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Uncertainty analysis of eddy covariance CO_2 flux measurements for different EC tower distances using an extended two-tower approach

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Abstract. The use of eddy covariance (EC) CO_2 flux measurements in data assimilation and other applications requires an estimate of the random uncertainty. In previous studies, the (classical) two-tower approach has yielded robust uncertainty estimates, but care must be taken to meet the often competing requirements of statistical independence (non-overlapping footprints) and ecosystem homogeneity when choosing an appropriate tower distance. The role of the tower distance was investigated with help of a roving station separated between 8 m and 34 km from a permanent EC grassland station. Random uncertainty was estimated for five separation distances with the classical two-tower approach and an extended approach which removed systematic differences of CO_2 fluxes measured at two EC towers. This analysis was made for a data set where (i) only similar weather conditions at the two sites were included, and (ii) an unfiltered one. The extended approach, applied to weather-filtered data for separation distances of 95 and 173 m gave uncertainty estimates in best correspondence with an independent reference method. The introduced correction for systematic flux differences considerably reduced the overestimation of the two-tower based uncertainty of net CO_2 flux measurements and decreased the sensitivity of results to tower distance. We therefore conclude that corrections for systematic flux differences (e.g., caused by different environmental conditions at both EC towers) can help to apply the two-tower approach to more site pairs with less ideal conditions.

1 Introduction

The net ecosystem exchange of CO_2 between the land surface and the atmosphere (NEE) can be determined with the eddy covariance (EC) method. Eddy covariance CO_2 flux measurements are commonly used to analyze the interactions between terrestrial ecosystems and the atmosphere which is important for the understanding of climate–ecosystem feedbacks. In this regard reliable EC data with appropriate uncertainty estimates are crucial for many application fields, such as the evaluation and improvement of land surface models (e.g., Braswell et al., 2005; Hill et al., 2012; Kuppel et al., 2012).

When using the term "uncertainty", we here focus on the random error following the definition in Dragoni et al. (2007). It differs from the systematic error in that it is unpredictable and impossible to correct (but can be quantified). Uncertainty does not accumulate linearly but "averages out" and can be characterized by probability distribution functions (Richardson et al., 2012). Systematic errors are considered to remain constant for a longer time period (> several hours). Ideally they can be corrected, but in the case of EC measurements this is still limited by either our understanding of various error sources or insufficient background data. Systematic errors arise not only from instrumental calibration and data processing deficits, but also from unmet underlying assumptions about the meteorological conditions (Richardson et al., 2012). A main assumption is that turbulence is always well developed in the lowest atmospheric boundary layer and responsible for the mass transport while horizontal divergence of flow and advection are assumed to be negligible (Baldocchi, 2001). Moreover, the EC method is based on the mass conservation principle, which requires the assumption of steady-state conditions of the meteorological variables (Baldocchi, 2003). In the case of CO_2 fluxes, night-time respiration is often underestimated due to low wind velocity conditions and a temperature inversion which hinders the upward carbon dioxide transport (Baldocchi, 2001). Hence, night-time data are commonly rejected for further analysis (Barr et al., 2006).

After a possible correction of the EC flux data for systematic errors a random error will remain which can arise from different sources such as (a) the assumption of a constant footprint area within a measurement interval and the negligence of flux footprint heterogeneity (e.g., due to temporal variability of wind direction, wind speed and atmospheric stability which causes temporal variations of the footprint area); (b) turbulence sampling errors which are related to the fact that turbulence is a highly stochastic process and especially the sampling or not sampling of larger eddies is associated with considerable random fluctuations of fluxes, even if they are already averaged over a 30 min period; and (c) instrumentation deficits that can, e.g., cause random errors in the measured variables (such as the CO_2 mixing ratio and the vertical wind velocity) used to calculate the net CO_2 flux (Aubinet et al., 2011, p. 179; Flanagan and Johnson, 2005).

Within the past decade, several approaches have been proposed to quantify the uncertainty of eddy covariance CO_2 flux measurements. With the "two-tower" or "paired tower" approach simultaneous flux measurements of two EC towers are analyzed (Hollinger et al., 2004; Hollinger and Richardson, 2005). For the uncertainty quantification with the two-tower approach, it is necessary that environmental conditions for both towers are nearly identical (Hollinger et al., 2004; Hollinger and Richardson, 2005). However, most eddy covariance sites do not have a nearby second EC tower to provide nearly identical environmental conditions. Therefore, Richardson et al. (2006) introduced the "one-tower" or "24 h differencing" method which is based on the two-tower approach. The main difference is that the uncertainty estimate is based on differences between fluxes measured on subsequent days if environmental conditions were similar on both days. Because most often environmental conditions are not the same on two subsequent days (Liu et al., 2006), the applicability of this method suffers from a lack of data and the random error is overestimated (Dragoni et al., 2007). The model residual approach (Dragoni et al., 2007; Hollinger and Richardson, 2005; Richardson et al., 2008) calculates CO_2 fluxes with a simple model and compares calculated values with measured values. The model residual is attributed to the random measurement error. The method is based on the assumption that the model error is negligible, which is however a very questionable assumption. Alternatively, if the high-frequency raw data of an EC tower are available, uncertainty can be estimated directly from their statistical properties (Billesbach, 2011). Finkelstein and Sims (2001) introduced an operational quantification of the instrumental noise and the stochastic error by calculating the auto- and cross-covariances of the measured fluxes. This method was implemented into a standard EC data processing scheme by Mauder et al. (2013). The advantage is that a second tower or the utilization of additional tools such as a simple model to estimate the EC measurement uncertainty is no longer required. However, many data users do not have access to the raw-data but to processed EC data only. Moreover, a large amount of solid metadata about the setup of the EC measurement devices is required (but often not provided at second hand) to obtain reliable raw-data based uncertainty estimates adequately. Therefore a two-tower based approach has still a large group of users. In particular with regard to pairs of nearby towers from local clusters which play an increasing role in the monitoring strategies of for example ICOS and NEON, and have already been employed in case studies (e.g., Ammann et al., 2007). Important advantages of the two-tower approach are (1) its simplicity and user friendliness, (2) its usability for relatively short non-gap-filled time series of several months and (3) the independence of a model.

The classical two-tower approach (Hollinger et al., 2004; Hollinger and Richardson, 2005; Richardson et al., 2006) is based on the assumption that environmental conditions for both EC towers are identical and flux footprints should not overlap, to guarantee statistical independence. Hollinger and Richardson (2005) use threshold values for three variables (photosynthetically active photon flux density PPFD, temperature and wind speed) to determine whether environmental conditions are equivalent. Independent of this definition, our understanding of "environmental conditions" includes both weather conditions and land surface properties such as soil properties (texture, density, moisture, etc.), plant characteristics (types, height, density, rooting depth, etc.), nutrient availability and fauna (micro-organisms, etc.), which are irregularly distributed and affect respiration and/or photosynthesis. Strictly speaking, if footprints do not overlap 100 %, the assumption of identical environmental conditions is already not fulfilled. When applying a two-tower based approach it is important to assure that systematic differences of the measured fluxes, which are partly caused by within-site or among-site heterogeneity, are not attributed to the random error estimate of the measured NEE. Our assumption that even within a site with apparently one uniformly distributed vegetation type (and for very short EC tower distances) land surface heterogeneity can cause significant spatial and temporal variability in measured NEE is, e.g., supported by Oren et al. (2006). They found that the spatial variability of ecosystem activity (plants and decomposers) and leaf area index within a uniform pine plantation contributes to about half of the uncertainty in annual eddy covariance NEE measurements while the other half is attributed to micrometeorological and statistical sampling errors. This elucidates the relevance of considering systematic flux differences caused by within site ecosystem heterogeneity when calculating a two-tower based uncertainty estimate.

Given the fact that site-specific, adequate uncertainty estimates for eddy covariance data are very important but still

Table 1. Measurement periods and locations of the permanent EC towers in Rollesbroich (EC1) and Merzenhausen (EC3) and the roving station (EC2).

	Coordinates	Site name	Distance to EC1	Measurement period	Alt. (m)
EC1	50.6219142 N/6.3041256 E	Rollesbroich	–	13.05.2011–15.07.2013	514.7
EC2	50.6219012 N/6.3040107 E	Rollesbroich	8 m	29.07.2011–06.10.2011	514.8
	50.6219012 N/6.3040107 E			05.03.2013–15.05.2013	
	50.6217990 N/6.3027962 E	Rollesbroich	95 m	07.10.2011–15.05.2012	516.3
	50.6210472 N/6.3042120 E			01.07.2013–15.07.2013	517.3
	50.6217290 N/6.3016925 E	Rollesbroich	173 m	24.05.2012–14.08.2012	517.1
	50.5027500 N/6.5254170 E	Kall-Sistig	20.5 km	14.08.2012–01.11.2012	498.0
				15.05.2013–01.07.2013	
EC3	50.9297879 N/6.2969924 E	Merzenhausen	34 km	10.05.2011–16.07.2013	93.3

often neglected due to a lack of resources, we are aiming to advance the two-tower approach so that it can also be applied if environmental conditions at both eddy covariance towers are not very similar.

The main objectives of this study were (1) to analyze the effect of the EC tower distance on the two-tower based CO_2 flux measurement uncertainty estimate and (2) to extend the two-tower approach with a simple correction term that removes systematic differences in CO_2 fluxes measured at the two sites. This extension follows the idea of the extended two-tower approach for the uncertainty estimation of energy fluxes presented in Kessomkiat et al. (2013). The correction step is important for providing a more reliable random error estimate. In correspondence with these objectives we analyzed the following questions. What is an appropriate EC tower distance to get a reliable two-tower based uncertainty estimate? Can the random error be quantified in reasonable manner with the extended two-tower approach, even though environmental conditions at both EC towers are clearly not identical? The total random error estimated with the raw-data based method (Mauder et al., 2013) was used as a reference to evaluate our extended two-tower approach based results.

