

Estimating terrestrial carbon dioxide and water fluxes in near-real time using GOES-R: progress to date and looking forward to GeoXO

Paul Stoy

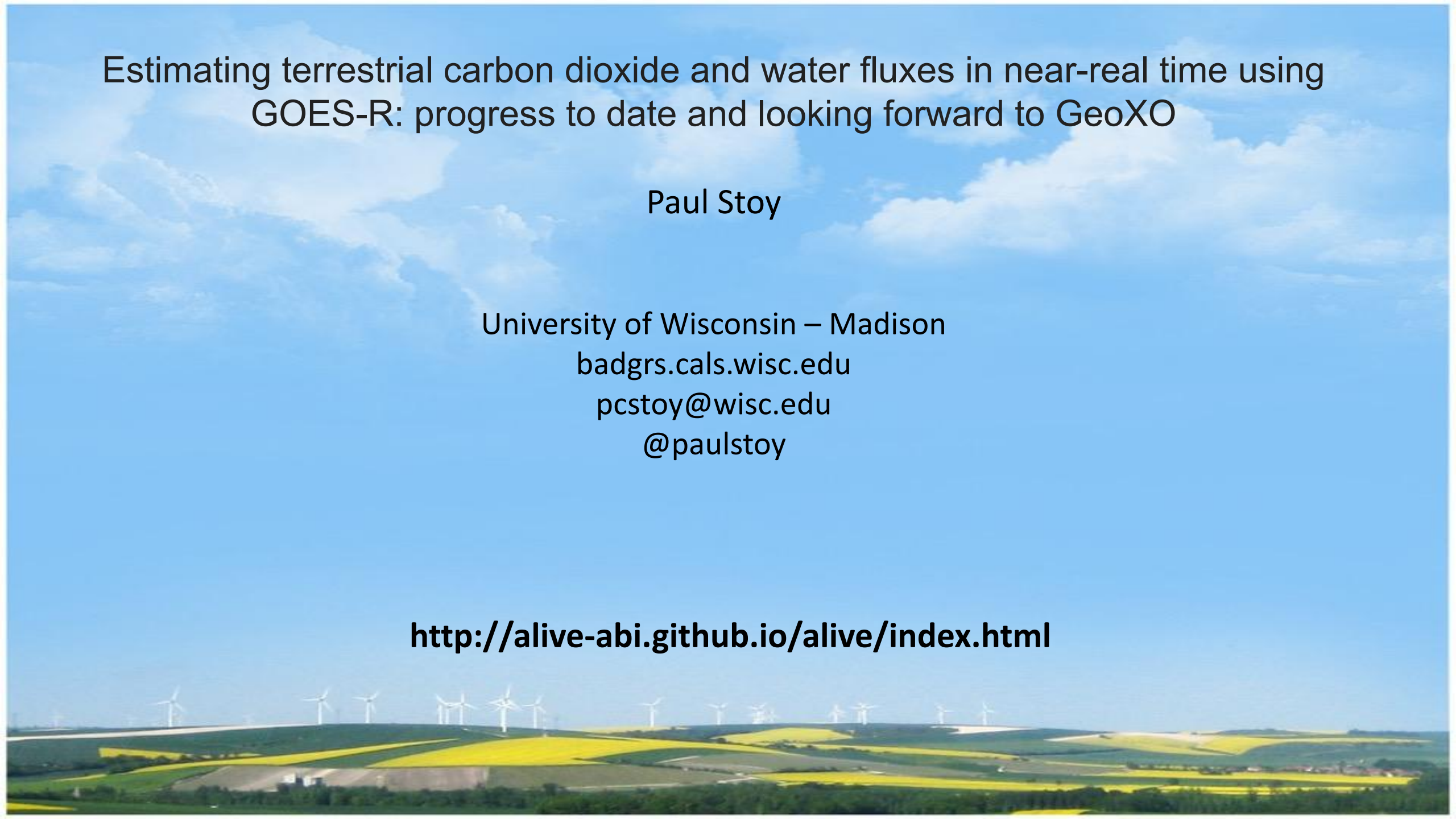
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<http://alive-abi.github.io/alive/index.html>



Funding



WISCONSIN
UNIVERSITY OF WISCONSIN-MADISON



Thanks!

ALIVE

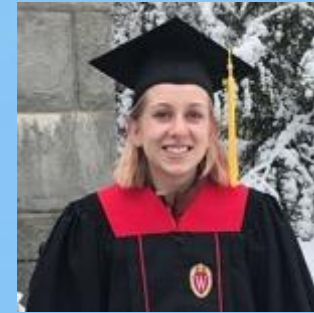
Advanced Baseline Imager Live
Imaging of Vegetated Ecosystems



Danielle Losos



Sadegh Ranjbar



Sophie Hoffman



Avanti Kekane

Data



neon
Operated by Battelle



Einara Zahn

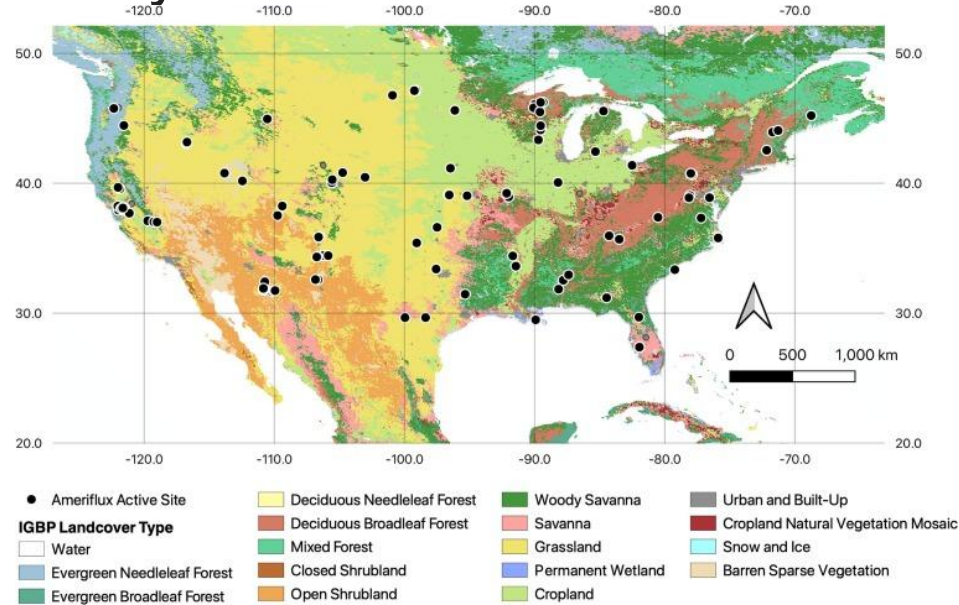


Elie Bou-Zeid

Bethany Blakeley
Ojaswee Shrestha
Ankur Desai

What is ALIVE?

