Characteristics of the relative sampling error and its application to flux aggregation in eddy covariance measurements

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Abstract

Using eddy covariance (EC) measurements, exchanges of energy, water, and carbon dioxide between the atmosphere and terrestrial ecosystem have been studied worldwide. EC measurements fundamentally operate under the hypotheses of stationarity and ergodicity. However, these hypotheses are disturbed in the real world by various factors generated by varying atmospheric and land surface conditions. The relative sampling error—a parameter quantifying this disturbance estimated by the average convergence in a time series—from a tangerine orchard is investigated to determine its range and terrestrial ecosystem have been studied worldwide. EC measurements fundamentally operate under the hypotheses of stationarity and ergodicity. However, these hypotheses are disturbed in the real world by various factors generated by varying atmospheric and land surface conditions. The relative sampling error—a parameter quantifying this disturbance estimated by the average convergence in a time series—from a tangerine orchard is investigated to determine its range.

1. Introduction

Since the early 1990s, eddy covariance (EC) measurements have gradually become a popular method to measure exchanges of heat, water vapor, and carbon dioxide between the atmosphere and terrestrial ecosystem (Wofsy et al., 1993; Baldocchi et al., 2001; Baldocchi, 2003). Currently, EC measurements are being performed at more than 500 stations as a principal method for monitoring such exchanges on a long-term basis across the globe (http://fluxnet.ornl.gov). This proliferation of observations contributes to understanding the exchanges characterized by various ecosystems (e.g., Luyssaert et al., 2007) and validating the exchanges estimated by satellite analyses and model predictions (e.g., Heinsch et al., 2006; Bonan et al., 2011).

EC measurements are based on hypotheses of stationarity and ergodicity of a time series with a fixed time length \( t \). These hypotheses are mainly disturbed by spatial heterogeneities such as variations in the roughness length, temperature, water content, photosynthesis, and respiration. There are combinations thereof under neutral and unstable atmospheric conditions as well as gravity waves and synoptic changes under stable atmospheric conditions (Katul et al., 2004). Under these disturbed circumstances, the length of \( t \) satisfying average convergence (Lumley and Panofsky, 1964; Businger, 1986) is longer than that under undisturbed circumstances. Additionally, even under undisturbed circumstances, the relative sampling error \( \varepsilon \)—a parameter quantifying the average convergence in a time series—does not approach zero because \( t \) cannot reach infinity in reality (Eq. 1.98 in Lumley and Panofsky, 1964; Lenschow et al., 1994). It is therefore meaningful to investigate the range of \( \varepsilon \), especially to determine the minimum value of \( \varepsilon \), under fixed \( t \) values of EC measurements for understanding the uncertainties in EC measurements due to disturbances of these hypotheses.

\( \varepsilon \) is divided into both a systematic component and a random component. The former can be disregarded as it is smaller under a practical length of \( t \) (Lenschow et al., 1994)—less than 4% \((t = 1.0 \text{ hr}; \text{Vickers et al., 2009})\). However, the latter cannot be neglected (Katul et al., 2004; Oren et al., 2006; Salesky et al., 2012), and its value fluctuates (Finkelstein and Sims, 2001; Richardson et al., 2006; Kim et al., 2011b) in EC measurements. Exchanges with large \( \varepsilon \) values are filtered out using quality control and quality assurance (QCQA; Foken et al., 2004) before aggregation of exchanges. However, the following issues still remain: first, the classification of qualities with the test of the developed turbulent conditions and the steady state test for QCQA are based on arbitrary values; second, measurement gaps inevitably increase in accordance with QCQA; finally, as the most important point, EC uncertainty information after QCQA is unknown. Here, if \( \varepsilon \) represents the integral turbulence characteristic, it can be a scaling parameter for the EC measurement quality. This potential is anticipated with the close relationship between \( \varepsilon \) and the similarity parameter \( \phi \) (Kim et al., 2015). Therefore, it is valuable to investigate the relationship...
between $\varepsilon$ and the integral turbulence characteristic in terms of both the utility of $\varepsilon$ as a quality parameter for EC measurements and the inference of $\varepsilon$ in previous studies filtered by traditional QCQA.

