Lecture 5 Micrometeorological Flux Measurements, Eddy Covariance, Implementation, Part 3, Errors, Uncertainties, Flux Partitioning and Gap Filling

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February 11, 2016

Introduction

In assessing eddy covariance data, especially from shared network databases, one needs to be cognizant of all the pitfalls and errors that may be associated with these data. Errors and uncertainties can arise from poor quality assurance (QA) and quality control (QC). Another set of errors stem from improper sensor performance associated with calibration drifts, spikes, sensor noise, signal filtering and if the analog to digital conversion is too coarse or if the sensor goes off range. Violation of the assumptions on which the eddy covariance method is based, like insufficient fetch, advection, storage, sampling too slow or too short can cause errors; these were treated in the previous chapter. And if these questionable data are rejected and replaced with gap filling methods there is uncertainty in the gap filling technique. These are among the topics discussed in this chapter.

When discussing uncertainty, we have to consider the two major types we may encounter. Eddy fluxes are affected by random and bias errors [Moncrieff et al., 1996]. Random errors tend to get smaller and smaller as long term averages are constructed. The bias errors are the most difficult to assess, minimize and remove. They can be fully or selectively systematic. The latter corresponds with nighttime flux loss associated with nocturnal CO2 exchange, when there is a decoupling of flow within and above the canopy; we will discuss this topic more in later sections. It is serious with CO2 exchange because it is of opposite sign and can be large. If this nocturnal loss is underestimated, large biases in annual net carbon exchange can accumulate. For example, a nocturnal bias error of 1 μ mol m⁻² s⁻¹ can add up to over 189 gC m⁻² y⁻¹ if it persists 12 hours a day for 365 days a year. For visual perspective of these annual carbon budget errors, consider a piece of computer printer paper, expanded in size to one meter, square. It weighs 76 g. So in essence, the annual error in eddy flux measurements of carbon exchange is less than the mass associated with a single piece of paper laid on the ground. Water vapor exchange is less sensitive to these systematic bias errors because evaporation is small at night.



Figure 1 Errors encounters in the field (adapted from Moncrieff et al.)

Testing for Errors and Biases

Micrometeorologists perform numerous tests to validate the application of their method when studying a new site. Computing transfer function spectral filtering errors, testing for energy balance closure, testing for the absences of flux divergence, quantifying storage and examining how well turbulence measurements match standard theories are among the most basic tests that will be performed. In the following sections we will evaluate these topics.

Energy balance closure

Energy balance closure is a widely-used metric to assess the data quality of eddy covariance measurements [*Leuning et al.*, 2012; *Oncley et al.*, 2007; *Twine et al.*, 2000; *K Wilson et al.*, 2002]. There is some controversy over the ability to close the surface energy balance. Several assessments of energy balance across many sites find that that energy balance closure is underestimated by 10 to 20%, suggesting that the eddy covariance method may be missing some flux of mass and energy [*Li et al.*, 2005; *Oncley et al.*, 2007; *Twine et al.*, 2000; *K Wilson et al.*, 2002].

But other investigators at individual sites often attain a reasonable level of energy balance closure (within 10%) when net radiation, soil heat flux, bole/canopy heat storage and photosynthetic energy conversion are measured properly and appropriate spectral corrections are applied to the eddy flux measurements [*L H Gu et al.*, 2007; *Heusinkveld et al.*, 2004; *Leuning et al.*, 2012; *Meyers and Hollinger*, 2004].

The following figure is an example measured over a jack pine stand in the boreal forest. About 93% of the variance in net radiation is accounted for by the flux measurements and there is a 7% difference in energy closure.



Figure 2 A test of energy balance closure over a jack pine forest on flat terrain and with extensive fetch. (Baldocchi and Vogel, 1996)

Another example comes from our study over grass.



Vaira Grassland, D296-366, 2000

Figure 3 Energy balance over a grassland

The interesting issue with our grassland site is that in later years we observed a gradual degradation of energy balance closure. The solution to this mystery was that our instruments were fenced off from the grazing cows. Over time the amount of biomass over the soil heat flux plates increased and starting insulating the ground. Only after we started accounting for changes in heat storage between the surface and the heat flux plate were we able to restore our adequate closure of the energy balance.

It can be argued that lack of energy balance closure does not necessarily indicate poor eddy flux measurements. With much debate and reflection on the topic, many of the key practitioners feel that the lack of energy balance closure is an example of 'death by a thousand cuts'. There are many unresolved issues relating to differences in footprints sensed by the energy sensors and the eddy flux instruments and sufficient statistical sampling of net radiation, soil heat flux and storage and direct errors in the measurement of these none eddy flux terms; net radiometers may see the tower and it has a small view footprint under the sensor, rather than weighting the upwind footprint; rarely are more than a handful of soil heat flux plates installed and they are subject to bias depending if they are buried deep or shallow, in the shade or an open spot. Hence, this author does not recommend correcting eddy flux measurements of CO_2 for the fractional imbalance of the energy balance closure as has been done in some instances [*A.G. Barr et al.*, 2006].

An informal survey seems to show good closure over short crops, windy conditions, active transpiration and using open path sensors. The NOAA team, including my group and Tilden Meyers, has observed good closure in such situations in independent studies, but using similar software, instruments. Shashi Verma's group also observes good closure over crops and grass, but it varies seasonally. Arguments that it is due to errors in soil heat flux can be circumvented by examining daily sums. In cases, with bad closure, this novel attempt does not alleviate the problem.

Wilson et al have conducted a 'global' analysis of energy balance closure using the FLUXNET data base across a range of climates, surface roughness and functional types (22 sites, 50 site years of data). They concluded that the mean imbalance across sites was about 20%., irrespective of method used (open vs closed path gas analyzers) and canopy surface. Energy balance closure was improved during windy conditions.

