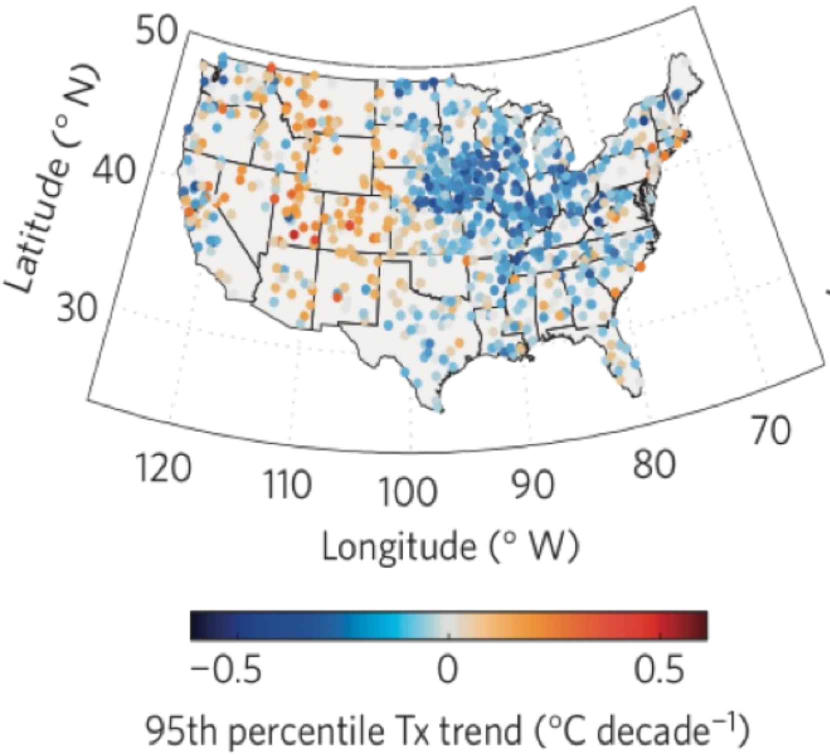
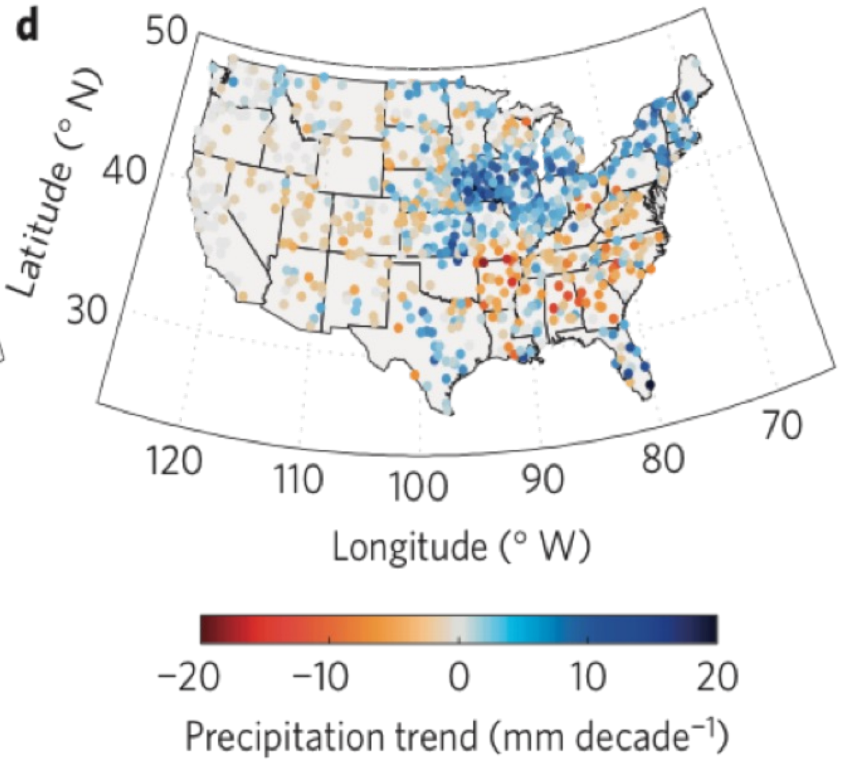
Earth observation of C dynamics
(of agricultural landscapes)

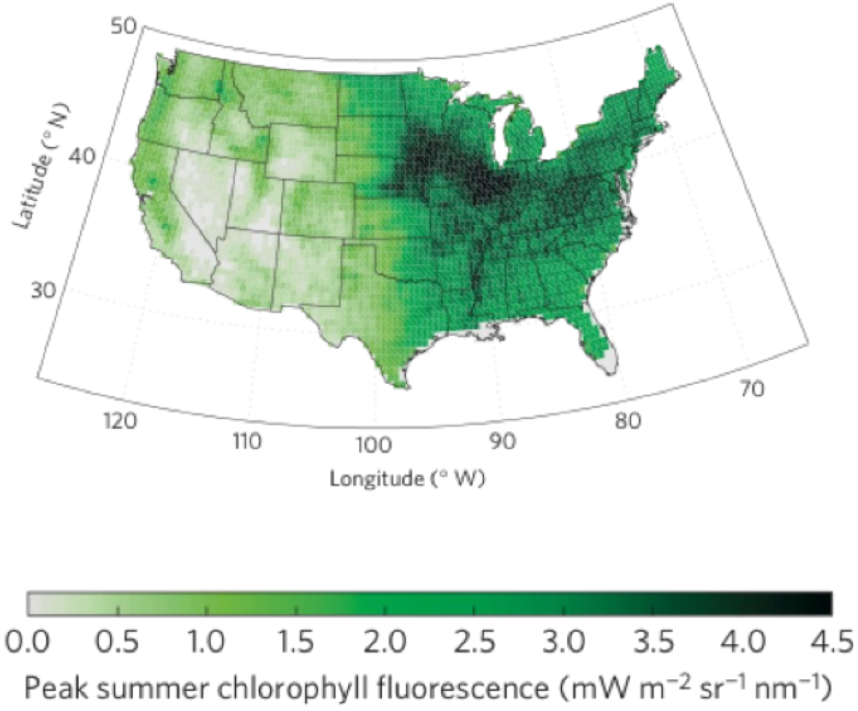
Christian Frankenberg
Caltech/JPL
and many others at Caltech/JPL

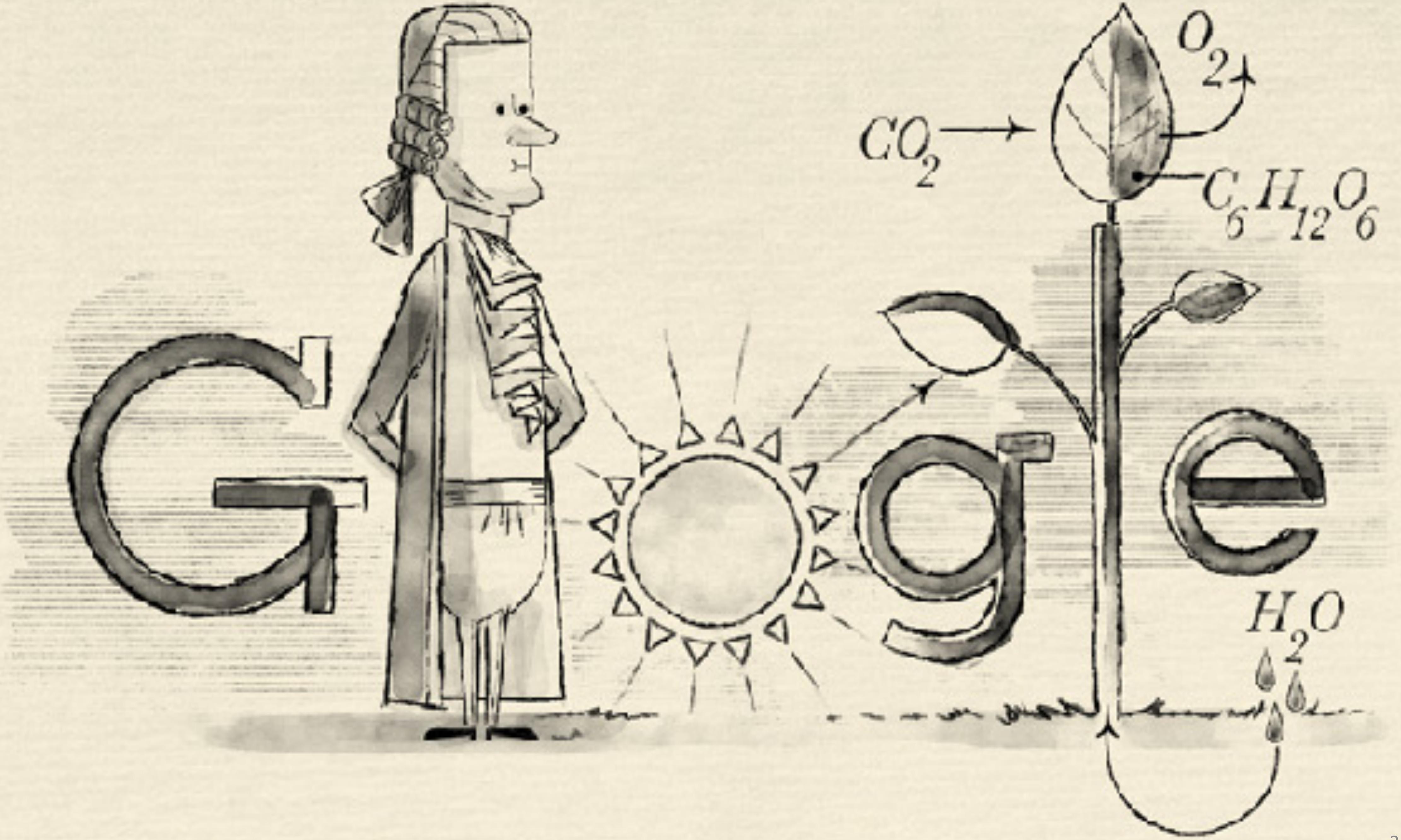
Crops are having an impact beyond just C

Mueller et al, NatCC, 2015



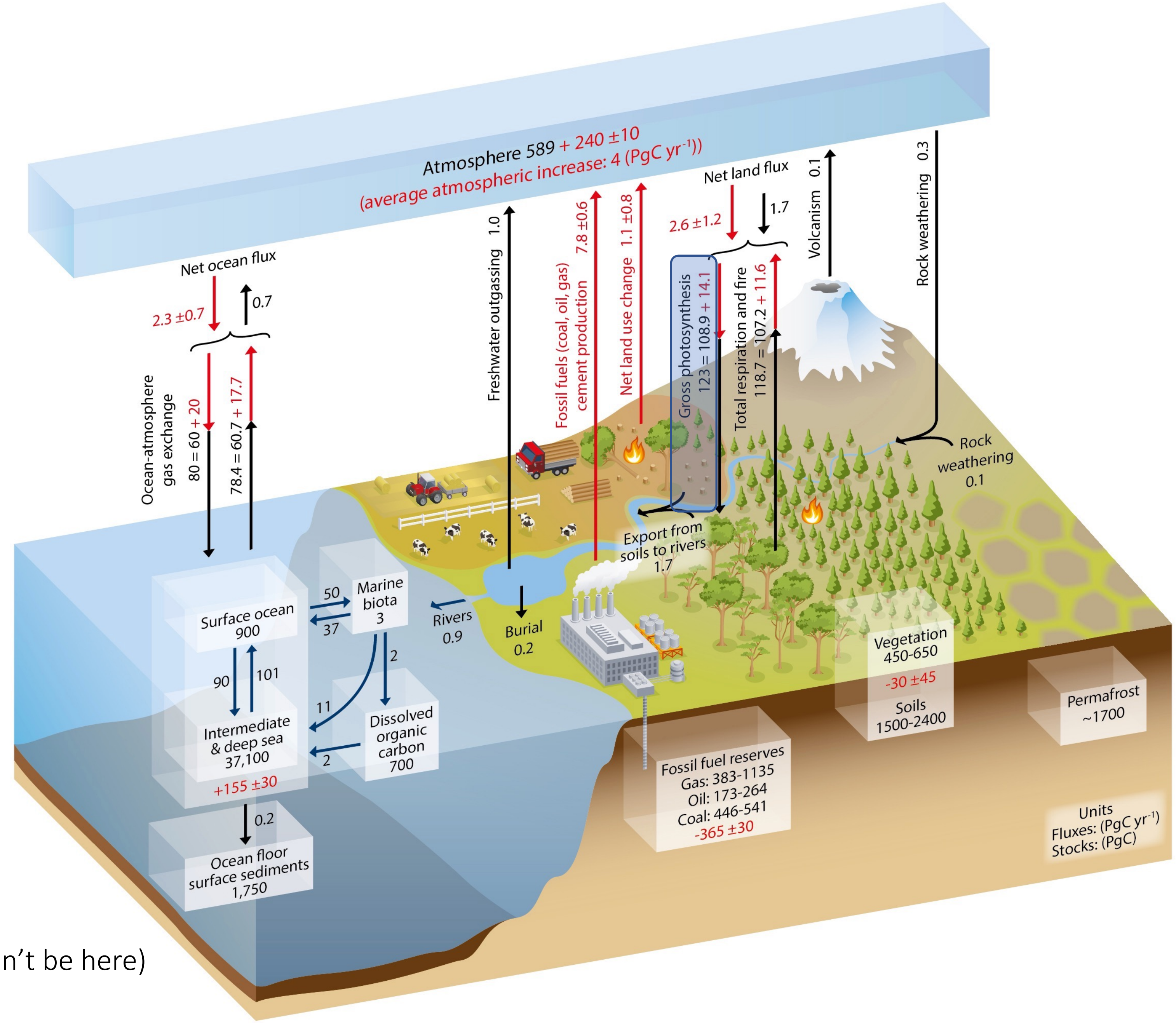






Google Doodle at birthday of Jan Ingenhousz, who first detected O_2 generation via photosynthesis (1779)

