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Pacific Northwest NATIONAL LABORATORY

# Towards improving crop representation in ELM

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Pacific Northwest National Laboratory

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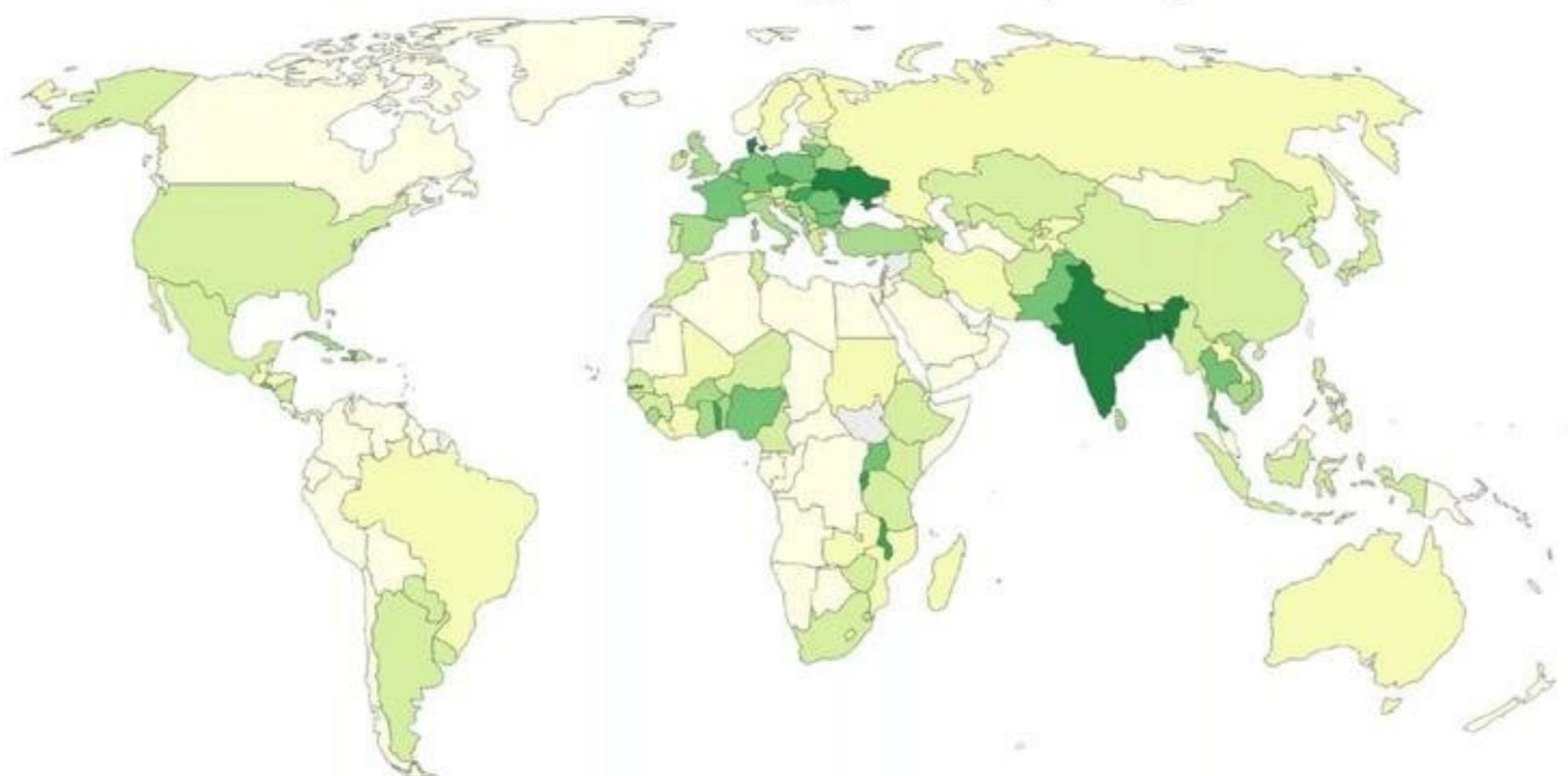
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# 11% of the global land is used for agriculture



Our World  
in Data

Share of land area used for arable agriculture, 2015



Source: World Bank

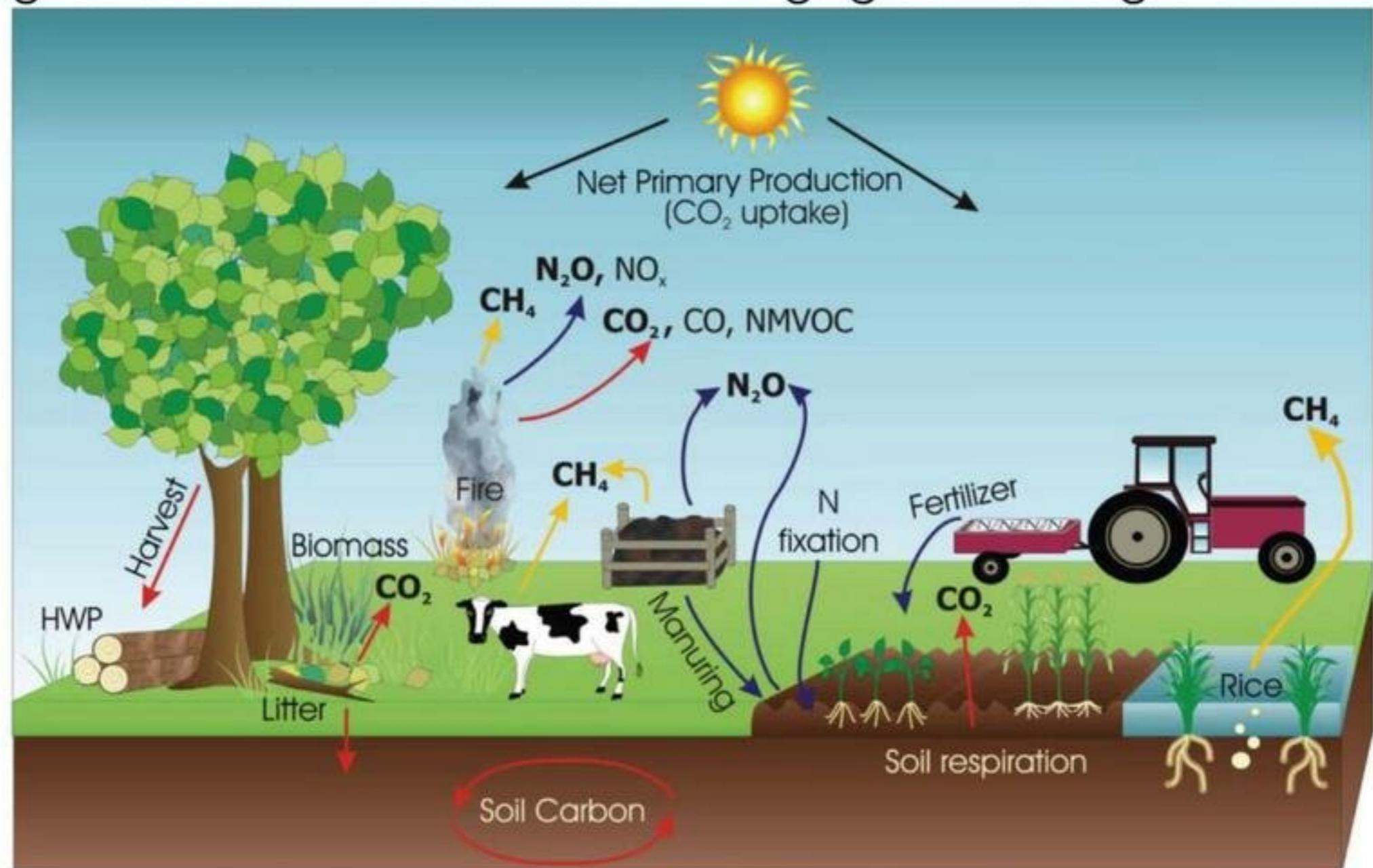
[OurWorldInData.org/yields-and-land-use-in-agriculture/](https://OurWorldInData.org/yields-and-land-use-in-agriculture/) • CC BY

