



🌿 Data Assimilation in terrestrial carbon cycle modelling

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Earth Observation**

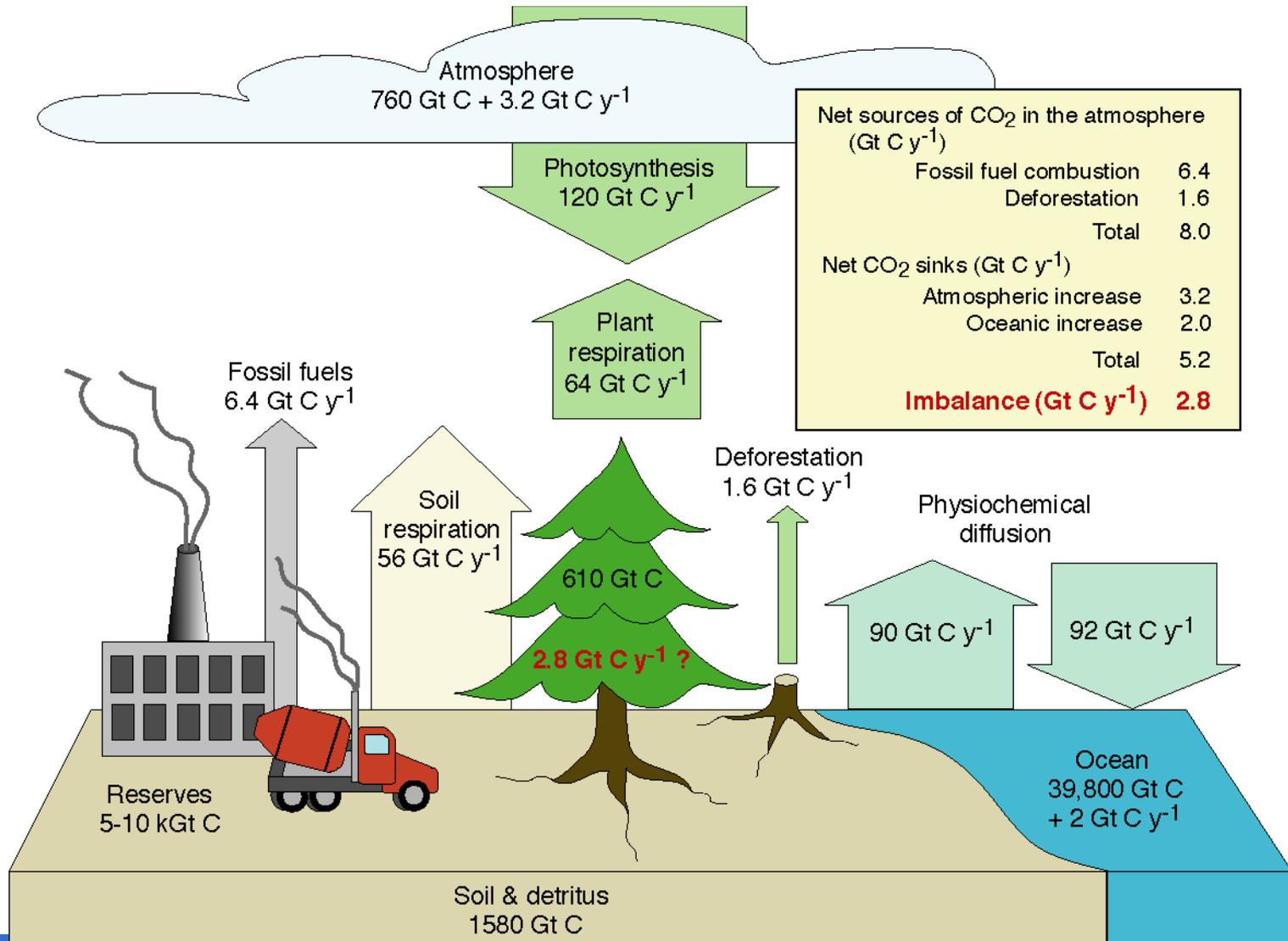
NATURAL ENVIRONMENT RESEARCH COUNCIL

Outline

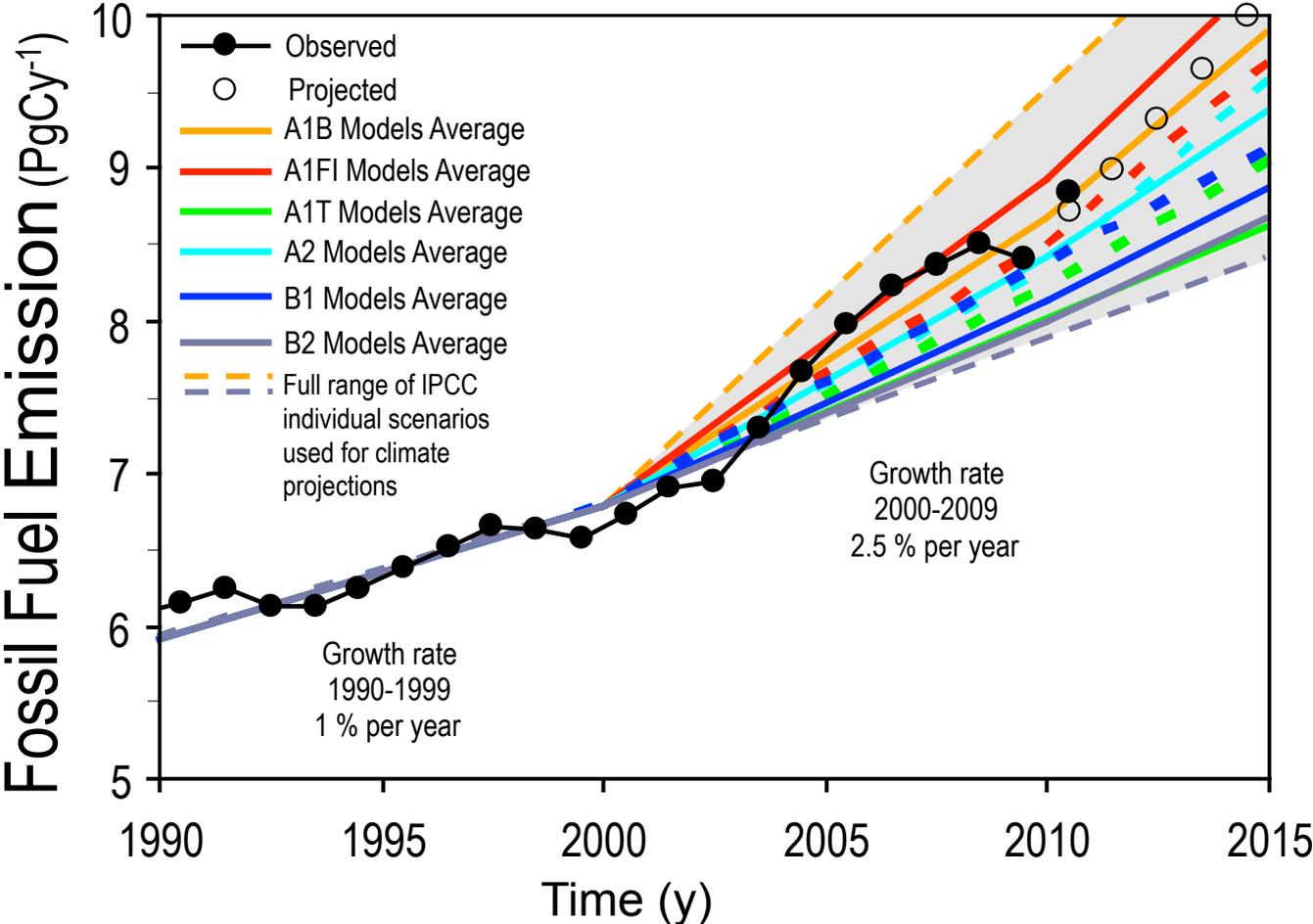
- Background to the carbon cycle
- CCDAS
- Particle filter method
- Results
- Comparison of particle filter and CCDAS
- Conclusions and future work



