Some applications of climate Data Assimilation

- Really two half lectures;
- An example of data assimilation for climate and biogeochemistry;
- An unfinished approach to model ensembles and a lesson on why it's sometimes good to go back to first principles.

Uncertainties in the relationship between concentrations and emissions

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"It's only a model"

(Monty Python and the Holy Grail)

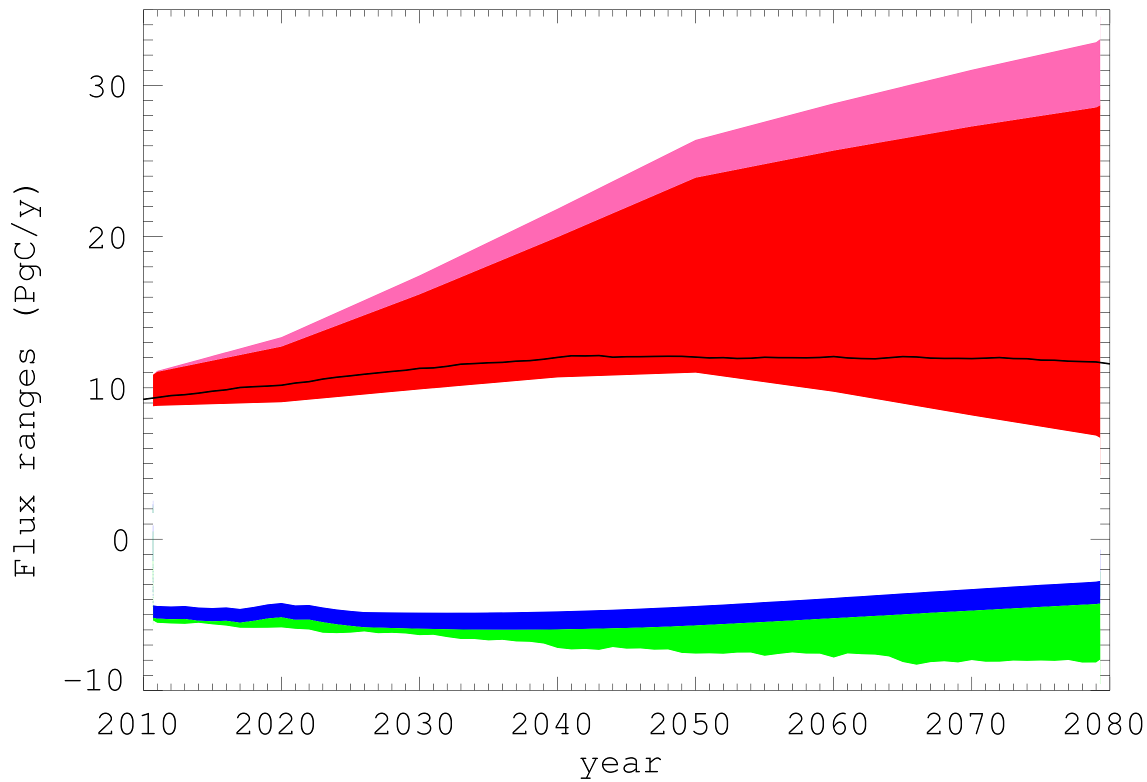
Papers

- This submitted to Philosophical Transactions of the Royal Society;
- Optimization from Koffi et al. (2010) almost submitted to Global Biogeochemical cycles.

Outline

- Uncertainties in the carbon cycle;
- A simple predictive model and its uncertainty;
- A little on sensitivity;
- Confronting the model with data;
- Conclusions.

Motivation



Ranges of global CO_2 fluxes. Red = anthropogenic, blue = ocean, green = land, pink = other vulnerabilities from Raupach et al., Tellus, 2010. Uptakes from IPCC-2007 Fig. 10.21. Black line shows emission scenario.

