in panel (b) are constrained to pass through the origin (intercept fixed at 0).

As shown in Table 4, the RMA regressions for F_v exhibit relatively strong correlations during the early morning and midday periods (r=0.898, n=63 and r=0.867, n=55, respectively). The corresponding slopes are 0.871 (95% CI: [0.732, 0.986]) for early morning and 0.916 (95% CI: [0.750, 1.087]) for midday, both close to unity but slightly lower than 1, indicating a modest amplitude compression. This

suggests that the UAV-based method is generally capable of reproducing the variability of CO_2 fluxes observed by the EC system, while tending to underestimate flux magnitudes under stronger exchange conditions. This behavior is consistent with the seasonal-scale results presented in Section 4.2.1 and likely reflects the increased sensitivity of the gradient method to strong flux events under limited vertical sampling resolution and short-term nonstationary conditions.

Table 4. Reduced major axis (RMA) regression statistics for comparisons between UAV-based measurements and flux tower observations, grouped by time of day (morning, noon, and evening). Results are reported for CO_2 flux (F_v) and friction velocity (u_*), including sample size (n), correlation coefficient (r), RMA slope, the 95% confidence interval (CI) of the slope, and the intercept. For u_*, the regression is constrained to pass through the origin (intercept fixed at 0).

Variables	Period	n	r	Slope	Slope of 95% CI	Intercept
F_v	Morning	63	0.898	0.871	[0.732, 0.986]	0.034
	Noon	50	0.867	0.916	[0.750, 1.087]	0.075
	Evening	54	0.235	1.730	[-1.598, 2.476]	0.002
$u*$	Morning	63	0.887	0.848	[0.926, 1.093]	0
	Noon	50	0.865	0.977	[0.790, 1.021]	0
	Evening	54	0.424	0.566	[0.679, 0.951]	0

In contrast, the agreement for F_v deteriorates substantially during the evening period, with a low correlation coefficient (r=0.235, n=54) and a highly uncertain slope (1.730, with a 95% confidence interval spanning both positive and negative values). The possible reason for such a comparison result is that, under low evening turbulence, both the UAV-based and EC-based flux measurements become less reliable, because the vertical turbulent exchange weakens and the relative influence of non-turbulent transport terms increases. Under such conditions, the UAV methodology is subject to larger uncertainties in the derived vertical fluxes and shows an apparent low bias relative to the EC measurements. It should be noted, however, that EC vertical flux measurements under such low turbulence conditions also bear large uncertainties, and hence this comparison only implies a low bias in the UAV methodology relative to the

731 EC methodology, and does not indicate the absolute errors in the UAV-determined F_v
732 nor that from the EC methodology. The diurnal variation of friction velocity (u_*)
733 derived from the tower system (Fig. S1) shows a clear asymmetry between morning
734 and evening transitions, with turbulence developing gradually after sunrise but
735 decaying rapidly in the evening, which helps explain the poorer agreement under
736 evening conditions. Furthermore, an analysis of the evening flux differences indicates
737 that both UAV- and tower-derived vertical CO_2 fluxes are associated with greater
738 uncertainties at evening, whereas the overall differences remain small and show no
739 significant seasonal variations. A more detailed analysis of the evening flux differences
740 is provided in the *SI Appendix* S3.

741 Figure 8 illustrates the seasonal and diurnal variability of the UAV-derived vertical
742 CO_2 fluxes across morning, noon, and evening periods for all four seasons. Distinct
743 diurnal patterns are evident in every season. Midday periods consistently exhibit the
744 strongest downward CO_2 fluxes, corresponding to maximum ecosystem uptake,
745 particularly in spring, summer, and autumn. In contrast, morning and evening fluxes
746 were much reduced from mid-day peaks, probably resulting from neutral or weakly
747 positive turbulent mixing as well as from combined effect of weaker uptake/emissions
748 of CO_2 under lower photosynthetic/respirational activities. This diurnal structure aligns
749 with the canonical coupling between solar radiation, canopy photosynthesis, and
750 boundary-layer turbulence.
751

