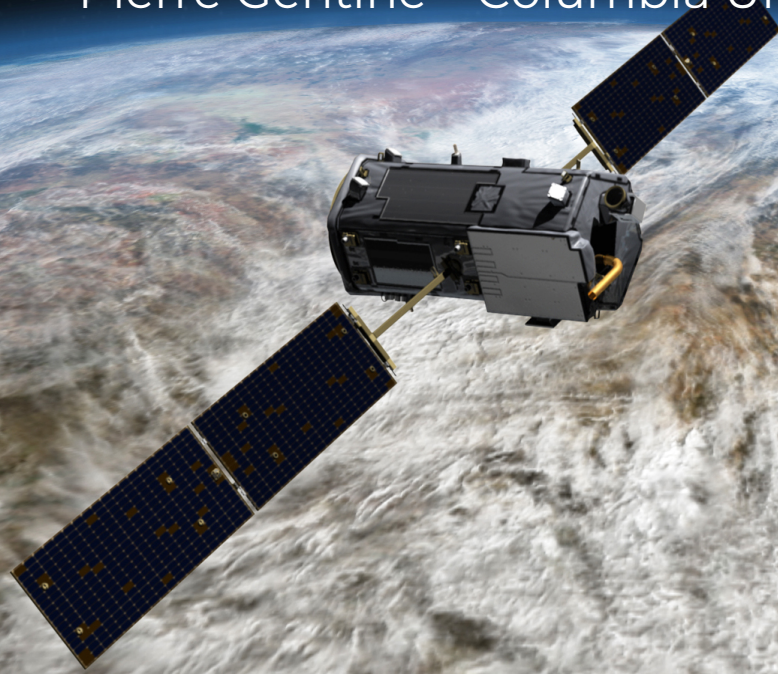


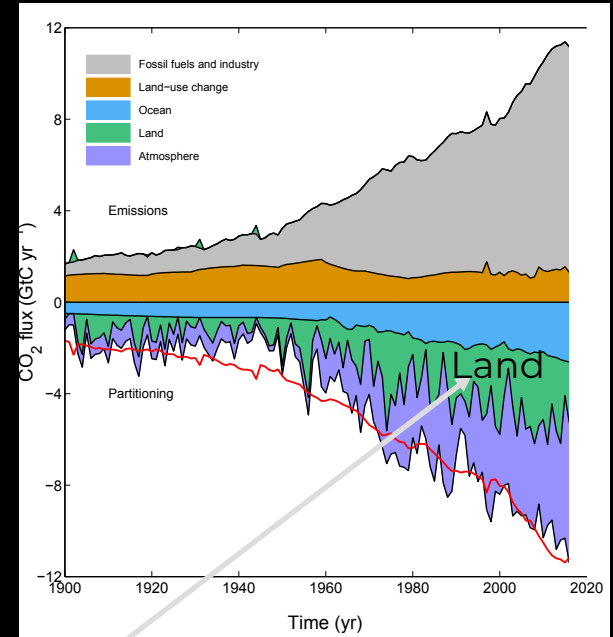
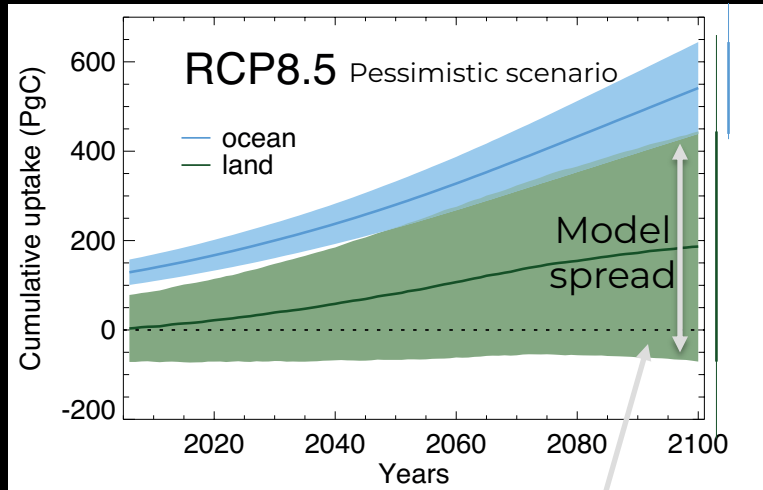
# Machine learning to investigate carbon-climate feedbacks

Pierre Gentine – Columbia University



# Introduction

## Biosphere



Large intermodel spread, large interannual variability  
Participate to the definition of  $[\text{CO}_2]=f(\text{emission flux})$