The Global Carbon Cycle



Fossil Fuel Emissions: Actual vs. IPCC Scenarios

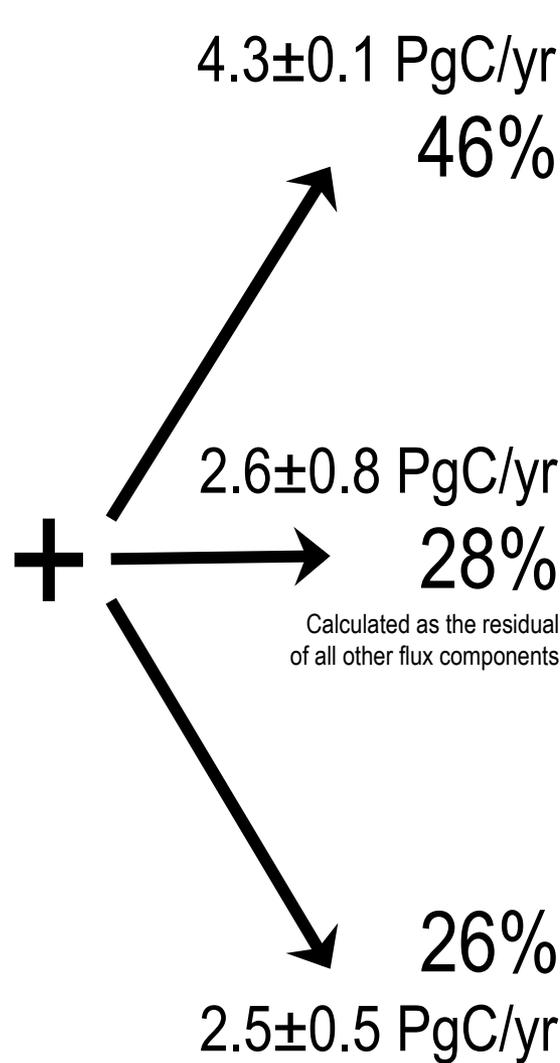


Fate of Anthropogenic CO₂ Emissions (2002-2011 average)

8.3±0.4 PgC/yr 90%

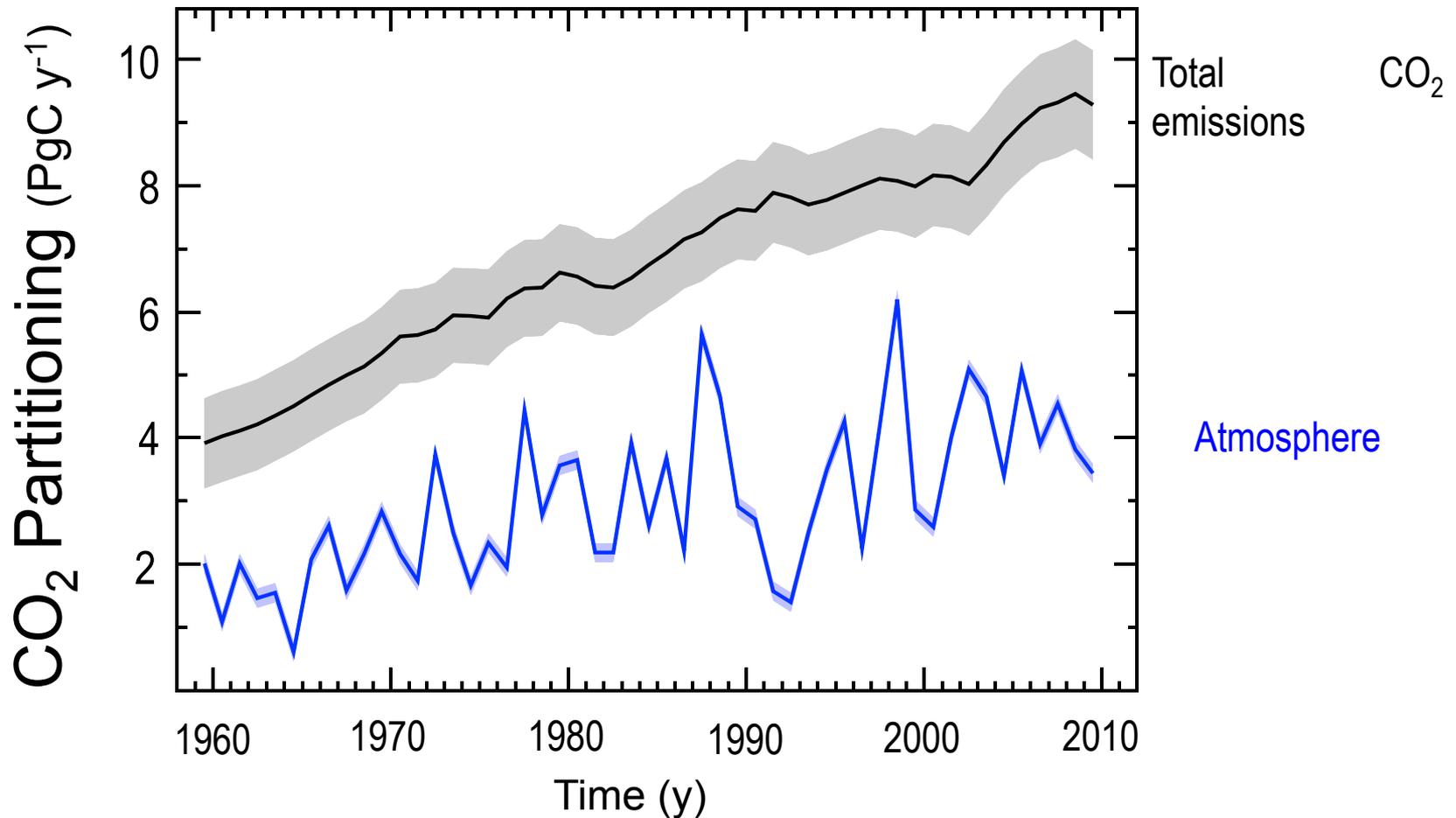


1.0±0.5 PgC/yr 10%

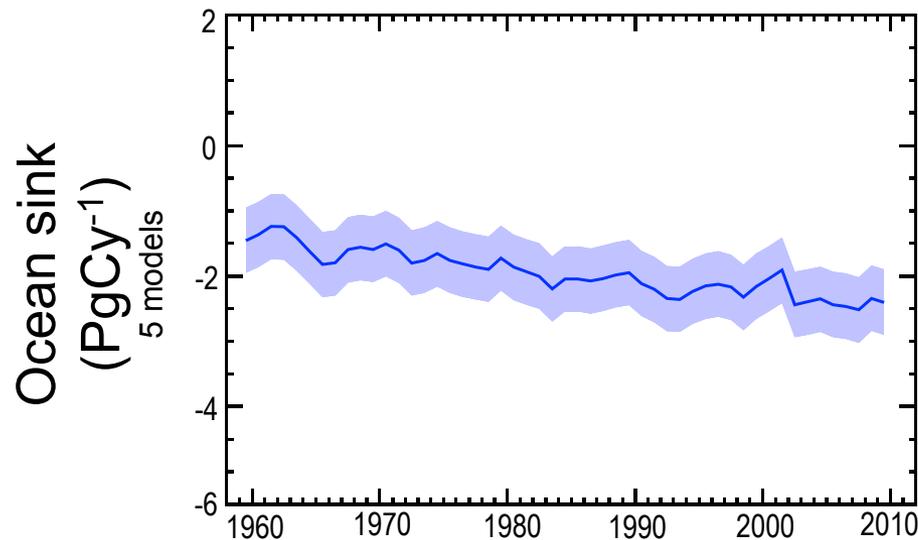
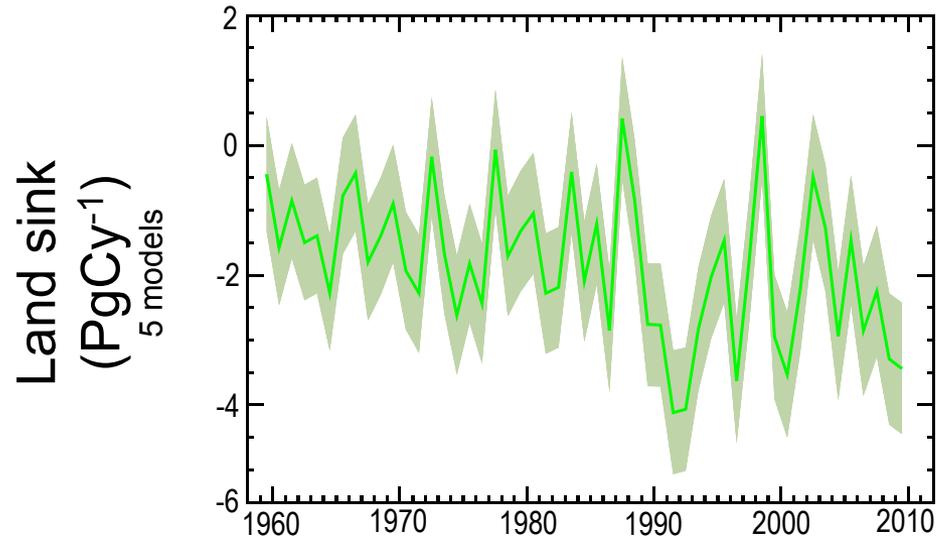


