The roles of model-data fusion in carbon cycle science

Michael Raupach
CSIRO Land and Water, Canberra, Australia
IGBP-IHDP-WCRP Global Carbon Project

With thanks to:
Damian Barrett, Peter Briggs, Pep Canadell, Helen Cleugh, Frank Dunin, John Finnigan, Dean Graetz, Kathy Hibbard, Heather Keith, Mac Kirby, Ray Leuning, Will Steffen, Brian Walker, YingPing Wang, Lu Zhang

CDAS Workshop, Boulder, CO, USA, 19 May 2002
Outline

1. The Global Carbon Cycle
2. Model-Data Fusion
3. Multiple Constraints
   • Toolbox
   • Examples
4. The Global Carbon Project
5. Future directions
Atmospheric CO$_2$: past and future

- Last 420,000 years: Vostok ice core record (blue)
- Last 100 years: Contemporary record (red)
- Next 100 years: IPCC BAU scenario (red)
Global carbon budget 1980-1999
Fluxes in GtC/year  (IPCC Third Assessment Report, Vol 1)

<table>
<thead>
<tr>
<th></th>
<th>1980s</th>
<th>1990s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atmospheric C accumulation</td>
<td>3.3 ± 0.1</td>
<td>3.2 ± 0.2</td>
</tr>
<tr>
<td>= Emissions (fossil, cement)</td>
<td>5.4 ± 0.3</td>
<td>6.4 ± 0.6</td>
</tr>
<tr>
<td>+ Net ocean-air flux</td>
<td>-1.9 ± 0.5</td>
<td>-1.7 ± 0.5</td>
</tr>
<tr>
<td>+ Net land-air flux</td>
<td>-0.2 ± 0.7</td>
<td>-1.4 ± 0.7</td>
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<tr>
<td>Net land-air flux</td>
<td>-0.2 ± 0.7</td>
<td>-1.4 ± 0.7</td>
</tr>
<tr>
<td>= Land use change emission</td>
<td>1.7 (0.6 to 2.5) Assume 1.6 ± 0.8</td>
<td></td>
</tr>
<tr>
<td>+ Terrestrial sink (residual)</td>
<td>-1.9 (-3.8 to 0.3)</td>
<td>-3.0 ± 1 (?)</td>
</tr>
</tbody>
</table>
Spatial distributions of C sources and sinks


- Latitude distribution of C sources from land, ocean, fossil-fuel emissions
- From atmospheric inversions (mean of 8 different models and data sets)
- Left bars: 1980s; right bars: 1990s

![Graph showing the spatial distribution of C sources and sinks across different latitudes and time periods.](image)

- **Southern (< 30S)**: ocean is a sink
- **Tropical (30S to 30N)**: land + ocean are roughly in net C balance
- **Northern (> 30N)**: land + ocean is a sink
Temporal variability in C sources and sinks
Roger Francey, CSIRO Atmospheric Research

![Graph showing temporal variability in C sources and sinks](image-url)
Major questions

- **Patterns and Variability:** What are the current geographical and temporal distributions of the major stores and fluxes in the global carbon cycle?

- **Processes, Controls and Interactions:** What are the control and feedback mechanisms – both anthropogenic and non-anthropogenic – that determine the dynamics of the carbon cycle over time?

- **Carbon Futures:** What are the likely dynamics of the global carbon cycle into the future?

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- Space scales: Global to local
- Time scales: 1 to $>10^6$ years
- Interactions between the natural C cycle and human influences on it
- Current relevance:
  - Measurement and management of terrestrial C sinks (political issue)
  - Future of the carbon-climate-human system over next century
Part 2: Model-data fusion

- What is it?
- Why is it important? The big questions
- Atmospheric data assimilation at three scales
  - Vegetation canopy
  - Atmospheric boundary layer
  - Globe
What is model-data fusion?

