

A New S5P-PAL HDO/H₂O Data Product and Its Application to Satellite-Based Evapotranspiration Estimation (ET)

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¹SRON, Leiden

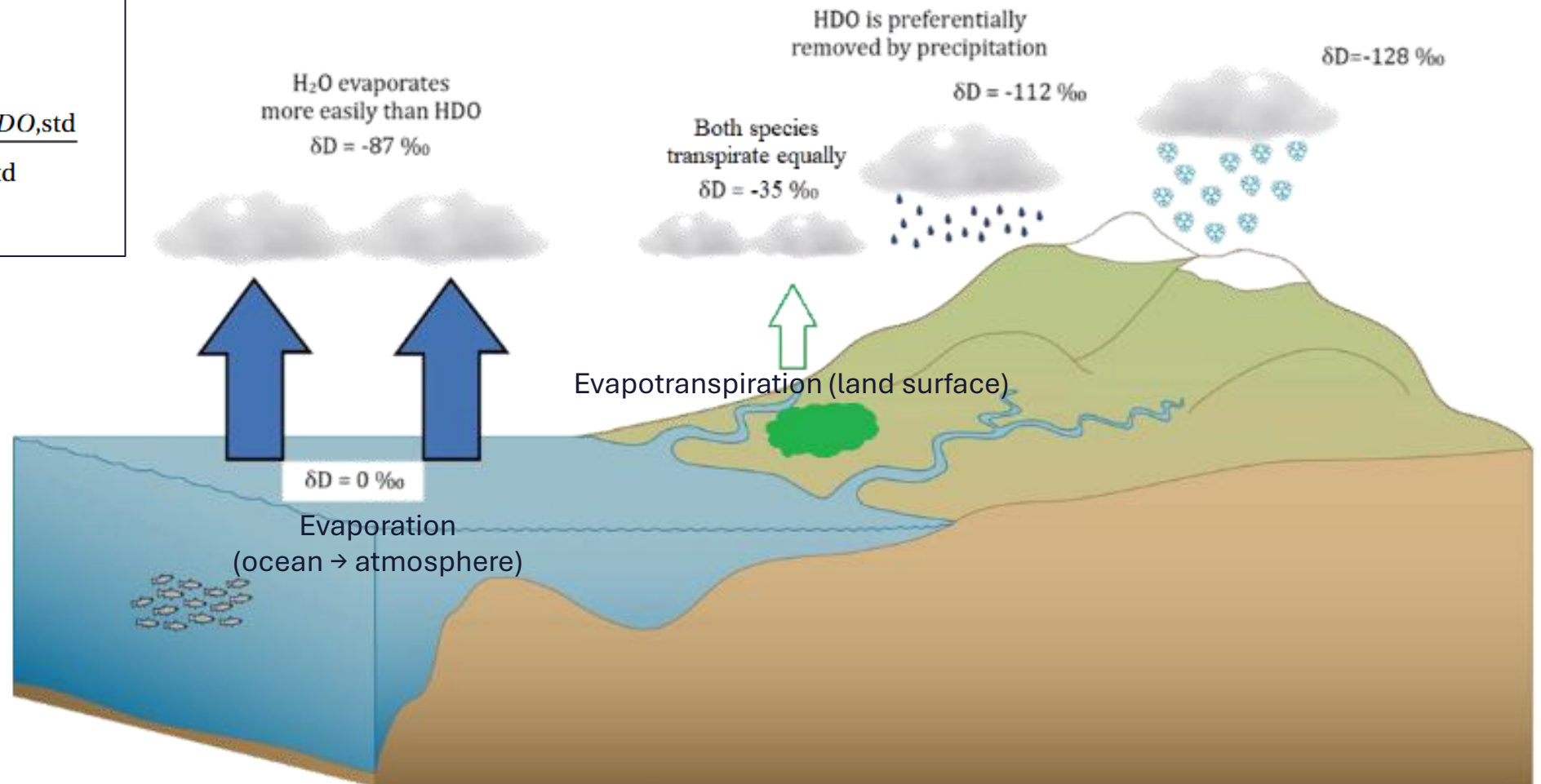
²JPL, California (Retired)