Eddy covariance

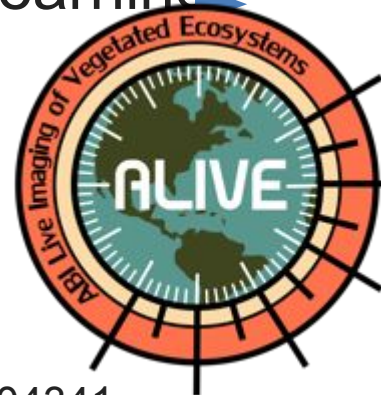


GOES-R data products



Machine Learning

An empirical benchmark for real-time carbon & water flux models



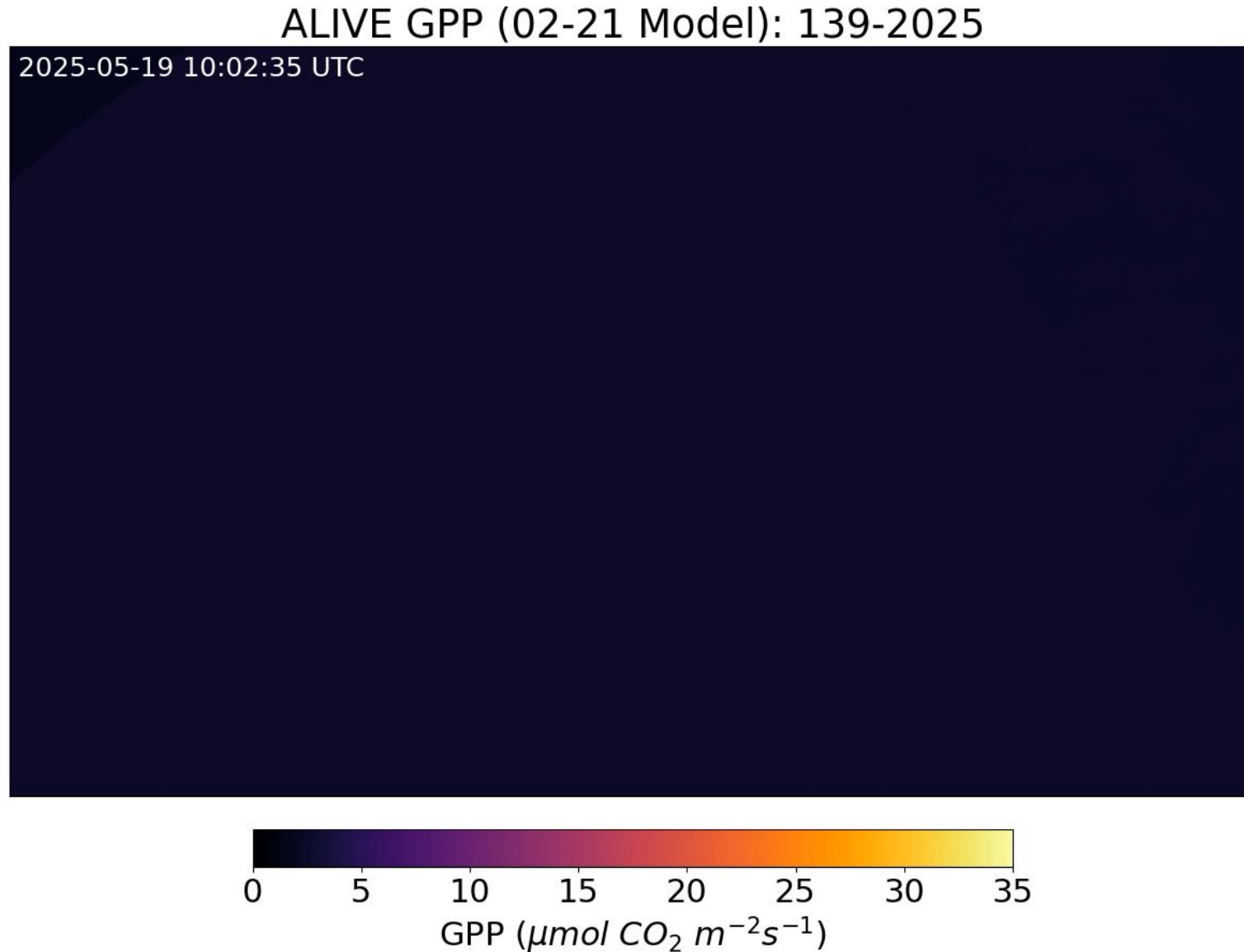
predictions

Ranjbar et al. (2024) <https://doi.org/10.1029/2024MS004341>

Losos et al. (2024) *Scientific Data* <https://doi.org/10.1038/s41597-024-03071-z>

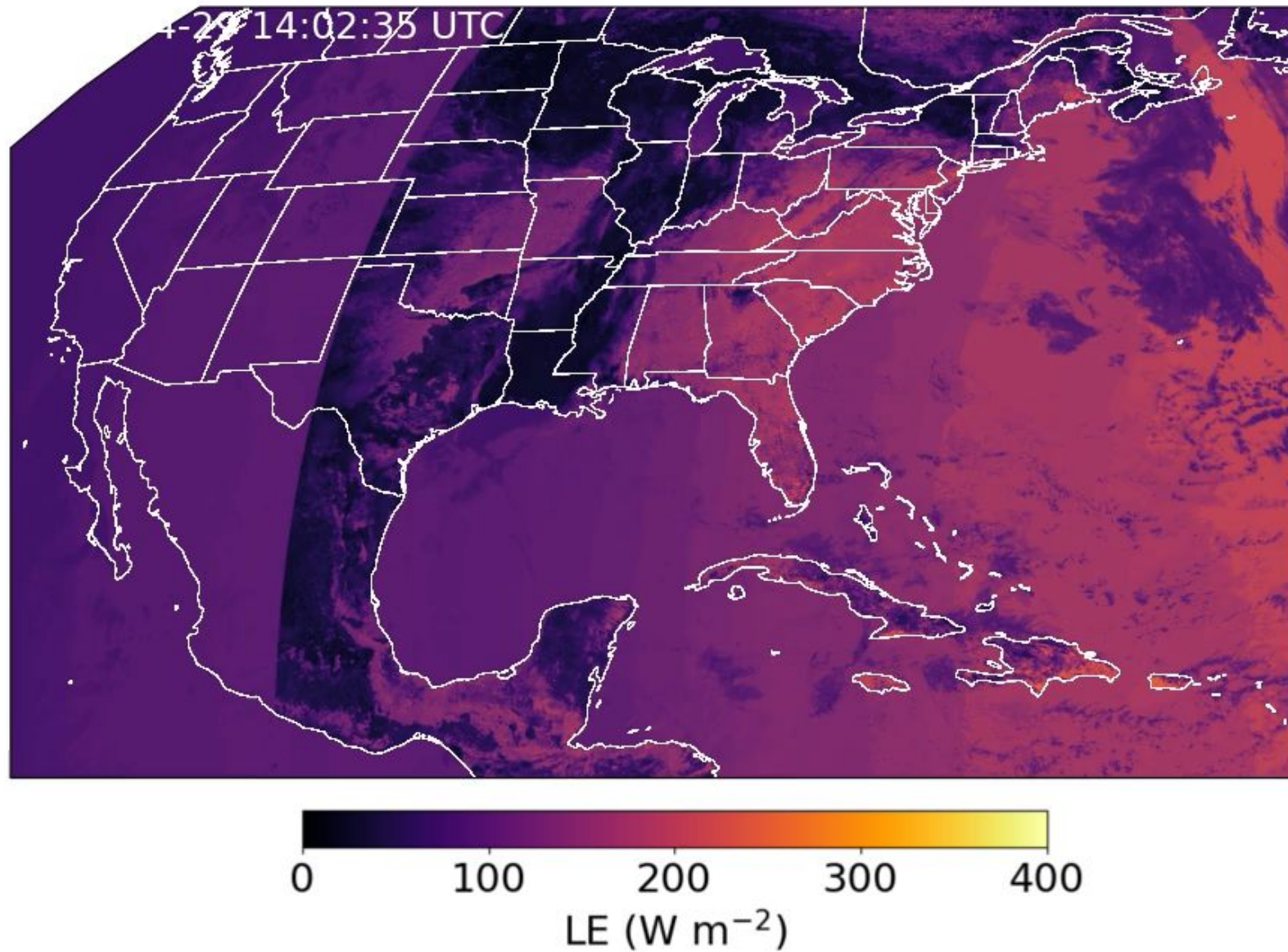
Losos et al. (2025) *RSE* <https://doi.org/10.1016/j.rse.2025.114759>

Yesterday's ALIVE Gross Primary Productivity (GPP) prediction



What do we need to make it better? 1. water fluxes, 2. KGML, 3. GeoXO

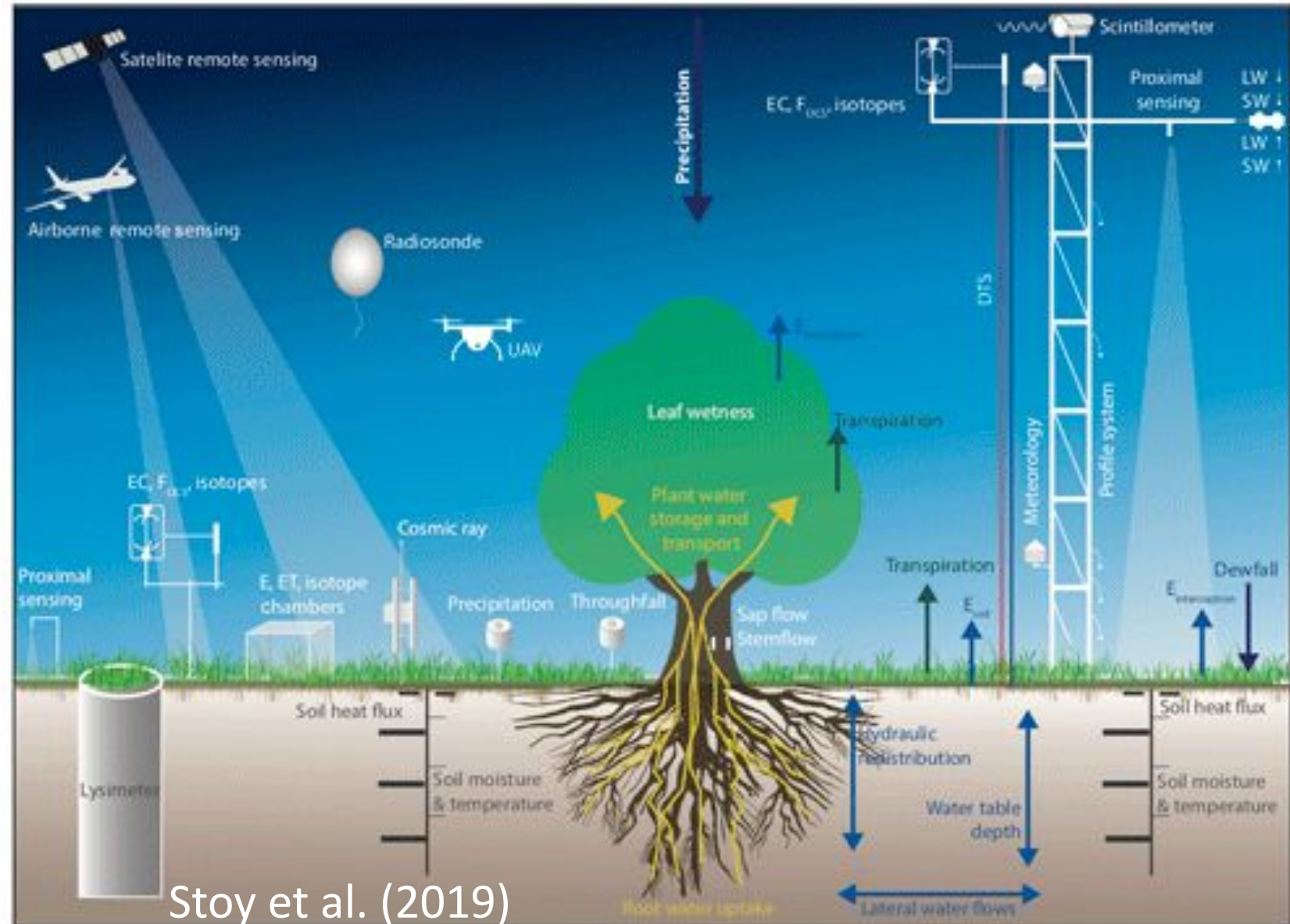
Primitive ALIVE evapotranspiration loop: We can do better!



