Assimilating EO Data into Terrestrial Carbon Cycle Models

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The current challenge in C cycle research

<table>
<thead>
<tr>
<th>Objective</th>
<th>To produce estimates &amp; predictions of ecosystem carbon exchange with quantifiable uncertainty.</th>
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<tbody>
<tr>
<td>Complications</td>
<td>Observations have gaps &amp; instrumental weaknesses. Models tend to oversimplify and may miss key processes and linkages.</td>
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<td>Solution</td>
<td>Data assimilation provides a method to combine models and data to produce a more accurate description of ecosystem dynamics.</td>
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Global Carbon Data Assimilation System

Geo-referenced emissions inventories

Atmospheric measurements

Remote sensing of atmospheric CO₂

Atmospheric Transport Model

Optimised fluxes

Optimised model parameters

Ocean time series

Biogeochemical pCO₂

Surface observation pCO₂ nutrients

Water column inventories

Ocean Carbon Model

Terrestrial Carbon Model

Eddy-covariance flux towers

Biomass soil carbon inventories

Ecological studies

Ocean remote sensing

Ocean colour

Atmospheric

Winds

SST

SSS

Remote sensing of vegetation properties

Growth cycle

Fires

Biomass

Radiation

Land cover/use

Source: Ciais et al. 2003 IGOS-P Integrated Global Carbon Observing Strategy
Terrestrial component

- Remote sensing of atmospheric CO₂
- Atmospheric Transport Model
- Terrestrial Carbon Model
- Optimised model parameters
- Optimised fluxes
- Climate and weather fields
- Terrestrial Carbon Model
- Eddy-covariance flux towers
- Biomass soil carbon inventories
- Ecological studies
- Remote sensing of vegetation properties
  - Growth cycle
  - Fires
  - Biomass
  - Radiation
  - Land cover/use
- Lateral fluxes
This lecture
Issues

◆ Monitoring
  Consistency of models and data:
  - are model and measurement quantities compatible?
  - comparability of values
  Timescales (re-analysis)

◆ Prediction
  Are model internal processes and parameters testable and credible?
$S$ is the state vector describing the vegetation-soil system.

The Functioning of a DVM

Climate → Parameters → DVM → Soil → $S_1$ → DVM → $S_2$
Calibrating the SDGVM phenology module with EO data
SIBERIA-II: Multi-Sensor Concepts for Greenhouse Gas Accounting of Northern Eurasia
5th Framework Project, 2002-2005
The Central Siberia dataset: ~ 2 M km²

Land cover (IIASA)  

1° x 1° forest map  

Lake Baikal
The CESBIO budburst algorithm

- Data set: SPOT-VEG 1999-2001
- Based on minimum in time-series of NDWI data
- Uncertainties in recovered budburst date ~ 7 days
The Date of budburst derived from minimum NDWI (VGT sensor, 2000) N. Delbart, CESBIO
When $\sum_{\text{days}} \min(0, T - T_0) > \text{Threshold}$, budburst occurs.

The sum is the red area. Optimise over the 2 parameters, Threshold and $T_0$ (minimum effective temperature).
The calibration procedure
Data - model comparison 1999

Budburst from NDWI data

Model budburst: optimised parameters
## Calibration parameters (forest only)

<table>
<thead>
<tr>
<th>Year</th>
<th>$T_0$ (degrees)</th>
<th>Threshold (degree-days)</th>
<th>MMSE (days)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1999</td>
<td>-2.9</td>
<td>117</td>
<td>6.0</td>
</tr>
<tr>
<td>2000</td>
<td>4.4</td>
<td>29</td>
<td>7.0</td>
</tr>
</tbody>
</table>
Green-up relation to N Pacific Index

The NP Index is averaged from April the previous year to March the present year.

- Observed greenup
- Modeled greenup
- North Pacific index

Day of Greenup vs. North Pacific Index over the years 1980 to 2000.
Effect of uncertainty in green-up day

![Chart showing the effect of uncertainty in green-up day on Monthly Net Primary Productivity (gC/m²/month). The chart compares NPP with threshold 100 degree.day and NPP with threshold 200 degree.day. The peak of NPP occurs around July, with a notable decrease in productivity in the winter months. The mean bud burst is marked by a triangle on the chart.]
‘True’ Assimilation

Vegetation model

Observation model (forward model)

Scattering or reflectance model

Modify model state to improve consistency between data and prediction

Compare prediction with measurement
Basis of radiation models (optical)

- pigments
- 'structure'
- dry matter
- water

Leaf scattering model

Leaf reflectance and transmittance

Graph showing normalized absorption with wavelength in nm.
Model of canopy scattering:
- Leaf properties
- Scattering object density (LAI), orientation, and spatial distribution
- Soil / understorey properties for low density canopies

solutions by analytical or numerical methods
Link to the C models

◆ **C models include concept of radiation model**
  – For calculation of intercepted radiation

◆ **Observation model**
  – Provides link from *subset* of C-model state variables to EO observation
  – Main linkages:
    ◆ LAI, Density (for limited conditions)
    ◆ leaf properties (hyperspectral data)
      – leaf dry matter, chlorophyll (nitrogen), water
      – xanthophyll cycle (light use efficiency)
Exploiting quantities derived from radiance
The propagation of the light follows the Beer-Lambert Law:

\[ I(l) = PAR \cdot \exp(-Kl) \]

One gets:

\[ fAPAR = 1 - \exp(-K \cdot LAI) \]

-> In SDGVMd, fAPAR and LAI are linked in a deterministic way.
Application of the models

- Testing C models (SDGVM)
  - Confront predictions with observations

![Graph showing trends over time]
A prediction-correction system

Time update “predict”

Measurement update “correct”
R<sub>total</sub> & Net Ecosystem Exchange of CO<sub>2</sub>

GPP

6 model pools
10 model fluxes
9 rate constants
10 data time series

C = carbon pools
A = allocation
L = litter fall
R = respiration (auto- & heterotrophic)

Temperature controlled
b) GPP data + model: SD=123

c) GPP & respiration data + model: SD=53

d) All data: SD=26
Pools and fluxes

Carbon model

Hydrology

Flux emulator

Predicted flux

State variable
Linking C and water fluxes

Flux

Input to emulator

Radiation, VPD temperature

Soils data

GPP

Driver data

Flux emulator

Predicted flux

State variable
Conclusions

- Calibration of DVM parameters with EO data provides a means to improve the predictive power of the models, e.g., phenology, fire.
- Well-developed forward models for scattering and reflectance exist; a current challenge is to interface them to biospheric models for monitoring and assimilation.
- Because of possible problems in derived products, such as fAPAR, assimilation of radiances seems preferable. However, this is dependent on how radiation absorption is represented in the biospheric model.
- Successful assimilation schemes have just been developed for biospheric models. By using existing forward models, these provide a framework for assimilating EO data.
- Watch this space!