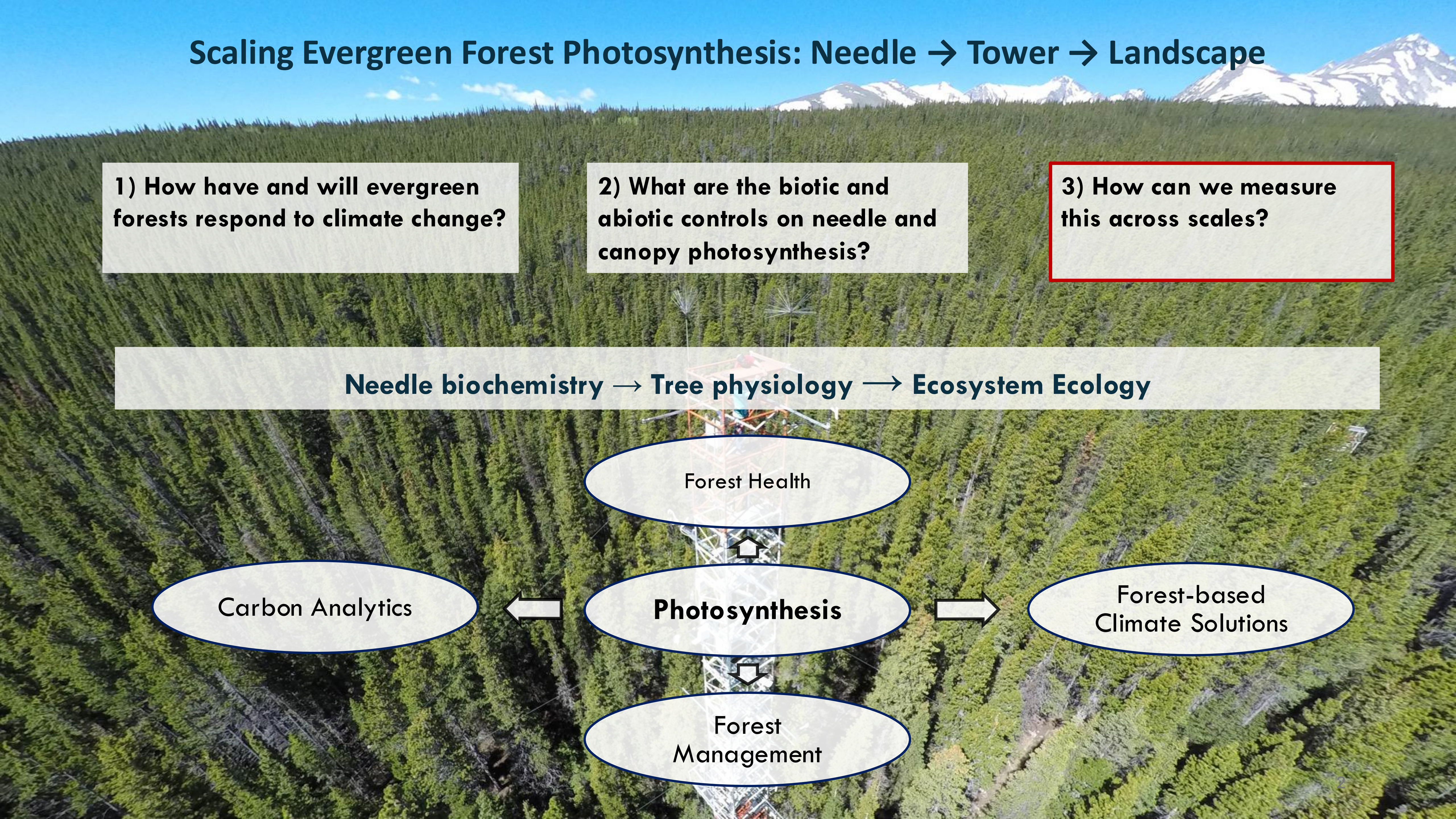
Scaling Evergreen Forest Photosynthesis: Needle → Tower → Landscape

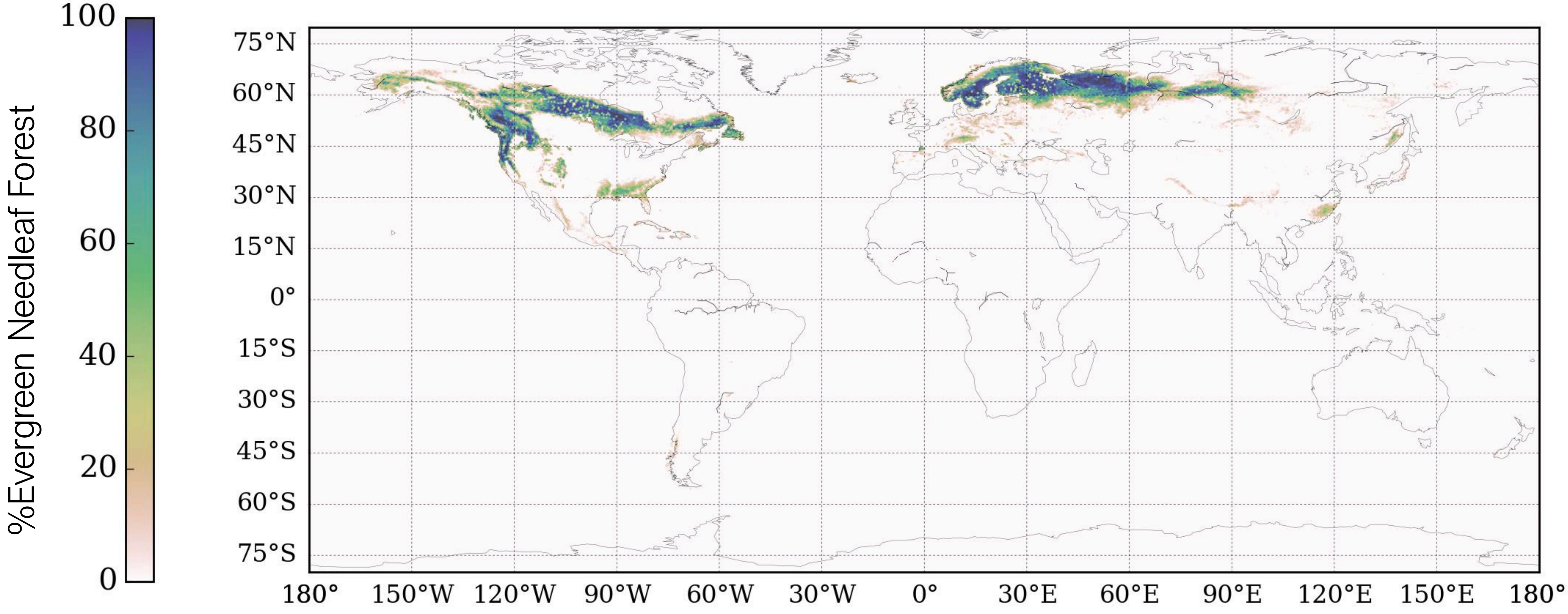
FLUXNET Workshop | Lawrence Berkeley National Lab | 9 July 2024

Troy Magney, Zoe Pierrat

Collaborators: Dave Bowling, Rui Cheng, Barry Logan, Christian Frankenberg, Jochen Stutz, Katja Grossmann, Jaret Reblin, Andrew Maguire


Scaling Evergreen Forest Photosynthesis: Needle → Tower → Landscape
1) How have and will evergreen forests respond to climate change?
2) What are the biotic and abiotic controls on needle and canopy photosynthesis?
3) How can we measure this across scales?
Needle biochemistry → Tree physiology → Ecosystem Ecology
Forest Health
Carbon Analytics
Photosynthesis
Forest-based Climate Solutions
Forest Management

Evergreen Needleleaf Forests (ENF) are widespread, provide critical ecosystem services, and play a major role in the global carbon cycle

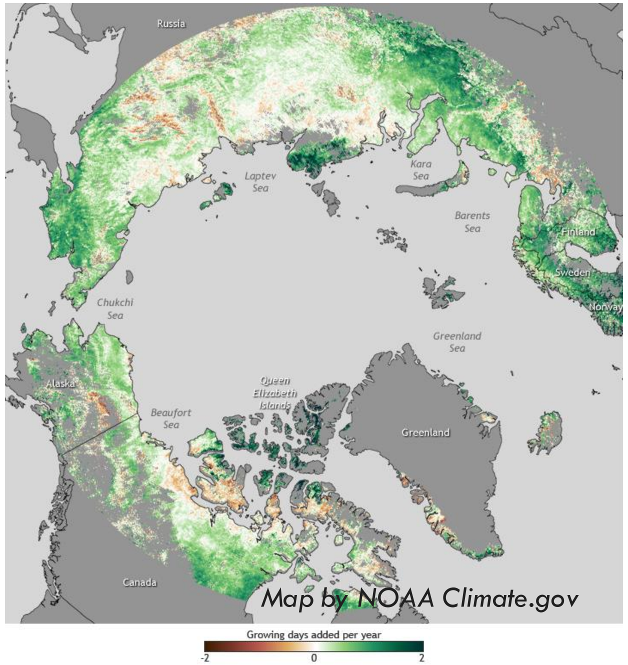


The impacts of anthropogenic climate change have made the fate of ENF highly uncertain

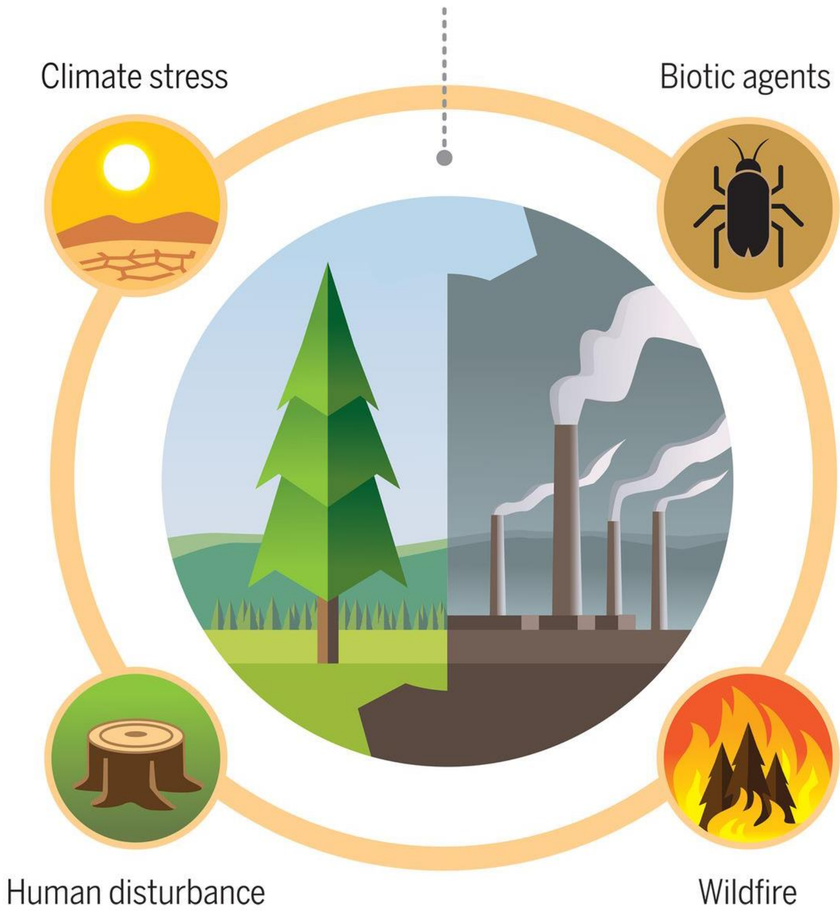
Widespread greening

From Cindy Star/NASA's Goddard Space Flight Center

Longer growing seasons



A myriad of climate related threats



Anderegg et al. 2020, Science

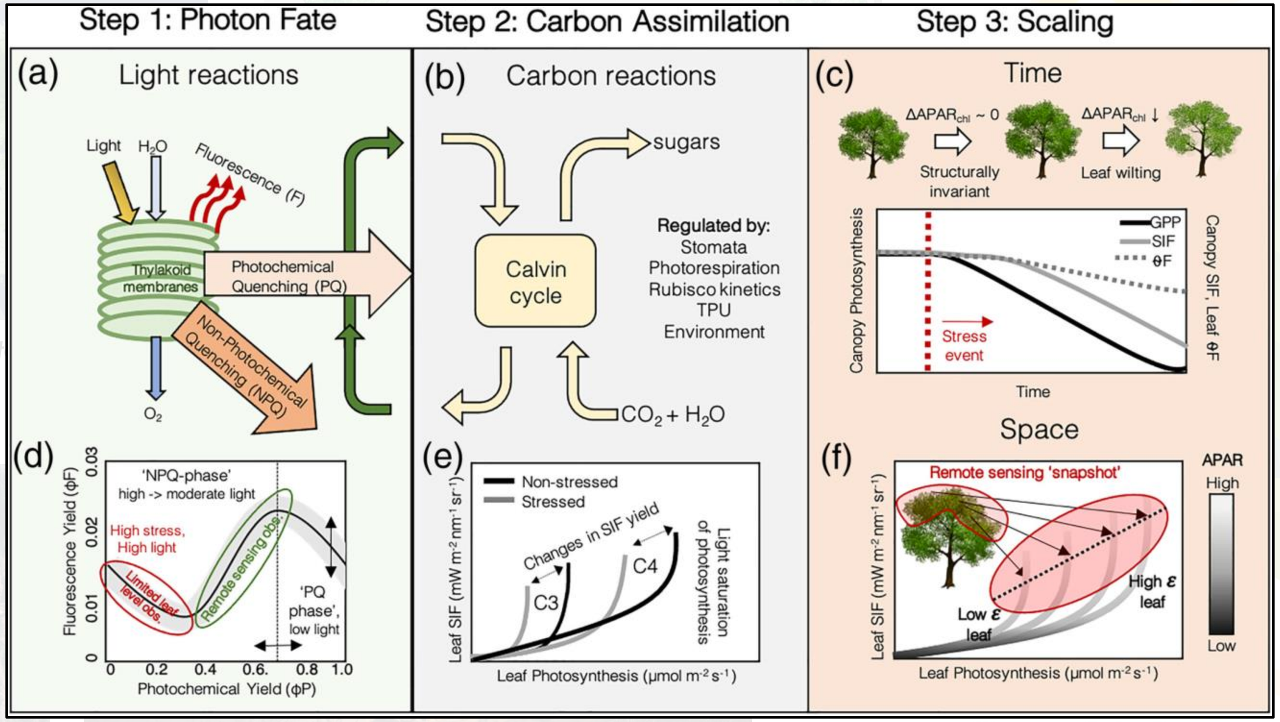
Insects and disease

Fire

Photosynthesis (the timing and magnitude of CO_2 uptake) plays a central role.

But it's challenging to measure across scales

And requires a nuanced understanding of the light and carbon reactions of photosynthesis



Geophysical Research Letters

COMMENTARY
10.1029/2020GL091098

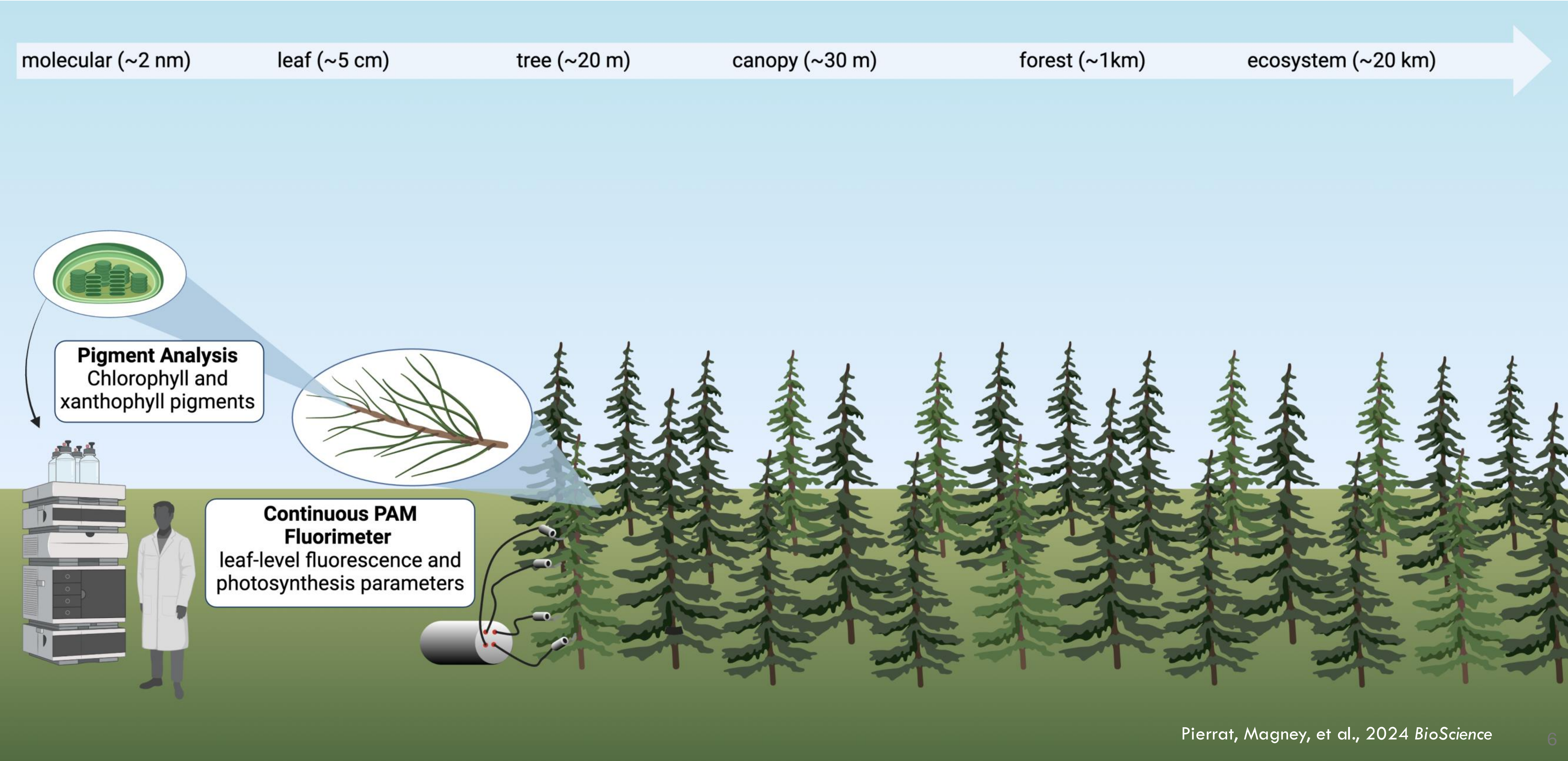
On the Covariation of Chlorophyll Fluorescence and Photosynthesis Across Scales

Troy S. Magney[1], Mallory L. Barnes[2], and Xi Yang[3]

Key Points:

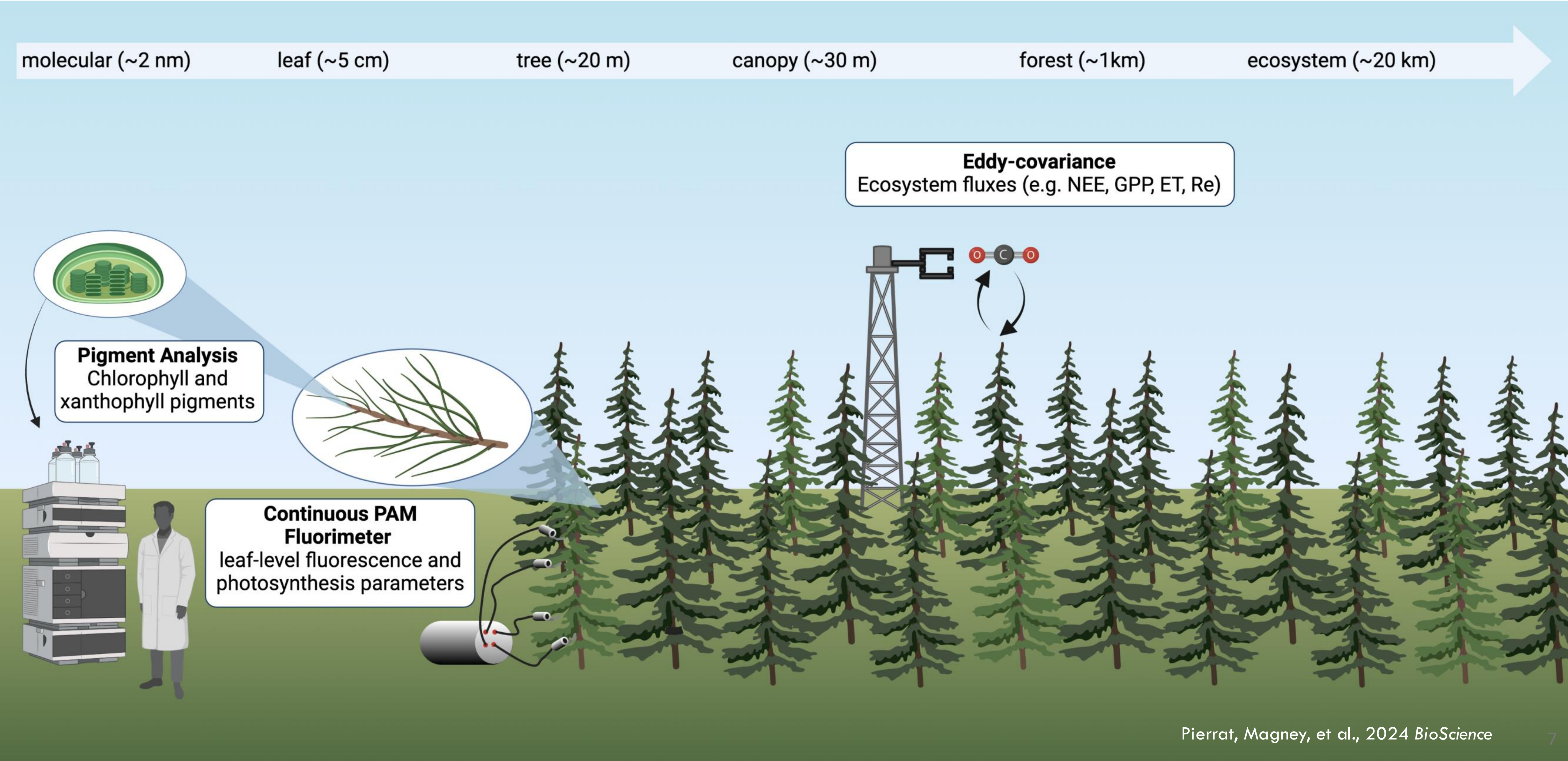
- Solar-induced fluorescence (SIF) is

At the leaf/needle scale we can quantify ENF photosynthetic parameters using pigment analysis, PAM fluorimetry, and gas-exchange



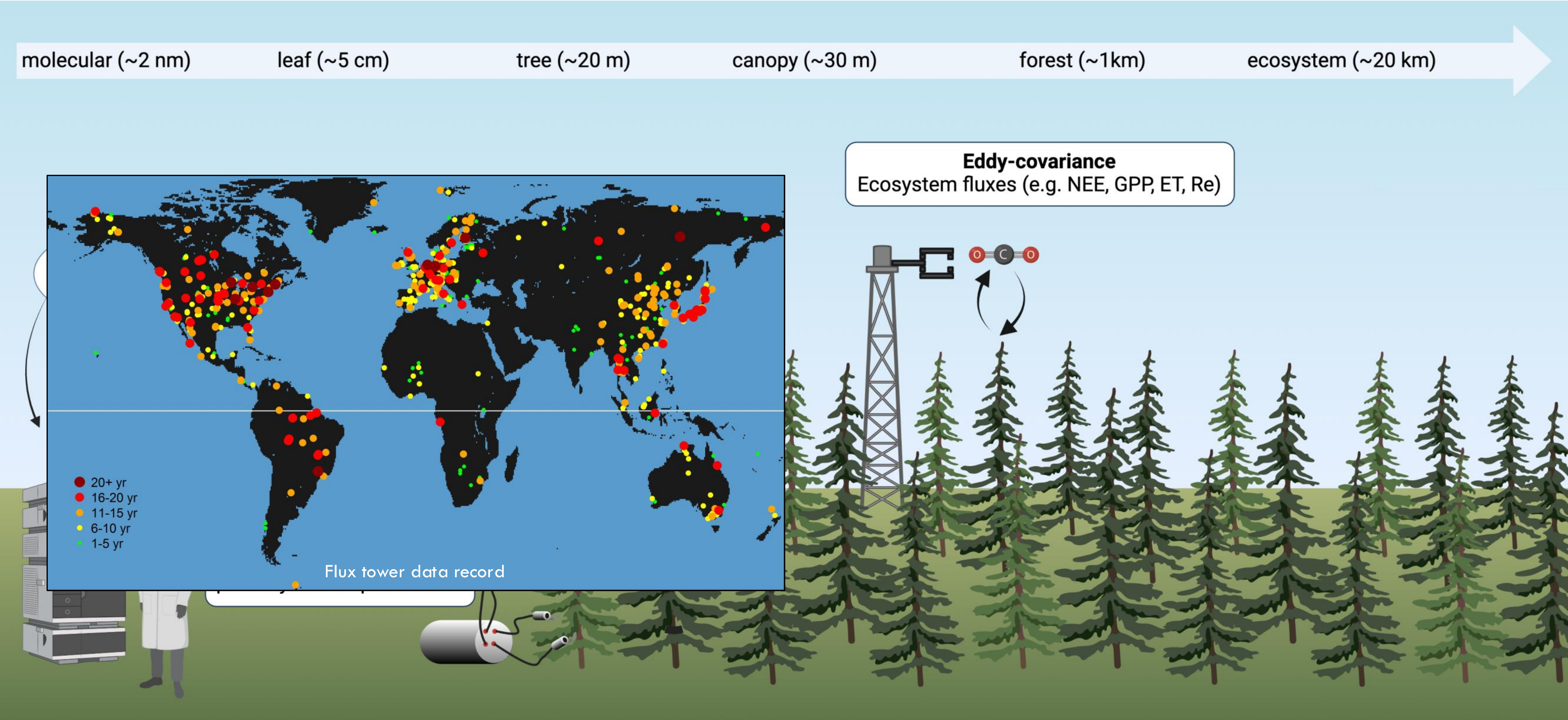
Pierrat, Magney, et al., 2024 *BioScience*

At the site/canopy-level we can use the eddy-covariance technique to derive gross-primary production (GPP)



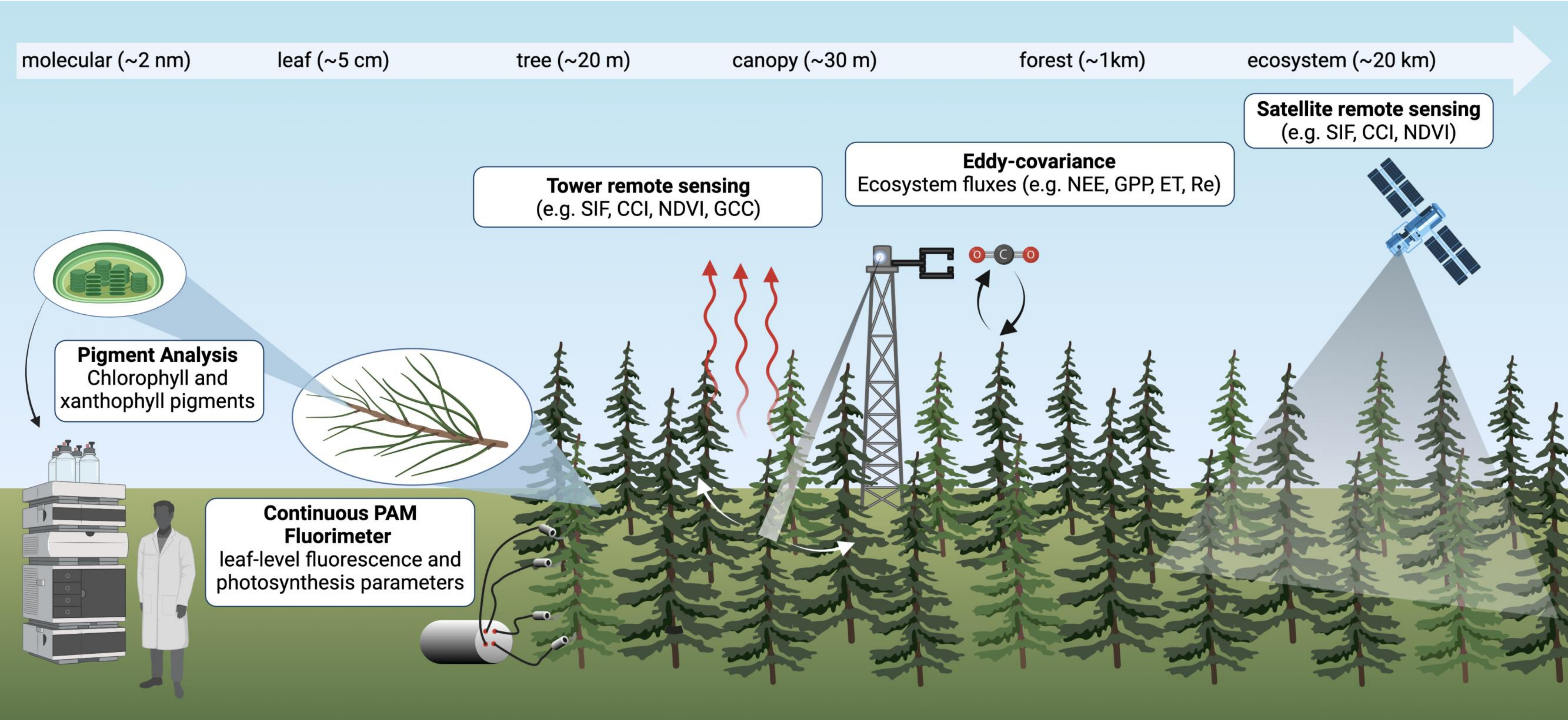
Pierrat, Magney, et al., 2024 *BioScience*

Site-level and flux tower observations are great….
but only optics can allow us to scale across space and time



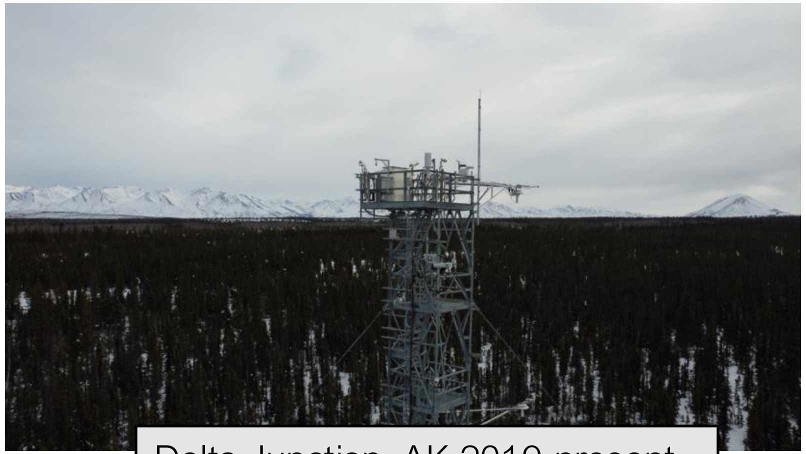
Pierrat, Magney, et al., 2024 *BioScience*

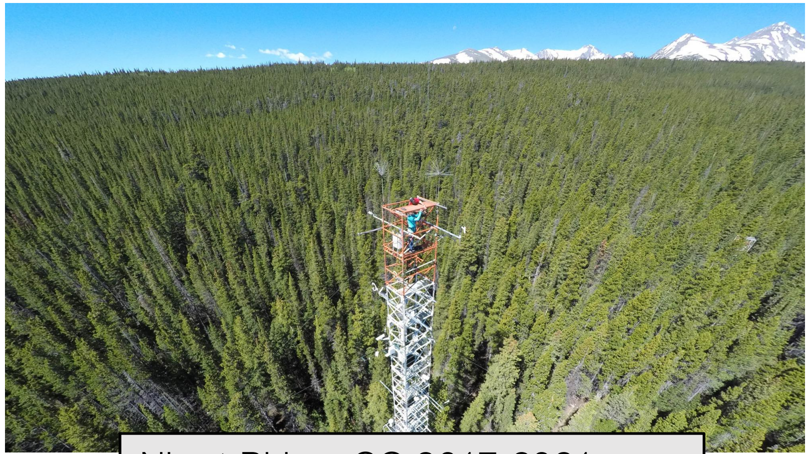
Tower and satellite-based optical metrics that are sensitive to underlying biology are an essential tool for understanding ENF



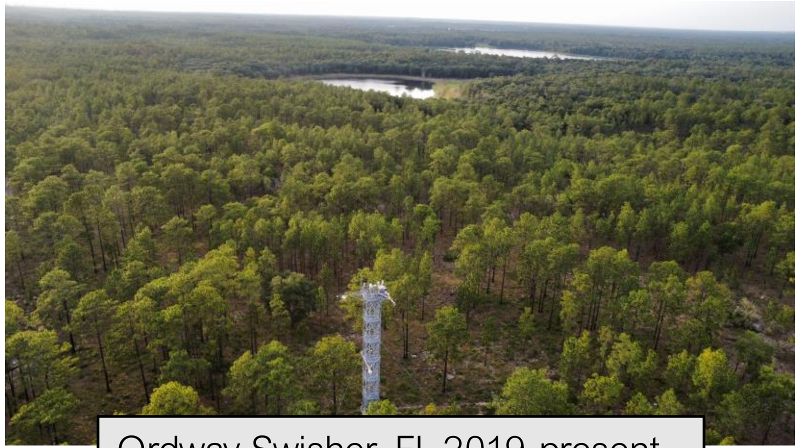
Pierrat, Magney, et al., 2024 *BioScience*

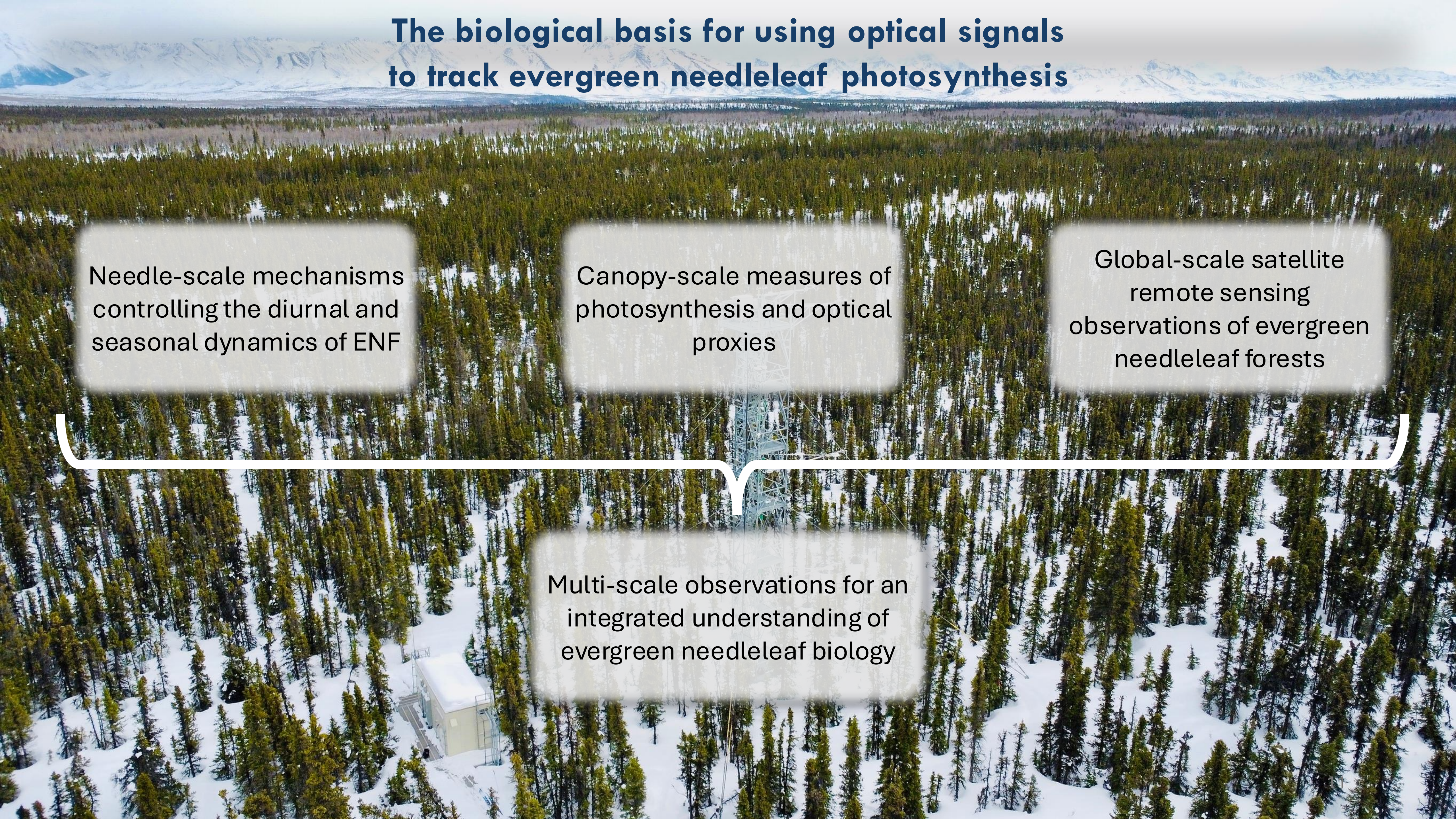
We can test this approach across ENF forests by collecting multi-scale data across a latitudinal gradient

