Catchment-CN: Using CLM Carbon Dynamics in the NASA GMAO Land Model

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(2) Science Systems and Applications Inc.
(3) GESTAR, Universities Space Research Association
(4) Atmospheric Chemistry and Dynamics Laboratory, NASA Goddard Space Flight Center
(5) Morgan State University

Overview

1. Introduction to Catchment-CN
2. Science Applications
    i. Impact of atmospheric carbon variability on terrestrial carbon fluxes
    ii. Impact of land initial conditions on sub-seasonal to seasonal (S2S) carbon forecasts
    iii. Evaluation of fire carbon emissions
    iv. Vegetation parameter optimization
3. Transition to Catchment-CN 5.0

Catchment-CN model

- Experimental land component in NASA GEOS Earth System Model
- Merger of Catchment LSM & CLM CN dynamics

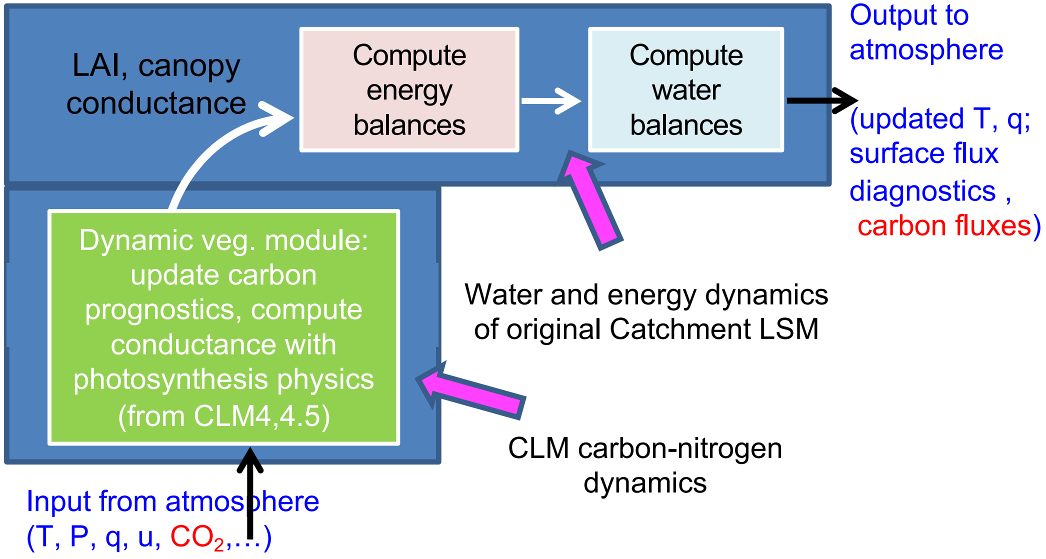
The Catchment LSM:

- Calculates all the water and energy balances
- Provides the CN model:
  - Soil moisture and temperature
  - Canopy temperature
  - Snow depth and coverage

The CN model:

- Calculates all the carbon and nitrogen fluxes and reservoirs, and
- Provides the Catchment LSM LAI and canopy conductance.

The Catchment-CN model



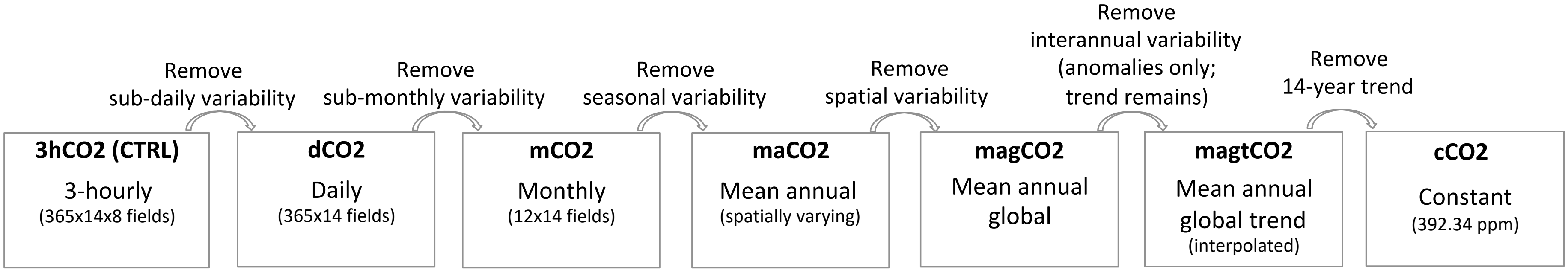
⇒ **We do not use CLM soil layer structure, hydrology, energy balance calculations, etc..**

⇒ **We use only CLM photosynthesis, stomatal conductance, and C and N flux and reservoir calculations.**

Science Applications

i. Impact of atmospheric CO2 variability on terrestrial biosphere

Objective: Quantify the sensitivity of terrestrial carbon fluxes (GPP) on the spatiotemporal variability of atmospheric CO2



Remove sub-daily variability

Remove sub-monthly variability

Remove seasonal variability

Remove spatial variability

Remove interannual variability (anomalies only; trend remains)

Remove 14-year trend

3hCO2 (CTRL)
3-hourly
(365x14x8 fields)

dCO2
Daily
(365x14 fields)

mCO2
Monthly
(12x14 fields)

maCO2
Mean annual
(spatially varying)

magCO2
Mean annual global

magtCO2
Mean annual global trend
(interpolated)

cCO2
Constant
(392.34 ppm)

Figure: Overview of experiments changing nature of atmospheric CO2 variability

Lee et al., 2018

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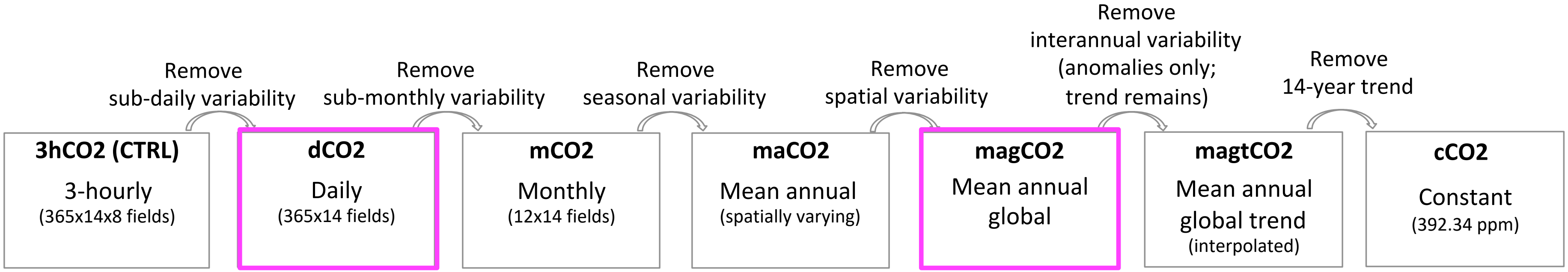

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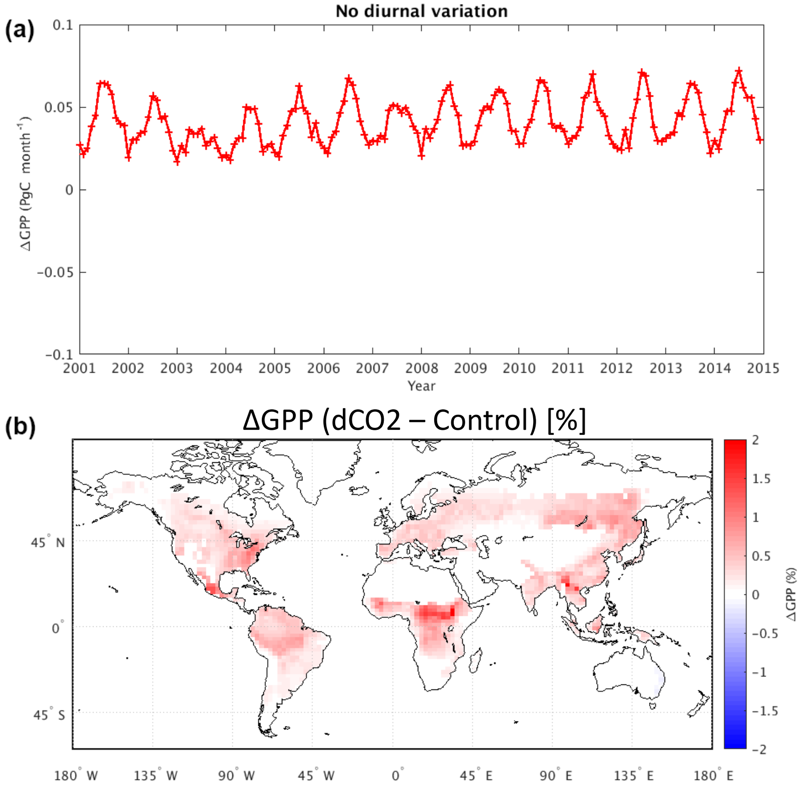