See Ranjbar et al. (in review)

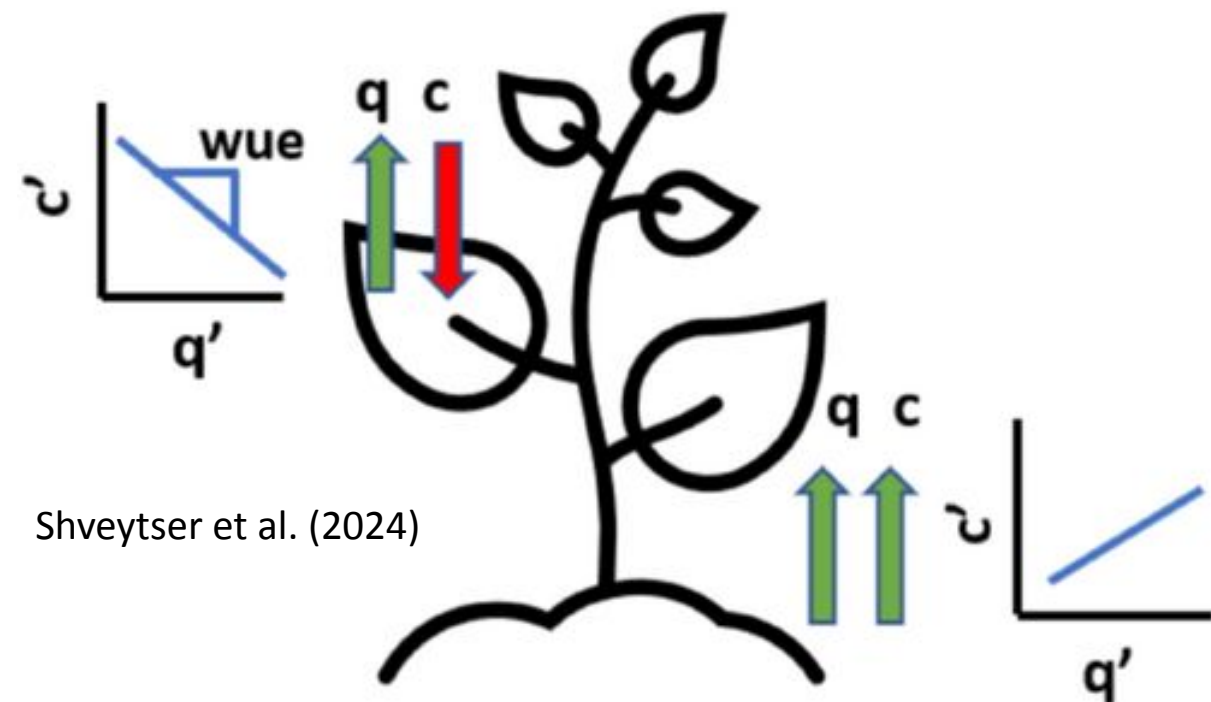
We also want process-based models

Challenge: The components of ET are relatively hard to measure



And the machine is hungry for data!

A solution: Flux partitioning to estimate evaporation and transpiration



CO₂ is a 'tracer' to estimate water sources
-E. Zahn

Articles / Volume 16, issue 12 / ESSD, 16, 5603–5624, 2024

<https://doi.org/10.5194/essd-16-5603-2024>

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Article

Assets

Peer review

Me

Data description paper | © ⓘ

Observational partitioning of water and CO₂ fluxes at National Ecological Observatory Network (NEON) sites: a 5-year dataset of soil and plant components for spatial and temporal analysis

Einara Zahn and Elie Bou-Zeid ✉

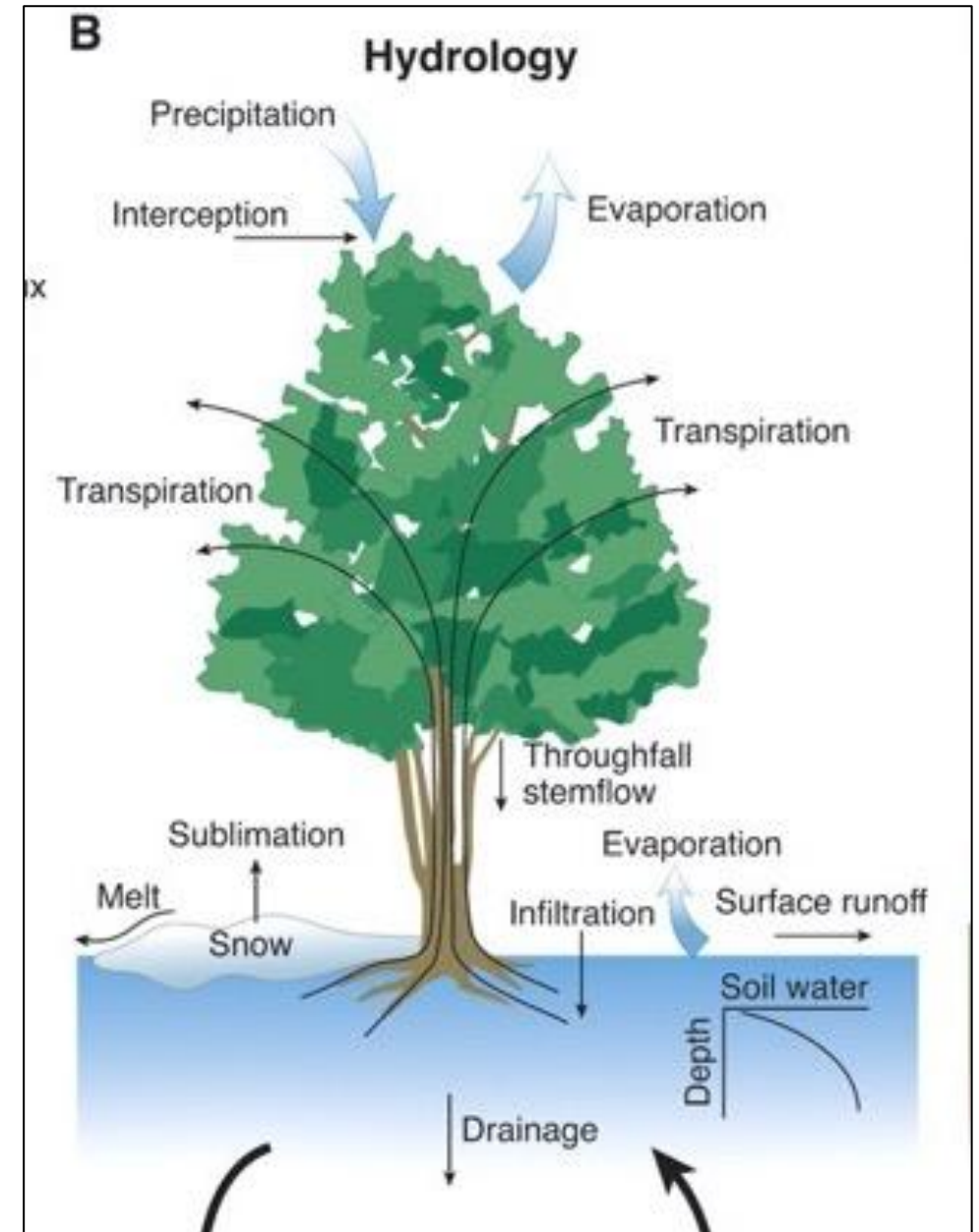
5-year time series of:

- Flux variance similarity (FVS)
- Conditional eddy covariance (CEC)
- **Conditional eddy accumulation (CEA)**
- Modified relaxed eddy accumulation (MREA)

At NEON eddy covariance sites

Challenge: Canopy-intercepted evaporation (E_i), is extremely hard to measure and happens quickly

Needs to be partitioned from Transpiration (T) & soil evaporation (E_s)



Bonan, 2008, Nature

A solution: Knowledge-guided machine learning to estimate E_i

Physical constraints:

$E_i = 0$ when time since precipitation > 24 hours

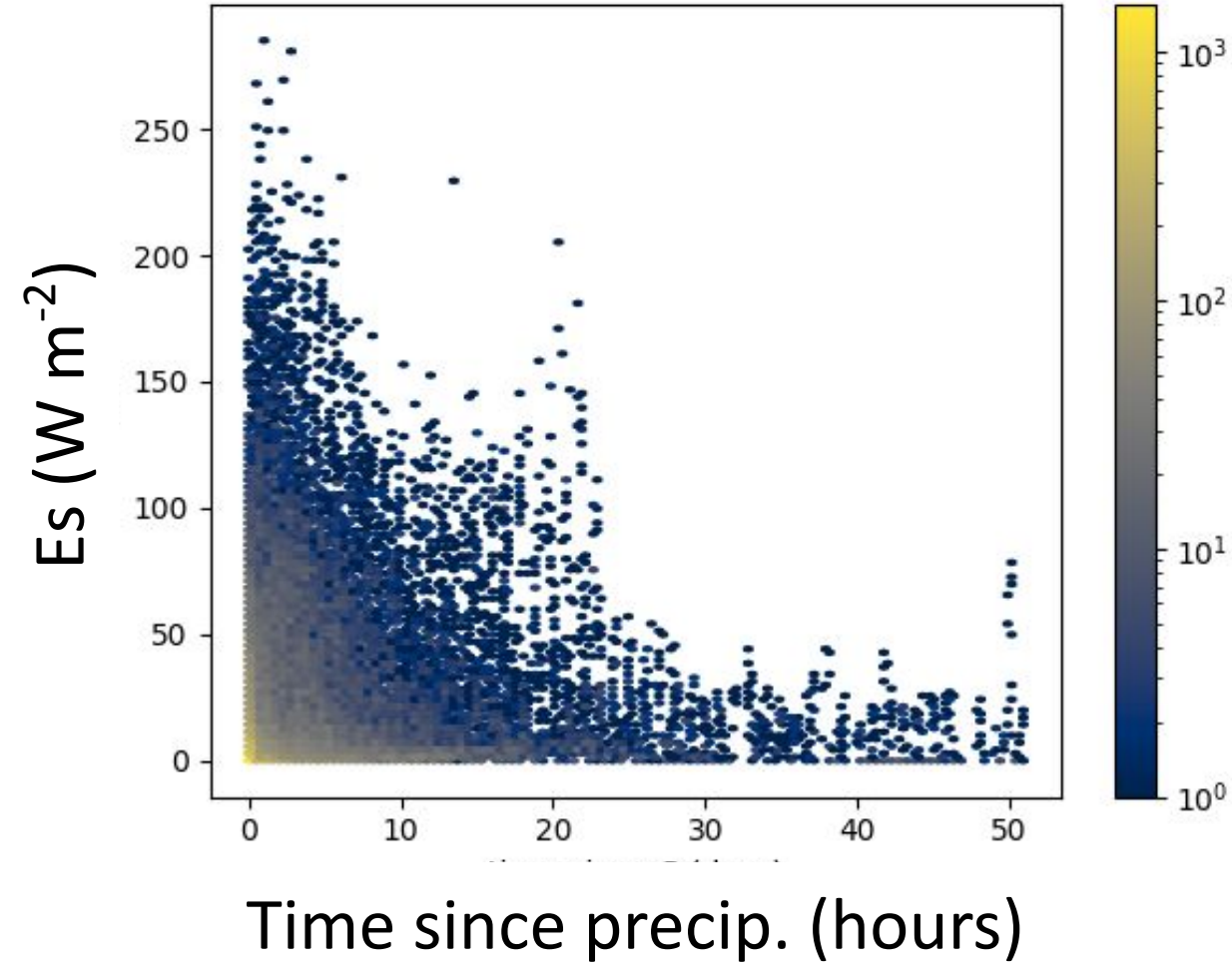
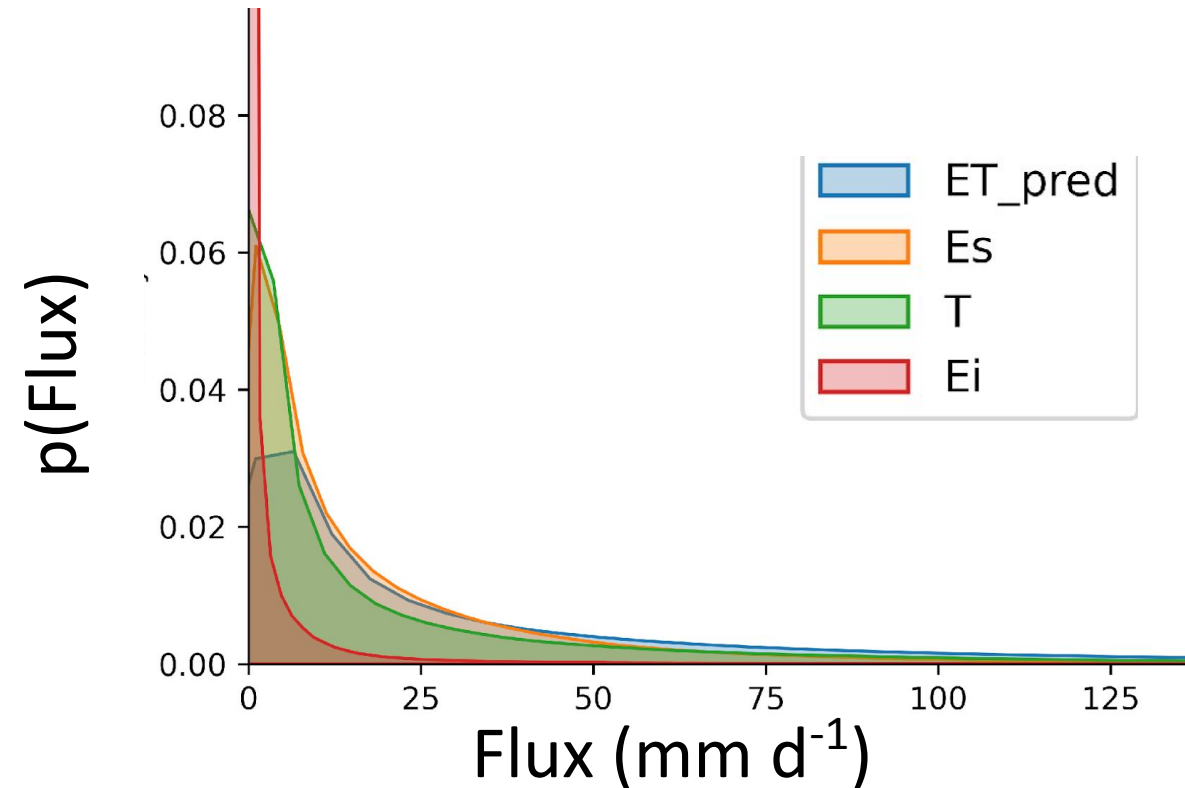
$E_i = 0$ eight hours after $T_{dew} \geq T_a$

$ET = T + E_s + E_i + \text{Deposition}$

$T_{CEA} = T + E_i$ (?)

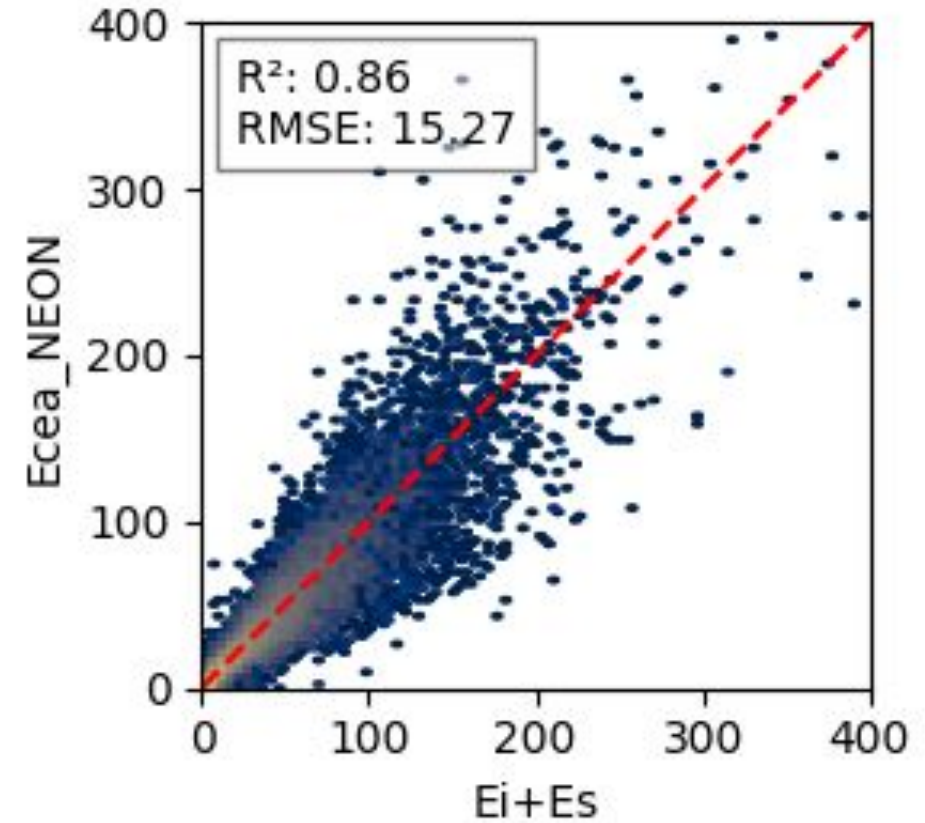
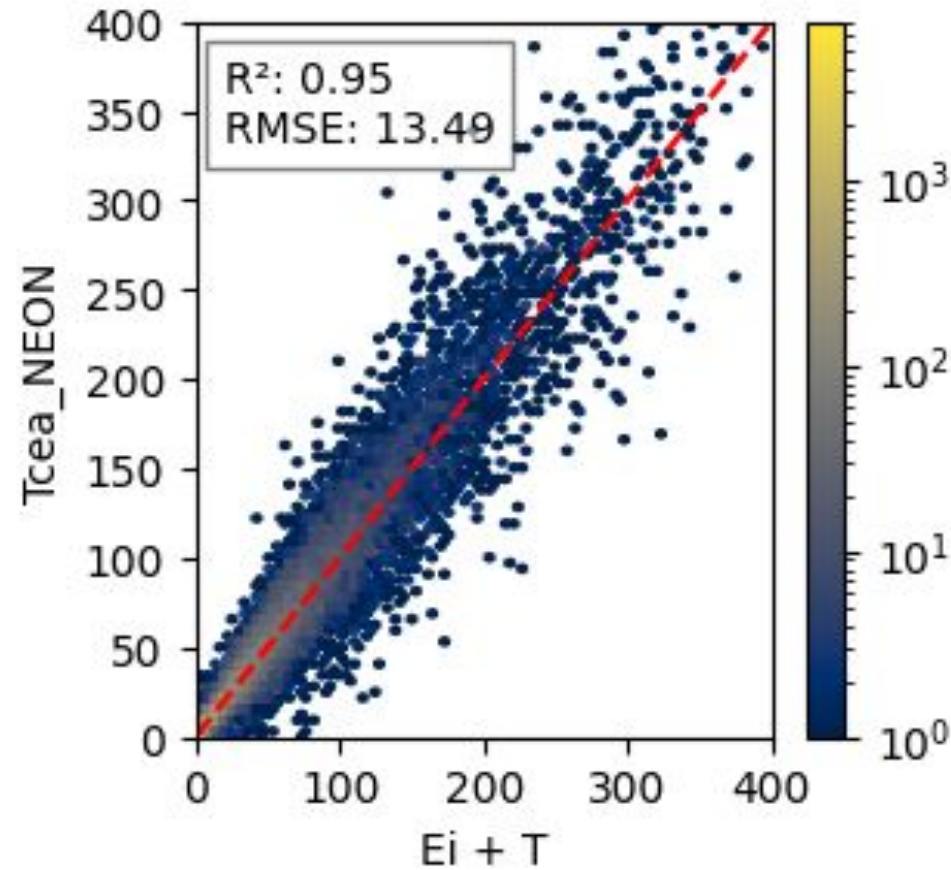
ET , T , E_s & E_i are positive

