Toward integrated seasonal predictions of carbon flux: lessons learned from NASA's subseasonal-to-seasonal predictions

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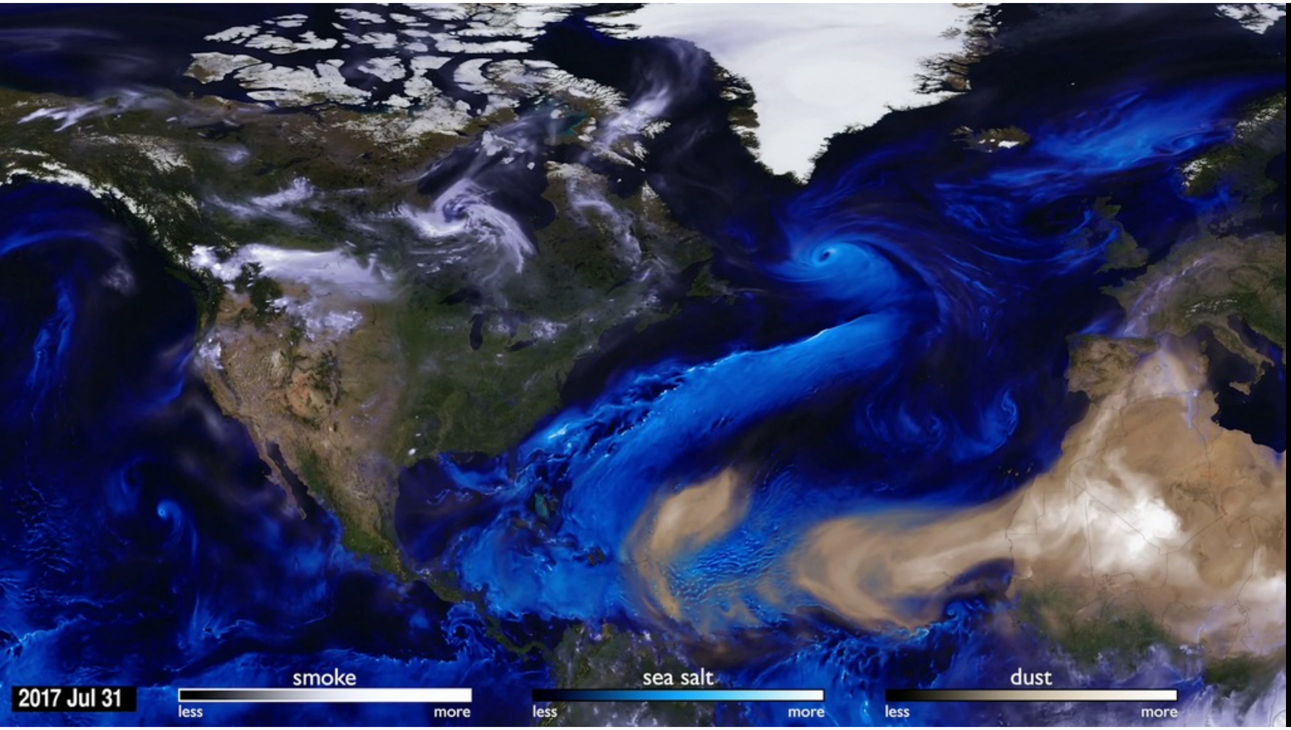
[6]Now at JGCRI

Outline

- Introduction to modeling at NASA
- Motivation for subseasonal to seasonal (S2S) forecasting
- Moving beyond meteorology – can we predict how the carbon cycle will change on seasonal timescales?
- What would a seasonal carbon forecast look like? Examples of predictions:
  - Human emissions
  - Fires
  - Land-atmosphere flux
- Summary and conclusions

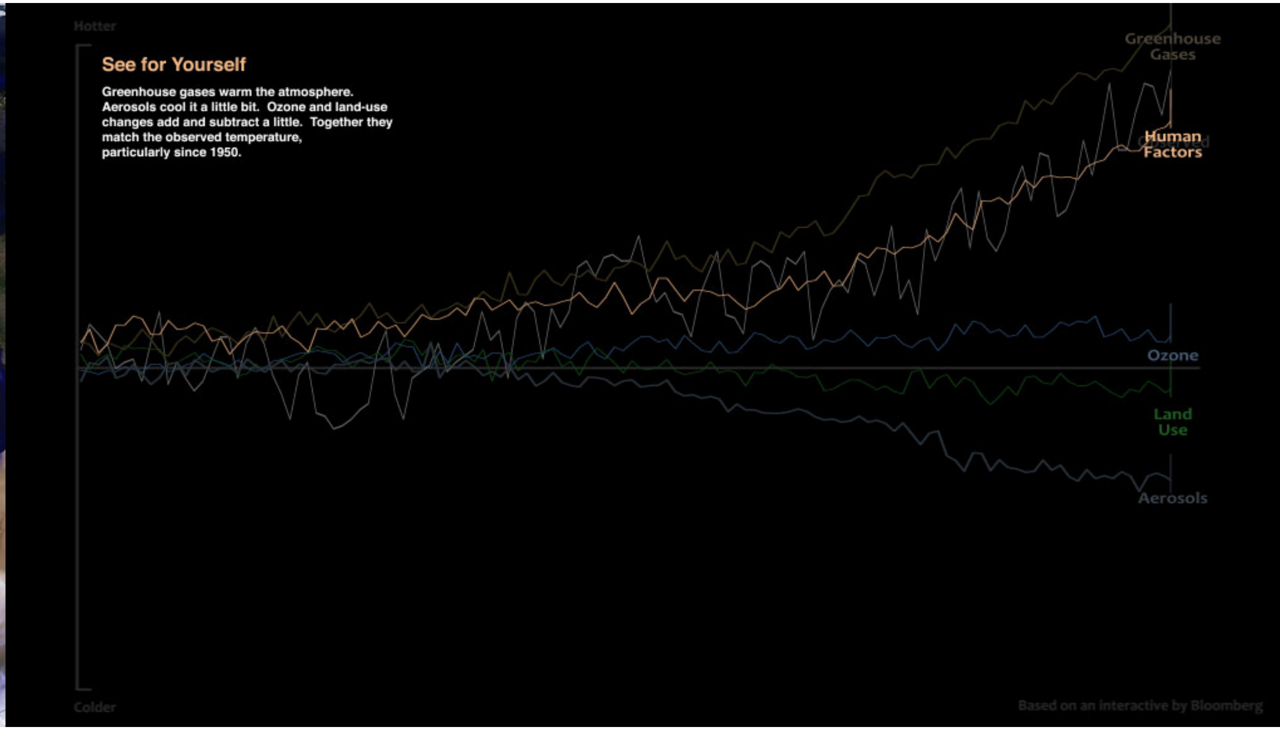
Earth System Modeling at NASA

Global Modeling and Assimilation Office (GMAO)



- Retrospective analysis of satellite era
- Seasonal-decadal prediction
- High spatial resolution
- Focus on data assimilation
- https://svs.gsfc.nasa.gov/12772

Goddard Institute for Space Studies (GISS)



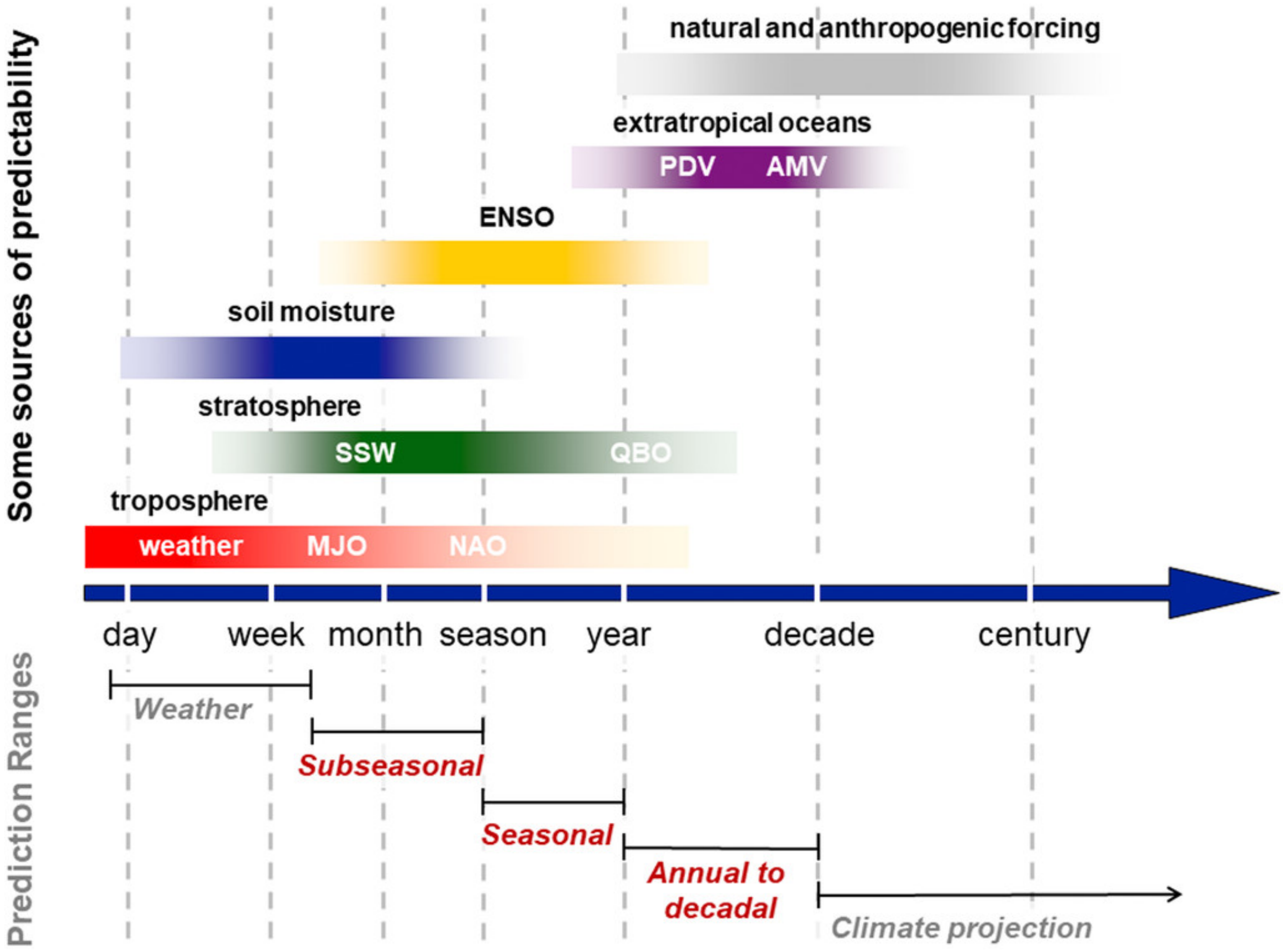
- Paleoclimate simulation capability
- Century-scale climate projections
- Support IPCC modeling ensembles
- New effort on comparative planetology
- https://svs.gsfc.nasa.gov/30615

Themes of GMAO's Research and Products

- Weather Analysis and Prediction
- Seasonal-to-Decadal Prediction
- Reanalysis
- Multi-Scale Modeling
- Observing System Science

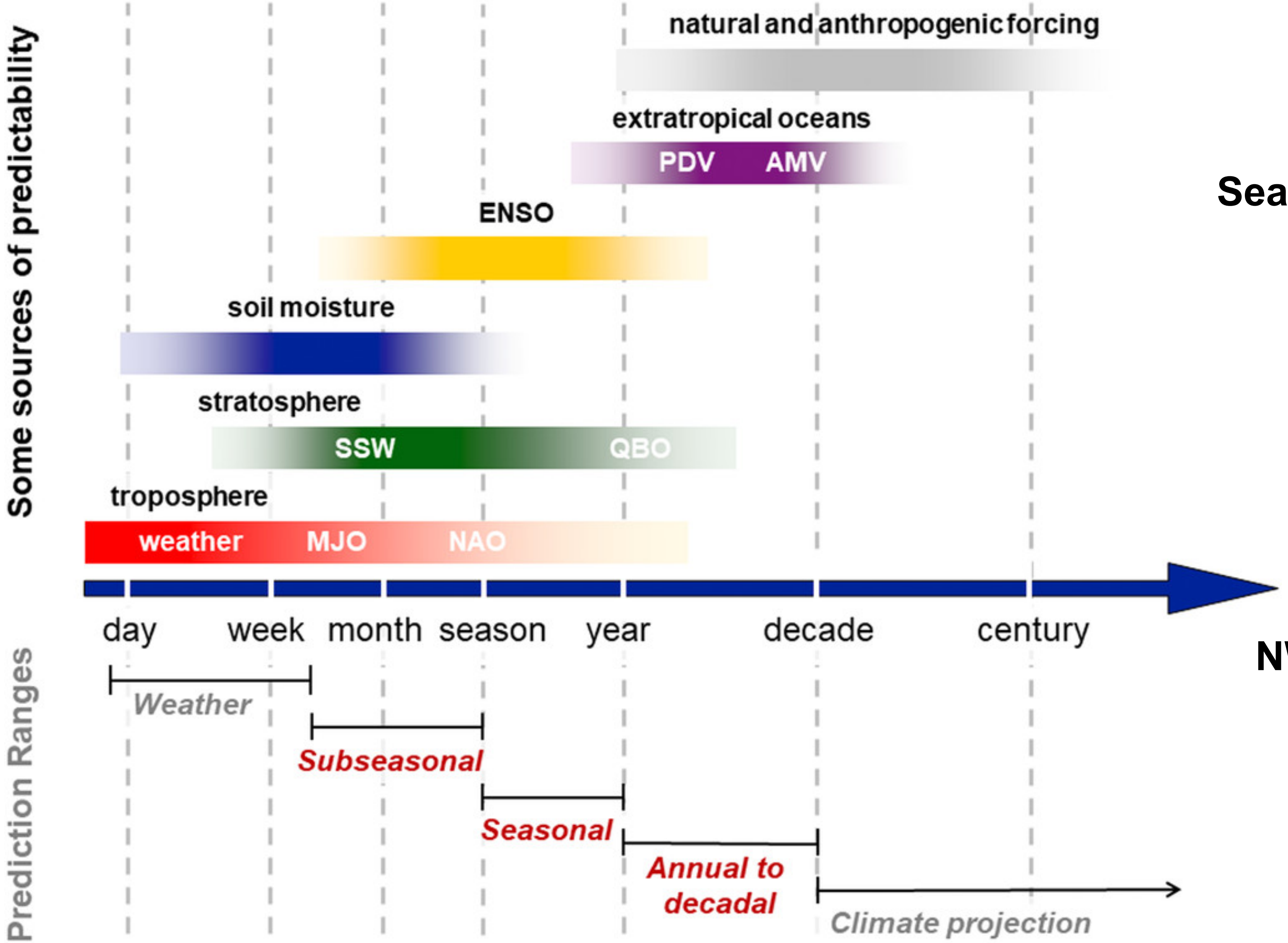
- Central theme is to use, support, and plan for NASA's Earth Observations
- Goddard Earth Observing System (GEOS) model and data assimilation system central to all components
- Modular system is highly flexible, can be configured to increase complexity depending on application
- Aerosol, carbon, and composition cut across, represented in each theme

Sources of predictability

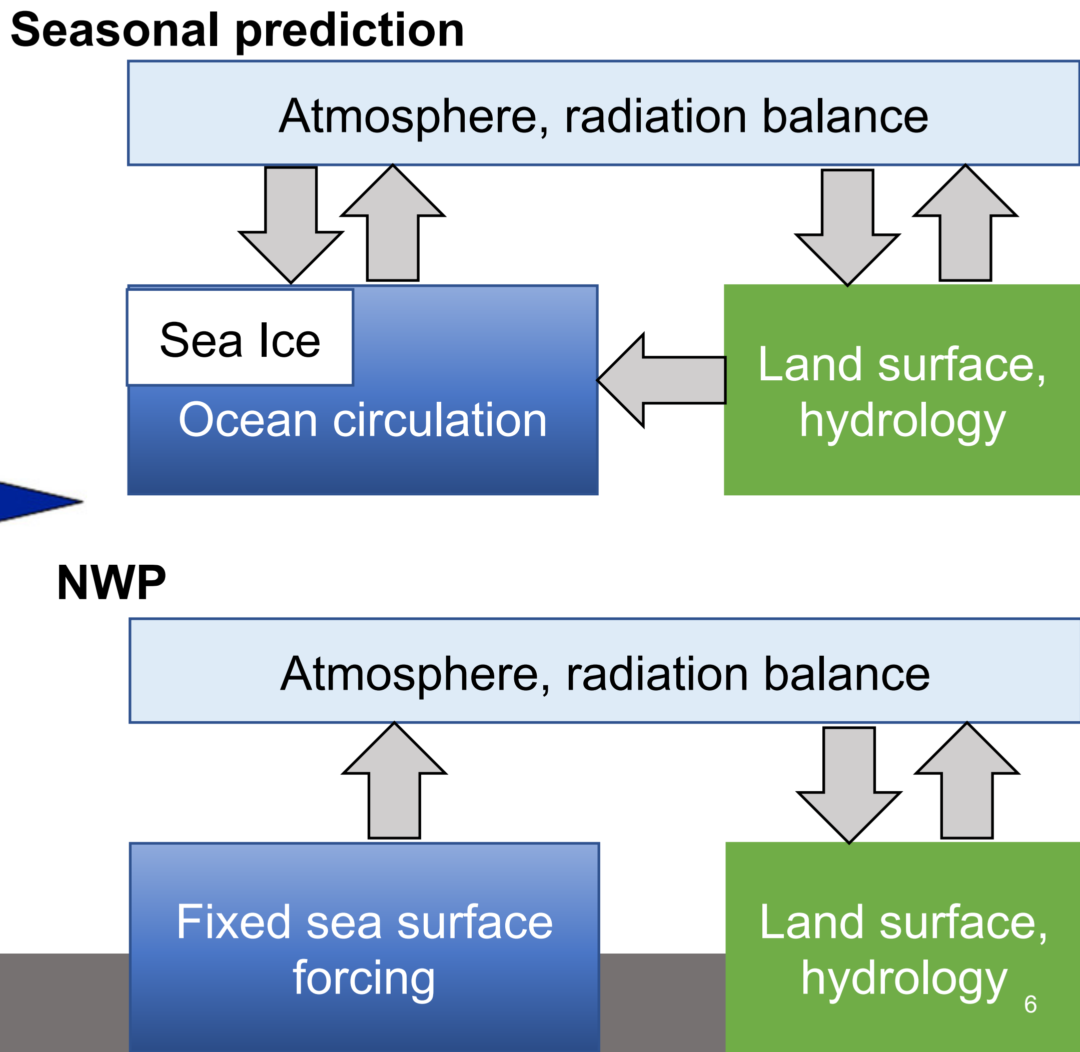


Merryfield et al., *BAMS*, 2020

Sources of predictability

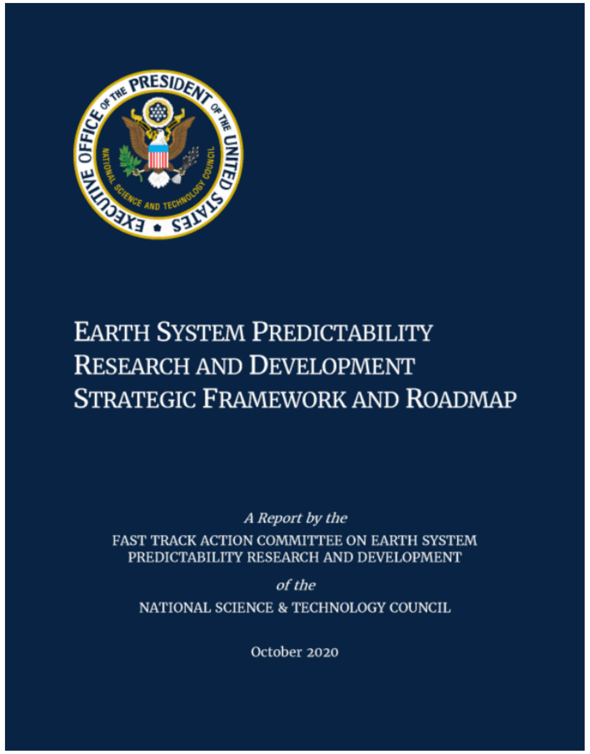


NWP and seasonal forecast models often share common components but are configured differently:



Merryfield et al., *BAMS*, 2020

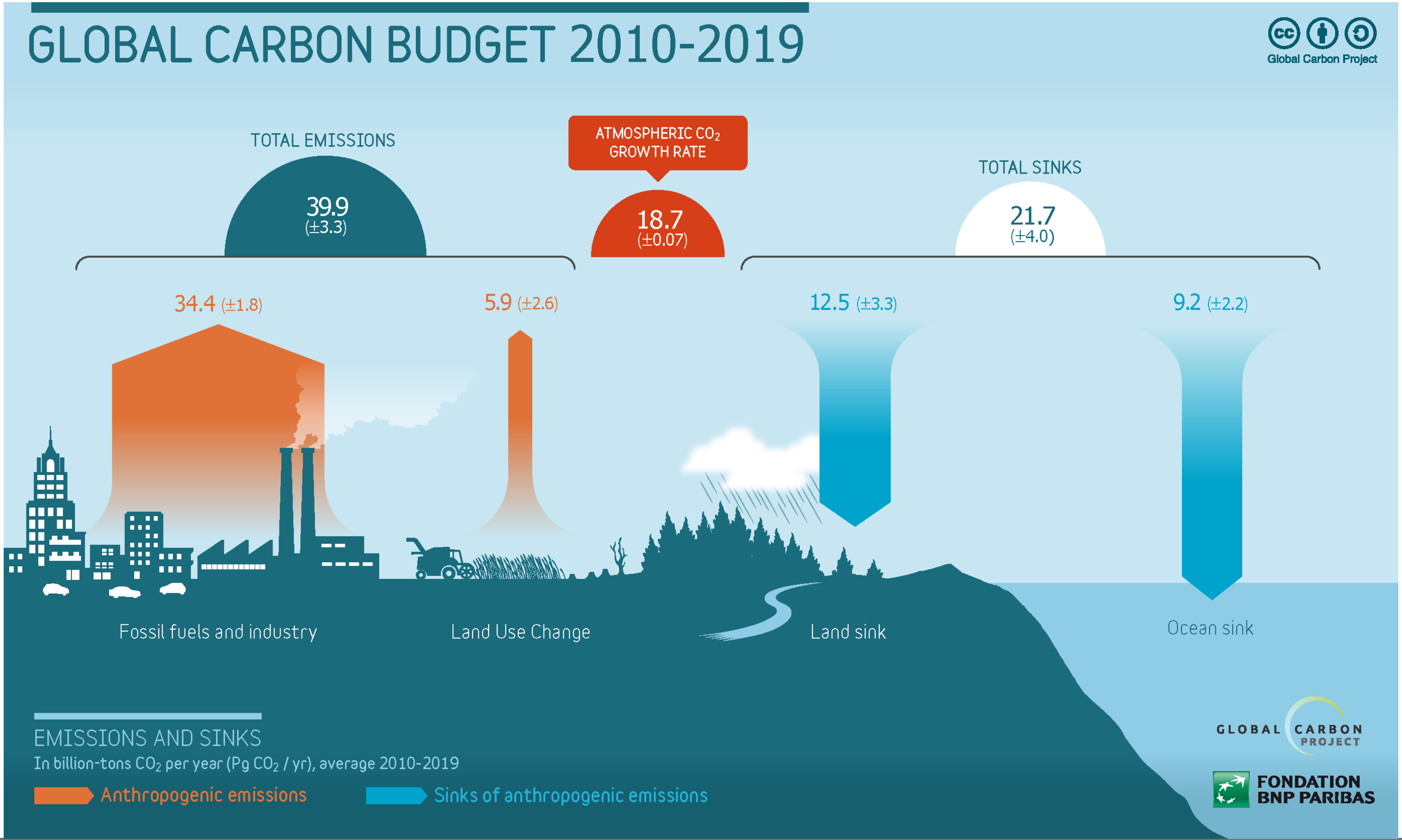
Applications supported by S2S meteorological predictions



Recent focus of attention from federal government coordinated by OSTP

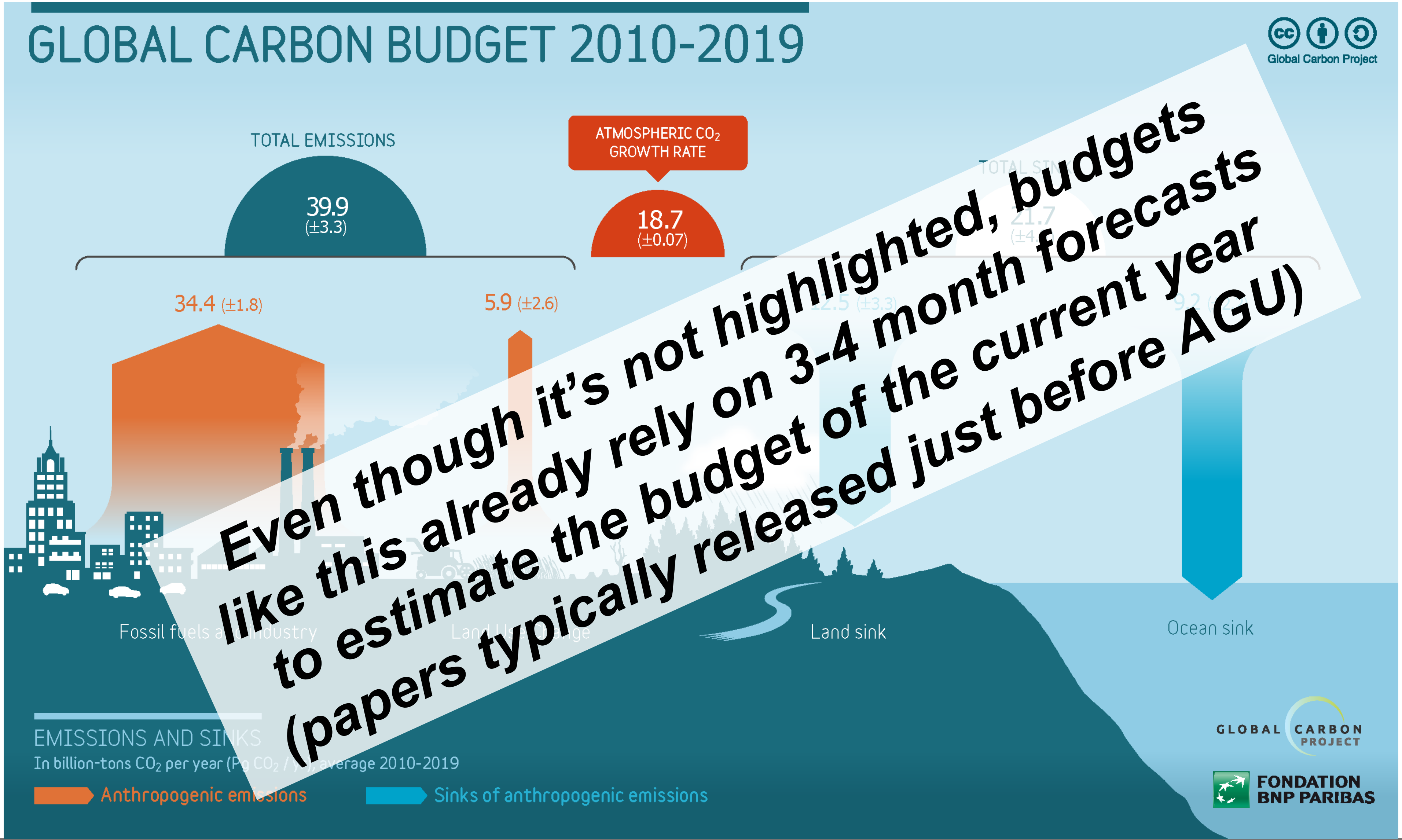
National Academies of Sciences, 2016

Very quick overview of the global carbon cycle



Friedlingstein et al., ESSD, 2020

Very quick overview of the global carbon cycle



Even though it's not highlighted, budgets like this already rely on 3-4 month forecasts to estimate the budget of the current year (papers typically released just before AGU)

Friedlingstein et al., ESSD, 2020

Could you predict how the carbon cycle is changing on S2S to interannual timescales?

Strong relationships between many components and known sources of predictability suggest yes:

- Connections between soil moisture and vegetation
- Relationship between ENSO phase and tropical ocean carbon flux
- Relationship between ENSO and atmospheric growth rate

Could you predict how the carbon cycle is changing on S2S to interannual timescales?

Strong relationships between many components and known sources of predictability suggest yes:

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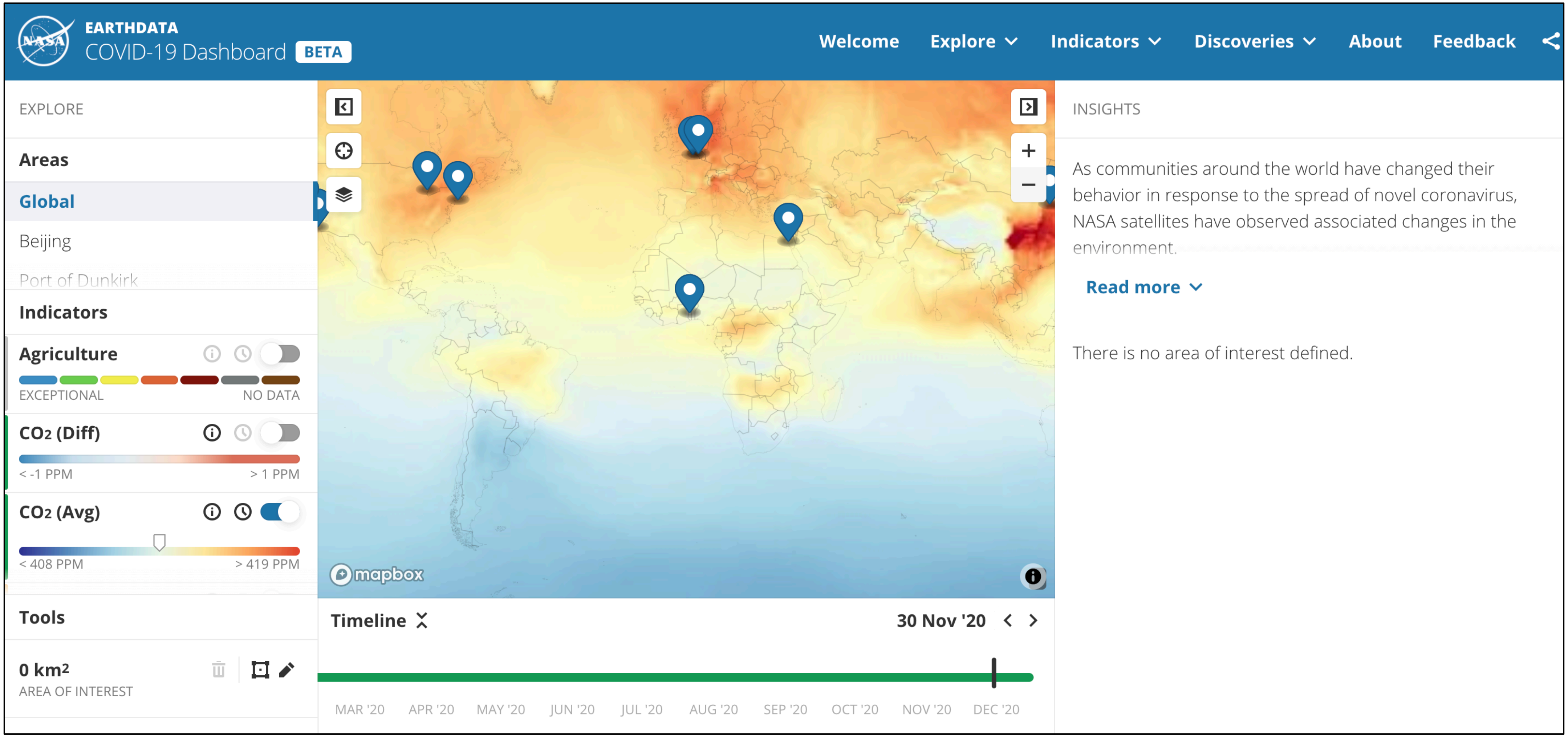
- Relationship between ENSO and atmospheric growth rate

Why would you predict how the carbon cycle is changing on S2S to interannual timescales?

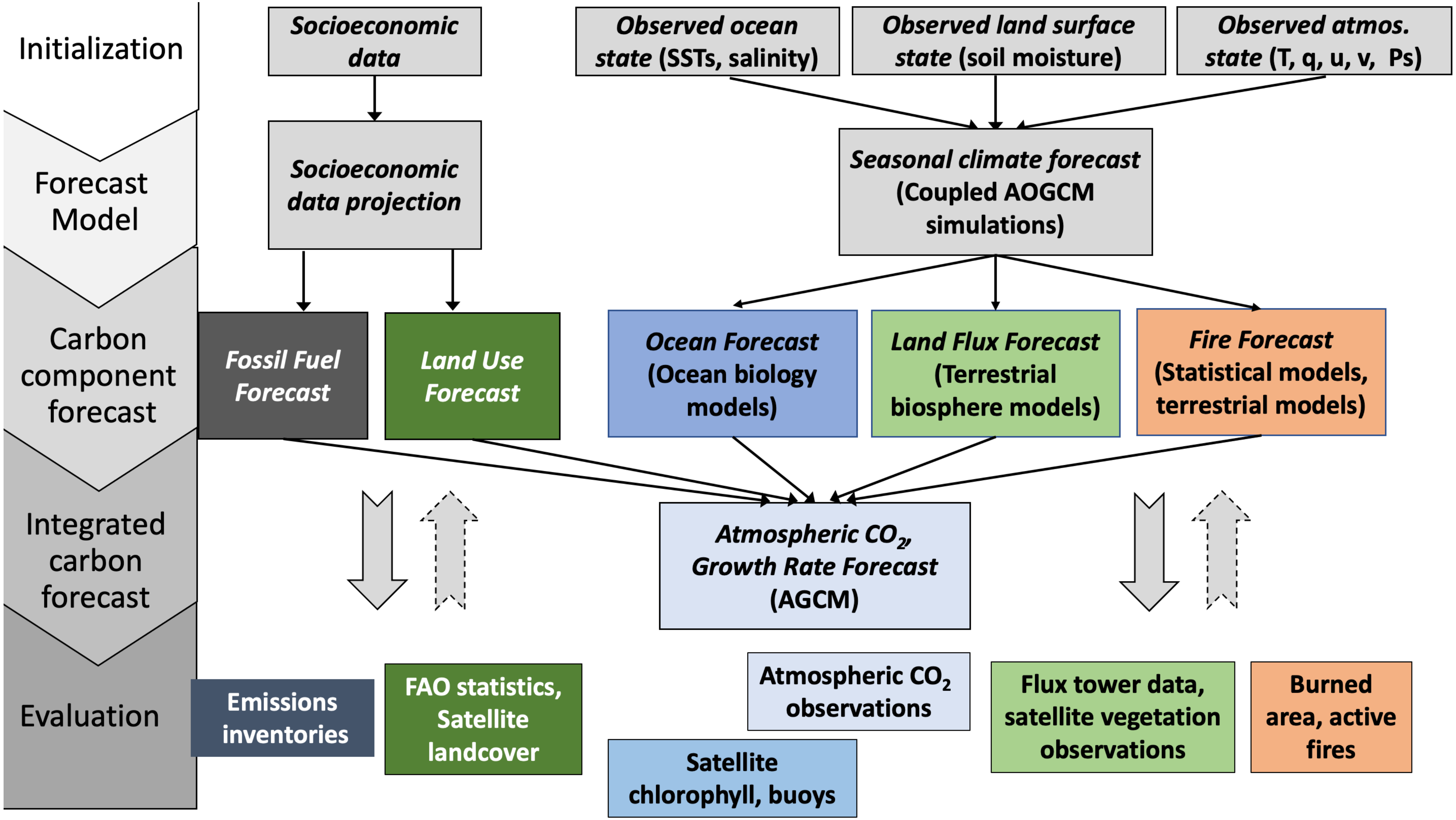
- Ability to test understanding of carbon cycle in real time
- Support better measurement opportunities – field campaigns and adaptive remote sensing
- Because of delays in running offline models and input datasets, a recent prediction might be the best information we have about current conditions
- Need to know how well S2S predictions support an array of applications – forestry, fire management, fisheries, agriculture
- High quality predictions could even have policy implications – helping countries understand their emissions and mitigation strategies (**spoiler alert* – not there yet)

Increase for near real time information on changes in CO_2 and other species since COVID-19