Despite the valiant attempts of Wilson et al to draw a solid conclusion, the jury is still out. There are still numerous issues to resolve including representativeness of net radiation balance with regards to the flux footprint, the role of cloud fields and low frequency contributions to fluxes (Finnigan and Leuning observe better closure with longer averaging times; we have observed better closure in climates with very clear skies, flat surfaces and short vegetation and strong winds).

The overview on energy balance closure by Leuning et al [*Leuning et al.*, 2012] suggests it is best to test such closure for 24 hour average or sums because this tends to cancel out uncertainties in measuring some of the storage terms. The following figure shows a marked improvement in energy balance closure with daily averages.



ig. 5. Frequency distributions for the slope of H + E versus $R_n - G_0$ (forced through ero) for half-hourly and daily averages of measurements reported in the La Thuile atset.

In other words the cumulative uncertainty of a number of terms seems to be a better explanation than the null hypothesis that we are measuring latent and sensible heat flux wrong.

And there are reasons to have confidence in eddy covariance measurements. First, we have seen that the method does a competent job of sampling the cospectra that drives the flux. Second, there is a body of data showing strong closure of the water balance, despite energy balance closure problems. Both Wilson et al [*K B Wilson et al.*, 2001], Barr et al [*A. G. Barr et al.*, 2000], and Scott show comparable agreement between annual sums of ET with water balance measurements, either from a watershed water balance, or using a pizeiometer based lysimeter. In other words, there is close agreement between annual sums of evaporation with eddy covariance and other hydrologic budgeting methods.

Minimizing and Testing for Other Errors

In evaluating a new site there are a number of recommended procedures to increase one's confidence on the quality and accuracy of the flux measurements, because all sites have some level of heterogeneity.

It is advised to compare one's flux system with another set of instrumentation, as is performed with the roving AmeriFlux system [*Schmidt et al.*, 2012]. If one has a duplicate system one can test for the effects of spatial heterogeneity on the interpretation of fluxes [*D D Baldocchi and Rao*, 1995; *Hollinger et al.*, 2004; *Katul et al.*, 1999; *Matthes et al.*, 2014]. Hollinger et al [*Hollinger et al.*, 2004], for example, found close agreement between annual sums of two flux systems separated by 700 m seeing a similar forest.



Fig. 3 Interannual variability of net ecosystem C exchange (NEE) at Howland is greater than the spatial variability observed by two towers in similar forest separated by ~ 775 m.

We have conducted paired flux measurements over an irrigated potato field, immersed in a dry desert, and find good agreement between duplicate flux systems as long as one is farther than 300 m from the upwind edge [*D D Baldocchi and Rao*, 1995].



Advection is difficult to measure and requires a horizontal set of instruments that are aligned along the wind [*Aubinet et al.*, 2010; *Aubinet et al.*, 2005a; *Feigenwinter et al.*, 2004; *Yi et al.*, 2008]. And because every circumstance is unique, there is no universal way to measure advection that may be suitable for tall and short vegetation on slope, steep or undulating terrain.

One way to test if advection is large is to conduct a flux divergence study [*Detto et al.*, 2010]. If advection is small in the surface and internal boundary layers we should measure no difference in flux with height. An investigation of 'flux divergence', over a less than ideal forest site on undulating terrain, is presented below.



Figure 4 Measurement of Flux divergence of heat over a deciduous forest.

In this case we found that the flux divergence of sensible heat was small between 29 and 36 m, giving us an increased degree of confidence on the accuracy of our measurements.

In another study, we examined flux divergence over a pasture near an estuary. In this case the advection of moisture caused the flux divergence of wq to be non zero. But the flux divergence of wc and wT was generally nill during the day.



Scaling Properties of Biologically Active Scalar Concentration Fluctuations

Fig. 12 Ensemble-averaged fluxes and flux divergence as a function of time of day for temperature, water vapour and carbon dioxide recorded during July–August 2009 (2600 runs). Plus signs on the top of each plot indicate hours when the null hypothesis that two samples derive from distributions with equal means (*t*-test with significance level = 0.05) can be rejected

In patchy landscapes, the flux measurement system views different types of vegetation from different wind sectors. In this situation, seasonal and annual fluxes need to be interpreted in terms of flux footprint models [*Gockede et al.*, 2004; *Rebmann et al.*, 2005; *Soegaard et al.*, 2003].

Canopy Storage

Yet, another source of error is when flows become decoupled and there is storage of material in the air space underneath the eddy flux system. Fortunately, on a daily, 24 hour integral basis, the storage term is small.



Figure 5

On the other hand, the storage term is significant on an hour by hour basis during the night.



Using flux data, not corrected for storage, to fit ecological and physiological models will produce model parameters that are in error.

Gap Filling Methods

From a practical standpoint it is impossible to expect any flux instrument system to function perfectly 24 hours a day, seven days a week, 365 days a year; from our own experience, we are able to retain about 80% of possible measurements over the course of a year. In practice, scientists subject their data to a variety of quality control and assurance criteria [*Foken and Wichura*, 1996; *Rebmann et al.*, 2005]. Doing so, however, introduces many gaps in the data record (30 to 40% on an annual basis; Falge et al., 2001). Consequently, data gaps are expected and are the rule, as data must be rejected during calibration periods, when instruments malfunction, as when they break or when rain, snow or other meteors cause sensors to spike or go off scale. And finally, the measurements must meet the standards held for interpreting micrometeorological, such as adequate fetch etc [*Foken and Wichura*, 1996].

Several methods for gap filling are being employed by the research community. The main ones in use include replacement with: linear interpolation, mean diurnal pattern, look up tables, semi-parametric models, and artificial neural networks [*E. Falge et al.*, 2001a; *Moffat et al.*, 2007; *Dario Papale*, 2012].

