Satellite Observations Reveal Seasonal Redistribution of Northern Ecosystem Productivity in Response to Interannual Climate Variability

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RUBISCO Science Friday
July 31, 2020

Remote Sensing of Environment 242 (2020) 111755

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Satellite observations reveal seasonal redistribution of northern ecosystem productivity in response to interannual climate variability

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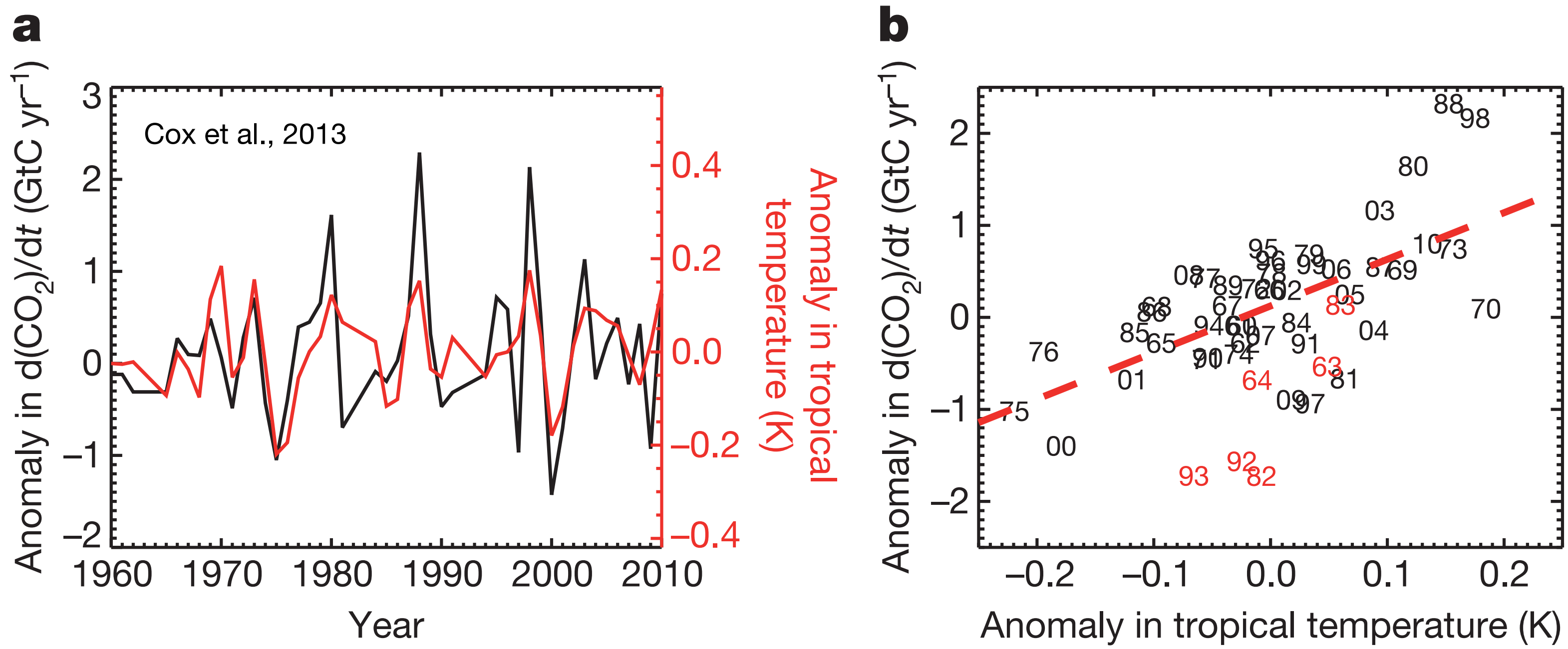
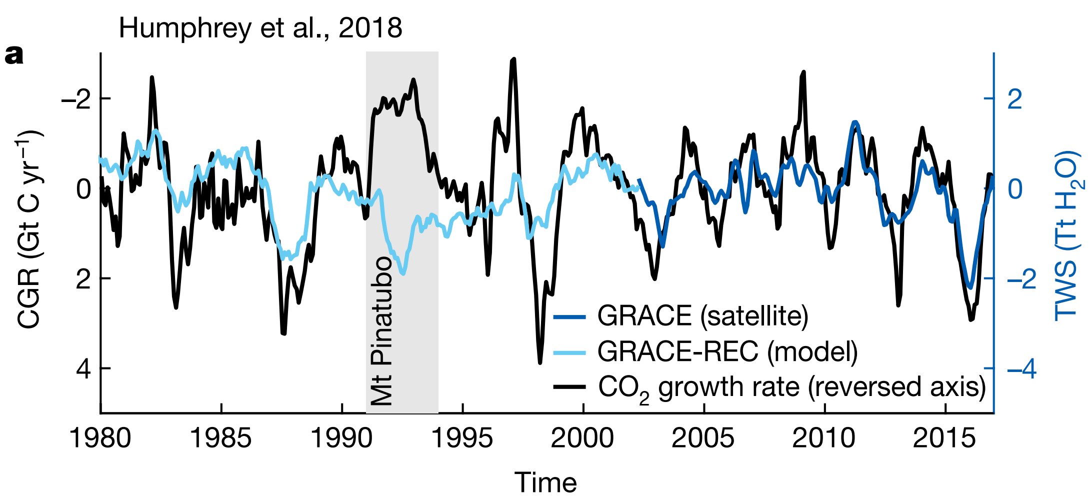
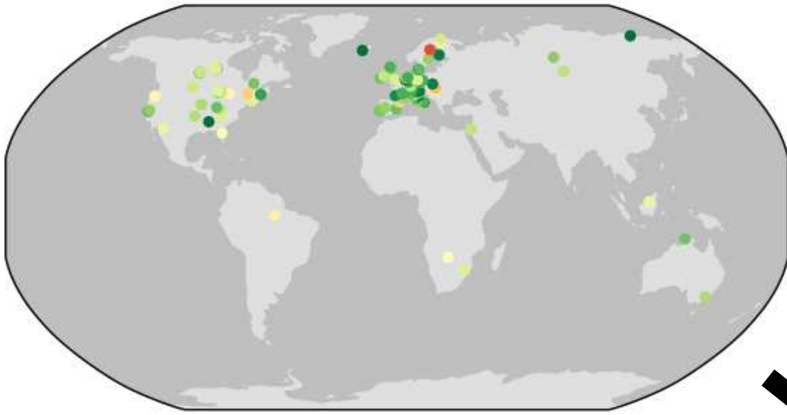
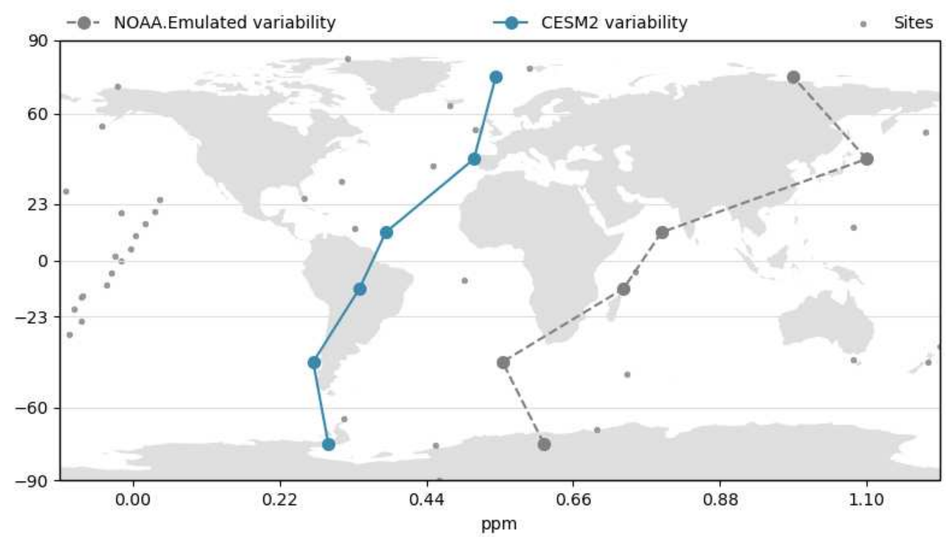
Accurately capturing relationships between climate drivers and land-atmosphere fluxes is crucial for a predictive ESM.



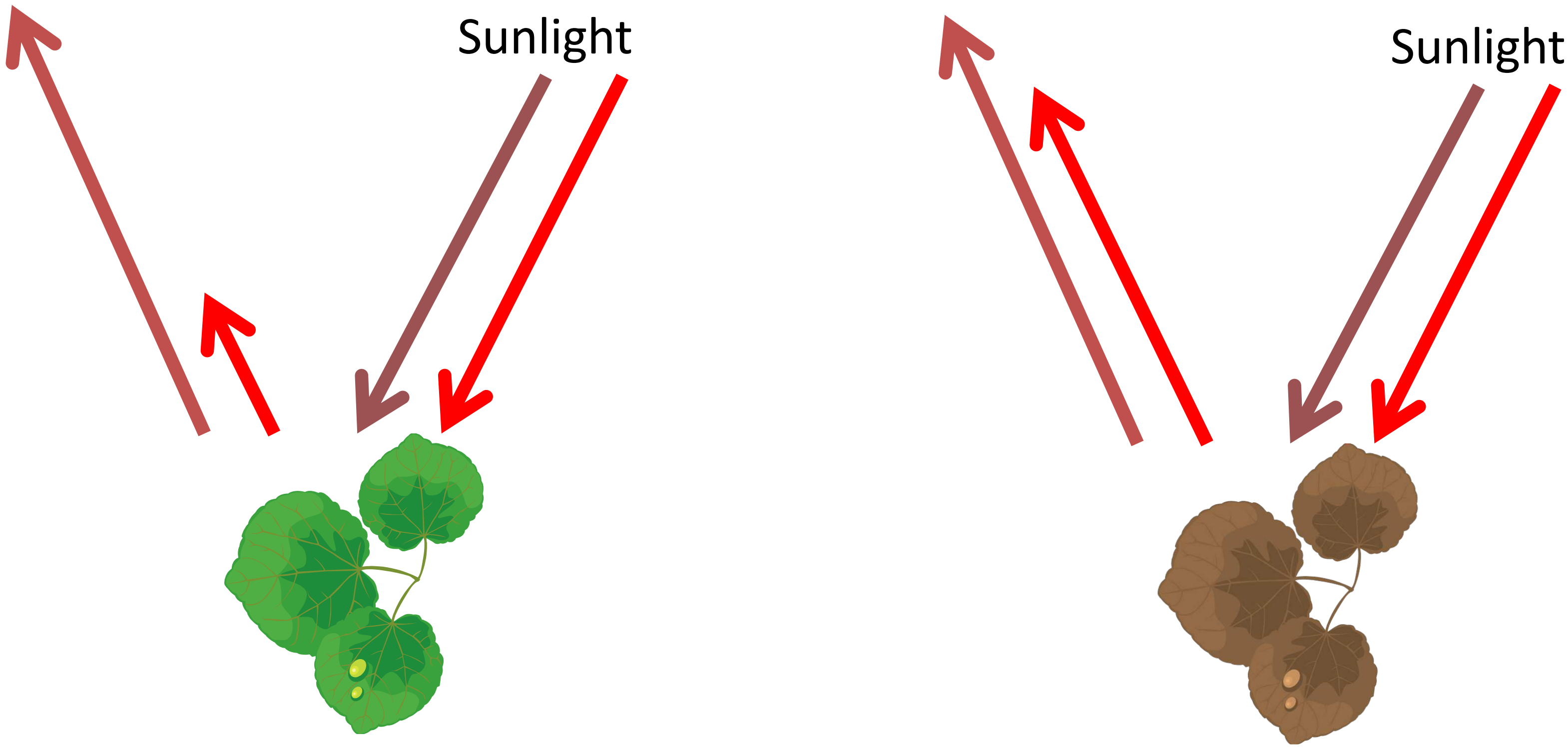


Ideally we need models to be consistent with constraints across spatial scales; this might require new constraints





Gridded satellite data about vegetation productivity historically derived from vegetation indices, which are not tied to photosynthetic mechanism

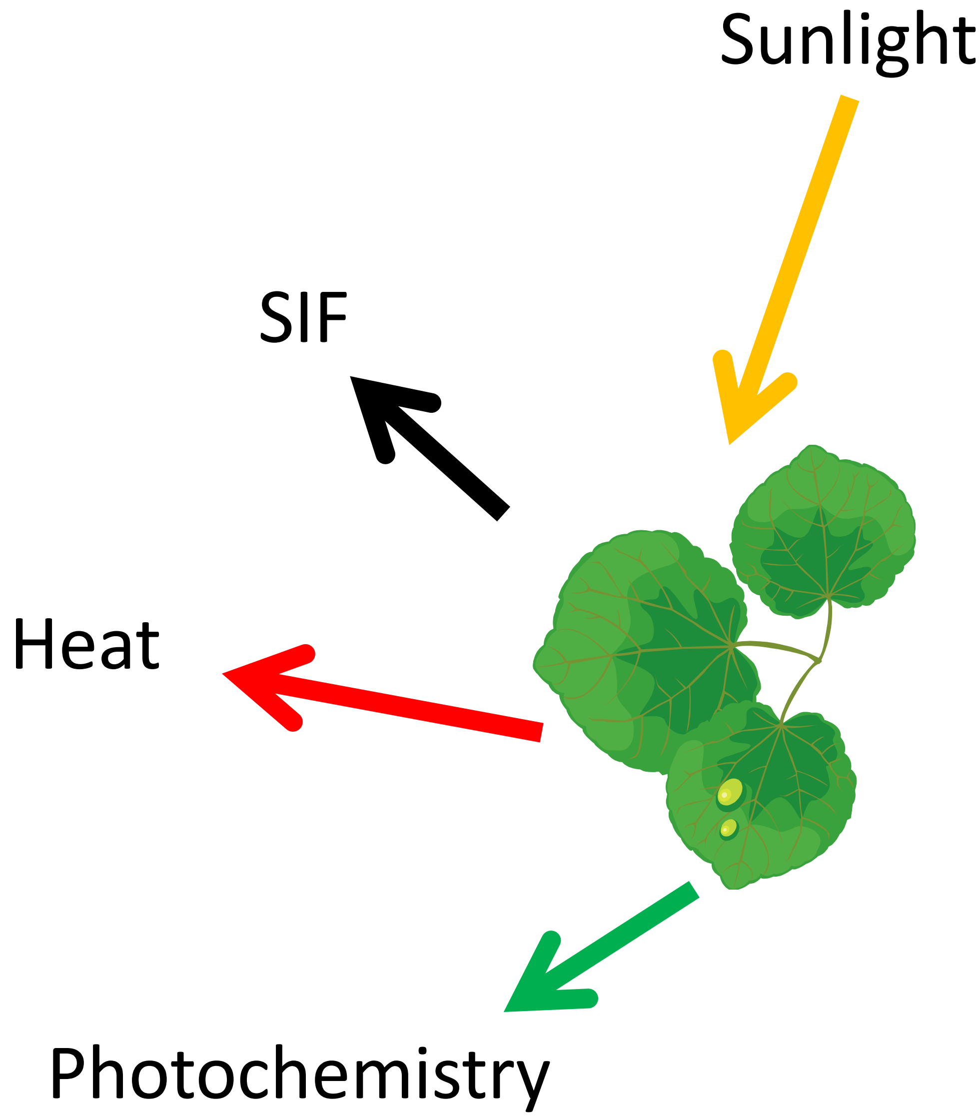


$$NDVI = (NIR - Red) / (NIR + Red)$$

Z. Butterfield

Solar-induced Chlorophyll Fluorescence provides a new remote-sensing based proxy for vegetation productivity