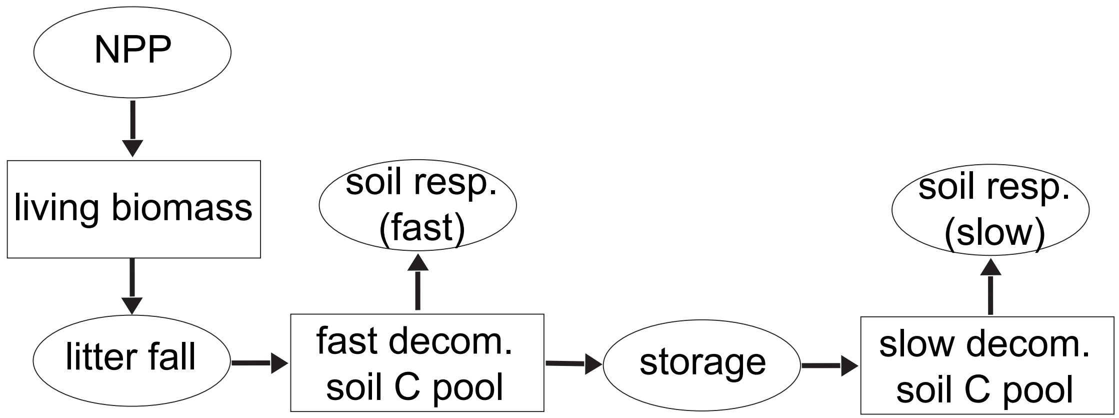
Sources of Terrestrial Model Uncertainty

- Different models include different processes;
- Equivalent processes are described with different equations;
- There are many uncertain parameters in these models.

Exploring Parameter Uncertainty

- Write simple box model of terrestrial carbon cycle
- Climate model $\rightarrow$ global model $\rightarrow$ simple model;
- Calculate sensitivities of future uptake to inputs;
- Calculate uncertainty of future uptake as function of uncertainty in input parameters;
- Assimilate current data and study reduced uncertainty on future uptakes.

Simple Model



$$\begin{aligned}\mathrm{NetUptake} = \quad & \mathbf{Production} - (1 - \mathbf{K}) \times \mathbf{LitterDecomposition} \\ & - \mathrm{SoilOutgassing}\end{aligned}$$

$$\mathrm{SoilOutgassing} \propto \mathrm{SoilPool} \times \omega^{\kappa} \mathbf{Q}_{10}^{T_a/10}$$

where ω = soil moisture and T_a = air temperature.

$$\frac{\partial \mathrm{SoilPool}}{\partial t} = \mathbf{K} \times \mathbf{LitterDecomposition} - \mathrm{SoilOutgassing}$$

