An overview on adjoint applications in Earth System Modelling

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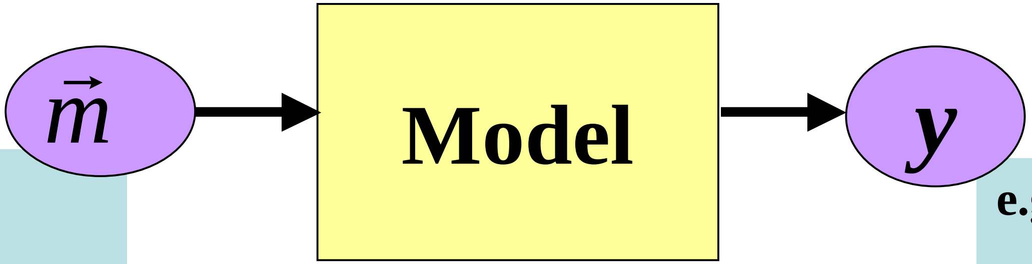
Overview

- Sensitivities
- Data Assimilation
- Uncertainty propagation
- Summary, Links

Sensitivities

Think of your model as a function:



e.g. initial or boundary cond., prognostics, or parameters

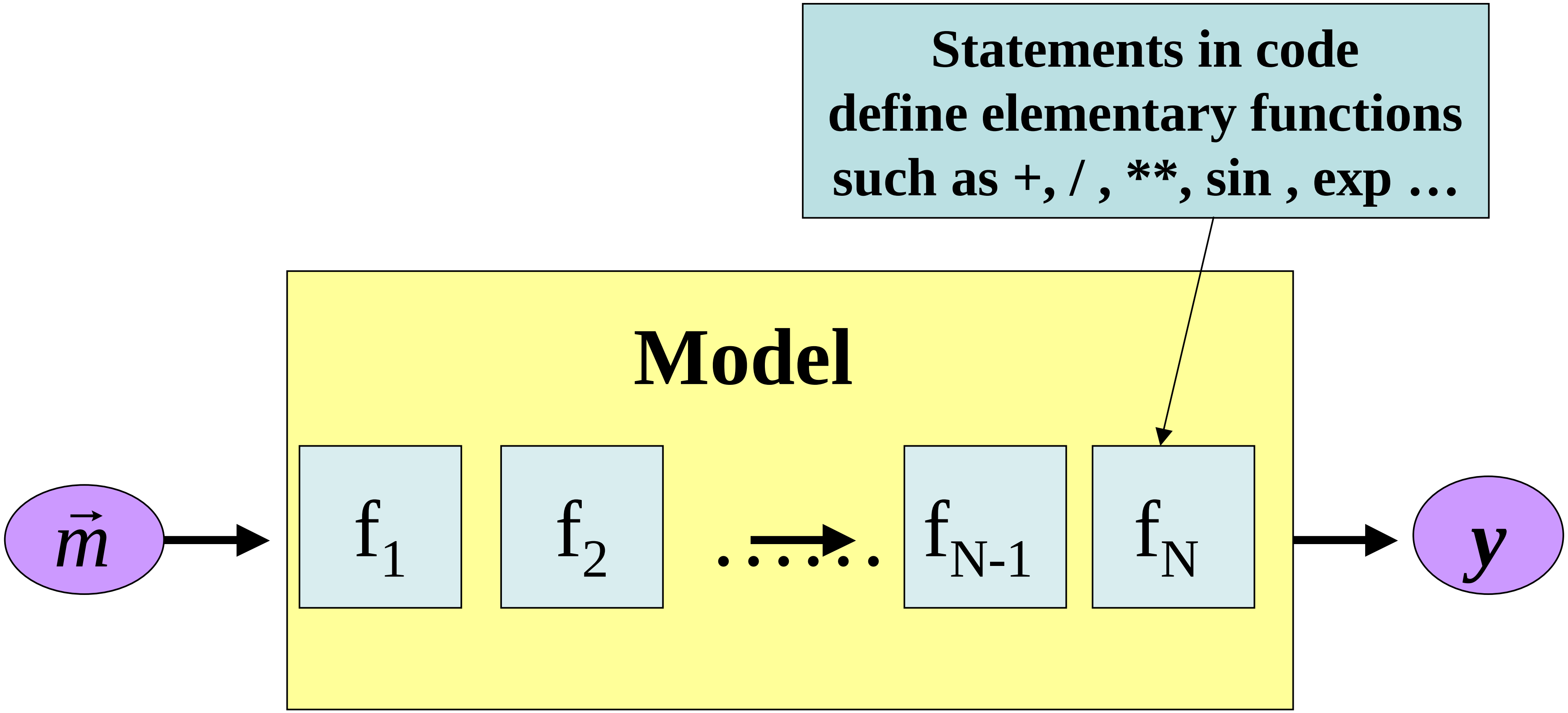
in any combination

e.g. a prognostic or diagnostic

Sensitivity is the derivative (gradient) of that function:

$$\nabla y$$

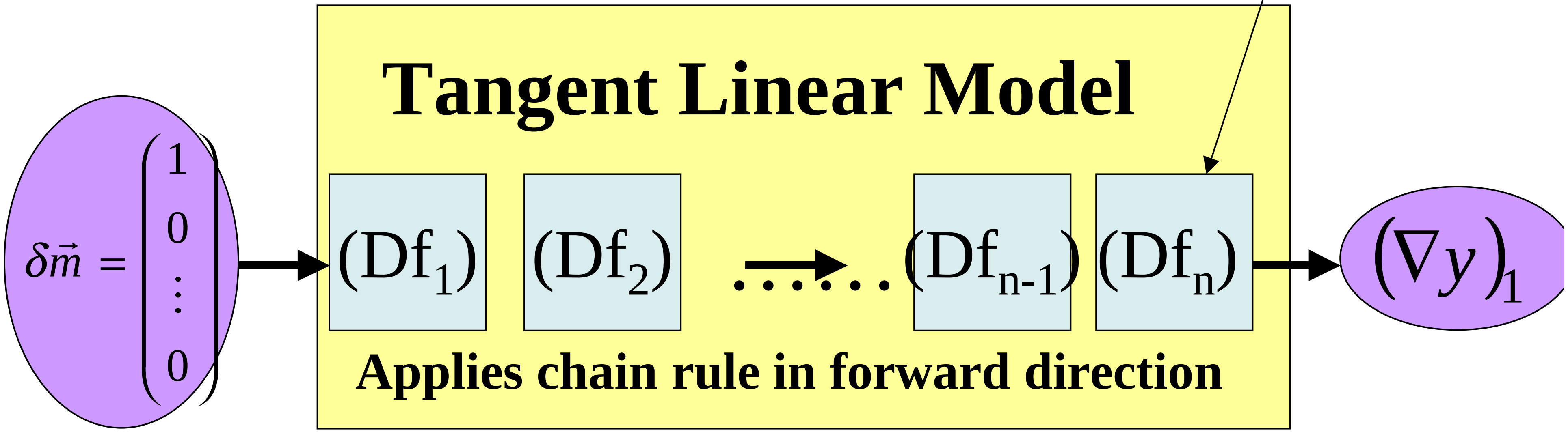
Sensitivities



Sensitivities by Automatic Differentiation

Cost for full derivative proportional to size of m!

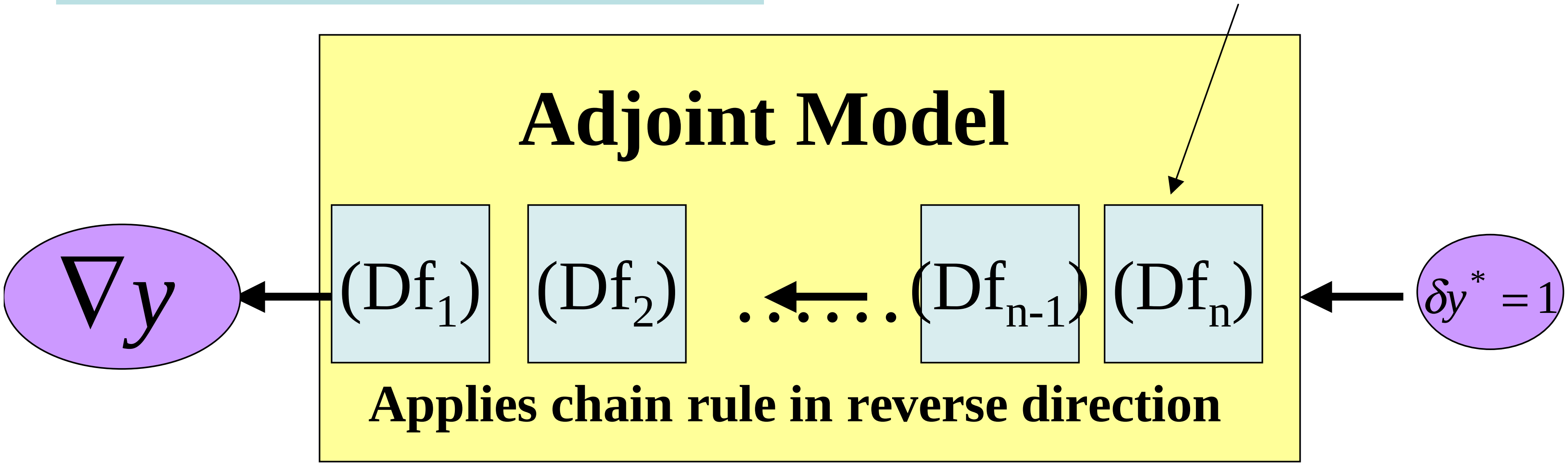
Derivatives of elementary functions are simple, they yield local Jacobians