Photons/energy must be accounted for, as photosynthesis, heat waste, or SIF



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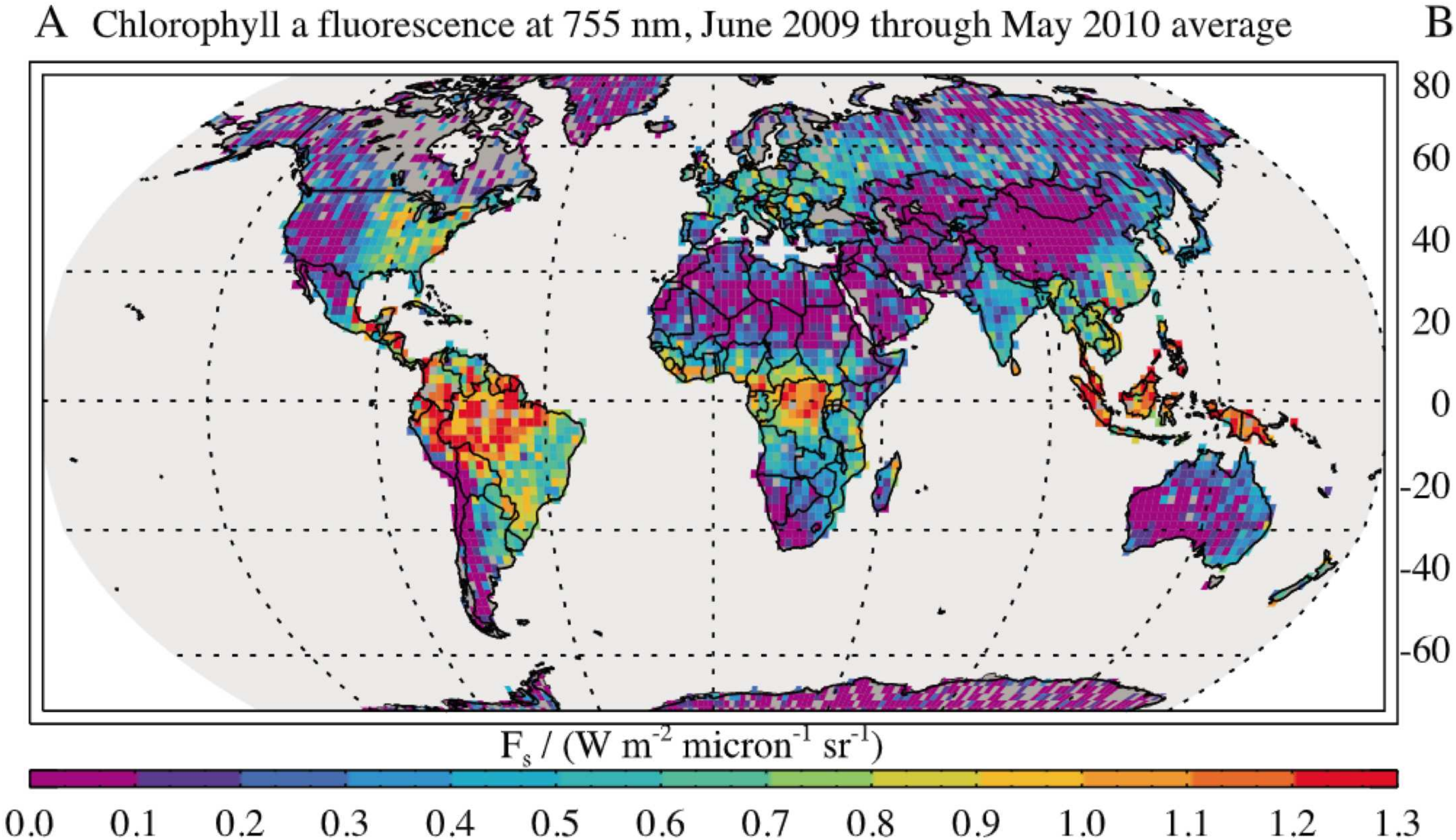
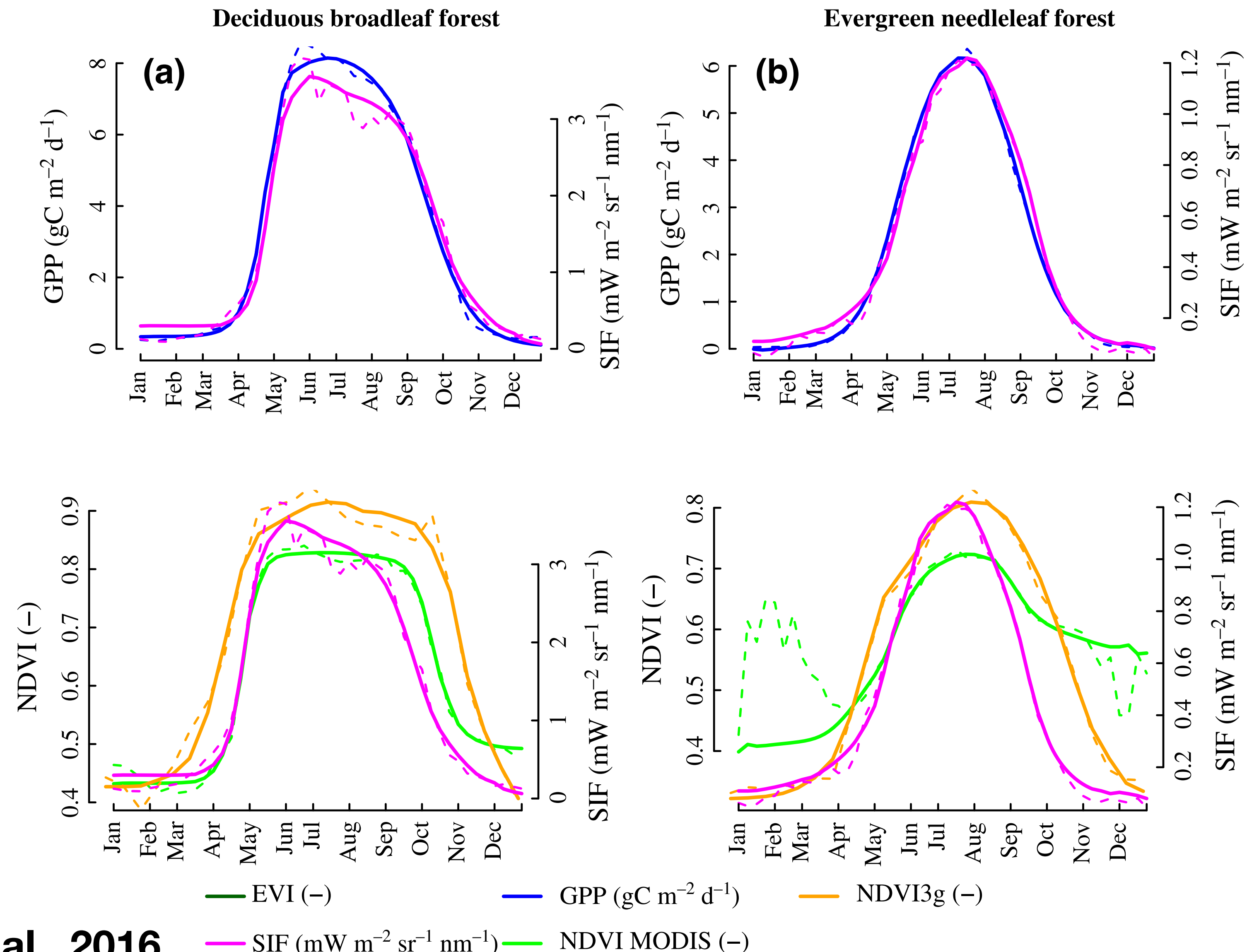
Satellite maps of SIF show correlation with modeled GPP



Frankenberg et al., 2011

SIF has shown strong correlations with tower-based GPP at seasonal scales, BUT there are substantial differences in shoulder seasons compared to other remote sensing metrics



Walther et al., 2016

For climate feedbacks we might care more about interannual variability — how do these compare?

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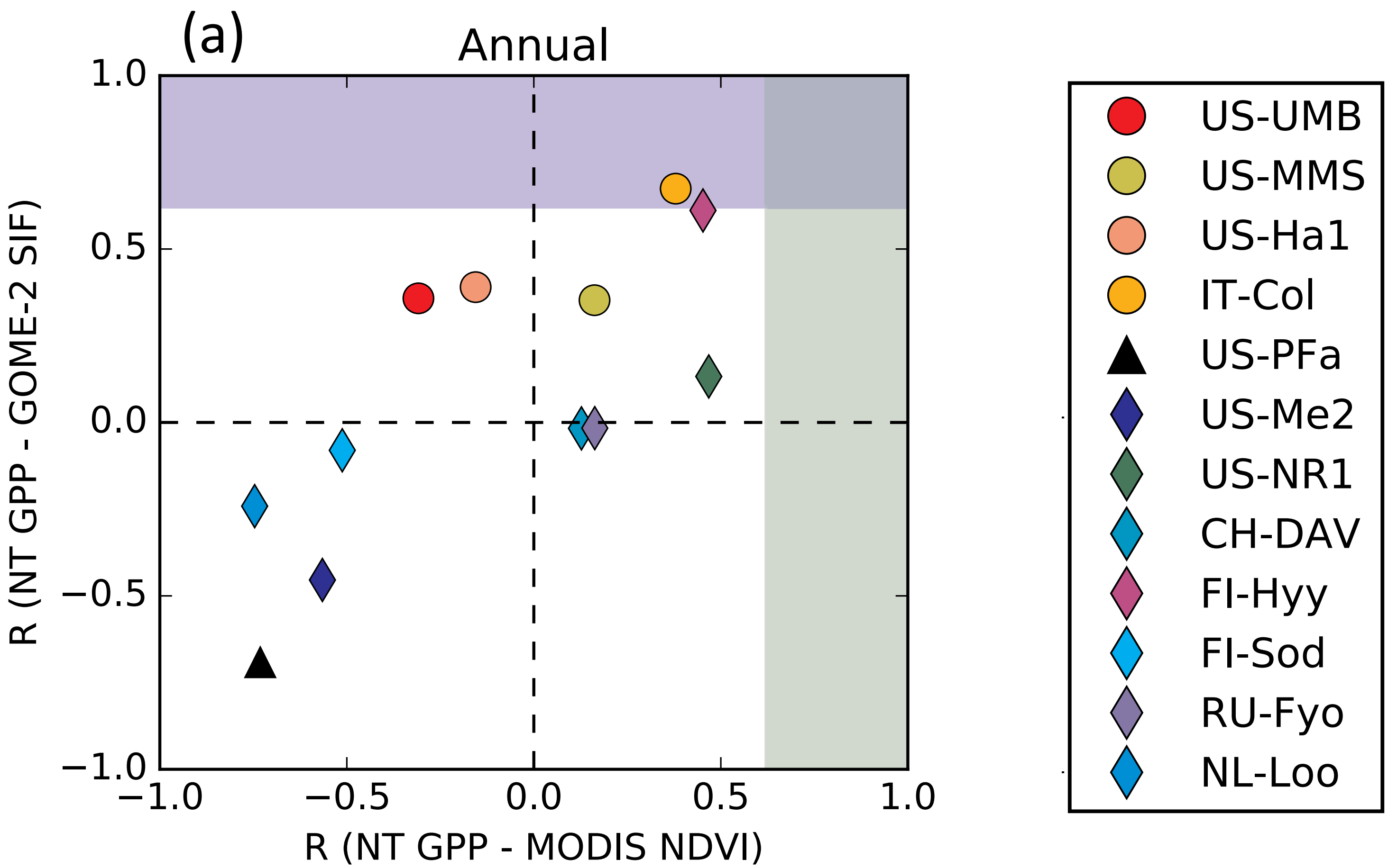
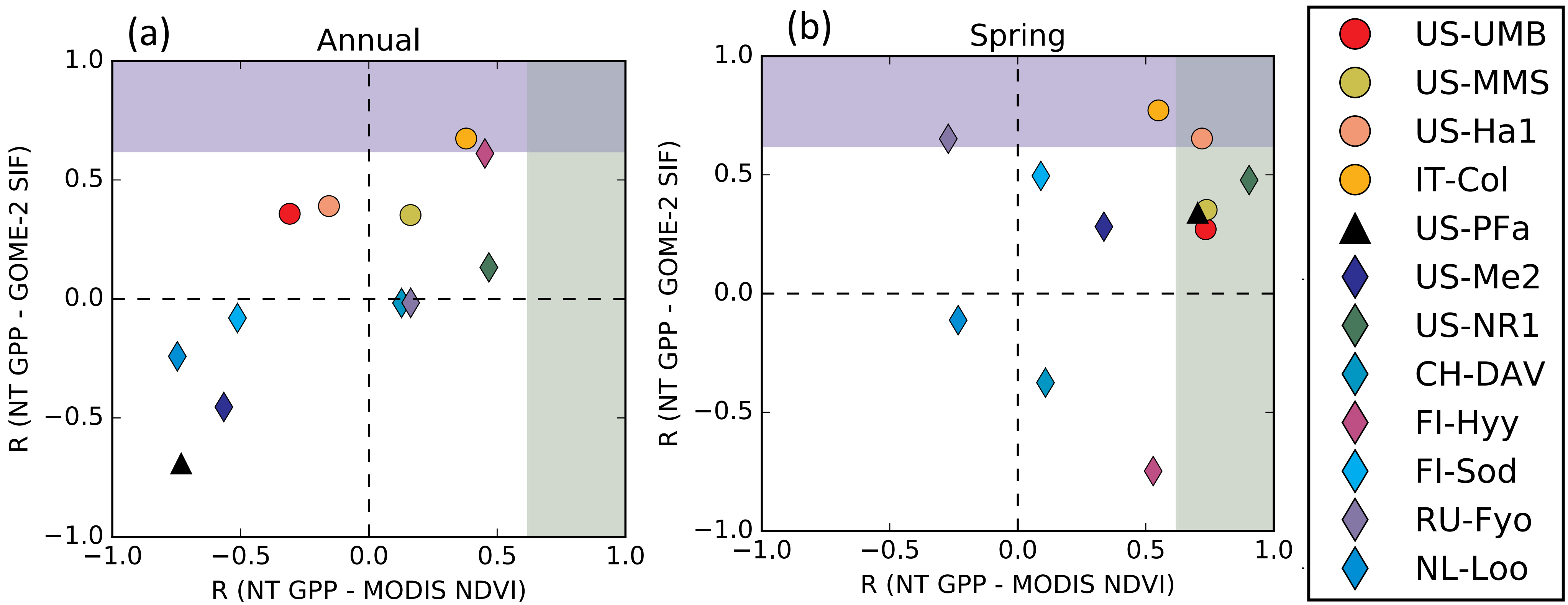


Annual productivity compares poorly with tower-based GPP for several remote sensing datasets

