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ScienceDirect
Agricultural and Forest Meteorology 147 (2007) 199–208
AGRICULTURAL AND FOREST METEOROLOGY
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A method to estimate the additional uncertainty in gap-filled NEE resulting from long gaps in the CO_2 flux record

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Received 5 February 2007; received in revised form 30 May 2007; accepted 6 June 2007

Abstract

Missing values in any data set create problems for researchers. The process by which missing values are replaced, and the data set is made complete, is generally referred to as imputation. Within the eddy flux community, the term ‘‘gap filling’’ is more commonly applied. A major challenge is that random errors in measured data result in uncertainty in the gap-filled values. In the context of eddy covariance flux records, filling long gaps (days to weeks), which are usually the result of instrument malfunction or system failure, is especially difficult because underlying properties of the ecosystem may change over time, resulting in additional uncertainties. We used synthetic data sets, derived by assimilating data from a range of FLUXNET sites into a simple ecosystem model, to evaluate the relationship between gap length and uncertainty in net ecosystem exchange (NEE) of CO_2. Uncertainty always increased with gap length and there were seasonal patterns in this relationship. These patterns varied among ecosystem types, but were similar within the same ecosystem type (e.g., deciduous forests). In general, gaps of ~3 weeks during the winter dormant season resulted in little additional uncertainty at any of the sites studied. At worst (i.e., during spring green-up in a deciduous forest) a week-long gap could result in an additional uncertainty of roughly ± 30 g C m^{-2} $year^{-1}$ (at 95% confidence). This uncertainty adds to the roughly ± 30 g C m^{-2} $year^{-1}$ (at 95% confidence) uncertainty that arises from random measurement error. Unlike uncertainties due to random error, long gap uncertainties can be minimized through vigilance and a rapid response to system failure. Some strategies for reducing the occurrence of long gaps are discussed.

Keywords: Data assimilation; Ecosystem physiology; Eddy covariance; Gap filling; Howland; Monte Carlo; Phenology; Random error; Uncertainty

1. Introduction

At field sites around the world (FLUXNET and associated regional networks such as AmeriFlux and CarboEuroFlux; see Baldocchi et al., 2001), the eddy covariance method is being used to make continuous measurements of surface-atmosphere exchanges of carbon, water, and energy. Missing values, or gaps, in these flux records are unavoidable, however, and result from instrument failure, system maintenance, precipitation, inadequate turbulence, and various other rejection criteria (e.g., Papale et al., 2006). Data gaps in time series present challenges for researchers, as imputation of missing values (i.e., ‘‘gap filling’’) is a prerequisite to estimating daily and annual sums of net ecosystem exchange (NEE) of CO_2 (Falge et al., 2001), or any other quantity for which a temporal integral is desired. NEE sums are of special interest to the global change research community because scaling site-level carbon balance information to regions and continents contributes to

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doi:10.1016/j.agrformet.2007.06.004

improved models and understanding of the global carbon cycle (Wofsy and Harriss, 2002).

Uncertainty in annual NEE can be attributed to systematic errors and biases (Goulden et al., 1996; Moncrieff et al., 1996; Loescher et al., 2006), which we will not consider here, as well as random measurement errors (Hollinger and Richardson, 2005; Richardson et al., 2006a) and uncertainties due to gap filling. One study reported that for a selection of eddy flux sites, data coverage for a given year averaged 65%, with a range between 90% and 40% (Falge et al., 2001). Previous efforts to quantify the uncertainty due to gap filling have used Monte Carlo techniques to determine the effect of random measurement errors on uncertainty in the parameterization of the gap-filling model (e.g., Richardson and Hollinger, 2005), which leads to uncertainty in the predicted values used to fill gaps. However, this approach ignores an additional, and potentially significant, source of uncertainty; because gaps are not distributed randomly throughout the year, long gaps (days to weeks), which are usually attributed to instrument failure, tend to be more common than would be expected by chance alone. It is generally acknowledged that long gaps are more difficult to fill than short gaps (Falge et al., 2001; Richardson et al., 2006c; Moffat et al., in review), because key ecosystem properties may change over time, thus creating a non-stationary time series. For example, previous studies have documented seasonal variation in canopy-level photosynthetic capacity (Hollinger et al., 2004), as well as the temperature sensitivity of respiration (Reichstein et al., 2005), and the relative contribution of soil respiration to ecosystem respiration (Davidson et al., 2006). Numerous factors can be invoked to explain changes in ecosystem function, including phenology (e.g., canopy green-up and senescence), physiological acclimation, indirect or lagged effects of climate, step changes in environmental factors (e.g., soil frost or snow melt) and even pest outbreaks or other disturbances. From the perspective of filling long gaps, the real problem is that without any data, it is impossible to know exactly how the ecosystem properties might have changed during the gap, a classic problem of known unknowns. For example, in temperate systems, a long gap in early spring could be especially problematic, because the dates at which photosynthetic uptake commenced, or the system changed from a carbon source to a carbon sink, would be unknown. Thus, long gaps may add considerable uncertainty to gap-filled estimates of annual NEE, but to date the uncertainty due to long gaps has yet to be quantified.

