A Bayesian synthesis inversion of the global carbon cycle: How do observations reduce uncertainties about future carbon sinks?

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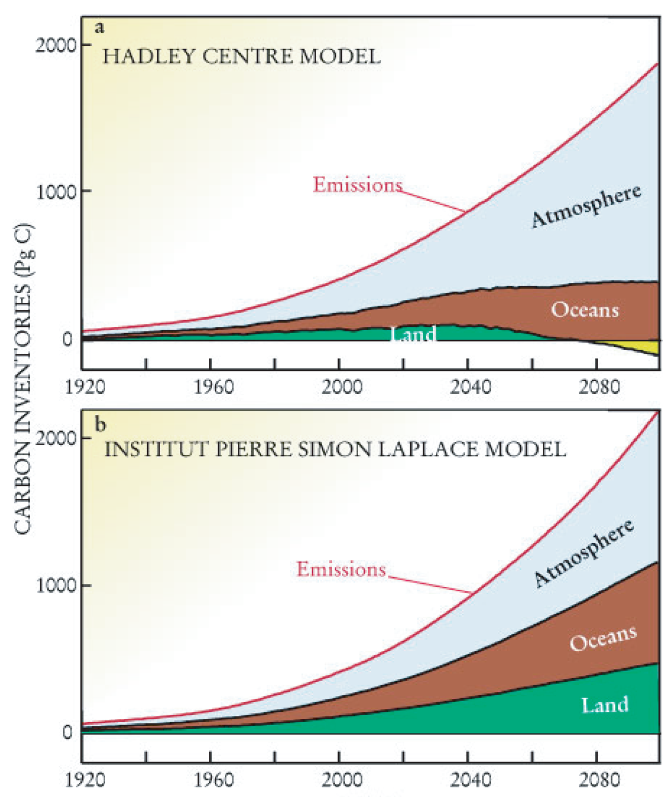
The carbon cycle: Current state of knowledge

The strength of the total carbon sink is well known
- CO_2 concentrations are measured accurately
- Detailed accounting of industrial emissions

Mechanisms governing sink strength are poorly understood
- Many feedbacks, such as respiration and temperature
- Large uncertainty in predictions of future sink strength

Coupled GCM/carbon cycle models estimate future sink
- Different models do not agree with each other:



Fully coupled models run under similar business as usual emissions scenarios

Cox et al. (2000): Terrestrial carbon sink becomes source around 2050

Dufresne et al. (2002): Terrestrial sink remains sink throughout 21st century

Differences arise from different respiration-temperature sensitivities and partitioning of soil and vegetation carbon.