Source: Ritchie and Rose, 2019

# Agriculture impacts regional and global climate



Agricultural activities can result in large green house gas emissions



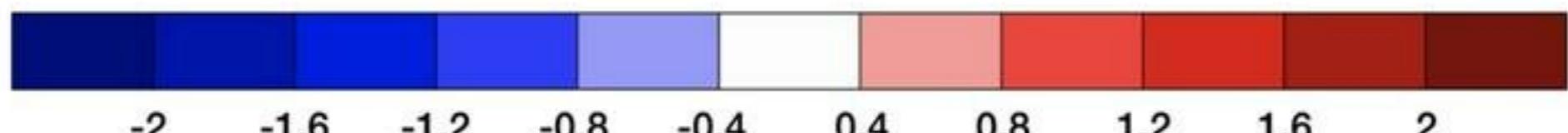
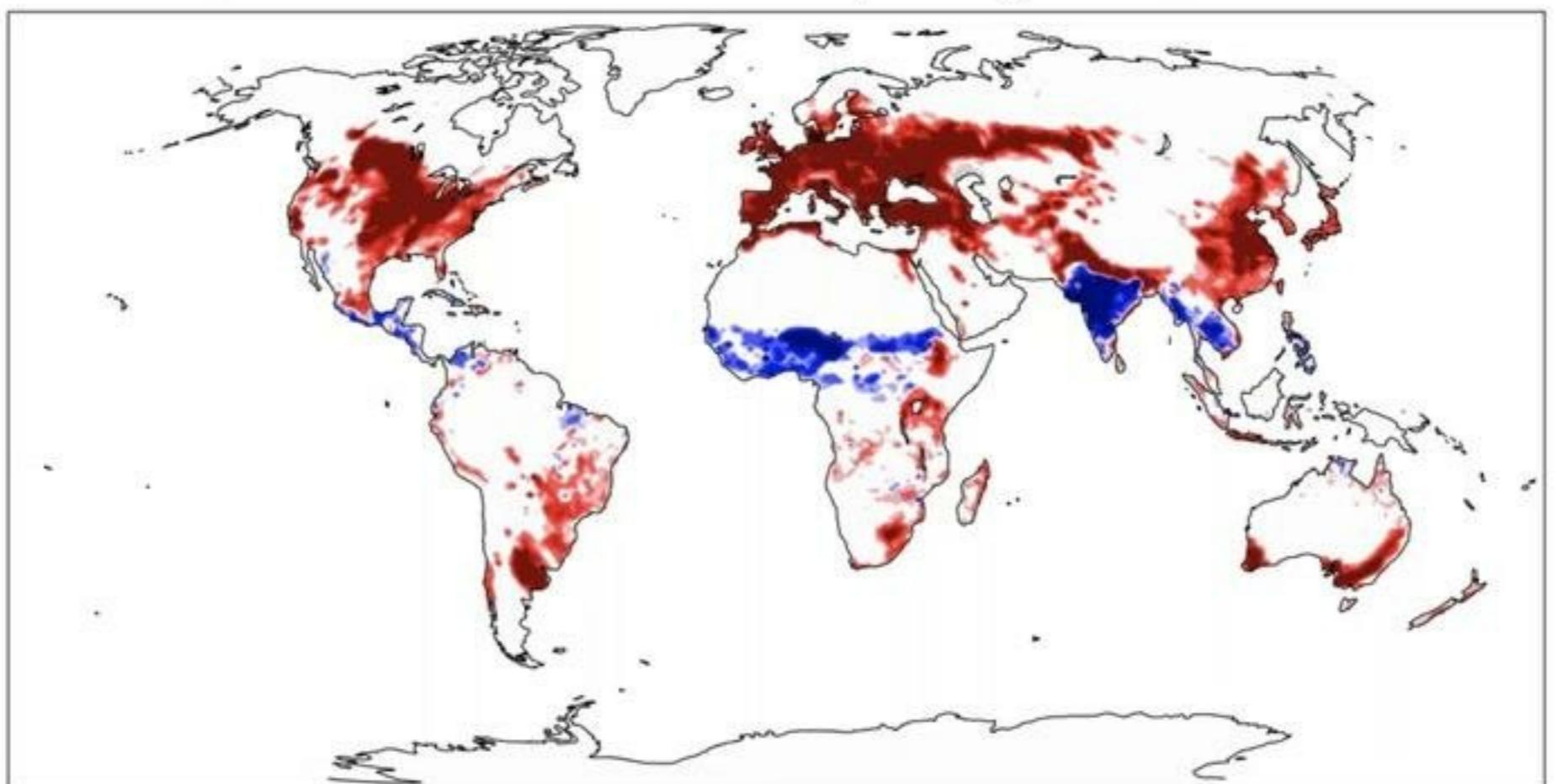
Source: [www.ecosystemmarketplace.com](http://www.ecosystemmarketplace.com)

# Adequate representation of crops has large impact on carbon fluxes



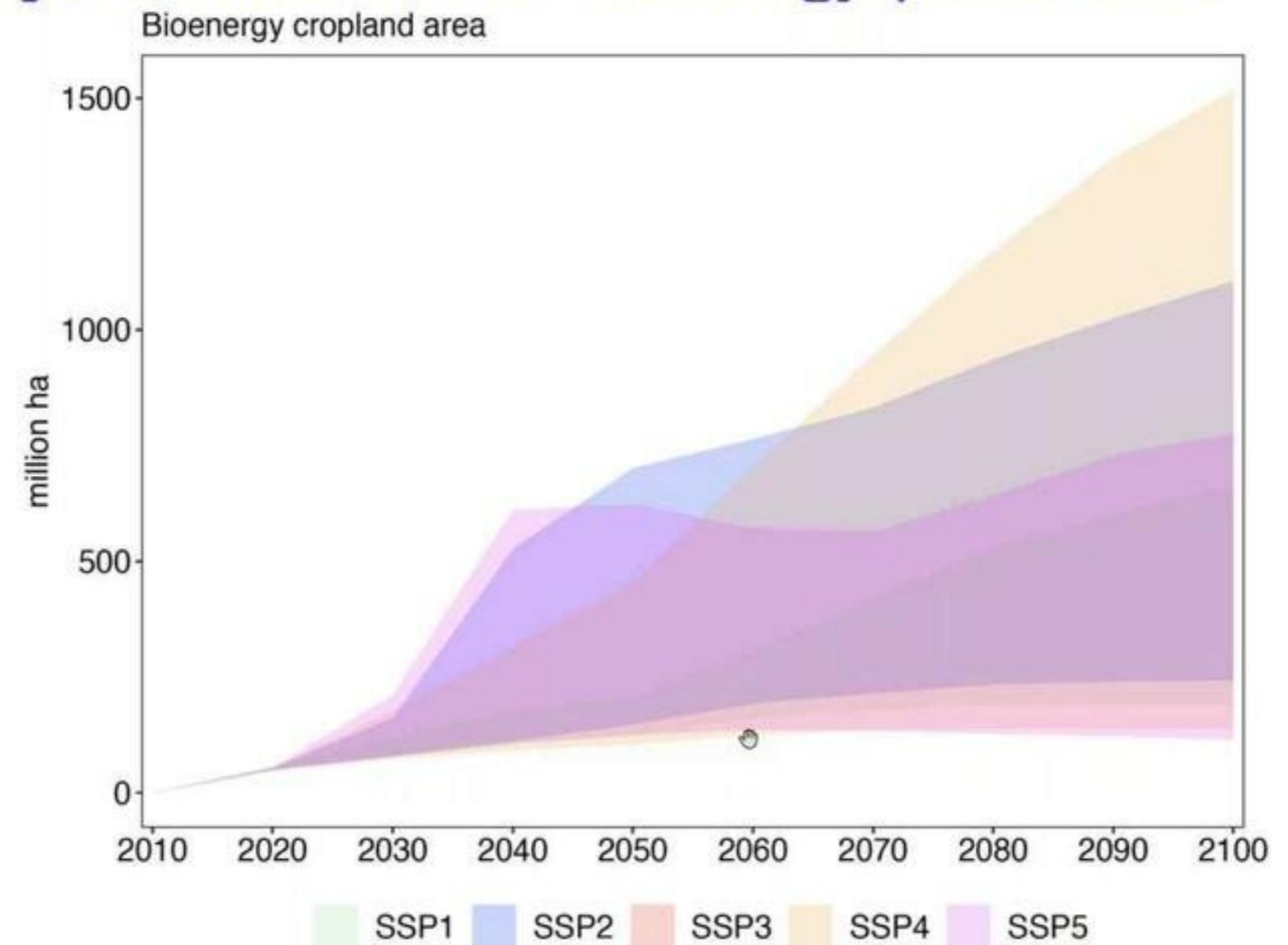
(b)

