# A BIRD'S EYE VIEW OF THE CARBON CYCLE

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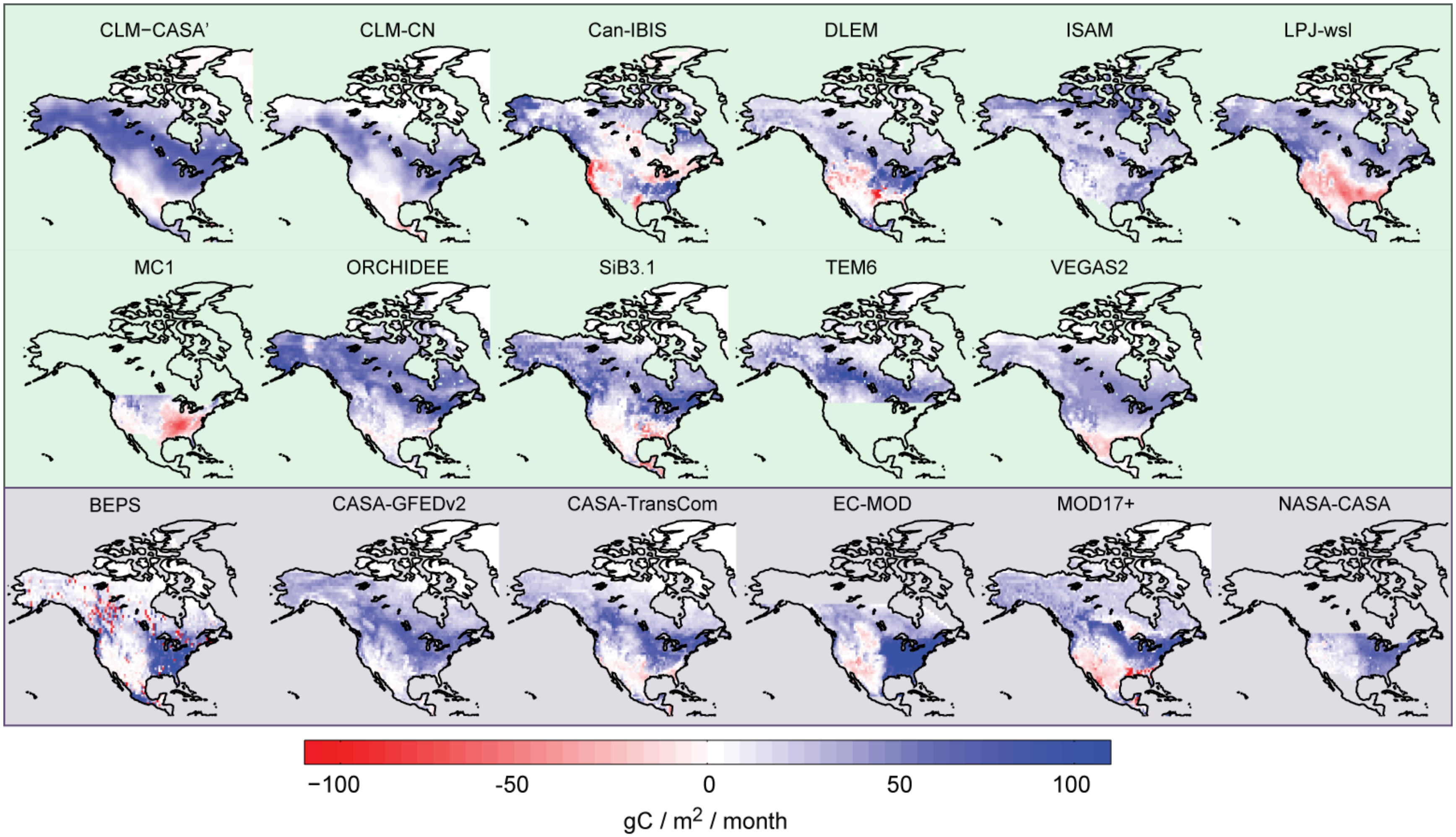
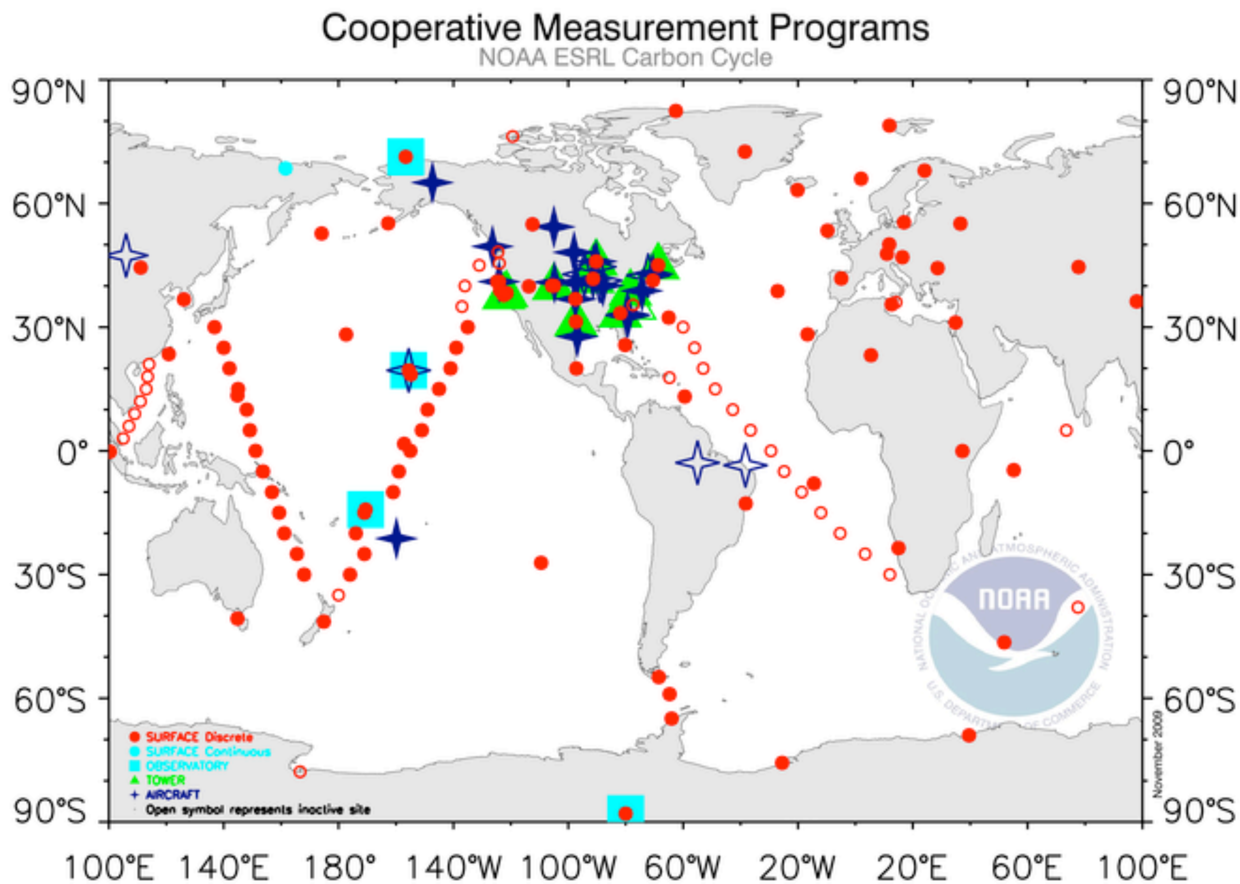
# Current natural carbon sinks




Huntzinger et al. (Ecol Model, 2012)

How can the atmosphere help?

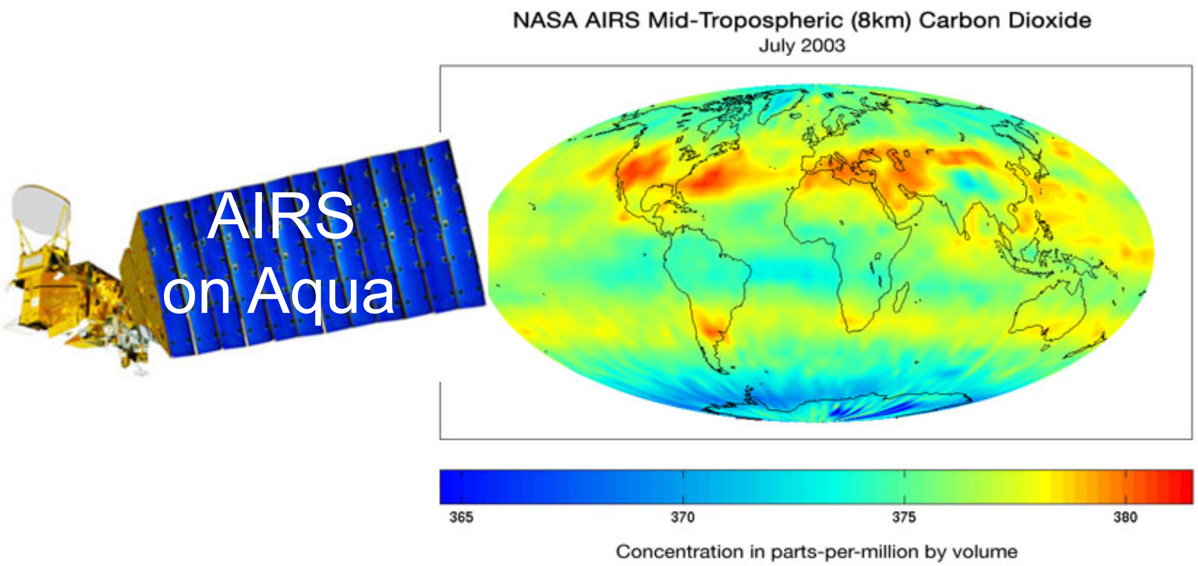
# In situ atmospheric $CO_2$ observations

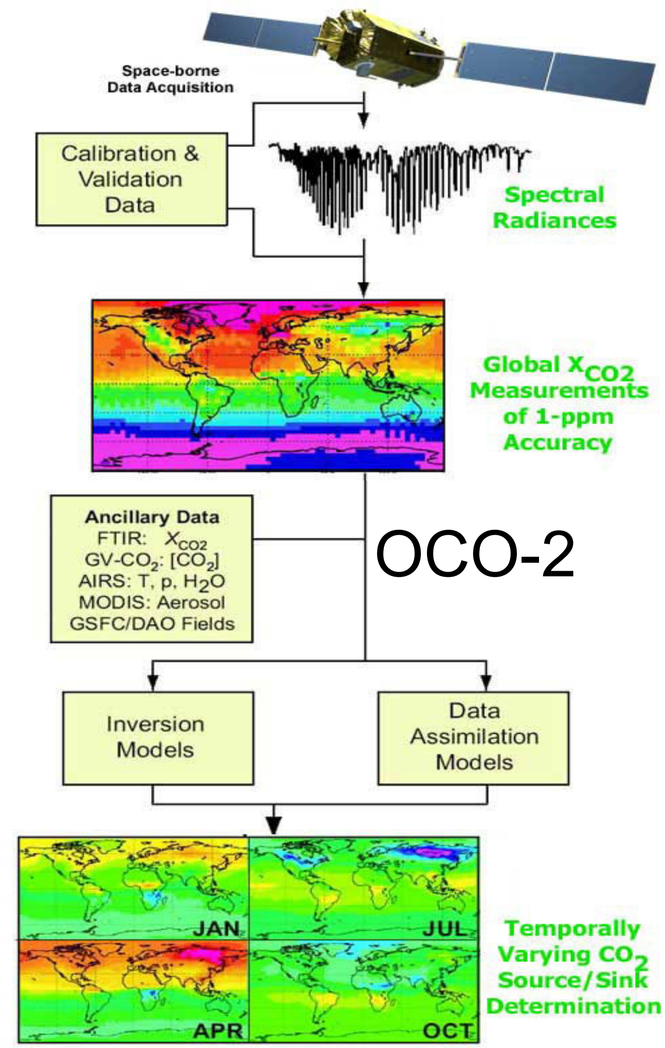



NOAA ESRL Carbon Cycle operates 4 measurement programs. Semi-continuous measurements are made at 4 baseline observatories, a few surface sites and from tall towers. Discrete surface and aircraft samples are measured in Boulder, CO. Presently, atmospheric carbon dioxide, methane, carbon monoxide, hydrogen, nitrous oxide, sulfur hexafluoride, the stable isotopes of carbon dioxide and methane, and halocarbon and volatile organic compounds are measured. Contact: Dr. Pieter Tans, NOAA ESRL Carbon Cycle, Boulder, Colorado, (303) 497-6678, pieter.tans@noaa.gov, http://www.esrl.noaa.gov/gmd/ccgg/.

