



Ecological Data Assimilation

The Flux Tower Story

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The Scene

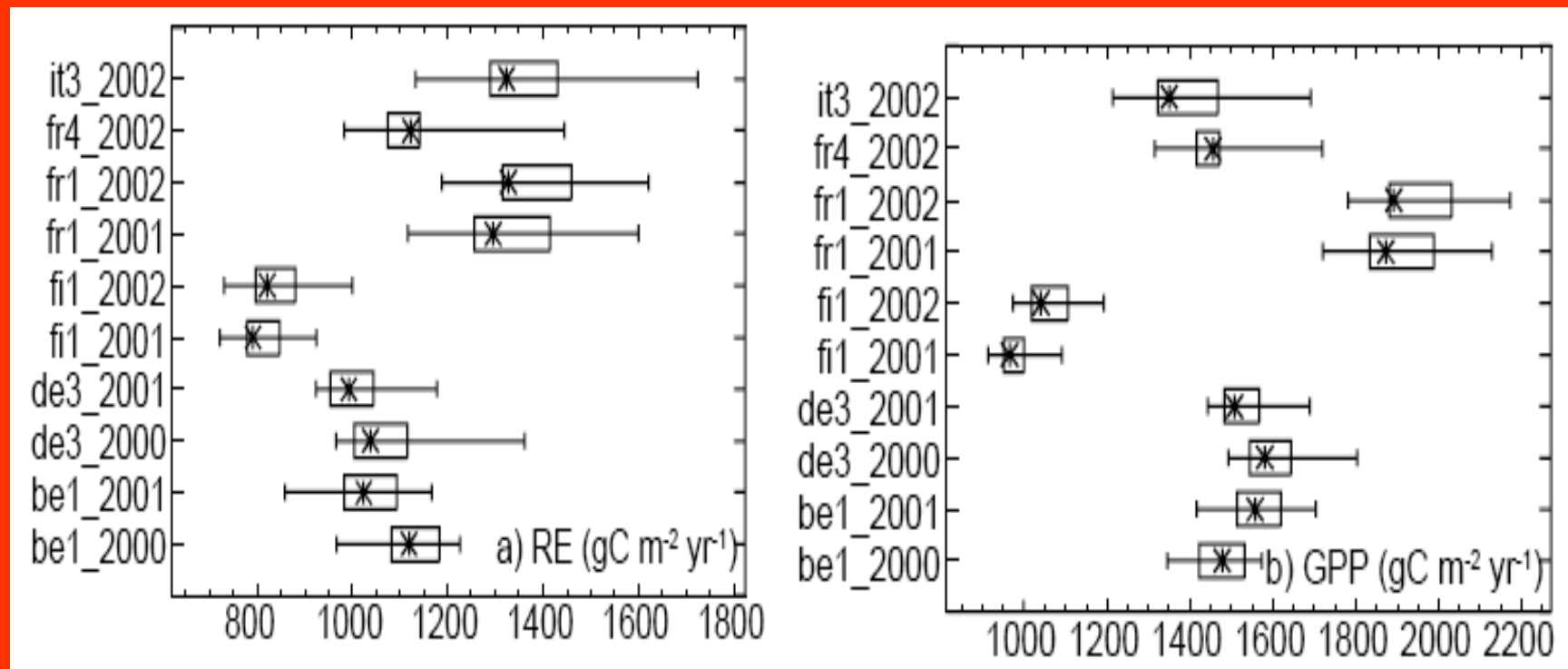
- An ecosystem or land-atmosphere model
 - With parameters, drivers, fluxes, stocks
 - Probably non-linear, might be chaotic
 - Many parameters are not well known (e.g., Q10)
- Driver data (filled?)
- Some observation you want to reproduce (e.g., CO₂ flux) - data has noise/uncertainty
- How to minimize model-data difference taking noise into account and estimate “true” parameters and their uncertainty?
 - Partly depends on the questions you were exploring with model

Why are we doing this?

- Prediction / State space exploration
 - Spatial scaling (model calibration)
 - Parameter estimation / comparison
 - Estimate unobserved state variables (GPP)
 - Mechanism testing / Model selection
 - Observation set consistency / value
 - Hypothesis testing
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- Flux towers are well suited to helping models do a better job at all of these...

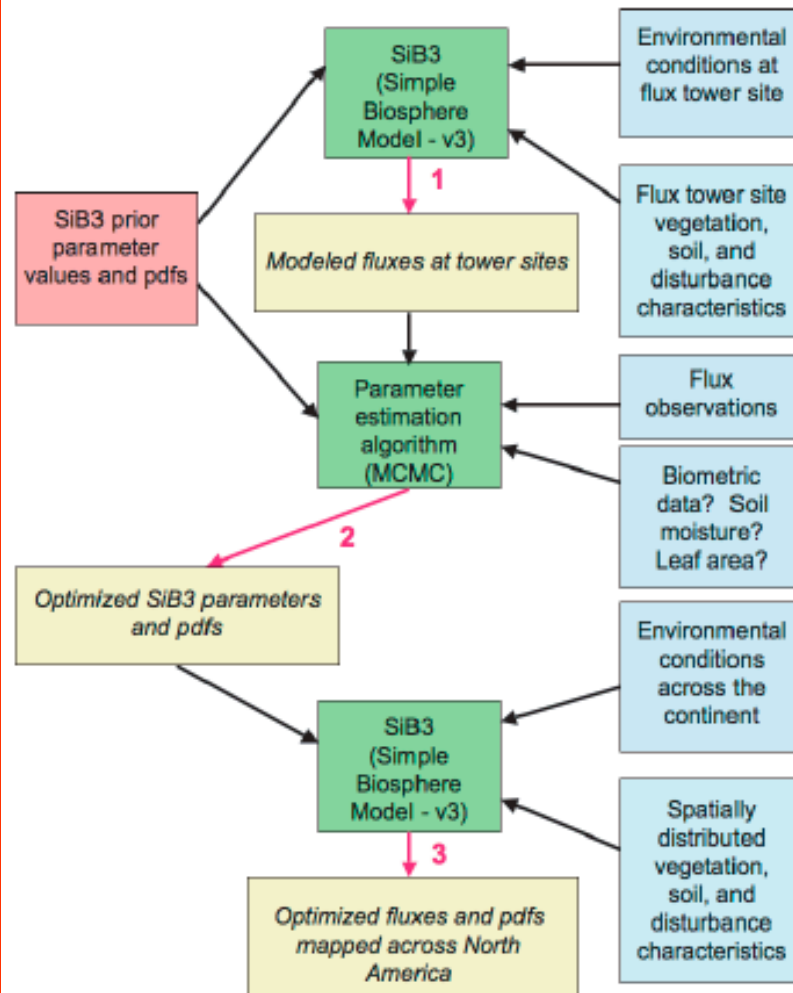
Desai et al., accepted, AgForMet (GPP/RE)
Moffatt et al., in press, AgForMet (Gaps)

- Flux tower gap filling and GPP/RE retrieval are kinds data assimilation



Courtesy T. Hilton and K. Davis

Model-data fusion framework Flux tower data assimilation framework



Questions within this framework:

1) How should flux towers be grouped when solving for SiB3 parameters?

2) How should the resulting optimized parameters be mapped across space?

3) How should this framework be linked to the atmospheric framework. Can we solve for model parameters at that stage?

Some solutions (simple data assimilation)

- Manual (guess parameters, run, compare, try again)
 - An army of students helps
- Least squares linear fits
- Maximum likelihood
- Steepest descent and gradient optimizers (e.g., Levenburg-Marquardt, Gauss-Newton)
- Better solution: let's ask Mathematicians and Meteorologists instead...