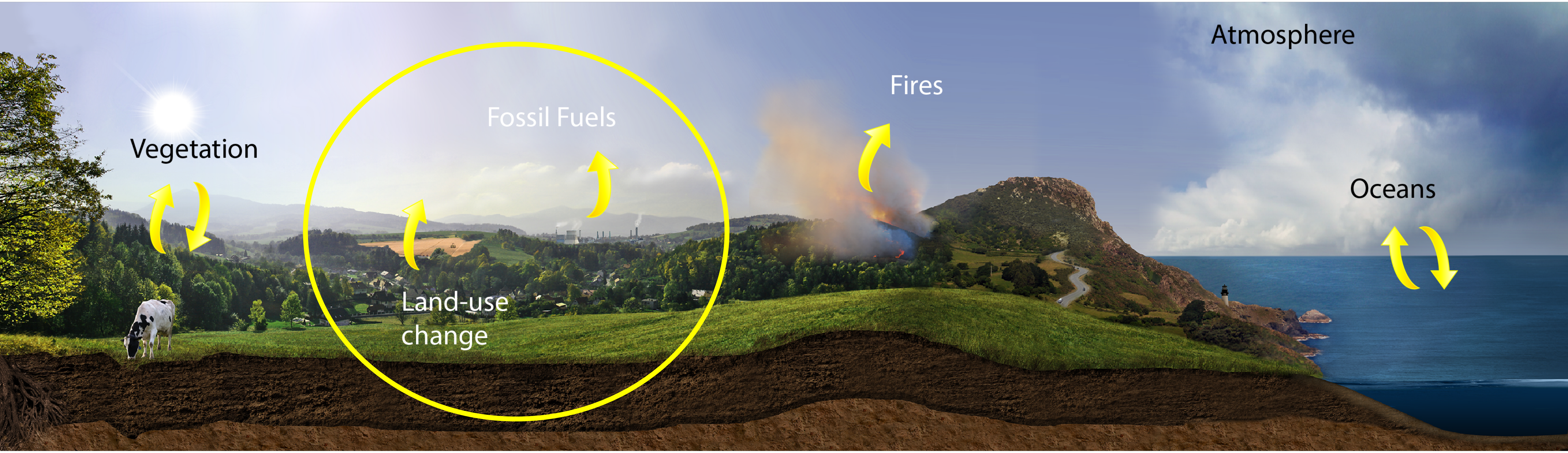


https://earthdata.nasa.gov/covid19/

Overview of a seasonal forecast system for carbon



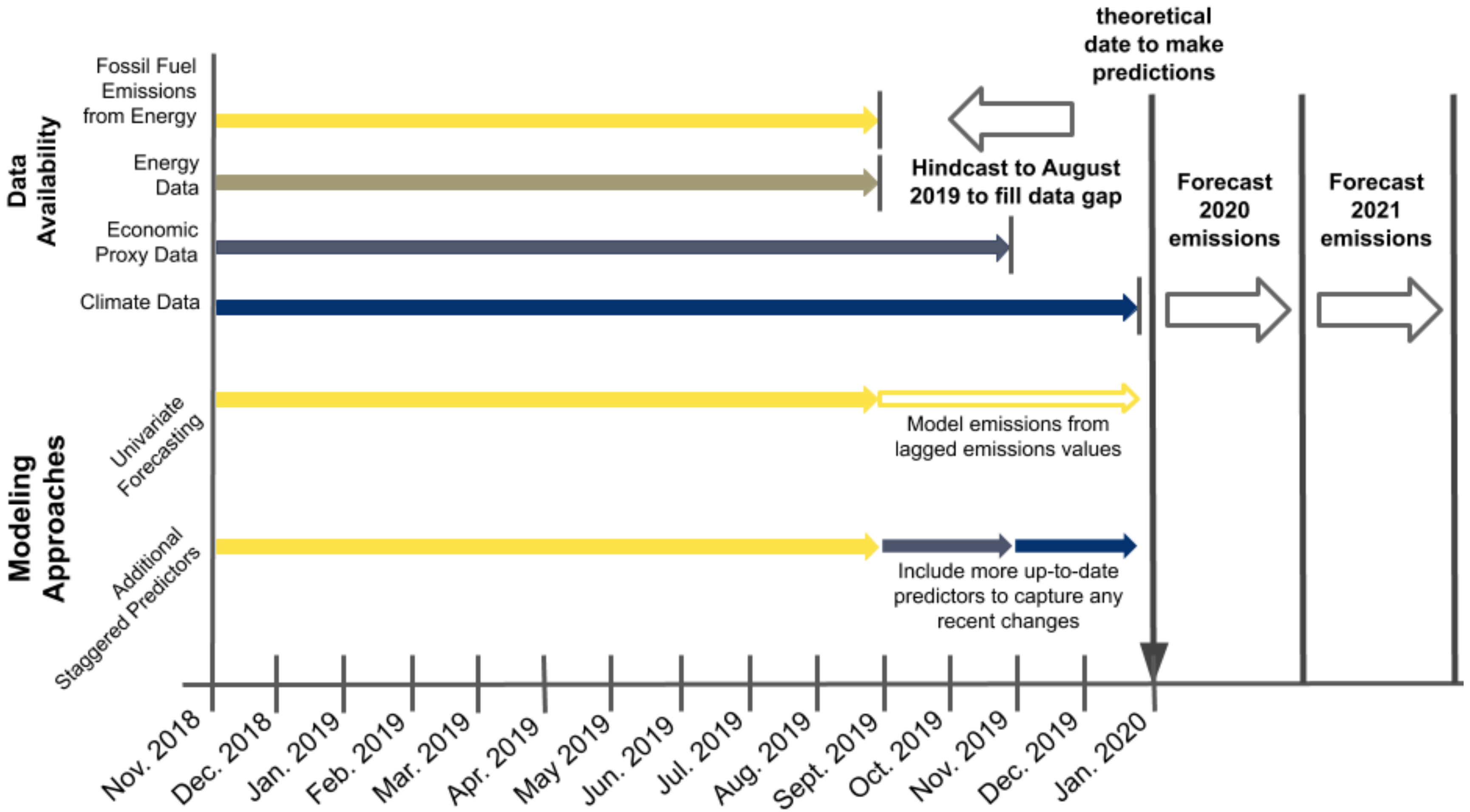
Carbon cycle components



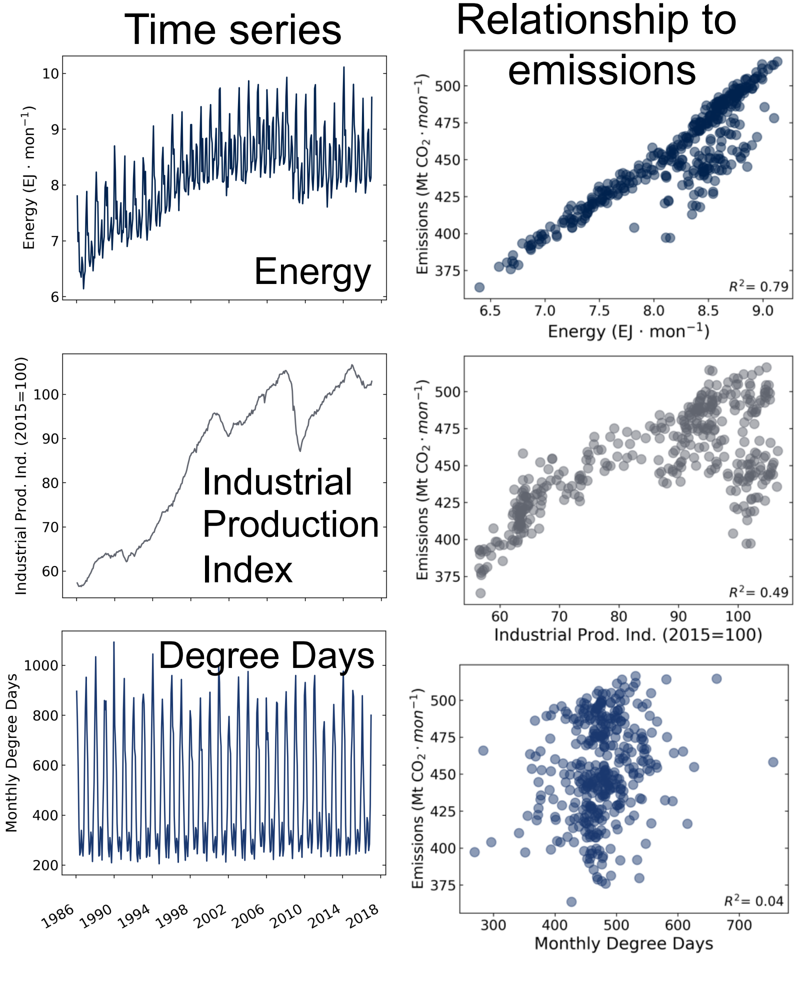
Credit: NASA/Jenny Mottar and Abhishek Chatterjee

Predictions of human emissions

Roadmap to fossil fuel emission forecast



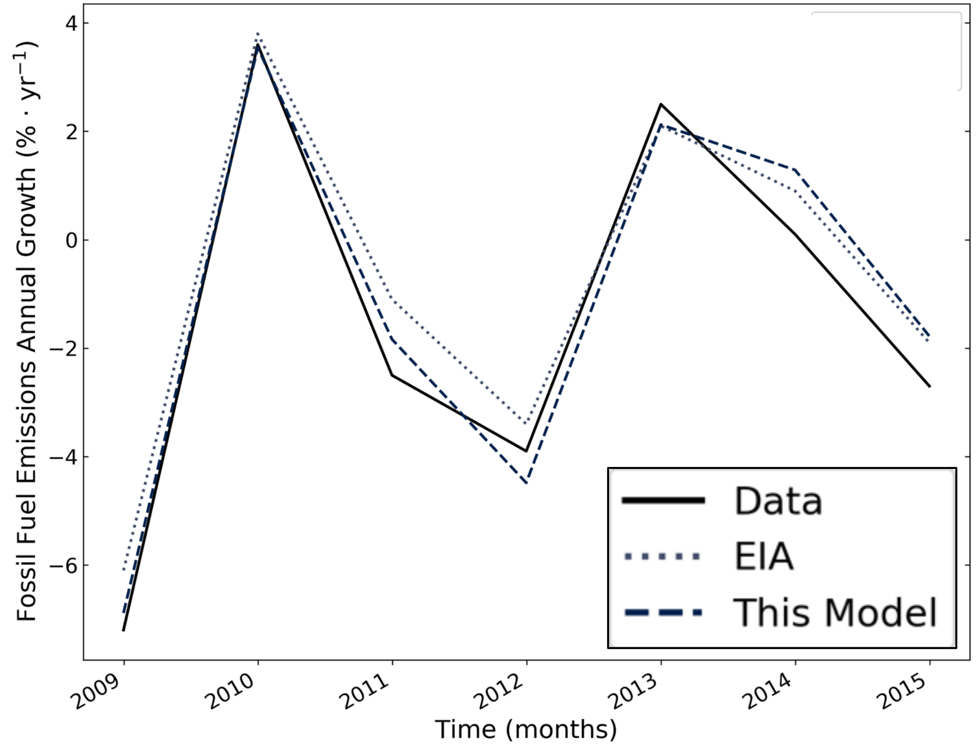
Potential U.S. predictors



Woodard et al., *in prep.*

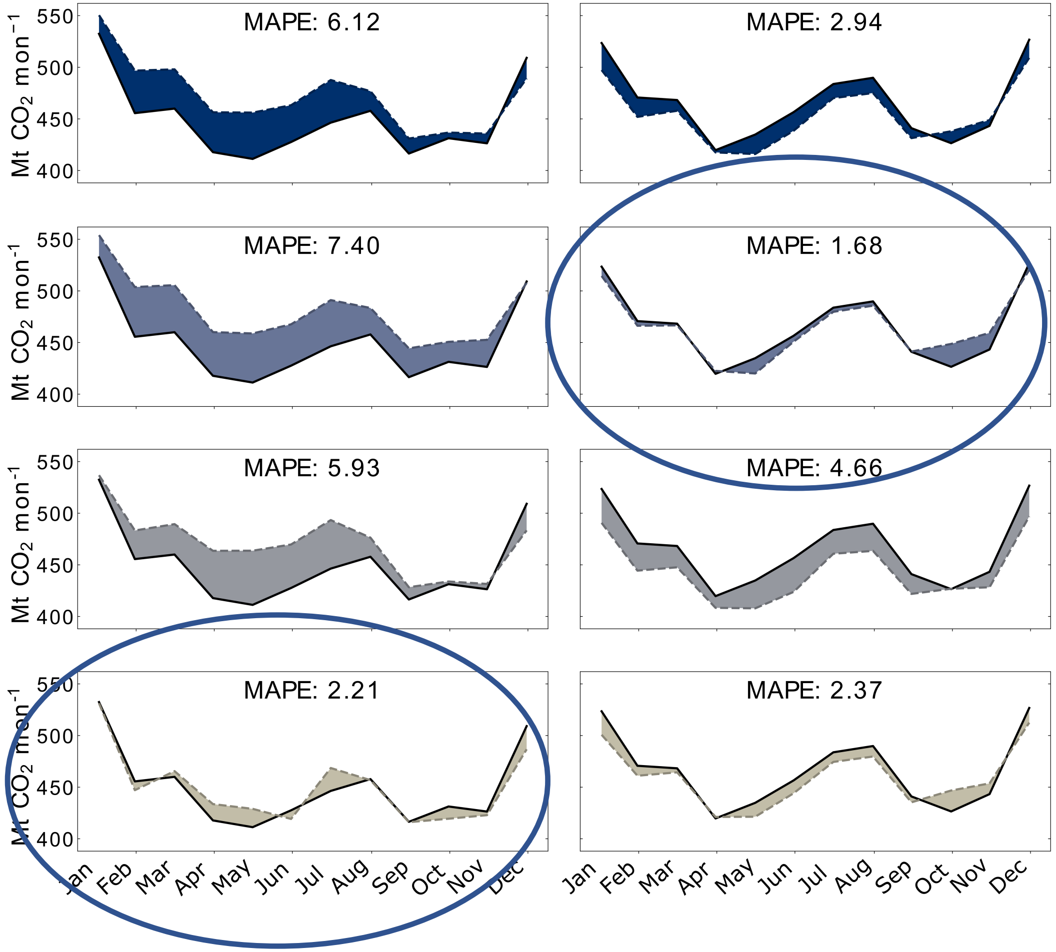
Forecasting fossil fuel emissions (1)

Performance of hindcast
(4-month historical period w/ incomplete data record)



Research model performs better than US EIA model (mean error of 0.74% vs 0.59%

Performance of 1-month forecasts (future period)



Predictors included

Emissions

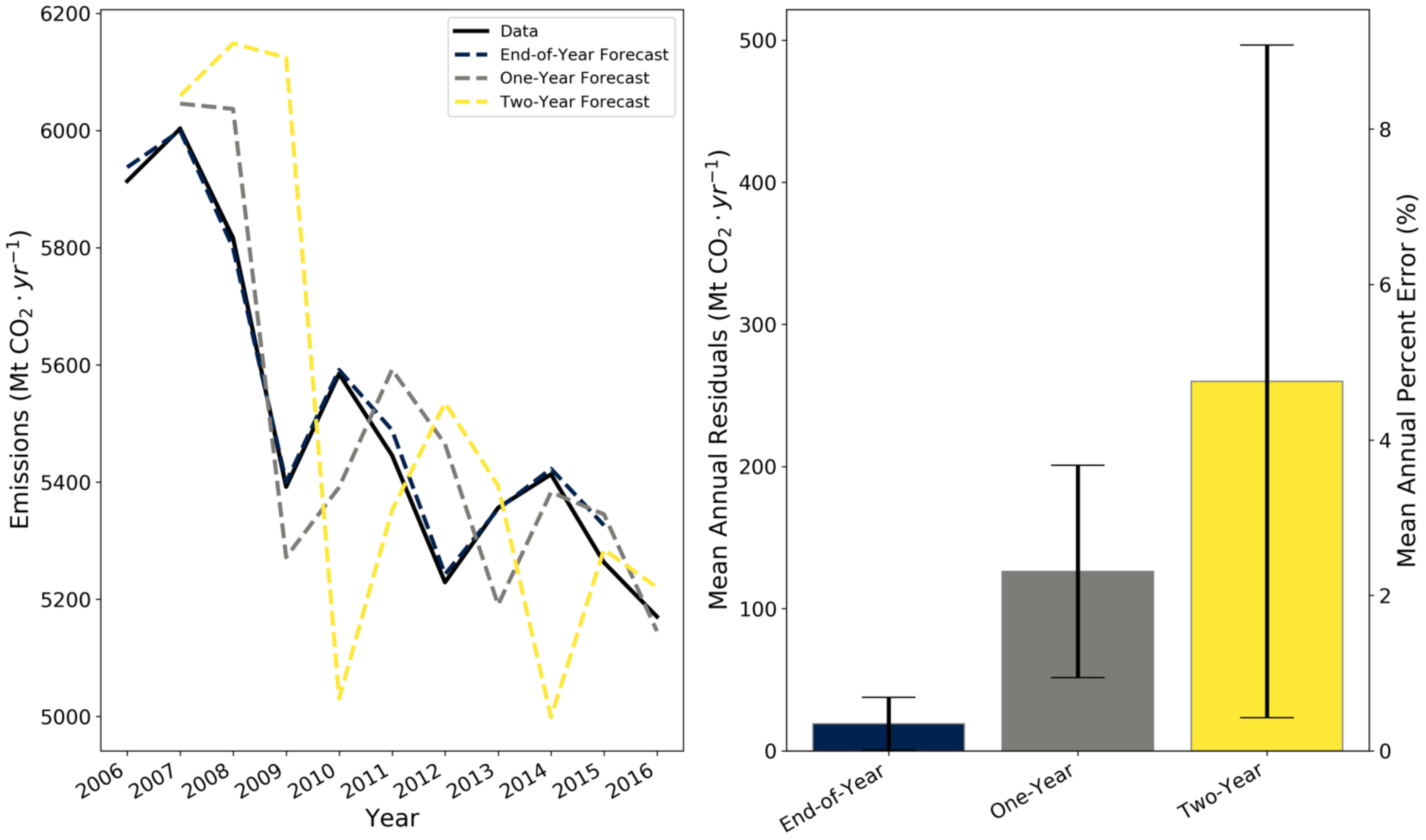
Emissions + non-CO_2 Fraction

Emissions + oil price

Emissions + industrial production index

Woodard et al., *in prep.*

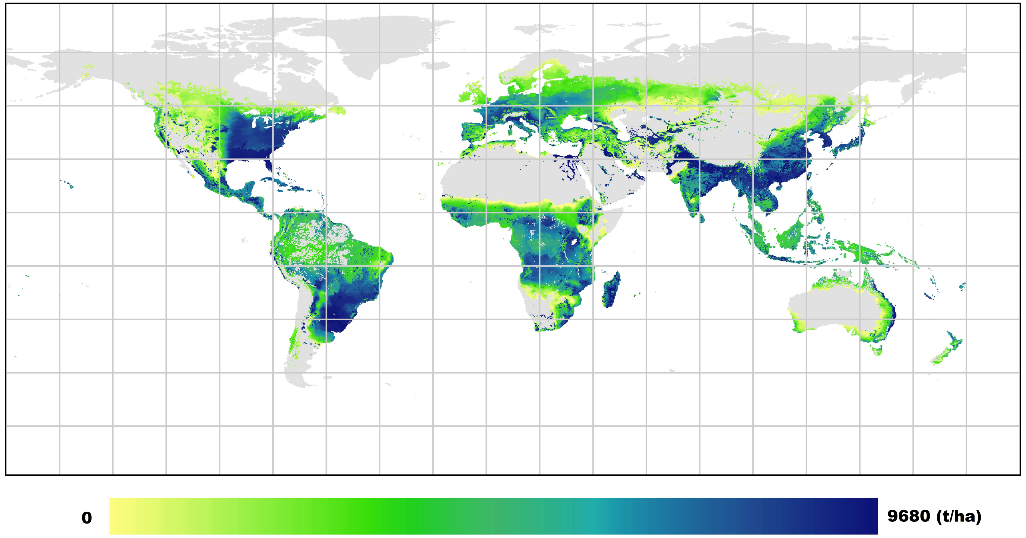
Forecasting fossil fuel emissions (2)