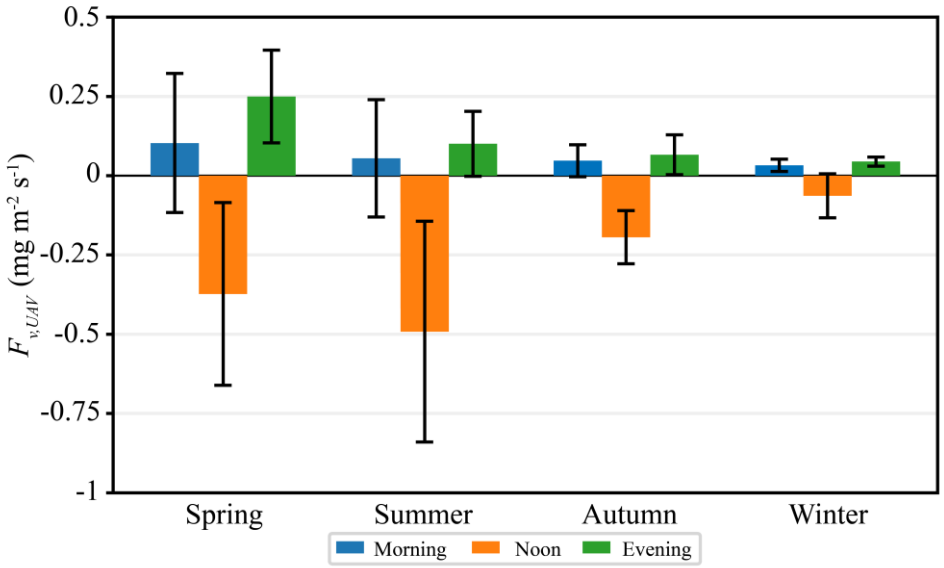


Figure 8. Seasonal variations of UAV-derived vertical CO_2 fluxes during morning, noon, and evening across spring, summer, autumn, and winter. Bars represent the mean flux for each period, and error bars indicate one standard deviation. Positive values denote upward (emission) fluxes, while negative values represent downward (uptake) fluxes.

Seasonal contrasts are equally pronounced. Summer and spring display the strongest net CO_2 uptake, consistent with favorable moisture conditions and strong radiative forcing in this subtropical forest. Autumn fluxes are weaker, reflecting declining photosynthetic activity, while winter fluxes cluster near zero, with negligible uptake or slight emissions across all periods. The ordering of seasonal uptake strength - summer > spring > autumn ≫ winter - is consistent with long-term EC observations at this site (Yu et al., 2008).

The observed diurnal and seasonal structures in the UAV-based vertical fluxes closely match those reported in previous tower-based studies at the Qianyanzhou station (Yu et al., 2006; Zhang et al., 2014) and in other temperate and subtropical forest ecosystems (Baldocchi, 2008; Goulden et al., 1996). These results therefore not only summarize the observed variability but also provide an ecologically meaningful consistency check for the UAV-based vertical flux approach.

4.3 Net CO_2 emission results

Figure 9 provides a three-dimensional visualization of the CO_2 mole fraction

anomaly field (ΔCO_2), calculated relative to a constant background value defined as the mean of the lowest 5% of the time-series CO_2 observations, along the walls of the 100×100×50 m^3 control volume during the morning flight on 8 August 2024. The reconstructed ΔCO_2 distribution exhibits pronounced spatial heterogeneity, with localized high-concentration patches embedded within relatively low-background regions. In particular, a distinct hotspot reaching ~40 ppm is observed near the upper-right sector of the box, while elevated ΔCO_2 values also form elongated bands along portions of the lateral walls. This non-uniform pattern indicates that the near-canopy CO_2 field was far from horizontally homogeneous during the sampling window, consistent with the expectation of enhanced stratification and limited mixing in early morning conditions.