2 Test sites and EC tower setup

The Rollesbroich test site is an extensively used grassland site, located in the Eifel region of western Germany (Fig. 1). The mean temperature in Rollesbroich is ∼ 7.7 °C and the mean precipitation is ∼ 1033 mm per year (Korres et al., 2010). Predominating soil types at the site are Cambisols with a high clay and silt content (Arbeitsgruppe BK50, 2001). The grass species grown in Rollesbroich are mainly ryegrass, particularly perennial ryegrass (*Lolium perenne*), and smooth meadow grass (*Poa pratensis*) (Korres et al., 2010). A permanent eddy covariance tower (EC1) is installed at the Rollesbroich site since May 2011 at a fixed position. The measurement height of the sonic anemometer (CSAT3, Campbell Scientific, Logan, UT, USA) and the open-path gas analyzer (Li7500, Li-Cor, Lincoln, NE, USA) is 2.6 m above ground. The canopy height was measured every 1–2 weeks and varied between 0.03 and 0.88 m during the measurement period. A second EC tower, the roving station (EC2), has been installed at four different distances (8, 95, 173 and 20.5 km) from EC1 for time periods ranging between 3 and 7.5 months (Table 1). The EC2 location "Kall-Sistig" 20.5 km northeast of Rollesbroich is another grassland site with similar environmental conditions as Rollesbroich. The vegetation in Kall-Sistig is extensively managed C3 grass, the same as for Rollesbroich. However, the average plant height measured between 14 August and 30 October 2012 was lower (∼ 0.15 m) than the respective average for Rollesbroich (∼ 0.2 m), which is also true for the plant height measured in May and June 2012 (Kall-Sistig: ∼ 0.22 m; Rollesbroich: ∼ 0.29 m). As in Rollesbroich, clayey-silty Cambisols are most widespread (Arbeitsgruppe BK50, 2001). The mean temperature for the entire measurement interval in Kall-Sistig (Table 1) measured at the EC station is 11.4 °C and the soil moisture 32 % compared to 11.0 °C and 35 % in Rollesbroich (same time interval for averaging). Additionally, a third EC tower was located in Merzenhausen at ∼ 34 km distance to EC1 (Fig. 1). Merzenhausen (MH) is an agricultural site, where winter wheat was grown during the measurement period. Both the land use conditions and the average weather conditions differ from those in Rollesbroich and Kall-Sistig. The climate at the lowland site Merzenhausen is comparable to the one in Selhausen at a distance of 13 km from Merzenhausen, where the mean precipitation is ∼ 690 mm a^{-1} and the yearly mean temperature ∼ 9.8 °C (Korres et al., 2010). The soils are mainly Luvisols with some patches of Kolluvisols (Arbeitsgruppe BK50, 2001). The measurement devices of EC2 and EC3 are the same as the EC1 devices and were installed 2.6 m above ground as well. Both, the sonic anemometers and the open-path gas analyzers have been calibrated every 1–3 months thoroughly

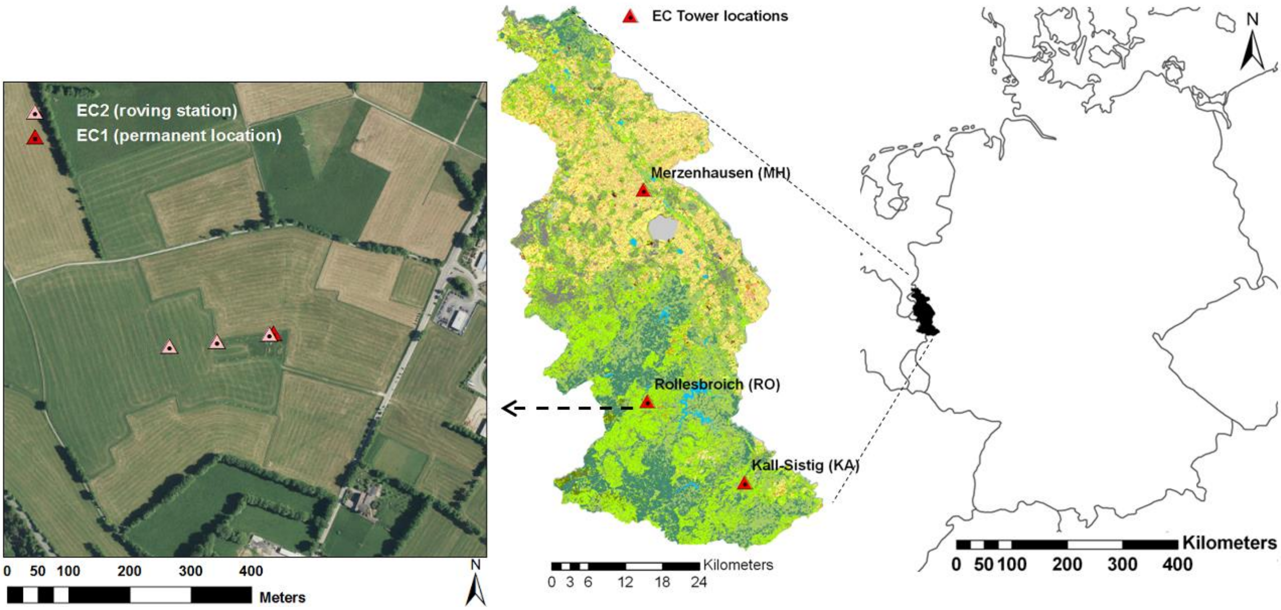

Figure 1. Eddy covariance (EC) tower locations in the Rur Catchment (center) including the Rollesbroich test site (left).

and consistently. Details on the EC data acquisition are summarized in Sect. 3.1.

Rollesbroich is part of the TERENO network (Zacharias et al., 2011). Information and additional data were collected showing that land surface properties are spatially heterogeneous distributed at the Rollesbroich site: (1) single fields at the Rollesbroich site are managed by different farmers; information the land owners provided, as well as periodic camera shots and grass height measurements around the EC towers indicated that the timing of fertilization and grass cutting as well as the amount of manure applied varied between the single fields during the measurement period; (2) soil type distribution as displayed in the German soil map shows heterogeneity (Arbeitsgruppe BK50, 2001); (3) soil carbon and nitrogen pools [$g\,kg^{-1}$] as well as bulk density [$g\,cm^{-3}$] and content of rock fragments [%] measured from April–May 2011 in three soils horizons at 94 locations across the Rollesbroich site are spatially highly variable (H. Schiedung 2013, personal communication); (4) during the eddy covariance measurement period, soil moisture and soil temperature data were collected in 10 min. resolution at three depths (5, 20 and 50 cm) and 84 points by the wireless sensor network ("SoilNet"; Bogena et al., 2009), calibrated for the Rollesbroich site by Qu et al. (2013). SoilNet data shows that soil moisture is heterogeneously distributed within the Rollesbroich site (Qu et al., 2014).

3 Data and methods

3.1 EC data processing

The EC raw data were measured with a frequency of 20 Hz and fluxes were processed for flux intervals of 30 min. The complete processing of the data was performed with the TK3.1 software (Bayreuth, Department of Micrometeorology, Germany; Mauder and Foken, 2011), using the standardized strategy for EC data calculation and quality assurance presented in detail by Mauder et al. (2013). The strategy includes established EC conversions and corrections such as, e.g., correction of spectral loss (Moore, 1986) and correction for density fluctuations (Webb et al., 1980). It includes tests on high-frequency data (site-specific plausibility limits, statistical spike detection) as well as on processed half-hourly fluxes such as stationarity and integral turbulence tests (Foken and Wichura, 1996). The tests on half-hourly fluxes are the basis for a standardized quality flagging according to Mauder and Foken (2011) that classifies flux measurements as high (0), moderate (1) or low (2) quality data. For this analysis only flux measurements assigned to 0 or 1 were used, while low-quality data were treated as missing values. Besides quality flags TK3.1 also provides footprint estimates (Kormann and Meixner, 2001) and uncertainty estimates that were used for interpreting and analyzing flux data. To avoid introduction of additional uncertainty no gap filling of flux time series was performed.

3.2 Uncertainty estimation based on the two-tower approach

The two-tower approach (Hollinger et al., 2004; Hollinger and Richardson, 2005; Richardson et al., 2006) defines the random error of NEE eddy covariance measurements as the standard deviation $\sigma(\delta)$ of the difference between the CO_2 fluxes [$\mu mol\,m^{-2}\,s^{-1}$] simultaneously measured at two different EC towers (NEE_1, NEE_2):

$$\sigma(\delta) = \frac{\sigma\ (NEE_1 - NEE_2)}{\sqrt{2}}. \tag{1}$$

Based on Eq. (1) we calculated the two-tower based uncertainty estimates using the NEE_1 data measured at the permanent EC tower in Rollesbroich (EC1) and the NEE_2 data of a second tower which was either the roving station (EC2) or – in case of the 34 km EC tower distance – another permanent EC tower (EC3, Table 1).

For comparison, the measurement uncertainty $\sigma(\delta)$ was calculated separately for each EC tower distance (Table 1) and independently for each of the following schemes:

1. The classical two-tower approach (Hollinger et al., 2004; Hollinger and Richardson, 2005; Richardson et al., 2006).
2. The classical two-tower approach including a filter for similar weather conditions (Sect. 3.4).
3. The extended two-tower approach with an added correction for systematic flux differences (sfd-correction; Sect. 3.3), without weather filter.
4. The extended two-tower approach with sfd-correction and the previously applied weather filter.

The uncertainty estimate of the two-tower approach is obtained by dividing the NEE data series into several groups ("bins") according to the flux magnitude and then using Eq. (1) to calculate the standard deviation $\sigma(\delta)$ for each group (Richardson et al., 2006). Finally, a linear regression function between the flux magnitude and the standard deviation can be derived. The linear correlation of the uncertainty and the flux magnitude can be explained by the fact that the flux magnitude is a main driving factor for the random error and can explain about 63 % of the variance in the CO_2 flux error as shown in a case study by Richardson et al. (2006). Accordingly, we calculated the standard deviation $\sigma(\delta)$ [$\mu mol\,m^{-2}\,s^{-1}$] based on 12 groups of the CO_2 flux magnitude; six groups for positive and six groups for negative fluxes. (NEE is positive if the amount of CO_2 released to the atmosphere via respiration is higher than the amount of CO_2 assimilated during photosynthesis. In contrast, negative NEE values denote a higher CO_2 uptake and a net flux from the atmosphere into the ecosystem.) Fixed class limits for the flux magnitude would have led to a different number of samples in each group. Now class limits were set such that all groups with positive NEE values had an equal amount of half-hourly data, the same holds for all groups with negative NEE values. For each single group the standard deviation $\sigma(\delta)$ was calculated using the single half-hourly flux differences of NEE_1 and NEE_2. The corresponding mean NEE magnitude for each group member was determined by averaging all half-hourly means of NEE_1 and NEE_2 in the respective group. Then, the linear regression equation was derived separately for negative and positive NEE values using the six calculated standard deviations $\sigma(\delta)$ and the six mean NEE values. This procedure was carried out for each data set of the five EC tower distances and again for each of the four uncertainty estimation schemes so that altogether 20×2 linear regression equations were derived. The significance of the correlation between the NEE magnitudes and the standard deviations $\sigma(\delta)$ was tested with the p-value determined with Student's t-test based on Pearson's product moment correlation coefficient r. Moreover, the 95 % confidence intervals of the slope and the intercept for each linear regression equation were determined. The linear regression equations were calculated imposing as constraint an intercept ≥ 0, because a negative standard deviation is not possible. With those linear regression equations, the uncertainty for the individual half-hourly NEE measurement values of the permanent EC tower in Rollesbroich (EC1) were estimated using the individual half-hourly NEE_1 values [$\mu mol\,m^{-2}\,s^{-1}$] as input (x) to calculate the corresponding uncertainty $\sigma(\delta)$ [$\mu mol\,m^{-2}\,s^{-1}$] (y).