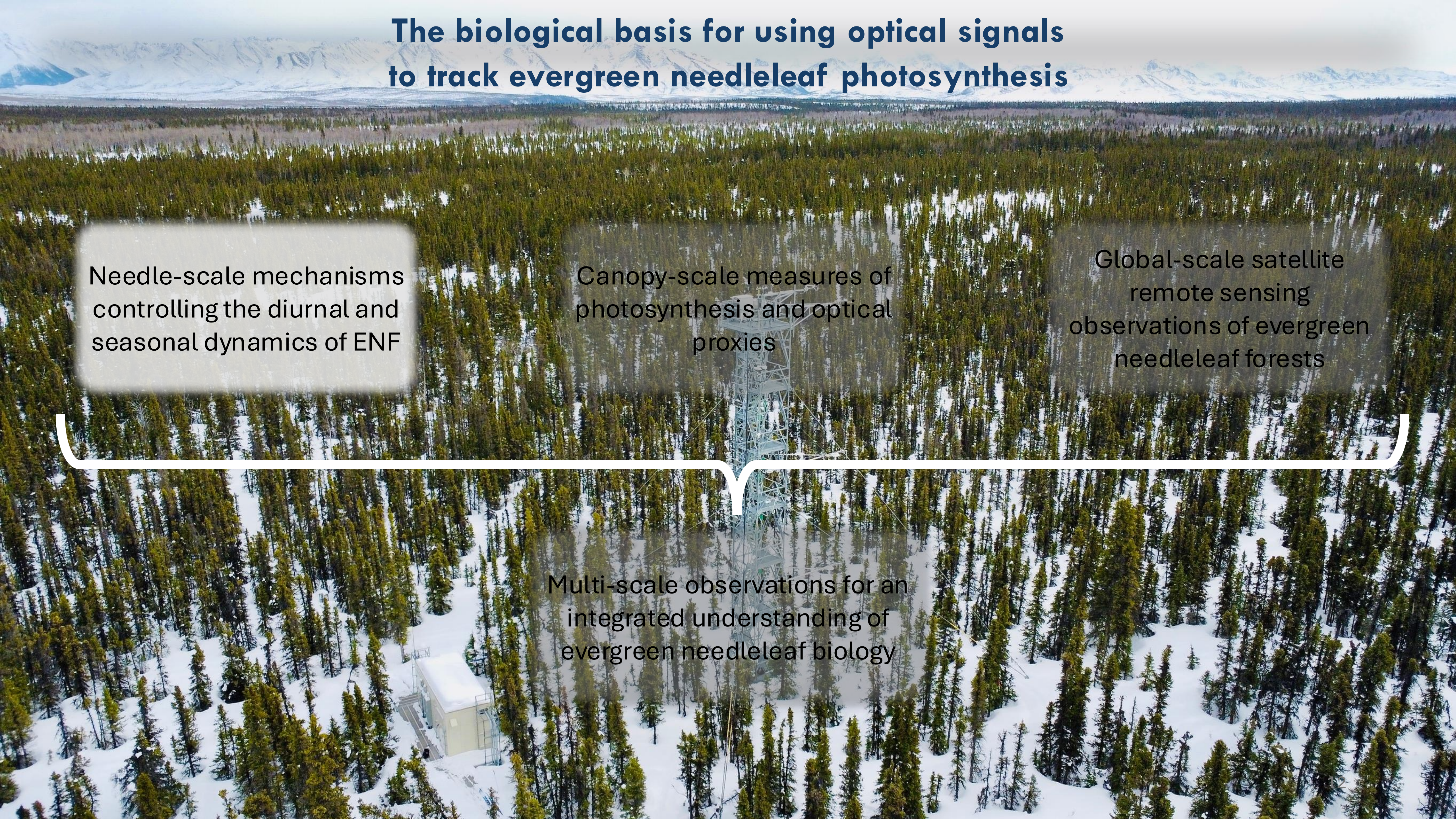

Delta Junction, AK 2019-present


Niwot Ridge, CO 2017-2021

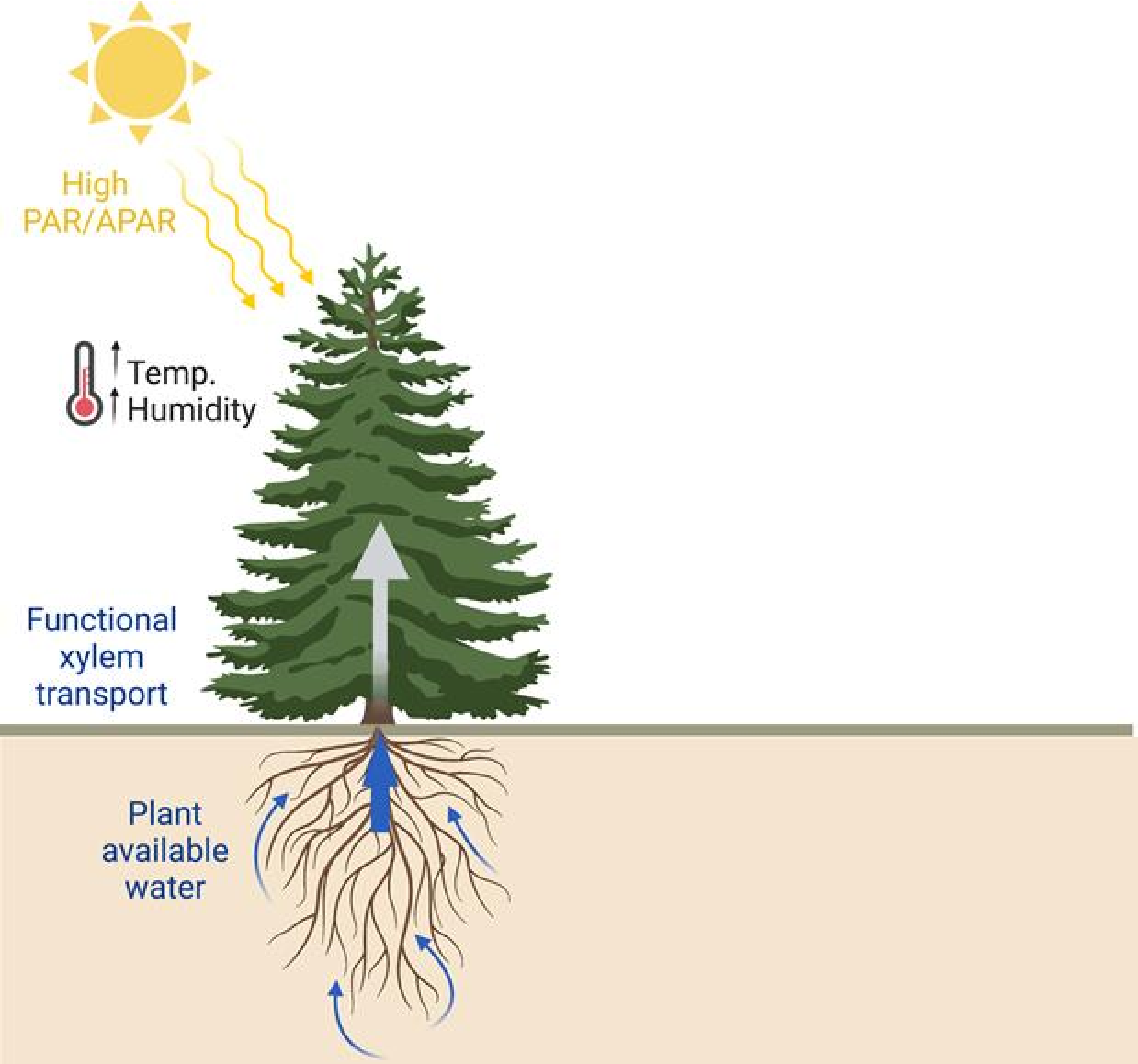

Old Black Spruce, Sask. 2018-present


Ordway Swisher, FL 2019-present

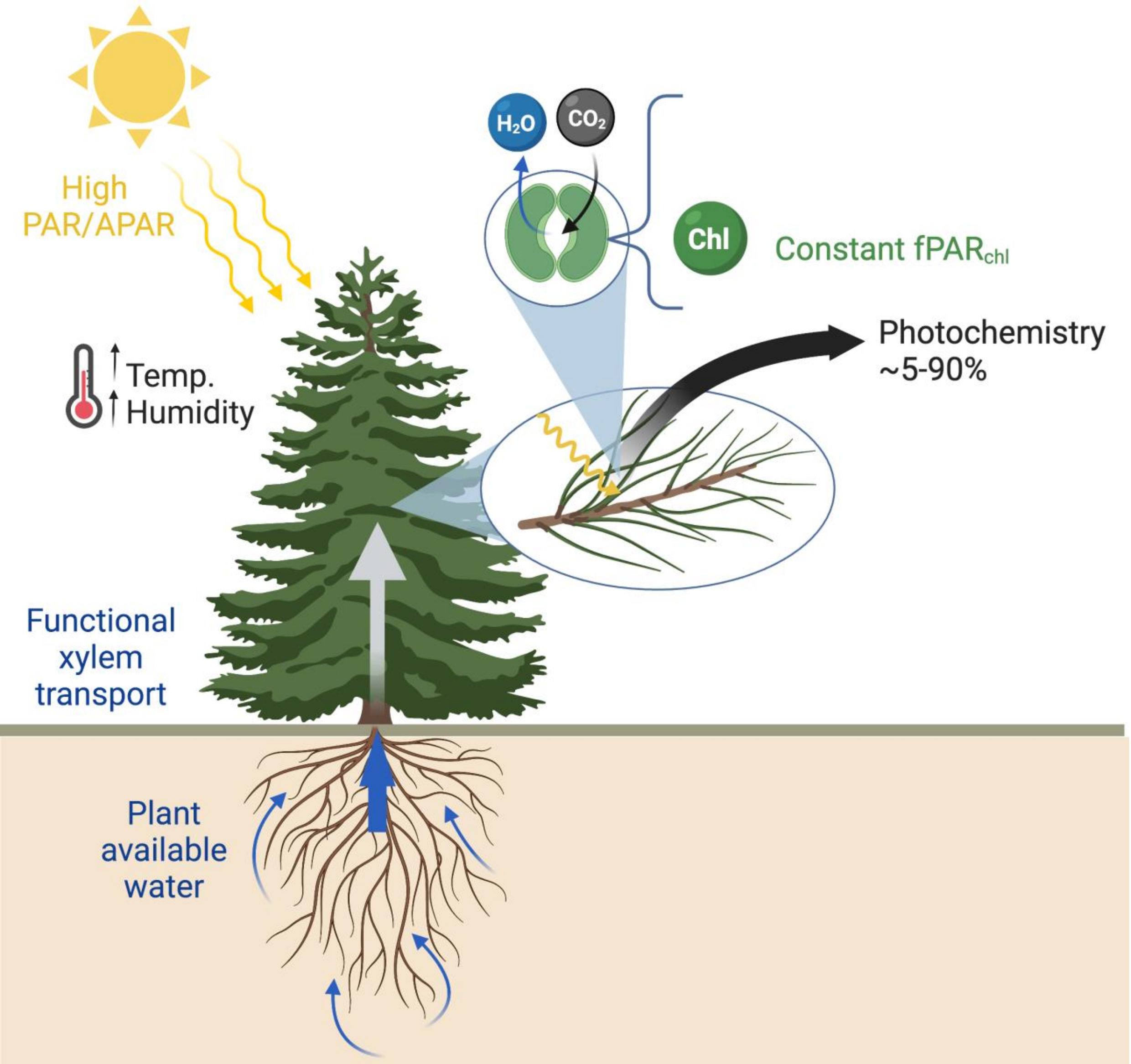

The biological basis for using optical signals
to track evergreen needleleaf photosynthesis
Needle-scale mechanisms controlling the diurnal and seasonal dynamics of ENF
Canopy-scale measures of photosynthesis and optical proxies
Global-scale satellite remote sensing observations of evergreen needleleaf forests
Multi-scale observations for an integrated understanding of evergreen needleleaf biology


The biological basis for using optical signals
to track evergreen needleleaf photosynthesis
Needle-scale mechanisms controlling the diurnal and seasonal dynamics of ENF
Canopy-scale measures of photosynthesis and optical proxies
Global-scale satellite remote sensing observations of evergreen needleleaf forests
Multi-scale observations for an integrated understanding of evergreen needleleaf biology

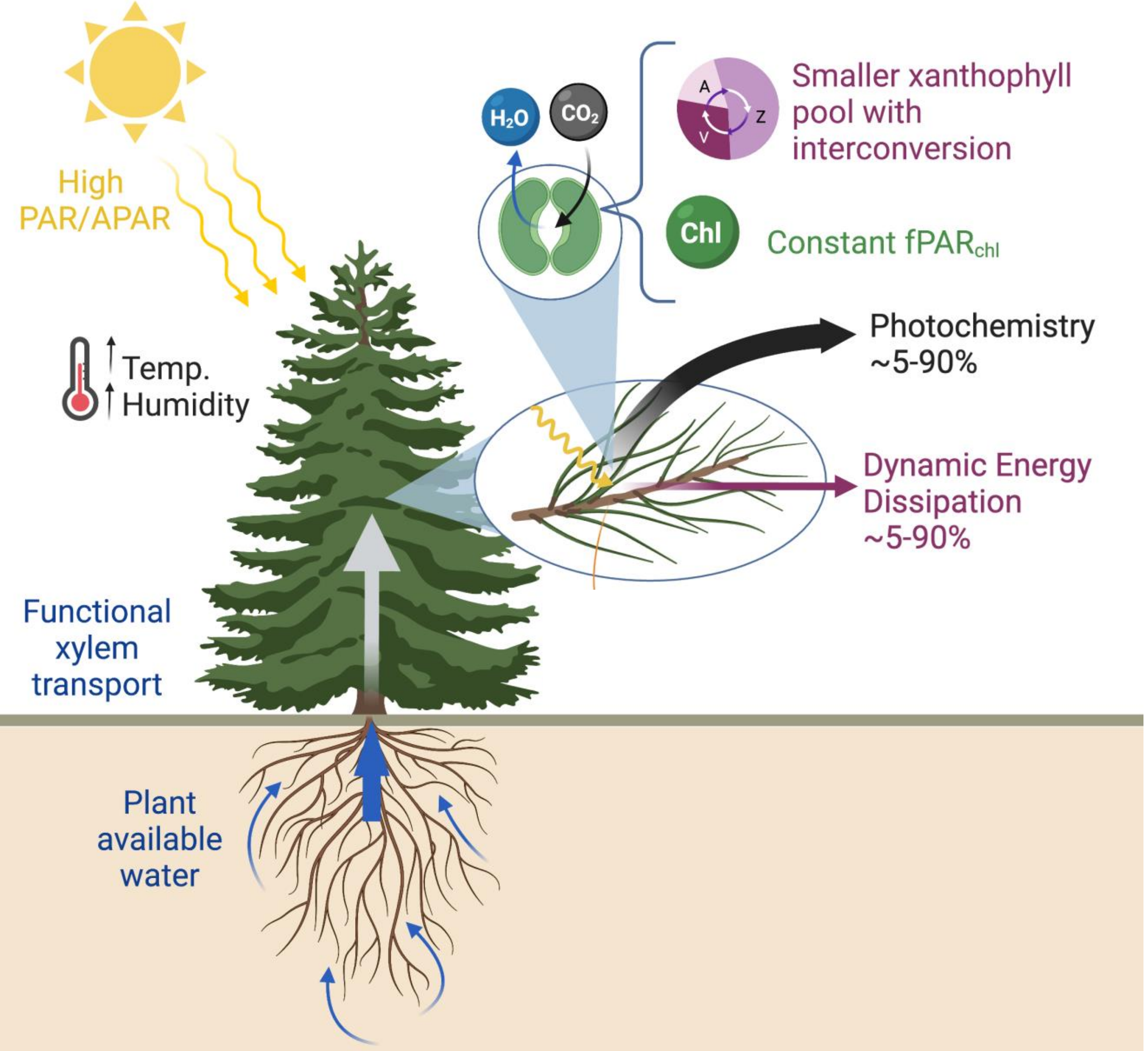
Environmental conditions regulate light harvesting at the needle scale



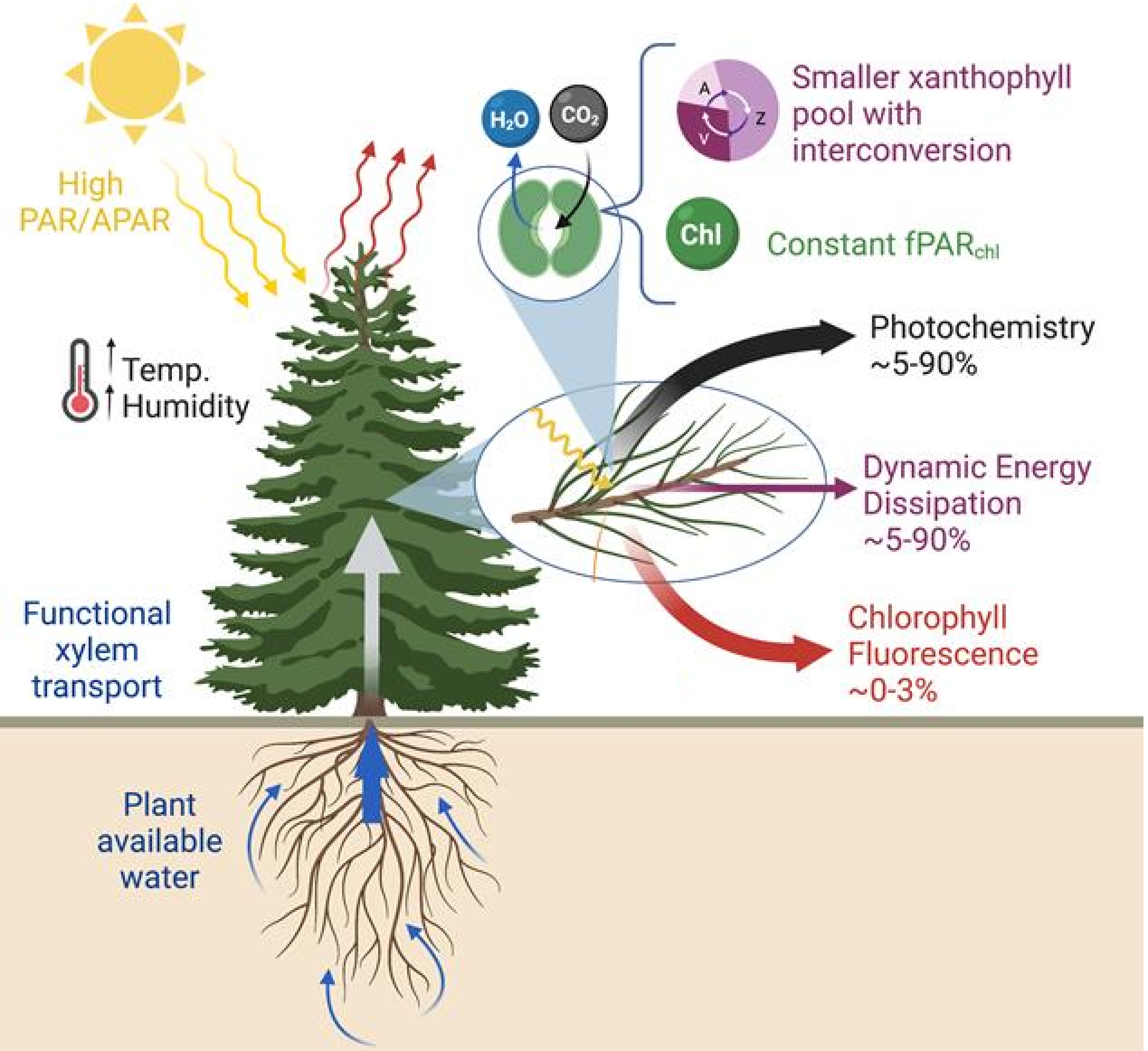
Evergreen species retain Chl year-round, but seasonally regulate light partitioning



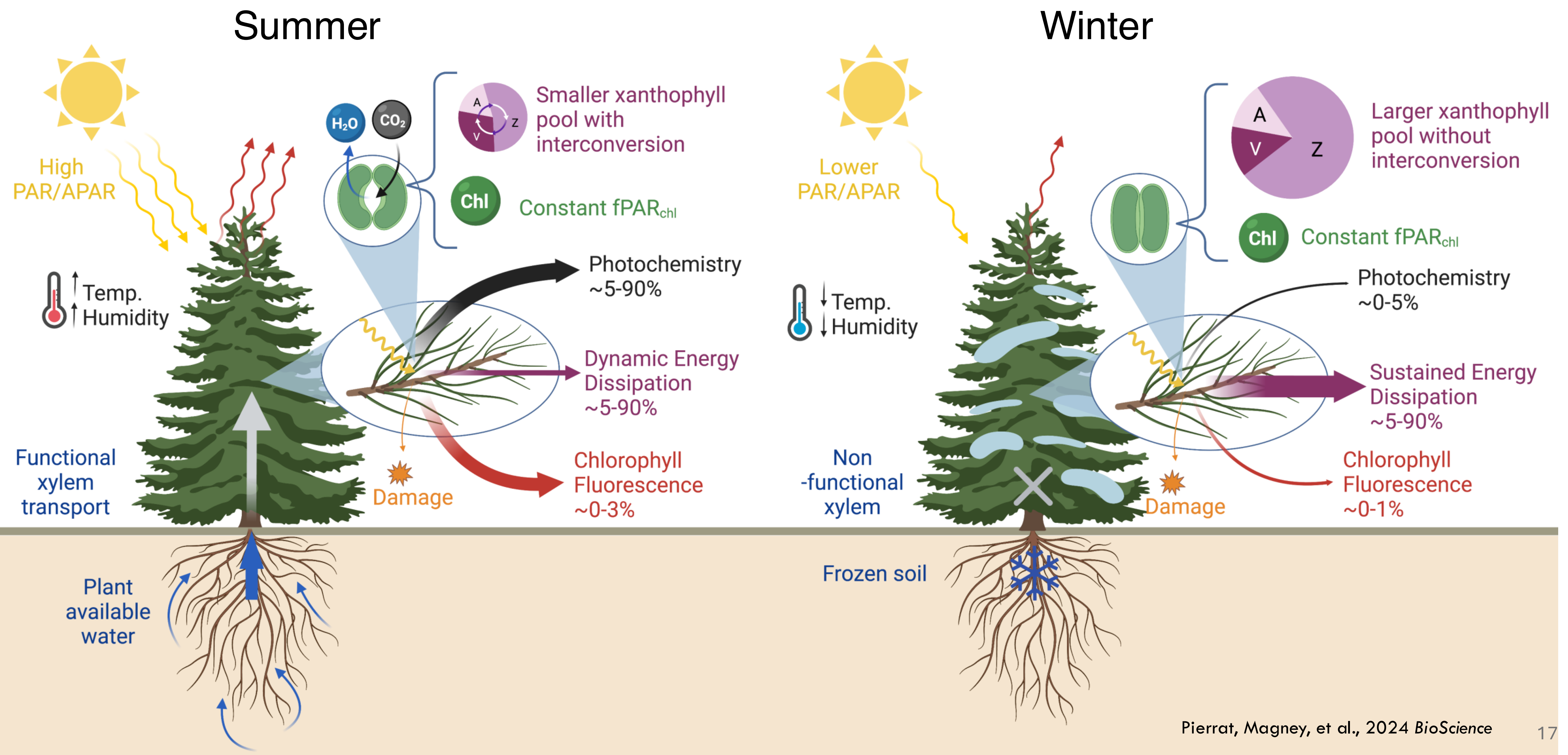
Plants can protect themselves from excess sunlight by safely dissipating the energy as heat (i.e., thermal energy dissipation)



Energy can also be re-emitted as fluorescence which is essentially an excited electron falling back down to its ground state

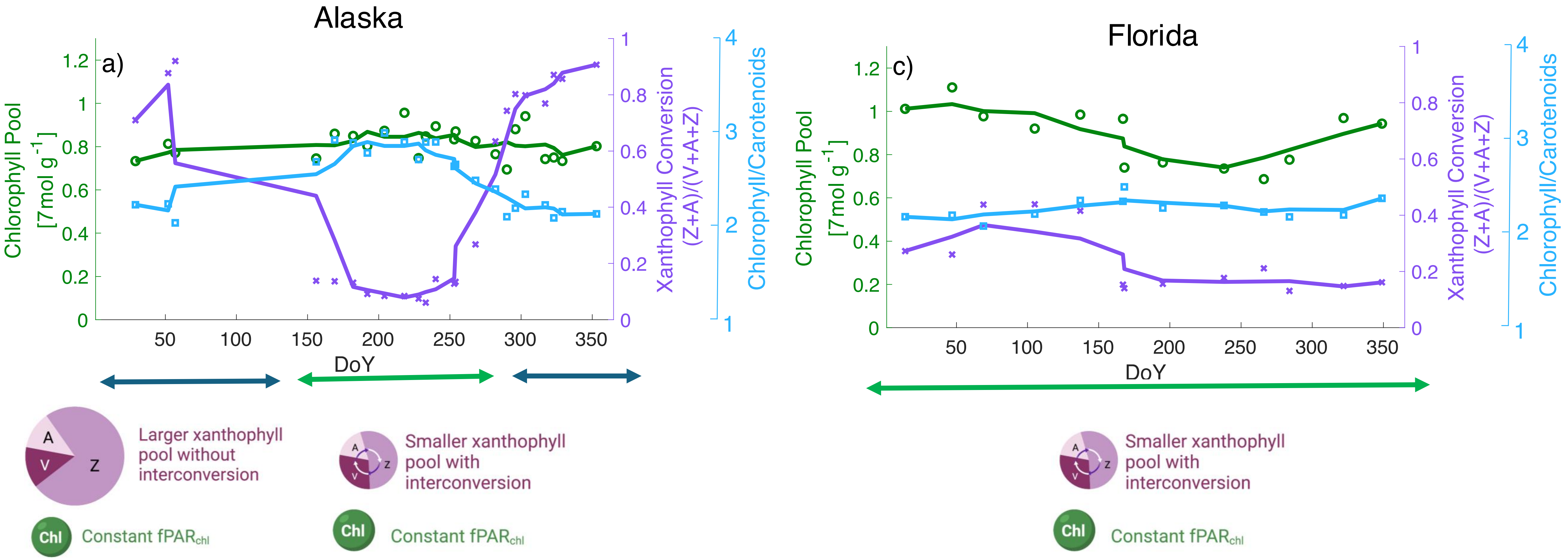


In many ENF, these processes also have a seasonal dependence due to harsh winters with sub-zero temperatures



Pierrat, Magney, et al., 2024 *BioScience*

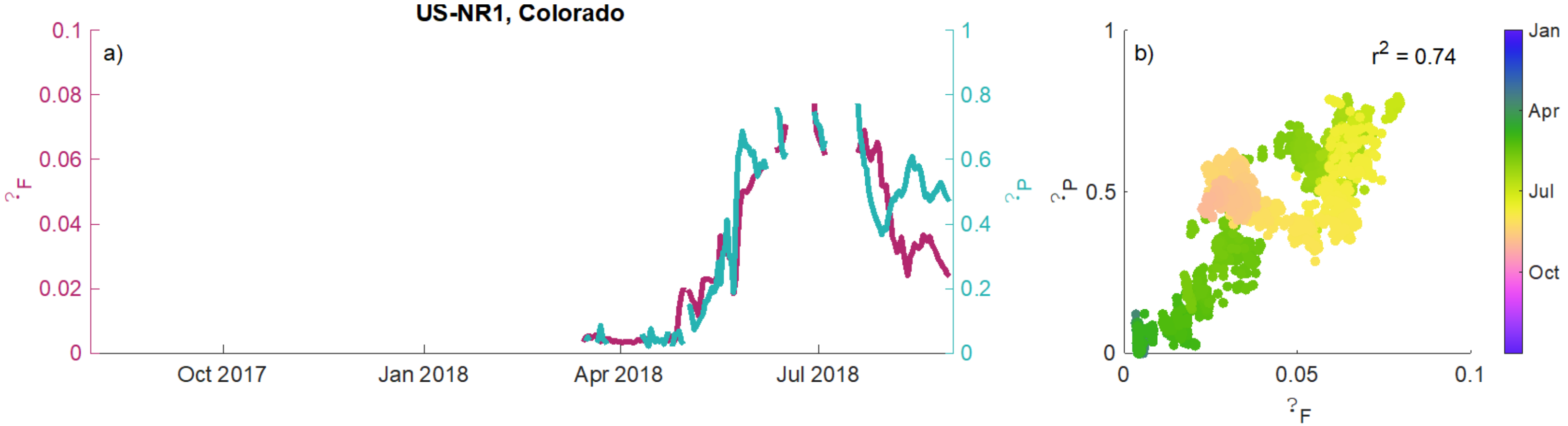
We observe changes in pigments that reflect seasonal heat-dissipation dynamics

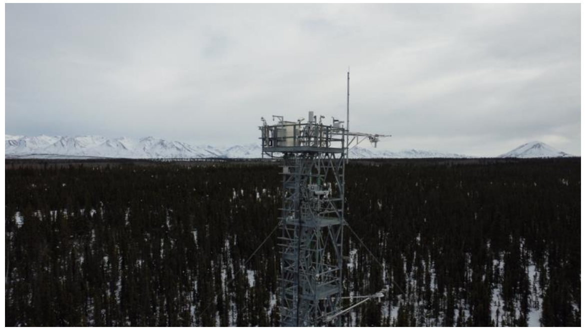


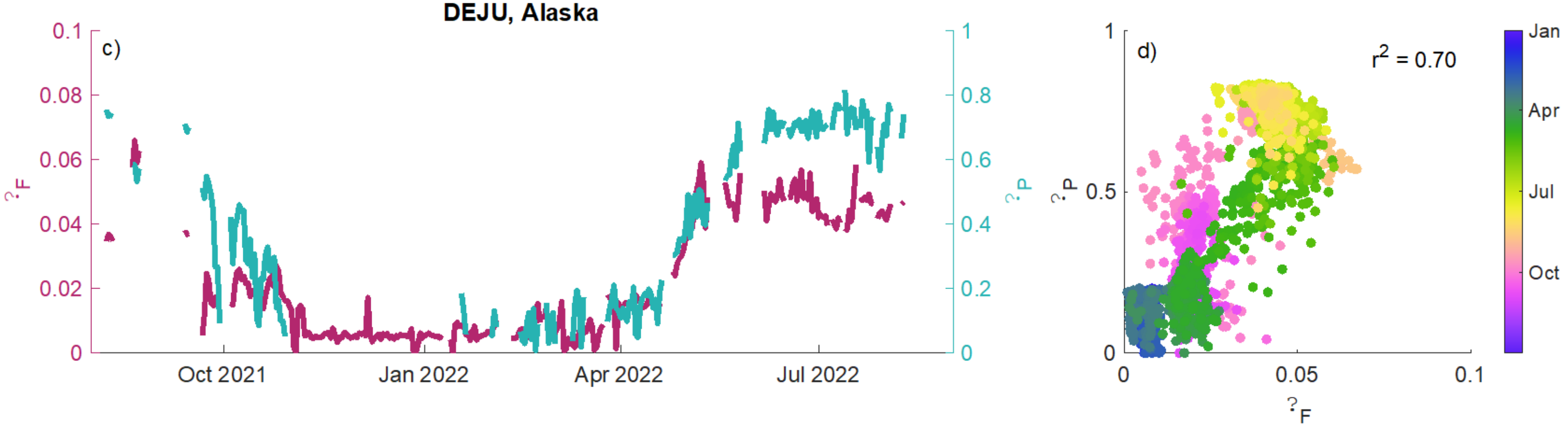
Pierrat, Magney, et al., 2024 *BioScience*

We also observe seasonal co-variation between yields of fluorescence and photosynthesis at the needle scale

ΦF = fluorescence yield
ΦP = photochemical yield



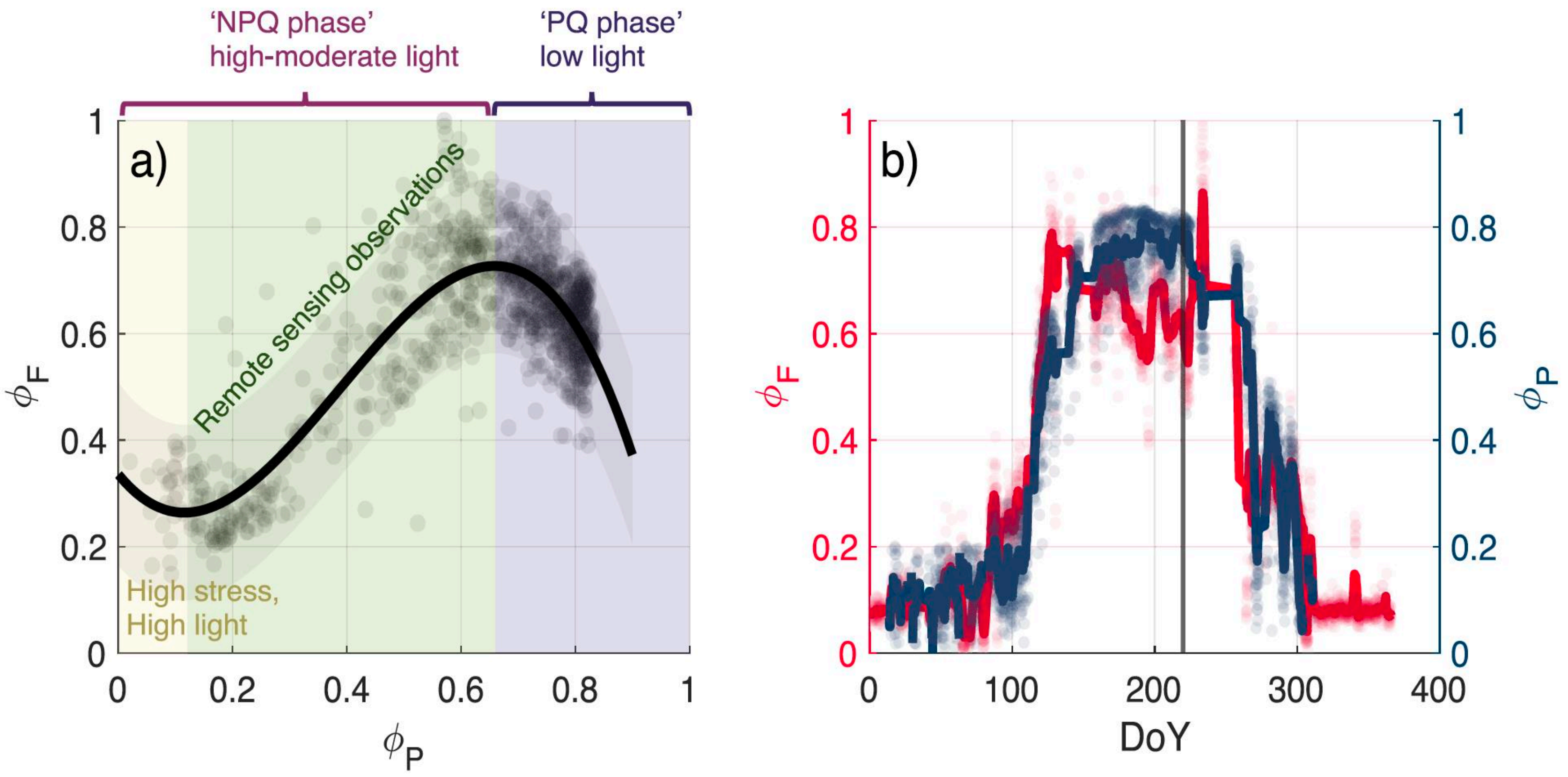




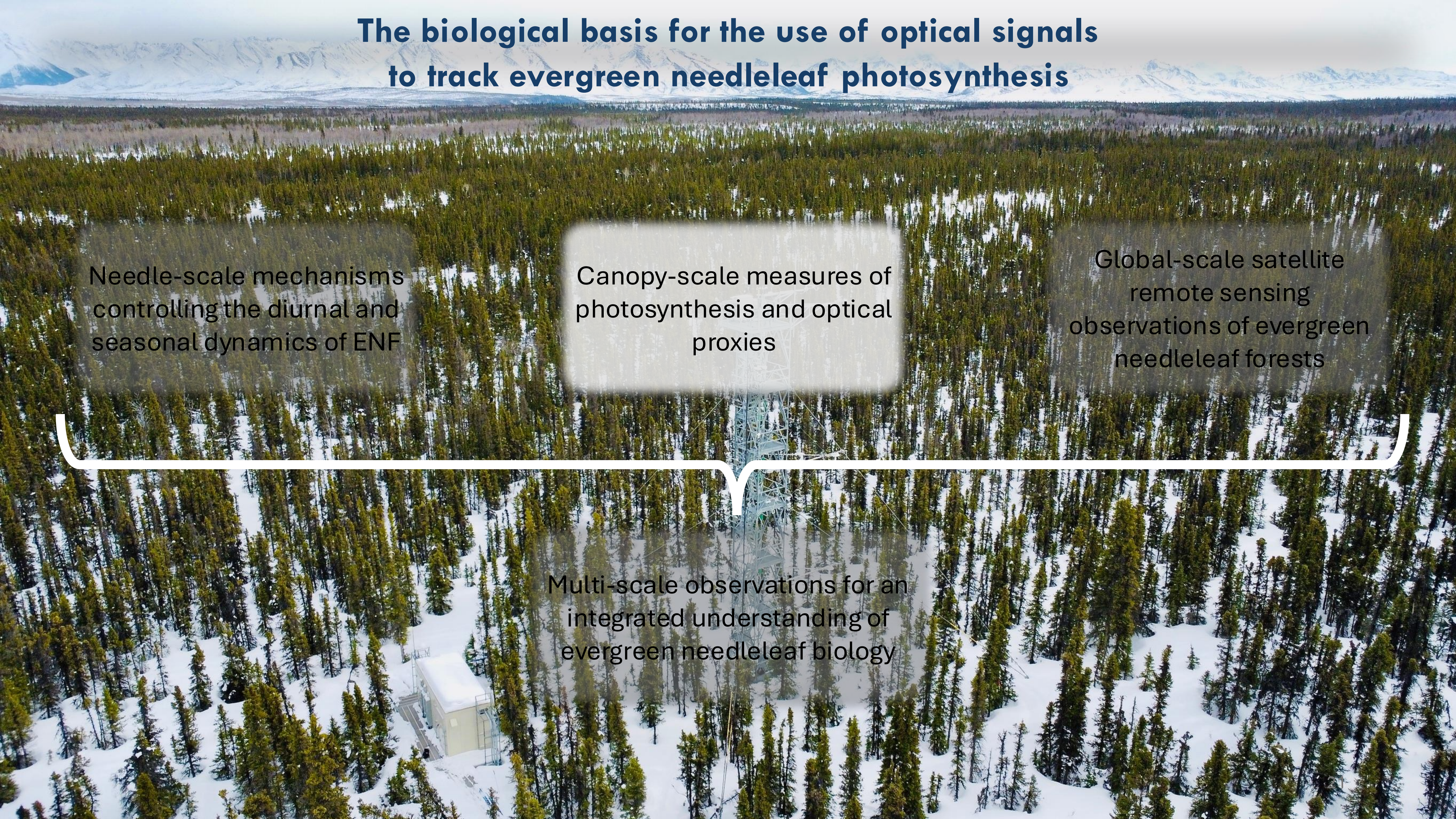
Pierrat, Magney, et al. *in press, Ecology*