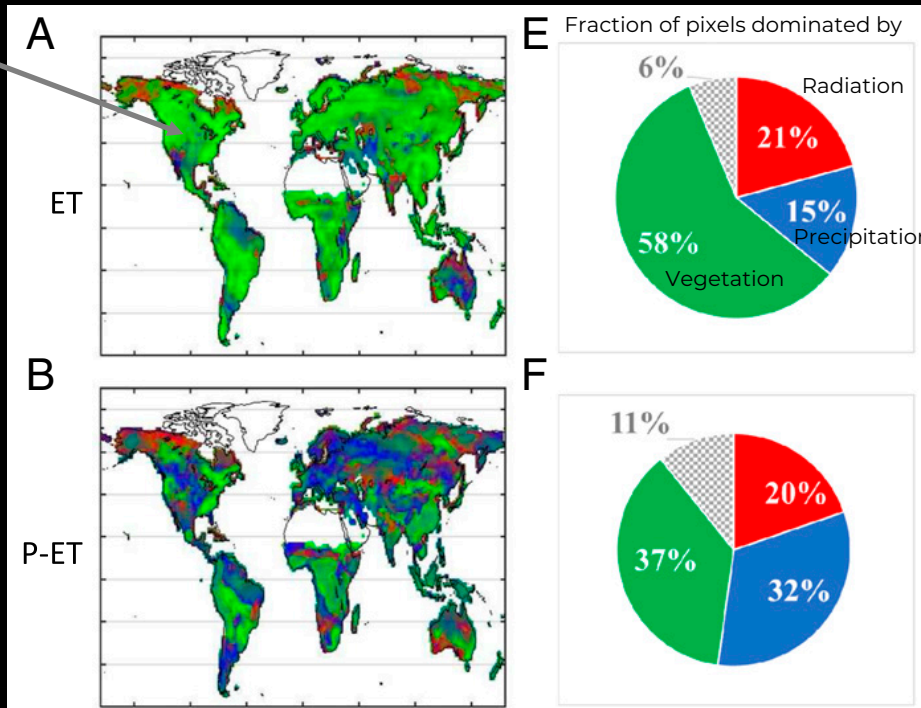
# Introduction

## Biosphere

Largely defines continental water cycle response  
(as it modulates evapotranspiration ET) (Lemordant et al., 2018)

Green: Veg.  
dominates  
changes  
By 2100

Evapotranspiration



# Addressing those challenges

How can we tackle those issues  
to better constrain those predictions?

## Approach:

Multiscale modeling/observations

Combined with physical and statistical (when needed) modeling

## Why now?

Golden age for Earth Observations (e.g. satellites)

+

Dramatic increase in computational power  
(many processes can now be resolved)

# Biosphere: photosynthesis

Largest terrestrial CO<sub>2</sub> flux: photosynthesis (GPP)

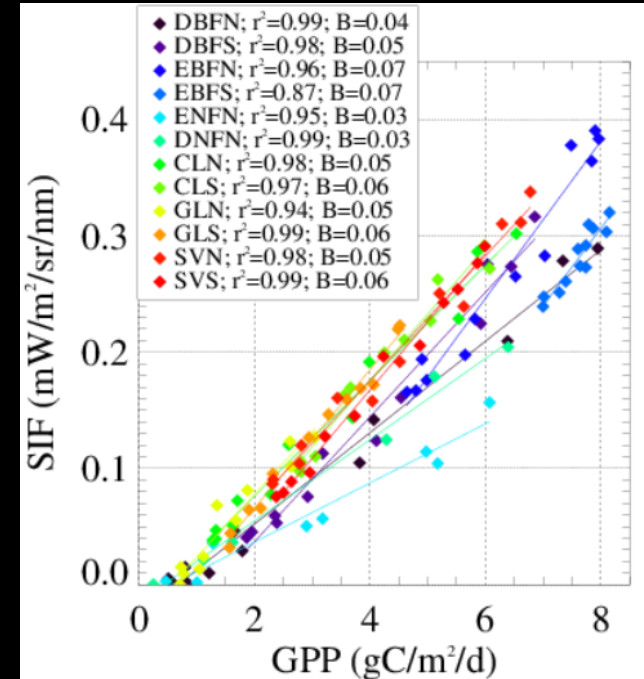
How can we constrain it to inform global env. changes?

We now have a proxy for photosynthesis, called **solar-induced fluorescence (SIF)**

During photosynthesis a plant absorbs energy through its chlorophyll

- % used for ecosystem gross primary production (GPP)
- % lost as heat
- % re-emitted (SIF: byproduct)

