

The Carbon Cycle Data Assimilation System CCDAS

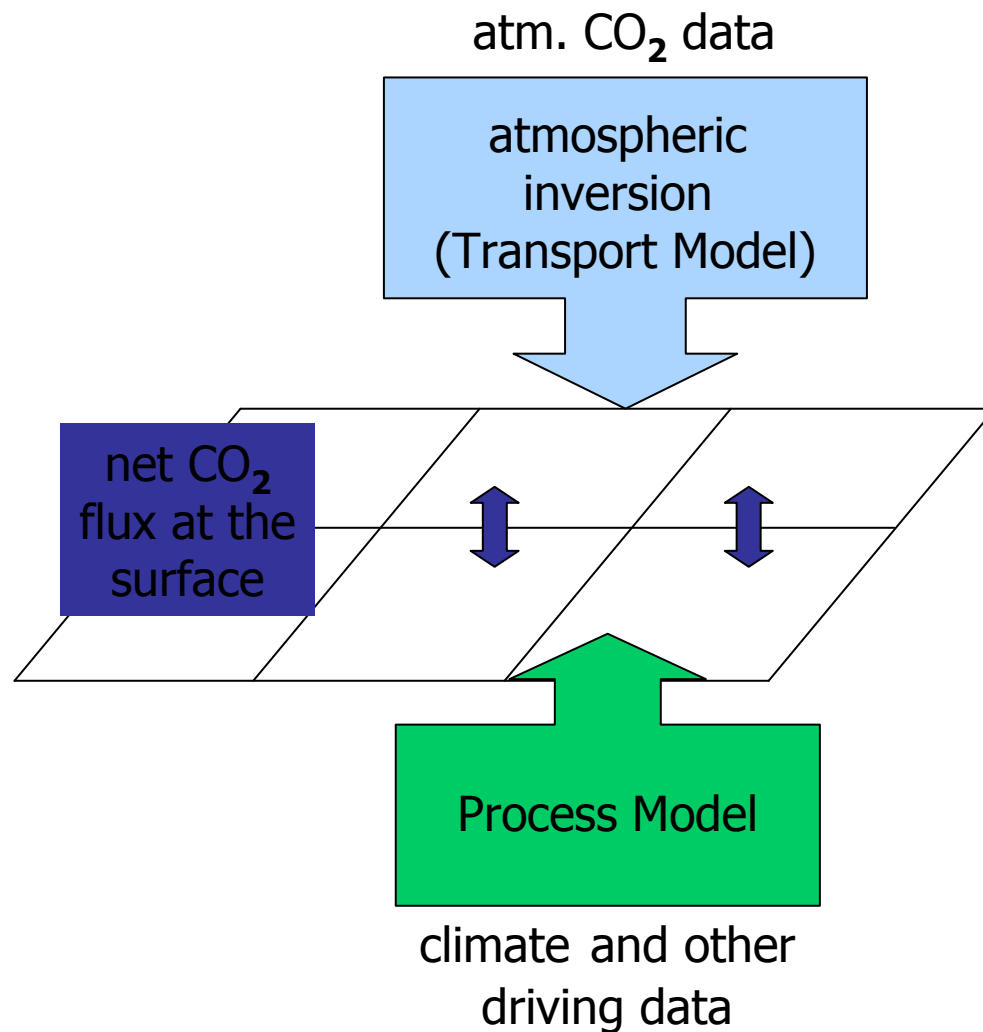
Marko Scholze



& CCDAS team

JULES science meeting, Edinburgh, 8 January 2009

„top-down“ vs. „bottom-up“



Advantages:

- Fluxes consistent with atm. data
- Estimation of uncertainties

Disadvantages:

- No process information
- Depends on prior assumptions

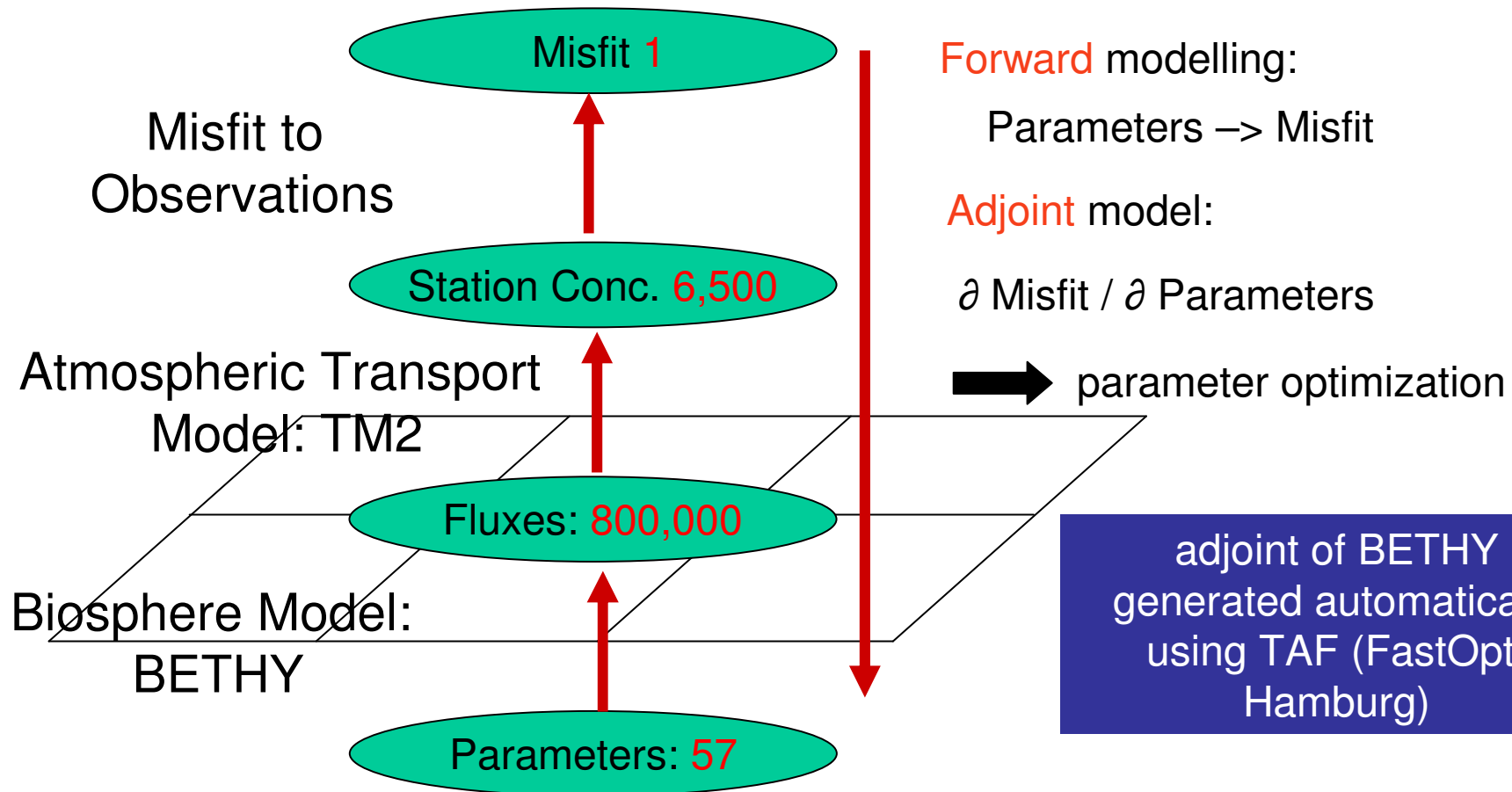
Advantages:

- Process understanding
-> prognostic modeling
- High resolution

Disadvantages:

- Global validation difficult
- Parameter validity

Carbon Cycle Data Assimilation Systems (CCDAS)



BETHY

$\Delta\text{lat}, \Delta\text{lon} = 2 \text{ deg}$

- **GPP:**

C3 photosynthesis – *Farquhar et al. (1980)*

C4 photosynthesis – *Collatz et al. (1992)*

stomata – *Knorr (1997)*

$\Delta t = 1 \text{ h}$

- **Plant respiration:**

maintenance resp. = $f(N_{\text{leaf}}, T)$ – *Farquhar, Ryan (1991)*

growth resp. \sim NPP – *Ryan (1991)*

$\Delta t = 1 \text{ h}$

- **Soil respiration:**

fast/slow pool resp., temperature (Q_{10} formulation) and moisture dependant

$\Delta t = 1 \text{ day}$

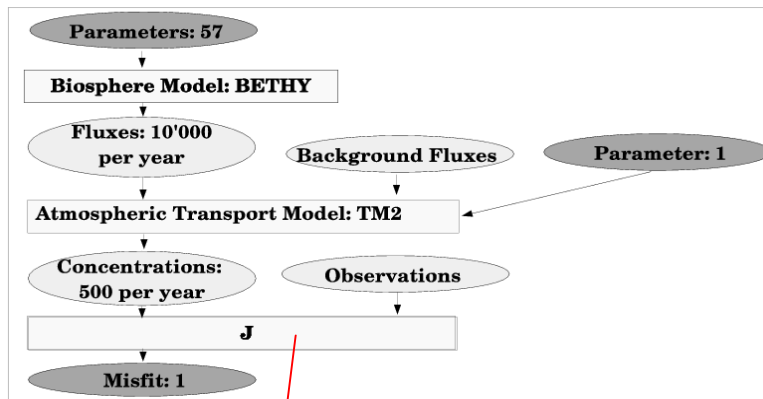
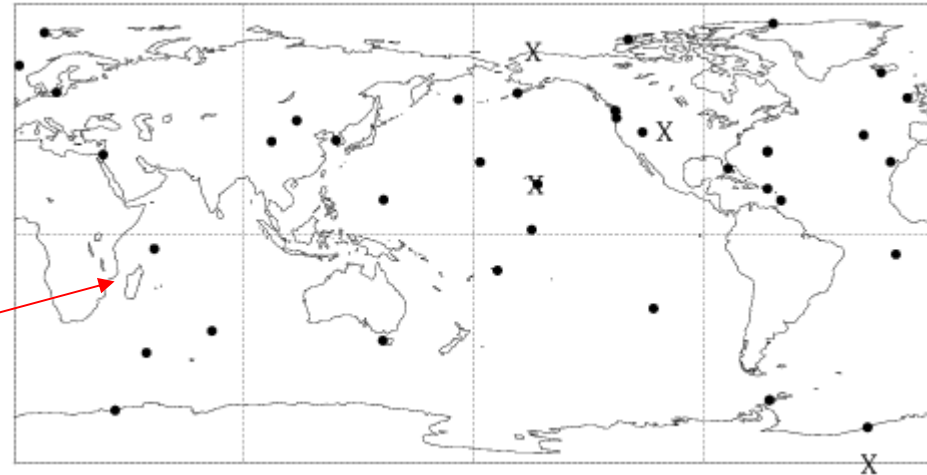
- **Carbon balance:**

average NPP = b average soil resp. (at each grid point)

$\beta < 1$: source
 $\beta > 1$: sink

CCDAS calibration step

- Terrestrial biosphere model BETHY (Knorr 97) delivers CO₂ fluxes to atmosphere
- Uncertainty in process parameters from laboratory measurements
- Global atmospheric network provides additional constraint



covariance of uncertainty in priors for parameters

covariance of uncertainty in measurements + model

priors for parameters

observed concentrations

$$J(\vec{p}) = \frac{1}{2} [\vec{p} - \vec{p}_0]^T \mathbf{C}_{p_0}^{-1} [\vec{p} - \vec{p}_0] + \frac{1}{2} [\vec{y}(\vec{p}) - \vec{y}_0]^T \mathbf{C}_{y_0}^{-1} [\vec{y}(\vec{p}) - \vec{y}_0]$$

Gradient Method

1st derivative (gradient) of $J(\vec{p})$ to model parameters \vec{p} :
$$-\partial J(\vec{p})/\partial \vec{p}$$

yields direction of steepest descent.

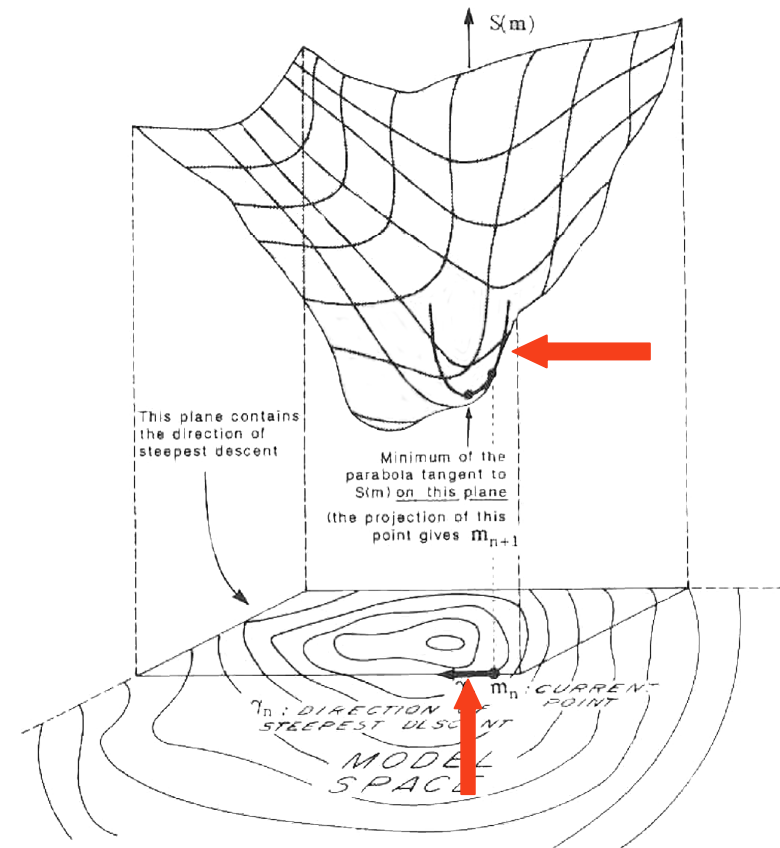
2nd derivative (Hessian) of $J(\vec{p})$:
$$\partial^2 J(\vec{p})/\partial \vec{p}^2$$

yields curvature of J .