Butterfield et al., 2020

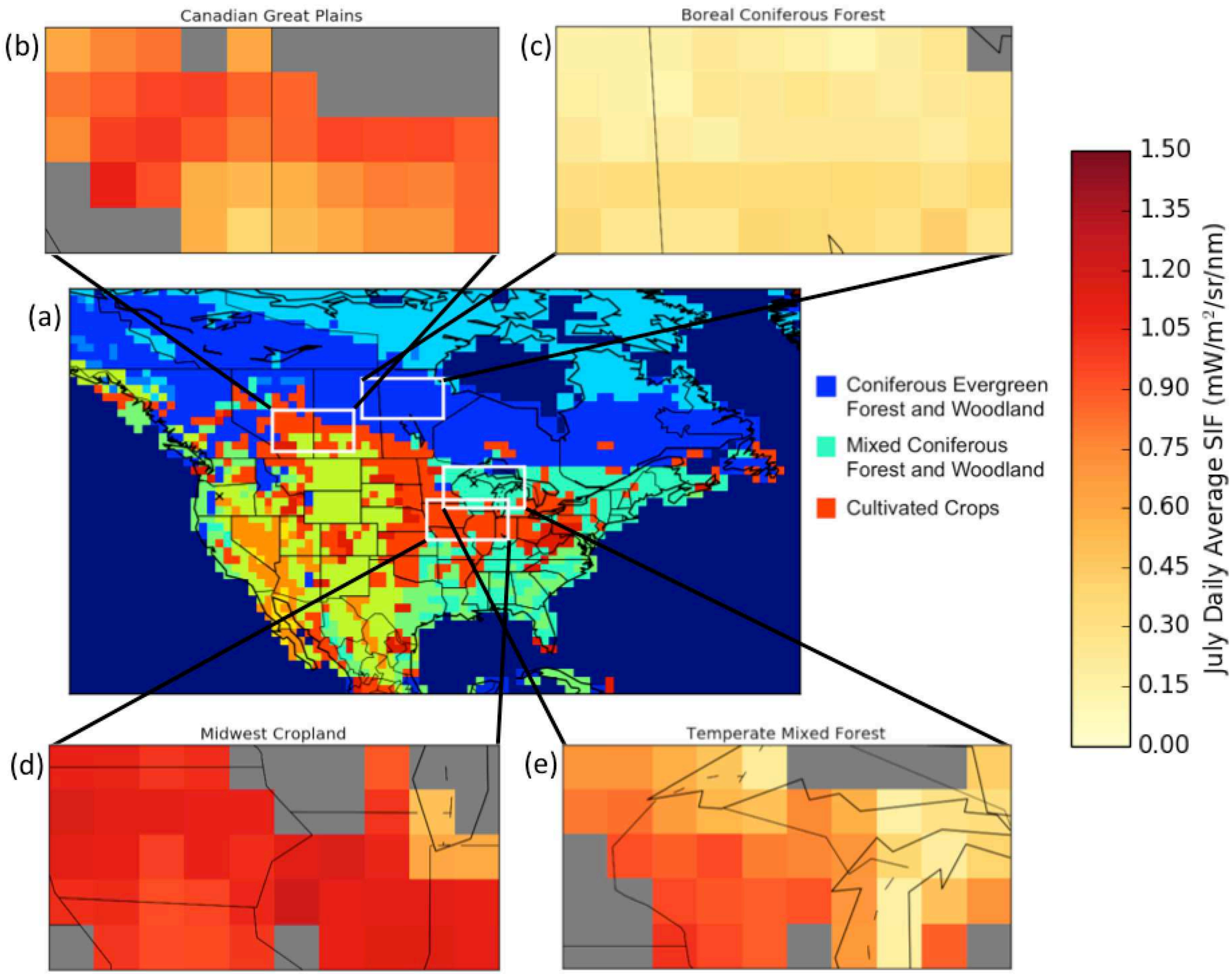
For climate feedbacks we might care more about interannual variability — how do these compare?



Slightly more favorable comparisons between spring productivity IAV

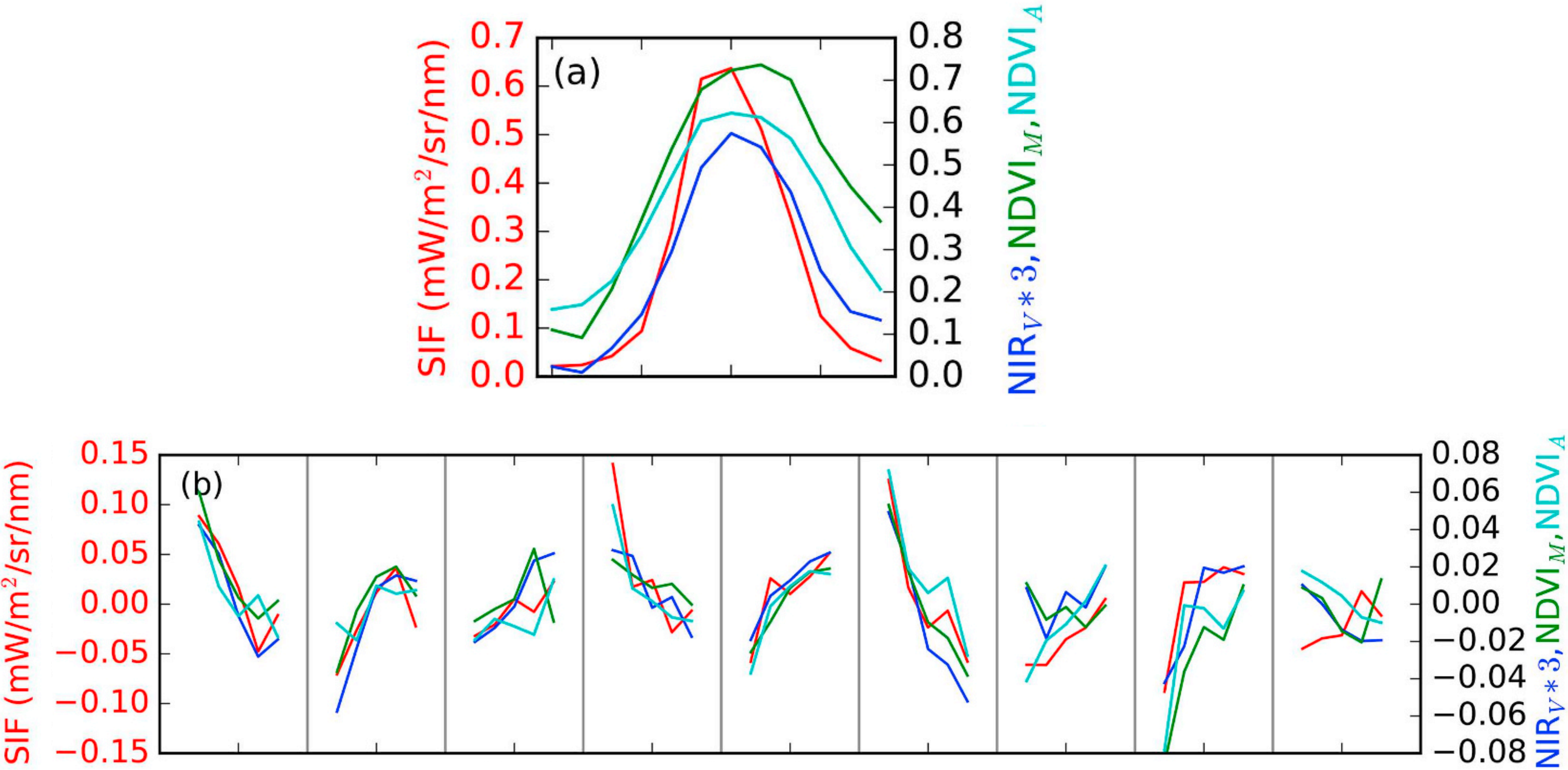
Butterfield et al., 2020

Conclusion: IAV in productivity is pretty noisy, maybe regional scale information can be used more robustly



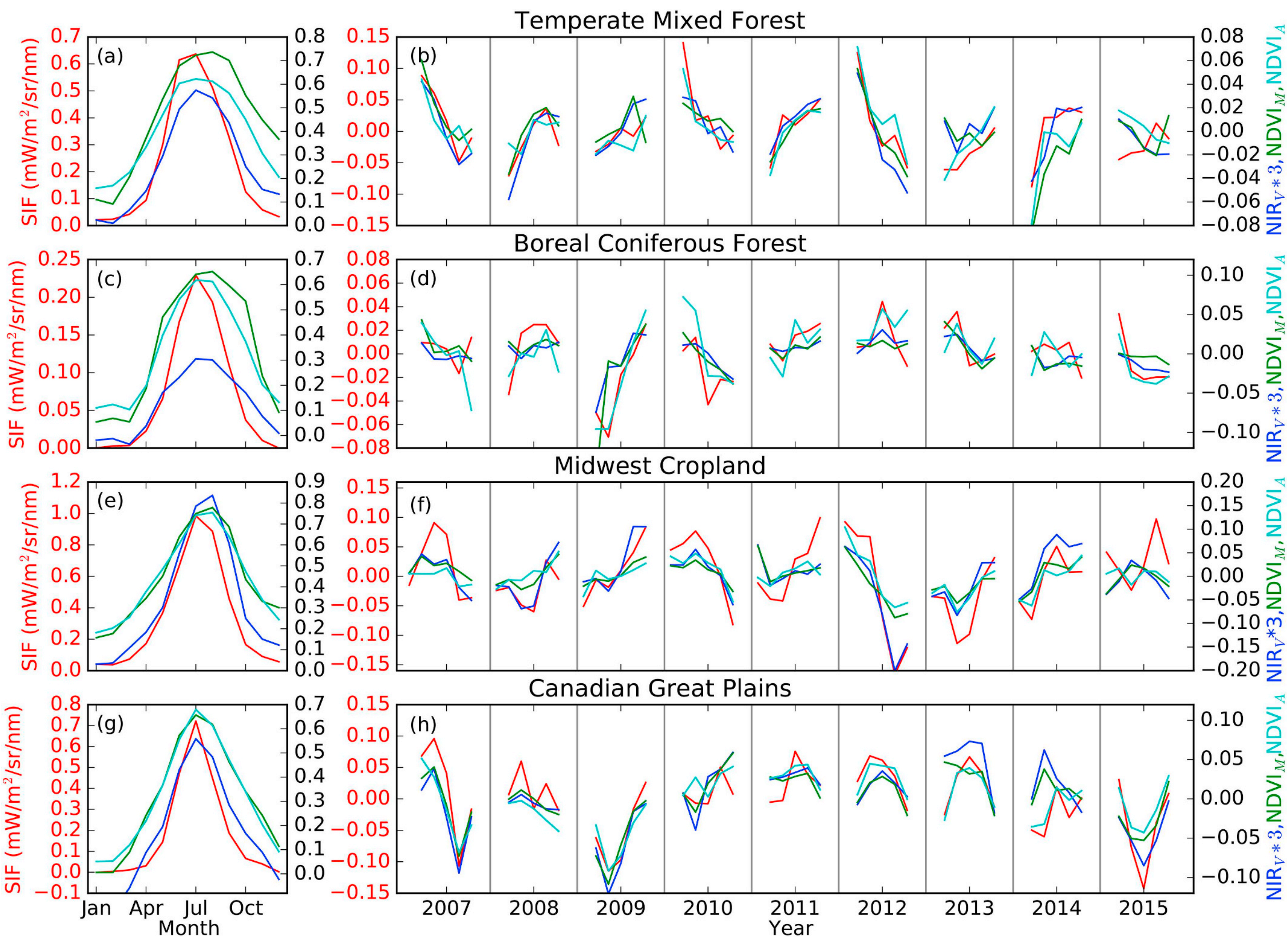
Butterfield et al., 2020

At regional scales, we see anticipated differences in seasonal cycle, but improved convergence in IAV

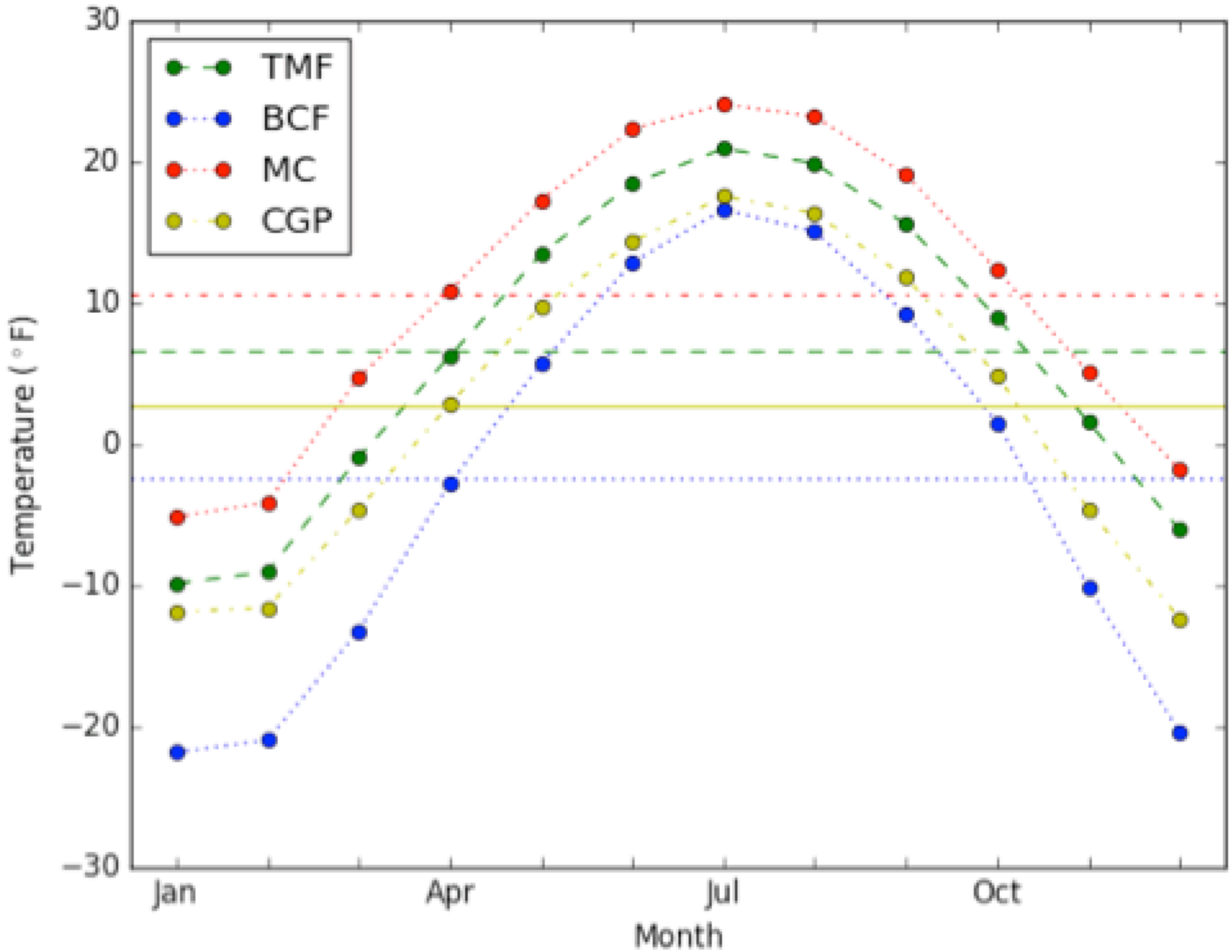


Butterfield et al., 2020

Quantitative differences remain across the four regions



We defined seasons based on temperature thresholds



	Spring	Summer	Fall
TMF	April, May	June, July	August, September, October
BCF	May, June	July	August, September, October
MC	April, May, June	July, August	September, October, November
CGP	April, May, June	July	August, September, October

