Regional to Continental Upscaling of AmeriFlux Data for Carbon Cycle Studies: Progress, Challenges, and New Directions

Jingfeng Xiao, Kenneth J. Davis
Penn State

Xuihui Zhou, Yiqi Luo, Tao Zhou
University of Oklahoma

Markus Reichstein, Martin Jung, Enrico Tomelleri, Christian Beer
Max-Planck Institute for Biogeochemistry

Li Zhang¹, Bruce K. Wylie²
Chinese Academy of Sciences¹; USGS EORS Data Center²

Leo Liu, Wenping Yuan
USGS EROS Data Center

Ankur Desai
University of Wisconsin, Madison

Maosheng Zhao, Steven Running
University of Montana

Ben Bond-Lamberty
Joint Global Change Research Institute

Steven C. Wofsy
Harvard University

2nd NACP All-Investigators Meeting
Feb. 17-20, 2009, San Diego, CA
FLUXNET: a global network of eddy covariance flux tower sites
Upscaling approaches

• Machine learning approaches
• Ecosystem models and data assimilation
• Water balance approaches
Upscaling of flux tower GPP and NEE to the northern Great Plains

Li Zhang and Bruce K. Wylie

lizhang@ceode.ac.cn    wylie@usgs.gov

<table>
<thead>
<tr>
<th>Site</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lethbridge</td>
<td>2000–2001</td>
</tr>
<tr>
<td>Fort Peck</td>
<td>2000,2002</td>
</tr>
<tr>
<td>Mandan</td>
<td>2000–2002</td>
</tr>
<tr>
<td>Miles City</td>
<td>2000–2001</td>
</tr>
<tr>
<td>Brookings</td>
<td>2006</td>
</tr>
<tr>
<td>CPER</td>
<td>2000–2001</td>
</tr>
</tbody>
</table>
Piecewise Regression (PWR) Tree Model

8-day Summaries
- Flux Tower
- Remote Sensing
- Climate
- Soil

C Flux Piecewise Regression

OUTPUT

500m and 8-day GPP/NEE Maps
Mean of annual NEE (2000-2006)

Continuous measures of GPP and NEE based on MODIS and AmeriFlux data


jing@psu.edu
Mean annual GPP and NEE (2001-2006)

Preliminary results
Annual NEE anomaly

\((g \, C \, m^{-2} \, yr^{-1})\)

Preliminary results
FLUXNET sites

Preliminary results

Martin Jung and Markus Reichstein et al.

mjung@bgc-jena.mpg.de; markus.reichstein@bgc-jena.mpg.de

3688 site-months from 188 sites
Input

- JRC-FAPAR (Gobron et al. 2006)
- mean annual FAPAR characteristics (max, min, mean, etc.)
- potential radiation
- CRU climatology (30 year means)
- (ECMWF ERA INTERIM air temperature)

Model Tree Induction Algorithm: TRIAL (Jung et al. in prep)
Mean annual GPP: 6.7 – 7 Pg C yr\(^{-1}\)  
Mean annual \(R_e\): 5 – 5.2 Pg C yr\(^{-1}\)  
Mean annual NEE: 1.5 – 2.0 Pg C yr\(^{-1}\)  

1998-2005 mean  

Preliminary results
Machine learning approaches

- Digest data from a large number of sites and years
- Capture nonlinear relationships
- Allow continuous and discrete variables as input variables
- Are not heavily influenced by outliers
- Are completely transparent
- Need large numbers of sites and years for robust models
- Difficult to estimate ecosystem respiration
- Do not account for immediate emissions
Upscaling approaches

- Machine learning approaches
- Ecosystem models and data assimilation
- Water balance approaches
Validation of MODIS GPP at Towers

Steve Running and Maosheng Zhao
(swrg@ntsg.umt.edu; zhao@ntsg.umt.edu)