Here we describe a method to quantify the uncertainties in annual NEE that are due both to random measurement error and to gap filling, including the additional uncertainty that can be attributed to long gaps. CO_2 flux data from a coniferous, two deciduous, two mixed species, and two Mediterranean sites, are combined with a simple model using data assimilation techniques (Gove and Hollinger, 2006) to generate synthetic, gap-free, time series. Using these synthetic data, we first determine the uncertainty in gap-filled NEE that can be attributed to random measurement errors, using a standard Monte Carlo approach. We then use an iterative, systematic procedure to determine relationships between gap length and starting date on NEE uncertainty, and use these relationships to estimate the additional uncertainty due specifically to long gaps. For each site–year of data, we present estimates of the total uncertainty in NEE that can be attributed to these two sources.

2. Data and method

2.1. Data sources

For this analysis, we used half-hourly eddy flux measurements of the net ecosystem exchange of CO_2 from four different ecosystem types (Table 1): (1) a spruce-dominated forest at the southern ecotone of the boreal forest (Howland, Maine, USA: 45.25°N, 68.73°W, Hollinger et al., 2004); (2) two beech-dominated temperate deciduous forests (Hesse, France: 48.67°N, 7.05°E, Granier et al., 2000; Hainich, Germany: 51.07°N, 10.45°E, Knohl et al., 2003); (3) a mixed beech/Douglas-fir forest (Vielsalm, Belgium; 50.30°N, 5.98°E, Aubinet et al., 2001); and (4) two oak-dominated Mediterranean forests (Roccarespampani, Italy: 42.40°N, 11.92°E, Tedeschi et al., 2006; Puechabon, France: 43.73°N, 3.58°E, Rambal et al., 2004). Quality control, flux corrections, and data editing were performed by the individual site investigators. Nocturnal data were filtered with site-specific u_* values (see Hollinger et al., 2004; Reichstein et al., 2005; Papale et al., 2006). Data from the European sites were assembled as part of a comprehensive evaluation of a standardized data processing algorithm (Papale et al., 2006) and a comparison of gap-filling techniques (Moffat et al., in review).

2.2. Development of synthetic data sets

Flux data were assimilated, on a site-by-site basis, into a simple ecosystem physiology model using an

Table 1
Total uncertainty in gap-filled annual flux sums that can be attributed to (1) random measurement errors, as they affect measured fluxes, filled gaps, and annual sums of NEE (ΣNEE); and (2) long gaps. Results are shown for a range of forested eddy flux sites. Uncertainties are presented as 95% confidence intervals (=2σ) of the annual sum, in g C m^{-2} $year^{-1}$. The total uncertainty represents the sum of the random uncertainty in NEE and the long gap uncertainty, added in quadrature

Site–year	Missing obs. (%)	2σ random uncertainty			Longest gap (days)	2σ long gap uncertainty	2σ total uncertainty
		Measured	Filled	ΣNEE			
Howland 1996	58	12	24	31	10	28	42
Howland 1997	58	13	25	34	15	19	39
Howland 1998	46	14	18	27	8	24	36
Howland 1999	38	16	17	28	20	29	40
Howland 2000	42	15	21	31	7	11	32
Howland 2001	39	17	17	30	5	8	31
Howland 2002	44	13	14	23	7	11	25
Howland 2003	49	14	20	28	6	10	30
Howland 2004	40	15	16	26	6	10	28
Hainich 2000	34	20	14	28	8	19	34
Hainich 2001	33	19	11	26	14	35	44
Hesse 2001	21	24	8	29	6	10	31
Hesse 2002	22	22	8	26	10	8	27
Puechabon 2002	36	17	12	23	4	10	25
Roccarespampani 2002	31	18	13	27	5	13	30
Vielsalm 2000	28	14	13	22	8	12	25
Vielsalm 2001	29	18	13	25	8	13	28

unscented Kalman filter, as described in detail by Gove and Hollinger (2006). The assimilation resulted in continuous, time-varying estimates of two parameters each for ecosystem respiration (based on the exponential model of Lloyd and Taylor, 1994) and gross canopy photosynthesis (based on the commonly used Michaelis–Menten hyperbolic light response, as described below). Once the seasonal trajectories of parameter values had been determined, they were used to generate continuous synthetic time series of net ecosystem exchange (sNEE) for each site–year.

2.3. Gap-filling protocol

Gap filling of NEE was conducted using the standard Howland gap-filling method, which is based on two non-linear regression models (Hollinger et al., 2004). This method was evaluated by Moffat et al. (in review), and despite the simplicity of the approach and minimal use of environmental covariates, performance was found to be comparable to that of many other gap-filling techniques.