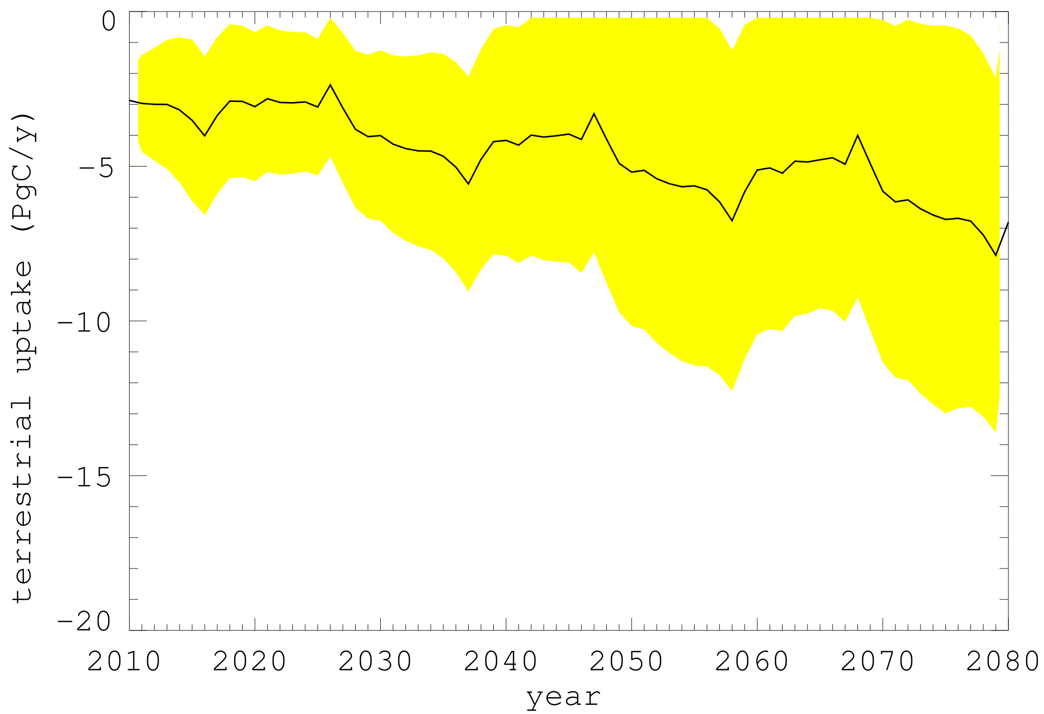
Technical Details

- Need derivatives of outputs of simple model and global model with respect to their inputs;
- Simple model can be differentiated by hand;
- Global model differentiated by the software "Transformation of Algorithms in FORTRAN" `http://www.fastopt.com`.

$$\text{Uncertainty(uptake)} = J \times \text{Uncertainty(parameters)} \times J^T$$

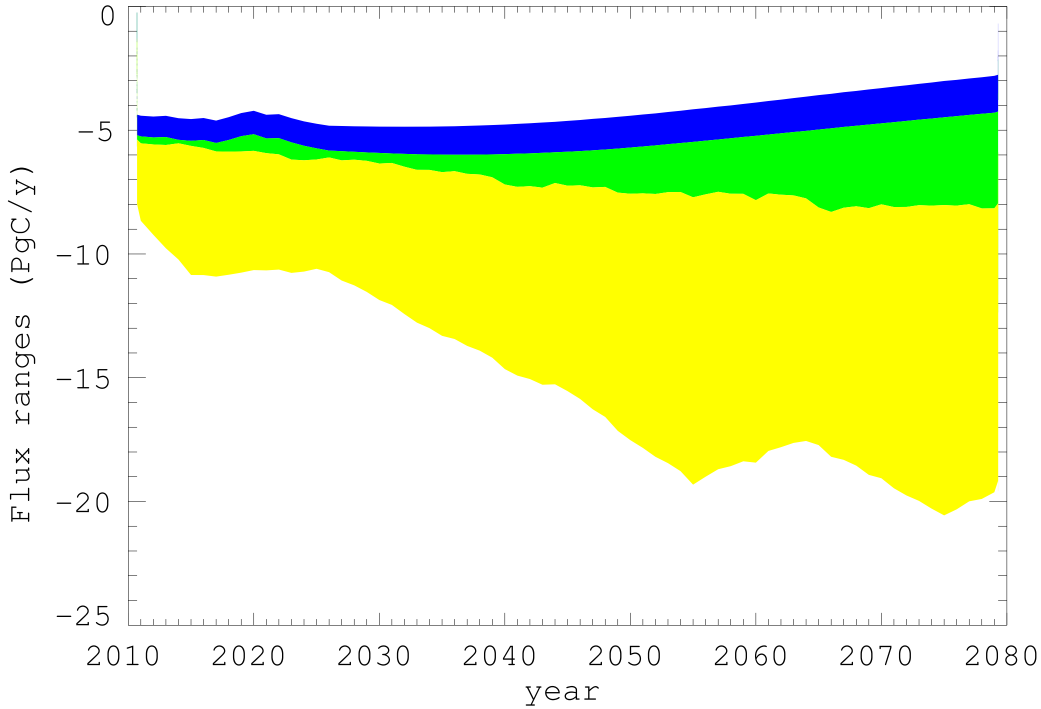
where J is derivative and T is transpose.