Small flux of a small flux: a very small and noisy flux



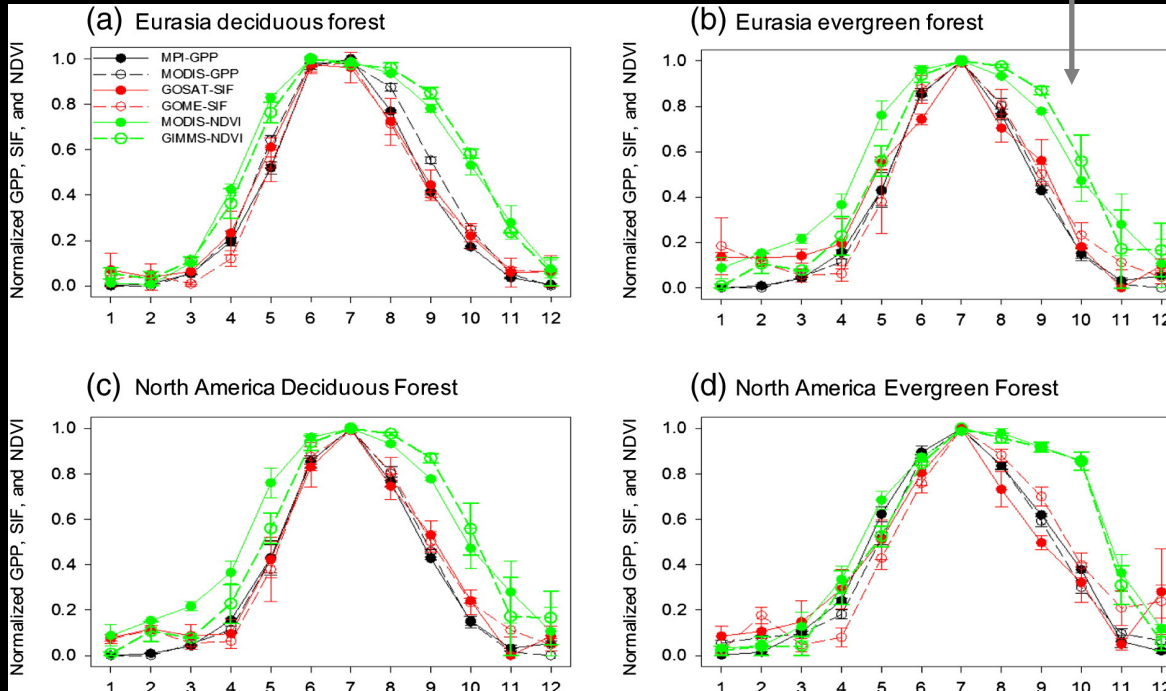
Photosynthesis

# Biosphere: photosynthesis

## Example of success with SIF

Better characterization of phenological cycle

NDVI exaggerates seasonal cycle



# Biosphere: photosynthesis

SIF is too noisy, not long enough or not sufficient resolution

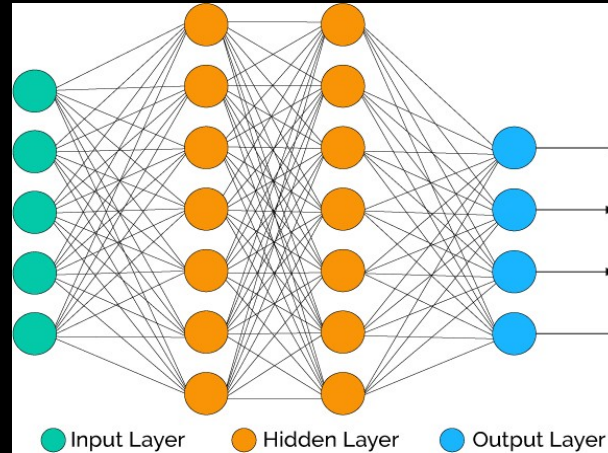
Use machine learning:

Reproduce SIF with MODIS (visible and near infrared channels):

higher accuracy and resolution, longer (2002-now)

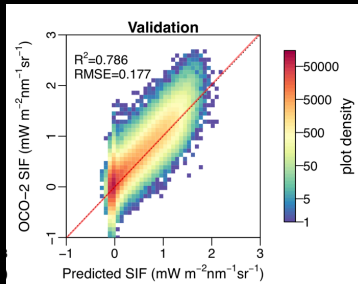
Called Contiguous SIF (CSIF)

MODIS  
channels



Contiguous  
Solar-induced fluorescence  
(CSIF)

Cost function:  
misfit to SIF  
observations



# Biosphere: photosynthesis

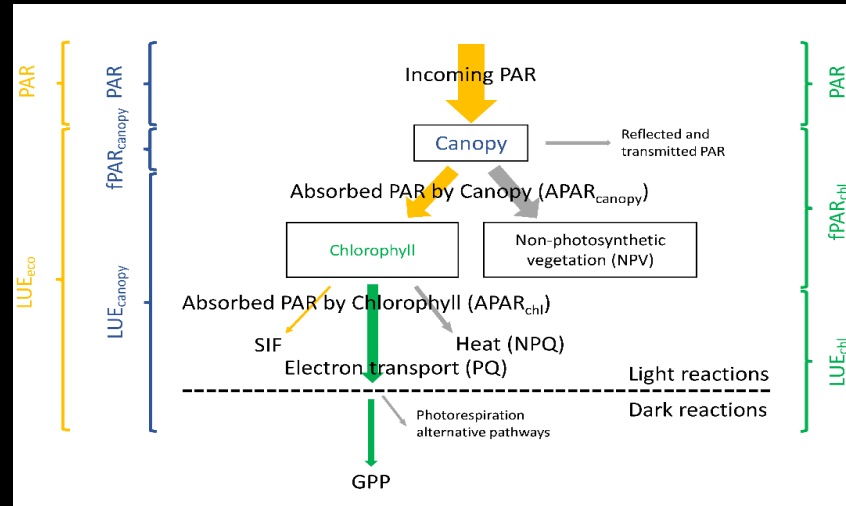
What is the rationale behind this?

Let us go back to the basics (light use efficiency a la Monteith)

$$GPP = LUE_{chl} \cdot fPAR_{chl} \cdot PAR$$

Similarly

$$SIF = Yield \cdot fPAR_{chl} \cdot PAR$$



$$\text{So } SIF = Yield / LUE_{chl} \cdot GPP$$

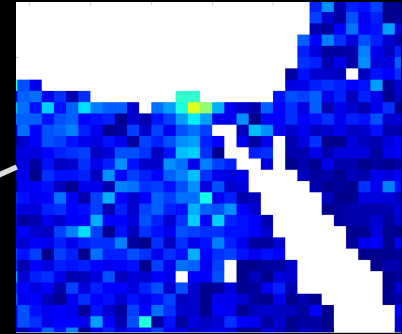
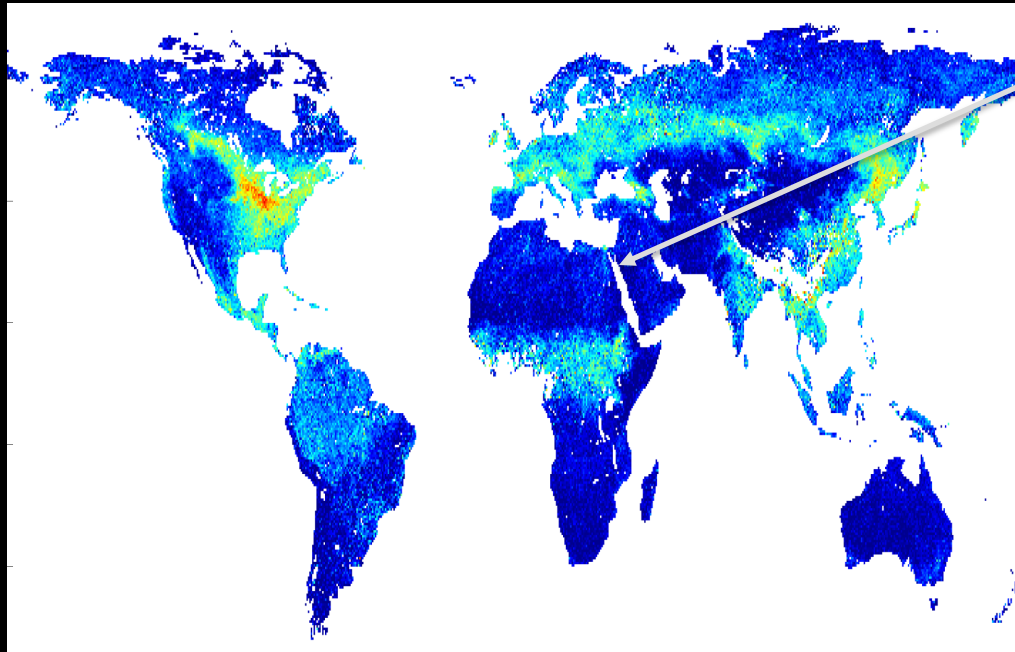
If Yield,  $LUE_{chl}$  are not varying much then