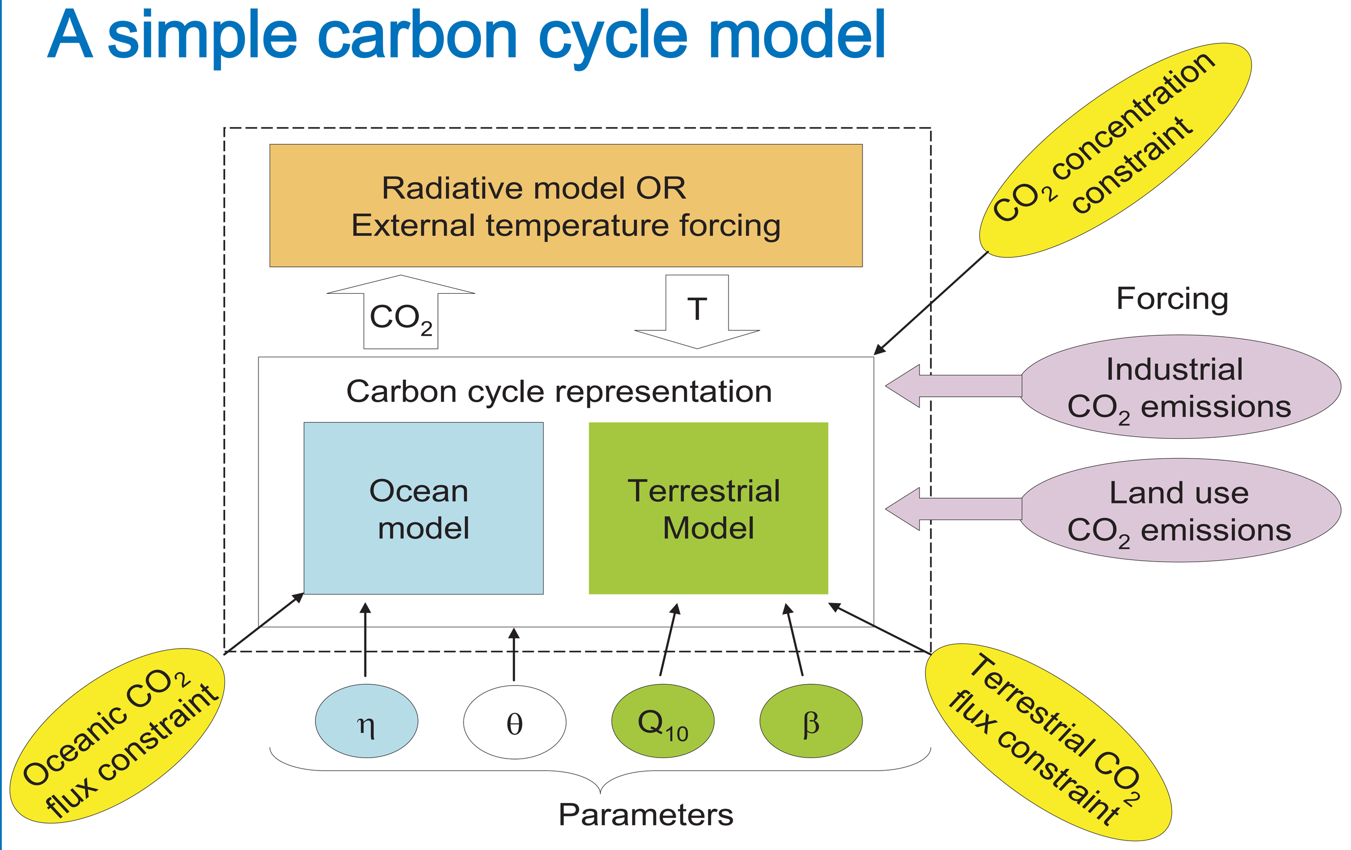
source: Sarmiento and Gruber, Physics Today (2002)

Potential pitfalls of this approach:
- Computationally expensive (~weeks per run)
- Very limited uncertainty estimates of predictions
- Upscaling problem of model parameters
- not calibrated with large-scale observations in a formal statistical sense