Uptake from Prior Model



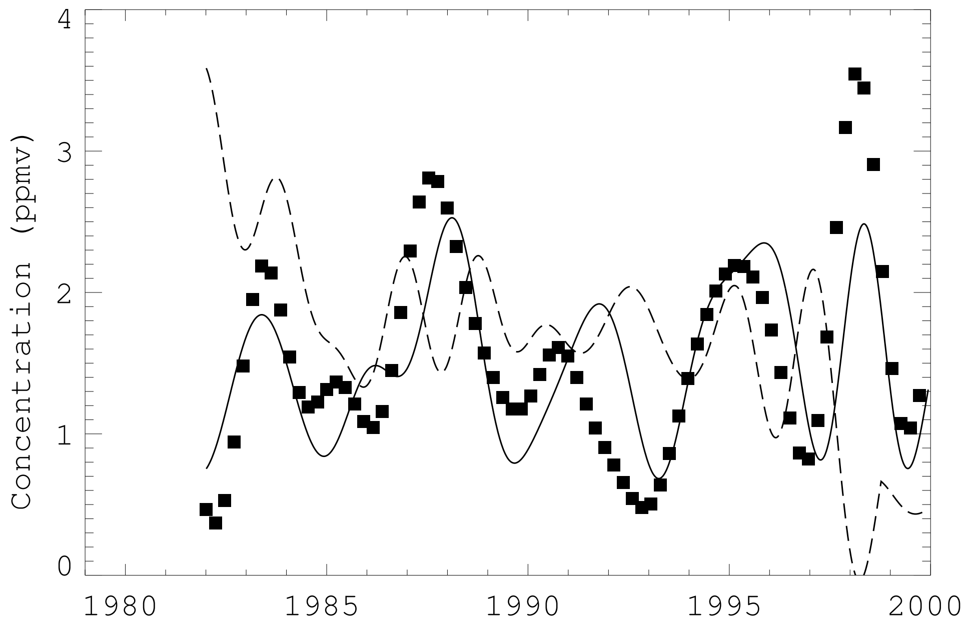
Terrestrial uptake (no climate change) from prior model and its 90% confidence interval. Uptake is anchored at its 2000–2010 value.

Comparison with Other Uncertainties



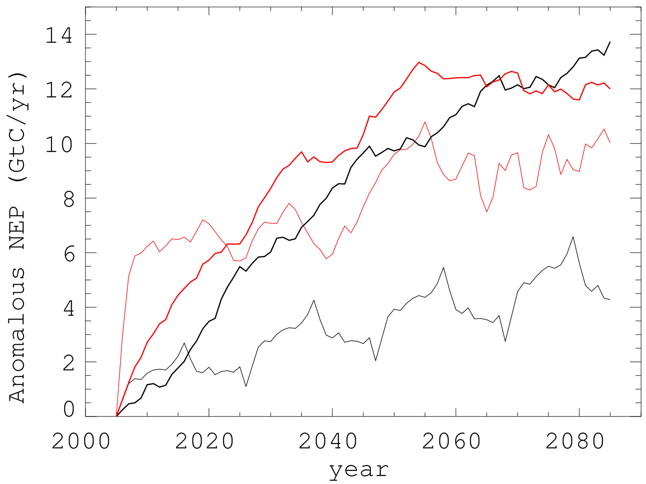
Range of uptakes, blue = ocean, green = land from IPCC models. The yellow band represents the 90% confidence interval of the uncertainty in the simple model.

Fitting Atmospheric Growth Rate



Smoothed global growth rate, squares = obs, dashed = prior, solid = optimised. Note the great improvement in phasing with the optimisation.