One set of gap filling methods include interpolating between missing data points, replacing missing data with estimates derived from non-linear regression models or lookup tables that depend upon climatic drivers like light, temperature and humidity as independent variables [*E. Falge et al.*, 2001b; *Iwata et al.*, 2005; *Lasslop et al.*, 2010; *Moffat et al.*, 2007; *Ruppert et al.*, 2006; *Stauch and Jarvis*, 2006]. A review on gap filling is provided by Papale [*Dario Papale*, 2012]. This approach needs continual updating and tuning as seasonal changes in leaf area, soil moisture, photosynthetic capacity will alter any derived relation.

The simplest method replaces missing data with information, for the corresponding hour, from the mean diurnal average (Falge et al. 2001). Investigators bin data by hour for a one to two week period, then use the time dependent ensemble mean to replace missing data. This approach has appeal, for the sampling errors about the hourly based ensemble means tend to be quite [*D D Baldocchi et al.*, 1997; *E. Falge et al.*, 2001b; *Moncrieff et al.*, 1996]. Spectral analyzes of data show that the repeat cycle of fronts occurs on a 5 to 7 days cycle, so although this technique may not accurately fill missing correctly for a particular circumstance, it will fill it with a correct mean.

Newer and more sophisticated statistical approaches to gap-filling have been implemented in recent year. These new methods include the multiple imputation method [*Hui et al.*, 2004], neural networks [*Dario Papale and Valentini*, 2003], genetic algorithms [*Ooba et al.*, 2006] and process-based models that are parameterized with existing data [*Gove and Hollinger*, 2006]. Inter-comparisons of gap filling methods indicate that the neural network method is among the best, but in general biases associated with different gap filling methods tend to be small [*E. Falge et al.*, 2001b; *D. Papale et al.*, 2006].

a. Neural Networks

With the advent of long-term flux measurement networks, scientists are search for methods to fill gaps with empirical data. With a desire not to bias the end results on the shape of the response functions, several European groups are adapting the use of neural networks ([*Moffat et al.*, 2007; *D. Papale et al.*, 2006]. Neural networks are defined as: " a network of many simple processing elements each having a small amount of local memory. The units are connected in layers with communication channels and operate only on their local data and data they receive from channels. Most neural networks have training rules and adjust the weight of their connections by data". Neural networks are able to 'learn' by adjusting weighting factors according to input information. Other strengths include their ability to be applied to complex problems that do not have predetermined algorithms defining their behavior, such as ecosystems.



Figure 6 after Papale and Valentini, 2003

Input data are scaled from 0 to 1 using

 $input(x) = 1 - \frac{\max(x) - value(x)}{\max(x) - \min(x)}$

Next the data are multiplied by a connection matrix

$$\overrightarrow{X} = A \cdot \overrightarrow{I}$$

The matrix A contains connections with the input notes and a hidden node layer, X. The number of columns of the matrix are determined by the number of input nodes. Next one scales the vector X with a offset value.

$$\vec{u} = \vec{X} + A_2$$

to produce

$$\vec{H}N(\vec{u}) = \frac{2}{1 + \exp(-2\vec{u})} - 1$$

The output matrix is:

$$O = A_3 \cdot \overrightarrow{H}N$$

And the definitive output value of the neural network is:

$$OV = O + A_4$$

Need to define V and O.



Fig. 2 Block diagram of an artificial neurone. Supposing that there are *n* inputs with signal $x_1, x_2, x_3, ..., x_n$ and weights $w_1, w_2, w_3, ..., w_n$. The weighted sum *a*, will be $a = x_1w_1 + x_2w_2 + x_3w_3 + ..., x_nw_n = \sum_{x=1}^n x_iw_i$ The *a* value, will enter into a transfer function *S*, and transformed according to different mathematical functions delivering the output *y* (see text).

Figure 7 After [Dario Papale and Valentini, 2003]

In Fig 3 we see an example of the performance of the neural network model of Papale and Valentini against eddy flux measurements, a regression-based gap filling algorithm of Falge and the CANOAK model





Figure 8 application of neural network model to assess NEP of a temperate forest

We are now adopting artificial neural networks routinelyto our meso-network of flux sites, using MATLAB packages. This gives us the flexibility to use the most suitable set of variables to fill gaps. For our rice, we use photosynthetically active radiation, air temperature, vapor pressure deficit, water table, friction velocity and day of year (to simulate phenology) to gap fill CO2 flux data. The following figure shows excellent agreement between 7 seasons/years of data and a trained neural network model.



CO2 Flux Measurements at Night

The thermal stratification during night is much different than during the day. At night temperature profiles are inverted, causing stable thermal stratification. Wind speed and turbulence is much reduced, causing large build-ups in concentration in the surface layer. Night time turbulence is also intermittent, due to the sporatic turbulence induced by gravity waves. The net situation is that it is very difficult to measure fluxes accurately at night. This issue has become one of much concern by the carbon flux community, as many sites report a significant underestimate of CO2 flux and a strong dependency with friction velocity. In essence, even though investigators attempt to measure bias errors due to storage, some CO2 seems to be leaking out of the control volume by how and how often storage profiles are measured. Small undulations in terrain can induce mean drainage flows that may pass undetected below the flux measurement system.

The most severe and controversial gap-filling correction being made is the so-called 'u* correction' to night-time respiration measurements. It is standard practice by the flux community to reject nocturnal CO2 flux measurements under low friction velocity conditions and replace them with values associated with more windier conditions [A. G. Barr et al., 2013; L Gu et al., 2005].