Source: NOAA-ESRL

# Satellite atmospheric $CO_2$ observations





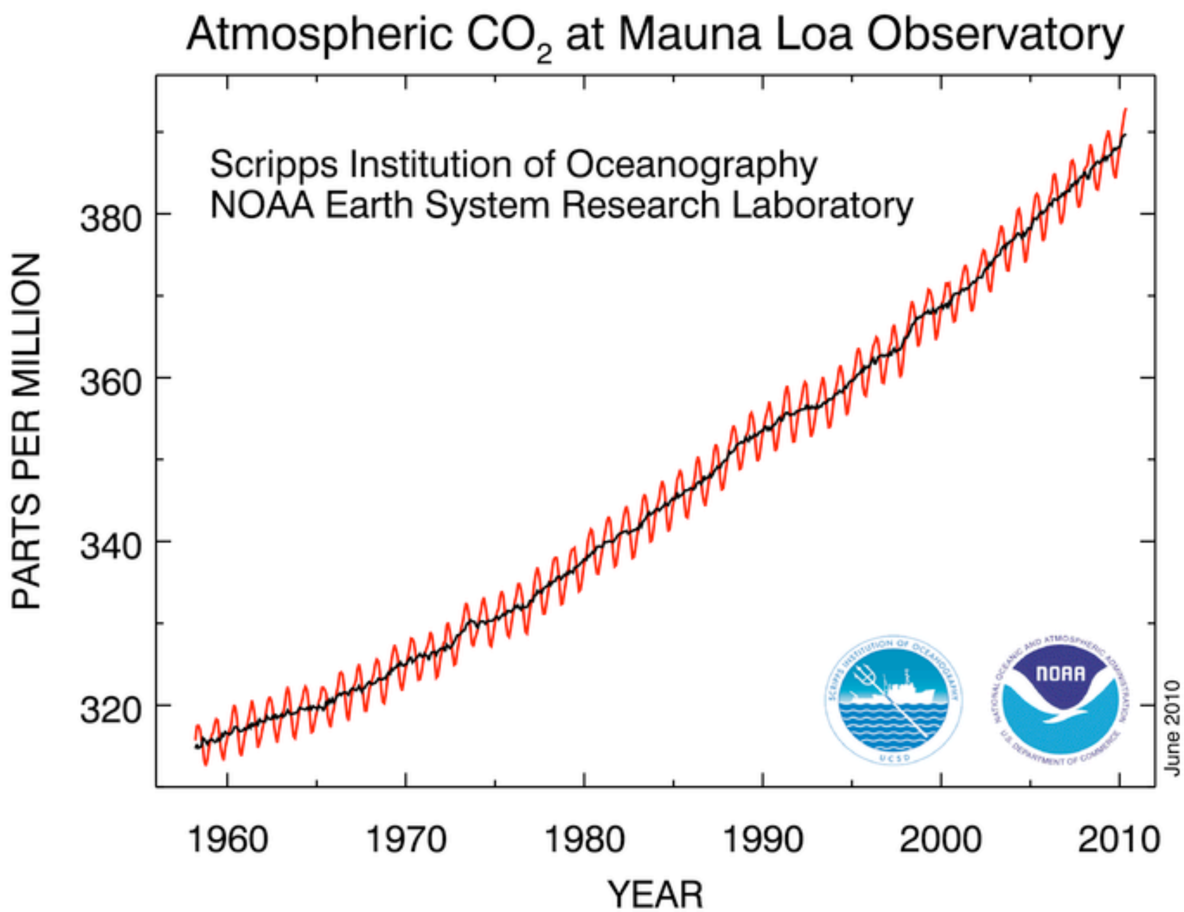
ASCENDS

Geo satellite(s)

etc.

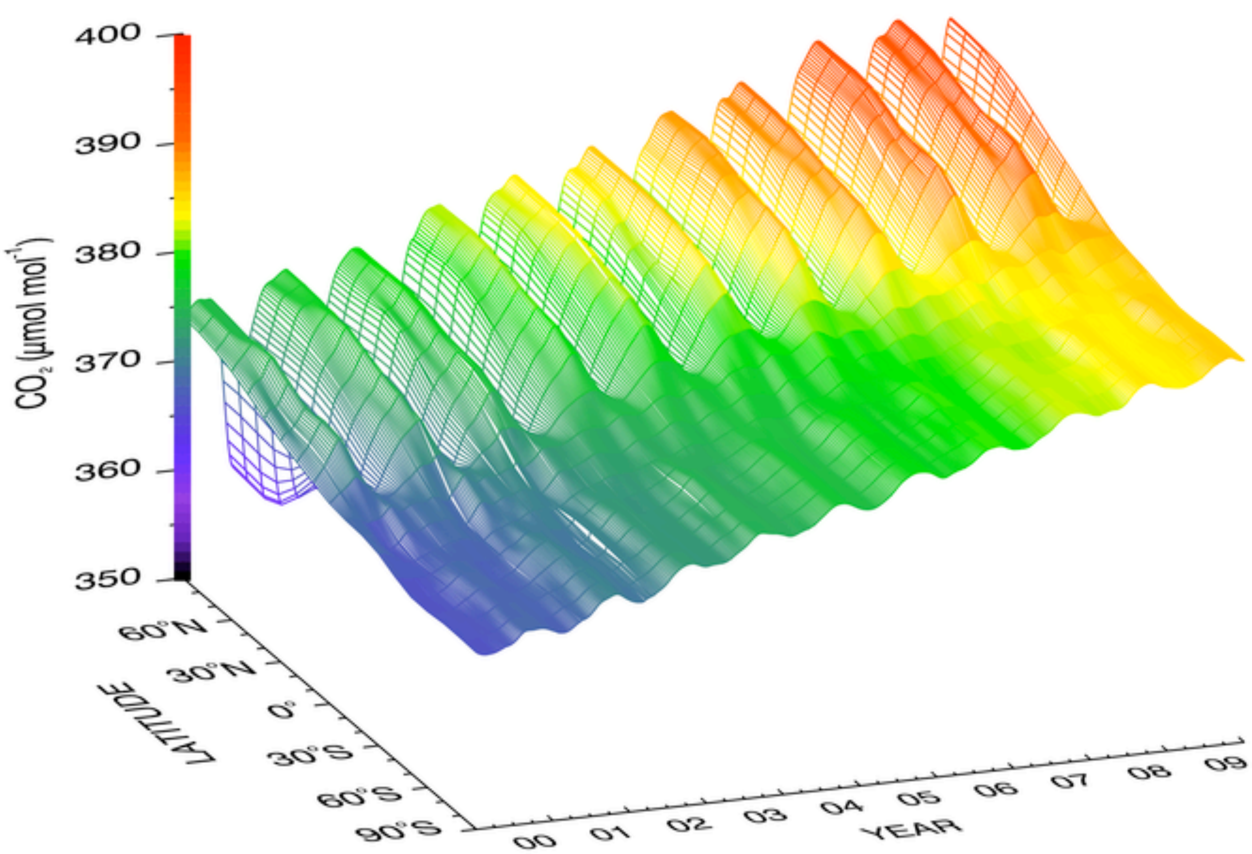
TES, SCIAMACHY, etc.