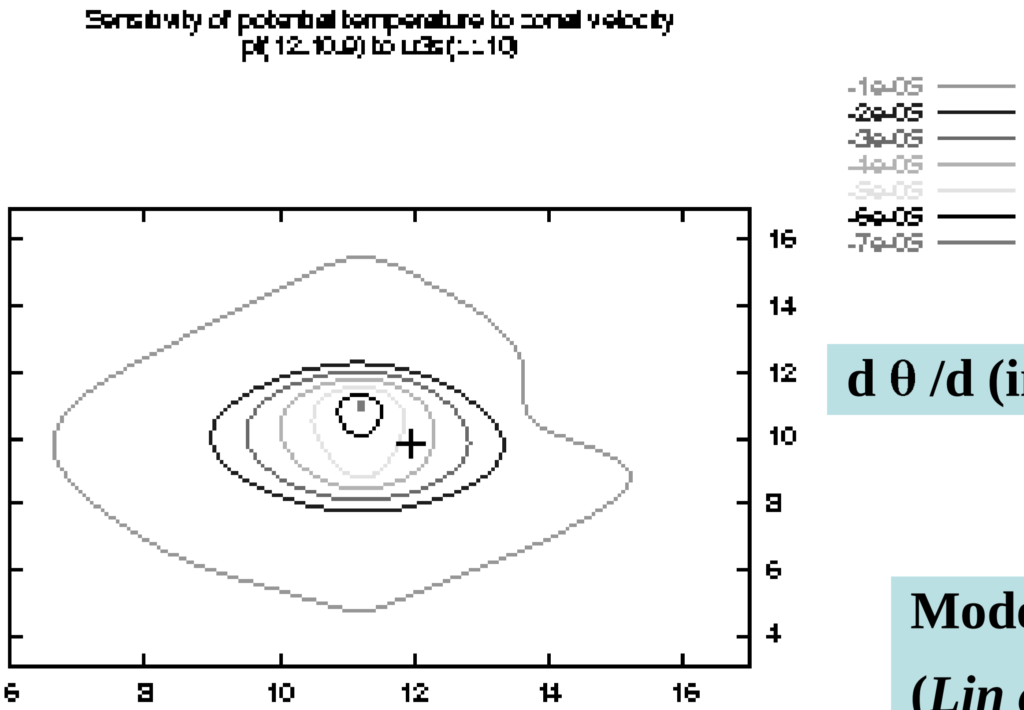
Adjoint Sensitivities

Cost is independent of size of m!

Derivatives of elementary functions are simple, they yield local Jacobians



Sensitivities of an AGCM



d θ /d (initial u 1 lev above) [K/(m/s)]

Model: dyn. core of NASA fvGCM

(*Lin and Rood, 96/97, Lin 97*)

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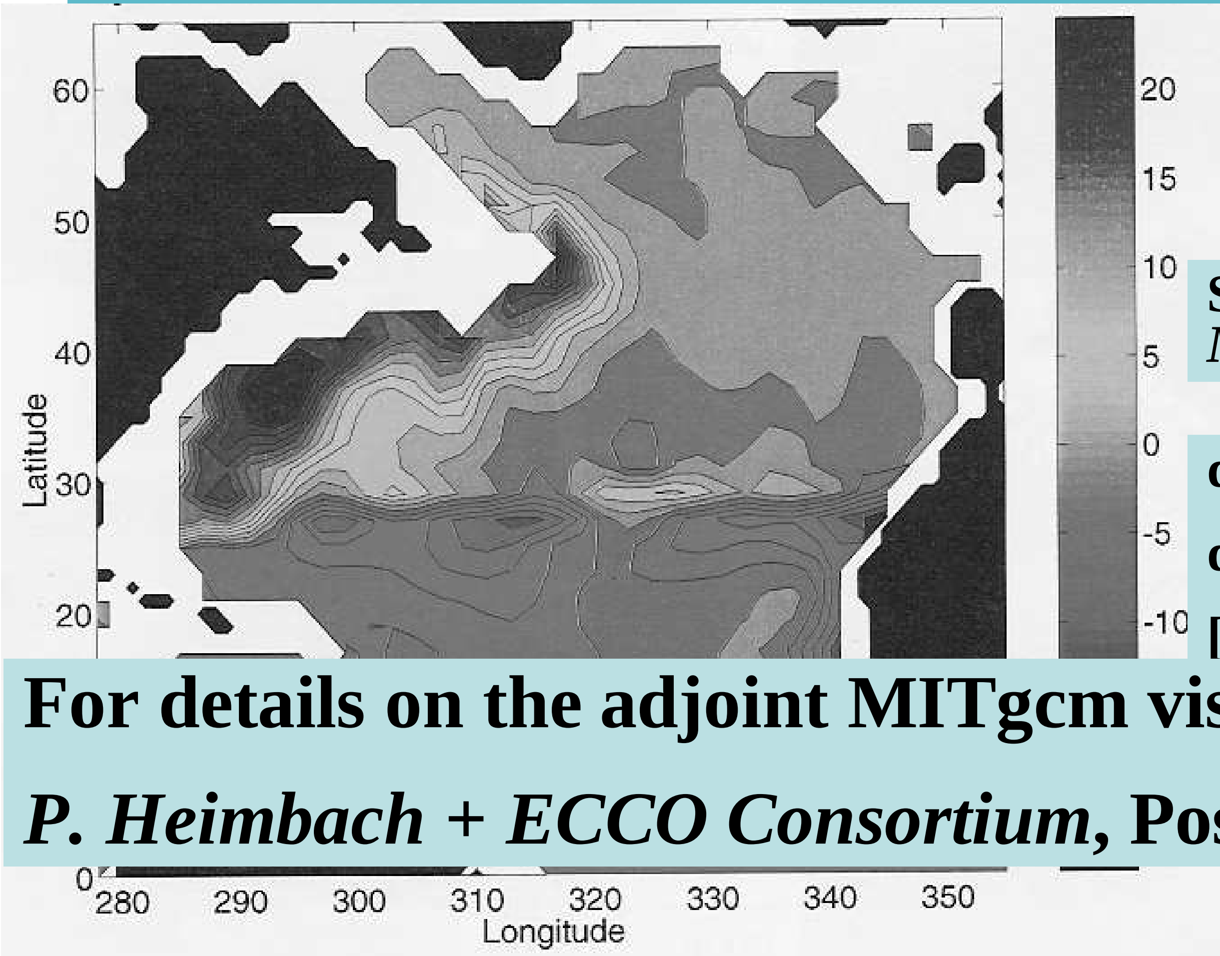
Sensitivities of an OGCM



Model: MITgcm,

Marshall et al. (1995)