Deposition is negative



Figures: S. Ranjbar

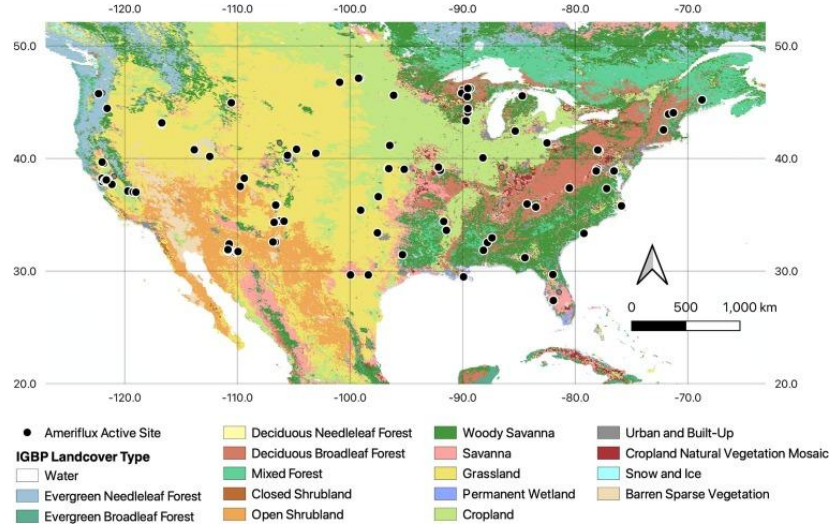
Should we take E_i from T?
KMGL likes it more when we do.