Remote sensing observations primarily occur during the ‘NPQ’ phase of the ΦF vs. ΦP relationship

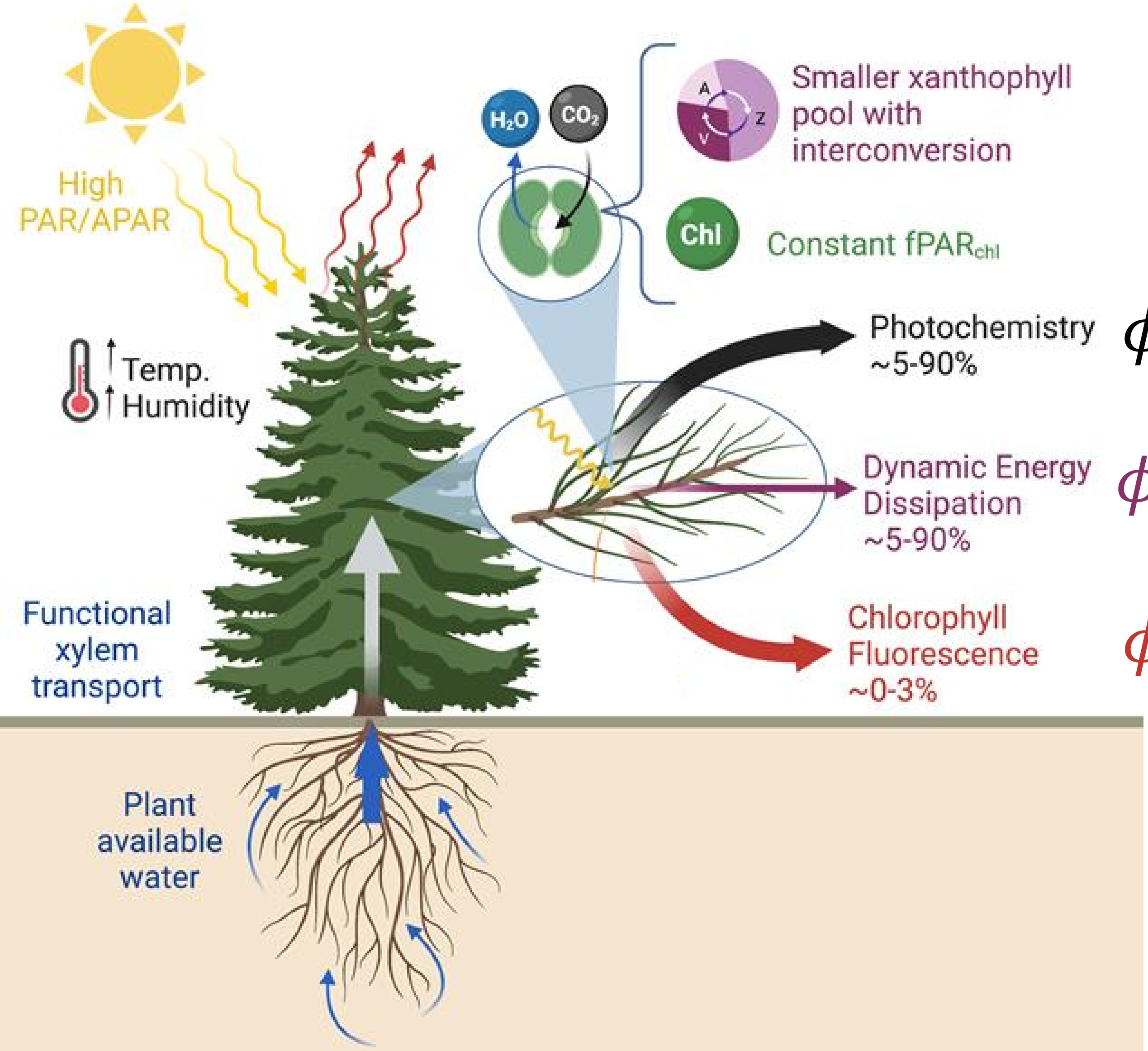
Delta Junction, Alaska



Pierrat, Magney, et al., 2024 *BioScience*
Pierrat, Magney, et al., *in press,* Ecology


The biological basis for the use of optical signals to track evergreen needleleaf photosynthesis
Needle-scale mechanisms controlling the diurnal and seasonal dynamics of ENF
Canopy-scale measures of photosynthesis and optical proxies
Global-scale satellite remote sensing observations of evergreen needleleaf forests
Multi-scale observations for an integrated understanding of evergreen needleleaf biology

Gross Primary Productivity (GPP) depends on both the amount of absorbed light, and the partitioning among these different pathways



ϕ_P

ϕ_N

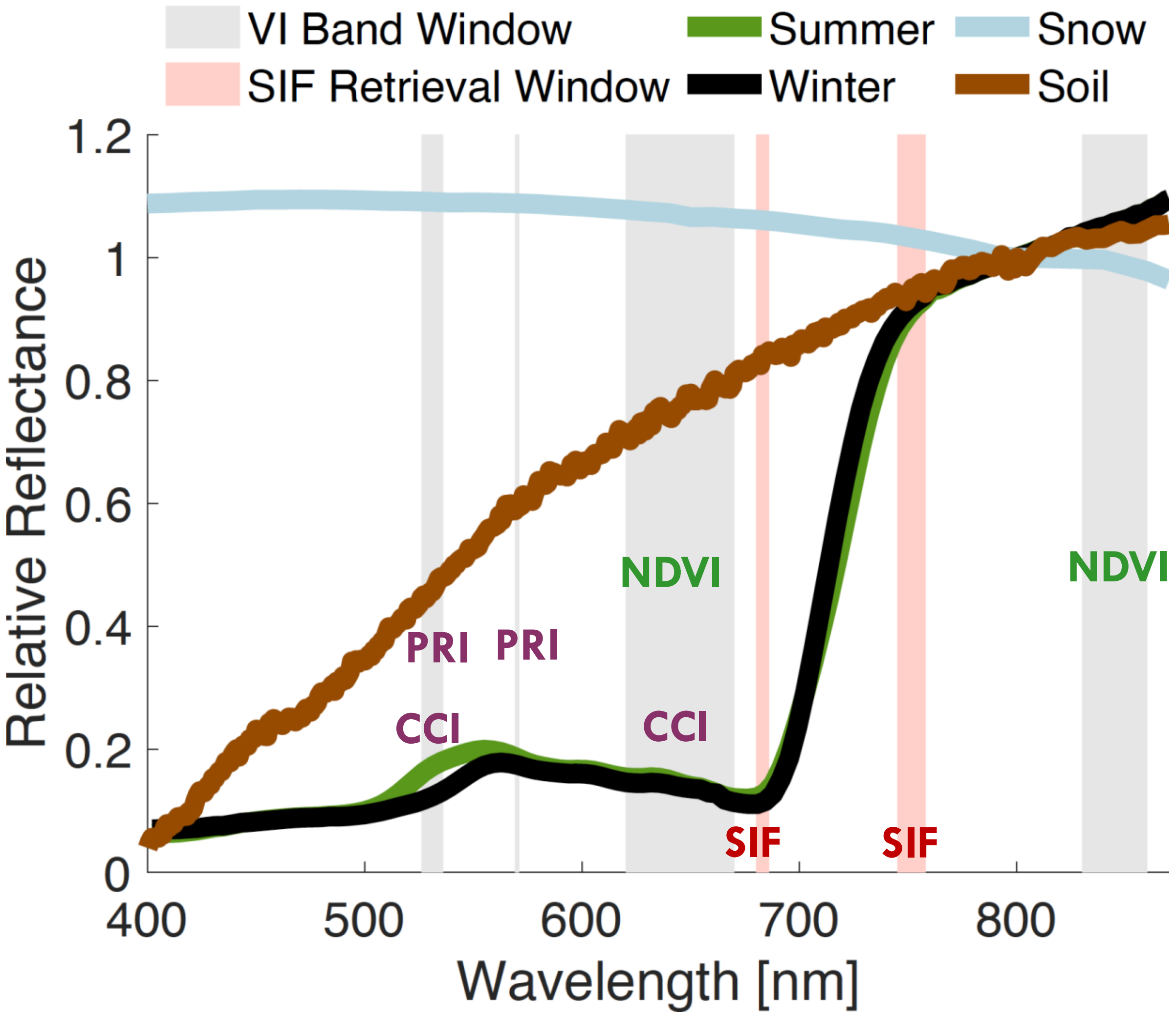
ϕ_F

$$1 = \phi_P + \phi_N + \phi_F$$

$$GPP = APAR_{Chl} * \phi_P$$

$$GPP = APAR_{Chl}(1 - \phi_N + \phi_F)$$

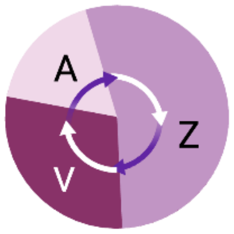
Optical metrics are sensitive to either the amount of absorbed light ($APAR_{chl}$) or energy partitioning



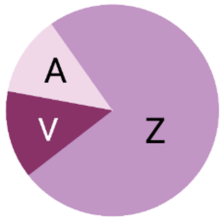
Pierrat, Magney, et al., 2024 *BioScience*

$$GPP = APAR_{Chl}(1 - \phi_N + \phi_F)$$

Normalized Diff. Veg. Index (NDVI)
Canopy Greenness



Photochemical Reflect. Index (PRI)
Dynamic Xanthophyll Interconversion



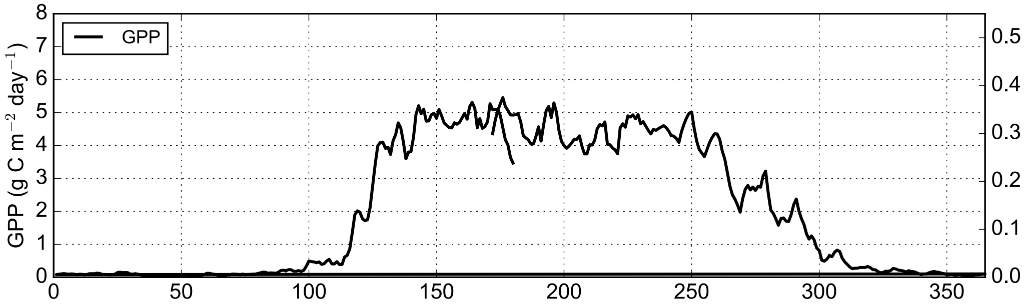
Chlorophyll:Carotenoid Index (CCI)
Sustained Xanthophyll Retention

Solar Induced Fluorescence (SIF)
Chlorophyll a fluorescence

A seasonal cycle at Niwot Ridge, Colorado

$$GPP = APAR_{Chl}(1 - \phi_N + \phi_F)$$

Niwot Ridge, CO



Day of Year

Magney et al., *PNAS*, 2019

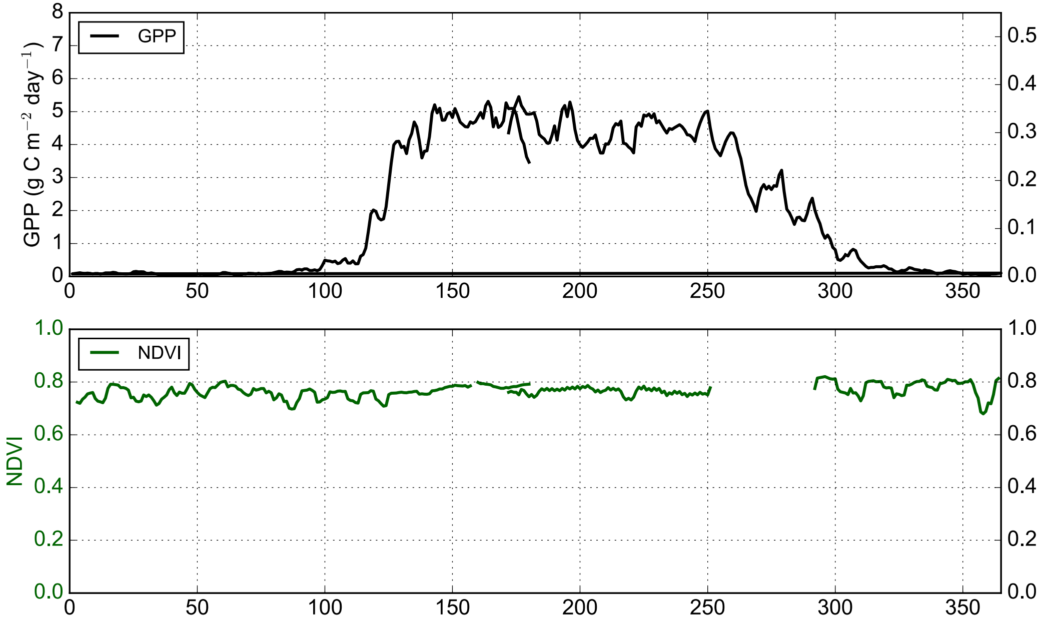
NDVI is constant because negligible change in Chl and structure

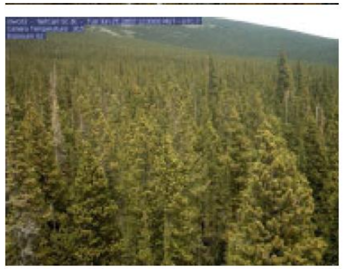
$$GPP = APAR_{Chl}(1 - \phi_N + \phi_F)$$

Normalized Diff. Veg. Index (NDVI)

Canopy Greenness

Niwot Ridge, CO





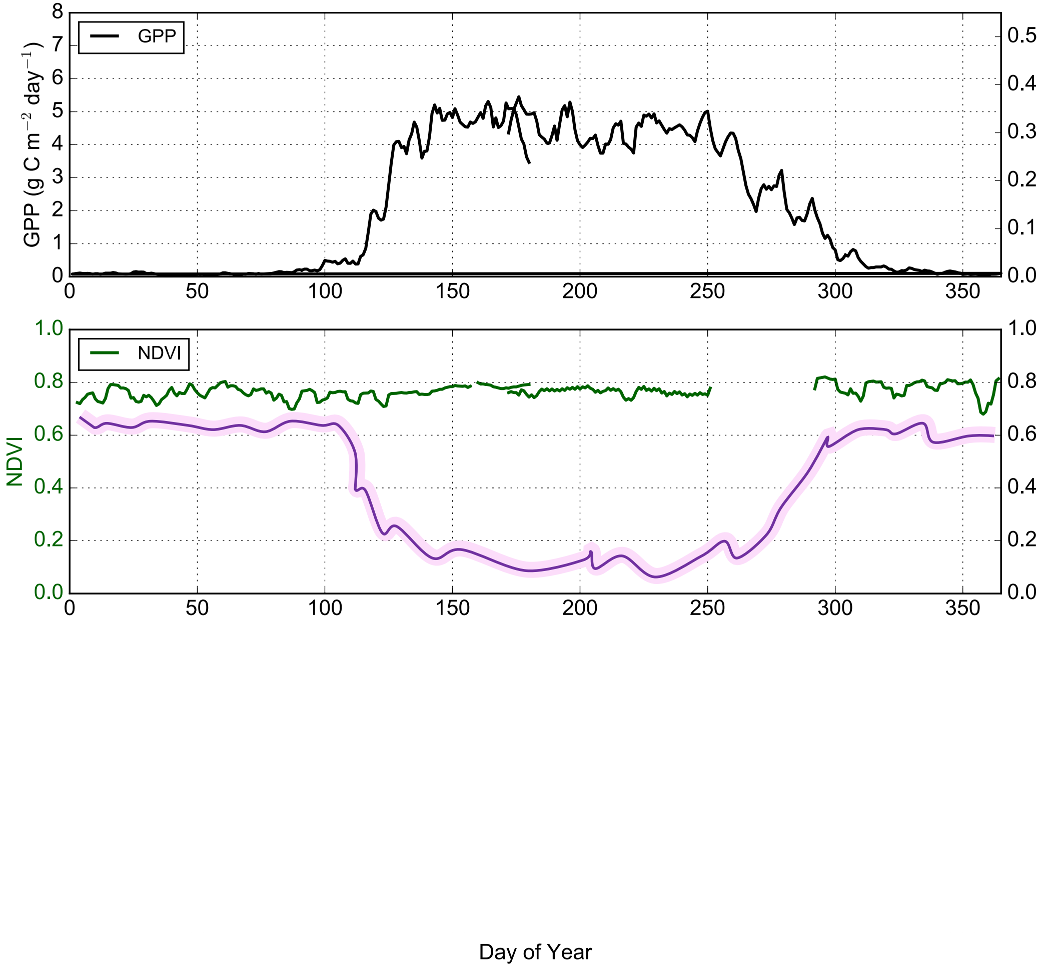
Day of Year

Magney et al., *PNAS*, 2019

Pigment based indices can tell us about photoprotective mechanisms

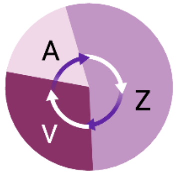
$$GPP = APAR_{Chl}(1 - \phi_N + \phi_F)$$

Niwot Ridge, CO



Normalized Diff. Veg. Index (NDVI)

Canopy Greenness



Photochemical Reflect. Index (PRI)

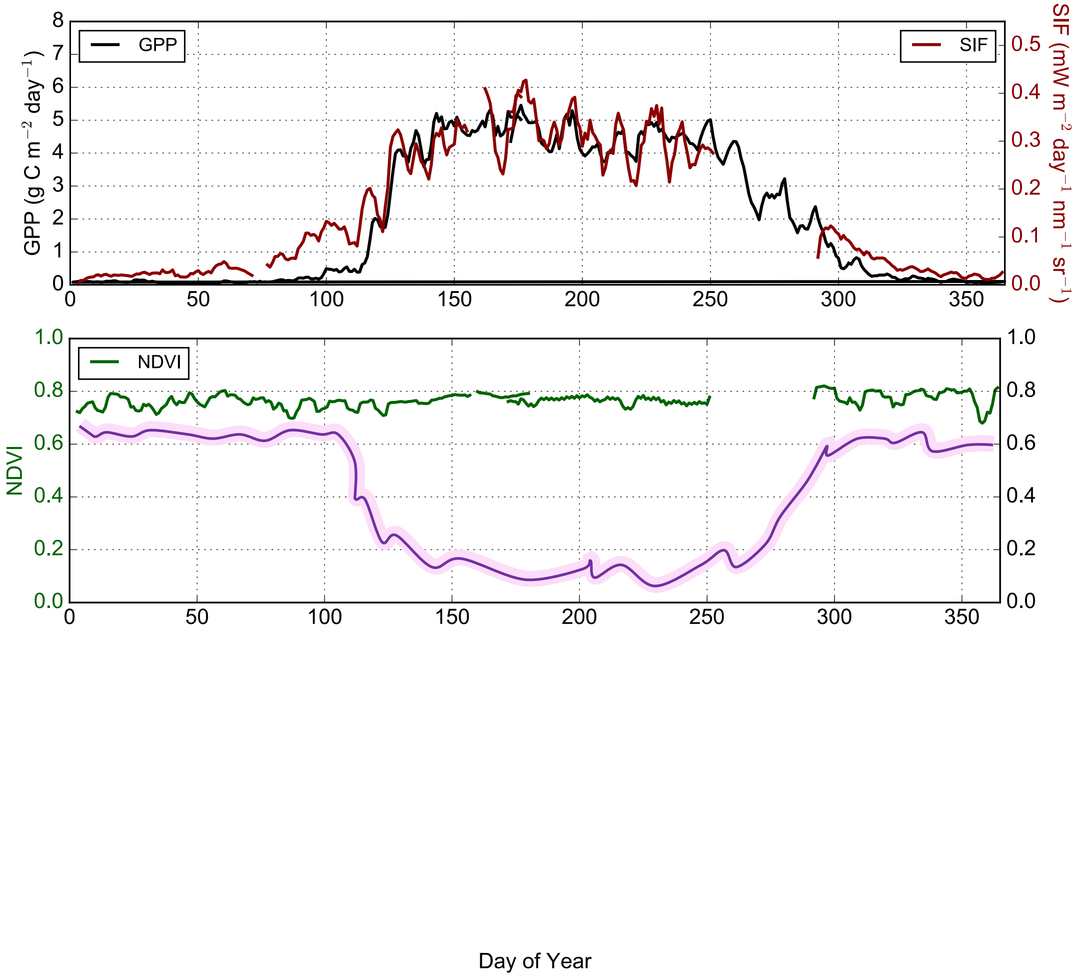
Integrated plant stress

Magney et al., *PNAS*, 2019

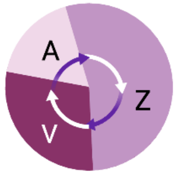
Solar-induced fluorescence is sensitive to both absorbed light and photochemistry

$$GPP = APAR_{Chl}(1 - \phi_N + \phi_F)$$

Niwot Ridge, CO



Normalized Diff. Veg. Index (NDVI)
Canopy Greenness



Photochemical Reflect. Index (PRI)
Integrated plant stress

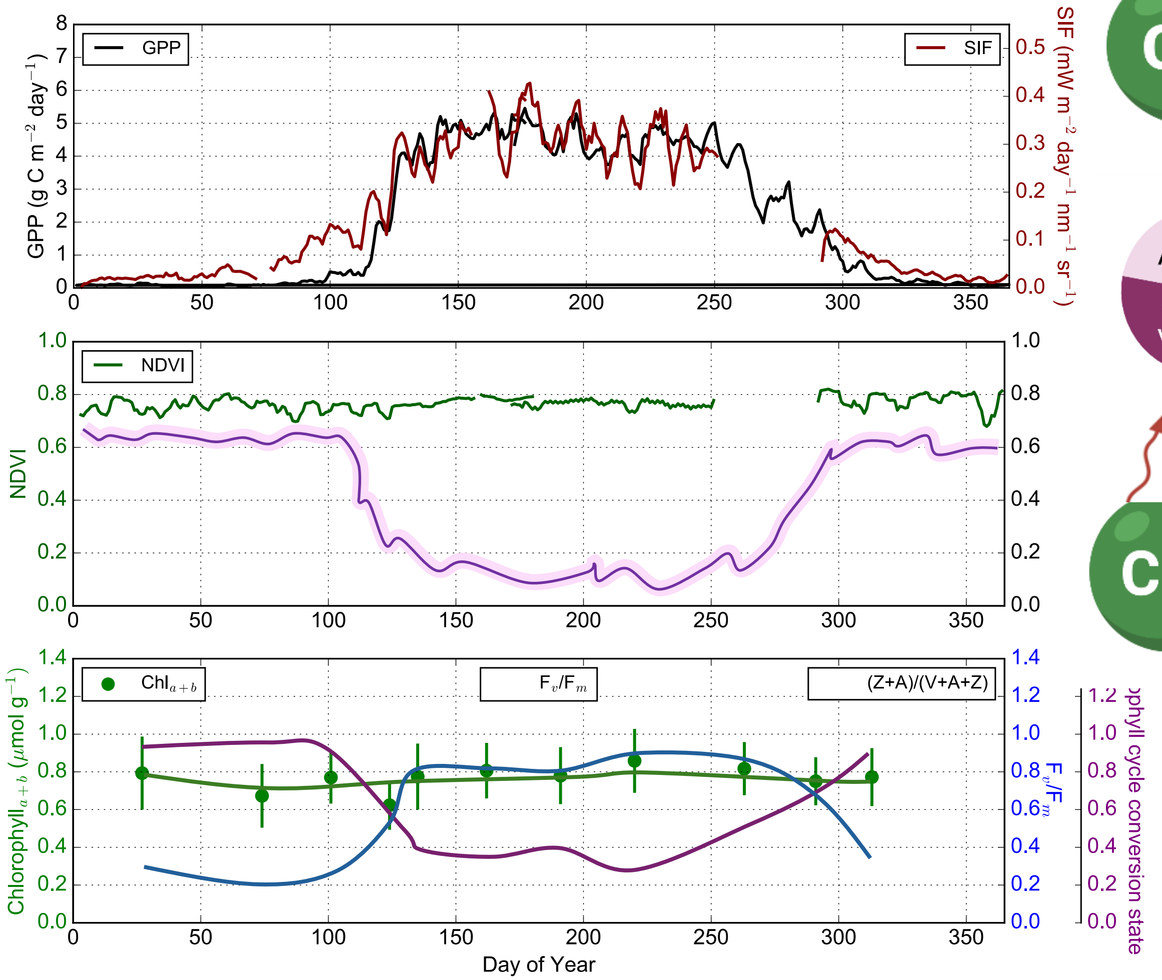
Solar Induced Fluorescence (SIF)
Chlorophyll a fluorescence

Magney et al., *PNAS*, 2019

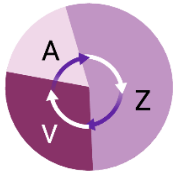
Covariation in the seasonality of field measured pigments and photochemistry

$$GPP = APAR_{Chl}(1 - \phi_N + \phi_F)$$

Niwot Ridge, CO



Normalized Diff. Veg. Index (NDVI)
Canopy Greenness



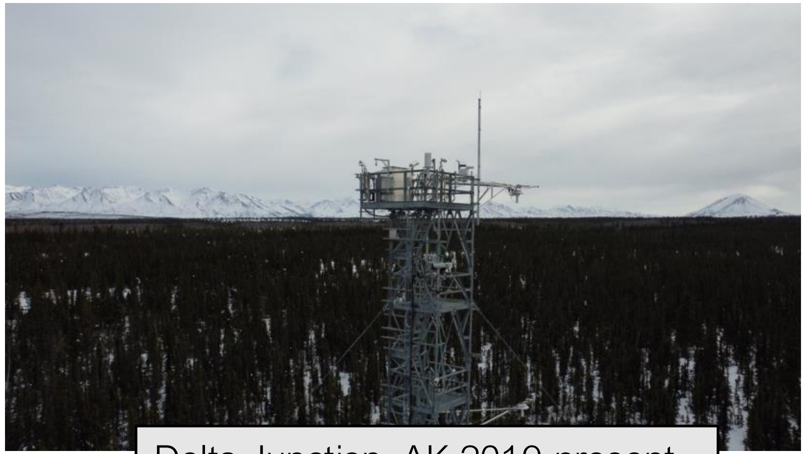
Photochemical Reflect. Index (PRI)
Integrated plant stress

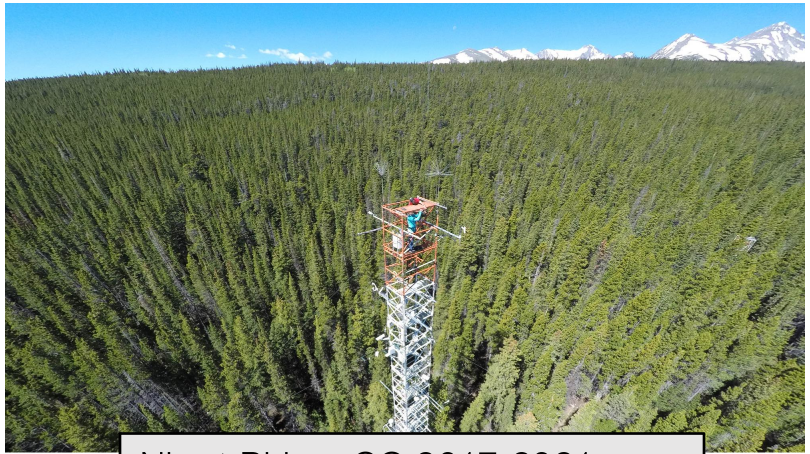
Solar Induced Fluorescence (SIF)
Chlorophyll a fluorescence

Seasonal cycles of needle pigments and photochemistry (in situ)

Magney et al., *PNAS*, 2019

Let’s test this approach across four evergreen sites

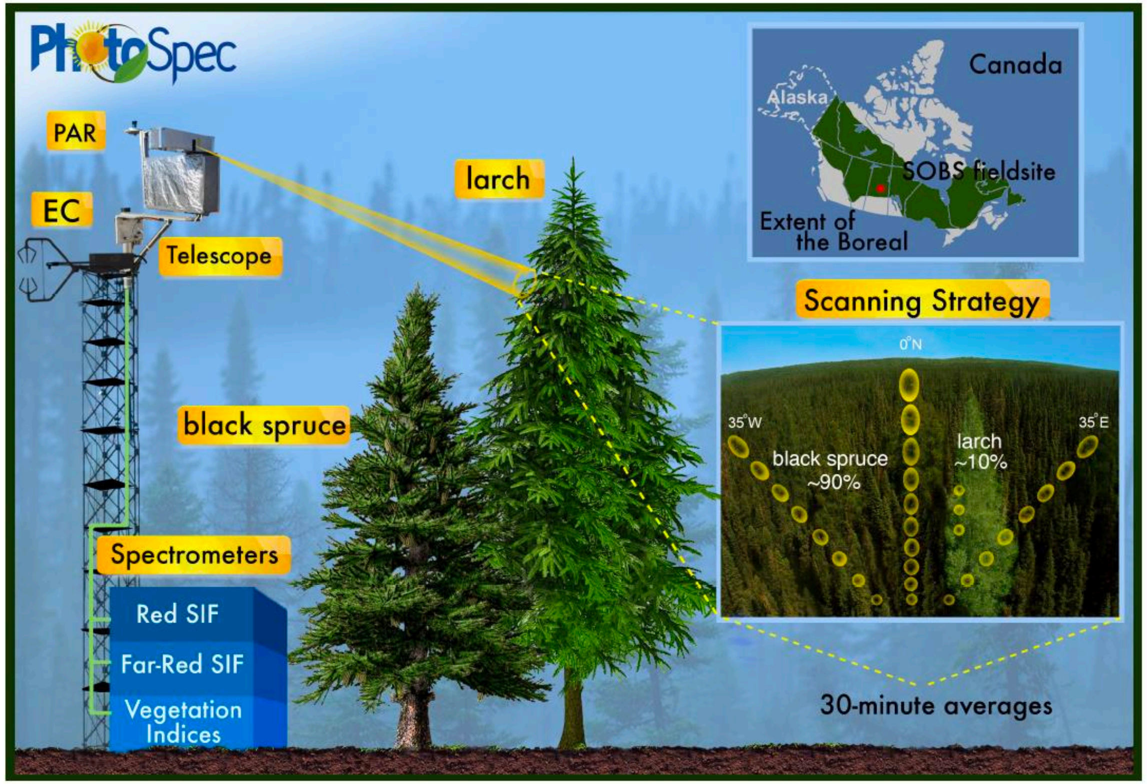

Delta Junction, AK 2019-present


Niwot Ridge, CO 2017-2021

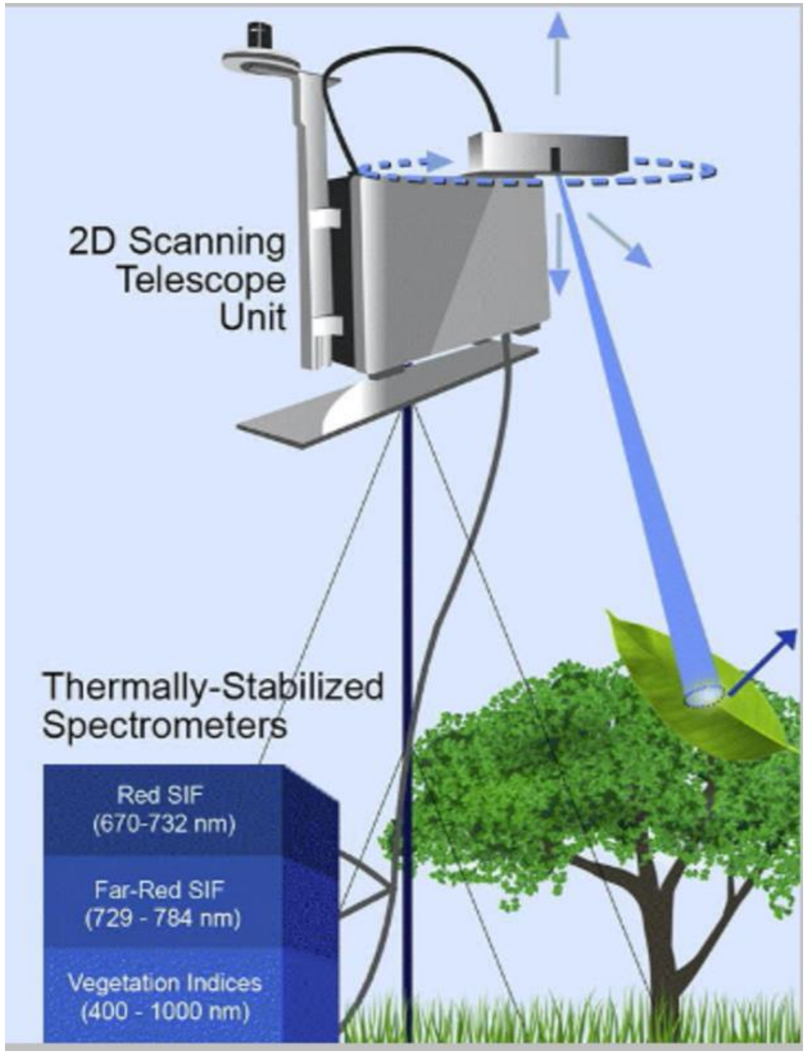

Old Black Spruce, Sask. 2018-present


Ordway Swisher, FL 2019-present

We use a scanning-tower spectrometer, PhotoSpec, for continuous tower-based measurements (~20 second retrievals)