Sensitivity and Adjoint by:
Marotzke et al. (1999)

d (1993 heat transport)/

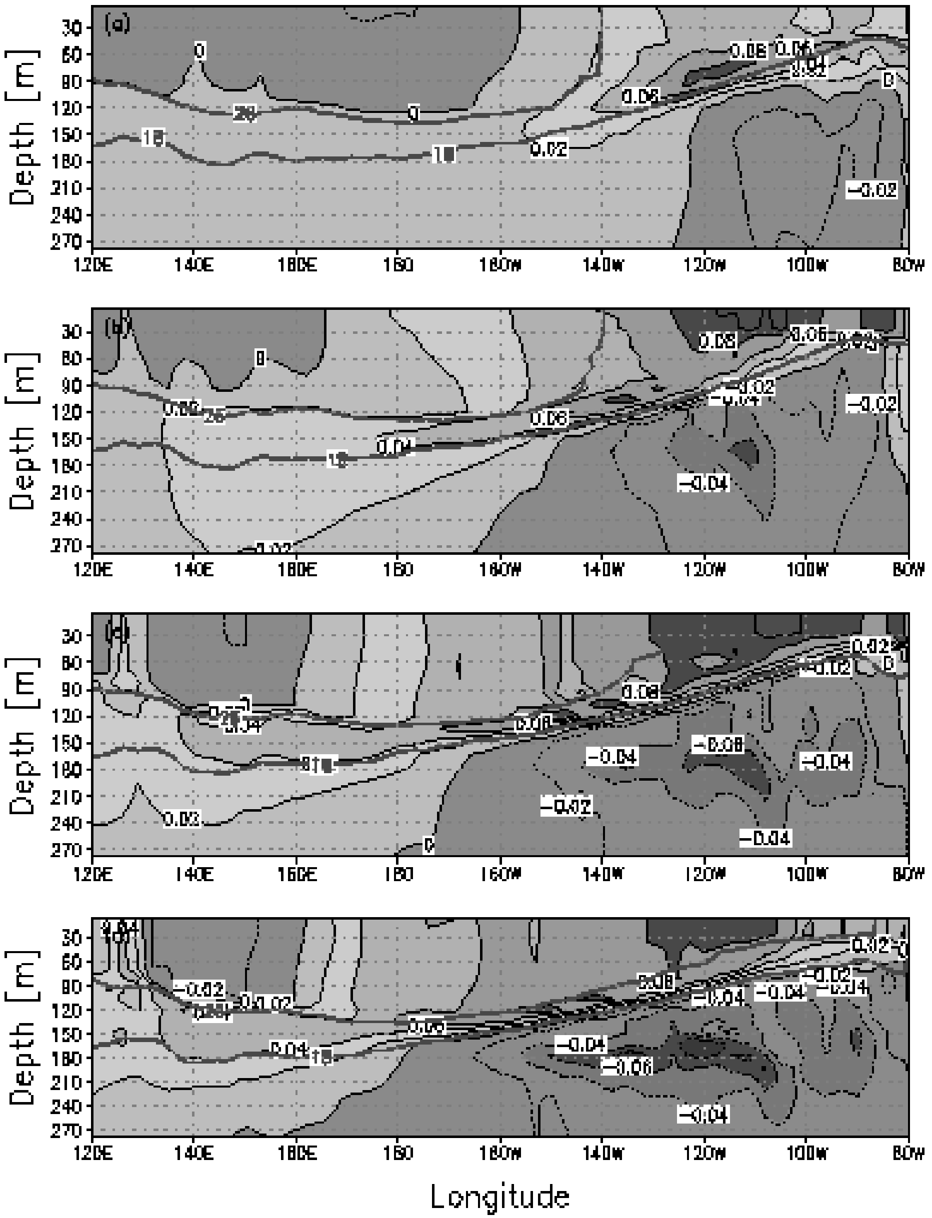
d (Salinity at Jan 1 at 1160)

[K/psu]

For details on the adjoint MITgcm visit:

***P. Heimbach + ECCO Consortium*, Poster Session A**

Sensitivities of OGCM + stat. Atmosphere (HCM)



Model: MOM3,

Pacanowski and Griffes (1999)

Adjoint and Sensitivity by:

Galanti et al. (2002)

d(T around 100W,60m at Dec 15)/dT

With lags: 1,3,5,7 month,

[no dimension]

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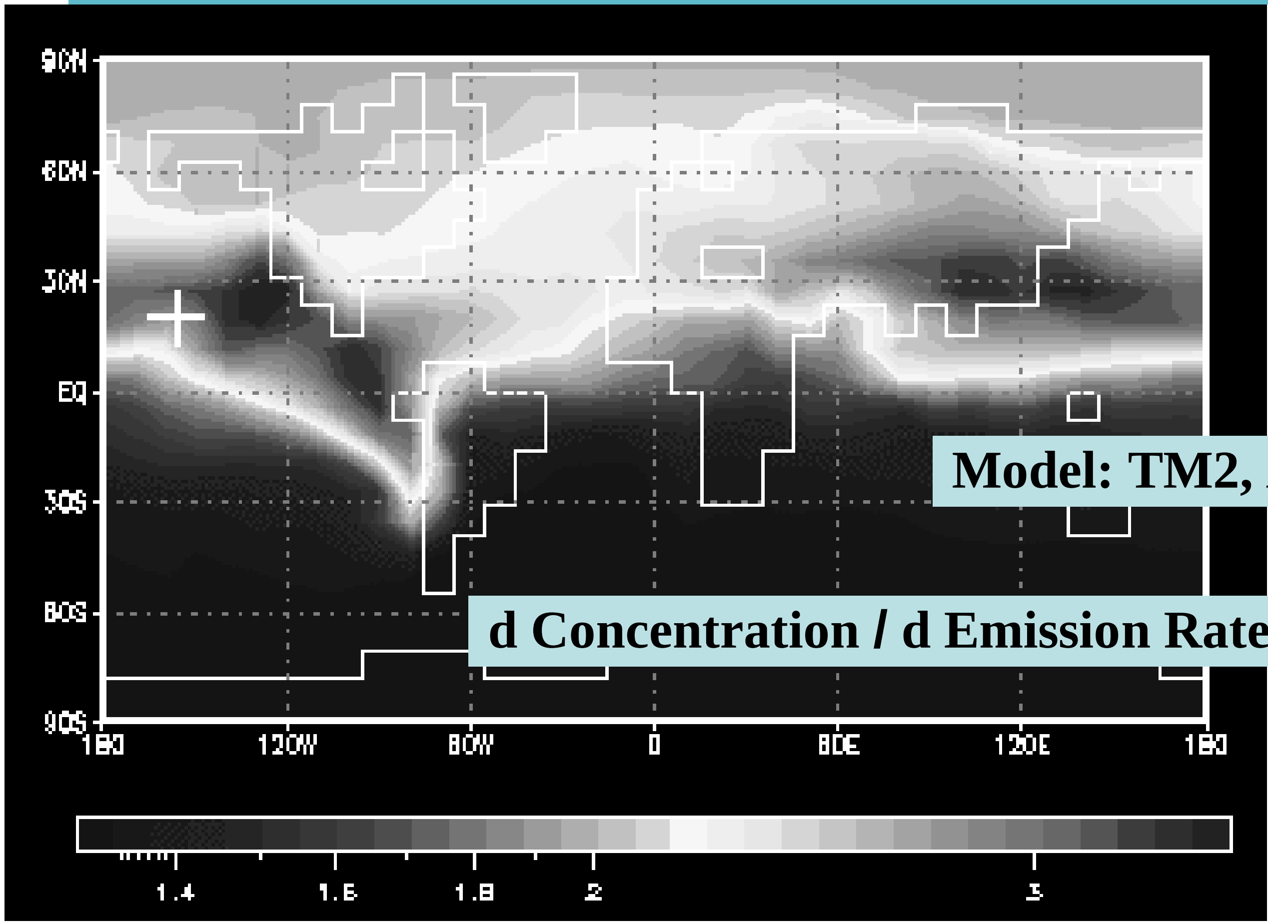
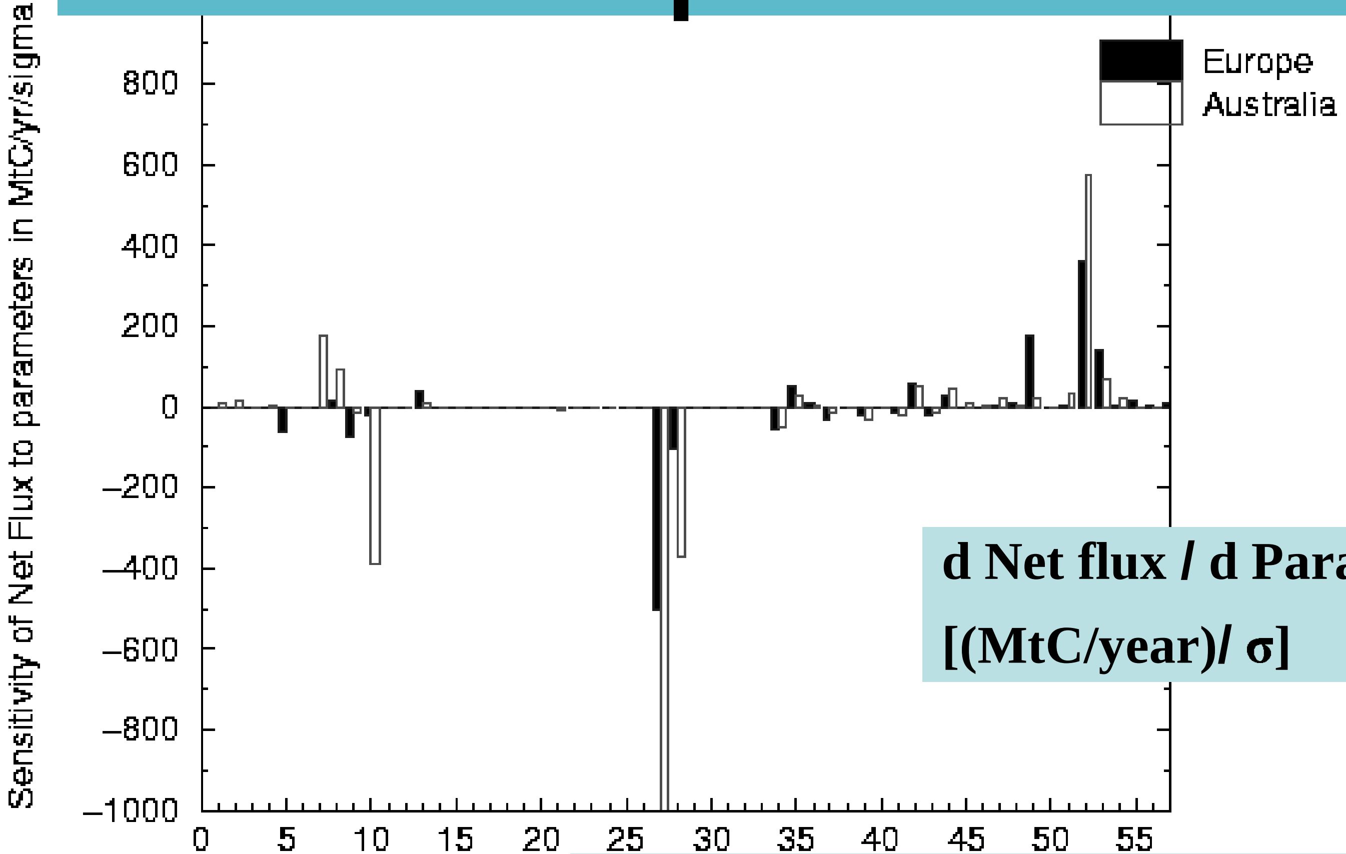
Sensitivities of a CTM