Figure: Impact of removing CO2 diurnal variability on GPP

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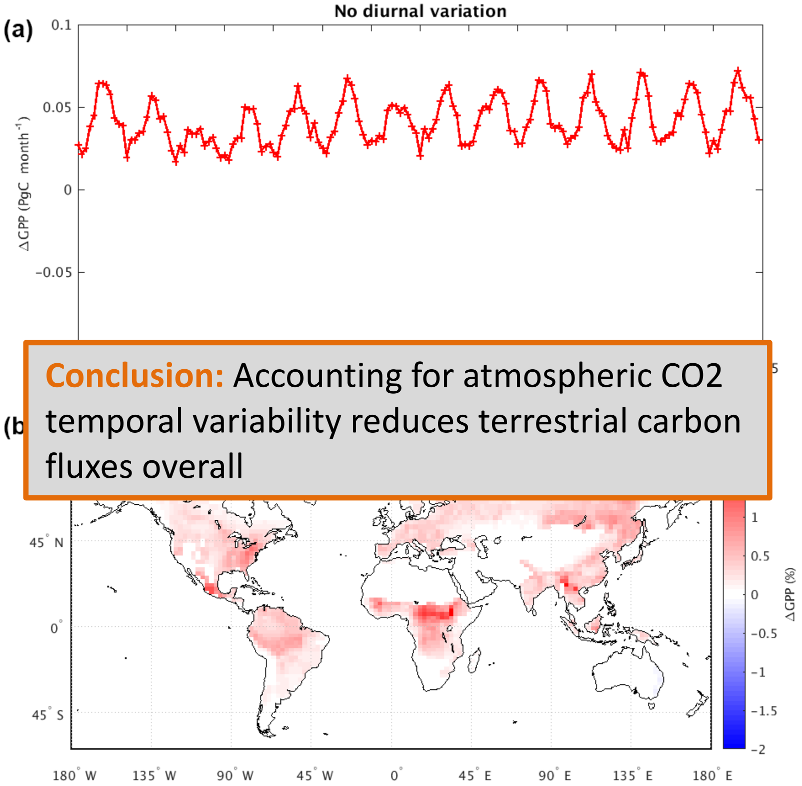

Conclusion: Accounting for atmospheric CO2 temporal variability reduces terrestrial carbon fluxes overall

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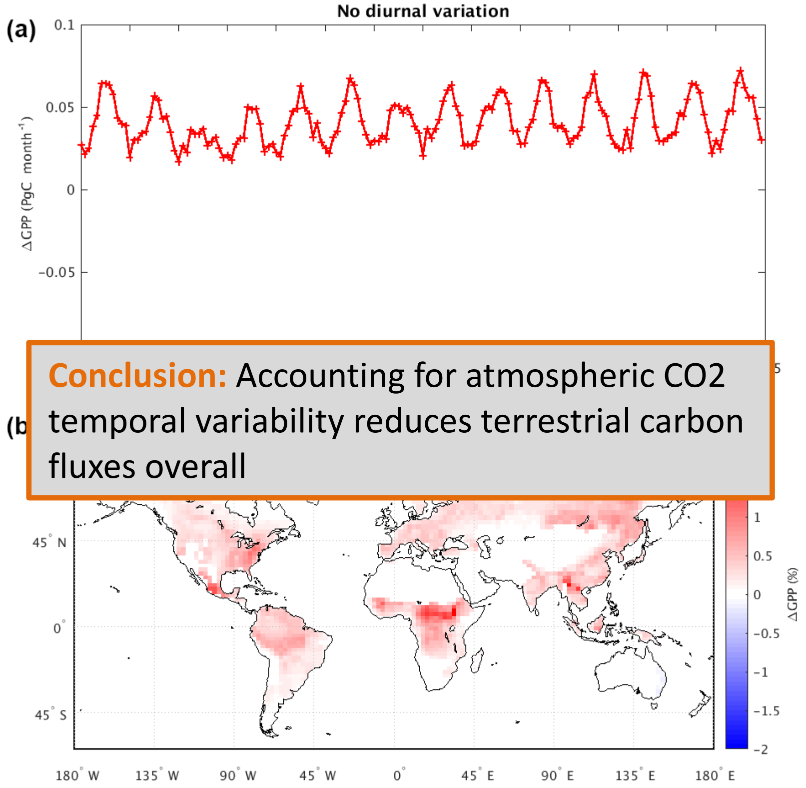

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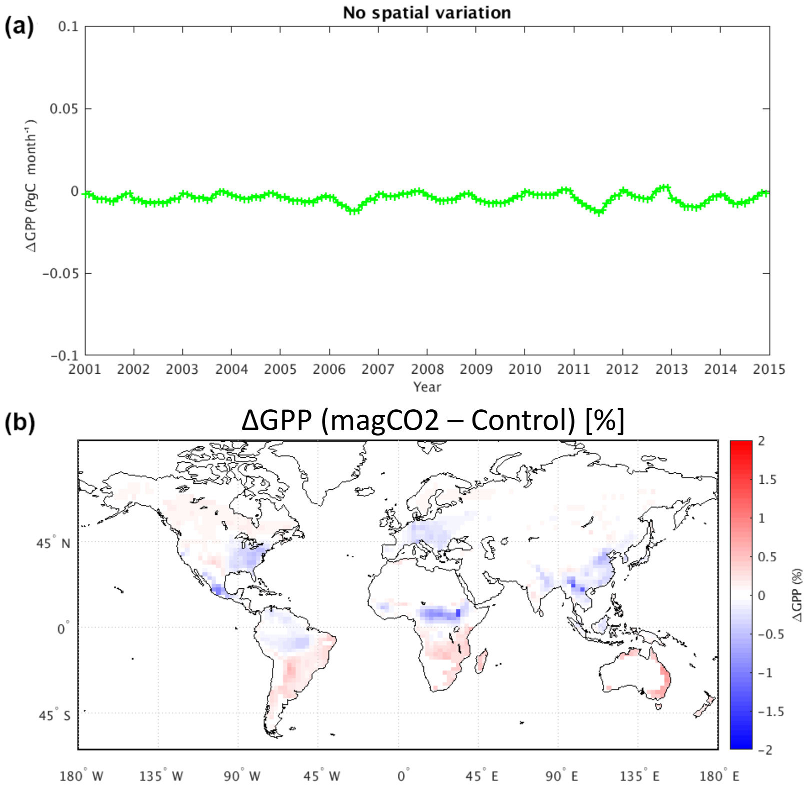