For background, the atmosphere's thermal stratification becomes stable at night and the flow near and below the vegetation can become decoupled with that above. In this situation, CO₂ may drain out of the control volume under investigation and not be measured by the eddy covariance system [*Aubinet et al.*, 2005b; *Sun et al.*, 2007]. Numerous teams has shown that the bias error increases as turbulent mixing, measured by

friction velocity (u*), decreases below a threshold [*Aubinet et al.*, 2000; *Barford et al.*, 2001; *Carrara et al.*, 2003; *Goulden et al.*, 1996; *L Gu et al.*, 2005; *Saleska et al.*, 2003; *Wohlfahrt et al.*, 2005]. The threshold, above which nocturnal CO₂ fluxes are insensitive to mixing, ranges between 0.1 and 0.5 m s⁻¹, depending on topography and canopy height [*Aubinet et al.*, 2000; *Loescher et al.*, 2006a]. Subsequently, correction factors are developed that re-scale nighttime respiration fluxes to the windy, well-mixed condition and are normalized by temperature, soil moisture and growth stage.

Shown below are two examples from our studies, relating nocturnal CO2 exchange and friction velocity. One can see that the results are noisy and it is hard to determine a distinct and certain threshold; r2 values are typically less than 0.40. Plus, there are issues relating to how strict or lax in picking this value. Picking a high threshold value has uncertainty due to the small body of data subject to high winds. There is also the problem of antecedent conditions. If a calm period is followed by sporadic turbulence, an extraordinarily large flux may be measured, but in practice it would be venting carbon accumulating over successive sampling periods.



Figure 9 Impact of friction velocity on CO2 flux densities at night. Under low wind speeds, CO2 seems to drain out of the control volume and not pass the imaginary line demarking the canopy atmosphere interface. This non-linear relation between CO2 flux and friction velocity is a common observation across the FLUXNET network, indicating an atmospheric rather than instrumental effect.



One alternative to the u* correction involves extrapolating of the daytime CO₂ flux-light response curve to zero [*Eva Falge et al.*, 2002; *Gilmanov et al.*, 2003; *Hollinger et al.*, 1998; *Lee et al.*, 1999; *Suyker and Verma*, 2001; *Xu and Baldocchi*, 2004]. At the daily time scale, there is a strong correlation between the two methods, but respiration rates, based on the extrapolation of light response curve, tend to underestimate (by 78 to 94%) respiration values corrected for u*.

A second alternative assumes that the rate of nocturnal respiration equals the maximum sum of the turbulent and storage fluxes observed over the night [*Van Gorsel et al.*, 2007]. This maximum respiratory efflux is noted to occur early in the evening before advection is established, so potential biases can be avoided. It is noteworthy, that this latest approach produces respiration rates that match independent estimates based on upscaling soil and leaf respiration measurements well.

A group from Oregon placed a second flux system near the floor of a forest and used those data to help guide and replace measurements that were rejected during calm conditions [*Thomas et al.*, 2013].

A key question associated with data evaluated in this review is: how accurate are the annual sums? Annual errors in F_N typically range between 30 and 100 gC m⁻² y⁻¹, with larger and smaller values having been reported [*Anthoni et al.*, 2004; *Goulden et al.*, 1996; *Hagen et al.*, 2006; *Hollinger and Richardson*, 2005; *Loescher et al.*, 2006b; *Moncrieff et al.*, 1996; *Oren et al.*, 2006; *Rannik et al.*, 2006]. Correcting F_N for insufficient nighttime mixing typically adds an additional respiratory flux on the order of 30 to 50 gC m⁻² y⁻¹, and thereby reduces F_N . The magnitude of this correction depends on

the choice of the cut-off value for u*, how tall the vegetation is and local topography [*Anthoni et al.*, 2004; *Aubinet et al.*, 2000; *A G Barr et al.*, 2002; *Loescher et al.*, 2006b; *D. Papale et al.*, 2006; *Saleska et al.*, 2003; *Xu and Baldocchi*, 2004].

Flux Partitioning

It has already been established that the eddy covariance method measures the net flux density, which in the case of net ecosystem CO2 exchange is the balance between ecosystem photosynthesis (denoted as GPP) and ecosystem respiration.

$$NEE = GPP - R_{eco}$$

To better understand the controls on these fluxes it is instructive to partition the net flux into its gross components like:

 $GPP = NEE + R_{eco}$

But this requires that we assess Reco independently. Fortunately, we can use a mix of day-night sampling and models to conduct this partitioning, as is shown for the alfalfa field below.



The basic idea is measure respiration at night, use those data to develop a model that can be applied during the day to subtract from NEE and compute GPP [*Eva Falge et al.*, 2002].

There are a variety of temperature dependent respiration models that can be used [*Reichstein et al.*, 2005].

$$R_{eco} = R_{ref} * \exp(E_a(\frac{1}{T_{ref} - T_0} - \frac{1}{T - T_0})) \ [Lloyd \ and \ Taylor, \ 1994]$$

$$R_{eco} = R_{ref} * \exp(\frac{E_a}{R}(\frac{1}{T_{ref}} - \frac{1}{T}))$$
 Arrhenius Equation

 $\mathbf{R}_{eco} = \mathbf{R}_{ref} Q_{10}^{(T-Tref)/10}$ van't Hoff equation

The key point is to adjust model parameters across the season to account for changes in photosynthetic capacity, leaf area, soil moisture and phenology.

Because this is uncertainty in the quality of nocturnal CO2 flux measurements, others have used a method that estimates ecosystem respiration by extrapolating the daytime CO2 Flux-light response curve to zero light levels [*Eva Falge et al.*, 2002; *Suyker and Verma*, 2001; *Xu and Baldocchi*, 2004]. In the following figure we see an example for an alfalfa field in California. In this case the zero intercept is well founded.