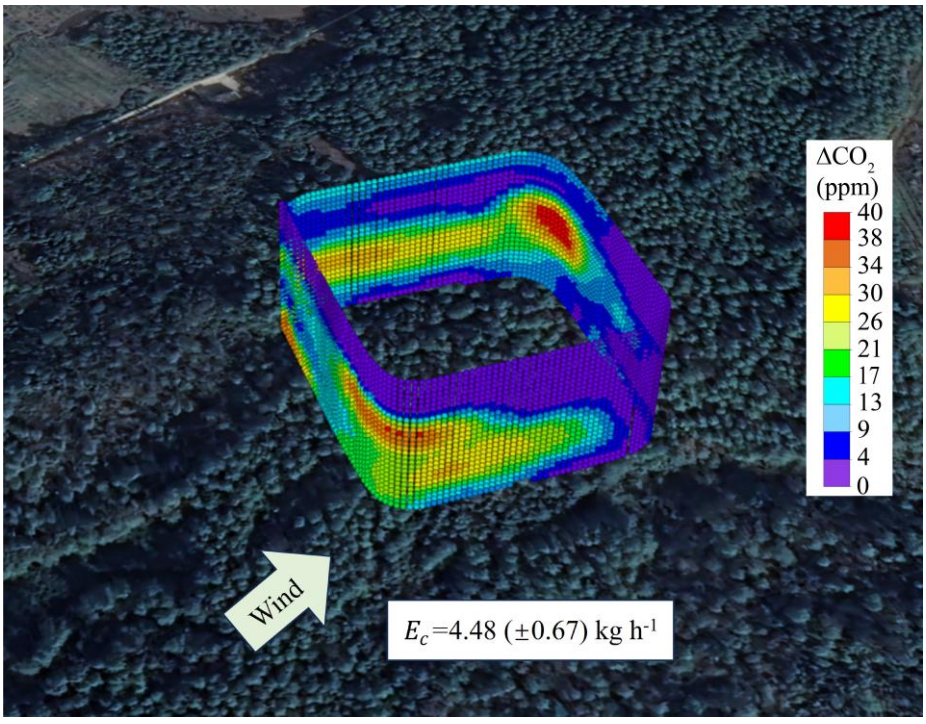


Figure 9. Three-dimensional distribution of the CO_2 mole fraction anomaly field (ΔCO_2), obtained from processed and interpolated UAV measurements following the procedure described in Section 2.3, within the 100×100×50 m^3 domain during the morning flight on 8 August 2024, relative to a constant background value.

The wind vector shown in Fig. 9 indicates a prevailing southwesterly flow. The spatial alignment of the ΔCO_2 enhancements with the box boundaries suggests that

lateral advection and flux divergence played a central role in shaping the observed concentration gradients: CO_2-enriched air masses are transported into the control volume on the upwind side and redistributed along the walls, producing strong cross-boundary gradients that dominate the mass balance. Consistent with this interpretation, the box-mass balance calculation yields a positive net exchange rate of E_c =4.48±0.67 kg h^{-1} for the 100×100×50 m^3 control volume. Breaking down the individual mass balance terms indicates that the horizontal component ($E_{C,H}$ = 4.22±0.63 kg h^{-1}) accounts for nearly all of the net emission in the control volume, whereas the vertical component is small ($E_{C,VT}$ = 0.26±0.04 kg h^{-1}). The near-zero vertical term is also consistent with the concurrent eddy-covariance observations similarly indicating a negligible turbulent vertical CO_2 flux. Therefore, the positive E_c primarily reflects net CO_2 inflow into the finite UAV sampling box driven by horizontal transport, that is, lateral convergence within the local control volume. This result should not be interpreted as the net CO_2 exchange between the entire forest ecosystem and the overall atmosphere, because the UAV box only encloses a limited area above the canopy. Instead, the box-based flux calculation is intended to quantify local CO_2 mass balance and to diagnose the contribution of horizontal advection, which can affect the interpretation and spatial representativeness of vertical CO_2 flux measurements.

Overall, the three-dimensional ΔCO_2 structure shown in Fig. 9 highlights that, at this moment, CO_2 exchange above the forest canopy was controlled predominantly by horizontal transport under heterogeneous concentration fields. This highlights the importance of resolving spatial gradients and lateral boundary fluxes in order to diagnose horizontal advection and local CO_2 redistribution within the UAV sampling box. These processes can affect the interpretation and spatial representativeness of vertical flux measurements from a single-point flux tower, but they are not directly observable from the tower measurement alone.

4.4 Spatial heterogeneity of net CO_2 emission

To verify whether net emissions (E_C) calculated using the mass-balance approach differ across spatial scales, emission computations were made for three box-shaped

control volumes constructed from the UAV flight tracks, with horizontal dimensions of 50×50 m^2, 100×100 m^2, and 150×150 m^2, respectively, and a common vertical extent of 50 m. The vertical contribution term $E_{C,VT}$ and the horizontal transport contribution term $E_{C,H}$ within each control volume were separately computed as per the detailed outlines above. In this analysis, $E_{C,H}$ was calculated separately for each box size using the corresponding box-pattern boundary observations, whereas $E_{C,VT}$ was derived from the paired vertical profile measurements collected during the same UAV flight. The net emissions were normalized by the areas of the boxes to give area-normalized emission intensity $e_C = E_C/A$, where A denotes the bottom area of the box. To minimize the influence of different time periods and seasons on the statistics, and according to the analysis in Section 4.2, the UAV measurements of CO_2 emissions collected in summer noon and autumn morning, which show better agreement with the flux tower comparisons, were selected for the spatial heterogeneity analysis. Under such a requirement, data from seven days of observations were used for the spatial heterogeneity analysis. Further examination of the measurement conditions during these periods showed that, for the summer noon cases, observations were conducted between 13:00 and 14:00 under predominantly southeasterly winds, while the fluxes measured by the fixed tower varied by less than 8% during the comparison period. For the autumn morning cases, observations were conducted between 06:00 and 07:00 under predominantly southwesterly winds, while the fluxes measured by the fixed tower varied by less than 5%. Overall, the observational conditions were considered sufficiently similar to support further comparative analysis.

