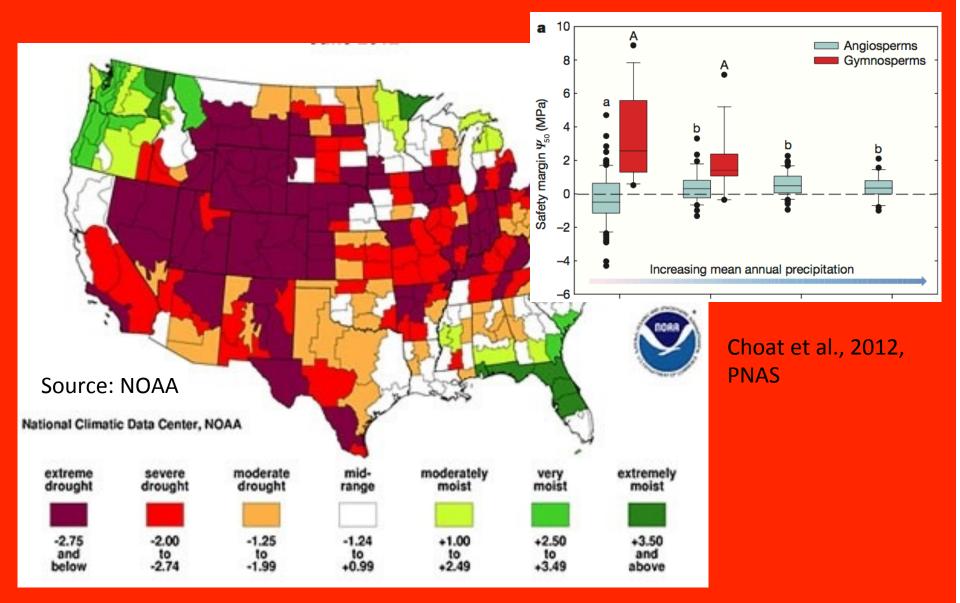
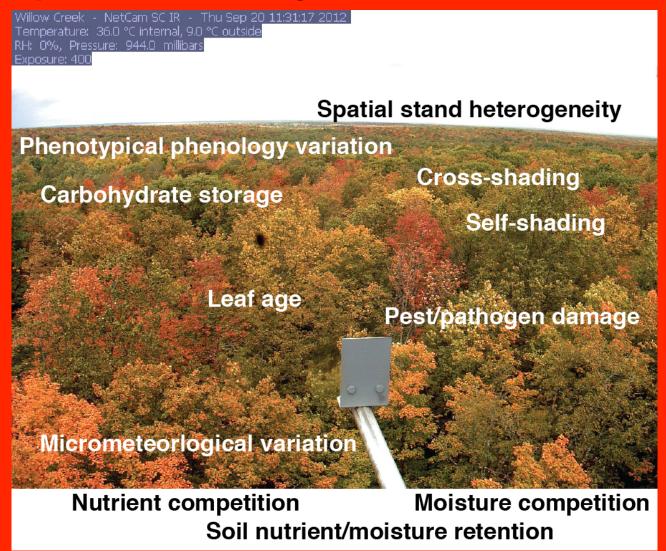


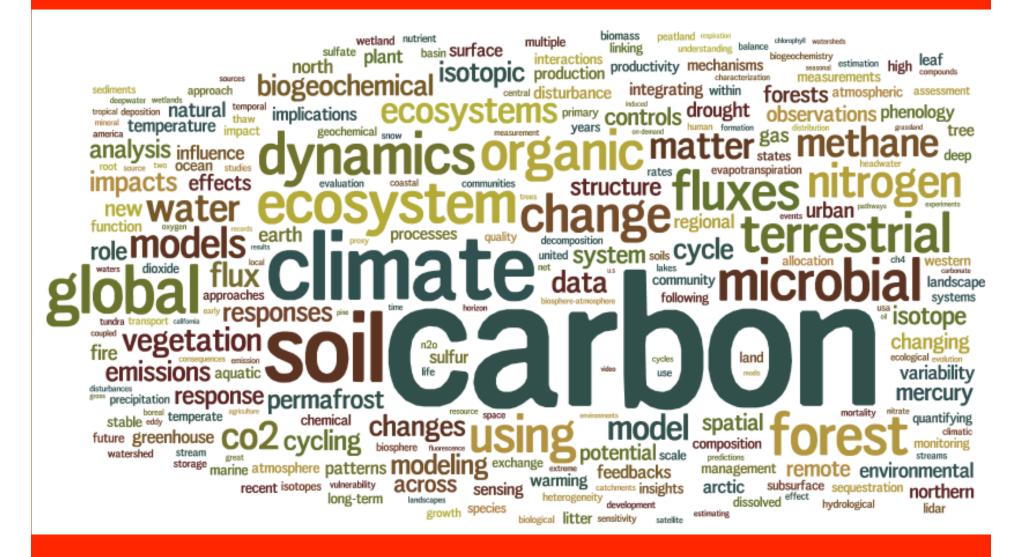
How do terrestrial plants respond to extremes?



