Data Assimilation of Leaf Area Index into the Community Land Model 5.0 to Constrain Decadal Global Carbon Dynamics

Xueli Huo[1], Andrew Fox[2], Timothy Hoar[3], Jeffrey Anderson[3], Hamid Dashti[1], William Smith[1], David Moore[1]

1. University of Arizona 2. National Center for Atmospheric Research 3. Joint Center for Satellite Data Assimilation

Introduction

More and more evidence shows that the global carbon cycle is responding to climate change. Community Land Model (CLM) can help us understand what is causing changes in the global carbon cycle, and evaluate whether global warming has and is likely to cause amplifying feedbacks to climate. However, the model is typically biased and the accuracy that represents the real world needs to be improved. Data assimilation (DA) is proven to be an effective and efficient way to correct model bias and improve model accuracy, and is used in our study to ensure that the model agrees with historical leaf area index (LAI) globally.

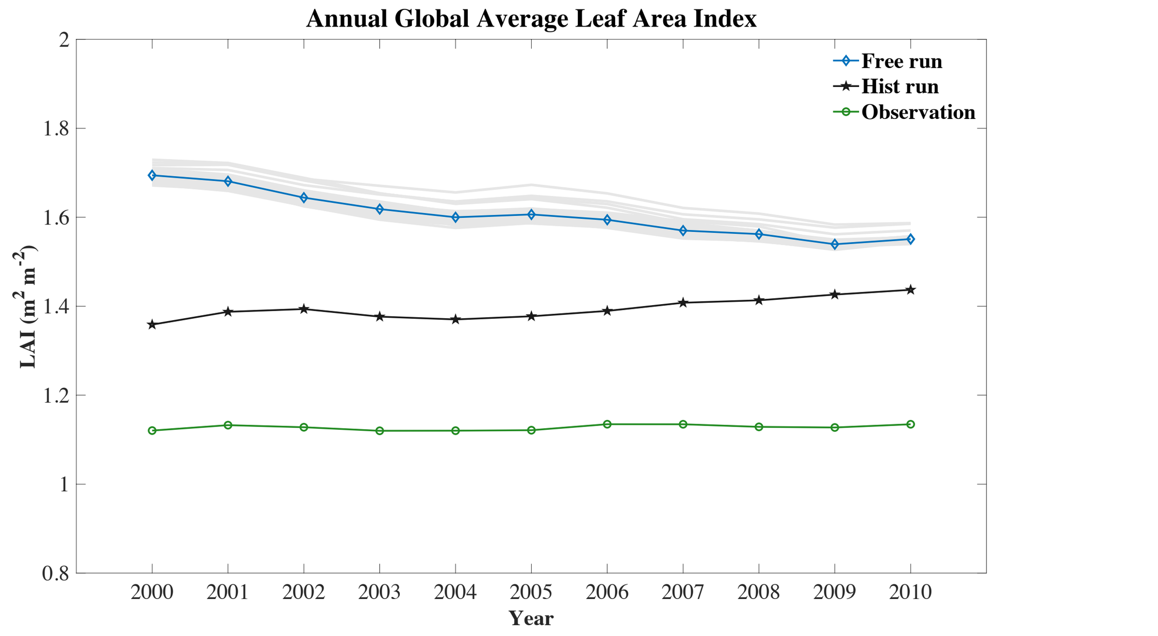


Figure 1. Time series of LAI from CLM5 BGC-Crop historical run (black line), 60-ensemble run forced with CAM reanalysis (grey line, blue line is the mean), and GIMMS LAI3g remote sensing observations.

Tools and Settings

CLM-DART Workflow

CLM-DART is developed and maintained by Data Assimilation Section in National Atmospheric Research (NCAR) (Anderson et al.,2009; Fox et al., 2019)