Key Diagnostic of the Carbon Cycle

Airborne Fraction of total emissions

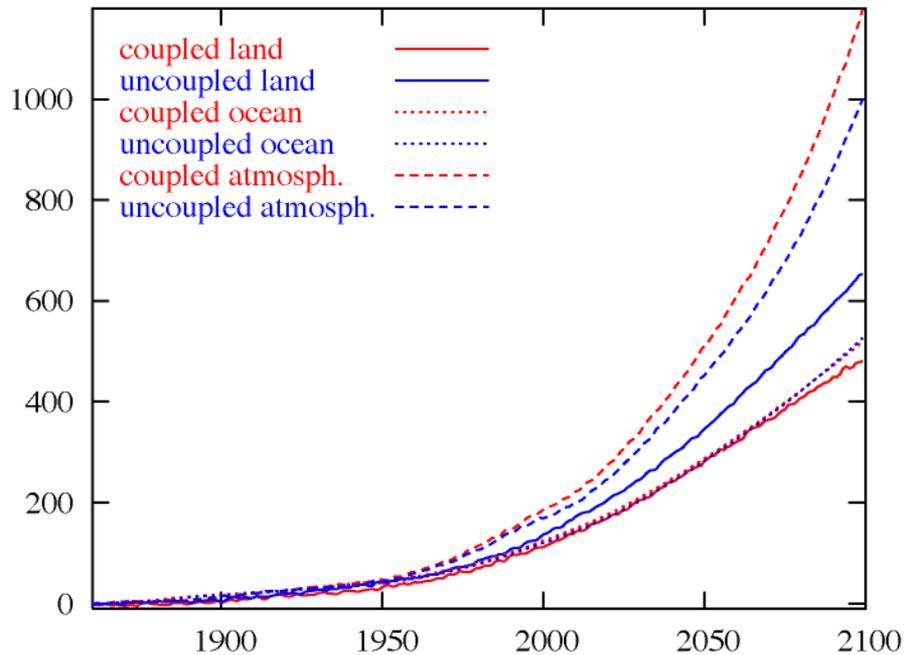


Modelled Natural CO₂ Sinks

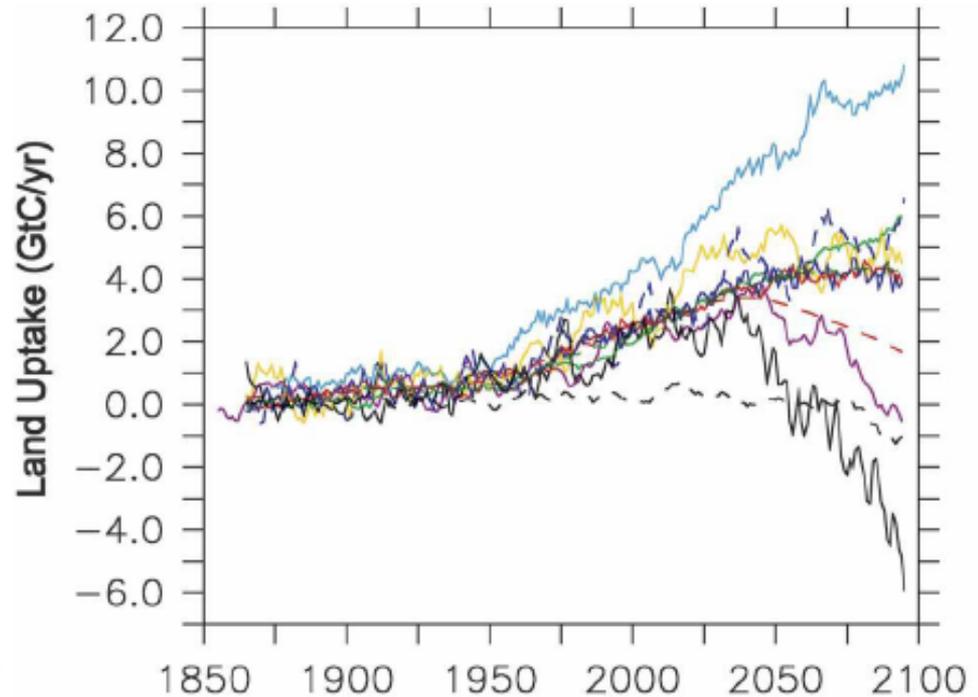


Carbon Cycle-Climate feedback

Change in carbon content [PgC]

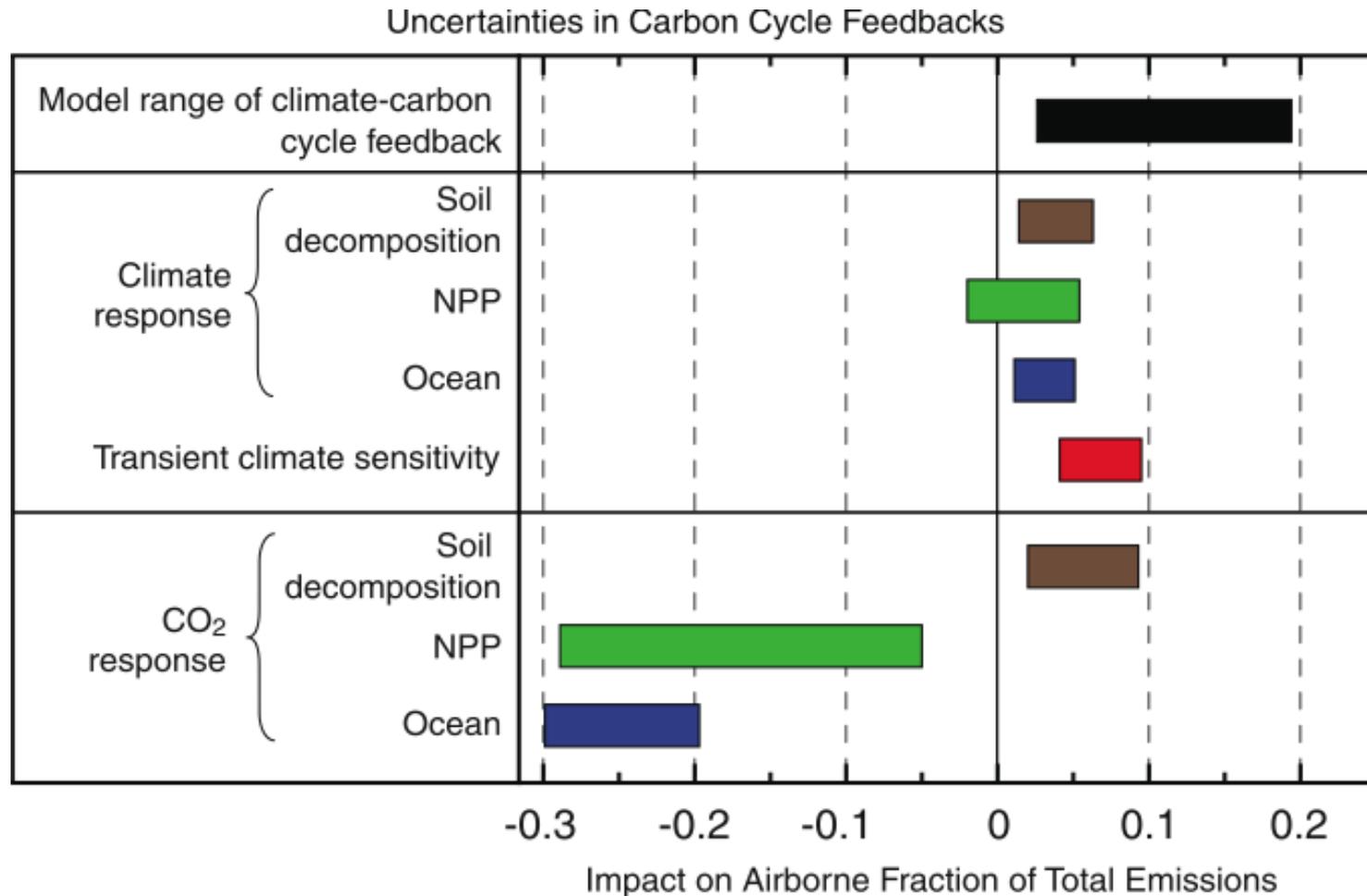


ECHAM5-MPIOM1-JSBACH
(Raddatz et al, 2007)