Nocturnal ($PPFD \leq 5\ \mu mol\ m^{-2}\ s^{-1}$) gaps were filled using a second-order Fourier regression model (Eqs. (1) and (2)), where $D_\pi = DOY \times 2\pi/365$ is in radians (Hollinger et al., 2004; Richardson et al., 2006c). This approach does not require any ancillary data (e.g., soil moisture or soil temperature), but it does assume that changes in ecosystem respiration (R_{eco}) are predominantly related to seasonal patterns, and that these seasonal patterns can be adequately captured by a second-order model.

$$NEE_{night} = R_{eco} \tag{1}$$

$$R_{eco} = f_0 + s_1 \sin(D_\pi) + c_1 \cos(D_\pi) + s_2 \sin(2D_\pi) + c_2 \cos(2D_\pi) \tag{2}$$

Daytime gaps were filled by using a Michaelis–Menten light response model, driven by solar PPFD, to estimate gross photosynthesis (Eq. (3)), with ecosystem respiration estimated from Eq. (2) added back in to give the net flux of CO_2 (Eq. (4)).

$$P_{gross} = A_{max}\left(\frac{PPFD}{PPFD + K_m}\right) \tag{3}$$

$$NEE_{day} = R_{eco} + P_{gross} \tag{4}$$

Parameters for R_{eco} were fit at the annual time step, whereas for P_{gross} the year was divided into 12 periods (months) of equal length, and separate parameters were fit for each period. A maximum likelihood optimization approach was adopted, as described elsewhere (e.g., Richardson and Hollinger, 2005; Richardson et al., 2006a).

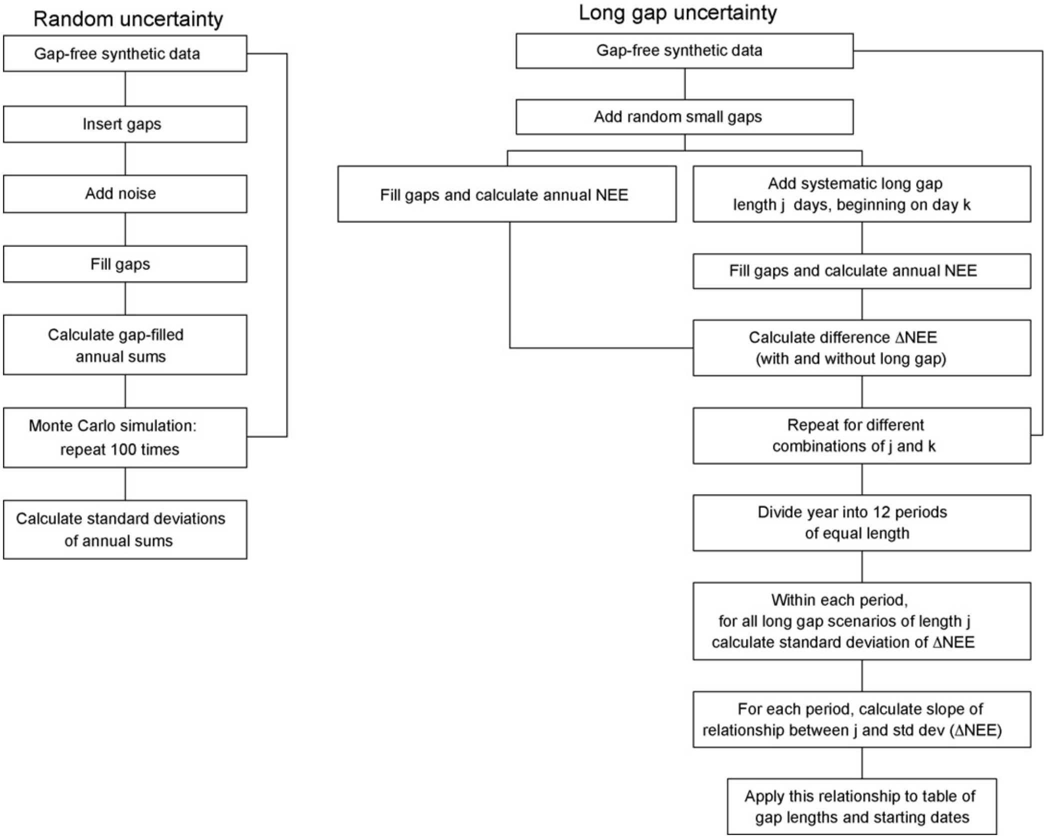

Fig. 1. Flowcharts illustrating the procedures followed to estimate random uncertainty (due to the combined effects of random measurement error and gap-filling uncertainty) and long gap uncertainty. Further details are given in text.