³TU Delft



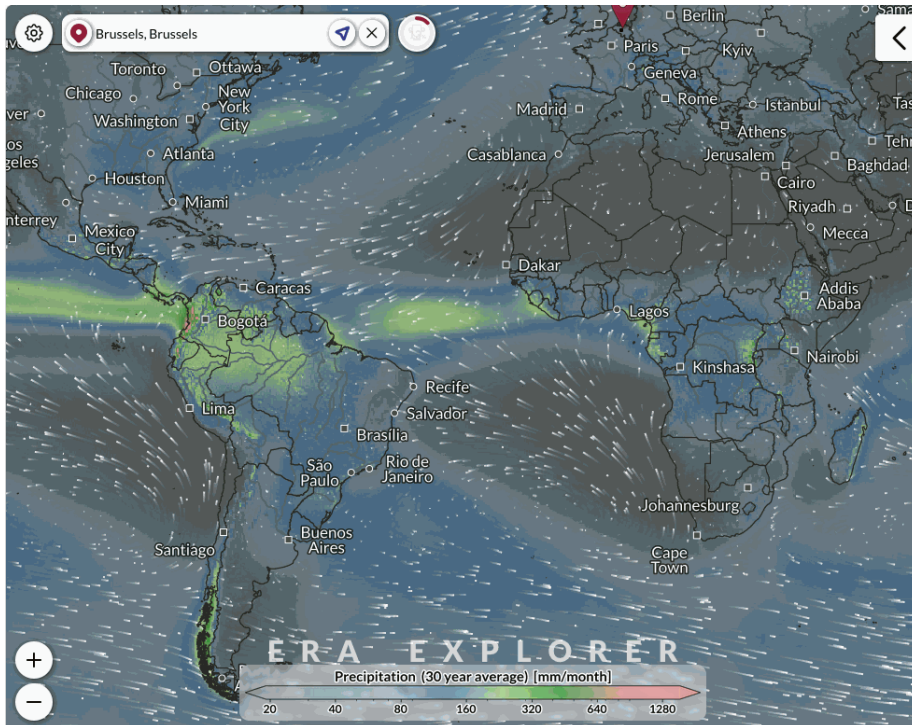
The Water Cycle: δD Traces ET and Precipitation

$$R_{HDO} = \frac{C_{HDO}}{C_{H_2O}}$$
$$\delta D = \frac{R_{HDO} - R_{HDO, std}}{R_{HDO, std}}$$



δD decreases progressively from ocean to continent — encoding both ET and precipitation history

ERA5 vs. Flux Towers: Global but Coarse, Precise but Sparse



ERA5 reanalysis — 25 km resolution, global

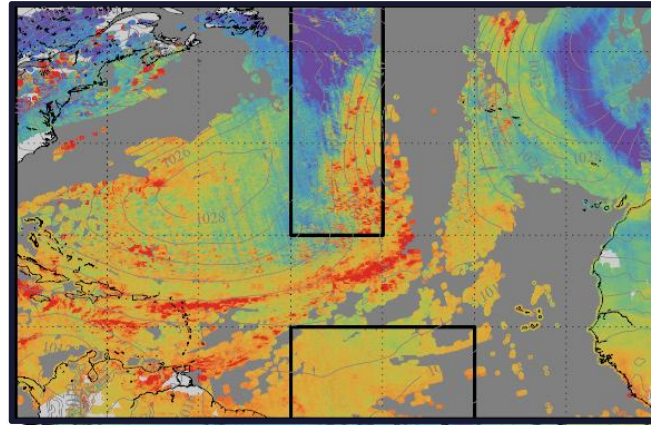


AmeriFlux / ICOS flux towers — point measurement (~1 km footprint, TROPOMI collocation ± 2 h) .

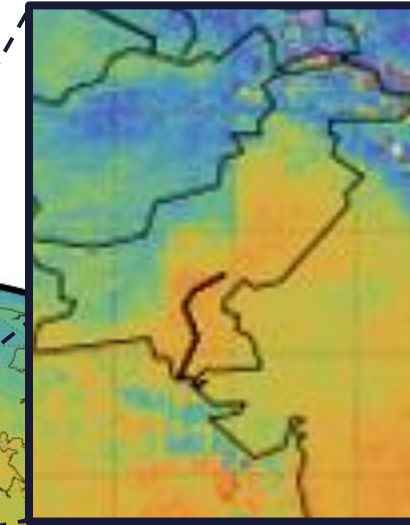
Neither alone is sufficient — satellites bridge the gap