How do ecosystem-scale responses vary from leaf-scale?



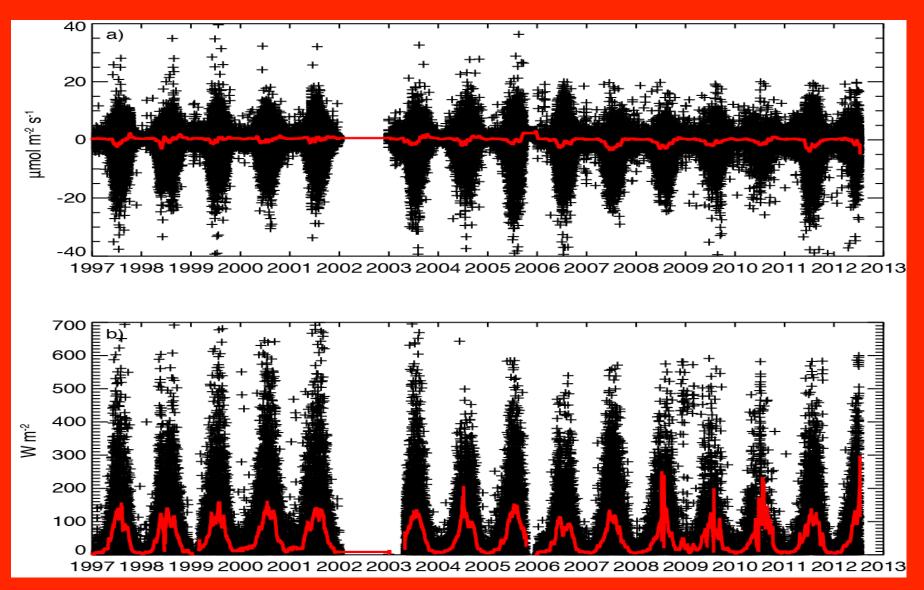
Where are we looking?



We have a very tall tower that might help!



Long-term NEE and ET has weak trends



What could we do with these data?

- Extract measure of productivity
- Identify modes of variability
- Derive standardized anomalies across modes of variability
- Assess autocorrelation of anomalies to recognize statistical significance
- Test for anomaly correlation and lagged anomaly correlation across all modes
- Build predictive anomaly models to identify causality

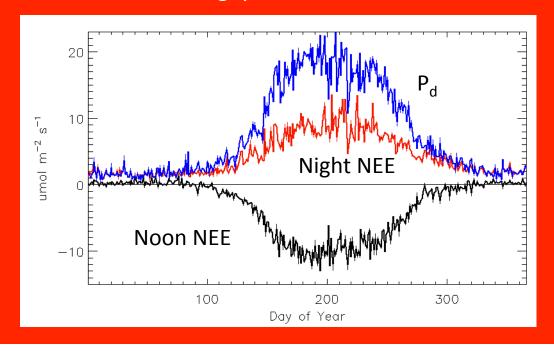
Why?

 Test 1. Positive lagged autocorrelation of productivity anomalies implies a strong internal feedback in response to extremes (e.g., nonstructural carbohydrate allocation)

- Test 2. At some timescales, moisture stress can overwhelm internal feedbacks and lead to decreased productivity
- Essential observational tests for scaling from leaf to ecosystem and evaluating/developing models

From NEE to Productivity

- Flux tower derived GPP is sensitive to model selection and gaps (Desai et al., 2008)
- INSTEAD: Use a data-based approach
 - P_d = Max nighttime observed NEE Mean noon (10-14)
 NEE
 - Reject noon NEE is > 50% gap-filled



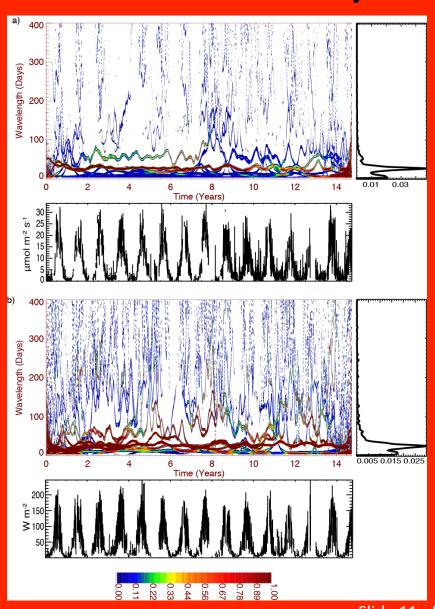
What to test?