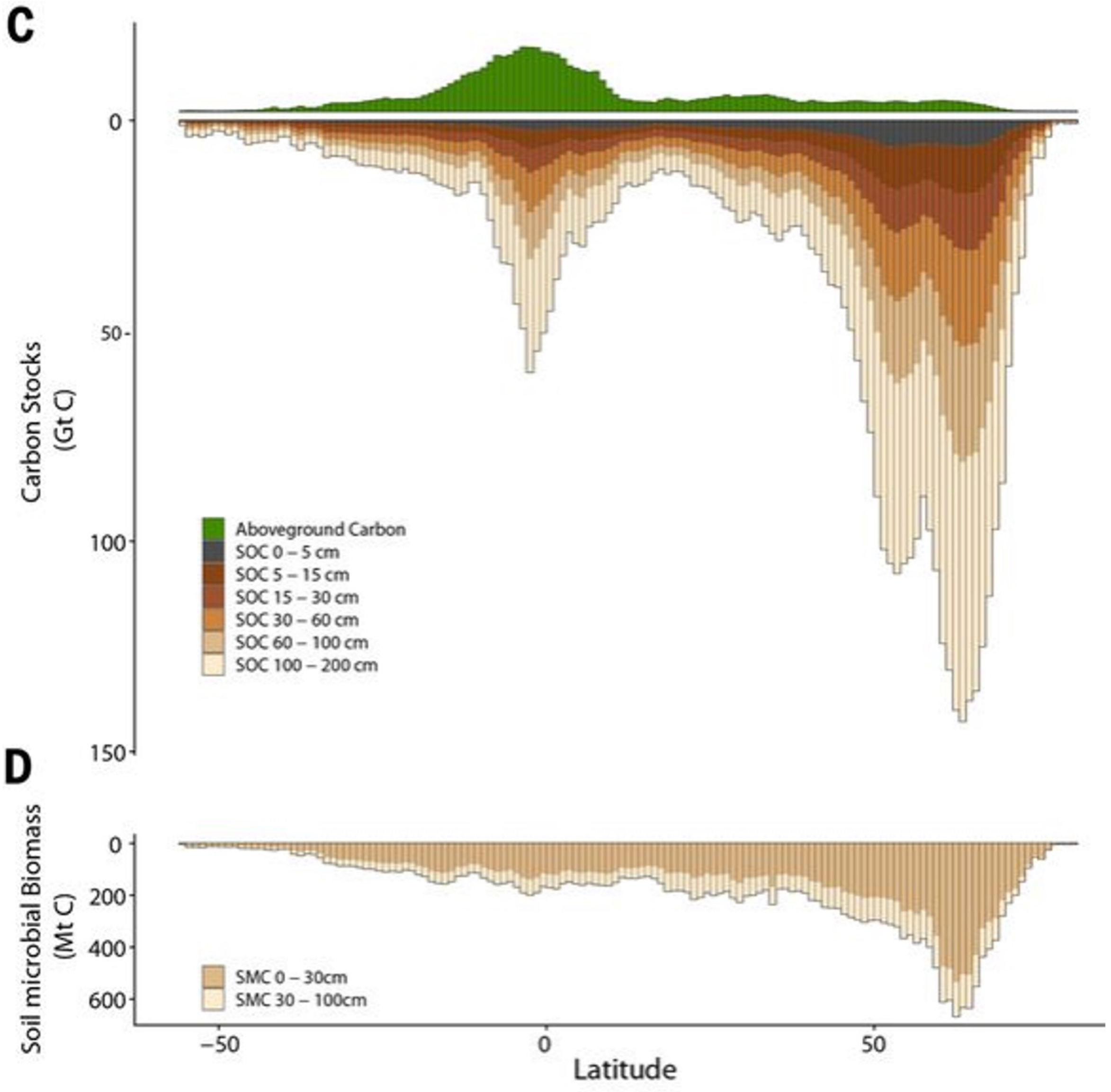
The Big Picture: Global Carbon Cycle



Gross Primary Production (GPP)
= Gross CO_2 uptake through photosynthesis
- Largest CO_2 sink on Earth
- Largest O_2 source
- Engine of most biogeochemical cycles (without it, we wouldn't be here)

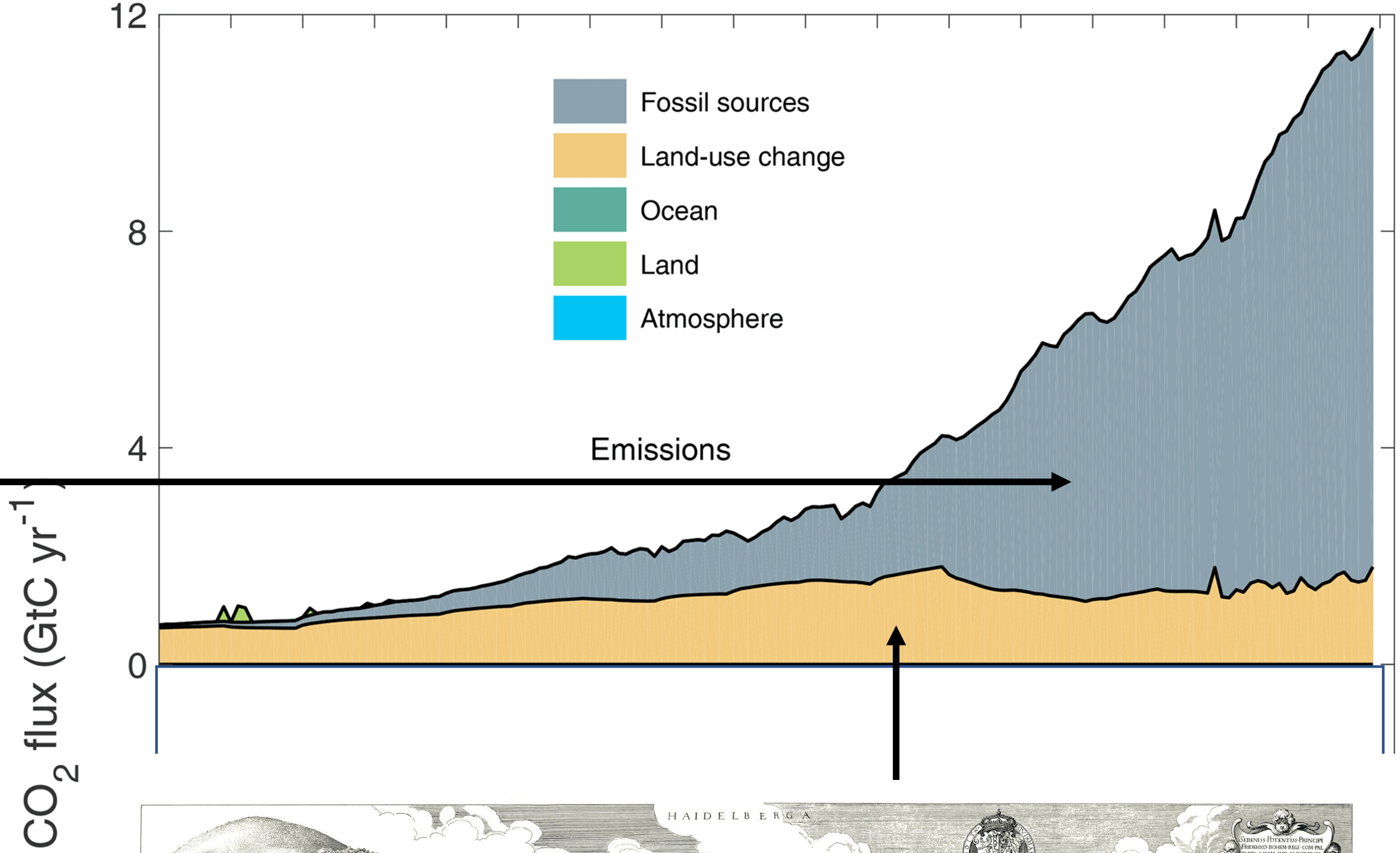
IPCC report

Importance of soils and OC



- More carbon is stored in the soil than above ground
- Especially at higher latitudes
- If changes in reservoirs are fractional, the soil will store more
- Microbes are driving turnover rates (act as catalysts)
- Different in agricultural systems

Crowther et al 2019



Processed digital image © 2019 by Claus Liepke info@digital-images-and-photos.com

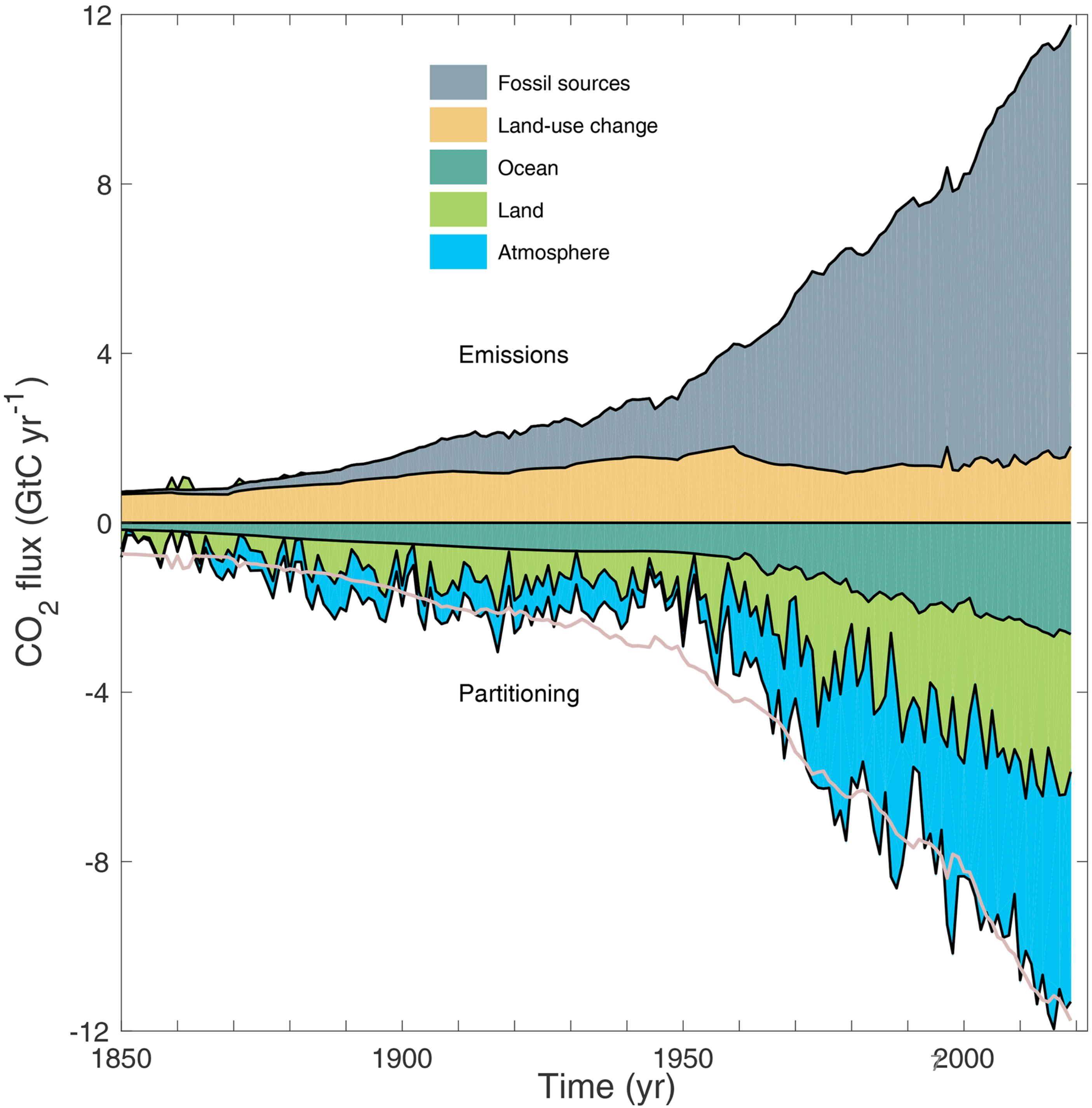
Global Carbon Budget 2020

Pierre Friedlingstein et al.

Motivation

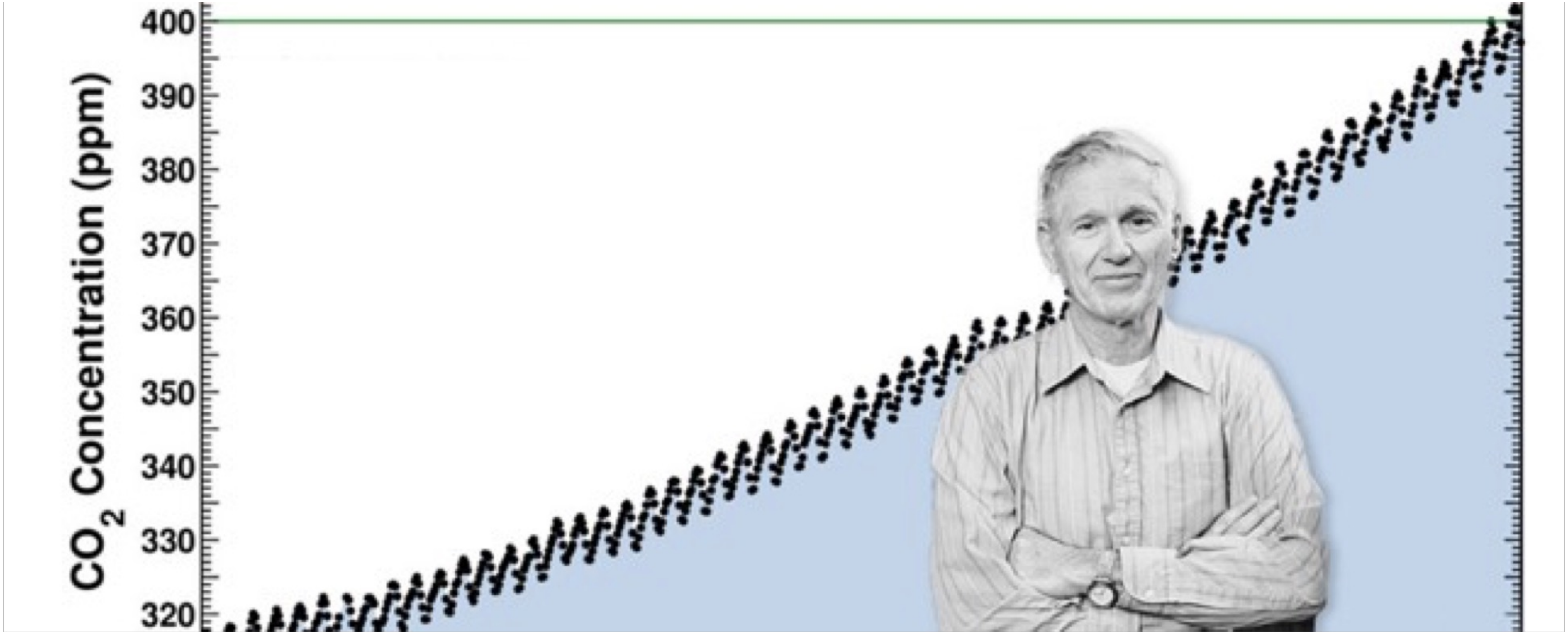
Plants are doing us a favor

Future of GPP will determine whether plants will continue to do us a favor by taking up CO_2.



Global Carbon Budget 2020
Pierre Friedlingstein et al.