If the CO_2 source-sink distribution in this region were spatially uniform, then by mass conservation the area-normalized emission intensity would be equal, i.e., $e_C(150) \approx e_C(100) \approx e_C(50)$ would be true. The means for the three box scales (see boxes in Fig. 10) were -0.25, -0.30, and -0.24 mg m^{-2} s^{-1}, respectively. This indicates a pronounced net CO_2 uptake (i.e., negative emissions) of the system as a whole during summer at noon, while the differences among spatial scales are clearly smaller than the 30% systematic uncertainty. This result may suggest relatively weak spatial

heterogeneity during the summer noon period. Furthermore, one-way ANOVA shows the mean differences in e_C among the three scales were not significant, with an ANOVA F-statistic of 0.349, indicating low between-group variance relative to within-group variance, and a p-value of 0.710, indicating that the observed differences could be readily explained by random variation rather than a true scale effect. Overall, under summer noon conditions, the area-normalized net exchange intensity is insensitive to the horizontal scales examined, and within-group variability dominates (Fig. 10).

In addition, during summer at noon, the median values of $E_{C,H}/E_{C,VT}$ in Table 5 remain very small (from -0.025 to -0.006), indicating that the net CO_2 budget is dominated by the vertical turbulent-exchange term. This conclusion is further supported by the absolute magnitudes of the two components: the median $E_{C,H}$ values range only from 0.0687 to 0.273 kg h^{-1}, whereas the corresponding median $E_{C,VT}$ values range from -13.6 to -2.77 kg h^{-1}. Under summer noon conditions, stronger turbulence and more efficient vertical mixing likely suppress the relative influence of horizontal CO_2 gradients, so that horizontal transport contributes only a minor fraction to the virtual control volume budget. Although the negative values of $E_{C,H}/E_{C,VT}$ indicate that the horizontal and vertical components often have opposite signs, the magnitude of $E_{C,H}$ remains much smaller than that of $E_{C,VT}$.

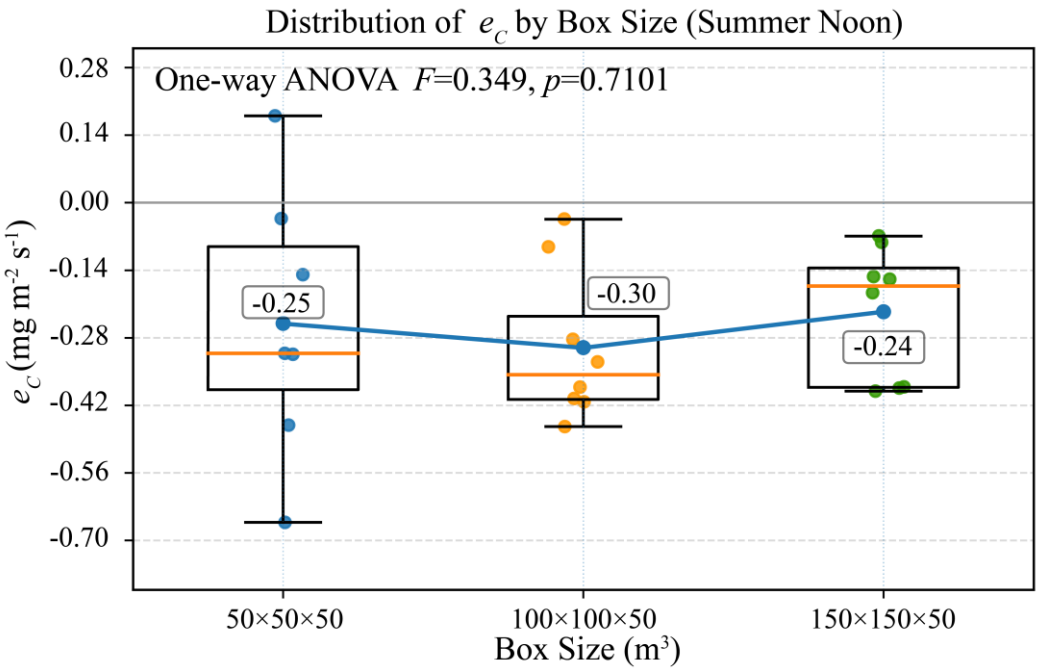


Figure 10. Distribution of e_C across box sizes (50×50×50 m^3, 100×100×50 m^3, 150×150×50 m^3) of summer noon. Boxes represent the interquartile range (*IQR*), the center line is the median, and whiskers extend to 1.5×*IQR*. Colored points are individual samples. The blue solid polyline connects the mean e_C of each group, with boxed numerical annotations. The reported F and p values denote the F-statistic and corresponding p-value from the one-way ANOVA, respectively.