Figures: S. Ranjbar

Adding surface meteorology to ALIVE: integrating the HRRR

Eddy covariance



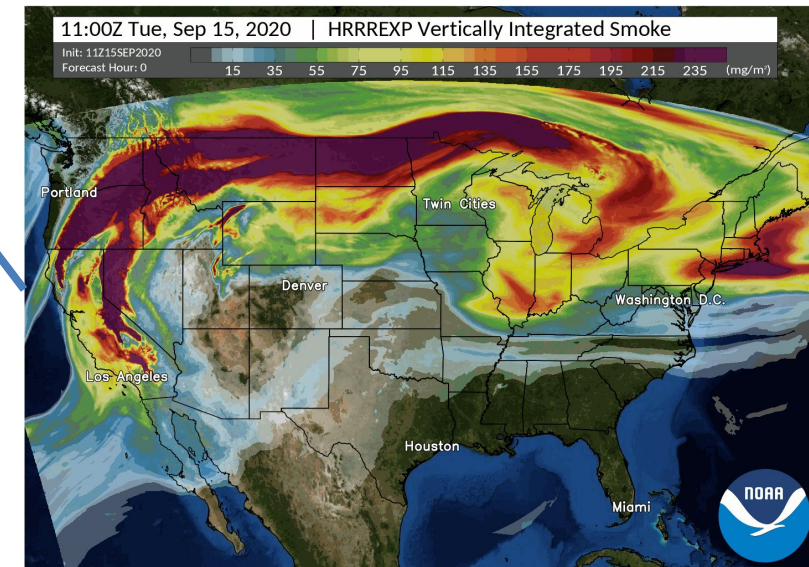
GOES-R data products



Machine Learning



HRRR



**Moving from 5 minutes to 1 hour
GOES-R CONUS pixels to 3 km**

ALIVE Evapotranspiration predictions coupling GOES-R & HRRR

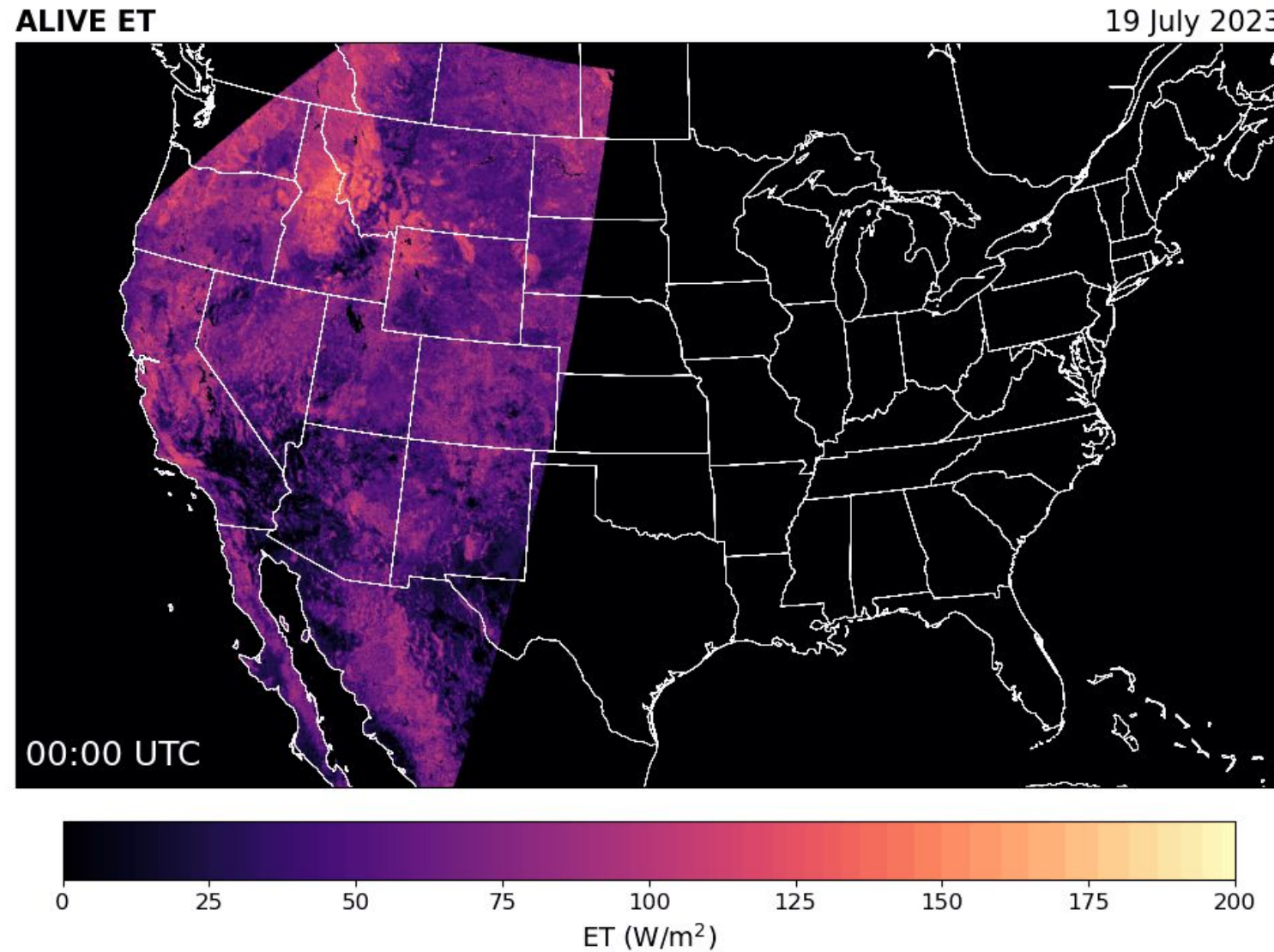


Figure: D. Losos

ALIVE workflow

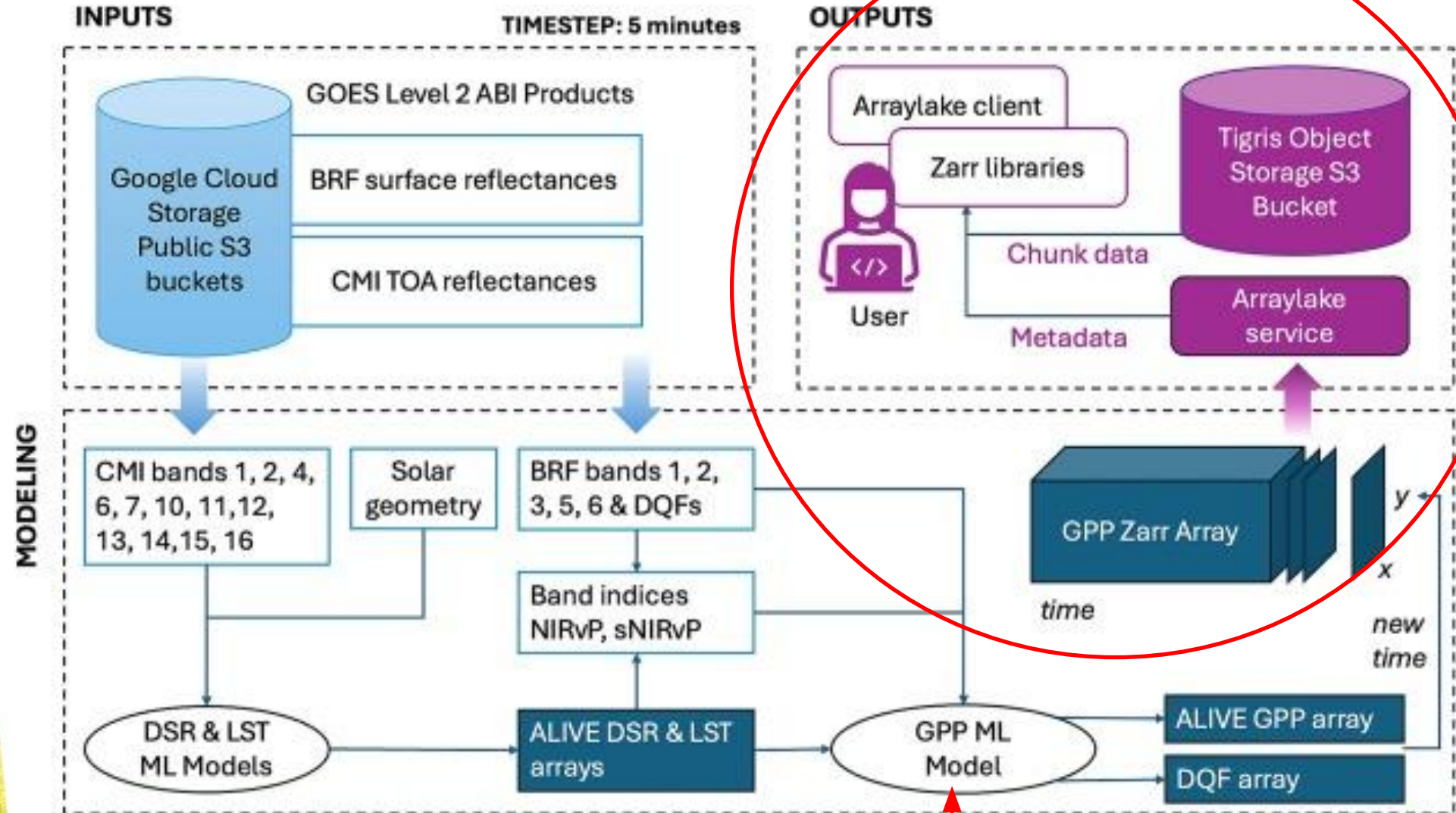


Fig. Losos (2025) RSE

LST: Ranjbar et al. (2025) <https://doi.org/10.1029/2024JH000464>

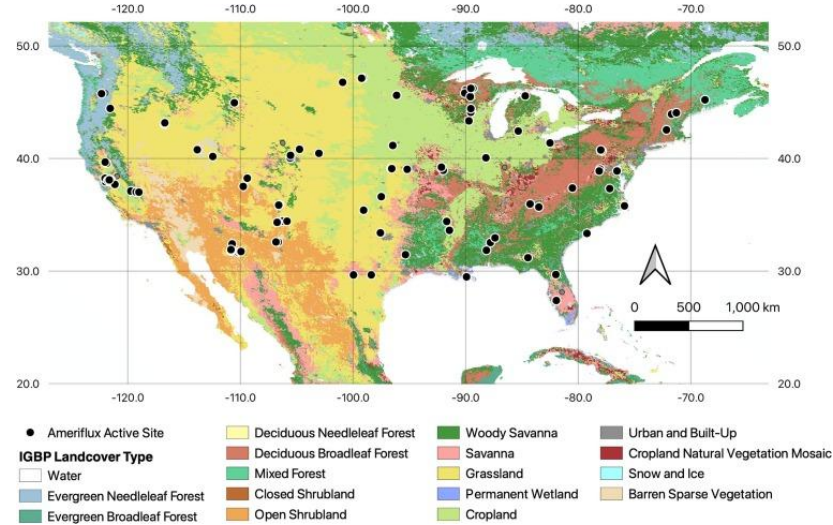
DSR: Ranjbar et al. (2024) <https://doi.org/10.1109/JSTARS.2024.3420148>

Vegetation indices: Ranjbar et al. (2024) <https://doi.org/10.1029/2024JG008240>

HRRR (RRFS)

Going forward:

Eddy covariance



GeoXO data products



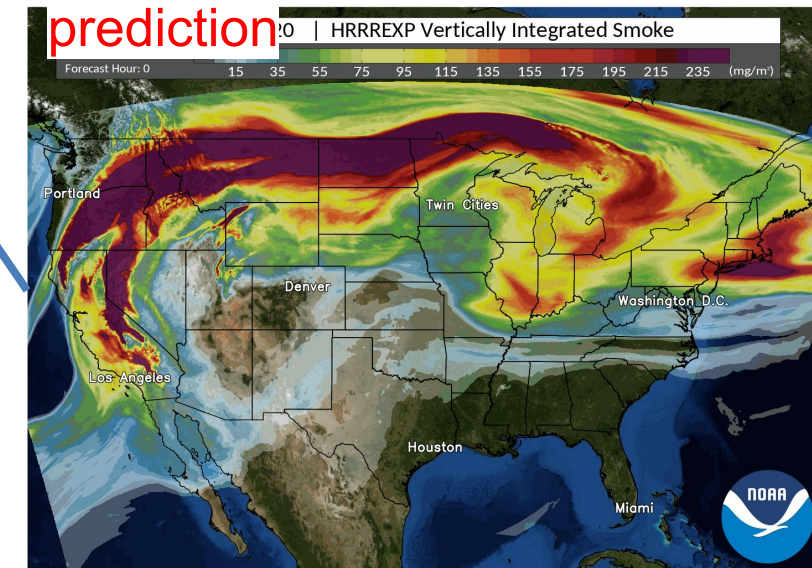
Applications:

Yield forecasting
Drought forecasting
Phenology prediction
Integration with high-res RS & models
More

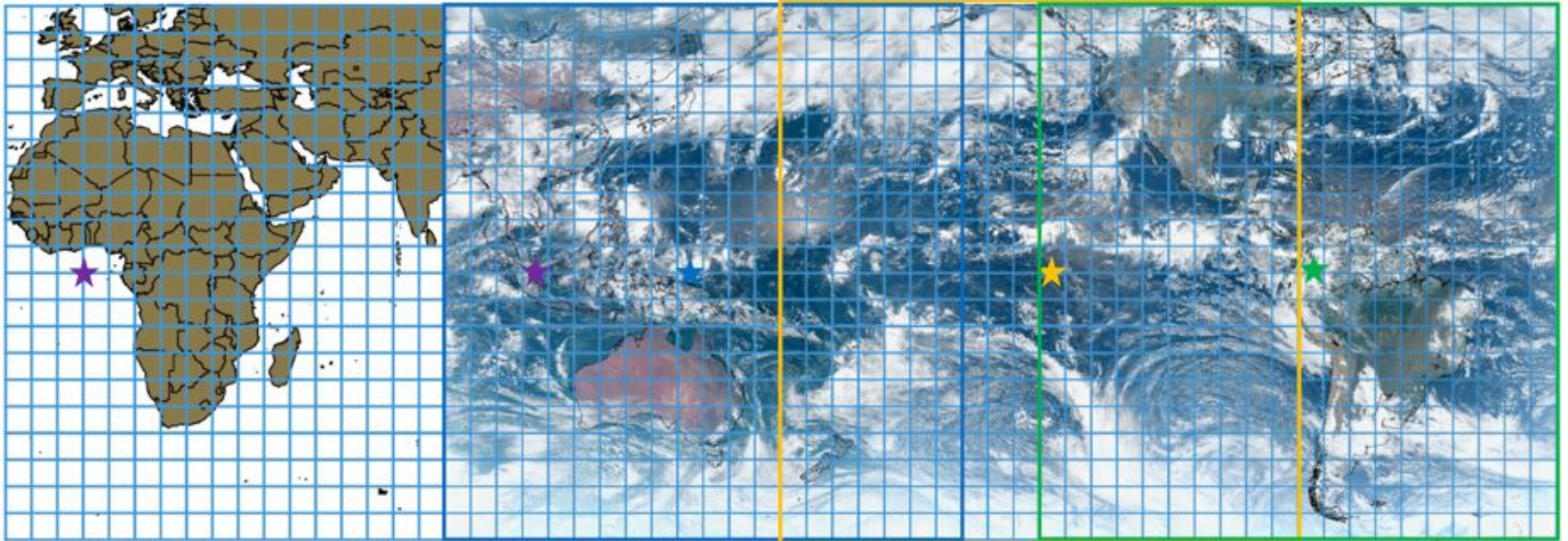
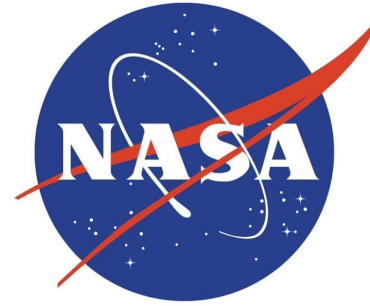
Knowledge
Guided
Machine
Learning



AI-enhanced weather prediction



Going forward: GEONEX



(MTG-I 1)

(FENGYUN-4) HIMAWARI8

GOES17

GOES16

GOES19

Funding

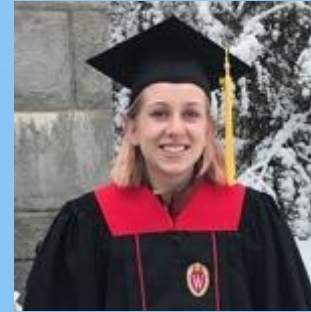
Thanks again!