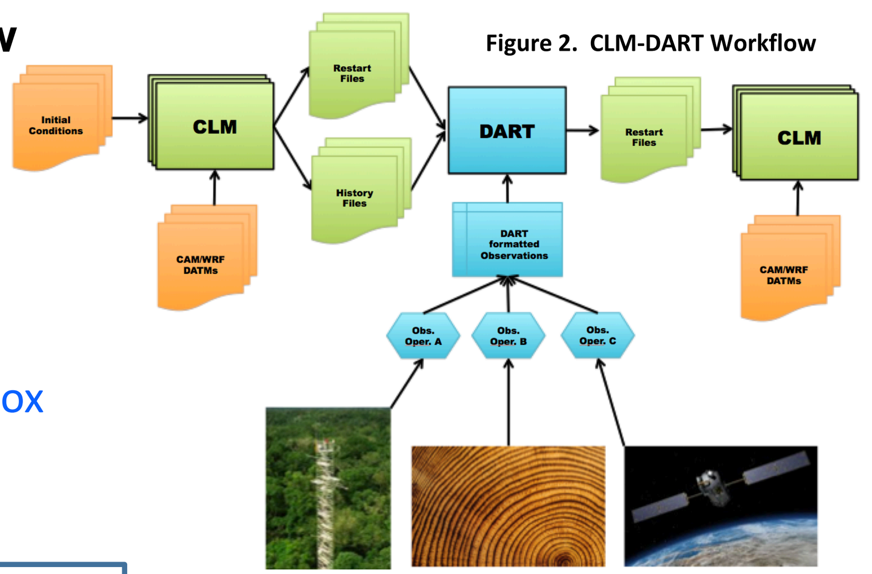


Figure 2. CLM-DART Workflow

Settings

Model : ***CLM5.0.06***
Resolution: f09_f09_mg17
Forcing Data: 60 CAM reanalysis ensemble (1.875degx2.5deg)
Time : 2000 Jan 1st to 2011 December 31st
Component configuration : 2000_DATM%GSWP3v1_CLM50%BGC-CROP_SICE_SOCN_MOSART_SGLC_SWAV

DA
Observation : GIMMS LAI3g version 2, a bi-weekly data product (*interpolated onto model resolution*)
Assimilation time: every 1st and 15th day each month
Observation error variance: 0.04
Outlier_threshold: 6
Time- and space-adaptive state-space inflation

