How does eddy covariance work?
The package of Eddy Covariance measurements:

1. Wind speed (momentum) 3-axes
2. Temperature
3. Water vapor
4. Solar radiation
5. Net radiation
6. “scalar” concentrations (CO$_2$, etc)
7. Soil heat flux
8. “ancillary” data
Measuring climate sensitivity: the scale problem:

Our best data is local

Our best tool for direct measurements of climate sensitivity of the carbon cycle

AERIAL VIEW

= Tower

NOT TO SCALE

Our best tool for direct measurements of climate sensitivity of the carbon cycle
Tracking correlated changes in concentration and vertical velocity
What is Fluxnet?
Distribution of global eddy covariance sampling effort relative to modeled GPP on a site basis.
Status of global models?

- Current models match local and some global observations but depend on variables and scales that are hard to validate.

- Current models give drastically different predictions under climate change despite similar skill levels for the present day.
Terrestrial carbon cycle feedbacks

• **Physiology**: Terrestrial uptake and release depend on temperature and precipitation.
• **CO$_2$ fertilization**: Terrestrial uptake depends on atmospheric CO$_2$ concentration.
• **Nutrient limitation**: The above feedbacks depend on nutrient cycles.
• **Ecosystem structure**: Terrestrial carbon storage depends on ecosystem type, which depends on climate.
Flux measurements
Models from EC data
Initial guess parameters

Optimized parameters

Cumulative NEE (g C/m$^2$)
An example:

Observed variability of fluxes

Niwot Ridge
Analyzed variability of processes
Warm springs accelerate growth but also evaporation, consistent with information from spatial flux patterns and atmospheric CO$_2$ trends.
Time-scale challenges with EC data

Of course, some parameters may have hit the edge simply because their prescribed ranges were too narrow. This possibility could be tested by increasing these parameter ranges and re-running the optimization. However, in preliminary experiments we found that it is difficult to do this without forcing other (previously well-constrained) parameters to be edge-hitting. If one parameter is allowed to take on unrealistic values, the model is only able to maintain its close match to the data if other parameters take on unrealistic values as well. Finally, parameters that vary by order of magnitudes (such as $K_W$) are indicative of multiplicative effects, and typically exhibit a highly skewed (e.g. logarithmic) distribution.

Error analysis and wavelet decomposition

The optimization resulted in significant reduction in overall error on the daily time scale, especially for periods of net uptake (Fig. 5). While the mean reduction in model-data RMS error is only from 1.37 to 0.972 g C m$^{-2} C_0$, the improvement in mid-summer maxima is very large, greatly improving the overall estimation of photosynthetic uptake. The greater improvement in summer vs. winter (uptake vs. release) is consistent with other model diagnostics. These results are consistent with an emerging conclusion that greater uncertainties remain in modeling respiration than photosynthesis on these timescales. The model, before and after parameter optimization, predicts much less variability in winter and nighttime respiration fluxes than the observations show; in fact, the observations show some periods of net carbon uptake in the winter. This area of disagreement probably reflects both missing processes in the model and observational uncertainty, although we do not know the exact causes yet. Comparison of modeled fluxes to other respiration (e.g. soil chamber) data will be valuable in diagnosing the causes of these model-data discrepancies.

The wavelet transformation complements the above analysis by visualizing the variance of the model, data, and model-data mismatch at multiple time scales (Fig. 8). The observations show large variance at the strongly forced diurnal and seasonal time scale and an overall correlation between frequency and variance, with variance declining at lower frequencies. This corresponds to the small magnitude of long-term NEE compared to photosynthetic and respiratory fluxes. The variance of the residuals, relative to the variance of the data, indicates the fit at each scale. The residual variance is low at the strongly forced diurnal and seasonal time scales. The ability of the optimization to fit the data's variability patterns at both of these time scales simultaneously, while using only a single parameter set, indicates the effectiveness of this approach, in which all the data are considered at once. Other methods of parameter estimation often produce different parameter values (e.g. different values for the $Q_{10}$ parameters) for the diurnal and seasonal fits (e.g. Reichstein et al., 2003). However, the residual variance generally increases at low frequencies. The model explains much of the variance in the strongly forced fluxes, but fails to capture interannual patterns of net carbon exchange, which are more heavily influenced by the internal dynamics of the ecosystem. These variance patterns indicate that the bulk of the information in even a decadal eddy covariance record, given the signal to noise of the record, is on the seasonal and shorter time scales.