$APAR_{chl} = fPAR_{chl} \cdot PAR$  is a good proxy for GPP (and SIF)



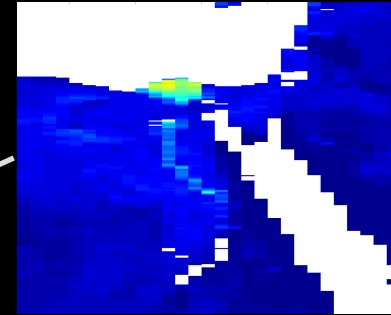
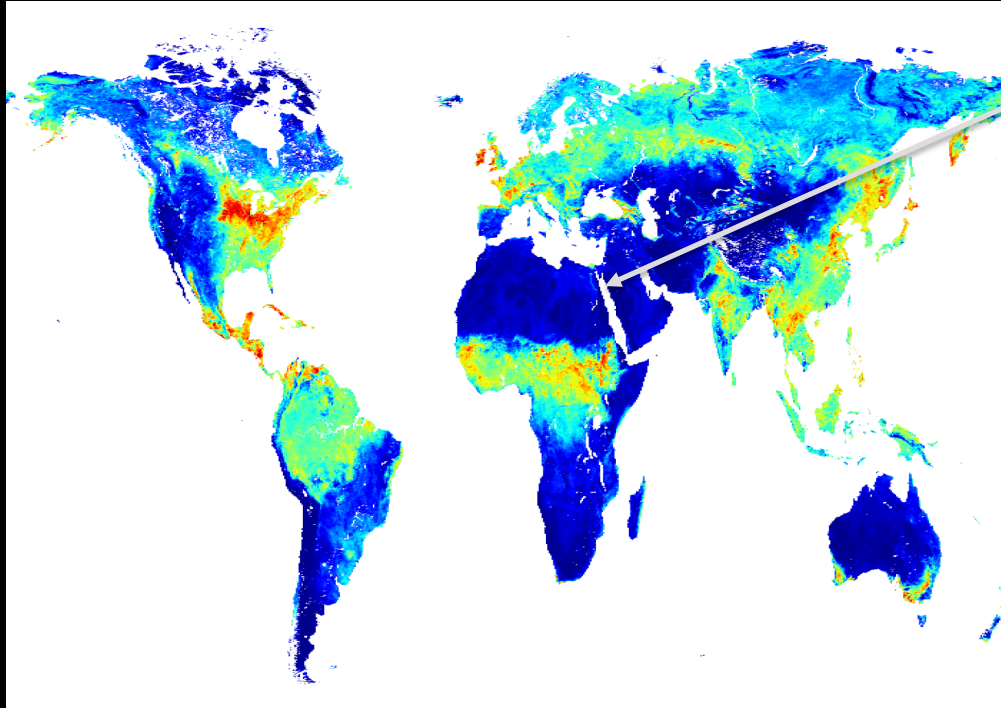
# Nile example

Original SIF (GOME-2) - 0.5 degree



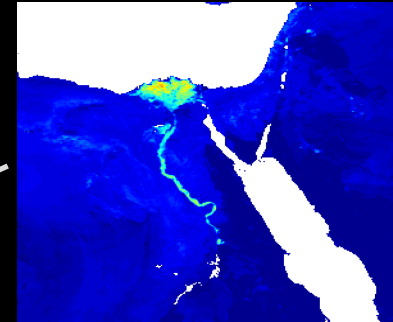
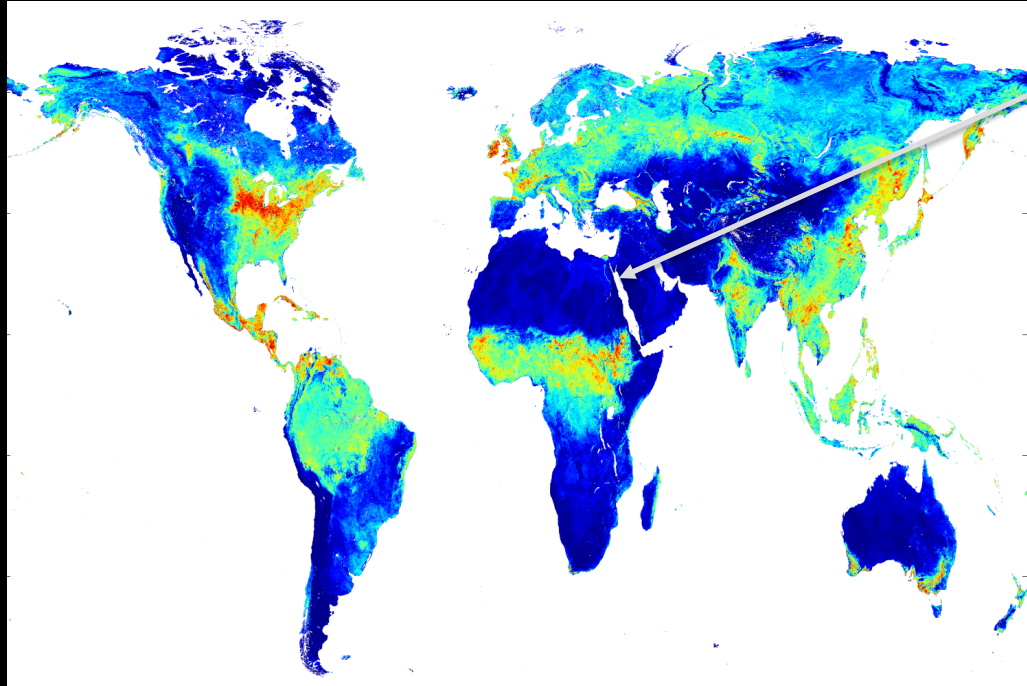
# Nile example

