Data assimilation in land surface schemes

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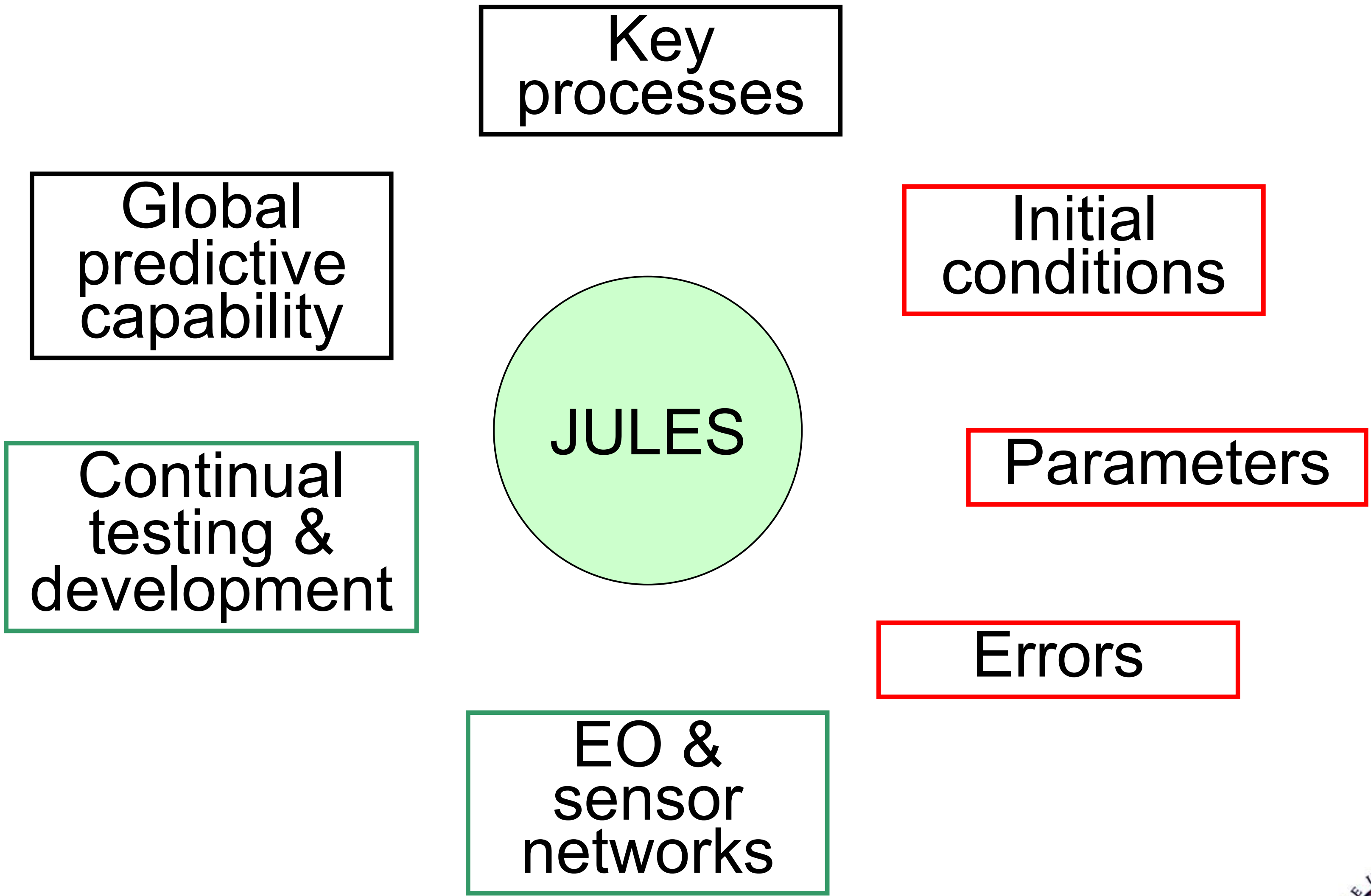
Outline

- Challenges for JULES
- Data assimilation
- Reflex: Assessing errors in extrapolating models
- Scaling
- Atmospheric constraints
- DA in JULES

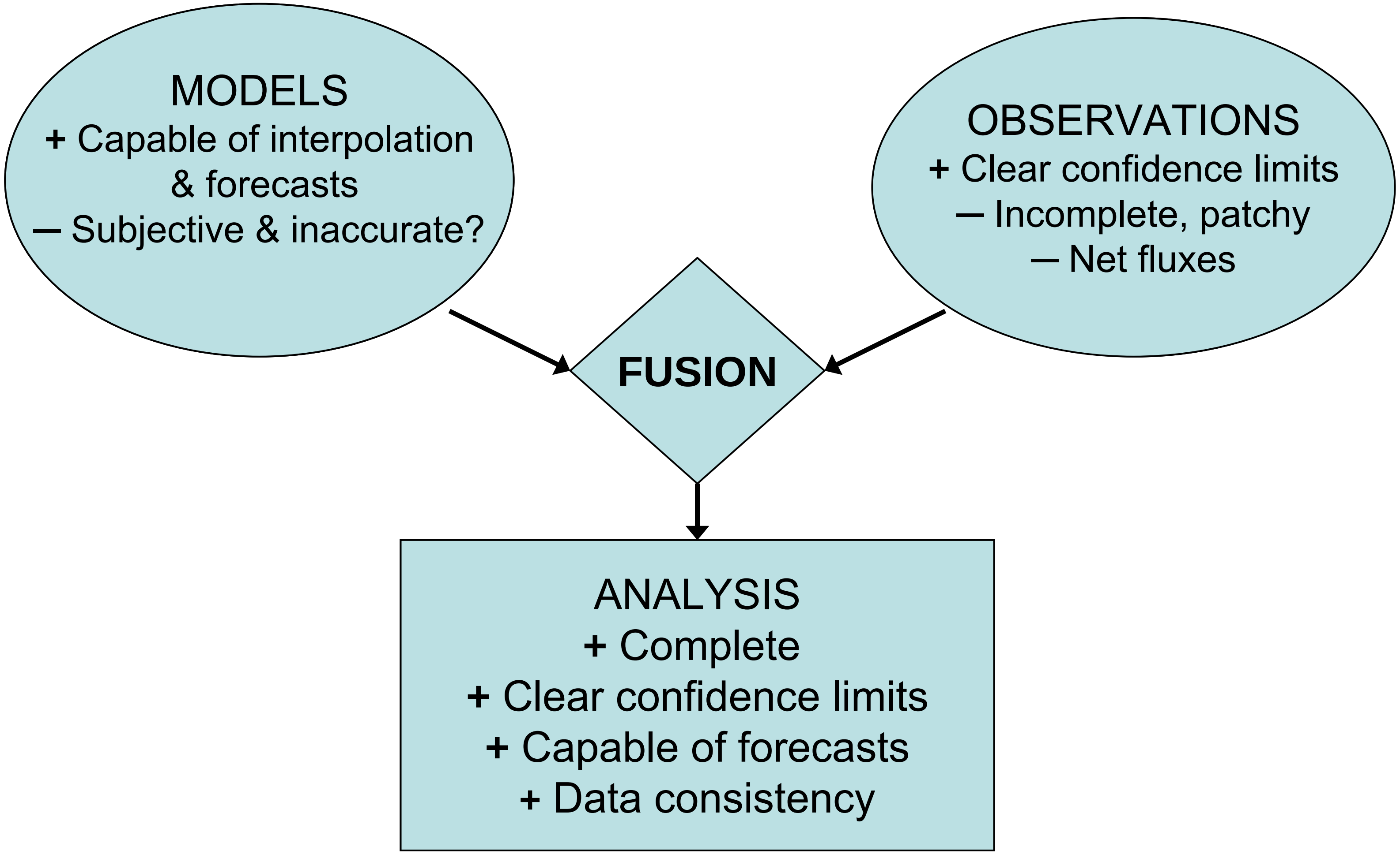
Challenges for the JULES team



The philosophy of data assimilation

- Observations and models contain useful information about the target system
- But ALL observations and models are subject to error - and may be subject to bias
- Models and observations can be combined to optimise information and quantify errors

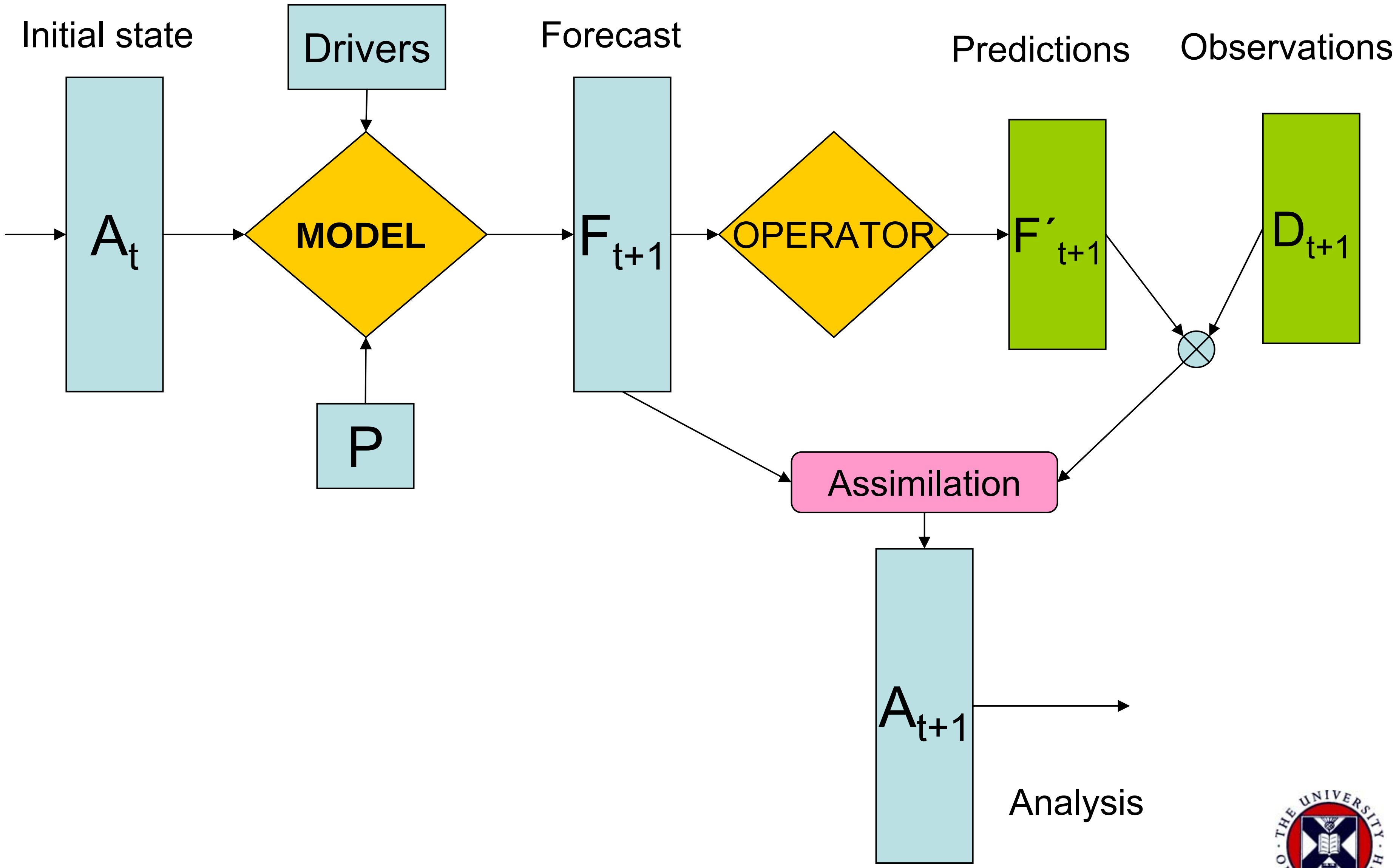
Improving estimates of land surface process