2.4. Monte Carlo simulations

We conducted standard Monte Carlo simulations (e.g., Press et al., 1992) to evaluate the effects of random measurement uncertainty and gap-filling uncertainty on annual NEE. The procedure was as follows (see also Fig. 1). First, we created gaps, as actually observed in each real site–year of data, in the corresponding synthetic data set. Then, artificial noise was added to the remaining observations. Based on results of Hollinger and Richardson (2005) and Richardson et al. (2006a), the noise (δ_i) was drawn from a double-exponential distribution with a standard deviation $\sigma(\delta_i)$ that scaled with the magnitude of the synthetic flux, sNEE_i, as

$$\sigma(\delta_i) = 0.62 + 0.63\mathrm{sNEE}_i \quad \text{for } \mathrm{sNEE}_i \geq 0 \tag{5a}$$

$$\sigma(\delta_i) = 1.42 - 0.19\mathrm{sNEE}_i \quad \text{for } \mathrm{sNEE}_i < 0 \tag{5b}$$

Next, we applied the gap-filling method described above, and determined annual sums of the noisy synthetic "measurements", filled gaps, and annual NEE. This procedure was repeated 100 times, and then standard deviations of the annual sums were calculated; we denote the uncertainty due to random measurement error (both as it affects the measurements and filled gaps) as σ_R(NEE). Note that σ_R(NEE) can be decomposed as follows:

$$\sigma_R(\mathrm{NEE}) = \sqrt{\begin{aligned}&\sigma^2(\Sigma_{\mathrm{measured}}) + \sigma^2(\Sigma_{\mathrm{filled}})\\ &+ 2\,\mathrm{cov}(\Sigma_{\mathrm{measured}}, \Sigma_{\mathrm{filled}})\end{aligned}} \tag{6}$$

The covariance term reflects the dependence of the filled values on the measurements, and therefore the direct coupling between random measurement error and gap-filling uncertainty.

2.5. Evaluation of long gap uncertainty

To evaluate the effect of long gaps on the total NEE uncertainty, we made use of the synthetic data time series for those site–years where the maximum gap length was 8 days or less: Howland (2001), Hesse (2001), Hainich (2000), Vielsalm (2000, 2001), Puechabon (2004), Roccarespampani (2002). As shown in Fig. 1, we added a combination of randomly inserted small (half-hourly) gaps and a single, systematically inserted, large gap (of length j days beginning on day k, for all j = 1–28 and all k = 1–365) to each synthetic data set. The small gaps were added such that the total number of gaps would be ≈30%. The placement of the small gaps was different for each of the 28 × 365 different long gap scenarios. In contrast to the simulations to evaluate the uncertainty due to random errors, no artificial noise was added to the synthetic data set. We filled the missing values in the synthetic data set, first with just the small gaps, and then again with both the small and large gaps, and then calculated the annual sum of gap-filled NEE for each. We then took the difference between these two annual sums, $\Delta NEE_{j,k}$, as a direct measure of the effect of a long gap of length j beginning on day k on the gap-filled annual sum of NEE. Once this had been done for each of the different long gap scenarios, we divided the year into 12 periods (months, m = 1–12) of equal length, and then for each combination of j and m, calculated the standard deviation of $\Delta NEE_{j,k}$ across all k in a particular month to give $\sigma_m(\Delta NEE_j)$. Finally, for each month we determined the slope, γ_m, of the relationship between gap length (in days) and $\sigma_m(\Delta NEE_j)$. We then returned to the actual NEE measurements for each site–year combination, and tabulated for each the length and starting date of every gap. The gap length (in days) was multiplied by the appropriate γ_m, and the resulting uncertainties in half-hourly NEE were added in quadrature to estimate the total additional uncertainty in annual NEE that could be attributed to long gaps, σ_{LG}(NEE).

2.6. Total NEE uncertainty

We estimated the total uncertainty in gap-filled NEE, σ_{TOT}(NEE), by adding uncertainty due to random measurement error and gap-filling uncertainty, as given by σ_R(NEE), and the uncertainty due to long gaps, as given by σ_{LG}(NEE), in quadrature:

$$\sigma_{TOT}(NEE) = \sqrt{\sigma_R^2 + \sigma_{LG}^2} \quad (7)$$

This calculation assumes that these two sources of uncertainty are independent of one another.

Below, we present aggregated uncertainty estimates as 2σ uncertainties, representing approximate 95% confidence intervals (but note that uncertainties for individual long gaps are reported as 1σ estimates). Uncertainty estimates have units of g C m^{-2} year^{-1}.

Results are presented for the following site–years of data: Howland (1996–2004), Hesse (2001, 2002), Hainich (2000, 2001), Vielsalm (2000, 2001), Puechabon (2002), Roccarespampani (2002).

3. Results

3.1. Monte Carlo analyses

Uncertainty due to random error, $2\sigma_R$(NEE), varied among site–years by about 50%, between ±23 and ±34 g C m^{-2} year^{-1} (Table 1). There was an approximately linear relationship (r = 0.52, n = 16) between the proportion of missing observations (φ, where $0 \leq \varphi \leq 1$) and $2\sigma_R$(NEE), with the uncertainty equal to 21.3 + 15.9φ (standard errors on reported coefficients are 2.6 and 6.7, respectively, and coefficients are significantly different from zero by t-test at $P \leq 0.001$ and 0.05). Note, however, that the relationship between φ and $2\sigma_R$ should not be extrapolated beyond the range of data used to fit the model, i.e., $0.2 < \varphi < 0.6$.