Results

1. Assimilate LAI observation into CLM

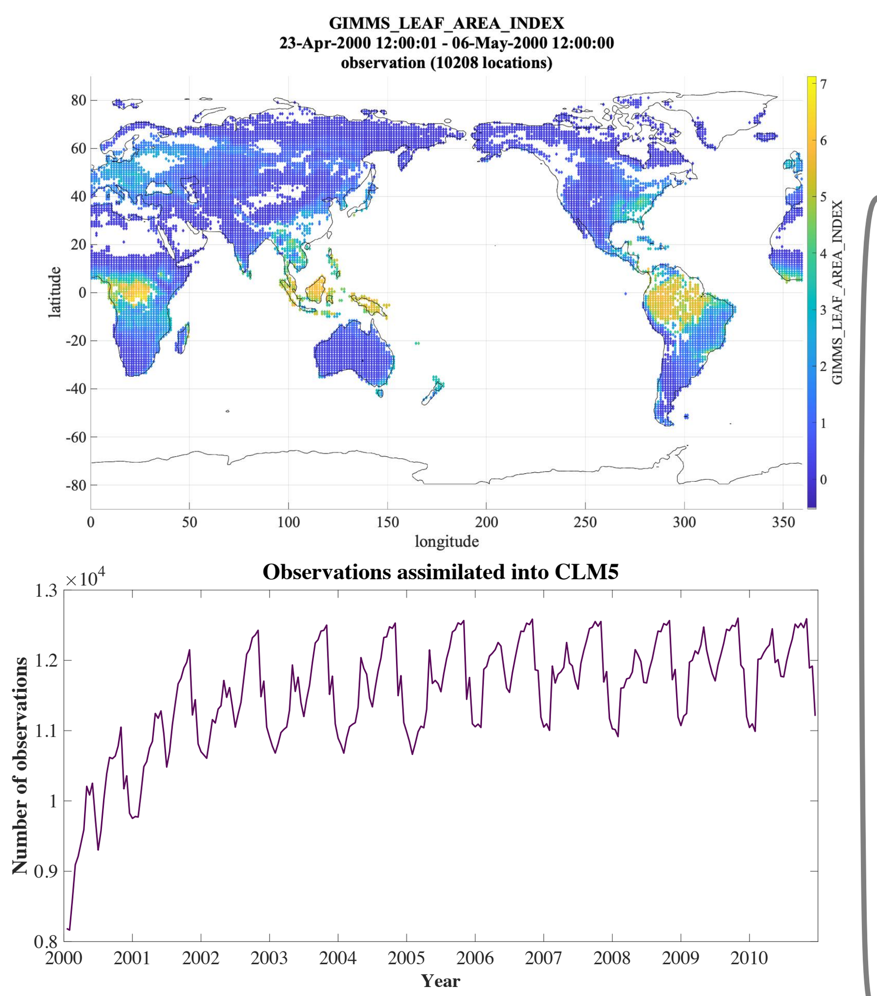


Figure 3. The upper figure shows a snapshot of observations assimilated into CLM5 on 2000-05-1; The lower one shows the time series of number of observations assimilated into CLM5 during the model time.

From Figure 3 we can see that a large number of observations of LAI are assimilated into the model.

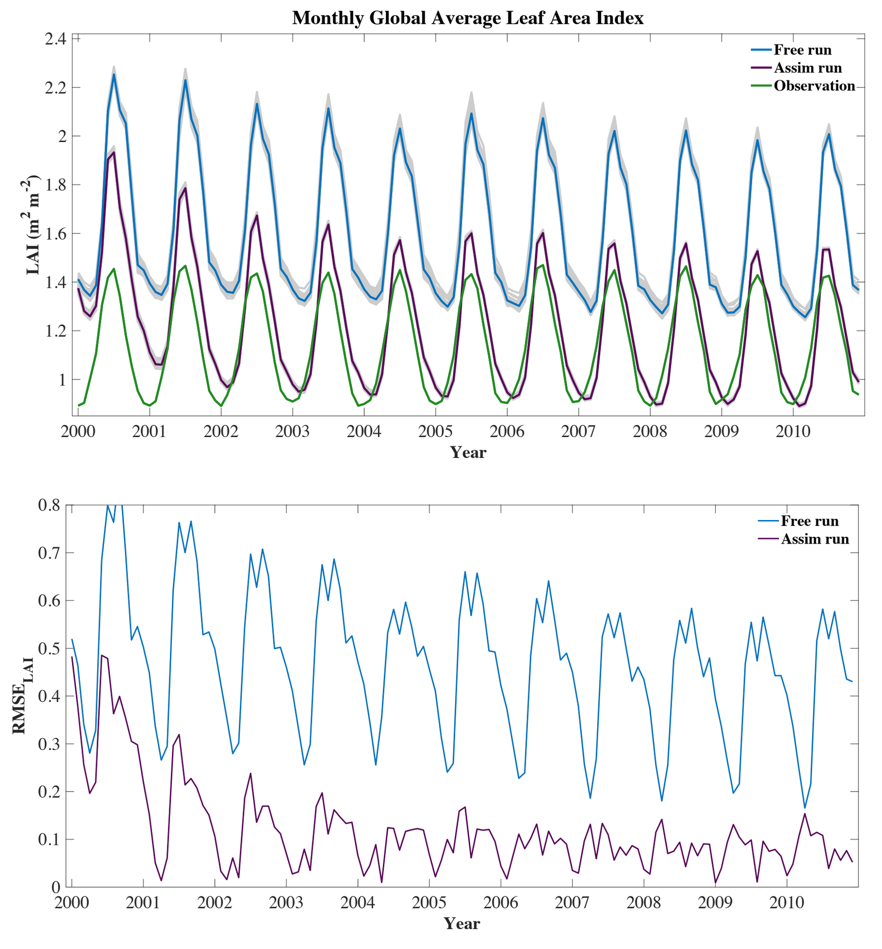


Figure 4. Upper: Time series of LAI in the free run (blue line), assimilation run (purple line) and observation (green line); Lower: RMSEs of LAI in free run and assimilation run.

From Figure 4 we can see that: 1) it took DA around four years (2000-2003) to push the modeled LAI in the assimilation run to be lower and close to the observation; 2) The modeled LAI in the assimilation run is close to observation during the last five years, i.e., 2006-2010, which is called the stable period hereinafter; 3) The modeled LAI in the assimilation run during the stable period is reduced by 25% compared with the free run.