Bayes' Theorem to the rescue

$$[A|B] = [AB] / [B]$$

$$[P|D] = ([D|P] [P]) / [D]$$

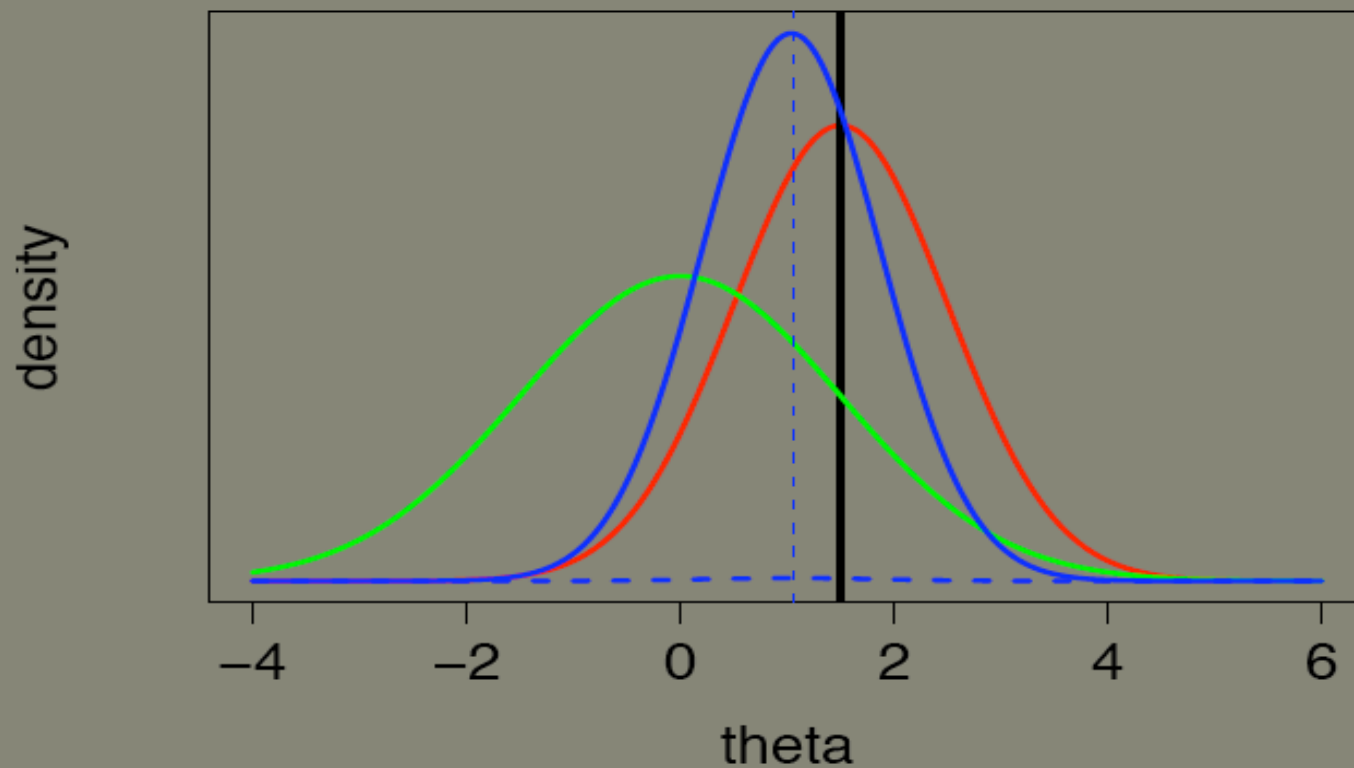
$$\text{(parameters given data)} = [\text{(data given parameters)} \times \text{(parameters)}] / \text{(data)}$$

$$\text{Posterior} = (\text{Likelihood} \times \text{Prior}) / \text{Normalizing Constraint}$$

In the long run, this is least-squares and Gaussian in the basic setup (can be modified). Main things needed for implementation are Forward operator and Likelihood function

Courtesy D. Nychka, NCAR

DATA = 1.5, PRIOR $N(0, (1.5)^2)$
Likelihood, POSTERIOR



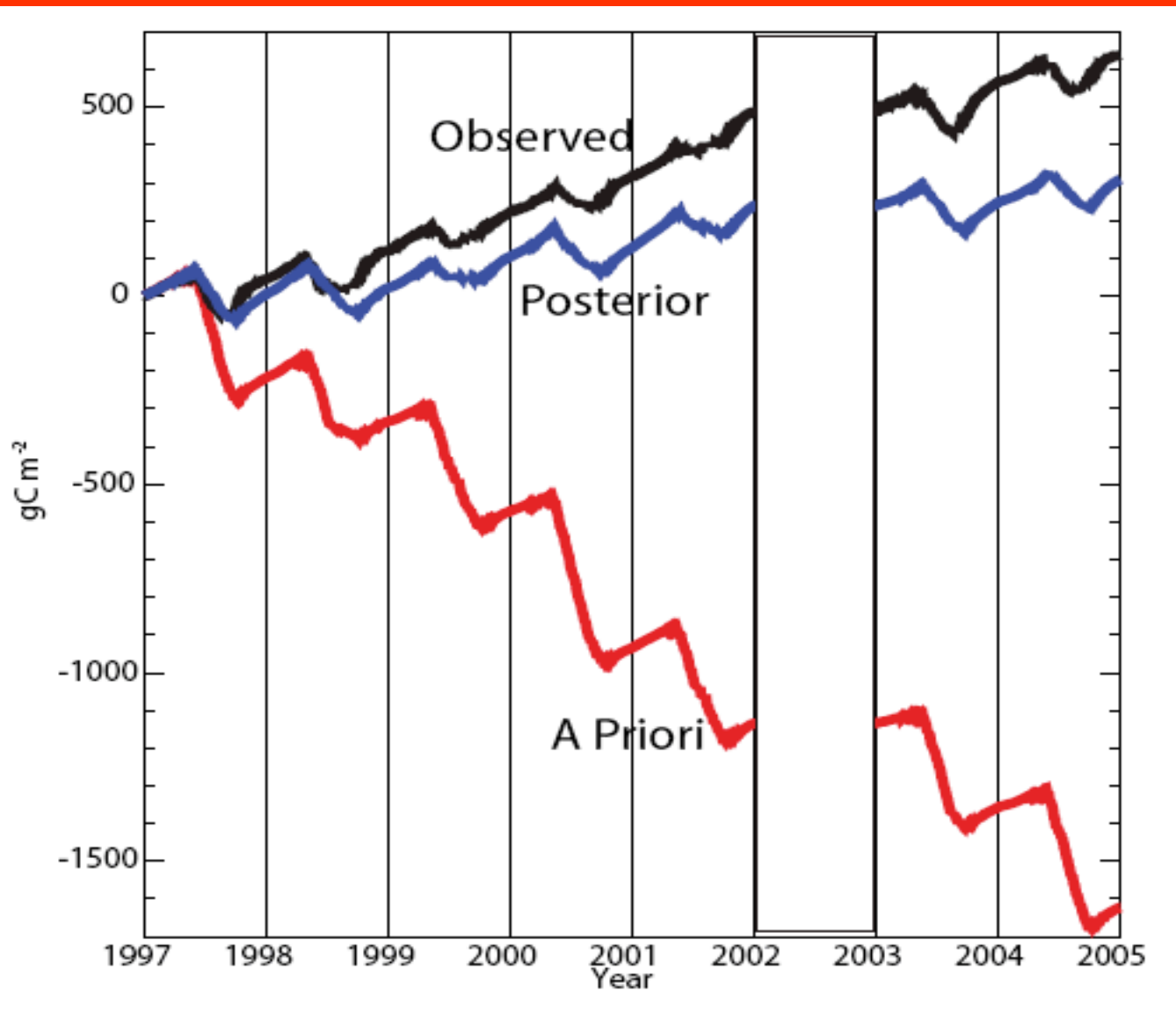
Leading to advanced data assimilation

- Direct parameter distribution exploration
- Markov Chain Monte Carlo (MCMC) - Metropolis-Hastings Algorithm (Metropolis et al, 1953) and other stochastic techniques
- (Ensemble) Kalman Filters and Smoothers
 - Good for expensive models, multiple datasets
- Genetic Algorithms - e.g., Stochastic Evolutionary Ranking Strategy (SRES)
- Neural networks
- Variational methods* (need to know adjoint)
- Tests with REFLEX, ...