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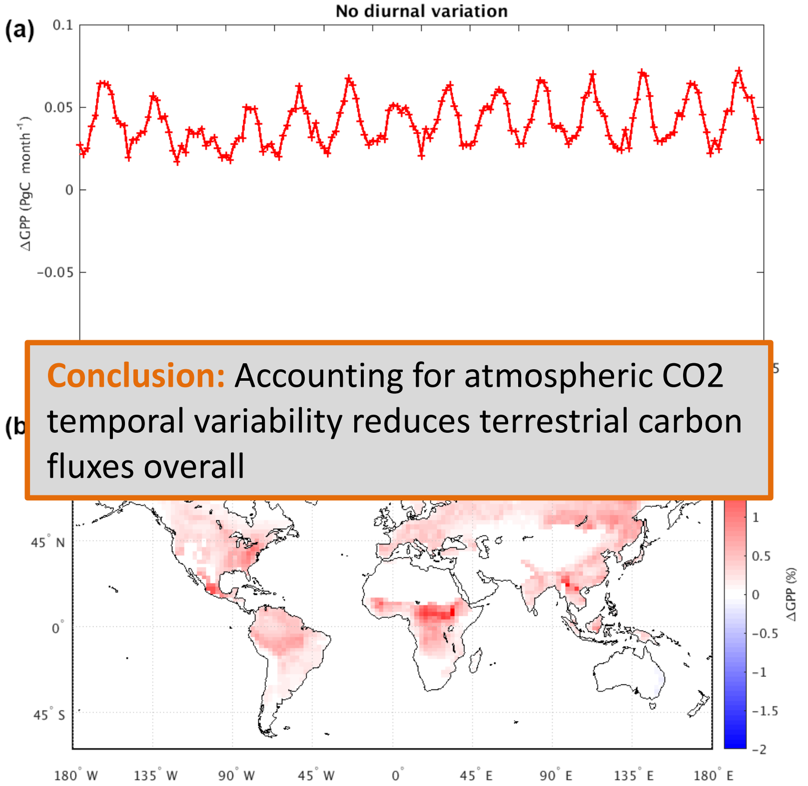

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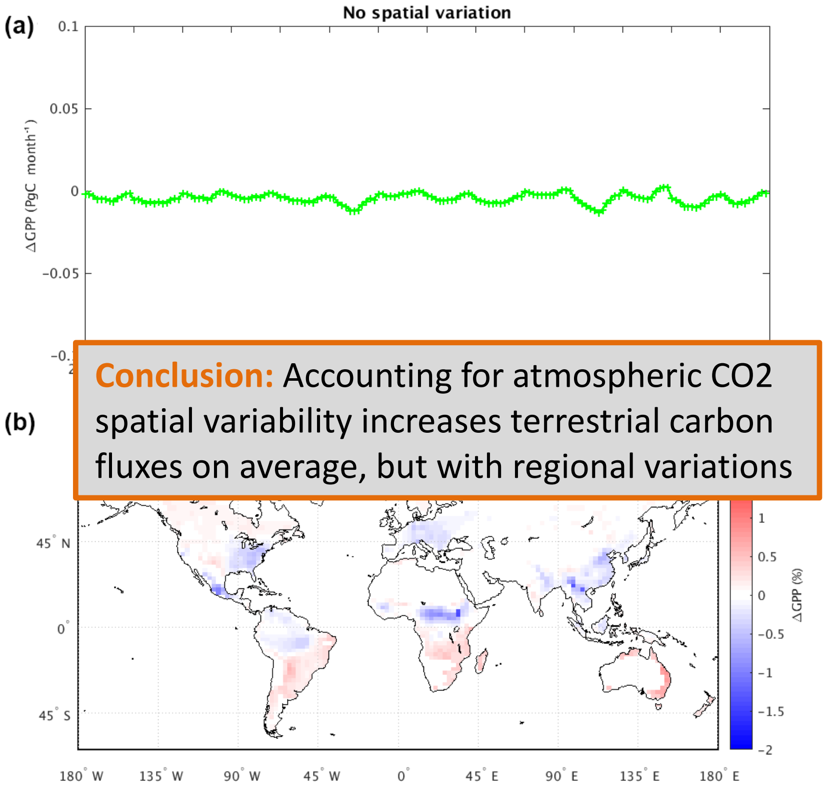

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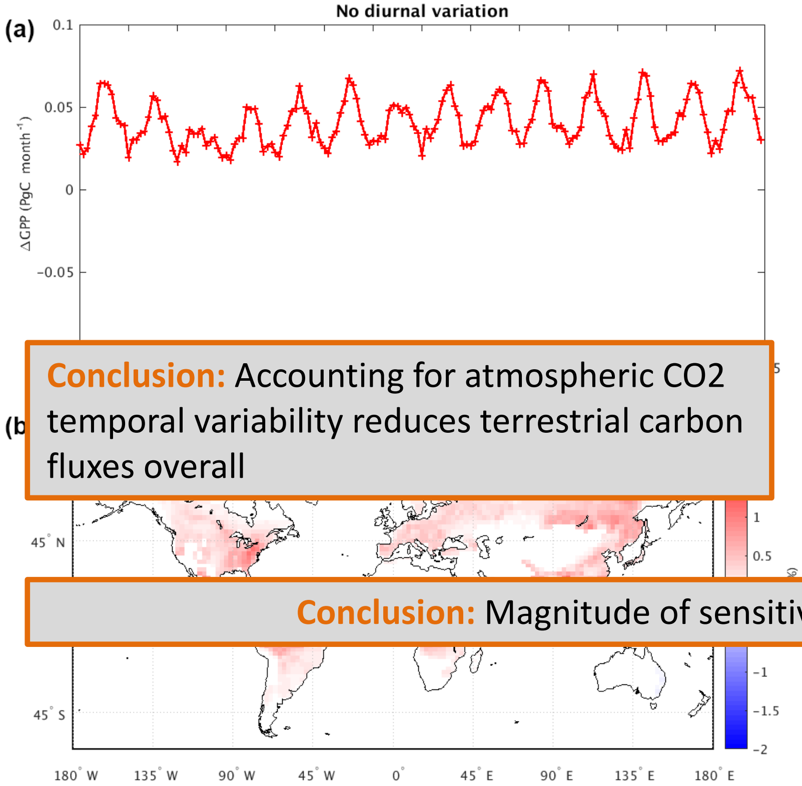

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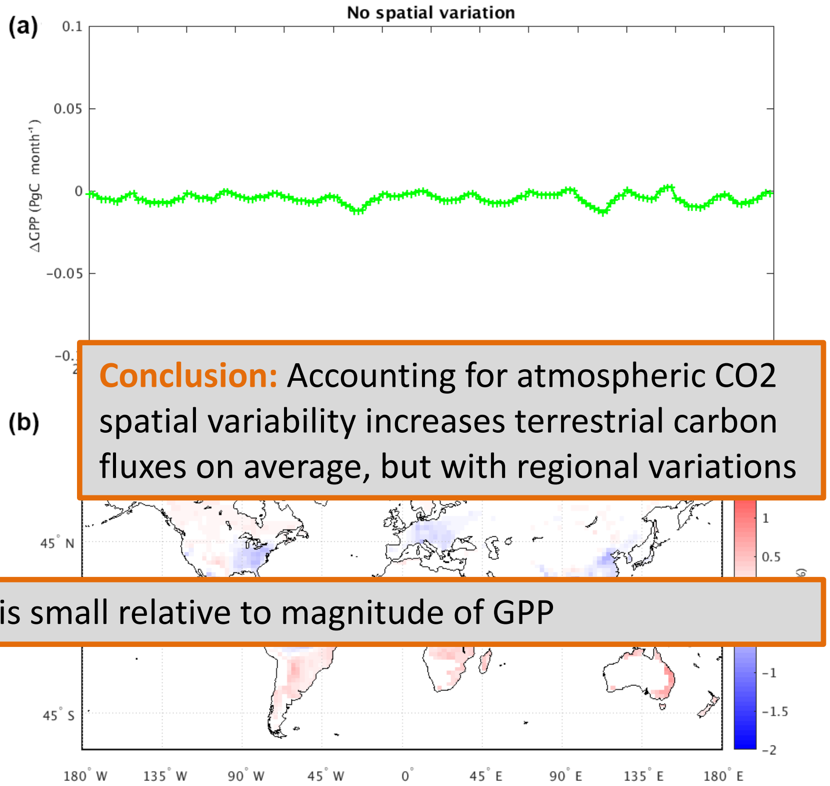

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Figure: Impact of removing CO2 spatial variability on GPP

Conclusion: Magnitude of sensitivities is small relative to magnitude of GPP

Lee et al., 2018

ii. Role of Land in S2S carbon forecasts

Objective: Investigate the impact of land initial conditions (IC) on subseasonal-to-seasonal (S2S) forecasts of GPP