# Global trends

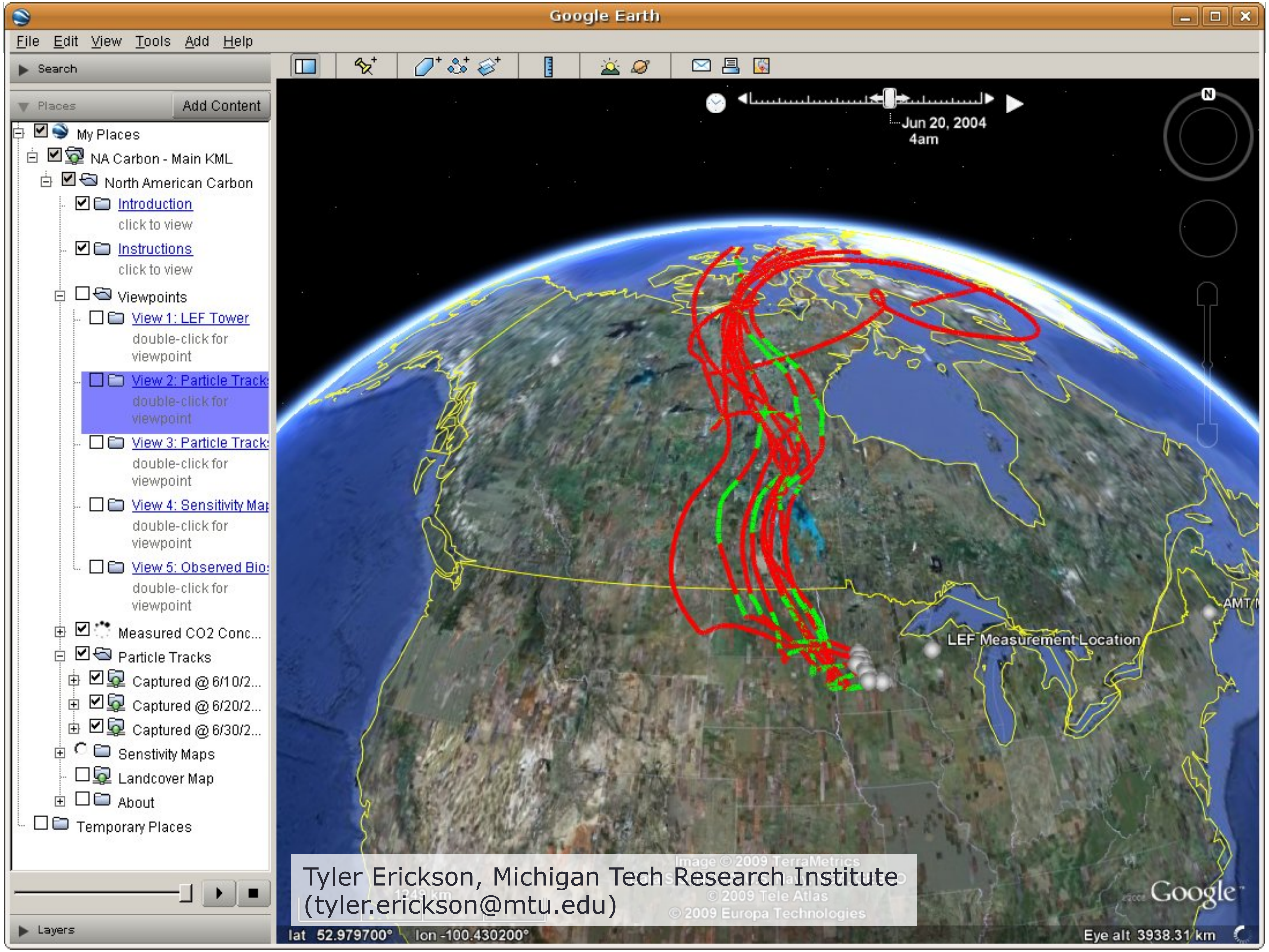



Source: NOAA-ESRL

# Regional variability

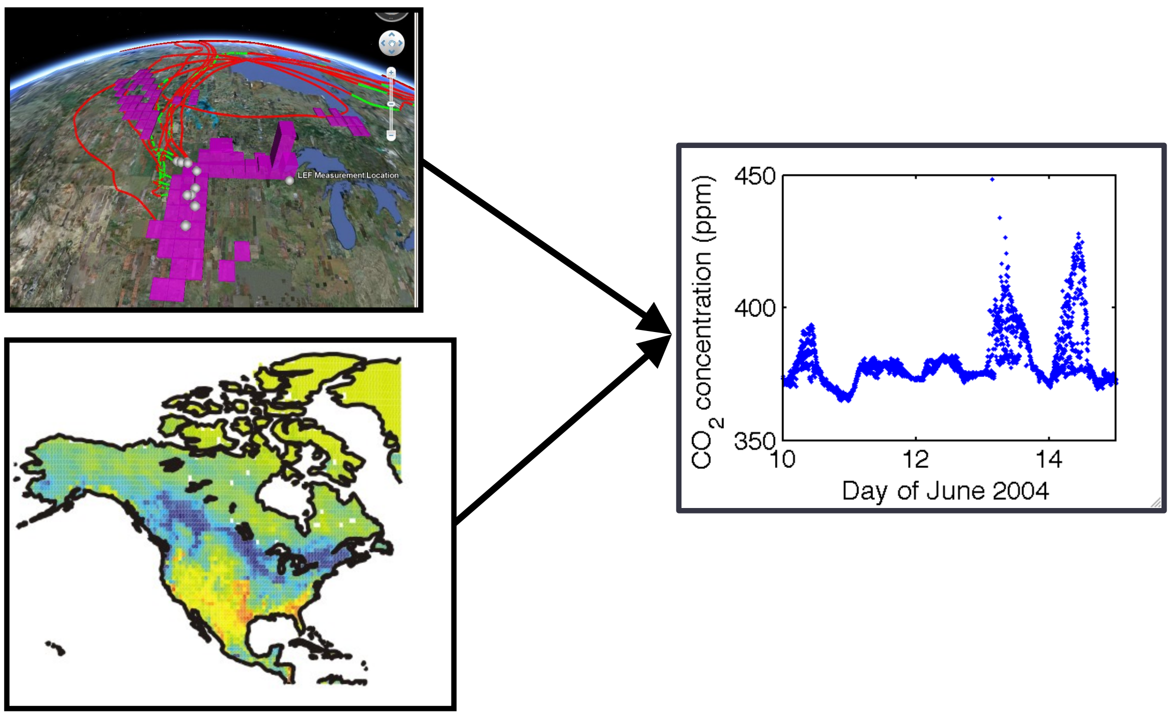



Source: NOAA-ESRL

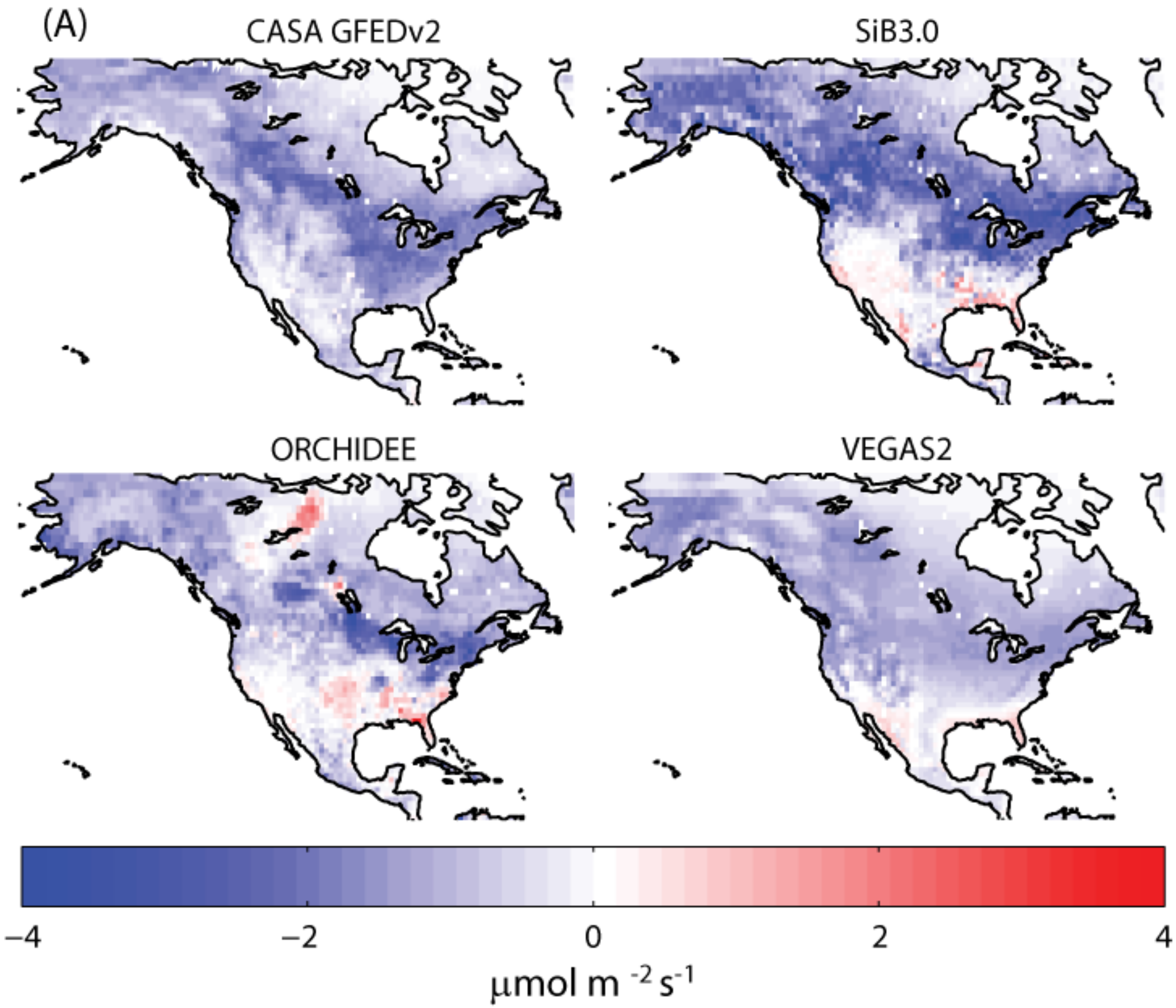


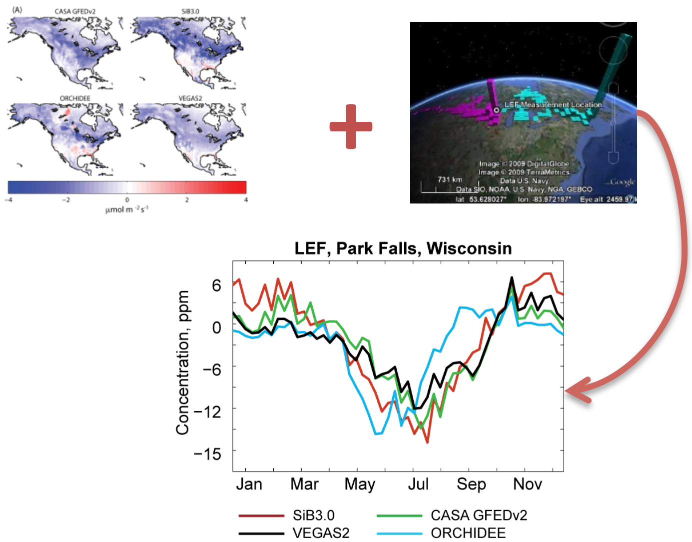

Tyler Erickson, Michigan Tech Research Institute
(tyler.erickson@mtu.edu)

# Flux model evaluation



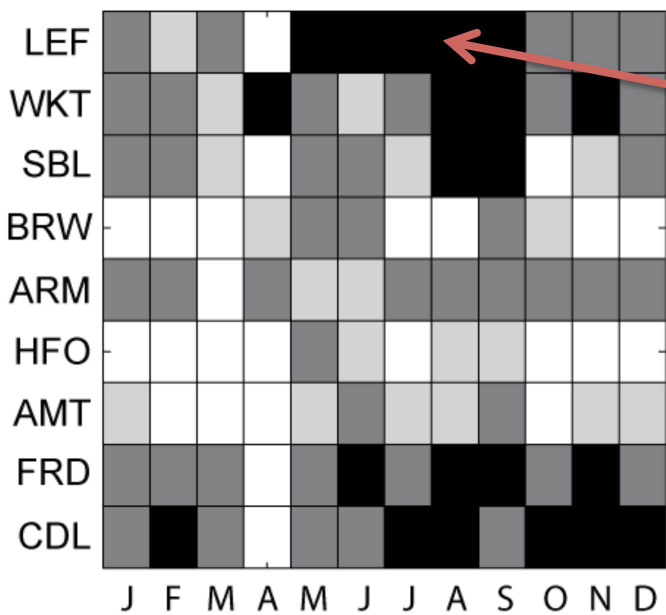
# What aspects of flux differences are observable?

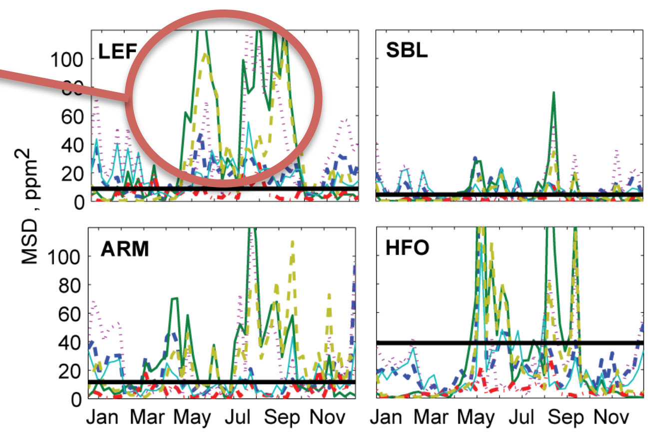




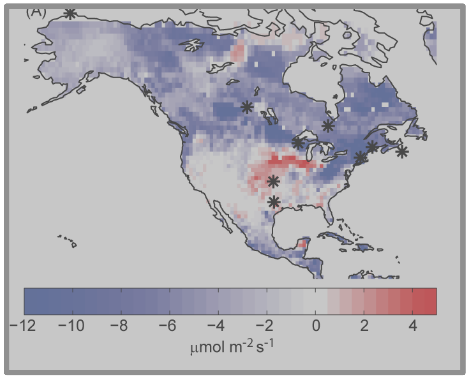

| Large-Scale Spatial | Seasonal Cycle | Fine-Scale Spatial | Diurnal Cycle |
|---|---|---|---|
| √ | √ | √ | √ |

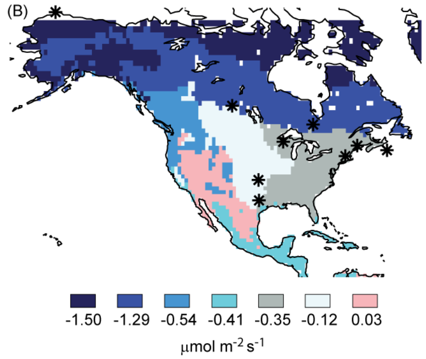
Good news: Atmospheric data can distinguish among models.

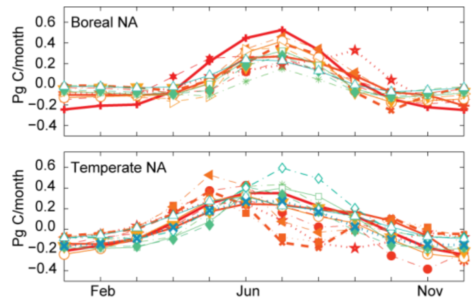


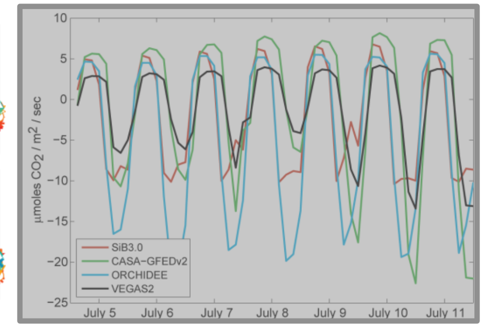




Huntzinger et al. (JGR 2011)