3.2. Long gap uncertainty

For conifer-dominated Howland, gaps of less than 5 days in length resulted in little or no additional uncertainty ($\sigma_m(\Delta NEE_j) < \pm 5$ g C m^{-2} year^{-1} for $i \leq 5$) in annual NEE, regardless of the time of year the gap occurred (Fig. 2A). During the winter and autumn months, very long gaps (20 days or more) did not add appreciably to the uncertainty. Additional uncertainty increased rapidly with increasing gap length during the spring and early summer (months 4–6): during this period $\sigma_m(\Delta NEE_j) \sim \pm 20$ g C m^{-2} year^{-1} for gaps of 20 days.

Results from the two deciduous forests, Hesse (Fig. 3A) and Hainich (Fig. 3B) suggested that within a given ecosystem type, the seasonal patterns of variation in $\sigma_m(\Delta NEE_j)$ are similar. The peak uncertainties (for

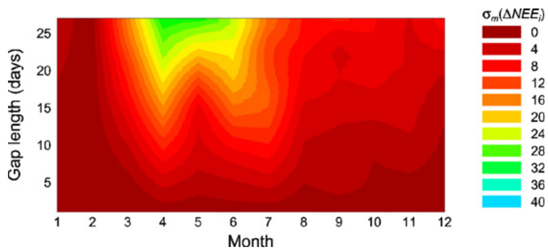

Fig. 2. Two-dimensional surface plot illustrating how uncertainty (1σ) in annual gap-filled NEE, expressed as $\sigma_m(\Delta NEE_j)$, varied as a function of time of year (x axis) and gap length (y axis). Data are shown for the Howland forest. Units are g C m^{-2} year^{-1}.

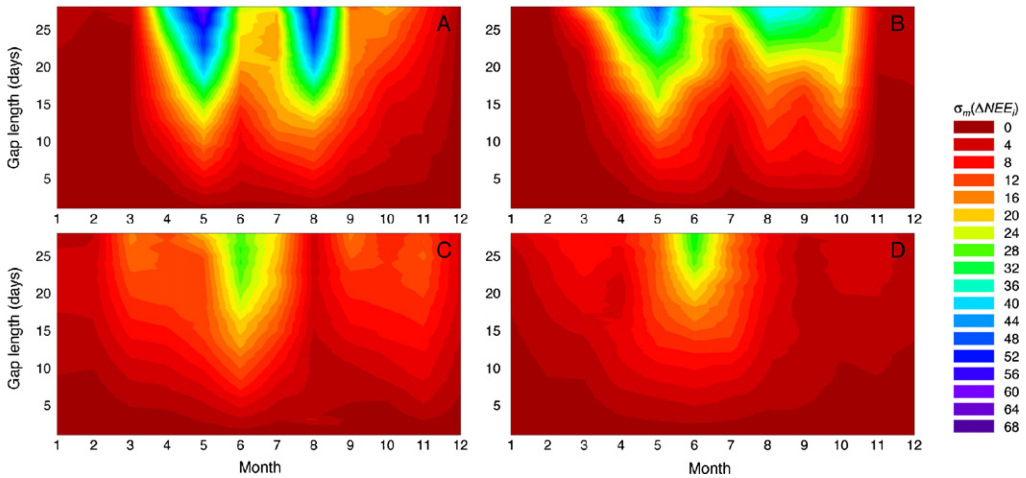

Fig. 3. Two-dimensional surface plots illustrating how uncertainty (1σ) in annual gap-filled NEE, expressed as $\sigma_m(\Delta\text{NEE}_j)$, varied as a function of time of year (x axis) (12 "months" of equal length) and gap length (y axis). Data are shown for two deciduous forests: (A) Hesse and (B) Hainich, and two Mediterranean forests, (C) Puechabon and (D) Roccarespampani. Units are g C m^{-2} year^{-1}.

the longest gaps) were slightly smaller for Hainich than Hesse, and this was probably due to the fact that measured fluxes at Hainich tended to be smaller. For both sites, uncertainties increased most rapidly with gap length during the spring (month 5) and late summer (month 8): a week-long gap during either of these months added a modest amount of additional uncertainty ($\sigma_m(\Delta\text{NEE}_j) \sim \pm 10$ g C m^{-2} year^{-1}). As at Howland, however, long gaps during the dormant winter season contributed only a small amount of additional uncertainty.

In Mediterranean systems, the patterns were somewhat different, as capturing the summer dormancy, rather than spring onset and autumn senescence (as at the deciduous sites), appeared to be the key challenge. For both Puechabon (Fig. 3C) and Roccarespampani (Fig. 3D), the largest long gap uncertainties occurred in month 6. Again, the similarity of the seasonal patterns between these two Mediterranean forests suggests that it may be possible to develop general relationships between gap length and uncertainty which can be applied to particular vegetation types.