The triple-residual problem (Michalak, 2013)

Fig. 8  Wavelet variance of the net ecosystem exchange of CO$_2$ observations (a) and of the normalized residual (b) (the model-data difference divided by the data).
What we need: Observations of climate sensitivity at the right scale

What we have:
- Observations of (limited) state variables at the right scale
  and
- Observations of climate sensitivity at the wrong scale
The Airborne Carbon in the Mountains Project
ACME sponsors and participants

Russ Monson
Britt Stephens
Ankur Desai
Dave Moore
Jielun Sun
Don Lenschow
Ja Hu
Stephan de Wekker
Steve Aulenbach
Sean Burns
Chun-Ta Lai
Heather Graven
And many others...
Airborne budgets over a seasonal cycle

The study domain

Designing budget flights
Niwot Ridge AmeriFlux Tower vs. CarbonTracker

![Graph showing NEE (umol/m²/s) over DOY for Niwot Ridge and CarbonTracker](image)
Sample and model a large domain, assess common features and variation.

Carbon tracker  SiP Model
Comparison of regional methods

Comparison of daily fluxes

Comparison of continuous methods
Niwot Ridge AmeriFlux Tower vs. CarbonTracker with Best Estimate from BLB
Carbon data assimilation in CLM

• Developed as a joint NCAR-NEON (JPL) activity
• Uses NCAR model and assimilation systems
• Goal: produce analyses and initial conditions for forecasting
Main components of CLM
Data Assimilation Research Testbed (DART)

- DART is a community facility for ensemble DA
- Uses a variety of flavors of filters
  - Ensemble Adjustment Kalman Filter
- Many enhancements to basic filtering algorithms
  - Adaptive inflation
  - Localization
- Uses new multi-instance capability within CESM

Observations

another cycle?

Yes

Assimilate

restarts

diagnostics

Done.

model_to_dart

new model states

advance model states

dart_to_model

initial model states
Observing system simulation experiment

- 80 member, 6 hourly climate reanalysis available, 1998 – 2010
- Each forces separate CLM ensemble member at 1° x 1°
- Generates spread in the land model states
- At 60 NEON sites observe:
  i. Leaf area index
  ii. Leaf nitrogen concentration
  iii. Net Ecosystem Productivity
  iv. Evapotranspiration

- 175,000 observations a month
NEON sites and Harvard forest flux tower
How predictable is terrestrial exchange?

Errors increase as soon as assimilation ends, but skill persists for years. We can diagnose why errors grow.
NEP – observations every 30 minutes
Mean NEP from 80 ensemble members
Reduction in LAI ensemble spread
Examples of other N and C pools - unobserved
Mean LAI from 80 ensemble members
LAI spread from 80 ensemble members
Reduction in LAI ensemble spread
Mean biomass from 80 ensemble members
Change in biomass ensemble spread
Change in NEP ensemble spread
Impact on forecast - biomass
Sensitivity to canopy chemistry parameters

C:N\textsubscript{leaf}

$F_{lnr}$

SLA

Soil Carbon (gC m\textsuperscript{-2})

NEE (gC m\textsuperscript{-2} a\textsuperscript{-1})

Parameter value

Time (years)

Year 1

Year 5

Year 10

Year 20

Year 40

Year 80
Leaf Nitrogen – observations every 12 days
Impact on forecast - $\Sigma\text{NEP}$
Current Directions

- Adding plant functional types to observation metadata and observation operators allowing effective aggregation to model grid cells
- Investigating temporal aggregation strategies for flux tower observations
- Testing use with existing MODIS LAI and new satellite data sets
- Adding additional, site specific observation types – soil respiration, soil moisture and temperature profiles
- Can we improve simulation of “slow” processes?