• Productivity, moisture, and temperature

| Abbreviation | Description | Source |
|--------------------|---|-------------------|
| P_d | Photosynthetic drawdown | Flux tower |
| EVI | Enhanced Vegetation Index, 8-day average | MODIS TERRA/AQUA |
| ET | Evapotranspiration | Flux tower |
| WUE | Water Use Efficiency (P_d/ET) | Flux tower |
| P _{recip} | Daily precpitation | NCDC + NARR |
| | | Reanalysis |
| Q_{soil} | 10 cm soil moisture | NARR Reanalysis |
| T_{mean} | Daily temperature | Flux tower + NCDC |
| T_{min} | Minimum daily temperature | Flux tower + NCDC |
| T_{max} | Maximum daily temperature | Flux tower + NCDC |
| T_{range} | Daily temperature range (max - min) | Flux tower + NCDC |
| LST | Land Surface Temperature, 8-day day/night | MODIS TERRA/AQUA |
| | average | |

Identifying modes of variability

- Hilbert-Huang Transform (HHT) well suited to gappy non-stationary data
- Discontinuous empirical mode decomposition (DEMD) based approach
- P_d and ET spectra show characteristic modes of variability at daily, weekly, monthly, seasonal scales

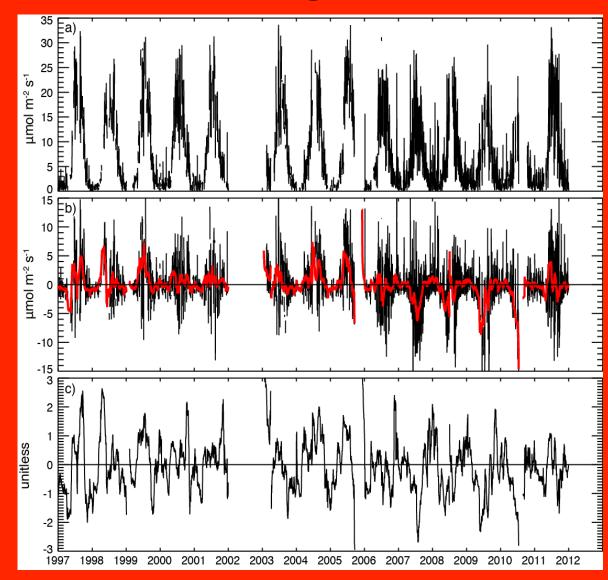


Desai B54A-02 AGU FM 2012

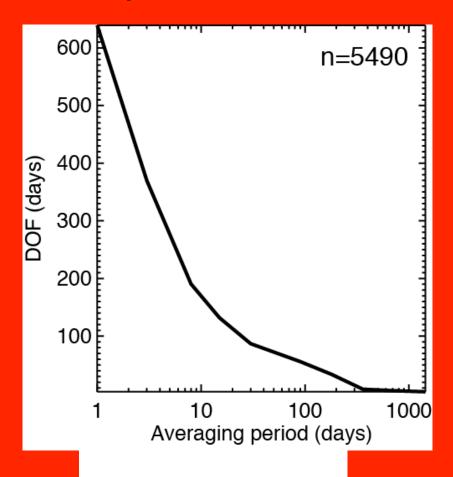
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Pet peeve 1: Standardizing anomalies

- Without anomalies, spurious correlation from orbital forcing are likely!
- Focus on standardized anomalies to normalize units



Pet peeve 2: Autocorrelation is a bugger

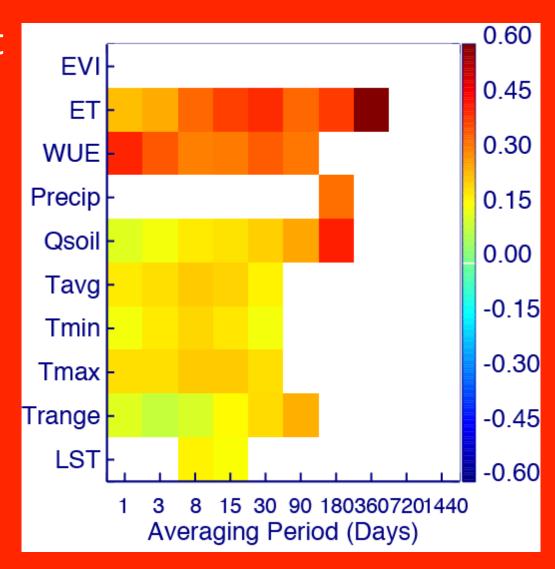


$$N_* = \frac{N}{\sum_{t=N/2}^{N} \left[\left(1 - \frac{t}{N} \right) \rho_t^X \rho_t^Y \right]}$$