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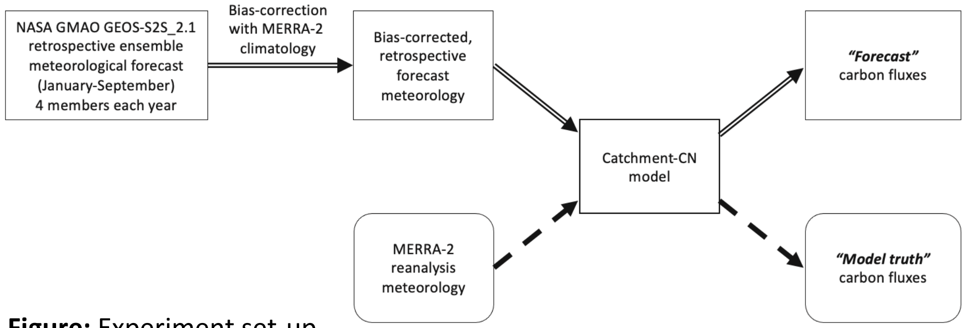

Figure: Experiment set-up

Lee et al., in prep

ii. Role of Land in S2S carbon forecasts

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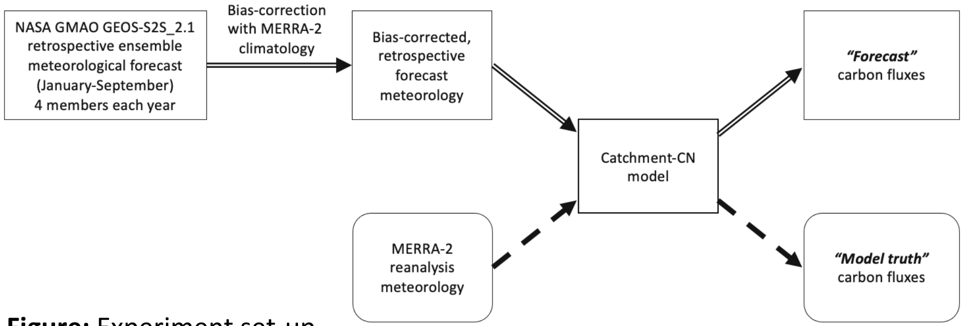
CTRL: Regular forecast, meteorology and land ICs vary temporally

EXP2016_met: Fixed (2016) meteorology; soil moisture and carbon states vary temporally -> impact of land ICs

EXP2016_met_sm: Fixed (2016) meteorology and soil moisture ICs; carbon states vary temporally -> impact of carbon ICs



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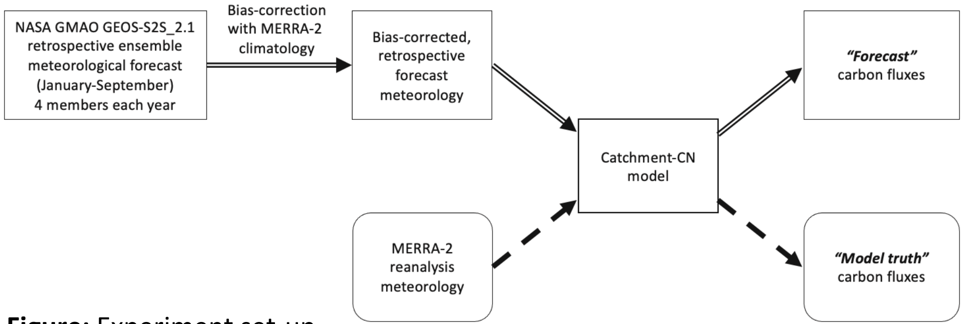
EXP2016_met_sm: Fixed (2016) meteorology and soil moisture ICs; carbon states vary temporally -> impact of carbon ICs

Conclusion: Land ICs significantly contribute to carbon forecast skill at spatial and temporal scales

Conclusion: Impact of soil moisture ICs dominates impact of carbon ICs at early lead months



NASA GMAO GEOS-S2S_2.1 retrospective ensemble meteorological forecast (January-September) 4 members each year

Bias-correction with MERRA-2 climatology

Bias-corrected, retrospective forecast meteorology

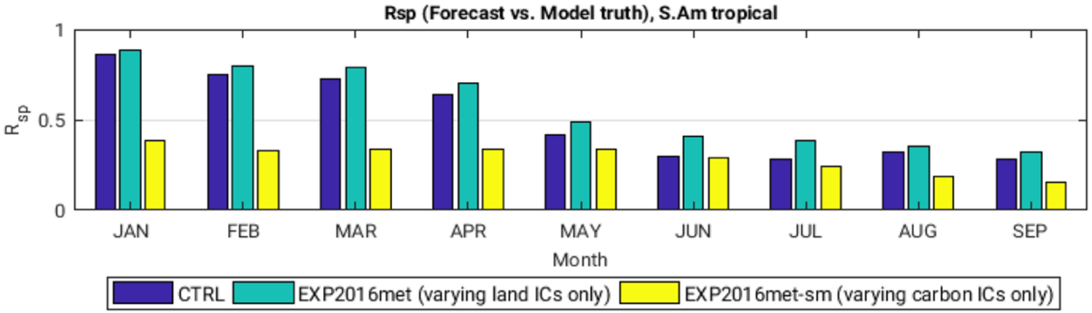
Catchment-CN model

MERRA-2 reanalysis meteorology

"Forecast" carbon fluxes

"Model truth" carbon fluxes

Figure: Experiment set-up



Lee et al., in prep

Figure: Spatial correlation between forecast GPP and model truth

iii. Evaluation of Wildfire simulations

Objective: Evaluate Catchment-CN4.5 fire carbon emissions and burnt area against Global Fire Emissions Database

Follette-Cook et al., in prep

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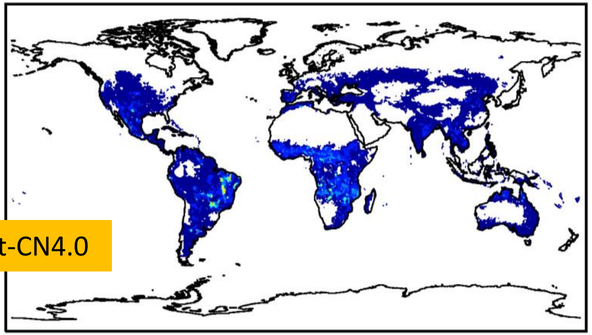
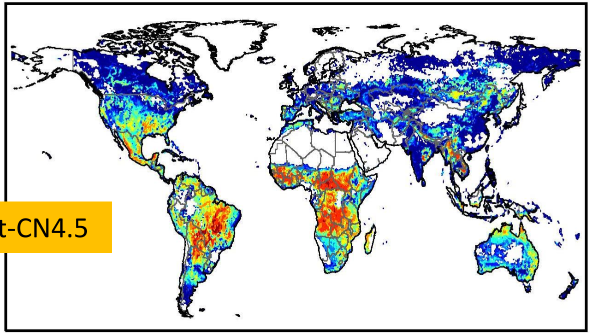
Fire burned area (1997 – 2016)

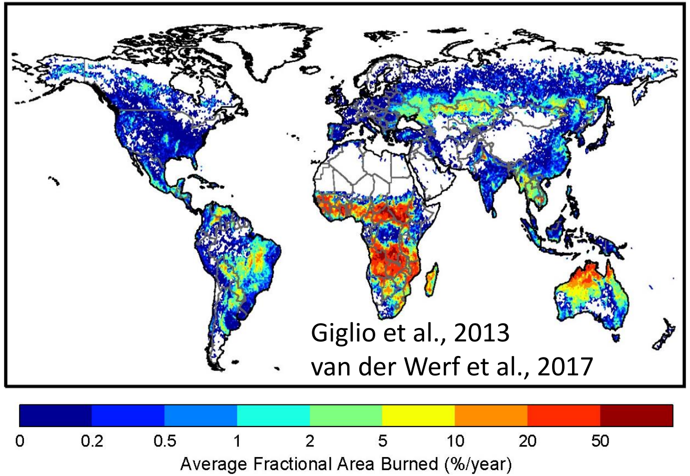


Catchment-CN4.0



Catchment-CN4.5

GFED v4.1s



Giglio et al., 2013
van der Werf et al., 2017

Conclusion: Catchment-CN4.5 captures observed wildfire impact better than Catchment-CN4.0