Approximates covariance of parameters.

cost function $J(\vec{p})$

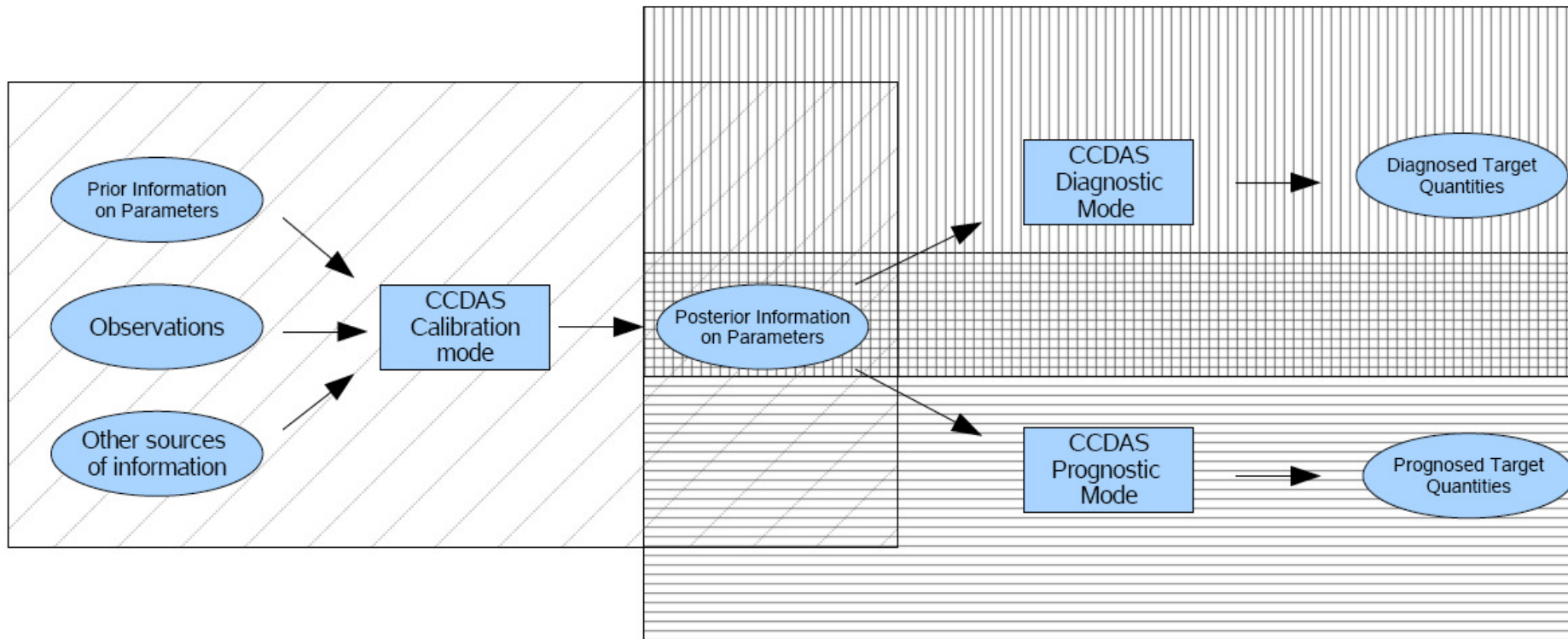
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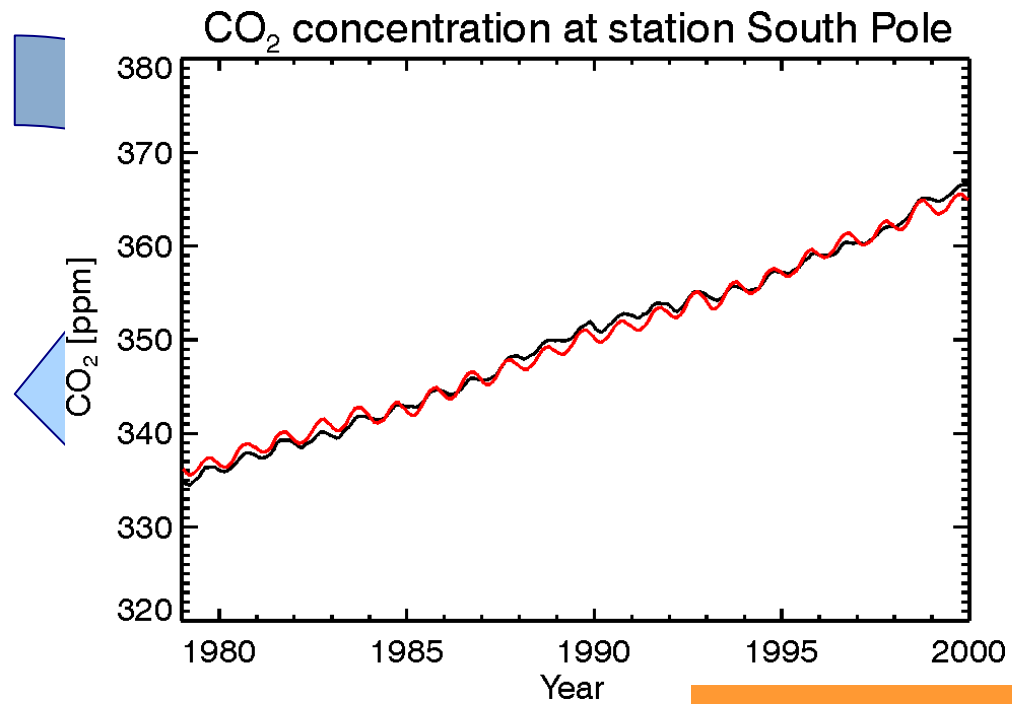
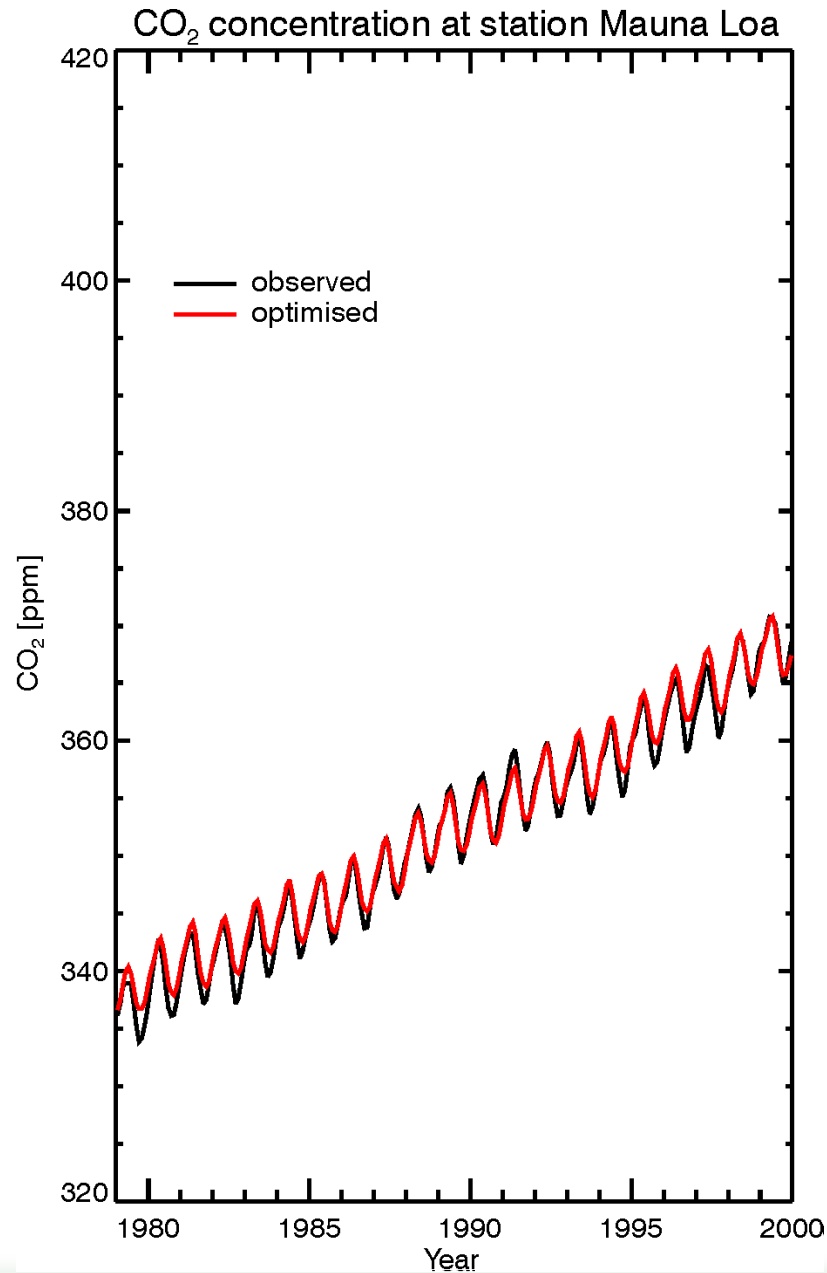
Model parameter space (\vec{p})