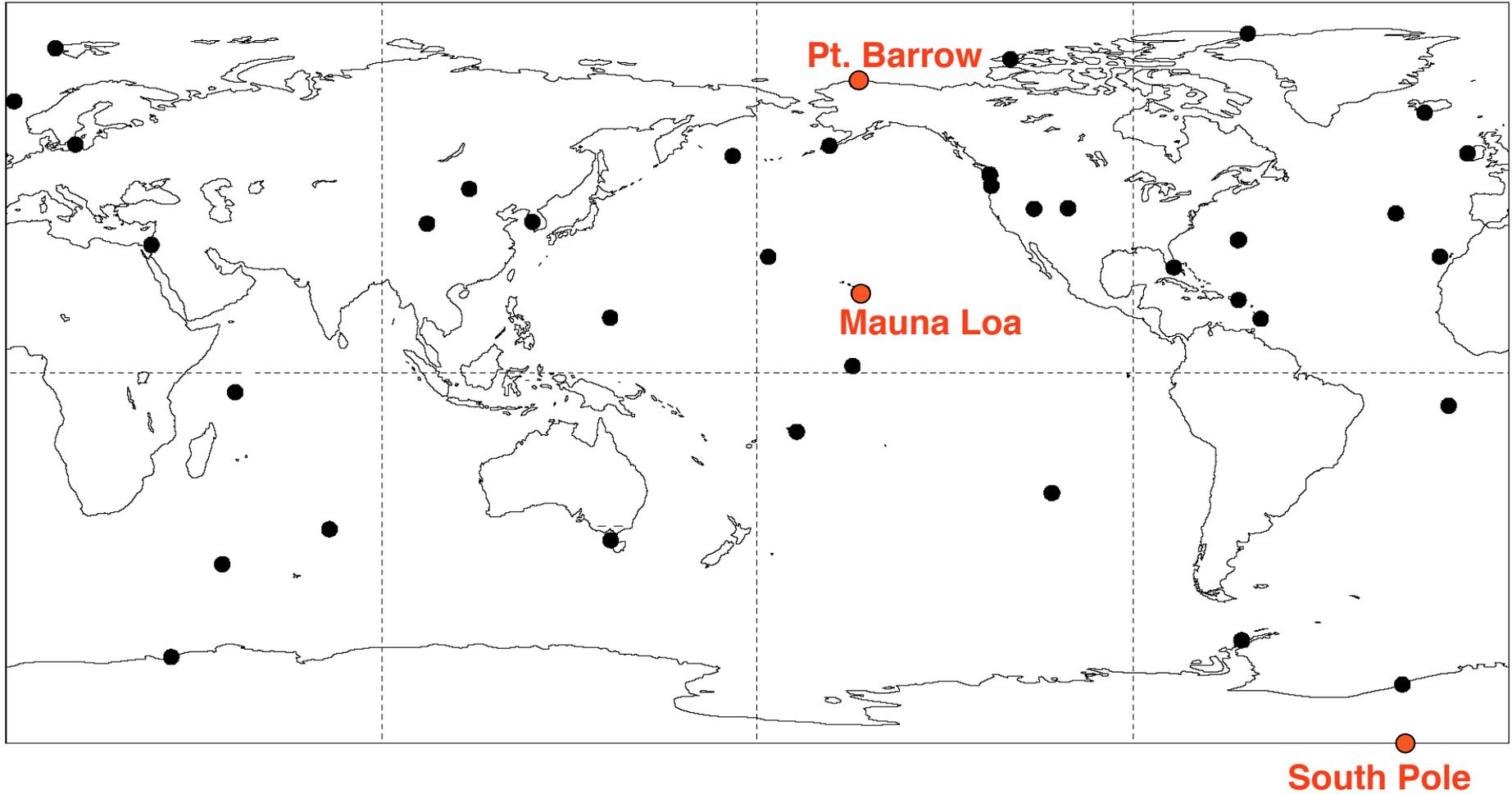


C4MIP results
(Friedlingstein et al. 2006)