Follette-Cook et al., in prep

iii. Evaluation of Wildfire simulations

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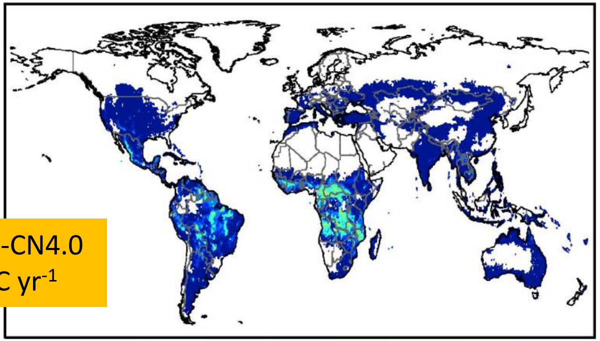
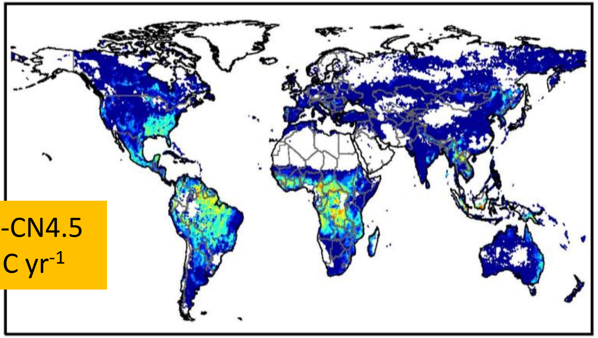
Fire carbon emissions (1997 – 2016)

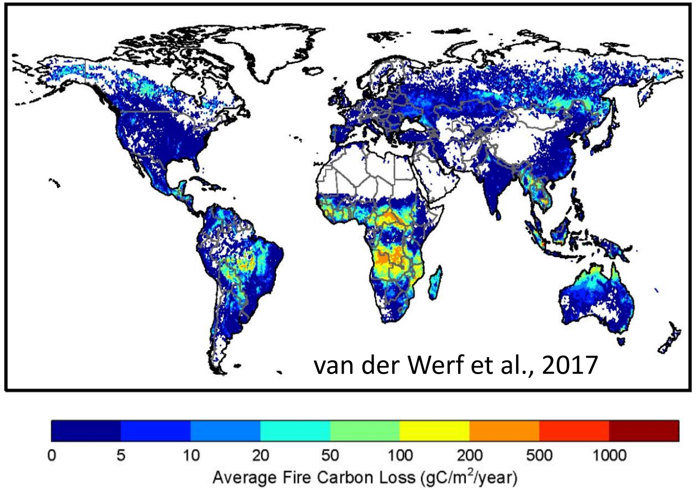
Catchment-CN4.0
~500 Tg C yr^{-1}



Catchment-CN4.5
~1700 Tg C yr^{-1}



GFED v4.1s
~2100 Tg C yr^{-1}



van der Werf et al., 2017

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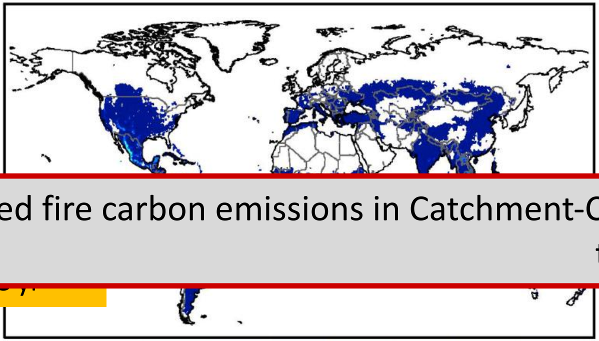

Improved fire carbon emissions in Catchment-CN4.5. However, these are accompanied by a reduced skill in modelling terrestrial carbon fluxes

GFED v4.1s
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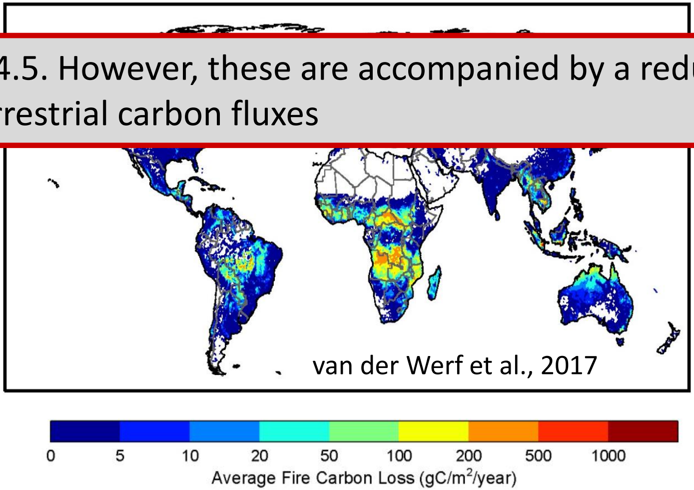

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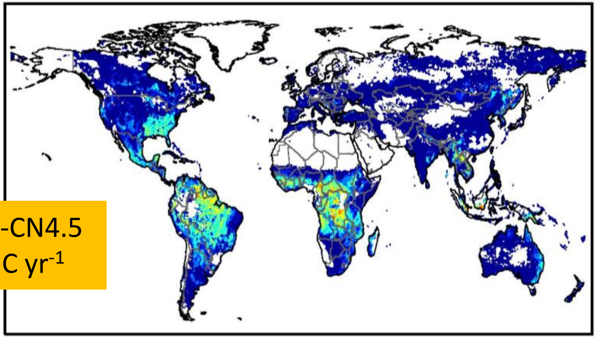


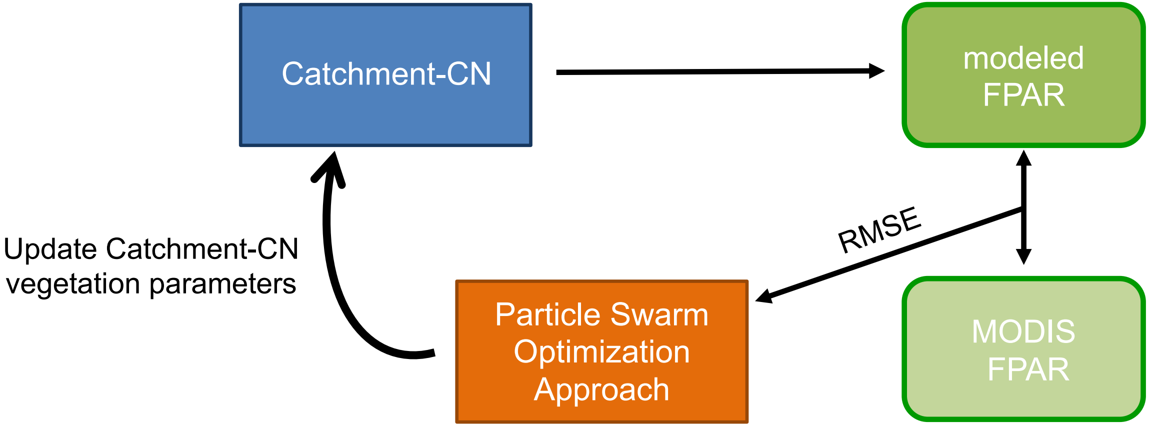
Catchment-CN4.5
~1700 Tg C yr^{-1}

Follette-Cook et al., in prep

iv. Vegetation Parameter Optimization

Objective: Use MODIS FPAR observations to optimize Catchment-CN vegetation parameters.