RMS Error: 254.1 gC m$^{-2}$ y$^{-1}$

% Error
- Avg: -1.6% (±34.2%)
- Max: 86.4%
- Min: -65.4%
MODIS NPP interannual anomalies
Landscape-scale model simulations of poorly-drained ecosystems

Ben Bond-Lamberty
(bondlamberty@pnl.gov)

Bond-Lamberty et al. 2007
Preliminary results
Regional NEE from 1997-2006 around WLEF tall tower (60km radius)

Ankur Desai
desai@aos.wisc.edu

IFUSE: Interannual Flux-tower Upscaling Sensitivity Experiment
EBL: Equilibrium Boundary Layer
ED: Ecosystem Demography Model
CT: CarbonTracker

(Desai et al. 2007, 2008, 2009)

Preliminary results
Preliminary results
MCI Synthesis Posters: 163 - Impacts of leaf phenology and water table on interannual variability of region carbon fluxes in mixed landscapes (Ankur R Desai, D Scott Mackay, Brent R Helliker, Paul R Moorcroft)

Preliminary results
Upscaling spatially distributed ecological data to constrain regional carbon sequestration

Xuhui Zhou, Tao Zhou, Yiqi Luo

zxuhui14@gmail.com; yluo@ou.edu

Data sets: NPP in leaves, stems, and roots, biomass in leaves, stems, fine litter, and roots and SOC in the three soil layers.

Preliminary results
Stochastic inversion: Bayesian approach

\[ p(c) \]

\[ p(Z|c) \]

\[ p(c|Z) \propto p(Z|c)p(c) \]

Prior knowledge

Observed Data

Model

Posterior information

Probability density function
Regional Terrestrial Ecosystem (TECO) Model

AVHRR NDVI  Solar Radiation  Temperature  Precipitation  Soil Texture

\[ \varepsilon^* \]

\[ \alpha_L \]
Foliage biomass \( (q_L) \)

\[ \alpha_W \]
Woody biomass \( (q_W) \)

\[ \alpha_R \]
Root biomass \( (q_R) \)

Net Primary Productivity

Fine litter \( (q_F) \)

Coarse litter \( (q_C) \)

Root layer1 \( (q_{R1}) \)

Root layer2 \( (q_{R2}) \)

Root layer3 \( (q_{R3}) \)

SOM layer1 \( (q_{S1}) \)

SOM layer2 \( (q_{S2}) \)

SOM layer3 \( (q_{S3}) \)

\[ \tau_L \]

\[ \tau_W \]

\[ \tau_C \]

\[ \theta_F \]

\[ \eta \]

\[ \tau_{FI} \]

\[ \tau_{CI} \]

\[ \theta_{SI} \]

\[ \tau_{S1} \]

\[ \theta_{S1} \]

\[ \tau_{S2} \]

\[ \theta_{S2} \]

\[ \tau_{S3} \]

22 parameters to describe carbon dynamics in ecosystems
Histograms of 22 estimated parameters for ENF

Preliminary results
Site Synthesis Posters: 136: Uncertainties in carbon residence time and sequestration in terrestrial ecosystems of the conterminous USA: A Bayesian approach (Xuhui Zhou, Tao Zhou, Yiqi Luo)

Preliminary results
Better constrained?
Global Estimation of Gross Primary Production using Eddy Covariance Tower and Remote Sensing Data

Shuguang (Leo) Liu, Wenping Yuan

(sliu@usgs.gov; wyuan@usgs.gov)

EC-LUE model

\[
GPP = \text{FPAR} \times \text{PAR} \times \varepsilon_{\text{max}} \times \text{Min}(W_s, T_s)
\]
\[
\text{FPAR} = 1.24 \times \text{NDVI} - 0.168
\]
\[
W_s = \frac{LE}{LE + H}
\]
\[
T_s = \frac{(T - T_{\text{min}}) \times (T - T_{\text{max}})}{(T - T_{\text{min}}) \times (T - T_{\text{max}}) - (T - T_{\text{opt}})^2}
\]