Model: TM2, *Heimann (1996)*

d Concentration / d Emission Rate [ppmv/(Pg/year)]

Sensitivities of a terrestrial biosphere model



d Net flux / d Parameter

[(MtC/year)/ σ]

Model: reduced version of BETHY, *Knorr (2001)*

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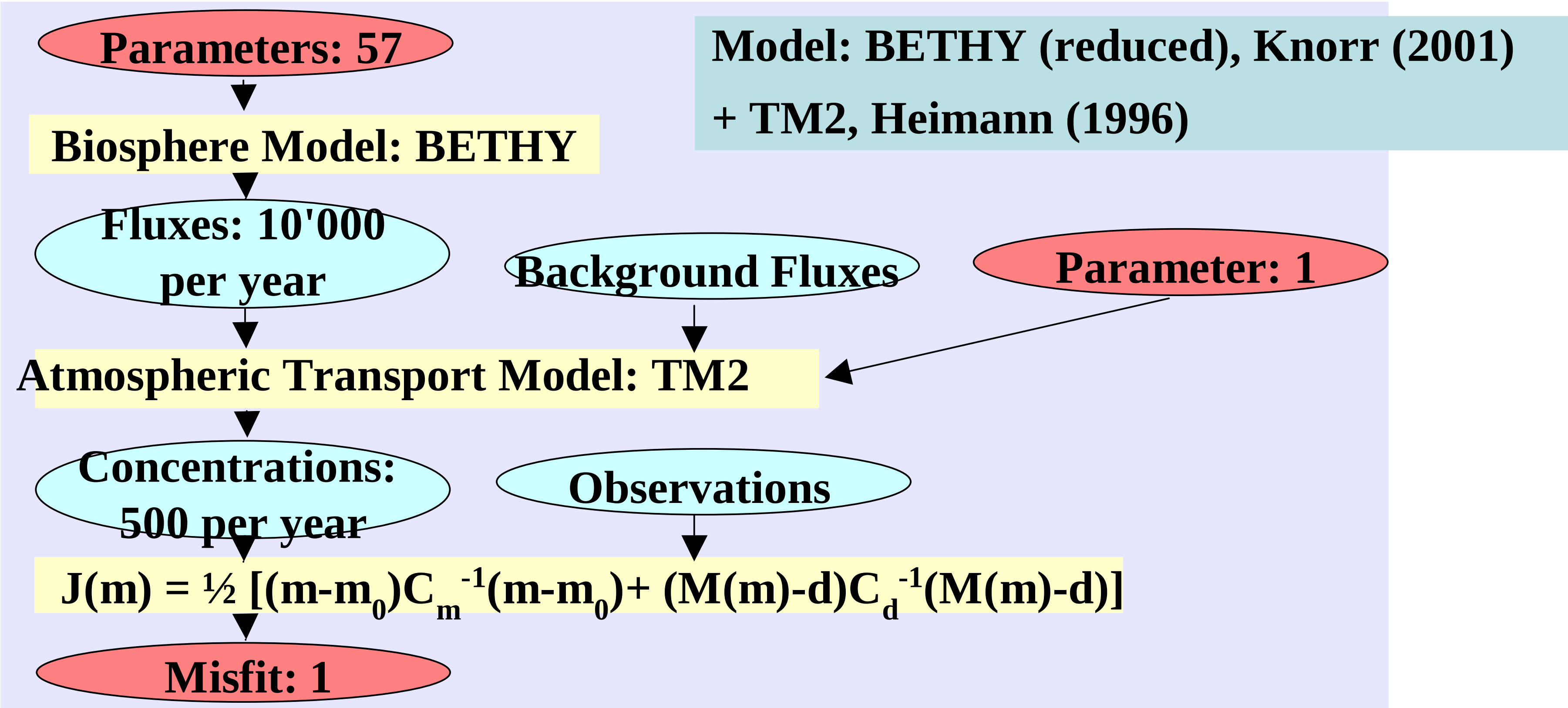
Calibration of biosphere model

within Carbon Cycle Data Assimilation System (CCDAS)



* **ocean:** Takahashi et al. (1999), LeQuere et al. (2000); **emissions:** Marland et al. (2001), Andres et al. (1996); **land use:** Houghton et al. (1990)

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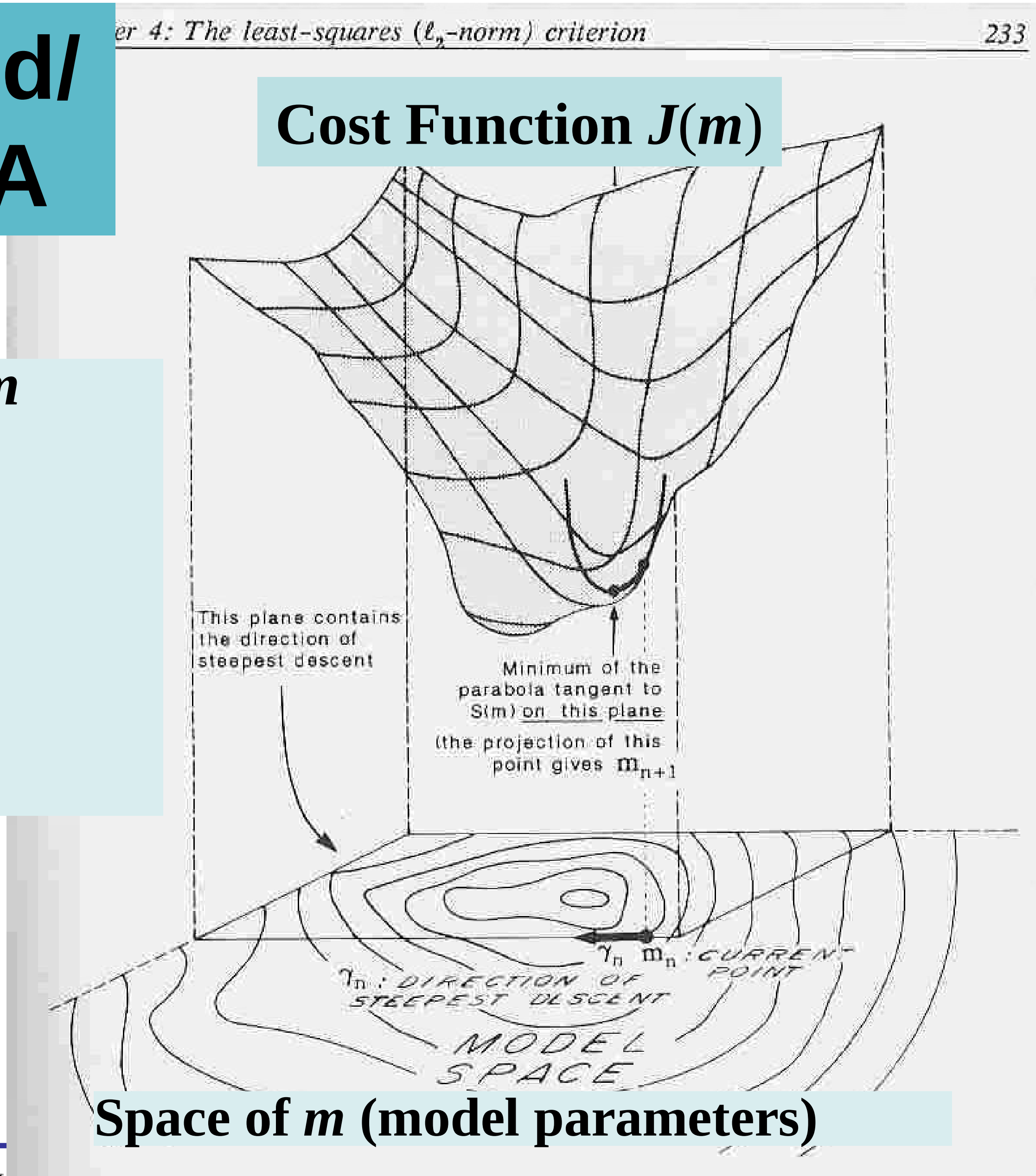
Adjoint Method/ Variational DA