Butterfield et al., 2020

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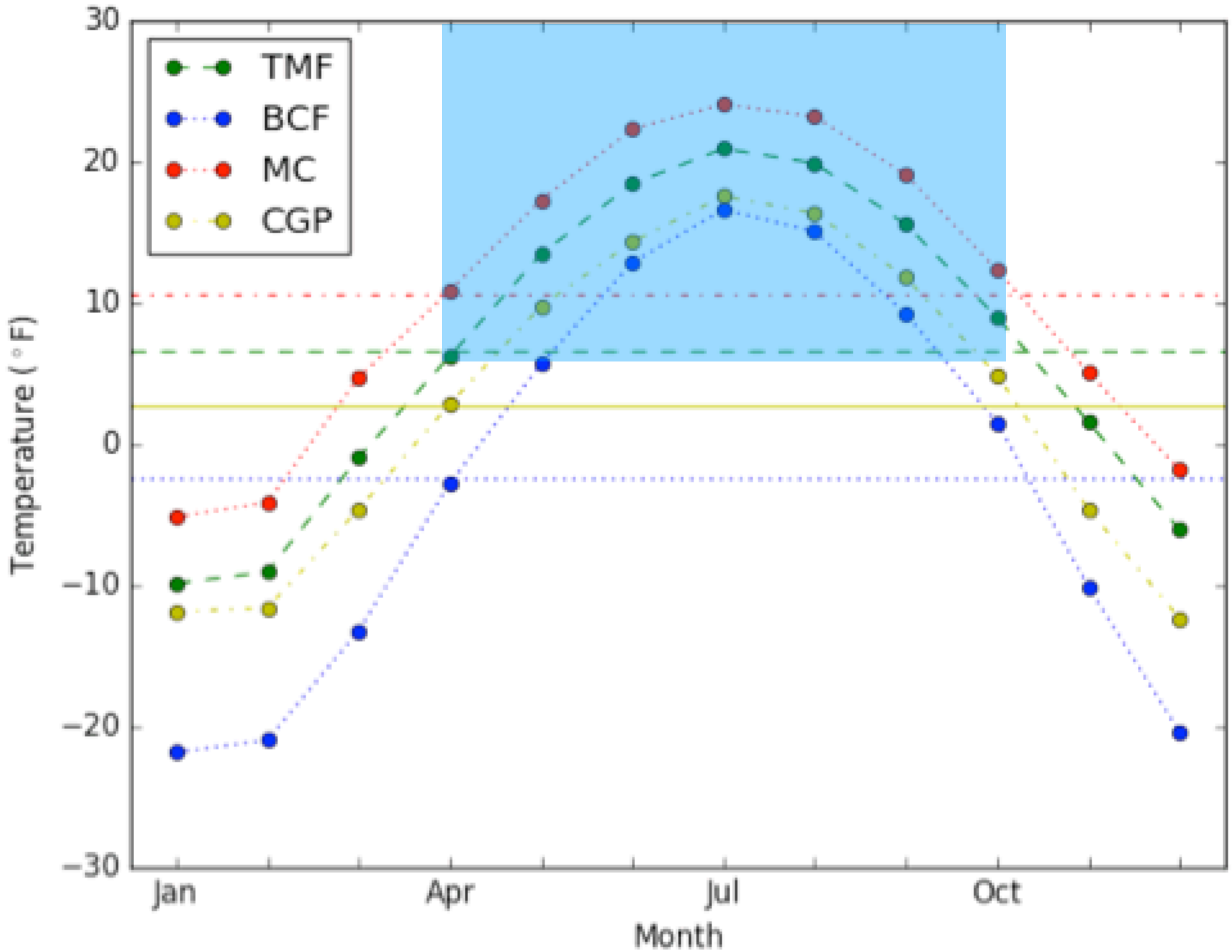

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Butterfield et al., 2020

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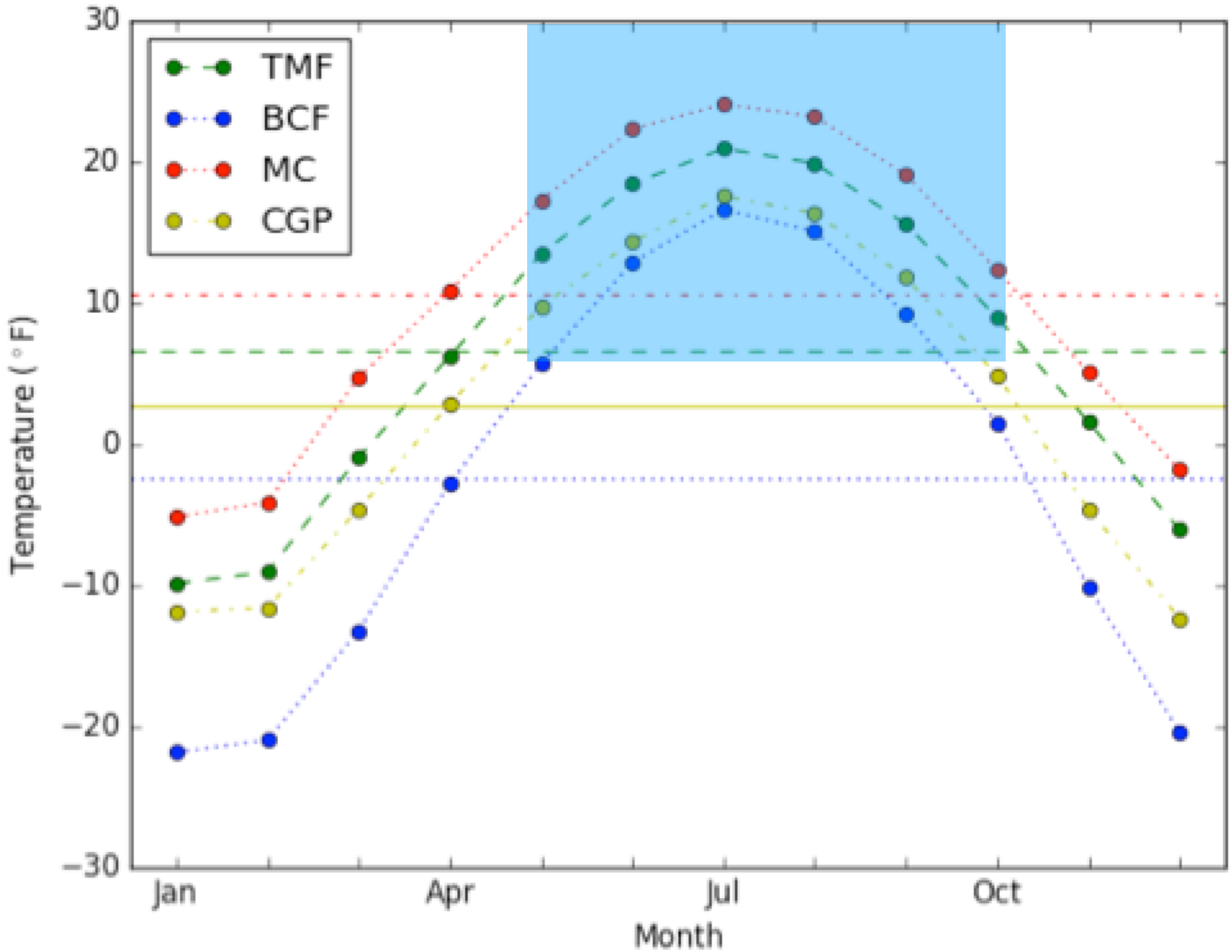

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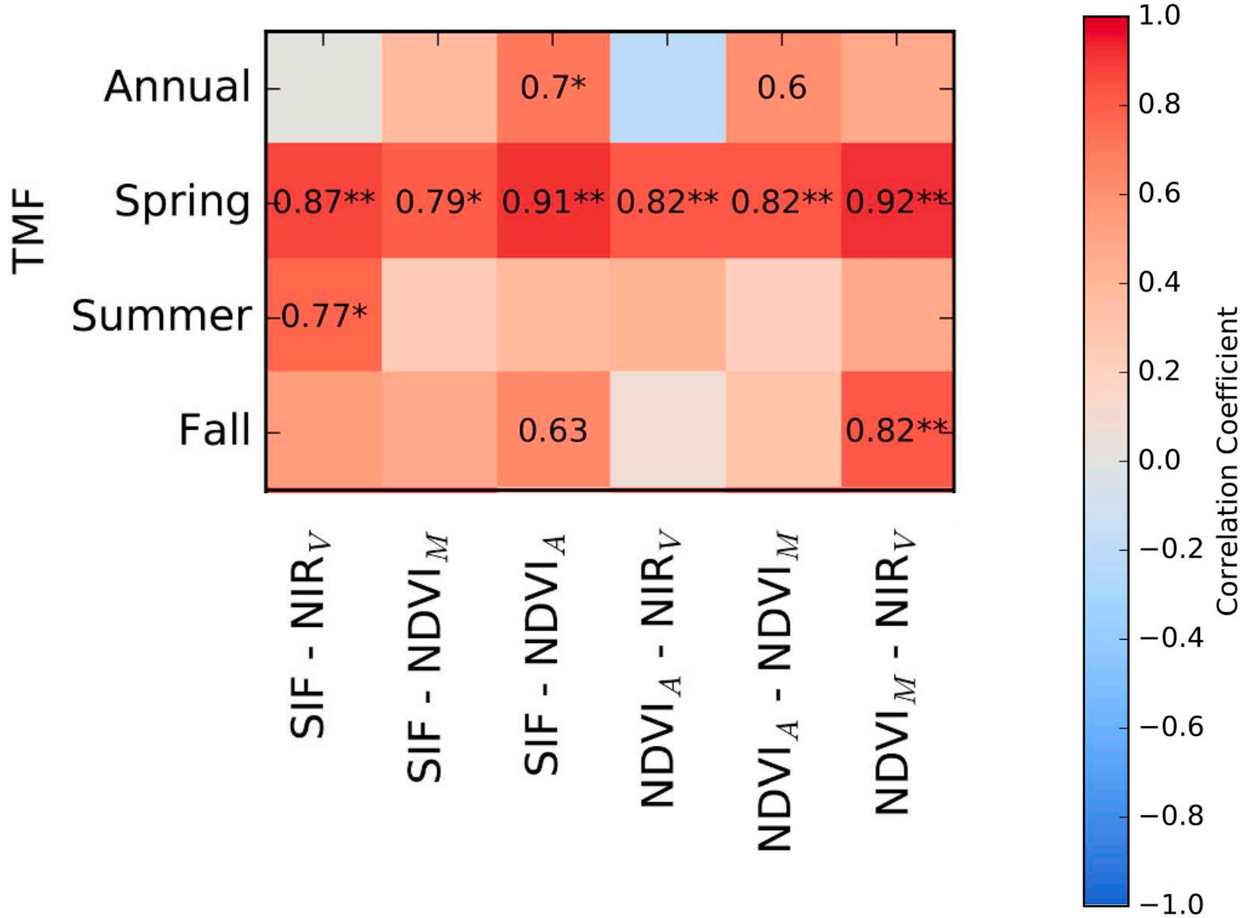
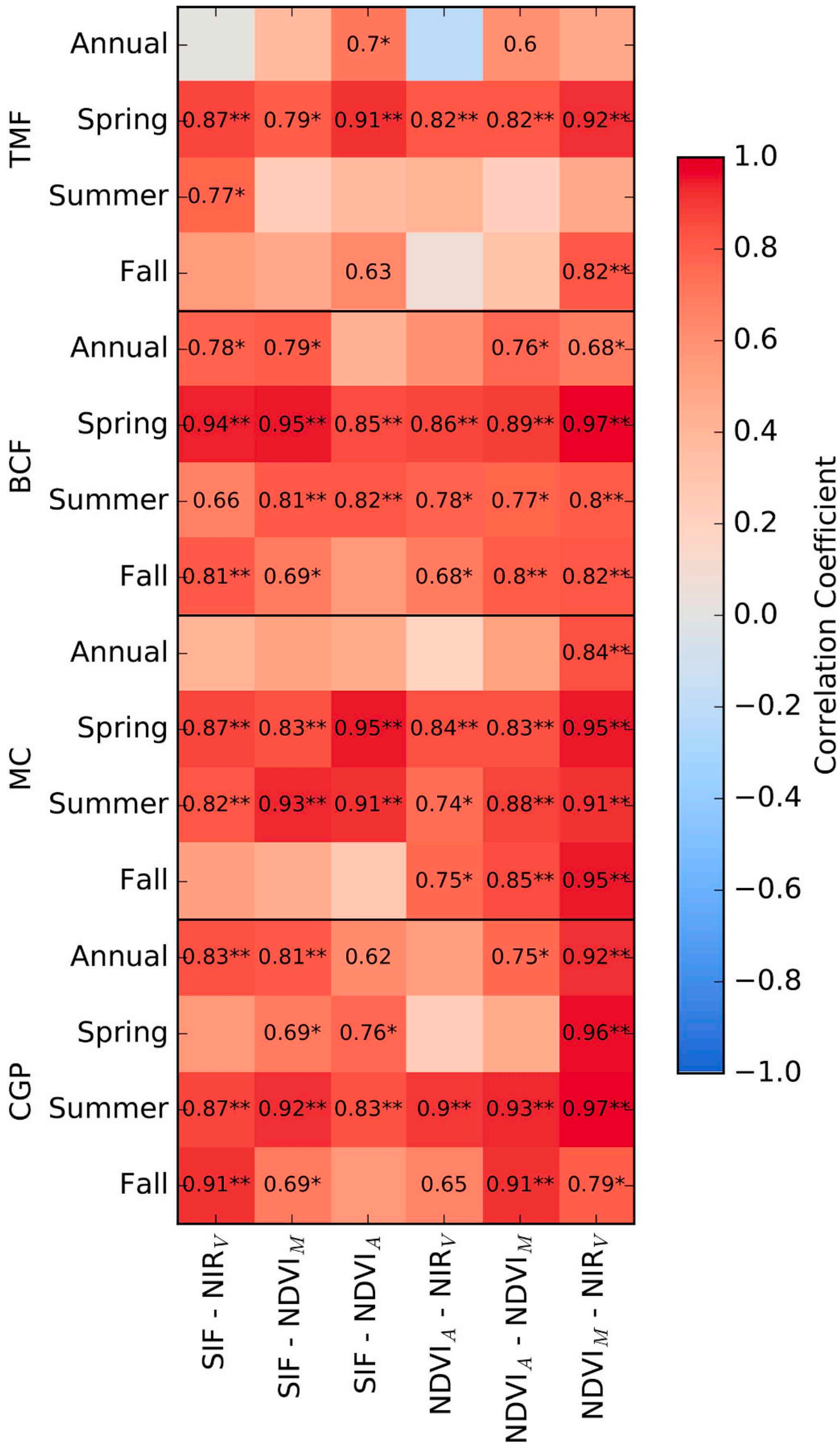
Butterfield et al., 2020

For temperate mixed forests, IAV in productivity metrics was generally only statistically significant during spring