The described calculation of the individual NEE uncertainty values was done for all half-hourly NEE data, including those data points that were discarded by the weather filter (Sect. 3.4) and/or the sfd-correction (Sect. 3.3). Hence, for each of the four two-tower based uncertainty estimation schemes the same amount of individual NEE uncertainty values was generated. These mean uncertainty estimates were used to evaluate the effect of the EC tower distance as well as the sfd-correction and the weather filter on the two-tower based uncertainty estimation. Even though Hollinger et al. (2004) and Richardson and Hollinger (2005) already pointed out that the two-tower approach assumes similar environmental conditions and non-overlapping footprints, we applied the classical approach for all EC tower distances, even if these basic assumptions were not fulfilled, to allow for a comparison of the results before and after the usage of the weather filter and the sfd-correction (extended two-tower approach).

3.3 Correction for systematic flux differences (sfd-correction)

Different environmental conditions and other factors such as instrumental calibration errors can cause systematic flux differences between two towers. Because these flux differences are not inherent to the actual random error of the measured NEE at one EC tower station they lead to an overestimation of the two-tower approach based uncertainty. Therefore, we extended the classical two-tower approach with a simple correction step for systematic flux differences (sfd-correction). The reason why systematic flux differences can statistically be separated quite easily from random differences of the EC flux measurements is their fundamentally different behavior in time: random differences fluctuate highly in time whereas systematic differences tend to be constant over time or vary slowly. The sfd-correction introduced is similar to the second correction step in Kessomkiat et al. (2013, Eq. (6) therein), but adapted to the measured NEE instead of latent and sensible heat fluxes. An averaging time interval of 12 hours was used to calculate the running mean for the sfd-correction. For each moving average interval, the mean NEE_{12h} of one EC tower (separately for EC1 and EC2) [$\mu mol\,m^{-2}\,s^{-1}$] and the mean CO_2 flux averaged over both EC towers NEE_{2T_12h} [$\mu mol\,m^{-2}\,s^{-1}$] were calculated to define the sfd-correction term which was used to calculate the corrected NEE_{corr} [$\mu mol\,m^{-2}\,s^{-1}$]:

$$NEE_{corr} = \frac{NEE_{2T\_12hr}}{NEE_{12h}} \times NEE, \tag{2}$$

where NEE is the single half-hourly, processed NEE value [$\mu mol\,m^{-2}\,s^{-1}$] of one EC tower. Only if both NEE data, NEE_{-EC1-} for the permanent EC1 tower and NEE_{-EC2-} for the second tower, were available at a particular half-hourly time step and if both values were either positive or negative, the respective data were included to calculate the correction term. The running averages were only calculated if at least 50 % of the data for NEE_{-EC1-} and NEE_{-EC2-} remained for averaging in that particular window. Due to the frequent occurrence of gaps in the data series the amount of available NEE_{corr} values considerably decreased by applying stricter criteria like 70 % or 90 % data availability (Table A2 in Appendix). We assume a 12 h averaging period to be long enough to exclude most of the random error part but short enough to consider daily changes of systematic flux differences. For a 6 h interval for instance, the uncertainty of the mean NEE is usually higher. For larger window sizes (24 or 48 h) further analysis was hampered by too many data gaps – i.e., the 50 % criterion was hardly ever fulfilled and not enough averages remained to allow for the two-tower based uncertainty estimation (Table A2). The correction was done separately for positive and negative fluxes, due to the different sources, properties and magnitudes of the CO_2 flux measurements and different errors for daytime (negative) and night-time (positive) fluxes (e.g., Goulden et al., 1996; Oren et al., 2006; Wilson et al., 2002).

The final sfd-corrected $NEE1_{corr}$ values for EC1 and $NEE2_{corr}$ values for EC2 should not be understood as corrected NEE flux data. They were used only to enhance the two-tower based uncertainty estimation in a way that systematic flux differences which cause an overestimation of the uncertainty are filtered out. Moreover, systematic flux differences at two EC towers are not to be confused with systematic errors, which are independent of the uncertainty estimation method and optimally corrected before the random error is estimated.

3.4 Filter for weather conditions

For larger distances of two EC towers, such as the 20.5 and 34 km distance in this study, different weather conditions can cause differences of the measured fluxes in addition to the different land surface properties. Some weather variables (e.g., temperature) are following a clear diurnal and annual course and differences in, e.g., temperature at two EC towers are therefore relatively constant. This is expected to cause rather systematic differences in the measured NEE which can be captured with the sfd-correction. However, other variables such as wind speed or incoming shortwave radiation are spatially and temporally much more variable, for example related to single wind gusts or cloud movement. Differences in the measured fluxes at two EC towers caused by those spatial–temporally highly variable weather variables cannot be captured well with the sfd-correction term due to this "random character". However, a weather filter can account for this because it compares the differences in weather variables at each single time step. Therefore a filter for similar weather conditions was applied in addition to the sfd-correction following Hill et al. (2012) and Richardson et al. (2006) to only include half-hourly NEE data, if the weather conditions at the second EC tower are similar to those at the permanent EC1 tower location in Rollesbroich. Following the definition in Richardson et al. (2006), similar weather conditions were defined by a temperature difference $< 3\,°C$; wind speed difference < 1 m/s and difference in PPFD $< 75\ \mu mol\,m^{-2}\,s^{-1}$. The weather filter was applied before the (classical) uncertainty estimation and the sfd-correction. As shown, e.g., in Tsubo and Walker (2005), the incoming shortwave radiation (or solar irradiance SI) and the photosynthetically active radiation (PAR) are linearly correlated. Accordingly SI and PPFD measured at the EC1 station in Rollesbroich were also linearly correlated. Because direct PPFD measurements were not available for all measurement periods, we derived a linear regression equation on the basis of all SI and PPFD data for the permanent EC tower station (EC1). Using this equation, missing PPFD values were estimated if only SI but no PPFD data were available at a certain time step.

3.5 Footprint analysis

The footprint analysis was applied to quantify the percentage footprint overlap of the two EC-stations during the measurement periods. This information was not used to filter the data but to allow for a better understanding of the mean uncertainty estimates for the different scenarios. Using the analytical model of Kormann and Meixner (2001) implemented in the TK3.1 software (Mauder and Foken, 2011), a grid of estimated source weights (resolution 2 m, extension 1 km by

1 km) was computed for each half-hour and station position. The overlap between the footprints of two simultaneously measuring towers was then quantified as

$$O_{12}(t) = \sum_{x=1}^{N}\sum_{y=1}^{M} \min(f_1(x,y,t), f_2(x,y,t)). \quad (3)$$

The indices 1 and 2 indicate the tower and t the time (in our case, half-hour). N and M are the number of pixels in east–west and north–south direction, x and y the respective running indices. The minimum function min includes the source weight f computed for the respective tower, x and y location, and half-hour. The O is 1 if both source weight grids are identical, and 0 in the case of no overlap. During stable conditions, the footprint area of a tower increases and can result in considerable source weight contributions from outside the modeling domain. Assuming that two footprints which overlap highly in the modeling domain likely continue to overlap outside the modeling domain, O as defined above might be low-biased in such cases. We therefore additionally considered a normalized version $O/\min(\Sigma\Sigma f_1, \Sigma\Sigma f_1)$ as an upper limit estimate of the overlap. The overlap for the additional sites Kall and Merzenhausen more than 20 km away was assumed to be zero.

3.6 Comparison measures

To compare and evaluate the two-tower based uncertainty estimates, we calculated random error estimates based on Mauder et al. (2013) as a reference. This reference method is independent of the two-tower based approach, because data of only one EC tower are used to quantify the random error of the measured fluxes and raw data instead of the processed fluxes are used. The raw-data based random error estimates – the instrumental noise $\sigma_{\text{cov}}^{\text{noise}}$ and the stochastic error $\sigma_{\text{cov}}^{\text{stoch}}$ – were calculated independently. Mauder et al. (2013) determine the instrumental noise based on signal autocorrelation. Following Finkelstein and Sims (2001) the stochastic error is calculated as the statistical variance of the covariance of the flux observations. Generally, $\sigma_{\text{cov}}^{\text{noise}}$ was considerably lower than $\sigma_{\text{cov}}^{\text{stoch}}$. The total raw-data based random error σ_{cov} [µmol m^{-2} s^{-1}] was calculated by adding $\sigma_{\text{cov noise}}$ and $\sigma_{\text{cov stoch}}$ "in quadrature" ($\sigma_{\text{cov}} = \sqrt{\sigma_{\text{cov stoch}^2} + \sigma_{\text{cov noise}^2}}$) according to Aubinet et al. (2011, p.176). The mean reference σ_{cov} used for the evaluation of the two-tower based random error estimates was calculated by averaging the single half-hourly σ_{cov} values for the permanent EC1 tower in Rollesbroich. In order to be consistent with the two-tower based calculations, exactly the same half-hourly time steps of the EC1 data series used for the two-tower based uncertainty estimation were used to calculate the corresponding mean reference values σ_{cov}. As indicator for the performance of the two-tower based uncertainty estimation schemes applied for the five different EC tower distances, the relative difference $\Delta\sigma_{\text{cov}}$ [%] of a two-tower based uncertainty value [µmol m^{-2} s^{-1}] and σ_{cov} [µmol m^{-2} s^{-1}] was calculated:

$$\Delta\sigma_{\text{cov}}\,[\%] = \frac{\sigma(\delta) - \sigma_{\text{cov}}}{\sigma_{\text{cov}}} \times 100. \quad (4)$$

Then, $\Delta\sigma_{\text{cov}}$ values were compared for the different EC tower separation distances and two-tower based uncertainty estimation schemes. The performance of the two-tower based uncertainty estimation was considered better if σ_{cov} [%] was closer to zero.