Tests of this method with more extensive datasets have shown good agreement on the seasonal and yearly bases as shown below.



[Suyker and Verma, 2001]



[Eva Falge et al., 2002]

Spurious Correlations among GPP and Reco?

It is well known in statistics that correlations between two variables with shared information from a third variable can be spurious [*Pearson*, 1896]. Hence it is warranted that we inspect whether or not estimates of GPP and Reco suffer from spurious correlation.

$$G = NEE_{day} - R_{eco,day} = x - z$$

$$R = NEE_{night} + R_{eco,day} = y + z$$

In a recent paper we derived the equation defining spurious correlation among G and R and evaluated it using day-night sampling with data from the FLUXNET database [*D Baldocchi et al.*, 2015].

$$r_{GR} = \frac{\overline{G'R'}}{\sigma_G \sigma_R} = \frac{\overline{x'y' + x'z' - z'y' - z'z'}}{(\overline{x'x' - 2x'z' + z'z'})^{1/2} (\overline{y'y' + 2y'z' + z'z'})^{1/2}}$$

$$r_{sc} = \frac{-z'z'}{(x'x' + \overline{z'z'})^{1/2}(y'y' + \overline{z'z'})^{1/2}}$$

We then expanded this analysis to the FLUXNET database that spans a spectrum of climate and plant functional types. We found, on average, that the correlation between gross photosynthesis and ecosystem respiration, using day-night sampling, was close to minus one (-0.828 + -0.130). For perspective, a large fraction of this correlation was real, as the degree of spurious correlation (Eq. 22) was -0.526. We conclude that the potential for spurious correlation between canopy photosynthesis and ecosystem respiration across the FLUXNET database was moderate. Looking across the database, we found that the least negative spurious-correlations coefficients (> -0.3) were associated with seasonal deciduous forests. The most negative spurious correlations coefficients (< -0.7) were associated with evergreen forests found in boreal climates.



If we apply the analysis to annual sums of G and R we find a lower degree of spurious correlation, rsc = -0.157.





Summary Comments

If you are starting a new study there are many things one should do and check.

1. find relatively flat site with uniform vegetation. Try to have fetch to height ratio greater than 100:1

- 1. Check for advection (flux divergence) by measuring flux profiles using two flux systems
- 2. Check for energy balance closure
- 3. Check power spectra and co-spectra. Are you measuring the full spectrum of flux contributing eddies.
- 4. See if there is instrument interference of winds or lags due to wind separation between wind and scalar sensors.
- 5. Look for systematic bias flows. Plot mean drag coefficient vs wind direction for a large body of data. Plots like this will also identify sensor drift.
- 6. Plot data and see if it falls within expected ranges. Look for unexplained outliers.
- 7. Watch calibrations and calibrate often.
- 8. Know your site and system well.

In this lecture we have discussed numerous procedures for producing turbulent flux estimates.

Below is a table surveying the key steps.

Summary of Data Processing

	Process
Realtime	Sample instruments at 10 to 20 Hz,
Sampling	depending on height of sensors and wind
	speed. $f_{sample} = 2$ times f_{cutoff} (f=nz/U)
	Store realtime data on hard disk
	Process realtime means, variances and
	covariances using digital recursive filters.
	Compute 30 or 60 minute averages of
	statistical quantities. Use to diagnose
	instrument and system performance
	Document data and procedures.
Post Processing,	Compute means, covariances and variances
hourly data	using Reynolds averaging
	Merge turbulence and meteorological data
	Apply calibration coefficients and gas law
	corrections to compute unit correct flux
	densities and statistics
	Apply transfer functions and frequency
	corrections
	Compute Storage and Advective fluxes

	Compute power spectra and co-spectra; examine instrument response and interference effects
Post Processing, daily data	Apply QA/QC and eliminate bad data
	Use gap filling methods and fill gaps
	Correct nighttime data if needed using such corrections as with well-mixed friction
	velocity, or check against independent measurements, such as soil respiration chambers
	Compute daily integrals
Yearly data	Compute annual means by integrating data set.

State of Art Discussion Topics

Discuss how eddy covariance measurements are used to evaluate models? How reliable is each measurement? What are proper averaging schemes? If we average, do we filter or miss episodes or interesting processes? How do we avoid testing 'apples' vs 'oranges'?

Night corrections of CO2 flux. Where is the material going? Do we correct with temperature corrected chamber measurements

Energy balance closure. Why? Is is a function of footprints and representativeness, net radiometers? Do we artificially close the energy balance and correct data? Do we apply these corrected estimates to the Webb Pearman Leuning corrections for CO2 exchange.

How good are spectral models for applying transfer functions. Can we use the current theory at night? What about inside a canopy?

How well does one need to measure the CO2 storage term? How many levels are needed? Where should they be placed? How often should one sample?

What does zero drift do to coordinate rotation and the estimate of eddy fluxes?

EndNote References

Anthoni, P. M., A. Freibauer, O. Kolle, and E.-D. Schulze (2004), Winter wheat carbon exchange in Thuringia, Germany, *Agricultural and Forest Meteorology*, *121*(1-2), 55-67. Aubinet, M., C. Feigenwinter, B. Heinesch, C. Bernhofer, E. Canepa, A. Lindroth, L. Montagnani, C. Rebmann, P. Sedlak, and E. Van Gorsel (2010), Direct advection measurements do not help to solve the night-time CO2 closure problem: Evidence from three different forests, *Agricultural and Forest Meteorology*, *150*(5), 655-664. Aubinet, M., et al. (2005a), Comparing CO2 Storage and Advection Conditions at Night at Different Carboeuroflux Sites, *Boundary-Layer Meteorology*, *116*(1), 63-93. Aubinet, M., et al. (2005b), Comparing CO₂ storage and advection conditions at night at different carboeuroflux sites, *Boundary-Layer Meteorology*, *116*(1), 63-94. Aubinet, M., et al. (2000), Estimates of the annual net carbon and water exchange of Europeran forests: the EUROFLUX methodology, *Advances in Ecological Research*, *30*, 113-175.