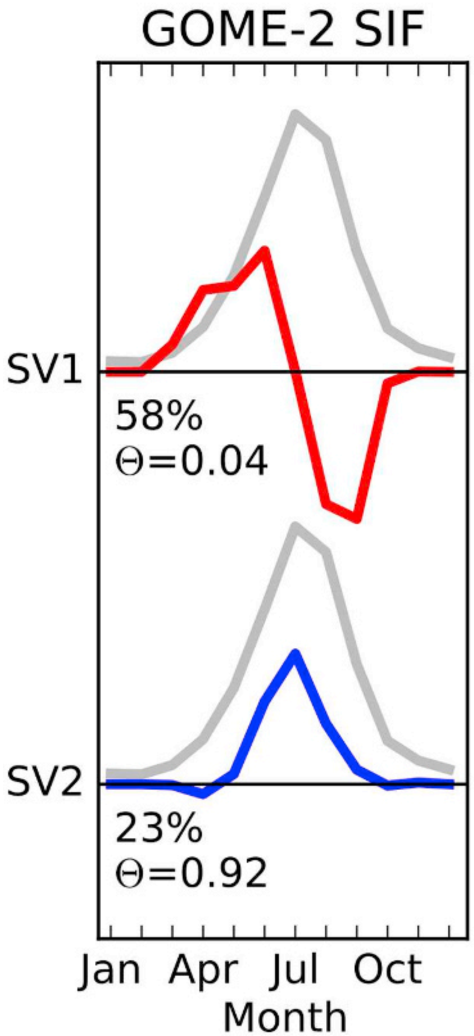
Butterfield et al., 2020



Other regions show more widespread statistically significant correlations, but annual scale correlations are generally weaker than those at seasonal timescales

Butterfield et al., 2020

We use singular value decomposition (SVD) to determine dominant modes of interannual variability at regional scales

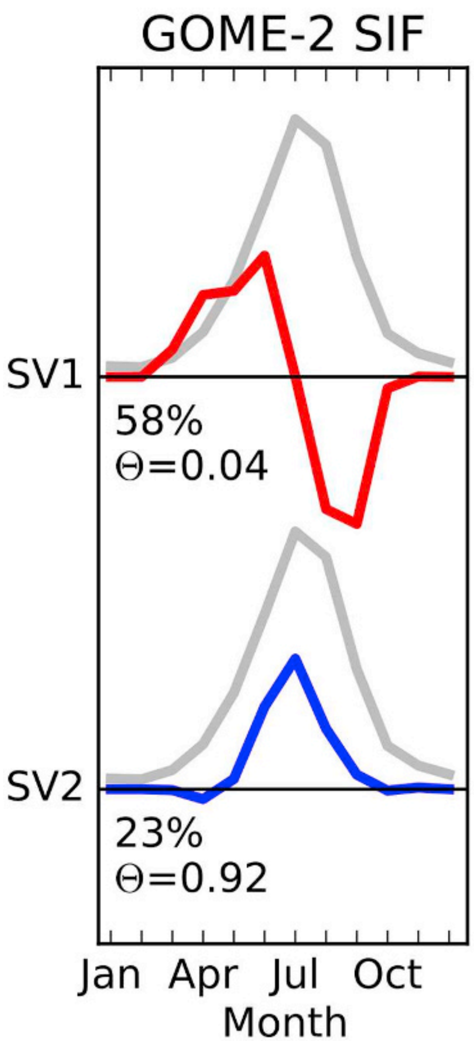


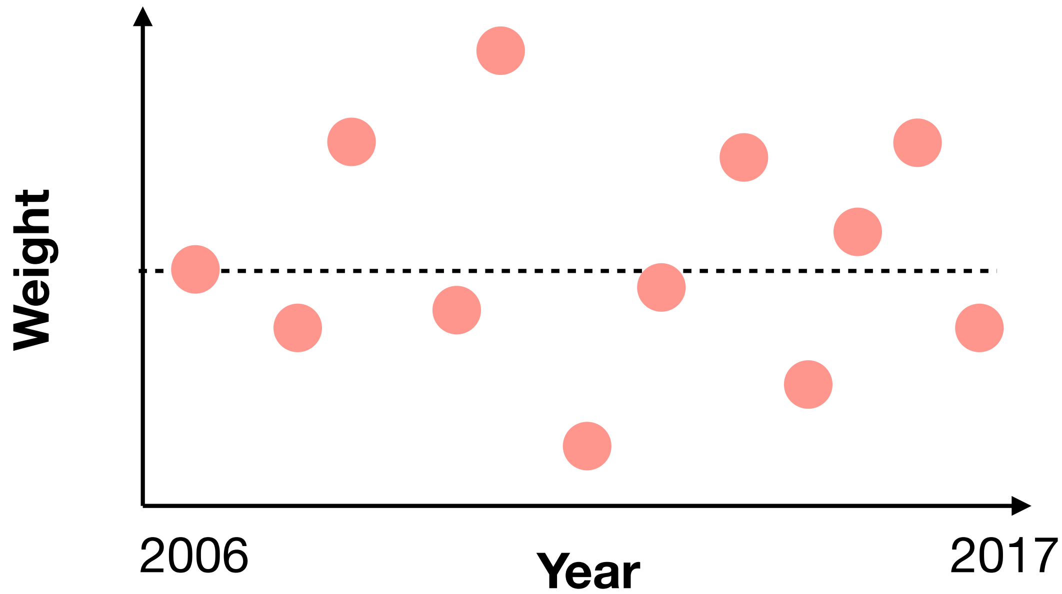
“Redistribution”

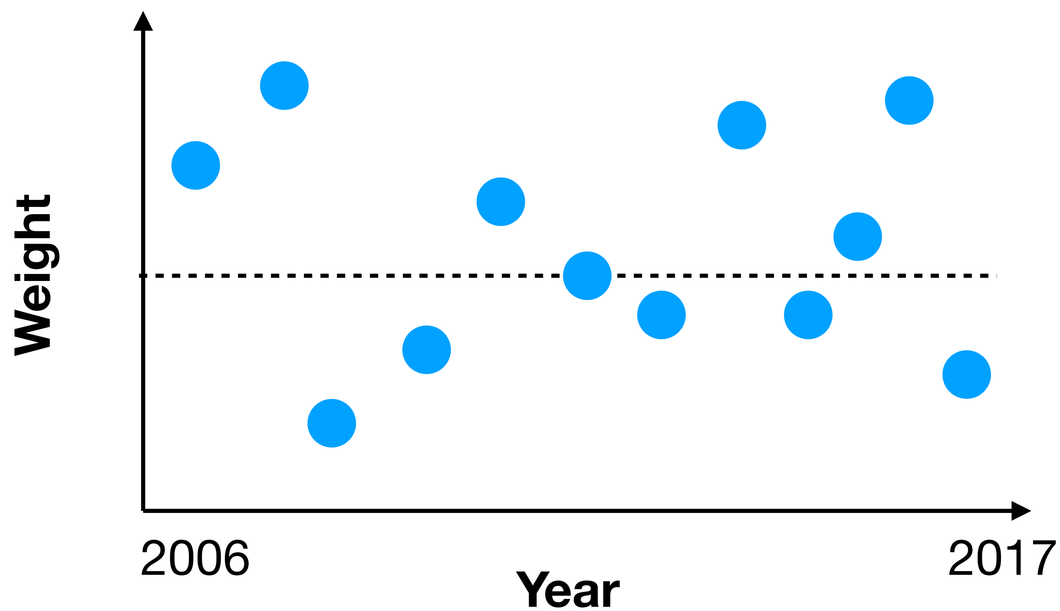
“Amplification”

Butterfield et al., 2020

SVD also tells us how important a given mode of variability is during a given year

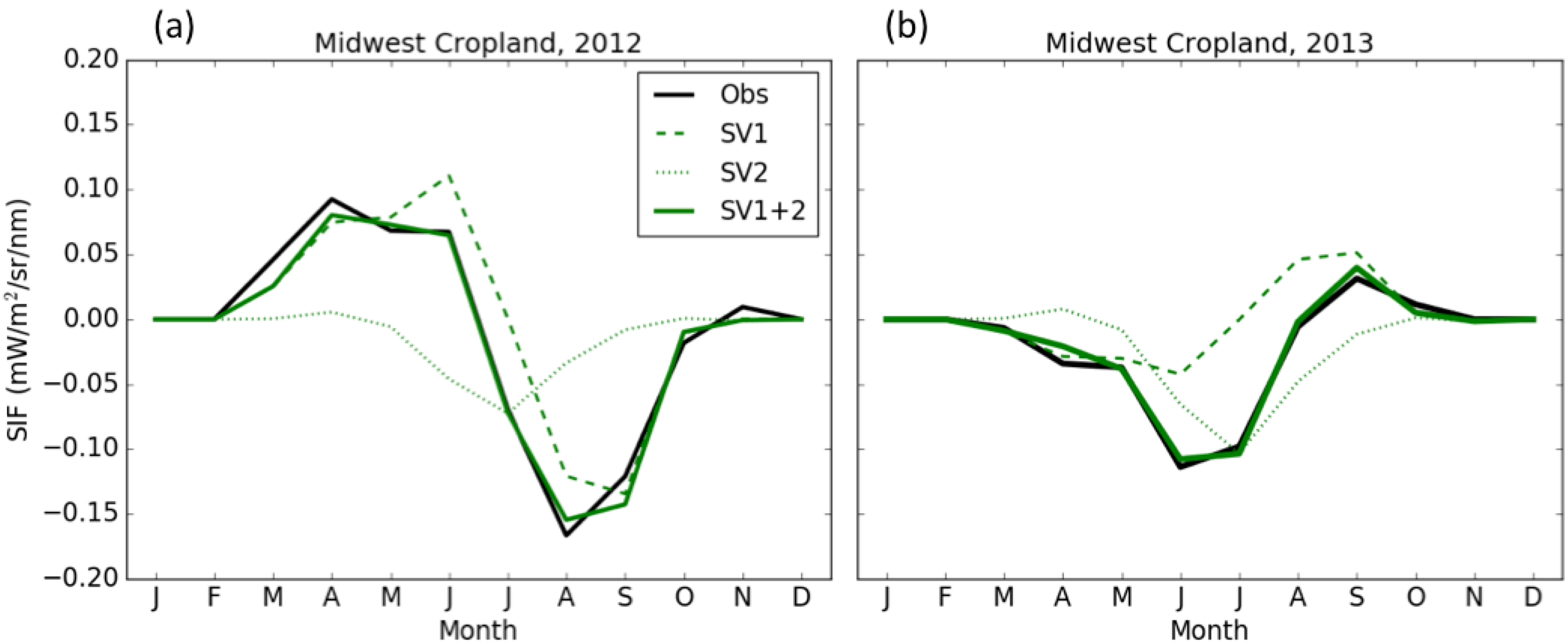






Butterfield et al., 2020

The amplification and redistribution vectors together account for majority of variance in the observational record



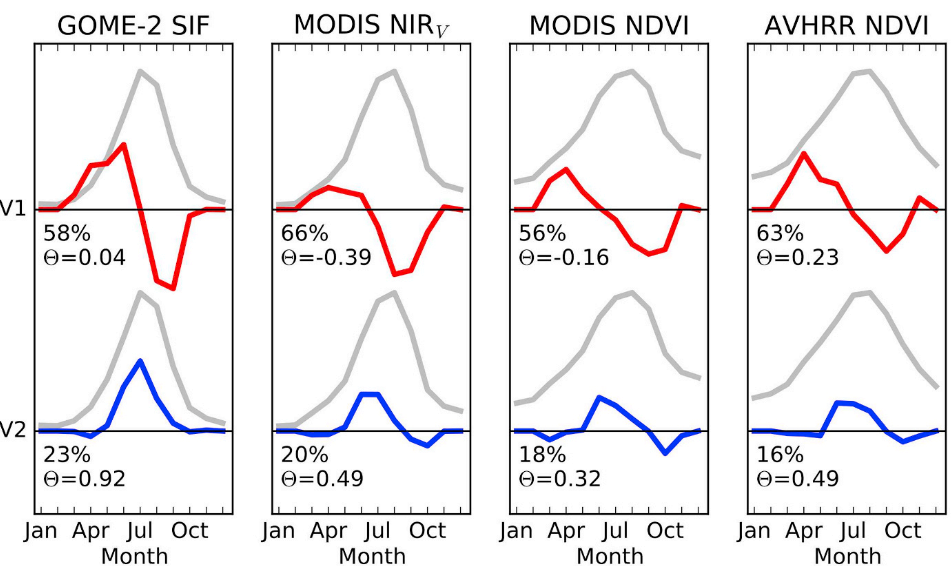
SV1 has large, positive weight
SV2 has modest, negative weight

SV1 has modest, negative weight
SV2 has strong, negative weight

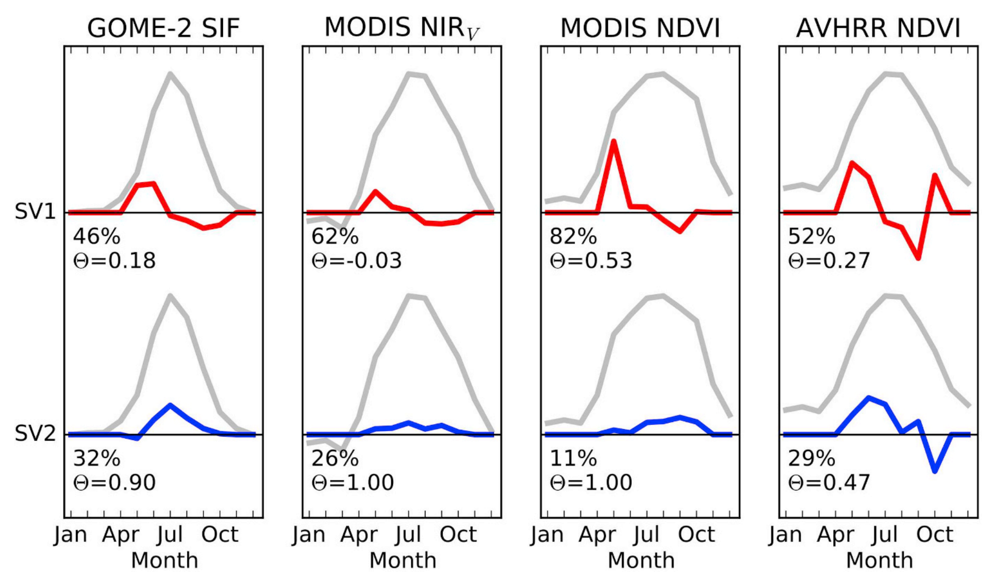
Butterfield et al., 2020

These modes of variability are common across regions and across datasets!