4 Results

4.1 Classical two-tower based random error estimates

Figures 2 and 3 show the linear regressions of the random error $\sigma(\delta)$ (also referred to as "standard error" or "uncertainty") as function of the NEE magnitude according to the classical two-tower approach for the different EC tower distances without weather filter (Fig. 2) and with weather filter (Fig. 3). The dashed linear regression lines denote that the linear correlation between $\sigma(\delta)$ and NEE is weak ($p > 0.1$), which is in particular true for the positive NEE values measured for 173 m and 20.5 km EC tower distances as well as for the negative NEE values for 20.5 and 34 km distance. The 95 % confidence intervals of the respective slopes and the intercepts are summarized in the Appendix (Table A1). Uncertainty estimation with the classical two-tower approach is critical for those larger distances because measured flux differences caused by different environmental conditions at both EC towers can superimpose the random error signal which, e.g., originates from instrumental or turbulence sampling errors. This weakens the correlation of the random error and the flux magnitude. This is not surprising since Hollinger et al. (2004) and Richardson and Hollinger (2005) already pointed out that similar environmental conditions are a basic assumption of the two-tower approach. Therefore, statements of how the weather filter affects the mean uncertainty estimate $\sigma(\delta)$ for those large distances need to be treated with caution.

The weather filtering only increased the correlation between the flux magnitude and the random error $\sigma(\delta)$ for positive fluxes for separation distances of 173 m and 20 km whereas in most cases the linear correlation was weakened, mainly due to a decreased number of samples in each averaging group of the NEE flux magnitude. Therefore, testing stricter weather filter criteria (e.g., wind speed < 0.5 m s^{-1}, PPFD < 50 µmol m^{-2} s^{-1}, Temp < 2 °C), which caused a decline of samples in each group from, e.g., $n > 1000$ to 24 or less, resulted in little meaningful results.

As illustrated in Table 2, the mean NEE uncertainty estimate based on the classical two-tower approach increased as a function of EC tower distance. However, without applying the weather filter, the mean uncertainty $\sigma(\delta)$ was nearly identical for the two largest distances (20.5 and 34 km), although,

Table 2. Mean NEE uncertainty [$\mu mol\,m^{-2}\,s^{-1}$] for five EC tower distances estimated with the classical two-tower approach, with and without including a weather filter ($\sigma(\delta)$, $\sigma(\delta)_f$). and with the extended two-tower approach (sfd-correction), also with and without including a weather filter ($\sigma(\delta)_{corr}$, $\sigma(\delta)_{corr,f}$). The table also provides the random error σ_{cov} [$\mu mol\,m^{-2}\,s^{-1}$] estimated with the raw-data based reference method (Mauder et al., 2013).

EC tower distance	N	$\sigma(\delta)$ ($\Delta\sigma_{cov}$)	$\sigma(\delta)_f$ ($\Delta\sigma_{cov}$)	$\sigma(\delta)_{corr}$ ($\Delta\sigma_{cov}$)	$\sigma(\delta)_{corr,f}$ ($\Delta\sigma_{cov}$)	σ_{cov}
8 m	3167	0.76 (18.8)	0.77 (20.5)	0.44 (−30.6)	0.44 (−30.8)	0.64
95 m	3620	1.30 (116.7)	1.50 (149.4)	0.65 (8.2)	0.60 (0.2)	0.60
173 m	2410	2.04 (98.5)	1.82 (77.0)	1.03 (−0.3)	1.00 (−2.5)	1.03
20.5 km	2574	2.72 (200.6)	2.35 (159.7)	1.52(67.8)	1.16 (28.7)	0.91
34 km	15571	2.73 (274.7)	2.86 (292.4)	1.18 (61.5)	1.14 (56.8)	0.73
mean		1.91	1.86	0.98	0.93	0.78

($\Delta\sigma_{cov}$): relative differences [%] between two-tower based uncertainty estimates and the references value σ_{cov} (Eq. 4)

e.g., the land cover and management in Merzenhausen (EC3 tower at 34 km separation) were different from the Rollesbroich site. As a result of the weather filtering, the mean uncertainty was less overestimated for the distances 173 m and 20.5 km. However, for the 95 m and 34 km distance, the overestimation of the uncertainty estimate increased by the weather filtering (Table 2). This implies that for the classical two-tower approach (without sfd-correction) weather filtering did not clearly reduce the overestimation of the uncertainty for largest EC tower distances (20.5 and 34 km) where weather filtering is expected to be particularly relevant.

Comparing the mean uncertainty estimates of the classical two-tower approach with the reference random error estimates σ_{cov} indicates that both with and without weather filter the uncertainties were overestimated (Table 2), for all EC tower differences. This could be expected for the large distances, because basic assumptions for the application of the classical two-tower approach are violated for these large distances. But results illustrate that even for short EC tower distances NEE uncertainty estimated with the classical two-tower approach is larger than the raw-data based estimates (Table 2).

4.2 Extended two-tower approach

The scatter plots in Fig. 4 illustrate the effect the sfd-correction (Eq. 2) had on the difference of the NEE data simultaneously measured at both EC towers (NEE_{-EC1-} and NEE_{-EC2-}). The sfd-correction reduced the bias and scattering, because systematic differences of the measured fluxes, e.g. induced by different environmental conditions, were removed. As expected, the effect of the sfd-correction was considerably higher for the larger EC tower distances because environmental conditions are also expected to differ more if the distance of two locations is larger. For the 8 m EC tower distance for instance, the effect of the sfd-correction is very minor because footprints are often nearly overlapping. However, for the EC tower distances $\geq$ 173 m, the bias and scattering of NEE_{-EC1-} and NEE_{-EC2-} was considerably reduced by the sfd-correction.

A comparison of Figs. 2 and 5 illustrates how the sfd-correction affected the linear regression of the NEE standard error as function of NEE flux magnitude: the sfd-correction considerably enhanced the correlation of NEE_{corr} and the standard error $\sigma(\delta)_{corr}$ for the EC tower distances 20.5 and 34 km from $R^2 \geq 0.15$ to $R^2 \geq 0.43$.

Applying the sfd-correction (without weather filter) reduced the mean uncertainty value by 41.6 to 56.9 % for the EC tower distances from 8m to 34 km. The relative differences $\Delta\sigma_{cov}$ indicate that the correction for systematic flux differences considerably improved the two-tower based uncertainty estimate for the distances > 8 m (Table 2): the difference $\Delta\sigma_{cov}$ was notably smaller (< 56.8 %) for all distances except the 8 m distance compared to $\Delta\sigma_{cov}$ determined with the classical two-tower approach (< 274.7 %). The most considerable improvement was achieved for the 95 m EC tower distance and the 173 m distance. Additional application of the weather filter (Fig. 6) on the sfd-corrected NEE_{corr} data reduced the mean uncertainty estimate $\sigma(\delta)_{corr}$ by 23.3 and 2.9 % for the 20.5 km and the 34 km EC tower distance and reduced $\Delta\sigma_{cov}$ by 57.7 and 7.7 %. The effect of the weather filter on the uncertainty estimates of the shorter EC tower distances was very minor (Table 2). The uncertainty estimates $\sigma(\delta)_{corr,f}$ determined with the extended two-tower approach agree best with the independent reference values σ_{cov} for the EC tower distances 95 and 173 m, suggesting that those distances were most suitable for the application of the extended two-tower approach.

4.3 Discussion

The results show that the two-tower based uncertainty estimates (both classical and extended two-tower approach) were smallest for the 8 m distance. This can be explained with the results of the footprint analysis: while the average percentage footprint overlap is 13 % (normalized 19 %) for

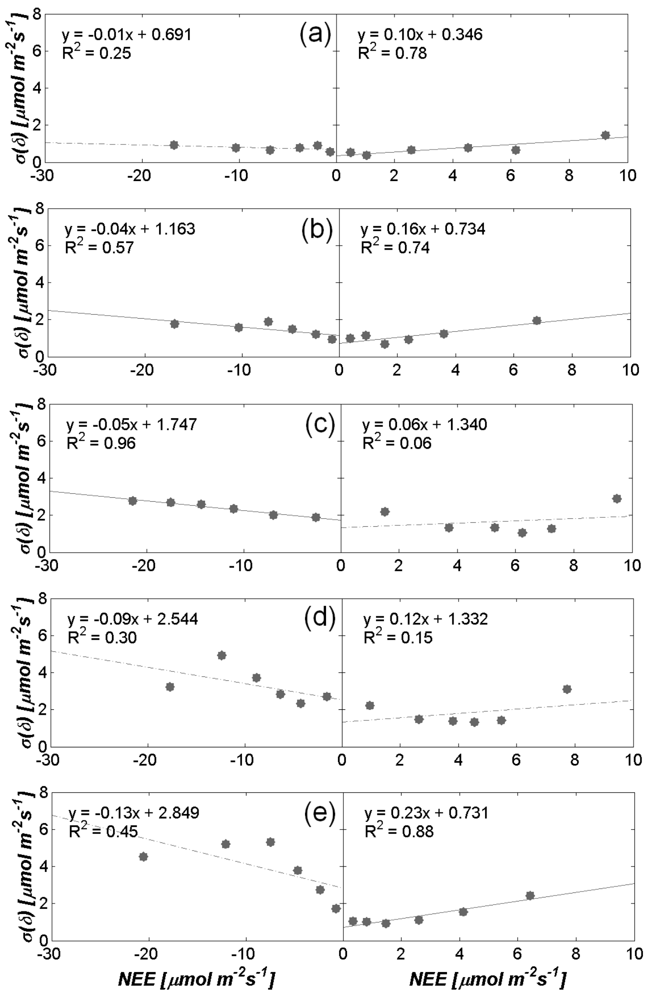

Figure 2. NEE uncertainty $\sigma(\delta)$ determined with the classical two-tower approach as function of the NEE flux magnitude for the EC tower distances 8 m **(a)**, 95 m **(b)**, 173 m **(c)**, 20.5 km **(d)** and 34 km **(e)**; dashed line: linear correlation not significant ($p > 0.1$).