The colored surface plots depicted in Figs. 2 and 3 provide a visual means of qualitatively assessing the impact of long gaps on NEE uncertainty. The patterns can be summarized in a quantitative way by calculating the estimated slope, γ_m, of the relationship between gap length and $\sigma_m(\Delta\text{NEE}_j)$ (Table 2). At all sites, the slope was lower in winter and steeper during the growing season, again reflecting the fact that uncertainty scales with flux magnitude. Across all months, the average

Table 2
Variation across the year (divided into 12 periods of equal length) in estimates of the slope, γ_m, of the relationship between uncertainty in gap-filled NEE and gap length (in days), expressed as the standard deviation of the annual gap-filled NEE in month m for gap length j, $\sigma_m(\Delta\text{NEE}_j)$, across a range of eddy flux sites. Units are (g C m^{-2} year^{-1}) day^{-1}

Month	Howland 2001	Roccarespampani 2002	Puechabon 2002	Vielsalm 2000	Vielsalm 2001	Hesse 2001	Hainich 2000
1	0.11	0.19	0.12	0.20	0.24	0.09	0.02
2	0.04	0.20	0.25	0.30	0.40	0.07	0.03
3	0.57	0.59	0.35	0.59	0.34	0.09	0.32
4	1.18	0.57	0.33	0.30	0.48	1.15	1.00
5	0.89	0.68	0.64	0.65	0.82	2.11	1.65
6	0.98	1.25	1.08	0.65	0.71	0.90	0.98
7	0.68	0.85	0.70	0.41	0.64	0.95	0.65
8	0.37	0.23	0.33	0.33	0.83	2.09	1.23
9	0.33	0.53	0.16	0.53	0.33	0.75	1.10
10	0.32	0.48	0.19	0.36	0.38	0.59	1.15
11	0.26	0.59	0.21	0.26	0.27	0.35	0.12
12	0.26	0.24	0.12	0.11	0.23	0.05	0.11

slope was at least 40% steeper for the deciduous sites than either of the other forest types.

Values of γ_m can be used to determine the length (λ) of a gap that would result in a specified level of uncertainty, σ_θ, i.e., $\lambda = \sigma_\theta / \gamma_m$. So, for example, a 9.5-day gap in month 5 at Hesse will result in a similar amount of additional uncertainty ($\sigma_\theta = \pm 20$ g C m^{-2} year^{-1}) as a 16.9-day gap in month 4 at Howland, or a 24.0-day gap in month 8 at Vielsalm.

We used the results presented in Table 1 to estimate the total uncertainty due to long gaps, expressed at 95% confidence as $2\sigma_{LG}$(NEE). Across 9 years of measurements at Howland, this additional uncertainty ranged from ±8 to 29 g C m^{-2} year^{-1} (Table 1). The lowest uncertainties ($\leq\pm 11$ g C m^{-2} year^{-1}) were obtained in years with both good overall data coverage (<50% missing observations) and no gaps longer than 7 days in length.

At the European sites, estimates of $2\sigma_{LG}$(NEE) spanned a similar range, ±8 to 39 g C m^{-2} year^{-1} (Table 1). The importance of minimizing long gaps during periods of active change is well illustrated by the Hainich results for 2000 and 2001: overall data coverage was similar for the 2 years (~33%), but the additional uncertainty associated with long gaps was nearly twice as high in 2001 (±35 g C m^{-2} year^{-1}) as in 2000 (±19 g C m^{-2} year^{-1}), largely because of a 14-day gap in month 10 that accounted for >90% of the long gap uncertainty in 2001.

3.3. Total NEE uncertainty

The total uncertainty in gap-filled NEE, $2\sigma_{TOT}$(NEE), which includes both random measurement uncertainty and long gap uncertainty, varied among sites, and ranged from ±25 (Howland 2002 and Puechabon 2002) to ±44 g C m^{-2} year^{-1} (Hainich 2001) at 95% confidence. Expressed relative to the annual net uptake, the total uncertainty at Howland ranged between 11% (2004) and 27% (1998) of annual NEE, with a mean across all 9 years of 19%. The Roccarespampani site is an extreme example, where the total uncertainty, ±30 g C m^{-2} year^{-1}, is comparable in magnitude to the annual NEE (≈40 g C m^{-2} year^{-1}, D. Papale, personal communication).

There were only two instances where the σ_{LG}(NEE) > σ_R(NEE), Howland 1999 (with a 20-day gap) and Hainich 2001 (with a 14-day gap); on the whole, the ratio of these two uncertainties (σ_{LG}/σ_R) was 0.58 ± 0.30, resulting in a considerably smaller contribution of σ_{LG}(NEE) to σ_{TOT}(NEE) because of the addition in quadrature (Eq. (6)).