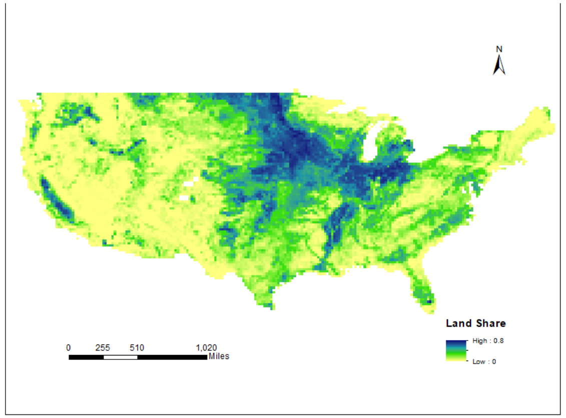
Woodard et al., *in prep.*

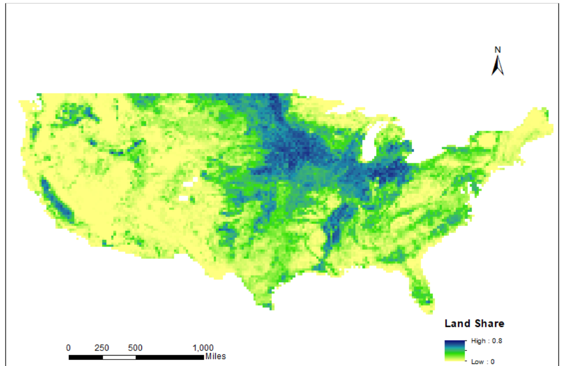
Land use predictions using economic models

Global cropland economic return (2000)



Cropland LUH 2011	Cropland prediction 2011



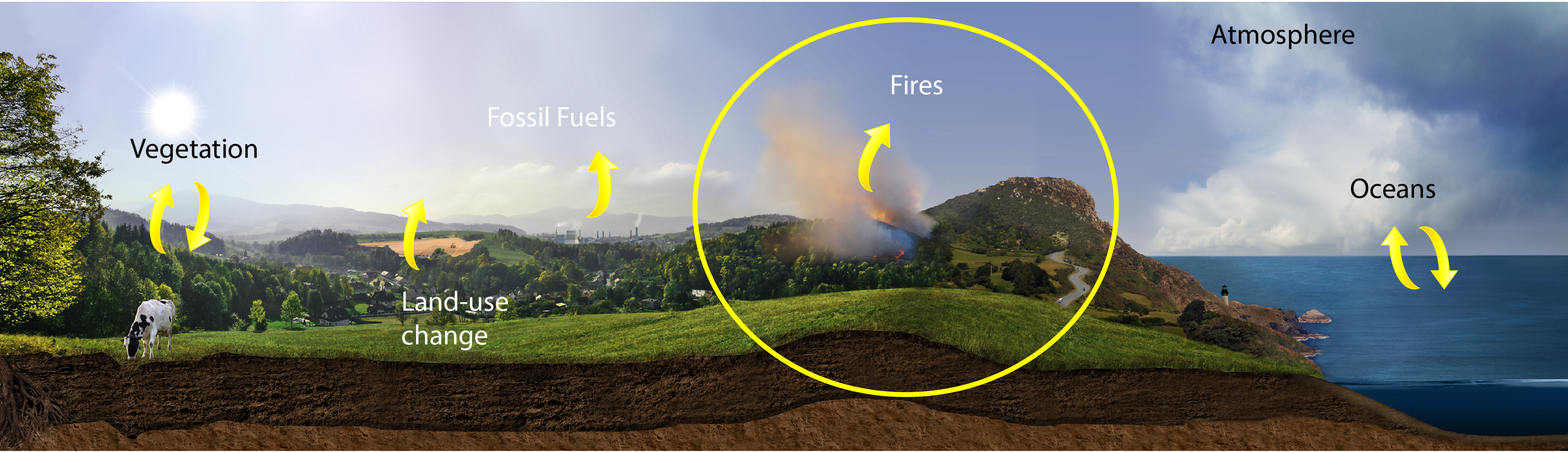


Absolute error RMSE: 0.033

- Simulation of major crop production using Agro-Ecological Zones model and cropland economic return calculation
- Development of Logistic Share Model of Land Use for Land Use prediction studies
- Applications in countries with reasonably good and accessible agricultural statistics (e.g. United States and Brazil)
- Because year-to-year changes are relatively small, greatest applications are on 2-5 year time horizon

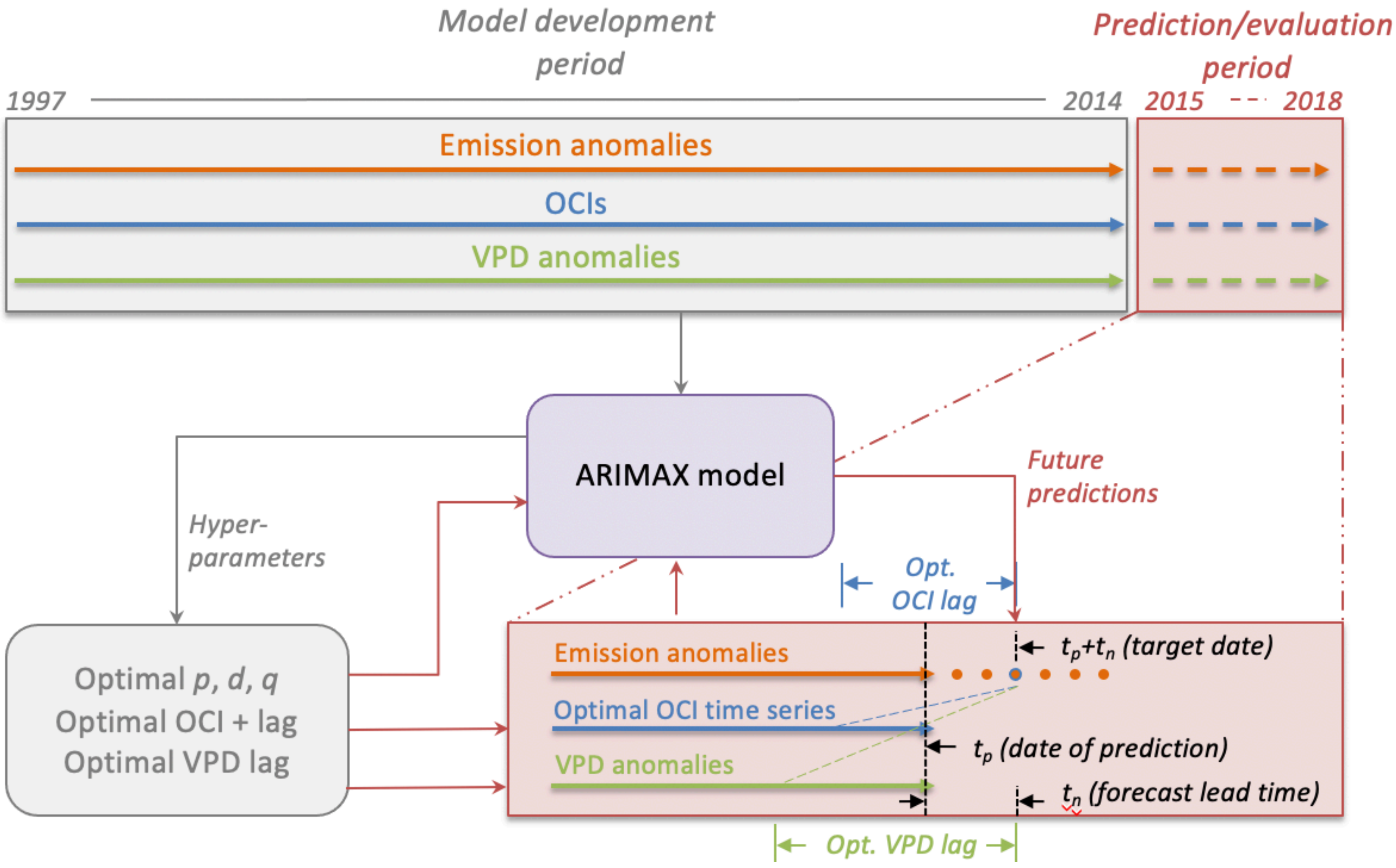
L. Sun and G. Hurtt, UMD

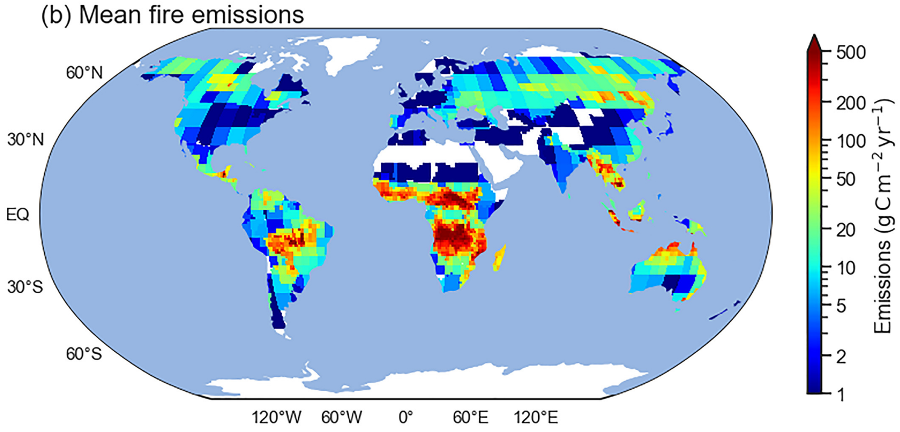
Carbon cycle components



Credit: NASA/Jenny Mottar and Abhishek Chatterjee

Statistical fire model



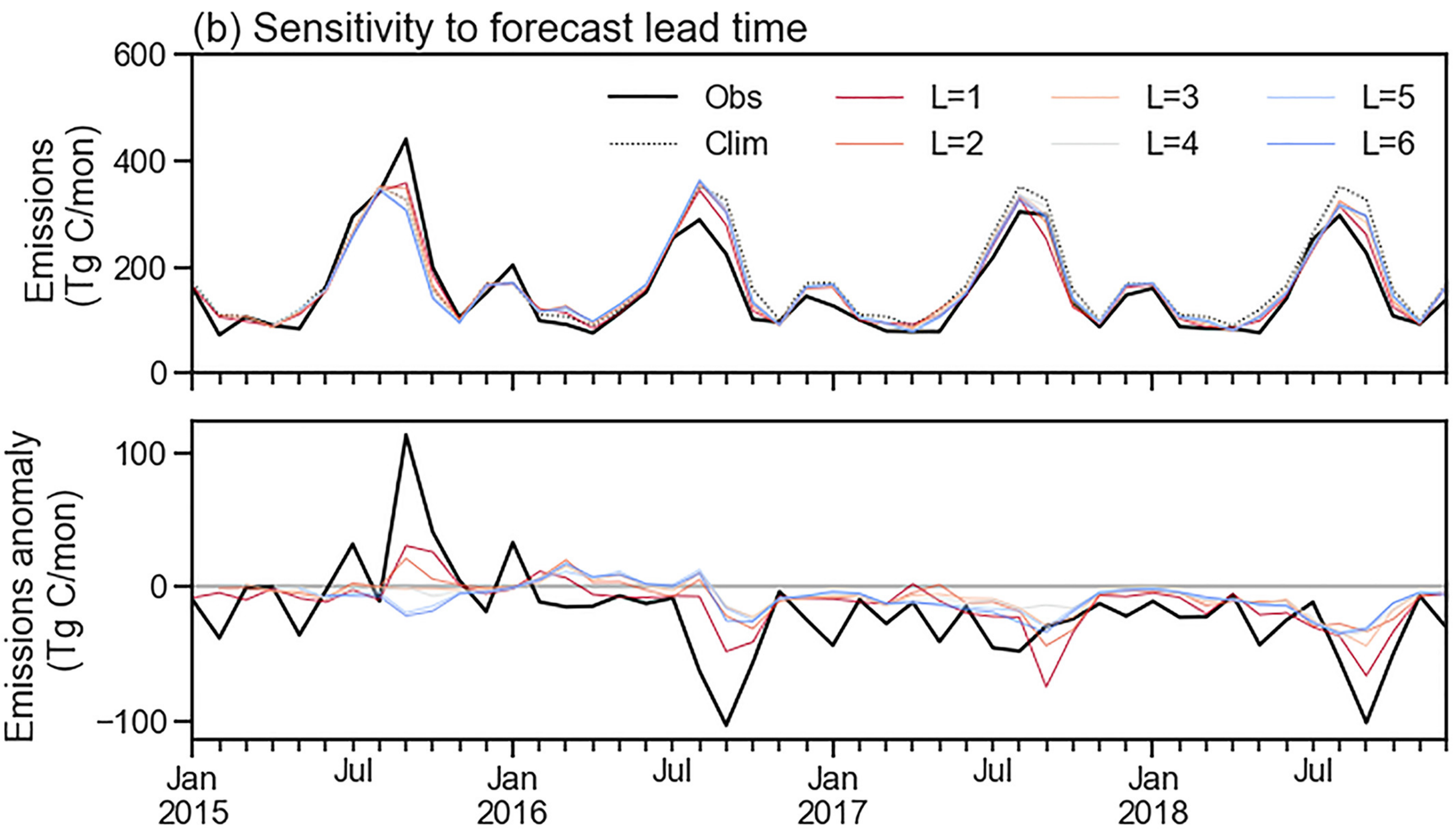


- Establish 'fire cohesive regions' with similar fire behavior and enough fires to establish statistical relationships (top)
- Analyze relationships between predictors which include emissions anomalies, ocean climate indices (large scale forcing), vapor pressure deficit (local scale forcing).
- Customized prediction model for each fire region

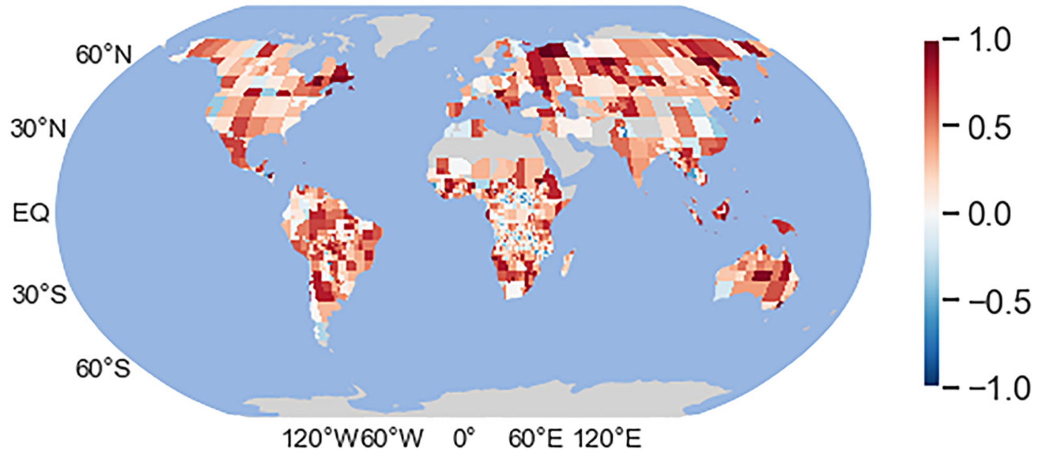
Chen et al., *JAMES*, 2020

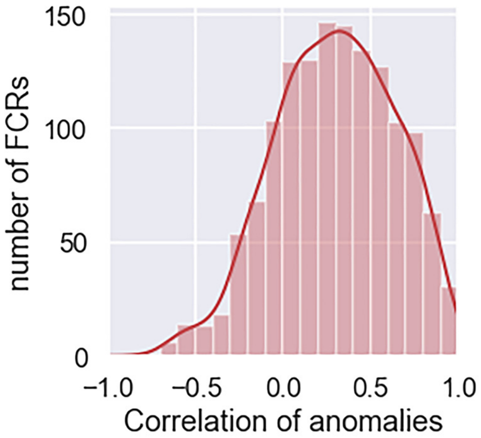
How well can we predict fires?