Filling of gaps in data represents a fundamental procedure when accessing EC measurements to aggregate exchanges. A few gap-filling methods have been developed to compensate for the absence of data caused by QCQA (Falge et al., 2001; Moffat et al., 2007). However, we cannot access the uncertainty information for exchanges compiled by these gap-filling methods. Ultimately, the exchanges reflected in EC measurements are employed to compare the exchanges measured at other EC sites to validate the performances of models or satellite analyses and to synthesize spatiotemporal exchanges by data assimilation. Therefore, it is important to know how to access the uncertainty information of EC measurements in their statistical aggregations.

Therefore, the purposes of this study are to 1) evaluate the minimum value of $\varepsilon$ for understanding the range of EC measurement uncertainties, 2) investigate the relationship between $\varepsilon$ and $\phi$ for presenting $\varepsilon$ as an EC quality parameter, and 3) suggest an aggregation method for EC measurements considering $\varepsilon$.

2. Instrumentation

Hourly time series data measured at a sampling frequency of 10 Hz were collected using a three-dimensional sonic anemometer (CSAT3: Campbell Scientific, Utah, USA) deployed at an average vegetation height of over 2.0 m in a tangerine orchard (leaf area index = 3; height = 2.0 m; location: 33.507883°N, 126.680908°E, 81 m a.s.l.) in Jeju, Korea. Additional specifications and details regarding the instrumentation for EC measurements are presented in Kim et al. (2015).

3. Basics

3.1 EC measurements

Under the assumption of atmospheric ergodicity, EC measurements estimate the net vertical flux $F$ of a specified quantity $\zeta$ during $t$ as the exchanges, which is basically defined by a kinematic eddy flux (Stull, 1988) as

$$ F_t = w^t \zeta^t, $$

(1)

where $w$ denotes the vertical wind velocity, and the overbar and prime symbols represent the operators of a time average and a turbulent fluctuation, respectively. Eq. (1) can also be described as follows:

$$ w^t \zeta^t = \frac{1}{N} \sum_{i=1}^{N} (w_i - \overline{w})(\zeta_i - \overline{\zeta}), $$

(2)

where $N$ and $i$ are the total number of samples measured over the same interval during $t$ and its time index in each time series, respectively. The sensible heat flux $H$ with Eq. (1) of which $\zeta$ is a temperature $T$ is represented as follows:

$$ H = \bar{p}_a C_p F_T, $$

(3)

where $\bar{p}_a$ and $C_p$ are the mean density of moist air and the specific heat of air, respectively. Hereafter, $F = F_t$ for brevity.

3.2 Calculation of $\varepsilon$

The relative sampling error of an EC measurement is practically calculated as follows:

$$ \varepsilon = \frac{\sigma_{\varepsilon}}{|F|}, $$

(4)

where

$$ \sigma_{\varepsilon} = \left[ \frac{1}{N} \left( \sum_{p=wi}^{m} \gamma_{\varepsilon}(p) \gamma_{\varepsilon}(p) + \sum_{p=wi}^{m} \gamma_{\varepsilon}(p) \gamma_{\varepsilon}(p) \right) \right]^{1/2} $$

(5)

(Finkelstein and Sims, 2001; Kim et al., 2011b). In Eq. (5), $m$ ($\geq 200$) is the number of samples that is sufficiently large to capture the integral time scale $T$, which constitutes a concept of the time scale and its integrability as one of the turbulence characteristics in the inertial boundary layer (Liemann, 1952). The auto-covariance and cross-covariance of the lag time $h$ are given by Eq. (6) and Eq. (7), respectively.

$$ \gamma_{\varepsilon}(\overline{h}) = \gamma_{\varepsilon}(\overline{-h}) = \frac{1}{N-h} \sum_{i=1}^{N-h} (w_i - \overline{w})(\zeta_i - \overline{\zeta}) $$

(6)

$$ \gamma_{w\zeta}(\overline{h}) = \gamma_{w\zeta}(\overline{-h}) = \frac{1}{N-h} \sum_{i=1}^{N-h} (w_i - \overline{w})(\xi_i - \overline{\xi}) $$

(7)