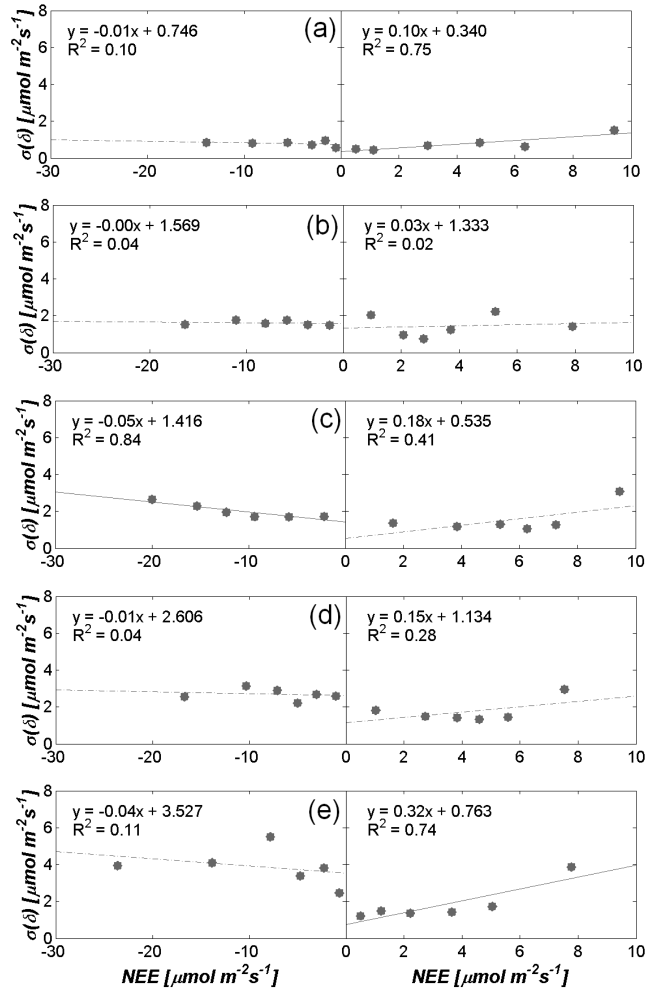

Figure 3. NEE uncertainty $\sigma(\delta)$ determined with the classical two-tower approach as function of the NEE flux magnitude including the application of the weather filter for the EC tower distances 8 m **(a)**, 95 m **(b)**, 173 m **(c)**, 20.5 km **(d)** and 34 km **(e)**; dashed line: linear correlation not significant ($p > 0.1$).

the 95 m EC tower distance and only 4 % (7 %) for the 173 m EC tower distance, it is 68 % (80 %) for the 8 m EC tower distance. The stronger overlap of the 8 m distance footprint areas is associated with a more frequent sampling of the same eddies. As a consequence, part of the random error was not captured with the two-tower approach. If EC towers are located very close to each other (< 10 m) and the footprint overlap approaches 100 %, only instrumental errors and stochasticity related to sampling of small eddies will be captured with the two-tower based uncertainty estimate. Because the EC measurements are statistically not independent if the footprints are overlapping, the classical EC tower method is not expected to give reliable uncertainty estimates for very short EC tower distances (Hollinger et al., 2004; Hollinger and Richardson, 2005). However, without applying the sfd-correction, the mean uncertainty estimate $\sigma(\delta)$ was higher than the raw-data based reference value σ_{cov} which includes both the instrumental noise $\sigma_{\text{cov}}^{\text{noise}}$ and the stochastic error $\sigma_{\text{cov}}^{\text{stoch}}$. The raw-data based $\sigma_{\text{cov}}^{\text{noise}}$ itself was only 0.04 μmol m^{-2} s^{-1} of 0.64 μmol m^{-2}s $^{-1}$ for the data set of the 8 m EC tower distance. The mean uncertainty value derived with the extended two-tower approach $\sigma(\delta)_{\text{corr,f}}$ for the same data set was lower than $\sigma(\delta)$ but still considerably higher than $\sigma_{\text{cov}}^{\text{noise}}$, suggesting that even at 8 m EC tower distance instrumentation errors were only a minor part of the two-tower based uncertainty estimate. For the larger separation distances 95 m or 173 m with notably less footprint overlap, turbulence sampling errors are almost fully accounted for by a two-tower approach. (It should be noted that forest stations, with a typically larger aerodynamic measurement height and footprint size, will require larger separation distances). However, different land surface properties and management are more likely for the larger separation distances

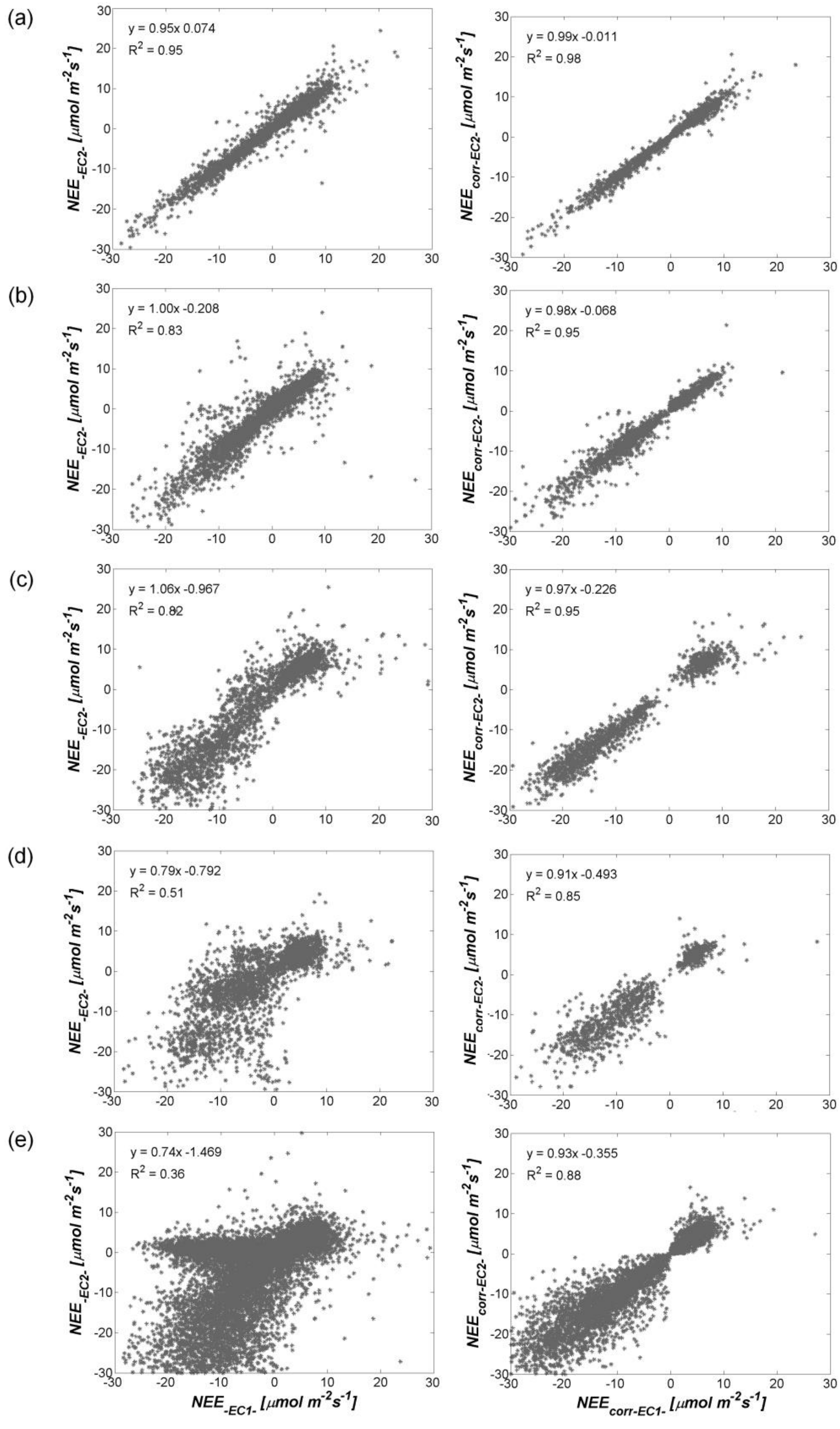

Figure 4. Scatter of the NEE measured at EC1 (NEE_{-EC1-}) and NEE measured at a second tower EC2/EC3 (NEE_{-EC2-}) for the uncorrected NEE (left) and the sfd-corrected NEE_{corr} (right) for the EC tower distances 8 m **(a)**, 95 m **(b)**, 173 m **(c)**, 20.5 km **(d)** and 34 km **(e)**.

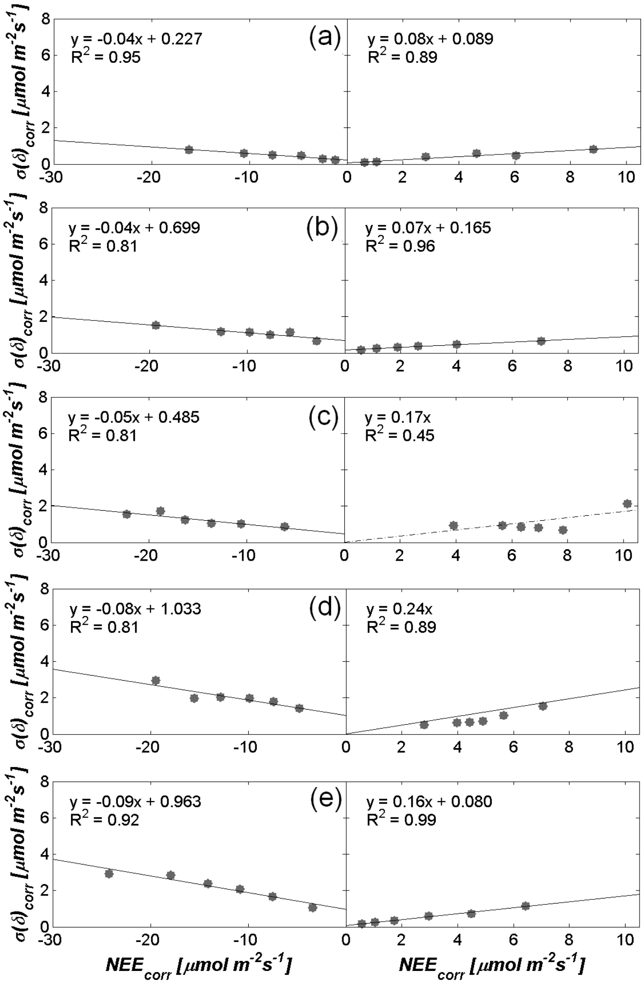

Figure 5. NEE uncertainty $\sigma(\delta)_{\mathrm{corr}}$ determined with the extended two-tower approach as function of sfd-corrected $\mathrm{NEE_{corr}}$ magnitude (Eq. 2) for the EC tower distances 8 m **(a)**, 95 m **(b)**, 173 m **(c)**, 20.5 km **(d)** and 34 km **(e)**; dashed line: linear correlation not significant ($p > 0.1$).