Danielle Losos



Sadegh Ranjbar



Sophie Hoffman



Avanti Kekane

Data



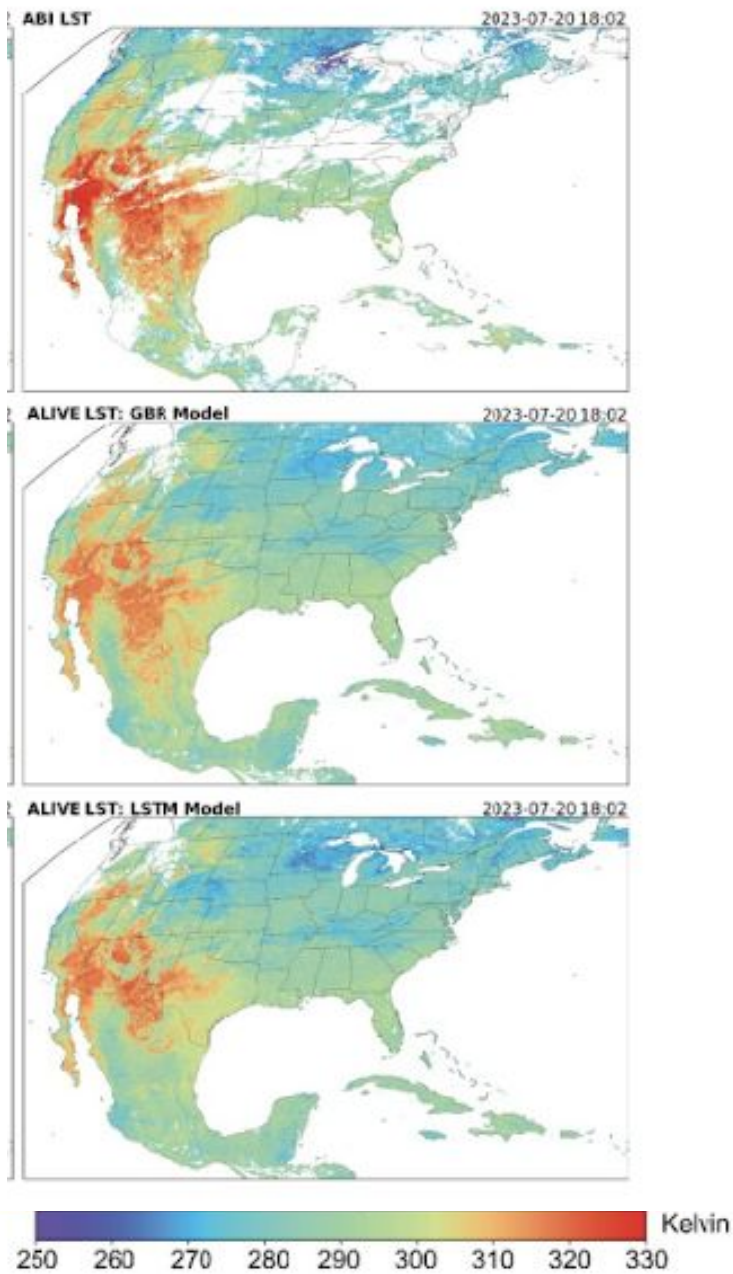
Einara Zahn



Elie Bou-Zeid



Sub-models for DSR and LST



LST: Ranjbar et al. (2025) <https://doi.org/10.1029/2024JH000464>

DSR: Ranjbar et al. (2024) <https://doi.org/10.1109/JSTARS.2024.3420148>

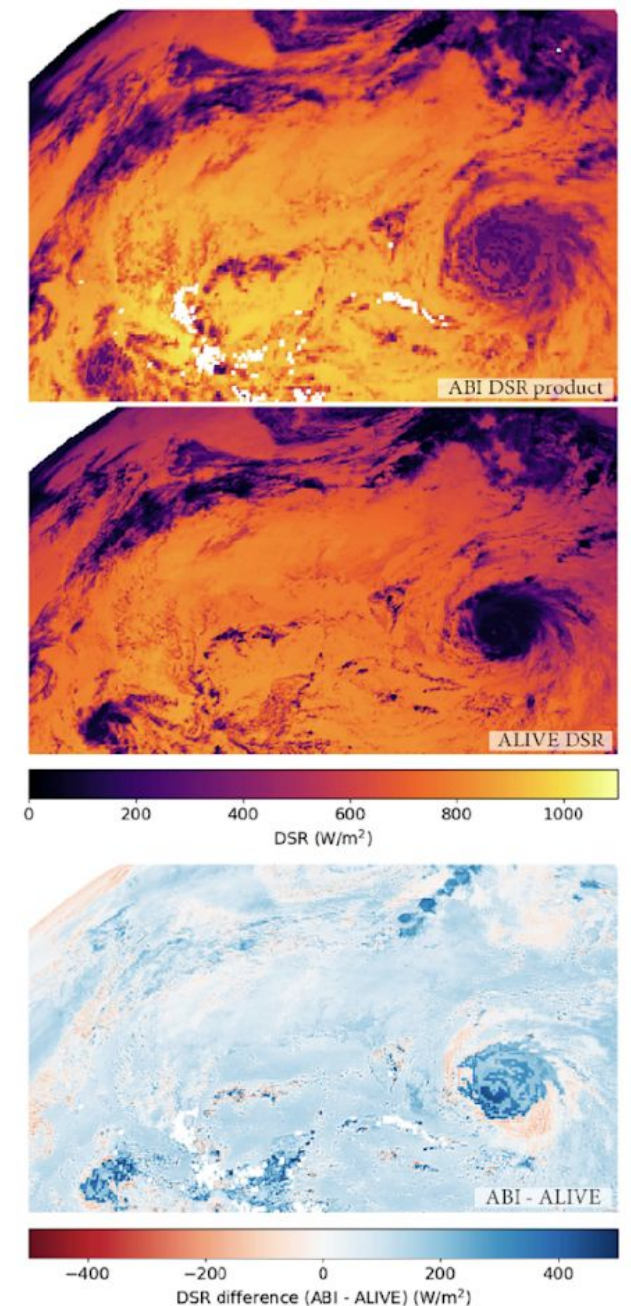
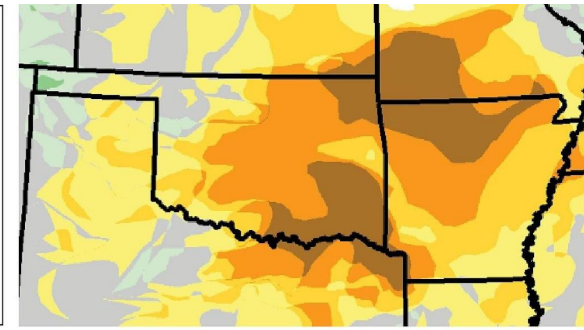
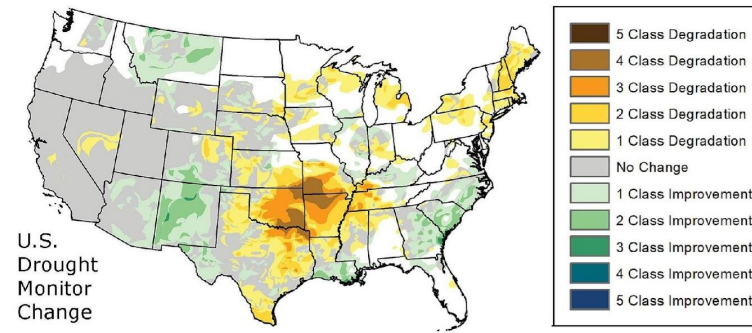
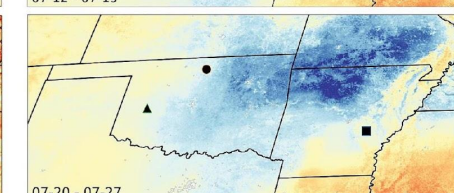
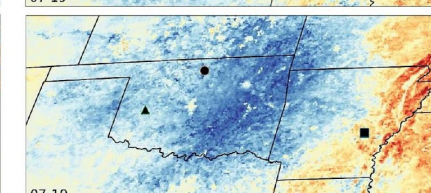
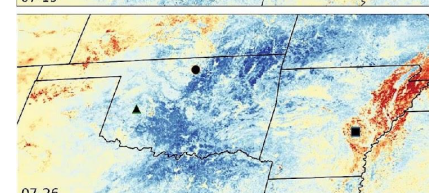
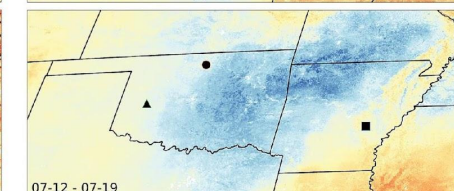
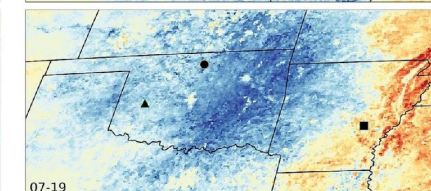
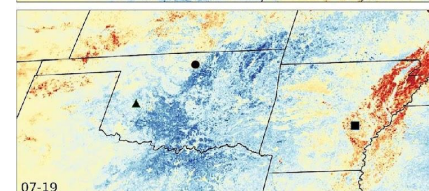
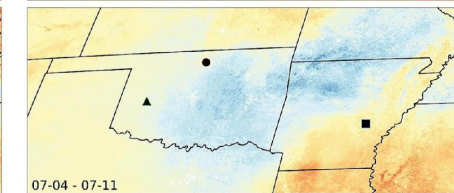
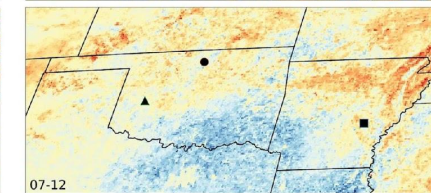
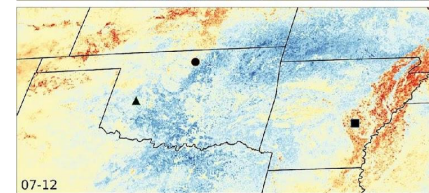
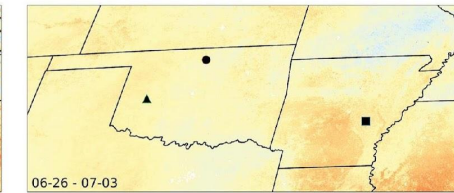
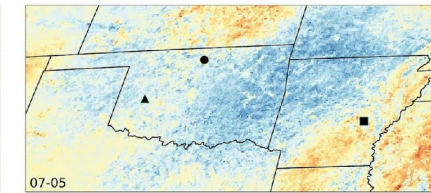
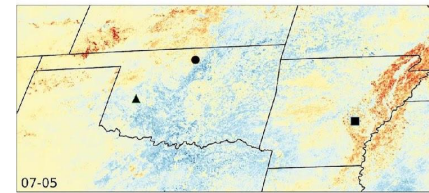
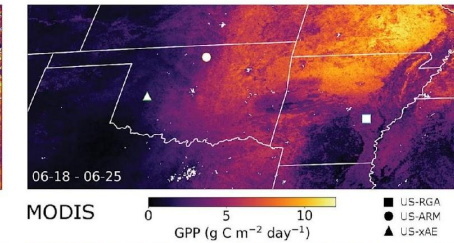
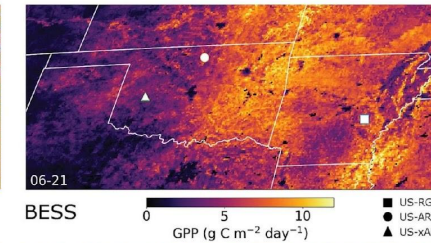
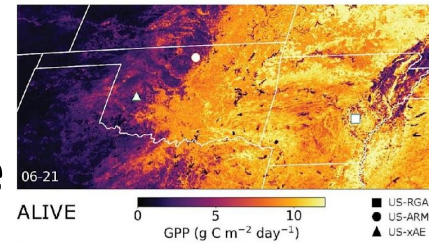