Contiguous SIF Modis - 0.5 degree



# Nile example

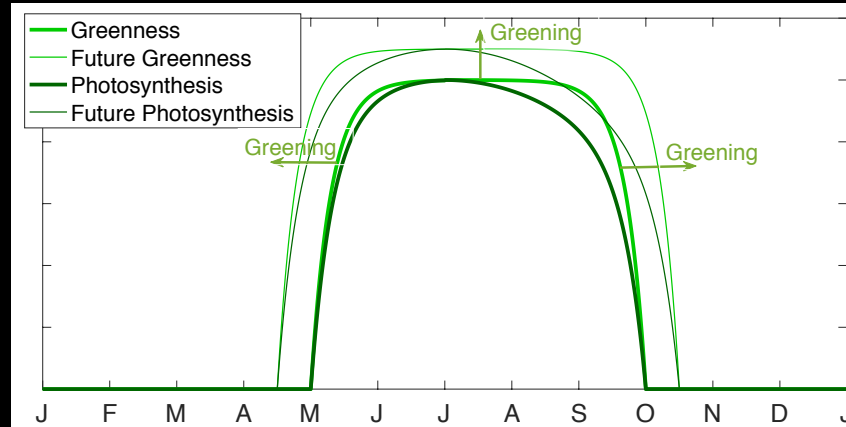
Contiguous SIF Modis - 0.05 degree



# Application 1. Northern latitude temperature sensitivity

Use Contiguous SIF to understand sensitivity to warming

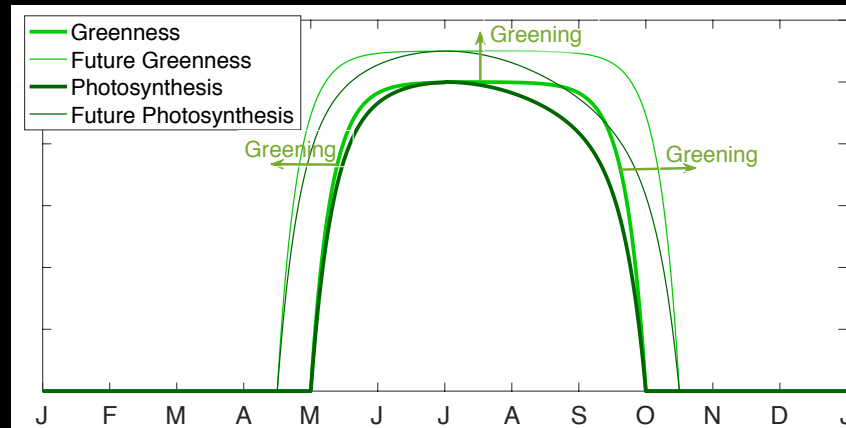
$T \uparrow \Rightarrow$  greener vegetation



# Application 1. Northern latitude temperature sensitivity

Use Contiguous SIF to understand sensitivity to warming

$T \uparrow \Rightarrow$  greener vegetation



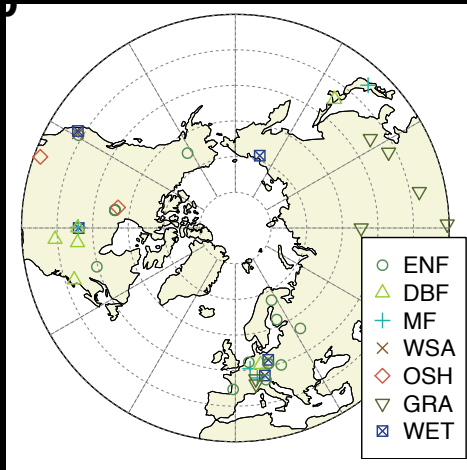
?