The total uncertainty was more strongly correlated with the length of the longest gap ($r = .70$, $P \leq 0.01$) than with the proportion of missing observations ($r = 0.45$, $P = 0.07$). This analysis suggests that as the length of the longest gap increases by 1 day, the total uncertainty increases by roughly 1.0 g C m^{-2} year^{-1}. While this offers a general rule of thumb for a rough approximation of the uncertainty, it is important to keep in mind that the timing of the long gaps is important (Table 2), and should to be taken into account if a more precise uncertainty estimate is required.

4. Discussion

Using data from six different eddy flux sites, we have endeavored to quantify the errors in annual NEE that can be attributed to two sources: (1) random measurement error, which affects not only measured data points but also gap-filled values, because the uncertainty of the raw measurements propagates to uncertainty in the gap-filling model; and (2) long gaps (≥1 day), which become more problematic as the ecosystem properties become less stationary. Although researchers have long known in a qualitative sense that long gaps are more problematic than short gaps, the long gap uncertainty has not been explicitly quantified. An important result is that this uncertainty is typically on the order of ±10 to 30 g C m^{-2} year^{-1} (i.e., not ±1 to 3 g C m^{-2} year^{-1} or ±100 to 300 g C m^{-2} year^{-1}), and is thus roughly comparable (usually smaller, but sometimes larger) in magnitude to random uncertainties.

Across all site–years, the uncertainty due to random errors was ±27 g C m^{-2} year^{-1} at 95% confidence; long gap uncertainty was about 40% smaller on average (±16 g C m^{-2} year^{-1}), but highly variable (standard deviation of 8 g C m^{-2} year^{-1}) across site–years, depending on the length and location of the long gaps during the year. Taking the long gap uncertainty into account resulted in a slight increase in estimated total uncertainty for some site–years (e.g., Howland 2001, Hesse 2002), but more than a 40% increase for other site–years (e.g., Howland 1999, Hainich 2001).

Our results indicate that long gaps are relatively benign during the dormant winter season in temperate ecosystems, and add little additional uncertainty. However, these results confirm that long gaps are especially pernicious during periods of active change in ecosystem properties, because when the flux data are missing, it is impossible to know the timing of magnitude of the change (Falge et al., 2001). For example, our results suggest that greater effort should be made to minimize the long gaps during rapid transitions into or out of dormancy: i.e., spring and autumn in temperate deciduous forests, and during summer in Mediterranean forests (Fig. 3, Table 1).

The results presented here have a number of features in common with previous findings concerning random flux measurement error (Richardson et al., 2006a). First, it appears that uncertainty patterns due to long gaps are broadly similar across sites with similar vegetation types (Fig. 3). Thus, it may be possible to apply the slope estimates, γ_m, developed here to other eddy flux sites around the world, provided the seasonal patterns of carbon uptake and release are similar. Second, the magnitude of the long gap uncertainty roughly scales with the magnitude of the fluxes: for a given gap length, uncertainties are smaller in Mediterranean and evergreen conifer forests than in temperate deciduous forests, and uncertainties are smaller in the dormant winter season than during the growing season.

4.1. Potential effects of gap-filling method

The uncertainties resulting from long gaps may depend somewhat on the gap-filling method used. The gap-filling method employed here makes use of very little additional environmental data; more complex methods, such as neural network models (Van Wijk and Bouten, 1999; Hagen et al., 2006; Richardson et al., 2006c), or models involving additional covariates, could potentially result in smaller long gap uncertainties. Reducing long gap uncertainties requires that the gap-filling method be better able to predict the ways in which ecosystem properties might vary over the course of a long gap. For example, a model making use of information about canopy phenology, based on field observations (Richardson et al., 2006b), radiometric measurements (Jenkins et al., 2007), or webcam imagery (Richardson et al., 2007) would, for temperate deciduous forests, likely reduce spring or autumn long gap uncertainties relative to a model without this information. Similarly, in Mediterranean systems, measured changes in soil water content would probably help to better predict the onset of water-limited summer dormancy—however, of the two Mediterranean sites in the present study, soil water content data were only available at one site. In both of these examples, ancillary data could provide important information, in the absence of fluxes themselves, about the stationarity of ecosystem properties. Of course, it is essential that ancillary data (as well as all other environmental covariates) themselves be gap free.

In a comprehensive comparison of close to 20 different gap-filling methods (including the standard Howland method employed here), Moffat et al. (in review) found that across a range of sites, performance of most methods (excepting two methods with much higher RMS errors) was generally acceptable, with RMS error for artificial ‘‘very short gap’’ and ‘‘short gap’’ scenarios typically varying by less than 30% across methods. The best methods (three different neural networks) appeared to be approaching the noise limits of the data. In the same study, RMS error for artificial ‘‘long gap’’ scenarios (three gaps, each 12 days long) was consistently higher than for shorter gap length scenarios, but along with the neural networks, the gap-filling method used here was among the least sensitive to degraded performance in response to long gaps. Overall long gap performance of the gap-filling method employed here was similar to the majority of other methods, which gives us confidence in the generality of the results presented in Tables 1 and 2. Thus, while it may be possible to reduce the long gap uncertainties somewhat by application of a better gap-filling method, we contend that uncertainties we estimate here are probably typical, given the range of gap-filling methods presently in use.