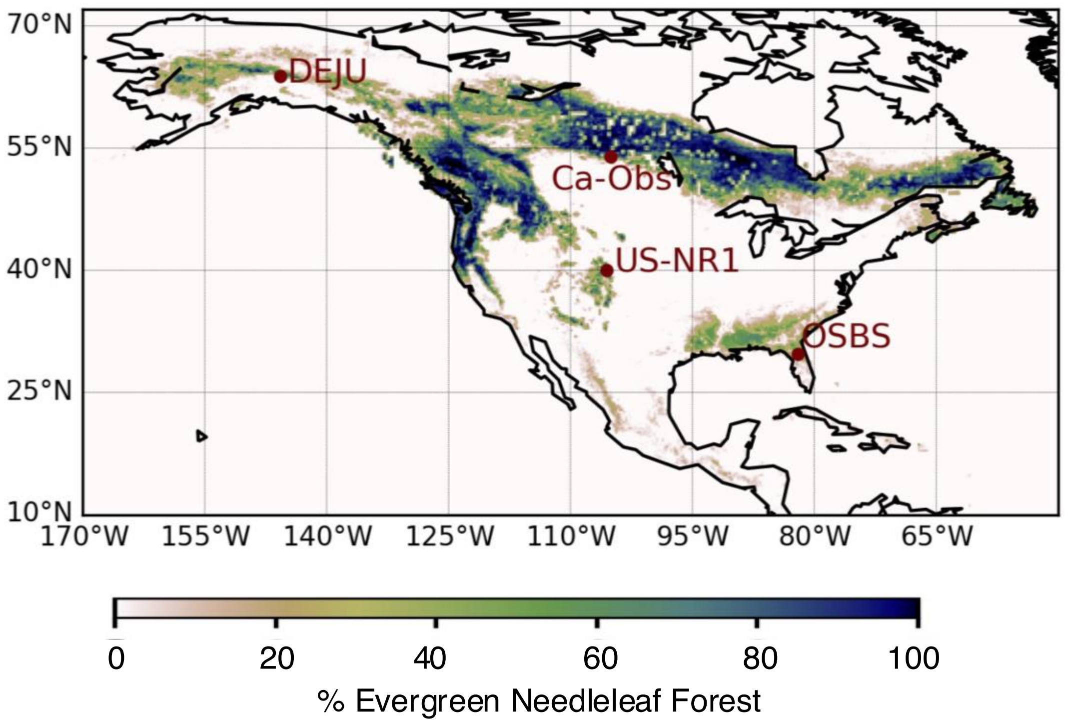


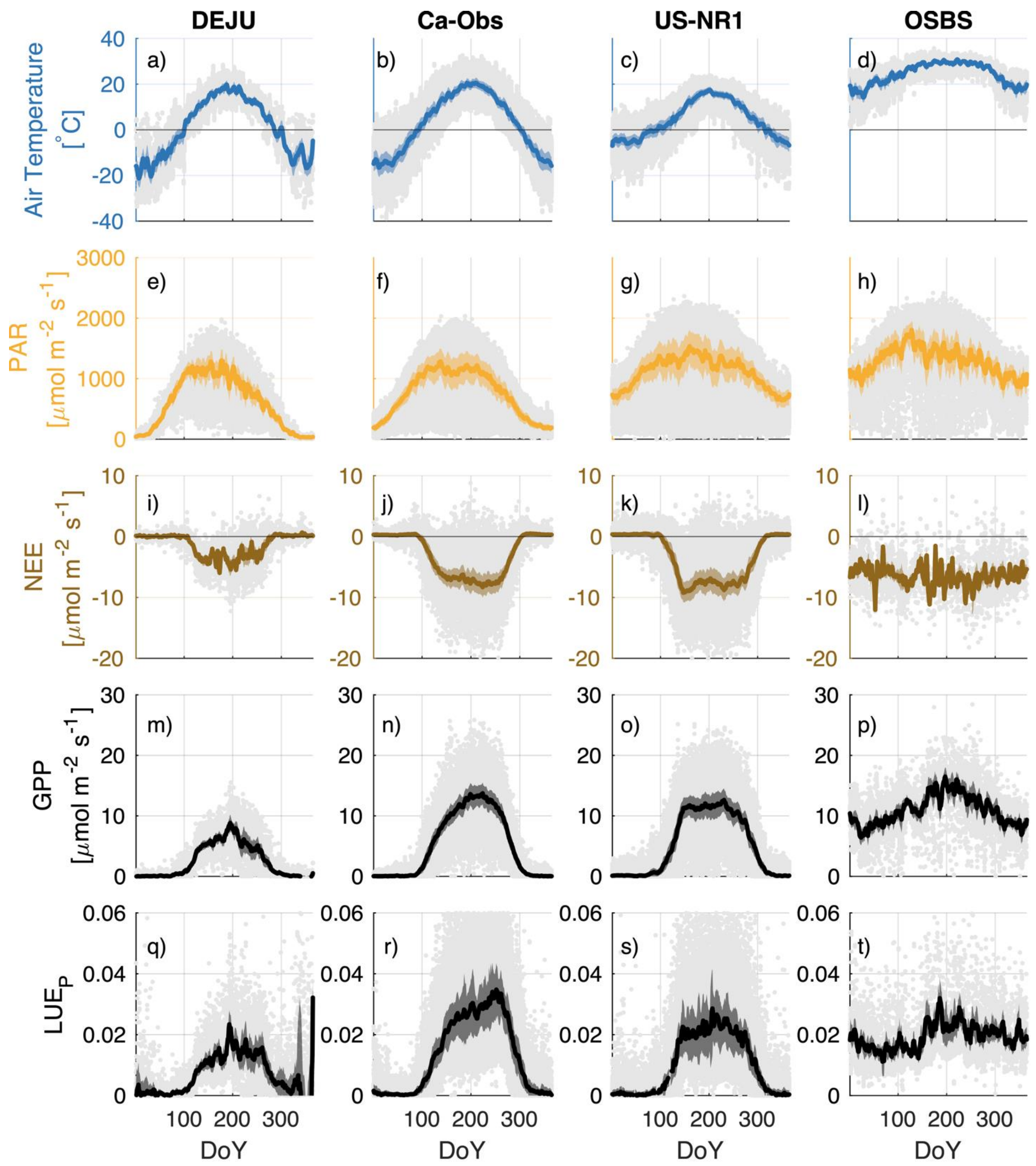
Pierrat, Magney, et al. 2022 *JGR-Biogeosciences*



Grossmann et al., 2018 *RSE*

Temperature and light drive the seasonal cycle of photosynthesis

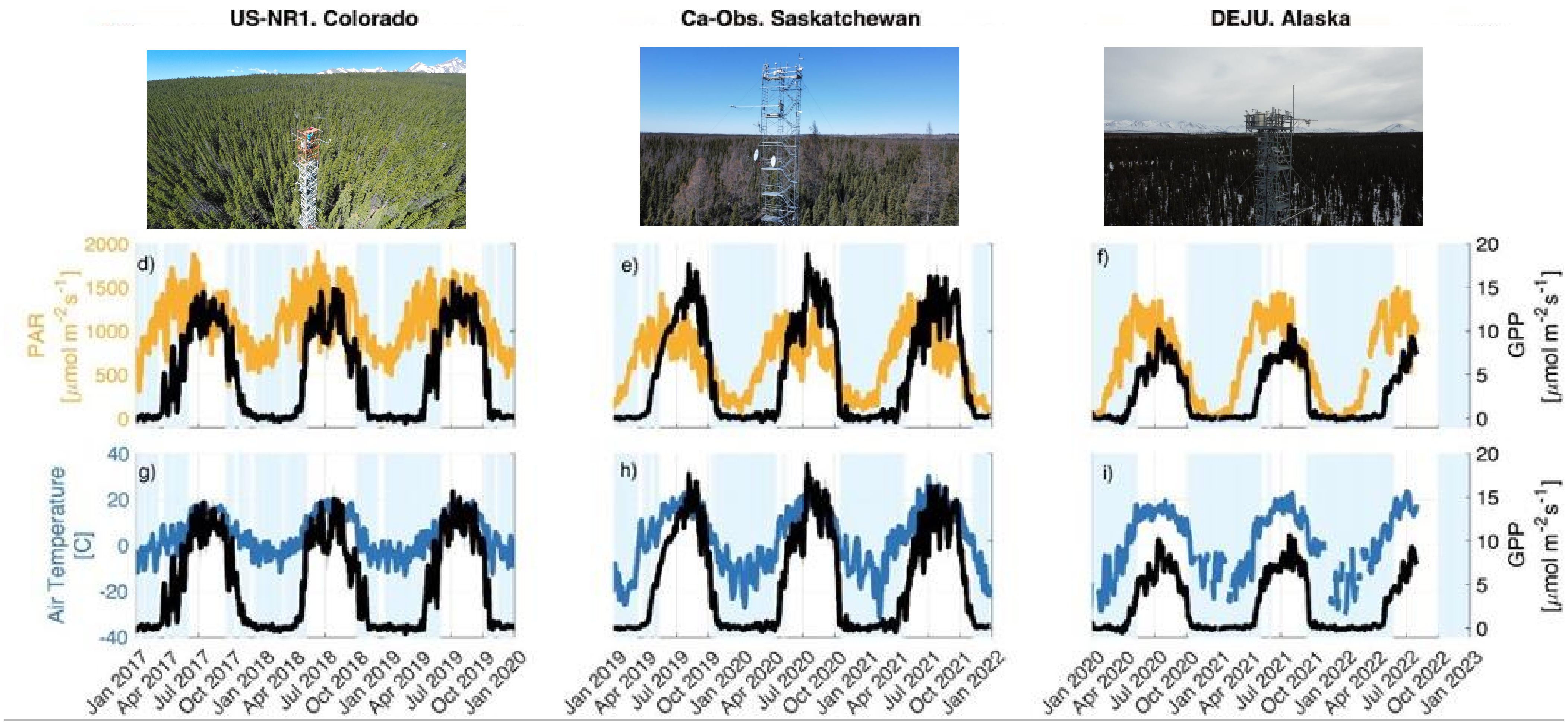




Pierrat, Magney, et al. 2024 *BioScience*

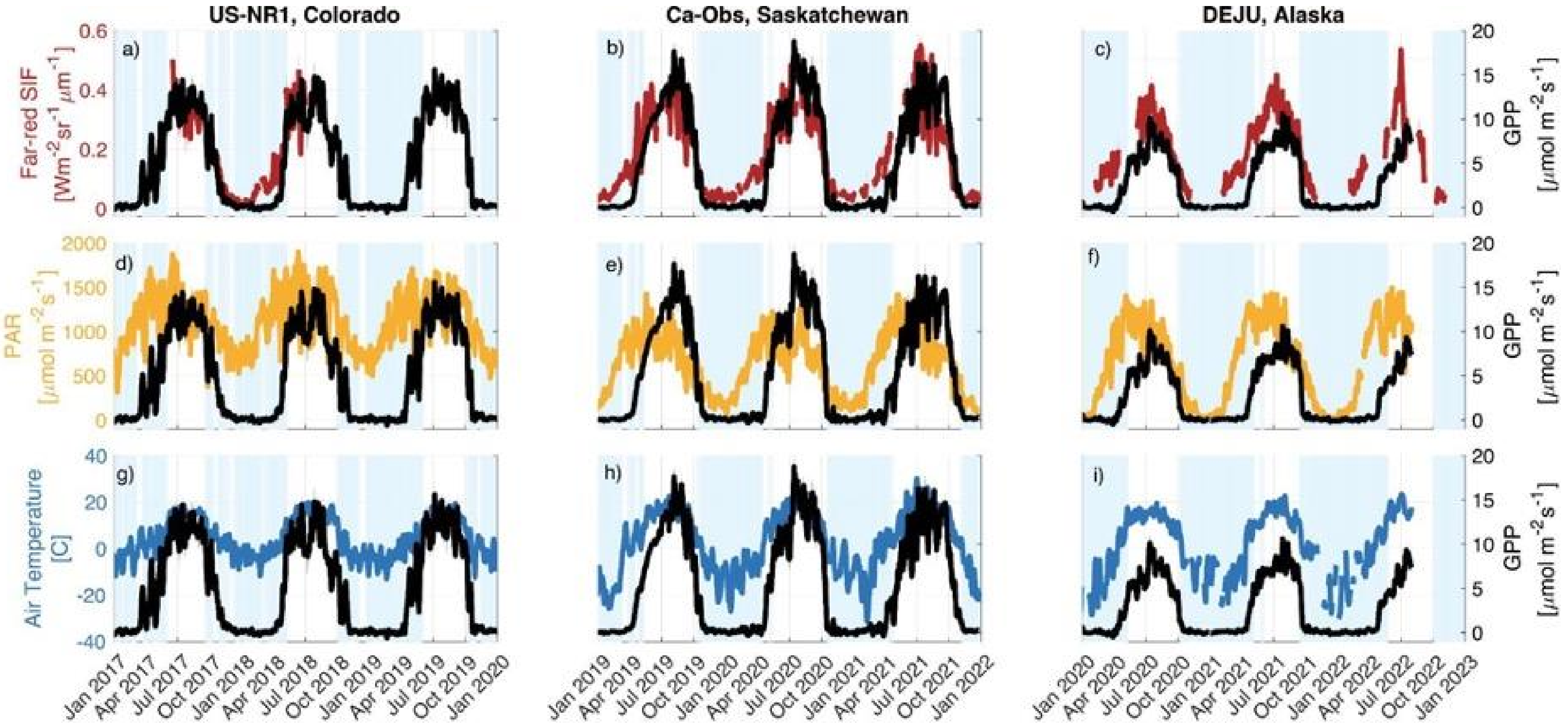
Photosynthesis (GPP) begins prior to snowmelt

Snow on canopy is indicated by blue vertical lines



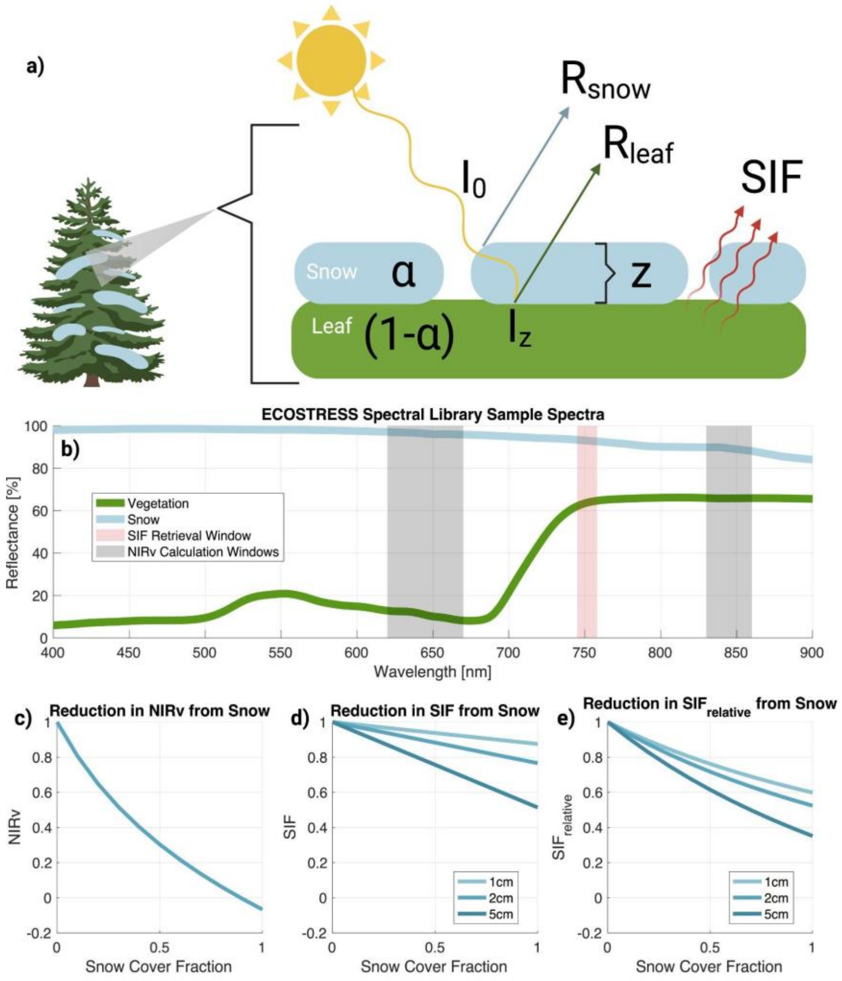
Pierrat, Magney, et al. *in press, Ecology*

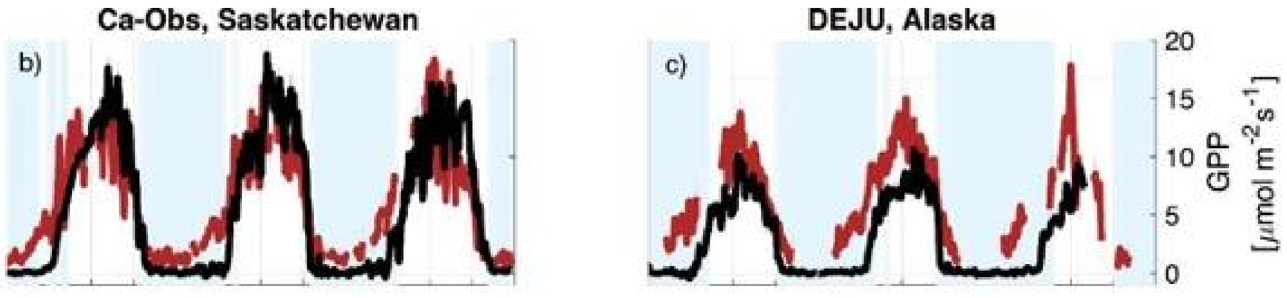
SIF has a light response to increasing PAR
Beginning prior to GPP onset



Pierrat, Magney, et al. *in press, Ecology*

How can we 'correct' for the light driven increase in SIF? And the impact of snow?



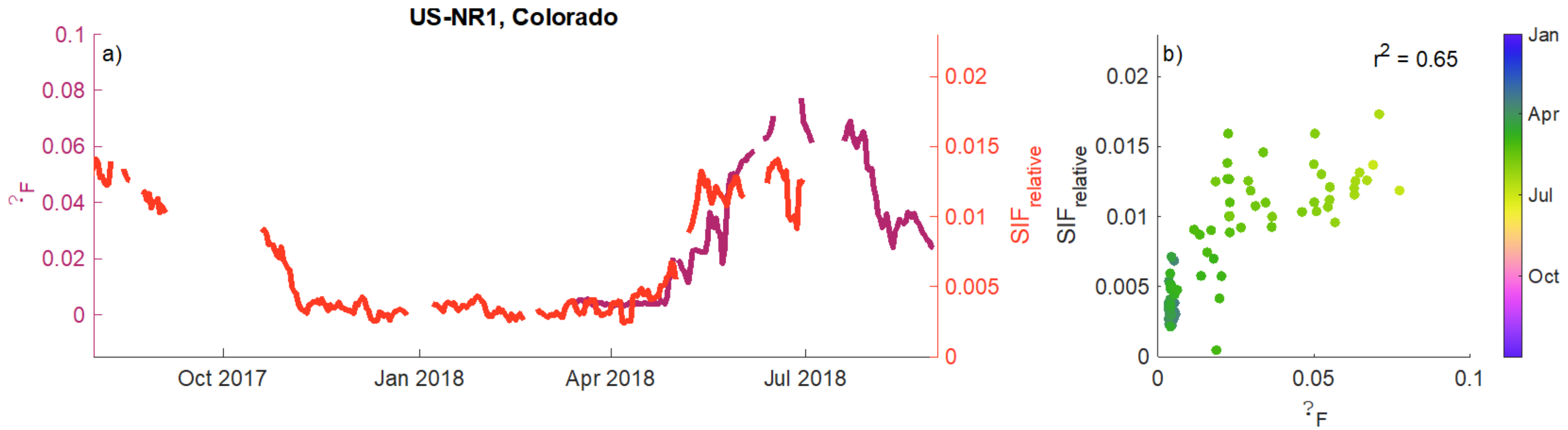


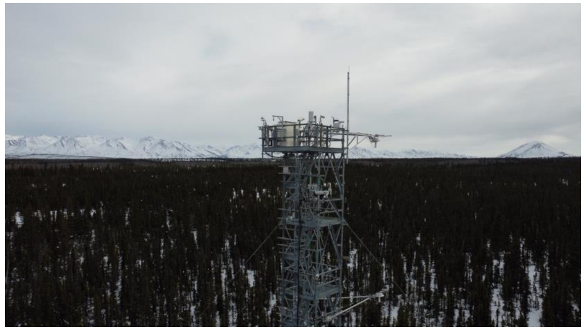
$$\text{Relative SIF} = \frac{\text{SIF}_{(751\text{-}771\ \text{nm})}}{\text{reflected radiance}_{(751\text{-}771\ \text{nm})}}$$

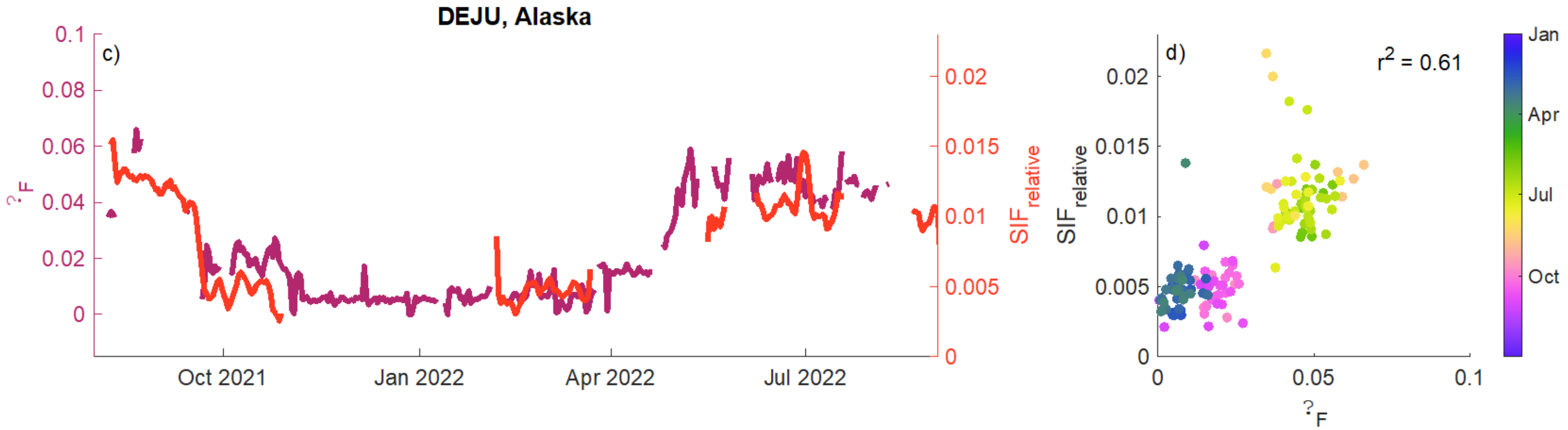
Pierrat, Magney, et al. *in press, Ecology*

How does the needle scale compare to the tower scale?

Comparing fluorescence yield (ΦF) with $SIF_{relative}$





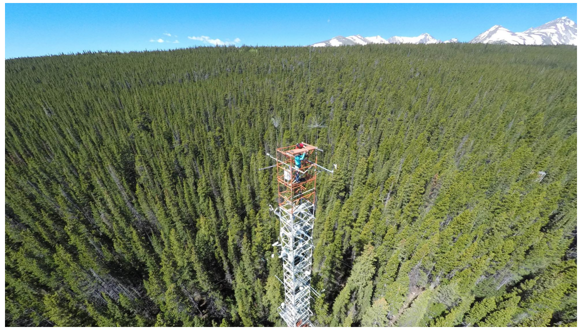


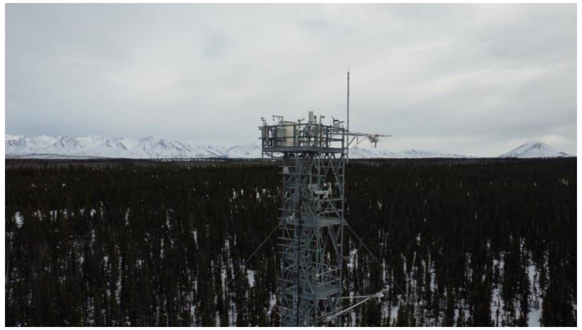
$SIF_{relative}$ = SIF / reflected radiance in the retrieval window

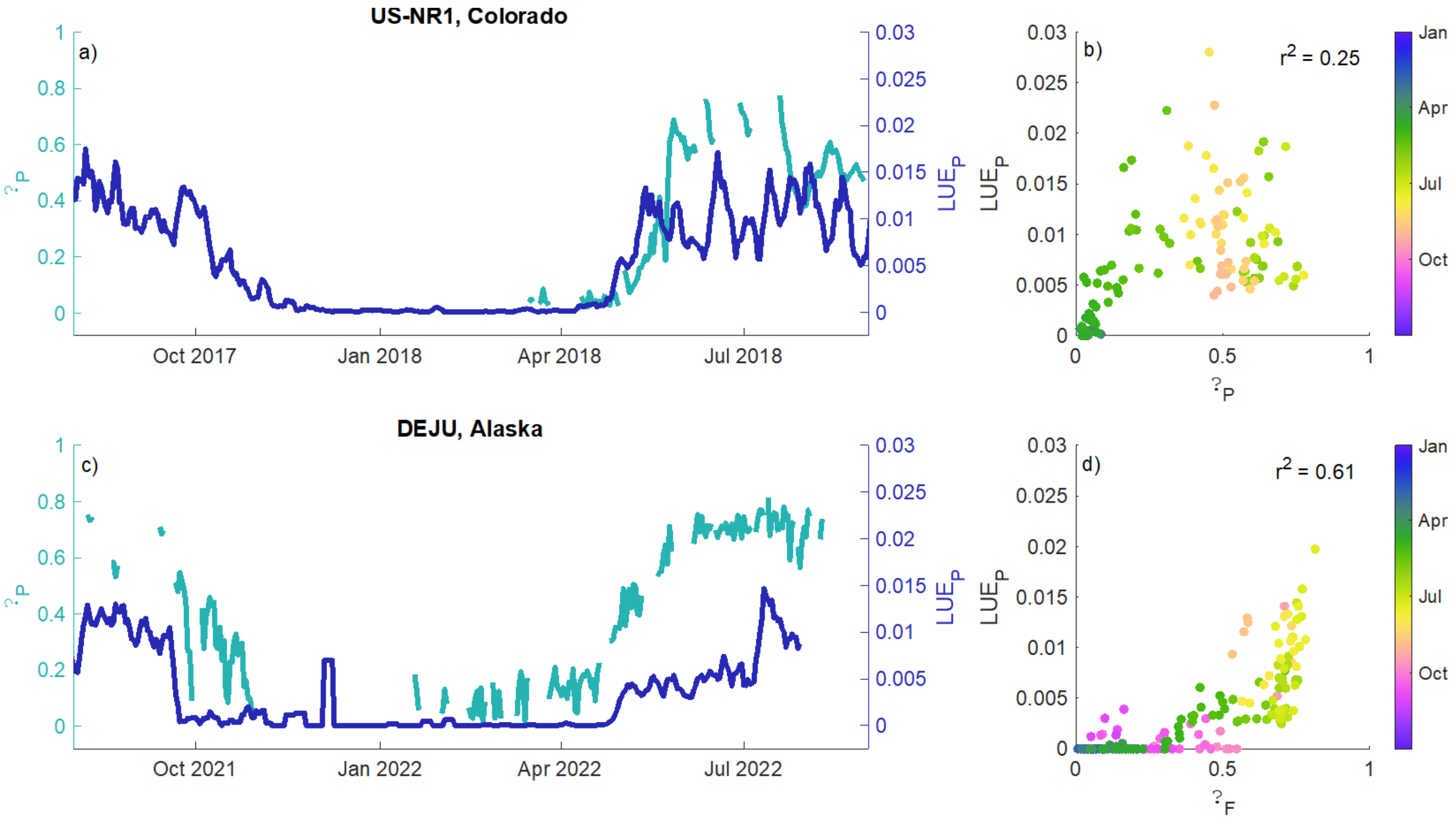
Pierrat, Magney, et al. *in press, Ecology*

How does the needle scale compare to the tower scale?

Comparing photochemical yield (ΦP) with light-use efficiency (LUE_P)



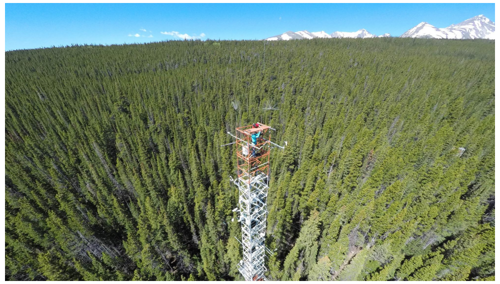


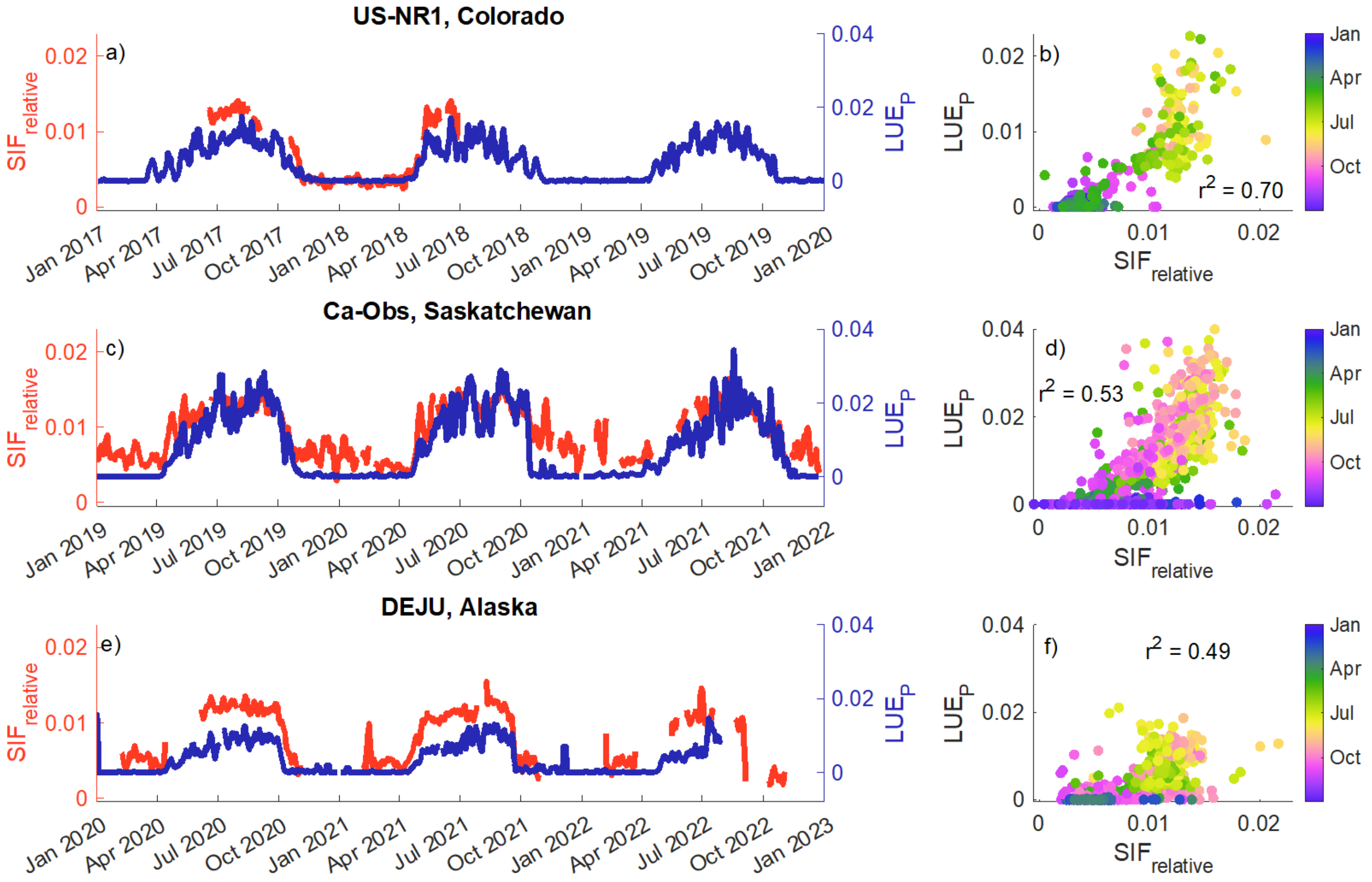


LUE_P = GPP/absorbed light (APAR)

Pierrat, Magney, et al. *in press, Ecology*

Taken together, $SIF_{relative}$ matches well with LUE_P at all 3 sites





Pierrat, Magney, et al. *in press, Ecology*

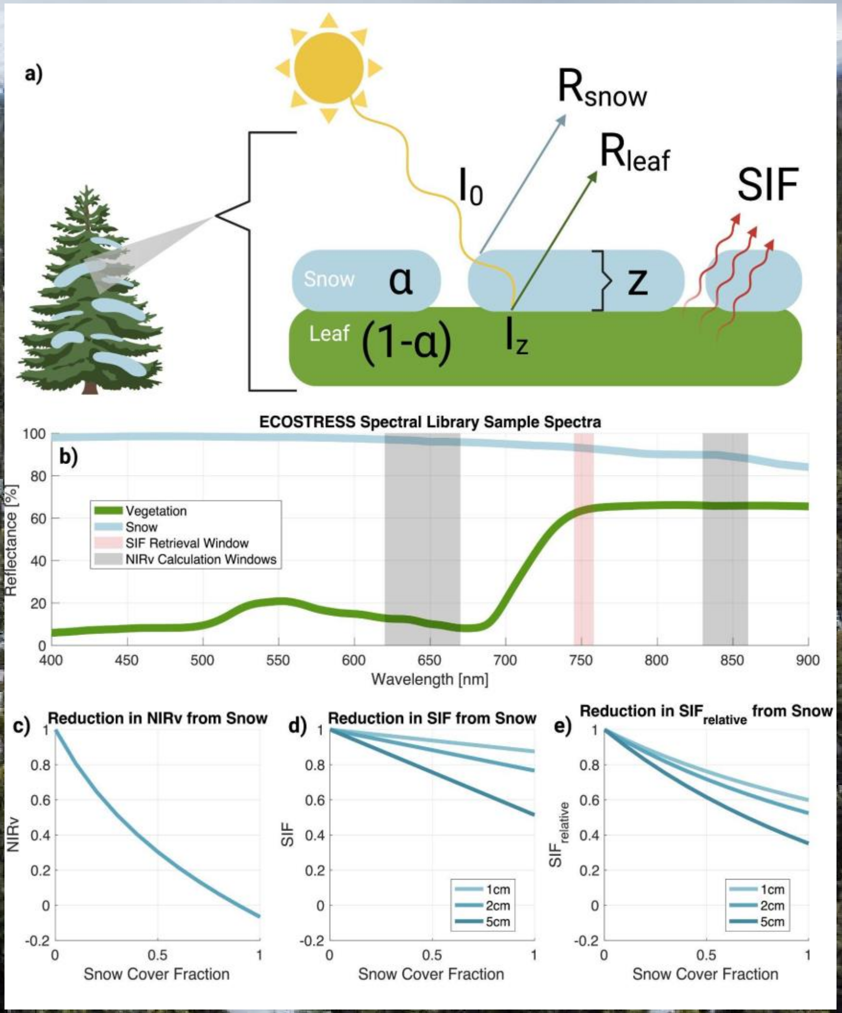
Correcting for SIF using $SIF_{relative}$ better tracks GPP onset