Figure 5 shows that compared with the observation, modeled LAI in the free run is overestimated in multiple regions, such as area in northern latitudes, Asia, tropical regions, and part of southern latitudes.

The result from the assimilation run is much more consistent with the observation globally.

And the lower right figure indicates that DA corrects the overestimated modeled LAI in the free run.

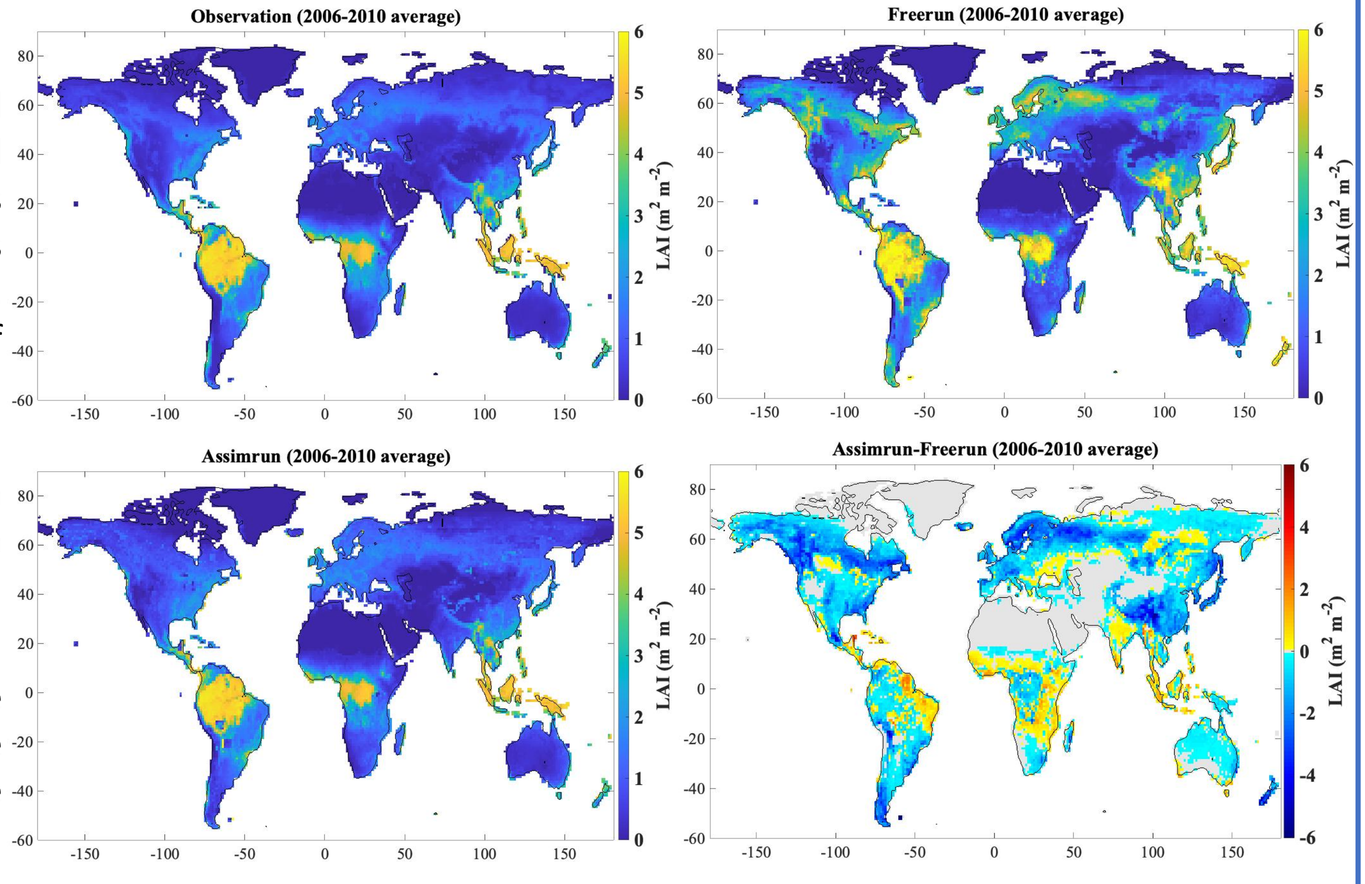


Figure 5. Spatial distribution of observed LAI (upper left), LAI in the free run (upper right), assimilation run (lower left) and the difference between assimilation run and free run (lower right) during stable period.