Global Scale Prediction of Emissions



Short lead (1-2 month) forecasts show some skill in predicting global emissions anomalies, but are unable to reproduce magnitude of observed anomalies





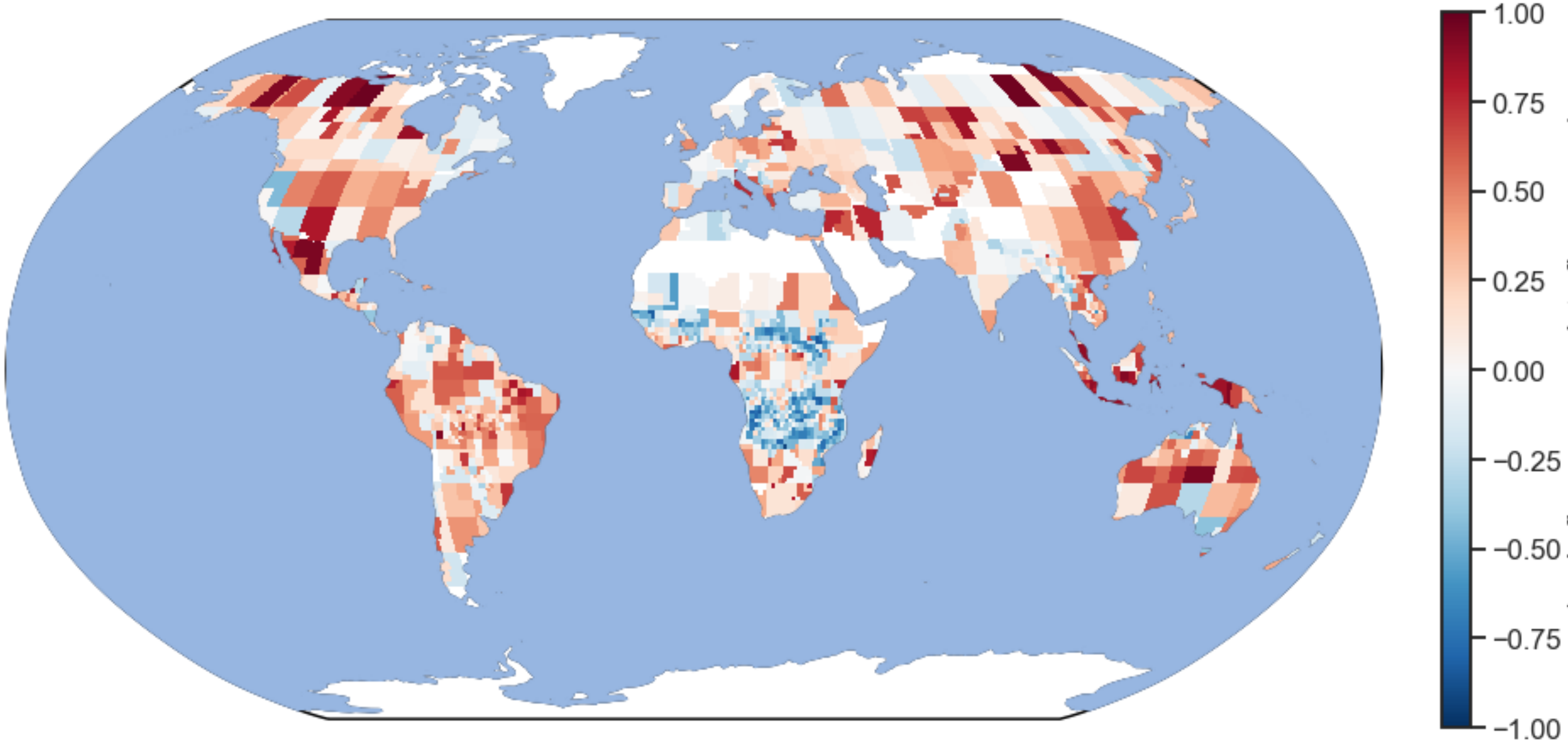
Regional performance is better – positive correlation between predicted (1-mo) and observed anomalies in most regions

Chen et al., *JAMES*, 2020

Value of simple lagged predictors provides value in many regions

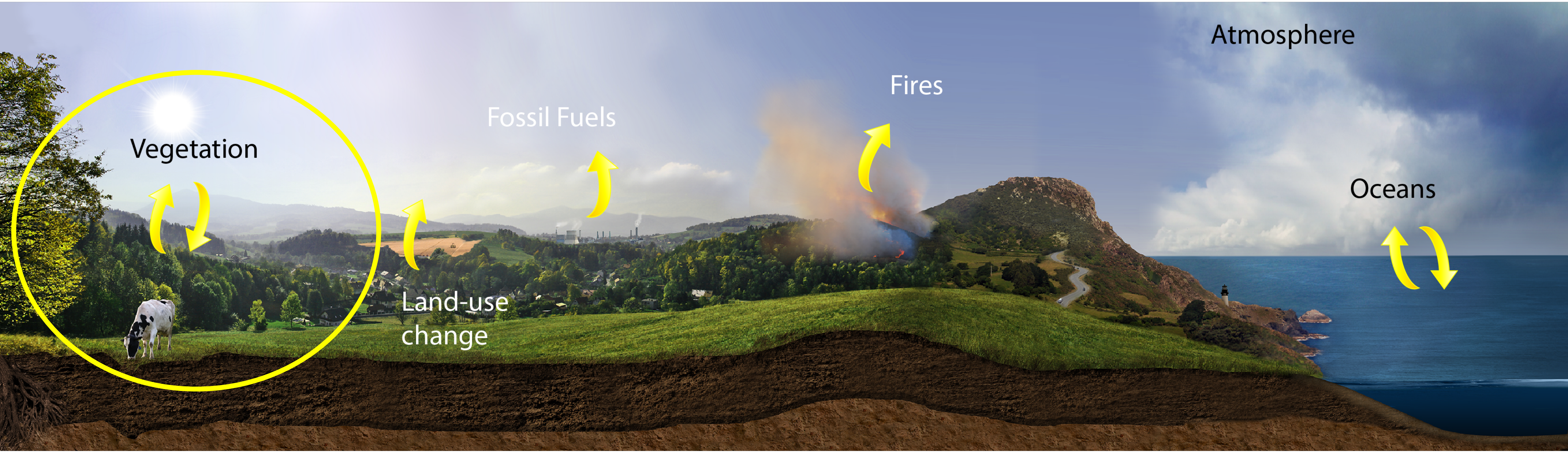
The strength of the early fire season provides information about activity in the late season, though the correlation can be positive or negative

Correlation between early, late fire season



Chen et al., *JAMES*, 2020

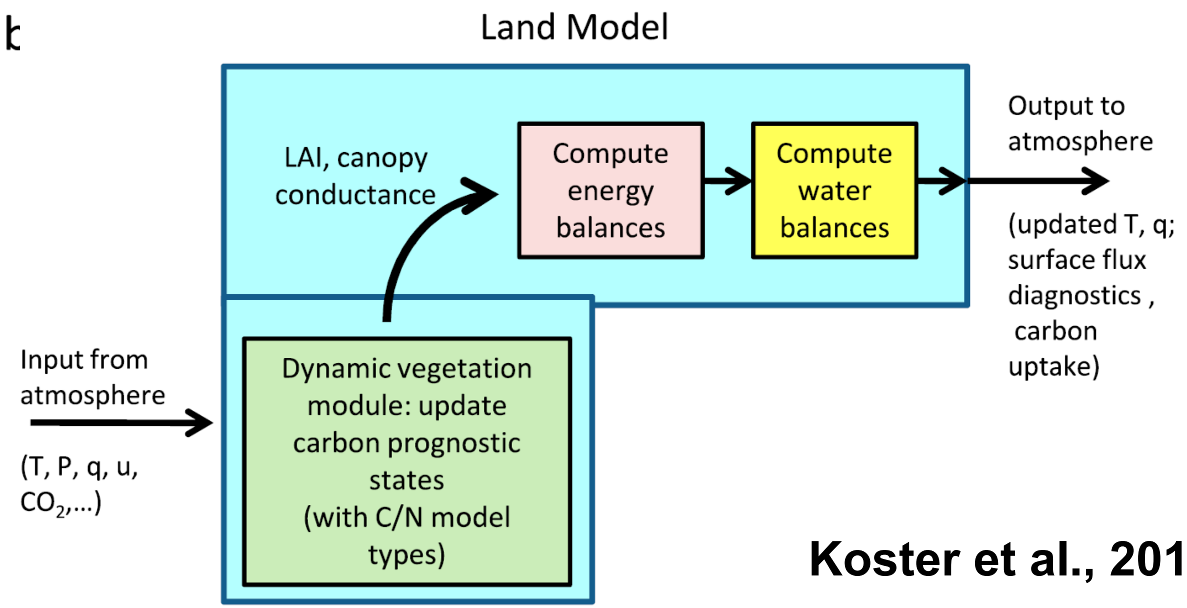
Carbon cycle components



Credit: NASA/Jenny Mottar and Abhishek Chatterjee

Forecasts of NEE using two terrestrial biosphere models

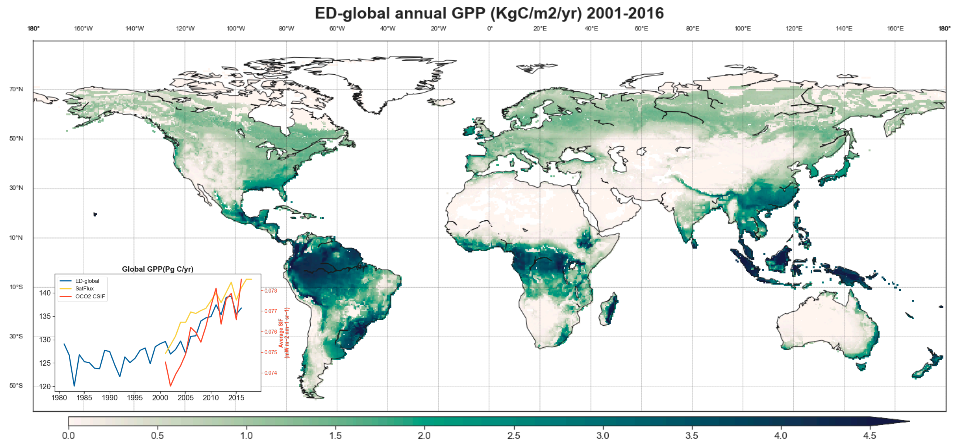
Catchment-CN

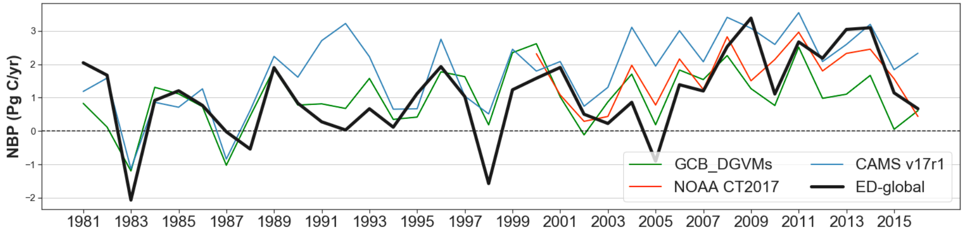


Koster et al., 2014

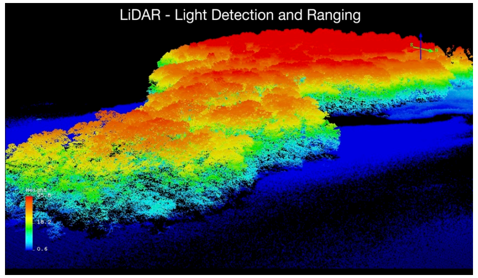
- Can be run offline or within GEOS modeling system – strong connection to met data assimilation and SMAP
- Merger of CLM C-N dynamics and GEOS water, energy balances

Global ED (UMD)

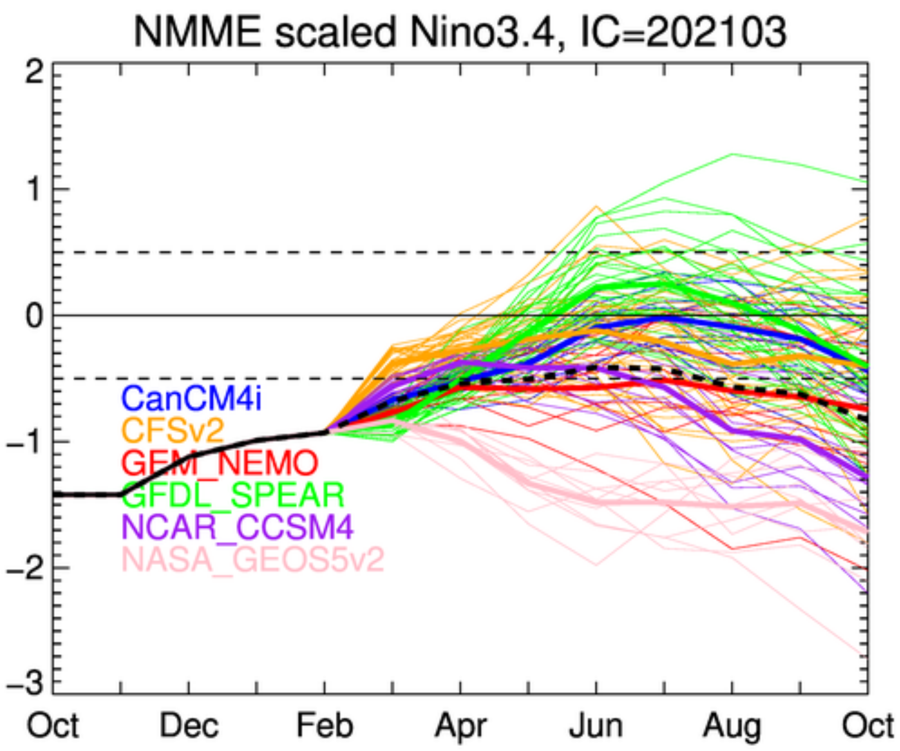




- Development of global Ecosystem Demography model (ED)
- Model-Data integration with remote sensing (LiDAR, Landsat)
- Applications in CMS, GEDI, IDS

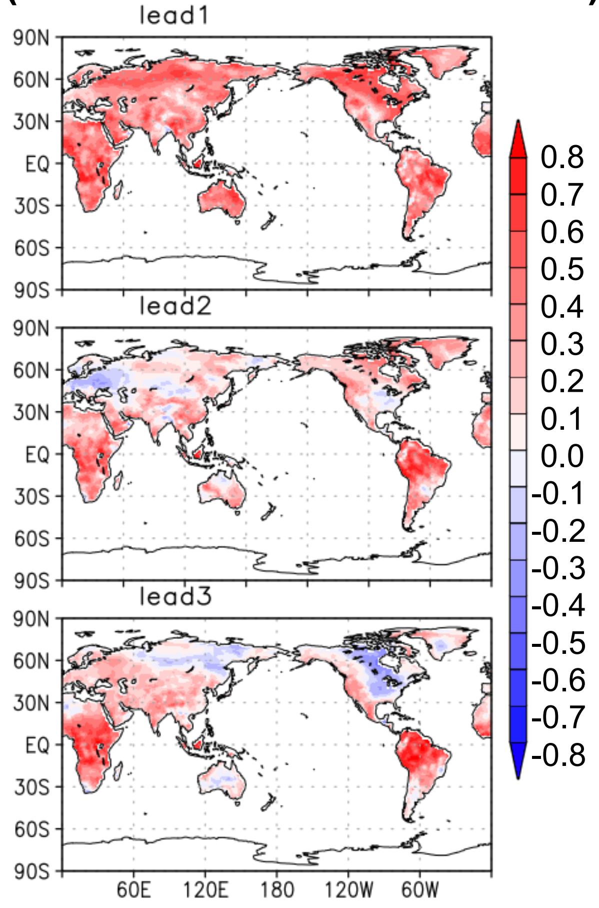


But first, a few notes about seasonal climate forecasts



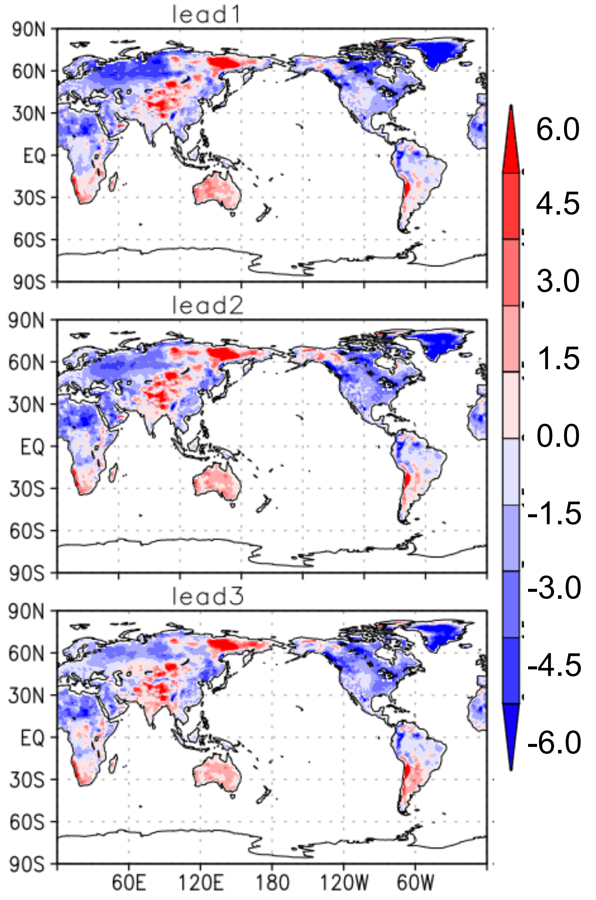
Different models can disagree substantially

Temperature Anomaly Correlation (GEOS December start dates)



Seasonal forecast are built to predict *anomalies*...