4. Revisitation

4.1 Concept of $\varepsilon$

Using Eqs. (4) and (5), $\varepsilon$ can be redefined as follows:

$$ \varepsilon = \frac{\left[ \frac{1}{N} \left( \sum_{p=wi}^{m} r_{w\varepsilon}(p) r_{w\varepsilon}(p) \sigma_w^2 + \sum_{p=wi}^{m} r_{w\varepsilon}(p) r_{w\varepsilon}(p) \sigma_{\varepsilon}^2 \right) \right]^{1/2}}{|r_{w\varepsilon}|}, $$

(8)

considering that $\gamma_{w\varepsilon}(p) = r_{w\varepsilon}(p) \sigma_w(p) \sigma_{\varepsilon}(p)$ and the standard deviation $\sigma$ is the same regardless of the lag time $p$. Here, $r$ is the correlation coefficient between two time series A and B and $r_{w\varepsilon}(p)$ is the autocorrelation or cross-correlation function between A and B. Here, $r$ is variable due to the variation in $p$ from $-m$ to $m$. Subsequent to fractional reduction by the common term $\sigma_w \sigma_{\varepsilon}$,

$$ \varepsilon = \frac{\left[ \frac{1}{N} \left( \sum_{p=wi}^{m} r_{w\varepsilon}(p) r_{w\varepsilon}(p) + \sum_{p=wi}^{m} r_{w\varepsilon}(p) r_{w\varepsilon}(p) \right) \right]^{1/2}}{|r_{w\varepsilon}|}, $$

(9)

can be obtained because $\sigma_w^2 \sigma_{\varepsilon}^2$ in the numerator of Eq. (8) can be a constant. Obviously,

$$ \varepsilon = v N^{-1} T, $$

(10)

where

$$ v = \frac{(T_a + T_c)^{1/2}}{|r_{w\varepsilon}|}, $$

(11)

when the integral timescale for the autocorrelation function is

$$ T_a = \sum_{h=-m}^{m} r_{w\varepsilon}(h) r_{w\varepsilon}(h), $$

(12)

and that for the cross-correlation function is

$$ T_c = \sum_{h=-m}^{m} r_{w\varepsilon}(h) r_{w\varepsilon}(h), $$

(13)
\[ T_r = \sum_{h=0}^{m} r_{x(h)} \phi_{x(h)}, \]  
(13)

Therefore, \( \varepsilon \) vanishes as \( N \) increases. Considering stationarity for fixed values of \( N \), it is possible to let \( \varepsilon \) reach a minimum over the assumption that maxima of \( |r_{\text{ac}}| \) has been defined together with minima of \( T_r \). \( T_r \) is an integrated area of a correlation function \( r(h) \)—as given in Eqs. (11), (12), and (13); the maximum is estimated by Kaimal and Finnigan (1994) as \( \approx 0.5 \), and the minima of \( T_r \) is revealed in consideration of the existence of the minimum fractional uncertainty (Kim et al., 2011a, b). Eq. (10) shows that \( \varepsilon \) is a function not only of \( N \) (Moncrieff et al., 1996) but also of \( F \), which consists of \( \mathcal{T} \) and \( \phi_{x(h)} \).

### 4.2 Similarity function and \( \varepsilon \)

Kim et al. (2015) revealed a close relationship between \( \varepsilon \) and the similarity function \( \phi \)—a traditional scaling parameter (Tillman, 1972) for QCQA of EC measurements based on the Monin-Obukhov similarity theory (MOST) estimated by Kaimal and Finnigan (1994). Figure 1 shows the same relationship as shown by Kim et al. (2015) between \( \varepsilon_{\text{rel}} = (\sigma / \theta_{\text{r}}) / \| \mathbf{w} \| \mathbf{T} \) and \( \phi = (\sigma / u_c) / \| \mathbf{w} \| \mathbf{T} \) with \( r^2 = 0.89 \), where \( u_c \) is the friction velocity. This result is not surprising in consideration of MOST because the atmospheric statistic normalized by an appropriate power of the scaling parameter becomes a universal function of \( \zeta \)—the ratio of height above the zero-plane displacement to the Monin-Obukhov length, called the Obukhov stability parameter. Likewise, \( \varepsilon \), which is \( \sigma \) normalized by \( |F| \), i.e., the \( \sigma \) of the covariance normalized by the absolute covariance, could be a universal function of \( \zeta \) as \( \phi \). Figure 2 shows a specific similarity function for \( \varepsilon \) as a model—the minimum fitting dotted line,