- Some names:
  - Inverse methods (atmospheric, oceanic, biogeochemical)
  - Synthesis inversion
  - Data assimilation
  - Parameter estimation
  - Multiple constraints
  - Model-data fusion

- Attempted definition: Model-data fusion = the introduction of observations into a modelling framework, to provide:
  - **Estimates** of model parameters (numbers we'd like to know but don't)
  - **Uncertainties** on parameters and model output
  - **Ability to reject** a model, through a measure of goodness of fit

(Heimann and Kasibhatla 2000; Press et al 1992, "Numerical Recipes")
Why model-data fusion is important

- We cannot do manipulative experiments with the earth system
- Many parameters are not measurable at earth system scales, because of
  - High small-scale spatial variability (e.g., leaf area index, any soil property)
  - High temporal variability (e.g., stomatal conductance)
  - Physical inaccessibility (e.g., most roots, deep soil, aquifers, most of ocean)
- Model-data fusion is the counterpart for earth system science of manipulative experimentation for classical process science
Atmospheric data assimilation (DA) to find fluxes from concentration measurements: general (1)

- Surface-air fluxes (or sources and sinks) of water, CO₂ and other entities alter atmospheric concentrations, leaving signals in the atmosphere.
- Atmospheric DA methods seek to find fluxes (F) or sources and sinks (S) from measurements of perturbations in concentrations (C).
- C perturbations are:
  - mixed by atmospheric diffusion
  - short-lived
  - contain inherent spatial averaging
- Scales: canopy, small plot, region (ABL), continent, globe
Atmospheric data assimilation (DA) to find fluxes from concentration measurements: general (2)

- Invert

\[ C_i - C_0 = \sum_j G_{ij} S_j \]

- by minimising

\[ J = \sum_i \left( \tilde{C}_i - \tilde{C}_0 - \sum_j G_{ij} S_j \right)^2 \]

\[ = \sum_i \left( \text{measured } C_i - \text{predicted } C_i \right)^2 \]
Atmospheric DA at canopy scale
Dispersion matrix or Green’s function

**Dispersion matrix:**
- Specifies C profiles from unit sources in a set of canopy layers
- Can be found with a forward Lagrangian model of canopy dispersion, either Eulerian (e.g., higher order closure) or Lagrangian (e.g., Localised Near Field)

Dispersion matrix from Localised Near Field (analytic Lagrangian) theory
Atmospheric DA at canopy scale

- Concentration profiles in Wagga wheat
- (Denmead et al. 1995)
  - Temperature
  - Humidity
  - \([\text{CO}_2]\]

Wagga, October 23
◆ Canopy EXAMPLE: Rice (Leuning 2000)
Inverse Lagrangian and eddy covariance estimates of latent heat and CO2 fluxes

![Graphs showing daily variation of latent heat and CO2 fluxes.](image-url)
**Canopy EXAMPLE:** Rice (Leuning 2000)
Vertical distribution of water vapour and $\text{CO}_2$ sources from Inverse Lagrangian
Atmospheric DA at boundary layer (ABL) scale

- **Temperature structure of CBL**
- **OASIS, Oct 1995, New South Wales (Cleugh and colleagues, CSIRO)**

Lockhart Airsonde Flights: October 25, 1995
Atmospheric DA at ABL scale

- CO$_2$ structure in CBL
- Mid-day CO$_2$ profile over a pasture landscape at Bungendore, NSW, in August 1973
- Garratt, Pearman and Denmead (1973, unpublished)
Atmospheric DA at ABL scale
Use of bulk Convective Boundary Layer (CBL) budgets

Horizontally fixed column: wind blows through sides and roof

Column moving with wind: roof grows with h(t), sides deform

\[
\frac{dc_a}{dt} = \frac{F_C}{\rho_a h} + \frac{\rho_+ (c_+ - c_a)}{\rho_a h} \left( \frac{dh}{dt} - W_+ \right)
\]

\[
\frac{d\delta_a}{dt} = \frac{F_C (\delta_p - \delta_a)}{\rho_a c_a h} + \frac{\rho_+ c_+ (\delta_+ - \delta_a)}{\rho_a c_a h} \left( \frac{dh}{dt} - W_+ \right)
\]