Table 5. Summary statistics of net CO_2 emission estimates (E_C) derived from three box sizes during summer noon and autumn morning. For each box size, n denotes the number of valid samples. Reported metrics include the mean and median of E_C (kg h^{-1}), the interquartile range (*IQR*), the median and standard deviation (*SD*) of the horizontal-transport contribution ($E_{C,H}$) and the vertical-exchange contribution ($E_{C,VT}$), as well as the median ratio $E_{C,H}/E_{C,VT}$. All emission estimates are expressed in kg h^{-1}.

	Summer Noon			Autumn Morning		
Box Size (m^3)	50×50×50	100×100×50	150×150×50	50×50×50	100×100×50	150×150×50
n	7	7	7	7	7	7
E_C Mean (kg h^{-1})	-2.24	-10.6	-18.6	0.166	7.64	9.35
E_C Median (kg h^{-1})	-2.79	-13.7	-12.8	0.138	7.25	11.3
IQR (kg h^{-1})	2.65	7.24	20.4	1.85	3.26	15.2
$E_{C,H}$ Median (kg h^{-1})	0.0687	0.0817	0.273	0.105	3.52	6.41
$E_{C,H}$ SD (kg h^{-1})	0.0162	0.0321	0.0732	0.0235	1.25	1.58
$E_{C,VT}$ Mdian	-2.77	-13.6	-12.5	0.033	3.73	4.85

($kg\ h^{-1}$) $E_{C,VT}$ *SD* ($kg\ h^{-1}$)	0.437	2.35	3.54	0.012	1.15	1.43
Median $E_{C,H}/E_{C,VT}$	-0.025	-0.006	-0.022	3.18	0.944	1.32

Another case study of spatial heterogeneity is based on the autumn morning dataset (Fig. 11). The mean values in Fig. 11 indicate that the emission intensities (e_C) derived for different box sizes (0.02, 0.21, and 0.11 mg m^{-2} s^{-1}, respectively) differ to some extent. The differences among box sizes are substantially larger than the uncertainty of the method used in this study (15%), representing e_C differ of various sizes. One-way ANOVA analysis also shows the differences in e_C among the three scales were significant (F=4.482, p=0.025). This provides direct evidence that the net CO_2 emission intensity derived for the three virtual control volumes above the canopy is spatially heterogeneous.

In contrast, during autumn morning, the role of horizontal transport becomes much more pronounced. The median values of $E_{C,H}/E_{C,VT}$ increase to 3.18, 0.944, and 1.32 for the 50×50×50, 100×100×50, and 150×150×50 m^3 control volumes, respectively. Importantly, these elevated ratios reflect not only the presence of horizontal CO_2 gradients, but also the fact that the vertical turbulent-exchange component is comparatively weak during this period. Specifically, the median $E_{C,H}$ values range from 0.105 to 6.41 kg h^{-1}, while the median $E_{C,VT}$ values range from 0.033 to 4.85 kg h^{-1}. This indicates that, under weak-turbulence morning conditions, horizontal CO_2 transport can become comparable to, or even exceed, the vertical turbulent component. Such behavior is consistent with enhanced spatial heterogeneity in CO_2 exchange across the different control volumes. As the control-volume scale increases, small-scale horizontal gradient structures are progressively averaged out, reducing the relative contribution of $E_{C,H}$ and leading to the observed scale dependence of E_C. The component-wise contribution analysis (Table 5) indicates that the relative contribution of the horizontal transport term is markedly enhanced. The median metric, median $E_{C,H}/E_{C,VT}$, is 3.18 for 50×50×50 m^3, 0.944 for 100×100×50 m^3, and 1.32 for

150×150×50 m^3. These results suggest that there is a significant spatial heterogeneity in the CO_2 emissions/uptake in the range covered by the different boxes leading to horizontal CO_2 concentration gradients, and as a result near-surface horizontal CO_2 gradients under the measured horizontal winds are non-negligible within small control volumes.