\[ \varepsilon_{\text{mod}} = \varepsilon_{\text{max}}(1 + 0.4 |\zeta|), \]
(14)

versus its measure—the scatters,

\[ \varepsilon_{\text{meas}} = \varepsilon(1 + 0.4 |\zeta|), \]
(15)

when \(-2 \leq \zeta \leq 2\). Consequently, the relative deviation (RD) for \( \varepsilon \) is

\[ RD = \left| \frac{\varepsilon_{\text{mod}} - \varepsilon_{\text{meas}}}{\varepsilon_{\text{mod}}} \right|, \]
(16)

and, in the same concept, \( RD_{\phi} \) is also can also be defined based on Eq. (9.9) in Foken et al. (2004). Supposing that the intercept of the regression line between \( \varepsilon_{\text{rel}} \) and \( \phi_{x(h)} \) in Fig. 1 is 0,

\[ RD = RD_{\phi} = RD_{\phi}, \]
(17)

Finally, rearranging Eq. (16) with the right part of Eq. (14) and Eq. (15) instead of \( \varepsilon_{\text{mod}} \) and \( \varepsilon_{\text{meas}} \) in consideration of Eq. (17), we can obtain

\[ \varepsilon = \varepsilon_{\text{max}}(1 + RD). \]
(18)

Conventionally, temperature is applicable to estimation of RD values to assess QCQA of \( H \) including latent heat flux (b of Table 9.4, c of Table 9.5, and Fig. 9.1 in Foken et al., 2004). In addition, \( \varepsilon_{\text{max}} \) of \( H \) is smaller than those of other fluxes (Kim et al., 2011b), and \( \varepsilon \) has a linear relationship to \( \phi \) of latent and carbon dioxide fluxes (Fig. 16 in Kim et al., 2015) similar

Fig. 1. Relationship between the temperature similarity parameter \( \phi_{x(h)} \) and the relative sampling error of the sensible heat flux \( \varepsilon_{\text{rel}} \) estimated by measurements from a tangerine orchard on Jeju Island, Korea, acquired during April 9–15, 2014 (○) and January 11–13, 2015 (×). The text within the panel describes the statistical information of a regression line between \( \phi_{x(h)} \) and \( \varepsilon_{\text{rel}} \). \( N \) denotes the sampling number, and \( r^2 \) denotes the coefficient of determination.

Fig. 2. Relationship between the relative sampling error of the sensible heat flux \( \varepsilon_{\text{rel}} \) and the atmospheric stability \( \zeta \) which is the ratio of a measurement height to the Obukhov length. The EC measurements are the same as those shown in Fig. 1 (○: April 9–15, 2014; ×: January 11–13, 2015). The dashed line denotes the minimum fitting of a similarity function for \( \varepsilon_{\text{rel}} \) as a model—\( \varepsilon_{\text{mod}} = 0.05 (1 + 0.4 |\zeta|) \) when \(-2 \leq \zeta \leq 2 \) based on Eq. (14).
to $H$ in Fig. 1. Thus, we can estimate $\varepsilon$ of studies using RD and $\zeta$ using a traditional QCQA approach regardless of scalar components because RD is a useful parameter for various fluxes (Foken et al., 2004).

4.3 Aggregation of $F$ for EC measurements

Bevington and Robinson (2003) suggest that the weighted mean is applicable to variables with nonuniform uncertainties and that $1/\sigma^2$ is useful as a weighting factor for the weighted mean. However, $1/\sigma^2$, where $\varepsilon = \sigma_r/F$, is used as the weighting factor in this study instead of $1/\sigma^2$ because $\sigma_r$ has a linear relationship to $F$ in EC measurements (Fig. 3; Kim et al., 2015). Additionally, the close relationship between $\varepsilon$ and $\phi$ (Subsection 4.2 and Fig. 1) is valid information because the similarity function is independent of $F$. Therefore,

$$\bar{F} = \frac{\sum_{i=1}^{n} F_i / \varepsilon_i}{\sum_{i=1}^{n} \varepsilon_i} \quad (19)$$

and

$$\sigma_F = \sqrt{\frac{\sum_{i=1}^{n} (F_i - \bar{F})^2 / \varepsilon_i^2}{\sum_{i=1}^{n} \varepsilon_i^2}} \quad (20)$$

are recommended for EC measurement aggregations based on Kim et al. (2015), where the tilde represents an operator of the weighted mean.