Use this to infer surface scalar flux or ecosystem discrimination from diurnal course of concentration or isotopic composition
ABL EXAMPLE 1: Daytime CBL budget estimates of trace gas fluxes at OASIS 1995 (Denmead et al 1999)

- Comparison of time-integrated (ICBL) budget and micromet measurements
- Heterogeneity (1 to 100 km) =>
  - can’t extrapolate accurately from near-surface C to mixed-layer C
  - Should include advection term in Eulerian budget, or use Lagrangian measurements
Atmospheric DA at ABL scale
Effects of height-time concentration variation near the ground

- OASIS, Oct 1995, Wagga, NSW (Griffith and Jamie, Wollongong University)

![Graph showing mixing ratio in parts per million (ppmv) over hours of the day for different heights.]

- 358 ppm
- 22 m
- 14 m
- 8 m
- 4 m
- 2 m
- 1 m
- 0.5 m
Atmospheric DA at global scale
Global Example 1:
Global CO$_2$ flux
distribution 1988-92

- Mean values (GtC/y)
  (Sum = - 2.9 GtC/y
   = - dCa/dt)

- Uncertainties (GtC/y)

- Peter Rayner, CSIRO
  Atmospheric Research
Global Example 2: Better temporal resolution reduces uncertainty
Peter Rayner, CSIRO Atmospheric Research

- 77 CO₂ sites
- Monthly average

- 77 CO₂ sites
- Daily average for Cape Grim
Part 3: Multiple Constraints

- Emphasis on terrestrial fluxes
- Techniques (a box of nuts and bolts)
- Kinds of observation
  - Atmospheric composition
  - Eddy fluxes and ecophysiology
  - Ecology and pedology
  - Remote sensing
- Examples to date
Techniques for model-data fusion

General problem

- We are given

<table>
<thead>
<tr>
<th>A set of ( M ) observations:</th>
<th>( \tilde{y} \in \mathbb{R}^M )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observation errors:</td>
<td>( y' = \tilde{y} - \langle \tilde{y} \rangle )</td>
</tr>
<tr>
<td>Covariance matrix for errors in observations:</td>
<td>( C = C_{ij} = \langle y'_i y'_j \rangle ) with inverse ( B = C^{-1} )</td>
</tr>
<tr>
<td>A model of the observed quantities:</td>
<td>( y(a) \in \mathbb{R}^M )</td>
</tr>
<tr>
<td>A set of ( K ) parameters:</td>
<td>( a \in \mathbb{R}^K )</td>
</tr>
<tr>
<td>Prior estimates for the ( K ) parameters:</td>
<td>( \tilde{a} \in \mathbb{R}^K )</td>
</tr>
<tr>
<td>Errors in the ( K ) prior parameter estimates:</td>
<td>( a' = \tilde{a} - \langle \tilde{a} \rangle )</td>
</tr>
<tr>
<td>Covariance matrix for errors in priors:</td>
<td>( c = c_{ij} = \langle a'_i a'_j \rangle ) with inverse ( b = c^{-1} )</td>
</tr>
</tbody>
</table>

- What parameters \( (a) \) give best agreement between model and observations?
- What are the uncertainties in these parameters, given the uncertainties in observations and prior parameter estimates?
- What is the goodness-of-fit?
Techniques for model-data fusion

General solution

- Provided the errors are Gaussian, the optimum parameters are
  \[^{a^*} = \min\left(J_y(a) + J_a(a)\right)\]
  with
  \[J_y(a) = \left[y(a) - \bar{y}\right]^T B \left[y(a) - \bar{y}\right]\]
  (cost function for model-measurement difference)
  \[J_a(a) = \left[a - \hat{a}\right]^T b \left[a - \hat{a}\right]\]
  (cost function for parameter-prior difference)