This scale sensitivity further highlights the true advantage of UAV observations for characterizing spatial heterogeneity. UAV measurements can provide multipoint, three-dimensional CO_2 distributions and associated wind speed gradient information within a short time window, enabling the simultaneous estimation of $E_{C,H}$ (horizontal transport) and $E_{C,VT}$ (vertical transport) within a consistent data framework. Moreover, by varying the box sizes, the same dataset can be re-aggregated into different spatial scales to facilitate a multi-scale comparison. In contrast, flux towers (eddy covariance) essentially measure point-based vertical turbulent fluxes, whose representativeness is determined by a footprint that varies with wind direction and atmospheric stability. As a result, flux tower observations yield a footprint-weighted effective flux, making it difficult to construct a spatial control volume and impossible to explicitly resolve the lateral transport term $E_{C,H}$. Therefore, box-size dependence driven by spatial heterogeneity is more readily captured by UAV observations, whereas flux towers are limited in both observation geometry and the types of physical quantities they can diagnose.

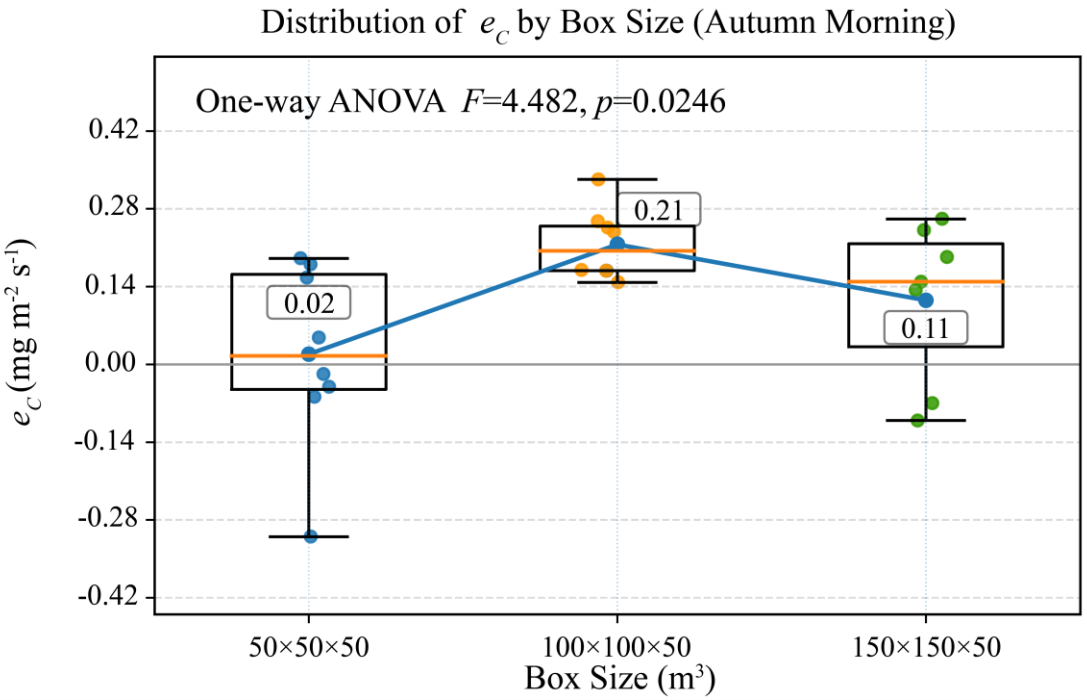


Figure 11. Distribution of e_C across box sizes (50×50×50 m^3, 100×100×50 m^3, 150×150×50 m^3) of autumn morning. Boxes represent the interquartile range (*IQR*), the center line is the median, and whiskers extend to 1.5×*IQR*. Colored points are individual samples. The blue solid polyline connects the mean e_C of each group, with boxed numerical annotations. The reported F and p values denote the F-statistic and corresponding p-value from the one-way ANOVA, respectively.

4.5 Computation of uncertainties

The uncertainty of the UAV-derived CO_2 emission estimates was evaluated by considering both measurement-related uncertainties and methodological uncertainties associated with the UAV-based three-dimensional flux quantification framework. The net CO_2 emission, E_C, was calculated from the horizontal transport contribution, $E_{C,H}$, and the vertical turbulent contribution, $E_{C,VT}$. Therefore, uncertainty was assessed for the input variables and calculation procedures involved in both terms.