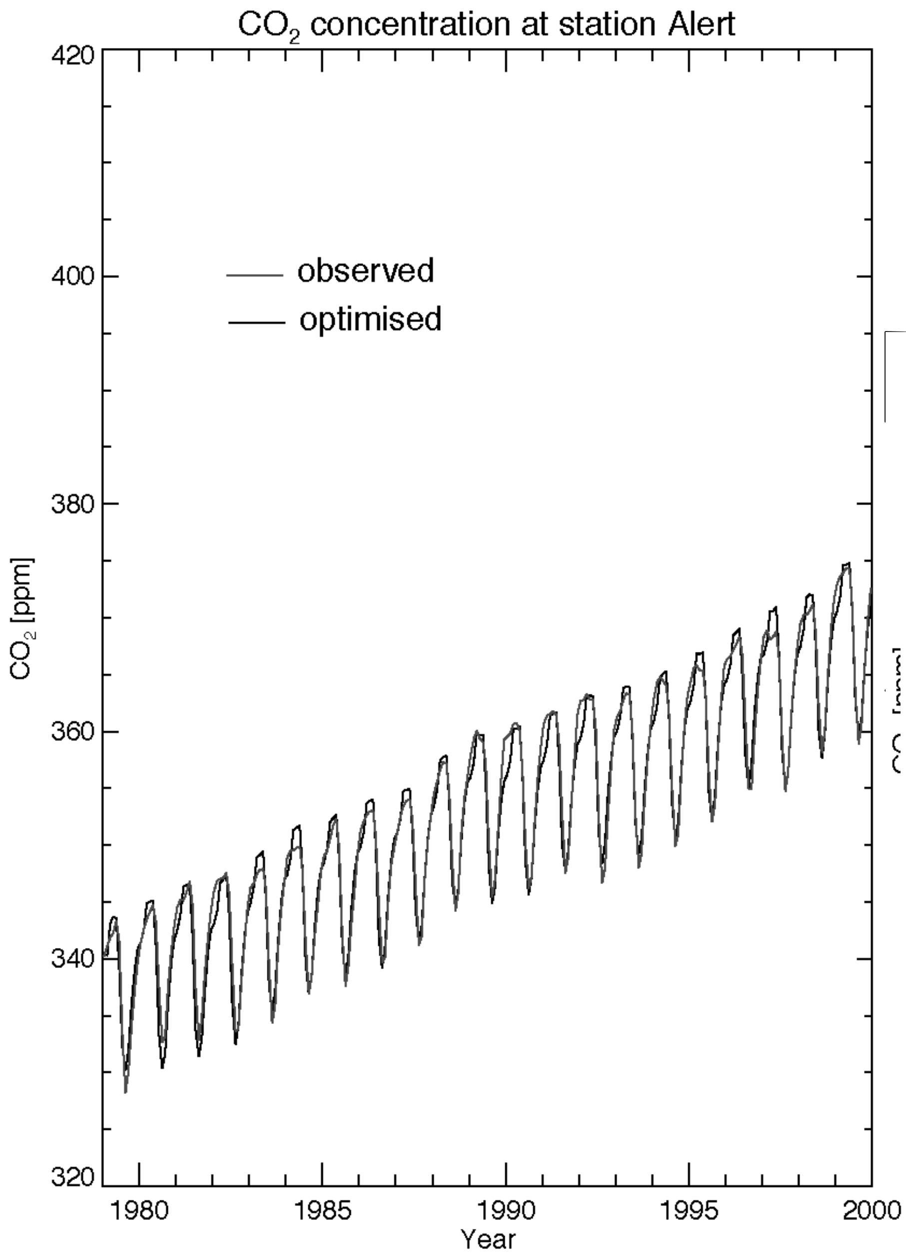
Gradient of $J(m)$ w.r.t. m points uphill !