- Use of prior estimates: omit -> maximum-likelihood parameter estimates
  include -> Bayesian parameter estimates
  (fold priors into measurement vector)

- Atmospheric data assimilation: \(y = (M \text{ predicted concentrations})\)
  \(a = (K \text{ sources})\)

  Problem is linear in \(a\) (for conserved species)

- Multiple constraints:
  \(y\) is a composite vector of multiple measurements
  \(a\) is a set of model parameters

  Problem is generally nonlinear in \(a\)
Techniques for model-data fusion

The linear case: solution for parameters

- Model (linear in parameters $a$):
  \[
  \mathbf{y} = \mathbf{F} \mathbf{a}
  \]

- This is an overdetermined system ($M>K$), so the optimum $a$ minimises $|\mathbf{F}a - \tilde{y}|$

- Singular Value Decomposition (SVD) of $\mathbf{F}$:
  \[
  \mathbf{F} = \mathbf{U} \mathbf{W} \mathbf{V}^T
  \]
  - $\mathbf{W} = \text{diag}(w_1, \ldots, w_K)$ is diagonal
  - Columns of $\mathbf{U}$ with nonzero $w_j$ form an orthonormal basis for range of $\mathbf{F}$ (in $\mathbf{y}$ space)
  - Columns of $\mathbf{V}$ with zero $w_j$ form an orthonormal basis for nullspace of $\mathbf{F}$ (in $\mathbf{a}$ space)

- Optimum solution for $a$:
  \[
  \mathbf{a}^* = \mathbf{U}^T \mathbf{W}^{-1} \mathbf{V} \tilde{y}
  \]
  \[
  a_k^* = \sum_{j=1}^{K} \frac{V_{kj} U_{mj} \tilde{y}_m}{w_j} \quad \text{(including only } w_j \neq 0)\]
Techniques for model-data fusion
The linear case: uncertainty in parameters

- Uncertainty in $\mathbf{a}$:

\[
\langle \hat{a}_j \hat{a}_k \rangle = \sum_{p,q=1,K}^{p,q=1,K} \frac{V_{jp} V_{kq} U_{mp} U_{nq}}{w_p w_q} C_{mn}
\]

\[
\langle \hat{a}_j \hat{a}_k \rangle = \sigma^2 \sum_{p=1,K} V_{jp} V_{kp} \frac{1}{w_p^2} \quad \text{(when } C_{mn} = \sigma^2 \delta_{mn})
\]

- Column vectors of the orthonormal matrix $\mathbf{V}$ are the principal axes of the error ellipsoid for the fitted parameters $\mathbf{a}$.
Techniques for model-data fusion
The linear case: goodness-of-fit of model

- Goodness-of-fit: \( J(a^*) \) has a chi-square distribution with \( M-K \) degrees of freedom

\[
\text{Prob}(J > \chi^2) = Q(\chi^2 | M-K) = 1 - P\left(\frac{M-K}{2}, \frac{\chi^2}{2}\right)
\]
with
\[
P(b, x) = \frac{1}{\Gamma(b)} \int_0^x e^{-s} s^{b-1} ds
\]

- \( Q(J(a^*)/M-K) \) is the fraction of data realisations more scattered around optimised plot than the actual data:
  - \( Q << 1 \) => improbably poor fit => reject model (or \( C_{mn} \) underestimated)
  - \( Q \) close to 1 => improbably good fit => \( C_{mn} \) is overestimated
Techniques for model-data fusion
The nonlinear case

- Nonlinear model (evaluated at $M$ points where observations exist):

  $$ y = f(a) $$

- Tangent Linear Model:

  $$ \delta y_m = \sum_{k=1}^{K} \frac{\partial f_m}{\partial a_k} \delta a_k $$

  or

  $$ \delta y = A \delta a \quad \text{with} \quad A = \text{Jacobian} \quad A_{mk} = \frac{\partial f_m}{\partial a_k} $$