Lots of activity

- Big focus on MCMC
 - Big problem with MCMC is need for many iterations to sample parameter space
 - Recall [D|P]
 - But others methods are gaining
- Some models with data assimilation routines developed or in development include SipNET, TREES, ORCHIDEE, BETHY, TRIFFID, ED, Biome-BGC, LoTEC, SiB3

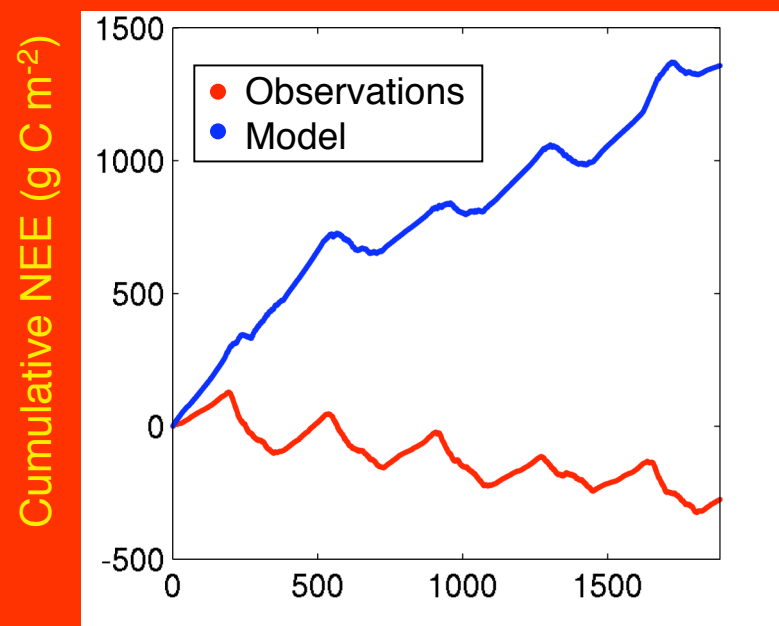
WLEF - Desai et al., in prep



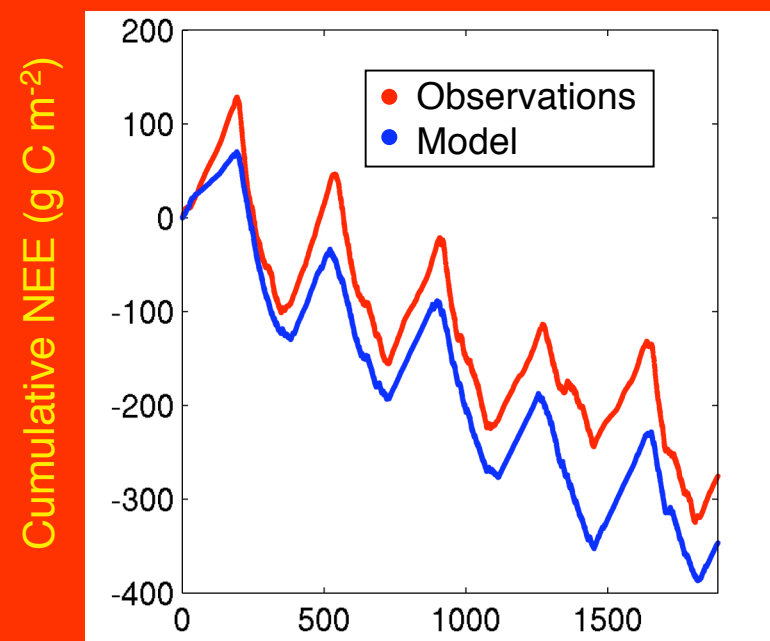
Desai et al, in prep

	Prior	Posterior
<i>Growth related parameters</i>		
photosynthetic capacity (amax)	112	58.6 +/- 2.2
growth respiration fraction	0.33	0.34 +/- 0.06
VPD modifier slope	0.05	0.066 +/- 0.009
Half saturation PAR	17	9.0 +/- 0.76
Light attenuation	0.5	0.67 +/- 0.02
WUE factor	10.9	13.4 +/- 0.46*
<i>Decomposition parameters</i>		
Lloyd-Taylor E0	309	448 +/- 121
Lloyd-Taylor T0	-46	-59.5 +/- 10.6
Turnover rate	0.03	0.19 +/- 0.02

