
John C. Lin, Brett Raczkka, Henrique Duarte, David R. Bowling, Jeffrey L. Anderson, Timothy J. Hoar, Christian Frankenberg, Philipp Koehler, Karen Yuen
Goal: Monitor carbon flux across complex terrain of Western US

Vulnerable carbon stocks, drastic change to landscape and ecosystem functioning
Overarching Goal: Develop Land surface data assimilation system, CLM5-DART

“Develop a carbon monitoring system across complex terrain of Rocky Mountains of Western US”

Solar Induced Fluorescence (SIF)
(TROPOMI, OCO-2/3, GOME-2)

Land Surface Temp (ECOSTRESS)

Snow Cover (MODIS)
CMS-Mountains-1 Review
Demonstration of strong SIF-GPP relationship for Western US evergreen species

Mechanistic evidence for tracking the seasonality of photosynthesis with solar-induced fluorescence

Troy S. Magnier*, David R. Bowling, Barry A. Logan, Katja Grossmann, Jochen Stutz, Peter D. Blanken, Sean P. Burns, Rui Cheng, Maria A. Garcia, Philipp Köhler, Sophia Lopez, Nicholas C. Parazoo, Brett Raczka, David Schimel, and Christian Frankenberg*

• SIF is a useful indicator of timing/magnitude of GPP (Niwot Ridge, CO)

• Traditional ‘green-ness’ indicators do not track seasonal GPP

• The GPP seasonality related to leaf pigment transition (xanthophyll cycle)
Demonstration of strong SIF-GPP relationship for Western US evergreen species

• Solar-induced fluorescence detected inter-annual variation in GPP and small disturbances with greater success than traditional satellite-based products.
Add representation of SIF within a land surface model: Community Land Model (CLM)

Sustained Nonphotochemical Quenching Shapes the Seasonal Pattern of Solar-Induced Fluorescence at a High-Elevation Evergreen Forest


![Diagram of SIF representation within CLM](Image)
Do more spatially resolved land surface maps and meteorology improve biomass simulations?

Fan et al., 2019:

Fine (1/24°) and Coarse (1/2°) CLM surface maps and GRIDMET meteorology

"The next questions are as follows: where and when, across the diverse and dynamic environments of the globe, do we expect that these terrain influences will matter to ESM predictions of large-scale water, energy, and biogeochemical fluxes? ...will the hillslope-scale structures, however, deterministic and predictable, simply average out over an ESM grid cell and hence matter little to global predictions?"
Meteorology data products for complex terrain tend to be too warm/dry

* $z > 2235$ m
75% of total AGB (NBCD2000 product, Kellndorfer et al., 2013)
Simulation of biomass is highly sensitive to meteorological biases and representation of water limitation.

Need to be aware of regions of ‘dead’ cells for assimilation system.
Dead cell regions inhibit functioning of assimilation system

Observation rejection map

Observations - Blue

Assimilation (w/obs) - Red
Free (no obs) - Black

Leaf Area

Biomass

Identifying the most favorable meteorological dataset and model configuration (GRIDMET – CLM5-PHS) helped avoid these dead cell regions that are highly resistant to assimilation updates.
Paths for continued land surface model improvement

Custom PFT parameterization

Hillslope, Subsurface Hydrology

Spatially Explicit – computationally unrealistic

Spatially Implicit – empirical, but less computation

Buotte et al., 2018

Fan et al., 2019
Land surface data assimilation system: CLM5-DART ‘Benchmark Case’

**Observations**

Aboveground Biomass
VOD – passive microwave (AMSR-E)

01-Jul-2000 --> 01-Jul-2000

Liu et al., (2015)

Leaf Area
(LAI3g), AVHRR, MODIS LAI

01-Jul-2000 --> 01-Jul-2000

Zhu et al., (2013)

**CLM 5 biosphere model**

Initial Prior State:

Fluxes: NEE
GPP
ER
ET

Biomass
Leaf Area

Soil carbon
Soil water

New Posterior State:

Fluxes: NEE + \(\Delta\)
GPP + \(\Delta\)
ER + \(\Delta\)
ET + \(\Delta\)

Biomass + \(\Delta\)
Leaf Area + \(\Delta\)

Soil carbon + \(\Delta\)
Soil water + \(\Delta\)
Land surface data assimilation system: CLM5-DART
‘Benchmark Case’

NASA CMS Biomass WG
(biomass products)

NASA CMS Uncertainty WG

Model State localization
- Leaf carbon
- Live stem carbon
- Dead stem carbon
- Leaf area index
- Fine root carbon
- Live coarse root carbon
- Dead coarse root carbon
- Live stem nitrogen
- Dead stem nitrogen
- Litter carbon, slow
- Litter carbon, medium
- Litter carbon, fast
- Litter nitrogen, slow
- Litter nitrogen, medium
- Litter nitrogen, fast
Assimilation of leaf area and biomass reduce simulated biomass, GPP, ER. Net carbon exchange holds steady.