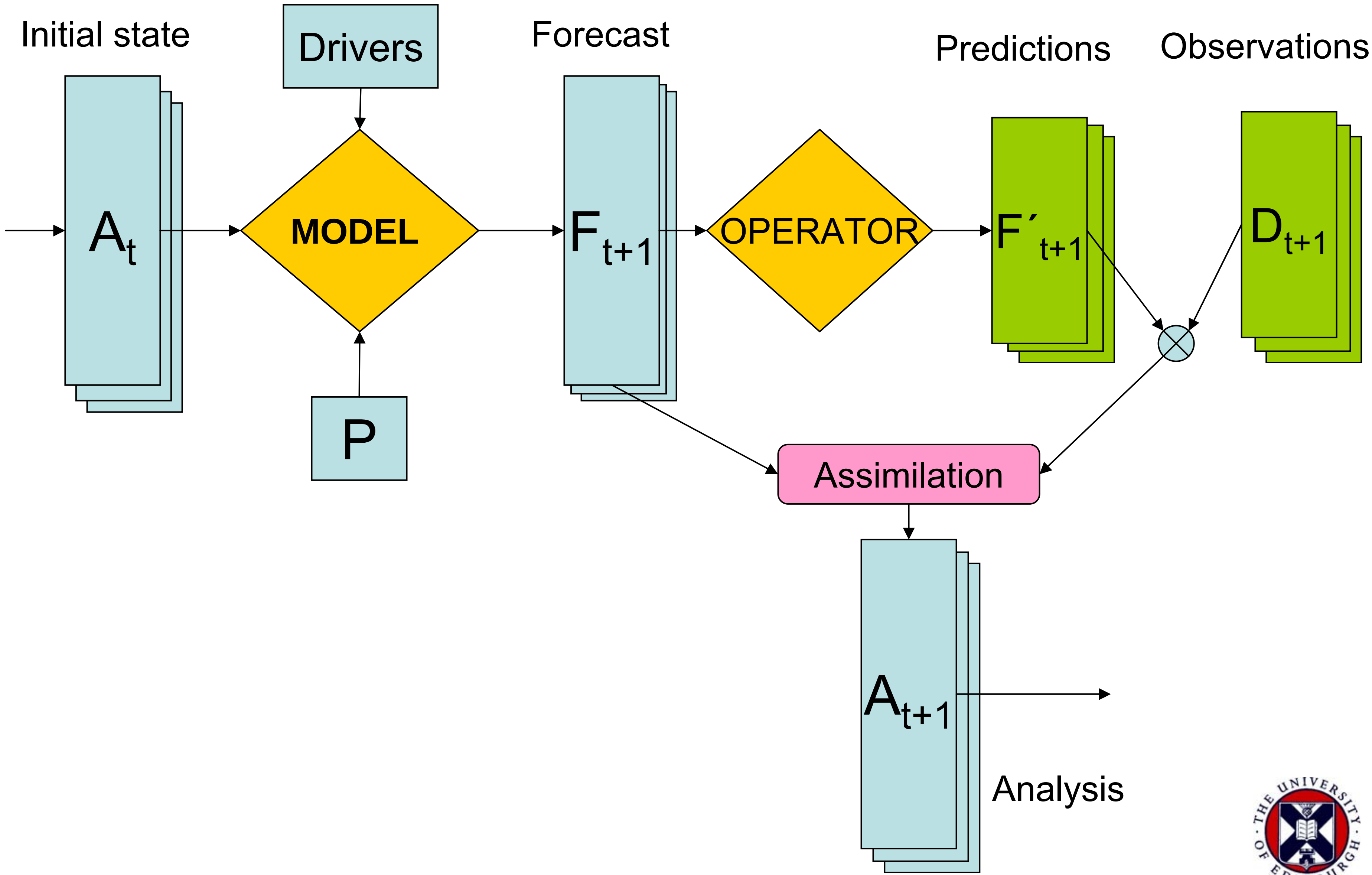
Approaches to data assimilation

- Sequential (predictor-corrector)