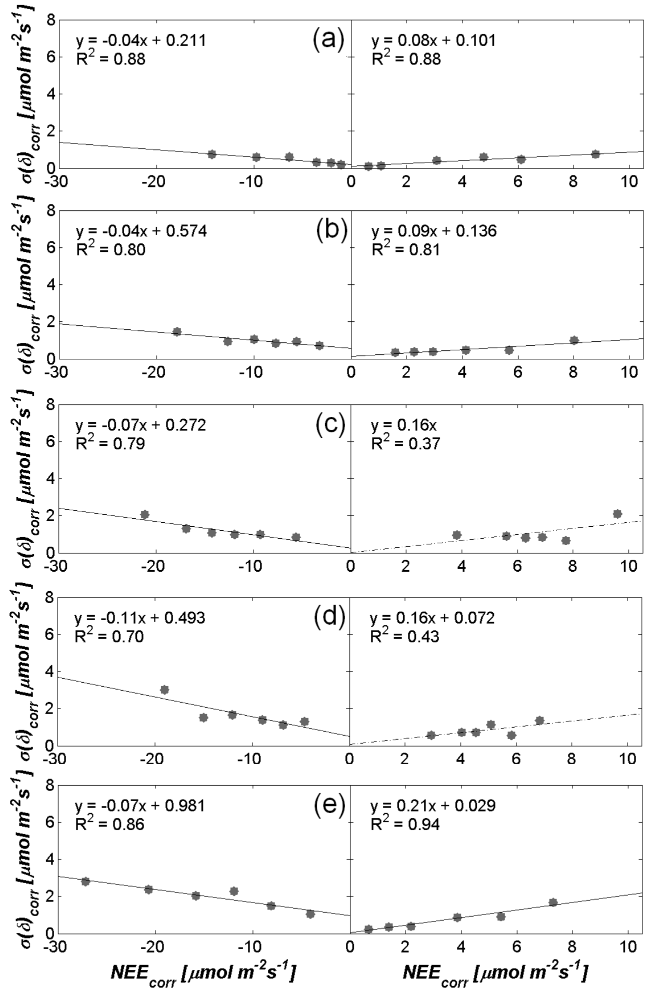

Figure 6. NEE uncertainty $\sigma(\delta)_{\mathrm{corr}}$ determined with the extended two-tower approach as function of sfd-corrected $\mathrm{NEE_{corr}}$ magnitude (Eq. 2) including application of the weather filter for the EC tower distances 8 m **(a)**, 95 m **(b)**, 173 m **(c)**, 20.5 km **(d)** and 34 km **(e)**; dashed line: linear correlation not significant ($p > 0.1$).

and can cause systematic flux differences that should not be attributed to the random error estimate. As outlined in Sect. 2, land surface properties related to management (e.g., nutrient availably due to fertilization), soil properties (bulk density, skeleton fraction), soil carbon–nitrogen pools, soil moisture and soil temperature are heterogeneously distributed at the Rollesbroich site. The effect of soil moisture, soil temperature and soil properties on CO_2 fluxes (respiration mainly) is well known (e.g., Herbst et al., 2009; Flanagan and Johnson, 2005; Xu et al., 2004; Lloyd and Taylor, 1994; Orchard and Cook, 1983) as well as the role of grassland management (e.g., Allard et al., 2007). Results indicate that an overestimation of the two-tower based uncertainty caused by different land surface properties in the footprint area of both EC towers can be successfully filtered out by the extended approach. It should be noted that a shorter moving average interval of the sfd-correction term (e.g., 6 h instead of the applied 12 hours window; Table A2) results in slightly lower uncertainty estimates compared to the reference. This can be explained by a possible "over-correction" of the NEE data related to a too-short moving average interval for calculating the sfd-correction term. It needs to be emphasized that the estimated mean NEE values of the moving average intervals are associated with uncertainty. As mentioned, the moving average interval should be long enough to exclude random differences of the simultaneously measured fluxes but short enough to limit the impact of non-stationary conditions. However, the 12 h running mean $\mathrm{NEE_1}$ and $\mathrm{NEE_2}$ values ($\mathrm{NEE_{12}}$) as well as the respective means of $\mathrm{NEE_1}$ and $\mathrm{NEE_2}$ ($\mathrm{NEE_{2T\_12}}$) used to calculate $\mathrm{NEE_{corr}}$ (Eq. 2) are uncertain because they still contain the random error part which cannot be corrected or filtered out. This uncertainty in the mean is expected to be higher for a shorter averaging interval such as 6 h. Therefore, completely correcting the difference in mean NEE slightly overcorrects systematic differences in NEE. In general results were not very sensitive to different moving average sizes of the sfd-correction term and data coverage percentages defined for this interval (Table A3).

It is expected that systematic differences in measured NEE caused by spatially variable land surface properties are stronger during the night than during the day since they affect respiration more directly than photosynthesis (see, e.g., Oren et al., 2006). Moreover, during night-time and/or winter (positive NEE), some conditions associated with lower EC data quality such as low turbulence, strong stability, and liquid water in the gas analyzer path prevail more often than in summer and/or daytime (negative NEE). The less severe cases of such conditions are not always completely eliminated by the quality control. In time series of eddy-covariance fluxes this typically shows up as implausible fluctuations of the flux during calm nights. This is reflected by plots of NEE flux magnitude versus uncertainty (Figs. 2–3, 5–6) showing higher uncertainties for positive compared to negative NEE data which agrees with previous findings (e.g., Richardson et al., 2006).

At very large EC tower distances (20.5 km, 34 km) footprints were not overlapping and the environmental conditions were considerably different; in particular for the EC tower setup Rollesbroich/Merzenhausen with different land use (grassland/crop) and climate conditions. For those distances, the relative difference $\Delta\sigma_{\text{cov}}$ between σ_{cov} and $\sigma(\delta)$ (classical two-tower approach) was much larger than $\Delta\sigma_{\text{cov}}$ between σ_{cov} and $\sigma(\delta)_{\text{corr,f}}$ (extended two-tower approach). $\Delta\sigma_{\text{cov}}$ was reduced by 85.7 % for the 20.5 km distance and 79.3 % for the 34 km if both sfd-correction and weather filter were used. However, after applying the sfd-correction and the weather filtering, the mean uncertainty estimate was still higher than the raw-data based reference value (Table 2), suggesting that for these large EC tower distances the sfd-correction and the weather filter do not fully capture systematic flux differences and that uncertainty is still overestimated by the extended two-tower approach. This can have different reasons. We assume the major reason is that the weather filter is supposed to capture all measured flux differences that can be attributed to different weather conditions at both EC towers which cannot be captured with the sfd-correction. Applying stricter thresholds could increase the efficiency of the weather filter but in our case the reduced data set was too small to allow further analysis. In general, the weather filter did not improve the uncertainty estimates as much as the sfd-correction. However, this does not imply that differences in weather conditions are negligible when applying the extended two-tower approach for larger EC tower distances. In fact the systematic part of measured EC flux differences between both towers caused by (steady, systematic) among-site differences in weather conditions were already partly captured with the sfd-correction. In contrast, such systematic differences were difficult to capture with the weather filter because much lower thresholds would have been required.

The absolute corrected and weather filtered uncertainty value $\sigma(\delta)_{\text{corr,f}}$ [μmol m^{-2} s^{-1}] was slightly lower for the 34 km EC tower distance than for the 20.5 km EC tower distance (Table 2). The raw-data based reference σ_{cov} [μmol m^{-2} s^{-1}] however was also smaller for the 34 km data set than for the 20.5 km data set which can be related to the different lengths and timing (i.e., different seasons) of the measurement periods for each of the five EC tower distances: The roving station was moved from one distance to another within the entire measurement period of ~ 27 months. During this entire time period of data collection, the length and timing of the single measurement periods varied for the five EC tower separation distances (Table 1). This is not optimal because the random error is directly related to the flux magnitude and the flux magnitude itself is directly related to the timing of the measurements. Because in spring and summer flux magnitudes are higher, the random error is generally higher as well (Richardson et al., 2006). To reduce this effect, we captured spring/summer as well as autumn/winter months in each measurement period. However, the timing of the measurements and the amount of data available were not the same for the five EC data sets. In particular the permanent EC tower in Merzenhausen was measuring considerably longer (> 2 years) than the roving station did for the other four EC tower distances. Therefore, differences of the mean uncertainty estimates for the five measurement periods were partly independent of the EC tower distance. This effect gets obvious when looking at the mean uncertainties σ_{cov} estimated with the reference method, which should be independent of the distance but were also found to be different for each data set of the five EC tower distances. Against this background, statements about how EC tower distances affect the two-tower based uncertainty estimate need to be treated with caution.

The NEE uncertainty $\sigma(\delta)_{\text{corr,f}}$ estimated for the grassland site Rollesbroich agrees well with the NEE uncertainty values for grassland sites by Richardson et al. (2006), and also the regression coefficients (Figs. 2–3, 5–6, Table A1) do not show large differences. This can be expected since Richardson et al. (2006) applied their method for a very well-suited tower pair with low systematic differences, such that the classical approach and our extended approach should approximately converge. However, identical results are unlikely because even for two very similar neighboring sites some systematic differences occur. In addition, the random error is expected to vary between sites (see, e.g., Mauder et al., 2013) which is in part related to instrumentation.