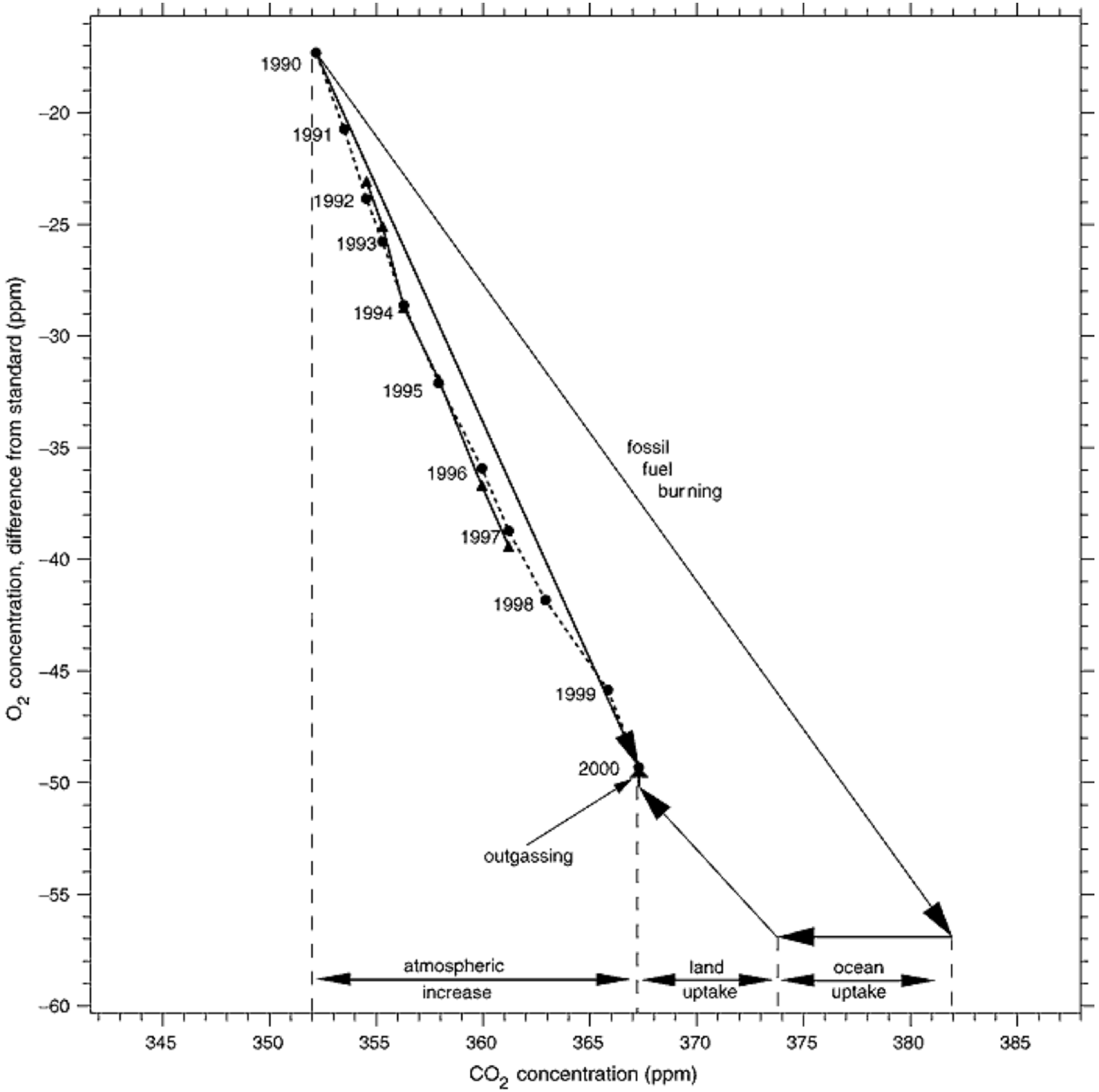
What do we know about global GPP? The top-down view from the atmosphere

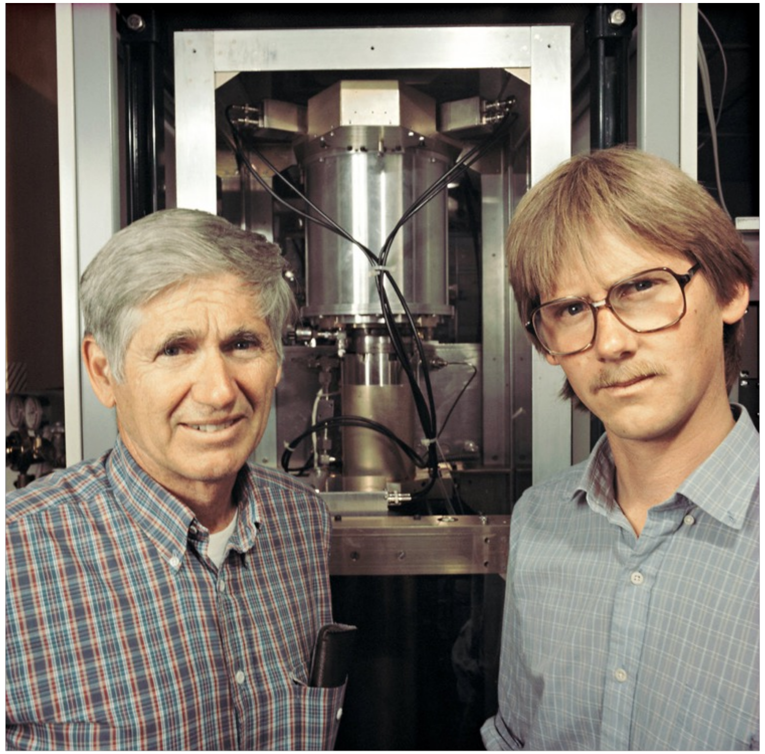


http://www.nytimes.com/2010/12/22/science/earth/22carbon.html

Where does it go? Using O_2 and CO_2

(The Keeling combo)





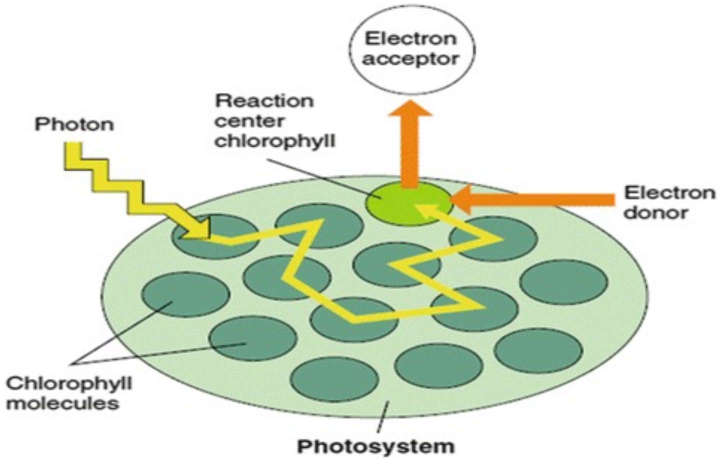
So, how do quantify carbon dynamics globally?

At the core: Photosynthesis in a nutshell
(excuses to real plant biologists)

- Step 1: **Harvest light** → absorb photons in the 400-700nm range that powers the light reactions (and releases O_2!)
- Step 2: **Fix carbon** → Use products from the light reactions to reduce CO_2
- Steps 1 and 2 need to be **coordinated** as they work in sequence (at least for regular C3 plants).

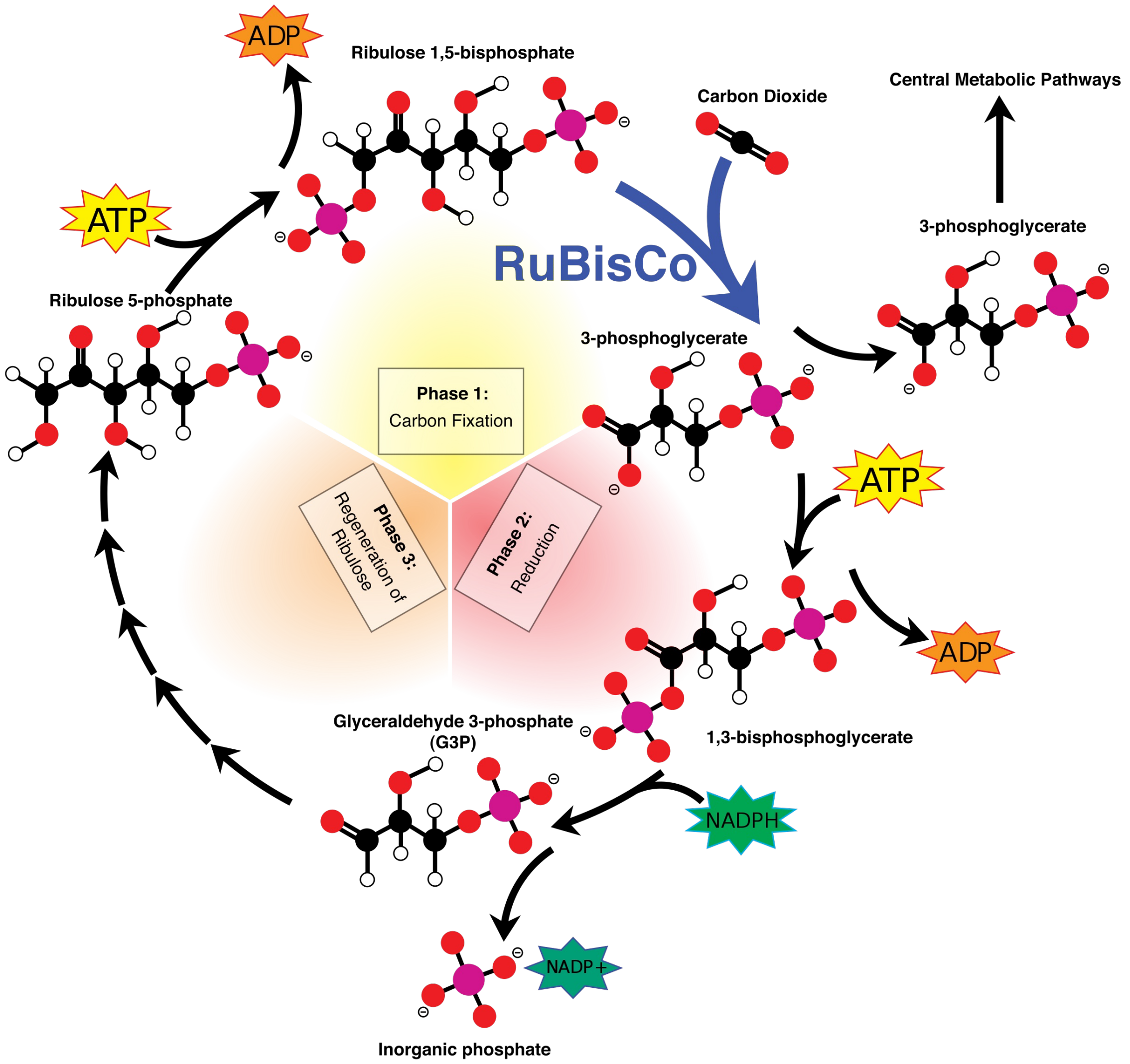
  A photosynthesis model basically computes the potential rates for Step 1 and Step 2 and determines the rate limiting.
  pCO_2 at chloroplast and overall absorbed light is almost all we need.

Photosynthesis Part I: The light reactions



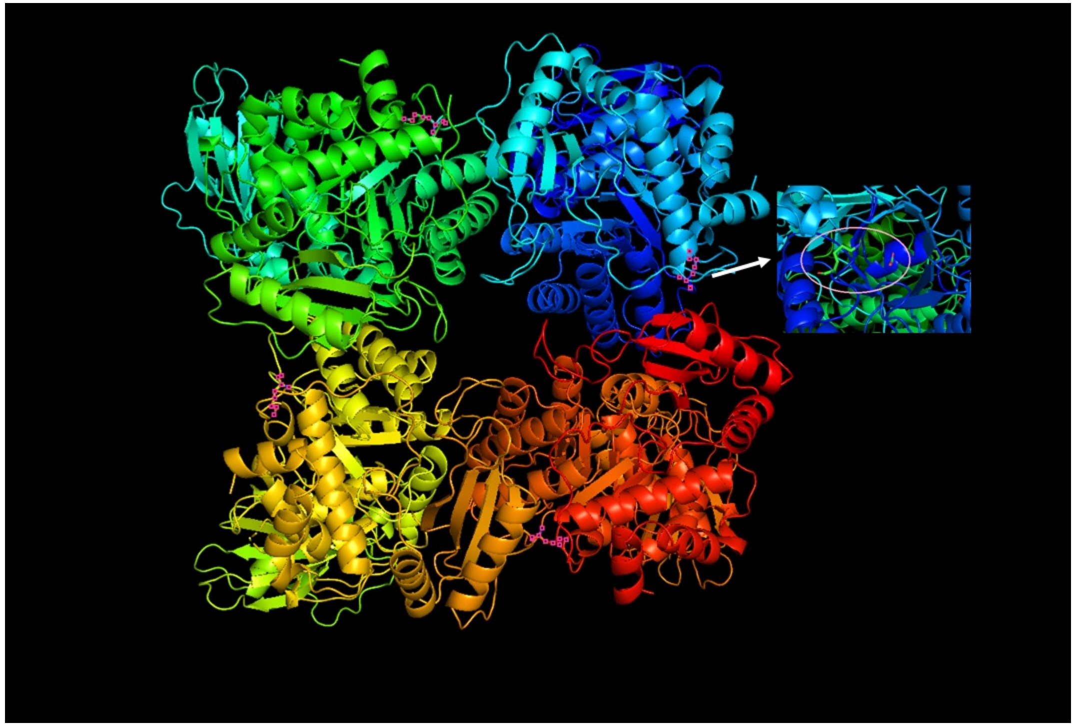
Photosynthesis Part II: The carbon reactions

Calvin-Bassham-Benson Cycle

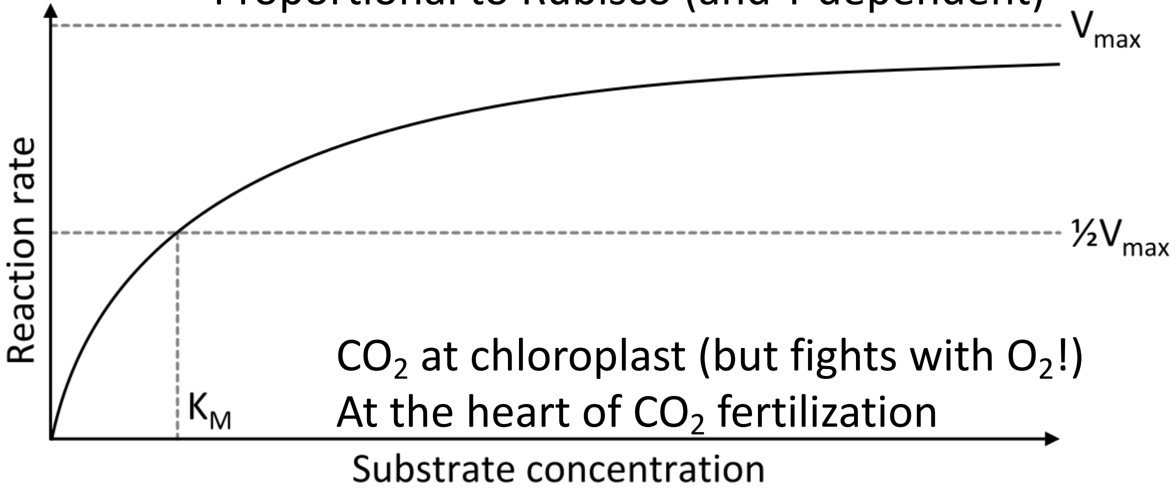


https://en.wikipedia.org/wiki/Calvin_cycle#/media/File:Calvin-cycle4.svg

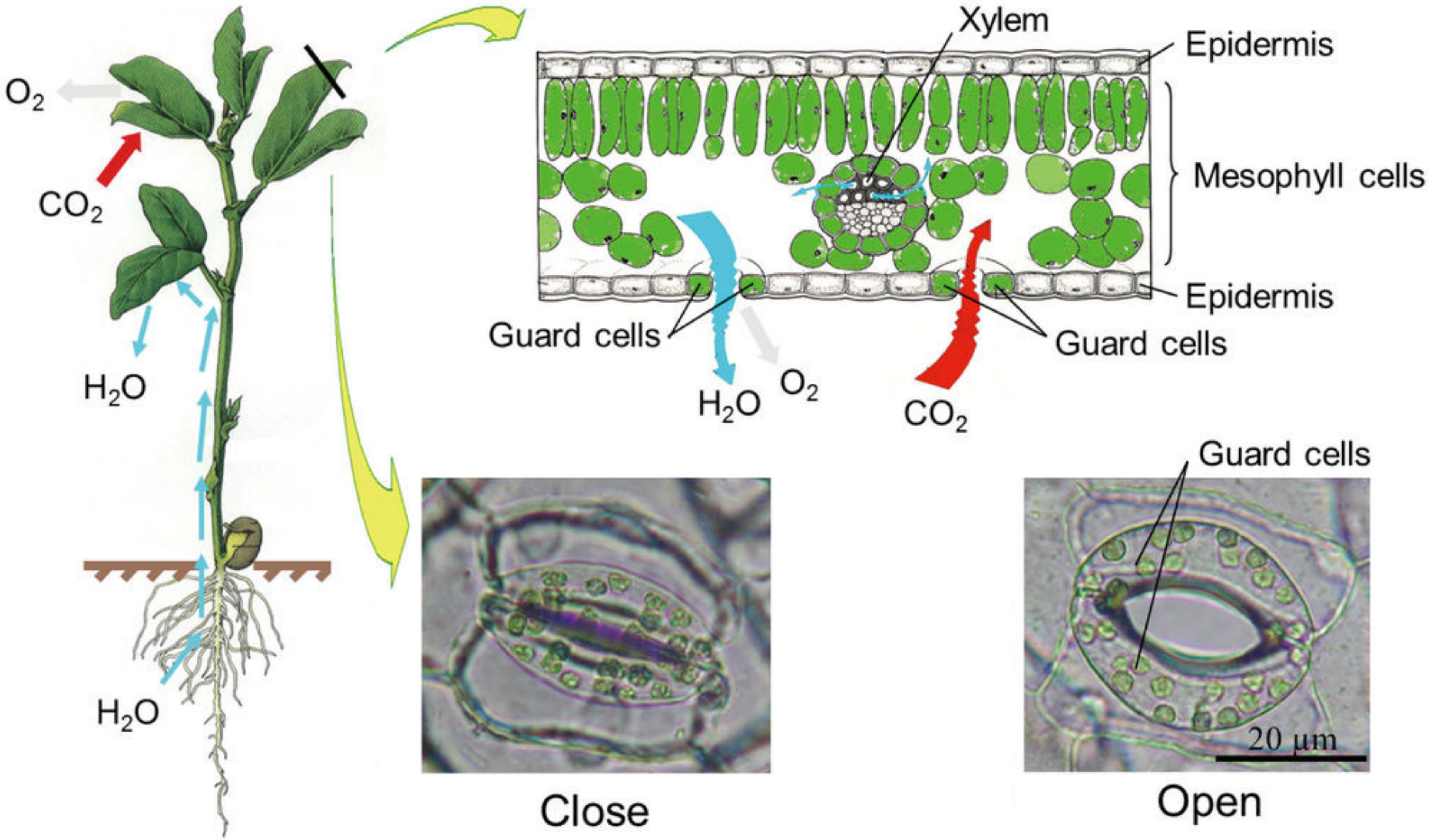
Rubisco
Ribulose-1,5-bisphosphate carboxylase oxygenase