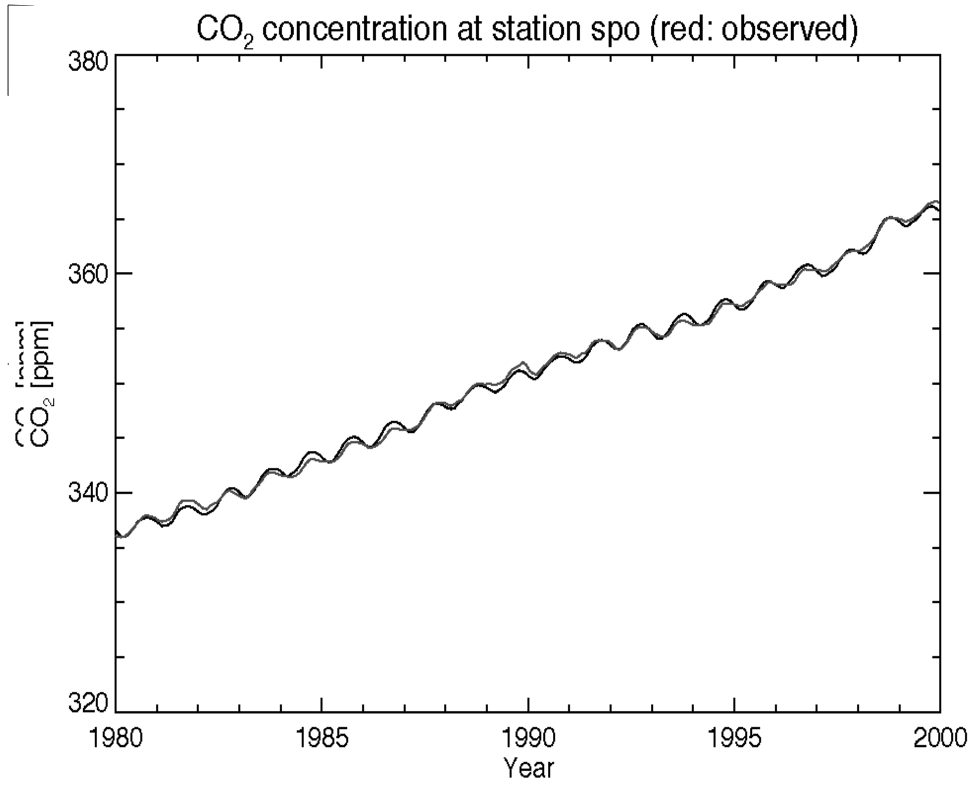
$$\nabla J(m)$$

Figure taken from **Tarantola** '87

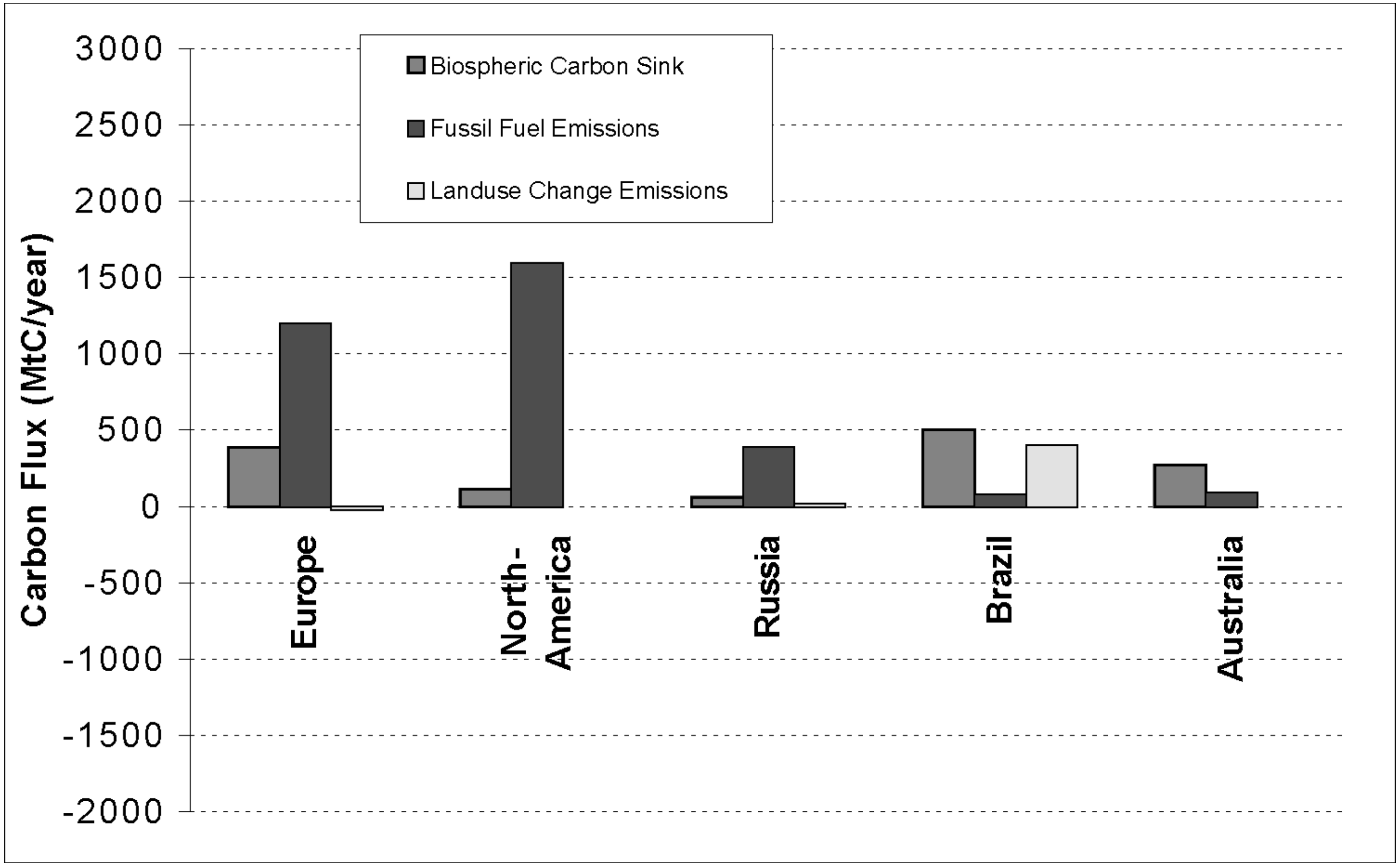


Optimisation CCDAS





Predictions of calibrated model CCDAS



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Covariances of Parameter-Uncertainties

Second Derivative (Hessian) of *J*(*m*) yields curvature of *J*, provides estimated uncertainty in m_{opt}

$$\mathbf{C}_m \approx \left\{ \frac{\partial^2 J(m_{opt})}{\partial m_{i,j}^2} \right\}^{-1}$$

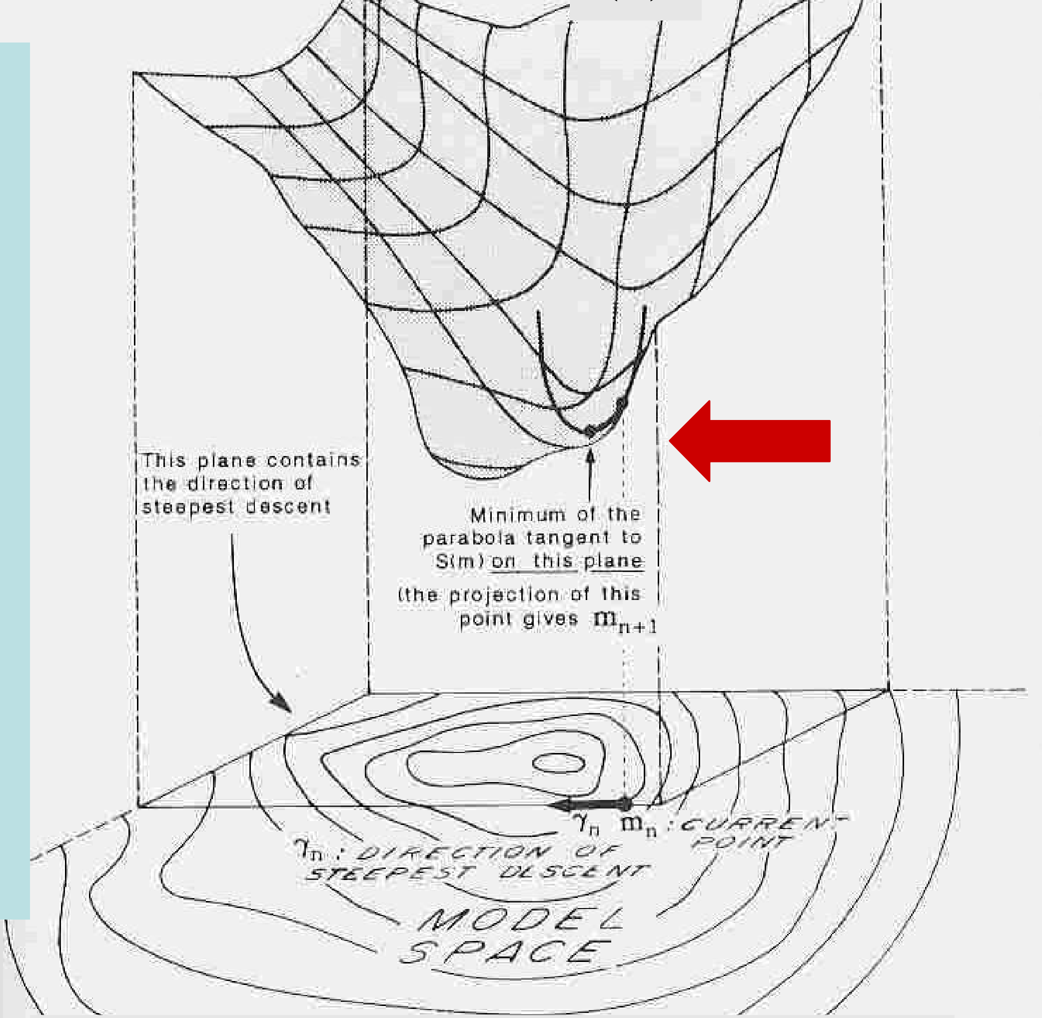


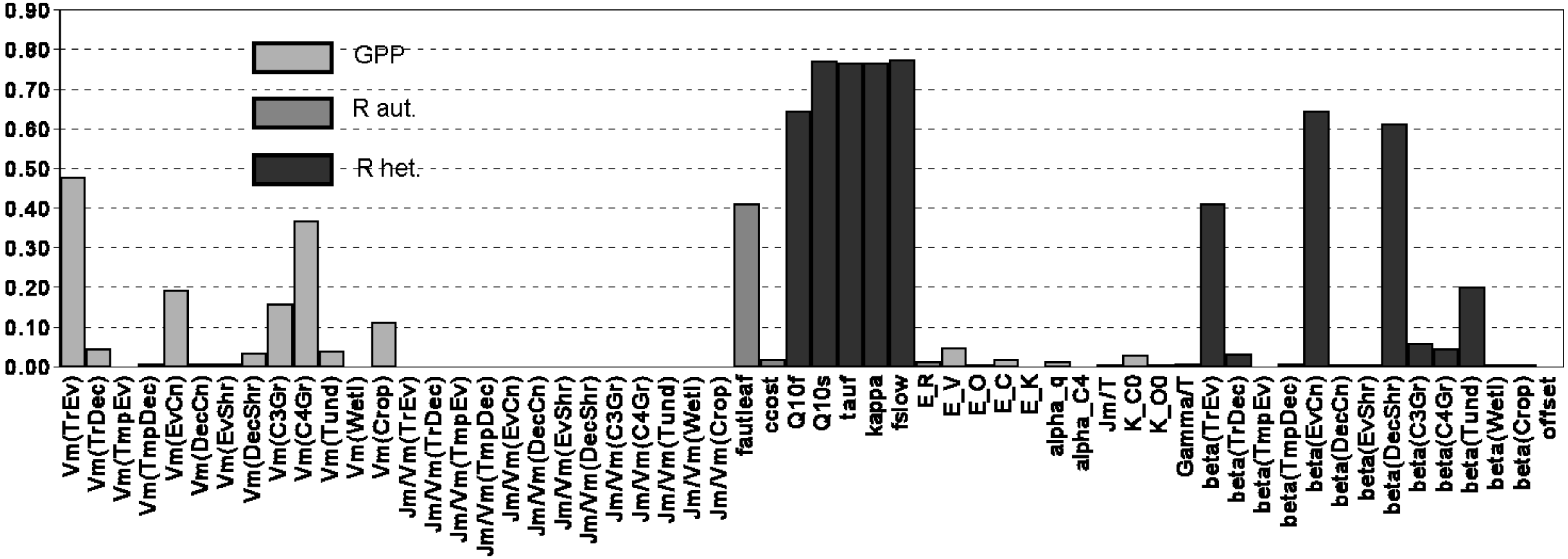
Figure taken from **Tarantola** '87

Space of *m* (model parameters)