Baldocchi, D., C. Sturtevant, and F. Contributors (2015), Does day and night sampling reduce spurious correlation between canopy photosynthesis and ecosystem respiration?, *Agricultural and Forest Meteorology*, 207(0), 117-126.

Baldocchi, D. D., and K. S. Rao (1995), Intra-field variability of scalar flux densities across a transition between a desert and an irrigated potato Advection field, *Boundary Layer Meterology.*, *76.*, 109-136.

Baldocchi, D. D., C. A. Vogel, and B. Hall (1997), Seasonal variation of carbon dioxide exchange rates above and below a boreal jack pine forest, *Agricultural and Forest Meteorology*, 83(1-2), 147-170.

Barford, C. C., S. C. Wofsy, M. L. Goulden, J. W. Munger, E. H. Pyle, S. P. Urbanski, L. Hutyra, S. R. Saleska, D. Fitzjarrald, and K. Moore (2001), Factors controlling long- and short-term sequestration of atmospheric CO₂ in a mid-latitude forest, *Science*, *294*(5547), 1688-1691.

Barr, A. G., G. van der Kamp, R. Schmidt, and T. A. Black (2000), Monitoring the moisture balance of a boreal aspen forest using a deep groundwater piezometer, *Agricultural and Forest Meteorology*, *102*(1), 13-24.

Barr, A. G., K. Morgenstern, T. A. Black, J. H. McCaughey, and Z. Nesic (2006), Surface energy balance closure by the eddy-covariance method above three boreal forest stands and implications for the measurement of the CO₂ flux, *Agricultural and Forest Meteorology*

The Fluxnet-Canada Research Network: Influence of Climate and Disturbance on Carbon Cycling in Forests and Peatlands, 140(1-4), 322-337.

Barr, A. G., T. J. Griffis, T. A. Black, X. Lee, R. M. Staebler, J. D. Fuentes, Z. Chen, and K. Morgenstern (2002), Comparing the carbon budgets of boreal and temperate deciduous forest stands, *Canadian Journal of Forest Research*, *32*, 813-822.

Barr, A. G., et al. (2013), Use of change-point detection for friction–velocity threshold evaluation in eddy-covariance studies, *Agricultural and Forest Meteorology*, *171-172*, 31-45.

Carrara, A., A. S. Kowalski, J. Neirynck, I. A. Janssens, J. C. Yuste, and R. Ceulemans (2003), Net ecosystem CO2 exchange of mixed forest in Belgium over 5 years, *Agricultural and Forest Meteorology*, *119*(3-4), 209-227.

Detto, M., D. Baldocchi, and G. G. Katul (2010), Scaling Properties of Biologically Active Scalar Concentration Fluctuations in the Atmospheric Surface Layer over a Managed Peatland, *Boundary-Layer Meteorology*, *136*(3), 407-430.

Falge, E., D. Baldocchi, J. Tenhunen, M. Aubinet, P. Bakwin, P. Berbigier, C. Bernhofer, G. Burba, R. Clement, and K. J. Davis (2002), Seasonality of ecosystem respiration and gross primary production as derived from FLUXNET measurements, *Agricultural and Forest Meteorology*, *113*(1-4), 53-74.

Falge, E., et al. (2001a), Gap filling strategies for defensible annual sums of net ecosystem exchange, *Agricultural and Forest Meteorology*, *107*(1), 43-69.

Falge, E., et al. (2001b), Gap filling strategies for defensible annual sums of net ecosystem exchange, *Agricultural and Forest Meteorology*, *107*, 43-69.

Feigenwinter, C., C. Bernhofer, and R. Vogt (2004), The influence of advection on the short term CO₂-budget in and above a forest canopy, *Boundary-Layer Meteorology*, *113*(2), 201-224.

Foken, T., and B. Wichura (1996), Tools for quality assessment of surface-based flux measurements, *Agricultural and Forest Meteorology*, 78(1-2), 83-105.

Gilmanov, T. G., S. B. Verma, P. L. Sims, T. P. Meyers, J. A. Bradford, G. G. Burba, and A. E. Suyker (2003), Gross primary production and light response parameters of four Southern Plains ecosystems estimated using long-term CO₂ -flux tower measurements, *Global Biogeochem. Cycles*, *17*, doi:10.1029/2002GB002023.

Gockede, M., C. Rebmann, and T. Foken (2004), A combination of quality assessment tools for eddy covariance measurements with footprint modelling for the characterisation of complex sites, *Agricultural and Forest Meteorology*, *127*(3-4), 175-188.

Goulden, M. L., J. W. Munger, S. M. Fan, B. C. Daube, and S. C. Wofsy (1996), Measurements of carbon sequestration by long-term eddy covariance: Methods and a critical evaluation of accuracy, *Global Change Biology*, 2(3), 169-182.

Gove, J. H., and D. Y. Hollinger (2006), Application of a dual unscented Kalman filter for simultaneous state and parameter estimation in problems of surface-atmosphere exchange, *J. Geophys. Res.-Atmos.*, *111*(D8), doi:1029/2005JD006021.

Gu, L., et al. (2005), Objective threshold determination for nighttime eddy flux filtering, *Agricultural and Forest Meteorology*, *128*(3-4), 179-197.

Gu, L. H., et al. (2007), Influences of biomass heat and biochemical energy storages on the land surface fluxes and radiative temperature, *J. Geophys. Res.-Atmos.*, *112*(D2), doi:10.1029/2006JD007425.