Increased sink  
(photosynthesis > respiration)

Increased source  
(photosynthesis < respiration)

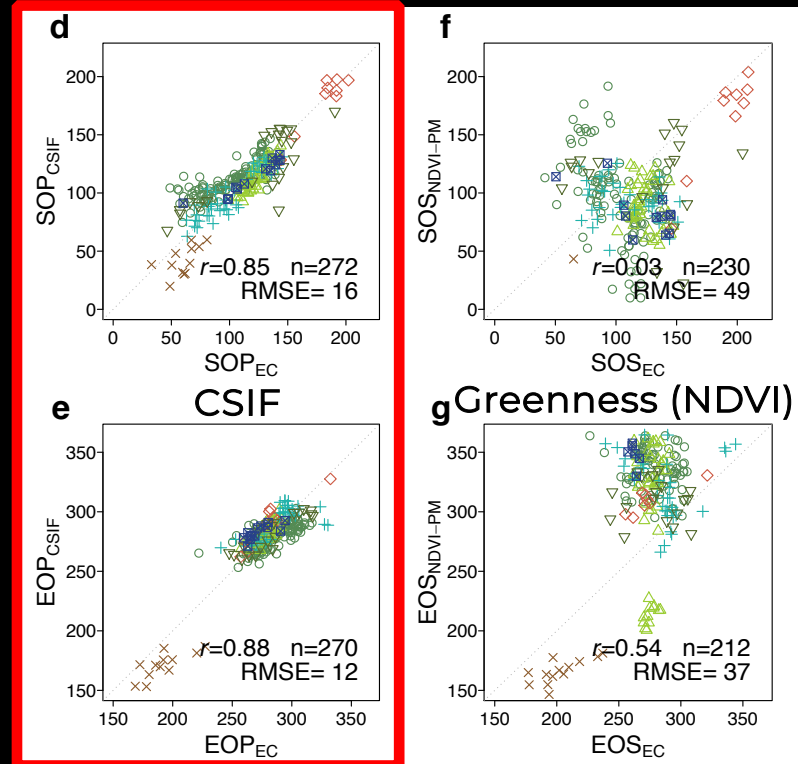
# Application 1. Northern latitude temperature sensitivity

## Contiguous SIF: comparison with eddy covariances



Start day of photosynthesis

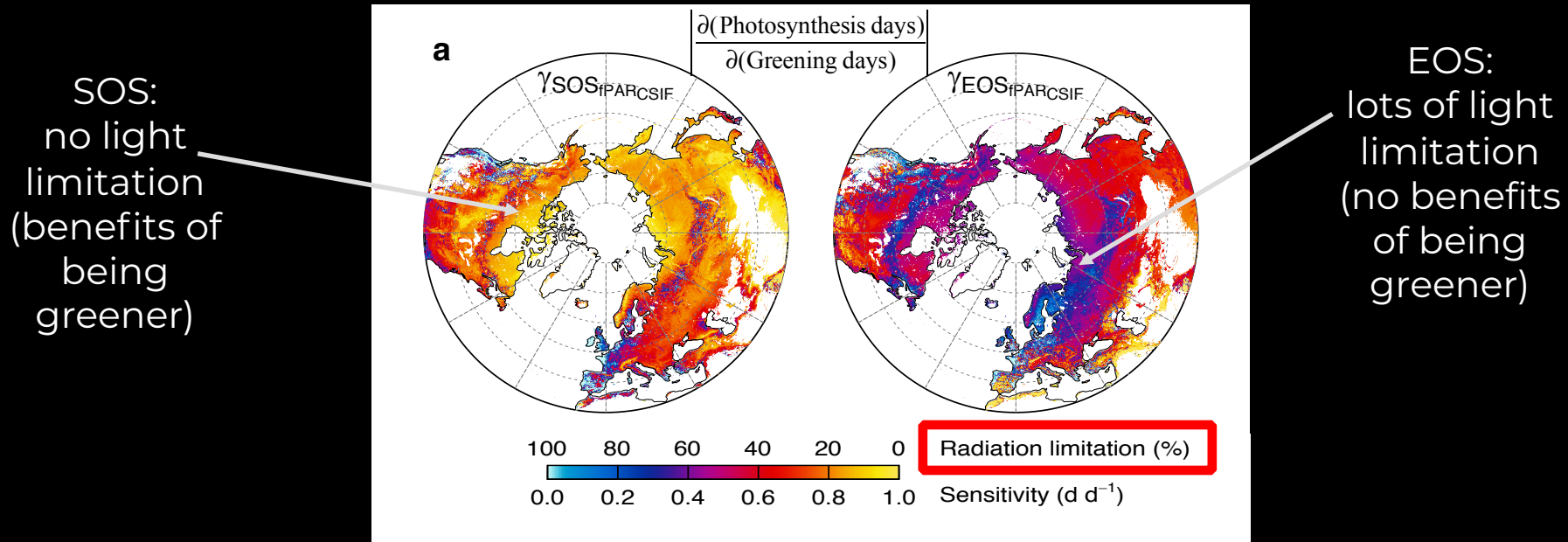
End day of photosynthesis



Eddy-covariance *in situ* observations

# Application 1. Northern latitude temperature sensitivity

Contiguous SIF: Start and End of season light limitation  
Day of photosynthesis gain per increased day of greening