Figure from Tarantola, 1987

CCDAS two-step procedure for inferring diagnostics and prognostics



Data fit (Calibration mode)



Rayner et al., 2005

Posterior uncertainties on parameters (Hessian mode)

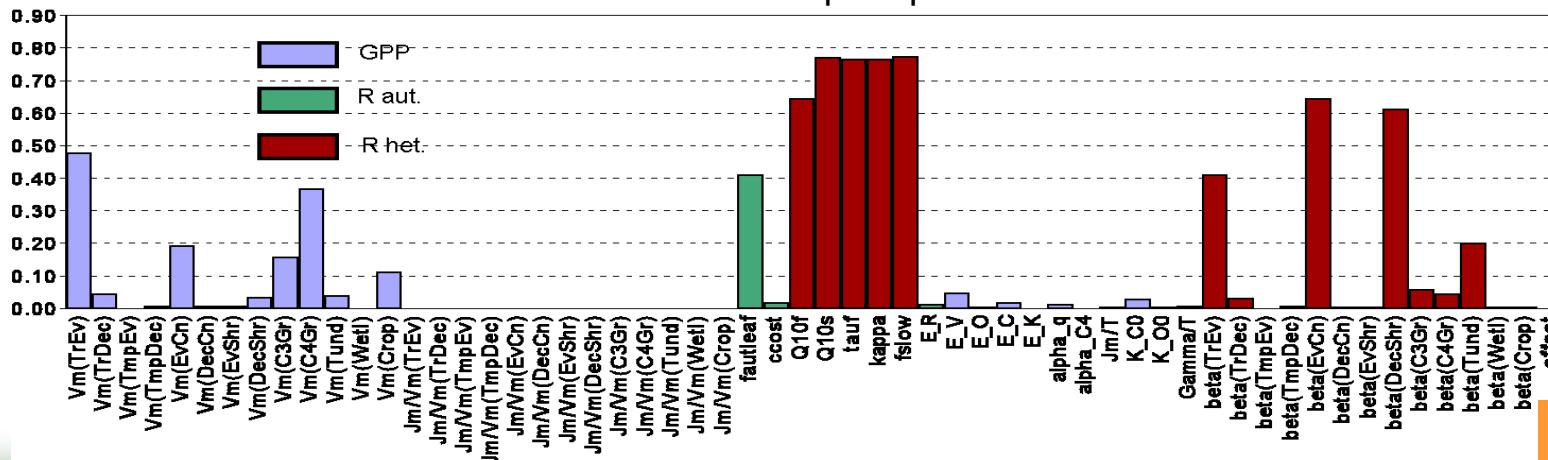
Use inverse Hessian of objective function to approximate posterior uncertainties

$$C_p \approx \left\{ \frac{\partial^2 J(\vec{p}_{opt})}{\partial p_{i,j}^2} \right\}^{-1}$$

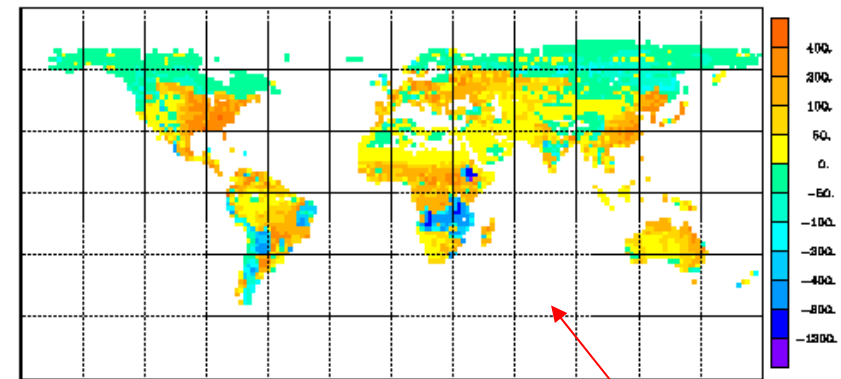
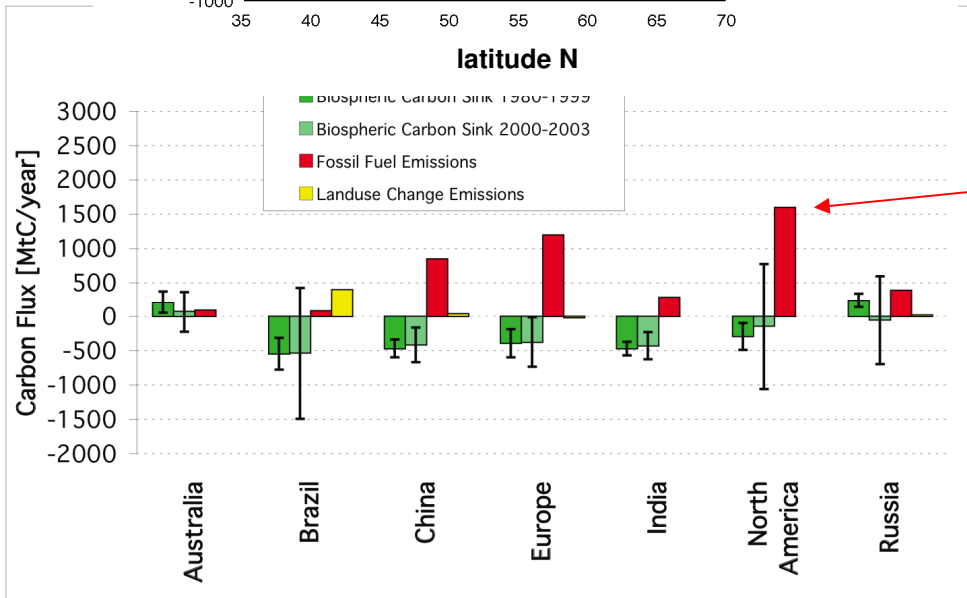
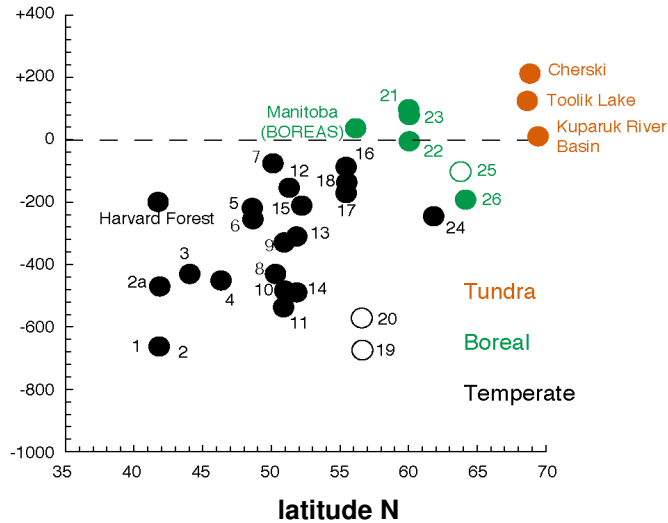
examples:

	first guess $\mu\text{mol/m}^2\text{s}$	optimized $\mu\text{mol/m}^2\text{s}$	prior unc. %	opt.unc. %	Vm(TrEv)	Vm(EvCn)	Vm(C3Gr)	Vm(Crop)
Vm(TrEv)	60.0	43.2	20.0	10.5	0.28	0.02	-0.02	0.05
Vm(EvCn)	29.0	32.6	20.0	16.2	0.02	0.65	-0.10	0.08
Vm(C3Gr)	42.0	18.0	20.0	16.9	-0.02	-0.10	0.71	-0.31
Vm(Crop)	117.0	45.4	20.0	17.8	0.05	0.08	-0.31	0.80

Relative Error Reduction $1 - \sigma_{opt}/\sigma_{prior}$

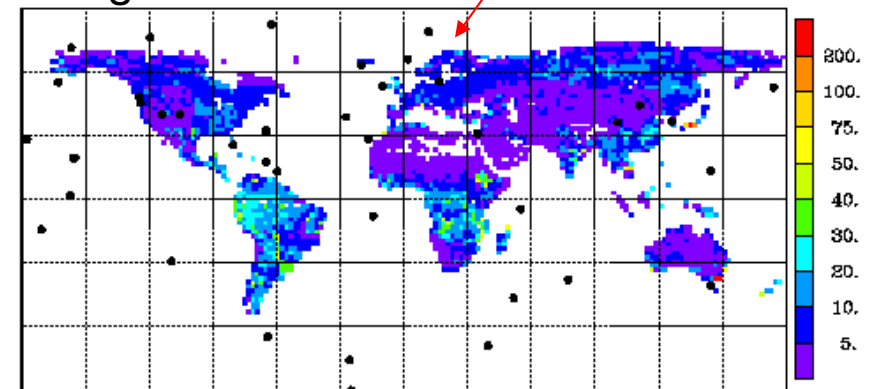


Net C fluxes and their uncertainties (CCDAS diagnostic mode)



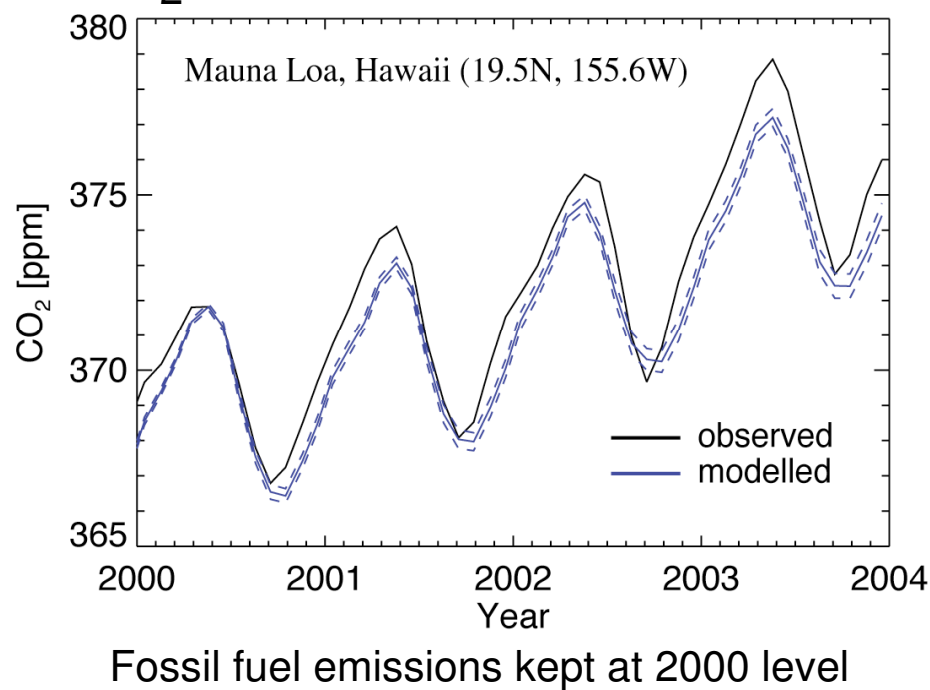
Examples for diagnostics:

- Long term mean fluxes to atmosphere ($\text{gC}/\text{m}^2/\text{year}$) and uncertainties
- Regional means