- Steepest descent:

  $$ a_{\text{new}} = a_{\text{old}} - \lambda \nabla_a J(a_{\text{old}}) $$

- Newton's method:

  $$ a_{\text{new}} = a_{\text{old}} - H^{-1} \cdot \nabla_a J(a_{\text{old}}) \quad \text{with} \quad H = \text{Hessian} = 2A^T B A $$

- Levenberg-Marquardt: interpolates between steepest descent and Newton

- Uncertainty and goodness-of-fit: use quasilinear analysis around minimum
Techniques for model-data fusion
Search methods

- **Linear model** \( (y = Fa) \):
  - SVD returns minimum directly for small to moderate number of parameters \( K \)
  - Kalman filter: for finding optimum time-dependent parameters

- **Nonlinear model** \([y = f(a) \text{ with nonlinear } f(a)]\):
  - Levenberg-Marquardt
    - Simple versions requires Jacobian matrix \( A = \text{grad}_a f \)
    - Good for small number of parameters \( K \)
  - Adjoint of Tangent Linear Model
    - A method for finding \( \text{grad}_a J \)
    - Good for large number of parameters \( K \)
    - Requires adjoint linear model \( A^* \) (obtained analytically or by symbolic differentiation)
    - Used in meteorological data assimilation
  - Genetic algorithm: good for lumpy objective functions \( J(a) \)
Multiple constraints: kinds of observation

- Atmospheric and oceanic composition
  - In-situ atmospheric data (baseline stations, flask network, towers)
  - In-situ oceanic data (cruises, buoys, ships of opportunity)
  - Space-based observations

- Eddy fluxes and ecophysiological data

- Ecological and pedological data

- Remote sensing of land and ocean surfaces
Atmospheric composition observations
Cape Grim Baseline Air Pollution Station

- CSIRO Atmospheric Research and Bureau of Meteorology
- Located on the northwest Tasmanian coast to sample air from the Southern Hemisphere marine boundary layer
Atmospheric composition

- GASLAB, CSIRO Atmospheric Research
- Baseline air at Cape Grim, NE Tasmania
Eddy fluxes

- OASIS 1995: Wagga Wagga region, NSW
- Eddy covariance and routine weather measurements at Browning site
- Surface: improved pasture, LAI about 1.5
- CSIRO Land and Water
Data: OASIS
Model: SCAM
FLUXNET
Integrating Worldwide $CO_2$ Flux Measurements
Biomass observations

Annual growth of Eucalypt species

- **Annual increment (tC/ha)**
  - **pauciflora**
  - **sieberi**
  - **globulus**

- **Control: aboveground**
- **P added**
- **Control: belowground**
- **P added**

- **CSIRO Forestry and Forest Products (Heather Keith)**
Remote sensing
NOAA AVHRR: the NDVI and Land Surface Temperature (LST) record

- Dean Graetz, CSIRO Earth Observation Centre
- Trajectory of the Australian continent in (LST, NDVI) space over 3 years

![Plot showing the trajectory of the Australian continent in (LST, NDVI) space over three years, with distinct periods marked as 1982-83 (Drought), 1983-84 (Transition), and 1984-85 (Wet).]
Techniques for model-data fusion
Multiple constraints (1: data)

- **Data** \( (\mathbf{y}) \) is a composite vector of multiple measurements, for instance:
  - \( (i = 1) \) Atmospheric composition
  - \( (i = 2) \) Eddy fluxes and ecophysiological data
  - \( (i = 3) \) Ecological and pedological data
  - \( (i = 4) \) Remote sensing

\[
\mathbf{a}^* = \min \left[ \left( \sum_{\text{data types } (i)} J_y^{(i)}(\mathbf{a}) \right) + J_a^{(i)}(\mathbf{a}) \right] \quad \text{with}
\]