The Kalman Filter



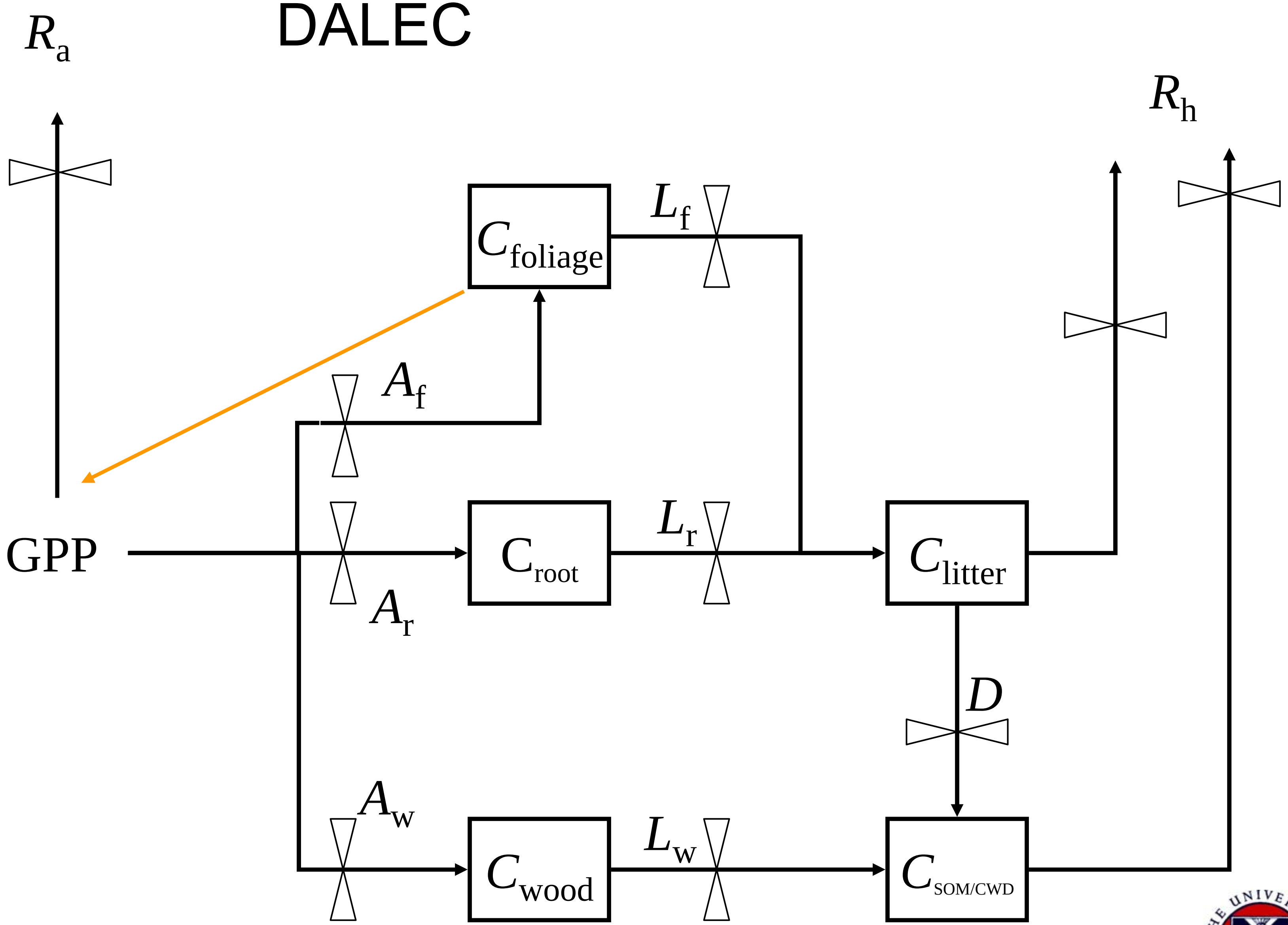
The Ensemble Kalman Filter

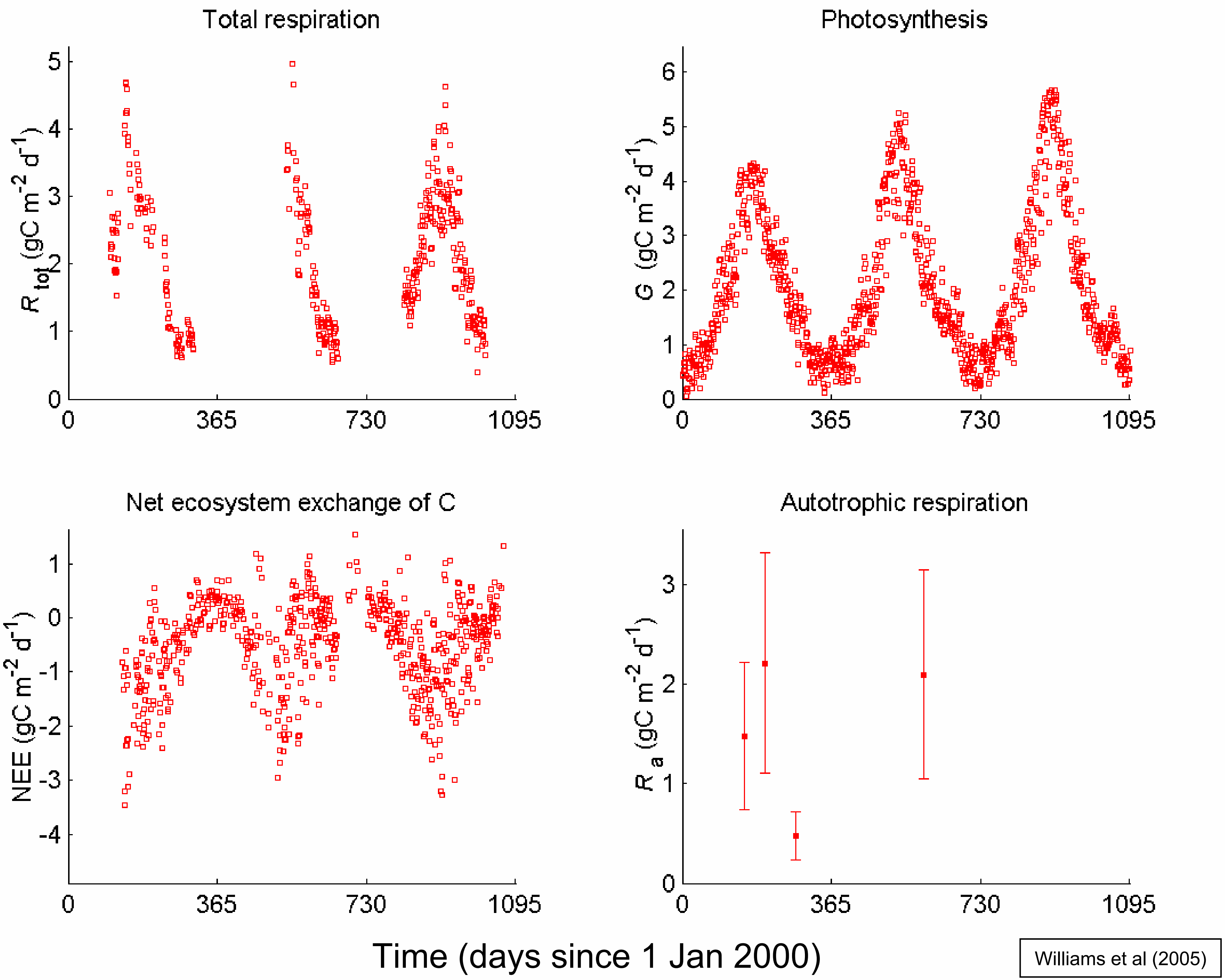


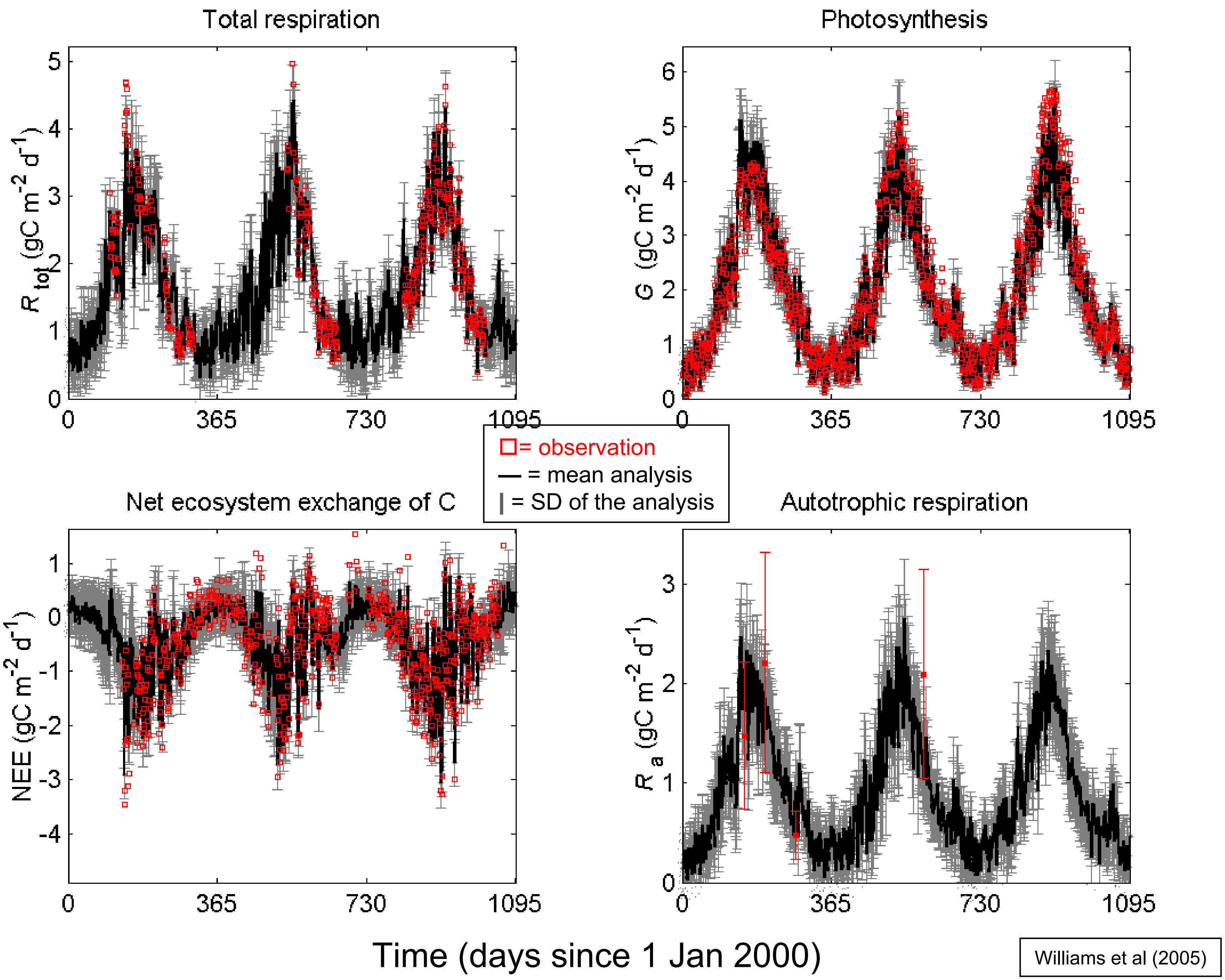
Observations – Ponderosa Pine, OR (Bev Law)

Flux tower (2000-2)
Sap flow
Soil/stem/leaf respiration
LAI, stem, root biomass
Litter fall measurements

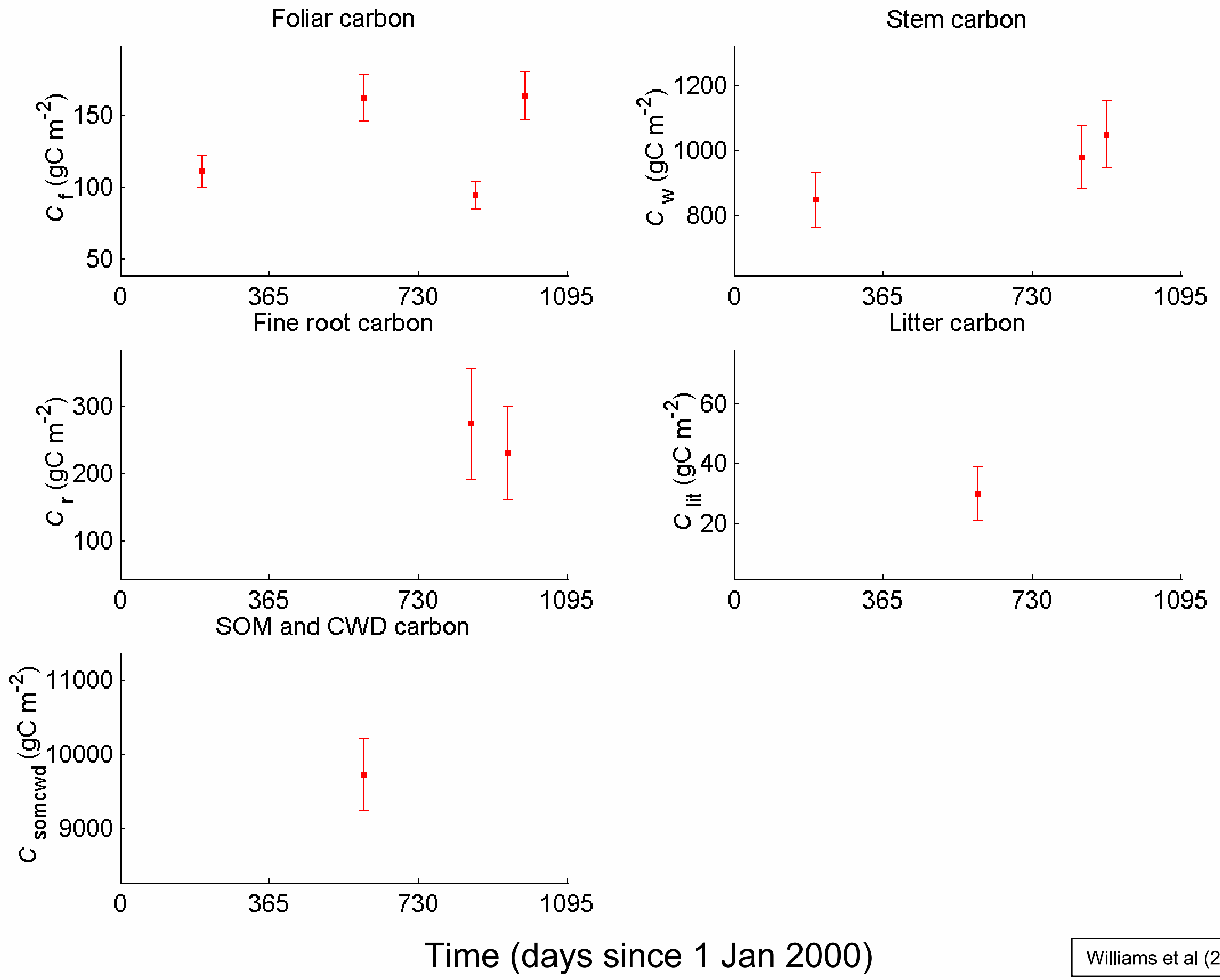
DALEC


R_a
R_h
$C_{foliage}$
L_f
A_f
GPP
C_{root}
L_r
C_{litter}
A_r
D
A_w
C_{wood}
L_w
$C_{SOM/CWD}$