Satellites have not been able to see this previously because of snow background

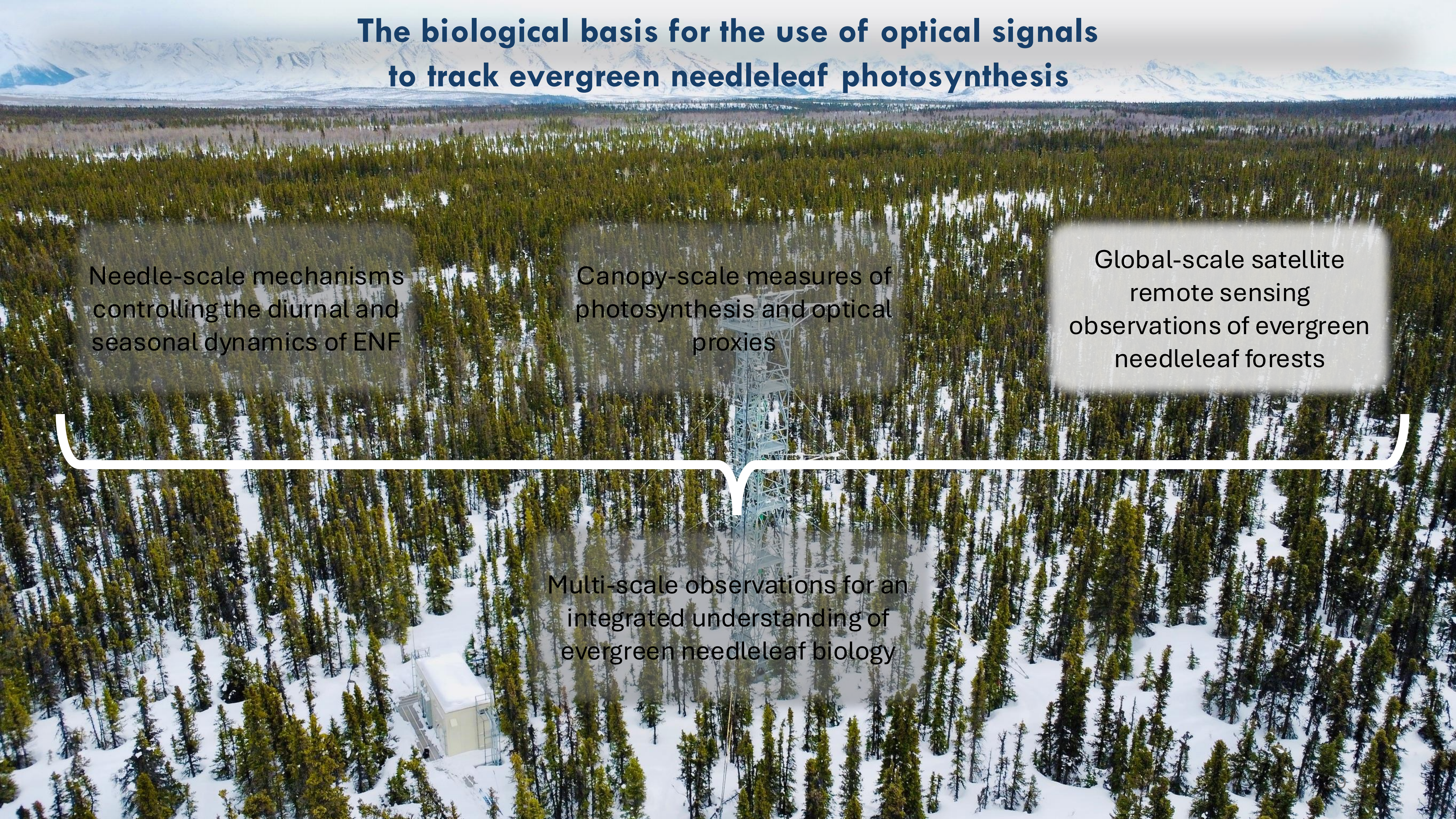
But now we can correct for snow using a physiologically sensitive index ($SIF_{relative}$)

To confirm this 'wakening' at a range of scales (needle -> tower -> satellite)

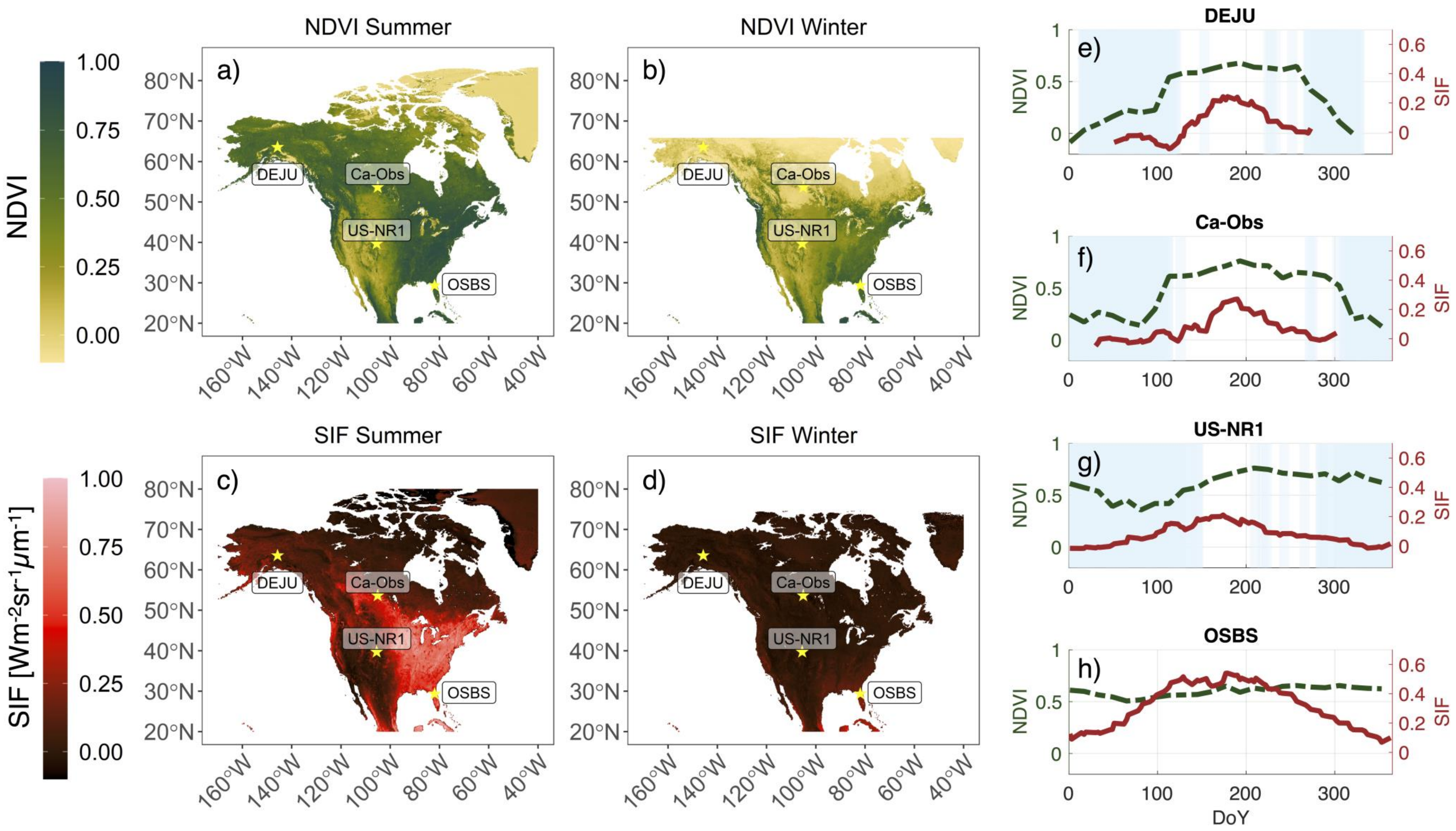
And hopefully gain a better understanding on the seasonal timing of photosynthesis in ENFs



Pierrat, Magney, et al. *in press, Ecology*

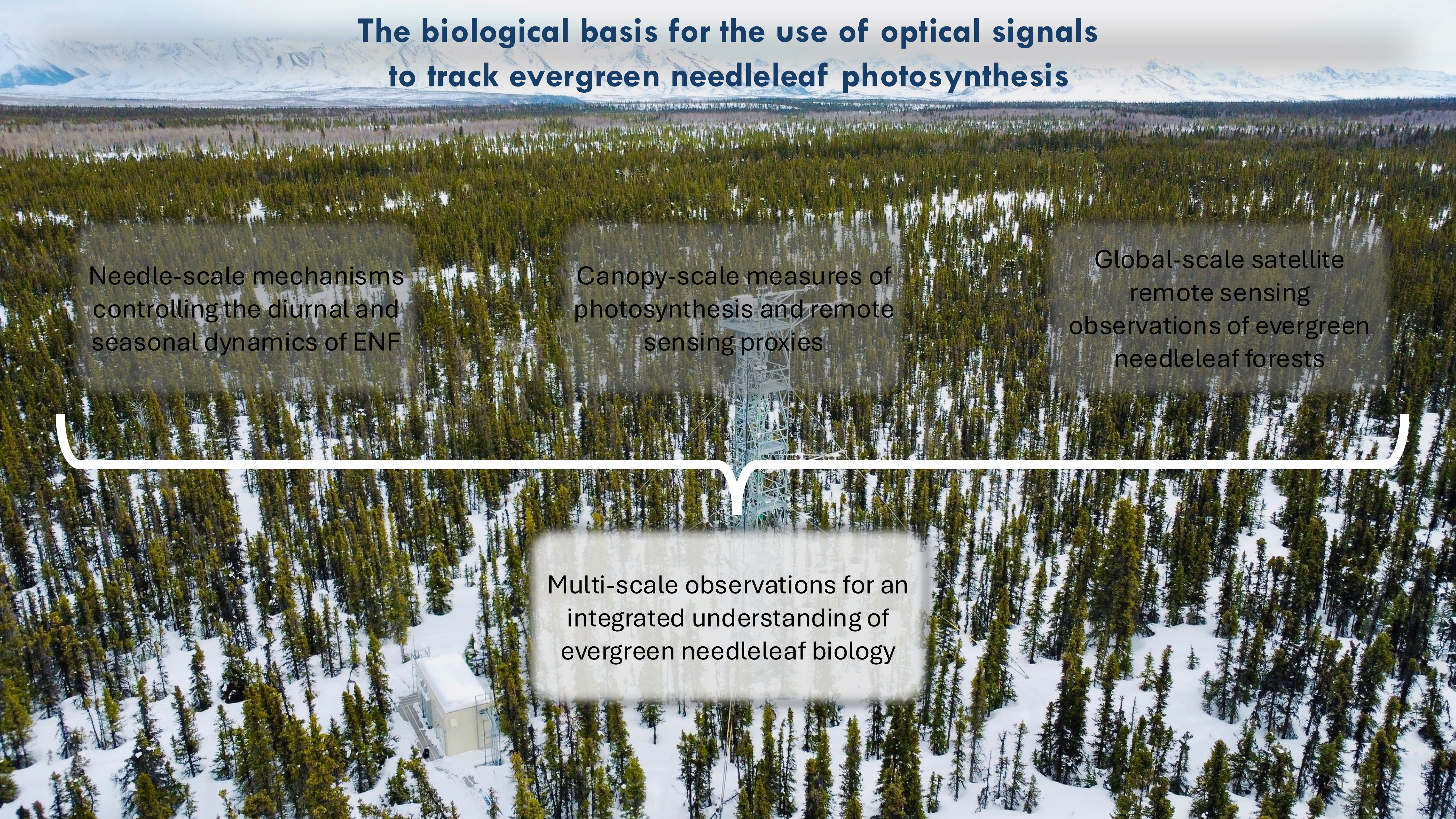

The biological basis for the use of optical signals
to track evergreen needleleaf photosynthesis
Needle-scale mechanisms controlling the diurnal and seasonal dynamics of ENF
Canopy-scale measures of photosynthesis and optical proxies
Global-scale satellite remote sensing observations of evergreen needleleaf forests
Multi-scale observations for an integrated understanding of evergreen needleleaf biology

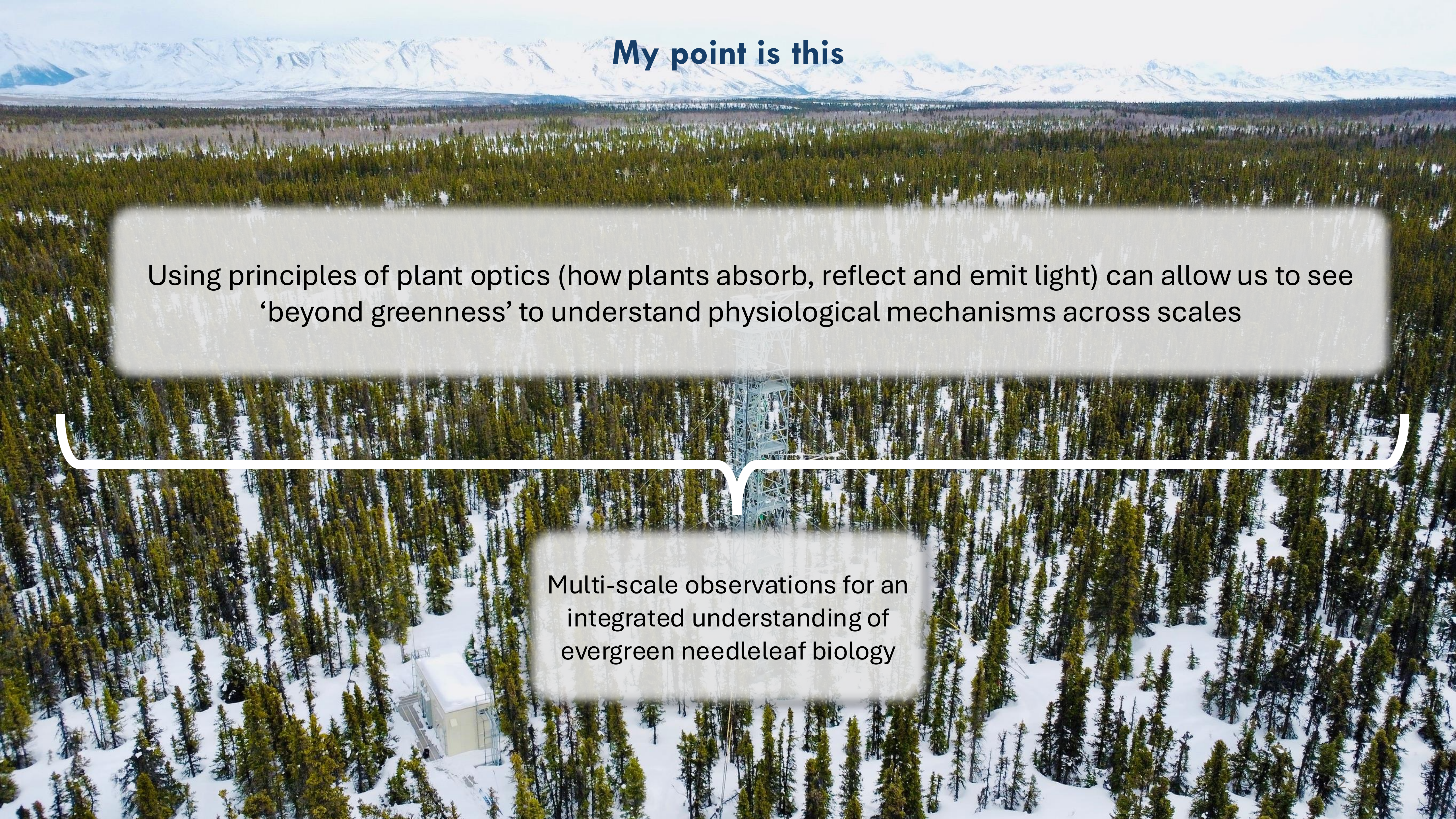
Satellite remote sensing expands the spatial range but there remains a need for mechanistic ground-based validation



Cheng, Magney, et al. 2022 *Environmental Research Letters*

Pierrat, Magney, et al. 2024 *BioScience*

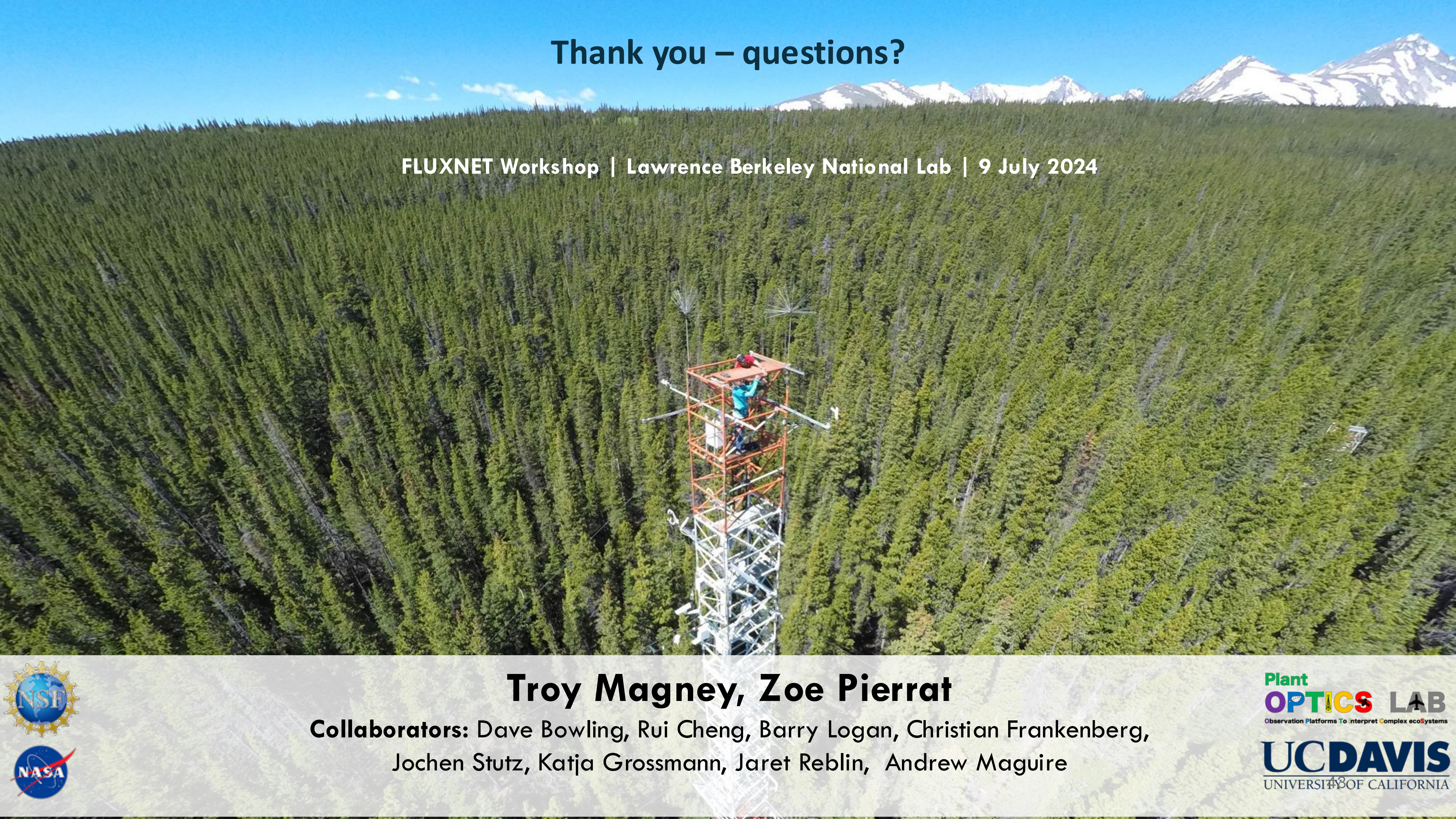

The biological basis for the use of optical signals
to track evergreen needleleaf photosynthesis
Needle-scale mechanisms controlling the diurnal and seasonal dynamics of ENF
Canopy-scale measures of photosynthesis and remote sensing proxies
Global-scale satellite remote sensing observations of evergreen needleleaf forests
Multi-scale observations for an integrated understanding of evergreen needleleaf biology



My point is this

Using principles of plant optics (how plants absorb, reflect and emit light) can allow us to see 'beyond greenness' to understand physiological mechanisms across scales

Multi-scale observations for an integrated understanding of evergreen needleleaf biology


Thank you – questions?
FLUXNET Workshop | Lawrence Berkeley National Lab | 9 July 2024
Troy Magney, Zoe Pierrat
Collaborators: Dave Bowling, Rui Cheng, Barry Logan, Christian Frankenberg, Jochen Stutz, Katja Grossmann, Jaret Reblin, Andrew Maguire
Plant OPTICS LAB
Observation Platforms To Interpret Complex ecoSystems
UC DAVIS UNIVERSITY OF CALIFORNIA

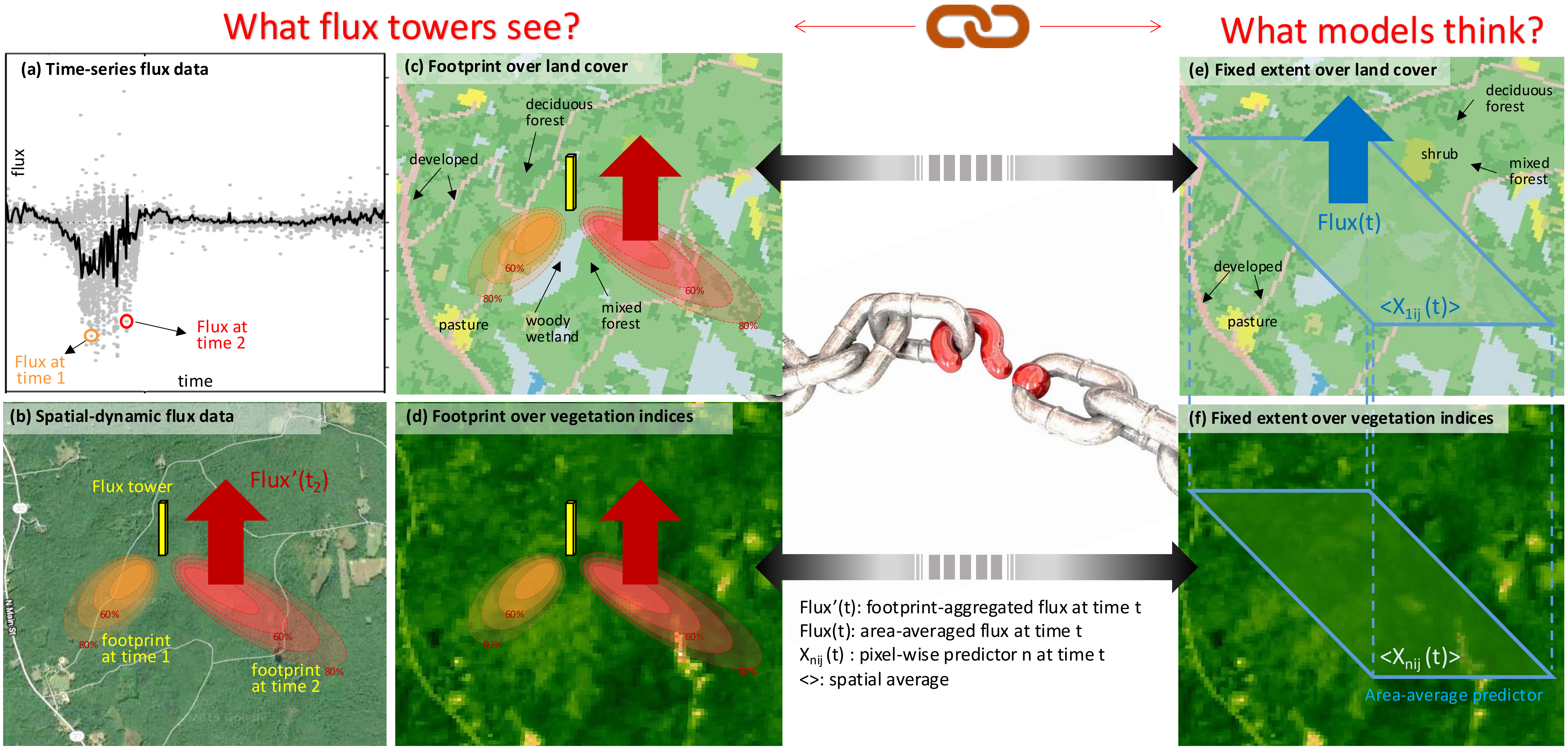
Bridge the link between flux towers and models to enable upscaling

Housen Chu[1],
Xiangzhong Luo[2],
Zutao Ouyang[3],
Patty Oikawa[4],
Thomas Fenster[4,5],
Camilo Rey-Sanchez[6],
Iryna Dronova[7], Alex Valach[8]
AmeriFlux Management Project and Site Teams

1 Lawrence Berkeley National Laboratory
2 National University of Singapore
3 Auburn University,
4 California State University – East Bay
5 University of California, Davis
6 North Carolina State University
7 University of California, Berkeley
8 Berner Fachhochschule BFH, Bern, Berne, Switzerland

AMERIFLUX

Background



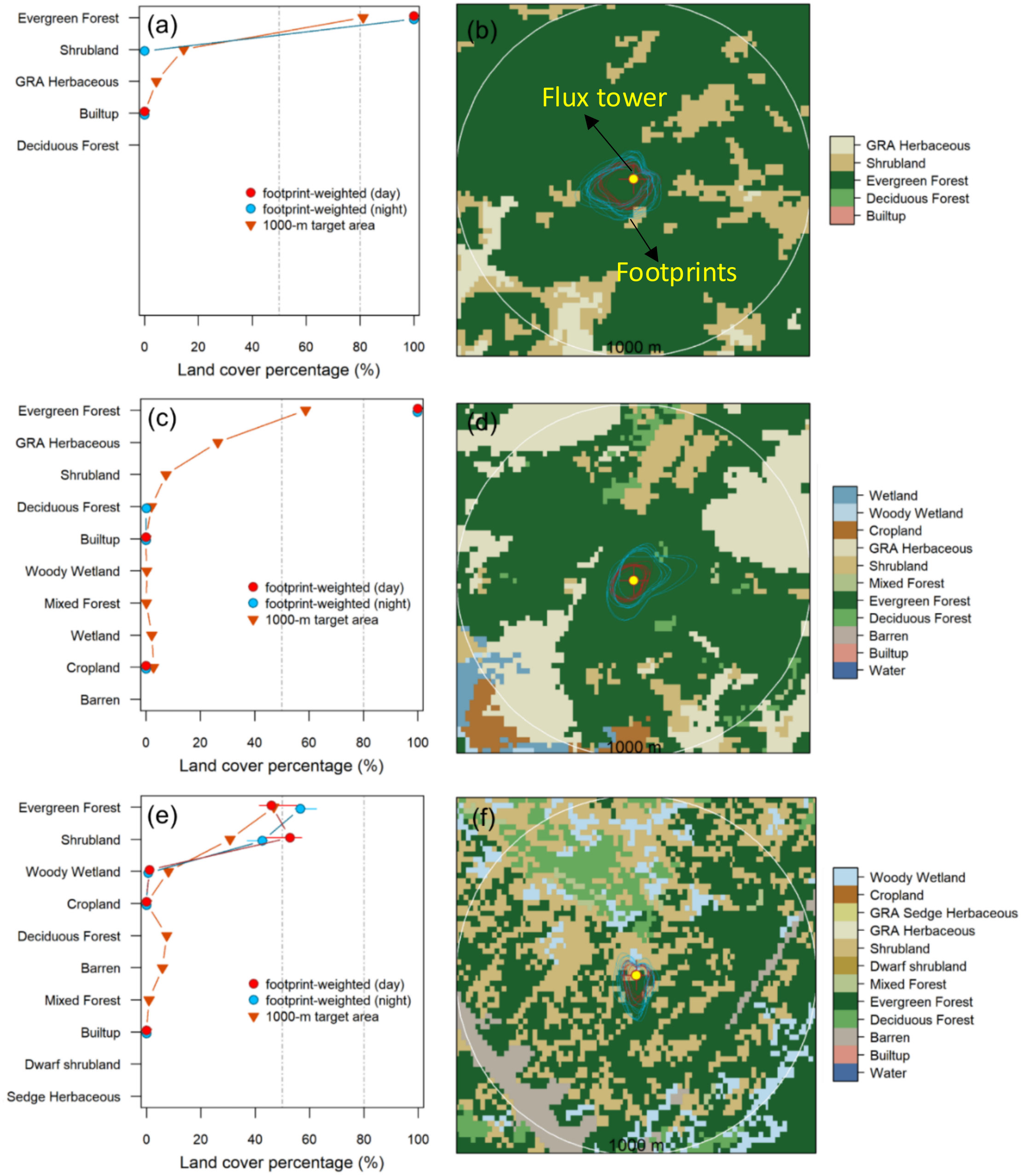
(Chen et al., 2012; Gockede et al., 2008; Rebmann et al., 2005; Wang et al., 2016)

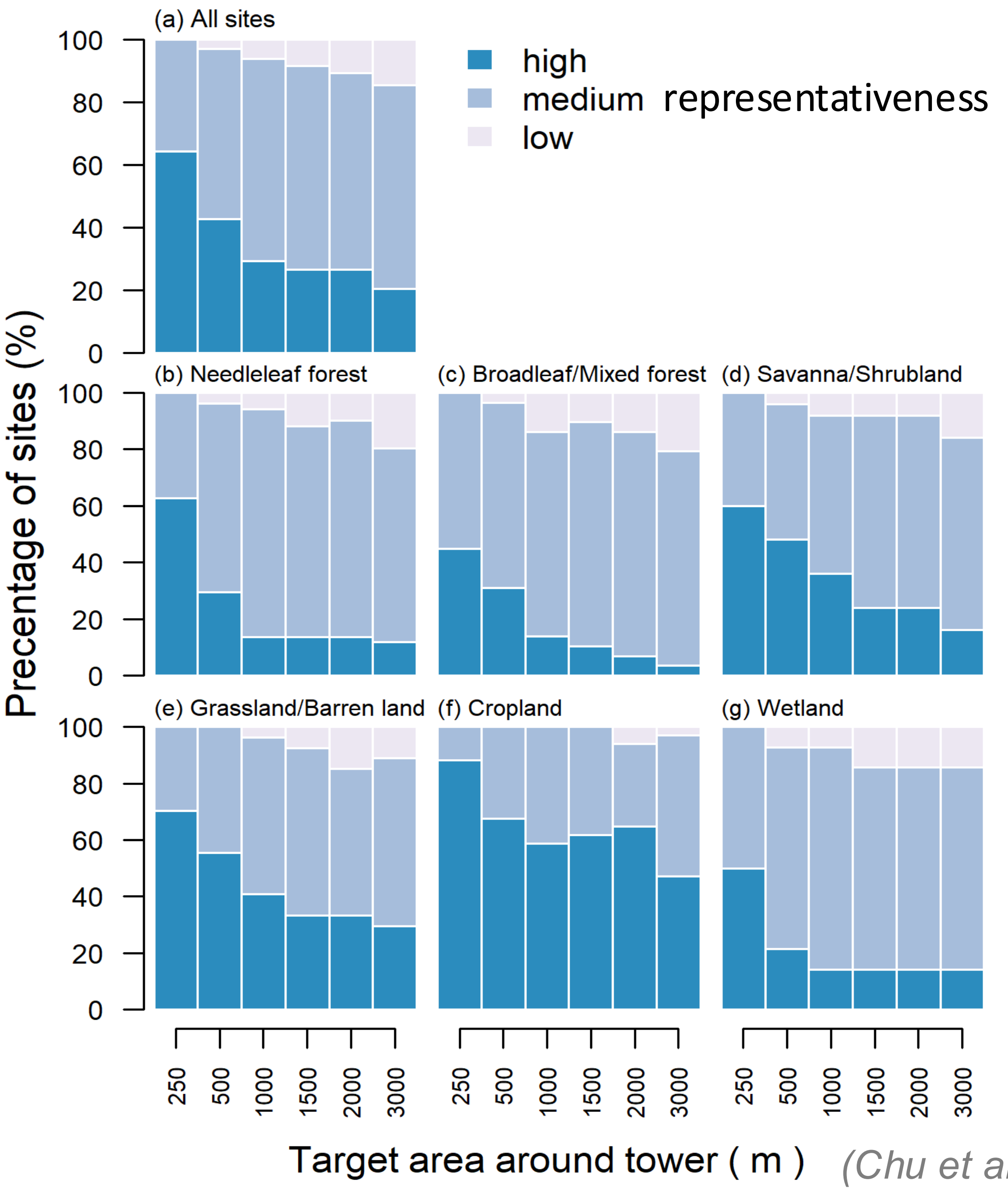
Representativeness based on land cover composition

High

Medium

Low





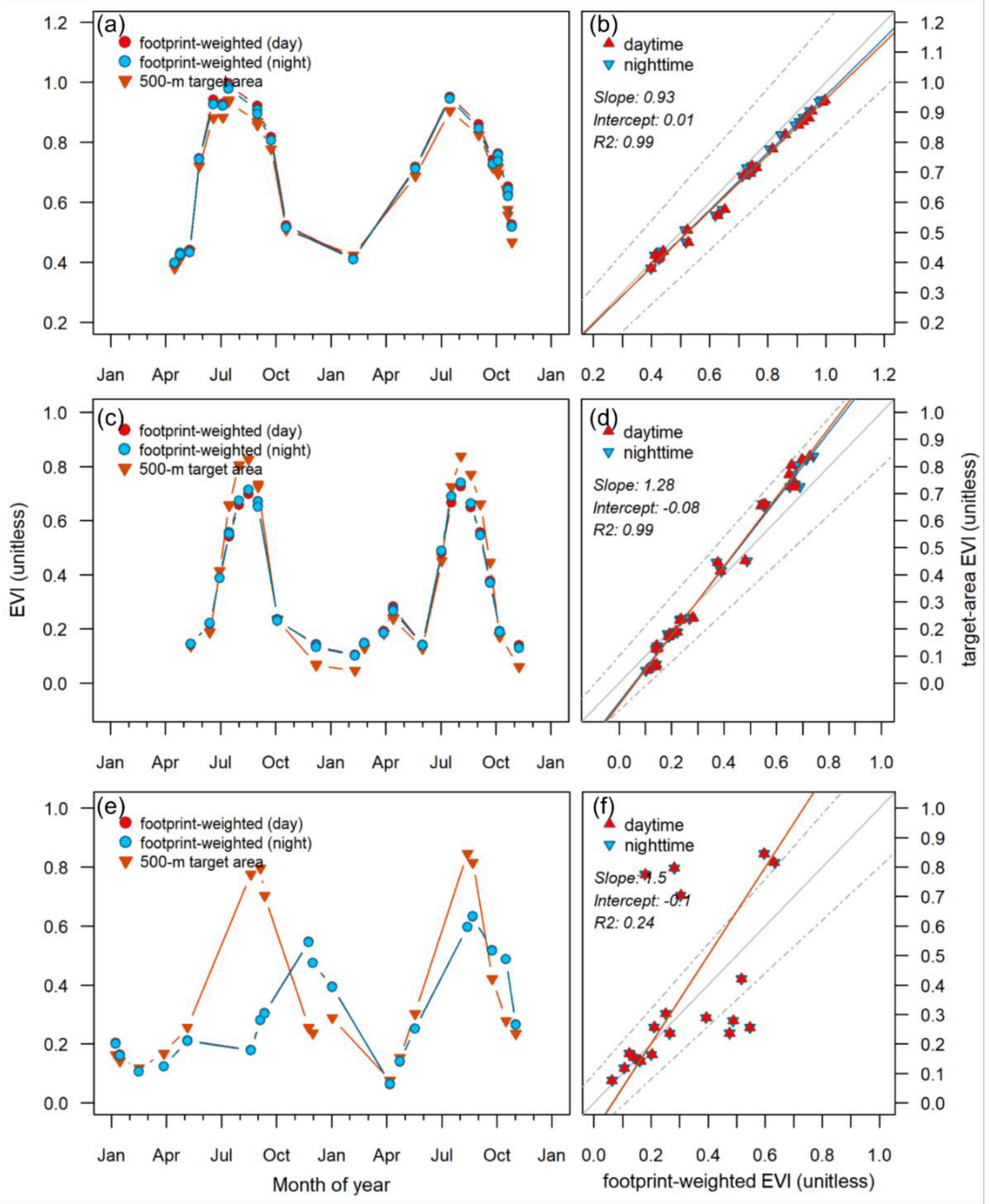
(Chu et al. 2021)

