„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)

Misfit to Observations
- Station Conc. 6,500
  - Atmospheric Transport Model: TM2
  - Biosphere Model: BETHY
  - Fluxes: 800,000
  - Parameters: 57

Forward modelling:
Parameters $\rightarrow$ Misfit

Adjoint model:
$\frac{\partial \text{Misfit}}{\partial \text{Parameters}}$

Parameter optimization

Adjoint of BETHY generated automatically using TAF (FastOpt, Hamburg)
BETHY

• **GPP:**
  C3 photosynthesis – *Farquhar et al. (1980)*
  C4 photosynthesis – *Collatz et al. (1992)*
  stomata – *Knorr (1997)*

• **Plant respiration:**
  maintenance resp. = $f(N_{\text{leaf}}, T)$ – *Farquhar, Ryan (1991)*
  growth resp. ~ NPP – *Ryan (1991)*

• **Soil respiration:**
  fast/slow pool resp., temperature ($Q_{10}$ formulation) and moisture dependant

• **Carbon balance:**
  average NPP = b average soil resp. (at each grid point)  
  $\beta < 1$: source  
  $\beta > 1$: sink  

$\Delta t = 1h$  
$\Delta \text{lat, } \Delta \text{lon} = 2 \text{ deg}$
CCDAS calibration step

- Terrestrial biosphere model BETHY (Knorr 97) delivers CO$_2$ fluxes to atmosphere
- Uncertainty in process parameters from laboratory measurements
- Global atmospheric network provides additional constraint

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

1\textsuperscript{st} derivative (gradient) of $J(\vec{p})$ to model parameters $\vec{p}$:
\[-\partial J(\vec{p})/\partial \vec{p}\]
yields direction of steepest descent.

2\textsuperscript{nd} derivative (Hessian) of $J(\vec{p})$:
\[\partial^2 J(\vec{p})/\partial \vec{p}^2\]
yields curvature of $J$. Approximates covariance of parameters.

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

\[
C_p \approx \left\{ \frac{\partial^2 J(p_{opt})}{\partial p_{i,j}^2} \right\}^{-1}
\]

<table>
<thead>
<tr>
<th>examples:</th>
<th>first guess</th>
<th>optimized</th>
<th>prior unc.</th>
<th>opt.unc.</th>
<th>Vm(TrEv)</th>
<th>Vm(EvCn)</th>
<th>Vm(C3Gr)</th>
<th>Vm(Crop)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vm(TrEv)</td>
<td>60.0 µmol/m²s</td>
<td>43.2 µmol/m²s</td>
<td>20.0 %</td>
<td>10.5 %</td>
<td>0.28</td>
<td>0.02</td>
<td>-0.02</td>
<td>0.05</td>
</tr>
<tr>
<td>Vm(EvCn)</td>
<td>29.0 µmol/m²s</td>
<td>32.6 µmol/m²s</td>
<td>20.0 %</td>
<td>16.2 %</td>
<td>0.02</td>
<td>0.65</td>
<td>-0.10</td>
<td>0.08</td>
</tr>
<tr>
<td>Vm(C3Gr)</td>
<td>42.0 µmol/m²s</td>
<td>18.0 µmol/m²s</td>
<td>20.0 %</td>
<td>16.9 %</td>
<td>-0.02</td>
<td>-0.10</td>
<td>0.71</td>
<td>-0.31</td>
</tr>
<tr>
<td>Vm(Crop)</td>
<td>117.0 µmol/m²s</td>
<td>45.4 µmol/m²s</td>
<td>20.0 %</td>
<td>17.8 %</td>
<td>0.05</td>
<td>0.08</td>
<td>-0.31</td>
<td>0.80</td>
</tr>
</tbody>
</table>

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

Rayner et al., 2005
Net C fluxes and their uncertainties
(CCDAS diagnostic mode)

Examples for diagnostics:
- Long term mean fluxes to atmosphere (gC/m²/year) and uncertainties
- Regional means

Rayner et al., 2005
CCDAS prognostic mode
here hindcasting 2000-2003

CO₂ concentration at Mauna Loa

Fossil fuel emissions kept at 2000 level

Regional carbon balances

Scholze et al., 2007
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

Reduction of uncertainty in process parameters

0.0: no reduction of unc.
0.5: unc. reduced to 50%
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

Kelley, MSc thesis, 2008
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

Hooker-Stroud, MSc thesis, 2008
CCDAS extension to include a model of seasonal fossil fuel emission

Fit to data Mauna Loa

- Reduced $\chi$-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

Hooker-Stroud, MSc thesis, 2008
CCDAS extension to include column integrated CO$_2$ 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 CO$_2$ 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)