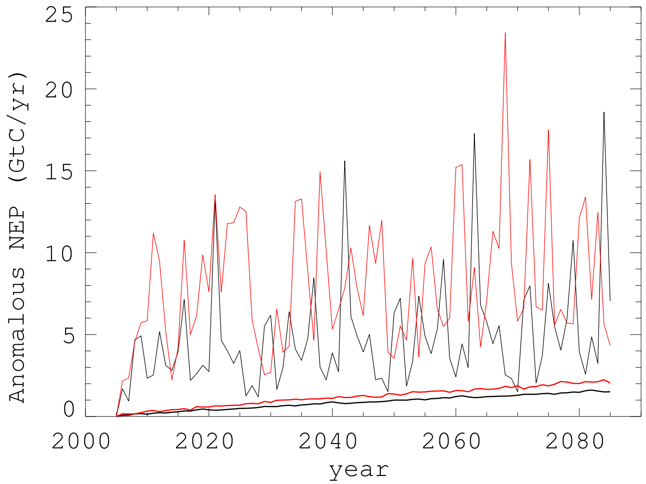
Comparing Uptakes



Decadal mean δNEP, 2000–2090. Black lines = current climate, red = climate change. Thin lines = prior parameters, thick = optimized.

- $\delta\text{NEP} = \text{NEP} - \overline{\text{NEP}}(t = 2000 - -2010)$
- Unrealistically rapid increase;
- High $\frac{\partial \text{GPP}}{\partial \text{CO}_2}$: 0.3PgC/yr/ppm cf FULLBETHY = 0.23 and LPJ = 0.19. ORCHIDEE anyone?

Comparing Uncertainties



Uncertainty in decadal mean δNEP, 2000–2090. Black lines = current climate, red = climate change. Thin lines = prior parameters, thick = optimized.

- Uncertainty in δNEP calculated as $\mathbf{C}(x) = J\mathbf{C}(p)J^T$ where $J = \frac{\partial x}{\partial p}$ and $\mathbf{C}$ is covariance;
- Uncertainties completely dominated by climate change;
- Partially reflects small uncertainty on photosynthesis parameters.

For those who prefer numbers

Case	sum (PgC)	Uncertainty (1σ PgC)
prior no-clim	278	126
prior clim-change	656	1141
optimized no-clim	717	78
optimized clim-change	799	107

Value and uncertainty for integrated $\delta\mathrm{NEP}$ from 2000–2090

Climate Feedback Parameter

- $G = \frac{\sum \delta \mathrm{NEP(climate)}}{\sum \delta \mathrm{NEP(noclimate)}}$;
- Can calculate $\frac{\partial G}{\partial p}$ (unpleasant) and hence uncertainty of G;

$$\sigma(G) = \sqrt{\nabla_p G \mathbf{C}(p) \nabla_p G^T}$$

- For $\mathbf{C}(p)$ diagonal (prior) this is simple sum.

Equations again

$$\text{SoilOutgassing} \propto \text{SoilPool} \times \omega^{\kappa} \mathbf{Q}_{10}^{T_a/10}$$

where $\omega =$ soil moisture and $T_a =$ air temperature.

$$\frac{\partial \text{SoilPool}}{\partial t} = \mathbf{K} \times \mathbf{LitterDecomposition} - \text{SoilOutgassing}$$

- $\sigma(G) = 3.54$ for prior;
- 80% from κ with rest from $\mathbf{Q}_{10}$ and $\mathbf{K}$;
- $\sigma(G) = 0.04$ posterior.

Conclusions

- Tangent linear models are fun;
- The carbon-cycle/climate feedback uncertainty is very large even within one model;
- For BETHY the sensitivity of respiration to soil moisture is the biggest contribution to uncertainty;
- The atmospheric record is sufficient to constrain this aspect of model dynamics.

Using Data Assimilation with Model Ensembles

- Work very much in progress;
- Similar efforts in physical climate.

Transcom

- How much uncertainty in inversions due to transport?
- Three phases: compare forward models, run known tracers, compare inversions;
- Law et al., Tellus, 1996, Denning et al., Glob. Biogeochem. Cyc. 1999, Gurney et al., Nature 2002, Baker et al., Glob. Biogeochem. Cyc., 2006.