\[
J_y^{(i)}(\mathbf{a}) = \left[ \mathbf{y}^{(i)}(\mathbf{a}) - \tilde{\mathbf{y}}^{(i)} \right]^T \mathbf{B}^{(i)} \left[ \mathbf{y}^{(i)}(\mathbf{a}) - \tilde{\mathbf{y}}^{(i)} \right] \quad \text{model-measurement difference for data type } i
\]

\[
J_a(\mathbf{a}) = [\mathbf{a} - \tilde{\mathbf{a}}]^T \mathbf{b} [\mathbf{a} - \tilde{\mathbf{a}}] \quad \text{(parameter-prior difference)}
\]
Techniques for model-data fusion
Multiple constraints (2: model)

- **Model** requirements:
  - Must have a forward model in which all observed quantities \((y)\) are state variables or derived from state variables by submodels (or: Stand on feet before trying to stand on head)
  - Predictions for different types of observable \([y^{(i)}]\) must involve some common parameters from the set \(a\) (otherwise no mutual constraint)
  - Parameters must be defined on **same scale** in all submodels

- Models will include a terrestrial biosphere model (TBM) and an atmospheric transport model (ATM - only if atmospheric concentrations are to be used)

- **TBM**:

  Conservation equations for stores \((x)\):
  \[
  \frac{\partial x_r}{\partial t} = \sum_{\text{processes } s} f_{rs}
  \]

  Phenomenological equations for fluxes \((f_{rs} = f)\):
  \[
  f = f(x, v, a)
  \]

  Equations for observables \((y)\):
  \[
  y = y(x, v, a)
  \]

  These include parameters \((a)\) and independent variables \((v)\)
Techniques for model-data fusion
Multiple constraints (3: constraints)

- Different data types yield different estimates of the same set of parameters $a$
Multiple constraints: Example 1
Heat, water and CO2 source profiles in a Siberian forest (Styles et al 2002)

◆ **Aim:** find source profiles of heat, water vapour and CO2, especially the canopy-ground partition, in a Siberian coniferous forest

◆ **Method:** nonlinear estimation of biological and physical parameters (rather than direct estimation of sources using Green's functions)

◆ **Data:** profiles of temperature, humidity, CO2, 13C and 18O in CO2, plus meteorological data

◆ **Optimised parameters:** ground/total flux ratios, photosynthetic capacity, Lagrangian turbulent time scale parameter, radiation extinction coefficients (total of 9 parameters)

◆ **Search method:** Levenberg-Marquardt

EXAMPLE 1: Siberian forest (Styles et al 2002)

- Profiles of CO2 and water vapour concentration (measured and fitted)
**EXAMPLE 1:** Siberian forest (Styles et al 2002)
- Compare inverse and eddy covariance fluxes

Fluxes with stability correction
- Water vapour
- Sensible heat

**CO2 flux without and with stability correction**
Multiple constraints: Example 2
Global CO2 data and terrestrial biosphere model (Kaminski et al 2002)

- **Aim:** Predict global distribution of terrestrial CO2 fluxes (NPP, respiration)
- **Method:** optimise parameters in a terrestrial biosphere model coupled with an atmospheric transport model, using CO2 data
- **Data:** annual cycle of CO2 concentration at about 80 sites, plus meteorological data
- **Optimised parameters:**
  - 2 biophysical parameters: light use efficiency (LUE) Q10 for heterotrophic respiration
  - $ \times $ 12 biomes
  - $ = $ 24 parameters
- **Constraint:** annual averages of NPP and heterotrophic respiration are equal
- **Search method:** adjoint (code generation with TAMC)
- **Reference:** Kaminski, Knorr, Rayner and Heimann (2002, Tellus, in press)
EXAMPLE 2: Global CO2 data and terrestrial biosphere model (Kaminski et al 2002)

- Fitted parameters
  - LUE
  - Q10

- Box: prior
  Cross, bar: fitted

- Reduced uncertainties (CO2 has constrained process information)