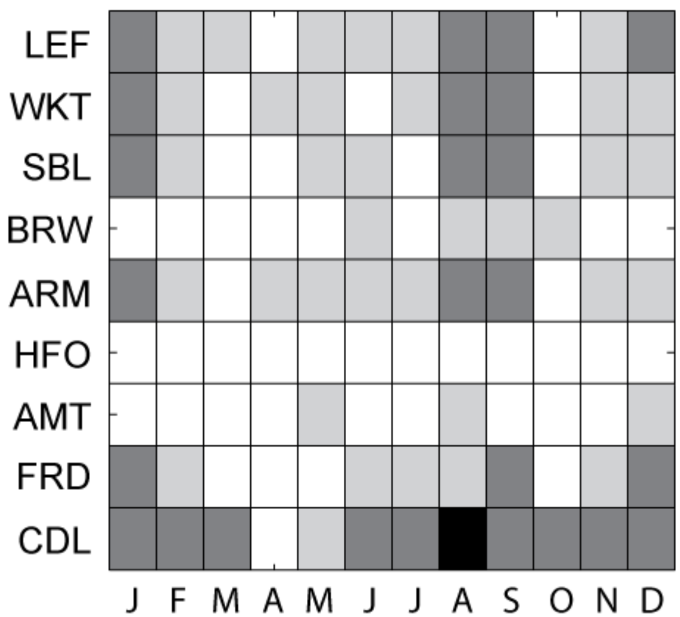


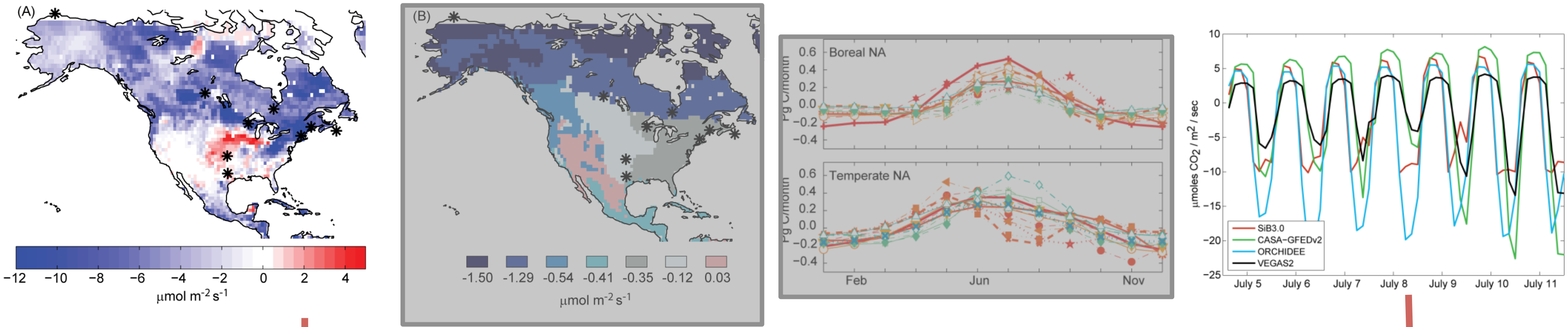




| Large-Scale Spatial | Seasonal Cycle | Fine-Scale Spatial | Diurnal Cycle |
|---|---|---|---|
| √ | √ | | |

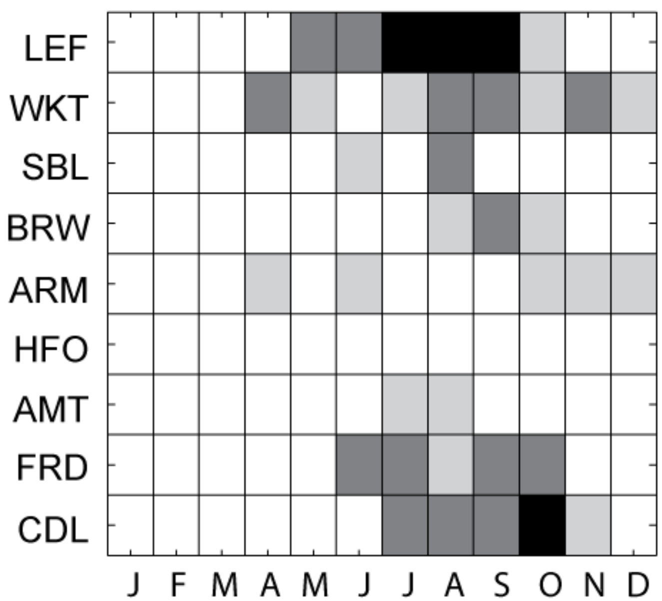



Atmospheric signal can detect differences in net flux over large regions and timing of the seasonal cycle

Huntzinger et al. (JGR 2011)



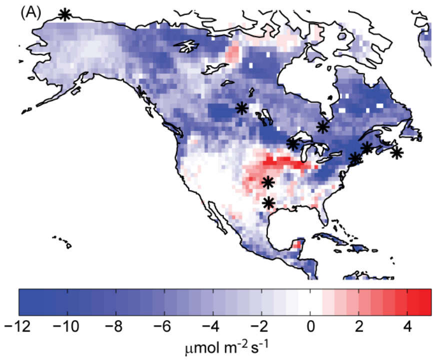

| Large-Scale Spatial | Seasonal Cycle | Fine-Scale Spatial | Diurnal Cycle |
|---|---|---|---|
| | | √ | √ |

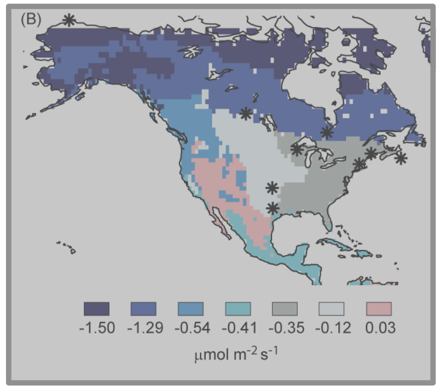


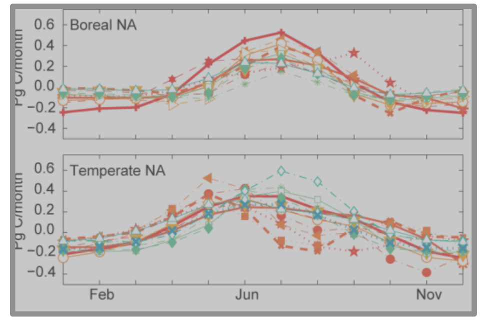

Atmospheric signal can detect differences in fine scale variability during the growing season

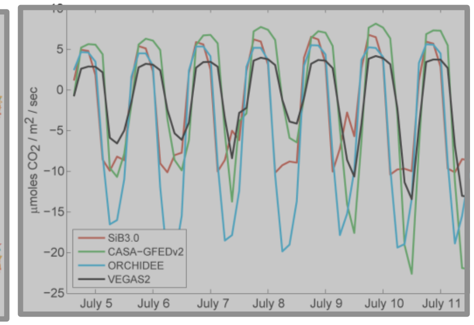
What is the relative importance of the spatial distribution of fluxes compared to timing and strength of their diurnal cycle?

Huntzinger et al. (JGR 2011)

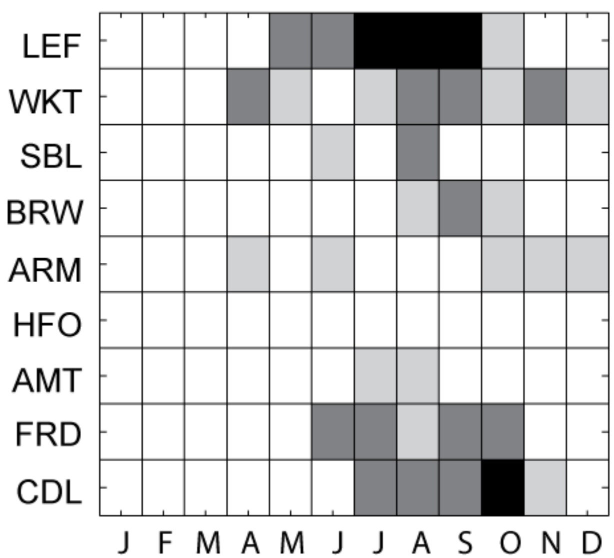


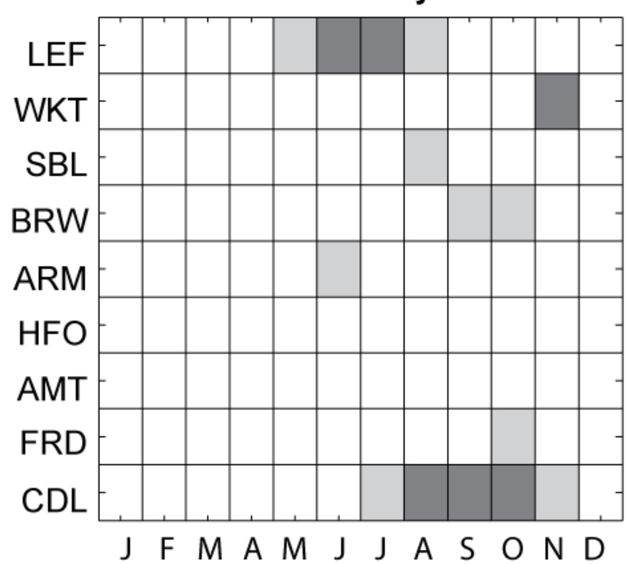




| Large-Scale Spatial | Seasonal Cycle | Fine-Scale Spatial | Diurnal Cycle |
|---|---|---|---|
| | | √ | |