Niwot Ridge - Sacks et al., 2006, GCB

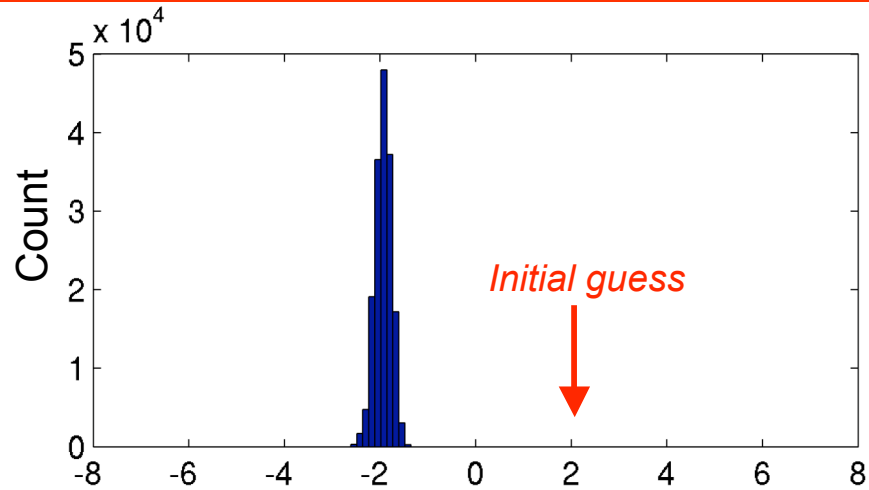


Days after Nov. 1, 1998

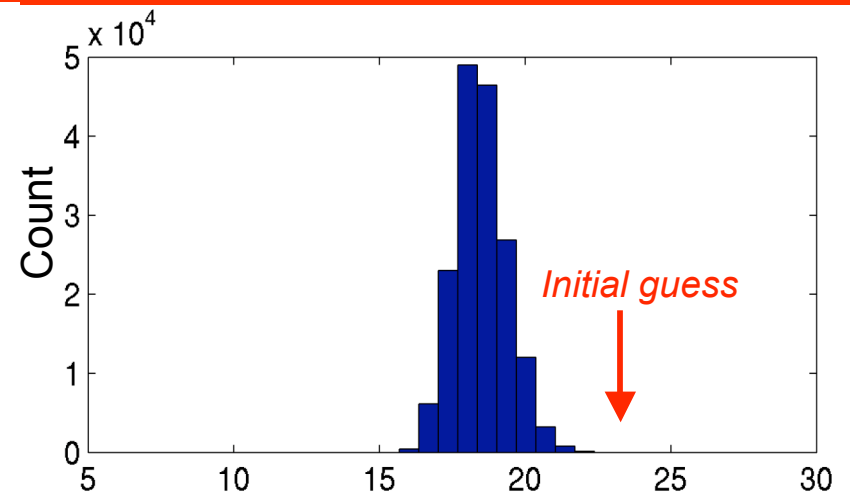


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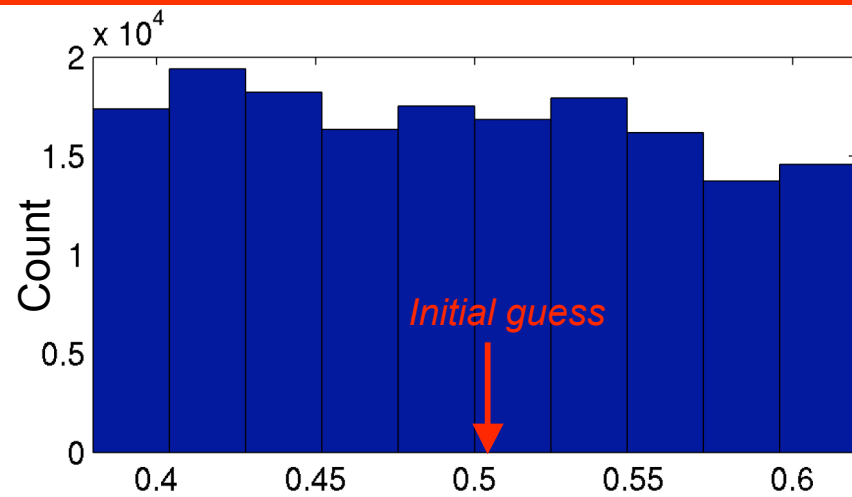
Sacks et al., 2006, GCB



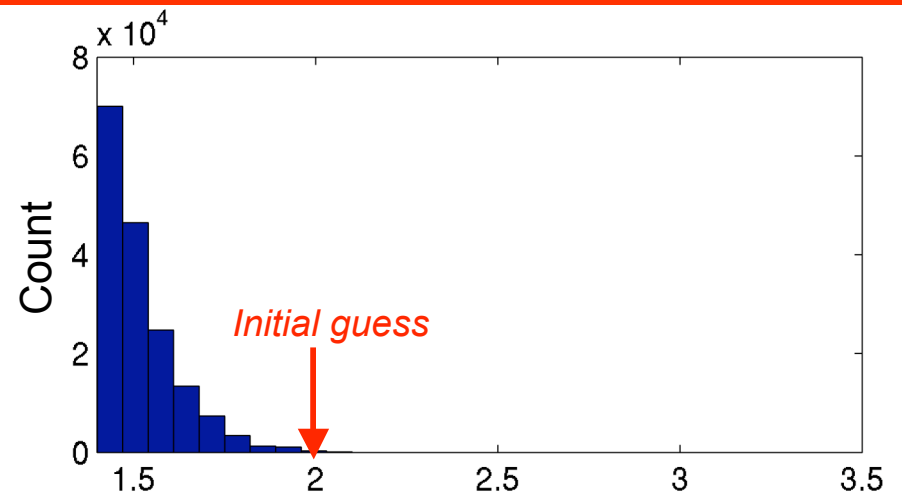
Min. temp. for photosynthesis



Optimum temp. for photosynthesis



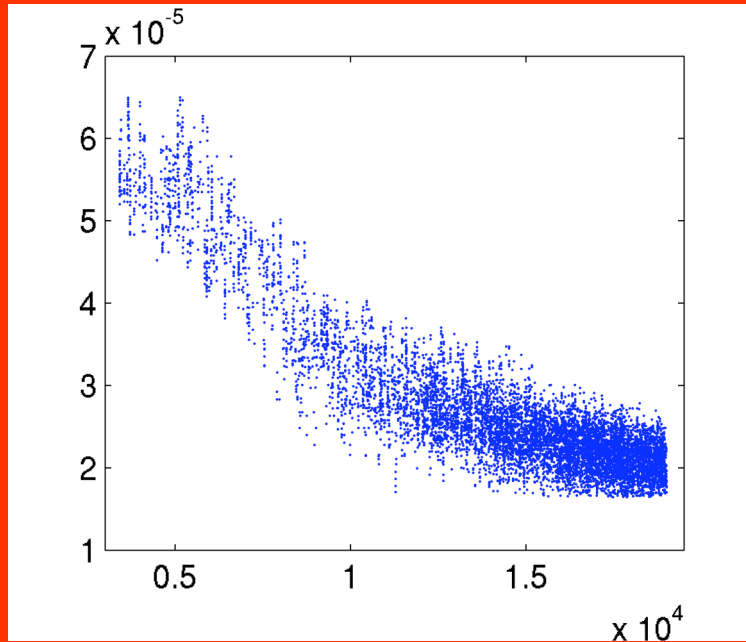
PAR attenuation coefficient



Soil respiration Q_{10}

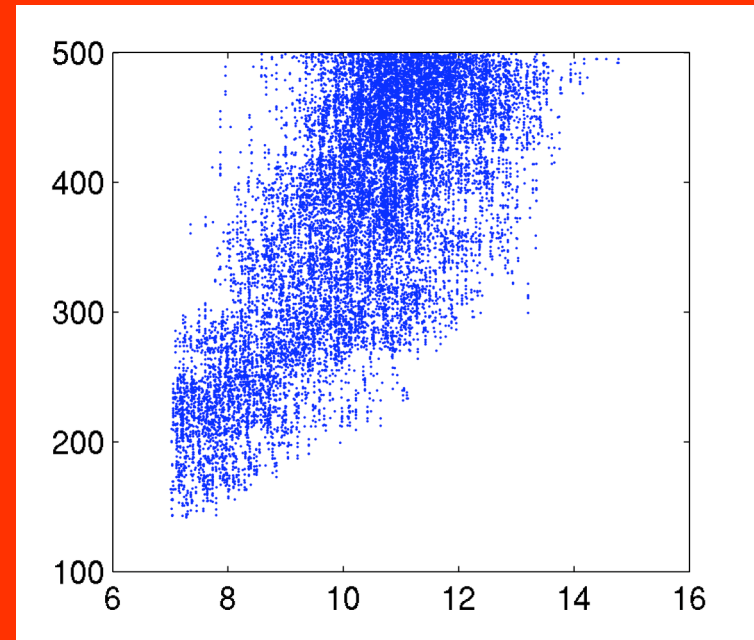
Sacks et al., 2006, GCB
Sacks et al., 2007, Oecologia

Base soil respiration rate
($\text{g C g}^{-1} \text{C day}^{-1}$)



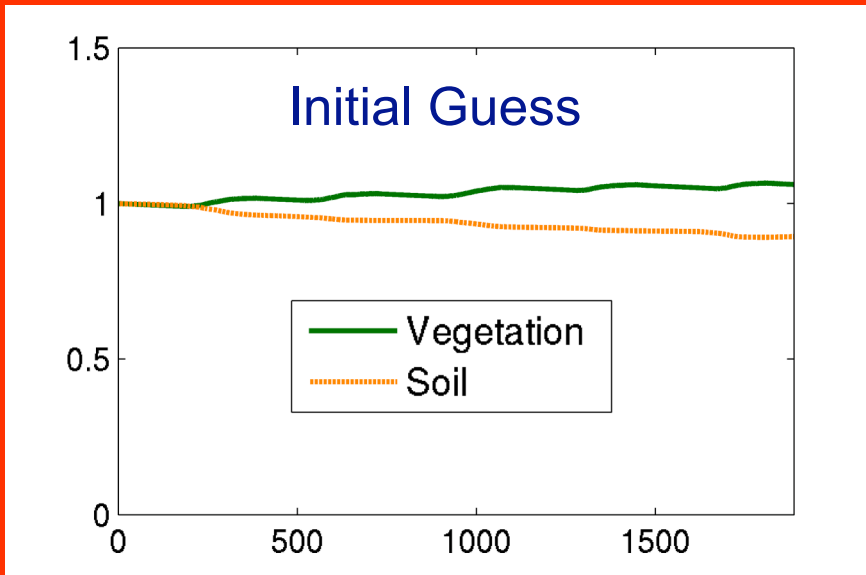
Initial soil C content
(g C m^{-2})