Maximum Monthly Average

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

Source: Lombardozzi et al., 2020

# Large projected increase in bioenergy production



Data source: Calvin et al., 2017

## 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.



# Addition of perennial crops





# Methodology for parameter optimization

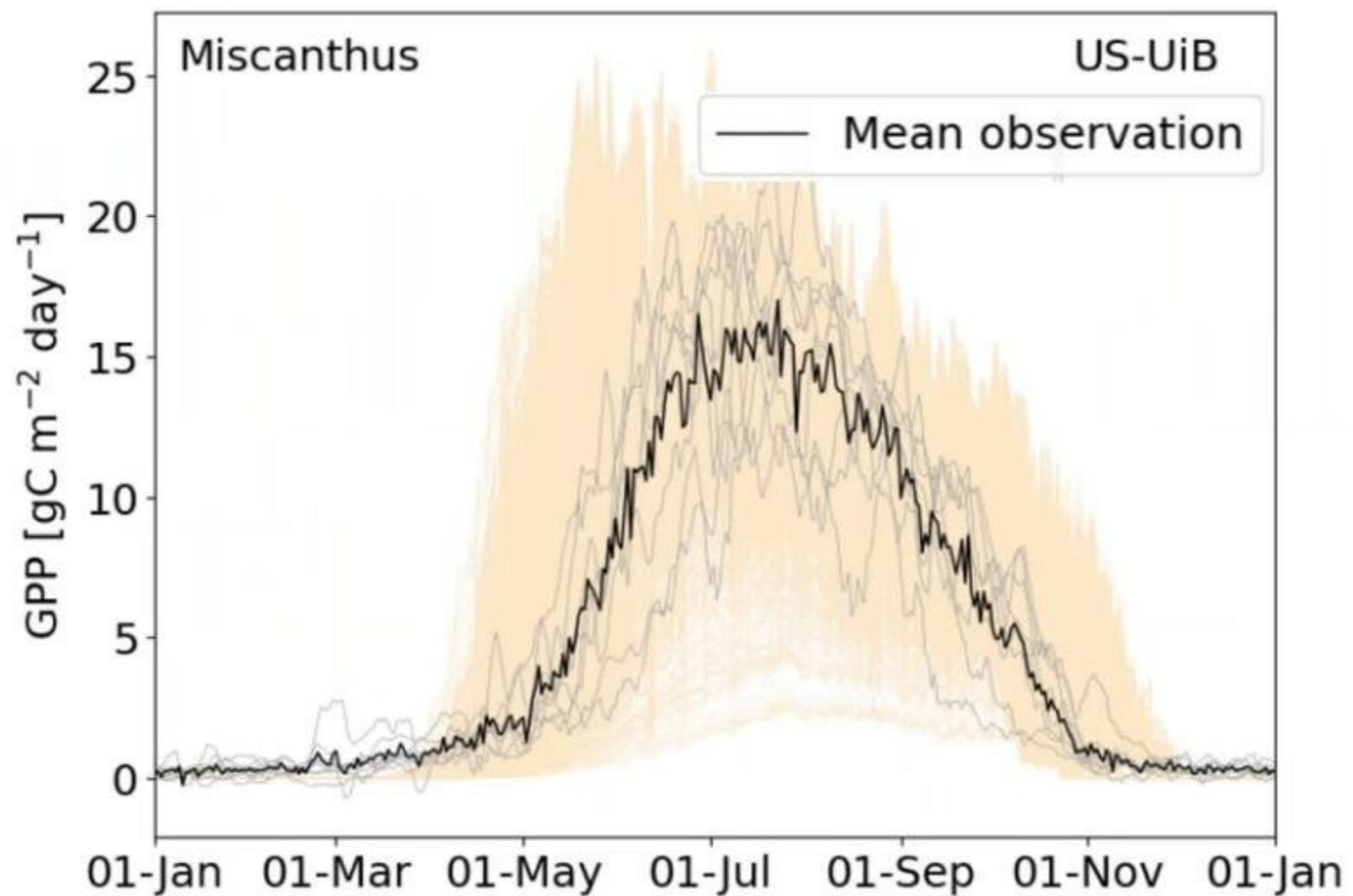
- ▶ Uncertainty Quantification Toolkit (UQTK) was utilized for developing surrogate models of ELM runs.

# Methodology for parameter optimization

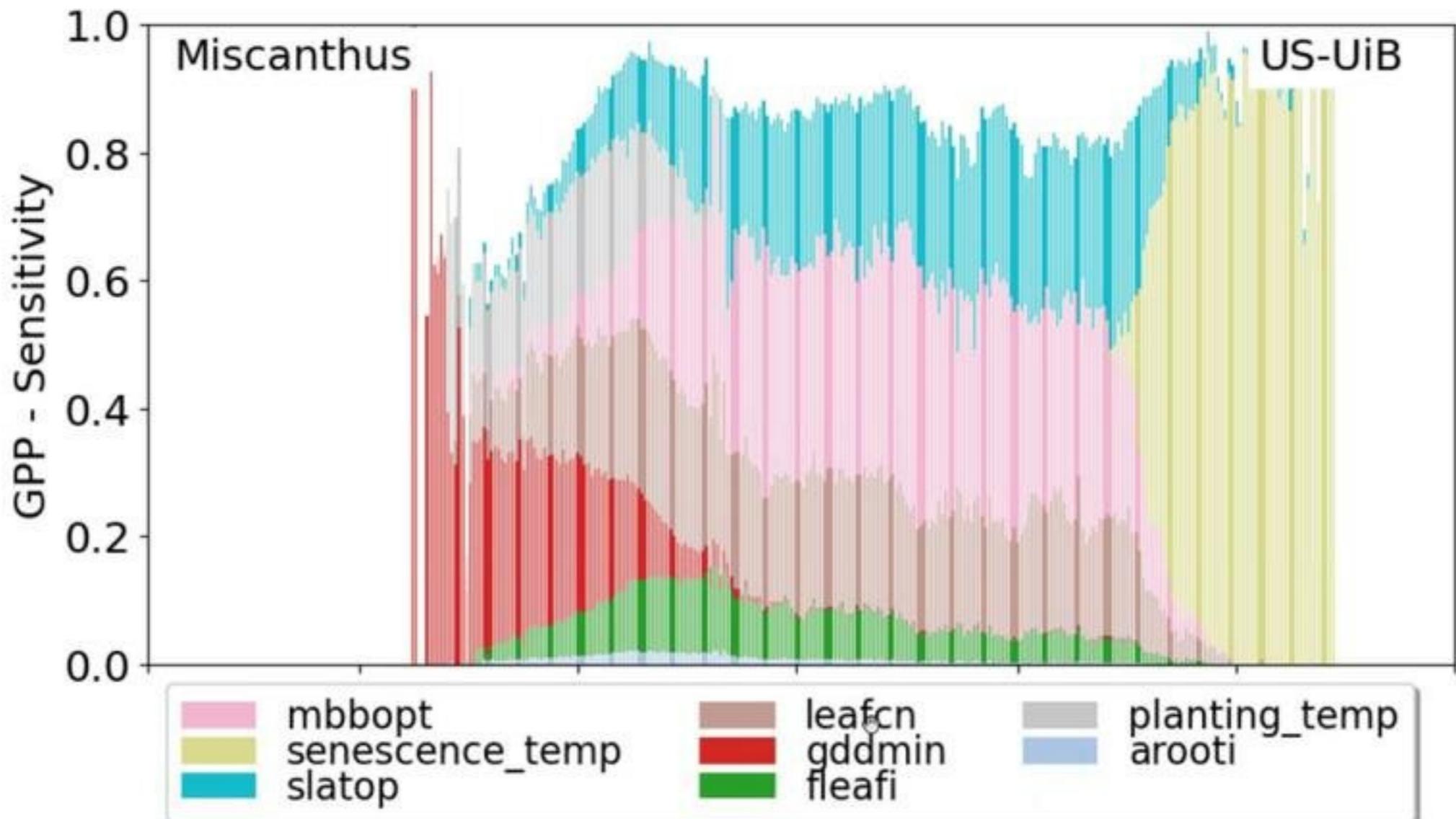


- ▶ [Uncertainty Quantification Toolkit \(UQTk\)](#) was utilized for developing surrogate models of ELM runs.
- ▶ Steps:
  - ▶ Crop parameters ( $n=20$ ) and their approximate ranges were identified for the sensitivity analysis.
  - ▶ A sample file was created containing a large sample of randomly distributed 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*).