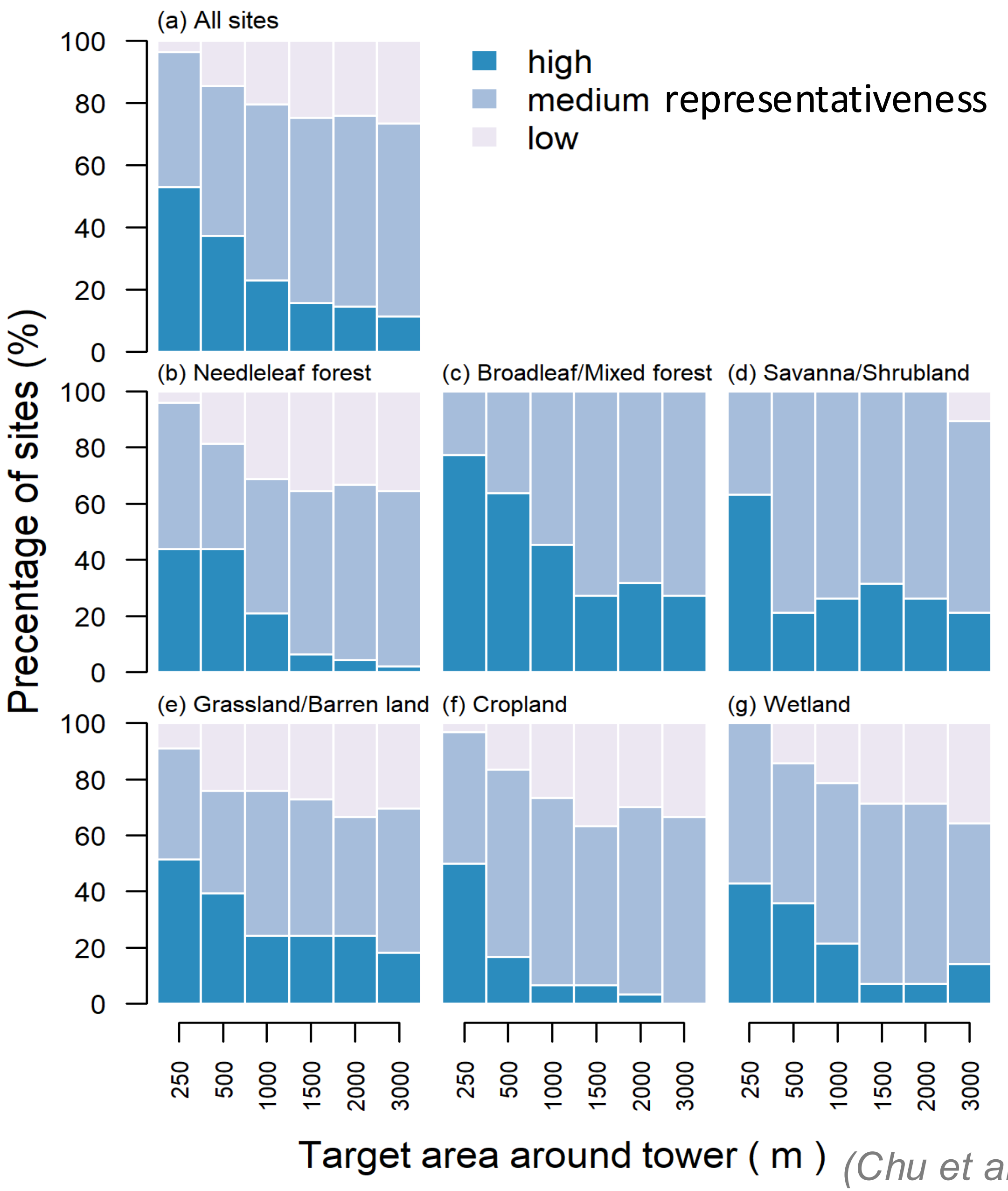
Representativeness based on EVI

High

Medium

Low



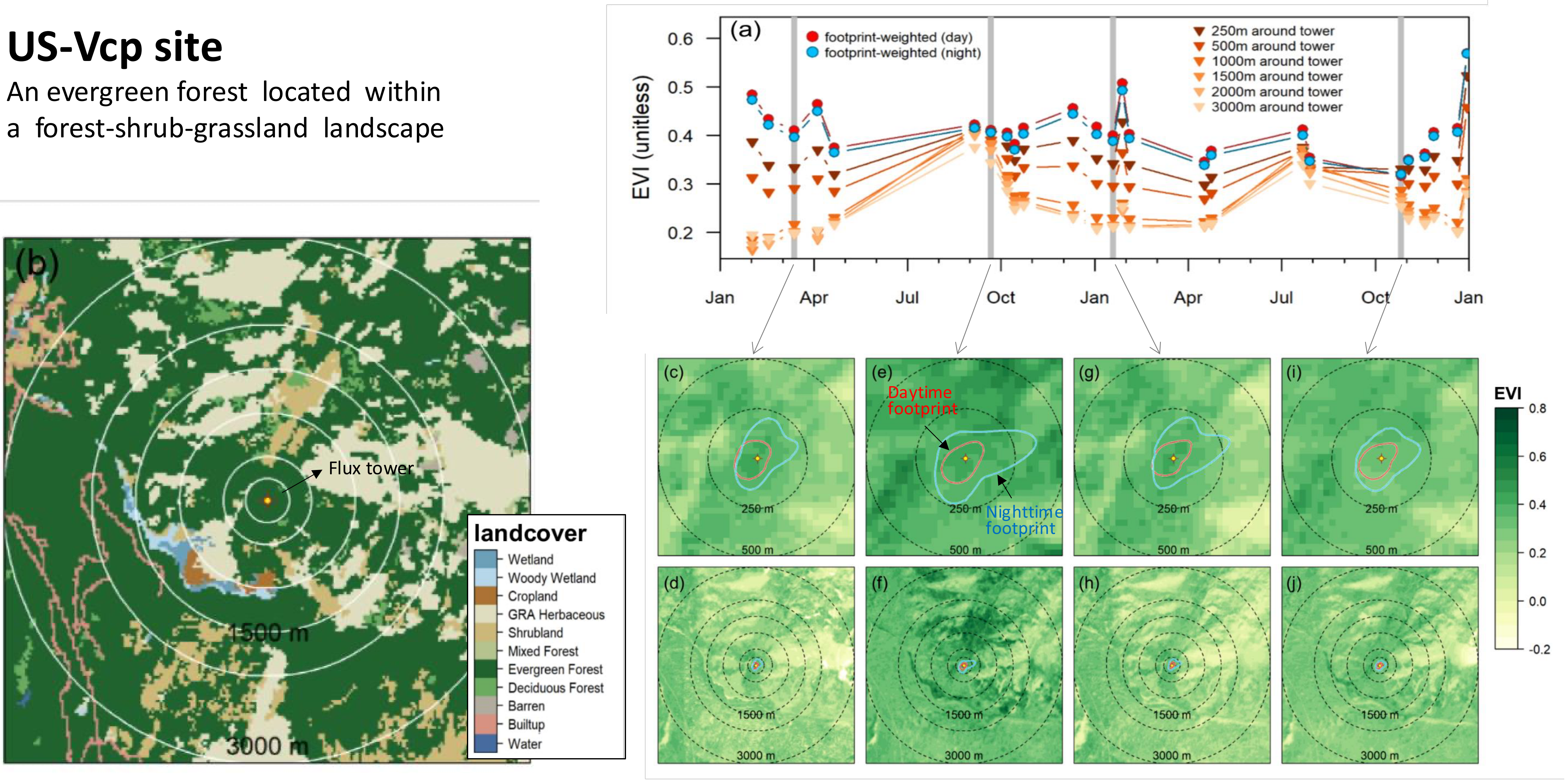


(Chu et al. 2021)

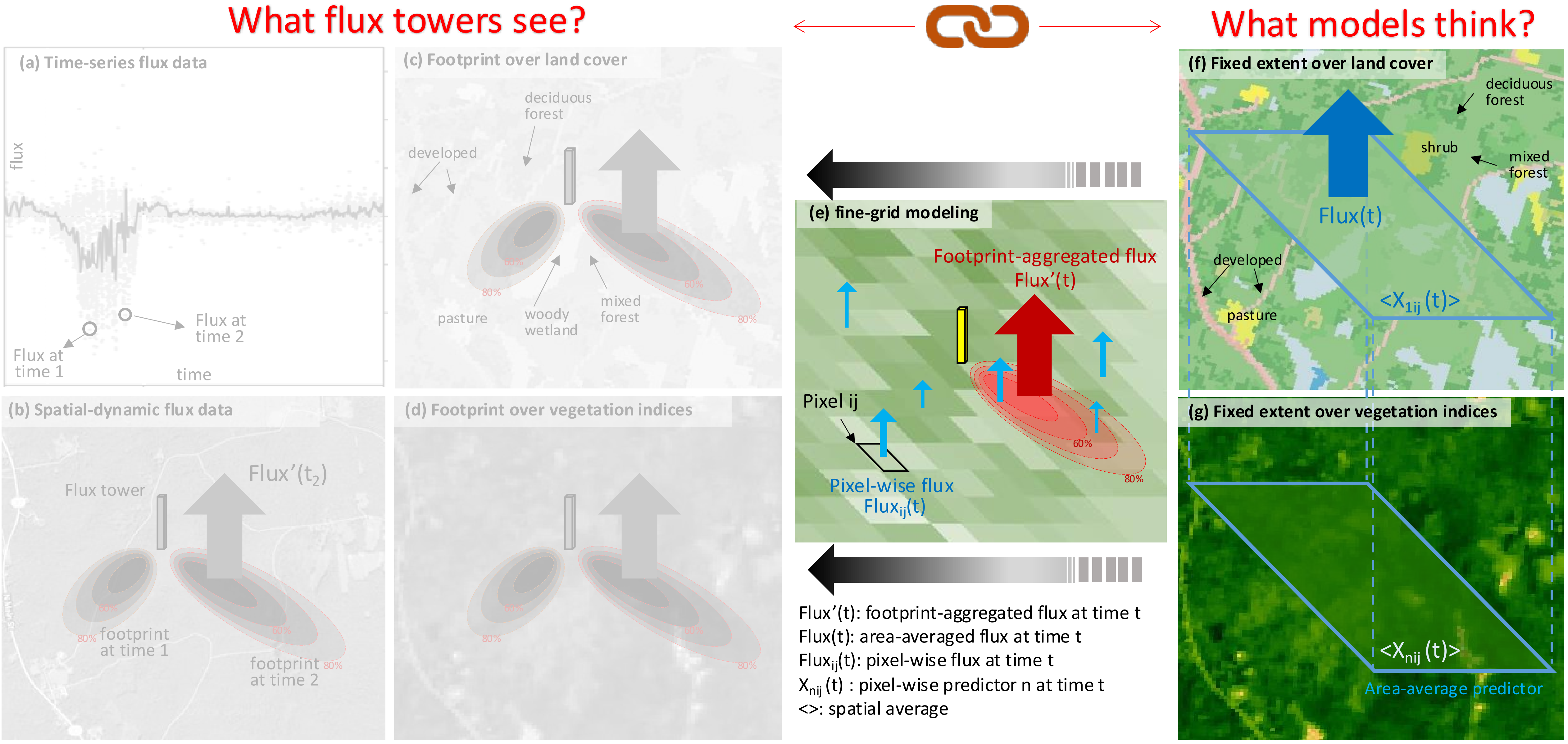
Example case – limited representativeness

US-Vcp site

An evergreen forest located within a forest-shrub-grassland landscape

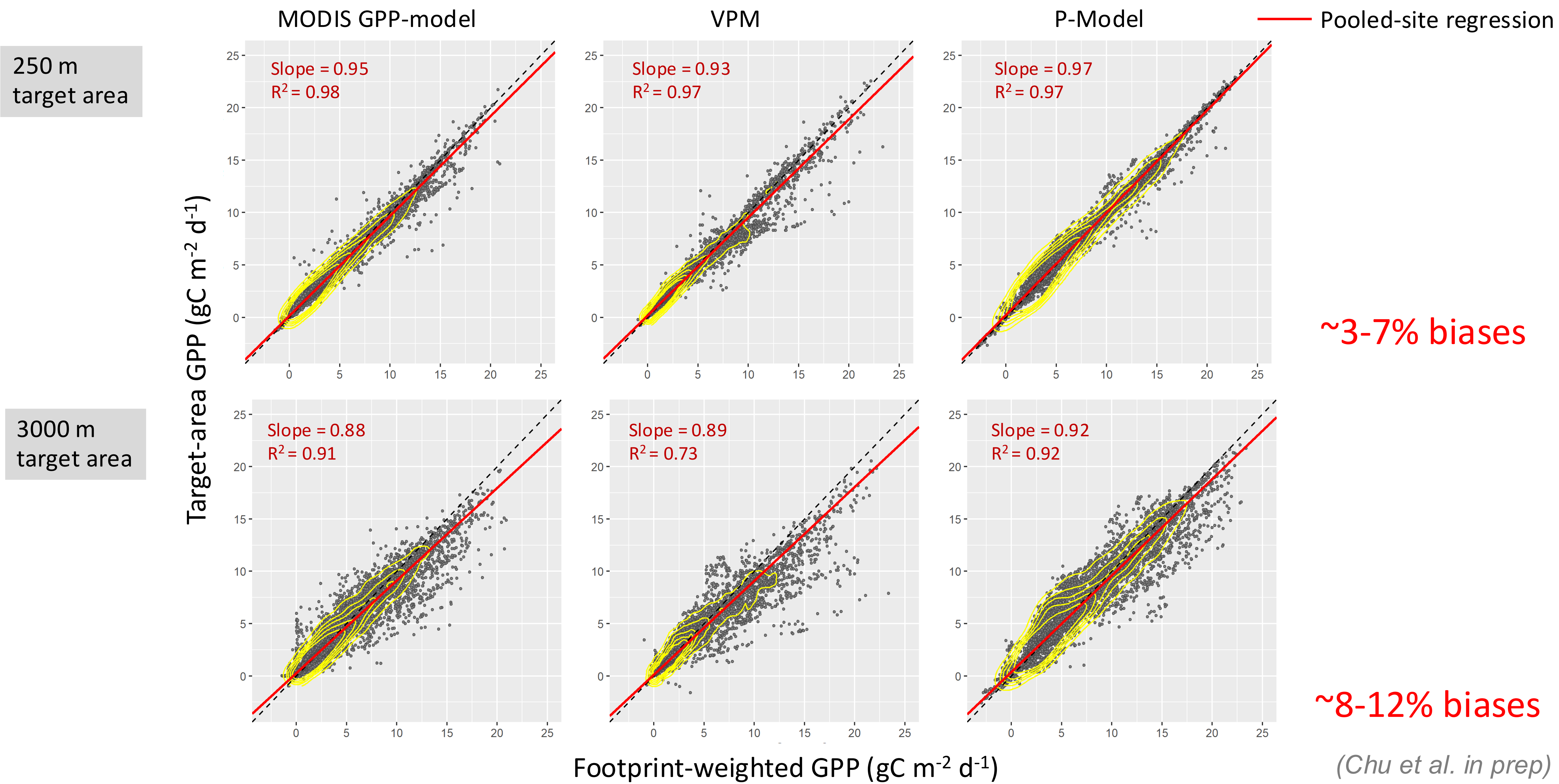


A fine-grid modeling approach



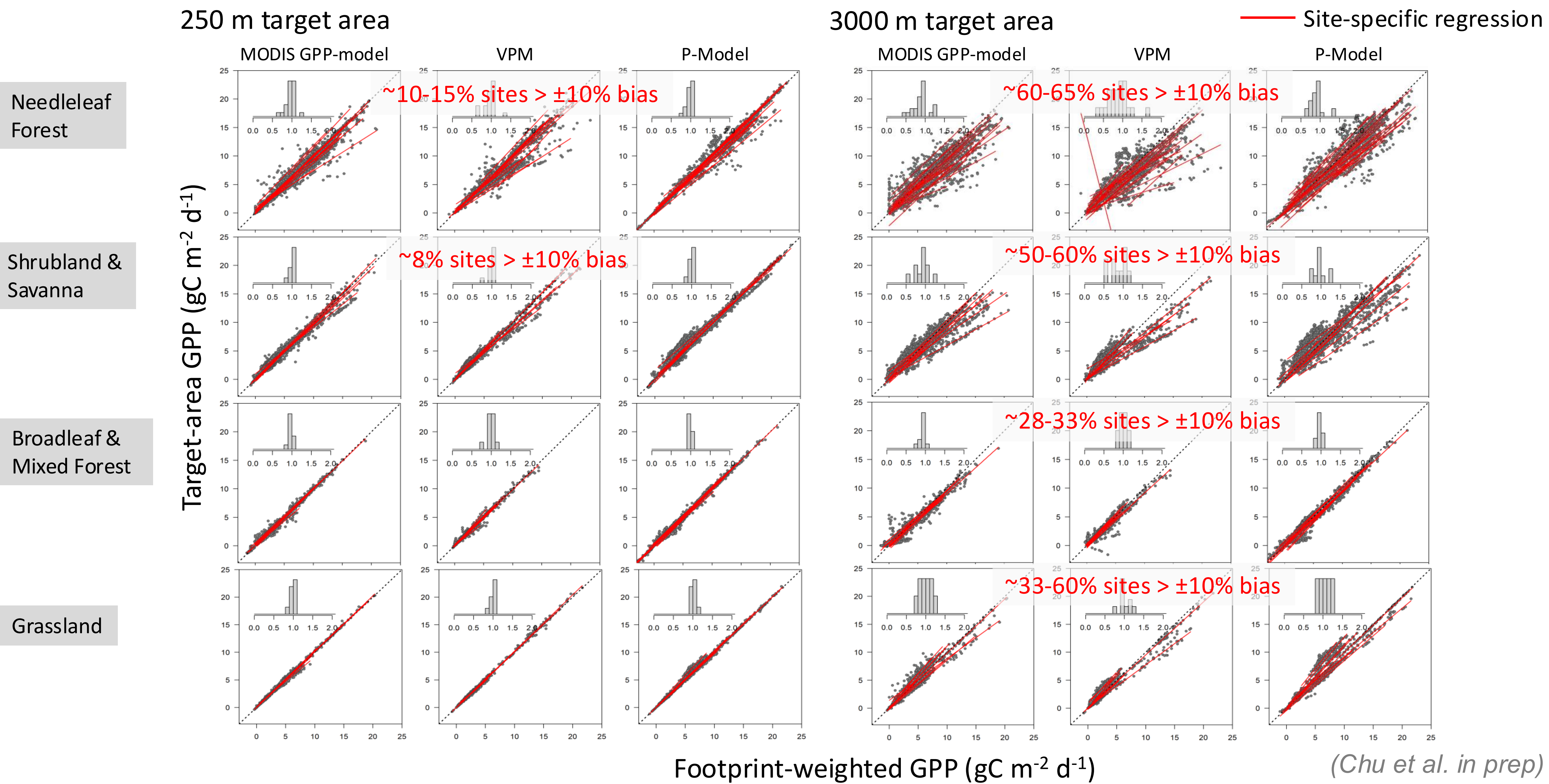
(Chen et al., 2010; Fu et al., 2014; Ran et al., 2016)

Footprint-weighted vs Target-area GPP (all sites)



(Chu et al. in prep)

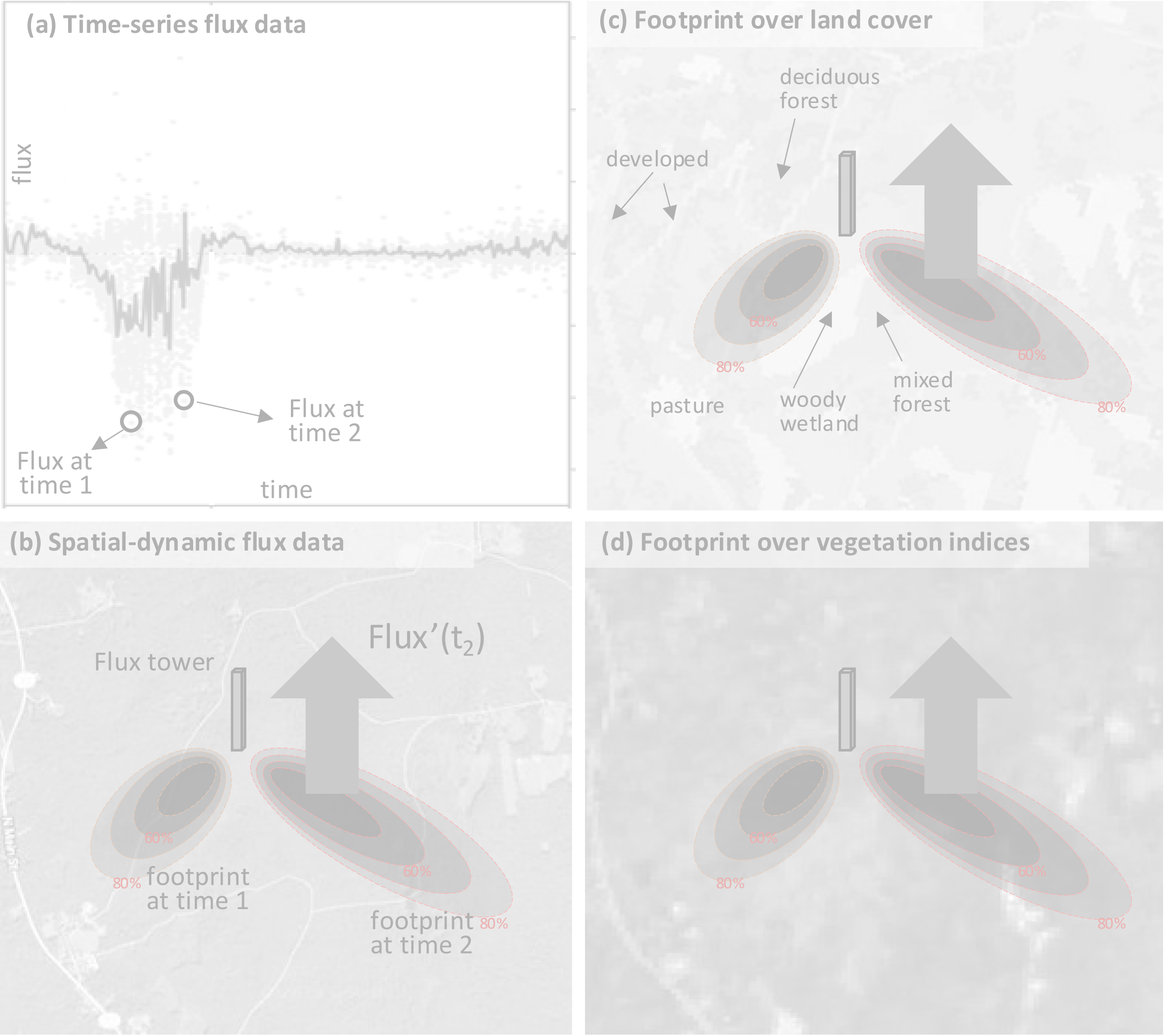
Footprint-weighted vs Target-area GPP (by ecosystem types)



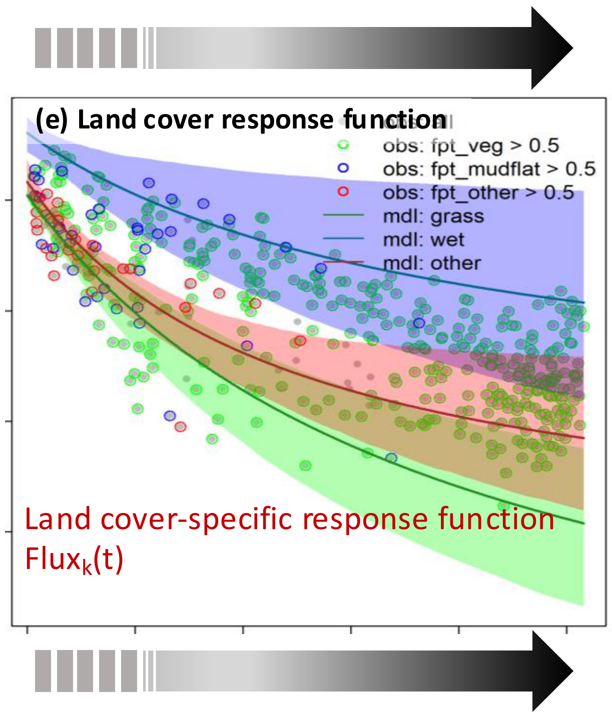
(Chu et al. in prep)

A footprint-informed decomposition approach

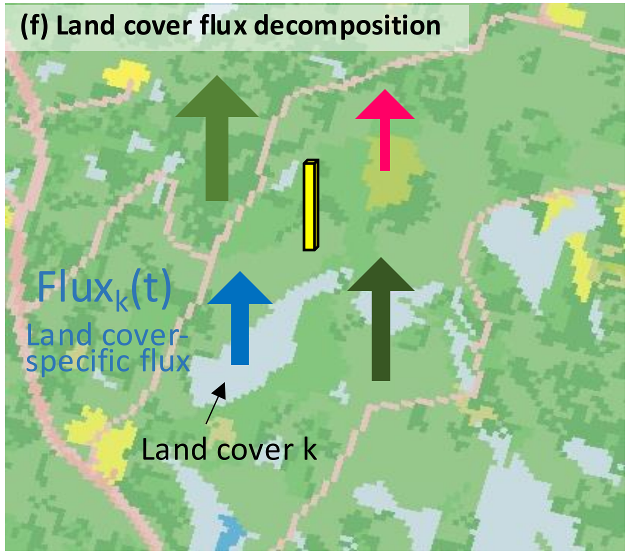
What flux towers see?

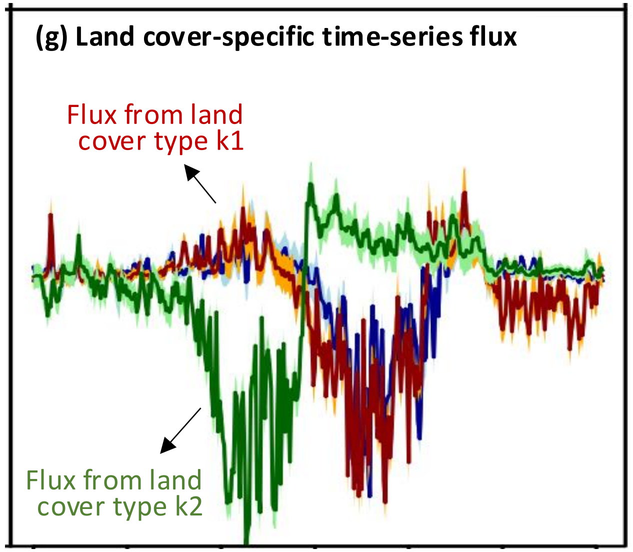


What models think?



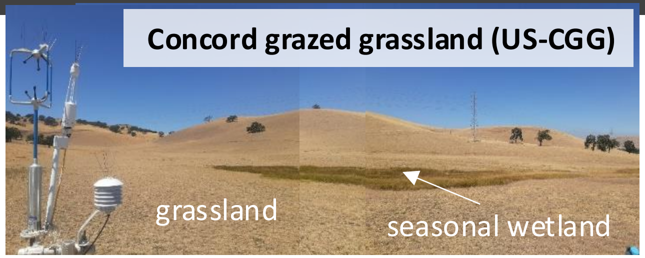
Flux'(t): footprint-aggregated flux at time t
$Flux_k(t)$: land cover-specific flux at time t
f(): model function

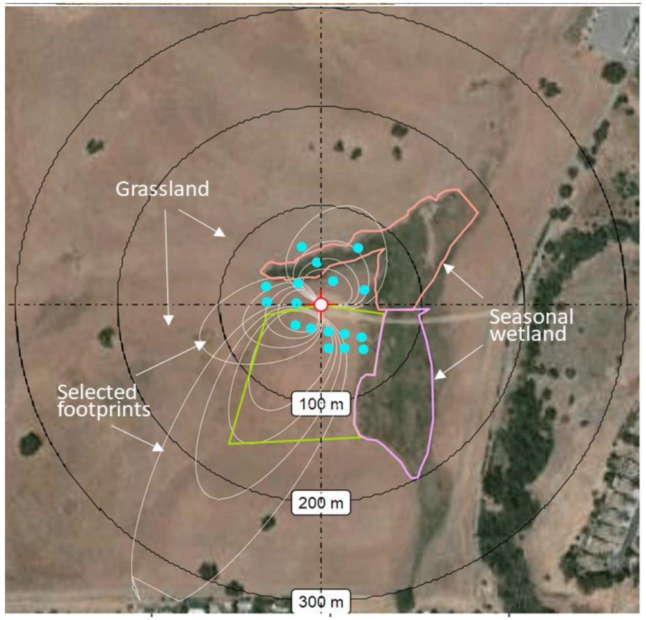


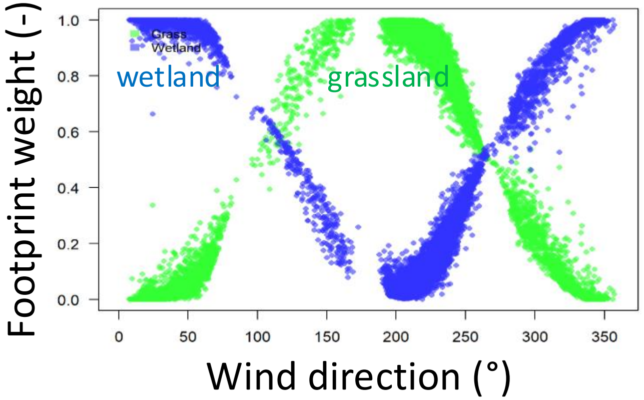


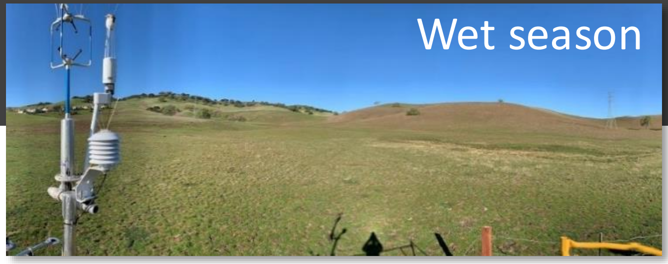
(Wang et al., 2006; Xu et al., 2017; Duman et al. 2018; Levy et al., 2020)

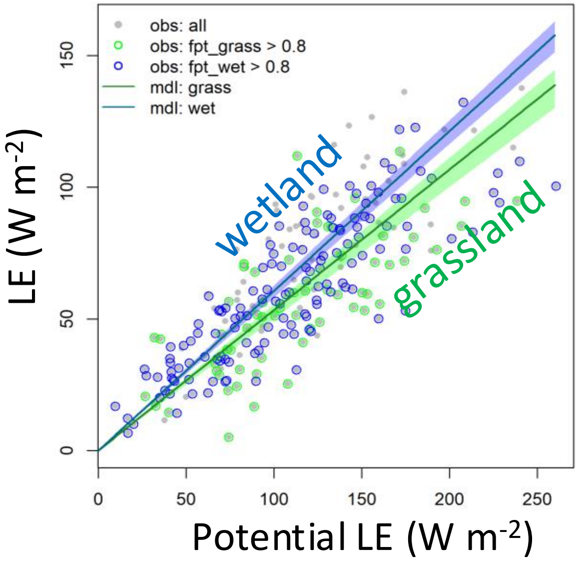
Simple case

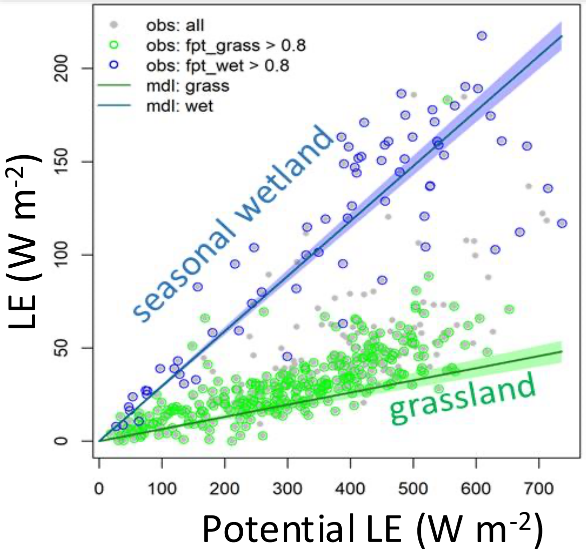


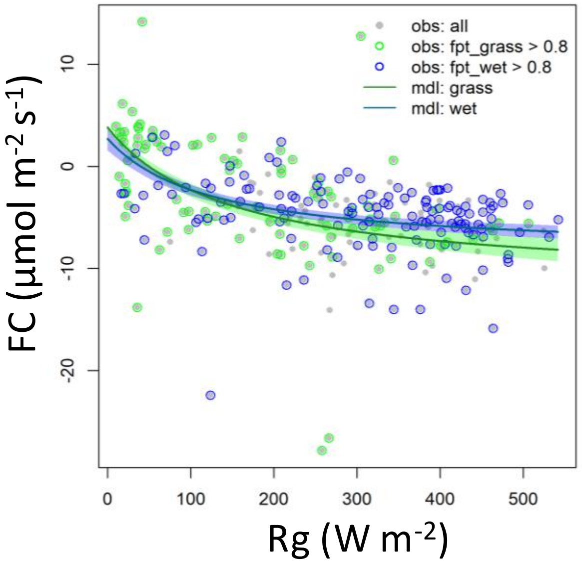


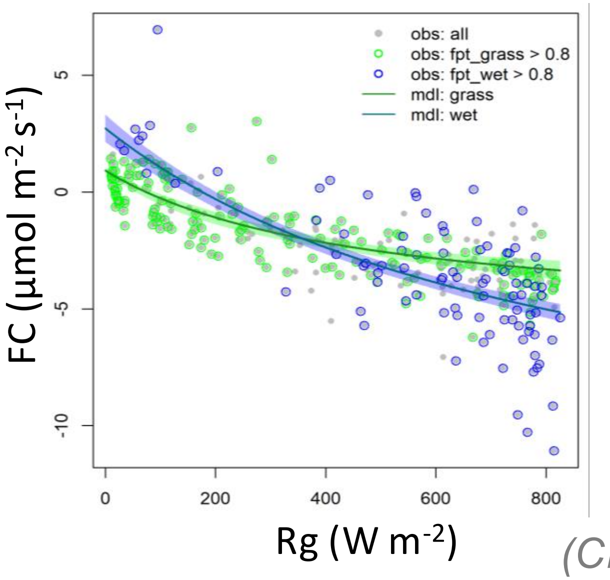






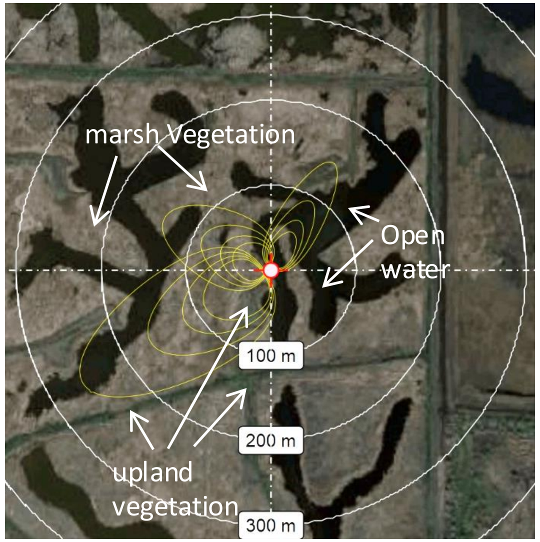


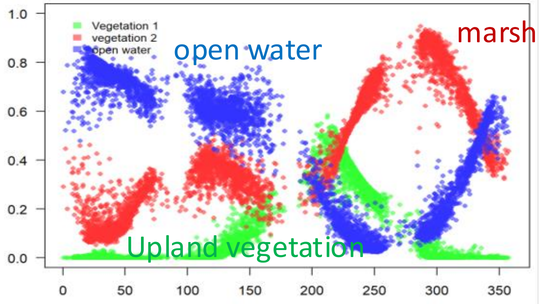




(Chu et al. in prep)

Complicated Case

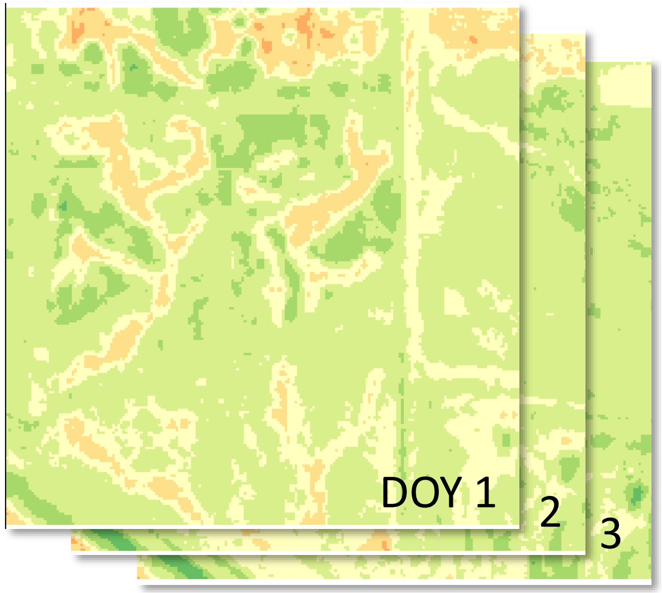


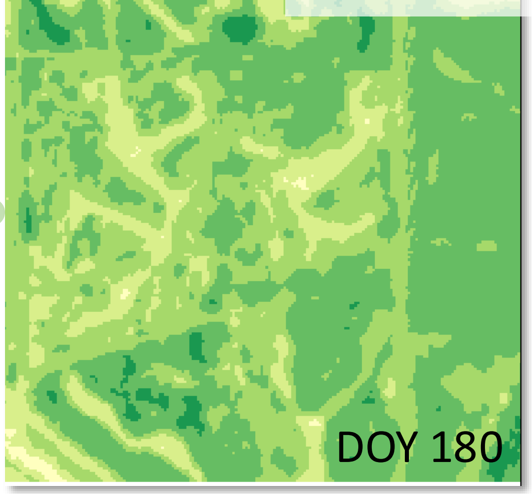


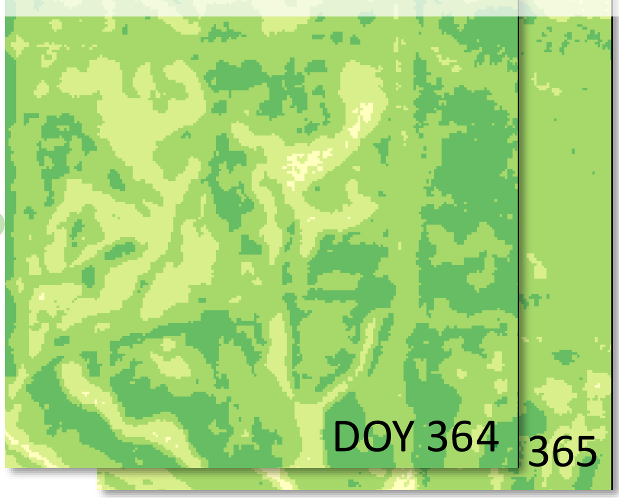
Wind direction (°)