Fig. 9. DSR_{ABI} , estimated $\text{DSR}_{\text{ALIVE}}$, and their differences (ABI-ALIVE) maps at hour 6 P.M. UTC on September 21, 2022, with a CONUS view from the GOES satellite.

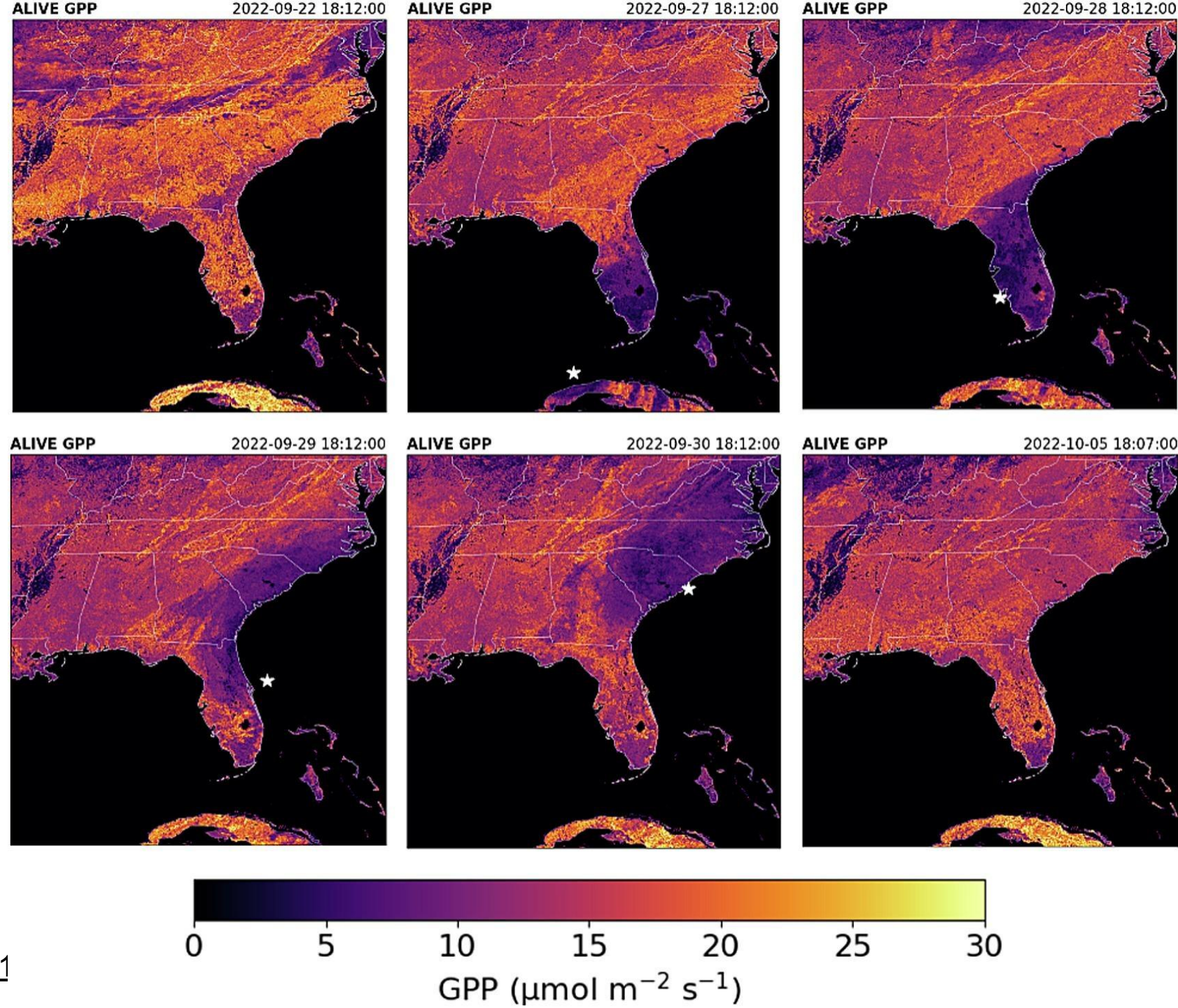
Example: Flash drought



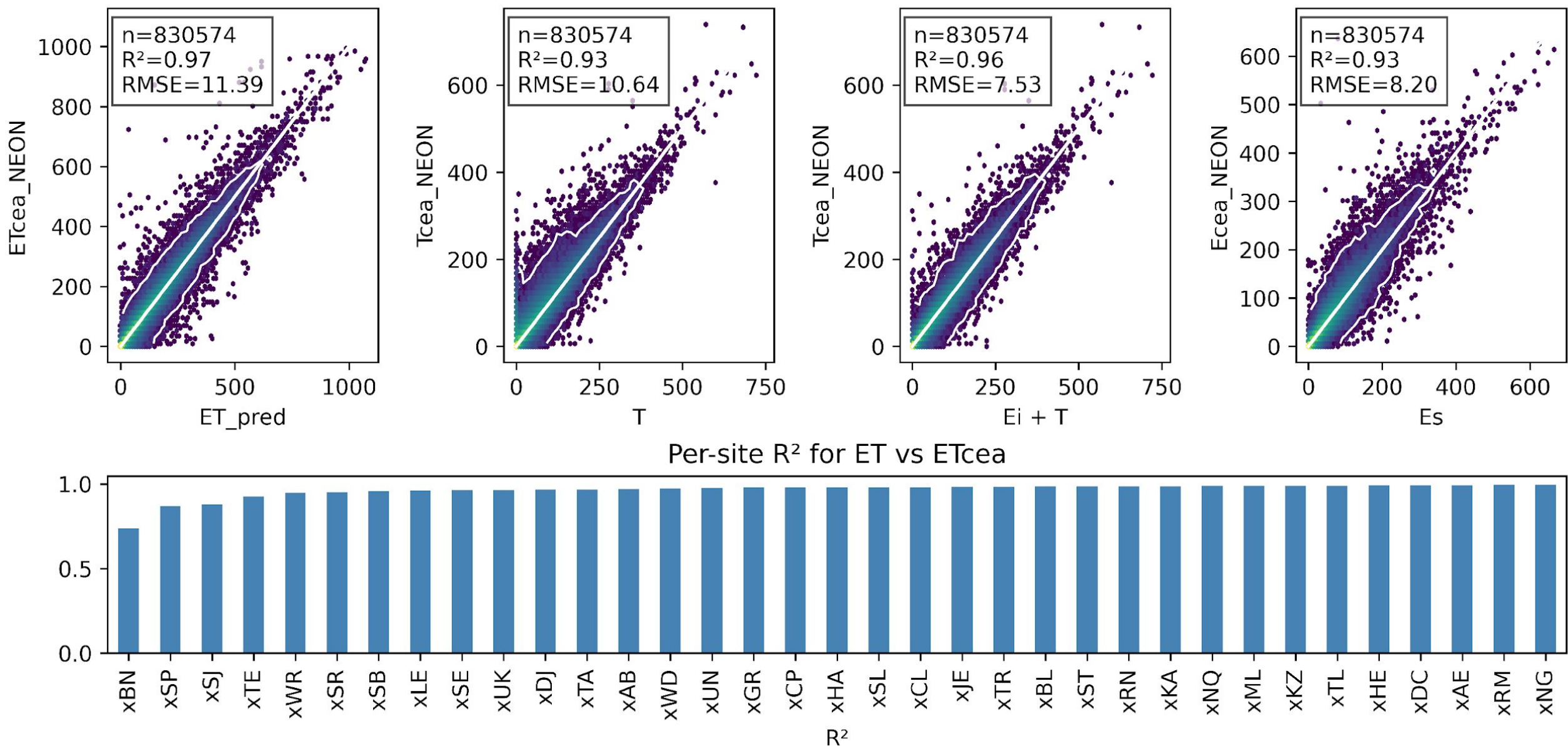
ALIVE estimates flash drought impacts to be more muted, but can find effects quickly



Example: Hurricane Ian



The model is happy because it has data. Does it get the physics right?



Figures: S. Ranjbar