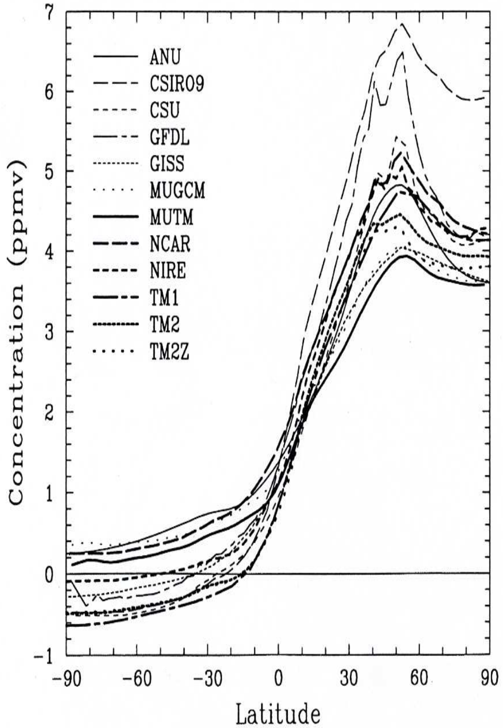


Fig. 3.1: Zonal annual surface mean concentration in ppmv due to fossil emissions.

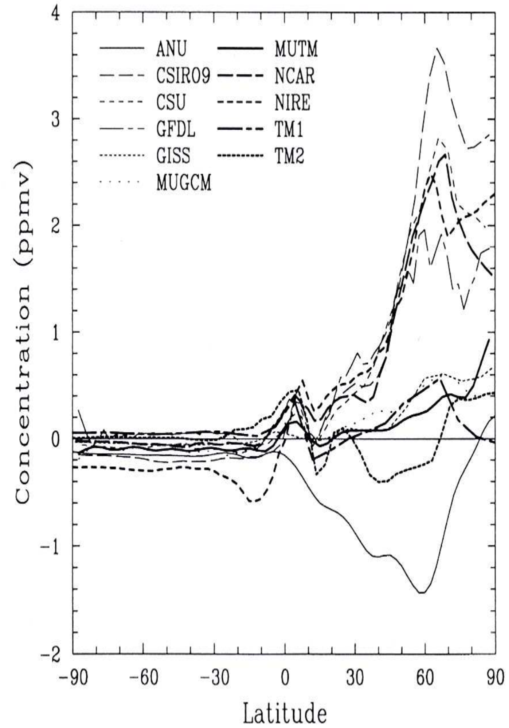


Fig 4.6: Zonal annual mean concentration in ppmv for the biosphere experiment.

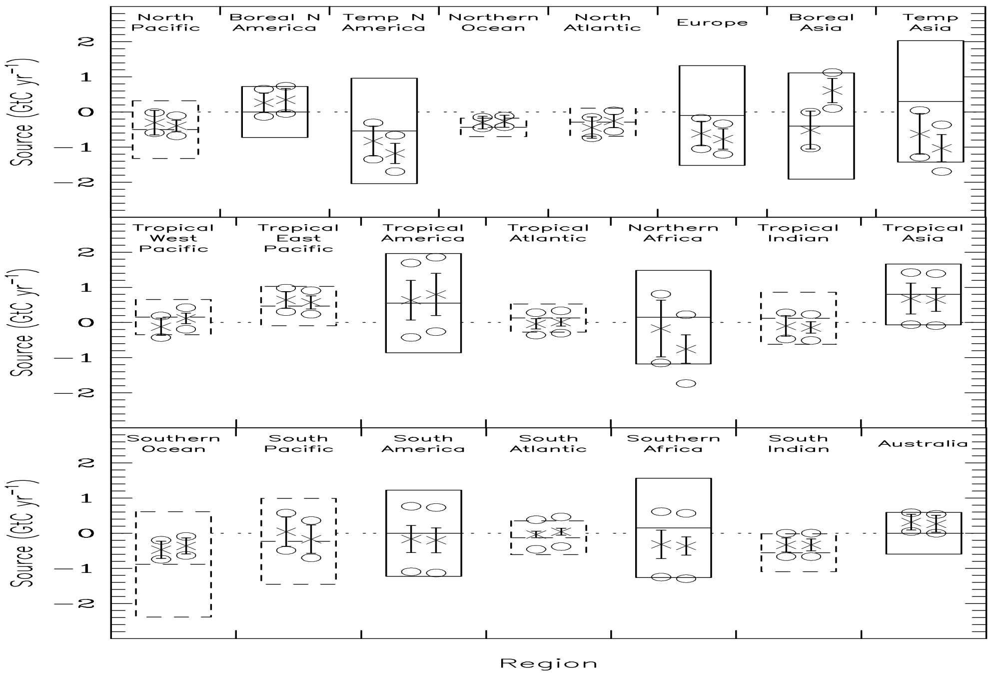
Zonal mean concentration from fossil fuel source