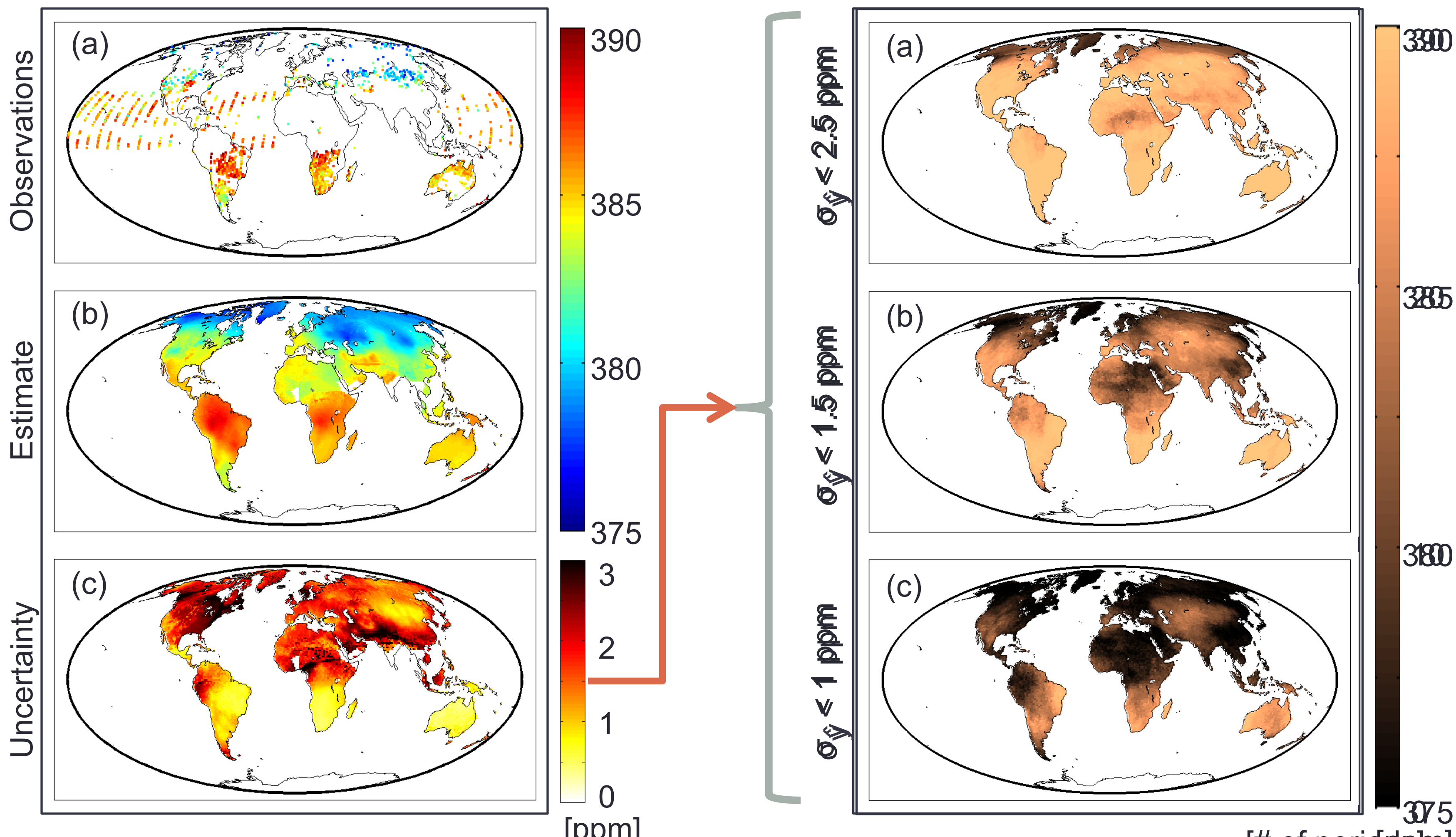



**No diurnal cycle**

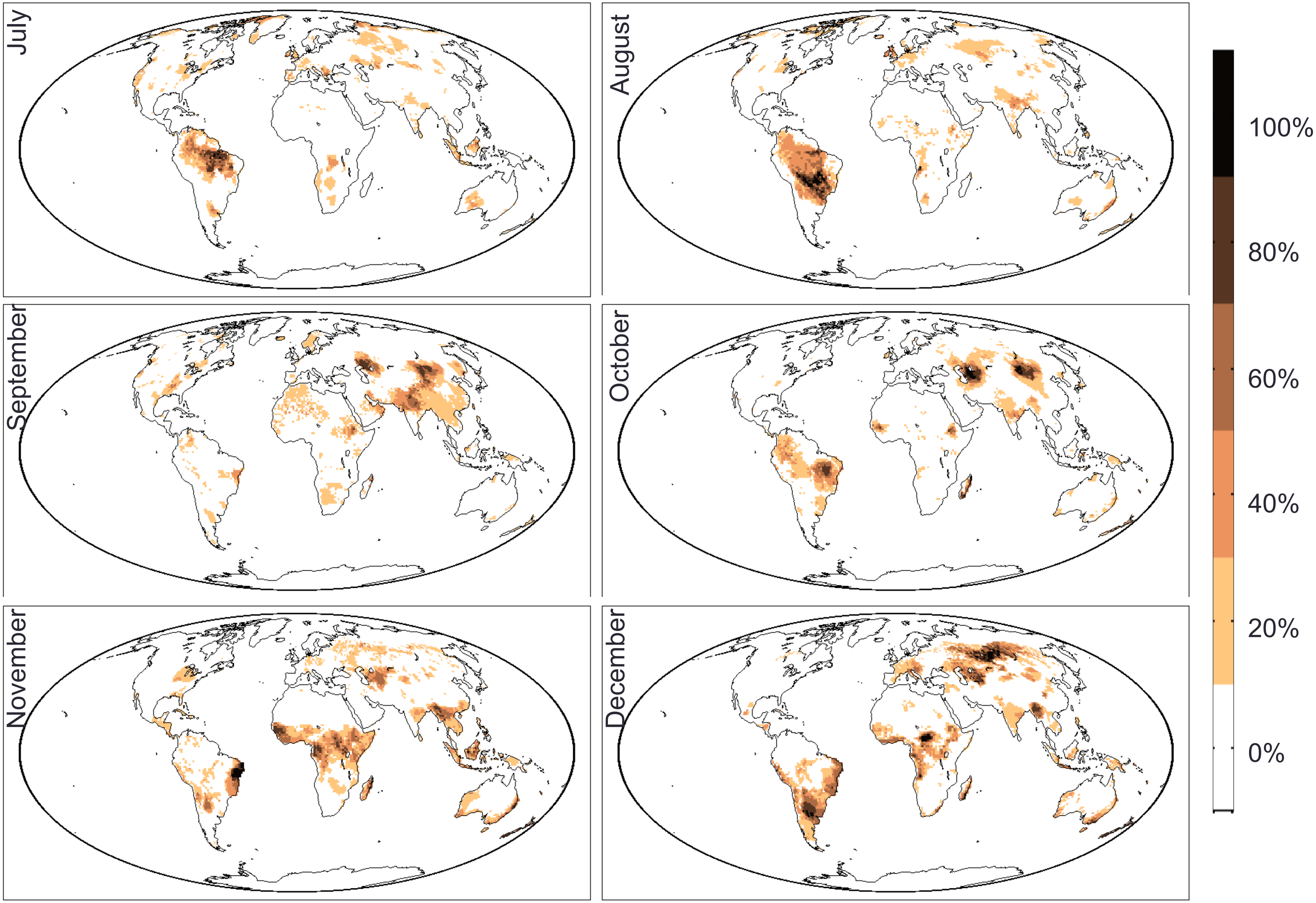



Huntzinger et al. (JGR 2011)

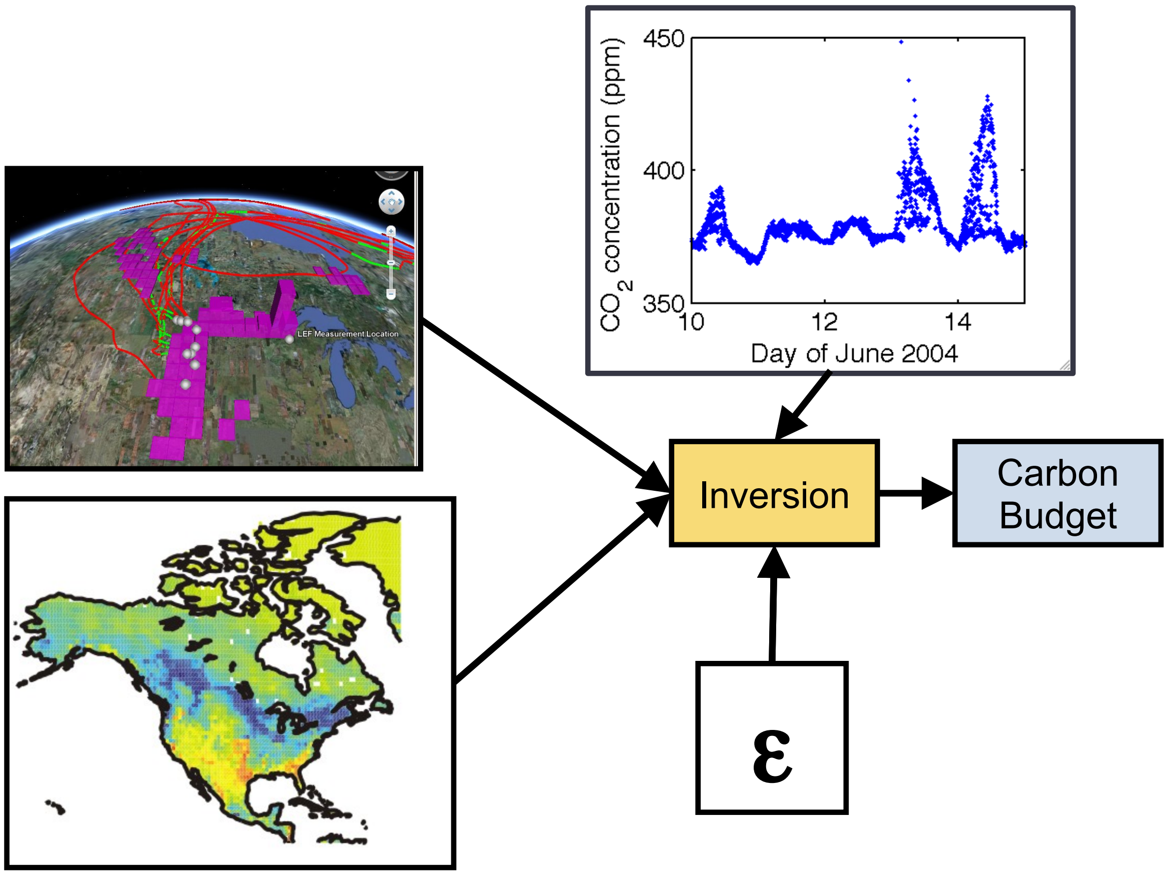
# ACOS GOSAT Level 3



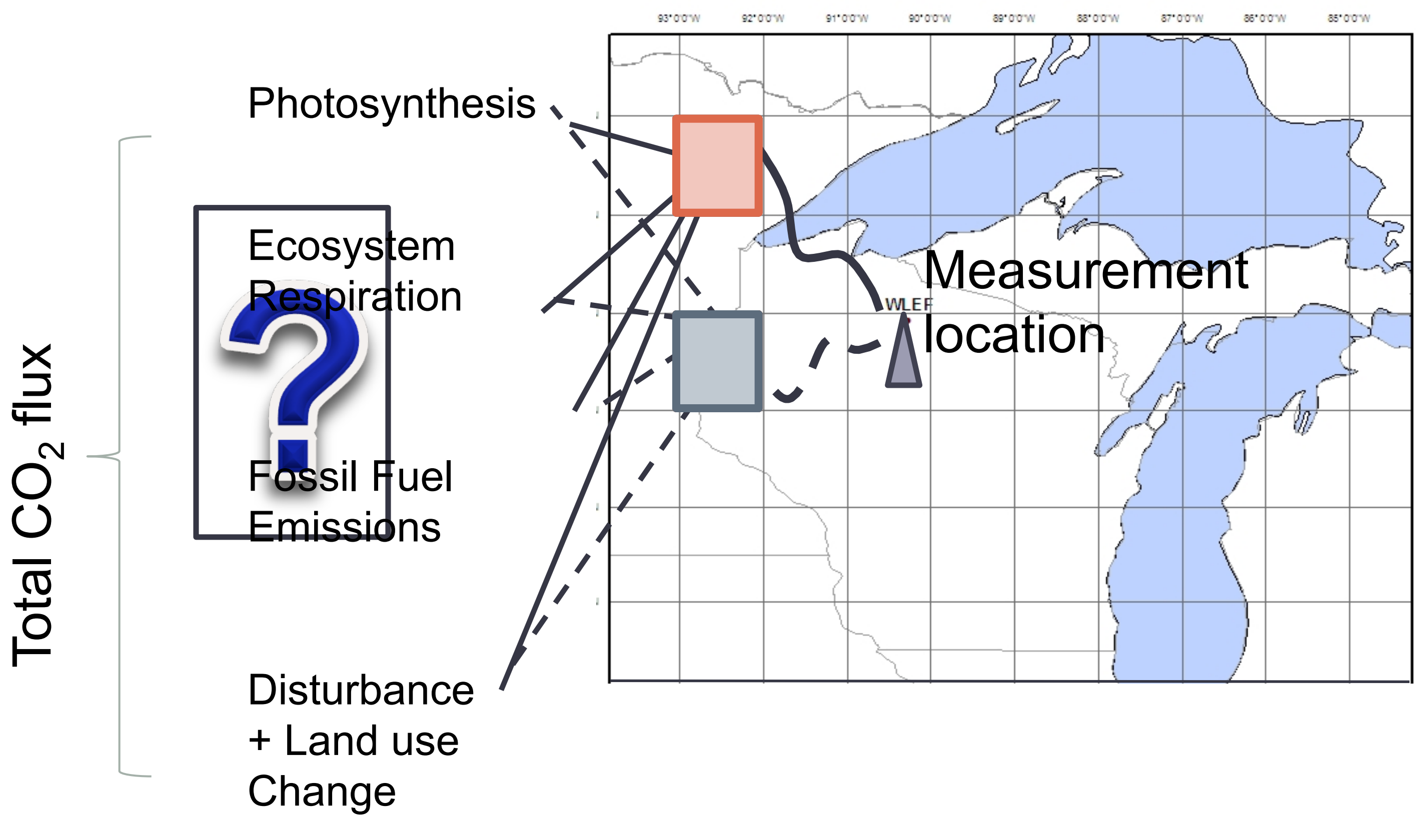

Hammerling, Michalak, O'Dell, Kawa (GRL, 2012)