# Ensemble captured GPP seasonality and peak



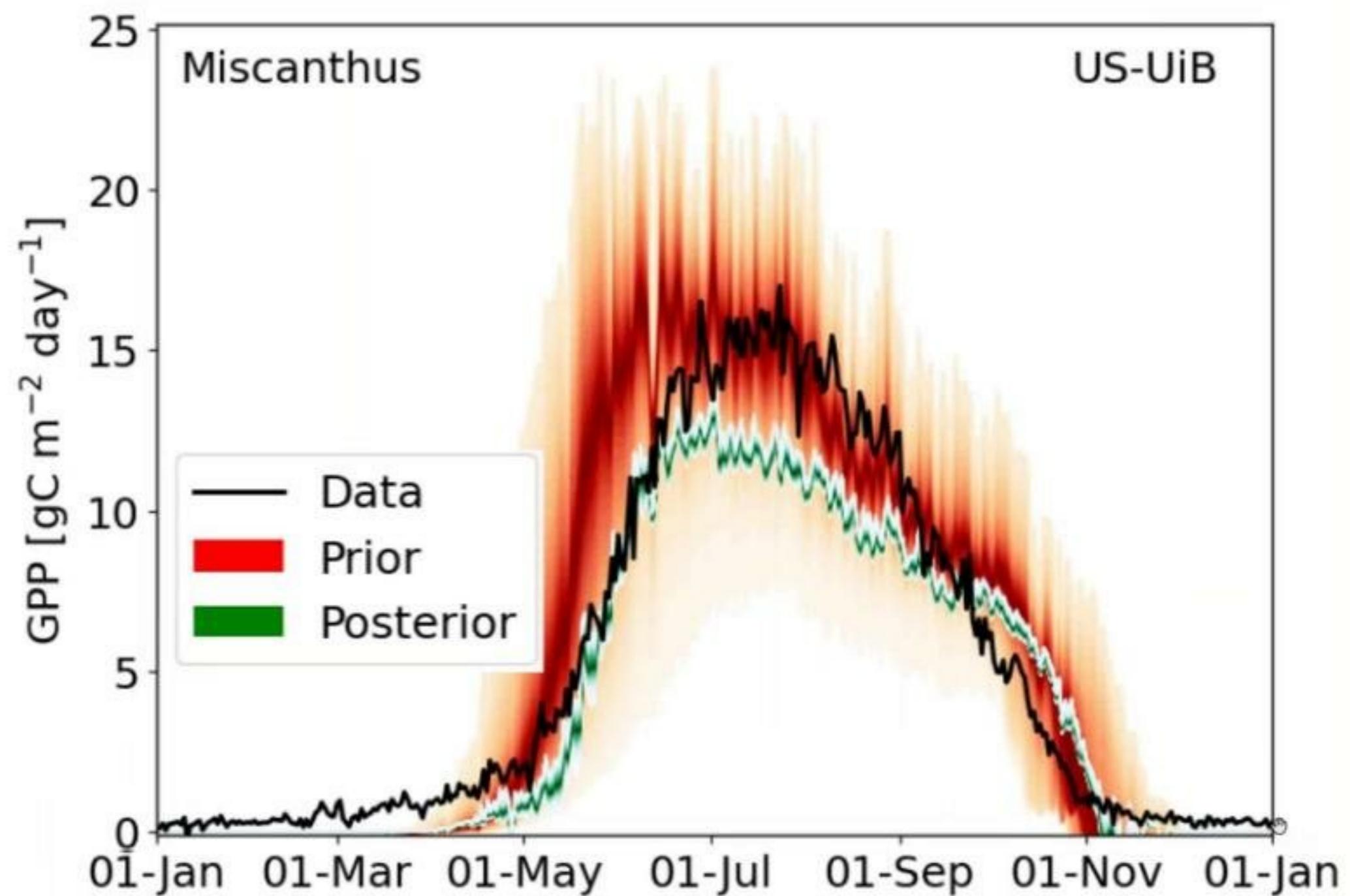
# Sensitivity analysis identified most influential parameters