The measurement-related uncertainty was divided into three components: CO_2 analyzer uncertainty (δ_{CO_2}) and wind measurement uncertainty (δ_V). These components were combined in quadrature to obtain the measurement-propagated uncertainty:

$$\delta_{meas}^2 = \delta_{CO_2}^2 + \delta_V^2 \quad (4.2)$$

Here, δ_{CO_2} represents the uncertainty associated with the measured CO_2 mole fraction,

including analyzer precision, calibration uncertainty, and short-term measurement noise. Wind-related uncertainty was included in δ_V, which includes uncertainty arising from the ultrasonic anemometer measurements, and the wind-correction procedure used to correct for these effects.

4.5.1 CO_2 analyzer uncertainty

The CO_2 analyzer uncertainty was estimated from the performance of the MIRA CO_2 analyzer and the ground-based intercomparison with the LI-7500 analyzer. The MIRA analyzer has an accuracy better than 0.2 ppm, whereas the CO_2 variations resolved during UAV sampling frequently exceeded several to tens of ppm. Therefore, the relative uncertainty associated with the CO_2 mole fraction measurement was small compared with the observed CO_2 gradients used in the flux calculations. In addition, the analyses shown in Figs. 4 and 5 indicate that the error caused by the MIRA CO_2 analyzer is almost negligible. Therefore, the contribution of δ_{CO_2} was conservatively set to 1%.

4.5.2 Wind measurement uncertainty

Wind measurement uncertainty was treated as a separate uncertainty component because wind speed and wind direction directly affect the horizontal transport term, and the turbulent exchange parameters used in the vertical flux calculation. For the uncertainty introduced by the wind-speed correction, based on the validation experiment reported by Yang et al. (2025), the corrected UAV wind speed showed a root mean square relative error of 0.28 compared with the meteorological tower reference measurements. Therefore, a conservative relative uncertainty of 28% was assigned to the residual wind-correction uncertainty. Additionally, the ultrasonic anemometer used on the UAV has a wind speed accuracy of ±0.2 m s^{-1} and a wind direction accuracy of ±1°. For typical flight-level wind speeds of 4-6 m s^{-1}, this corresponds to a relative error of about 5% in the horizontal wind components. Considering the combined effects of these two factors, the final contribution of δ_V was estimated to be 28.5% using the uncertainty propagation method.

4.5.3 Methodological uncertainty

In addition to measurement-related uncertainty, the UAV-based flux estimates are also affected by methodological uncertainty associated with the flux quantification framework itself.

For the horizontal transport term, $E_{C,H}$, methodological uncertainty arises mainly from discrete sampling along the box-pattern flight path, spatial reconstruction of lateral boundary fluxes. The resulting uncertainty is collectively referred to as $\delta_{spatial}$. Because the UAV samples the control-volume boundaries along discrete trajectories rather than continuously measuring the entire boundary surface, the reconstructed lateral flux depends on the interpolation or averaging method used to integrate the boundary observations. To evaluate spatial reconstruction uncertainty ($\delta_{spatial}$), $E_{C,H}$ was recalculated using alternative treatments of the discrete box-pattern observations, including linear interpolation (this study), nearest-neighbor, and segment averaging. The spread among the resulting $E_{C,H}$ estimates was used to quantify the uncertainty associated with boundary discretization and spatial reconstruction. Three representative cases from different seasons (spring morning: 12 May 2024; summer noon: 20 August 2023; and autumn noon: 3 December 2024) were selected for the calculation. Finally, the uncertainties in E_C calculated using the different methods were 6% (nearest-neighbor) and 8% (segment averaging), respectively. Therefore, this study conservatively adopted $\delta_{spatial}$=8% to represent the uncertainty caused by spatial reconstruction.

For the vertical turbulent contribution term, $E_{C,VT}$, the methodological uncertainty was mainly associated with the flux-gradient approach. Because the CO_2 analyzer uncertainty was small, the uncertainty in $E_{C,VT}$ was assumed to be dominated by uncertainty in the turbulent exchange coefficient, which was estimated from wind-related variables, including the three-dimensional wind components and friction velocity. Therefore, the flux-gradient uncertainty ($\delta_{gradient}$) was evaluated based on the wind-speed uncertainty. Based on the wind-correction validation and uncertainty propagation described above, the wind-related uncertainty was estimated to be 28.5%, which was used as a conservative uncertainty estimate for the turbulent exchange

coefficient and propagated into the $E_{C,VT}$ calculation. The same three representative cases used for the uncertainty analysis of $E_{C,H}$ were also used for $E_{C,VT}$. The resulting uncertainties were 3%, 2%, and 5%, respectively. These values were relatively small because the friction velocity and turbulent exchange coefficient were calculated using temporal gradient interpolation, which partly smoothed random wind-speed errors and reduced their influence on the final $E_{C,VT}$ estimates. Therefore, this study conservatively adopted $\delta_{gradient}$=5% to represent the uncertainty associated with the flux-gradient methodology.