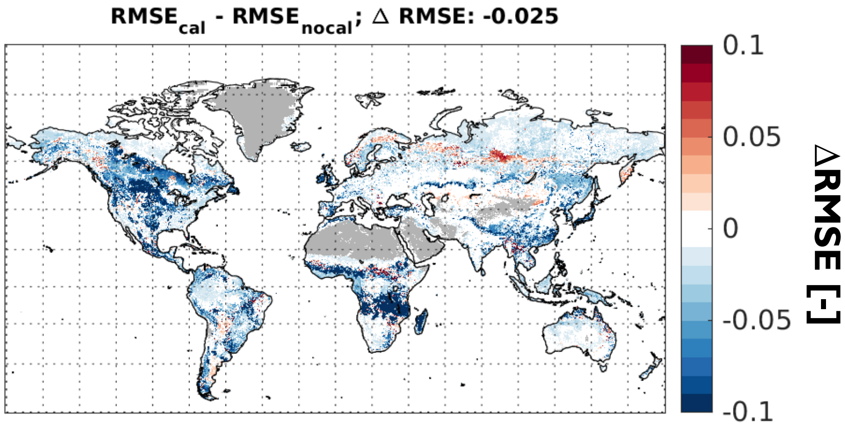
- Calibration parameters:
  - Timing of phenological cycle (seasonal variability)
  - Photosynthetic efficiency (bias)
  - Carbon storage/allocation (interannual variability)



Kolassa et al., 2020

iv. Vegetation Parameter Optimization

Change in RMSE vs MODIS FPAR

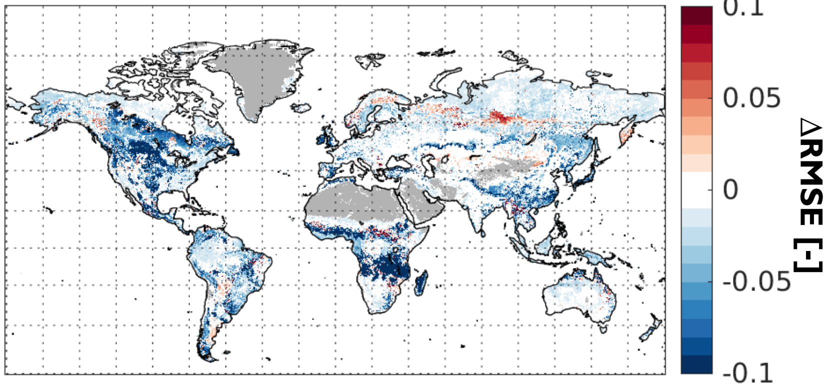


Kolassa et al., 2020

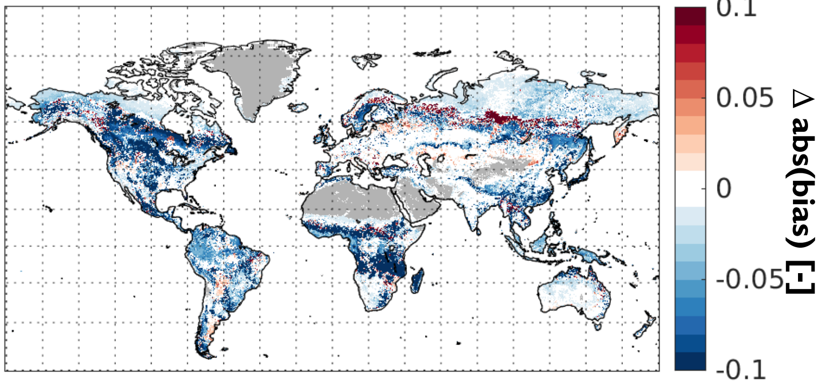
iv. Vegetation Parameter Optimization

Change in RMSE vs MODIS FPAR

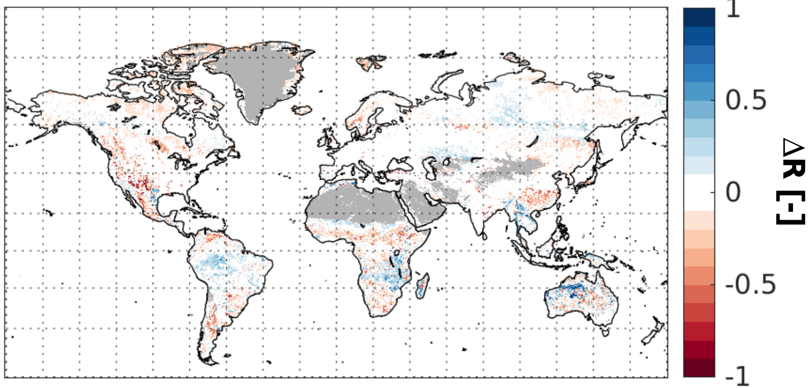
RMSE_{cal} - RMSE_{nocal}; Δ RMSE: -0.025



abs(bias)$_{cal}$ - abs(bias)$_{nocal}$; Δ abs(bias): -0.035



R_{cal} - R_{nocal}; Δ R: -0.0075



- Dominance of bias in model error skews calibration towards efficiency parameters

Kolassa et al., 2020

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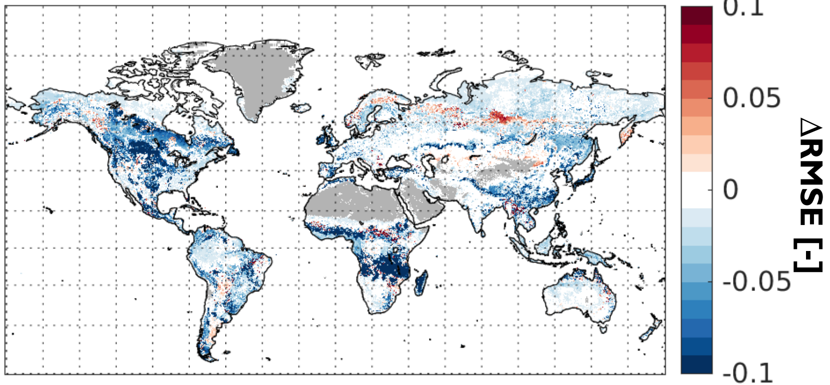

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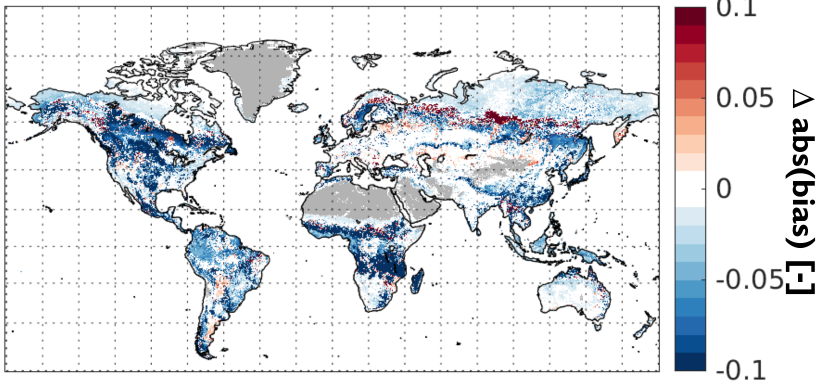

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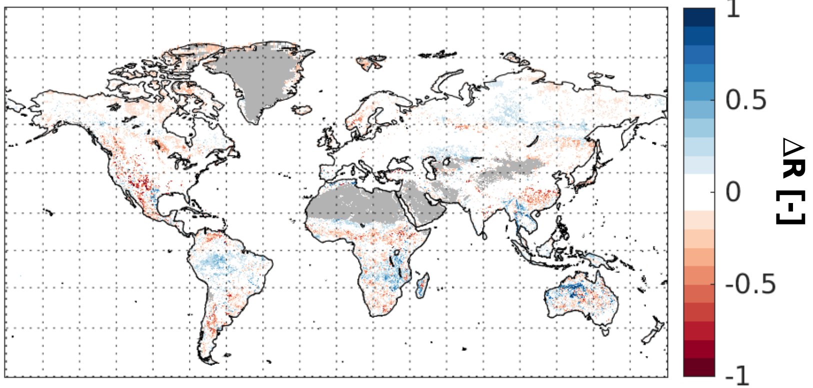

- Dominance of bias in model error skews calibration towards efficiency parameters

Conclusion: Two-stage calibration to address first the bias and then the timing would be more effective