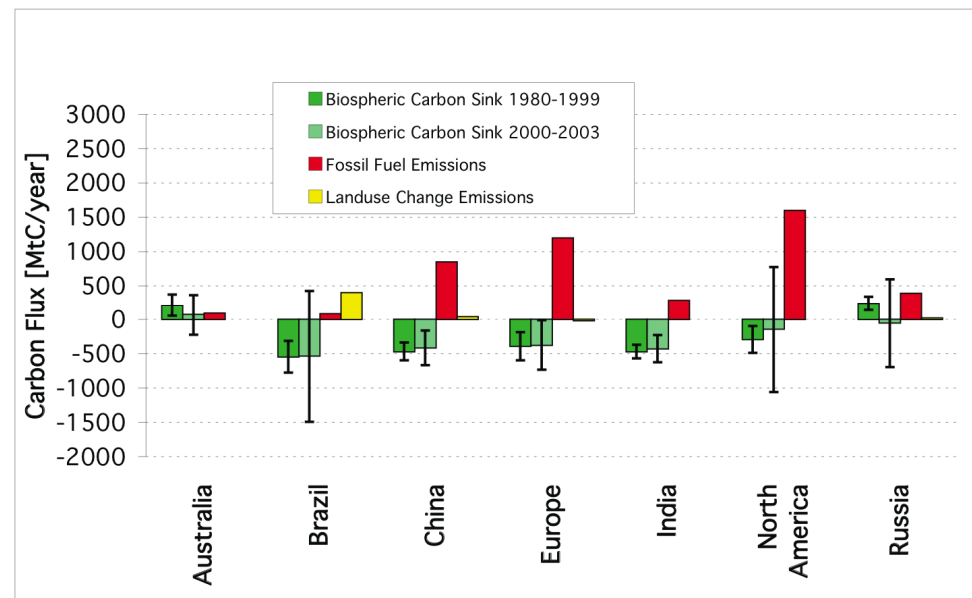


CCDAS prognostic mode here hindcasting 2000-2003

CO₂ concentration at Mauna Loa

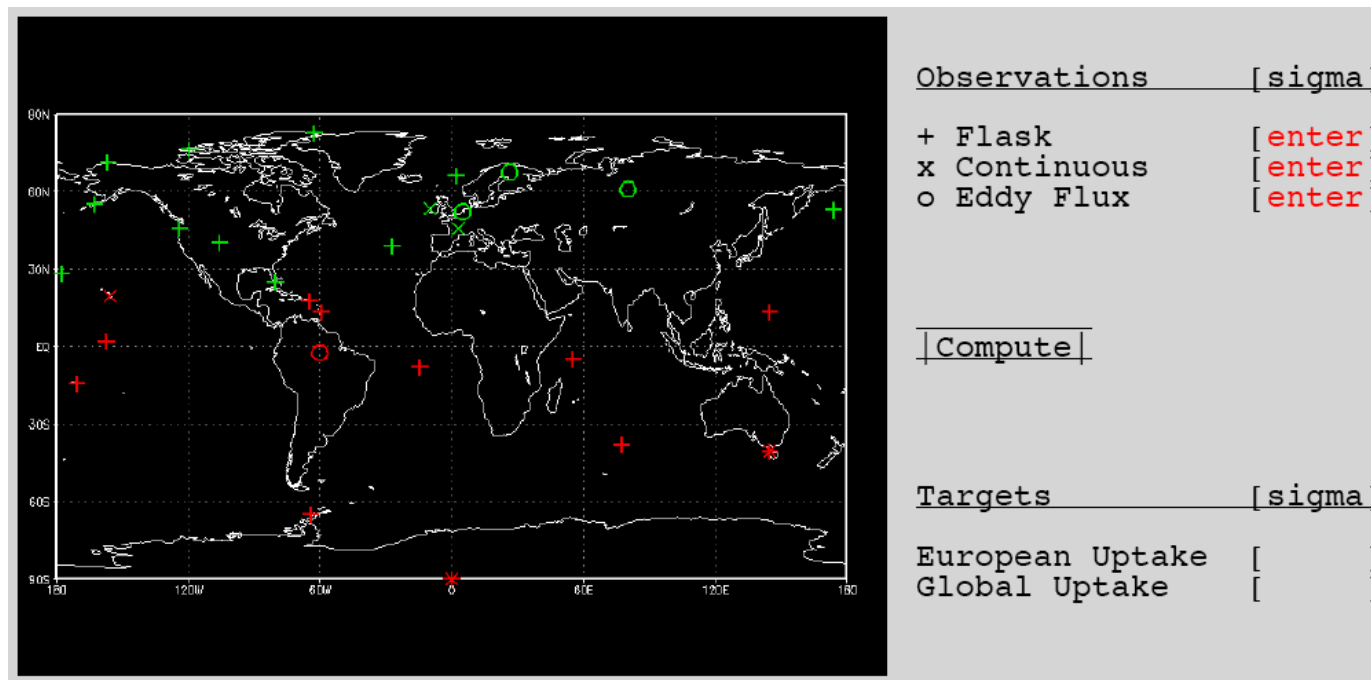


Regional carbon balances



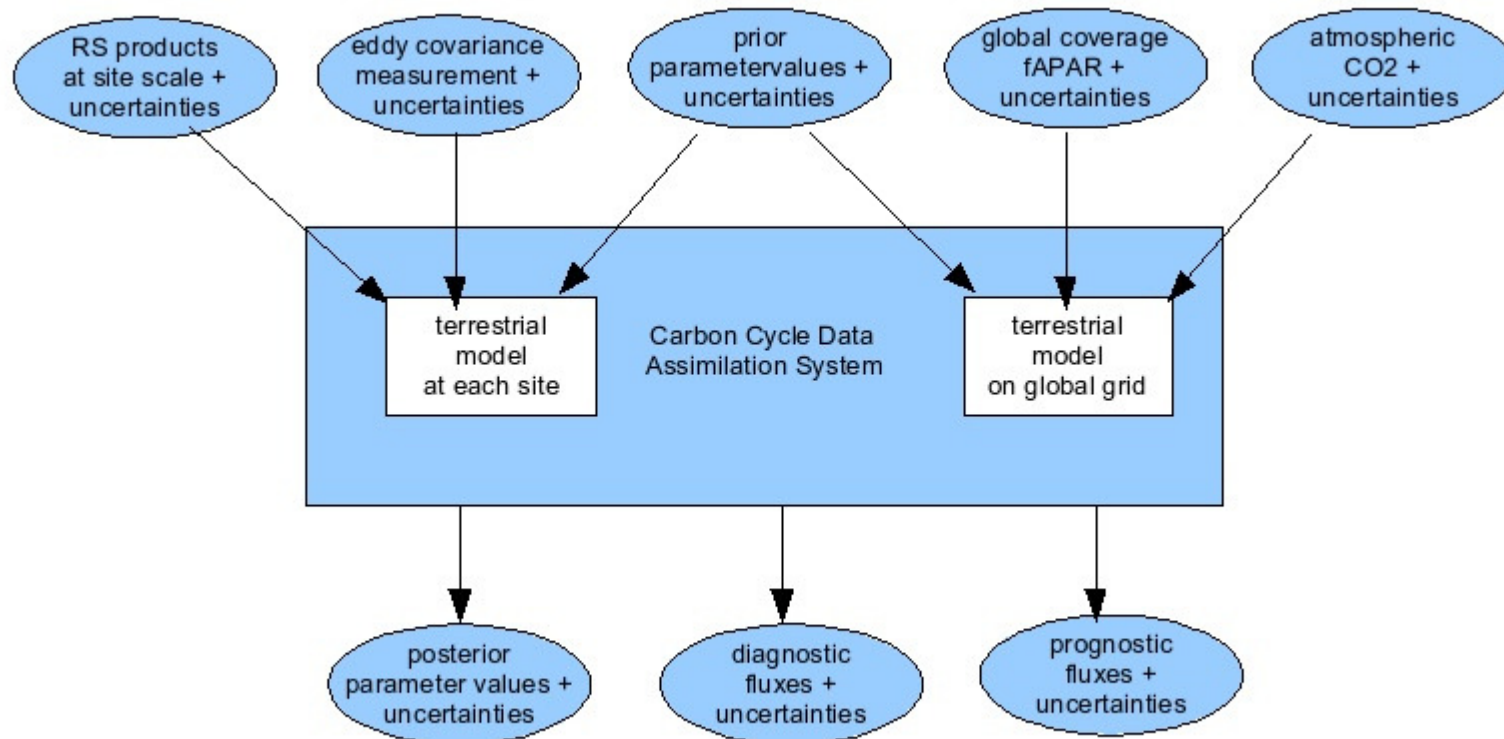
CCDAS application: network design

Construction of an interactive tool that, for a given network and a given target quantity, can approximate the uncertainty with which the value of the target quantity is constrained by the observations.



CCDAS is central modelling tool in a network designer (EU FP6 funded, more info on www.imecc.ccdas.org)