Observations - Blue
Assimilation (w/obs) - Red
Free (no obs) - Black

### Western US Assimilation overview

<table>
<thead>
<tr>
<th>Simulation Name</th>
<th>AGB (kgC m⁻²)</th>
<th>LAI (m²)</th>
<th>GPP (gC m⁻² month⁻¹)</th>
<th>ER (gC m⁻² month⁻¹)</th>
<th>NEP (gC m⁻² month⁻¹)</th>
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</thead>
<tbody>
<tr>
<td>Free</td>
<td>1.98</td>
<td>1.31</td>
<td>48.18</td>
<td>47.18</td>
<td>1.00</td>
</tr>
<tr>
<td>State-15</td>
<td>1.33</td>
<td>0.93</td>
<td>37.08</td>
<td>39.52</td>
<td>-2.43</td>
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<tr>
<td><strong>State-9</strong></td>
<td><strong>1.36</strong></td>
<td><strong>0.96</strong></td>
<td><strong>38.49</strong></td>
<td><strong>37.21</strong></td>
<td><strong>1.28</strong></td>
</tr>
<tr>
<td>State-4</td>
<td>1.44</td>
<td>0.92</td>
<td>37.01</td>
<td>37.15</td>
<td>-0.05</td>
</tr>
</tbody>
</table>
Was the assimilation successful? Diagnosing observation acceptance rate and RMSE

Observations - Blue
Assimilation (w/obs) - Red
Free (no obs) - Black
Our assimilation estimate of carbon uptake much weaker than another observation-constrained product (FLUXCOM)

CLM5-DART vs. FLUXCOM (observation constrained, machine learning, model ensemble)

- GPP mismatch
- ER very similar
- NEP: strong winter mismatch
Our assimilation estimate of carbon uptake much weaker than another observation-constrained product (FLUXCOM)

CLM5-DART not getting high elevation uptake, low elevation neutral

- AGB observations in interior West relatively low
- Water variables in CLM not receiving direct adjustments, (downstream variables)
Opportunities for improved assimilation: PFT specific observations

The assimilation adjustments to natural vegetation looks fine, crops are resistant to assimilation adjustments

• Robert Kennedy, OSU (LandTrender biomass)
Opportunities for improved assimilation: expanding CLM adjusted state variables

Leaf carbon
Live stem carbon
Dead stem carbon
Leaf area index
Fine root carbon
Live coarse root carbon
Dead coarse root carbon
Live stem nitrogen
Dead stem nitrogen
Litter carbon, slow
Litter carbon, medium
Litter carbon, fast
Litter nitrogen, slow
Litter nitrogen, medium
Litter nitrogen, fast

• Should expand to include soil carbon, water state variables.
CMS-Mountains-II
CMS-II (Lin 2018) advances

• Successfully extended the CLM5 ensemble simulation through 2018 (2019)
• We are poised to add new data streams for 1998-2019 assimilation
CMS-II (Lin 2018) goals: add data streams

• Successfully extended the CLM5 ensemble simulation through 2018 (2019)
• We are poised to add new data streams for 1998-2019 assimilation

Add Observation Streams
• GLASS LAI
• LandTrendr biomass (PFT)
• ECOSTRESS, LST
• SIF-TROPOMI
• SNODAS

Assimilation framework
CMS-II (Lin 2018) goals: High resolution TROPOMI-SIF to diagnose phenology

- Characterize seasonal phenology based on elevation, slope and aspect

- Provide insight into phenological transition across elevation gradient

- Implement this understanding into improved phenological model in CLM 5
CMS-II (Lin 2018) goals: Forest Health Early Warning System

CAUSE: Negative Water Balance

SYMPTOM: Stress

SIF, NDMI, $T_{\text{skin}}$

WARNING to Stakeholders

PROGNOSIS: Forest Health in Future Climate

Planning, Adaptation, Management

OUTCOME: Mortality

Community Land Model
Questions?
Meteorological datasets tend to be too warm/dry across Western US

- Meteorological biases at Niwot Ridge, Colorado
- High temp
- High SW radiation
- Low precip
- Asking for trouble within a water limited region

Default CLM4.5

Products with bias improvement

PRISM-based (Abatzoglou)
Simulation of biomass is highly sensitive to meteorological biases and representation of water limitation.