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Supplement of

UAV-based method for measuring CO_2 emissions in forest ecosystems

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S1. Quality control of turbulence data

The data quality control procedures are as follows:

(1) Extreme-value check. Based on the instrument measurement range, values exceeding the instrument's range are removed, as shown in Table. S1.

Table. S1 Extremum detection

Variable	Unit	Frequency	Measurement range
u,v	m/s	5Hz	-45, 45
w	m/s	5Hz	-5, 5
T_s	℃	5Hz	-40, 70
CO_2	ppm	~1Hz	0, 1000

(2) Using the principle of variance analysis, a threshold of five times the standard deviation (5σ) was applied to screen the turbulence data and remove noise.

(3) Amplitude resolution check

Under weak-wind and stable conditions, the amplitude resolution of the time series may be too low to capture turbulent fluctuations, resulting in step-like (staircase) time series. Low amplitude resolution may also be associated with malfunctions of the instrument or the data-processing system. If the proportion of zero values in the probability density function (PDF) of a series exceeds 70%, the series is considered to have insufficient amplitude resolution and is deemed to have failed the amplitude resolution check.

(4) Higher-order statistical moment test. Compared with a Gaussian distribution, abnormally large or small higher-order statistical moments may indicate problems with the instrument or the data logging system. The skewness S and kurtosis K of the data are calculated, defined as:

$$S = \frac{E(x-\mu)^3}{\sigma^3} \tag{S1}$$

$$K = \frac{E(x-\mu)^4}{\sigma^4} \tag{S2}$$

where σ is the sample standard deviation and μ is the sample mean. If $|S| > 2$, or $K > 8$, or $K < 1$, the series is considered to have failed the higher-order moment test.

(5) Stationarity test. Stationarity means that the statistical properties of a turbulence field do not vary with time. Almost all turbulence statistical theories are built

on the assumption of stationarity. In reality, atmospheric turbulence is influenced by diurnal cycles and various weather systems and, strictly speaking, is not stationary. However, if a relatively short observation period is used and measurements are taken under relatively steady meteorological conditions (e.g., without the passage of large-scale weather systems or the influence of gravity waves) and over a relatively flat underlying surface, atmospheric turbulence can be approximated as stationary.

In practical testing, the data to be examined can be divided into M segments (M is generally chosen as 4-8, with a default of 6). The covariance for each segment is calculated as:

$$(\overline{x'w'})_i = \frac{1}{N-1}\left[\sum_j x_j w_j - \frac{1}{N}\sum_j x_j \sum_j w_j\right] \tag{S3}$$

where N is the number of samples in each segment, x and w can be two different series or the same series: the former is used to test the stationarity of fluxes (e.g., x as temperature and w as vertical wind speed), and the latter is used to test the stationarity of the series itself. The arithmetic mean of the M covariances is then computed as:

$$\overline{x'w'} = \frac{1}{M}\sum(\overline{x'w'})_i \tag{S4}$$

The covariance of the entire (unsegmented) dataset is:

$$(\overline{x'w'})_0 = \frac{1}{MN-1}[\sum x_j w_j - \frac{1}{MN}\sum x_j \sum w_j] \tag{S5}$$

If $\left|\frac{\overline{x'w'}-(\overline{x'w'})_0}{(\overline{x'w'})_0}\right| > 30\%$, the data are considered non-stationary and are deemed to have failed the stationarity test.

S2. Comparative analysis of fluxes during the morning and evening periods

The diurnal variation of friction velocity (u_*) exhibits a clear asymmetry between the morning and evening transitions, with turbulence developing gradually after sunrise but decaying rapidly in the late afternoon. The increased variability under evening conditions reflects enhanced instability and contributes to the larger uncertainties observed in flux estimates. The results clearly demonstrate a pronounced asymmetry between the morning and evening periods. After sunrise, turbulence develops gradually,

leading to increasing u_* values and more stable flux conditions. In contrast, during the late afternoon and evening, turbulence decays rapidly and the atmosphere transitions toward stable stratification, resulting in lower u_* values and increased variability.