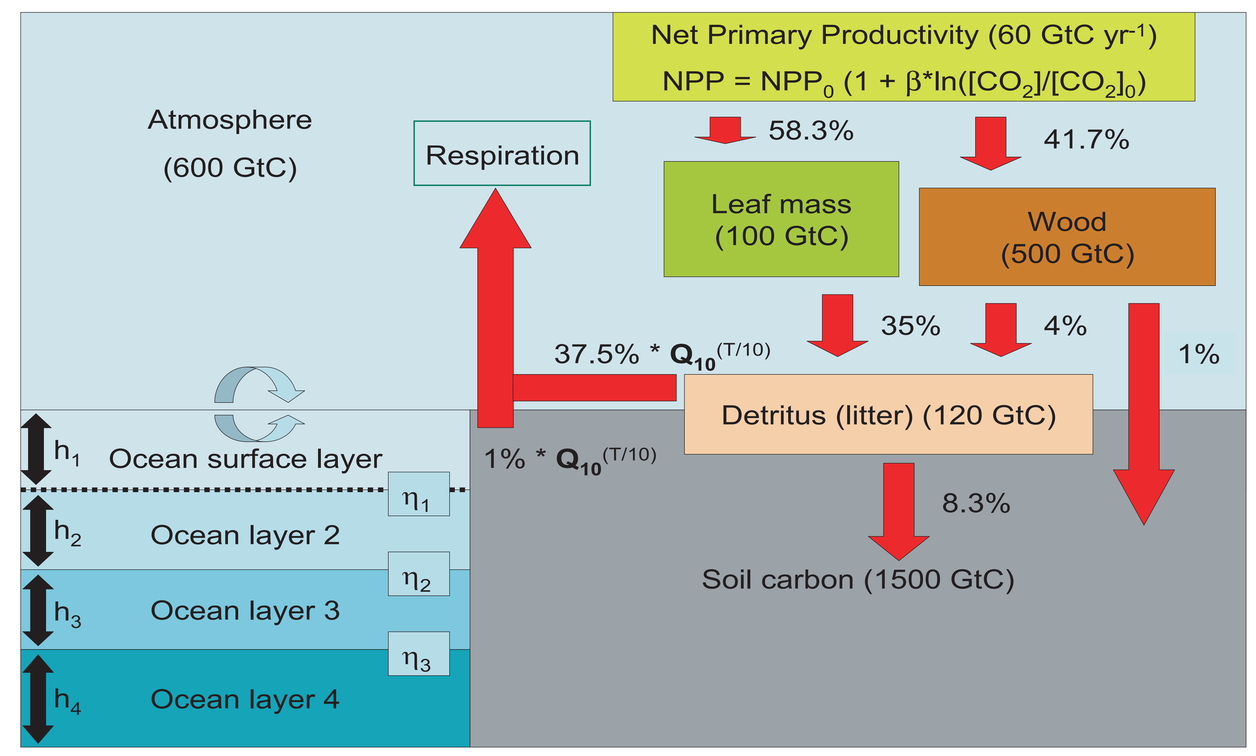
Objectives

Main question: What can we achieve with a simple model?
- Isolate and analyze key carbon cycle parameters
- Assimilate global-scale historical observations or estimates of CO_2 concentrations and fluxes
- Obtain probability density functions of key parameters
- Make probabilistic predictions about the future CO_2 sink
- Evaluate utility of observation systems to reduce parametric uncertainty and, therefore, sink uncertainty

A simple carbon cycle model



Carbon cycle representation



Model input and variable parameters

All model input, output, parameters and constraints are global averages or sums

Input: annual CO_2 emissions and temperature (1850-2004)
- Industrial emissions: Marland et al. dataset
- Land-use emissions: Houghton et al. dataset
- Temperature: Jones et al. data (interannually varying) or simple radiative model (smooth)

Parameters and prior ranges:

Prior bounds are basic physical constraints

Carbon cycle parameters (terrestrial and oceanic):

Q_{10} - Respiration temperature sensitivity (> 1, dimensionless)
Governs strength of respiration-temperature feedback

β - Carbon fertilization factor (> 0, dimensionless)
Logarithmic increase in NPP in response to increasing CO_2

η - Thermocline diffusivity (> 0 m yr^{-1})
Governs strength of ocean carbon sink

Statistical parameter:

θ - Lag-1 autocorrelation coefficient (-1 to 1, dimensionless)
Accounts for autocorrelation in the residuals of CO_2 concentrations

Assimilating historical observations

Goal: to determine probability density functions (PDFs) of parameters given observational constraints.