Proportional to Rubisco (and T dependent)



Photosynthesis Part III:
How do we get CO_2 to the chloroplast? The role of stomata



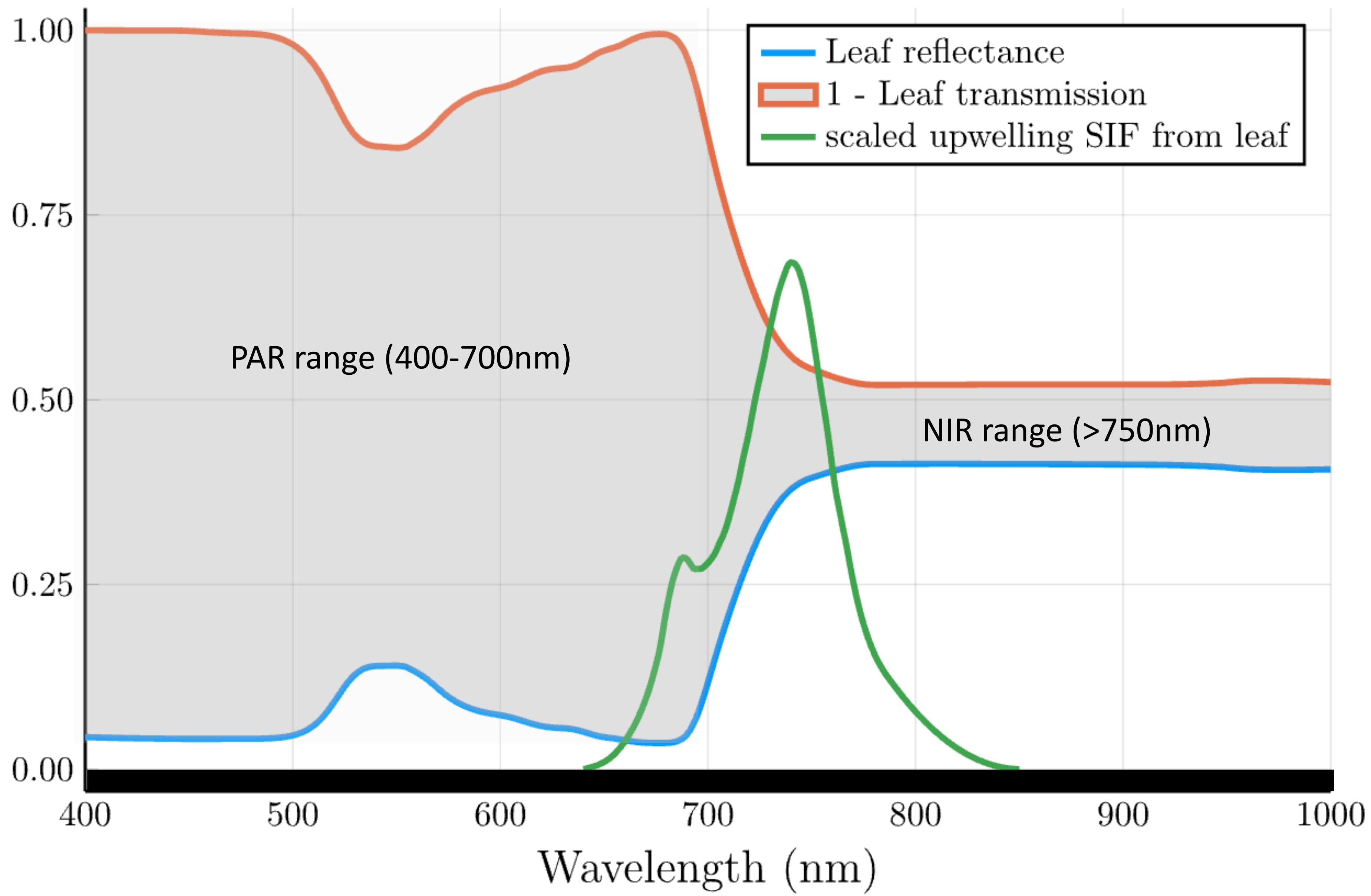
Stomatal conductance (thus evaporation) is coordinated with photosynthesis! This is the main reason it had to be put into land surface models in the first place.

CO_2 up, conductance down

Vapor pressure deficit up, conductance down

http://www.aip.nagoya-u.ac.jp/en/public/nu_research/images/20171109155402.jpg

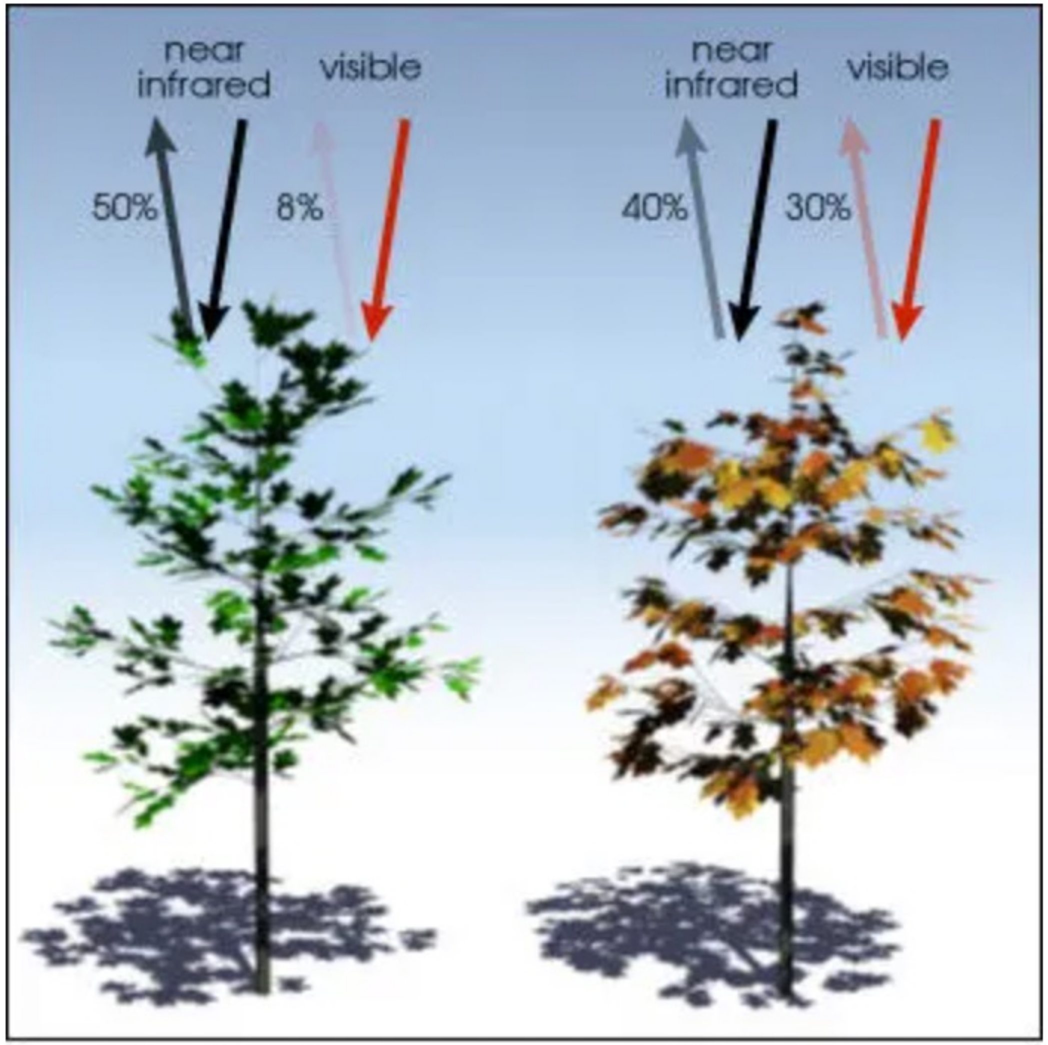
Remote sensing information on Step 1: **Harvest light**



The world as seen by the human eye (PAR range)

The world in the near infrared (>800nm)

NDVI Normalized **D**ifferential **V**egetation **I**ndex

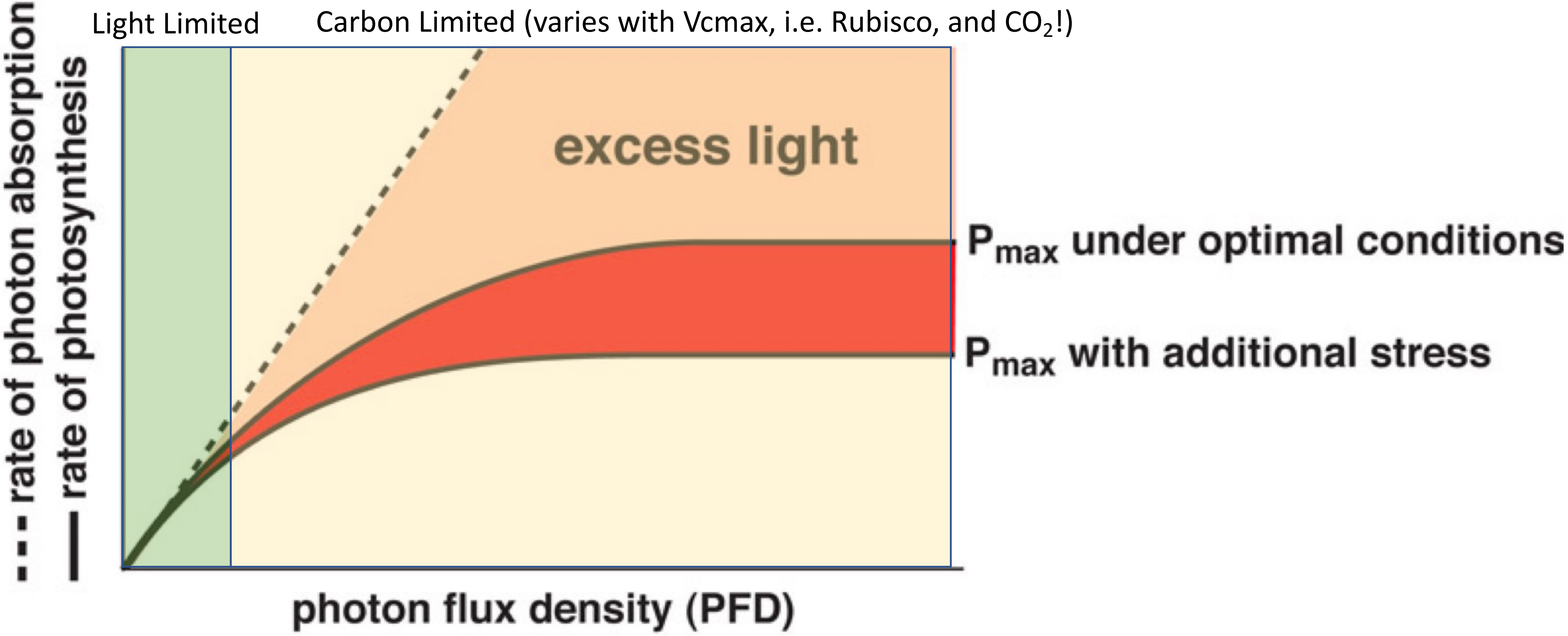


$$\frac{(0.50 - 0.08)}{(0.50 + 0.08)} = 0.72 \qquad \frac{(0.4 - 0.30)}{(0.4 + 0.30)} = 0.14$$

Image courtesy of NASA.

https://developers.google.com/earth-engine/tutorials/community/modis-ndvi-time-series-animation

NDVI can tell us about absorbed light, but…



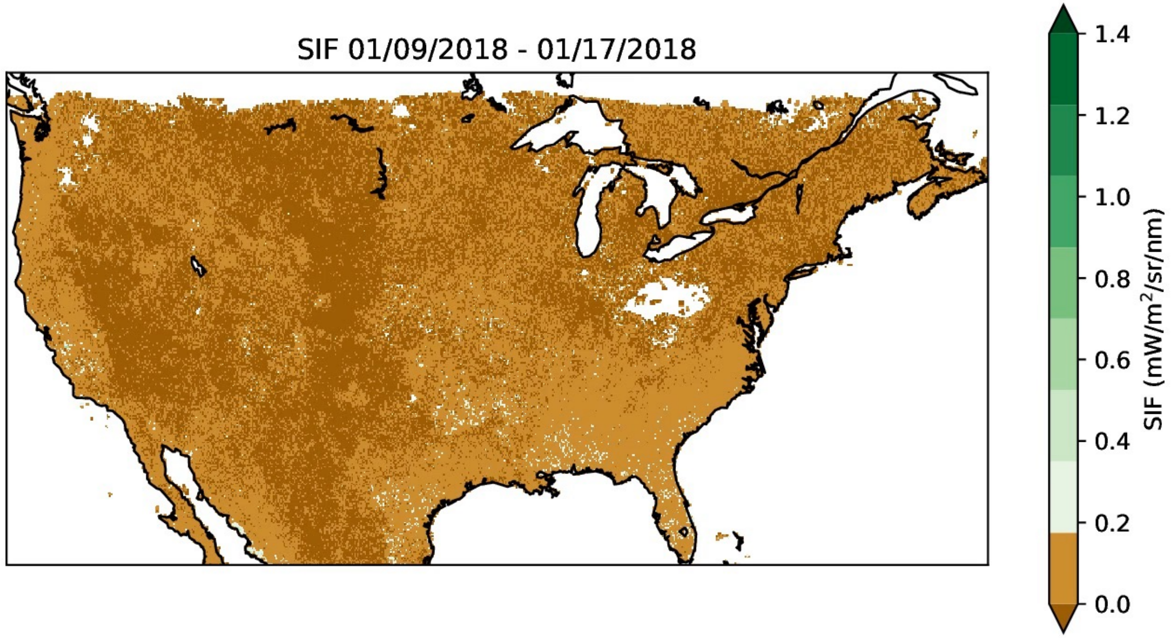
A different way to look at the light reactions (Electron Transport Rate)