Hagen, S. C., B. H. Braswell, E. Linder, S. Frolking, A. D. Richardson, and D. Y. Hollinger (2006), Statistical uncertainty of eddy flux-based estimates of gross ecosystem carbon exchange at Howland Forest, Maine, *J. Geophys. Res.-Atmos.*, *111*(D8), doi:10.1029/2005JD006154.

Heusinkveld, B. G., A. F. G. Jacobs, A. A. M. Holtslag, and S. M. Berkowicz (2004), Surface energy balance closure in an arid region: role of soil heat flux, *Agricultural and Forest Meteorology*, *122*(1-2), 21-37.

Hollinger, D. Y., and A. D. Richardson (2005), Uncertainty in eddy covariance measurements and its application to physiological models, *Tree Physiol.*, 25(7), 873-885.

Hollinger, D. Y., F. M. Kelliher, E.-D. Schulze, G. Bauer, A. Arneth, J. N. Byers, J. E. Hunt, T. M. McSeveny, K. I. Kobak, and I. Milukova (1998), Forest-atmosphere carbon dioxide exchange in eastern Siberia, *Agricultural and Forest Meteorology*, *90*(4), 291-306.

Hollinger, D. Y., et al. (2004), Spatial and temporal variability in forest-atmosphere CO2 exchange, *Global Change Biology*, *10*(10), 1689-1706.

Hui, D., S. Wan, B. Su, G. Katul, R. Monson, and Y. Luo (2004), Gap-filling missing data in eddy covariance measurements using multiple imputation (MI) for annual estimations, *Agricultural and Forest Meteorology*, *121*(1-2), 93-111.

Iwata, H., Y. Malhi, and C. von Randow (2005), Gap-filling measurements of carbon dioxide storage in tropical rainforest canopy airspace, *Agricultural and Forest Meteorology*, *132*(3-4), 305-314.

Katul, G., et al. (1999), Spatial variability of turbulent fluxes in the roughness sublayer of an even-aged pine forest, *Boundary-Layer Meteorology*, 93(1), 1-28.

Lasslop, G., M. Reichstein, D. Papale, A. D. Richardson, A. Arneth, A. Barr, P. Stoy, and G. Wohlfahrt (2010), Separation of net ecosystem exchange into assimilation and respiration using a light response curve approach: critical issues and global evaluation, *Global Change Biology*, *16*(1), 187-208.

Lee, X. H., J. D. Fuentes, R. M. Staebler, and H. H. Neumann (1999), Long-term observation of the atmospheric exchange of CO₂ with a temperate deciduous forest in southern Ontario, Canada, *Journal of Geophysical Research*, *104*(D13), 15975-15984. Leuning, R., E. van Gorsel, W. J. Massman, and P. R. Isaac (2012), Reflections on the surface energy imbalance problem, *Agricultural and Forest Meteorology*, *156*, 65-74. Li, Z. Q., G. R. Yu, X. F. Wen, L. M. Zhang, C. Y. Ren, and Y. L. Fu (2005), Energy balance closure at ChinaFLUX sites, *Science in China Series D-Earth Sciences*, *48*, 51-62.

Lloyd, J., and J. A. Taylor (1994), On the Temperature-Dependence of Soil Respiration, *Functional Ecology*, 8(3), 315-323.

Loescher, H. W., B. E. Law, L. Mahrt, D. Y. Hollinger, J. Campbell, and S. C. Wofsy (2006a), Uncertainties in, and interpretation of, carbon flux estimates using the eddy covariance technique, *Journal of Geophysical Research-Atmospheres*, *111*(D21). Loescher, H. W., B. E. Law, L. Mahrt, D. Y. Hollinger, J. Campbell, and S. C. Wofsy (2006b), Uncertainties in, and interpretation of, carbon flux estimates using the eddy covariance technique, *J. Geophys. Res.-Atmos.*, *111*(D21), doi:10.1029/2005JD006932. Matthes, J. H., C. Sturtevant, J. Verfaillie, S. Knox, and D. Baldocchi (2014), Parsing variability in CH4 fluxes at a spatially heterogeneous wetland: Integrating multiple eddy covariance towers with high-resolution flux footprint analysis, *Journal of Geophysical Research: Biogeosciences*, 2014JG002642.

Meyers, T. P., and S. E. Hollinger (2004), An assessment of storage terms in the surface energy balance of maize and soybean, *Agricultural and Forest Meteorology*, *125*(1-2), 105-115.

Moffat, A. M., et al. (2007), Comprehensive comparison of gap-filling techniques for eddy covariance net carbon fluxes, *Agricultural and Forest Meteorology*, *147*(3-4), 209-232.

Moncrieff, J., Y. Malhi, and R. Leuning (1996), The propogation of errors in long-term measurements of carbon and water, *Global Change Biology*, *2*, 231-240.

Oncley, S. P., et al. (2007), The Energy Balance Experiment EBEX-2000. Part I: Overview and energy balance, *Boundary-Layer Meteorology*, *123*(1), 1-28.

Ooba, M., T. Hirano, J.-I. Mogami, R. Hirata, and Y. Fujinuma (2006), Comparisons of gap-filling methods for carbon flux dataset: A combination of a genetic algorithm and an artificial neural network, *Ecol. Model.*, *198*(3-4), 473-486.

Oren, R., C. I. Hseih, P. Stoy, J. Albertson, H. R. McCarthy, P. Harrell, and G. G. Katul (2006), Estimating the uncertainty in annual net ecosystem carbon exchange: spatial variation in turbulent fluxes and sampling errors in eddy-covariance measurements, *Global Change Biology*, *12*(5), 883-896.