Model constraints: CO_2 concentrations and fluxes
- CO_2 from Law Dome ice core, Mauna Loa observatory
- Cumulative ocean flux: Sabine et al. (2004)
  119 +/- 19 anthropogenic PgC through 1995
- Decadal ocean fluxes: McNeil et al. (2003)
  1.6, 2.0 +/- 0.4 PgC yr^{-1} (1980s, 90s)

Method: Markov Chain Monte Carlo
- Begin with initial guesses for parameters
- Calculate likehood of observations given model

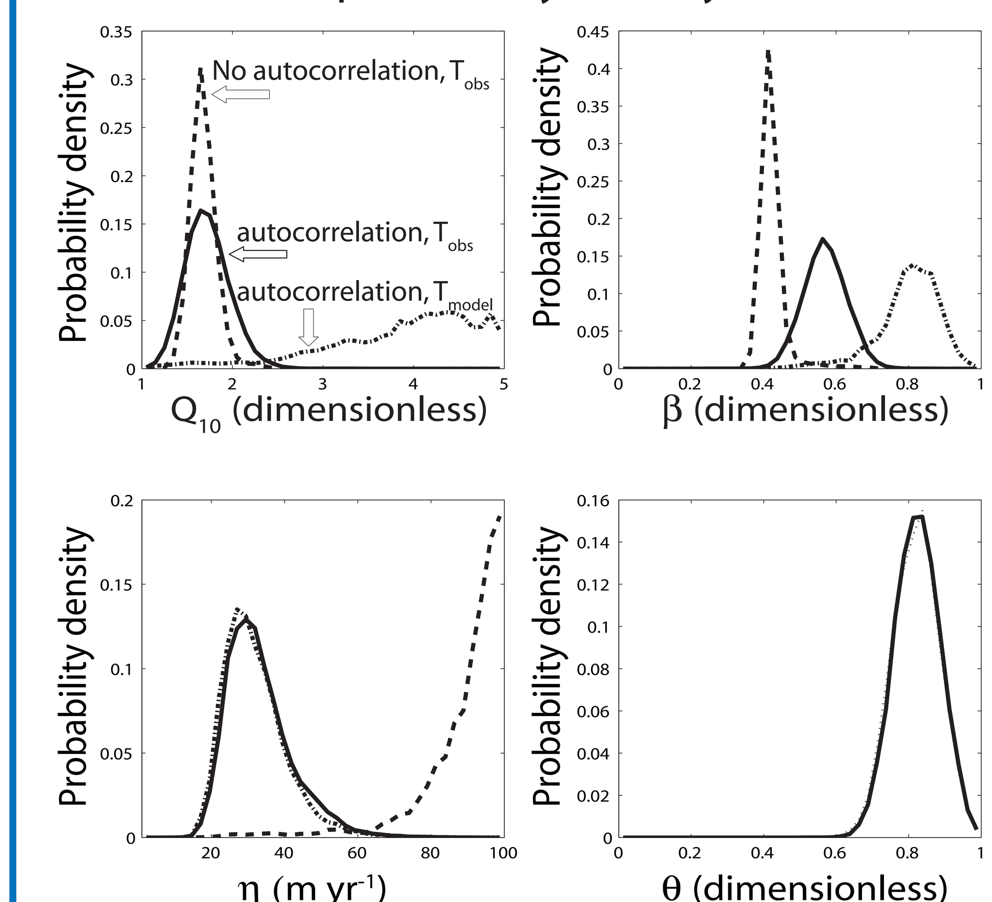
$$L(D \mid Y^i) = \prod_{i=1}^{m} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(D_j - Y_j^i)^2}{2\sigma^2}\right)$$

D = observations
Y = model predictions
σ = observation error

- Can be extended to account for Lag-1 autocorrelation (θ)
- Perturb parameters, recalculate L, check for acceptance
- Repeat above until chain converges
- Construct parameter PDFs from chain and likelihood info

Results

Parameter probability density functions (PDFs)