(c) Midwest Cropland



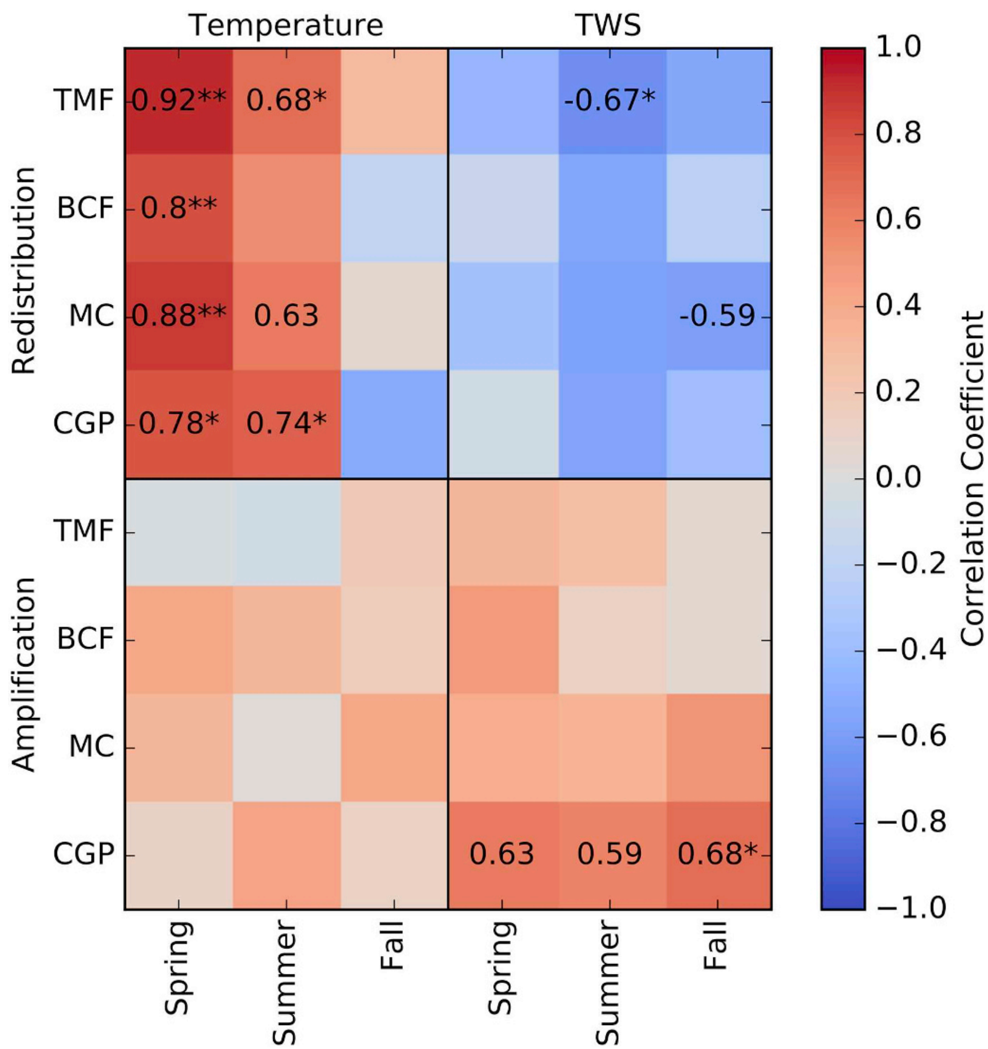
(b) Boreal Coniferous Forest



Butterfield et al., 2020

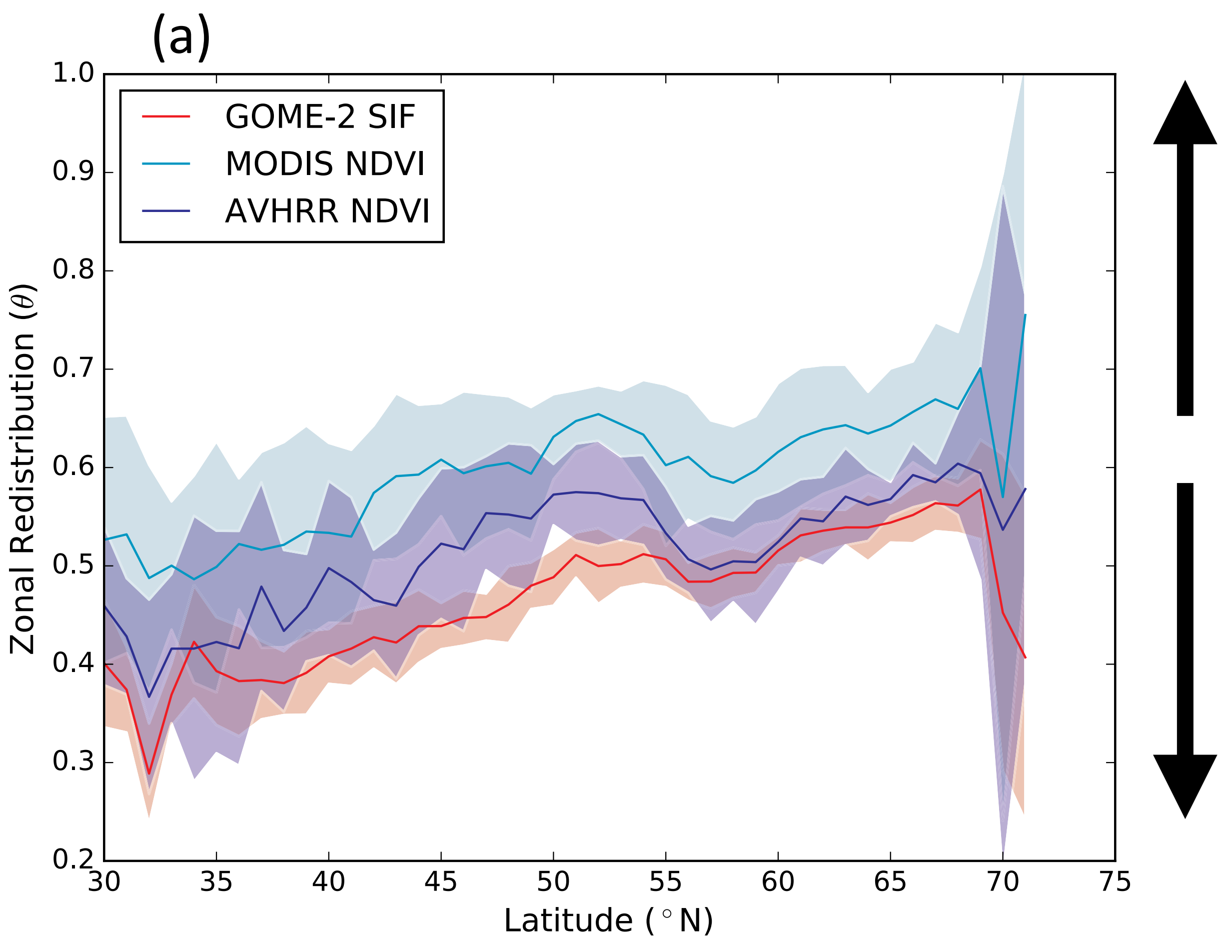
What can we do with the SVD results??

Correlation between annual weights and IAV in climate variables reveals drivers of modes of variability



Butterfield et al., 2020

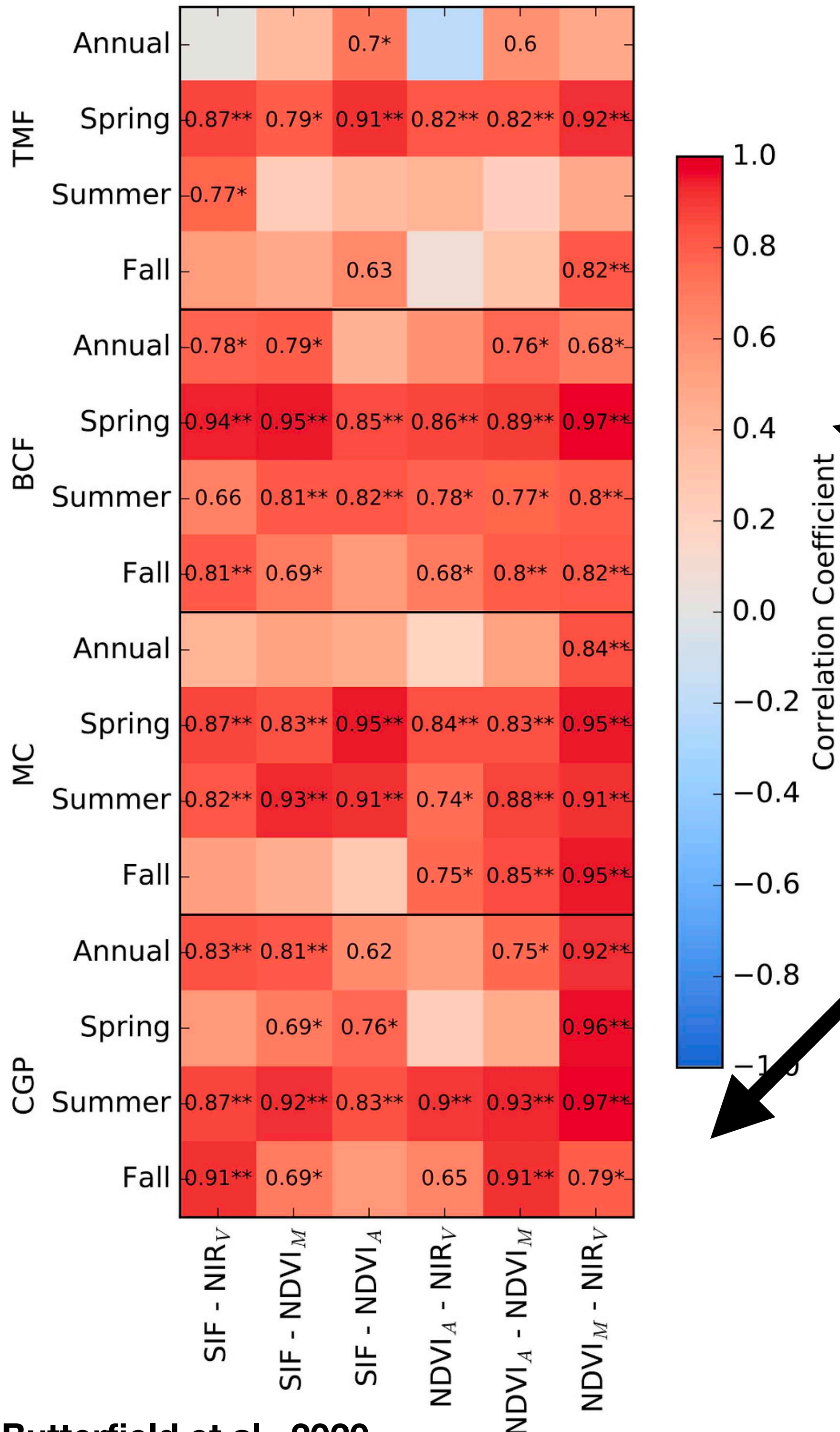
Extent to which redistribution predominates is larger at low latitudes than high latitude



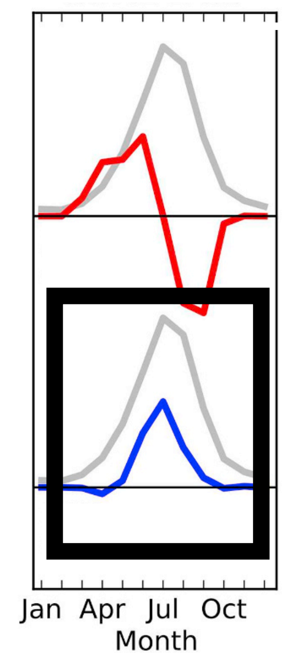
More amplification: uniform changes across all months of growing season

More redistribution: compensating changes across months of growing season

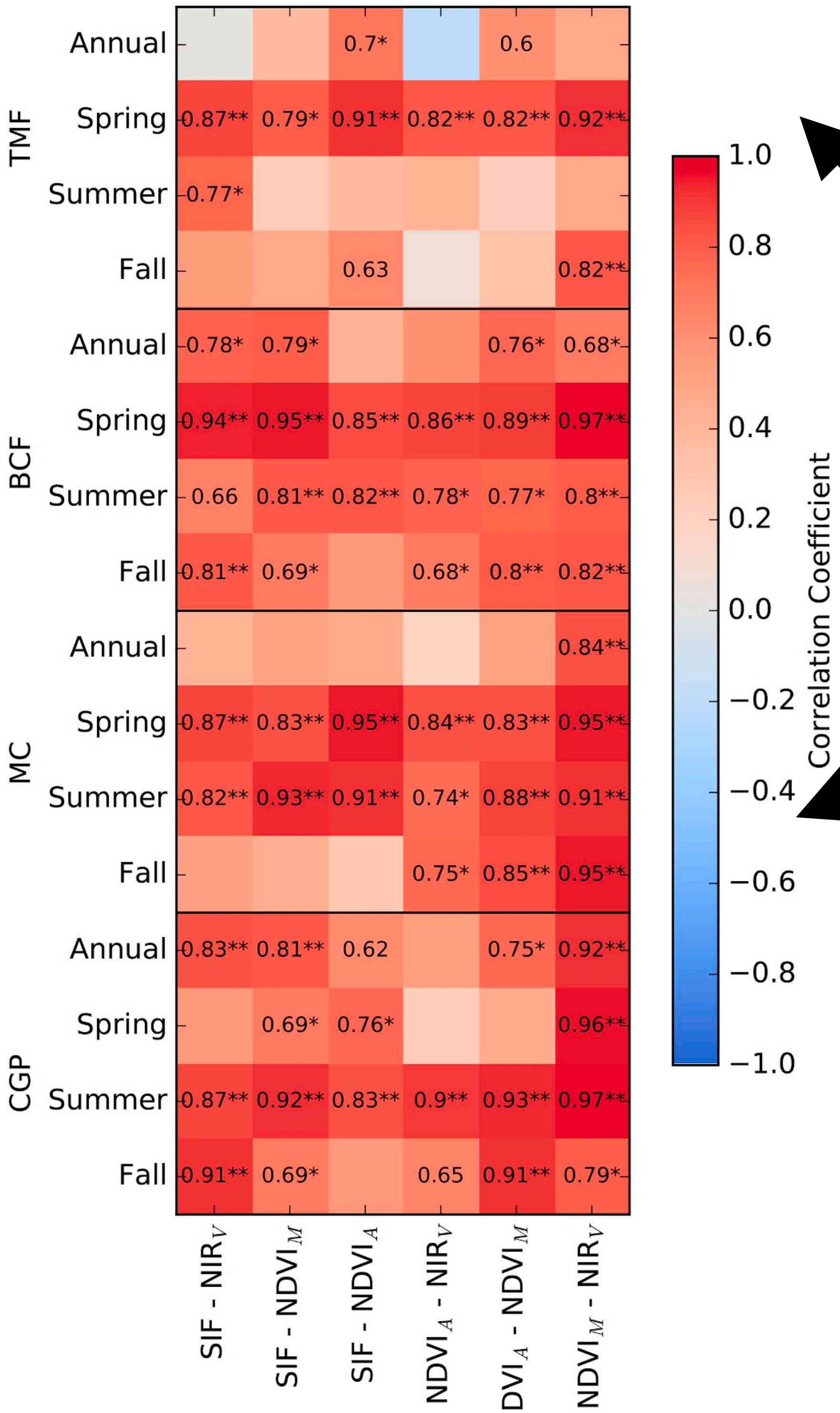
Butterfield et al., 2020



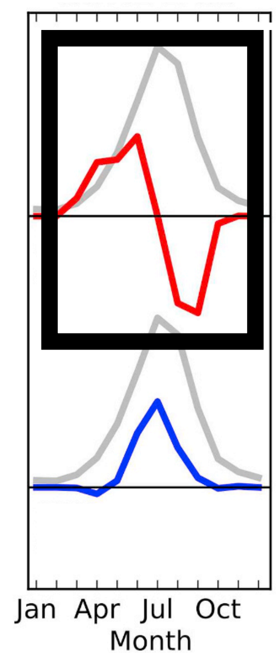
High latitude regions have more amplification, generally stronger correlations in summer and annual