Parameter Uncertainties after optimisation

Relative reduction of parameter- uncertainty after optimisation:

$$1-\frac{\sigma_{post}}{\sigma_{prior}}$$



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Propagating Uncertainties

The model (with optimised parameters) is used to compute diagnostics, *y*, (e.g. CO_2 fluxes):

$$y = y(m_{opt})$$

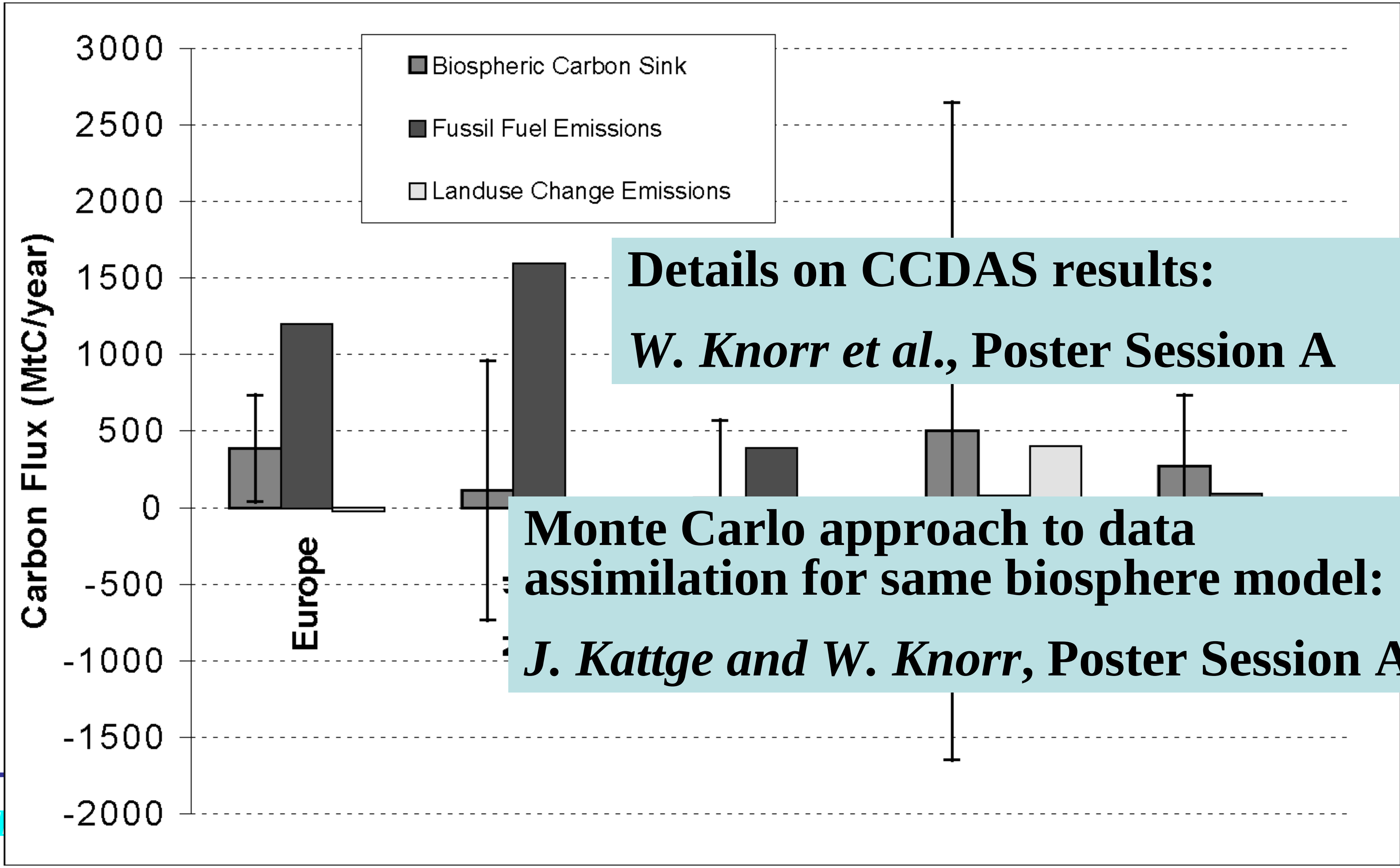
Covariance of uncertainty in y:

$$\mathbf{C}_y \approx \left(\frac{\partial y_i(m_{opt})}{\partial m_j} \right) \mathbf{C}_m \left(\frac{\partial y_i(m_{opt})}{\partial m_j} \right)^T$$

adjoint or tangent linear model

covariance of parameter uncertainties

Regional Net Carbon Balance and Uncertainties



Details on CCDAS results:

***W. Knorr et al.*, Poster Session A**

Monte Carlo approach to data assimilation for same biosphere model:

***J. Kattge and W. Knorr*, Poster Session A**

Summary of CCDAS-Approach

- CCDAS tests given combination of model formulation + set of observations + prior assumptions
- CCDAS delivers optimal parameters + uncertainties, and diagnostics/prognostics + uncertainties
- CCDAS allows fair comparison of different model formulations because it chooses optimal parameter set
- Sensitivities and comparison with observations are tough tests for the model and are providing many hints for model development
- Model is permanently improved within CCDAS, quick updates of derivative code via automatic differentiation (TAF)
- Numbers are based on version we were not yet happy with

Adjoint Applications Summary

Shown

- **Sensitivity Analysis**
- **Data Assimilation/Optimisation**
- **Uncertainty Propagation**

Not shown:

- **Singular Vectors/Stability Analysis**
- **Targeted Observations**

Some automaticly generated Adjoints of ESM-components

AGCMs:	PUMA, MM5, fvGCM
OGCMs:	HOPE, MITgcm, MOM3
Biosphere:	BETHY
CTMs:	TM2,TM3
Seaice:	MITgcm
Ocean waves:	WAM
Socioeconomics:	SIAM

Summary

- Adjoints support model development
- Automatic generation of adjoints reduces delays from model development to adjoint applications
- There are adjoints for many ESM components

Posters/Links

Poster Session A (until 1pm tomorrow)

- *P. Heimbach + ECCO Consortium*: Maintaining Adjoint of MITgcm
- *W. Knorr et al.*: CCDAS results
- *J. Kattge and W. Knorr*, BETHY+Monte Carlo

- www.CCDAS.org
- www.ecco-group.org
- www.FastOpt.com, at Hamburg, Schanzenstr. 36

BETHY

(Biosphere Energy-Transfer-Hydrology Scheme)

Δlat, Δlon = 2 deg

- **GPP:**

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

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

  stomata – *Knorr (1997)*

Δt=1h

- **R_{aut}:**

  maintenance respiration = $f(N_{leaf}, T)$ – *Farquhar, Ryan (1991)*

  growth respiration ~ NPP – *Ryan (1991)*

Δt=1h

- **R_{het}:**

  fast/slow pool resp. = $w^{\kappa} Q_{10}^{T/10} C_{fast/slow} / \tau_{fast/slow}$

  τ_{slow} –> infin.

  average NPP = β average R_{het} (at each grid point)

