Towards improving crop representation in ELM

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11% of the global land is used for agriculture

Share of land area used for arable agriculture, 2015

Source: World Bank, Ritchie and Rose, 2019
Agriculture impacts regional and global climate

Agricultural activities can result in large greenhouse gas emissions

Source: www.ecosystemmarketplace.com
Adequate representation of crops has large impact on carbon fluxes

(b) Maximum Monthly Average

Change in Gross Primary Productivity (g C m$^{-2}$ d$^{-1}$)

Source: Lombardozzi et al., 2020
Large projected increase in bioenergy production

Research objective
Expansion of ELM crop model to include perennial bioenergy crops.
Adding perennial bioenergy crops to ELM

**Challenges**

- Reducing the bias between observed and simulated fluxes requires optimizing the various crop parameters.
- Computationally prohibitive due to model’s complexity.
- Studies have utilized parameter values based on observations or one-at-time calibration.
- Fail to account for the impact of parameter interactions.

Sinha et al., [In Review GMD]
Addition of perennial crops
Methodology for parameter optimization

- Uncertainty Quantification Toolkit (UQTk) was utilized for developing surrogate models of ELM runs.

Sinha et al., [In Review GMD]
Methodology for parameter optimization

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- Steps:
  - Crop parameters ($n=20$) and their approximate ranges were identified for the sensitivity analysis.
  - A sample file was created containing a large sample of randomly distributed parameters within their specified range.
  - Offline Land Model Testbed (OLMT) was used for submitting, managing, and post processing a large ensemble (2000) of runs.
  - Surrogate models developed for ELM simulations (forward modeling).
  - Sobol indices (variance based decomposition) estimated for parameter selection.
  - Observational data utilized for optimizing parameters (inverse modeling).

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Sinha et al., [In Review GMD]
Ensemble captured GPP seasonality and peak

Sinha et al., [In Review GMD]
Sensitivity analysis identified most influential parameters.

Miscanthus daily GPP was most sensitive to parameters associated with:
- Stomatal conductance (mbbopt) and specific leaf area (slatop)
- Leaf CN allocation (leafcn)
- Leaf onset (gddmin) and leaf senescence (senescence_temp).

Sinha et al., [In Review GMD]
Calibrated values closely match the observations.

Sinha et al., [In Review GMD]
Calibrated values closely match the observations
# Optimized parameter values for perennial crops

<table>
<thead>
<tr>
<th>ELM variable</th>
<th>Description</th>
<th>Input range</th>
<th>Miscanthus</th>
<th>Switchgrass</th>
</tr>
</thead>
<tbody>
<tr>
<td>planting_temp</td>
<td>Average 10-day temperature required for plant emergence</td>
<td>275 – 285</td>
<td>282</td>
<td>277</td>
</tr>
<tr>
<td>gddmin</td>
<td>Minimum growing degree days</td>
<td>50 – 320</td>
<td>100</td>
<td>93</td>
</tr>
<tr>
<td>senescence_temp</td>
<td>Average 10-day temperature for leaf senescence</td>
<td>280 – 290</td>
<td>283</td>
<td>290</td>
</tr>
<tr>
<td>fleafi</td>
<td>Leaf CN allocation coefficient</td>
<td>0.5 – 0.95</td>
<td>0.5</td>
<td>-</td>
</tr>
<tr>
<td>leafcn</td>
<td>Leaf CN ratio</td>
<td>15 – 35</td>
<td>35</td>
<td>35</td>
</tr>
<tr>
<td>slatop</td>
<td>Specific leaf area (SLA) at top of canopy</td>
<td>0.01 – 0.07</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>q10_mr</td>
<td>Temperature sensitivity for MR</td>
<td>1.3 – 3.3</td>
<td>2.1</td>
<td>2.3</td>
</tr>
<tr>
<td>mbbopt</td>
<td>Ball–Berry model equation slope</td>
<td>4 – 12</td>
<td>8.4</td>
<td>9.5</td>
</tr>
</tbody>
</table>

Sinha et al., [In Review GMD]
Validation results in small RMSE for carbon fluxes

![Graphs showing validation results for Miscanthus and Switchgrass with RRMSE values 0.24 and 0.21 respectively.]
Main takeaways / Next steps

▶ Implemented perennial crop modeling in ELM.
▶ Carbon and energy fluxes were most sensitive to parameters associated with:
  ▶ Stomatal conductance
  ▶ Specific leaf area
  ▶ Leaf CN allocation
  ▶ Phenological parameters
▶ Simulated carbon fluxes captured the observed seasonality and matched the observed magnitudes.
▶ For miscanthus, simulated harvest occurs few months before the observations resulting in reduced yield.
▶ Lays the foundation for future work examining the impact of bioenergy crops on climate.

Sinha et al., [In Review GMD]
Crop rotation practiced globally for increasing yield
Transition from C4 annual to C3 N-fixing

Data source: Hurtt et al., 2020
Crop rotation practiced globally for increasing yield

Transition from C4 annual to C3 N-fixing

Research objective

Corn/soybean rotation implementation, calibration, and validation using spatially varying observations.
Second study - Crop rotation implementation & calibration

- Utilized dynamic landunit to implement crop rotation in ELM.
Next steps

- Improving corn soybean calibration to reduce bias between observed and simulated LAI and yield.
Corn soybean rotation in ELM landuse timeseries
Corn soybean rotation in ELM landuse timeseries

CFT - Corn — 2001

CFT - Soybean — 2001

percent crop functional type on the crop landunit (% of landunit) [unitless]
Thank you