- GPP: gross primary production (g C m\(^{-2}\) d\(^{-1}\));
- PAR: the incident photosynthetically active radiation (MJ m\(^{-2}\));
- fPAR: the fraction of PAR absorbed by the vegetation canopy;
- \(\varepsilon_{\text{max}}\): potential light use efficiency (g C m\(^{-2}\) MJ\(^{-1}\) APAR), 2.14 g C m\(^{-2}\) MJ\(^{-1}\) APAR;
- LE: latent heat (MJ m\(^{-2}\)); H: sensible heat (MJ m\(^{-2}\))
- T: air temperature (°C); Tmin, Tmax and Topt: minimum, optimal and maximum temperature for plant growth;
- \(T_s\) and \(W_s\) are the downward-regulation scalars for the respective effects of temperature and moisture on LUE of vegetation, \(T_{\text{min}} = 0, T_{\text{max}} = 40, T_{\text{opt}} = 20.16\);

(Yuan et al. AFM, 2007)
Calibrating sites (Red): 30; Validating sites (Green): 24
Cover nearly all forests, grasslands and croplands ecosystem types
Annual GPP: EC-LUE model

Preliminary results
A satellite-based biosphere parameterization for net ecosystem CO2 exchange: Vegetation Photosynthesis and Respiration Model (VPRM)

Steven Wofsy et al.  (swofsy@deas.harvard.edu)

Figure 1. Schematic diagram of the Vegetation Photosynthesis Respiration Model (VPRM). EVI: Enhanced Vegetation Index; LSWI: Land Surface Water Index; FAPAR_{PAV}: the fraction of incident light absorbed by the photosynthetically active vegetation in the canopy; T_{scale}, P_{scale}, and W_{scale}: scalars for temperature, leaf phenology, and canopy water content, respectively. Gross Ecosystem Exchange (GEE) is the light-dependent part of Net Ecosystem Exchange (NEE), and Respiration (R) is the light-independent part. MODIS refers to the Moderate Resolution Imaging Spectroradiometer onboard the NASA Terra and Aqua satellites; PAR₀, λ, α, and β are the four model parameters, one set per vegetation type.
Figure 6. (left) Observed and predicted monthly mean NEE (μmole m$^{-2}$ s$^{-1}$) for calibration sites (solid symbols) and validation sites (open symbols) excluding WLEF. Regression line for all sites (dotted line) is very similar to the regression for validation sites only (dashed line). (right) Mean NEE by site (except WLEF) for the growing season. Line labeled (0,1) has zero intercept and slope = 1 ("1:1 line"). Regression lines are labeled similarly.
Probabilistic Estimates of Regional Carbon Flux

Enrico Tomelleri and Markus Reichstein et al.

(email addresses)

GPP model:

\[ GPP = 0.45 \cdot FAPAR \cdot SW_{rad} \cdot f(T_{min}) \cdot f(VPD_{day}) \cdot \varepsilon_{max} \]

An empirical light use efficiency model given by the relationship between primary productivity, solar radiation (SWrad), minimum temperature (Tmin) and daily vapor pressure deficit (VPDday). The last two factors are used as scalars determining the reduction of the maximum light use efficiency (\(\varepsilon_{max}\)).

\[ R_{ECO} \text{ model:} \]

\[ R_{ECO} = \left( R_{LAI=0} + a_{LAI} LAI_{MAX} + k_2 GPP \right) \cdot e^{E_0 \left( \frac{1}{T_{ref}-T_0} - \frac{1}{T-T_0} \right) \cdot \frac{ak + P(1-\alpha)}{k + P(1-\alpha)}} \]

(Migliavacca et al., in prep.)

A semi-empirical model which uses air temperature (Ta), 30-days running average of precipitation (P) as abiotic predictors of respiration and daily GPP as biotic predictor. The relationship between maximum site LAI and reference respiration is introduced to take into account the its spatial variability within each PFT.