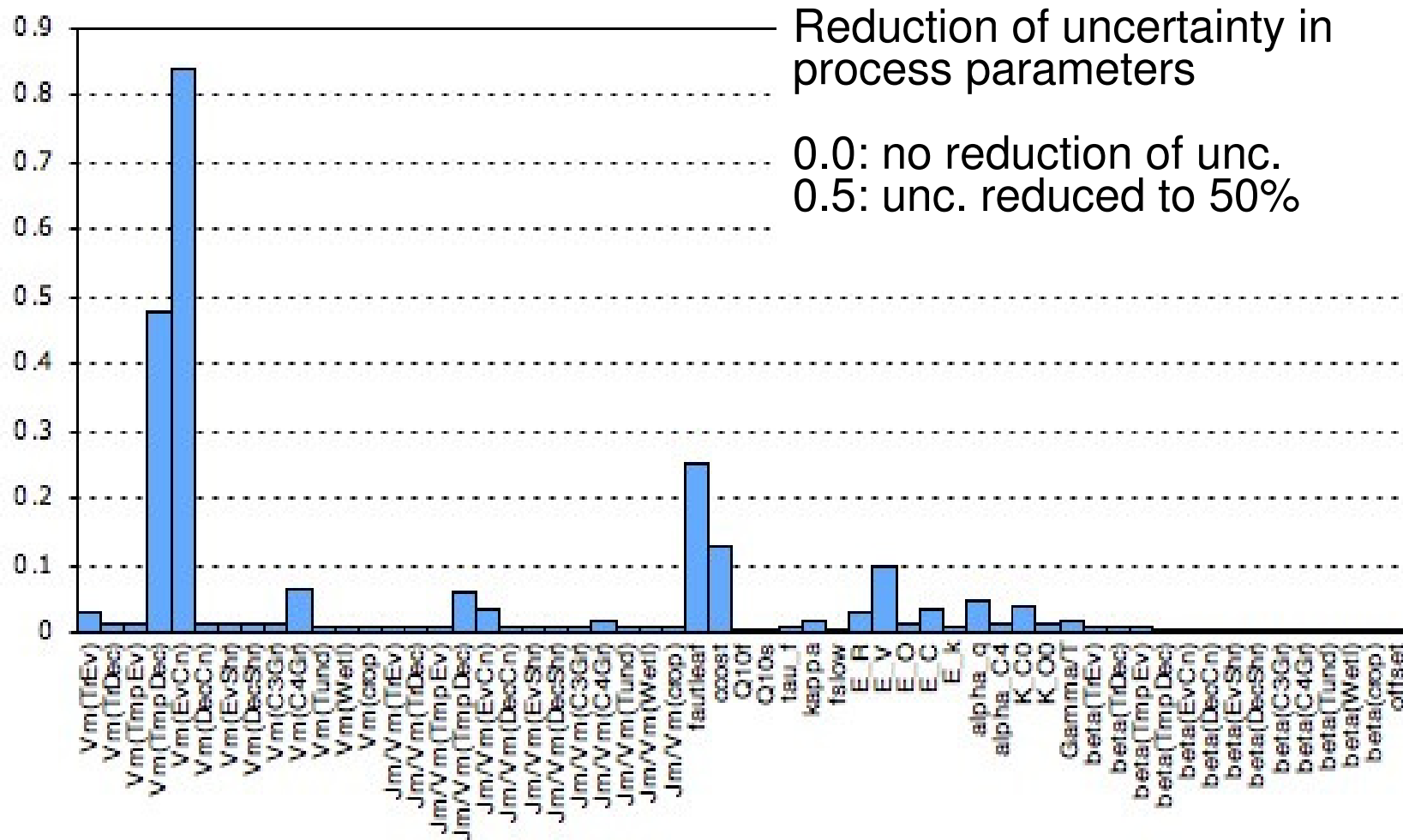
CCDAS extension to include remotely sensed vegetation activity (FAPAR) as additional constraint



Assess the impact of remote sensing products in terms of reducing uncertainties of the terrestrial contribution to the global carbon cycle (ESA funded, more info on www.rs.ccdas.org).

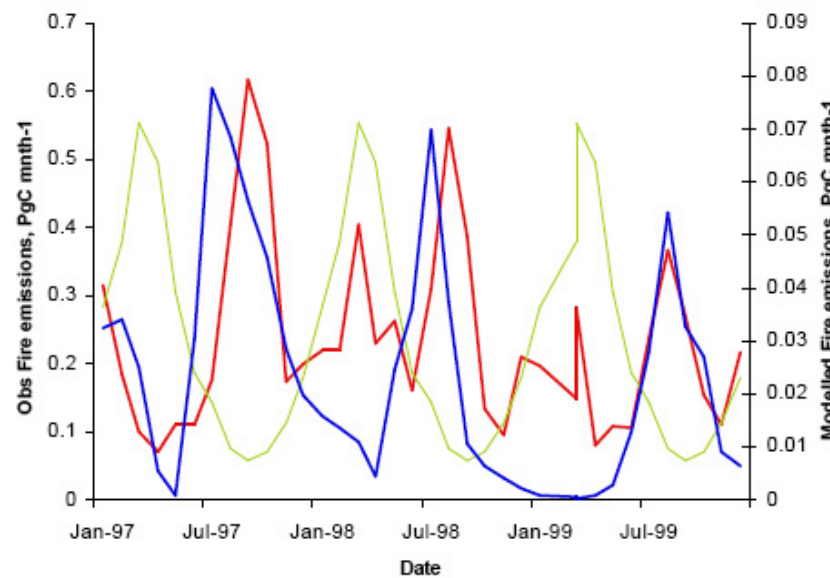
Simultaneous Assimilation at all 6 sites

MERIS FAPAR + Flux data

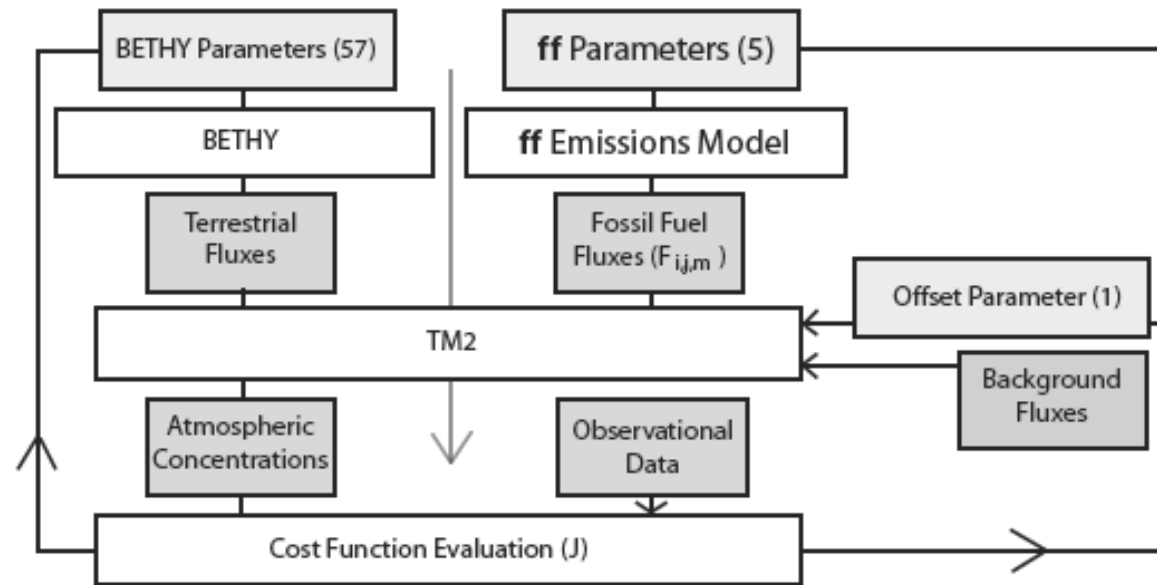


CCDAS extension to include a prognostic fire model

- FireStatistical emissions Global model (FISSLING) developed within CCDAS, based on GlobFIRM
- Calculates burnt area and carbon emissions on monthly time scale
- 13 additional control parameters: combustion completeness per PFT
- Burnt area compares well against observations, however, emissions still need some more work