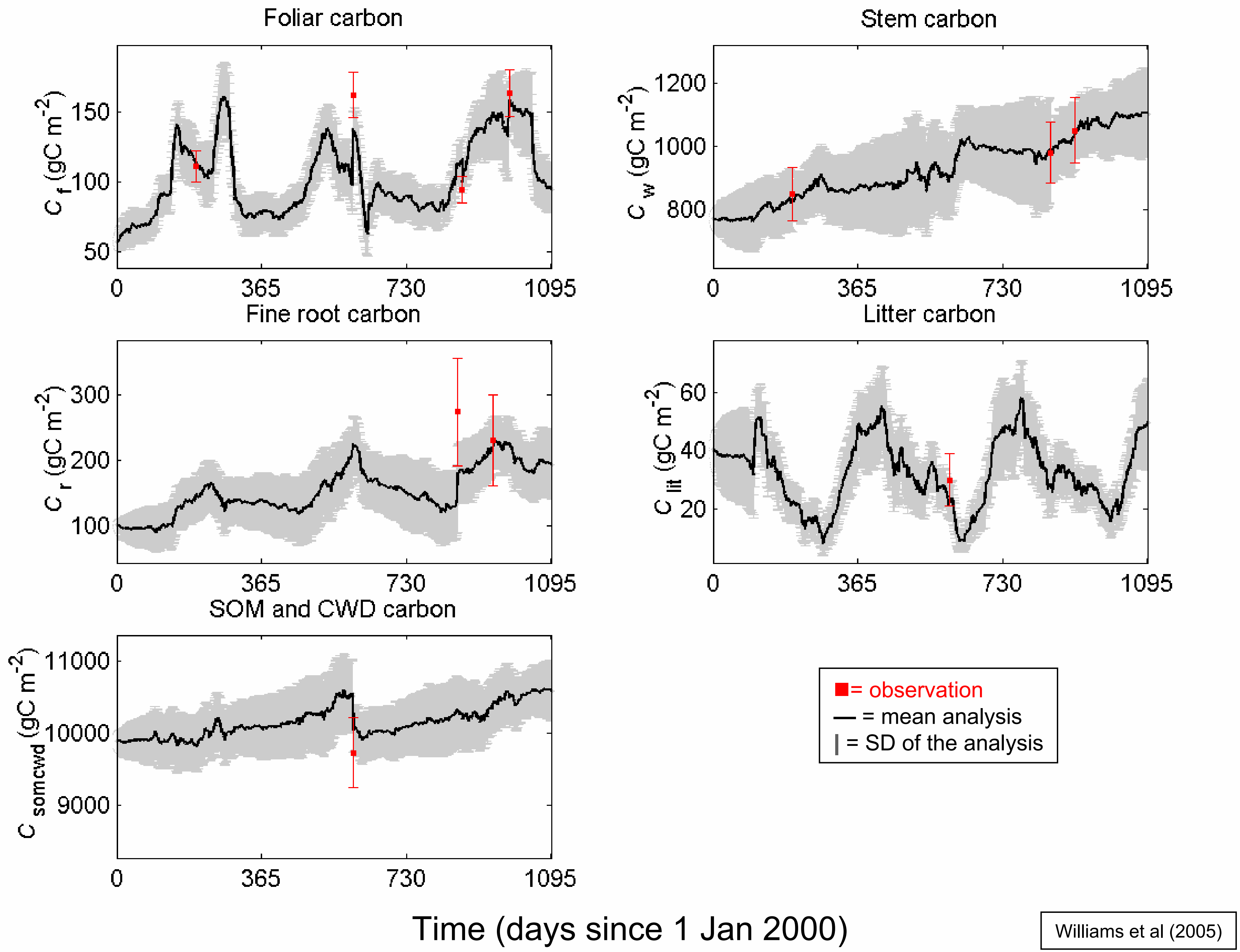

Total respiration
Photosynthesis
Net ecosystem exchange of C
Autotrophic respiration
R_{tot} (gC m^{-2} d^{-1})
G (gC m^{-2} d^{-1})
NEE (gC m^{-2} d^{-1})
R_a (gC m^{-2} d^{-1})
0
365
730
1095
Time (days since 1 Jan 2000)
Williams et al (2005)



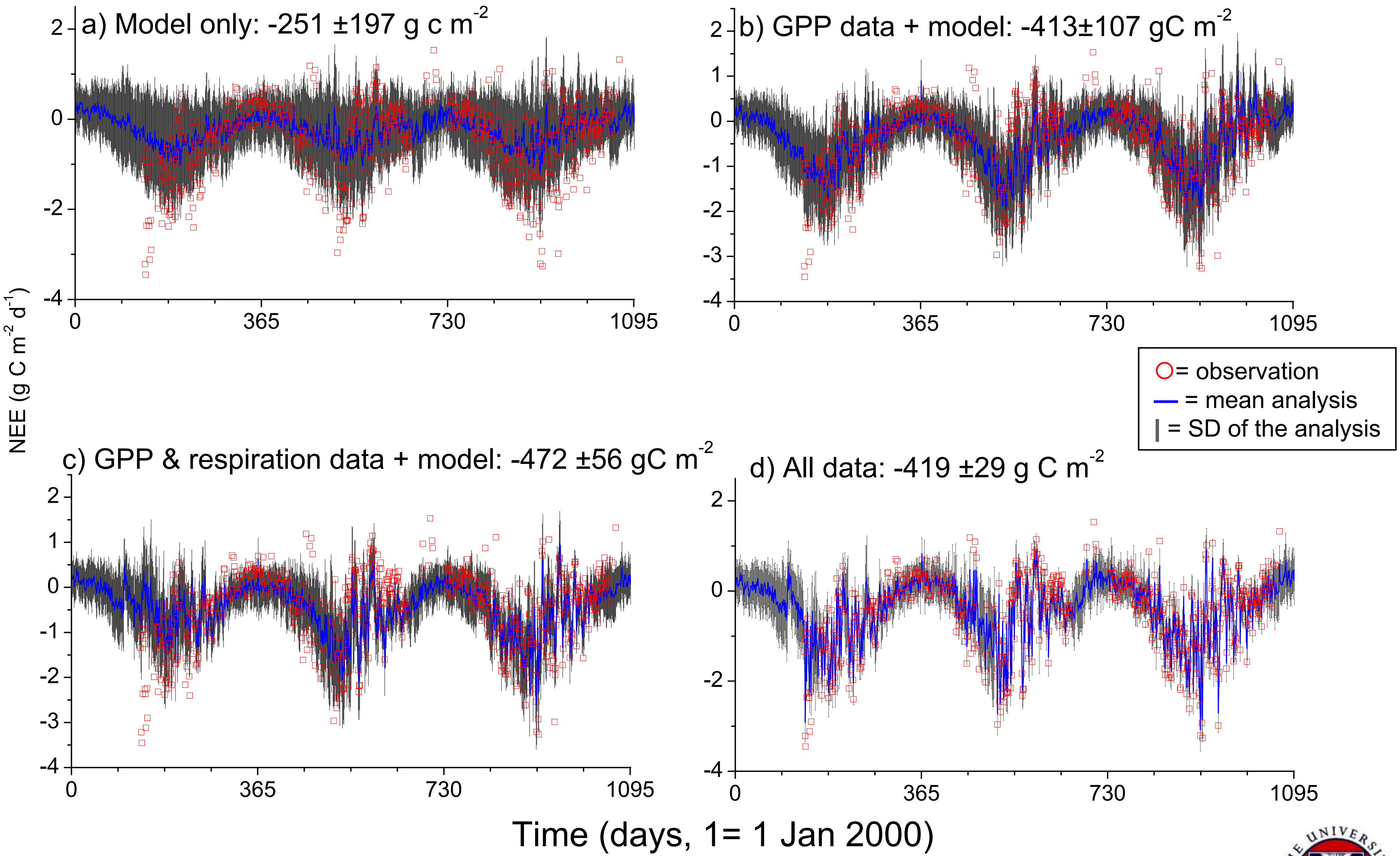
Total respiration
Photosynthesis
Net ecosystem exchange of C
Autotrophic respiration
R tot (gC m-2 d-1)
G (gC m-2 d-1)
NEE (gC m-2 d-1)
R a (gC m-2 d-1)
0
365
730
1095
□= observation
— = mean analysis
| = SD of the analysis
Time (days since 1 Jan 2000)
Williams et al (2005)



Williams et al (2005)


Foliar carbon
Stem carbon
Fine root carbon
Litter carbon
SOM and CWD carbon
= observation
= mean analysis
= SD of the analysis
Time (days since 1 Jan 2000)
Williams et al (2005)

Data brings confidence

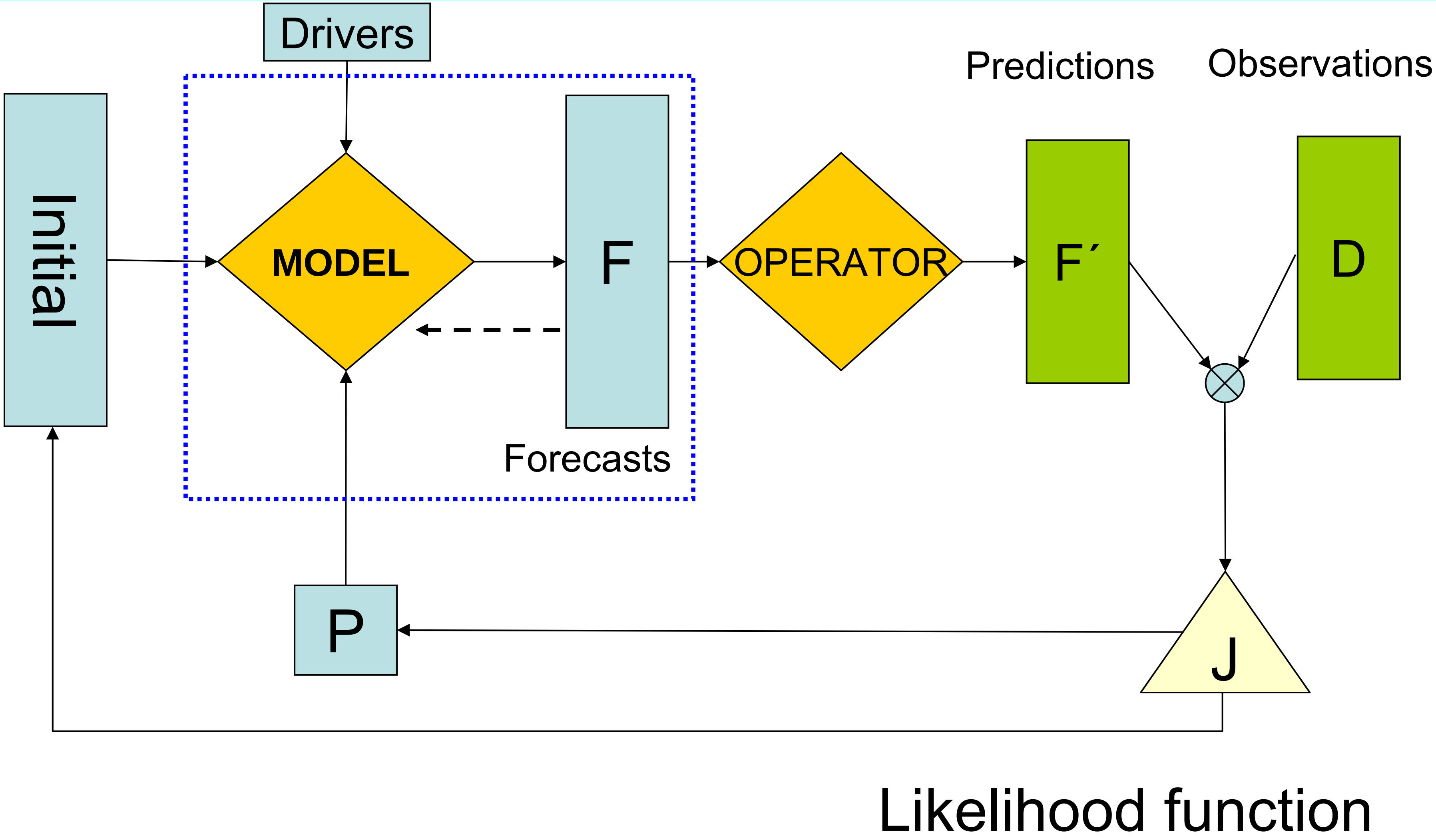


Williams et al (2005)

Approaches to data assimilation

- Sequential (predictor-corrector)
- Inversion techniques
  - Monte Carlo
  - Adjoint