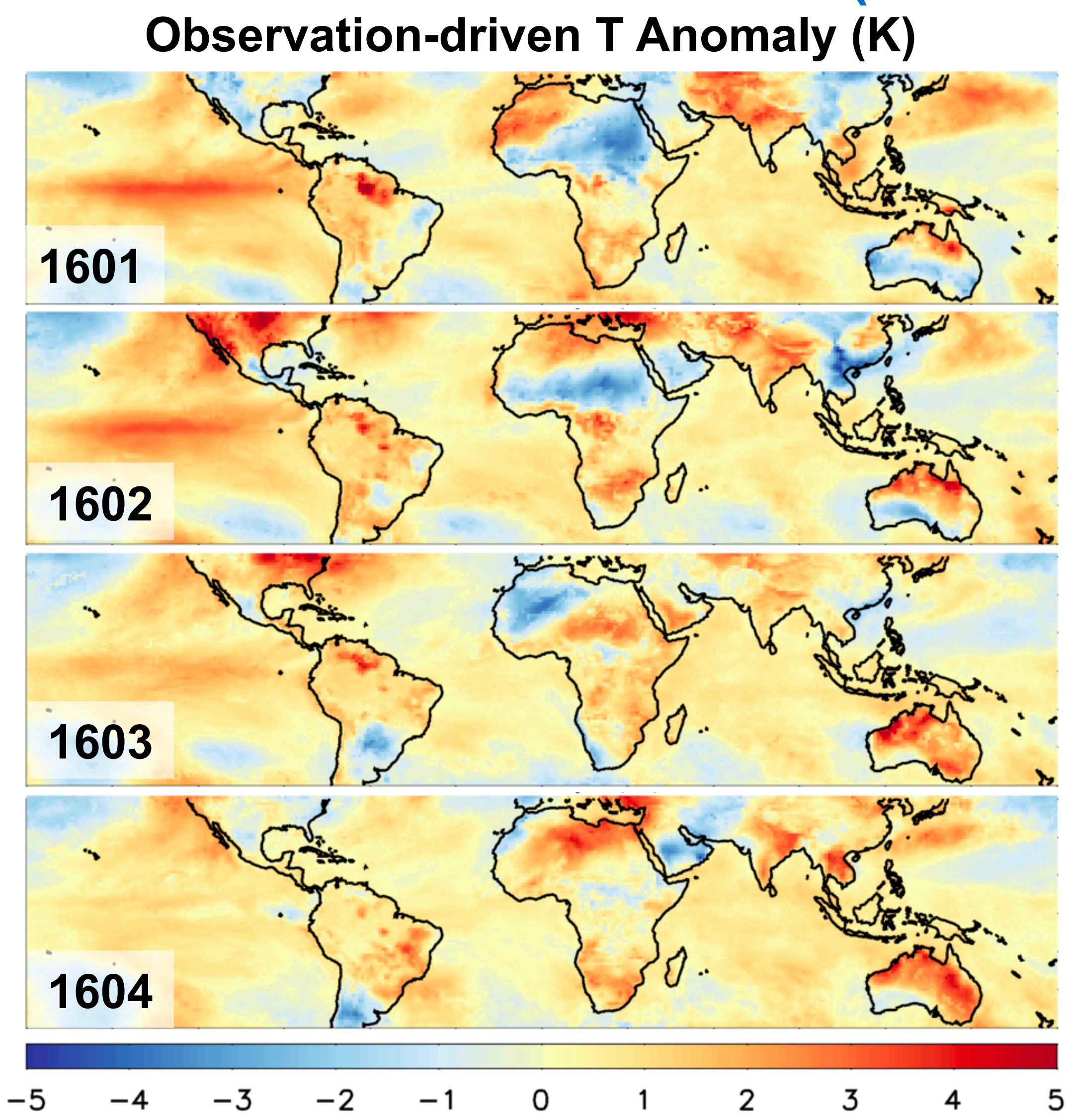
GEOS Temperature Bias (K)

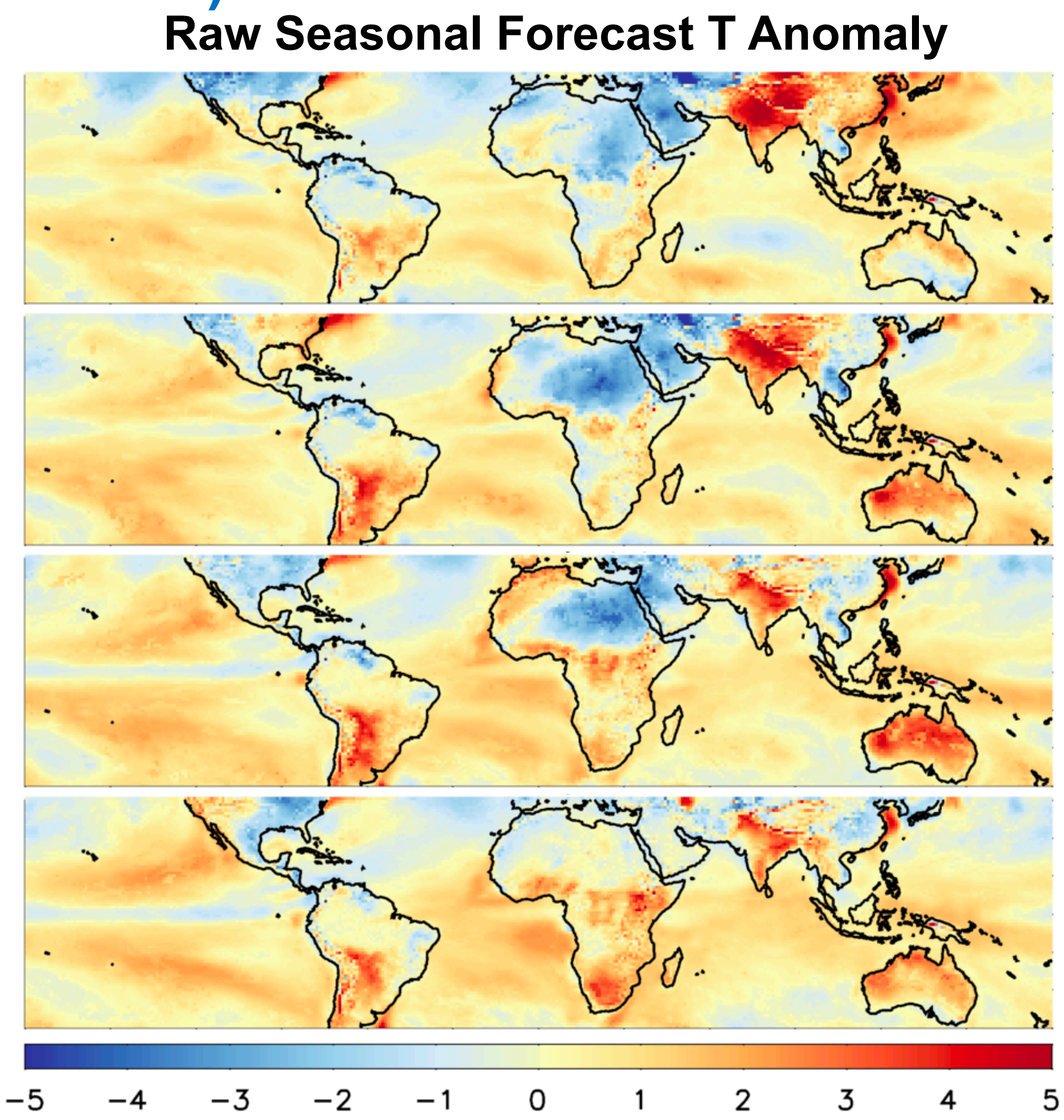


But typically contain substantial biases

https://www.cpc.ncep.noaa.gov/products/NMME/, https://gmao.gsfc.nasa.gov/seasonal/

Example: Predicted 2016 temperature anomalies (lead months 1-4)





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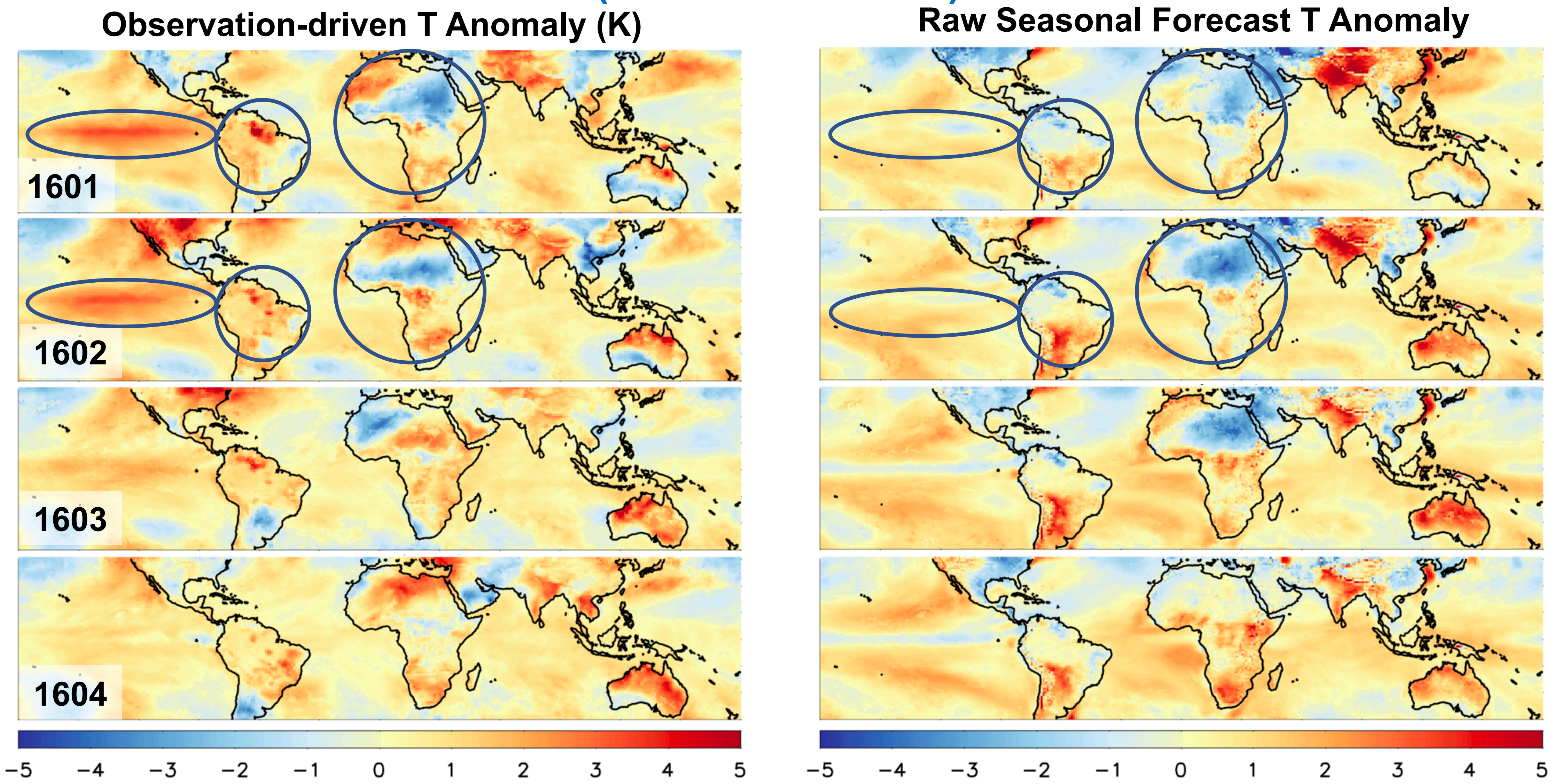
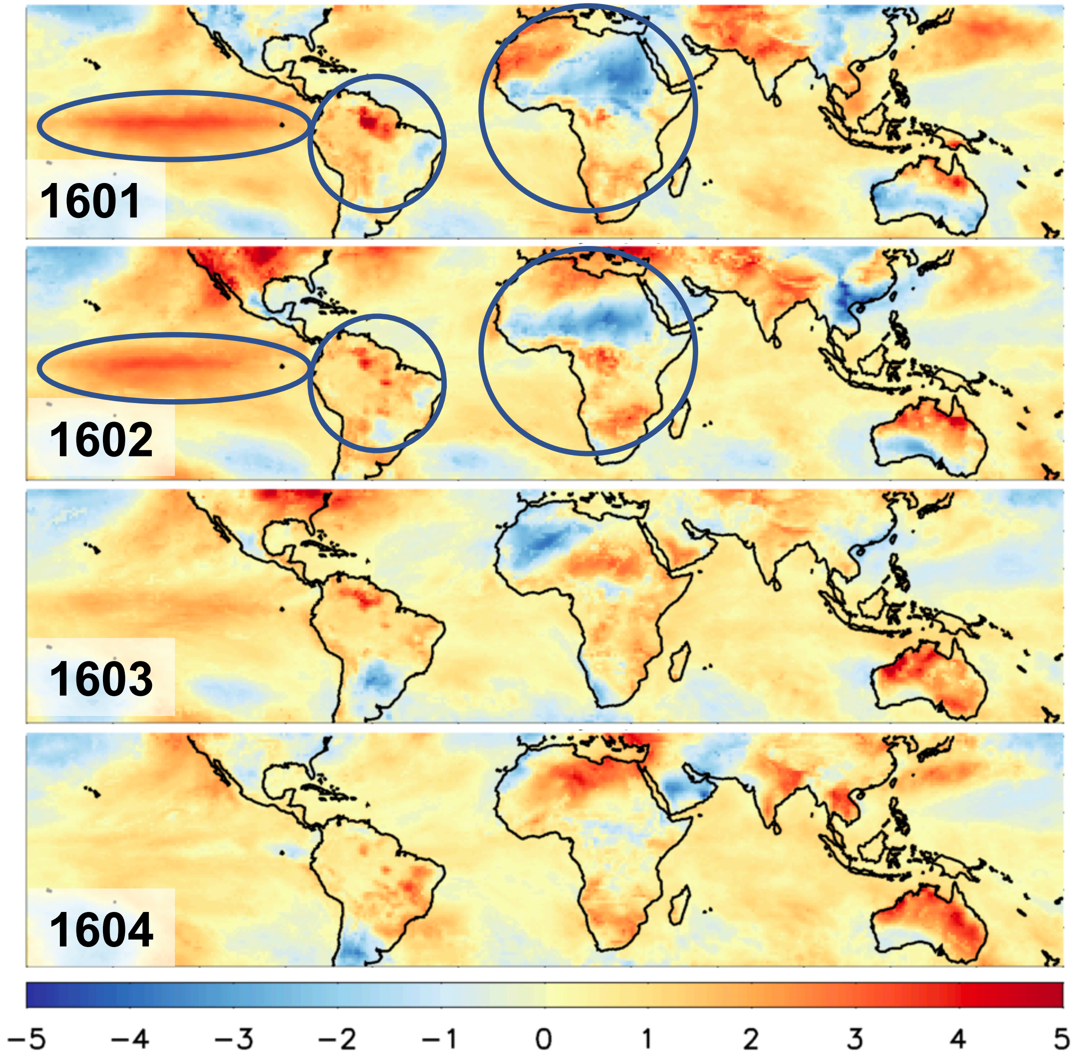
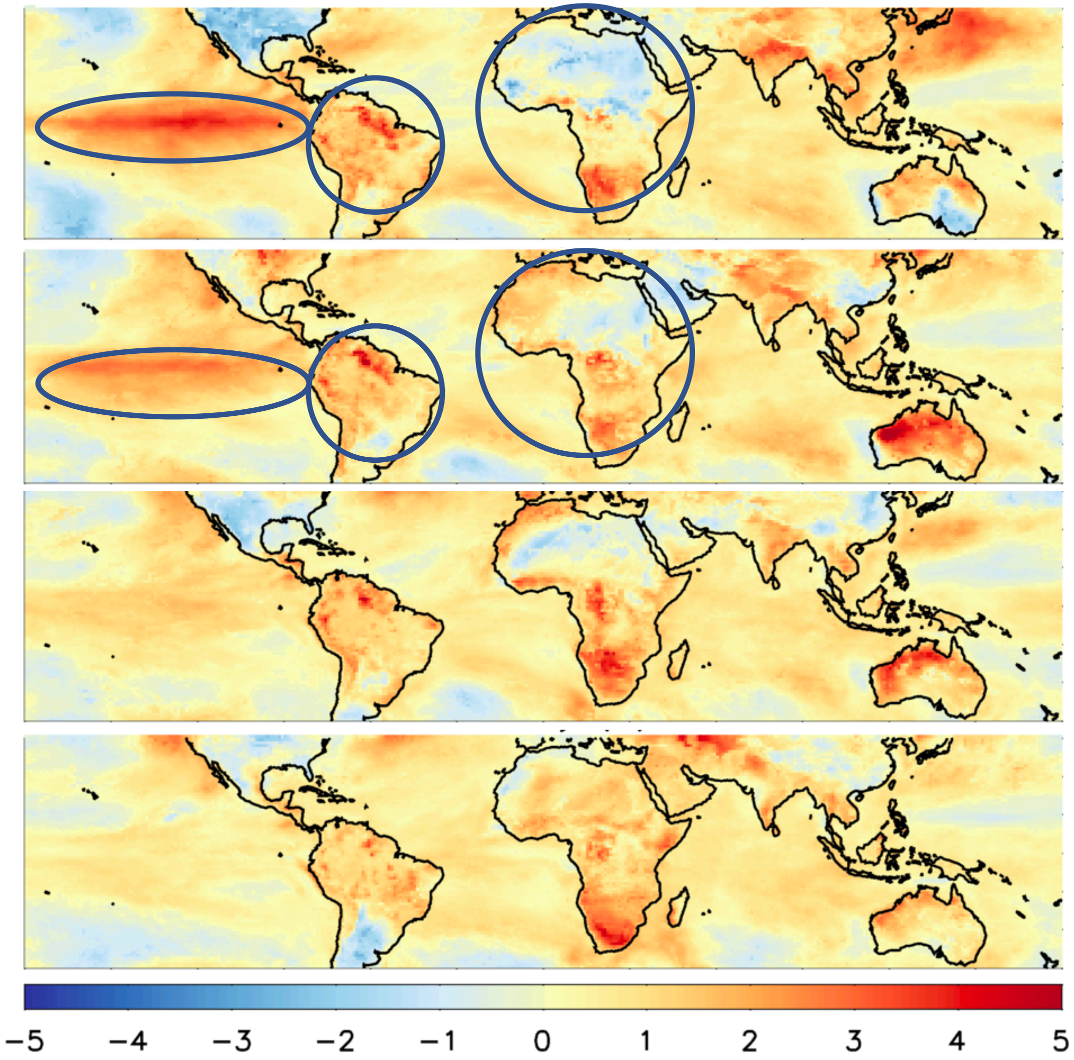


Example: Predicted 2016 temperature anomalies including bias correction relative to MERRA-2

Observation-driven T Anomaly (K)