July
August
September
October
November
December
100%
80%
60%
40%
20%
0%

# Flux model updating



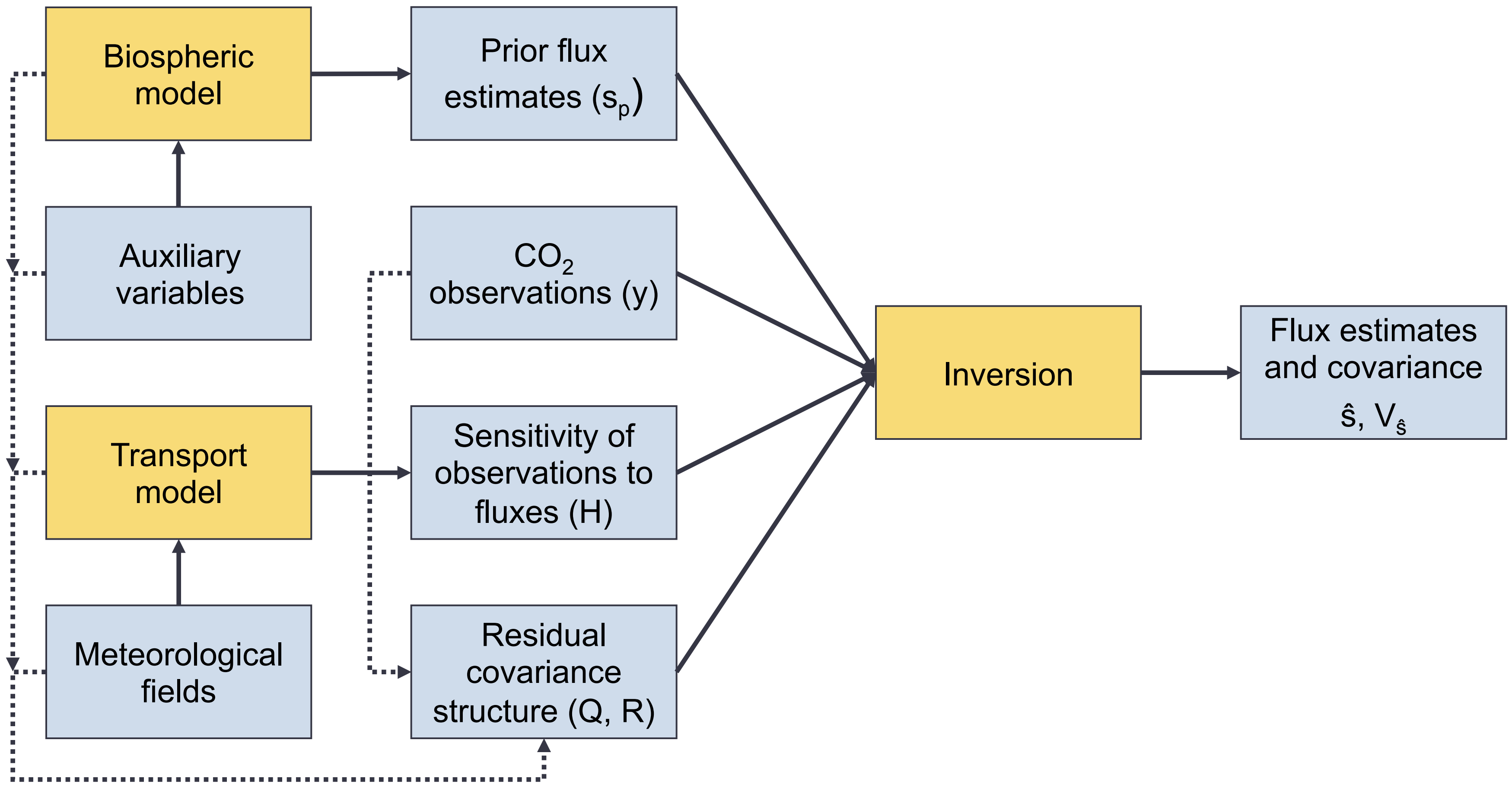
# Atmospheric inverse modeling



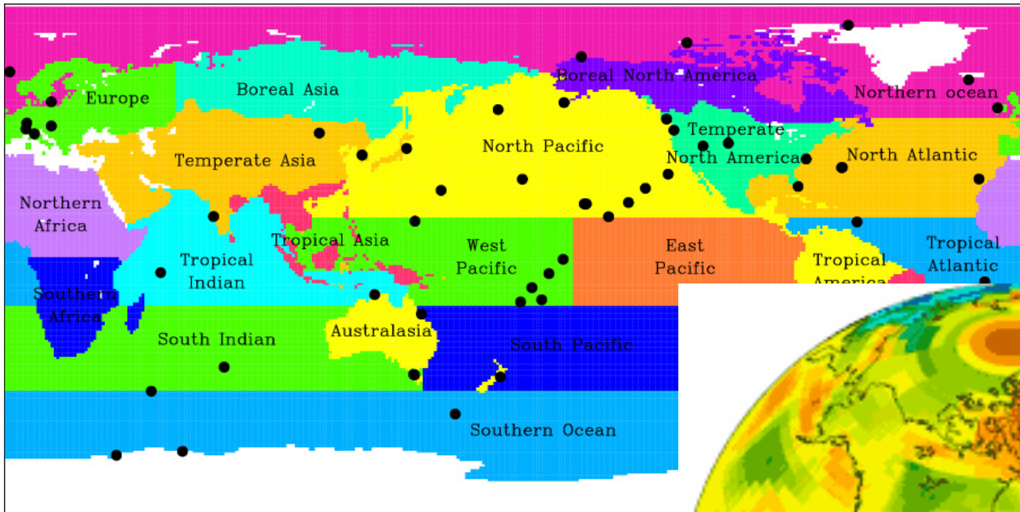

Source: Kim Mueller, U. Michigan (now a UCAR/AMS congressional fellow)

# Bayesian Inverse Problem

$$L_{\mathbf{s}} = \frac{1}{2}(\mathbf{y} - \mathbf{H}\mathbf{s})^T \mathbf{R}^{-1}(\mathbf{y} - \mathbf{H}\mathbf{s}) + \frac{1}{2}(\mathbf{s} - \mathbf{s}_p)^T \mathbf{Q}^{-1}(\mathbf{s} - \mathbf{s}_p)$$

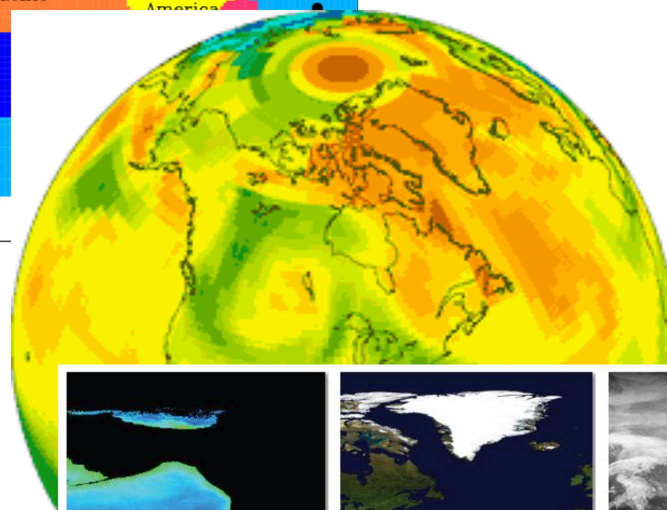


# Examples of Bayesian Inversion Studies



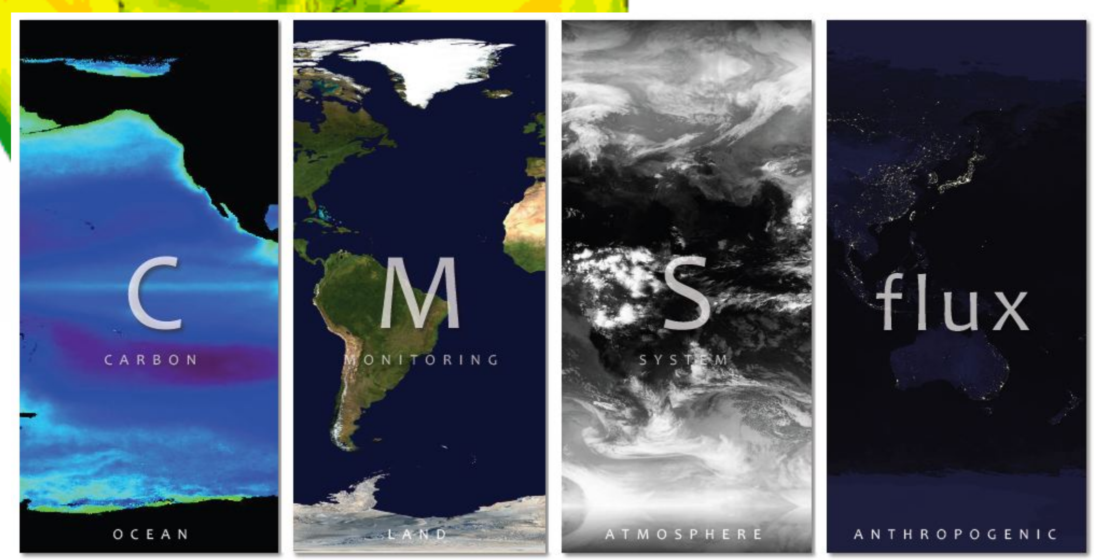

**TransCom3:**
*Estimates*: Continental; Monthly
*Prior:* CASA
*Observations:* in situ
*Numerics:* "Batch"

Now 100s of publications

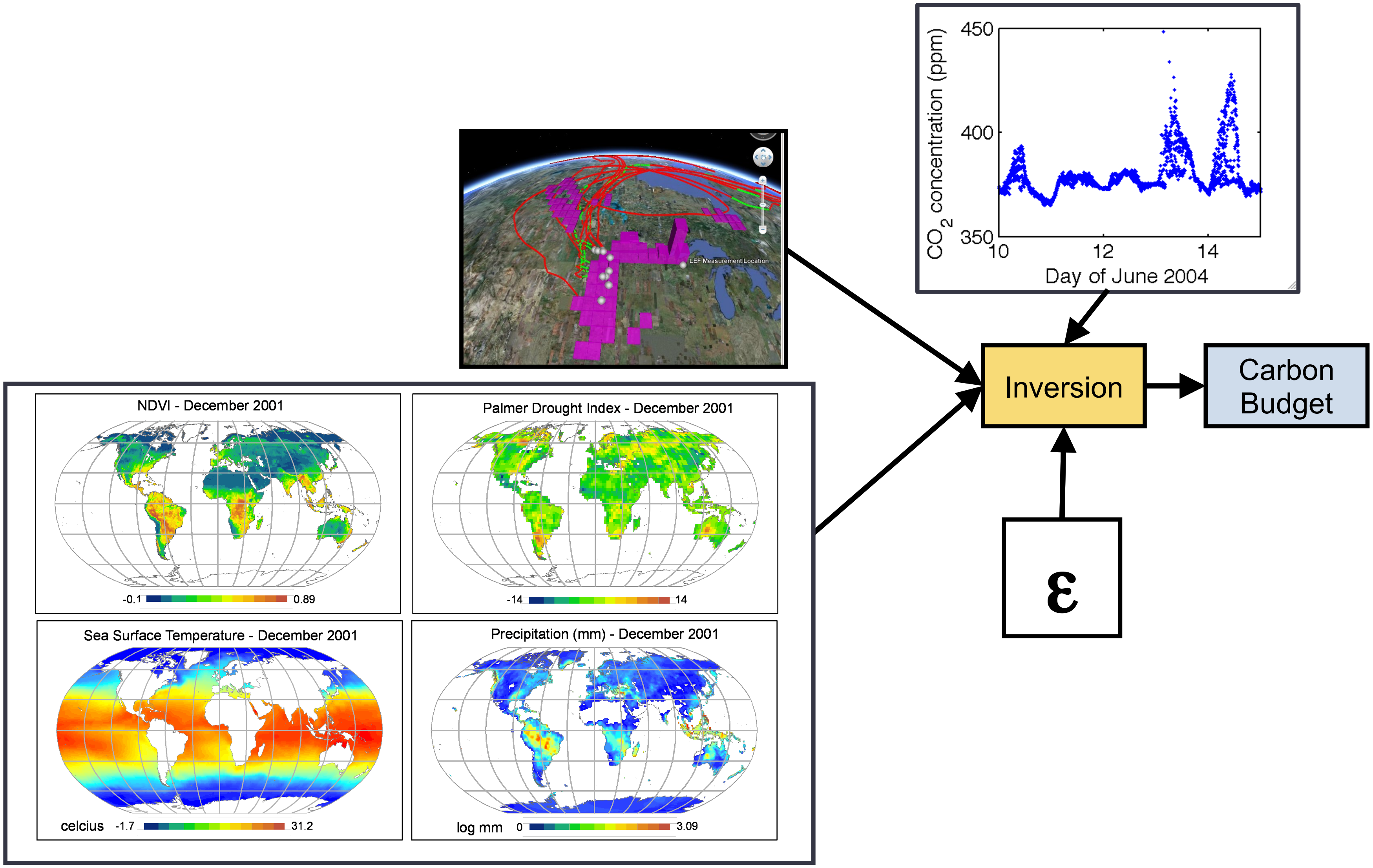


**CarbonTracker:**
*Estimates:* Ecoregion; Weekly
*Prior:* CASA (+ others)
*Observations:* in situ
*Numerics:* Ensemble SRF