Monte Carlo Inversion



Assimilating 30 minute flux data

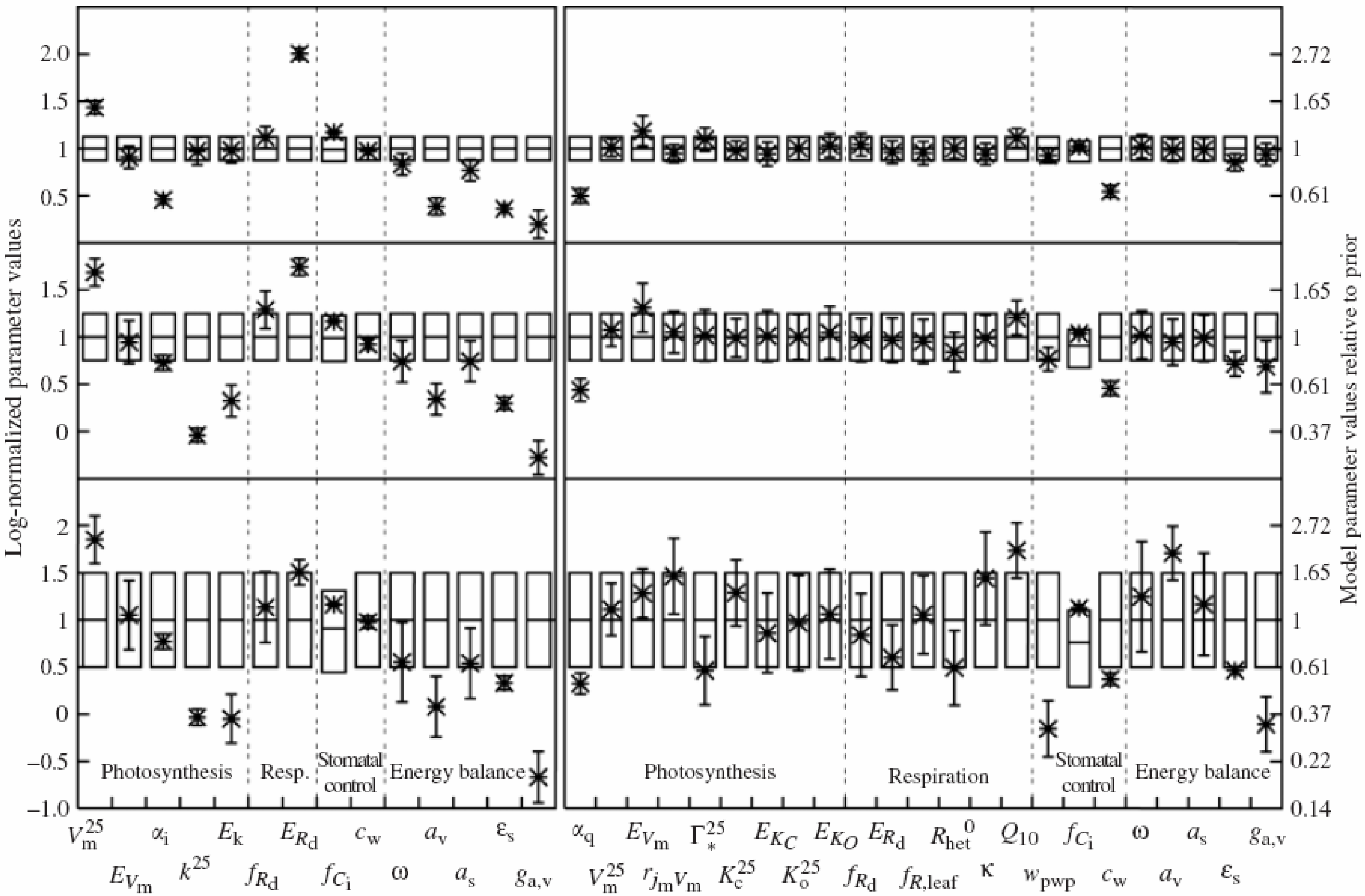


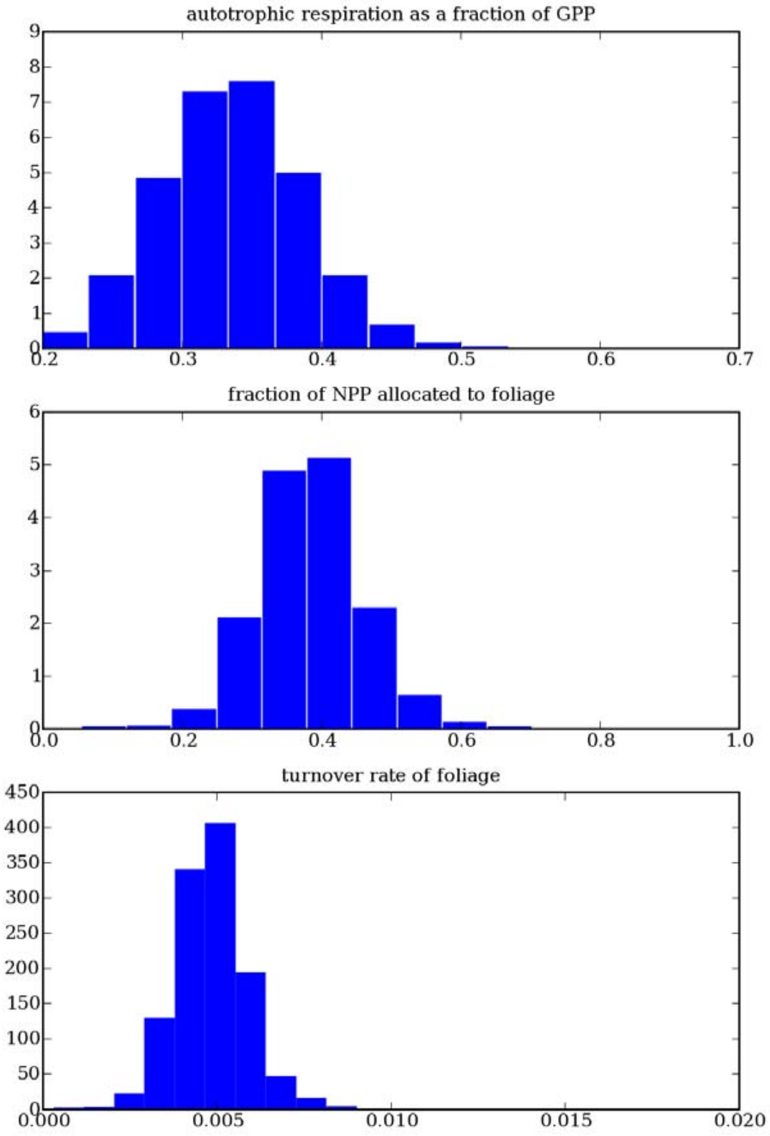
Fig. 2 Prior and posterior parameter values and uncertainties for the log-normalized parameters (transformation to model parameters see Eqn (7)). The boxes show means and one standard deviation of assumed prior parameters (SD = 0.125, 0.25, 0.5). Crosses show the posterior means, and error bars 1 SD of the posterior parameters. Left: Biosphere Energy-Transfer Hydrology (BETHY) model C4 version constrained with data from FIFE site; right: BETHY C3 version constrained with data from Loobos site. The axis on the right hand side shows the model parameter values divided by their respective priors for comparison (does not apply to parameter f_{C_i}).

Bayesian calibration

Autotrophic respiration at a fraction of GPP

Fraction of NPP allocated to foliage

Turnover rate of foliage



David Cameron: CEH Edinburgh

REgional Flux Estimation eXperiment (REFLEX)

- To compare the strengths and weaknesses of various MDF/DA techniques
- To quantify errors and biases introduced when extrapolating fluxes
- www.carbonfusion.org

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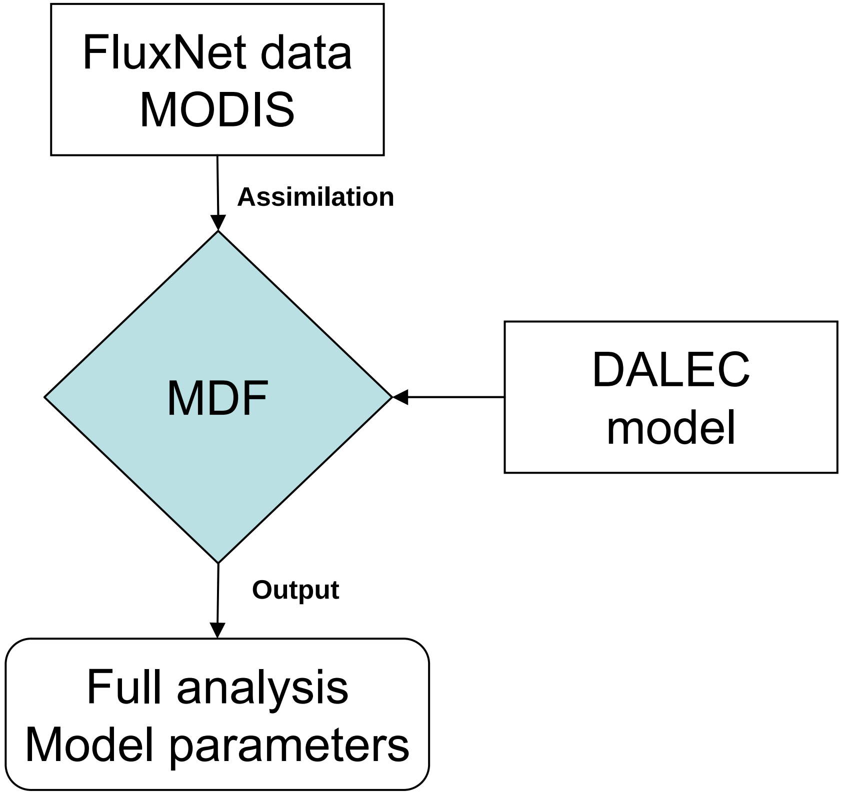
REgional Flux Estimation eXperiment (REFLEX)