While it has long been known in a qualitative sense that long gaps are more difficult to fill than short gaps, these results provide a quantitative means by which an estimate of this uncertainty can be obtained. We propose that the results in Table 2 provide the information necessary to come up with rough estimates of the additional uncertainty due to long gaps, which may be adequate in most situations—uncertainty estimates are, by nature, imprecise. If site investigators choose to use a new gap-filling method, or one that is especially (in)sensitive to long gaps, then the step-by-step method presented in Fig. 1 can be applied to come up with estimates of both random and long gap uncertainties.

4.2. Strategies for reducing long gaps

The results presented here indicate that the additional uncertainty due to long gaps in flux measurement records can be comparable to that due to accumulated random errors in the half-hourly flux measurements, although in most cases it is somewhat smaller than this. However, whereas random uncertainty due to the stochastic nature of turbulence cannot be eliminated, uncertainty due to long gaps can be minimized through vigilant monitoring of system function, and a rapid response to system failures.

With a modest investment in cyberinfrastructure, continuous system oversight can be maintained even at distant field sites. Many solutions exist, but to use the Howland AmeriFlux site as an example, we use remote access software (UltraVNC, freely available at http://ultravnc.sourceforge.net/) to access field computers and to verify full system functionality over the Internet. The four flux systems we run on-site are all connected to the field server via a wireless local area network. Dataloggers are connected to the field server either via serial ports or through the local network, and environmental data are automatically downloaded every 24 h (good quality, gap-free environmental data are a prerequisite to accurately gap-filling NEE time series). While regular site visits are still desirable, daily remote monitoring of the system is vastly superior to relying on weekly trips to the site to ensure proper system function. Near real-time access to all data streams means that instrument failures, power interruptions, and even gross IRGA calibration errors can all be identified within 24 h (rather than within 7 days) and dealt with promptly. Results presented here suggest that this vigilance is more important at some times of the year (e.g., spring and early summer at Howland) than others (e.g., winter). Careful attention to system function, especially at these critical times of the year, will enable site investigators to reduce the uncertainties in annual NEE.

An alternative, although more costly, approach would be to introduce redundancy into the measurement system. Ideally, this would consist of a completely independent set of instruments, data logging devices, as well as an independent power supply system. While this approach would likely be adequate to eliminate long gaps resulting from catastrophic failure of the primary system, it would still be necessary to fill short gaps resulting from periods with inadequate turbulence or precipitation, which would affect primary and secondary systems similarly.

5. Conclusion

Long gaps are an additional source of uncertainty in gap-filled NEE, and this uncertainty has not previously been quantified. The additional uncertainty comes from not knowing how the ecosystem properties that affect flux exchange are changing during the gap. Historic flux records can be analyzed to determine the rate at which ecosystem responses to environmental forcing change at different times of the year. Gaps that occur at times when the rate of change is high, such as springtime for deciduous forests, add more uncertainty than gaps occurring at other times of the year. Investigators need to pay careful attention to flux measurement systems during periods of active change in ecosystem properties. With vigilance, this uncertainty can be reduced to a level that is acceptably small ($\leq$10 g C m^{-2} year^{-1} at 95% confidence) compared to the other sources of uncertainty in annual NEE, in particular random measurement error and gap-filling uncertainty.

Combining long gap uncertainty with other previously recognized sources of random uncertainty resulted in a total net annual carbon exchange uncertainty (at 95% confidence) of between 25 and 45 g m^{-2} s^{-1}. (Note that these estimates are separate from any systematic errors, e.g., bias due to advection.) For this selection of sites, the uncertainties are <10% to ~100% of annual uptake. These estimates of the uncertainty in annual net carbon exchange permit quantitative comparisons with model results and guidance in model inverse analyses. They also provide information necessary for informed policy decision making, e.g., with regard to regional and continental scale carbon accounting.

Acknowledgements

The authors thank Antje Moffat for organizing, and the Max Planck Institute for Biogeochemistry for sponsoring, the Jena Gap Filling Workshop held in September, 2006. Dario Papale is thanked for compiling the Carboeurope data set, and site PIs Marc Aubinet (Vielsalm), Werner Kutch (Hainich), André Granier (Hesse), Serge Rambal (Puechabon) and Ricardo Valentini (Roccarespampani) are thanked for making their data available. The Howland AmeriFlux site is supported by the Office of Science (BER), U.S. Department of Energy, Interagency Agreement No. NE-AI02-07ER64355. Howland flux data are available at http://public.ornl.gov/ameriflux/ subject to AmeriFlux ''Fair-use'' rules.

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