2. Impact of assimilating LAI on modeled GPP and LE

During the stable period, the modeled GPP is reduced by 17.7% and LE is reduced by 6% in the assimilation run compared with free run (Fig 6).

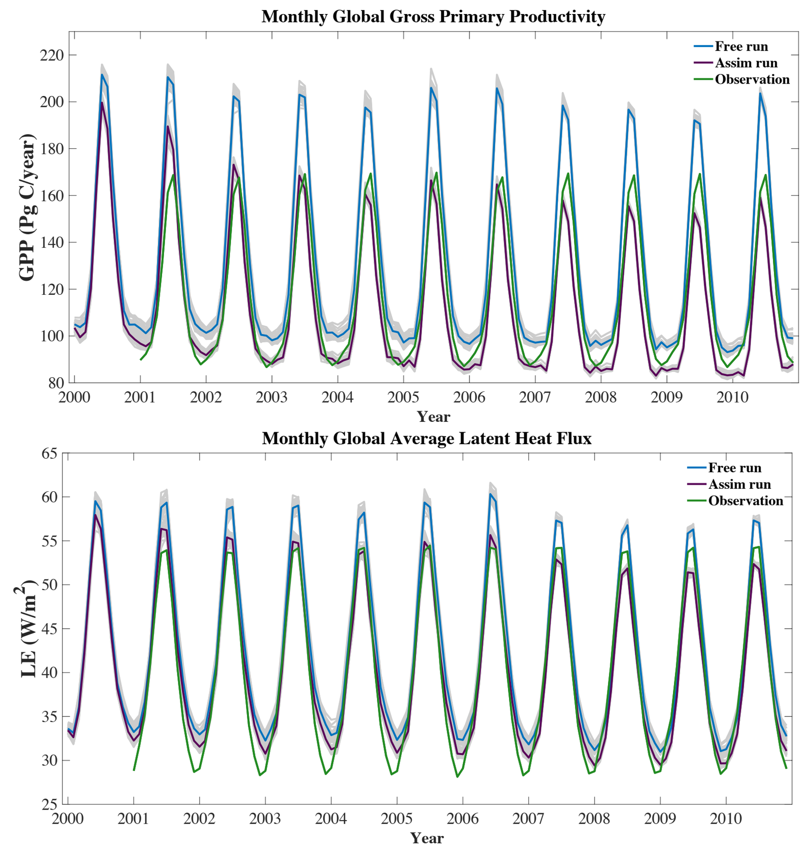


Figure 6. Time series of GPP (upper) and LE (lower).

3. Investigation of LAI on PFT level

A consistent decreasing trend of the three variables are found in northern latitude, Asia, south tip of South America and New Zealand in assimilation run (Fig 7). However, a reverse pattern is found in the tropical regions.