Butterfield et al., 2020

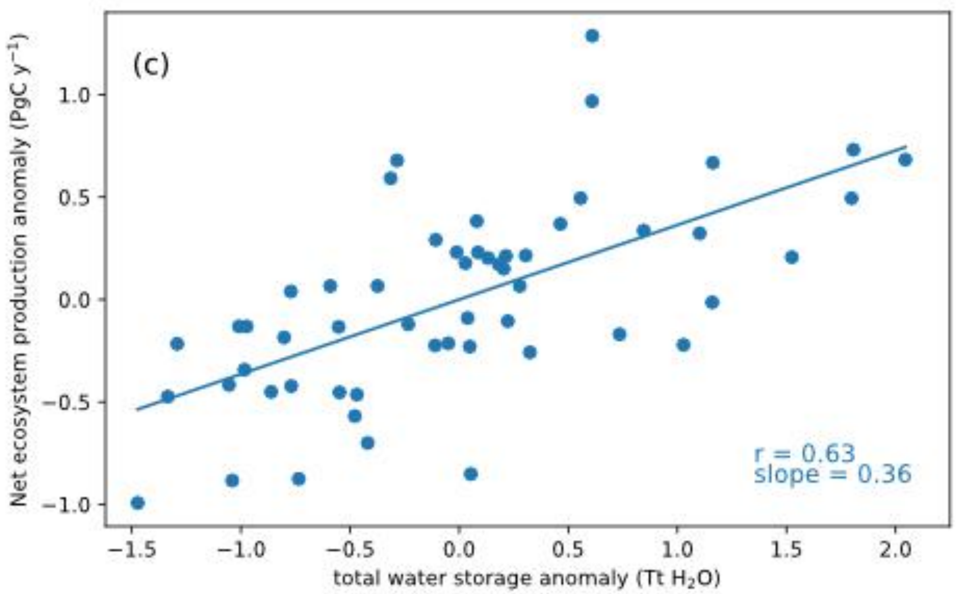


Midlatitude regions have more redistribution, generally stronger correlations in spring



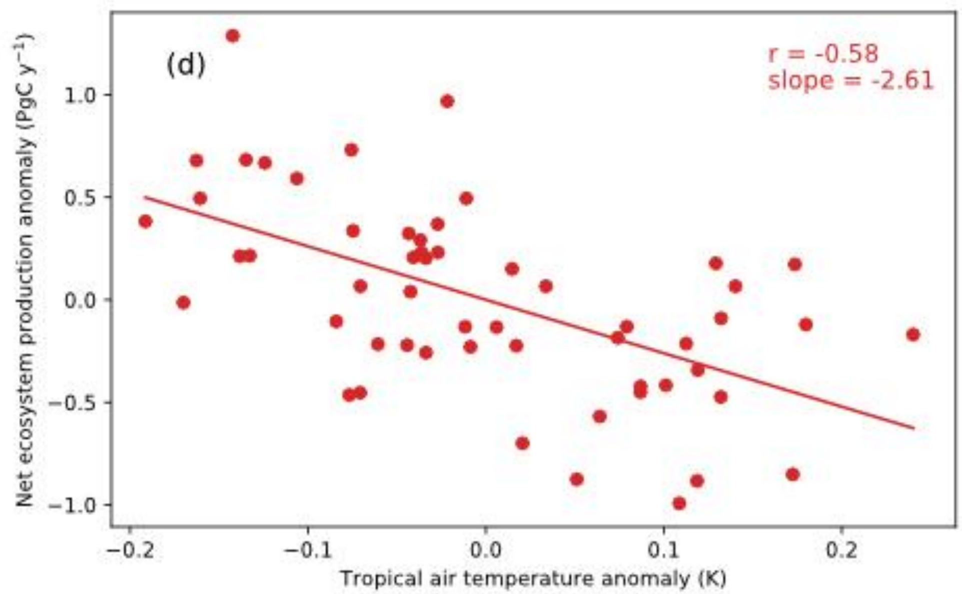
Butterfield et al., 2020

Applying this approach to a model: Understanding reasons behind low CO_2 IAV in CESM2



Observed: 1.3 Pg C (Tt H_2O)$^{-1}$

Humphrey et al., 2018

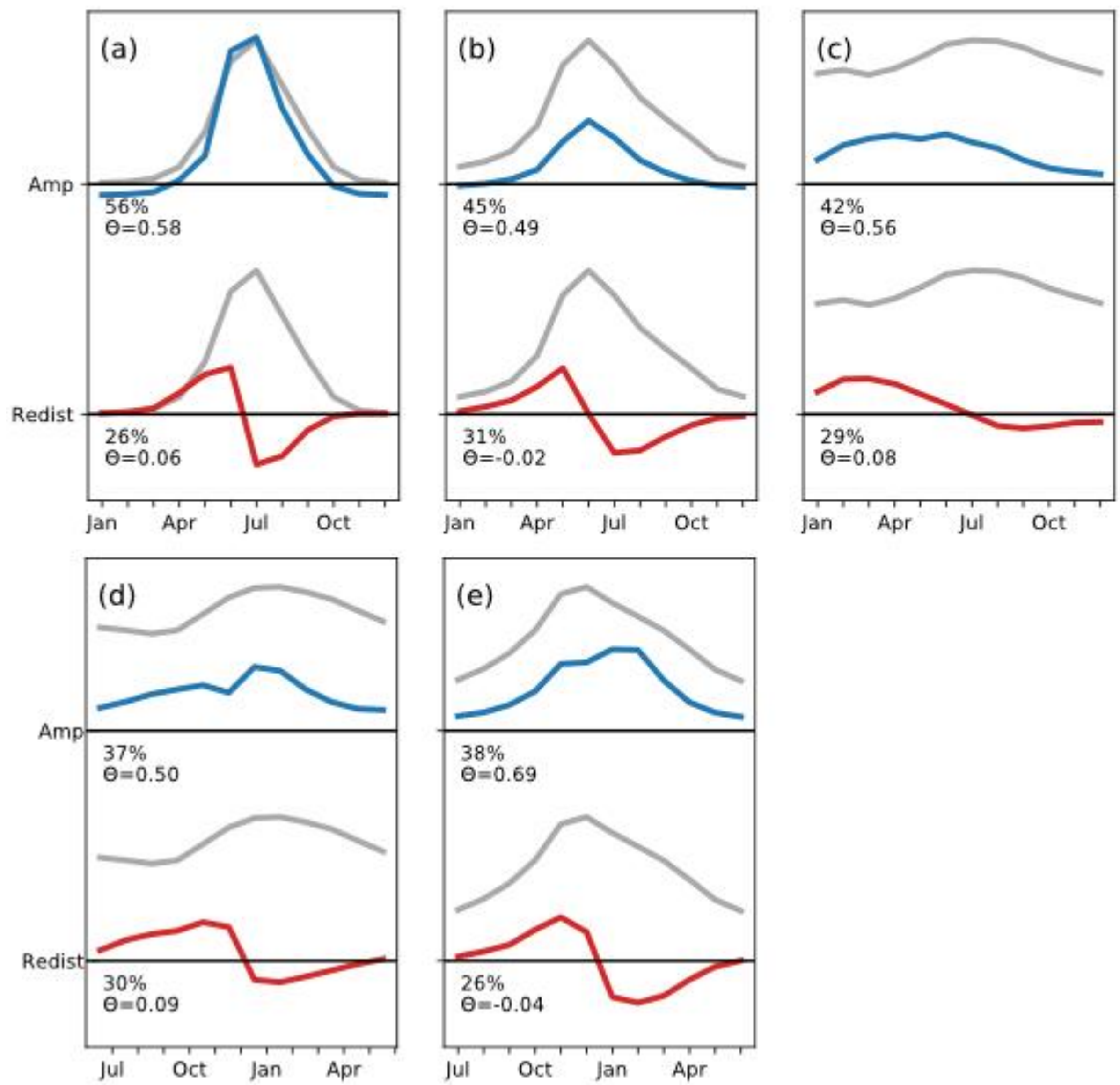


Observed: 5-6 Pg C y^{-1} K^{-1}

Cox et al., 2013; Keppel-Aleks et al., 2018

Wieder et al., in prep

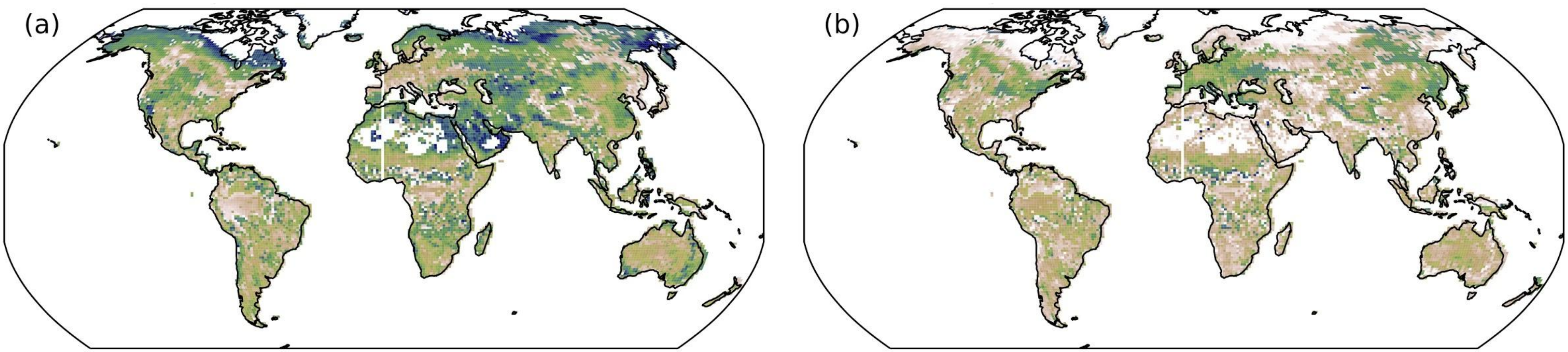
Model singular vectors are similar to those in satellite constraints, suggesting modes of variability in CESM are reasonably captured

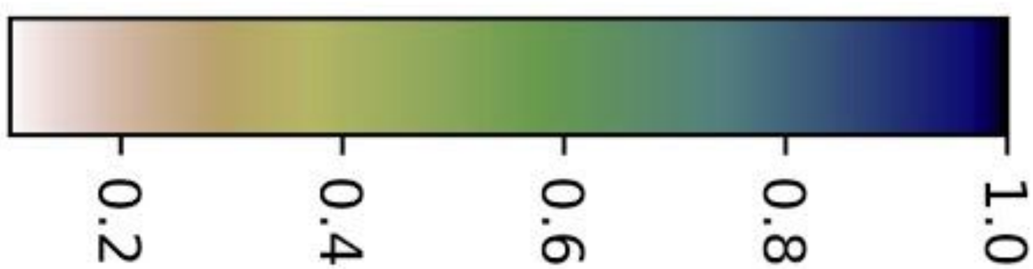


Wieder et al., in prep

First two singular vectors explain a large fraction of variability (>75%) most locations, with major exception being tropical forests