5 Conclusions

When estimating the uncertainty of eddy covariance net CO_2 flux (NEE) measurements with a two-tower based approach it is important to consider that the basic assumptions of identical environmental conditions (including weather conditions and land surface properties) on the one hand and non-overlapping footprints on the other hand are contradicting and impossible to fulfill. If the two EC towers are located at a distance large enough to ensure non-overlapping footprints, different environmental conditions at both EC towers can cause systematic differences of the simultaneously measured fluxes that should not be included in the uncertainty estimate. This study for the grassland site Rollesbroich in Germany showed that the extended two-tower approach which includes a correction for systematic flux differences (sfd-correction) can be used to derive more reliable (less overestimated) uncertainty estimates compared to the classical two-tower approach. An advantage of this extended two-tower approach is its simplicity and the fact that there is no need to quantify the differences in environmental conditions (which is usually not possible due to a lack of data). Comparing the uncertainty estimates for five different EC tower distances showed that the mean uncertainty estimated with our extended two-tower approach for the 95 and 173 m distances were nearly identical to the random error estimated with the raw-data based reference method. This suggests that these distances were most appropriate for the application of the extended two-tower approach in this study. Accordingly, we consider the regressions in Fig. 6b, c to be most reliable. Also for the largest EC tower distances (20.5 km, 34 km) the sfd-correction significantly improved the correlations of the flux magnitude and the random error and significantly reduced the difference to the independent, raw-data based reference value. We therefore conclude that if no second EC tower is available at a closer distance (but available further away), a rough, probably overestimated NEE uncertainty estimate can be acquired with the extended two-tower approach although environmental conditions at the two sites are not identical.

A statement about the transferability of our experiment to other sites and EC tower distances requires further experiments. However, we assume transferability is given if both EC towers are located at sites of the same vegetation type (e.g., C3-grasses, C4-crops, deciduous forest, coniferous forest). Flux differences caused by a different phenology can be very hard to separate from the random error estimate, even though they are expected to be mainly systematic and could therefore be partly captured with the sfd-correction. Moreover, the EC raw data should be processed in the same way (as done here) and the measurement devices should be identical and installed at about the same measurement height. It is also important that the instruments are calibrated thoroughly and consistently. Because this was true for the three EC towers included in this study, we conclude that systematic flux differences that are corrected for with the sfd-correction arise mainly from different environmental conditions whereas calibration errors are assumed to have a very minor effect. Different weather conditions at both EC tower sites are a main drawback for applications of the two-tower approach. While systematic differences of the weather conditions are expected to be captured by the sfd-correction, less systematic weather fluctuations – e.g., related to cloud movement – are difficult to be filtered of the two-tower based uncertainty estimate. Applying very strict thresholds can lead to a too-small data set, especially if the measurement periods are short. If EC raw data are available, we recommend to use an uncertainty estimation scheme like the one presented in Mauder et al. (2013). Raw-data based NEE uncertainty estimation methods like the one suggested by Finkelstein and Sims (2001) and implemented by Mauder et al. (2013) have not been extensively applied yet and – to the best of our knowledge – never been compared to the ones derived with the more well-known two-tower approach. The fact that the two uncertainty estimates (extended two-tower approach and raw-data based reference) give very similar results therefore contributes to the confidence in both methods.

Appendix A

Table A1. Summary of the 95 % confidence intervals for the linear regression coefficients of the NEE magnitudes – standard error relationships determined with Eq. (1) for the four two-tower based correction schemes and the five EC tower distances

Variables:	Two towers:	m	m_{lower}	m_{upper}	b	b_{lower}	b_{upper}
$NEE_{negative}/\sigma(\delta)$	EC1/EC2 (8 m)	−0.012	−0.041	0.017	0.691	0.442	0.940
	EC1/EC2 (95 m)	−0.045	−0.099	0.010	1.163	0.680	1.647
	EC1/EC2 (173 m)	−0.052	−0.067	−0.036	1.747	1.537	1.957
	EC1/EC2 (20.5 km)	−0.088	−0.272	0.097	2.544	0.696	4.392
	EC1/EC3 (34 km)	−0.130	−0.330	0.069	2.849	0.772	4.926
$NEE_{negative}/\sigma(\delta)_f$	EC1/EC2 (8 m)	−0.008	−0.043	0.026	0.746	0.497	0.995
	EC1/EC2 (95 m)	−0.005	−0.036	0.026	1.569	1.286	1.853
	EC1/EC2 (173 m)	−0.055	−0.088	−0.021	1.416	1.009	1.824
	EC1/EC2 (20.5 km)	−0.011	−0.087	0.066	2.606	1.929	3.284
	EC1/EC3 (34 km)	−0.039	−0.190	0.113	3.527	1.737	5.317
$NEE_{negative}/\sigma(\delta)_{corr}$	EC1/EC2 (8 m)	−0.036	−0.048	−0.024	0.227	0.125	0.329
	EC1/EC2 (95 m)	−0.043	−0.072	−0.014	0.699	0.379	1.018
	EC1/EC2 (173 m)	−0.052	−0.087	−0.017	0.485	−0.059	1.030
	EC1/EC2 (20.5 km)	−0.085	−0.142	−0.028	1.033	0.312	1.754
	EC1/EC3 (34 km)	−0.092	−0.129	−0.055	0.963	0.421	1.505
$NEE_{negative}/\sigma(\delta)_{corr,f}$	EC1/EC2 (8 m)	−0.040	−0.060	−0.019	0.211	0.053	0.369
	EC1/EC2 (95 m)	−0.044	−0.074	−0.013	0.574	0.252	0.895
	EC1/EC2 (173 m)	−0.071	−0.122	−0.021	0.272	−0.440	0.983
	EC1/EC2 (20.5 km)	−0.106	−0.204	−0.009	0.493	−0.685	1.671
	EC1/EC3 (34 km)	−0.070	−0.108	−0.031	0.981	0.346	1.616
$NEE_{positive}/\sigma(\delta)$	EC1/EC2 (8 m)	0.101	0.027	0.174	0.346	−0.024	0.715
	EC1/EC2 (95 m)	0.161	0.028	0.294	0.734	0.285	1.183
	EC1/EC2 (173 m)	0.061	−0.284	0.406	1.340	−0.775	3.455
	EC1/EC2 (20.5 km)	0.118	−0.272	0.507	1.332	−0.500	3.164
	EC1/EC3 (34 km)	0.235	0.113	0.356	0.731	0.323	1.140
$NEE_{positive}/\sigma(\delta)_f$	EC1/EC2 (8 m)	0.101	0.020	0.182	0.340	−0.080	0.760
	EC1/EC2 (95 m)	0.029	−0.299	0.357	1.333	−0.114	2.780
	EC1/EC2 (173 m)	0.179	−0.122	0.480	0.535	−1.316	2.385
	EC1/EC2 (20.5 km)	0.145	−0.174	0.464	1.134	−0.365	2.632
	EC1/EC3 (34 km)	0.320	0.059	0.580	0.763	−0.330	1.857
$NEE_{positive}/\sigma(\delta)_{corr}$	EC1/EC2 (8 m)	0.083	0.043	0.123	0.089	−0.106	0.284
	EC1/EC2 (95 m)	0.074	0.054	0.094	0.165	0.094	0.236
	EC1/EC2 (173 m)	0.172	−0.093	0.436	−0.110	−1.979	1.759
	EC1/EC2 (20.5 km)	0.245	0.122	0.367	−0.328	−0.938	0.282
	EC1/EC3 (34 km)	0.162	0.135	0.189	0.080	−0.015	0.175
$NEE_{positive}/\sigma(\delta)_{corr,f}$	EC1/EC2 (8 m)	0.078	0.037	0.118	0.101	−0.102	0.303
	EC1/EC2 (95 m)	0.090	0.030	0.150	0.136	−0.142	0.414
	EC1/EC2 (173 m)	0.163	−0.132	0.459	−0.040	−2.081	2.000
	EC1/EC2 (20.5 km)	0.159	−0.094	0.413	0.072	−1.205	1.349
	EC1/EC3 (34 km)	0.205	0.132	0.279	0.029	−0.278	0.337

m_{lower}; m_{upper}: lower and upper 95 % confidence interval for slope m; b_{lower}; b_{upper}: lower and upper 95 % confidence interval for intersect b; $\sigma(\delta)$, $\sigma(\delta)_f$: uncertainty estimated with classical two-tower approach without and with weather filter (f); $\sigma(\delta)_{corr}$, $\sigma(\delta)_{corr,f}$: uncertainty estimated with extended two-tower approach.

Table A2. R^2 for NEE uncertainty determined with the extended two-tower approach (including sfd-correction and weather filter) as function of NEE_{corr} magnitude and for 20.5 km EC tower distance. Results are given for different moving average time intervals (6 h, 12 h, 24 h) and data coverage percentages (25 %, 50 %, 70 %) for the calculation of the sfd-correction factor (Eq. 2).

	6 h	12 h	24 h
30 %	0.73, **0.84**, *(937)*	0.92, **0.72** *(904)*	0.84, **0.82**, *(597)*
50 %	0.58, **0.85**, *(710)*	0.7, **0.43**, *(463)*	–, –, *(32)*
70 %	0.77, **0.78**, *(408)*	0.66, **0.08**, *(148)*	–, –, *(0)*

Normal: for negative NEE; bold: for positive NEE; (): total number of half-hourly NEE left after sfd-correction and weather filter to build bins for NEE uncertainty versus NEE magnitude regressions (Fig. 5 for 12 h and 50 %)

Table A3. Relative difference [%] of mean uncertainty $\sigma(\delta)_{corr,f}$ estimated with the extended two-tower approach and the reference σ_{cov} for EC tower distances > 8 m.

Diff	$\Delta\ \sigma_{cov}$ (6 h)	$\Delta\ \sigma_{cov}$ (12 h)	$\Delta\ \sigma_{cov}$ (24 h)
30 %	−0.8, **39.3**	4.8, **55.5**	10.9, **59.9**
50 %	−9.3, **32.5**	−1.5, **41.2**	–
70 %	−10.5, **24.3**	−5.2, **10.2**	–

Normal: mean $\Delta\sigma_{cov}$ for 95 and 173 m distance; bold: mean $\Delta\sigma_{cov}$ for 20.5 and 34 km distance.