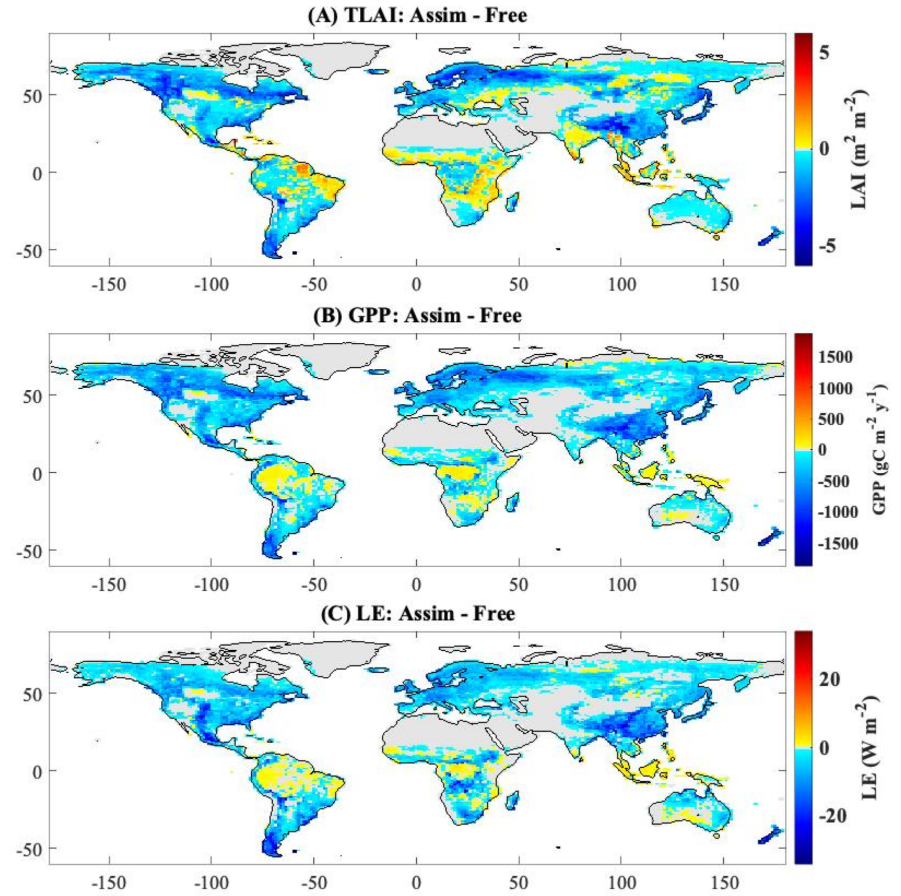


Figure 7. Difference between assimilation run and free run in LAI, GPP, and LE

3. Investigation of LAI on PFT level

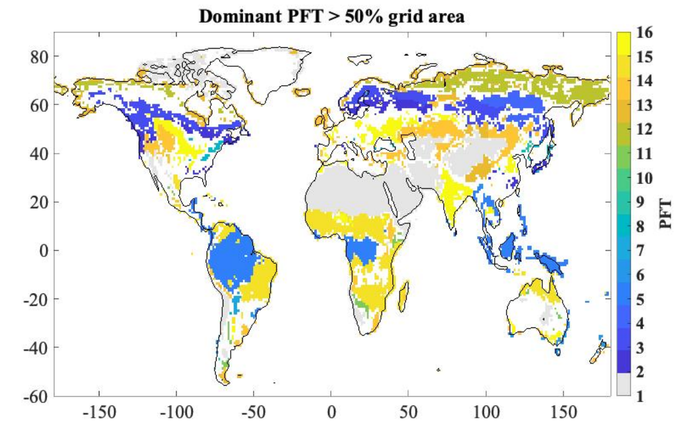


Figure 8. The geographic distribution of dominant plant function type (PFT). 1. Bare ground; 2. Needleleaf Evergreen Temperate Tree; 3. Needleleaf Evergreen Boreal Tree; 4. Needleleaf Deciduous Boreal Tree; 5. Broadleaf Evergreen Tropical Tree; 6. Broadleaf Evergreen Temperate Tree; 7. Broadleaf Deciduous Tropical Tree; 8. Broadleaf Deciduous Temperate Tree; 9. Broadleaf Deciduous Boreal Tree; 10. Broadleaf Evergreen Shrub; 11. Broadleaf Deciduous Temperate Shrub; 12. Broadleaf Deciduous Boreal Shrub; 13. C3 Arctic Grass; 14. C3 Grass (non-Arctic); 15. C4 grass; 16. Crops

The reverse pattern is where the dominant plant functional type is broadleaf evergreen tropical tree (Fig 8).