Introduction to Solar Induced Chlorophyll Fluorescence

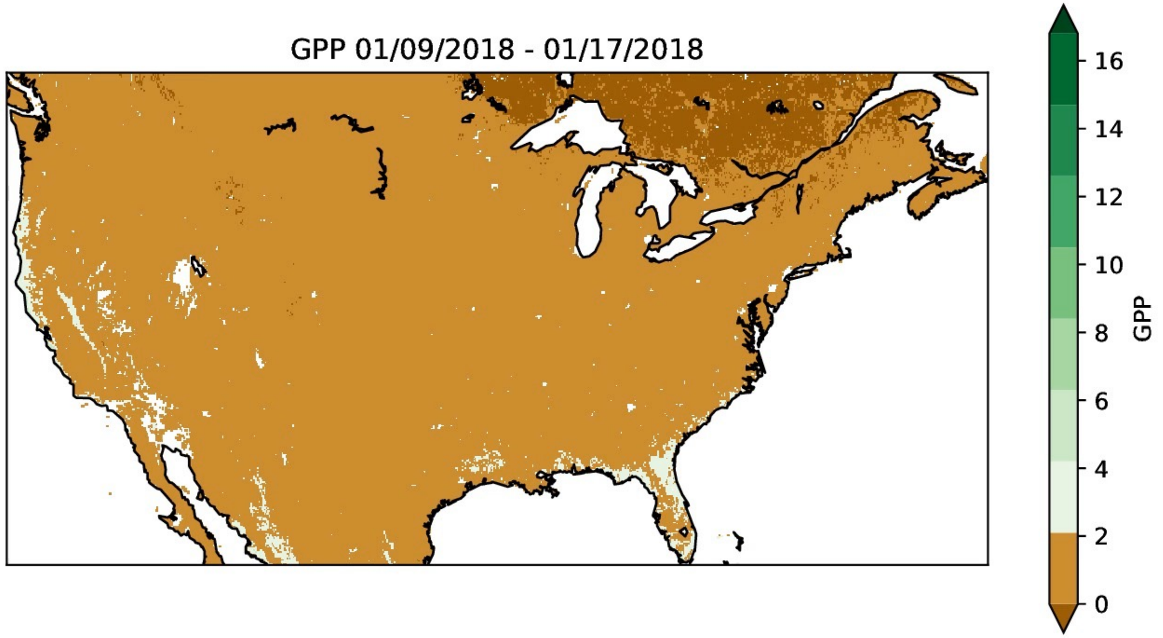
- A small fraction of the absorbed light is being re-emitted as fluorescence (>700nm, just tiny overlap with the visible spectral range).
- This happens even for dissolved chlorophyll solution (e.g., in alcohol). See figure on the right.

TROPOMI, global coverage in <1week Köhler, Frankenberg et al

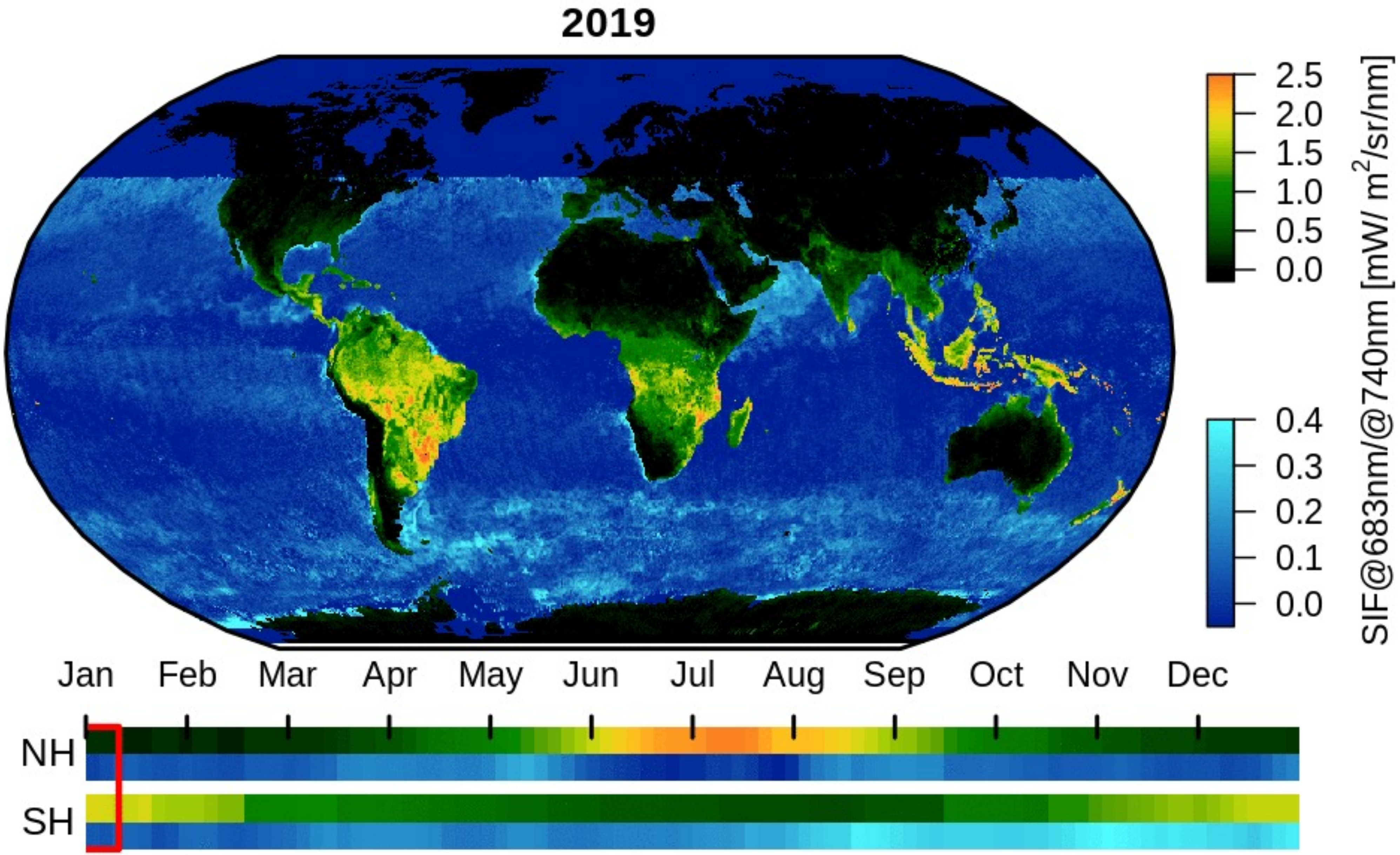
TROPOMI SIF (Caltech)



Model GPP (MPI Jena)



Red and Far-Red SIF, covering phytoplankton as well

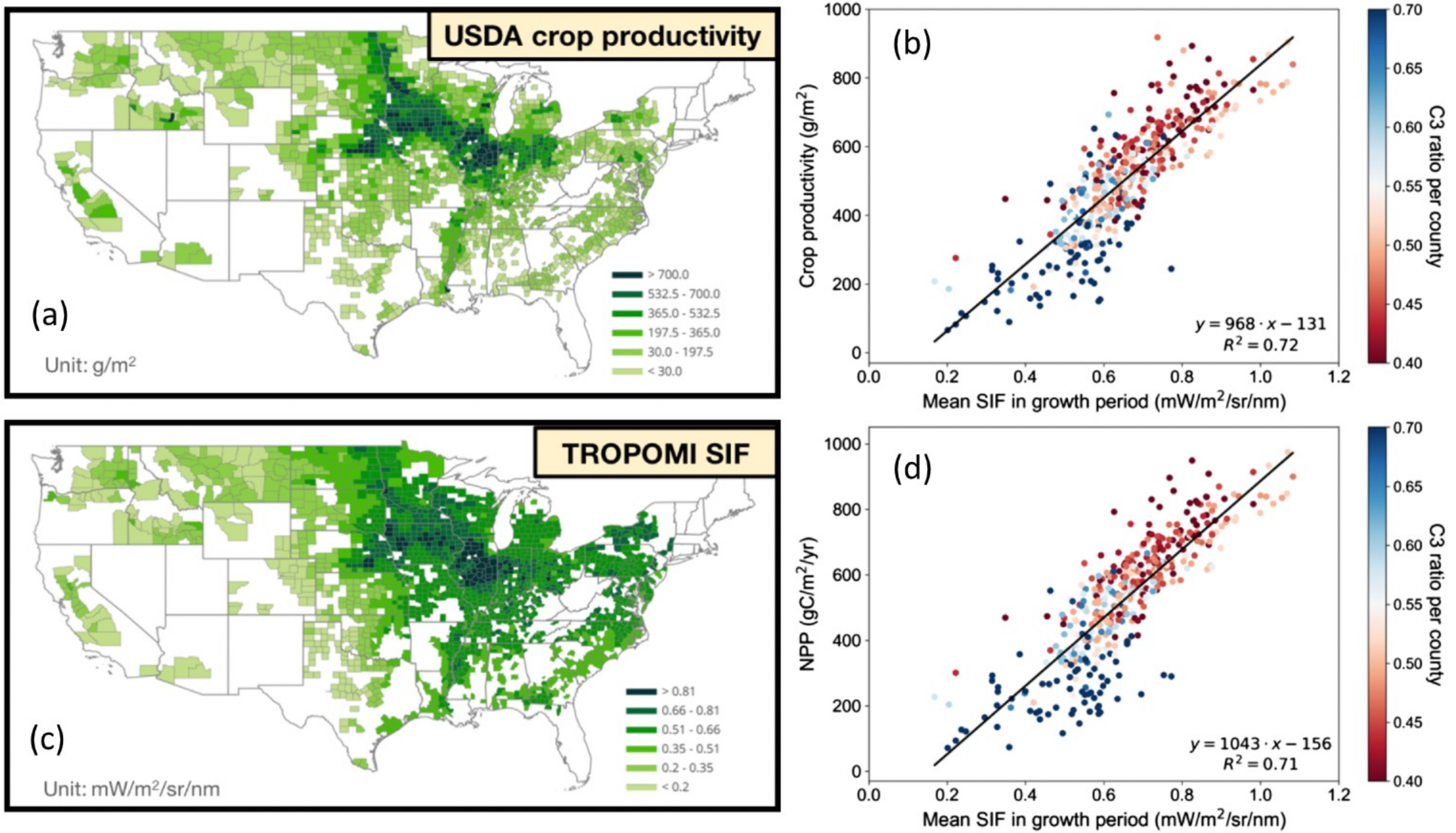


Köhler, P., Behrenfeld, M.J., Landgraf, J., Joiner, J., Magney, T.S. and Frankenberg, C., 2020. Global Retrievals of Solar-Induced Chlorophyll Fluorescence at Red Wavelengths With TROPOMI. *Geophysical Research Letters*, *47*(15), p.e2020GL087541.

From the Ground to Space: Using Solar-Induced Chlorophyll Fluorescence to Estimate Crop Productivity

Liyin He[1], Troy Magney[1,2], Debsunder Dutta[1,3], Yi Yin[1], Philipp Köhler[1], Katja Grossmann[4,5], Jochen Stutz[4], Christian Dold[6], Jerry Hatfield[6], Kaiyu Guan[7,8], Bin Peng[7,8], and Christian Frankenberg[1,9]

A look at crops!



For comparison, we have about 1600g/m^2 in the atmosphere

From the Ground to Space: Using Solar-Induced Chlorophyll Fluorescence to Estimate Crop Productivity

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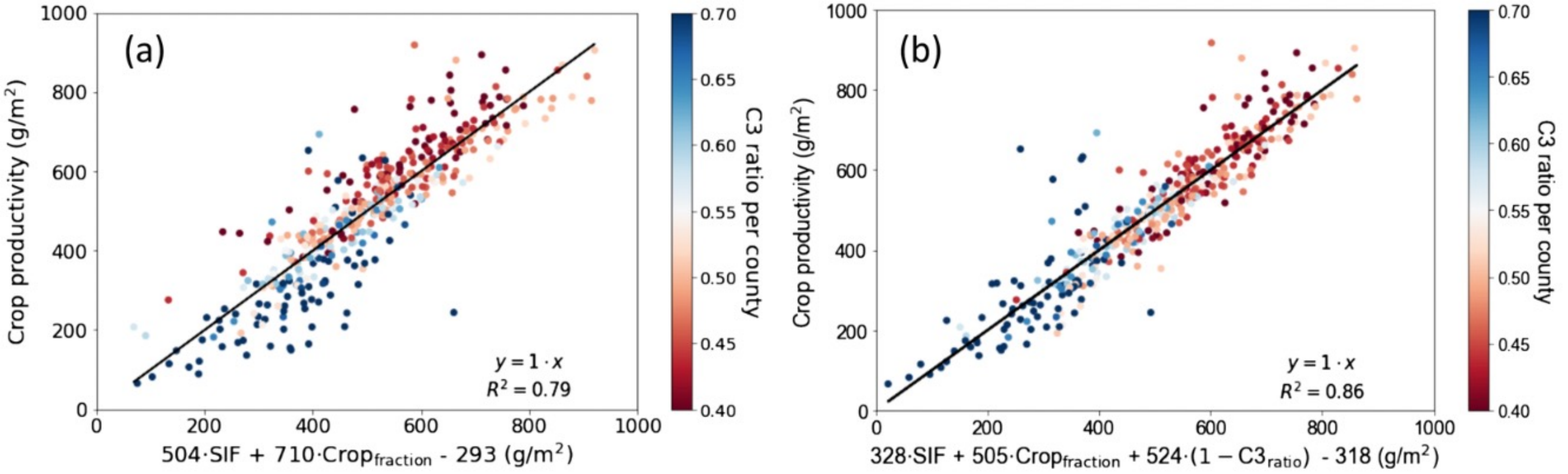
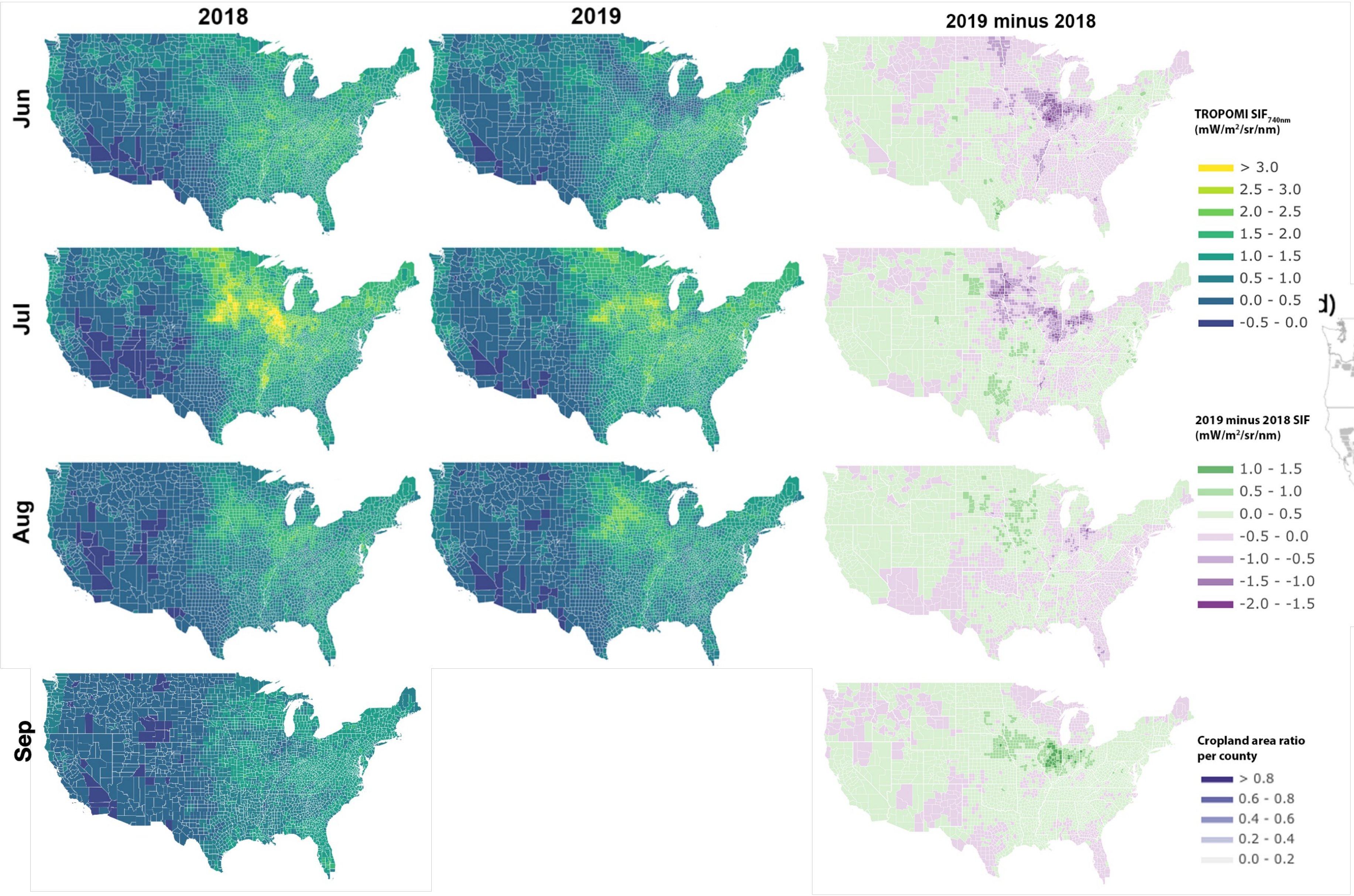
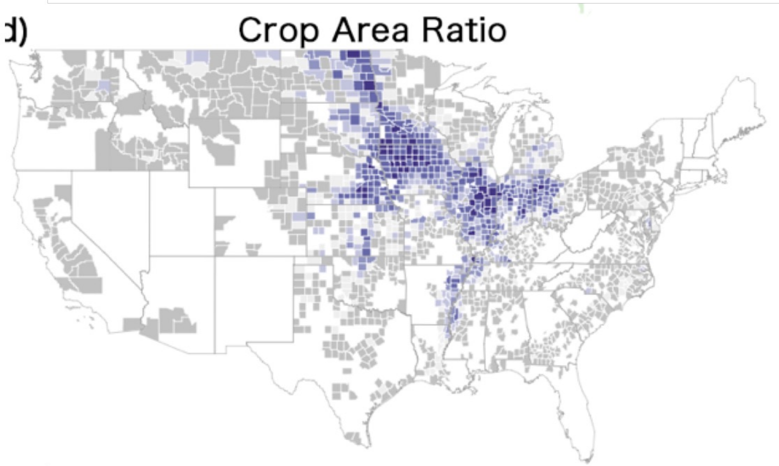