This asymmetry is reflected in the larger scatter and lower turbulence intensity during the evening period, which increases the relative contribution of storage and advective processes and leads to greater uncertainties in both UAV-derived and tower-based flux estimates. As a result, the agreement between the two methods is substantially poorer in the evening compared to the morning.

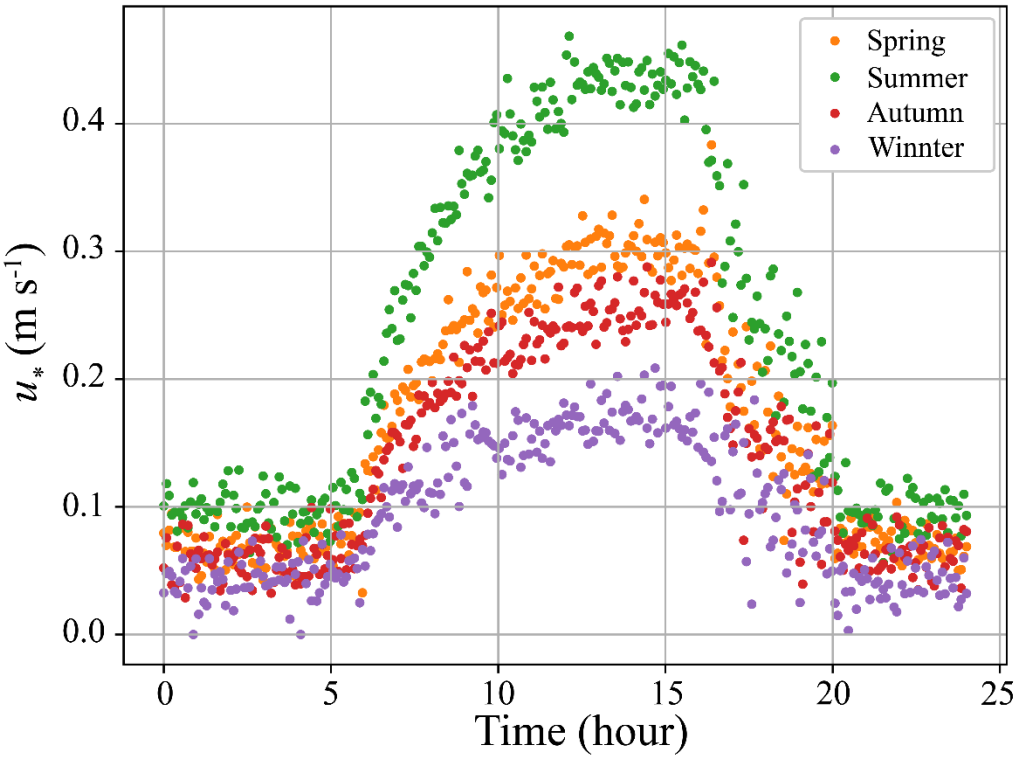


Fig. S1. Diurnal variation of friction velocity (u_*) for four seasons.

S3. Analysis of the evening flux differences

In the late afternoon to evening, as radiative forcing weakens and a stable stratification develops, turbulence above the canopy diminishes, leading to much reduced vertical fluxes (Wharton et al., 2017; Kiefer and Zhong, 2013). Consequently, the relative contributions of flux source-sink terms, storage, and horizontal transport-particularly advection and non-stationary transport under weak-wind conditions-increase, rendering the stationarity and horizontal homogeneity assumptions of the

eddy covariance (EC) method more susceptible to violation. Aubinet et al. (2002) and Gu et al. (2005) also reported that under low-turbulence evening conditions, the EC method substantially underestimates ecosystem respiration fluxes.