C content of leaves per unit area
(g C m^{-2})

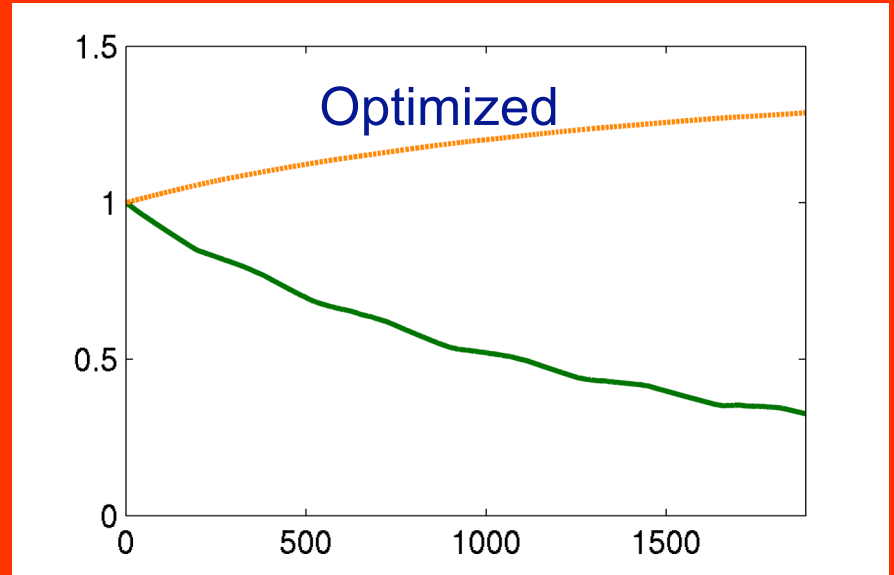


PAR half-saturation point
($\text{mol m}^{-2} \text{day}^{-1}$)

Fraction of initial pool size

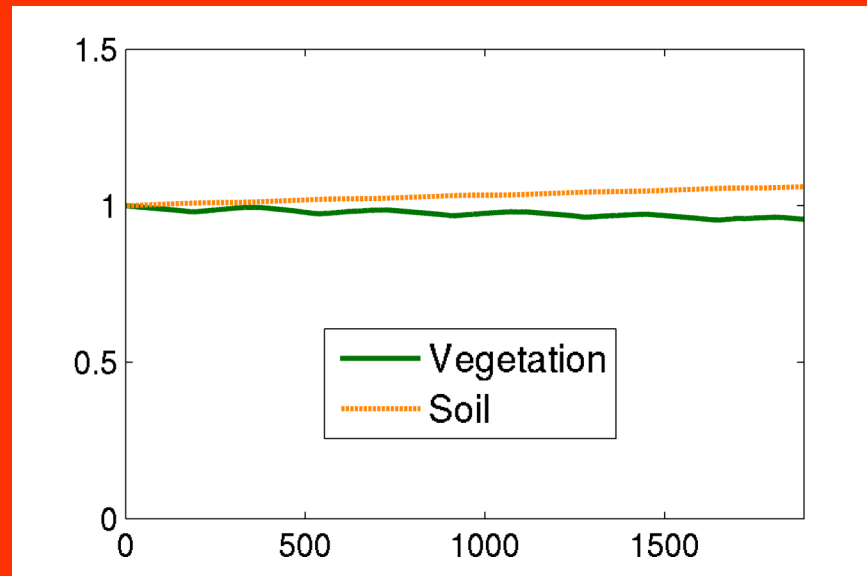


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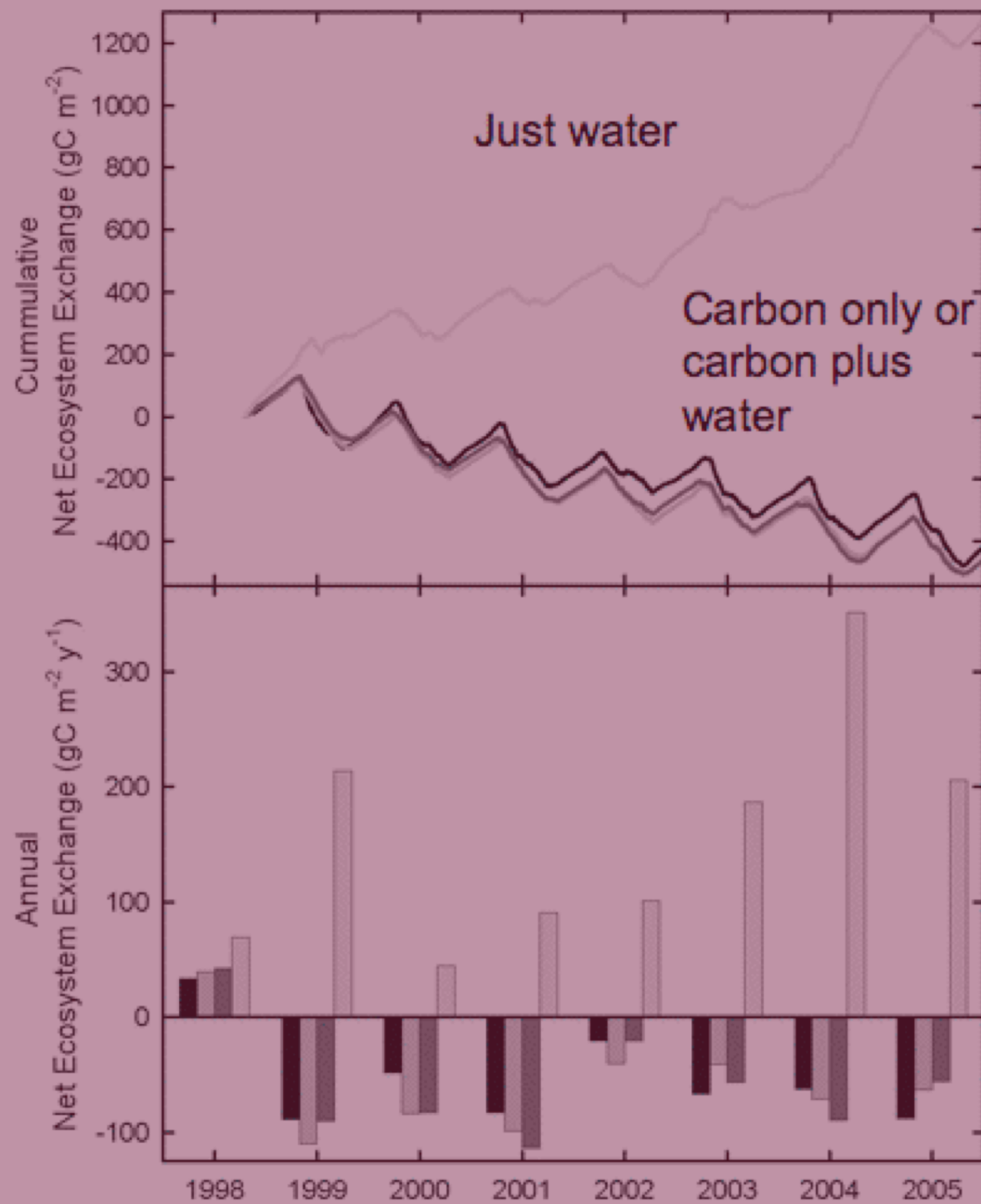