Zonal mean response to annually balanced biosphere source

Transcom III

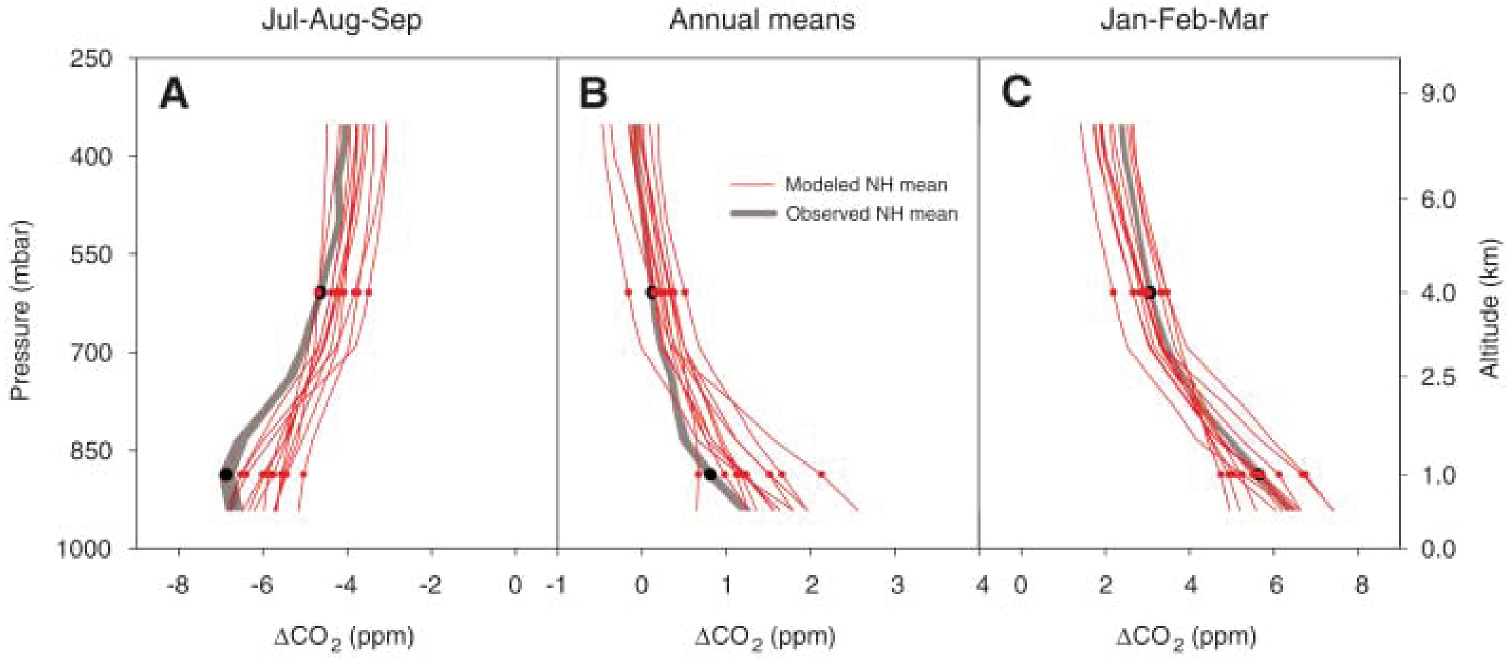
- Run inversions changing only response functions from different models;
- Data and uncertainties, prior and uncertainties and algorithm fixed.
- Annual mean case: 26 response functions, 17 models;
- Seasonal and interannual cases: 268 response functions, 12 models.