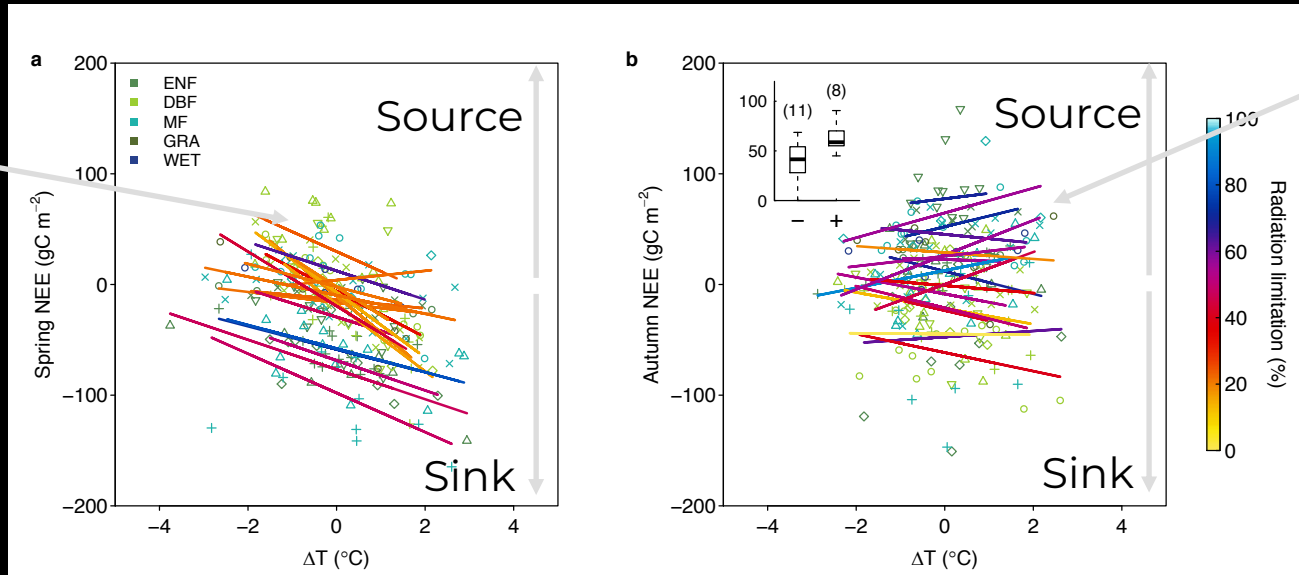


Greening: beneficial for beginning of season  
not much benefits for end of season (light limitations)

# Application 1. Northern latitude temperature sensitivity

Validation: *In situ* eddy-covariance Net Ecosystem Exchange (NEE)

$$\text{NEE} = -(\text{Photosynthesis} - \text{Respiration}) < 0 \Rightarrow \text{Sink}$$



SOS  
no light  
limitation  
(benefits of  
being  
greener)

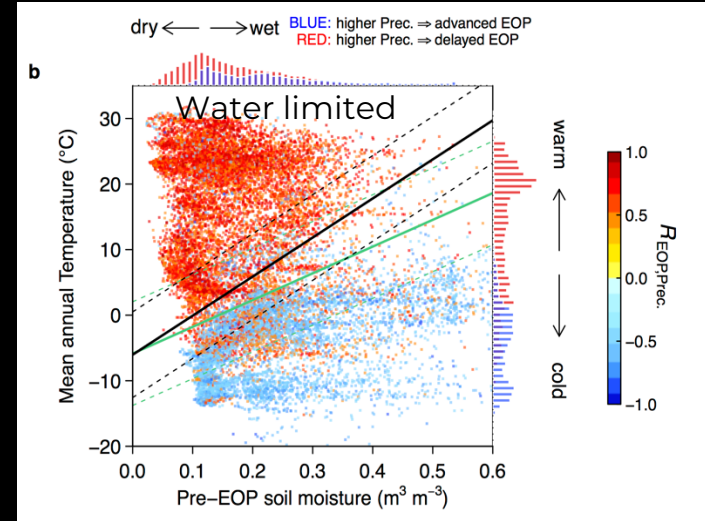
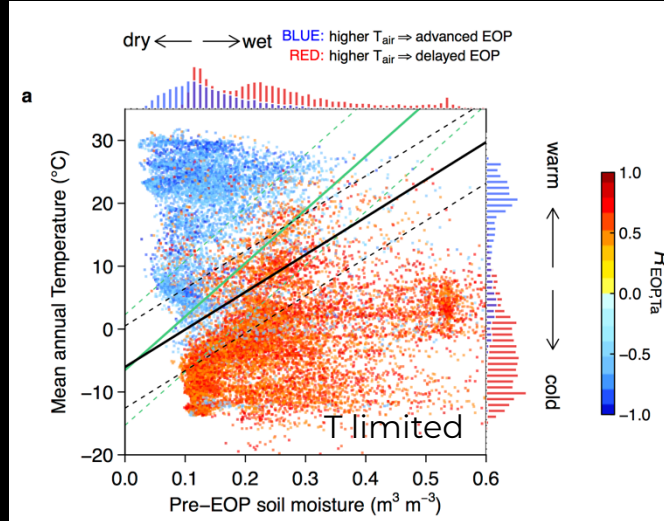
EOS  
lots of light  
limitation  
(no benefits of  
being greener,  
increased  $\text{CO}_2$   
source with  
increased T)

Temperature beneficial for beginning of season  
not much benefits for end of season (light) but large spatial variations  
Models do not capture this



# Application 2. End of season water stress

End of photosynthesis (EOP) date:  
dependence on pre-season T (Reanalysis) and Soil moisture (SMAP)  
**Correlation (EOP, T)** **Correlation (EOP, P)**