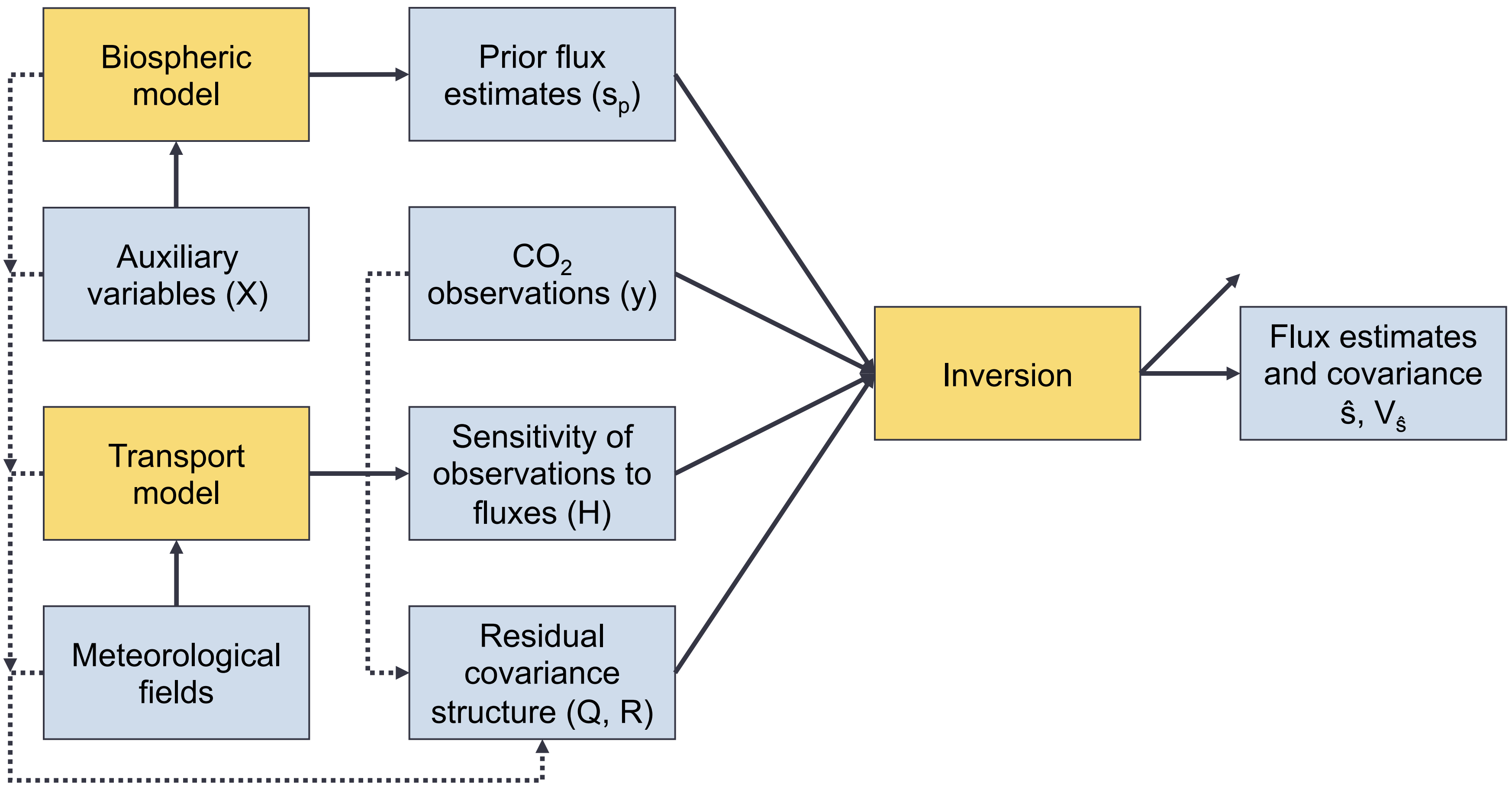
**JPL CMS flux:**
*Estimates:* 4º x 5º; monthly
*Prior:* CASA, CASA-GFED
*Observations:* GOSAT
*Numerics:* 4d-VAR



# Atmospheric inverse modeling

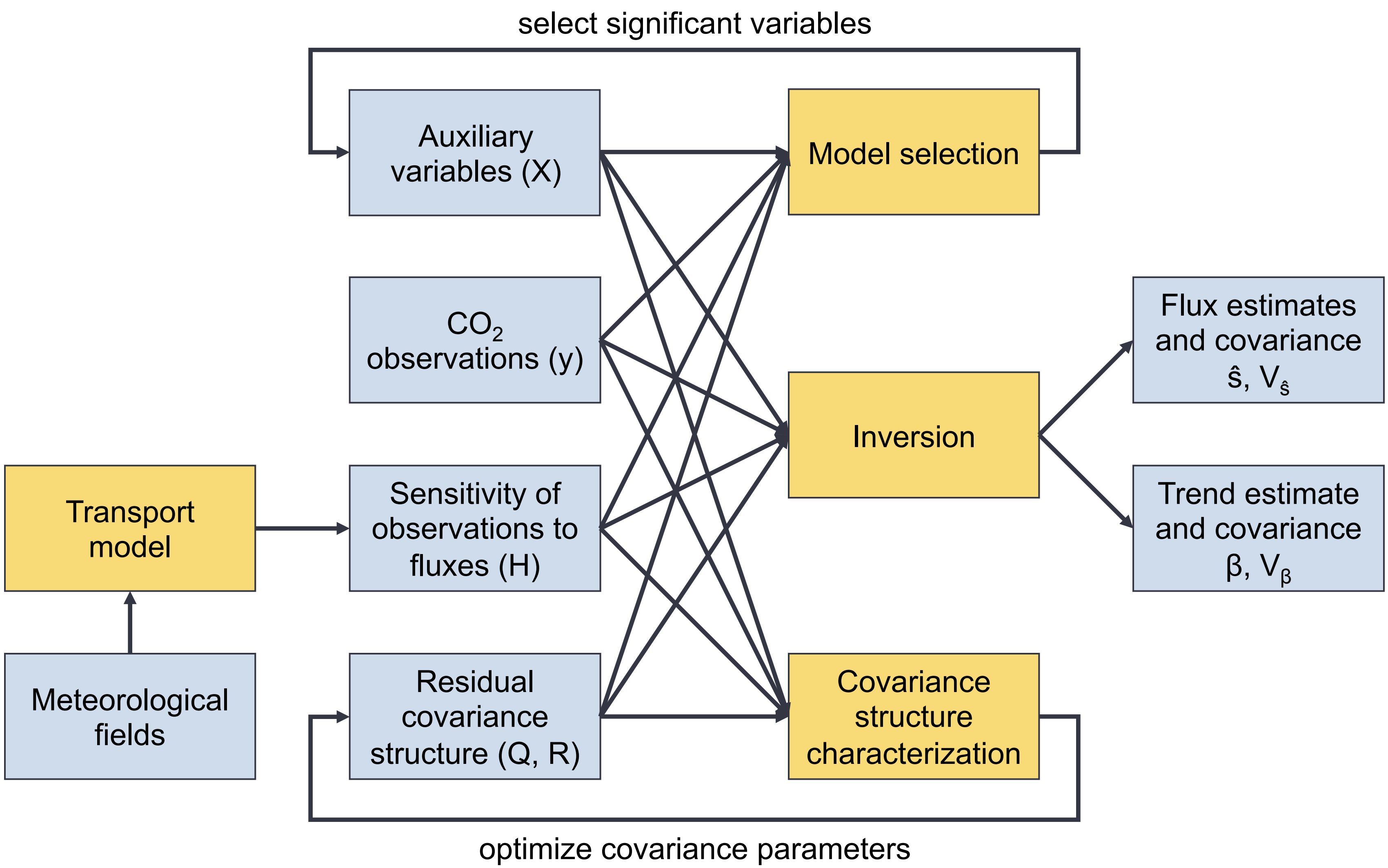


# Synthesis Bayesian inversion




Michalak et al. (JGR, 2004), Mueller et al. (JGR, 2008),
Gourdji et al. (JGR, 2008; ACP 2010; BGD 2011), Miller et al. (JGR, 2012)

# Geostatistical inversion model




Michalak et al. (JGR, 2004), Mueller et al. (JGR, 2008),
Gourdji et al. (JGR, 2008; ACP 2010; BGD 2011), Miller et al. (JGR, 2012)

# Geostatistical inversion model

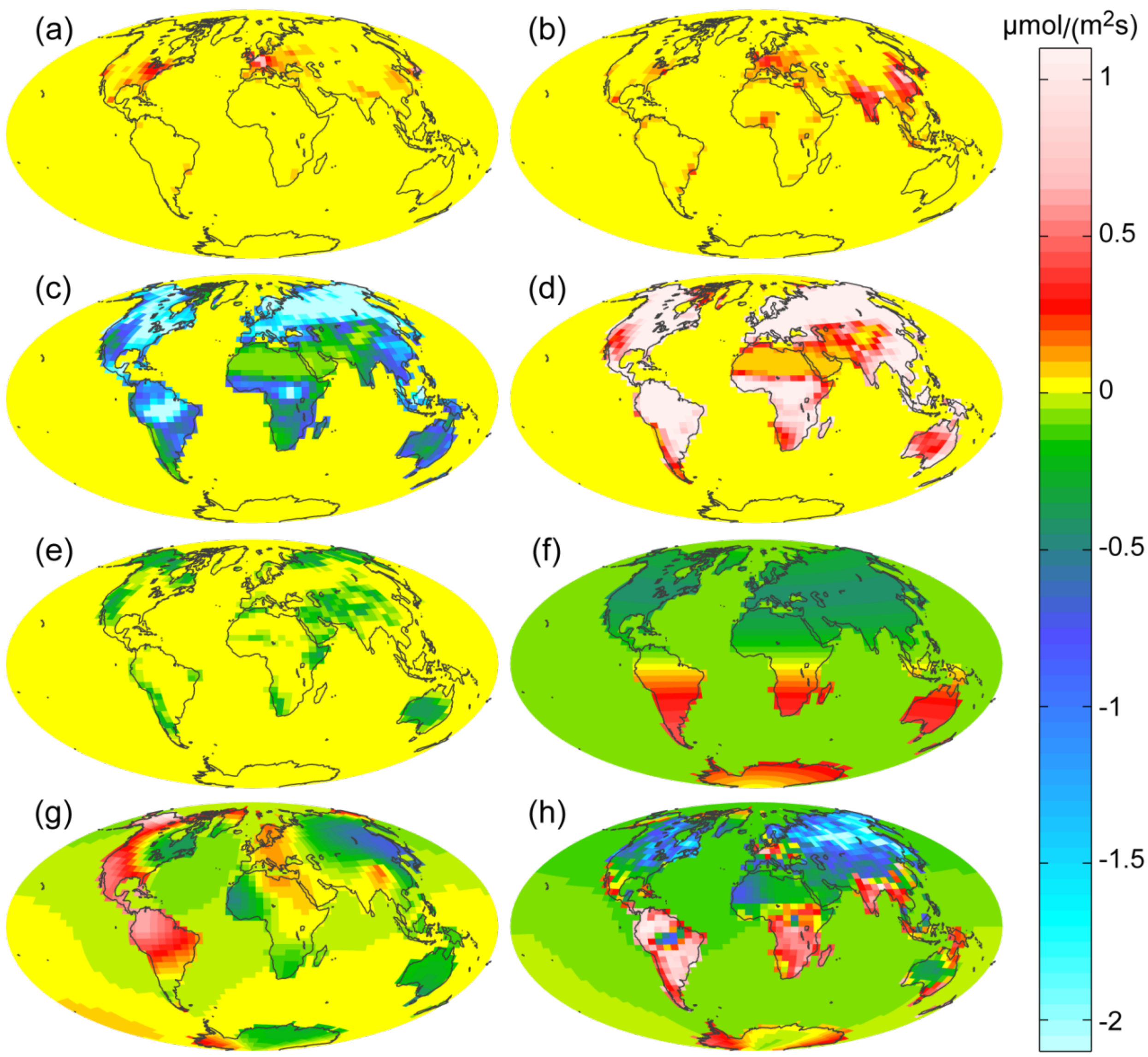
$$L_{\mathbf{s},\boldsymbol{\beta}} = \frac{1}{2}(\mathbf{y}-\mathbf{Hs})^T \mathbf{R}^{-1}(\mathbf{y}-\mathbf{Hs}) + \frac{1}{2}(\mathbf{s}-\mathbf{X}\boldsymbol{\beta})^T \mathbf{Q}^{-1}(\mathbf{s}-\mathbf{X}\boldsymbol{\beta})$$

- **y** = atmospheric $CO_2$ concentration measurements
- **H** = transport or sensitivity matrix
- **s** = (unknown) $CO_2$ flux distribution
- **X** and $\boldsymbol{\beta}$ = model of the trend
- **R** = model-data mismatch covariance
- **Q** = spatiotemporal covariance of flux residuals

$$\hat{\mathbf{s}} = \mathbf{X}\hat{\boldsymbol{\beta}} + \mathbf{QH}^T\boldsymbol{\xi}$$

Michalak et al. (JGR, 2004), Mueller et al. (JGR, 2008),
Gourdji et al. (JGR, 2008; ACP 2010; BGD 2011), Miller et al. (JGR, 2012)