Optimization of model parameters

MCMC/Metropolis algorithm
A priori distribution of model parameter (Heinsch et al., 2003/Migliavacca in prep.)
Flux uncertainties (Richardson et al., 2006)
Locally dense measurement network
GPP: 4.1 Pg C yr\(^{-1}\) (±0.73)

\(R_e:\) 3.2 Pg C yr\(^{-1}\) (±0.47)

Preliminary results
Mean annual NEE: 0.9 Pg C yr\(^{-1}\)

Preliminary results
Ecosystem models and data assimilation

- Ecosystem knowledge and processes
- Improving model parameterization and structure
- More realistic estimates of carbon fluxes than “traditional” models
- Propagation of uncertainties
Upscaling approaches

• Machine learning approaches
• Ecosystem models and data assimilation
• Water balance approaches
Water balance approach

\[ GPP = WUE \cdot ET \]

empirical correlation of flux-tower estimated inherent WUE to LAI and soil properties

\[ \rightarrow \] estimation via remote sensing and soil maps, weighted by precipitation distribution and accounting for \(C_3/C_4\) differences

At watershed scale:
Precipitation – Runoff - Interception

Christian Beer and Markus Reichstein, Max Planck Institute for Biogeochemistry, Jena, Germany
cbeer@bgc-jena.mpg.de; markus.reichstein@bgc-jena.mpg.de
Spatial variability of inherent WUE

European forest sites

Plant available WHC of soil

WUE$_{VPD}$ [gC/kgH2O*hPa]

R$^2$=0.6

LAI

Christian Beer and Markus Reichstein, Max Planck Institute for Biogeochemistry, Jena, Germany

Beer et al., GRL, 2007
Very high values (comparable to tropical rain forest) at the eastern coast.

Uncertainties due to water extraction by man and low VPD.

Preliminary results

Christian Beer and Markus Reichstein, Max Planck Institute for Biogeochemistry, Jena, Germany
4.1 **Tomelleri et al.**

Xiao et al.  
MODIS GPP

**Table: GPP (Pg C yr\(^{-1}\))**

<table>
<thead>
<tr>
<th></th>
<th>GPP (Pg C yr(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>MODIS</td>
<td>6.2</td>
</tr>
<tr>
<td>Xiao et al.</td>
<td>7.1</td>
</tr>
<tr>
<td>Martin et al.</td>
<td>6.7-7.0</td>
</tr>
<tr>
<td>Tomelleri et al.</td>
<td>4.1</td>
</tr>
</tbody>
</table>

**Median annual GPP [gC/m\(^2\)]**

Beer et al.

<table>
<thead>
<tr>
<th>No vegetation</th>
<th>100 - 200</th>
<th>300 - 400</th>
<th>600 - 800</th>
<th>1,000 - 1,200</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 - 100</td>
<td>200 - 300</td>
<td>400 - 600</td>
<td>800 - 1,000</td>
<td>&gt; 1,200</td>
</tr>
</tbody>
</table>

**Preliminary results**

Liu and Yuan

**Jung et al.**
Summary on progress

- Various methods and spatial scales
- Spatial patterns and year-to-year variations
- A new and alternative estimate to ecosystem carbon uptake
- Regional carbon budget
- Extreme climate events and disturbances
- Diagnosis, attribution, and decision support
- Starting to look at uncertainties
## Challenges: flux tower representativeness