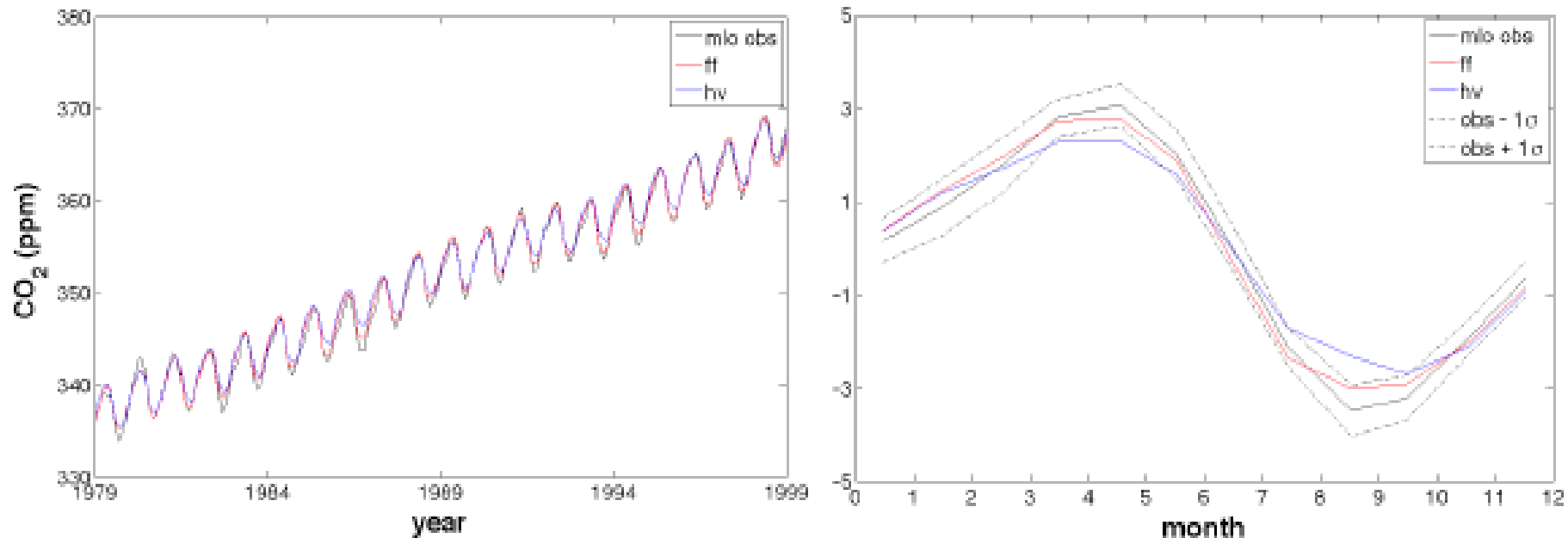
CCDAS extension to include a model of seasonal fossil fuel emission



- Annual fossil fuel emissions from CDIAC distributed over 5 regions according to population density
- Latitudinal dependant seasonal cycle imposed upon base level
- Seasonal amplitude per region is control parameter

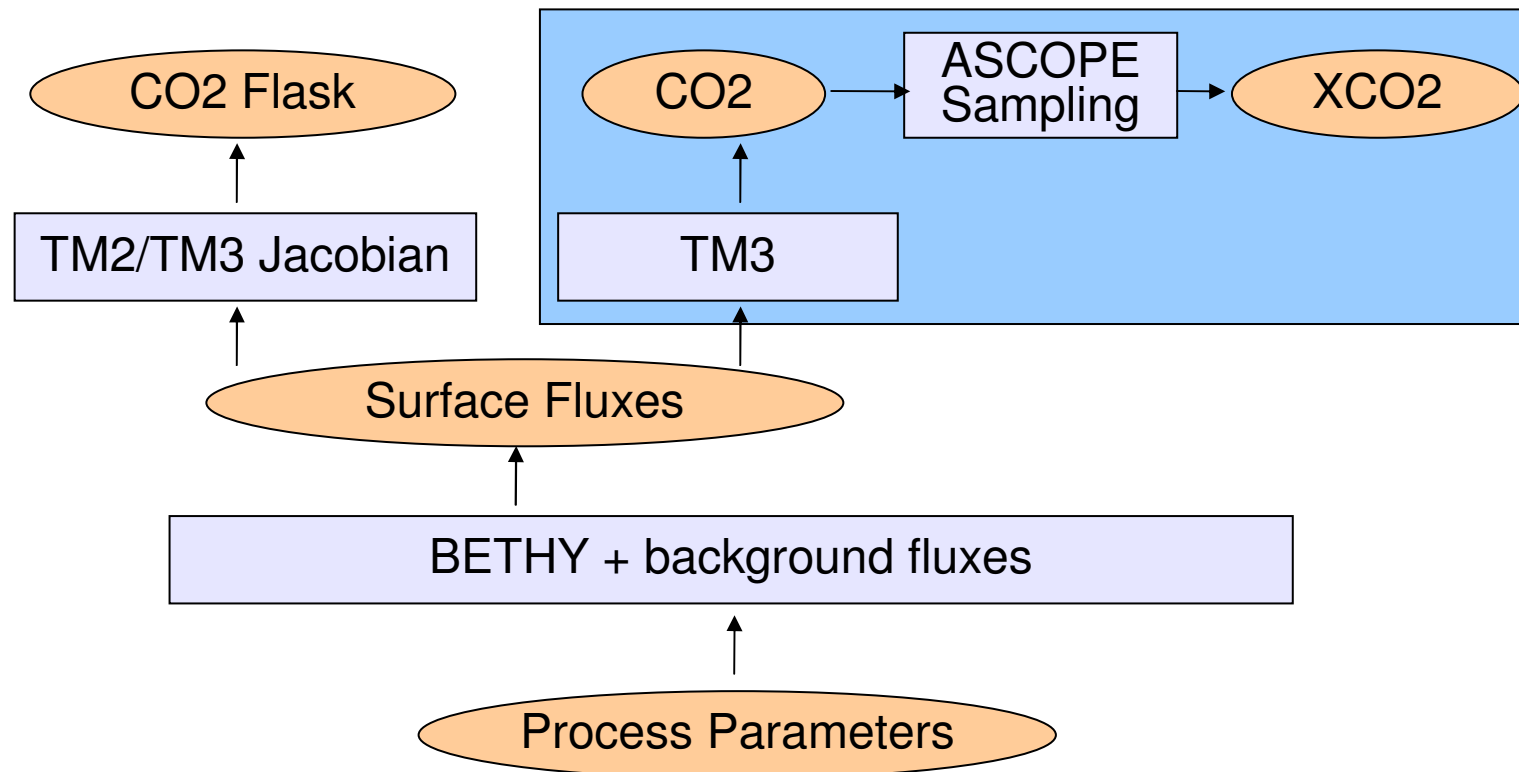
CCDAS extension to include a model of seasonal fossil fuel emission

Fit to data Mauna Loa



- Reduced χ -square improved with ff-model (2.23 vs 1.73)
- In optimisation with ff-model parameters related to GPP changed most as compared to standard CCDAS

CCDAS extension to include column integrated CO₂ data as additional constraint



Demonstration study for the design of the European Space Agency's candidate Earth Explorer mission A-SCOPE, which will provide column-integrated CO₂ concentration data (ESA funded).

Summary

- CCDAS tests a given combination of observational data + model formulation with uncertain parameters
- CCDAS delivers optimal parameters, diagnostics, and their posterior uncertainties
- CCDAS builds the core of a network design tool
- More processes in CCDAS: fire & seasonal fossil fuel
- More data for CCDAS:
 - Remotely sensed vegetation activity (FAPAR)
 - CO₂ fluxes from eddy flux towers
 - satellite CO₂ columns (also network design)