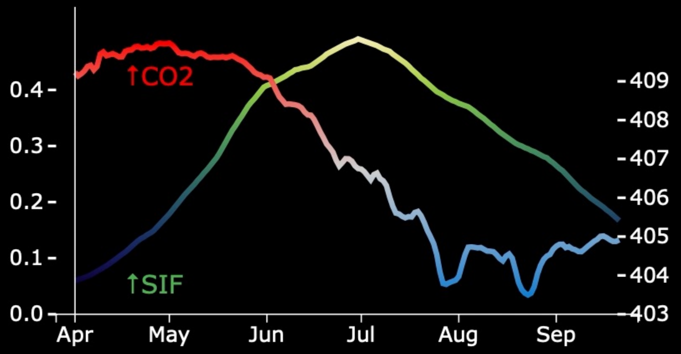
Yin, Byrne, Frankenberg et al, AGU Advances 2020

SIF and CO_2 Explorer

This animation highlights the seasonal variations in plant growth and in atmospheric CO2 concentrations. Plant growth is indicated by solar-induced chlorophyll fluorescence (SIF) and CO2 is simulated by a model.

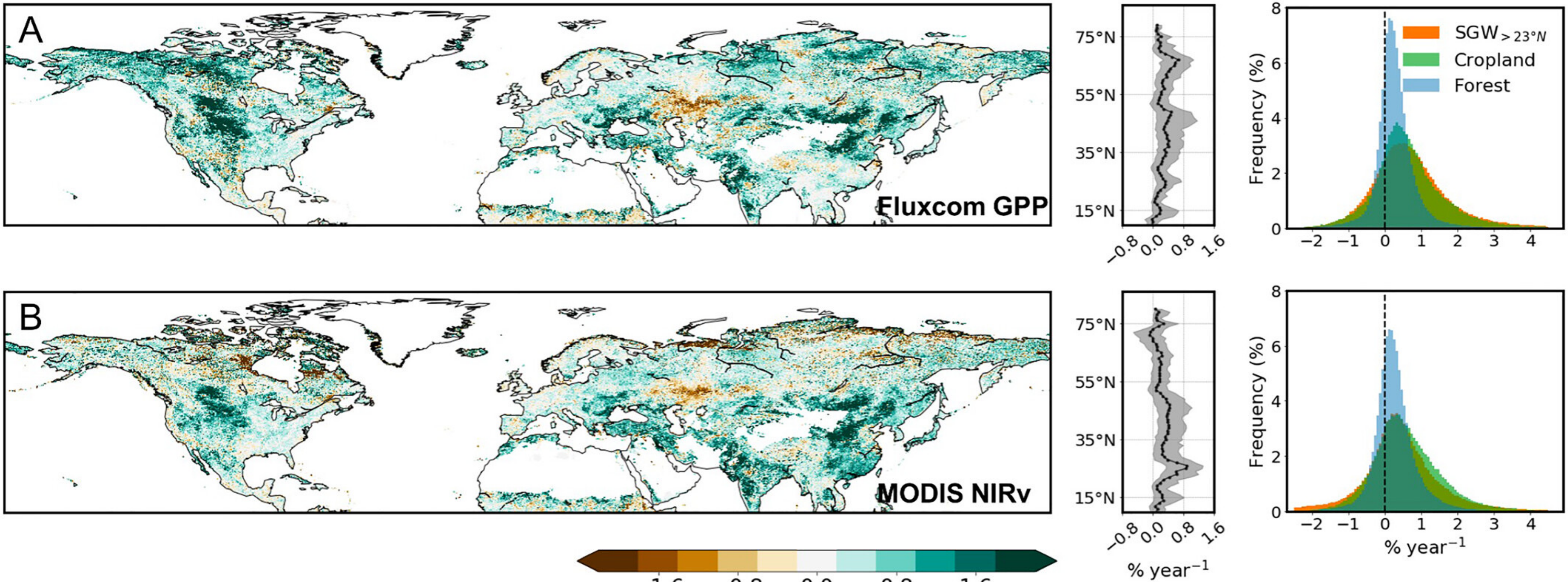
As spring starts, photosynthetic activity increases, drawing CO2 out of the atmosphere to make sugar molecules and hence reducing the atmospheric CO2 concentration -- most significantly near the surface.

SIF	Date	CO_2
0.06	4/1/2018	409.1



Remote-Sensing Derived Trends in Gross Primary Production Explain Increases in the CO_2 Seasonal Cycle Amplitude

Liyin He, Brendan Byrne, Yi Yin, Junjie Liu, Christian Frankenberg



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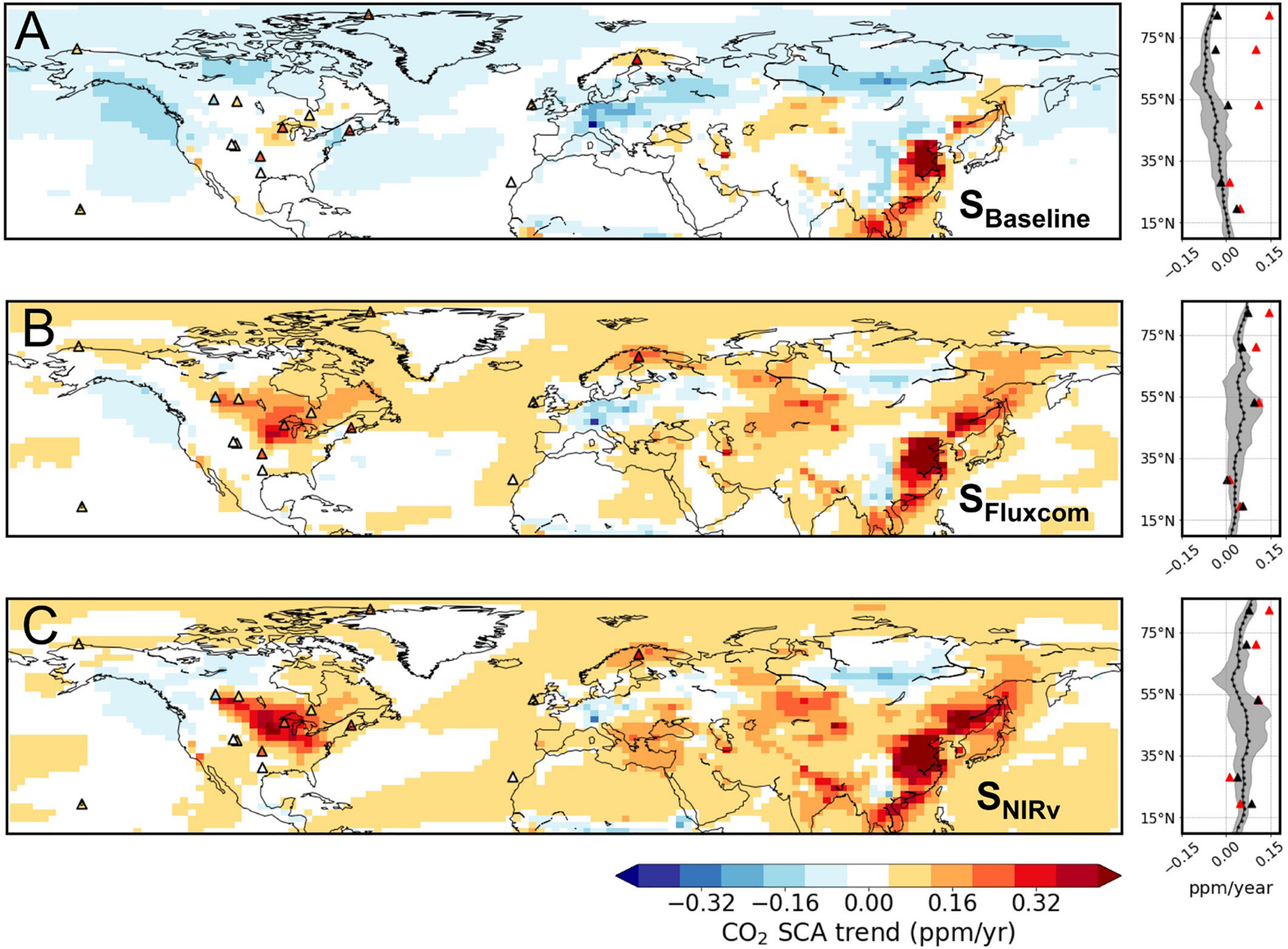
Liyin He

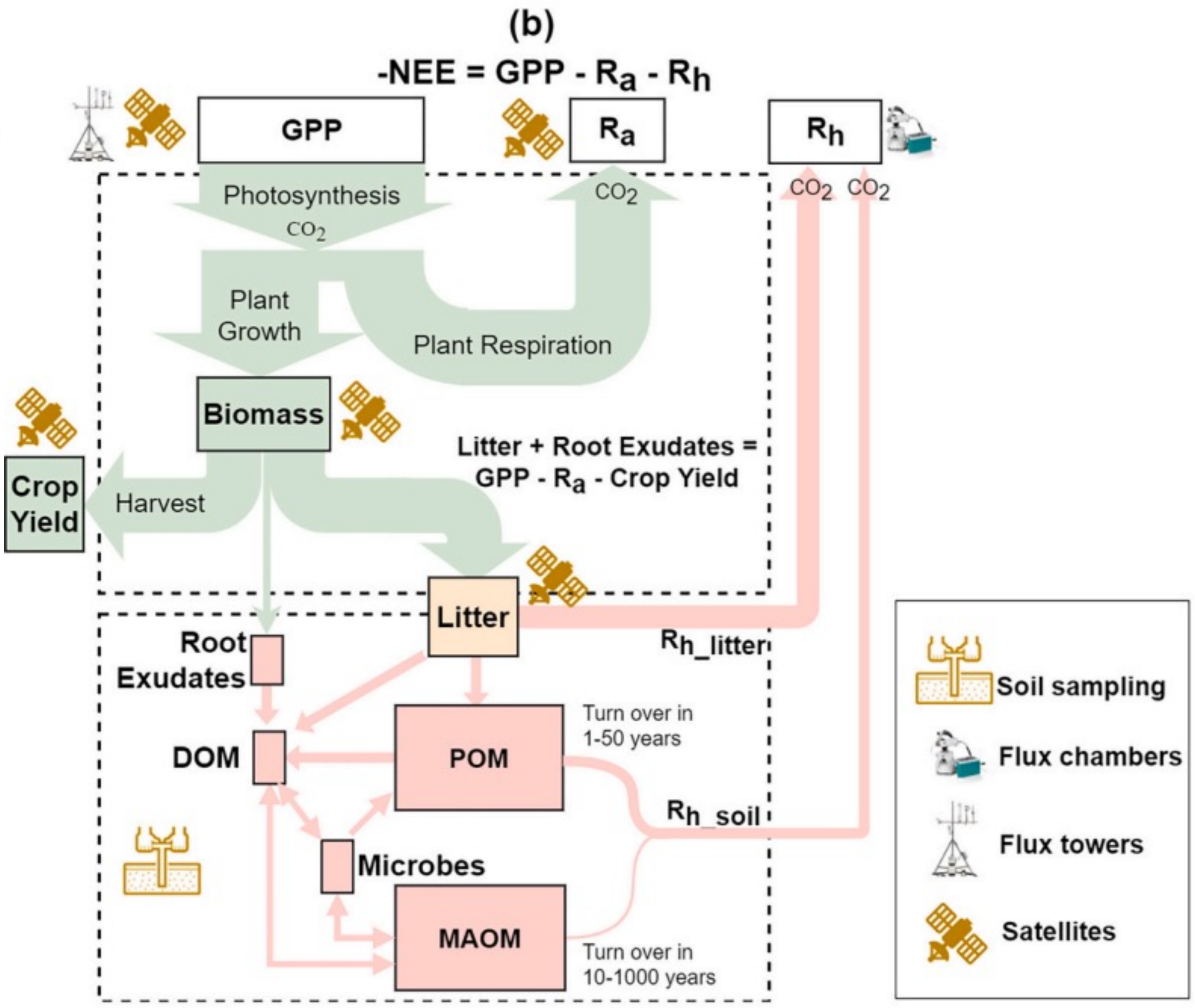


Crops are playing an increasingly important role in the global carbon cycle.

Where does the Carbon go?
How much stays in the soil?