- High fitted LUE in high latitude biomes

- Pseudoflux data in 1 biome (broadleaf evergreen) halves uncertainty in that biome
**EXAMPLE 2:** Global CO2 data and terrestrial biosphere model (Kaminski et al 2002)

- Predicted NPP with NPP from Potsdam Intercomparison
EXAMPLE 2: Global CO2 data and terrestrial biosphere model (Kaminski et al 2002)

- Predicted [CO2] compared with observations
Multiple constraints: Example 3
Ecological data to constrain the terrestrial C cycle (Barrett and Xu 2002)

- **Aim:** Predict spatial distribution of long-term mean NPP and C stores, with uncertainties, for the Australian continent

- **Method:** optimising parameters in a terrestrial C cycle model

- **Data:** NPP, biomass, litter, soil C at up to 600 nominally undisturbed sites across Australia (from literature) plus meteorological data

- **Optimised parameters:** turnover times, C allocation ratios, humification ratios, light use efficiency

- **Constraint:** steady state

- **Search method:** Genetic algorithm

EXAMPLE 3: Ecological data (Barrett and Xu 2002)

- Heterotrophic respiration as a function of depth

Soil C flux from heterotrophic respiration:
- More than 89% from < 20cm depth
- More than 98% from < 50cm depth
**EXAMPLE 3a:** Data and BGC model (Raupach et al 2002)
- Australian Net Primary Production, without and with agricultural inputs

- Australian NPP without agricultural inputs of nutrients and water
- Ratio: \(\frac{\text{NPP with agric}}{\text{NPP without agric}}\)

EXAMPLE 3a: Data and BGC model (Raupach et al. 2002)

- Continental N balance
Multiple constraints: Example 4
Atmospheric, ecological and remote sensing data (Wang and Barrett 2002)

- **Aim:** Predict spatial distribution of long-term mean NPP, NEP, model parameters and other derived quantities (with uncertainties) for the Australian continent
- **Method:** optimising parameters in coupled ATM (DARLAM) and TBM (CBM)
- **Data:** Cape Grim CO2 plus VAST ecological data set
- **Optimised parameters:** photosynthetic and respiration parameters in CBM
- **Constraint:** steady state
- **Search method:** Kalman filter
Estimates of CBM parameters

Mean of maximum electron transport rate

Plant respiration rate at 20C

Leaf respiration rate at 20C

Soil respiration rate at 20 C
Monthly C flux for SE Australia (region D) using approach I (white) or I+II (red)
EXAMPLE 4: Dust

- Predictions for the dust storm of 9 February 1996:
  - dust entrainment flux
  - Surface (10 m) dust concentration
  - Column-integrated concentration
  - Friction velocity and threshold friction velocity

- Lu and Shao (2001)
EXAMPLE 4:
Dust

- Correlation between scattering coefficient and wind speed at Tinga Tingana, South Australia, Birdsville Race Day dust storm (1 September 2000)
EXAMPLE 5
Distribution of anthropogenic C sources

- Earth at night
Earth System Science Partnership

Integrated Regional Studies

START, PAL, others

Joint Projects on Global Sustainability

Carbon
Water
Food

WCRP

Diversitas

IGBP

IHDP
Global Carbon Project: Science Themes

1. Patterns and Variability
   - Focus 1: Patterns and variability in the contemporary carbon cycle

2. Processes, Controls, and Interactions
   - Focus 2: Processes contributing to current C sources and sinks

3. Carbon Futures
   - Focus 3: Carbon cycle dynamics and evolution
Global Carbon Project: Activities

◆ Pilot Activities (1-2 years)
  1. Summer Schools on integrative aspects of the global carbon cycle (first on Data-Model Assimilation, Colorado 2002)
  2. Rapid Assessment of Carbon Cycle (jointly with SCOPE) – 2003
  3. Attribution of terrestrial carbon sinks as per the Kyoto Protocol requirements (elevated CO2, N deposition, forest age structure) (jointly with IPCC and GCTE)