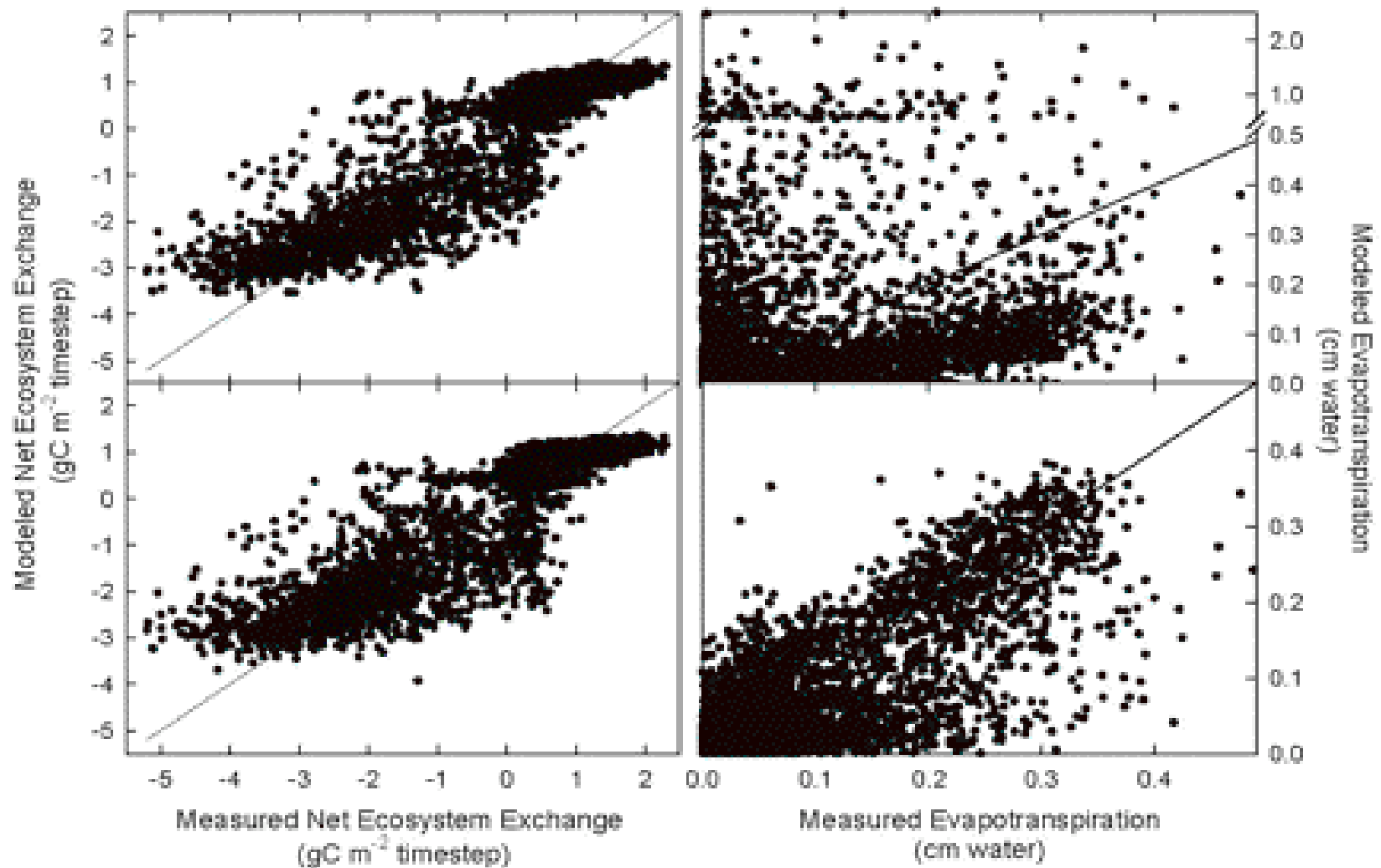
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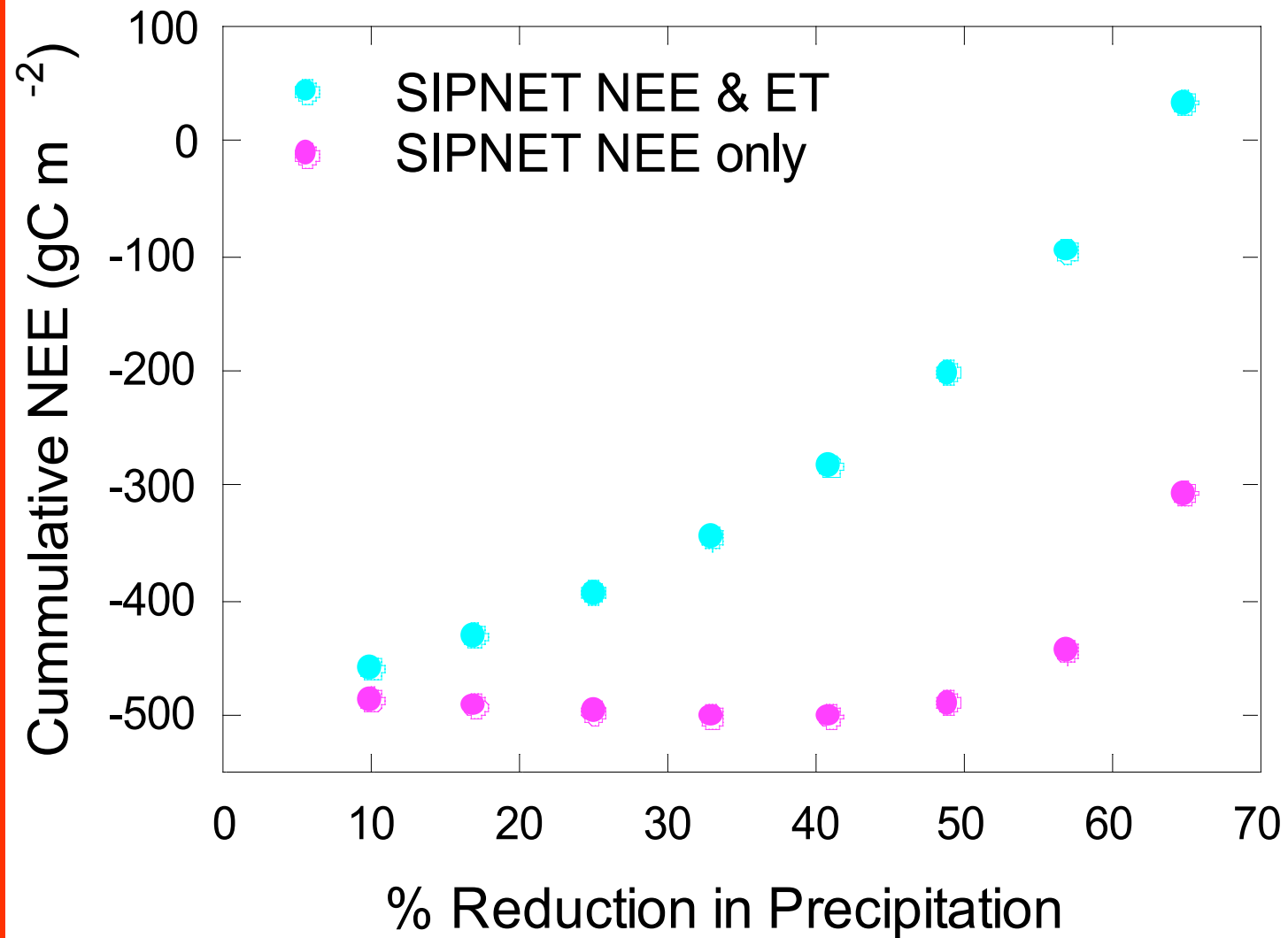