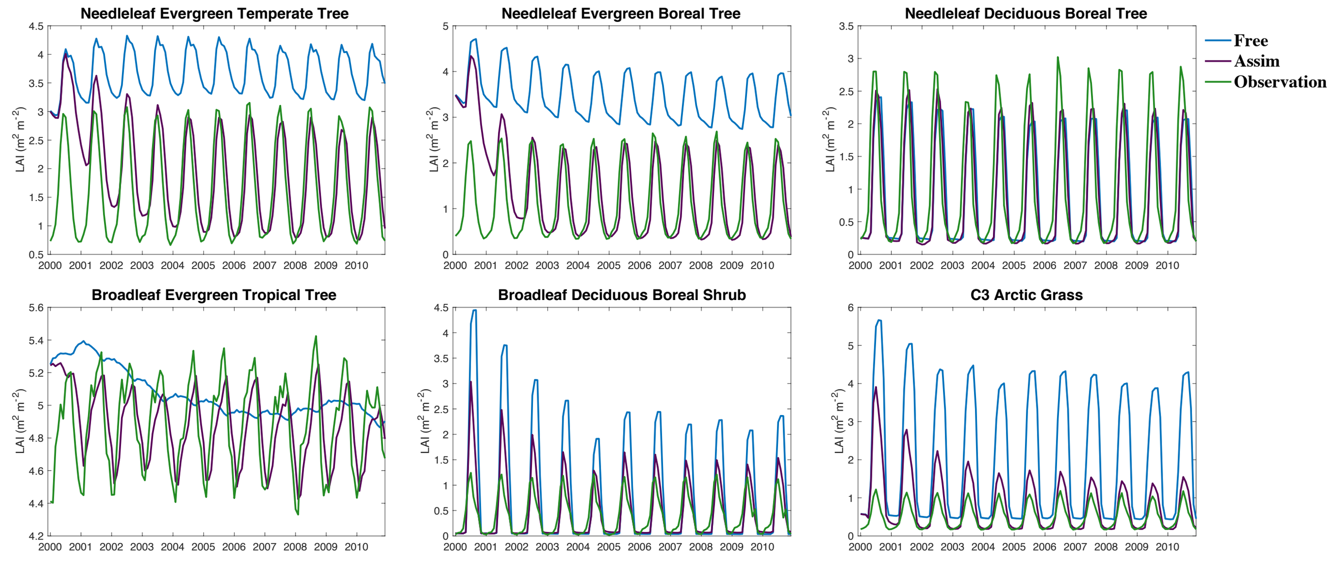
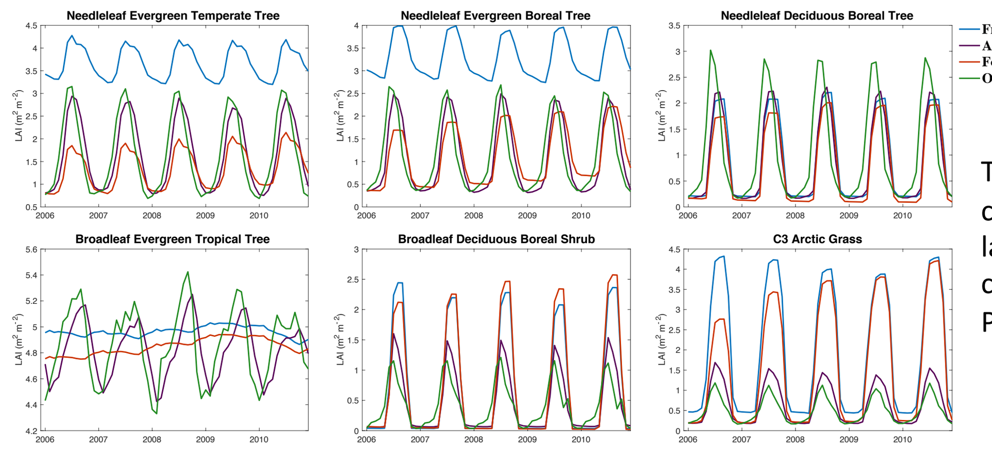


Figure 9. Time series of LAI on different plant functional types (PFTs) in free, assimilation run and observation

From Figure 9 we can see DA introduces a seasonality into the modeled LAI in assimilation run. The average modeled LAI is lower compared with free run, however, the peak LAI in assimilation run could generate higher production which results higher GPP in the assimilation run, which explains the reverse patter shown in Fig 7.

4. Persistence of DA correction into forecast



The persistence of DA correction in woody PFTs last longer into future compared to nonwoody PFTs.

Figure 10. Time series of LAI on different plant functional types (PFTs) to investigate persistence of DA correction

Conclusions

1. By assimilating LAI into CLM5.0, we reduced the positive bias of LAI by 25% on the global average. GPP was reduced by 17.7% and LE was reduced by 6% globally.
2. Forecast persistence in woody plant functional types (except BETT) was longer than the persistence in non-woody plant functional types.
3. A spatial- and temporal- varying adaptive inflation allowed to reduce LAI bias across different plant function types/regions globally.

huoxl90@email.arizona.edu