Fraction explained by Amplification | **Fraction explained by Redistribution**

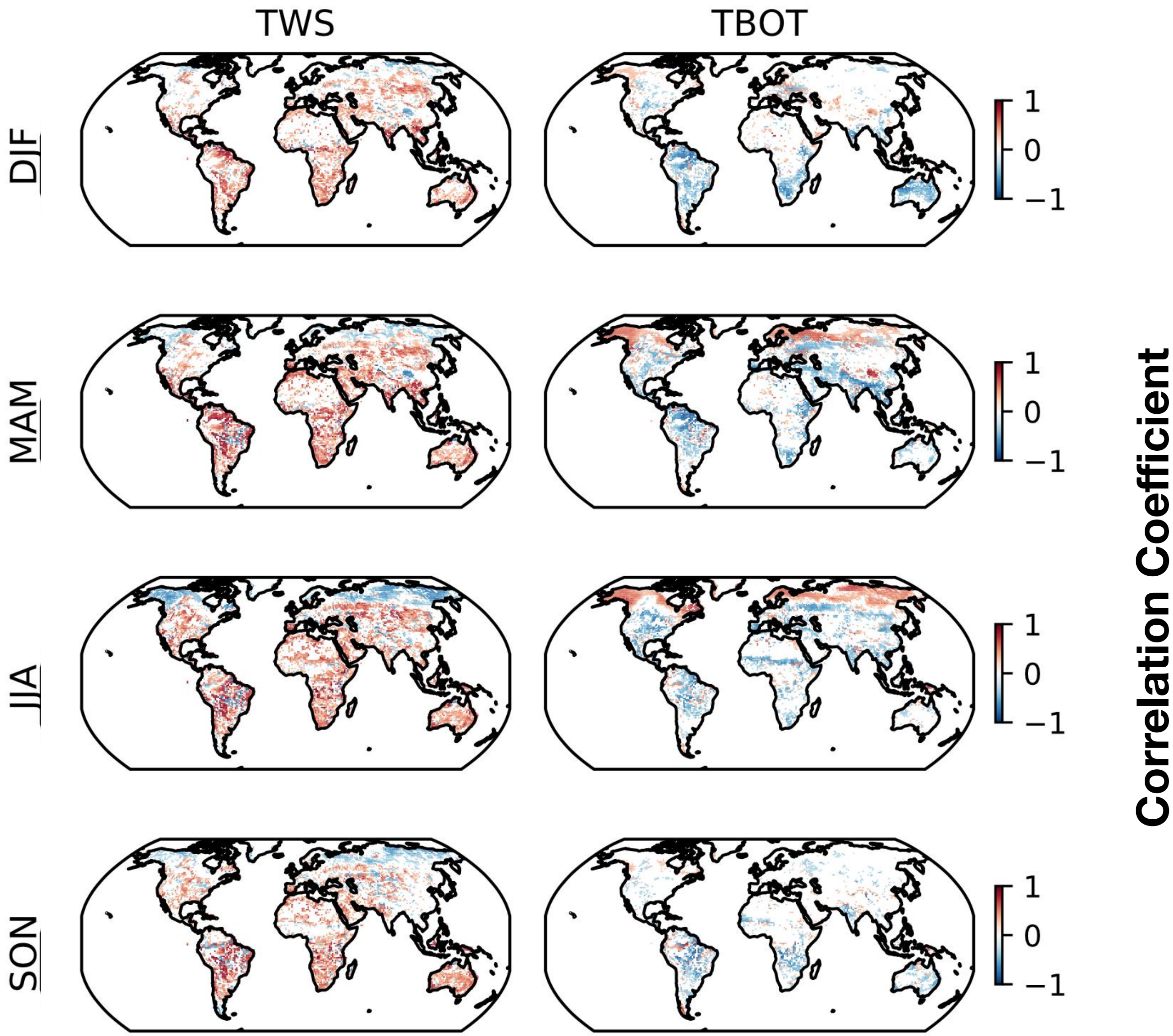




R^2

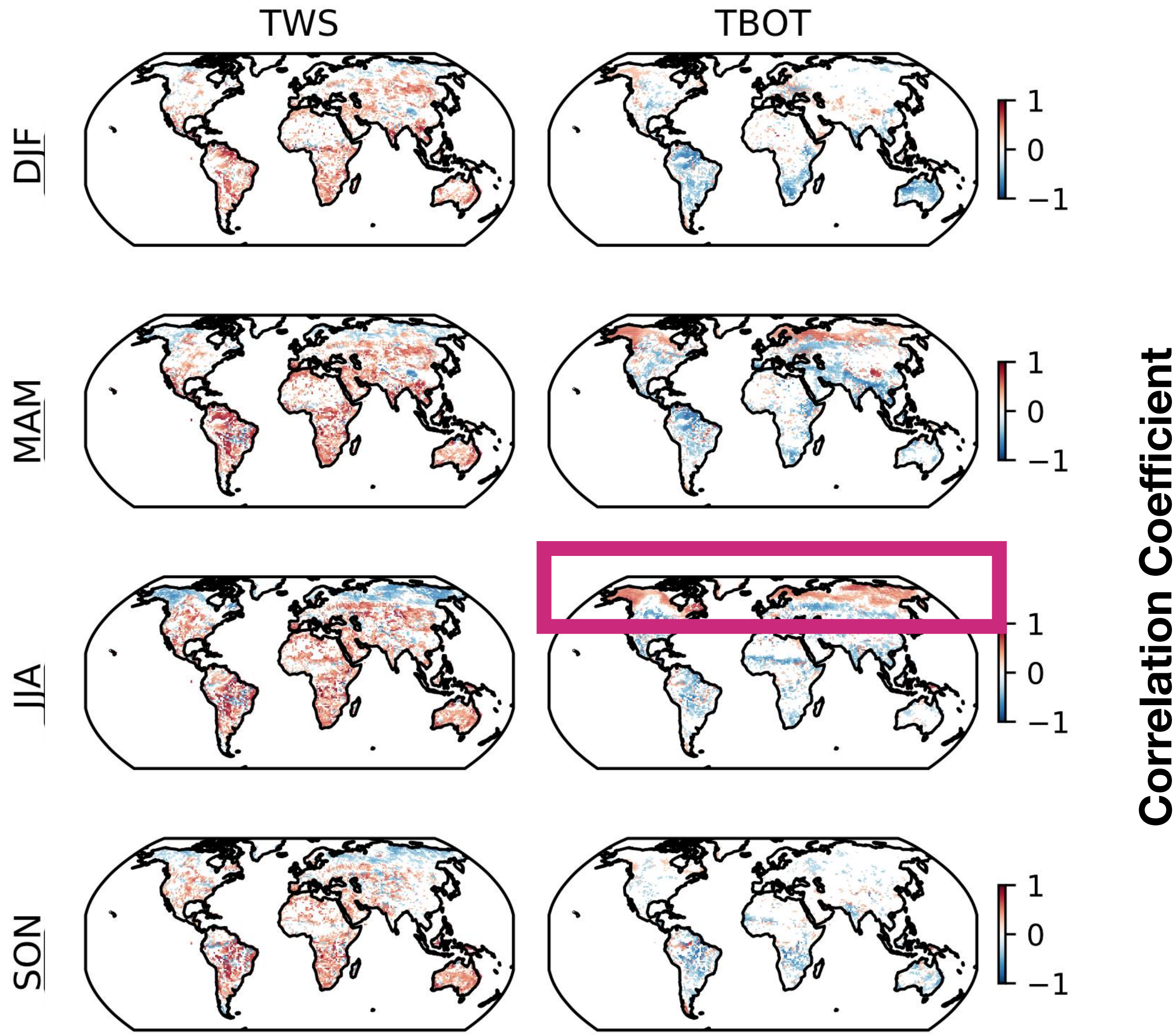
Wieder et al., in prep

We can assess how the annual weights correlate with climate drivers at the gridcell level



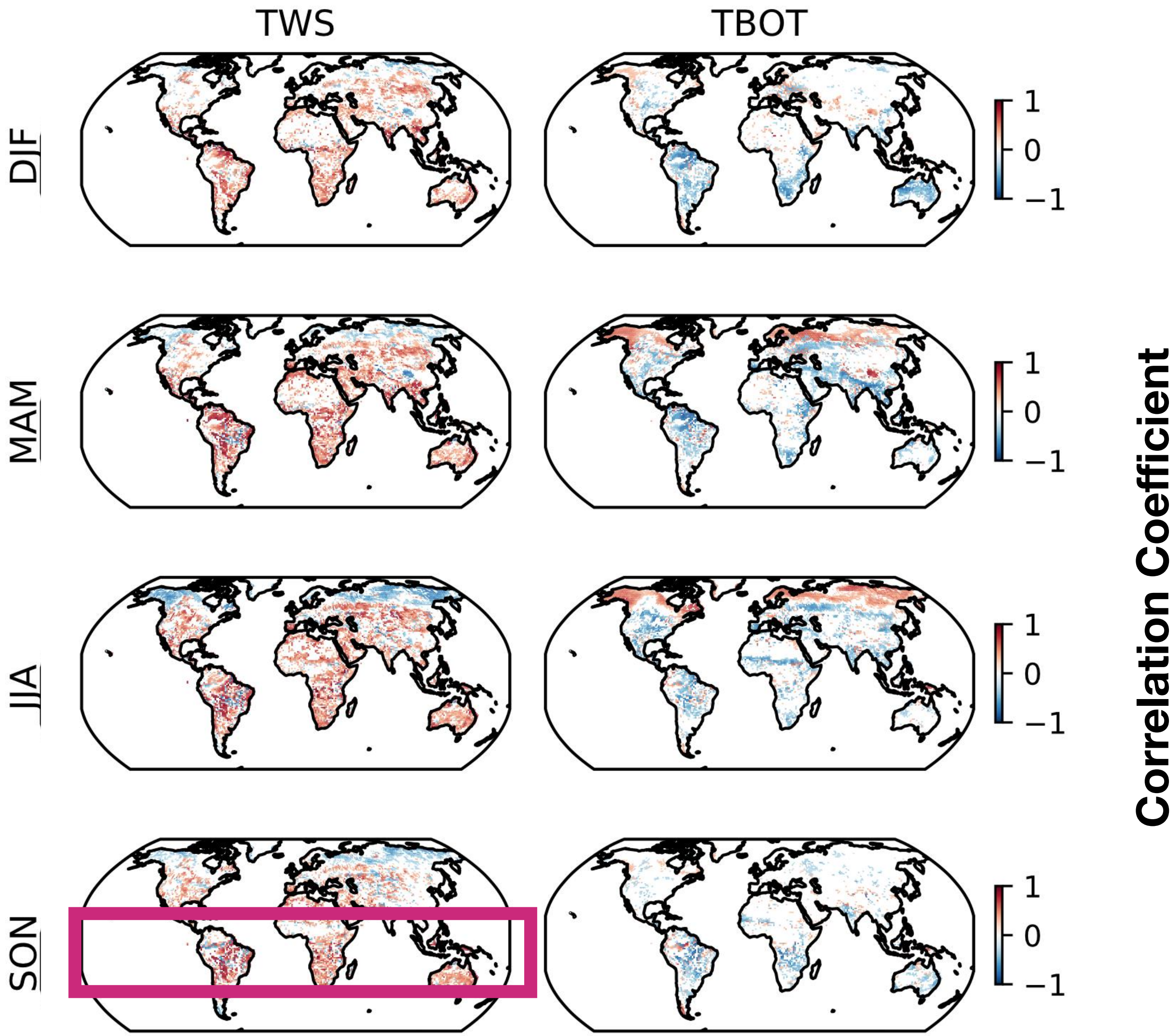
Wieder et al., in prep

Amplification correlated with high summer temperature at high latitudes



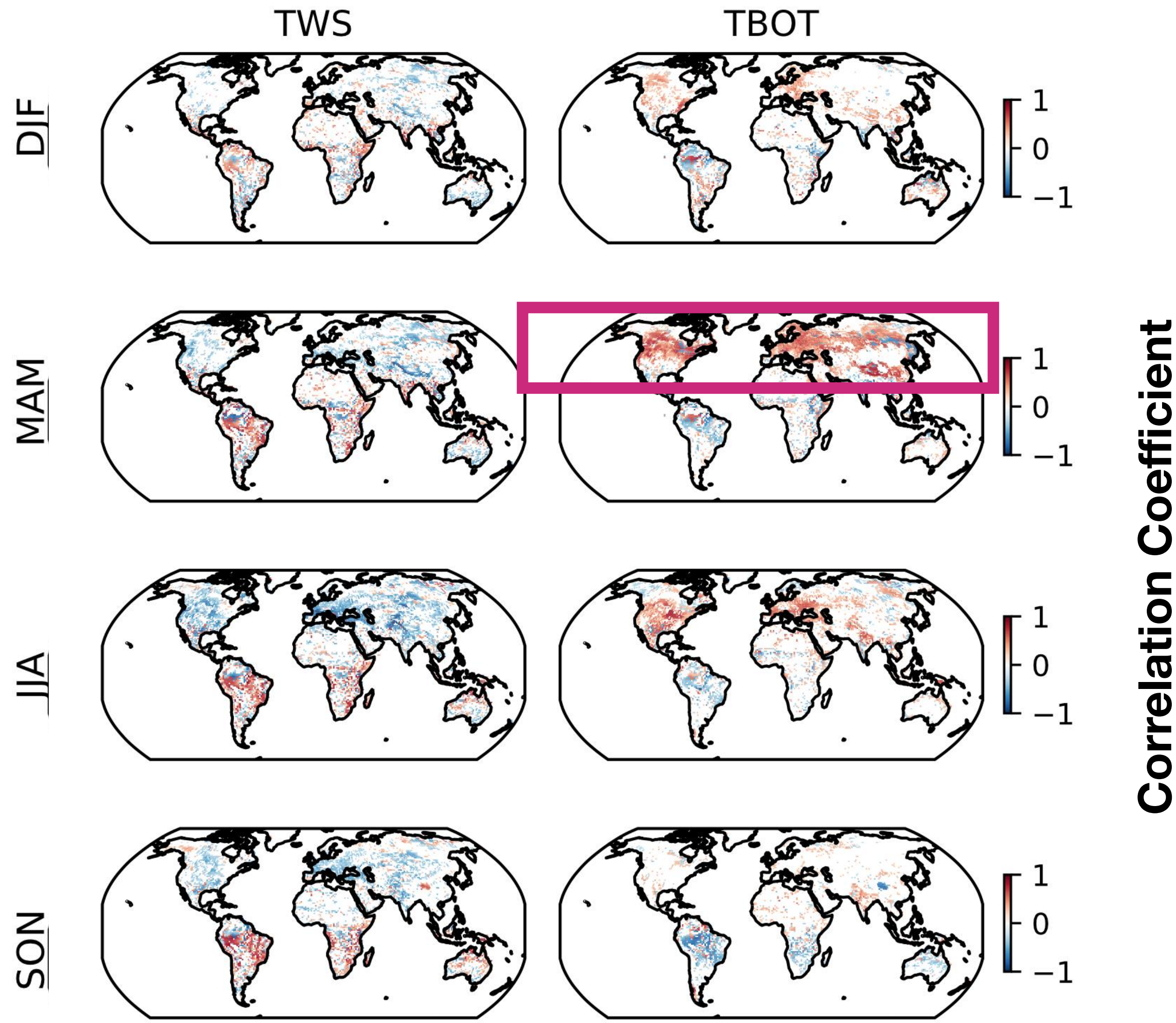
Wieder et al., in prep

Amplification correlated with high water availability in SON within the tropics



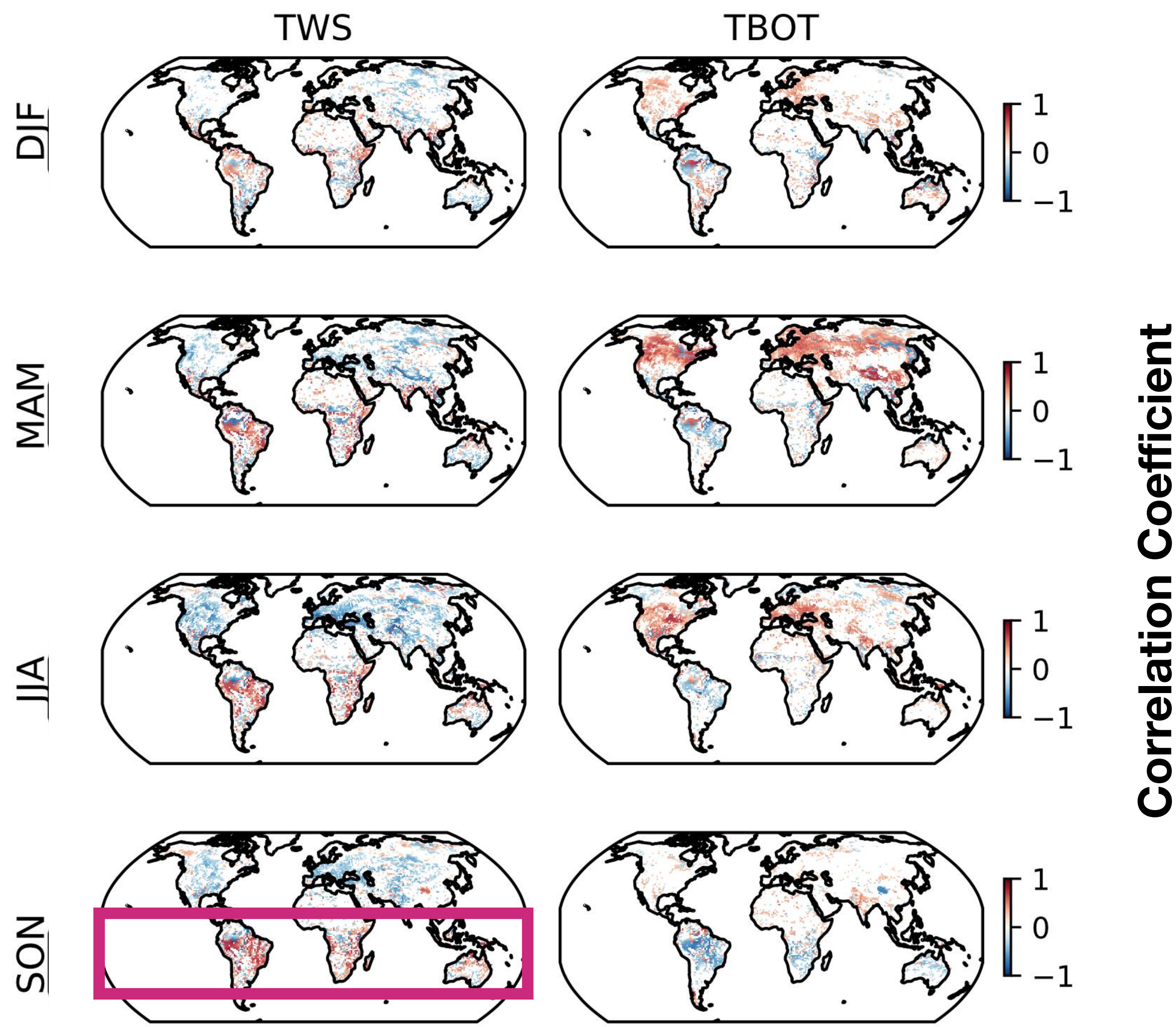
Wieder et al., in prep

Redistribution correlated with high spring temperatures in boreal/ temperate regions



Wieder et al., in prep

Redistribution shows mixed patterns with temperature and moisture across tropical forests



Wieder et al., in prep

IAV in primary productivity is noisy, but information converges at regional scales

SVD approach illustrates modes of variability that dominate IAV signal, which can be useful for determining whether a model is qualitatively (if not quantitatively) getting it "right"

Observational constraints show that high latitude ecosystems are less redistributive: it is hard to catch up given a late spring; conversely it may be hard to deplete water resources given a highly productive spring

IAV can't be interpreted properly without the context of a mean annual cycle