Joint parameter PDF is not normally distributed. Single parameter projections

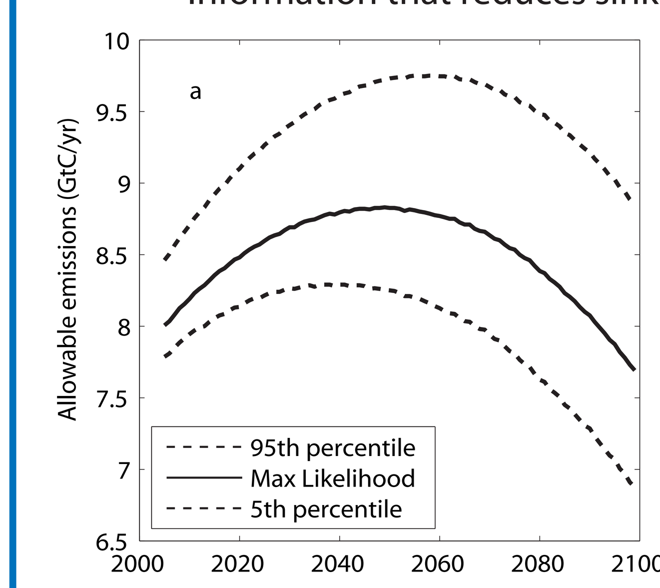
Neglecting autocorrelation in the likelihood function biases parameter estimates.

Driving the model with observed temperature results in sharper PDFs (less uncertainty)

Q_{10} and β display a significant positive correlation
- High respiration and high NPP similar to low respiration and low NPP

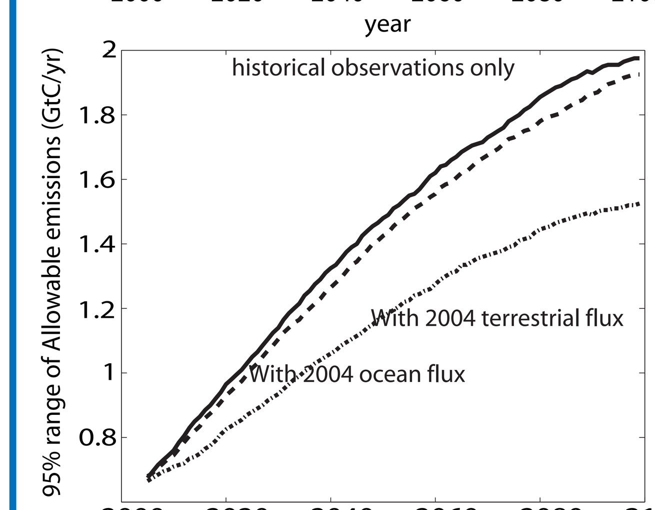
η and β display a significant negative correlation
- High ocean sink, low land sink similar to high land sink, low ocean sink

How do new observations reduce sink uncertainty?
- Consider a strategy that requires CO_2 stabilization at 550 ppm
- Key question: How much anthropogenic CO_2 per year can be emitted?
- Uncertainty in sink strengh causes uncertainty in allowable emissions
- Information that reduces sink uncertainty can have economic value



Probabilistic predictions run using parameter PDFs under the S550 stabilization scenario from 2005-2100

Allowable emissions uncertainty caused entirely by sink uncertainty.
Uncertainty grows with time
Most of the uncertainty is caused by Q_{10} and β (terrestrial parameters)



How would additional observations reduce sink strength uncertainty?
Consider assimilating hypothetical new observations into the model:
2004 terrestrial flux: 2.2 +/- 0.4 GtC yr^{-1}
2004 ocean flux: 2.5 +/- 0.4 GtC yr^{-1}
derived from max. likelihood solution

Terrestrial flux observation reduces uncertainty much more than ocean flux observation, given our model structure
temperature signal helps to partition respiration and NPP, reduce spread in β and Q_{10}

Limitations
- no ocean circulation or biology; no ocean climate response mechanism
- no consideration of precipitation, regionally varying climate or vegetation
- Did not consider uncertainty in land-use emissions in optimization

Conclusions

- Neglecting autocorrelation in the residuals of CO_2 concentration causes overconfident and biased results
- Model parameters are not normally distributed
- Driving the model with historical temperature provides information to constrain parameters and reduce uncertainty
- Terrestrial flux observations can considerably reduce future sink uncertainty

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