Training Runs

Deciduous forest sites

Coniferous forest sites

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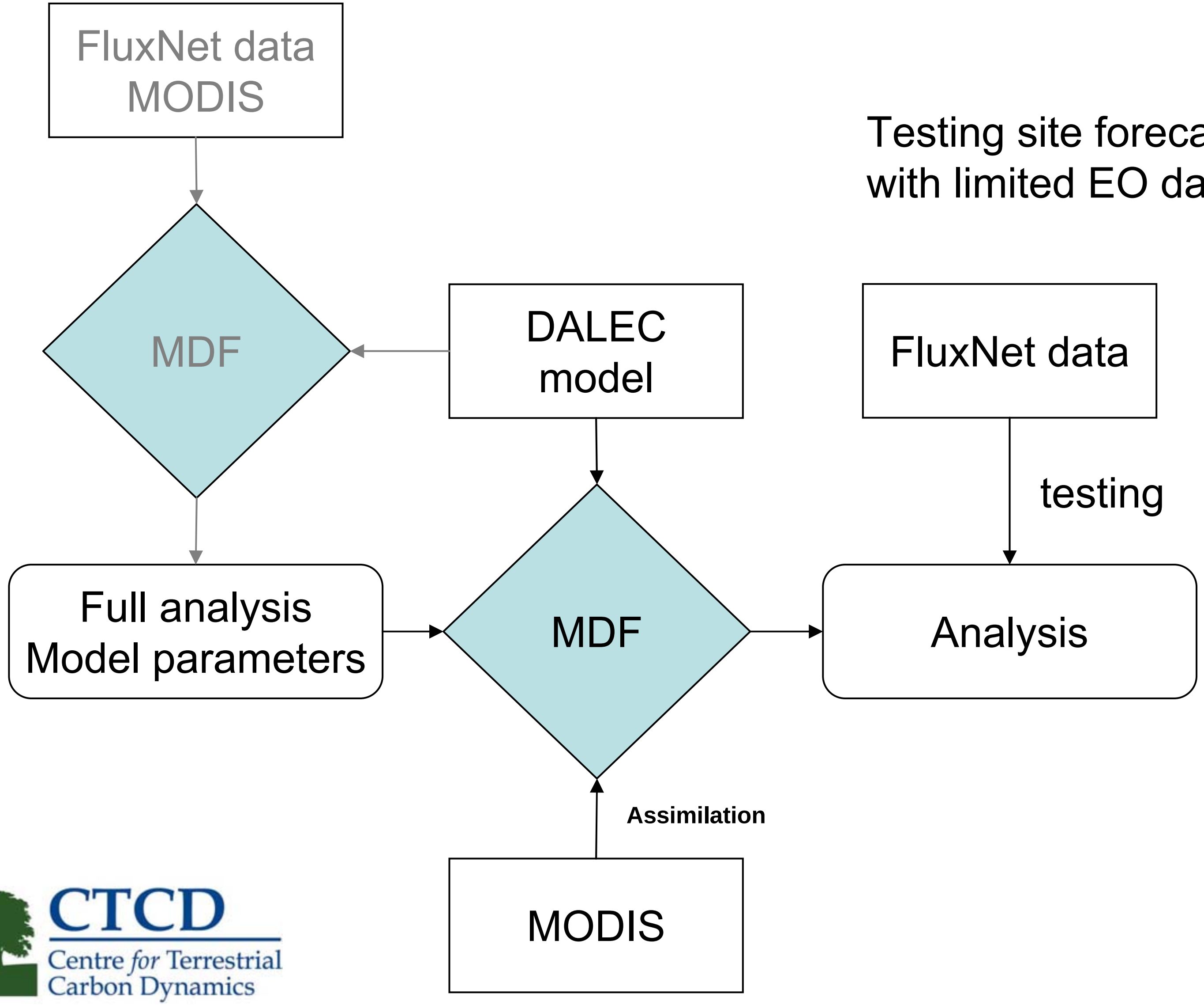
The University of Edinburgh

REgional Flux Estimation eXperiment (REFLEX)



Testing site forecasts
with limited EO data

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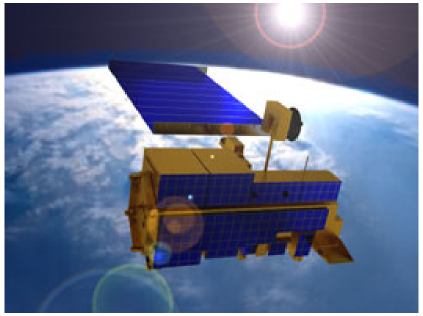
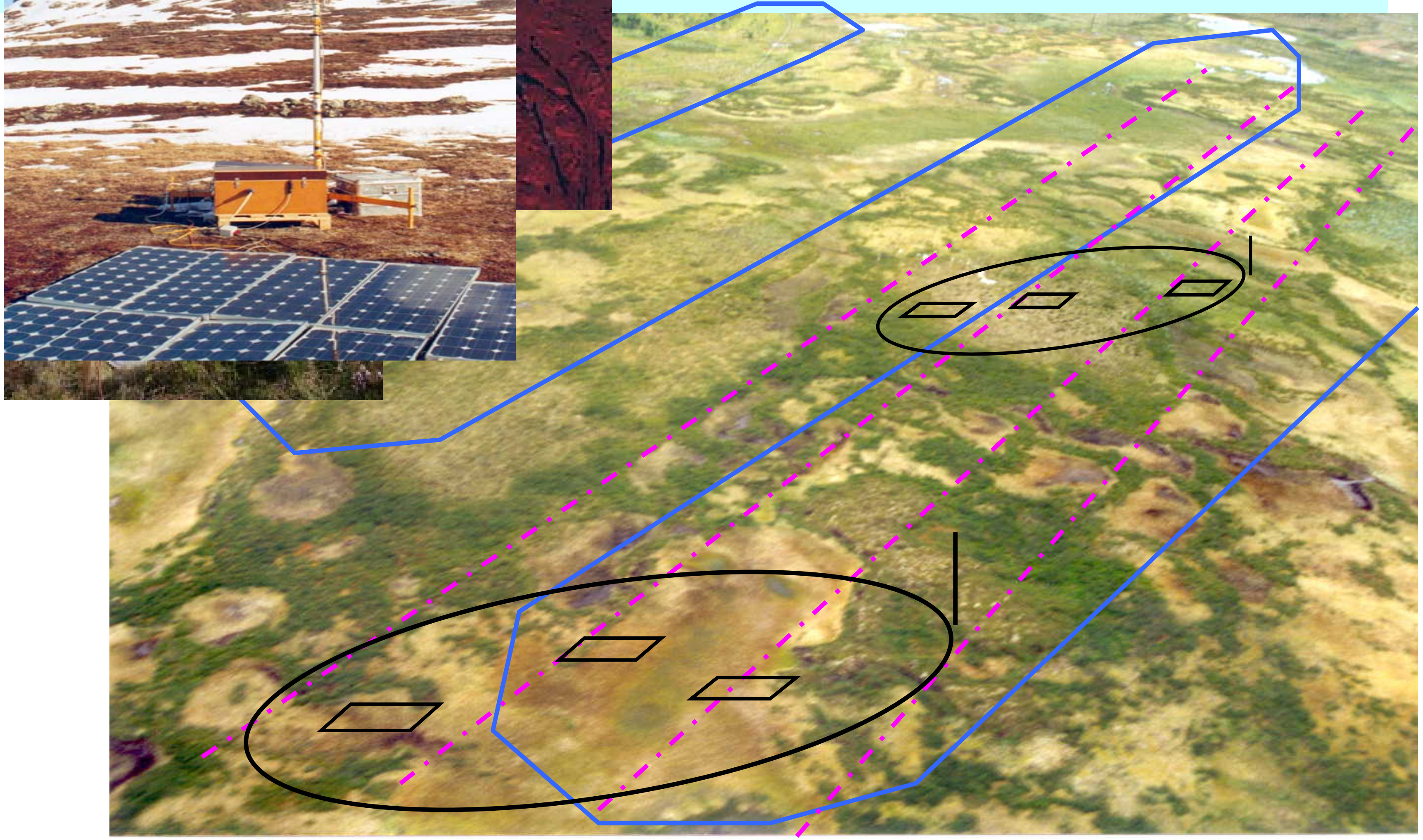
Scaling