Papale, D. (2012), Data Gap Filling, in *Eddy Covariance: A Practical Guide to Measurement and Data Analysis*, edited by M. Aubinet, T. Vesala and D. Papale, pp. 159-172, Springer Netherlands, Dordrecht.

Papale, D., and R. Valentini (2003), A new assessment of European forests carbon exchanges by eddy fluxes and artificial neural network spatialization, *Global Change Biol*, *9*, 525-535.

Papale, D., et al. (2006), Towards a standardized processing of Net Ecosystem Exchange measured with eddy covariance technique: algorithms and uncertainty estimation, *Biogeosciences*, *3*(4), 571-583.

Pearson, K. (1896), Mathematical Contributions to the Theory of Evolution.--On a Form of Spurious Correlation Which May Arise When Indices Are Used in the Measurement of Organs, *Proceedings of the Royal Society of London*, 60(359-367), 489-498.

Rannik, Ü., P. Kolari, T. Vesala, and P. Hari (2006), Uncertainties in measurement and modelling of net ecosystem exchange of a forest, *Agricultural and Forest Meteorology*, *138*(1-4), 244-257.

Rebmann, C., et al. (2005), Quality analysis applied on eddy covariance measurements at complex forest sites using footprint modelling, *Theor. Appl. Climatol.*, 80(2 - 4), 121-141.

Reichstein, M., et al. (2005), On the separation of net ecosystem exchange into assimilation and ecosystem respiration: review and improved algorithm, *Global Change Biology*, *11*(9), 1424-1439.

Ruppert, J., M. Mauder, C. Thomas, and J. Luers (2006), Innovative gap-filling strategy for annual sums of CO₂ net ecosystem exchange, *Agricultural and Forest Meteorology*, *138*(1-4), 5-18.

Saleska, S. R., et al. (2003), Carbon in Amazon Forests: Unexpected Seasonal Fluxes and Disturbance-Induced Losses, *Science*, *302*(5650), 1554-1557.

Schmidt, A., C. Hanson, W. S. Chan, and B. E. Law (2012), Empirical assessment of uncertainties of meteorological parameters and turbulent fluxes in the AmeriFlux network, *Journal of Geophysical Research*, *117*(G4).

Soegaard, H., N. O. Jensen, E. Boegh, C. B. Hasager, K. Schelde, and A. Thomsen (2003), Carbon dioxide exchange over agricultural landscape using eddy correlation and footprint modelling, *Agricultural and Forest Meteorology*, *114*(3-4), 153-173.

Stauch, V. J., and A. J. Jarvis (2006), A semi-parametric gap-filling model for eddy covariance CO₂ flux time series data, *Global Change Biology*, *12*(9), 1707-1716.

Sun, J., S. P. Burns, A. C. Delany, S. P. Oncley, A. A. Turnipseed, B. B. Stephens, D. H. Lenschow, M. A. LeMone, R. K. Monson, and D. E. Anderson (2007), CO2 transport over complex terrain, *Agricultural and Forest Meteorology*, *145*(1-2), 1-21.

Suyker, A. E., and S. B. Verma (2001), Year-round observations of the net ecosystem exchange of carbon dioxide in a native tallgrass prairie, *Global Change Biology*, 7, 279-289.

Thomas, C. K., J. G. Martin, B. E. Law, and K. Davis (2013), Toward biologically meaningful net carbon exchange estimates for tall, dense canopies: Multi-level eddy covariance observations and canopy coupling regimes in a mature Douglas-fir forest in Oregon, *Agricultural and Forest Meteorology*, *173*, 14-27.

Twine, T. E., W. P. Kustas, J. M. Norman, D. R. Cook, P. R. Houser, T. P. Meyers, J. H. Prueger, P. J. Starks, and M. L. Wesely (2000), Correcting eddy-covariance flux underestimates over a grassland, *Agricultural and Forest Meteorology*, *103*(3), 279-300. Van Gorsel, E., R. Leuning, H. A. Cleugh, H. Keith, and T. Suni (2007), Nocturnal

carbon efflux: reconciliation of eddy covariance and chamber measurements using an alternative to the u*-threshold filtering technique, *Tellus B*, 59(3), 397-403.

Wilson, K., A. Goldstein, E. Falge, M. Aubinet, D. Baldocchi, P. Berbigier, C. Bernhofer, R. Ceulemans, H. Dolman, and C. Field (2002), Energy balance closure at FLUXNET sites, *Agricultural and Forest Meteorology*, *113*(1-4), 223-243.

Wilson, K. B., P. J. Hanson, P. J. Mulholland, D. D. Baldocchi, and S. D. Wullschleger (2001), A comparison of methods for determining forest evapotranspiration and its components: sap-flow, soil water budget, eddy covariance and catchment water balance, *Agricultural and Forest Meteorology*, *106*(2), 153-168.

Wohlfahrt, G., C. Anfang, M. Bahn, A. Haslwanter, C. Newesely, M. Schmitt, M. Drosler, J. Pfadenhauer, and A. Cernusca (2005), Quantifying nighttime ecosystem respiration of a meadow using eddy covariance, chambers and modelling, *Agricultural and Forest Meteorology*, *128*(3-4), 141-162.

Xu, L., and D. D. Baldocchi (2004), Seasonal variation in carbon dioxide exchange over a Mediterranean annual grassland in California, *Agricultural and Forest Meteorology*, *123*(1-2), 79-96.

Yi, C. X., D. E. Anderson, A. A. Turnipseed, S. P. Burns, J. P. Sparks, D. I. Stannard, and R. K. Monson (2008), The contribution of advective fluxes to net ecosystem exchange in a high-elevation, subalpine forest, *Ecol. Appl.*, *18*(6), 1379-1390.