5. Results and discussion

5.1 Minimum value of $\varepsilon$

Figure 4 presents $r(h)$ with its minimum line in our measurements using the following equation proposed by Finkelstein and Sims (2001)

$$r(h) = e^{-\frac{h^a}{b}} \quad (21)$$

The fitting parameter $a$ is 0.7, while $b$, which is approximately $T$, is a variable depending on the combination of $w$ and $T$ (Kim et al., 2015). The minimum $b$ value for each function $r_{ww}(h)$, $r_{TT}(h)$, and $r_{WT}(h)$ is approximately 0.32, 1.15, and 0.27 s, respectively. The other $b$ value for $r_{ww}(h)$—here, $\zeta$ represents water vapor or carbon dioxide—is greater than that for $r_{TT}(h)$, and the value for $r_{WT}(h)$ is also greater than that for $r_{ww}(h)$, although the data are not

![Fig. 3. Relationship between the sensible heat flux $H$ and its sampling error $\sigma_H$ estimated by the same EC measurements shown in Fig. 1 (●: April 9–15, 2014; ×: January 11–13, 2015). The dashed diagonal designates 1.00 by 0.05, namely, the 5% line of the relative sampling error of the sensible heat flux $\varepsilon_H$.](image)
shown here. These results are comparable to those of Lenschow et al. (1994). With the fitting parameters for \( b \), the calculated minimum value of \( \epsilon \), \( \varepsilon_{\text{min}} \), is estimated as 3% using Eq. (10); we can obtain the same \( \epsilon \) value with Eq. (48) in Lenschow et al. (1994). From these results, we can reason that the time series of \( \zeta \) is inherently more difficult to satisfy the stationary condition than that of \( w \) and \( \epsilon \) is a function of \( N \) as \( v = 5 \) under conditions of stationarity. Nevertheless, the \( \epsilon \) value estimated by Eq. (4) using the same time series does not approach a value of less than 5% (Fig. 3). Hereafter, we assign 5% to \( \epsilon \) under stationarity conditions for \( t = 1 \text{ hr} \) because Eq. (21) may have uncertainty in accordance with the approximation of \( a \) and \( b \). Therefore, the variation in \( \epsilon \) for the 1.0 h time series of EC measurements ranges from 5% to infinity, and that for the 0.5 h time series ranges from \(- \sqrt{N_{0.05}}/N_{0.5h} \) times of the \( \epsilon \) for the 1.0 h time series—to infinity.

5.2 Range of \( \epsilon \) after traditional QCQA

Using Eq. (18) with \( \varepsilon_{\text{min}} = 5\% \), which is defined in subsection 5.1, the ranges of \( \epsilon \) using the classification of RD based on Foken et al. (2004) are listed in Table 1. The RD classification suggests that the filtered EC measurements in classes 1–4 of RD are used as fundamental research, such as the development of parameterizations, and those in classes 1–5 are used for the continuously running systems of the FLUXNET program. Throughout our analysis, it is expected that the \( \epsilon \) values of hourly EC measurements filtered by traditional QCQA for fundamental research are 5%–16% and those for the FLUXNET program are 5%–18%, and the corresponding half-hourly \( \epsilon \) values are 7%–22% and 7%–25%, respectively. Therefore, Eq. (18) is helpful for estimating the values of \( \epsilon \) using traditional QCQA, and then it is possible to compare \( F \) among various

| Class | RD (%) | \( \epsilon \) (%) |
|-------|--------|------------------|
| 1     | 0–15   | 5–10             | 7–15             |
| 2     | 16–30  | 6–12             | 8–17             |
| 3     | 31–50  | 7–14             | 9–19             |
| 4     | 51–75  | 8–16             | 11–22            |
| 5     | 76–100 | 9–18             | 12–25            |
| 6     | 101–250| 10–32            | 14–45            |
| 7     | 251–500| 18–54            | 25–76            |
| 8     | 501–1000 | 30–99       | 42–140           |
| 9     | 1001– | 55–             | 78–              |

EC measurement sites and to validate model predictions and satellite measurements statistically on the basis of these results.