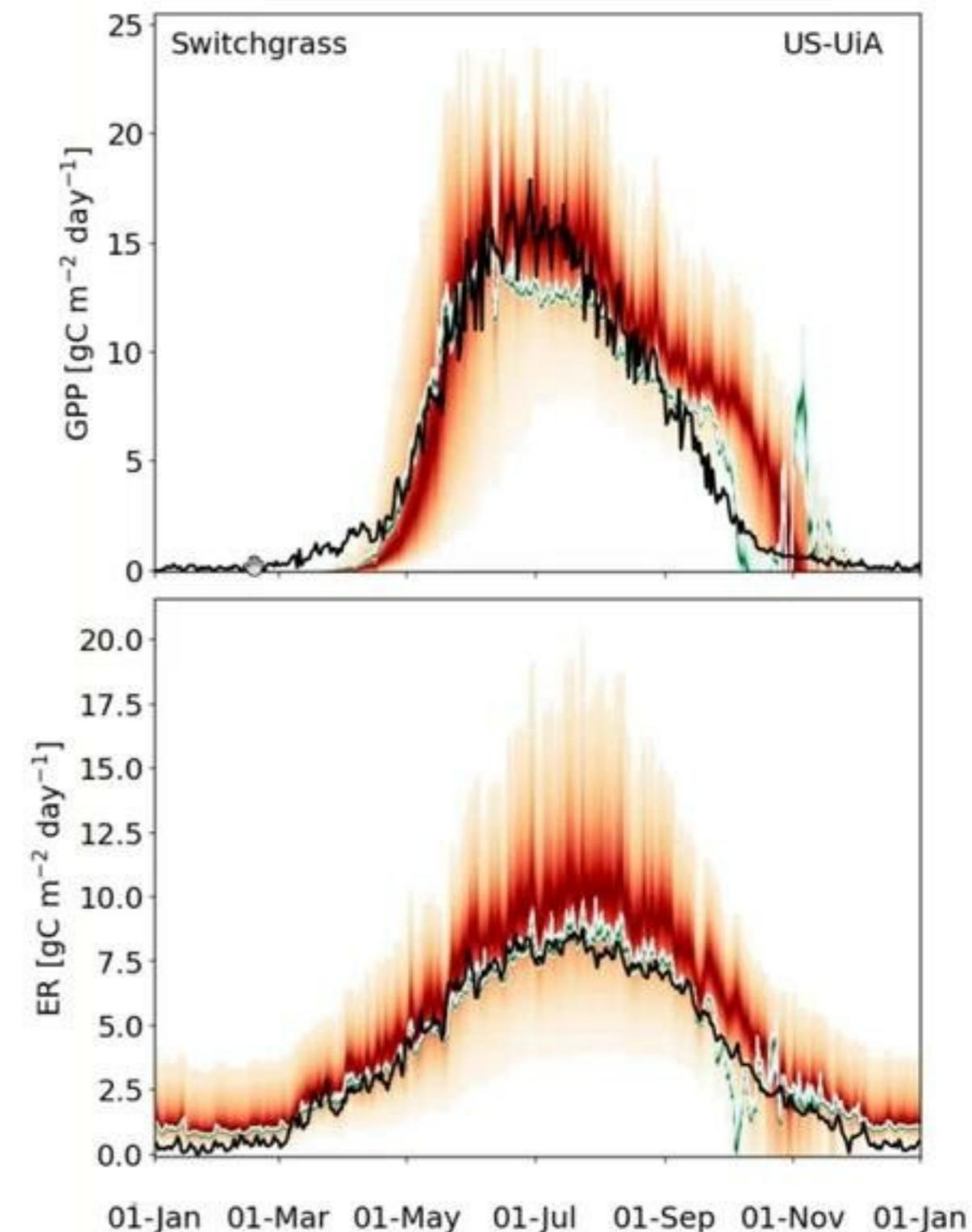
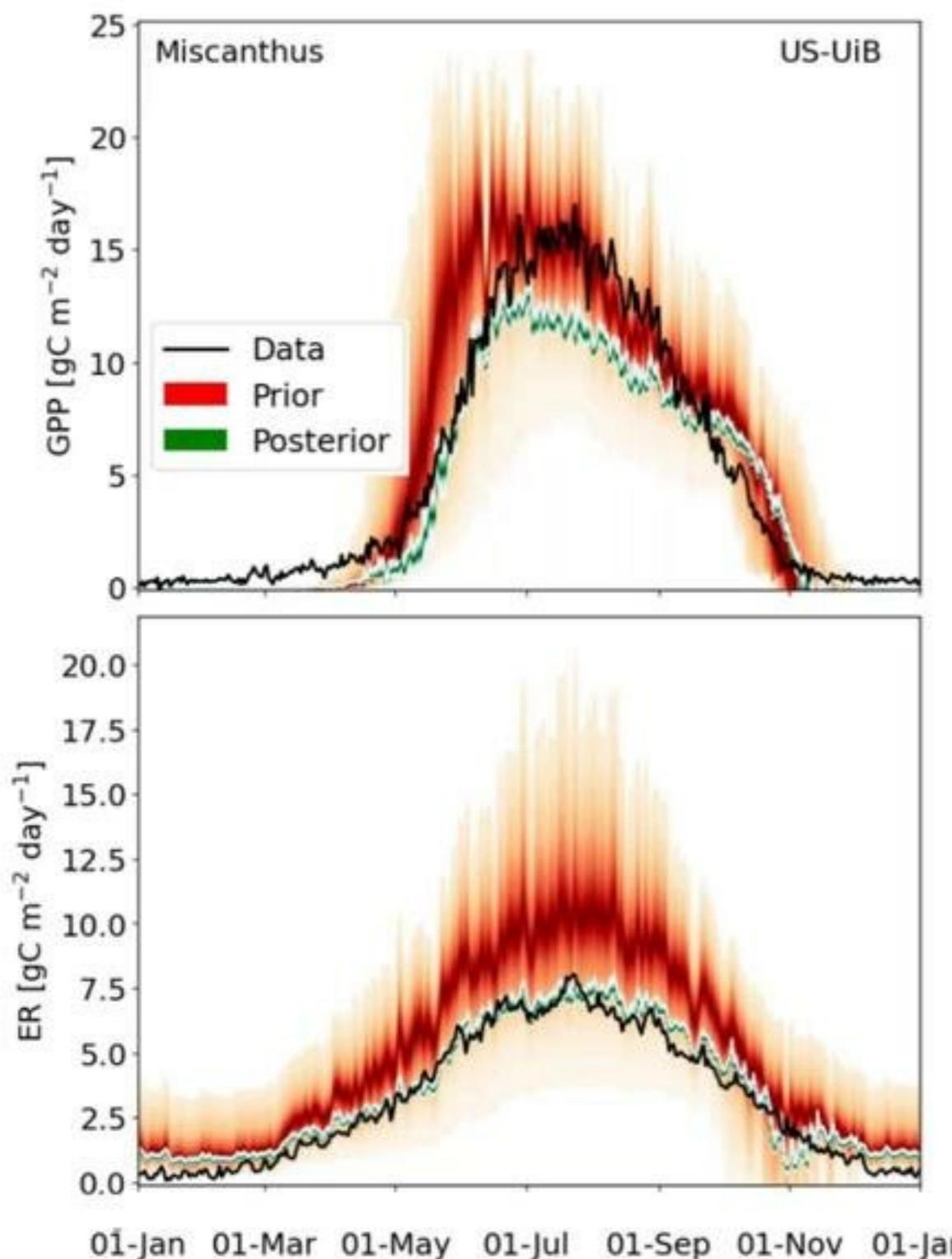
Miscanthus daily GPP was most sensitive to parameters associated with:

- ▶ Stomatal conductance (`mbbopt`) and specific leaf area (`slatop`)
- ▶ Leaf CN allocation (`leafcn`)
- ▶ Leaf onset (`gddmin`) and leaf senescence (`senescence_temp`).