The combined uncertainty was therefore expressed as:

$$\delta^2_{combined} = \delta^2_{CO_2} + \delta^2_V + \delta^2_{spatial} + \delta^2_{gradient} \quad (4.3)$$

where $\delta_{spatial}$ represents the uncertainty associated with spatial reconstruction of lateral boundary fluxes, $\delta_{gradient}$ represents uncertainty associated with the vertical flux-gradient calculation.

4.5.4 Total estimated uncertainties

By combining the uncertainties components, including CO_2 analyzer uncertainty (δ_{CO_2}), wind measurement uncertainty (δ_V), and methodological uncertainty ($\delta_{spatial}$ and $\delta_{gradient}$), the total relative uncertainty of the UAV-derived CO_2 emission rates can be obtained through quadrature addition. Finally, the calculated total uncertainty was 30%.

5 Conclusions

This study developed and field-evaluated a UAV-based methodology to quantify three-dimensional CO_2 emission over a forest ecosystem by explicitly resolving both vertical exchange and horizontal advection within a three-dimensionally unified mass-balance approach, making use of an integrated UAV measurement platform and a computational algorithm that evaluates both horizontal and vertical fluxes based on a specifically designed flight strategy. Extensive applications of this methodology at the Qianyanzhou subtropical plantation forest site demonstrate that the methodology can

robustly determine canopy-scale CO_2 exchange. Vertical CO_2 fluxes derived from UAV vertical profiles are in good agreement with those determined from collocated eddy covariance (EC) flux tower observations across seasons, with a Pearson correlation coefficient of $r = 0.9$ based on 167 paired samples, indicating that the UAV-based gradient method reproduces both the magnitude and variability of vertical turbulent exchange under typical daytime conditions. The UAV-based vertical fluxes showed clear diurnal and seasonal patterns over the forest ecosystem at Qianyanzhou, with the strongest uptake around midday during the growing season and near-neutral exchange in winter. However, vertical fluxes of UAV and EC diverge under weak turbulence during the evening stable period, highlighting increased uncertainties for both profile-based retrievals and tower-based estimates under low vertical flux conditions.

Box-pattern UAV measurements further reveal that horizontal transport can be a dominant term under certain conditions. Enhanced CO_2 concentrations on the virtual walls of the flight boxes and wind vectors show pronounced spatial heterogeneity and lateral gradients, especially in the morning, indicating that advection-driven convergence/divergence may substantially shape the CO_2 mass balance within the UAV-defined control volume above the forest canopy, processes that cannot be directly resolved from single-tower measurements. A multi-scale analysis using different box sizes (50×50×50, 100×100×50, and 150×150×50 m^3) shows that net emission estimates can exhibit scale dependence, reflecting the spatial heterogeneity of sources/sinks. These results highlight the value of UAV observations for determining spatial heterogeneity in short term ecosystem carbon exchange with the atmosphere, a task unfit for single-site measurements, for diagnosing when and where the assumption of horizontal homogeneity becomes invalid, and for quantifying lateral flux contributions explicitly. The horizontal flux analysis should therefore be interpreted as a diagnostic of local advective redistribution and spatial representativeness above the canopy, not as a measure of whole-forest lateral CO_2 export or import.

Overall, the combined box-profile UAV framework provides a flexible and spatially explicit complement to conventional EC monitoring, offering an effective

pathway to bridge the observational gap between point-scale tower fluxes and larger-scale heterogeneities, particularly over heterogeneous canopies and complex terrain. In conclusion, UAV-based platforms offer a transformative opportunity for observing ecosystem-atmosphere CO_2 exchange in three dimensions. With continued methodological refinement and broader application, such systems are well positioned to become an essential component of next-generation carbon observation strategies in forest ecosystems and beyond.

Data availability. Data are available upon request to the corresponding author upon reasonable request.

Author contributions. HS built the unmanned aerial vehicle platform, developed the corresponding emission inversion model, and carried out the data processing, and drafted the initial version of the manuscript. SML supervised the development of the inversion model and the experimental validation in the paper, and carried out a second round of revisions to the manuscript. YW provided some key data used in the paper. YY and TH provided the wind speed correction method used in the inversion model and the validation results for horizontal emissions, respectively. KC, CL, and JZ provided assistance with the field observation experiments and revisions to the manuscript. ZM and FY provided all flux tower data from the Qianyanzhou station. JG and XG provided support for unmanned aerial vehicle flights.

Competing interests. The contact author has declared that none of the authors has any competing interests.

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