◆ Core Activities (5-10 years)
  1. Improving understanding of space-time patterns in the contemporary carbon cycle
  2. Emergent properties of the coupled carbon cycle-climate system
  3. Carbon cycle consequences of regional development pathways
  4. Evolution of carbon sources and sinks through the 21st century
Global Carbon Project: Operational structure

- Scientific Steering Committee (15 members plus 3 co-chairs)
- Executive Subcommittee of SSC
- Offices (each with an executive officer, possibly shared with another program)
  - Australia
  - US
  - Japan
  - Others
- Working with other projects and stakeholders
  - GCP Framework document: now under community review
  - Joint implementation (SCOPE, IGCO, Ocean CO2, ...)

Working with other projects and stakeholders
Human-biosphere interaction as a dynamical system: a two-equation model

- **State variables:**
  - $B(t) = \text{biomass}$
  - $H(t) = \text{human population}$

- **Dynamical equations:**
  - $\frac{dB}{dt} = N - kB - E$
  - $\frac{dH}{dt} = g(E - mH)$

- **Model for resource production:**
  - $E = cBH$
  - more humans extract more biospheric resource
  - each human extracts better as the biomass increases (B is a surrogate for quality of life)
Human-biosphere interaction as a dynamical system: a two-equation model

- Dynamical equations: \( \frac{dB}{dt} = N - kB - E \), \( \frac{dH}{dt} = g (E - mH) \)

- Model for resource production: \( E = cBH \)

- Parameters:
  - \( N \) = Net Primary Production of biomass
  - \( k \) = rate constant for autotrophic respiration
  - \( c \) = rate constant per human for resource usage
  - \( m \) = biomass maintenance need per human
  - \( g \) = population growth rate

- Steady states:
  - \( B = \frac{N}{k}, \ H = 0 \) (attractor when \( H(0) = 0 \))
  - \( B = \frac{m}{c}, \ H = \frac{N}{m} - \frac{k}{c} \) (attractor when \( H(0) > 0 \))
Human-biosphere interaction as a dynamical system
Trajectories on a (B,H) plane for 6 scenarios

- Eden
- Occupy
- Disaster
- Grow
- Subsist
- Exploit
Human-biosphere interaction as a dynamical system: a two-equation model

- Conclusions from this simple model:
  - Captures many aspects of human-biosphere interactions
    - when $H(0) > 0$: steady-state $B$ is independent of NPP
      steady-state $H$ increases with NPP
    - when $H(0) = 0$: steady-state $B$ increases with NPP
  - growth, crash, equilibrium (Flannery: the Future Eaters)
  - subsistence (low $m$) $\Rightarrow$ high $H$, low $B$ at steady state
  - rapid growth (high $g$) $\Rightarrow$ instability, wild oscillations
  - exploitative resource use (high $c$) $\Rightarrow$ low $B$, lowish $H$ at steady state
  - These define properties of $m$, $g$ and $c$ for a resilient system
  - Surprising, unexpected results (though understandable with 20/20 vision of hindsight)
  - Qualitative only, should not be pushed too far into the quantitative
Some directions over 5-10 years

◆ **Observations**
  - Increasing international coordination of in-situ observational networks
  - Continuing challenges with data consistency and longevity, especially for research-based networks (e.g., Fluxnet) and national data (e.g., stocks)
  - Atmospheric composition measurements from space

◆ **Model-data fusion**
  - Multiple-constraint approaches will become widespread
  - Weather and climate models will assimilate BGC data for their own purposes
  - Extensions to other entities (gases, dust, …)
  - Possibilities for environmental monitoring and management (water, …)
  - Search for models of human dimensions of global change which satisfy formal criteria for model-data fusion

◆ **Global management of the C cycle**
  - Terrestrial sinks will remain a political issue (uncertainty, equity, longevity)
  - Increased stress on conservation, efficiency, energy transformations
Thanks

Hilary Talbot