# Global GIM $CO_2$ flux estimation

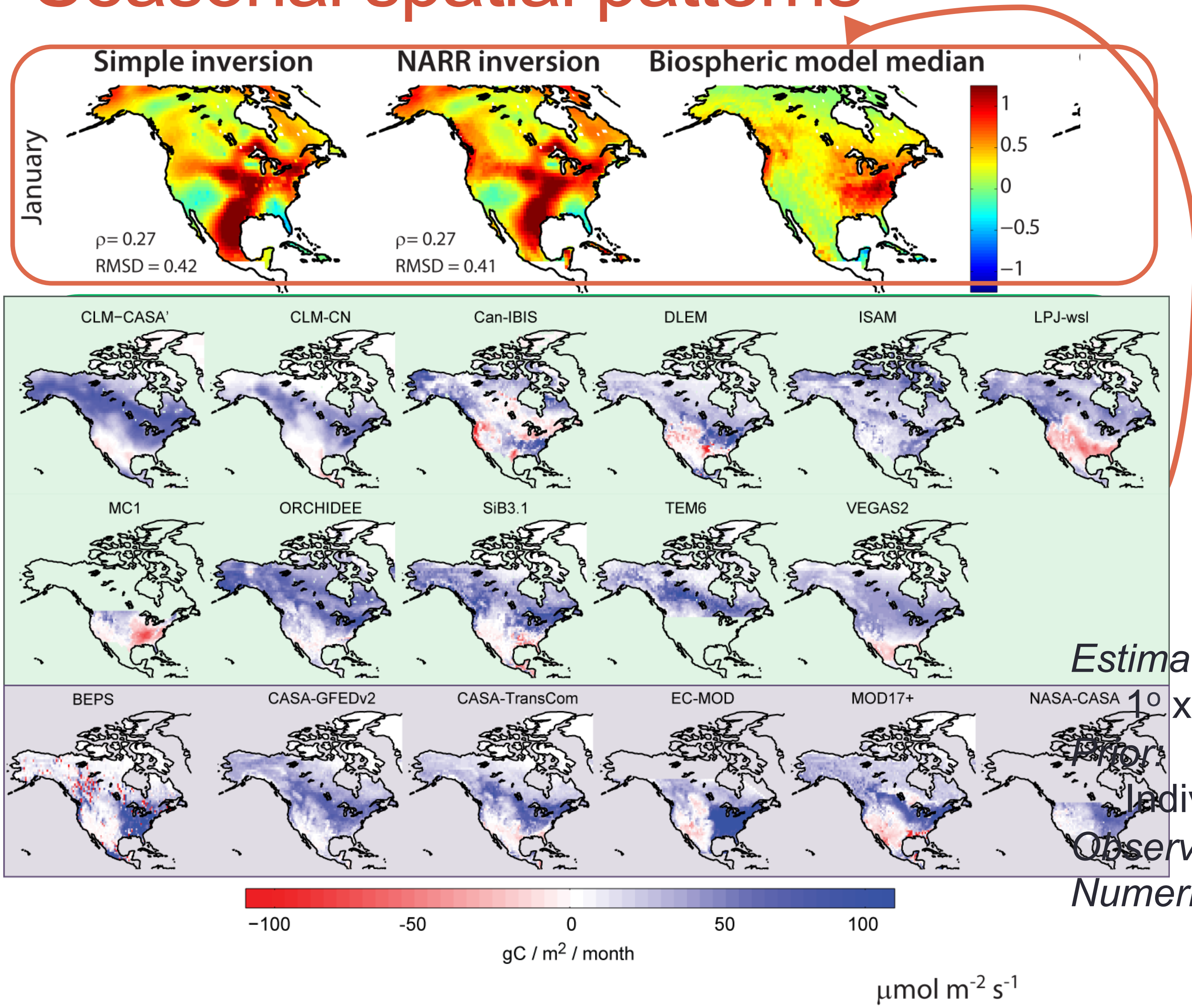



Contributions of components to flux in July 2000:

(a) GDP Density
(b) Population density
(c) LAI
(d) fPAR
(e) % shrub cover
(f) Latitudinal gradient & ocean constant
(g) Stochastic residual
(h) Full best estimates

*Estimates:* 4° x 5°; monthly
*Prior:* Individual aux. vars.
*Observations:* in situ
*Numerics:* "Batch"

# Seasonal spatial patterns



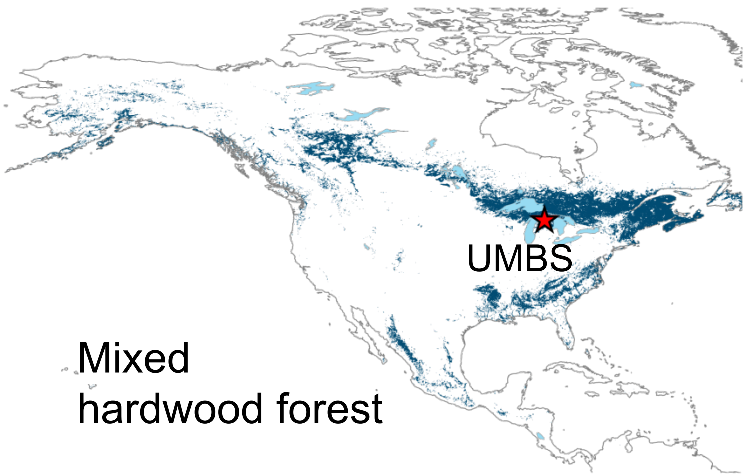

*Estimates:* 1° x 1°; 3-hourly

*Prior:* Individual aux. vars.

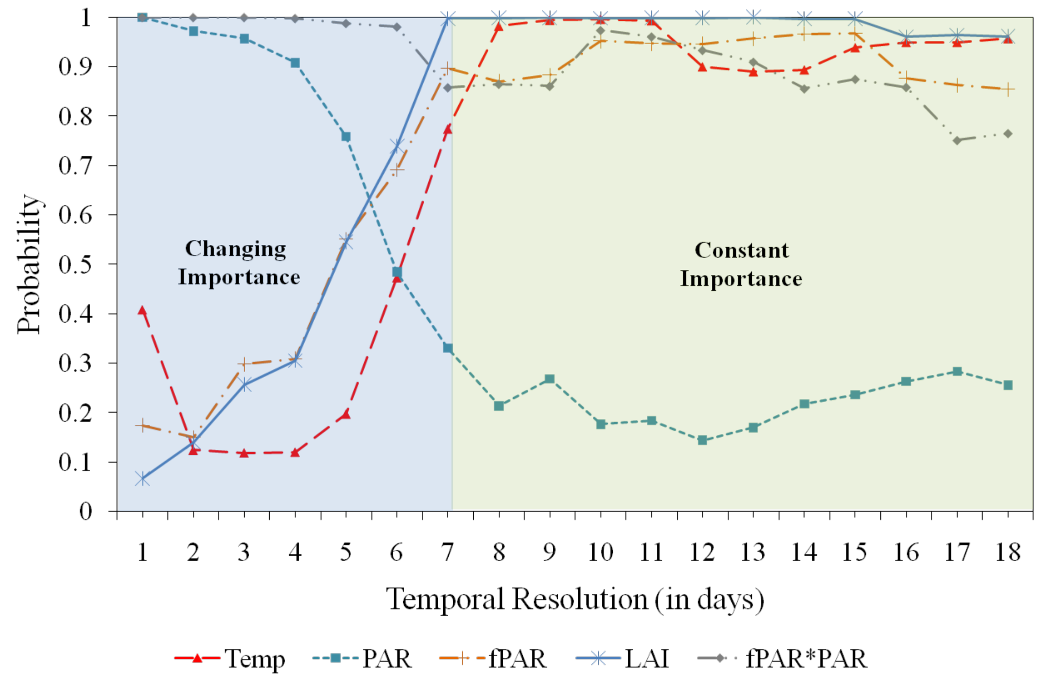
*Observations:* in situ

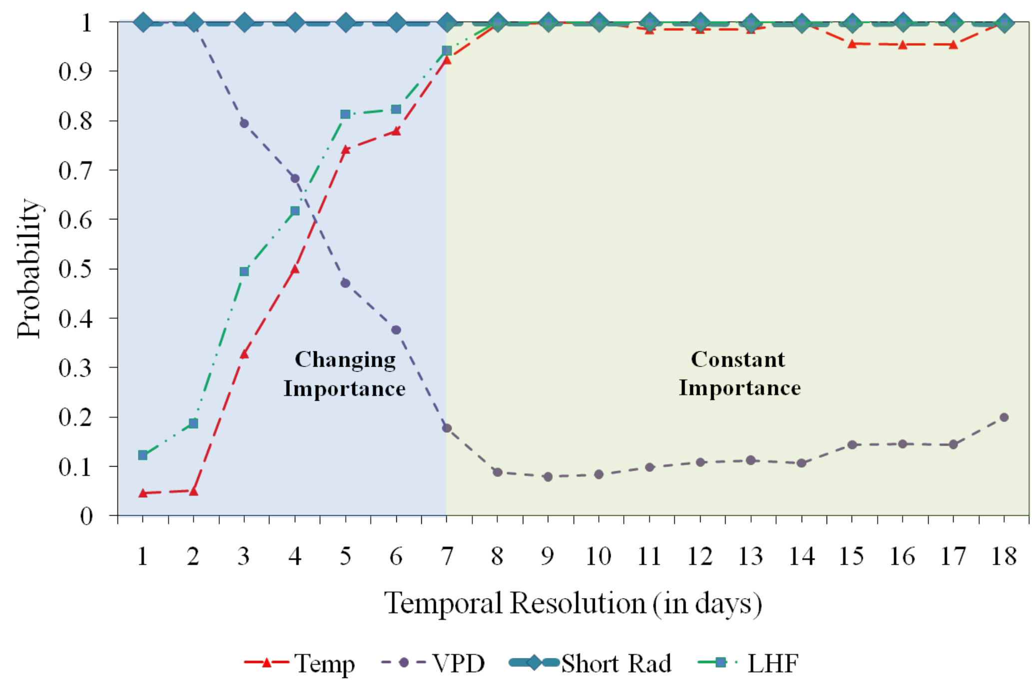
*Numerics:* “Batch”

# Scale dependence








Yadav et al. (BG 2010);
Mueller, et al. (GBC 2010)

# Challenges

- Low sensitivity and/or indirect observations
- Heterogeneity
- Uncertainty / biases / systematic errors
- Massive data volume
- Massive state space

# Challenges

- Low sensitivity and/or indirect observations
  - Inverse problems
  - Ill-posed problems
  - Use of ancillary data
- Heterogeneity
- Uncertainty / biases / systematic errors
- Massive data volume
- Massive state space

# Challenges

- Low sensitivity and/or indirect observations
- Heterogeneity
  - Multiscale
  - Space-time variability
  - Nonstationarity
- Uncertainty / biases / systematic errors
- Massive data volume
- Massive state space

# Challenges

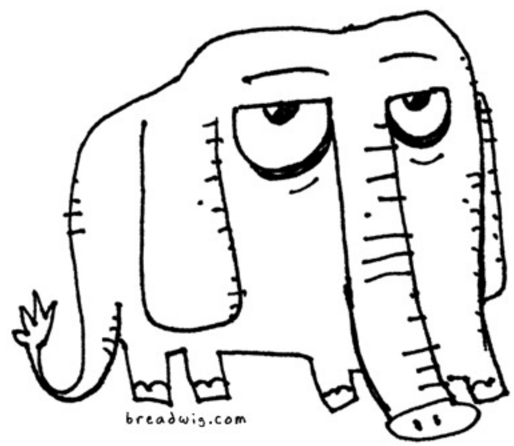
- Low sensitivity and/or indirect observations
- Heterogeneity
- Uncertainty / biases / systematic errors
  - Epistemic error
  - Non-Gaussian errors
  - Multiple sources of uncertainty
- Massive data volume
- Massive state space

# Challenges

- Low sensitivity and/or indirect observations
- Heterogeneity
- Uncertainty / biases / systematic errors
- Massive data volume
- Massive state space

# Summary and conclusions

- Development of statistical approaches, guided by scientific understanding, presents an opportunity to maximize information retrieved from observations
- Flux information provided by atmospheric observations is (space- and time-) scale dependent
- Flux diagnosis and attribution methods should not prescribe "unknown" variability




"There's chocolate smeared all over your manuscript!
Have these data been fudged?!"

All models are wrong … we make tentative assumptions about the real world which we know are false but which we believe may be useful … the statistician knows, for example, that in nature there never was a normal distribution, there never was a straight line, yet with normal and linear assumptions, known to be false, he can often derive results which match, to a useful approximation, those found in the real world.

(*Box*, 1976)