iscale approach



www.abacus-ipy.org

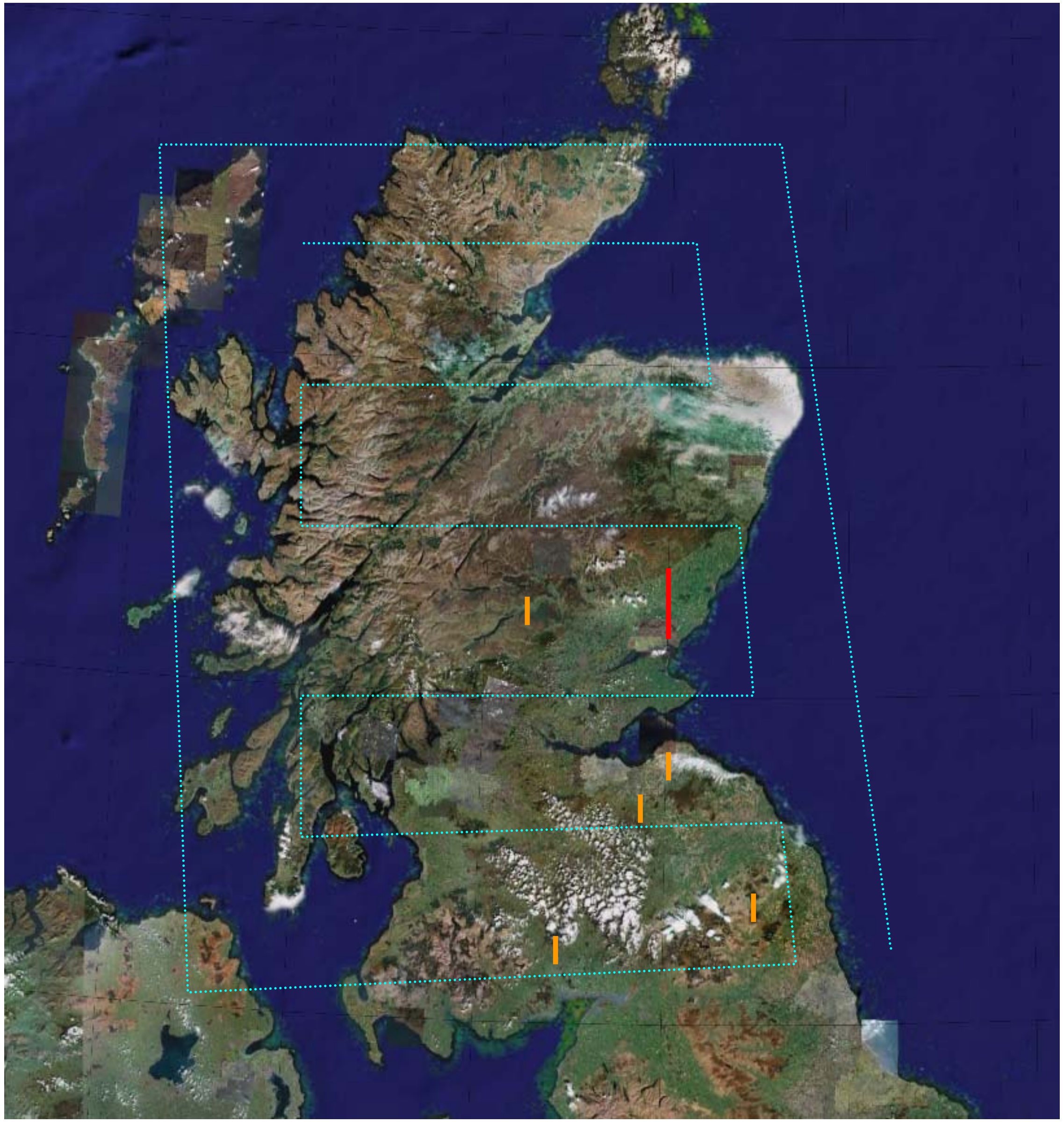
Process models
-upscaling

EO data:
-landcover
-phenology

Flux towers
-processes
-parameters

Geostats
-Spatial drivers
-Uncertainty

Tall tower
/aircraft
-Check on
upscaling
-Inversions



CTCD

Linking fluxes to atmospheric $[CO_2]$

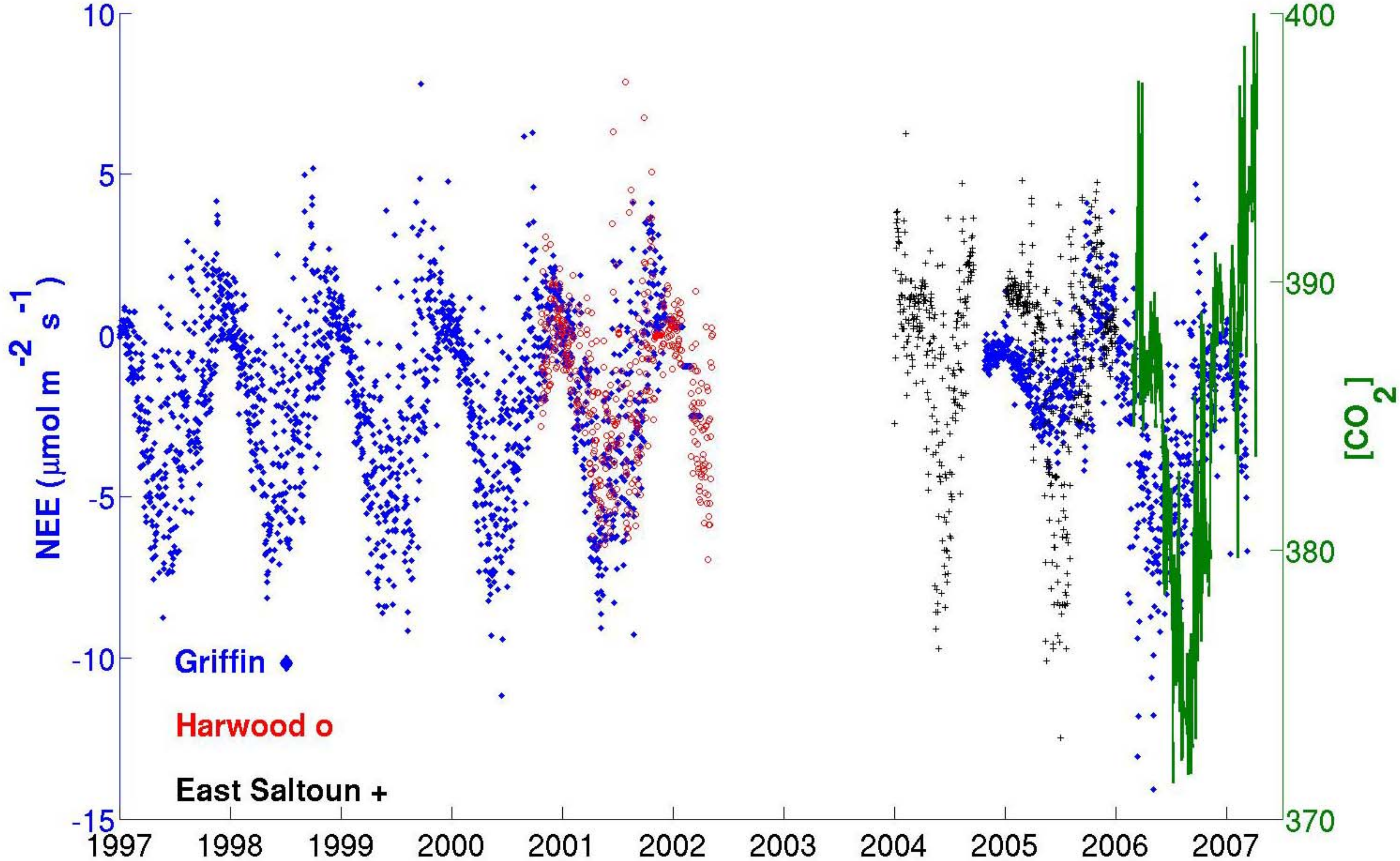


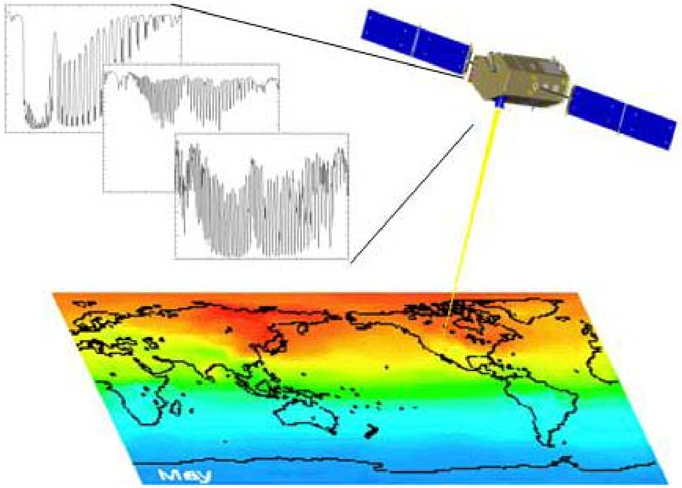
Figure by Paul Parrish, data from J Moncrieff & J Grace

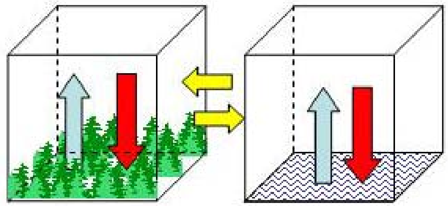
The Orbiting Carbon Observatory (OCO)

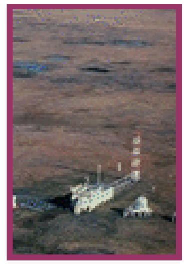
OCO will acquire the space-based data needed to identify CO_2 sources and sinks and quantify their variability over the seasonal cycle

Approach:

- **Collect spatially resolved, high resolution spectroscopic observations of CO_2 and O_2 absorption in reflected sunlight**
- **Use these data to resolve spatial and temporal variations in the** *column averaged CO2 dry air mole fraction, X_{CO2}* **over the sunlit hemisphere**
- **Employ independent calibration and validation approaches to produce X_{CO2} estimates with random errors and biases no larger than 1 - 2 ppm (0.3 - 0.5%) on regional scales at monthly intervals**