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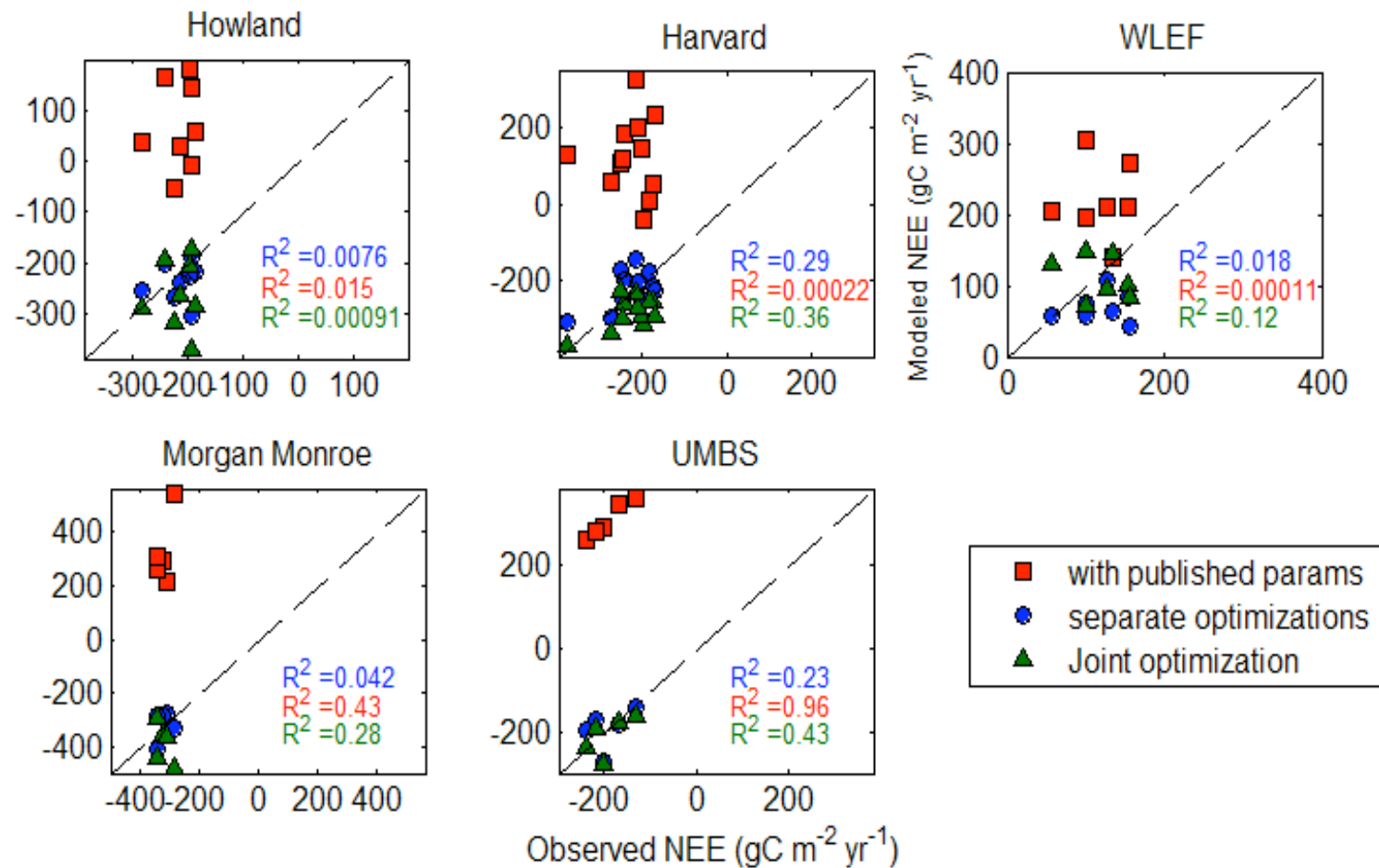


D. Moore, in prep, AgForMet



Ricciuto et al., in press, AgForMet

Ricciuto et al., submitted



Ricciuto et al., submitted

Parameter	Published	HV	HW	WL	MM	UM
CS	10.0	4.81	4.827	9.81	10.7	7.37
Q_{10H}	2.0	1.47	2.394	3.28	1.92	2.65
θ_{opt}	0.55	0.843	0.717	0.745	0.685	0.764
θ_{fac}	0.8	1.00	0.320	0.858	1.00	1.00
θ_c	0.30	0.247	0.129	0.240	0.285	0.239
θ_w	0.13	0.00	0.0498	0.0534	0.00	0.00
n_{DBL}	0.036	0.149	0.250	0.130	0.100	0.112
n_{10NL}	0.030	0.140	0.045	0.0430	0.0500	0.0516
α_{BL}	0.06	0.0535	0.117	0.0314	0.0498	0.0353
α_{NL}	0.06	0.0274	0.021	0.483	0.249	0.340
Q_{10VM}	2.0	2.23	1.74	2.36	2.15	2.04
$T_{low\ BL}$	-5.0	1.48	-40.0	-9.70	6.06	-1.83
T_{lowNL}	-15.0	3.55	3.41	-1.80	10.0	-20.0
T_{uppBL}	33.0	50.0	50.0	50.0	50.0	50.0
T_{uppNL}	28.0	11.66	50.0	50.0	10.0	49.1
D_c	0.09	0.0192	0.0266	0.0249	0.0371	0.0282
R_g	0.25	0.107	0.0500	0.122	0.0500	0.0500
R_{dc}	0.015	0.00822	0.0208	0.0183	0.001 9	0.00866
Q_{10RD}	2.0	1.49	1.61	2.00	1.100	1.33
T_{off}	0.0	11.6	0.80	9.30	14.3	11.4
β_{off}	0.90	0.678	0.850	0.672	0.172	0.517
γ_p	14.5	18.2	13.4	16.5	20.0	38.7
$-(L \log L)$	N/A	157209	100989	69511	68554	61217

Well-constrained parameters:

leaf nitrogen

quantum efficiency

T_{lower}

phenology (T_{off})