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References

Allard, V., Soussana, J.-F., Falcimagne, R., Berbigier, P., Bonnefond, J. M., Ceschia, E., D'hour, P., Hénault, C., Laville, P., Martin, C., and Pinarès-Patino, C.: The role of grazing management for the net biome productivity and greenhouse gas budget (CO_2, N_2O and CH_4) of semi-natural grassland, Agricul. Ecosys. Environ., 121, 47–58, 2007.

Ammann, C., Flechard, C. R., Leifeld, J., Neftel, A., and Fuhrer, J.: The carbon budget of newly established temperate grassland depends on management intensity, Agricul. Ecosys. Environ., 121, 5–20, 2007.

Arbeitsgruppe BK50: Allgemeine Informationen zur Bodenkarte 1?, 50 000–55 000 (Geol. Dienst Nordrh.-Westf.), 2001.

Aubinet, M., Vesala, T., and Papale, D.: Eddy Covariance: A Practical Guide to Measurement and Data Analysis, Springer Verlag, 2011.

Baldocchi, D. D.: Assessing ecosystem carbon balance: problems and prospects of the eddy covariance technique, Ann. Rev. Ecol. Systemat., 33, 1–33, 2001.

Baldocchi, D. D.: Assessing the eddy covariance technique for evaluating carbon dioxide exchange rates of ecosystems: past, present and future, Glob. Change Biol., 9, 479–492, 2003.

Barr, A. G., Morgenstern, K., Black, T. A., McCaughey, J. H., and Nesic, Z.: Surface energy balance closure by the eddy-covariance method above three boreal forest stands and implications for the measurement of the CO_2 flux, Agricul. Forest Meteorol. 140, 322–337, 2006.

Billesbach, D. P.: Estimating uncertainties in individual eddy covariance flux measurements: A comparison of methods and a proposed new method, Agricul. Forest Meteorol., 151, 394–405, 2011.

Bogena, H. R., Huisman, J. A., Meier, H., Rosenbaum, U., and Weuthen, A.: Hybrid Wireless Underground Sensor Networks: Quantification of Signal Attenuation in Soil, Vadose Zone J., 8, 755–761, 2009.

Braswell, B. H., Sacks, W. J., Linder, E., and Schimel, D. S.: Estimating diurnal to annual ecosystem parameters by synthesis of a carbon flux model with eddy covariance net ecosystem exchange observations, Glob. Change Biol., 11, 335–355, 2005.

Dragoni, D., Schmid, H. P., Grimmond, C. S. B., and Loescher, H. W.: Uncertainty of annual net ecosystem productivity estimated using eddy covariance flux measurements, J. Geophys. Res.-Atmos., 112, 1–9, 2007.

Finkelstein, P. L. and Sims, P. F.: Sampling error in eddy correlation flux measurements, J. Geophys. Res., 106, 3503–3509, 2001.

Flanagan, L. B. and Johnson, B. G.: Interacting effects of temperature, soil moisture and plant biomass production on ecosystem respiration in a northern temperate grassland, Agricul. Forest Meteorol., 130, 237–253, 2005.

Foken, T. and Wichura, B.: Tools for quality assessment of surface-based flux measurements, Agricul. Forest Meteorol., 78, 83–105, 1996.

Goulden, M. L., Munger, J. W., Fan, S. M., Daube, B. C., and Wofsy, S. C.: Measurements of carbon sequestration by long-term eddy covariance: Methods and a critical evaluation of accuracy, Glob. Change Biol., 2, 169–182, 1996.

Herbst, M., Prolingheuer, N., Graf, A., Huisman, J. A., Weihermüller, L., and Vanderborght, J.: Characterization and Understanding of Bare Soil Respiration Spatial Variability at Plot Scale, Vadose Zone J., 8, 762, doi:10.2136/vzj2008.0068, 2009.

Hill, T. C., Ryan, E., and Williams, M.: The use of CO_2 flux time series for parameter and carbon stock estimation in carbon cycle research, Glob. Change Biol., 18, 179–193, 2012.

Hollinger, D. Y. and Richardson, A. D.: Uncertainty in eddy covariance measurements and its application to physiological models, Tree Physio., 25, 873–885, 2005.

Hollinger, D. Y., Aber, J., Dail, B., Davidson, E. A., Goltz, S. M., Hughes, H., Leclerc, M. Y., Lee, J. T., Richardson, A. D., Rodrigues, C., Scott, N. A., Achuatavarier, D., and Walsh, J.: Spatial and temporal variability in forest–atmosphere CO_2 exchange, Glob. Change Biol., 10, 1689–1706, 2004.

Kessomkiat, W., Hendricks-Franssen, H.-J., Graf, A., and Vereecken, H.: Estimating random errors of eddy covariance data: An extended two-tower approach, Agricul. Forest Meteorol., 171, 203–219, 2013.

Kormann, R. and Meixner, F. X.: An Analytical Footprint Model For Non-Neutral Stratification, Bound.-Lay. Meteorol., 99, 207–224, 2001.

Korres, W., Koyama, C. N., Fiener, P., and Schneider, K.: Analysis of surface soil moisture patterns in agricultural landscapes using Empirical Orthogonal Functions, Hydrol. Earth Syst. Sci., 14, 751–764, doi:10.5194/hess-14-751-2010, 2010.

Kuppel, S., Peylin, P., Chevallier, F., Bacour, C., Maignan, F., and Richardson, A. D.: Constraining a global ecosystem model with multi-site eddy-covariance data, Biogeosciences, 9, 3757–3776, doi:10.5194/bg-9-3757-2012, 2012.

Liu, H., Randerson, J., Lindfors, J., Massman, W., and Foken, T.: Consequences of Incomplete Surface Energy Balance Closure for CO_2 Fluxes from Open-Path CO_2 / H_2O Infrared Gas Analysers, Bound.-Lay. Meteorol., 120, 65–85, 2006.

Lloyd, J. and Taylor, J. A.: On the Temperature Dependence of Soil Respiration, Funct. Ecol., 8, 315, doi:10.2307/2389824, 1994.

Mauder, M. and Foken, T.: Documentation and instruction manual of the Eddy covariance software package TK3, Univ.Bayreuth, Abt. Mikrometeorologie, 2011.

Mauder, M., Cuntz, M., Drüe, C., Graf, A., Rebmann, C., Schmid, H. P., Schmidt, M., and Steinbrecher, R.: A strategy for quality and uncertainty assessment of long-term eddy-covariance measurements, Agricul. Forest Meteorol., 169, 122–135, 2013.

Moore, C. J.: Frequency response corrections for eddy correlation systems, Bound.-Lay. Meteorol., 37, 17–35, 1986.

Orchard, V. A. and Cook, F. J.: Relationship between soil respiration and soil moisture, Soil Biol. Biochem., 15, 447–453, 1983.

Oren, R., Hsieh, C.-I., Stoy, P., Albertson, J., Mccarthy, H. R., Harrell, P., and Katul, G. G.: Estimating the uncertainty in annual net ecosystem carbon exchange: spatial variation in turbulent fluxes and sampling errors in eddy-covariance measurements, Glob. Change Biol., 12, 883–896, 2006.

Qu, W., Bogena, H. R., Huisman, J. A., and Vereecken, H.: Calibration of a Novel Low-Cost Soil Water Content Sensor Based on a Ring Oscillator, Vadose Zone J., 12, 1–10, 2013.

Qu, W., Bogena, H. R., Huisman, J. A., Martinez, G., Pachepsky, Y. A., and Vereecken, H.: Effects of soil hydraulic properties on the spatial variability of soil water content: evidence from sensor network data and inverse modeling, Vadose Zone J., 13, doi:10.2136/vzj2014.07.0099, 2014.

Richardson, A. D., Hollinger, D. Y., Burba, G. G., Davis, K. J., Flanagan, L. B., Katul, G. G., William Munger, J., Ricciuto, D. M., Stoy, P. C., Suyker, A. E., Verma, S. B., and Wofsy, S. C.: A multi-site analysis of random error in tower-based measurements of carbon and energy fluxes, Agricul. Forest Meteorol., 136, 1–18, 2006.

Richardson, A. D., Mahecha, M. D., Falge, E., Kattge, J., Moffat, A. M., Papale, D., Reichstein, M., Stauch, V. J., Braswell, B. H., Churkina, G., Kruijt, B., and Hollinger, D. Y.: Statistical properties of random CO_2 flux measurement uncertainty inferred from model residuals, Agricul. Forest Meteorol., 148, 38–50, 2008.

Richardson, A. D., Aubinet, M., Barr, A. G., Hollinger, D. Y., Ibrom, A., Lasslop, G., and Reichstein, M.: Uncertainty Quantification. Eddy Covariance, A Practical Guide to Measurement and Data Analysis 173–209, 2012.

Tsubo, M. and Walker, S.: Relationships between photosynthetically active radiation and clearness index at Bloemfontein, South Africa, Theoret. Appl. Climatol., 80, 17–25, 2005.

Webb, E. K., Pearman, G. I., and Leuning, R.: Correction of flux measurements for density effects due to heat and water vapour transfer, Quarterly J. Roy. Meteorol. Soc., 106, 85–100, 1980.

Wilson, K., Goldstein, A., Falge, E., Aubinet, M., Baldocchi, D., Berbigier, P., Bernhofer, C., Ceulemans, R., Dolman, H., Field, C., Grelle, A., Ibrom, A., Law, B., Kowalski, A., Meyers, T., Moncrieff, J., Monson, R., Oechel, W., Tenhunen, J., Valentini, R., and Verma, S.: Energy balance closure at FLUXNET sites, Agricul. Forest Meteorol., 113, 223–243, 2002.

Xu, L., Baldocchi, D.D., and Tang, J.: How soil moisture, rain pulses, and growth alter the response of ecosystem respiration to temperature, Global Biogeochem. Cy., 18, GB4002, doi:10.1029/2004GB002281, 2004.

Zacharias, S., Bogena, H., Samaniego, L., Mauder, M., Fuß, R., Pütz, T., Frenzel, M., Schwank, M., Baessler, C., Butterbach-Bahl, K., Bens, O., Borg, E., Brauer, A., Dietrich, P., Hajnsek, I., Helle, G., Kiese, R., Kunstmann, H., Klotz, S., Munch, J. C., Papen, H., Priesack, E., Schmid, H. P., Steinbrecher, R., Rosenbaum, U., Teutsch, G., and Vereecken, H.: A Network of Terrestrial Environmental Observatories in Germany, Vadose Zone J., 10, 955–973, 2011.