Planet Fusion Product

- PlanetScope CubeSats – based
- Calibrated, geo-referenced, gap-filled
- Daily / 3-m resolutions
- R/G/B/NIR bands: NDVI

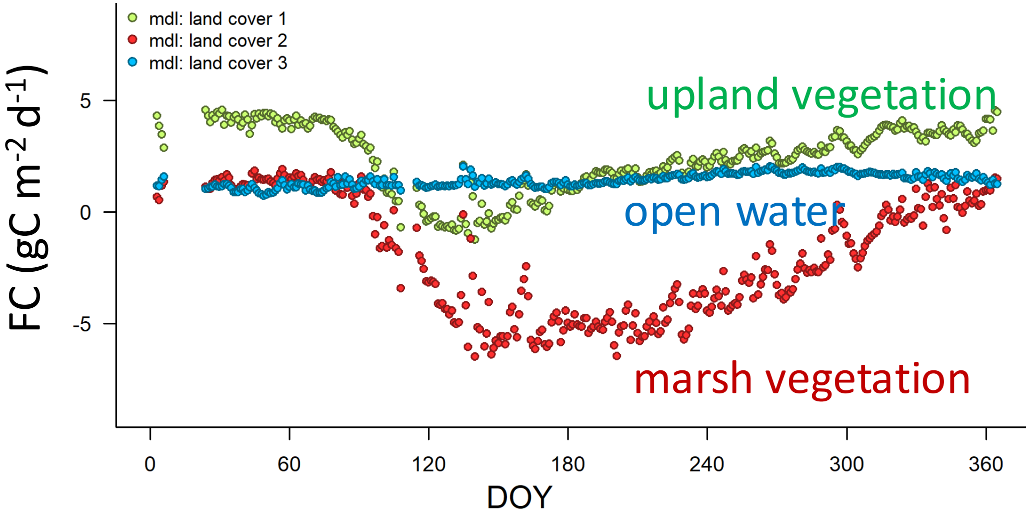


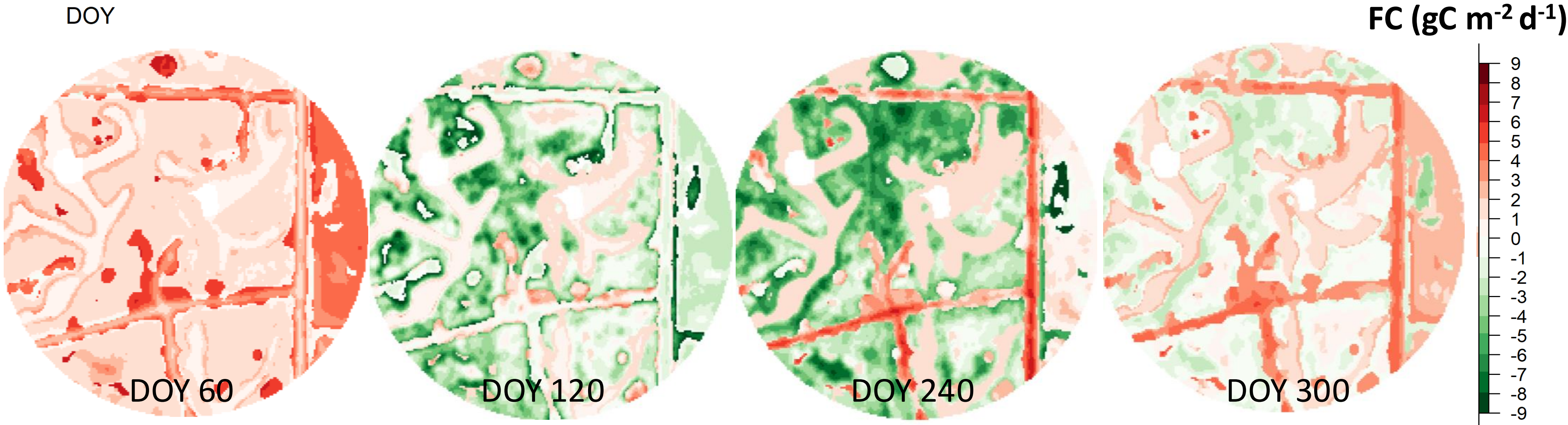




(Chu et al. in prep)

Spatiotemporal Constraints





(Chu et al. in prep)

Summary

Footprint representativeness of AmeriFlux sites

- Large-scale eddy-covariance flux datasets need to be used with footprint-awareness
- Using a fixed-extent target area across sites can bias model-data integration
- Most sites do not represent the dominant land-cover type at a larger spatial extent
- A representativeness index provides general guidance for site selection and data use

Footprint-informed decomposition approaches

- Few, mostly done at single-site studies
- Variation in Core models
  - Biophysical model (Duman et al., 2018, Wang et al., 2006)
  - Remote-sensing model (Ran et al., 2016, VPM)
  - Statistical model (Levy et al., 2020, e.g., linear additive model; Xu et al., 2017a multi-linear model)
  - Land surface model (Wang et al. 2022; CLM-Microbe)
  - Machine learning (Xu et al., 2017b; Metzger, 2018, Environmental Response Function)
  - Hybrid approach (Wiesner et al. 2022)
- Additional constraints/inputs
  - Chamber flux measurements (Rey-Sanchez, et al., 2018)
  - Lysimetric measurements (Joy & Chávez 2021)
  - Spatial drivers/characteristics – remote sensing (Xu et al., 2017b)

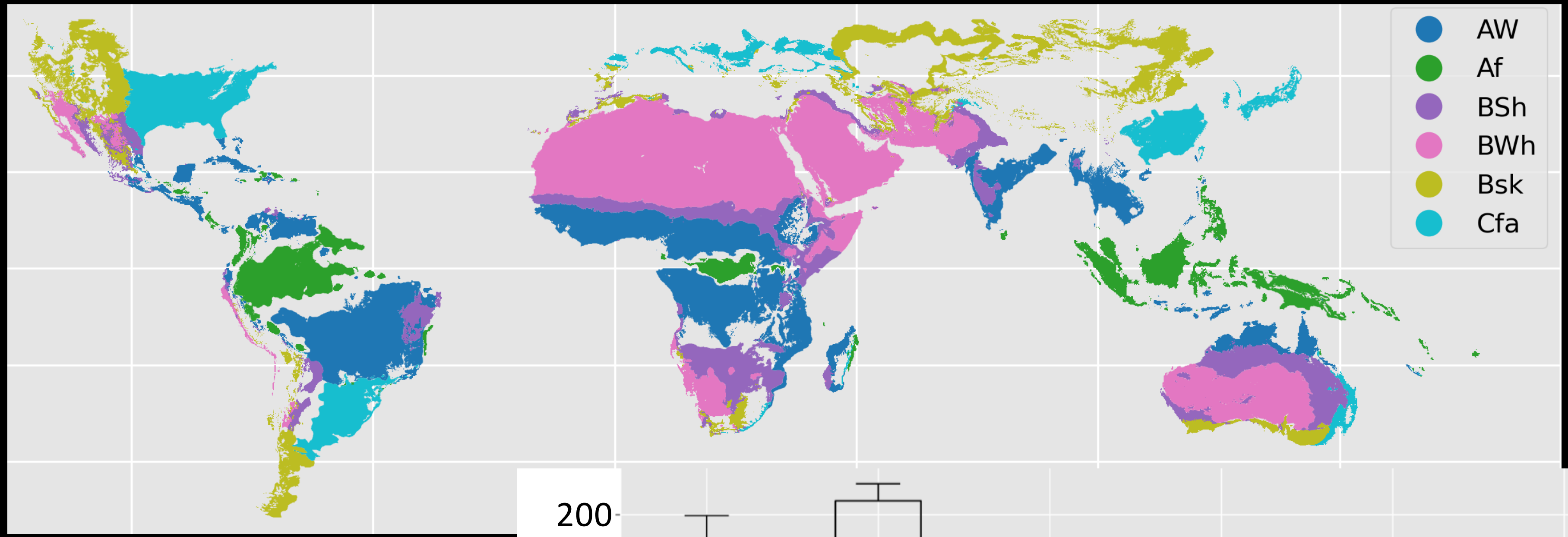
Foundation Models for Vegetation Growth and Carbon Sequestration

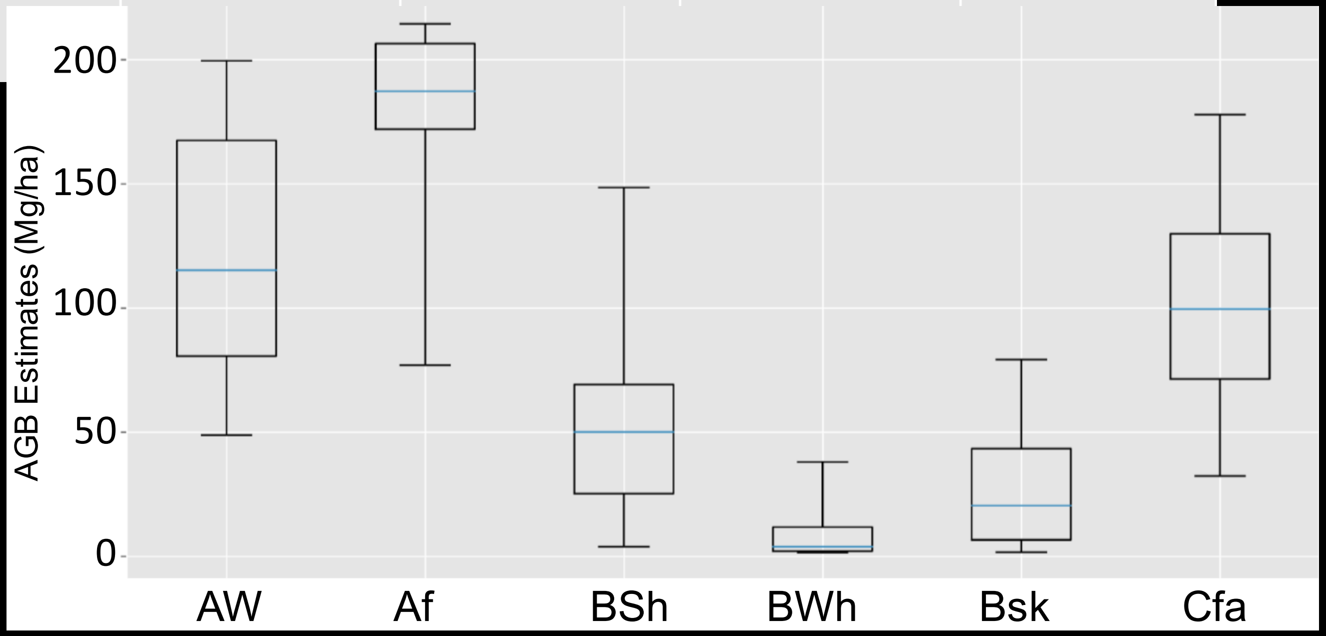
Levente Klein
IBM Research, NY

Carbon Sequestration

Maintaining and, ultimately, increasing **vegetation coverage** is likely the **most impactful** approach to **globally capture carbon**.

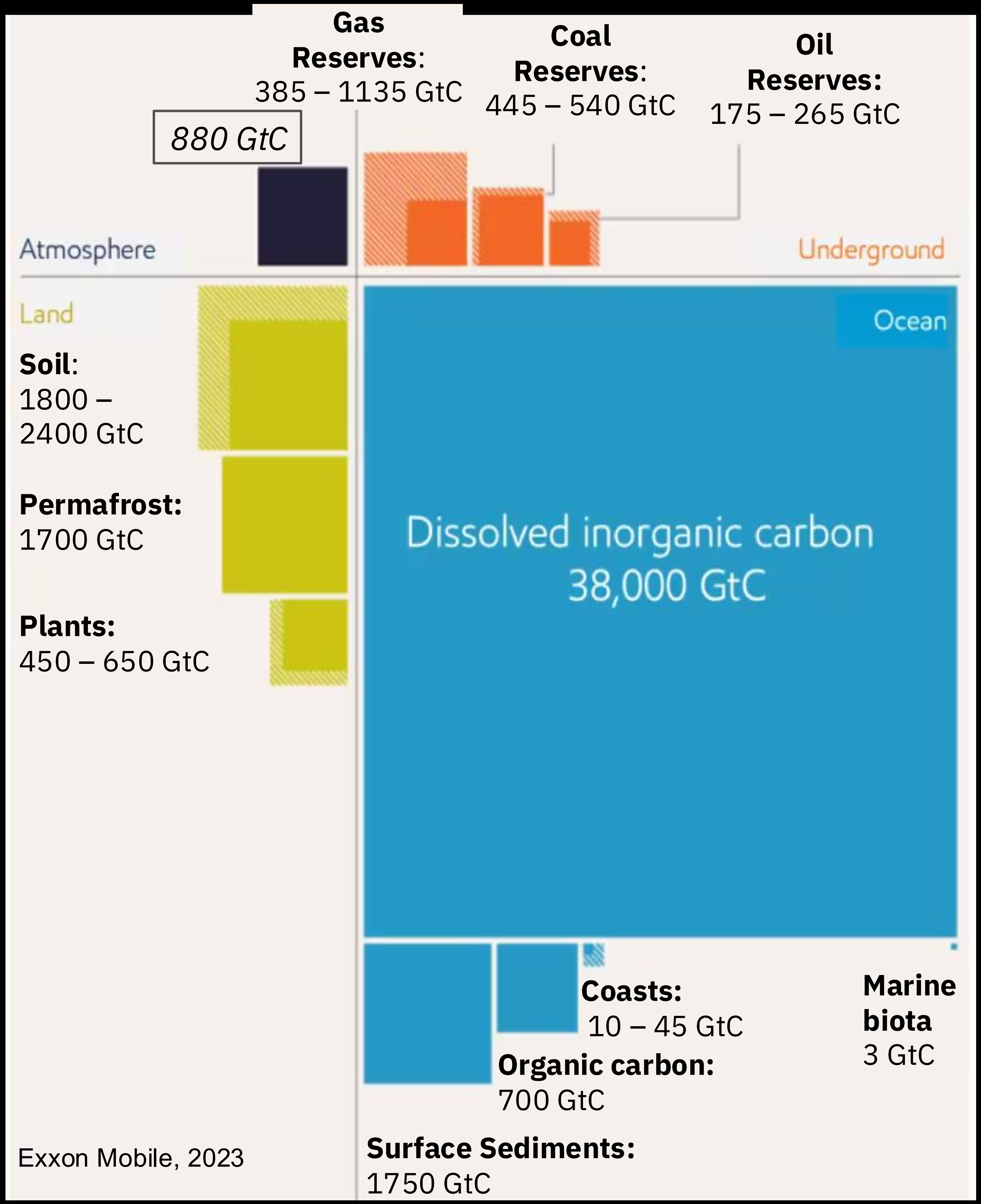
Biomass is a crucial **parameter** for **quantifying carbon** stored in vegetation, and **estimating it poses challenges**.





Biomes
AW: Tropical wet
Af: Tropical rainforest
Bsh and **Bsk**: Semiarid
BWh: Arid,
Cfa: Humid subtropical

Nathaniel, J., Klein, L. J., Watson, C. D., Nyirjesy, G., & Albrecht, C. M. (2022). Aboveground carbon biomass estimate with Physics-informed deep network. *arXiv preprint arXiv:2210.13752*.



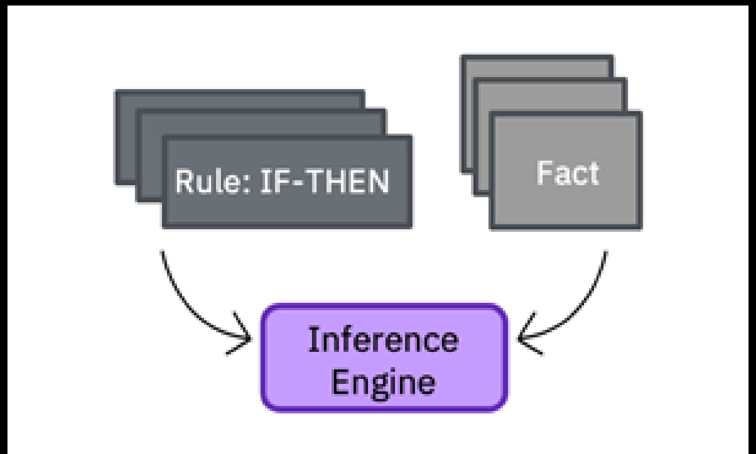
Exxon Mobile, 2023

The evolution of AI and the emergence of Foundation Models

80s Big data

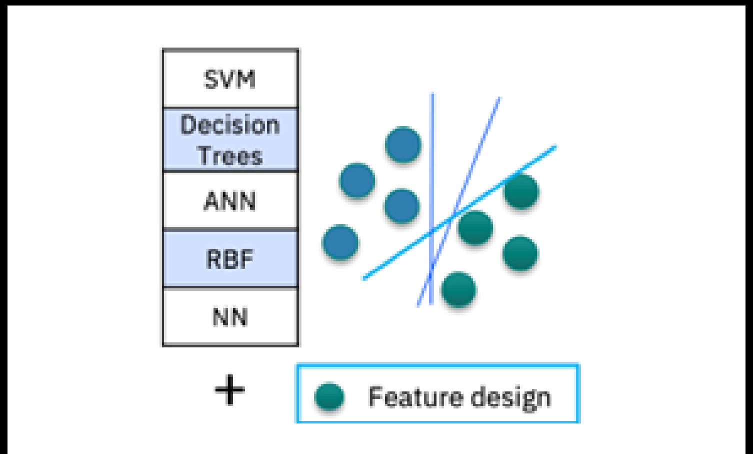
80s to ~2010 Massive data
+
Compute

2010 -2017+ Self-supervision at scale
+
Massive data
+
Compute



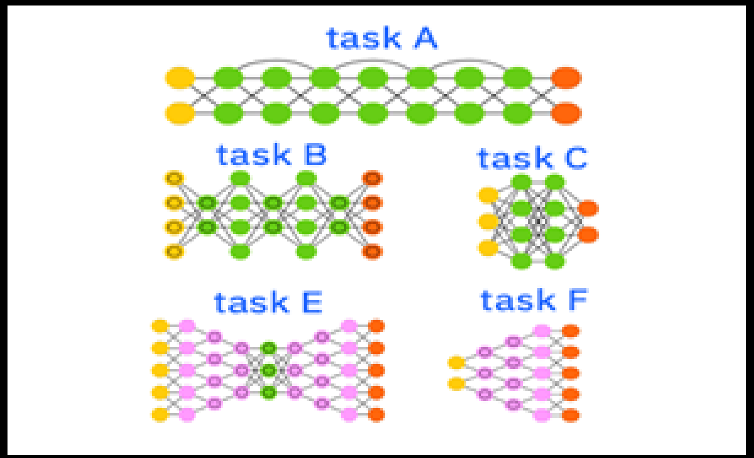
Expert Systems

Hand-crafted symbolic representations



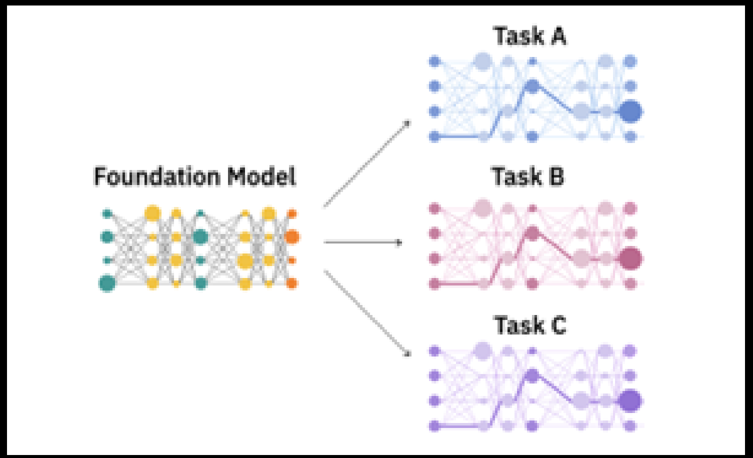
Machine Learning

Task-specific hand-crafted feature representations



Deep Learning

Task-specific learnt feature representations



Foundation Models

Generalizable & adaptable learnt representations

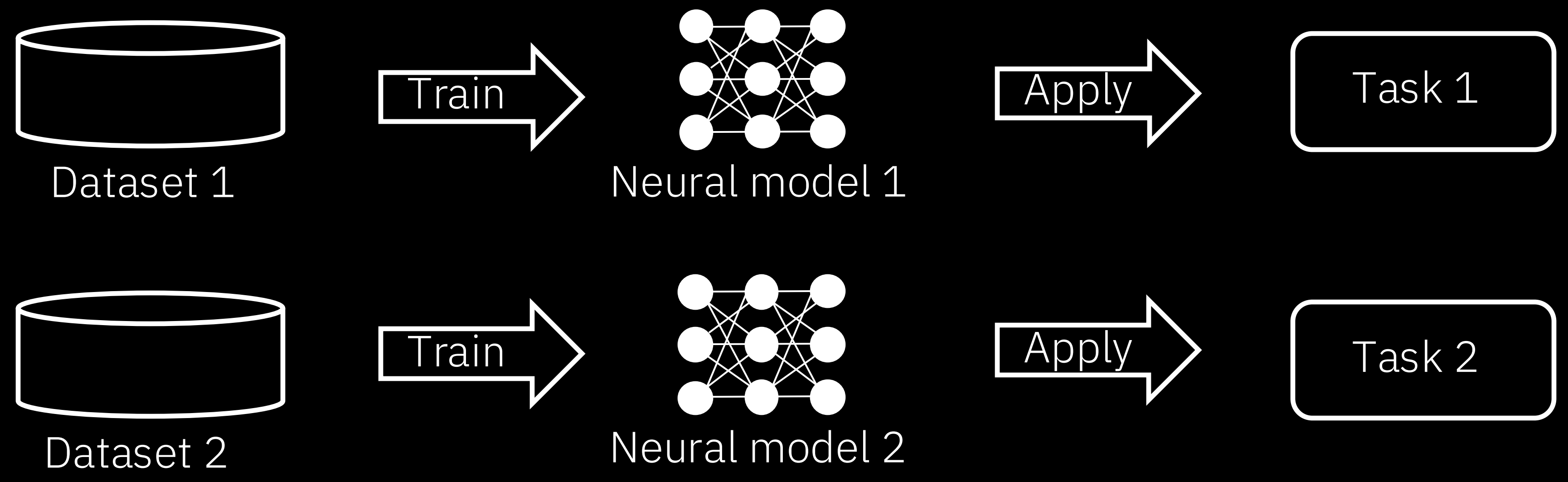
AI Algorithms, techniques and tools

AI models as platforms

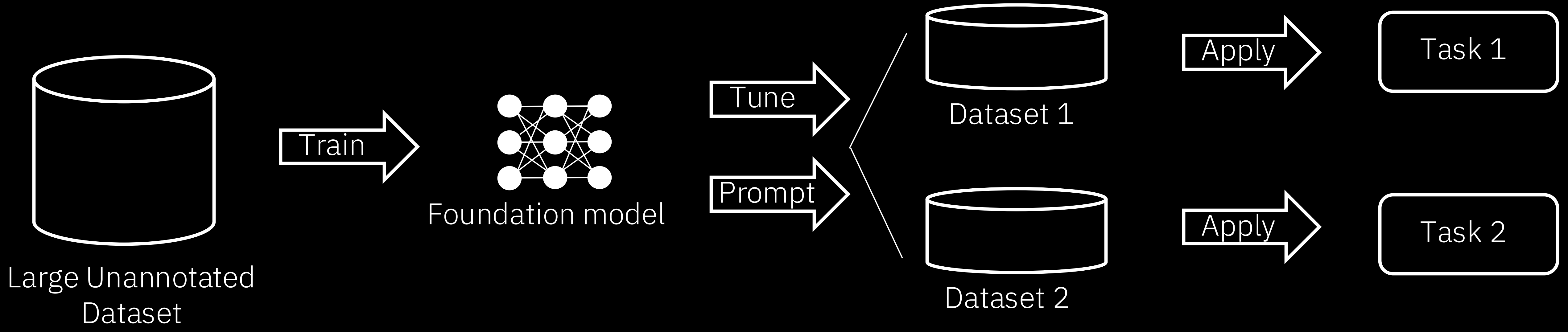
A fundamental shift

What are foundation models?

Conventional Machine Learning Systems



Foundation Model Systems



Geospatial use cases (samples)

Detecting wildfires

Detecting floods

Classifying trees

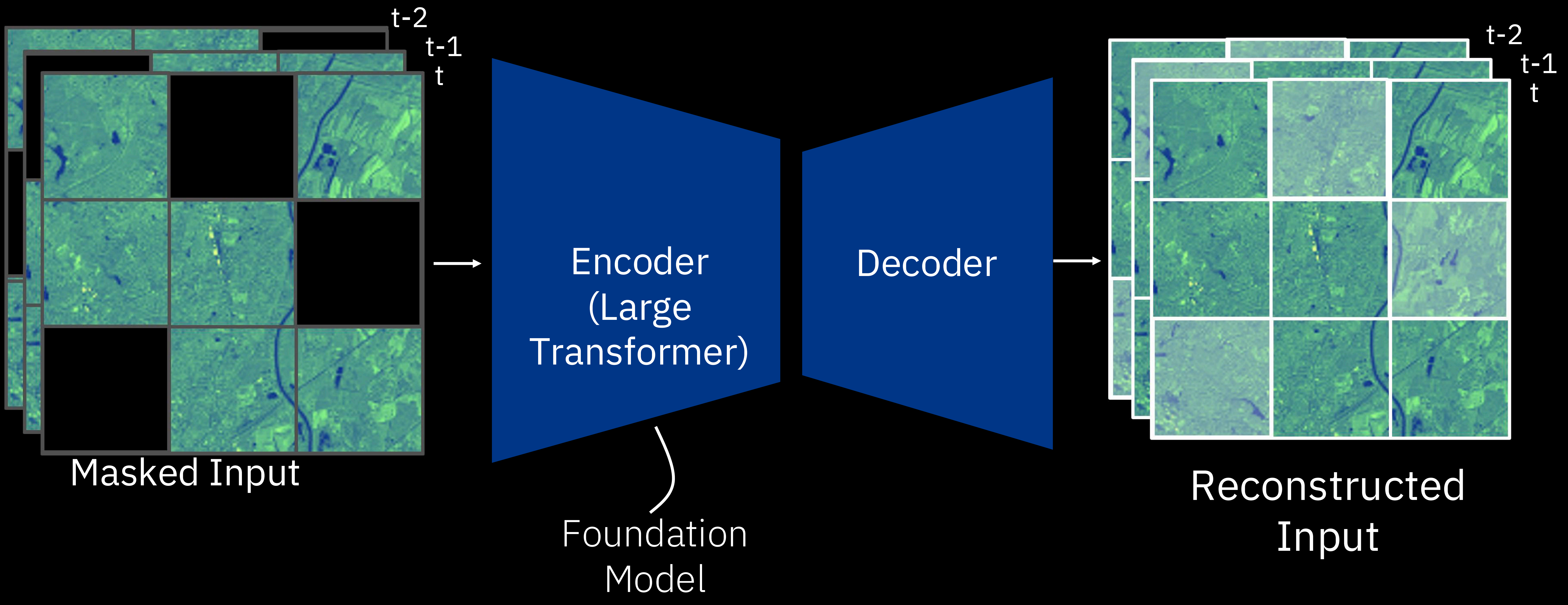
Monitoring GHGs

ESG use cases (samples)

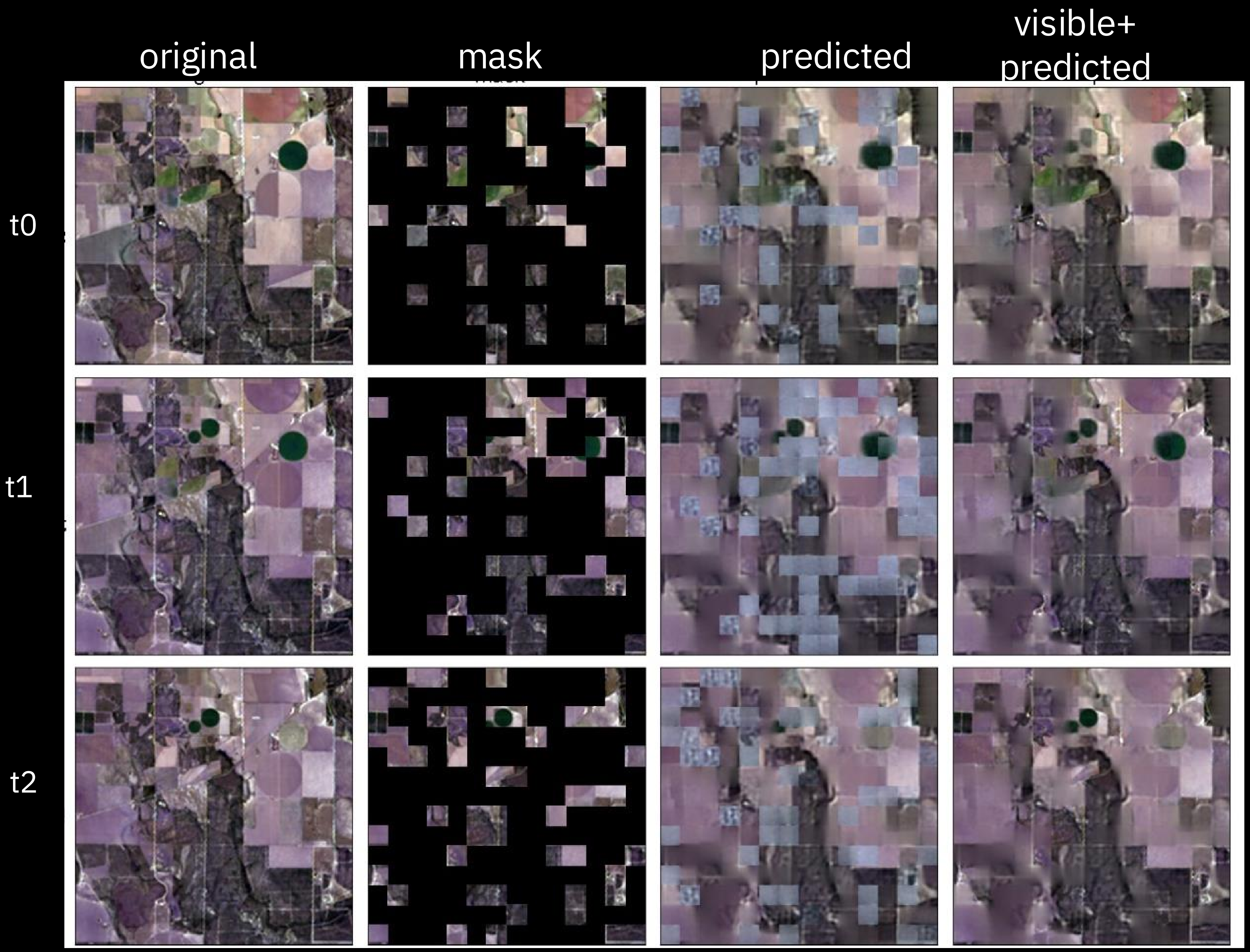
Scope 3 Emissions

Q&A Chatbot for ESG

Self-supervised Learning to Pre-train Foundation Models

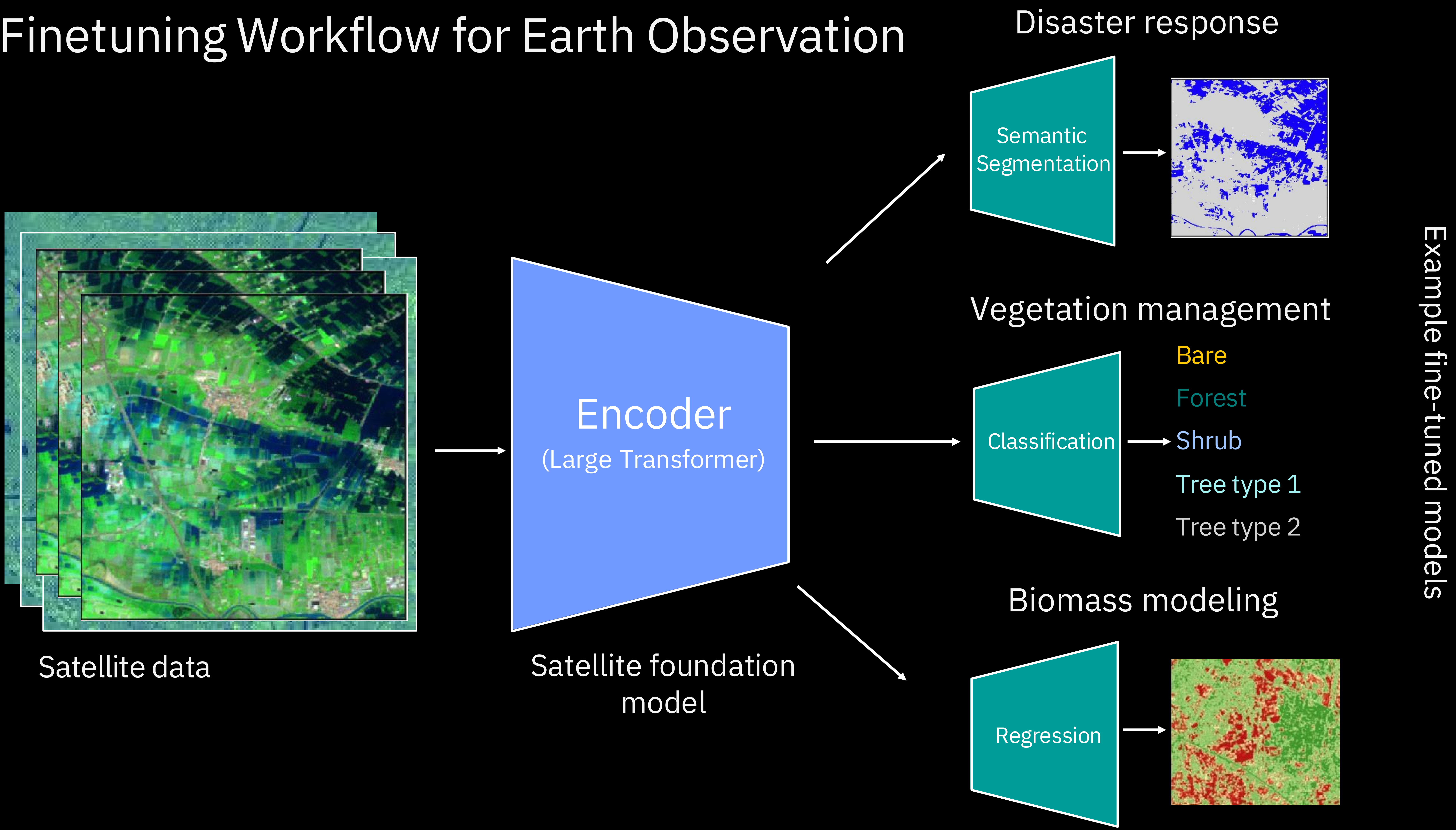


Pretraining Results with 100M Foundation Model



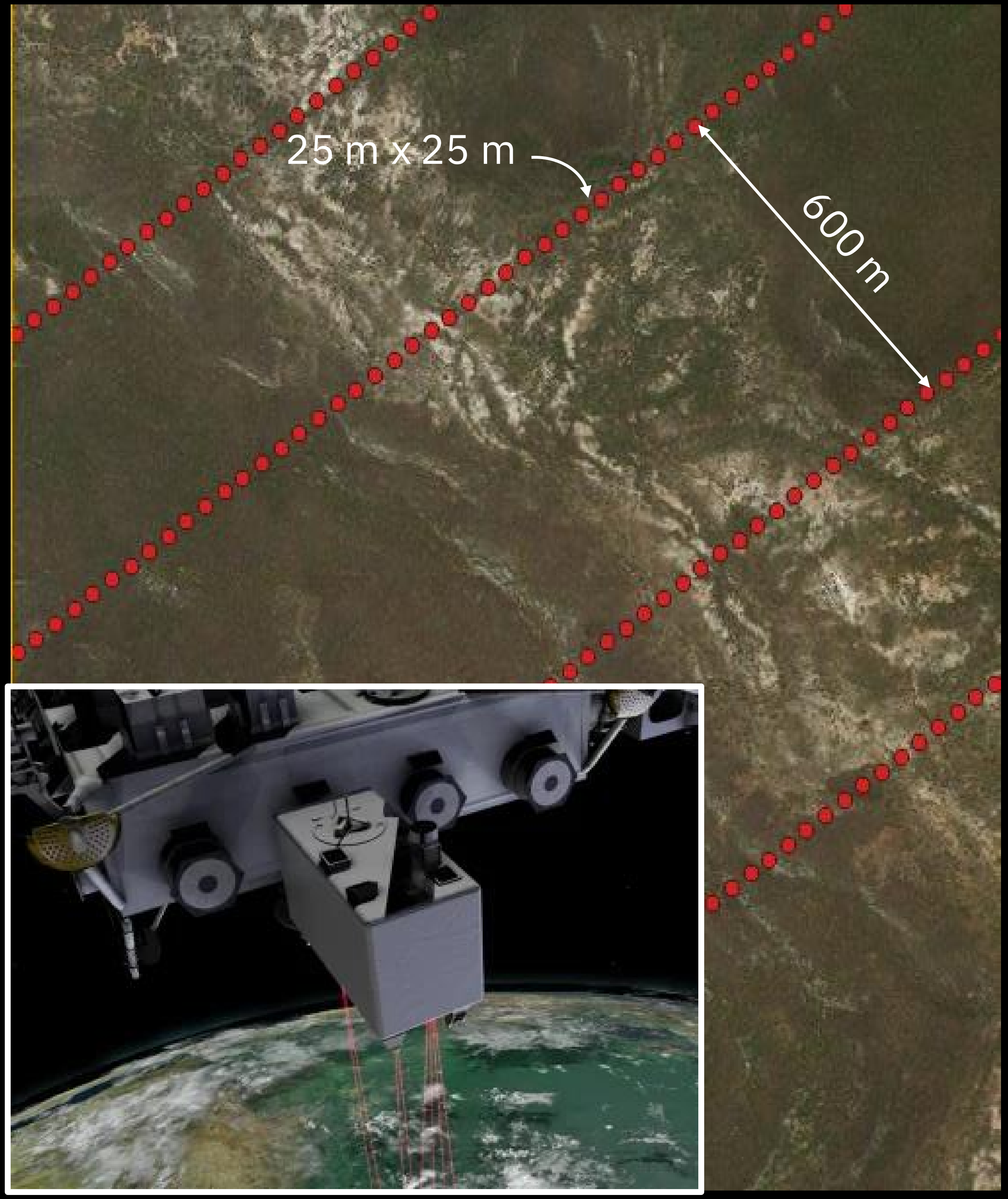
- Excellent spatial and temporal reconstruction performances
- Training MSE loss of 0.0283, and validation loss of 0.0364 with 75 % masking
- All the pre-training runs were conducted in the IBM watsonx platform using up to 64 NVIDIA A100 GPUs.