A scalable framework for quantifying field-level agricultural carbon outcomes

Kaiyu Guan[a,b,c,1,*], Zhenong Jin[d,e,1,**], Bin Peng[a,b,*], Jinyun Tang[f,***], Evan H. DeLucia[a,g], Paul C. West[h,i], Chongya Jiang[a,b], Sheng Wang[a,b], Taegon Kim[d,j], Wang Zhou[a,b], Tim Griffis[k], Licheng Liu[d], Wendy H. Yang[a,g,l], Ziqi Qin[a,b], Qi Yang[d], Andrew Margenot[a,m], Emily R. Stuchiner[a], Vipin Kumar[n], Carl Bernacchi[a,o], Jonathan Coppess[p], Kimberly A. Novick[q], James Gerber[h], Molly Jahn[r], Madhu Khanna[p], DoKyoung Lee[a,m], Zhangliang Chen[a], Shang-Jen Yang[s]

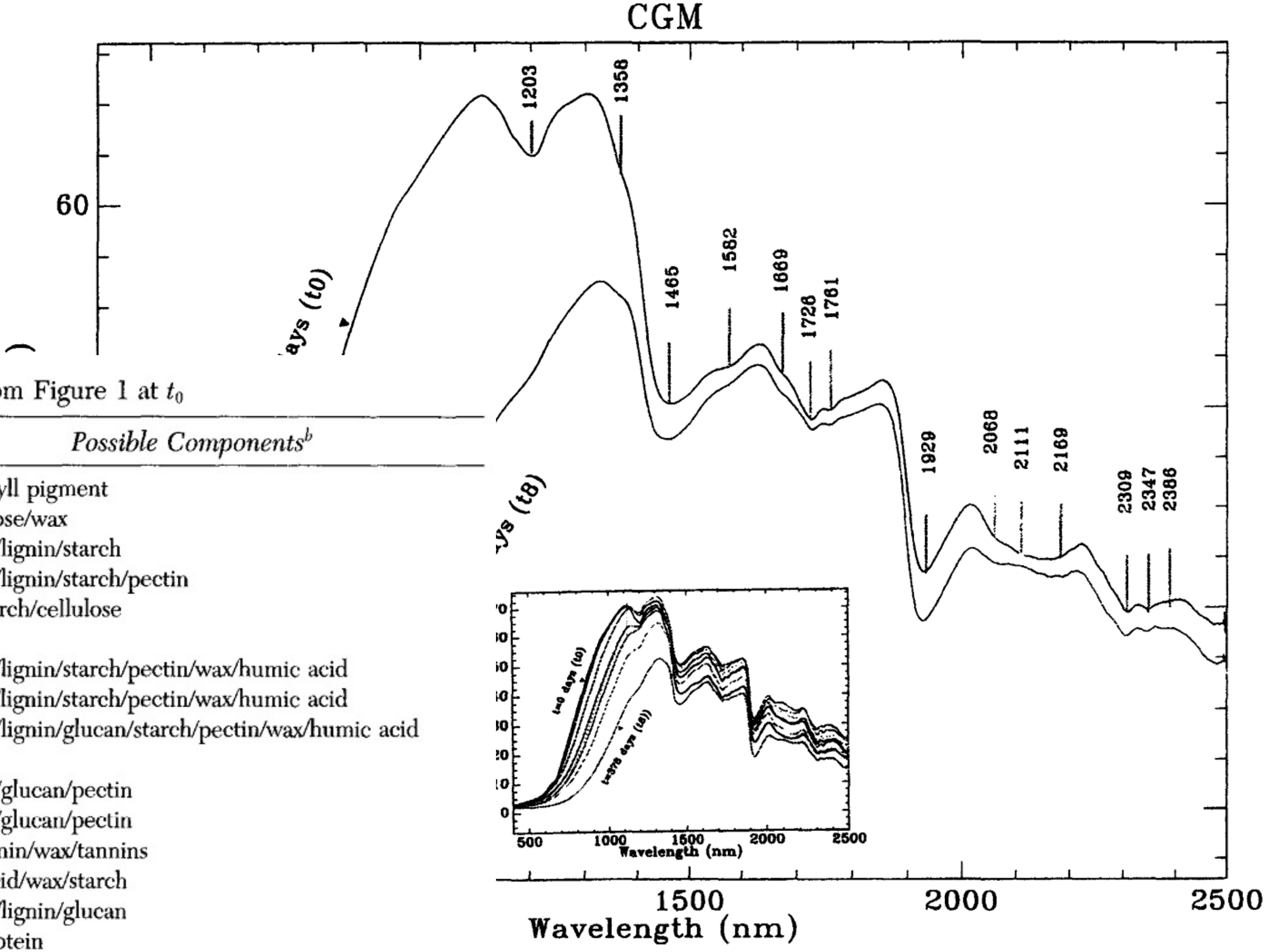


$$\Delta SOC = (\text{Input}) - (\text{Output})$$
$$= (\text{Litter} + \text{Root Exudates}) - (R_{h\_litter} + R_{h\_soil})$$
$$= (GPP - R_a - \text{Crop Yield}) - (R_h)$$
$$= -NEE - \text{Crop Yield}$$

The Reflectance Spectra of Organic Matter in the Visible Near-Infrared and Short Wave Infrared Region (400–2500 nm) during a Controlled Decomposition Process

E. Ben-Dor, Y. Inbar,† and Y. Chen‡*

RSE, 1997



at represent the two extreme composting stages t_0=0 days and t_8=378 days for the CGM.
ox shows the spectral of all intermediate decomposition stages.

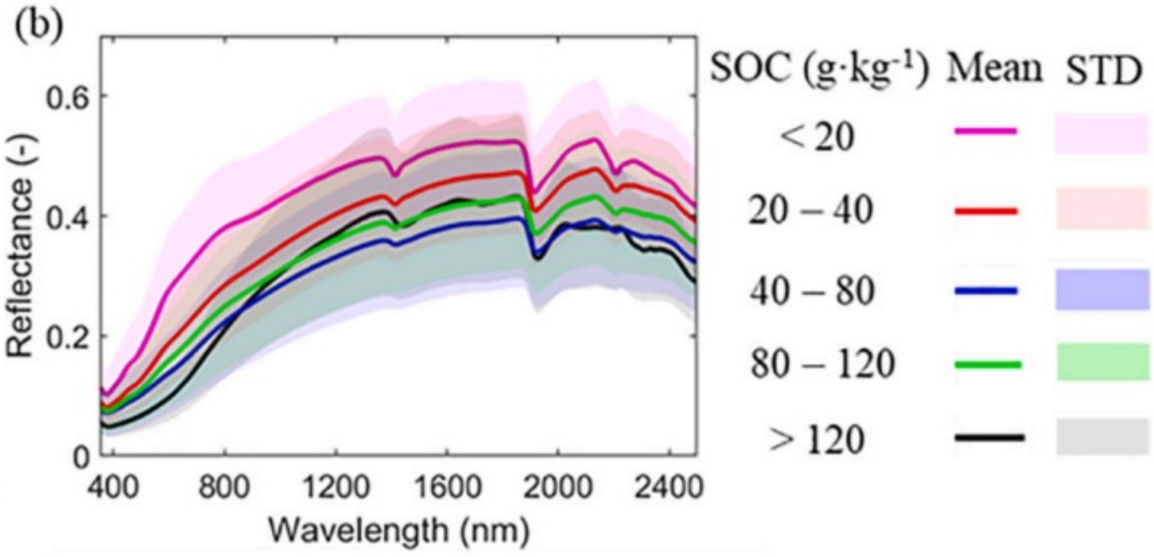
Table 2. Suggested CGM Assignments for the Major Absorption Features Extracted from Figure 1 at t_0

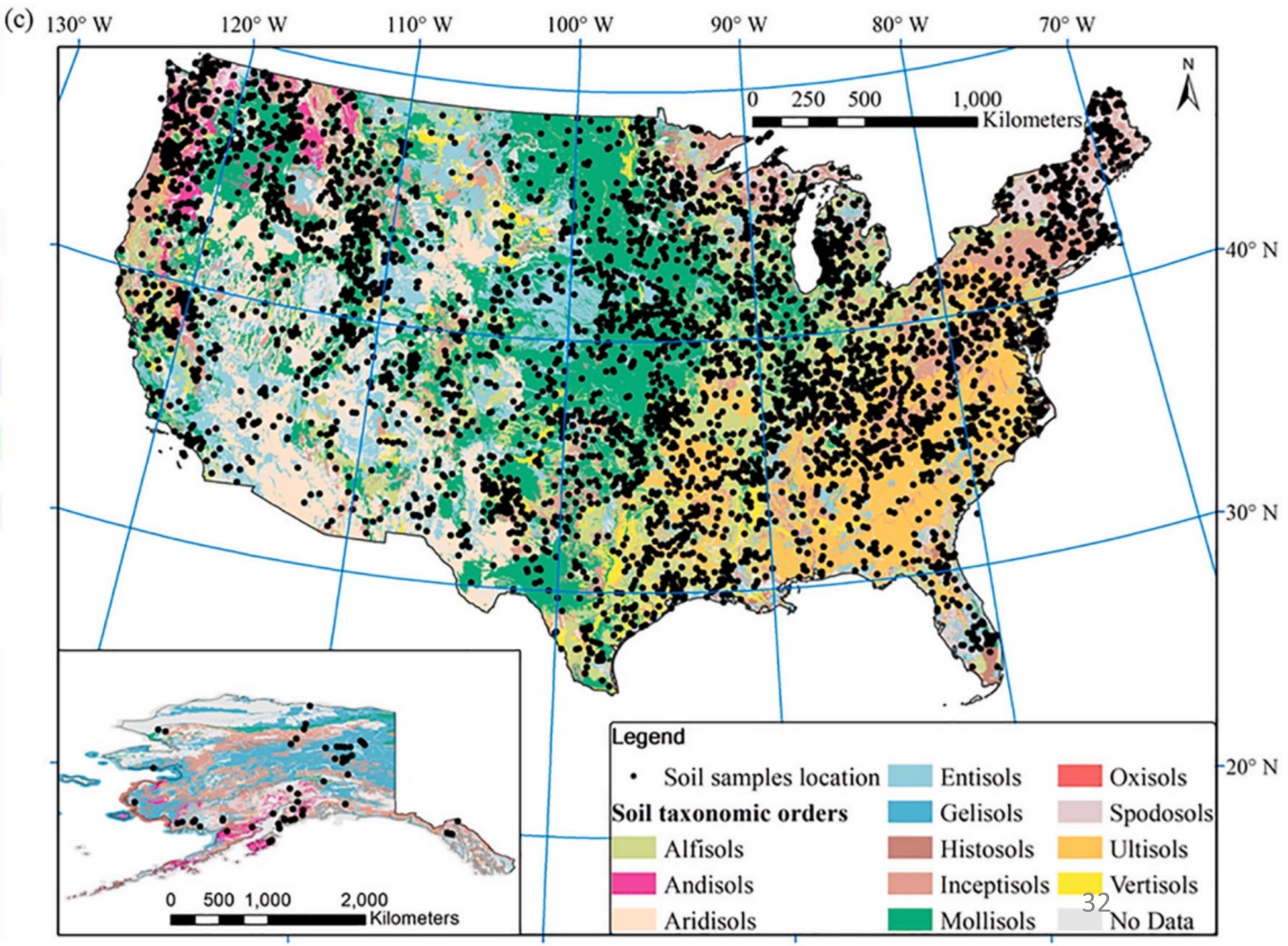
CGM Wavelength (nm)	*Assignments*[a]	*Possible Components*[b]
664		Chlorophyll pigment
1203		Oil/cellulose/wax
1358	OH in water	Cellulose/lignin/starch
1465	OH in water ($\upsilon_2 + \upsilon_3$); CH_2	Cellulose/lignin/starch/pectin
1582	OH in water (2υ); H-bonded OH group	Pectin/starch/cellulose
1669	2υ aromatic C—H stretch	
1726	2υ of aliphatic C—H stretch	Cellulose/lignin/starch/pectin/wax/humic acid
1761	2υ of aliphatic C—H stretch	Cellulose/lignin/starch/pectin/wax/humic acid
1929	OH in water ($\upsilon_1 + \upsilon_3$); 3υ of —C=O and of —COOH, C=O of ketonic carbonyl, $CONH_2$	Cellulose/lignin/glucan/starch/pectin/wax/humic acid
2068	3υ of aromatic C=C, COO—hydrogen bond, C=O	Cellulose/glucan/pectin
2111	3υ of aromatic C=C, COO—hydrogen bond, C=O	Cellulose/glucan/pectin
2169	3υ of aromatic C=C	Starch/lignin/wax/tannins
2309	3υ of aliphatic C—H, aromatic ring stretch	Humic acid/wax/starch
2347	3υ of aliphatic C—H	Cellulose/lignin/glucan
2386	3υ of COO—, CH_3	Pectin/protein

[a] Calculated from well-assigned IR features of the exact population.
[b] Taken from Elvidge (1990), Curran et al. (1992), and McLellan (1991a,b).

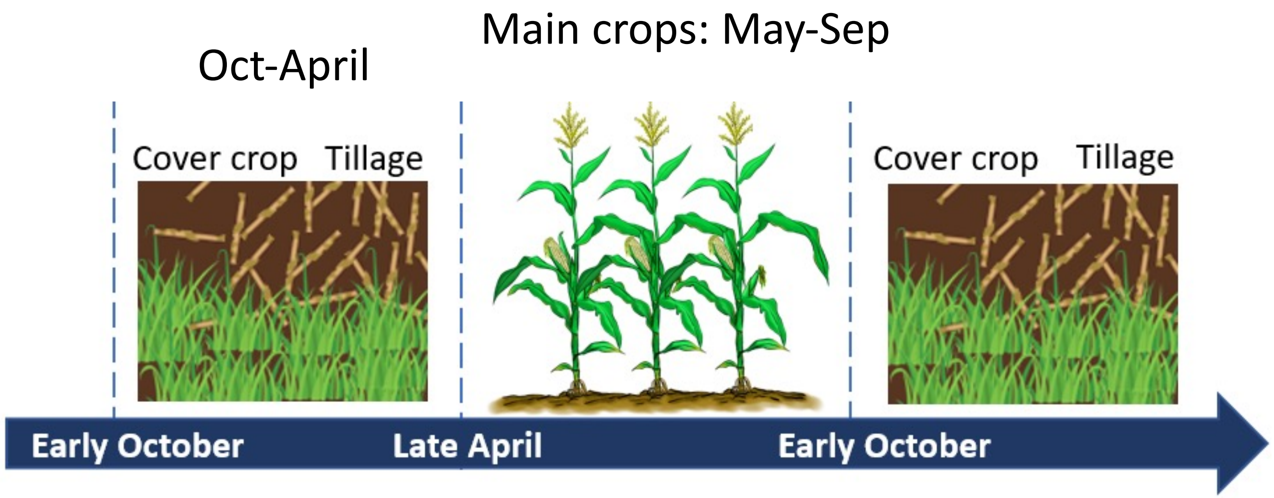
Using soil library hyperspectral reflectance and machine learning to predict soil organic carbon: Assessing potential of airborne and spaceborne optical soil sensing

Sheng Wang [a,b,*], Kaiyu Guan [a,b,c,d,*], Chenhui Zhang [a,c,d], DoKyoung Lee [a,b], Andrew J. Margenot [a,b], Yufeng Ge [e], Jian Peng [c,d], Wang Zhou [a,b], Qu Zhou [a,b], Yizhi Huang [d]