Kolassa et al., 2020

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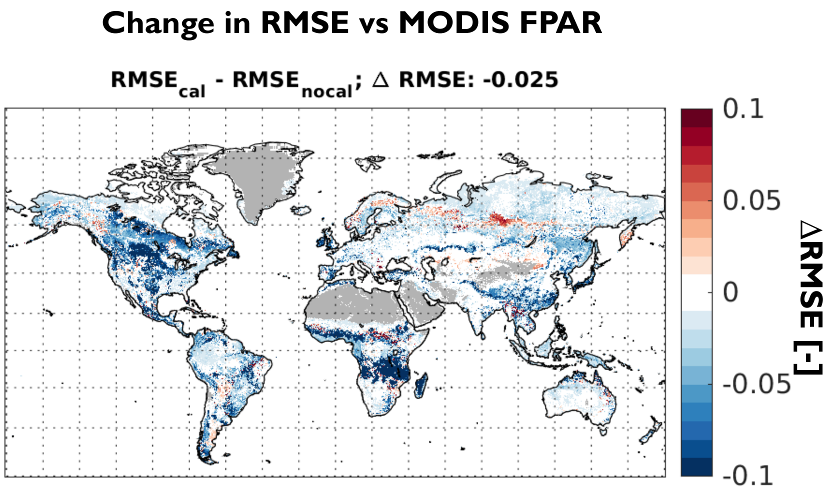

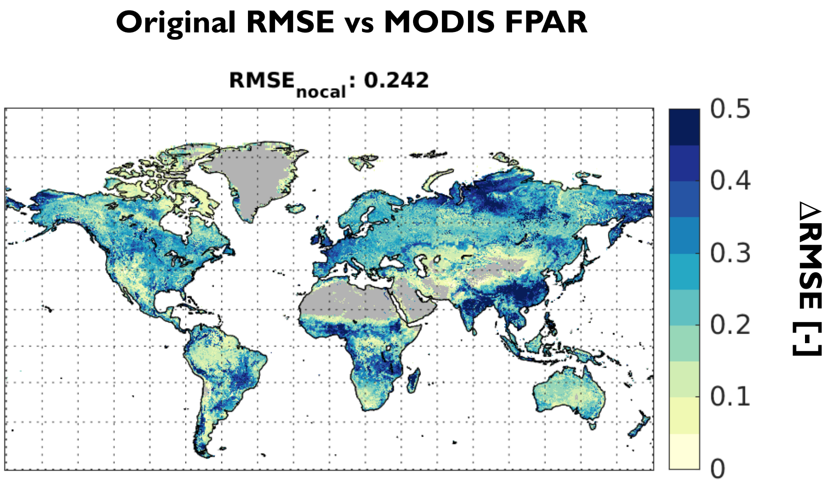

- Calibration is effective, but skill changes are small relative to total error

Conclusion: Parameter estimation can only reduce a part of the total model error, model structure changes are needed to address remaining error

Kolassa et al., 2020

Looking ahead: Work with CatchmentCN5.0

Catchment-CN5.0: Catchment + CLM5.0

Applications:

(Relatively) Immediate:
-- Analyses of fire in the climate system, including all feedbacks between land and atmosphere (trace gas emissions from fire)
-- Incorporation of CatchmentCN5.0 (in some form) into the next version of the operational S2S forecast system – allow initialization and evolution of vegetation phenology to influence forecasts
-- More studies of the linkages between the water, energy, and carbon cycles in the coupled land/atmosphere system (improvements from plant hydraulics)

Longer-term goals:
-- Incorporation of CatchmentCN5.0 into the full suite of GMAO operational systems, including reanalysis generation
-- Studies of the carbon cycle with fully coupled ocean/land/atmosphere system

References

1. Bonan, G.B., Lawrence, P.J., Oleson, K.W., Levis, S., Jung, M., Reichstein, M., Lawrence, D.M. and Swenson, S.C., 2011. Improving canopy processes in the Community Land Model version 4 (CLM4) using global flux fields empirically inferred from FLUXNET data. Journal of Geophysical Research: Biogeosciences, 116(G2).
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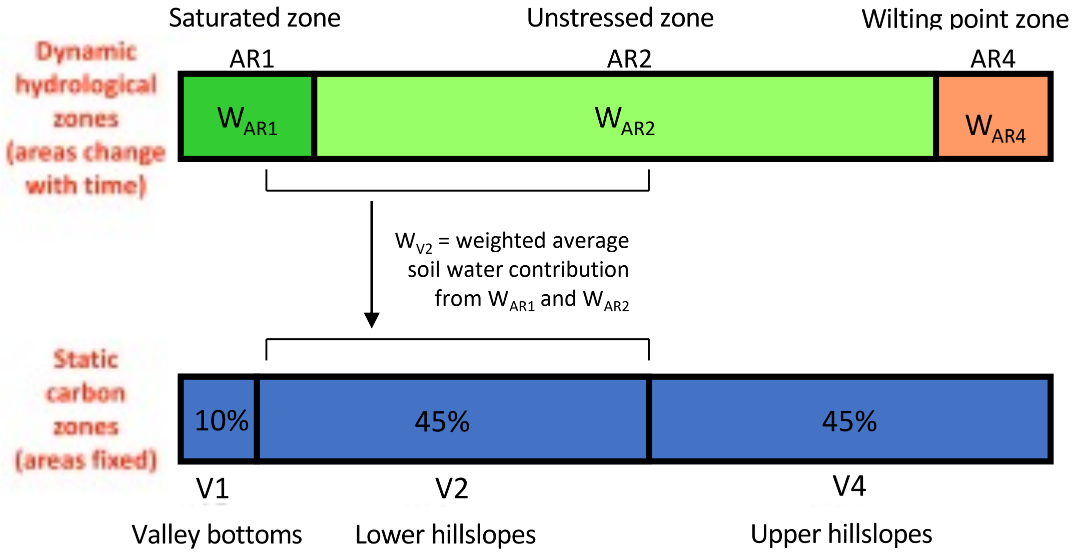
3. Lee, E., Zeng, F.W., Koster, R.D., Weir, B., Ott, L.E. and Poulter, B., 2018. The impact of spatiotemporal variability in atmospheric CO 2 concentration on global terrestrial carbon fluxes. Biogeosciences, 15(18), pp.5635-5652.
4. Kolassa, J., Reichle, R.H., Koster, R.D., Liu, Q., Mahanama, S. and Zeng, F.W., 2020. An Observation-Driven Approach to Improve Vegetation Phenology in a Global Land Surface Model. Journal of Advances in Modeling Earth Systems, 12(9)

Extra Slides

Catchment-CN model

Each basic Catchment land surface element is separated into:

- Three dynamic hydrological zones that vary with time depending on water availability
- Three static carbon zones (10%, 45%, 45%) with independent carbon states traced in each.