Gurney et al., Nature, 2002



Inversion results for the control (left bar) and no-biosphere (right bar). Mean fluxes are the 'X'. Positive = source. Prior flux and uncertainty: horizontal bar and boxes (land in green, ocean in blue). Within model uncertainty = circles, between model uncertainty = length of vertical bars. Regions are shown in their approximate north-south and east-west relationship.

Impact of Vertical Transport on Inversions



Notes

- Stephens et al., Science, 2007;
- Compared different models against independent climatology of profiles;
- Did not consider posterior uncertainty;
- Main point that not all models are equal.

The Approach

- Use statistical techniques to choose among an ensemble;
- Include the choice of model as an extra unknown;
- Produce a PDF among the models;
- Weight means etc by this PDF

Set-up

- Prior PDF for fluxes and data as for Gurney et al., Nature, 2002, i.e Gaussian;
- Uniform prior distribution for model choice (every model equally likely);
- Relative probability for each model depends on overlap between simulation and data (size of black triangle).

Making a long story short

- Collection of linear models $\mathbf{H}_1 \ldots \mathbf{H}_N$s
- Let $G(\vec{\mu}, \mathbf{C})$ be Gausian distribution with mean $\vec{\mu}$ and covariance $\mathbf{C}$

$$P(\vec{x}, \mathbf{H}) \propto G(\vec{x} - \vec{x}_0, \mathbf{C}(\vec{x}_0) * G(\vec{y} - \mathbf{H}\vec{x}, \mathbf{C}(\vec{y}))$$

$$P(\mathbf{H}) = \int d\vec{x} P(\vec{x}, \mathbf{H})$$

Skipping the painful algebra

$$P\mathbf{H} \propto \left[\det \mathbf{H}\mathbf{C}(\vec{x}_0)\mathbf{H}^T + \mathbf{C}(\vec{y})\right]^{-0.5} \exp -\frac{1}{2}(\vec{y} - \mathbf{H}\vec{x}_0)^T \left[\mathbf{H}\mathbf{C}(\vec{x}_0)\mathbf{H}^T + \right.$$

$$\sum P(\mathbf{H}_i) = 1$$

- Can be calculated without ever performing an inversion;
- Similar to maximum value of $P(\vec{x}, \mathbf{H})$.

Sample of Tabulated values

Model	$P(\mathbf{H})$
JMA-CDTM.maki	0.66
MATCH.law	0.29
MATCH.bruhwiler	0.02
SKYHI.fan	1e-7

- Unrealistically strong discriminant (7 orders of magnitude)
- Problem over-determined so many obs left to discriminate among models
- Model error $(\mathbf{C}(\vec{y})$ should not be independent.

Applications and Problems

- Using data assimilation to improve model structure as well as parameters;
- Choosing among an ensemble of models;
- Unusually dependent on proper formulation of uncertainties.

Summary for Today

- Climate DA is possible and can help us improve climate prediction;
- We can learn a lot by propagating uncertainty into prediction;
- We can extend DA beyond improving a particular model into the domain of model choice but it’s not easy in real cases.

Overall Summary

- Data assimilation best thought of as a statistical problem;
- Watch the statistics of inputs and results carefully;
- There's a lot to gain by considering more than just the best guess for unknowns and simulations;
- The basic theory is flexible enough for interesting extensions, like model choice but sometimes you have to go back to first principles.