Carbon Cycle-Climate feedback: breakdown of uncertainties

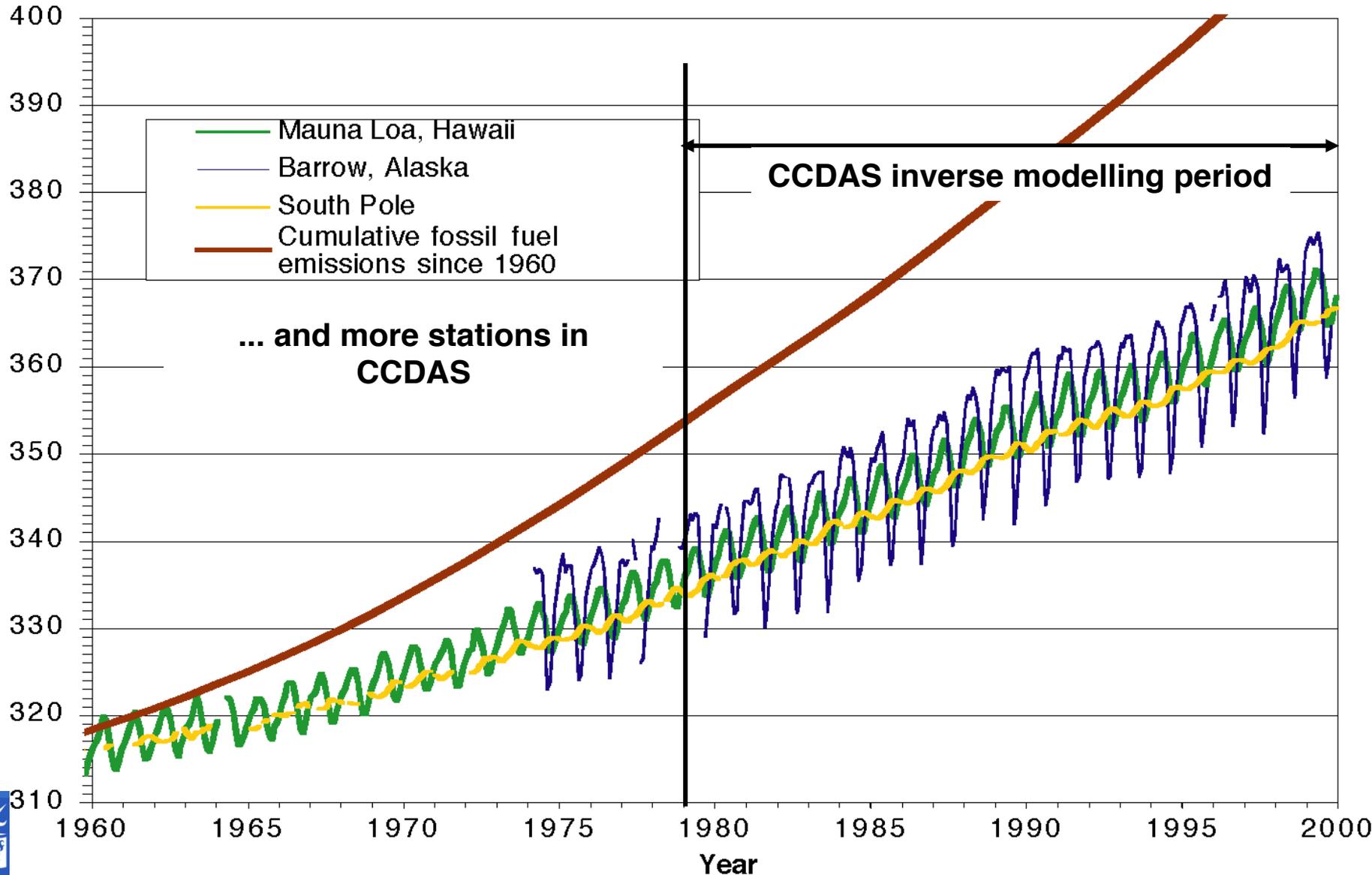


The atm. CO₂ Station Network



South Pole

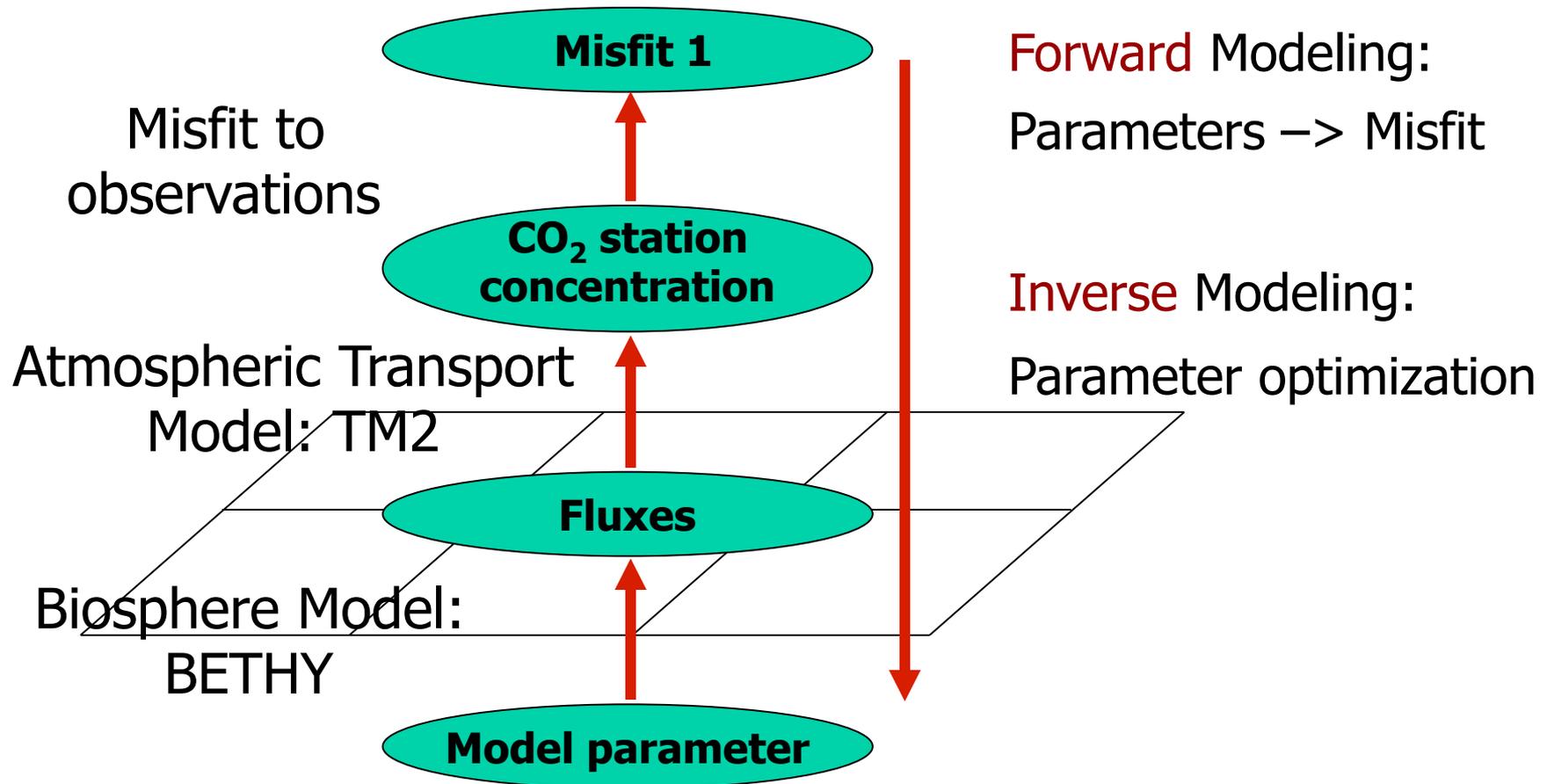
Atmospheric CO₂ Measurements



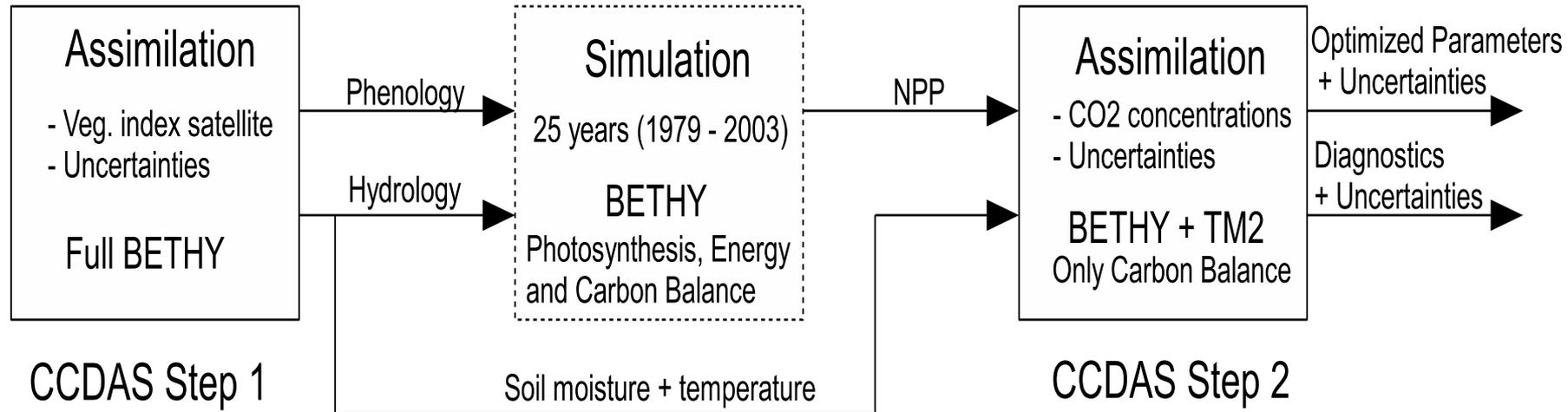
Need for Parameter Estimation

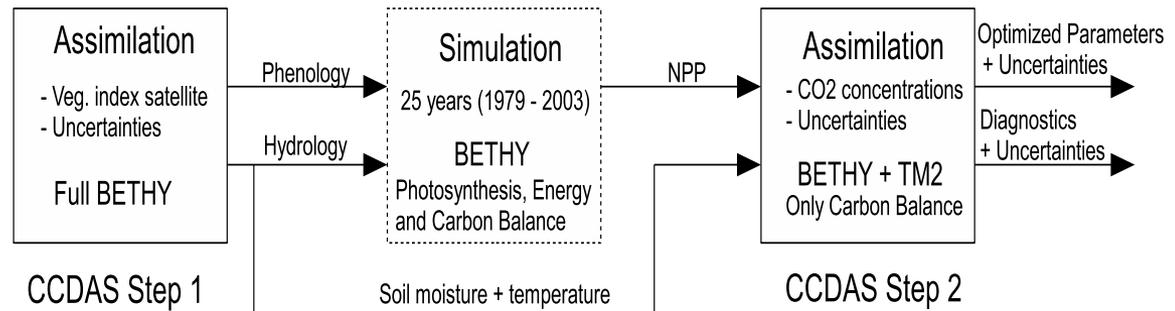
- Advanced models for coupled systems (e.g. land-atmosphere or ocean-atmosphere models) involve the coupling of many biological, chemical and physical processes
- Increase in the complexity of those models also leads to an increase in the number of parameters
- Prior parameter values usually based on “expert knowledge”
- If no reliable estimates can be provided for a parameter, it remains highly uncertain
- Uncertainty of the parameter might substantially contribute to the overall model output uncertainty
- Parameter optimisation methods can be used to constrain the parameters against observations

🌿 Assimilation of CO₂ with an inverse modelling system



CCDAS



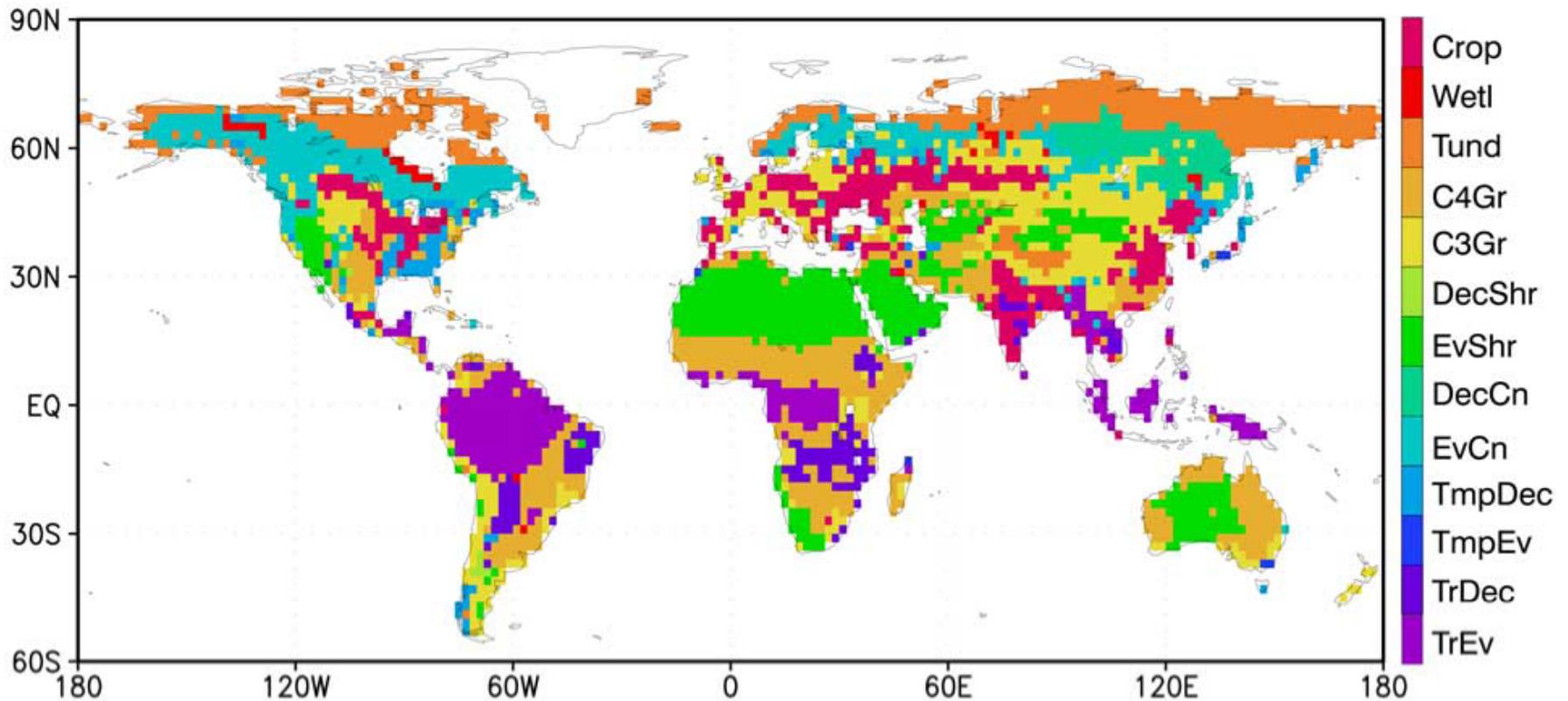


- Further simplification of step 2
- 13 plant functional types
- 6 process parameters
 - 5 global
 - 1 plant functional type dependent