Δt=1day

β<1: source

β>1: sink

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Some larger TAF derivatives

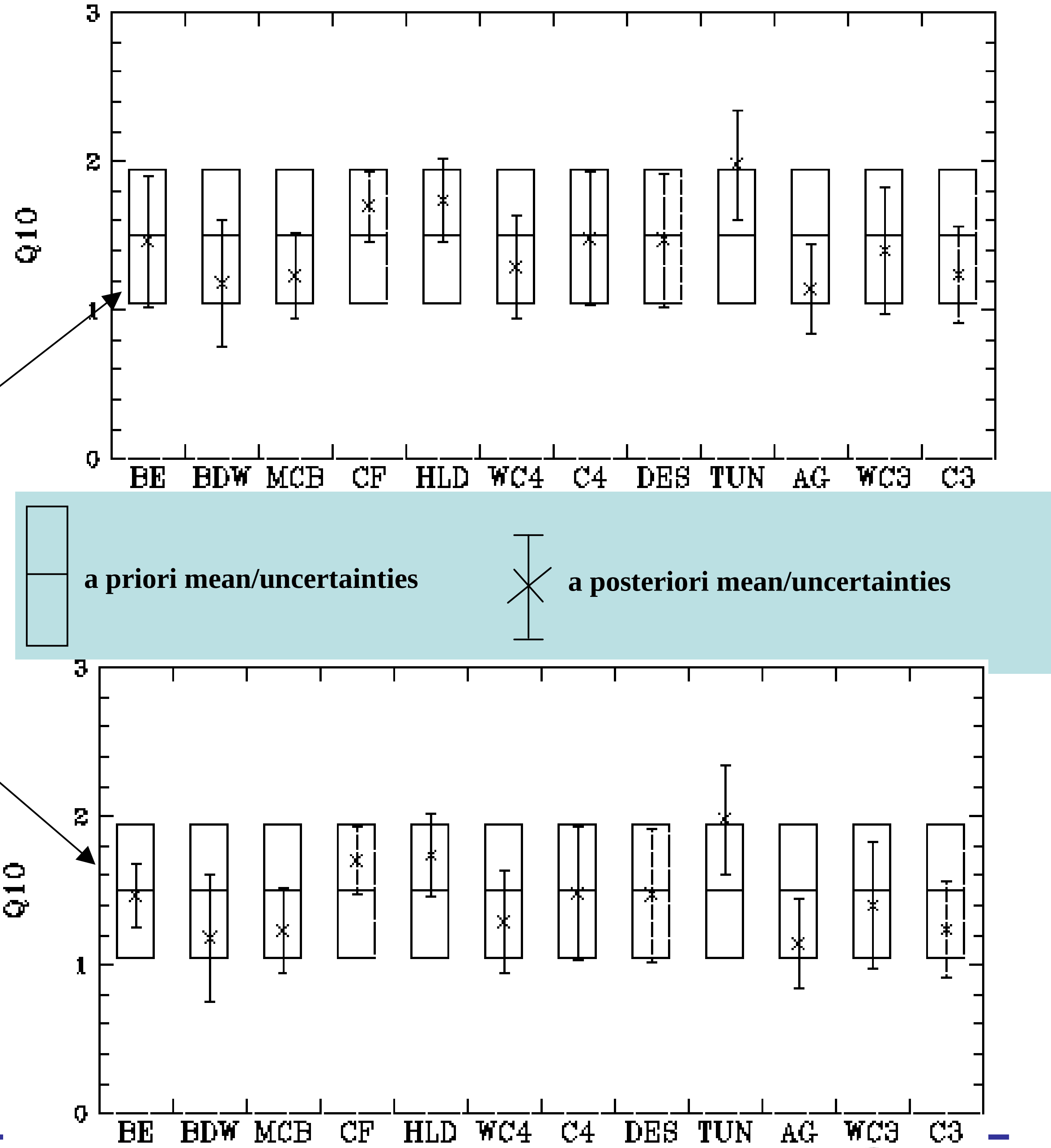
Model (Who)	Lines	Lang	TLM	ADM	Ckp	HES
NASA/NCAR (w. Todling & Lin)	87'000	F90	2.7	6.8	2 lev	-
MOM3 (Galanti & Tziperman)	50'000	F77	Yes	4.6	2 lev	-
MITGCM (ECCO Consortium)	100'000	F77	1.8	5.5	3 lev	11.0/1
BETHY (w. Knorr, Rayner, Scholze)	5'500	F90	1.5	3.4	2 lev	50/12
Nav.-Stokes-Solver (Hinze, Slawig)	450	F77	-	2.0	steady	-
NSC2KE	2'500	F77	2.4	3.4	steady	9.8/1
HB_AIRFOIL (Thomas & Hall)	8'000	F90	-	3.0		-

- Lines: total number of Fortran lines without comments
- Numbers for TLM and ADM give CPU time for (function + gradient) relative to forward model
- HES format: CPU time for Hessian * n vectors rel. t. forw. model/ n
- 2 (3) level checkpointing costs 1 (2) additional model run(s)

Comparison shows impact of a (pseudo) flux measurement in the broadleaf evergreen biome on Q10 estimated by an inversion of SDBM:

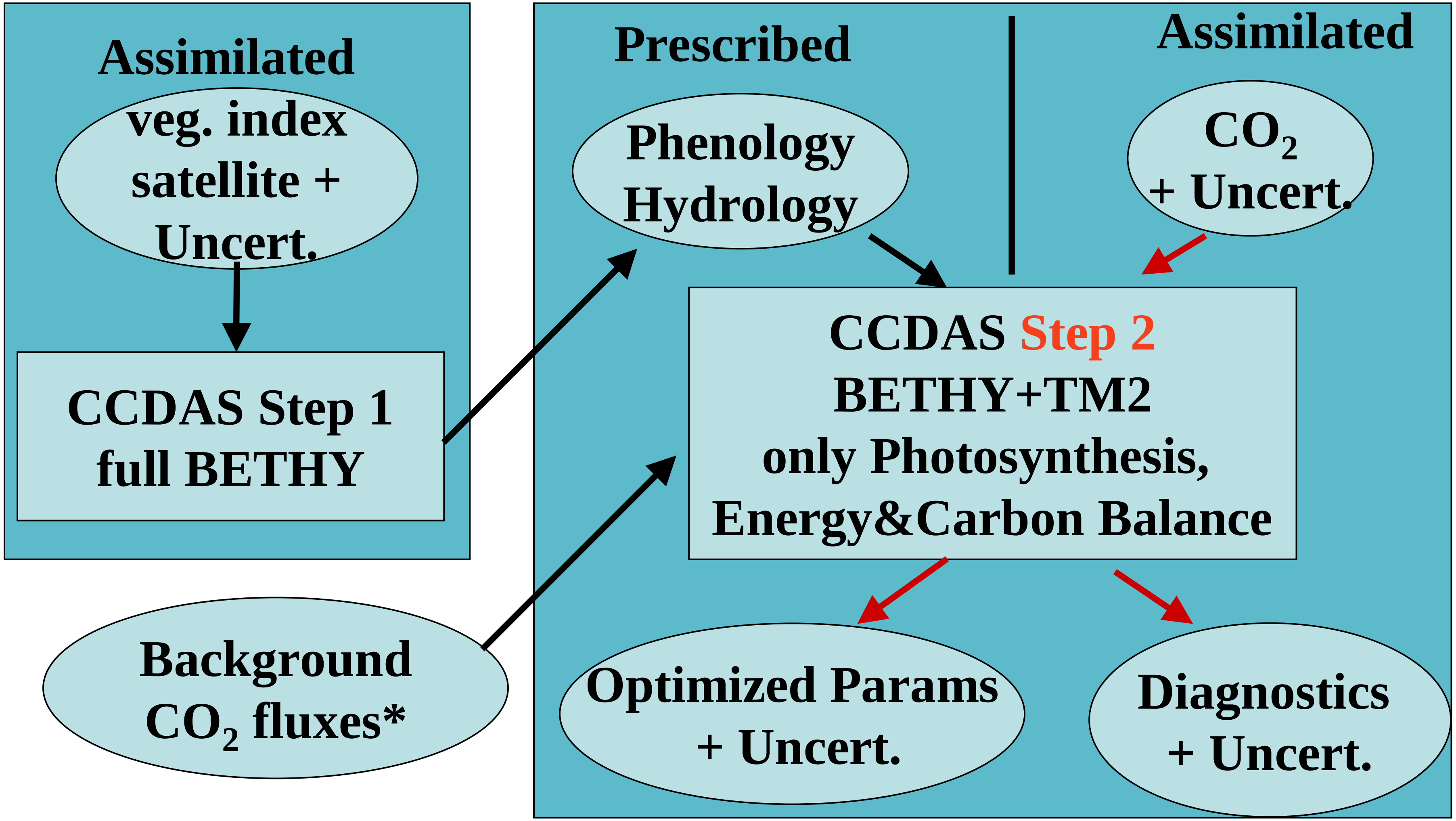
***Upper panel*:**
only concentration data

***Lower panel*:**
concentration data +
pseudo flux measurement
(mean: as predicted
sigma: 10gC/m^2/year)



Details:
Kaminski et al., GBC, 2001

Carbon Cycle Data Assimilation System (CCDAS)



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