- Autocorrelated data overstates N for significance tests
- Used approach of Bretherton et al (1999) to estimate true degrees of freedom (DOF) of correlating time series as a function of autocorrelation

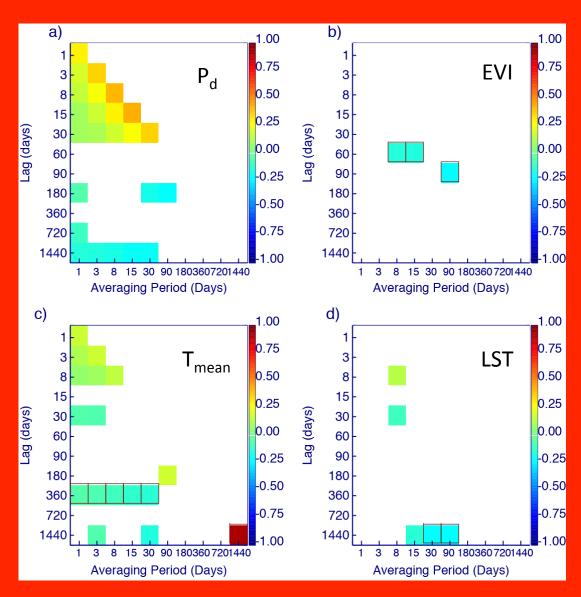
What do you get?

- Only significant correlations
 shown
- Moisture and temperature anomalies positively correlate with P_d at subannual scales

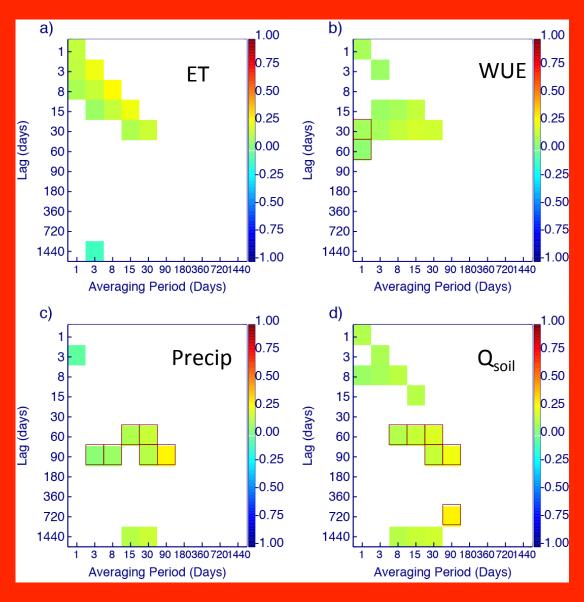


Lags are interesting

- Red squares = correlations > autocorrelation
- Remotely sensed variables (EVI,LST) have limited ability to predict P_d
- Previous year
 weekly-monthly
 temperature has a
 weak negative
 relationship to P_d



Moisture lags even more interesting



- Earlier season (2-3 month) weekly-seasonal precipitation/soil moisture has strongest predictive effect on P_d
- Beyond that, P_d autocorrelation dominates

Granger causality approach concurs

- Approach of Detto et al (2012) to build multiple-lag regression to P_d
- Limited predictive ability beyond monthly scale
- Moisture variables continue to be interesting

| Variable/Averaging | 1 | 3 | 8 | 15 | 30 | 90 |
|--------------------|-----|------|------|-------|----|----|
| period (Days) | | | | | | |
| EVI | | | | | | |
| | | | | | | |
| T _{mean} | 1 | 3 | 8 | | | |
| | | | | | | |
| LST | | | | | | |
| | | | | | | |
| ET | 1-3 | 3 | 8-15 | 15 | | |
| | | | | | | |
| WUE | 1-3 | 3-30 | 8-30 | 15-30 | 30 | |
| | | | | | | |
| P_{recip} | 3 | | | 60 | 60 | |
| | | | | | | |
| Q_{soil} | | | 60 | 60 | 60 | |

Thoughts?

- Strong AR-1 autocorrelation for P_d supports a short term internal feedback at daily to seasonal scales
- Soil moisture is important, even in mesic forests, especially for early season moisture availability, which impacts late season photosynthetic stress
- 15-years of data may still be not long enough to credibly evaluate interannual to decadal scale modes of variability (see also recent Harvard Forest papers)
- Remotely sensed vegetation indices may not be so useful for detecting GPP anomalies
- Next steps: Model evaluation, multi-site evaluation

Thanks!

More at:

- Desai, A.R., submitted. Influence and predictive capacity of climate anomalies on daily to decadal extremes in canopy photosynthesis. Photosynthesis Research, #PRES-S-12-00139.
- http://flux.aos.wisc.edu / desai@aos.wisc.edu / +1-608-218-4208
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