Process parameters

Parameter	Description	Global	By PFT
$Q_{10,f}$	Soil respiration temperature factor, fast pool	X	
$Q_{10,s}$	Soil respiration temperature factor, slow pool	X	
τ_f	Fast pool soil carbon turnover time	X	
κ	Soil moisture dependence parameter	X	
f_s	Fraction of fast soil decomposition	X	
β	Net CO ₂ sink factor		X

BETHY Plant Functional Types



Rayner et al. (2005)

CCDAS

- Iterative minimisation of the cost function

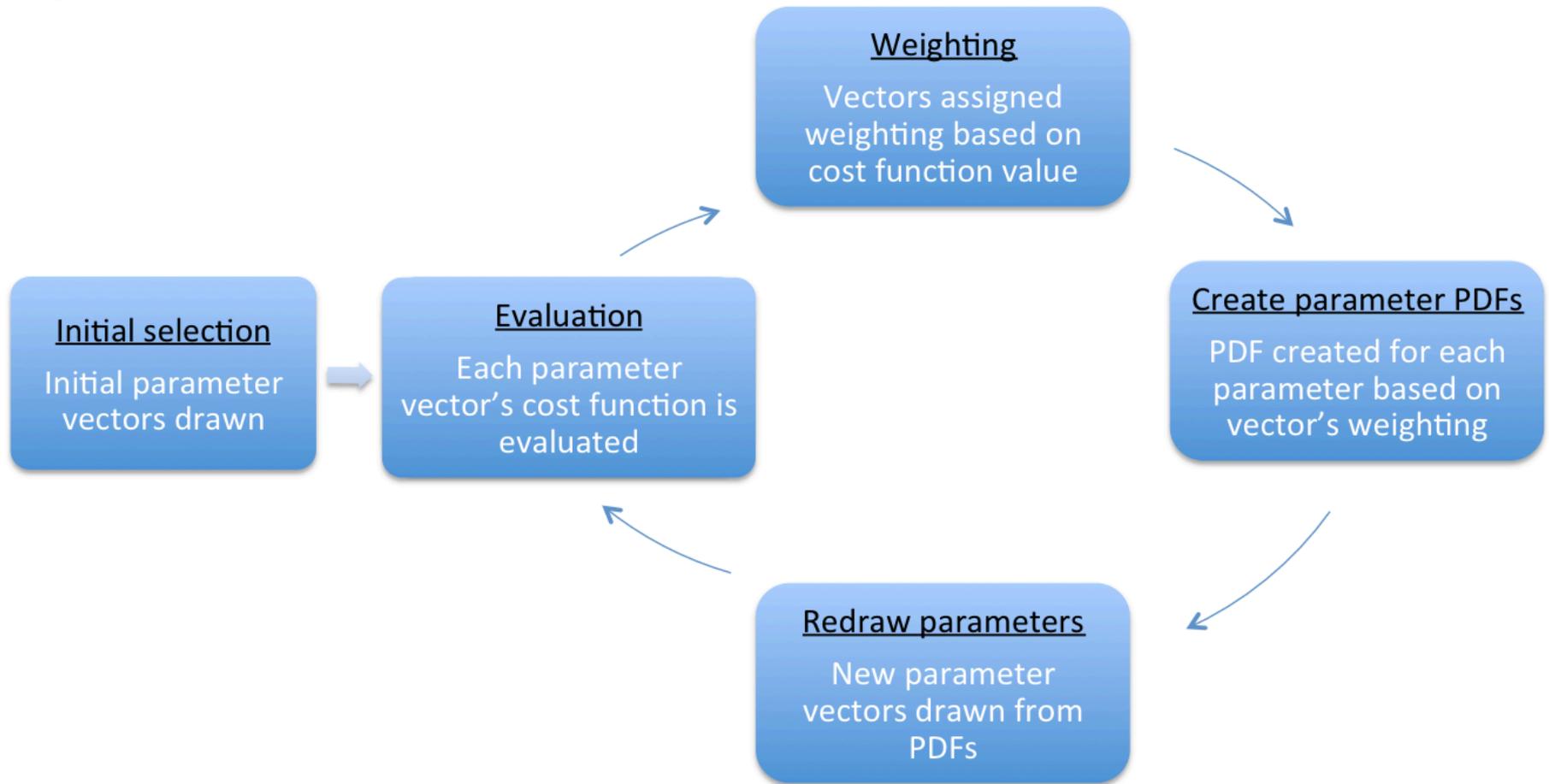
$$J(x) = \left((x - x_0)^T C_{x_0}^{-1} (x - x_0) \right) + \left(M(x) - c \right)^T C_c^{-1} \left(M(x) - c \right)$$

- Optimisation uses the gradient of $J(\mathbf{x})$ with respect to the parameters
- Second order derivatives (Hessian) at minimum provide approximation of parameter uncertainties (a posteriori): $\mathbf{C}_{p_0}^{-1} = \partial^2 J(\mathbf{x}_{p_0}) / \partial \mathbf{x}^2$
- Uncertainties on target quantities (e.g. net flux, NEP) via linearisation of model (Jacobian matrix):

$$\mathbf{C}_{\text{NEP}} = \partial \mathbf{M} / \partial \mathbf{x} \mathbf{C}_{p_0} \partial \mathbf{M} / \partial \mathbf{x}^T$$

- All derivatives provided via automatic differentiation of model code (TAF)

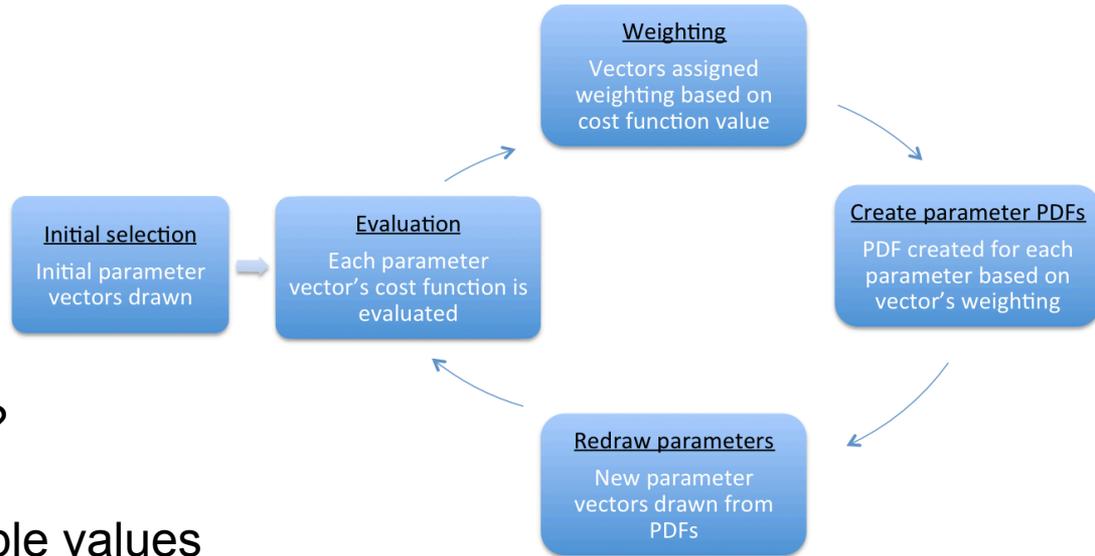
Parameter estimation using a particle filter



Parameter estimation using a particle filter

1. Initial selection:

- 1 Uniform distribution
 - What to pick as limits?
- 2 Gaussian distribution
 - Physically unreasonable values