## Calibrated values closely match the observations



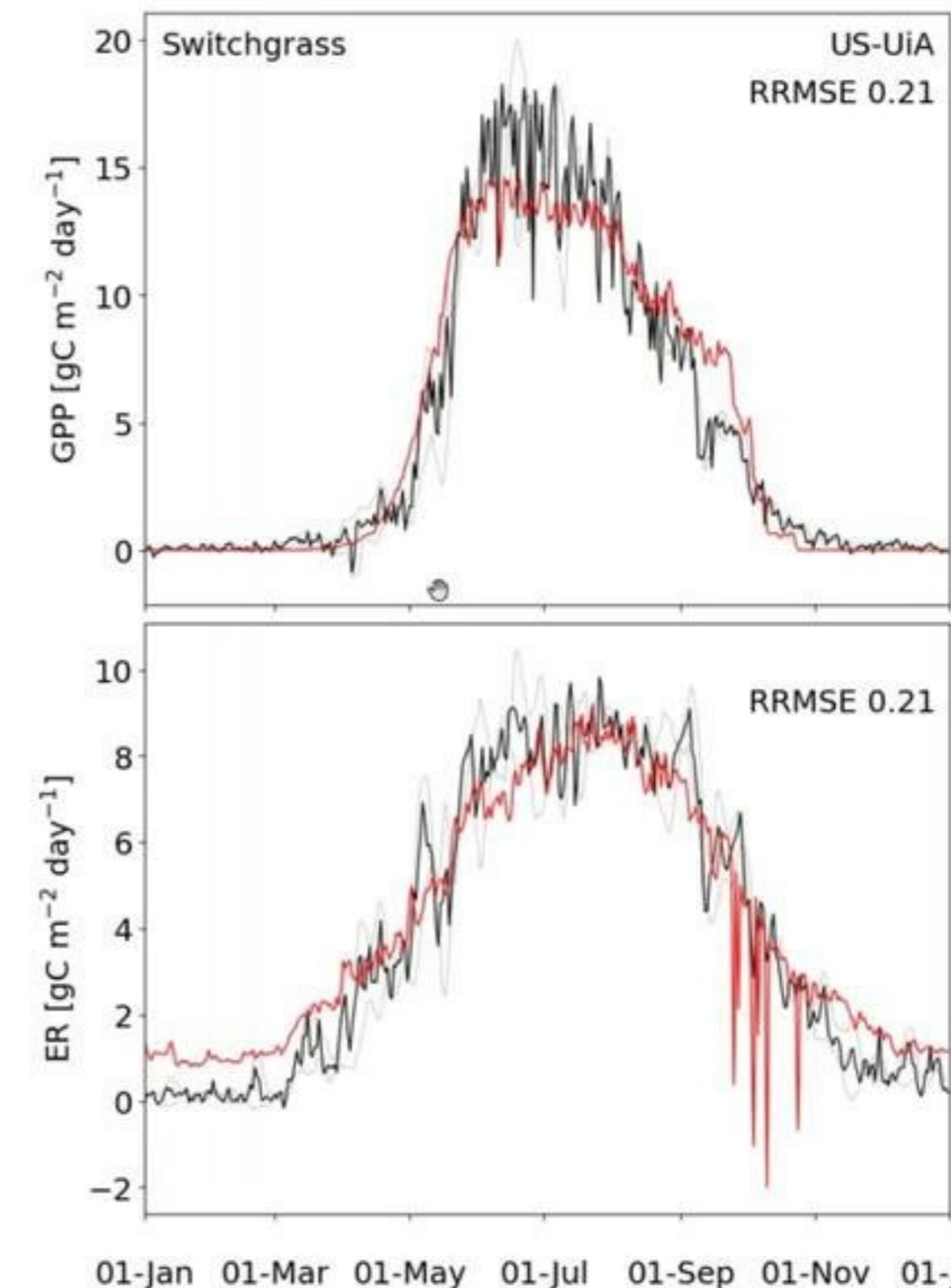
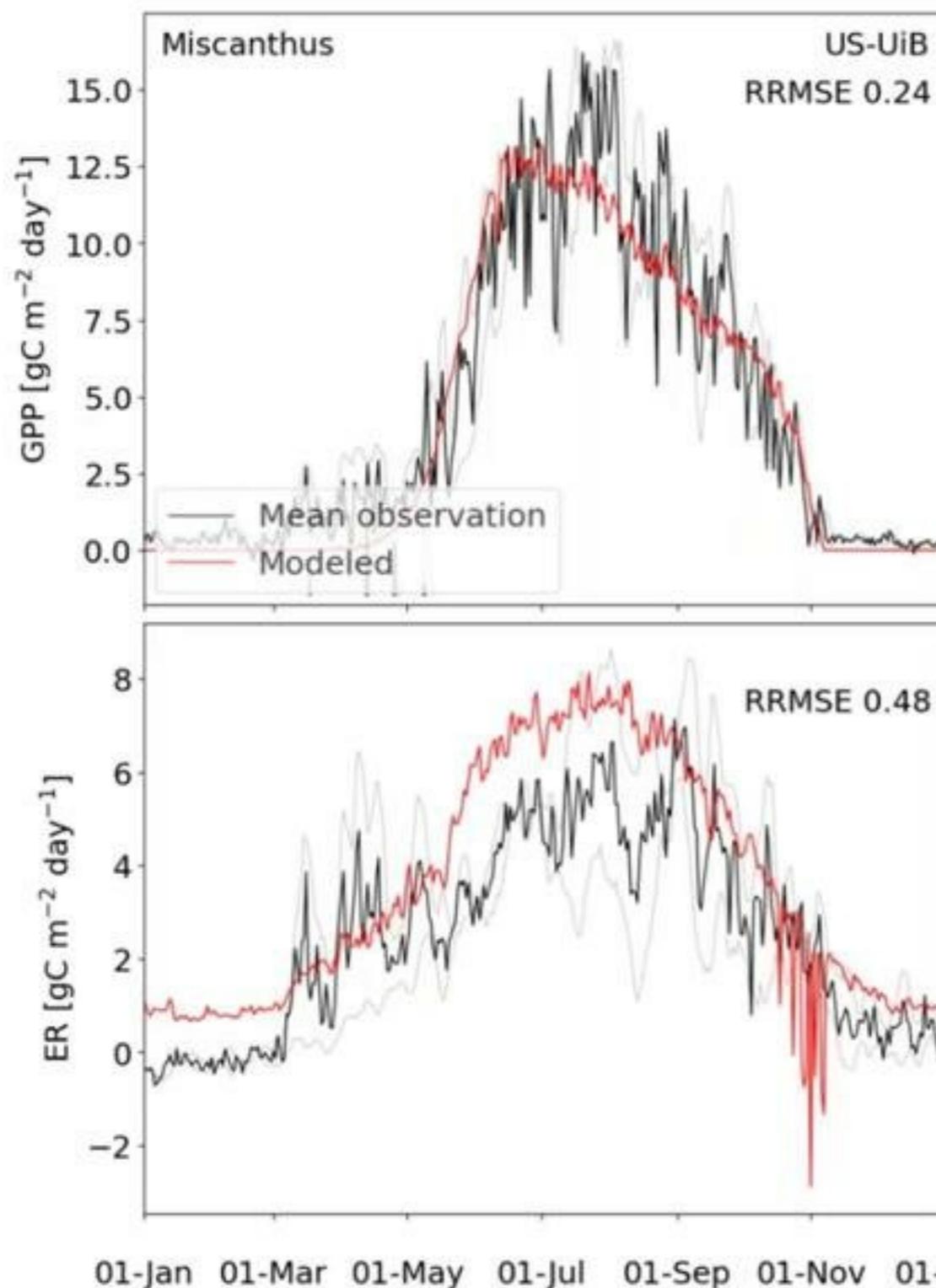
# Calibrated values closely match the observations



# Optimized parameter values for perennial crops

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

# Validation results in small RMSE for carbon fluxes



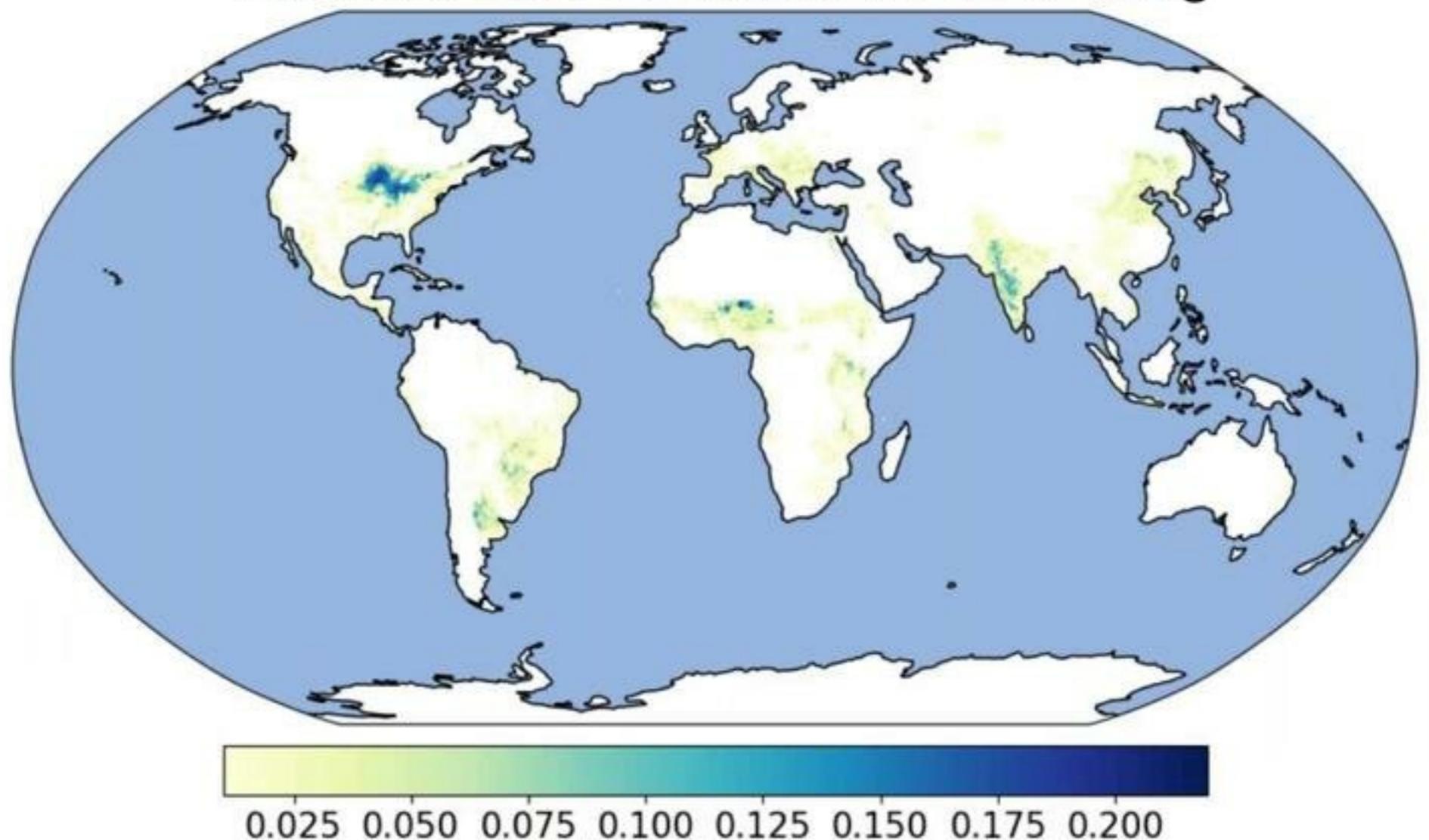
## Main takeaways / Next steps



- 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.