Finetuning Workflow for Earth Observation

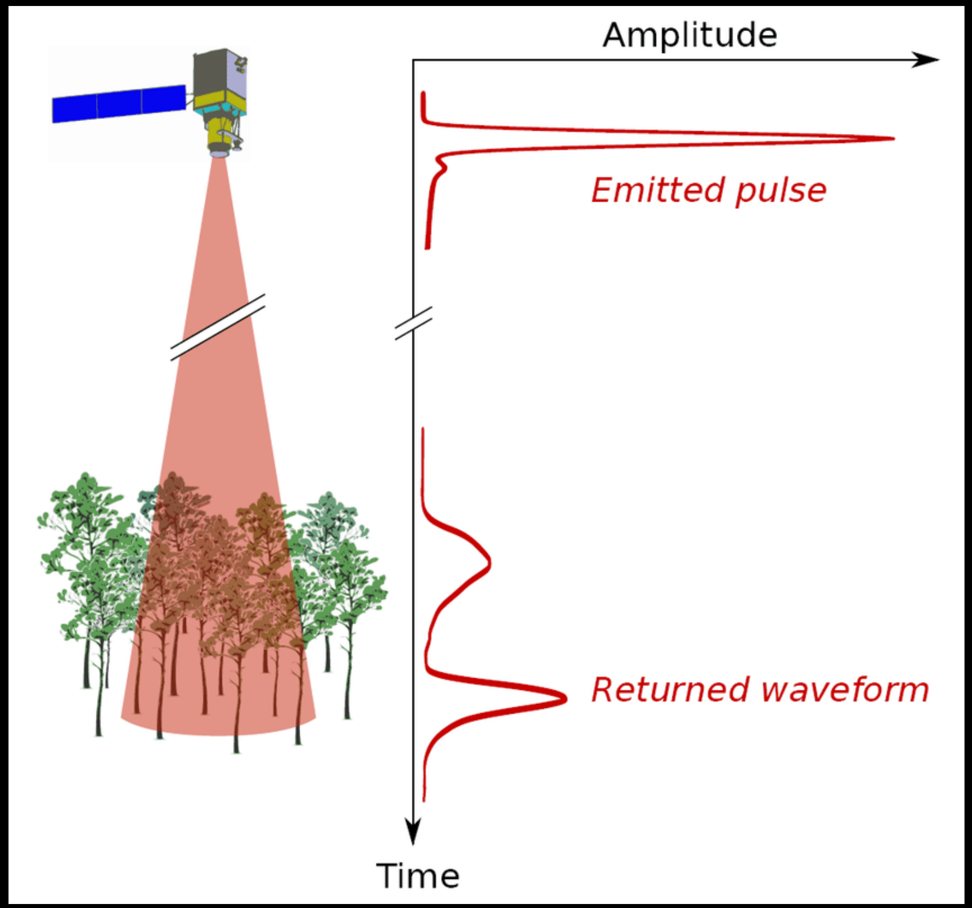


Above Ground Biomass Estimation

LIDAR Observations
from International Space Station

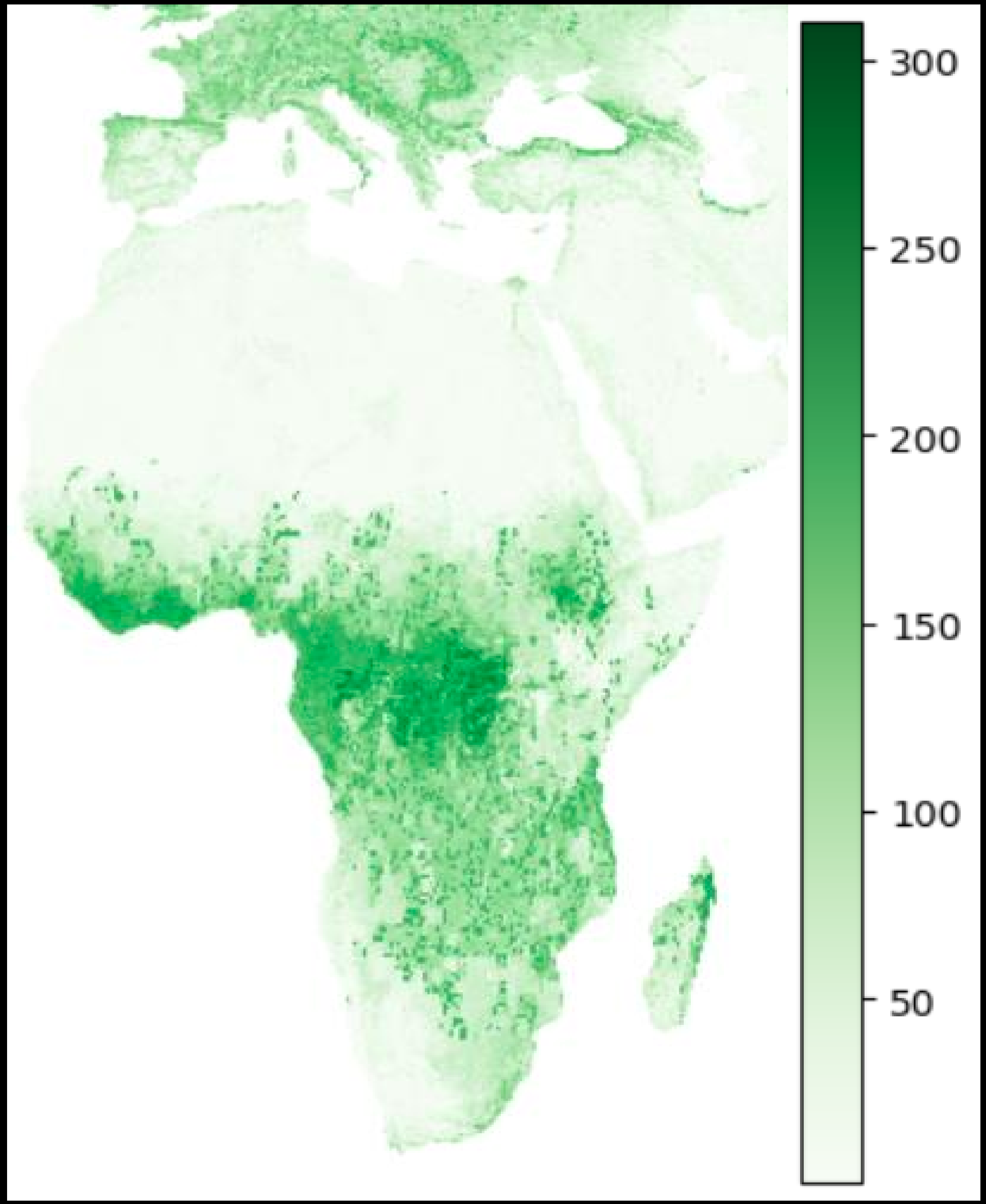


LIDAR Signal



Approach
- Sparse LIDAR data as ground truth for Prithvi fine-tuning
- Prithvi to estimate tree height from high-resolution satellite images

Natural Carbon Stock Estimation



Above Ground Carbon Biomass [Mg C/ha]

CO2-e, Carbon and Above Ground Biomass

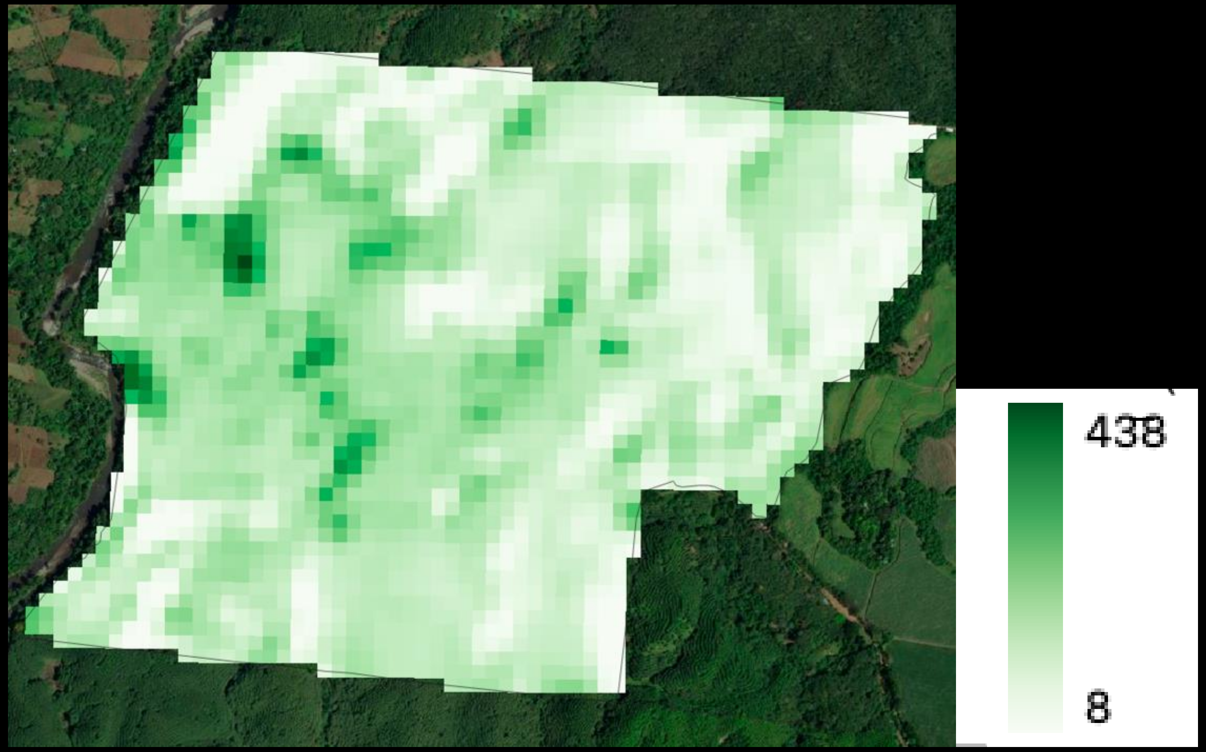
source	Total Carbon (ton CO2-e)
2019 Verra report*	38,125.06
IBM model (adjusted for area as per Verra)	35,854.44

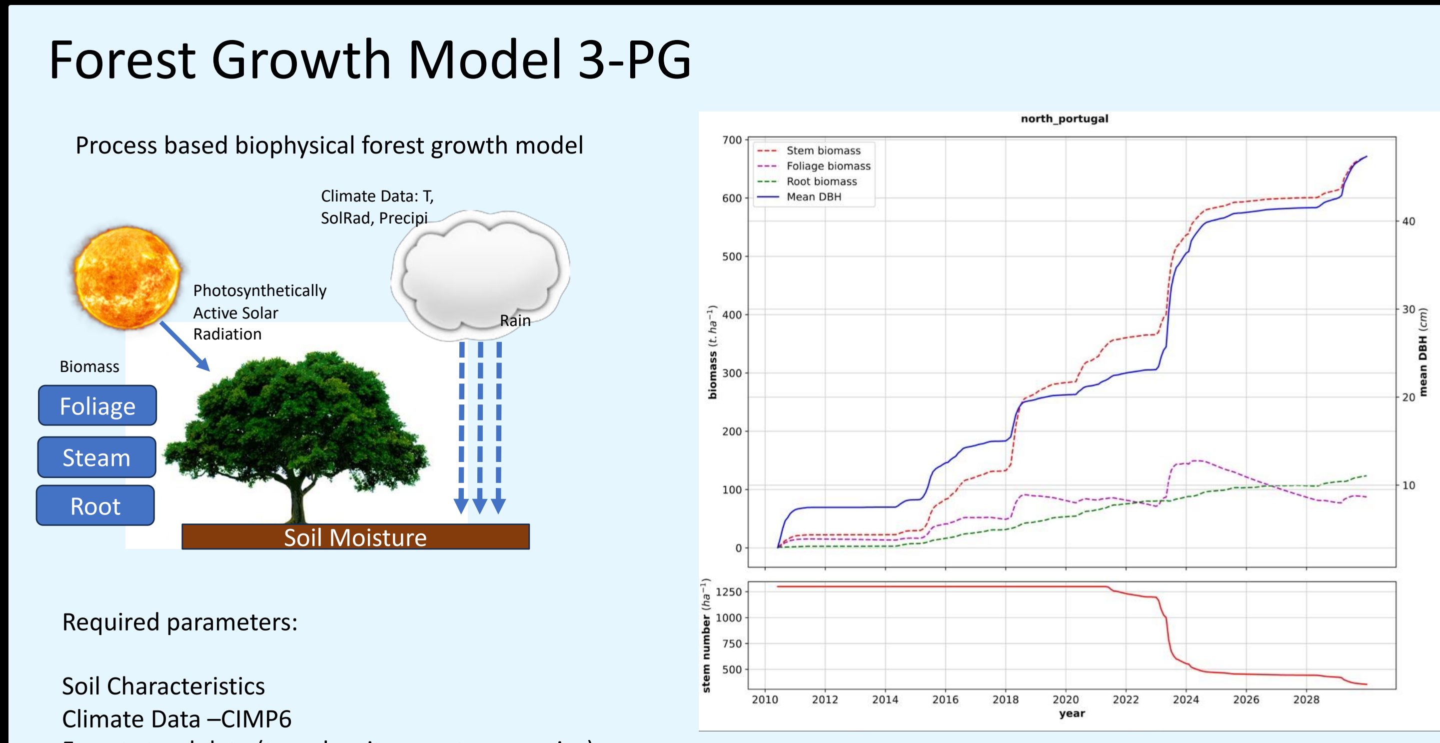
source	AGB (ton)
2019 Verra report*	16,875
IBM model (adjusted for area as per Verra)	15,870

source	Mean AGBD (t/ha)
2019 Verra report*	119.3
IBM model	111.8

Above Ground Biomass and Carbon Calculation

- Computed as a fraction of total carbon
- Ratio of Below to Above Ground biomass is 0.22
- Carbon is 50% total biomass
- Carbon = (0.27) * CO2-e

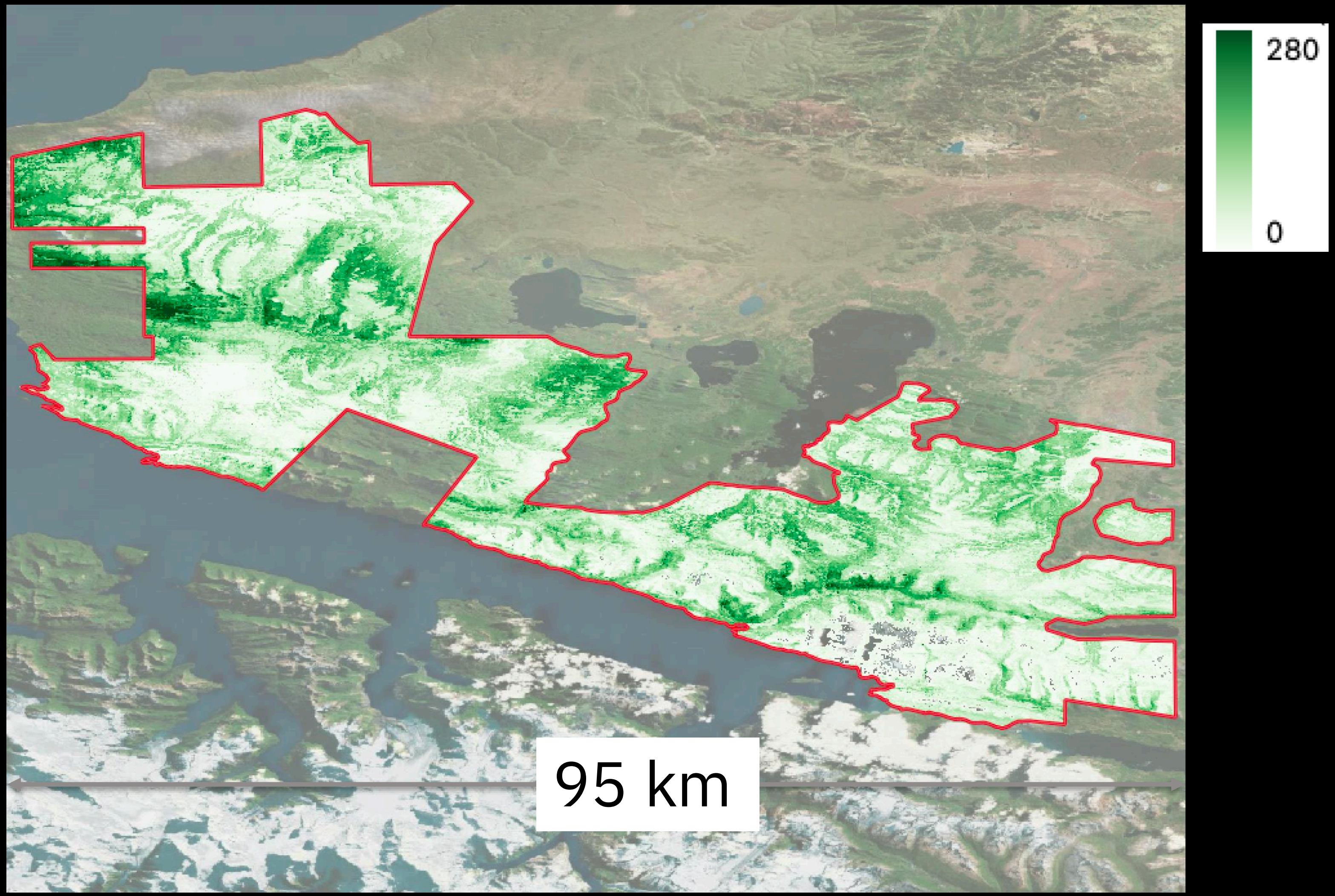


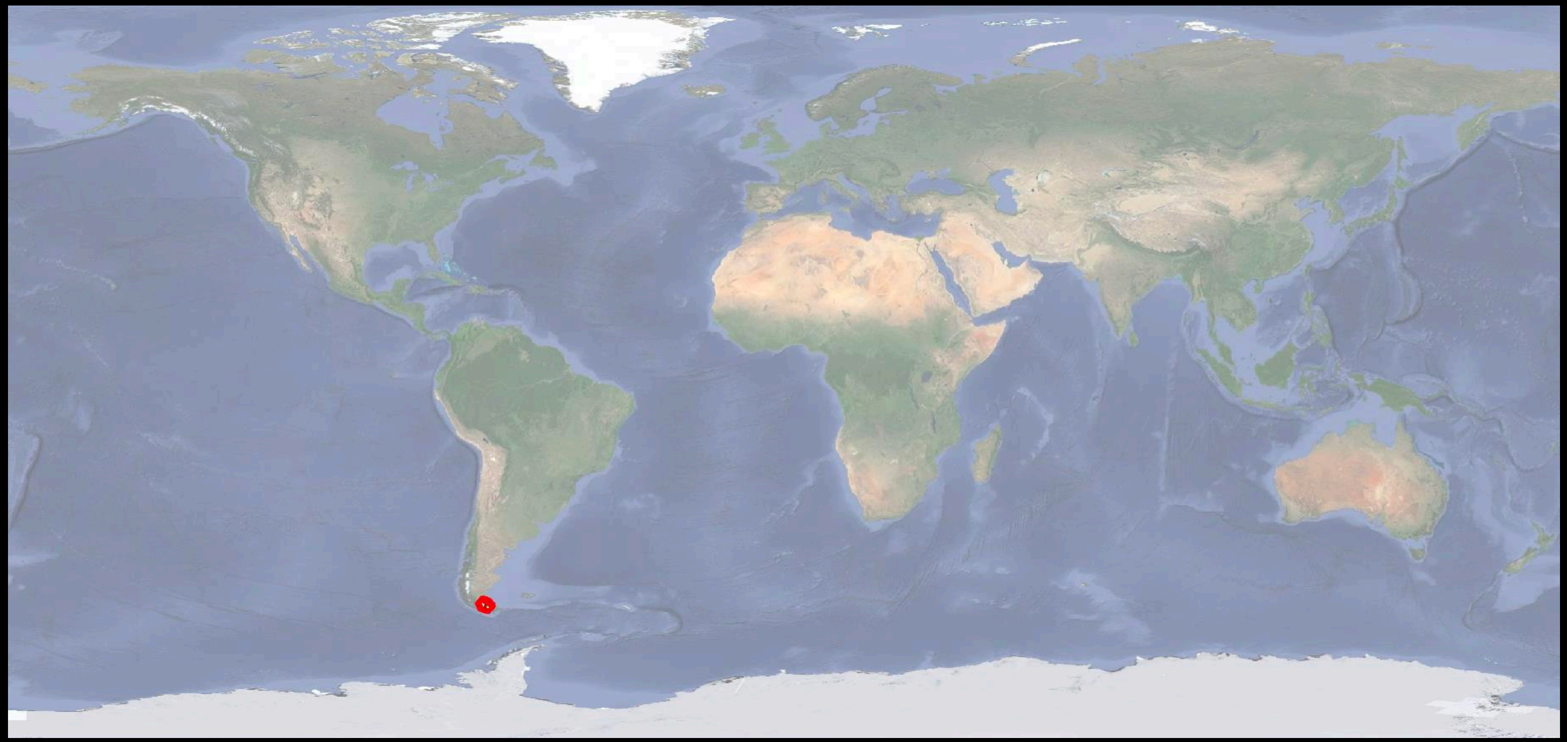


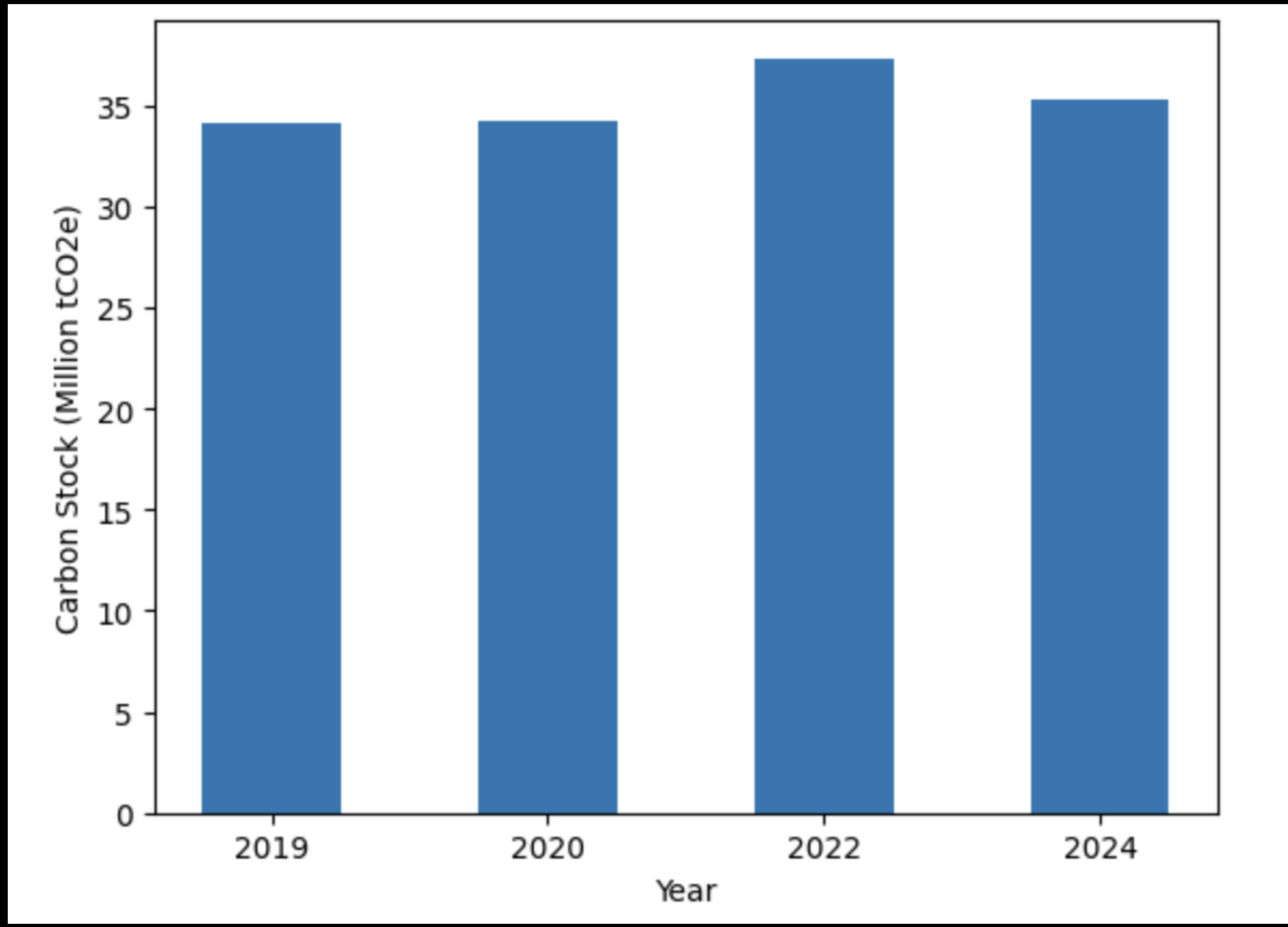
Prediction of Eucalyptus Globulus growth in North Portugal from 2010 to 2030.

Above Ground Biomass

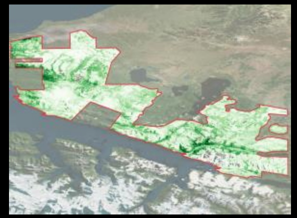
AGBD (t/ha)



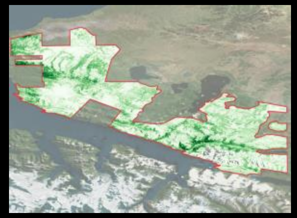




Total Carbon Stored in Vegetation

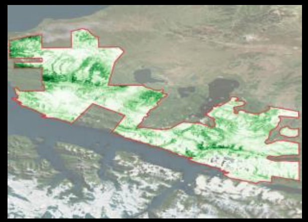


2019



2020

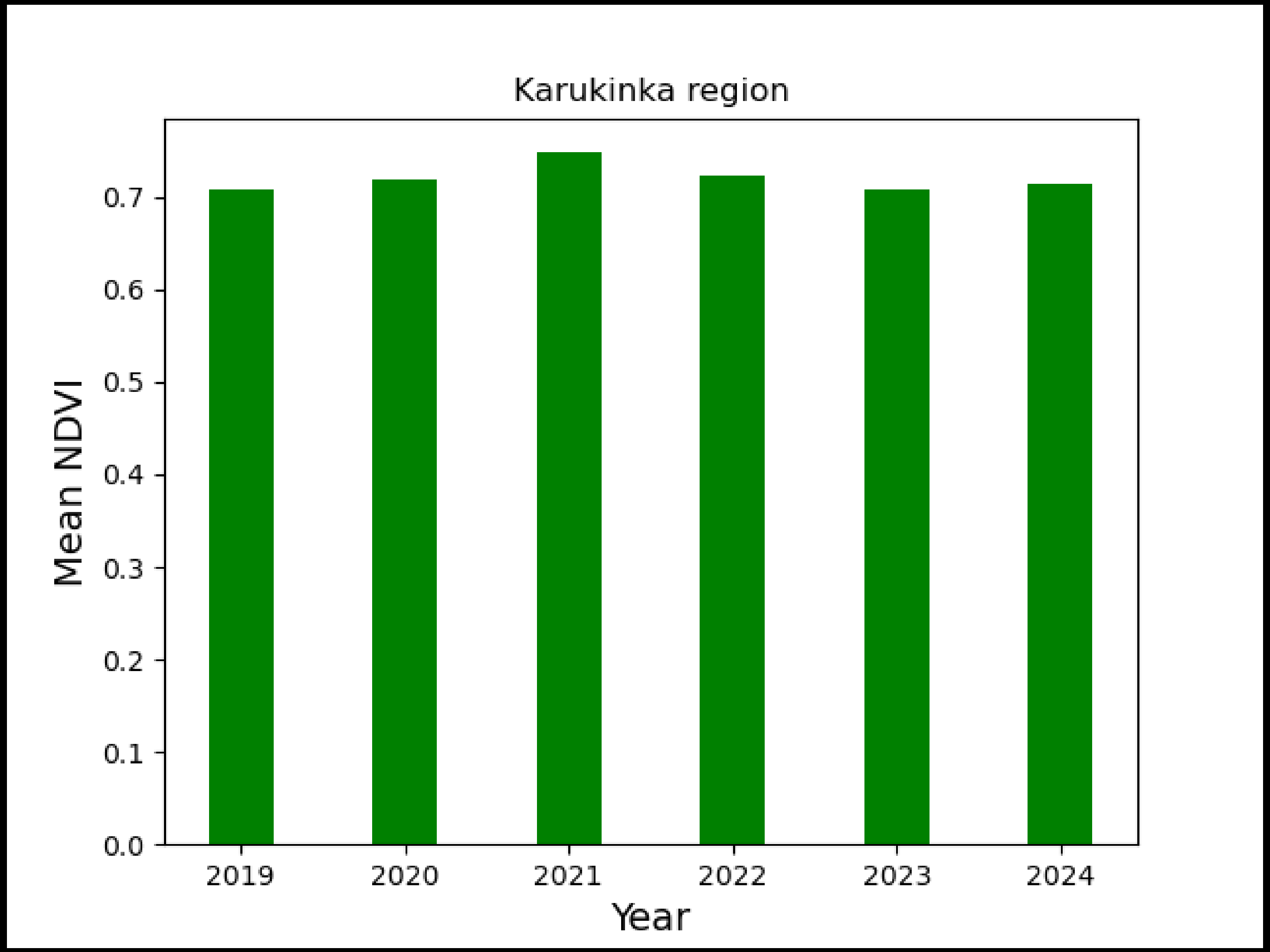
2022



2024

Carbon Sequestration; Carbon Pool Growth

Forest Greenness has year to year fluctuations



2019

2020

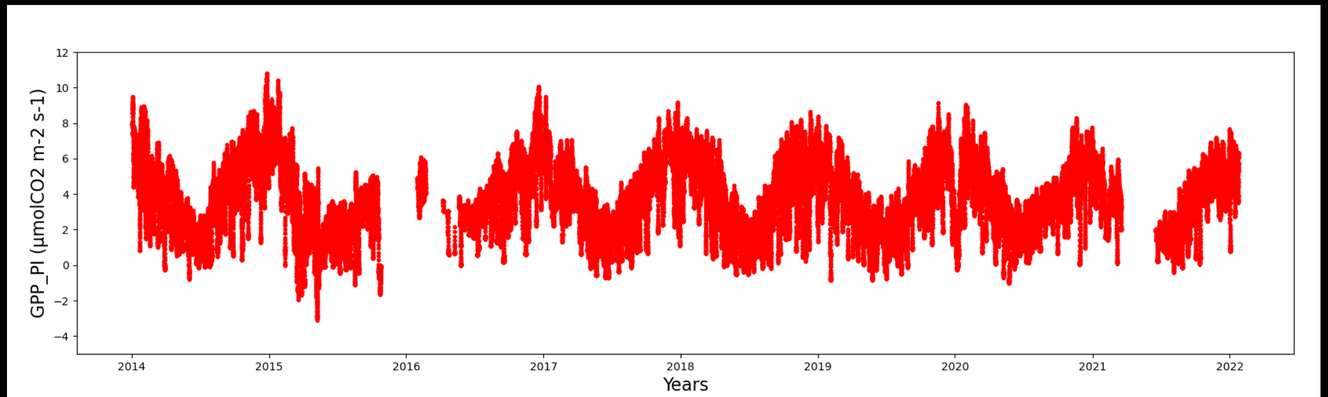
2021

2022

2023

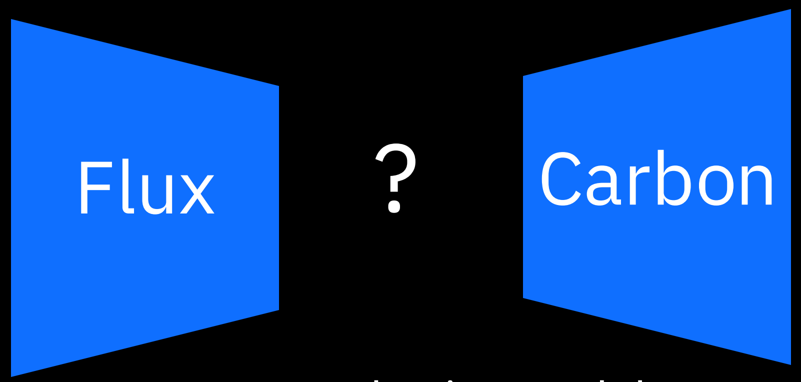
2024

Chile, a mixed forest but not in the sense of deciduous vs evergreen but in the sense of broadleaf vs conifer trees. They are all evergreen species. GPP values decreasing, year to year-how to relate to carbon flux?



Ameriflux, **CL-SDF: Senda Darwin Forest**

Training data: synthetic flux data to capture growth across ecoregions



- Physics Model
- AI model
- Physics Informed AI model

Outlook

Foundation Model provide self supervised models that are generalizable across large geographic regions. For local measurements, the model require finetuning of parameters.

Finetuning the model for year-to-year change in carbon sequestered require filed measurements (tree parameters, LiDAR or Flux Tower data)

Integration of AI/biophysics models that capture vegetation growth require either more data or specialized domain expertise.