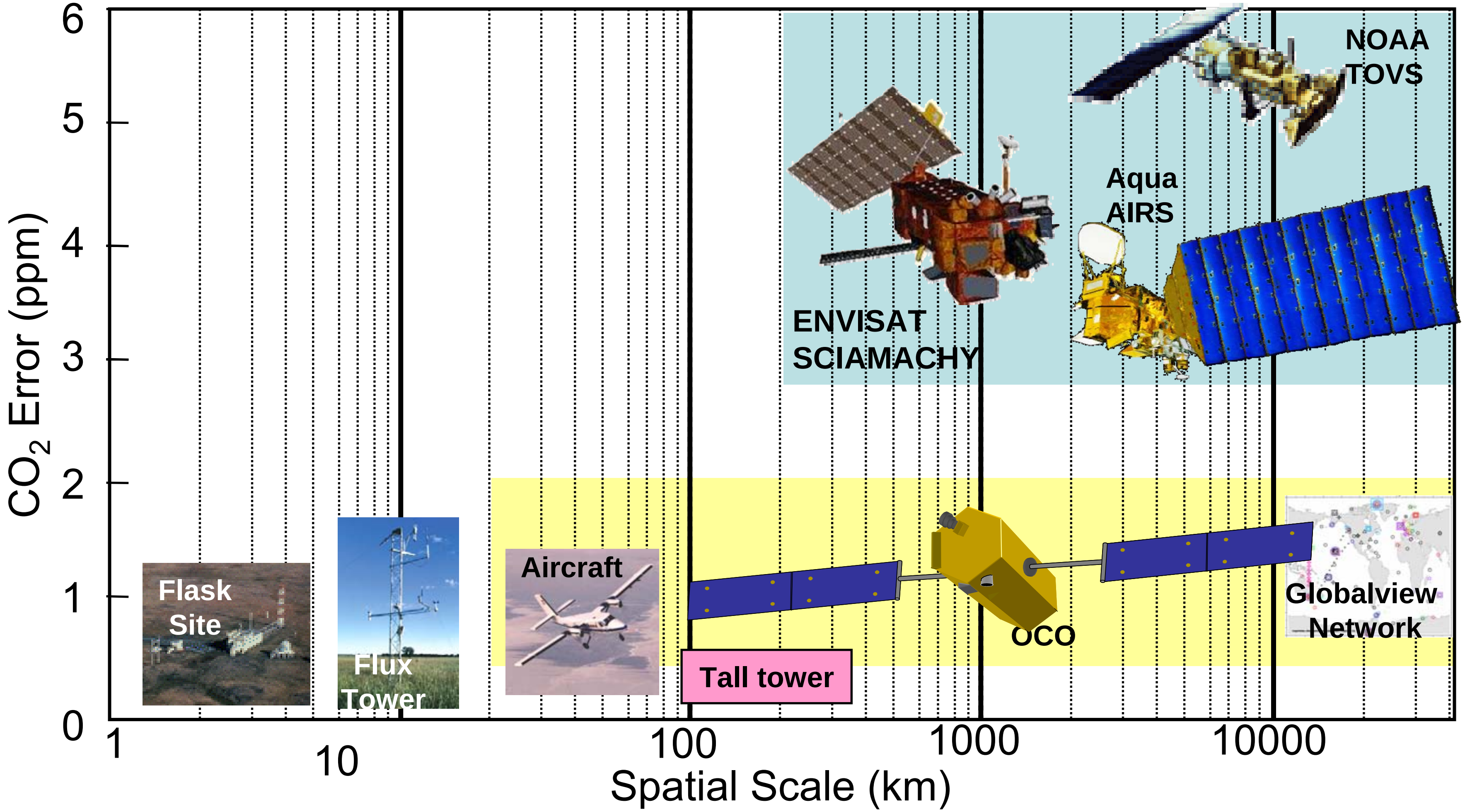






Source: David Crisp, JPL

Spanning measurement scales

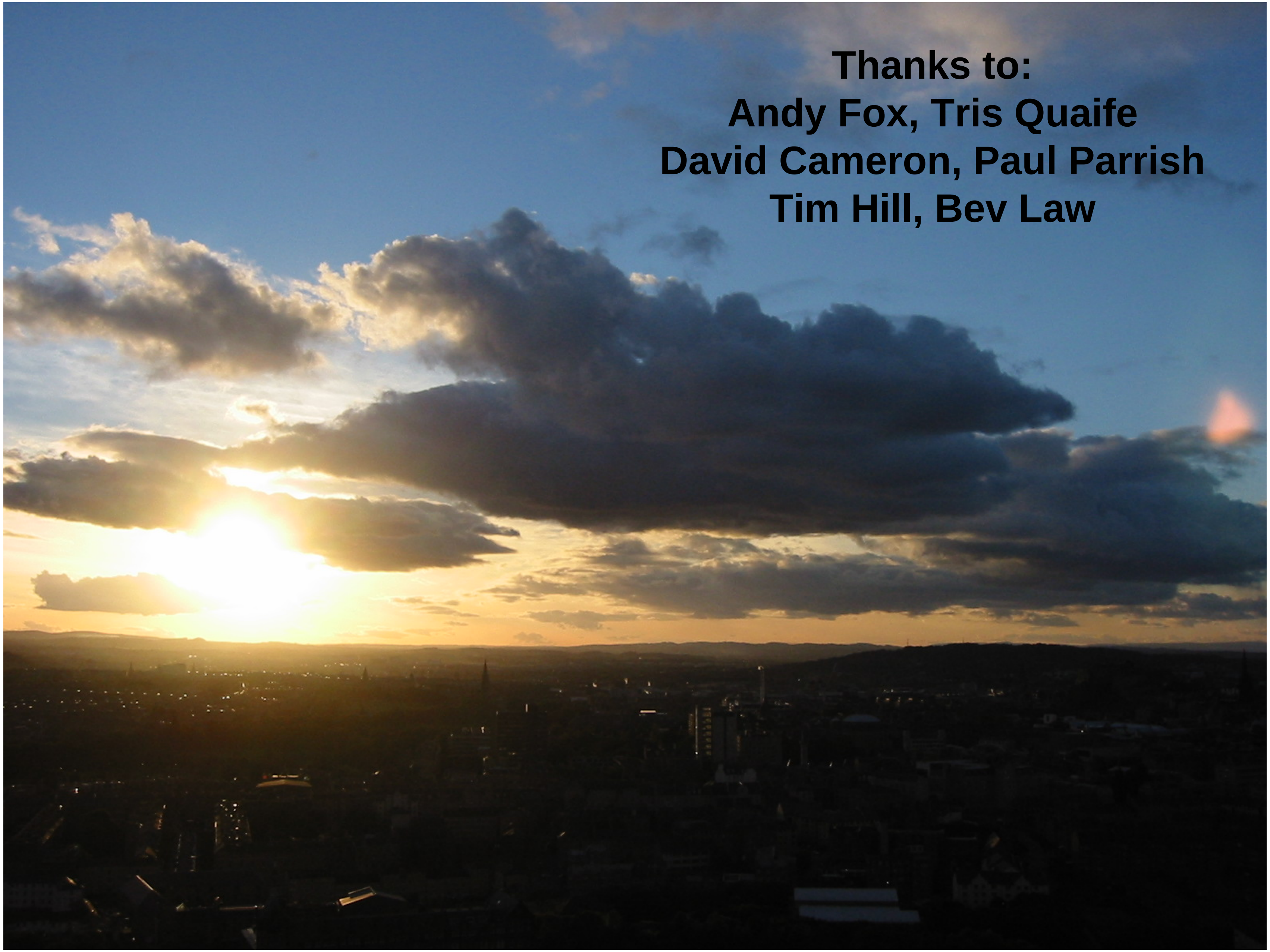


OCO will make precise global measurements of X_{CO2} over the range of scales needed to monitor CO_2 fluxes on regional to continental scales.

Source: David Crisp, JPL

A strategy for JULES?

- LOCAL: DA for local parameter PDFs, process testing, C-water interactions, full state descriptions. *FluxNet, IPSL, NCAR, ACCESS*.
- REGIONAL: upscaling, coupling to/inverting atmospheric data/models. *CarboEurope, ABACUS*.
- GLOBAL: Global assimilation with optical, CO_2, water, temperature remote sensing, flasks. *NCEO & CCDAS*.


Thanks to:
Andy Fox, Tris Quaife
David Cameron, Paul Parrish
Tim Hill, Bev Law

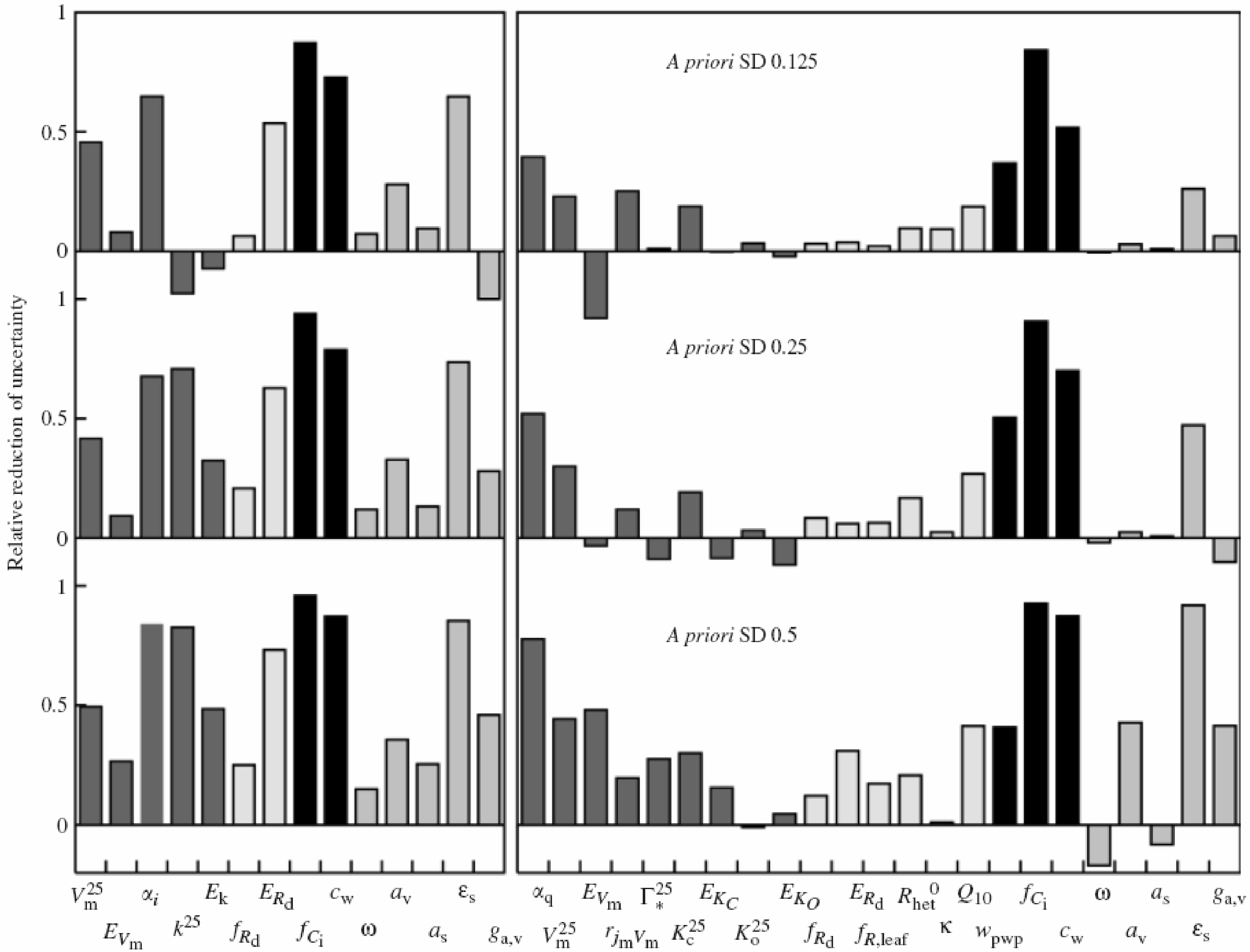
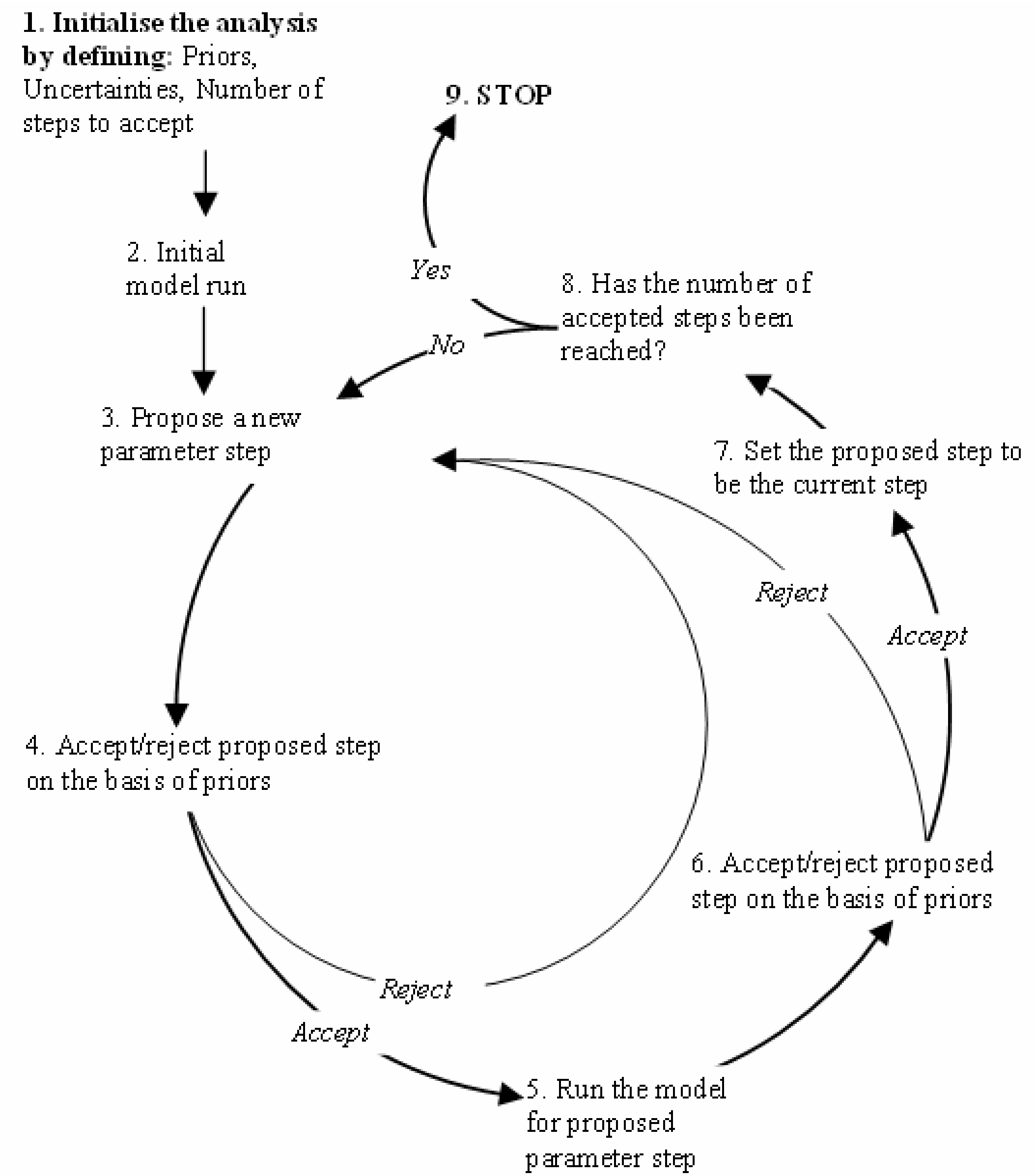


Fig. 3 Relative reduction of uncertainty of parameter values. Zero or negative relative error reduction indicates that no information about a particular parameter could be gained, one would mean perfect knowledge of the inversion. Left: Biosphere Energy-Transfer Hydrology (BETHY) model C4, FIFE site; Right: BETHY C3, Loobos site. Gray shadings denote (from left to right): photosynthesis, carbon balance, stomatal control, and energy/water balance.

Monte

Carlo

Inversion



Tim Hill, PhD thesis