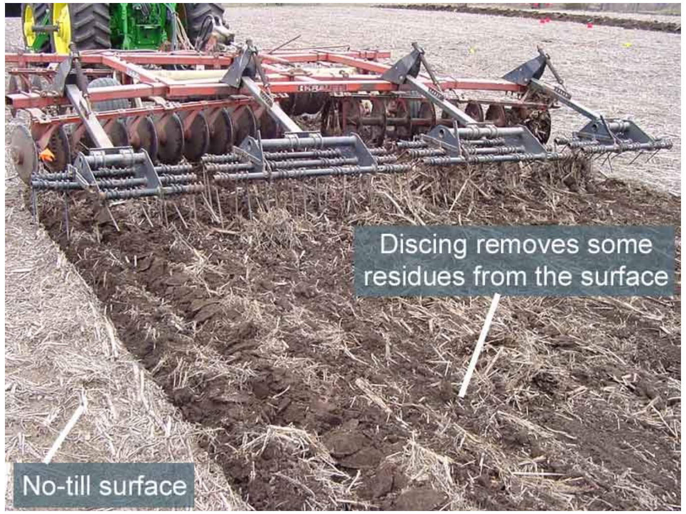


Remote sensing applications for agroecosystem monitoring



Application 1: Soil organic carbon

Application 2: Tillage practices

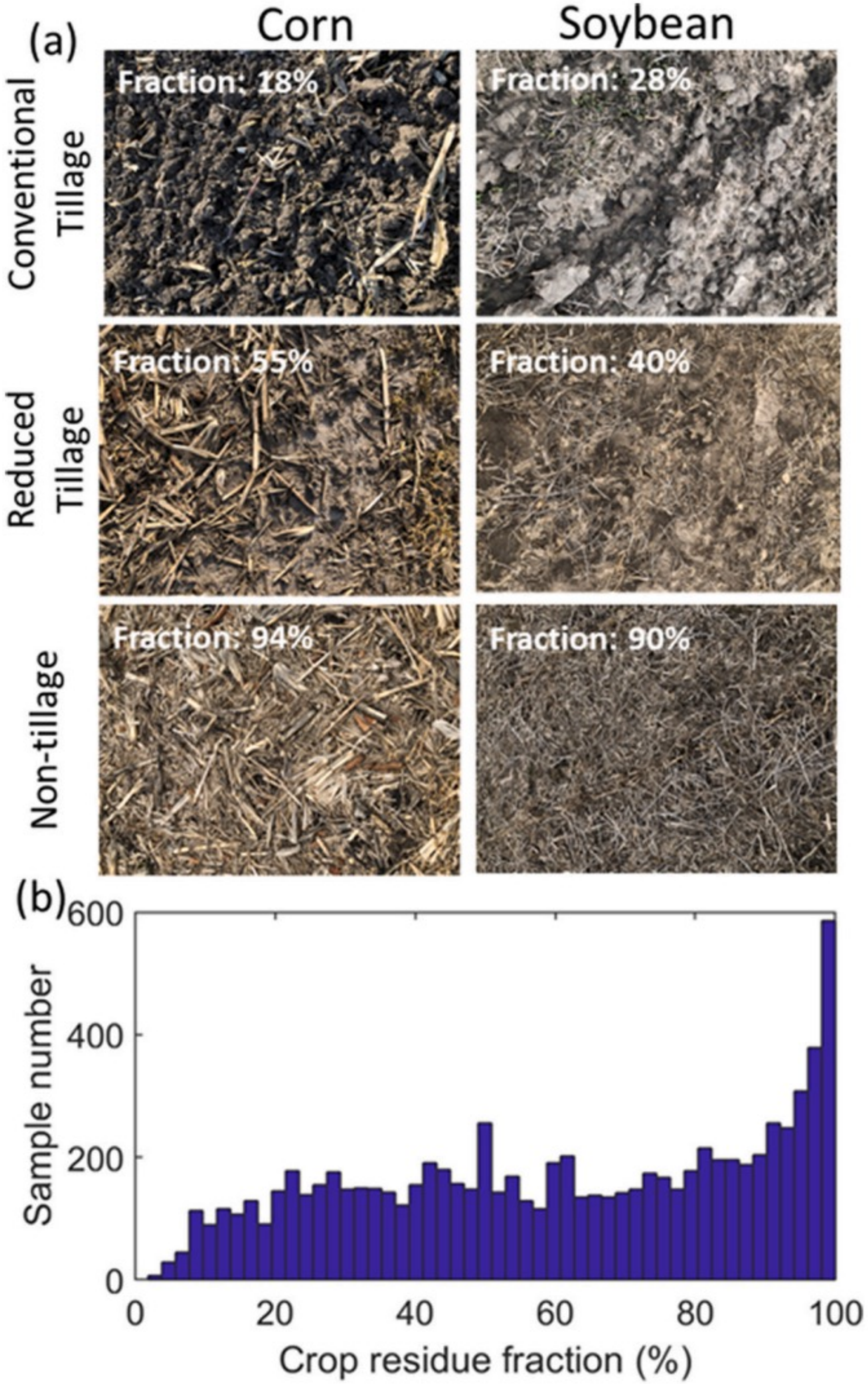


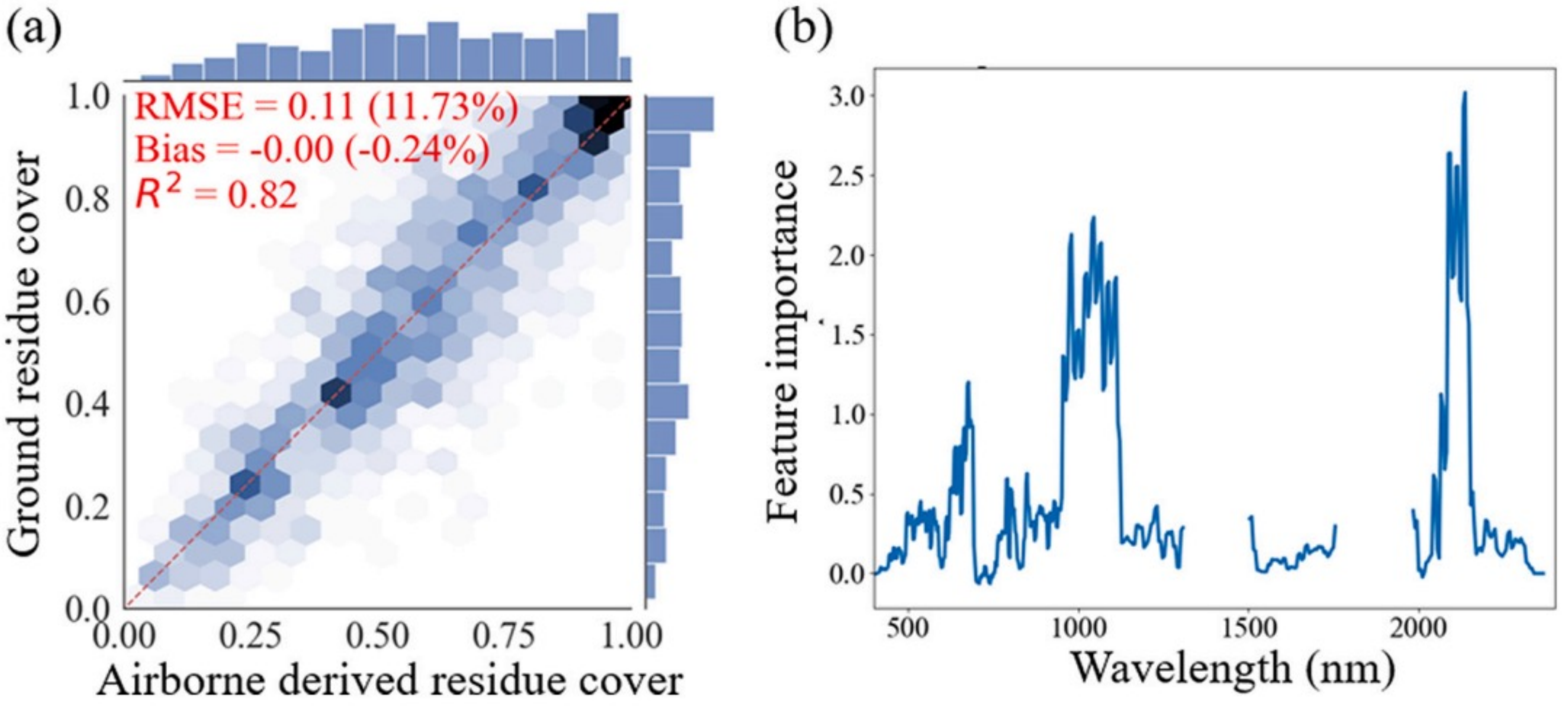
Application 3: Cover crop

Application 4: Crop characteristics

Cross-scale sensing of field-level crop residue cover: Integrating field photos, airborne hyperspectral imaging, and satellite data

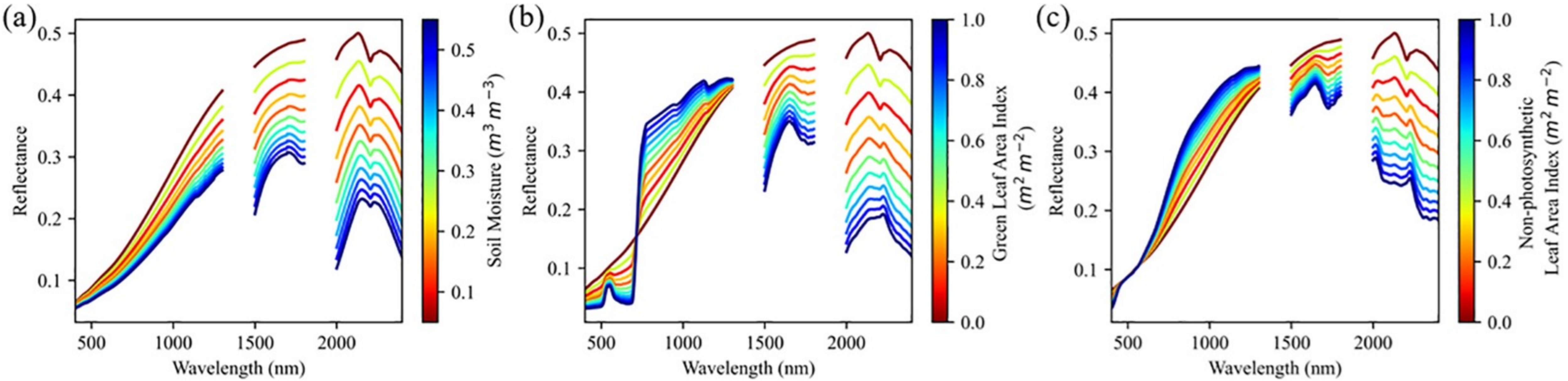
Sheng Wang [a,b,*], Kaiyu Guan [a,b,c,d,*], Chenhui Zhang [a,c,d], Qu Zhou [a,b], Sibo Wang [c], Xiaocui Wu [a,b], Chongya Jiang [a,b], Bin Peng [a,b,c], Weiye Mei [a,b], Kaiyuan Li [a,b], Ziyi Li [a,b], Yi Yang [a,b], Wang Zhou [a,b], Yizhi Huang [d], Zewei Ma [a,b]





Quantify topsoil organic carbon concentration from multi-scale sensing data

Soil moisture | Green vegetation | Crop residue



Wang et al. 2022. Using soil library hyperspectral reflectance and machine learning to predict soil organic carbon: assessing potential of airborne and spaceborne optical soil sensing. *Remote Sensing of Environment*. 271, p.112914.

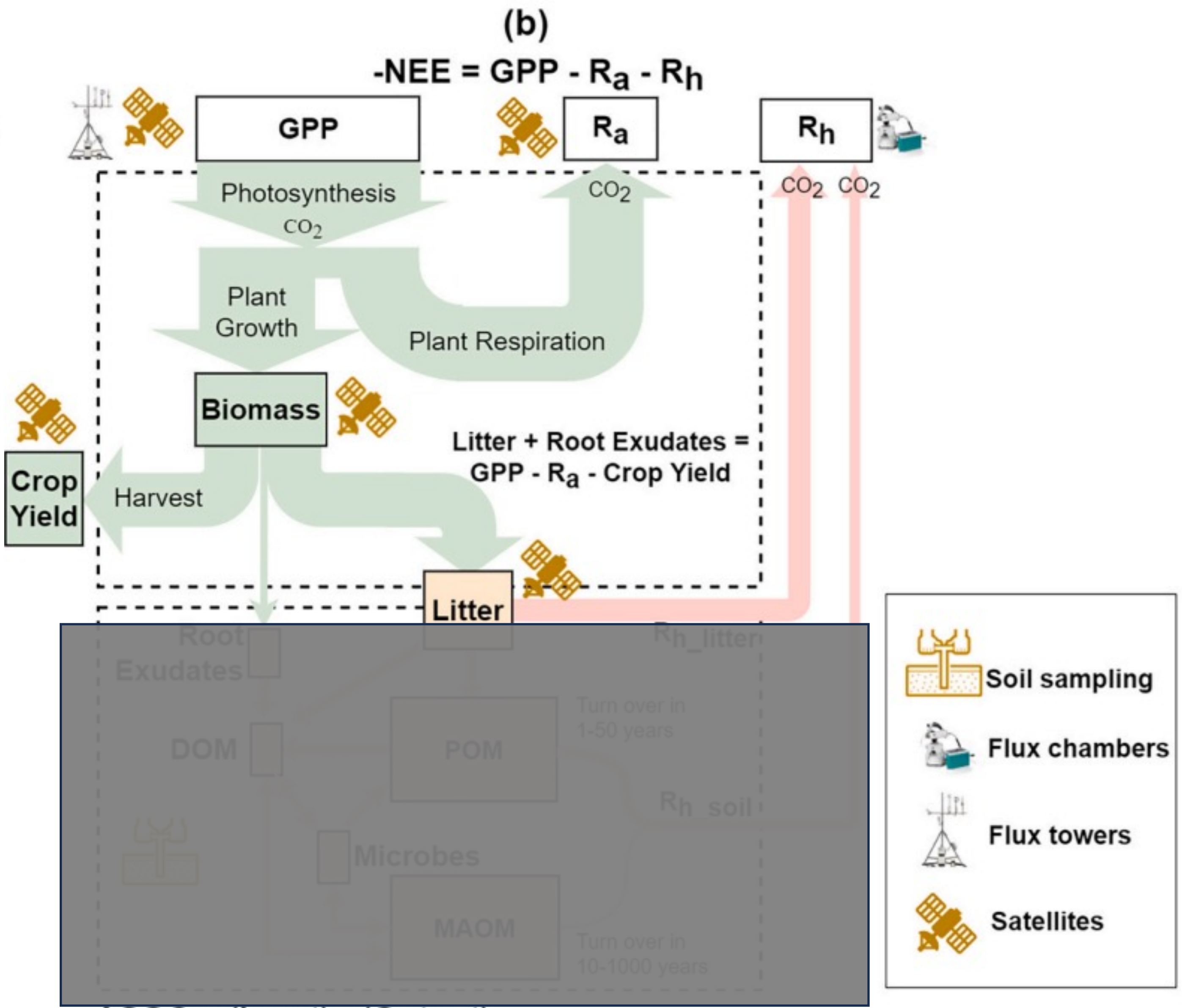
A scalable framework for quantifying field-level agricultural carbon outcomes

Kaiyu Guan[a,b,c,1,*], Zhenong Jin[d,e,1,**], Bin Peng[a,b,*], Jinyun Tang[f,***], Evan H. DeLucia[a,g], Paul C. West[h,i], Chongya Jiang[a,b], Sheng Wang[a,b], Taegon Kim[d,j], Wang Zhou[a,b], Tim Griffis[k], Licheng Liu[d], Wendy H. Yang[a,g,l], Ziqi Qin[a,b], Qi Yang[d], Andrew Margenot[a,m], Emily R. Stuchiner[a], Vipin Kumar[n], Carl Bernacchi[a,o], Jonathan Coppess[p], Kimberly A. Novick[q], James Gerber[h], Molly Jahn[r], Madhu Khanna[p], DoKyoung Lee[a,m], Zhangliang Chen[a], Shang-Jen Yang[s]

The challenge

Remote sensing is "blind" to the subsurface

How to relate what we can observe to total carbon storage?



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The challenge

- Spatial variation within any given field can be larger than year-to-year changes in SOC
- As a result, soil sampling is infeasible as a short-term (i.e. annual) quantification method but is well positioned to set the SOC baseline or periodic verification (after 5+ years) of practice changes
- Remote sensing techniques (particularly hyperspectral) have shown potential to monitor SOC, **but**:
  - RS only detects soil carbon at the surface, **not the the soil profile to full depth** (for H_2O, we have GRACE, there is no equivalent for SOC)
  - crop residues, green vegetation cover, and soil moisture have a **confounding impact** on spectral signals