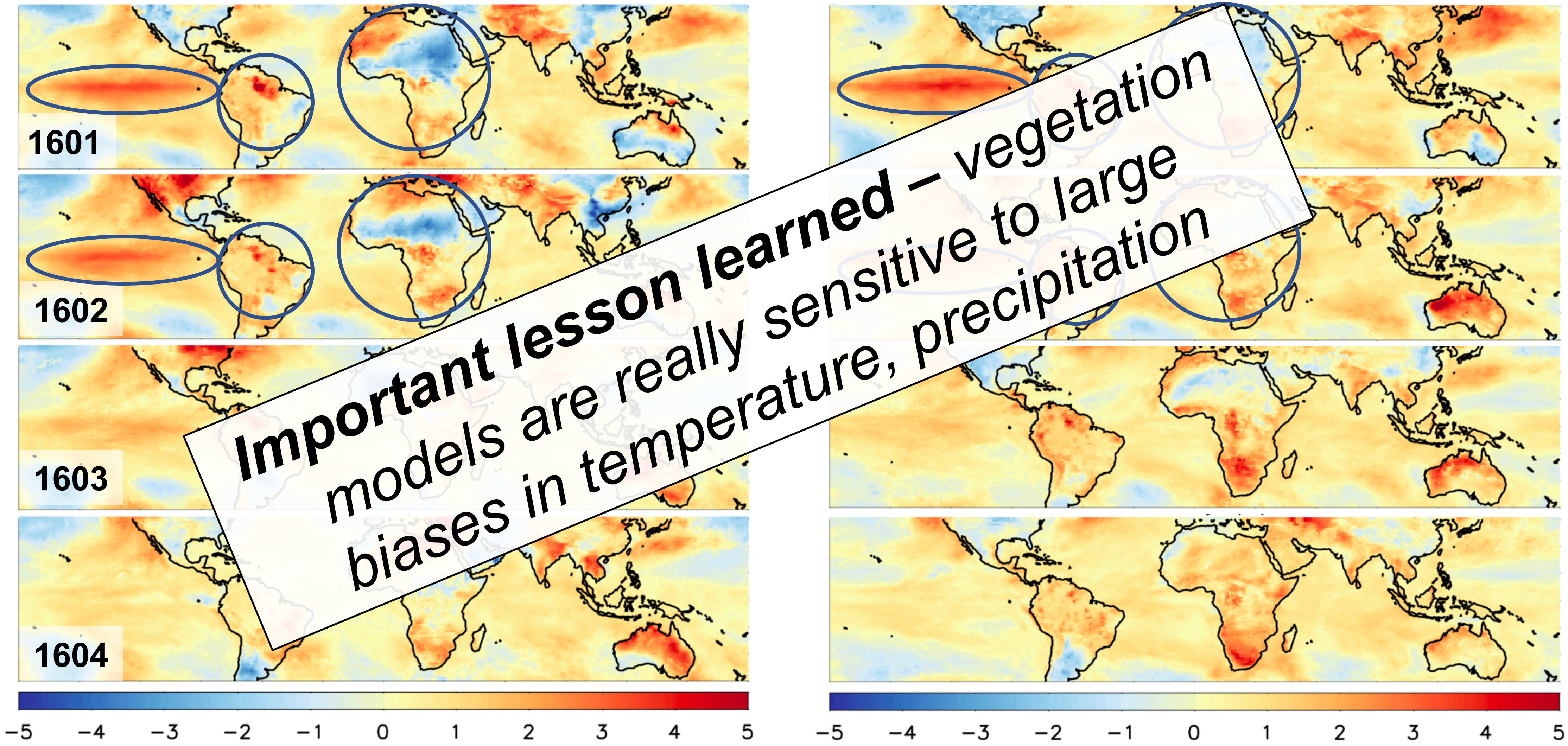


Bias-corrected Seasonal Forecast Anomaly



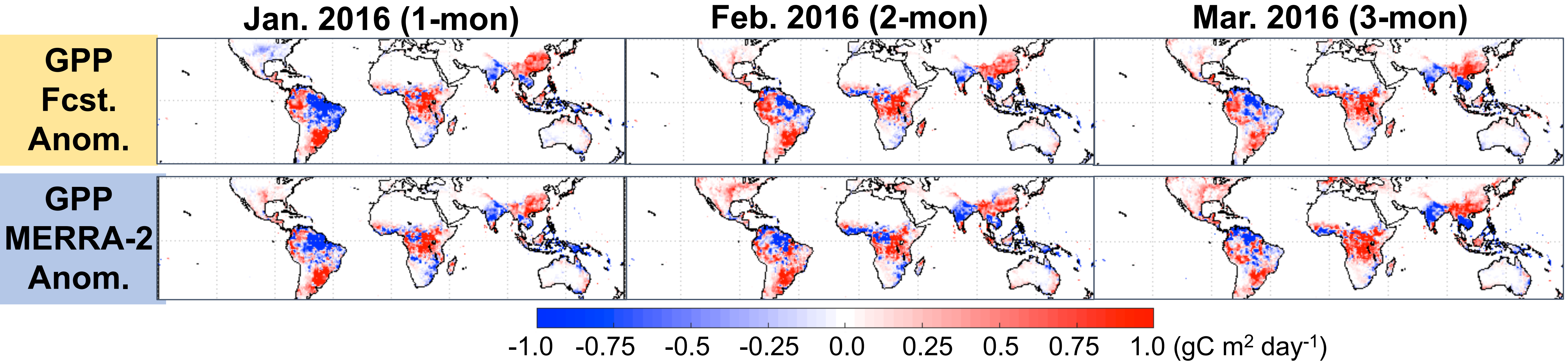
Example: Predicted 2016 temperature anomalies including bias correction relative to MERRA-2

Observation-driven T Anomaly (K) | **Bias-corrected Seasonal Forecast Anomaly**



Important lesson learned – vegetation models are really sensitive to large biases in temperature, precipitation

Catchment-CN Flux Anomalies (model truth)



Next steps:

- Use bias-corrected seasonal forecast meteorology to drive biosphere models
- Compare to simulation driven by reanalysis (observed) meteorology
- GPP = Gross Primary Production, amount of carbon fixed by biomass during photosynthesis

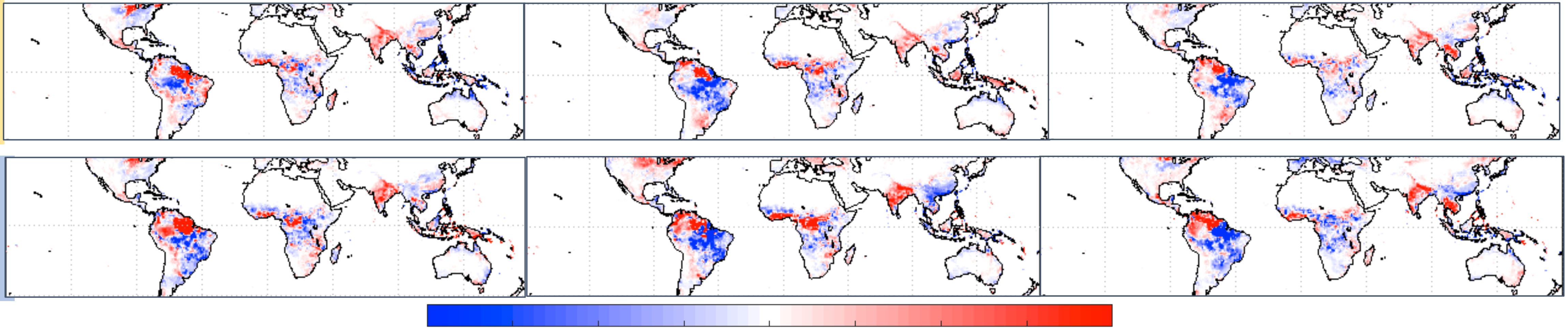
Lee et al., *in prep.*, 2021

Catchment-CN Flux Anomalies (model truth)

- With bias-corrected seasonal forecast meteorology, the model is largely able to reproduce the spatial pattern of GPP estimated using reanalysis data
- NBE = Net Biome Production, net exchange of carbon between ecosystem and atmosphere
- NBE = Ecosystem respiration + fire emissions – GPP

NBE Fcst. Anom.

NBE MERRA-2 Anom.

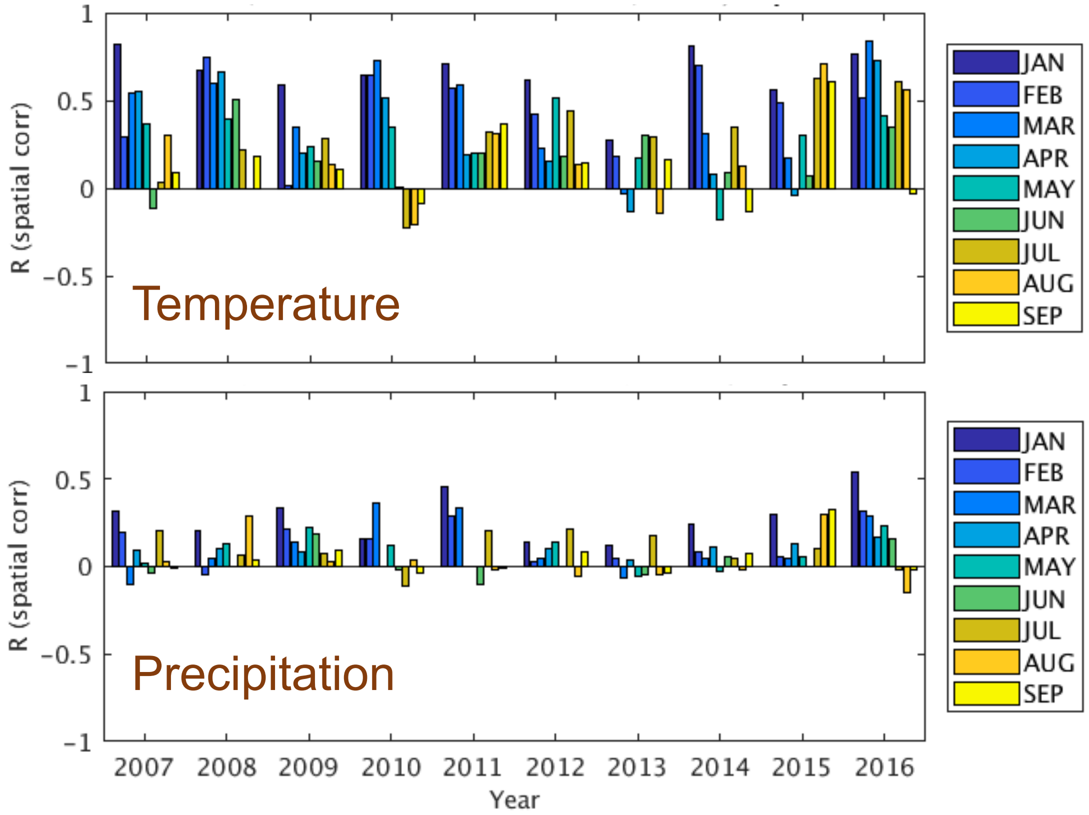


Lee et al., *in prep.*, 2021

Assessing the potential predictability of land flux forecasts (model truth experiments)

- 10 years of biosphere model hindcasts (2007-2016) starting in December
- Anomalies in GPP and NBE calculated for seasonal hindcasts and reanalysis driven simulation
- *Spatial anomaly correlation coefficient* assesses ability of forecast to reproduce the anomaly pattern - for example, where should we look for an interesting event?
- *Temporal anomaly correlation coefficient* assesses ability of forecast to predict unusual event at a given location

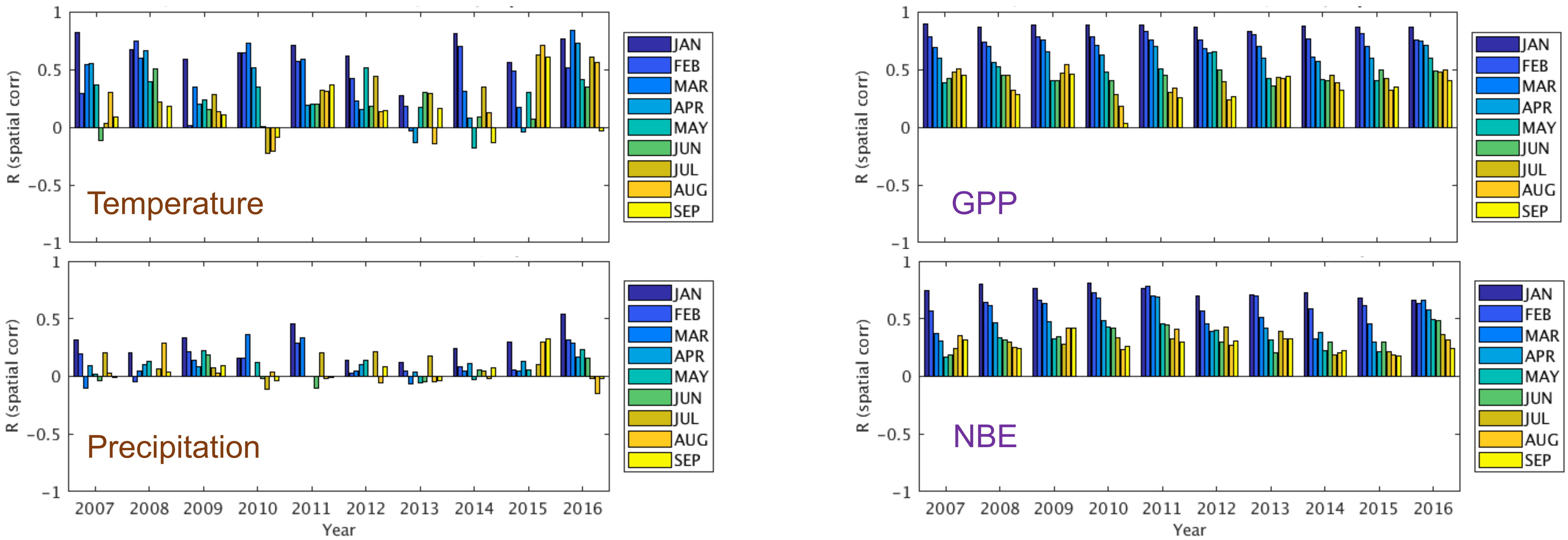
Tropical spatial anomaly correlations



- Temperature predictions perform best in first few months though this can vary substantially by year
- Temperature is easier to predict than precipitation

Lee et al., *in prep.*, 2021

Tropical spatial anomaly correlations



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- Temperature is easier to predict than precipitation

Predictions of carbon flux (GPP, NBE) anomalies are better than the forecasts of the underlying meteorological variables

Lee et al., *in prep.*, 2021

Assessing contributions to land carbon predictability

Two additional sets of experiments:

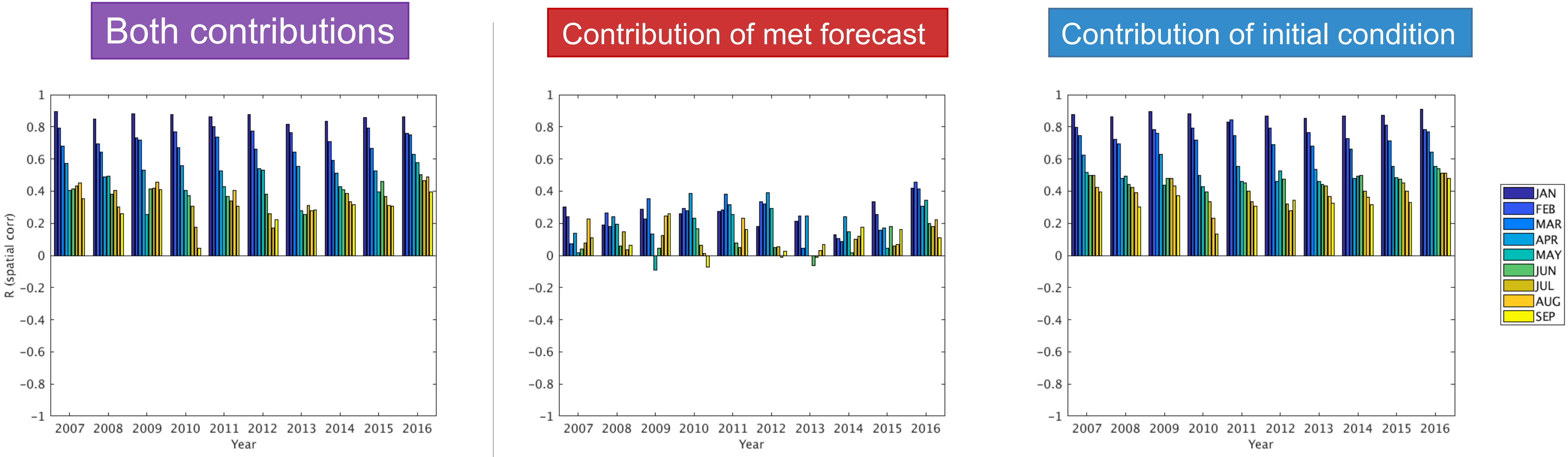
[Set 1] Apply 2016 Jan 1st Initial condition under different meteorology

[Set 2] Apply 2016 forecast meteorology for all ten years (2007-2016)

	2007 init	2008 init	2009 init	2010 init	2011 init	2012 init	2013 init	2014 init	2015 init	2016 init
2007 met (4 members)	**X**									X
2008 met (4 members)		**X**								X
2009 met (4 members)			**X**							X
2010 met (4 members)				**X**						X
2011 met (4 members)					**X**					X
2012 met (4 members)						**X**				X
2013 met (4 members)							**X**			X
2014 met (4 members)								**X**		X
2015 met (4 members)									**X**	X
2016 met (4 members)	X	X	X	X	X	X	X	X	X	**X**

Lee et al., *in prep.*, 2021

Most of the predictability comes from initialization rather than skillful climate forecast

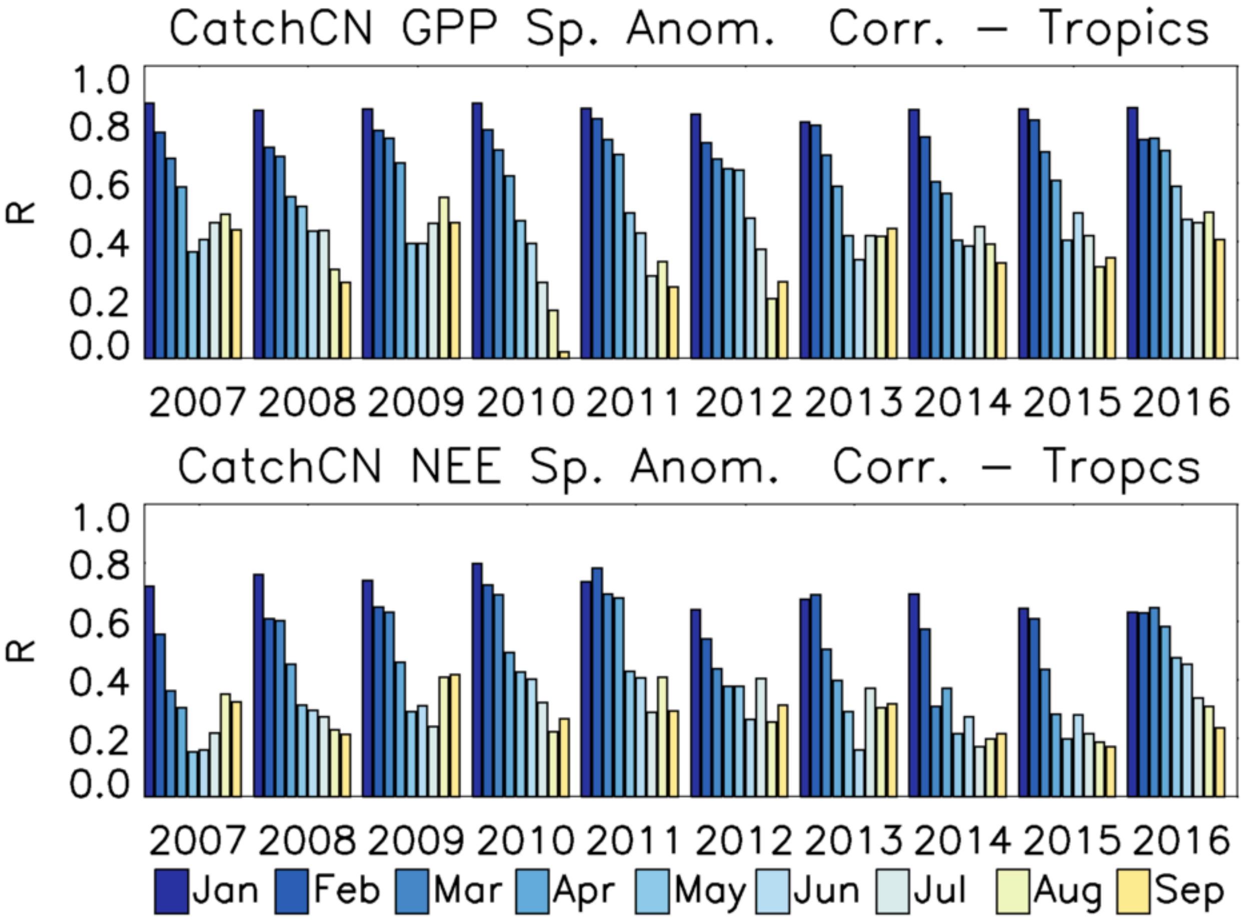


Contribution of land initial condition (mainly soil moisture) is larger than the contribution from predicted meteorology