# Crop rotation practiced globally for increasing yield

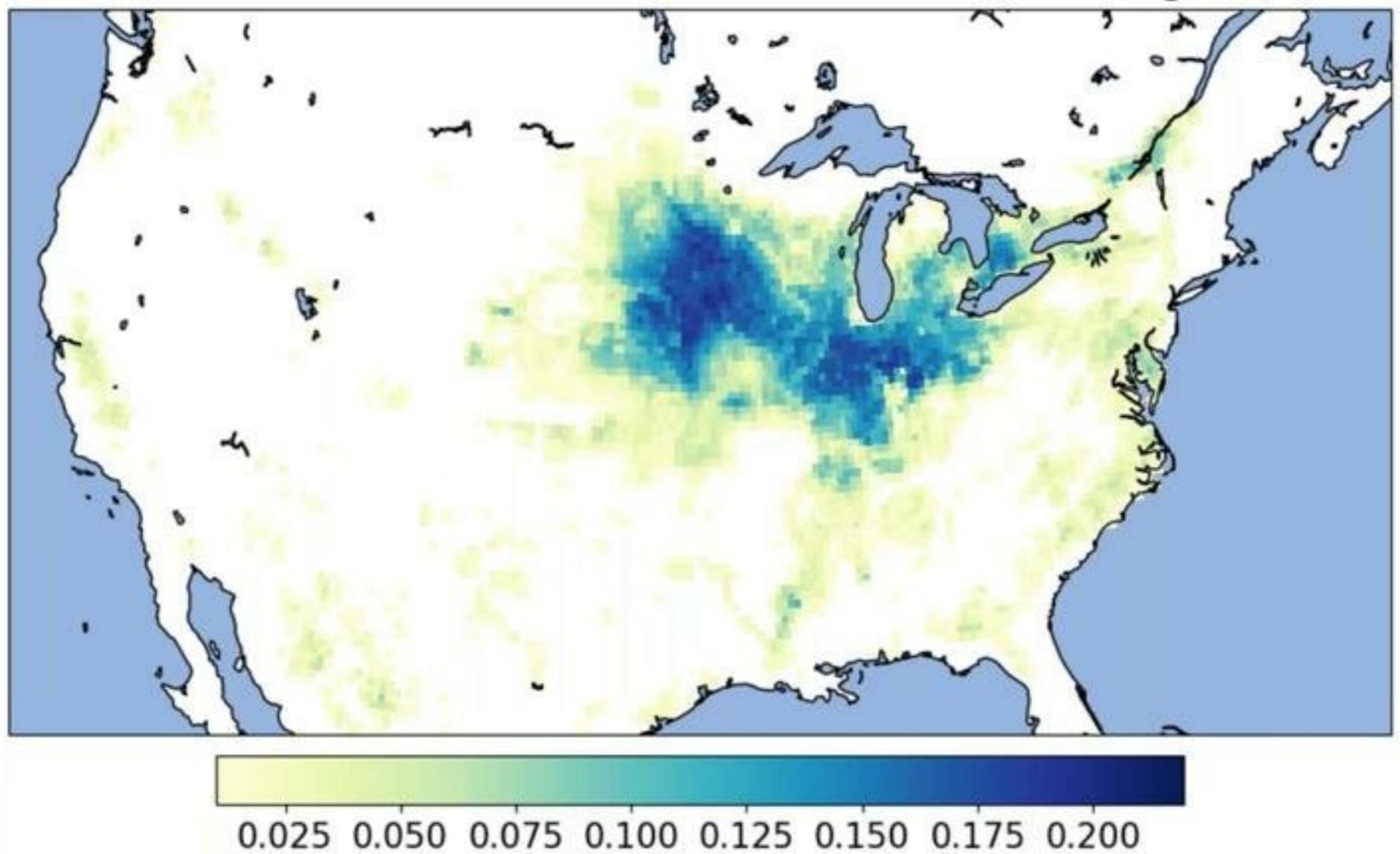
## Transition from C4 annual to C3 N-fixing