Poorly constrained parameters

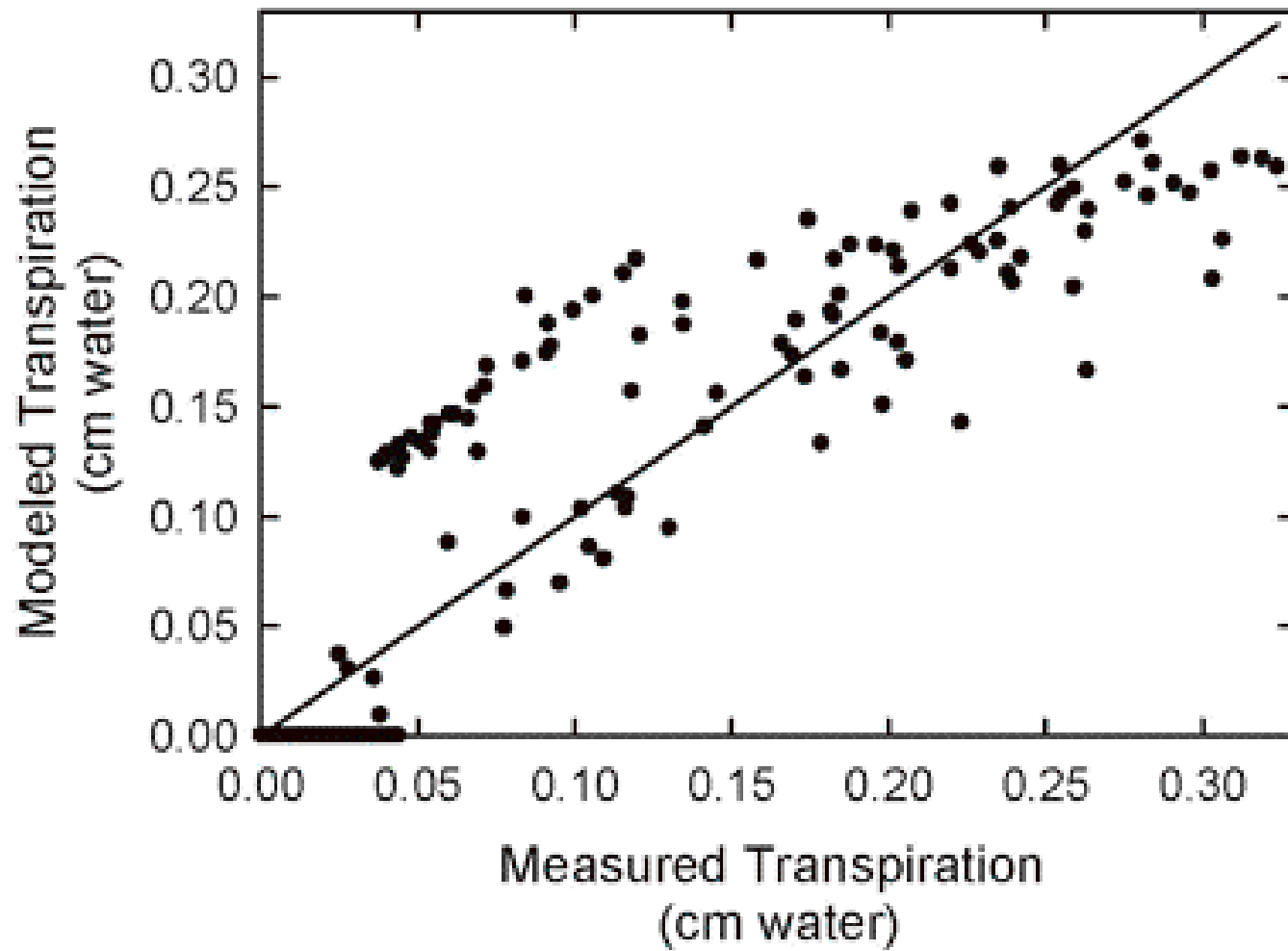
autotrophic respiration

soil moisture parameters

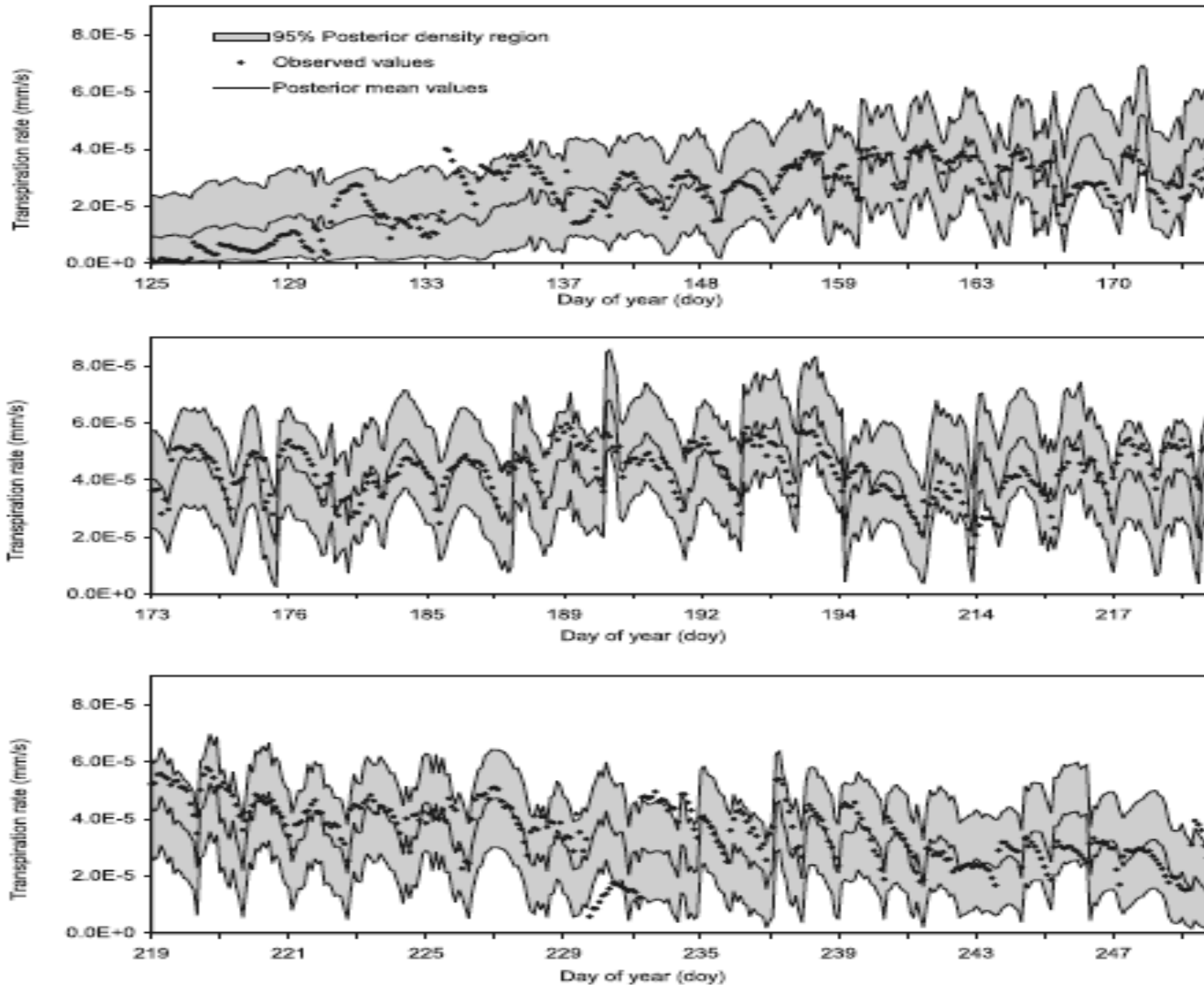
Difference from published

Coherence across space

Moore et al., submitted



Samanta et al., 2007, WaterResourcesRes.



A Request and Future Directions

- For model optimization / data assimilation - missing flux data is not necessarily a big deal
- But: Filled driver data (micromet, soil temp, radiation) are generally needed
- Note: Driving data vs assimilated data is an arbitrary choice (as long as you can build a forward operator)
- We can assimilate not just CO₂/H₂O flux, but also concentrations, micromet, radiation, wind, isotopes, chamber flux, inventory data, sapflux
- Assimilation of multiple towers promising, but consistent data sets needed

Thanks

- Thanks to the PSU/ UW-Madison/ NCAR/ SUNY-Buffalo/ CSU/ ORNL/ King's College / WHRC/ ChEAS flux data assimilation collective and funders, DOE, NICCR, NSF, NASA, USDA