Due to the correlation coefficient between the fluxes calculated by the flux tower and those derived from the UAV was very low during the evening, and a low correlation coefficient alone cannot fully explain the relationship between the two datasets, an additional analysis of the flux differences was therefore carried out. Figure S2 presents the seasonal distributions of evening CO_2 flux differences, defined as $\Delta F_v = F_{v,UAV} - F_{v,Tower}$, for spring, summer, autumn, and winter. Overall, the distributions of evening ΔF_v show similar central tendencies across the four seasons. The mean values are small, with absolute values generally smaller than 0.1 mg m^{-2} s^{-1}, indicating that the evening CO_2 flux differences between UAV-based estimates and flux tower measurements are small in magnitude for all seasons. The one-way analysis of variance (ANOVA) further confirms that the seasonal differences in evening ΔF_v are not statistically significant. Specifically, the ANOVA yielded an F-statistic of 2.50, which indicates that the variability between seasons is 2.50 times greater than the variability within seasons. However, the p-value of 0.0699, which is greater than 0.05, indicates that these seasonal differences are not statistically significant, meaning that the observed differences could be due to random variation rather than a true seasonal effect. These ANOVA results are consistent with the distribution patterns illustrated in the boxplots, which show no evident systematic seasonal shifts in evening flux differences.

Overall, the evening ANOVA analysis further confirms, from a statistical perspective, the consistency between UAV-based and flux tower vertical flux observations at the seasonal scale. When combined with the results obtained from the RMA regression analysis presented above, it can be seen that although flux measurements under evening conditions are associated with relatively higher uncertainties, the overall differences between UAV-derived and tower-based observations remain small and do not exhibit pronounced seasonal shifts. This indicates that, despite the apparent low bias using the RMA regression analysis under weak evening turbulence conditions, CO_2 fluxes derived from the UAV platform are not

statistically different from those derived from tower-based measurements.

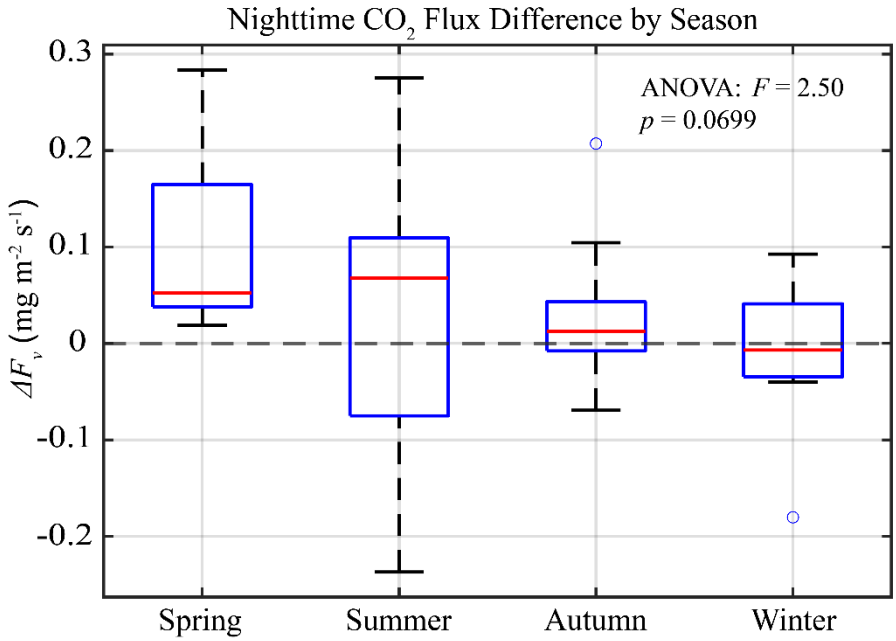


Figure S2. Boxplots of evening differences in CO_2 fluxes (ΔF_v) between UAV and flux tower observations across four seasons. The boxes indicate the interquartile range with median values shown as horizontal lines, small circles represent outliers and whiskers represent 1.5 times the interquartile range. The number of data points in this figure is 12 for spring, 15 for summer, 20 for autumn, and 7 for winter.

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