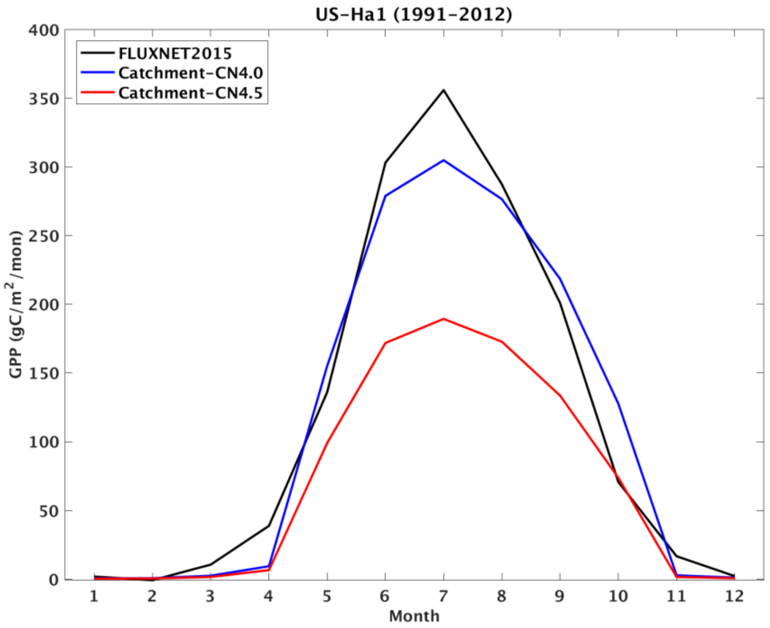


Koster et al., 2014

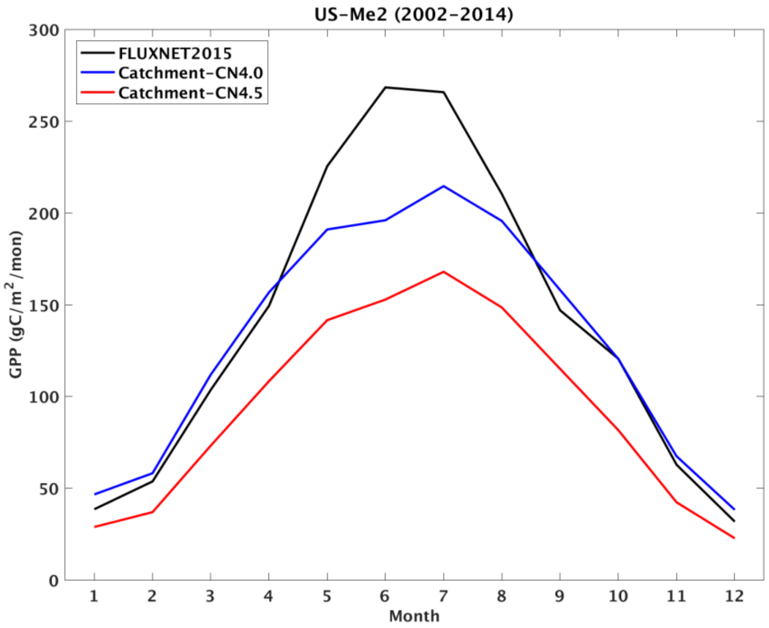
Our treatment of subgrid- scale hydrology can thus capture topographical effects on vegetation distributions.

Performance of Catchment-CN4.5 – GPP

(42.54N, 72.17W)
Deciduous Broadleaf Forest



(44.45N, 121.56W)
Evergreen Needleleaf Forest



Follette-Cook et al., in prep

Main issue with Catchment-CN4.5 GPP

NCAR

CLM4 C,N | CLM4 Energy, Water | Qian et al. (2006) Forcing data

⇨ GPP=165 Pg C yr^{-1} **TOO HIGH!**

(Bonan et al. 2011)

Update to CLM4.5

CLM4.5 C,N | CLM4 Energy, Water | Qian et al. (2006) Forcing data

⇨ GPP=130 Pg C yr^{-1} **About right**

(Bonan et al. 2011, 2012)

GMAO

CLM4 C,N | Catchment Energy, Water | MERRA-2 Forcing data

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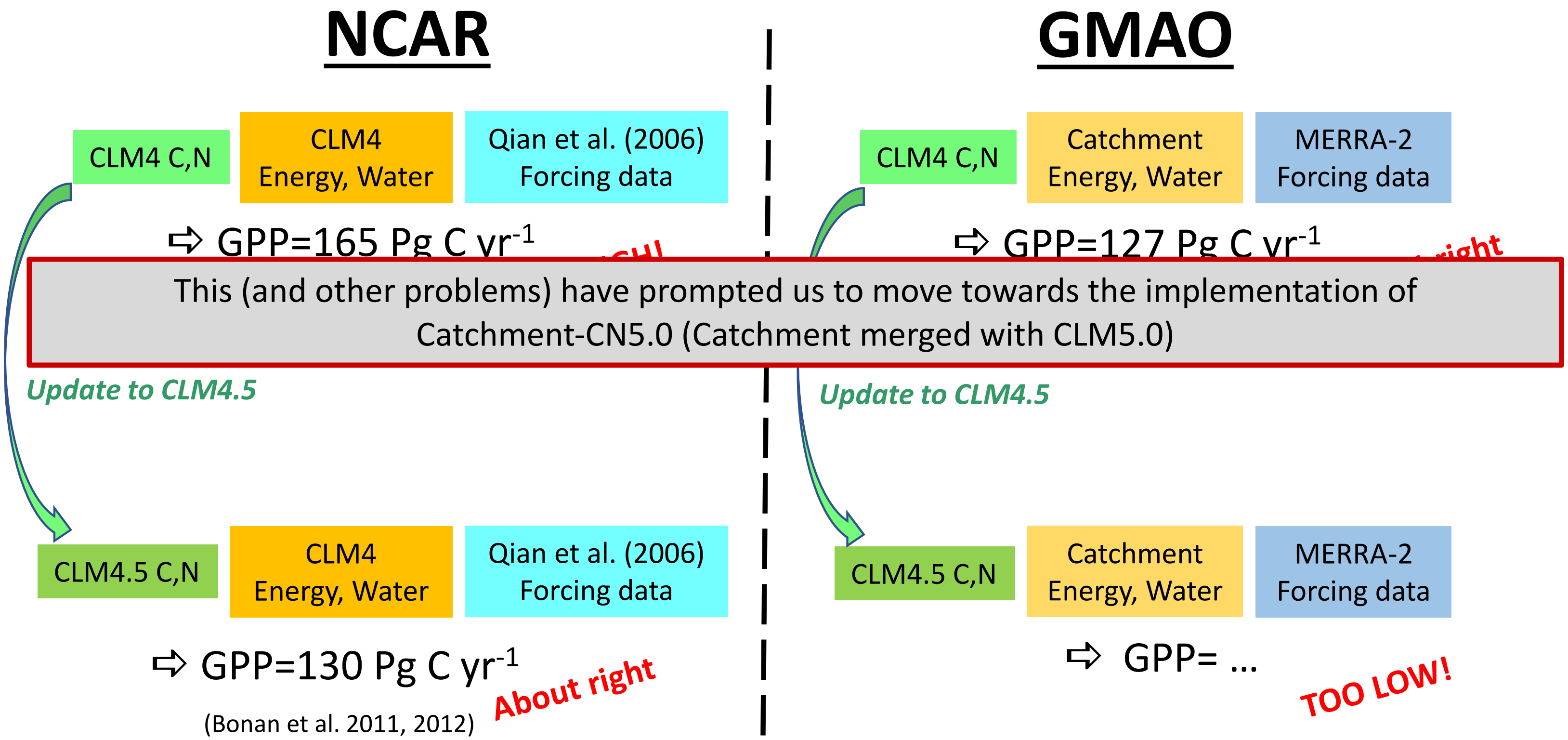

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GMAO

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CLM4.5 C,N | **Catchment Energy, Water** | **MERRA-2 Forcing data**

⇨ GPP= … **TOO LOW!**

This (and other problems) have prompted us to move towards the implementation of Catchment-CN5.0 (Catchment merged with CLM5.0)

Science changes to be implemented in Catchment-CN5.0

Vegetation:

- **Introduction of plant hydraulics and hydraulic redistribution**
- **Stomatal conductance formulation choice: Medlyn (default) or Ball-Berry; based on N-limited photosynthesis**
- *FATES ecosystem demography*
- *Ozone damage to plants*

Nitrogen:

- **More mechanistic representation of nitrogen cycle through Fixation and Uptake of Nitrogen (FUN) model**
- **Introduction of separate soil nitrogen pools**
- **Nitrogen uptake has 'carbon cost' for plants**
- Variable C:N ratio in leaves
- Leaf nitrogen, photosynthesis and stomatal conductance vary according to nitrogen cost
- Inclusion of Leaf Use of Nitrogen for Assimilation (LUNA) model: Vcmax dependent on leaf N and environmental drivers -> prognostic

Carbon:

- Fixed carbon allocation
- Weaker decrease of soil carbon decomposition rate with depth
- Stronger soil moisture control on decomposition

Fire:

- Fire occurrence and spread depends on fuel wetness for non-peat fires
- **Simulation of trace gas emissions**

Crop:

- **A multitude of crop functional types (CFTs) that are treated independently from PFTs**
- Coupled to an irrigation model