2. Evaluation:

Cost function is evaluated for each parameter

$$J(x) = (M(x) - c)^T C_c^{-1} (M(x) - c)$$

Parameter estimation using a particle filter

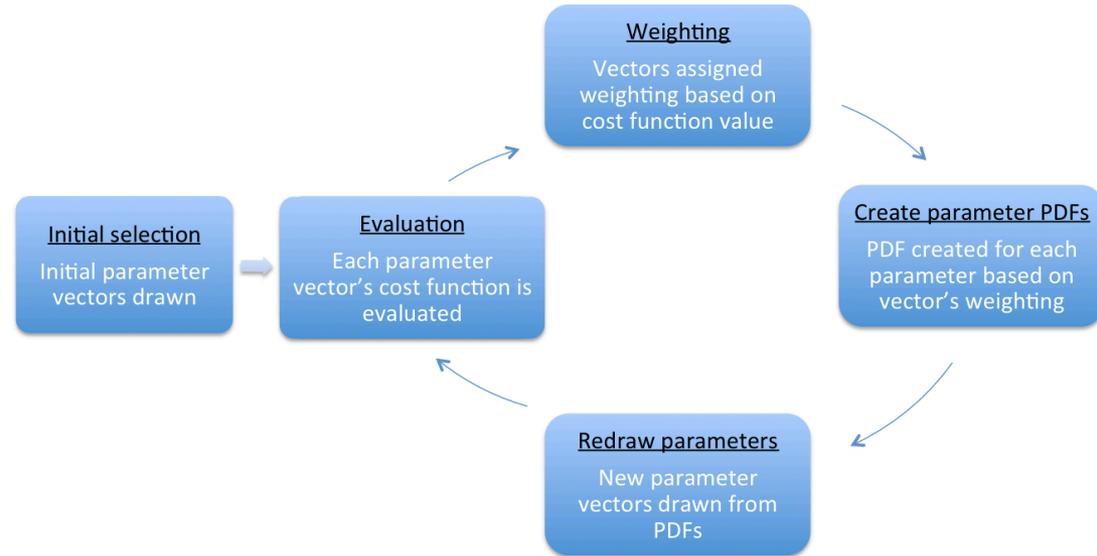
3. Weighting:

1 Gaussian:

$$w = \exp\left(\frac{-cf}{cf_0}\right)$$

2 Lorenz:

$$W = \frac{1}{1+cf}$$



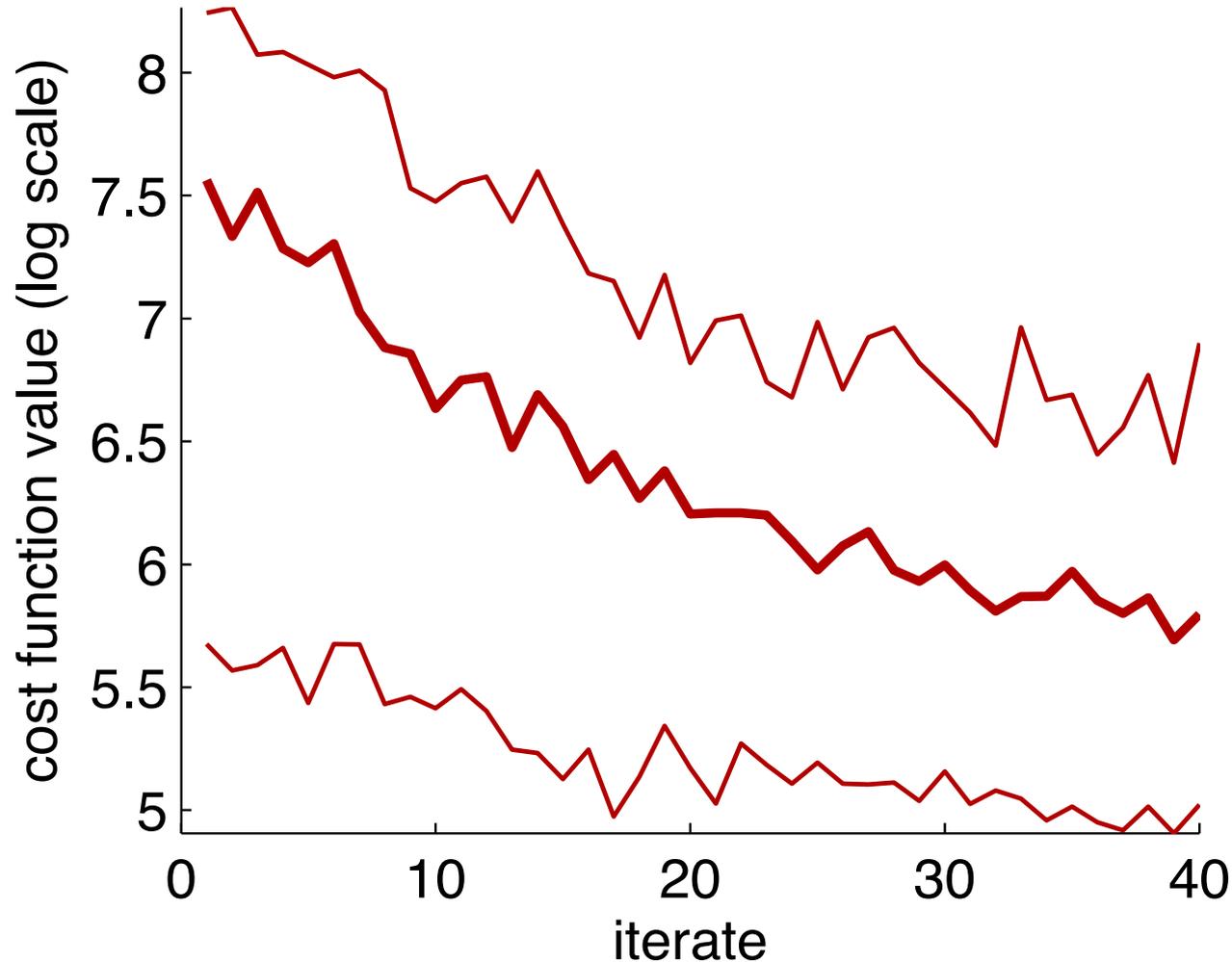
4. Create parameter pdfs:

- 1 Gaussian pdf
 - Weighted mean and weighted standard deviation
- 2 Constructed pdf
 - tricky

5. Redraw parameters:

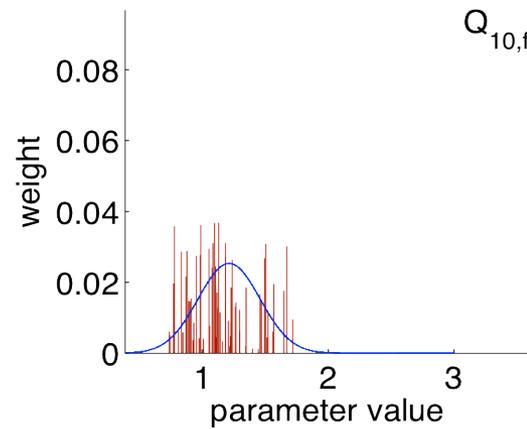
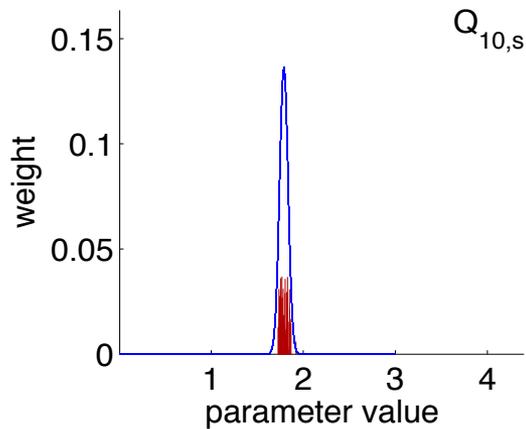
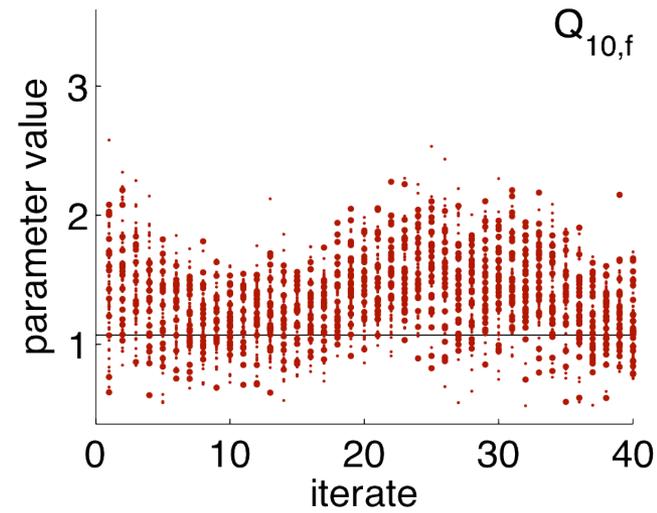
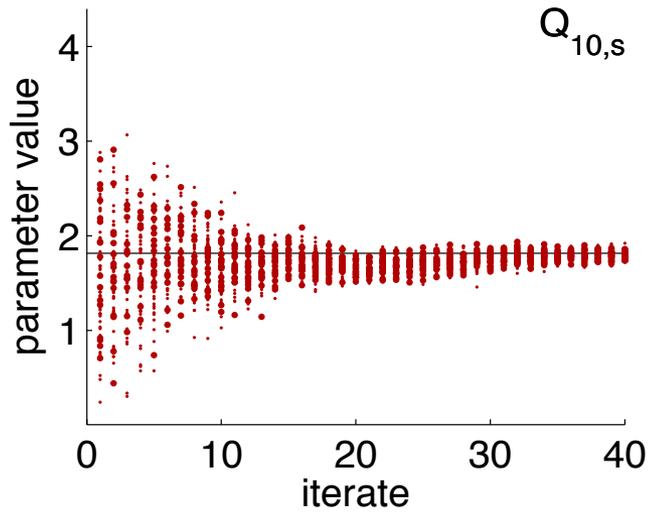
Results