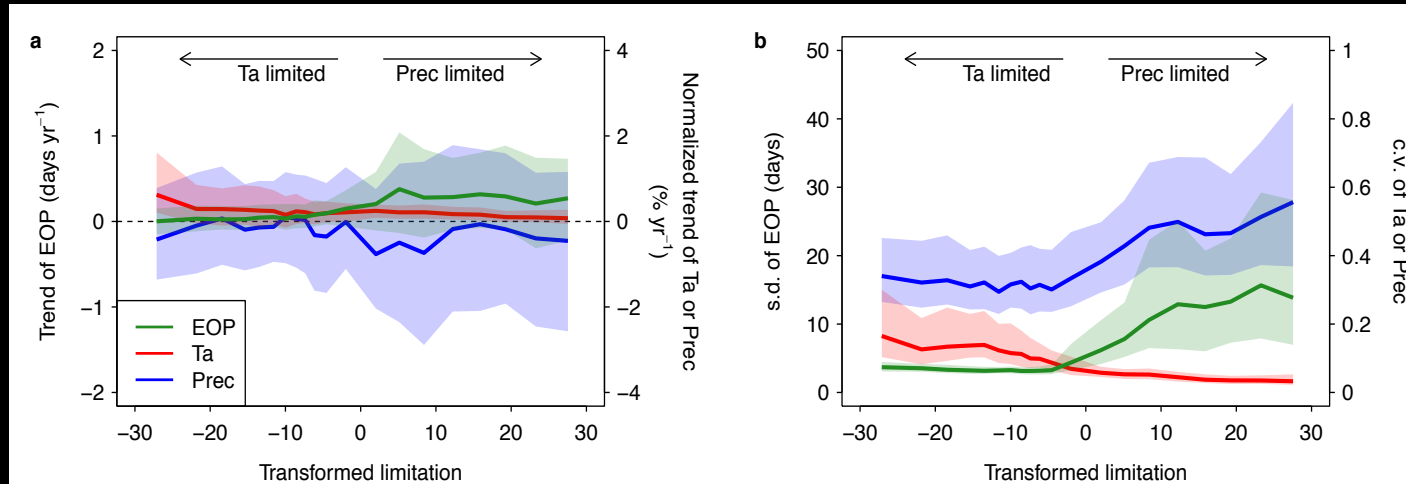
**Regions not T limited are water limited**  
**Clear separation between them using Support Vector Machine classification**  
**Confirmed by eddy covariances (not shown)**

# Application 2. End of season water stress

Interannual Variability (IAV) still dominates the signal

Trend in CSIF

IAV in CSIF



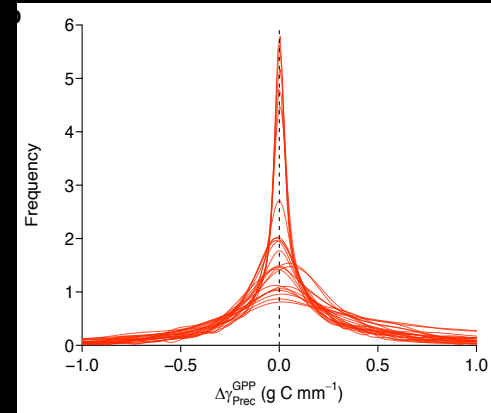
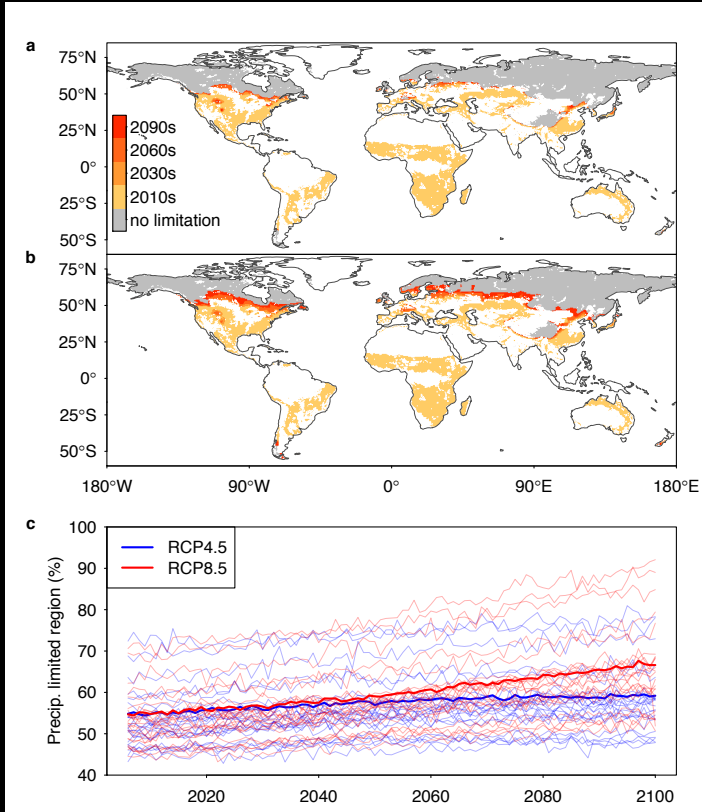
Limitation

Trend is still too weak compared to trend in MODIS record  
Turn to Earth System Models that relatively correctly capture this threshold

# Application 2. End of season water stress

## Future prediction of regions with EOP limited by precipitation

Change dominated by warming (demand) not by precipitation (supply, too variable)



Little change in P sensitivity

# Conclusions

Machine learning applied to remote sensing  
as a "filter" for noisy but good data

Two examples of end of season impact on carbon uptake:

## 1. Light limitation

Machine-learning retrievals of photosynthesis provide **new observational constraints** on GPP response across climates/ecosystems

- Cold regions: Light is the main regulator of end-of-season photosynthesis and carbon uptake temperature sensitivity

## 2. Dryness change

Clear threshold dependent on both T and P

Supply vs. demand


Demand T change is expected to have more future impact than P


# Next steps

Not just correlations, we want to **assess causation**,  
**predict** (e.g. climate change) and **interpret**

- 1) **Causation**: need to decompose cause and consequence,  
i.e. **directionality** and **strength**

Case i:  
*Bidirectional coupling* 

Case ii:  
*Unidirectional coupling* 

Example 1:  
*External forcing of non-coupled variables* 

Example 2:  
*Complex model* 

- 2) **Prediction**: implies good out-of-sample generalization  
(beside basic overfitting avoidance)
- 3) **Interpretability** (black boxes)

THANK YOU

Questions?