Data source: Hurtt et al., 2020

# Crop rotation practiced globally for increasing yield

Transition from C4 annual to C3 N-fixing



Data source: Hurtt et al., 2020

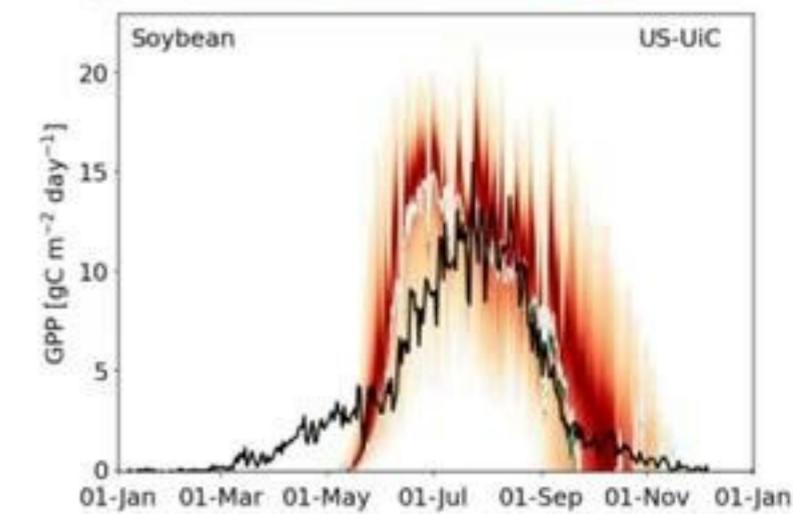
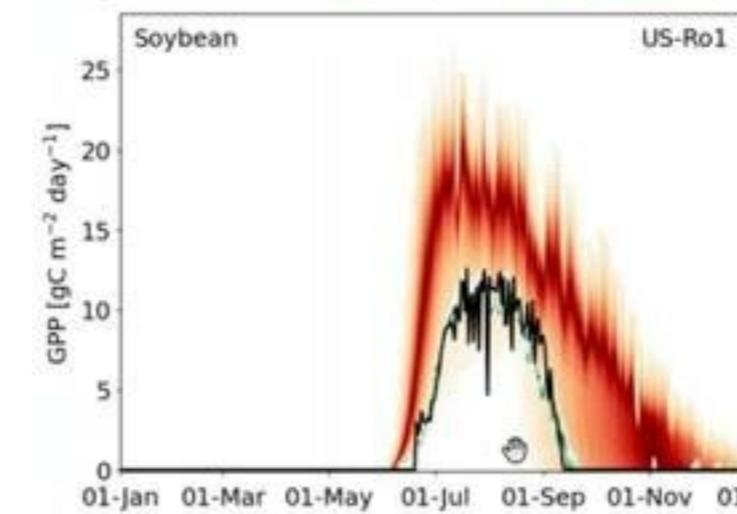
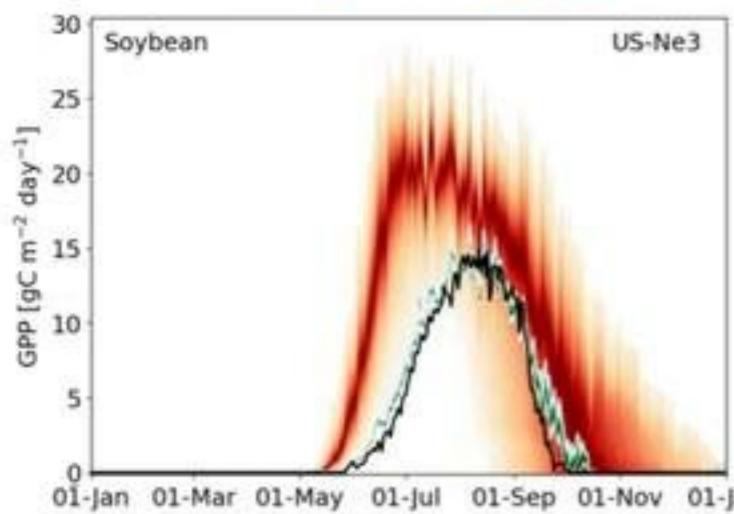
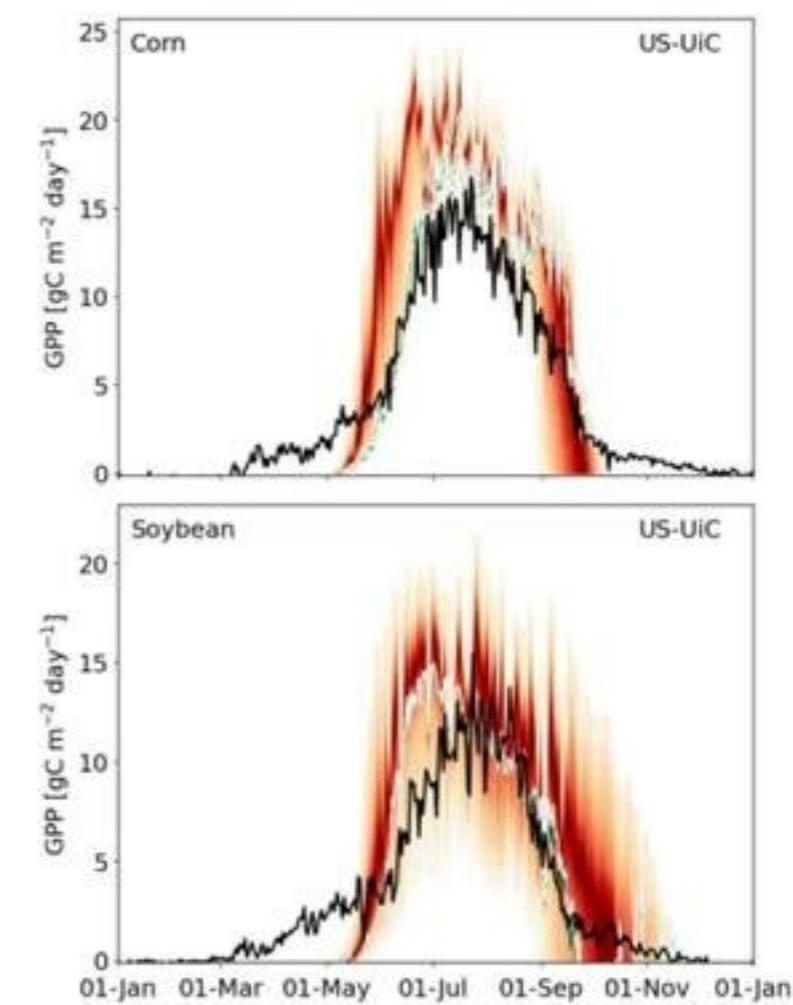
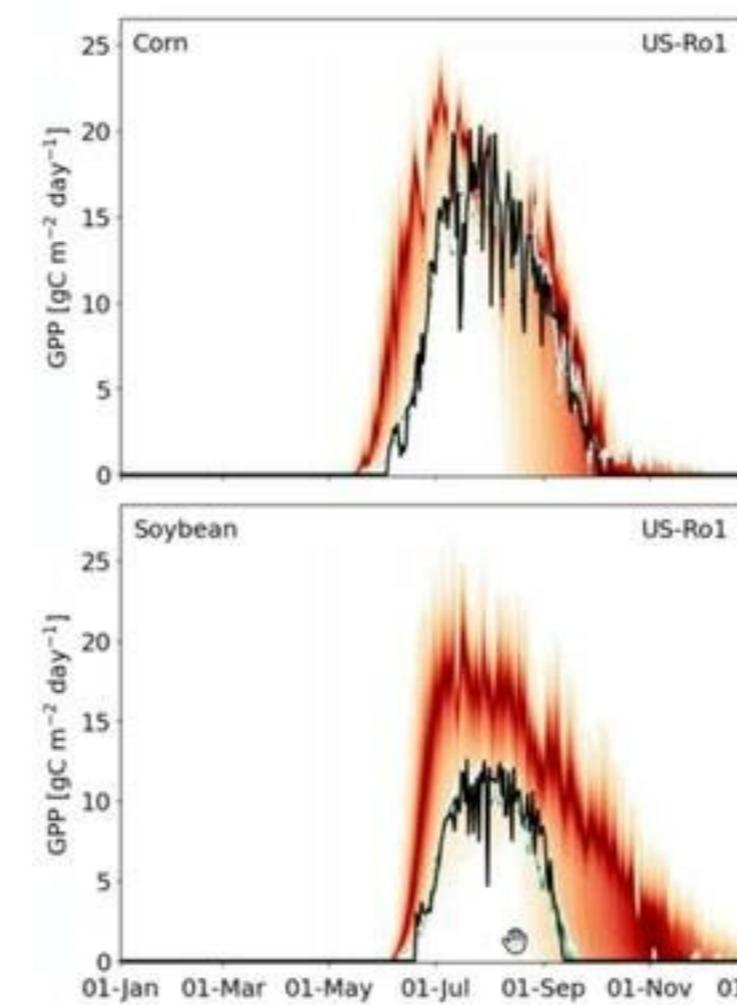
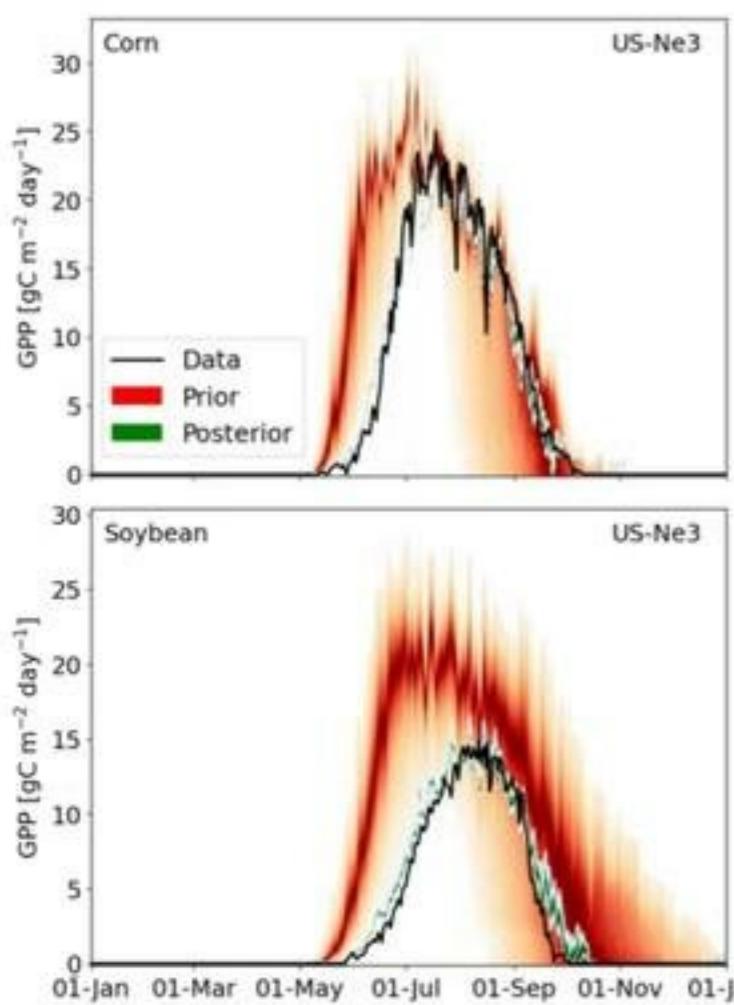
## Research objective

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