<table>
<thead>
<tr>
<th>CLASS</th>
<th>CLASS NAME</th>
<th>DESCRIPTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Evergreen Needleleaf Forests</td>
<td>Lands dominated by trees with a percent canopy cover $&gt;60%$ and height exceeding 2 meters. Almost all trees remain green all year. Canopy is never without green foliage.</td>
</tr>
<tr>
<td>2</td>
<td>Evergreen Broadleaf Forests</td>
<td>Lands dominated by trees with a percent canopy cover $&gt;60%$ and height exceeding 2 meters. Almost all trees remain green all year. Canopy is never without green foliage.</td>
</tr>
<tr>
<td>3</td>
<td>Deciduous Needleleaf Forests</td>
<td>Lands dominated by trees with a percent canopy cover $&gt;60%$ and height exceeding 2 meters. Consists of seasonal needleleaf tree communities with an annual cycle of leaf-on and leaf-off periods.</td>
</tr>
<tr>
<td>4</td>
<td>Deciduous Broadleaf Forests</td>
<td>Lands dominated by trees with a percent canopy cover $&gt;60%$ and height exceeding 2 meters. Consists of seasonal broadleaf tree communities with an annual cycle of leaf-on and leaf-off periods.</td>
</tr>
<tr>
<td>5</td>
<td>Mixed Forests</td>
<td>Lands dominated by trees with a percent canopy cover $&gt;60%$ and height exceeding 2 meters. Consists of tree communities with interspersed mixtures or mosaics of the other four forest cover types. None of the forest types exceeds 60% of landscape.</td>
</tr>
<tr>
<td>6</td>
<td>Closed Shrublands</td>
<td>Lands with woody vegetation less than 2 meters tall and with shrub canopy cover is $&gt;60%$. The shrub foliage can be either evergreen or deciduous.</td>
</tr>
<tr>
<td>7</td>
<td>Open Shrublands</td>
<td>Lands with woody vegetation less than 2 meters tall and with shrub canopy cover is between 10-60%. The shrub foliage can be either evergreen or deciduous.</td>
</tr>
<tr>
<td>8</td>
<td>Woody Savannas</td>
<td>Lands with herbaceous and other understorey systems, and with forest canopy cover between $30-60%$. The forest cover height exceeds 2 meters.</td>
</tr>
<tr>
<td>9</td>
<td>Savannas</td>
<td>Lands with herbaceous and other understorey systems, and with forest canopy cover between $10-30%$. The forest cover height exceeds 2 meters.</td>
</tr>
<tr>
<td>10</td>
<td>Grasslands</td>
<td>Lands with herbaceous types of cover. Tree and shrub cover is less than 10%.</td>
</tr>
<tr>
<td>12</td>
<td>Cropland</td>
<td>Lands covered with temporary crops followed by harvest and a bare soil period (e.g., single and multiple cropping systems. Note that perennial woody crops will be classified as the appropriate forest or shrub land cover type.</td>
</tr>
</tbody>
</table>
Challenges: disturbances and stand age

Forest Disturbance and North American Carbon Flux

North America’s forests are thought to be a significant sink for atmospheric carbon. Currently, the rate of sequestration by forests on the continent has been estimated at 0.23 petagrams of carbon per year, though the uncertainty about this estimate is nearly 50%. This offsets about 12% of the fossil fuel emissions from the continent [Pacala et al., 2007]. However, the high level of uncertainty in this estimate and the scientific community’s limited ability to predict the future direction of the forest carbon flux reflect a lack of detailed knowledge about the effects of forest disturbance and recovery across the continent.

The North American Carbon Program (NACP), an interagency initiative to better understand the distribution, origin, and fate of North American sources and sinks of carbon, has highlighted forest disturbance as a critical factor constraining carbon dynamics [Woody and Harris, 2002]. National forests typically accumulate carbon in woody biomass and soils for decades or centuries, until a disturbance event triggers accelerated release of stored carbon back to the atmosphere. A host of disturbance agents, such as fire, disease, insect outbreaks, drought, and harvesting, can perturb forest systems, each with different effects on carbon cycling.

Immediately after a major disturbance, a forest stand commonly acts as a source of carbon to the atmosphere until respiration from decomposers becomes less than photosynthetic uptake from regrowing.
Expected results for the near future

• Incorporating stand age and disturbances
• Quantifying extrapolation errors (eddy flux + input variables)
• Investigating realism of uncertainty estimates
• Reducing uncertainties of carbon fluxes
• Employing ensemble methods
• Synthesis with other forward models and atmospheric inversions
Quasi operational?