The filtered EC measurements guarantee further analyses at these confidence levels; however, gaps produced by filtering EC measurements with traditional QCQA have become an obstacle to such guarantees. Therefore, it is important to minimize gaps with \( \epsilon \) regardless of the rejection of measurements throughout the filtering because EC measurements with \( \epsilon \) information are applicable to statistical aggregations without rejection. In other words, it is better to consider all EC measurements for aggregations without the rejection of observations using arbitrary QCQA criteria.

5.3 Credit of \( \tilde{F} \) considering \( \epsilon \)

Figure 5 shows the results of a comparison between \( \tilde{H} \) considering \( \varepsilon_{\text{ip}} \) (the closed cycles with gray error regions) and \( \tilde{H} \) considering \( \varepsilon_{\text{ip}} \) (the open cycles with black error regions). The vertical bar at the bottom panel designates the acquisition ratio (AR) of hourly EC measurements at each time of day; e.g., the 57% AR at 00:00 in the left panel means that 4-day EC measurements observed at 00:00 are available for a week.

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Fig. 5. The mean diurnal variation of the sensible heat flux \( H \) estimated by the same EC measurements shown in Fig. 1. The closed circle and shaded region denote the weighted mean \( \tilde{H} \) trend and its standard deviation \( \sigma \) on the basis of Eq. (19) and Eq. (20), respectively, and the open circle and whiskers are the arithmetic mean \( \tilde{H} \) trend and its standard deviation \( \sigma \), respectively.
(the opened cycles with error tails) of the mean diurnal variation (Falge et al., 2001) of the EC measurements for two periods. \( \bar{H} \) and \( \tilde{H} \) are respectively 6.93 ± 0.74 and 6.16 ± 1.10 MJ m\(^{-2}\) day\(^{-1}\) (Fig. 5a) and 0.33 ± 0.63 and 0.76 ± 0.75 MJ m\(^{-2}\) day\(^{-1}\) (Fig. 5b), though neither pair of results was statistically significant. However, we cannot overlook the error difference in accordance with the mean method because \( \bar{H} \) during the period shown in Fig. 5b ranged from −0.30 to 0.96 MJ m\(^{-2}\) day\(^{-1}\), which indicates both a heat source and a heat sink, while \( \tilde{H} \) ranged from 0.01 to 1.51 MJ m\(^{-2}\) day\(^{-1}\), which indicates only a heat source. It is important not to eliminate the possibility of a heat sink by considering error information. In other words, we have to minimize the loss of measurement information by applying a proper aggregation method for EC measurements. In addition, \( |\tilde{H}| \) is underestimated in a fully systematic manner (Moncrieff et al., 1996). This bias originates from a trait of the arithmetic mean method to which the same weighting value is applied even though \( e_H \) is not the same among \( H \); a certain \( H \) having a large \( e_H \) value needs a longer \( t \) to ensure the average convergence than the fixed \( t \) hence the consistently missing low-frequency components of the cospectrum of \( w' \) and \( T' \) causes this bias. Remarkably, a large \( \epsilon \) appeared at a small value of \( |F| \), potentially because the atmospheric conditions were inappropriate for EC measurements from dusk to dawn. This finding demonstrates that the traditional method has the possibility to underestimate \( |F| \) in those aggregations.

6. Conclusion

The \( \epsilon \) parameter of EC measurements established based on the stationarity of time series is required not only for the comparison of \( F \) among sites but also for the validation of the spatiotemporal \( F \) estimated by remote sensing and numerical modeling because of varying atmospheric conditions and diverse land surfaces affect EC measurements. This study shows the following: first, \( \epsilon_{\text{min}} = 5\% \), which implies that the error in EC measurements reaches at least 5% even under the condition of near stationarity in the real world; second, \( \epsilon = \epsilon_{\text{min}} (1 + \text{RD}) \), which is one of the similarity functions of MOST under the condition of stationarity; finally, \( F = \sum (F_i/\epsilon_i)/(1/\epsilon^2) \), which reliably calculates the exchanges of energy, water, and carbon dioxide using EC measurements. Therefore, \( \epsilon \) deserves not only to be one of the parameters used for the estimation of measurement quality but also to become a weighing factor for the mean in EC measurement aggregations.

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