- 64 particles
- 40 iterations
- Gaussian initial sampling
- Gaussian resampling



Results

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- 40 iterations
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- Gaussian resampling



Parameter transformations

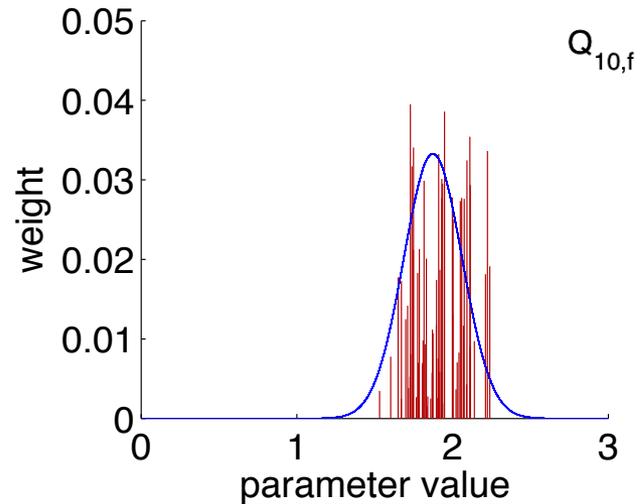
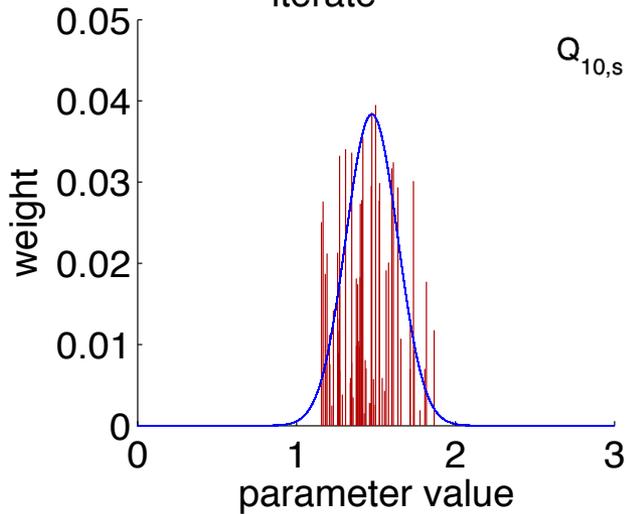
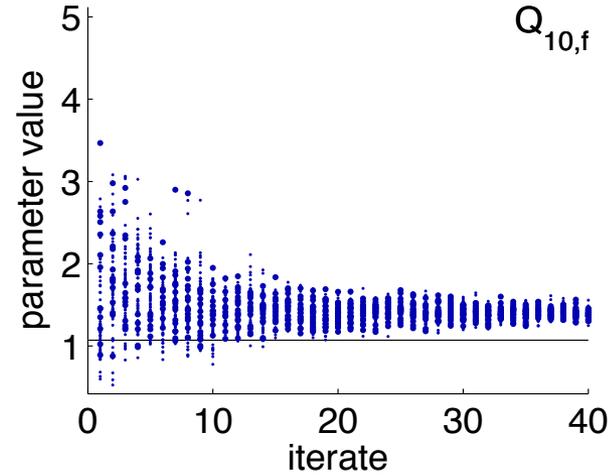
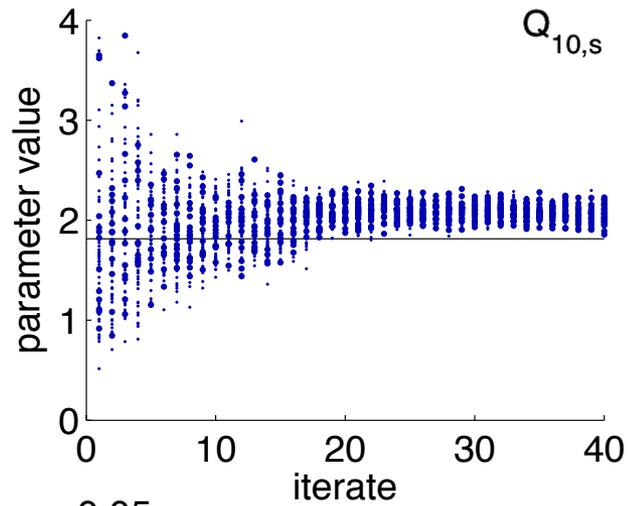
Perform the optimisation in a transformed parameter space, thus ensuring that when back-transformed the optimal parameter values are within the physically meaningful domain

Different transformations:

- Log: limits parameters above a specified value
- Double bounded log: limits parameters between two values



Results



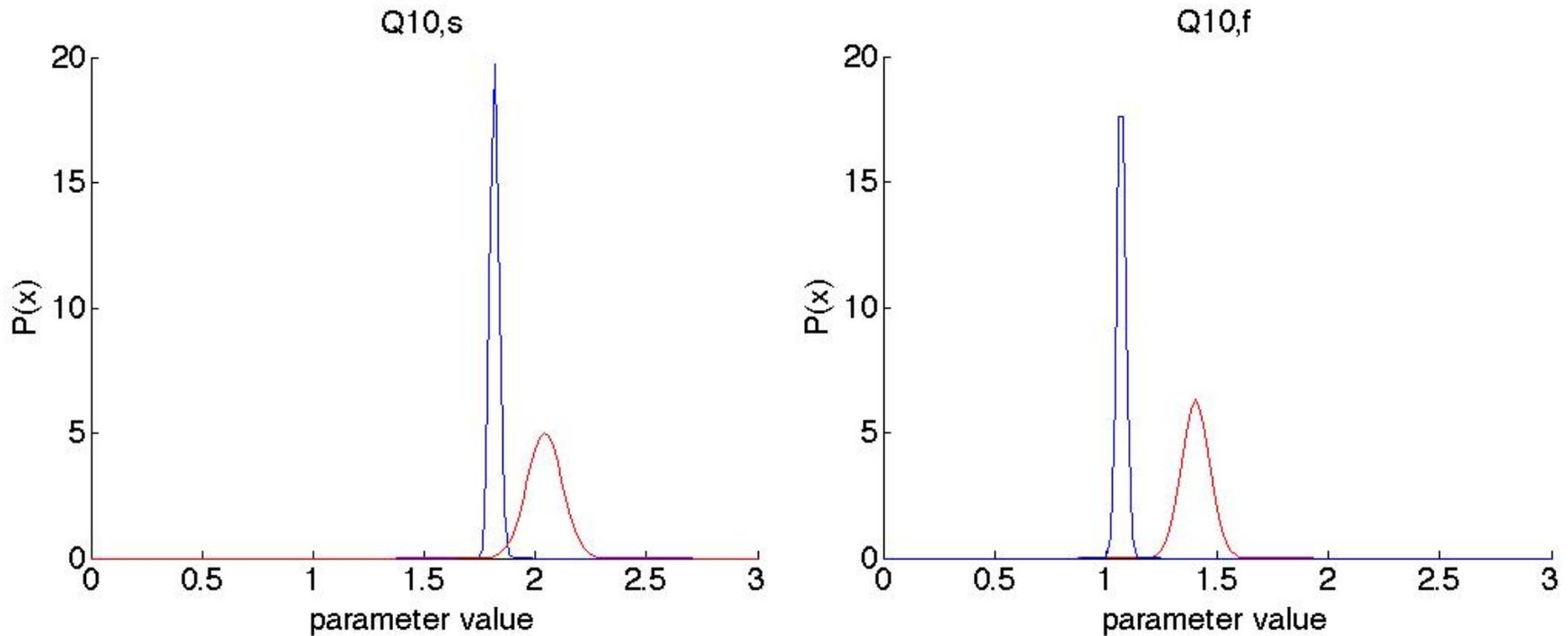
Comparison to CCDAS

	CCDAS	Particle Filter
Cost function Value	9667	17572

Parameter	Initial Value	CCDAS optimised value	Particle Filter optimised value	Initial uncertainty	CCDAS optimised uncertainty	Particle Filter weighted standard deviation
1 $Q_{10,f}$	1.5	1.069	1.40357865	0.75	0.016	0.063
2 $Q_{10,s}$	1.5	1.817	2.0419128	0.75	0.019	0.080
3 τ_f	1.5	3.435	12.8101455	3.0	0.120	1.146
4 κ	1	0.571	0.3050932	9.0	0.011	0.091
5 f_s	0.2	0.735	0.55894275	0.2	0.004	0.033



Comparison to CCDAS



CCDAS
Particle Filter

Conclusions

- Have set up a particle filter to estimate terrestrial carbon cycle parameters
- Have included parameter transformations to ensure physically meaningful optimal parameter values

Still need to

- Determine which set up provides the most consistent results
- Would like to have results closer to that of CCDAS