Lee et al., *in prep.*, 2021

Results seem to hold up across multiple models

Model 1 – Catchment-CN



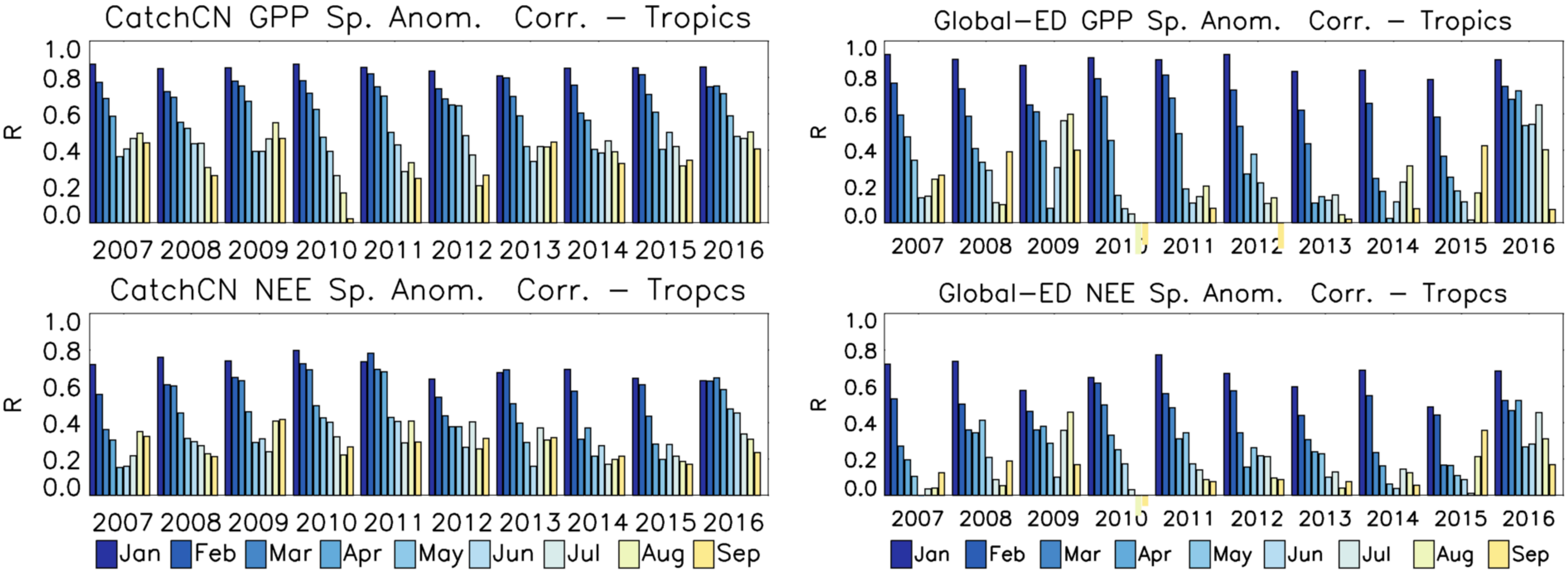
Big-leaf model, adapted from CLM

E. Lee, F. Zeng, G. Hurtt, and L. Ma

Results seem to hold up across multiple models

Model 1 – Catchment-CN

Model 2 – Global ED (UMD)



Big-leaf model, adapted from CLM

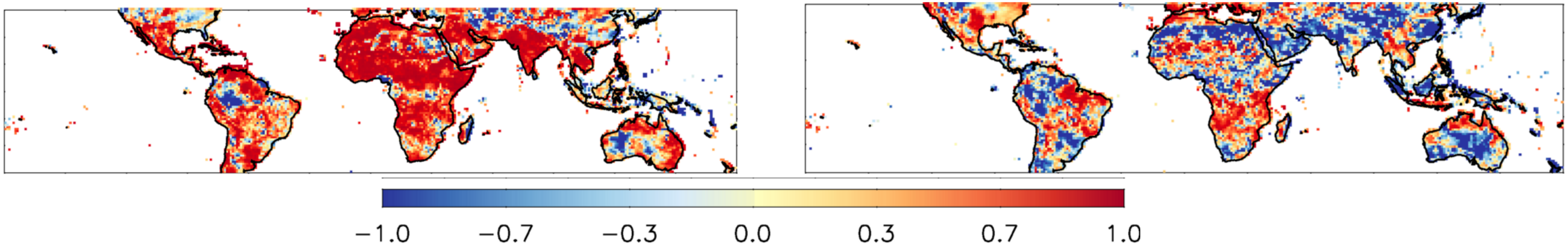
Global version of individual-based ED model

E. Lee, F. Zeng, G. Hurtt, and L. Ma

But how well do the forecasts compare with *observations*?

Model truth evaluation – Temporal anomaly correlation (1-mo)

Model truth evaluation – Temporal anomaly correlation (4-mo)

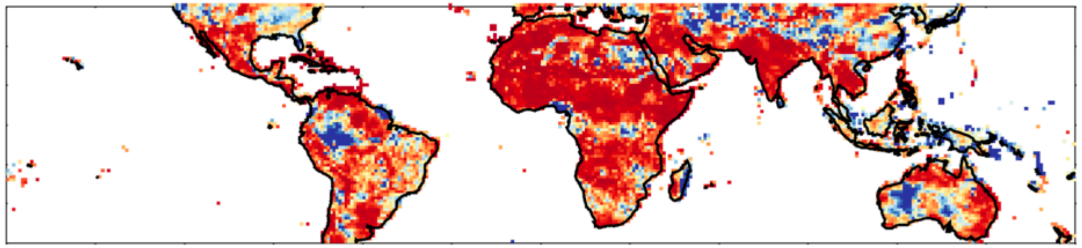


‘Model truth’ experiments show that seasonal land carbon forecasts are capable of reproducing reanalysis driven results at 1-2 month lead times - seasonal forecast meteorology is able to support this type of application

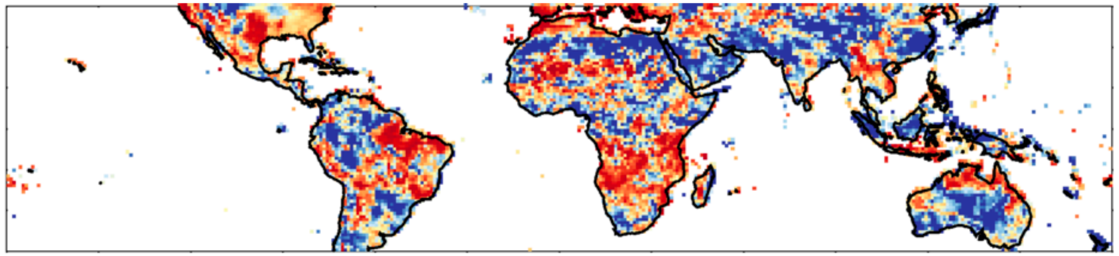
Lee et al., *in prep.*

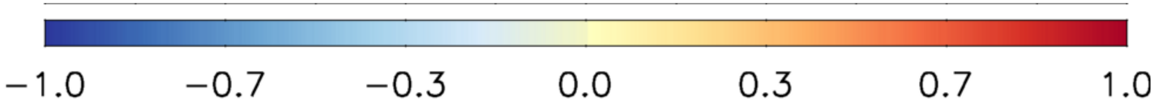
But how well do the forecasts compare with *observations*?

Model truth evaluation – Catchment-CN
Temporal anomaly correlation (1-mo)



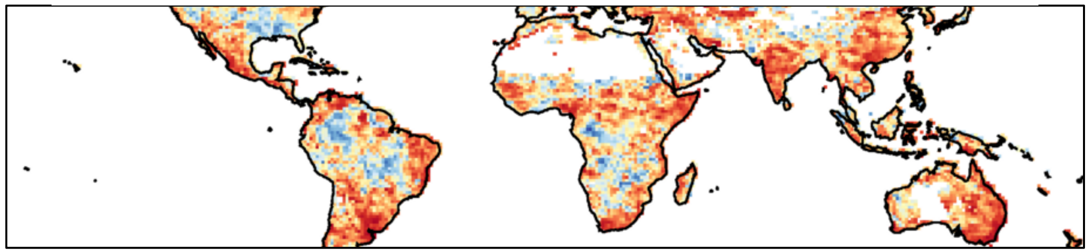
Model truth evaluation – Catchment-CN
Temporal anomaly correlation (4-mo)



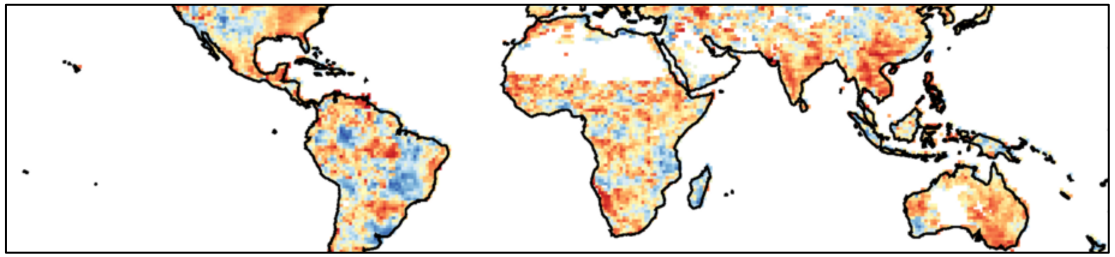


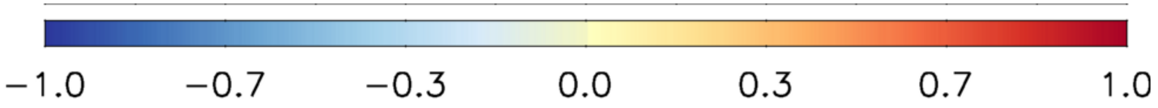
Comparison with MODIS-based FluxSat GPP product (Joiner and Yoshida, 2020)

FluxSat evaluation – Temporal anomaly correlation (1-mo)



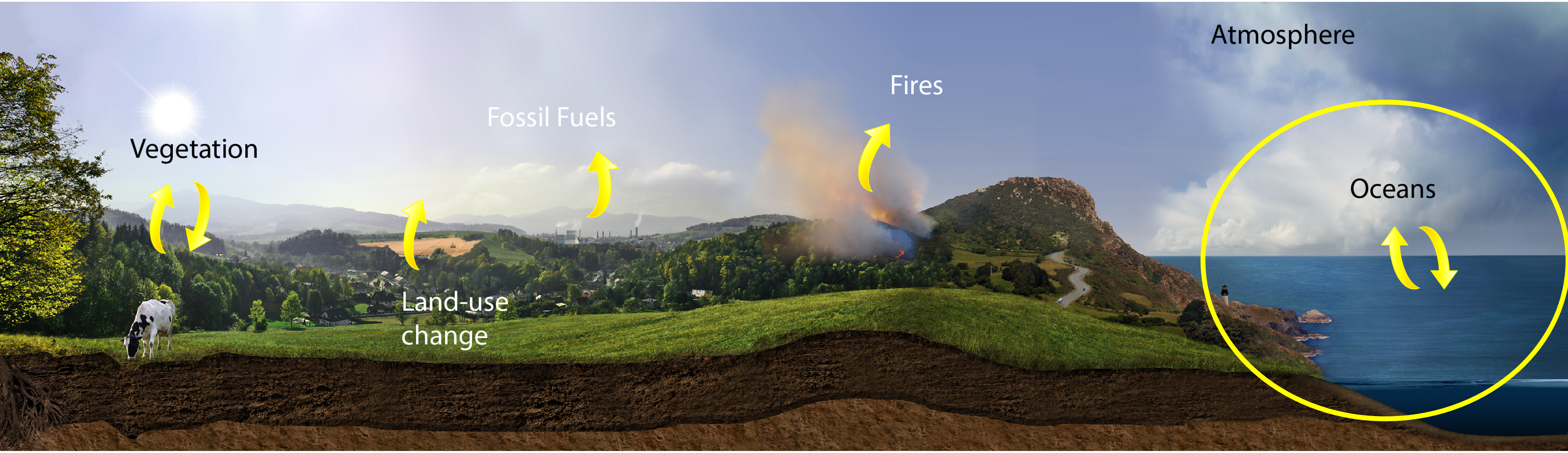
FluxSat evaluation – Temporal anomaly correlation (4-mo)





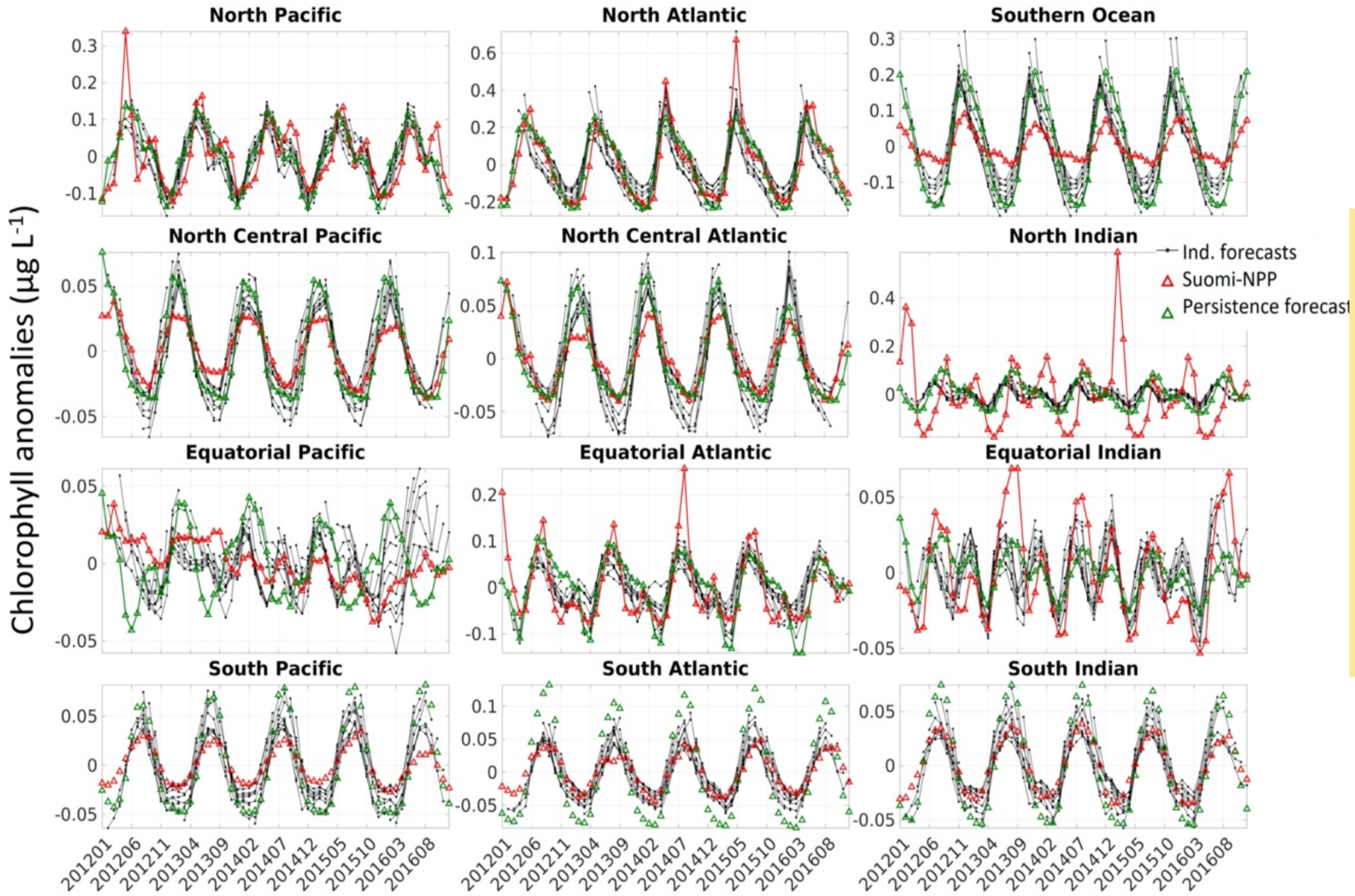
Lee et al., *in prep.*

Carbon cycle components



Credit: NASA/Jenny Mottar and Abhishek Chatterjee

What about ocean predictions?



Still work in progress. Comparisons suggest that seasonal predictions can reproduce a model simulation driven with reanalysis meteorology, but still fall short when compared with observations.

Similar findings from NCAR's CESM (e.g. Lovenduski et al., 2019)

Rousseaux et al., accepted, 2021

Summary and conclusions

NASA has supported research into seasonal carbon cycle predictions and we find some level of predictability for all major carbon cycle processes - land use change, atmospheric growth, fires, NEE, as well as ocean and fossil fuel (not shown). Some other lessons learned

- Timescales (months-years) and methods (statistical vs dynamic models) vary
- Certain things (e.g. volcanoes, recessions) are not predictable
- Bias correction is critically important, especially for terrestrial biosphere models
- Most skill within first 3 months for fossil fuel, fire, and land flux predictions
- Good initial conditions can often triumph over moderate or poor forecasts
- Model predictions are only as good at representing reality as the underlying simulations

Points that need more discussion:

- Who are the users of carbon cycle forecasts? What priority should modeling centers place on these aspects of Earth system prediction?
- What metrics can we use to evaluate forecasts and benchmark improvements over time
- How do we characterize forecast uncertainty (e.g. ensemble simulations, multi-model methods)?