TROPOMI HDO/H₂O: Daily Global Isotopologue Columns

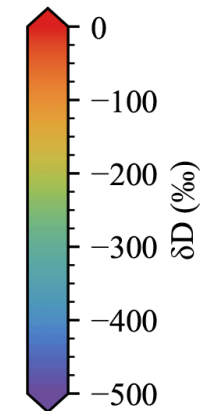
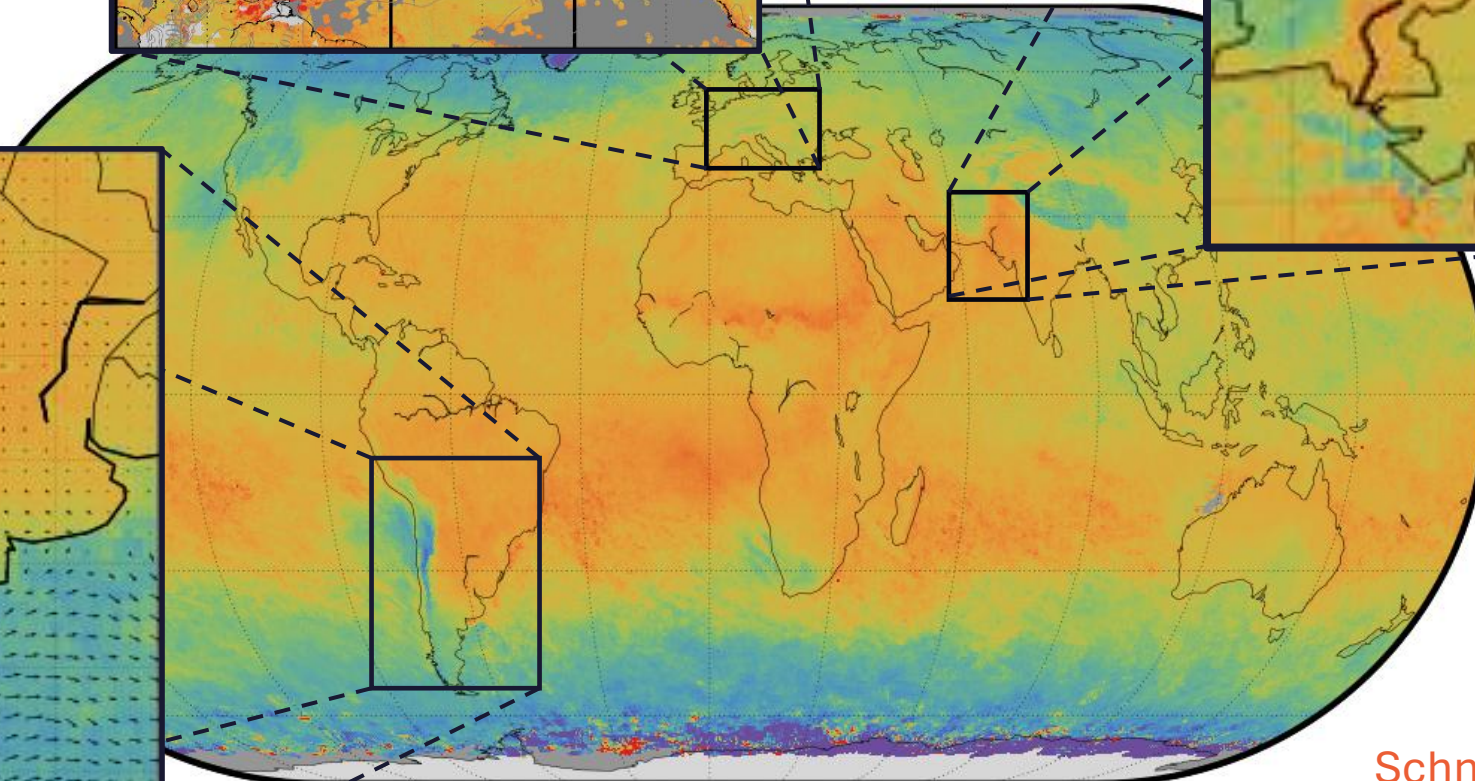
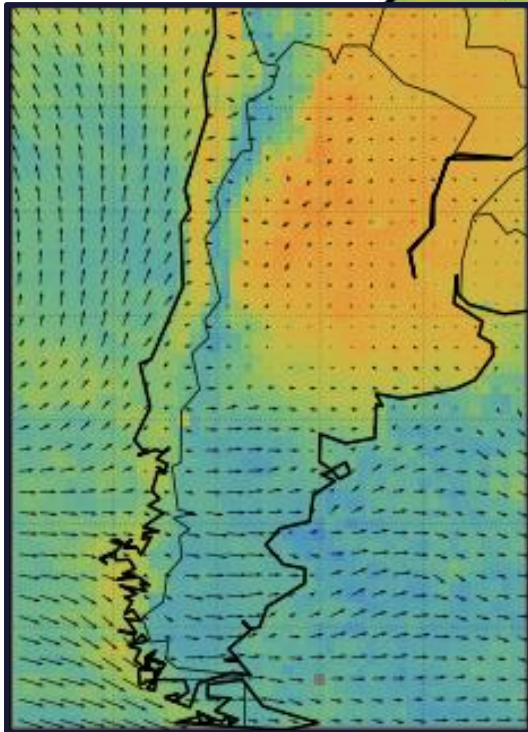
Single overpass:
(North Atlantic cyclone)



Indus river (India)



Rain pattern
(Patagonia)

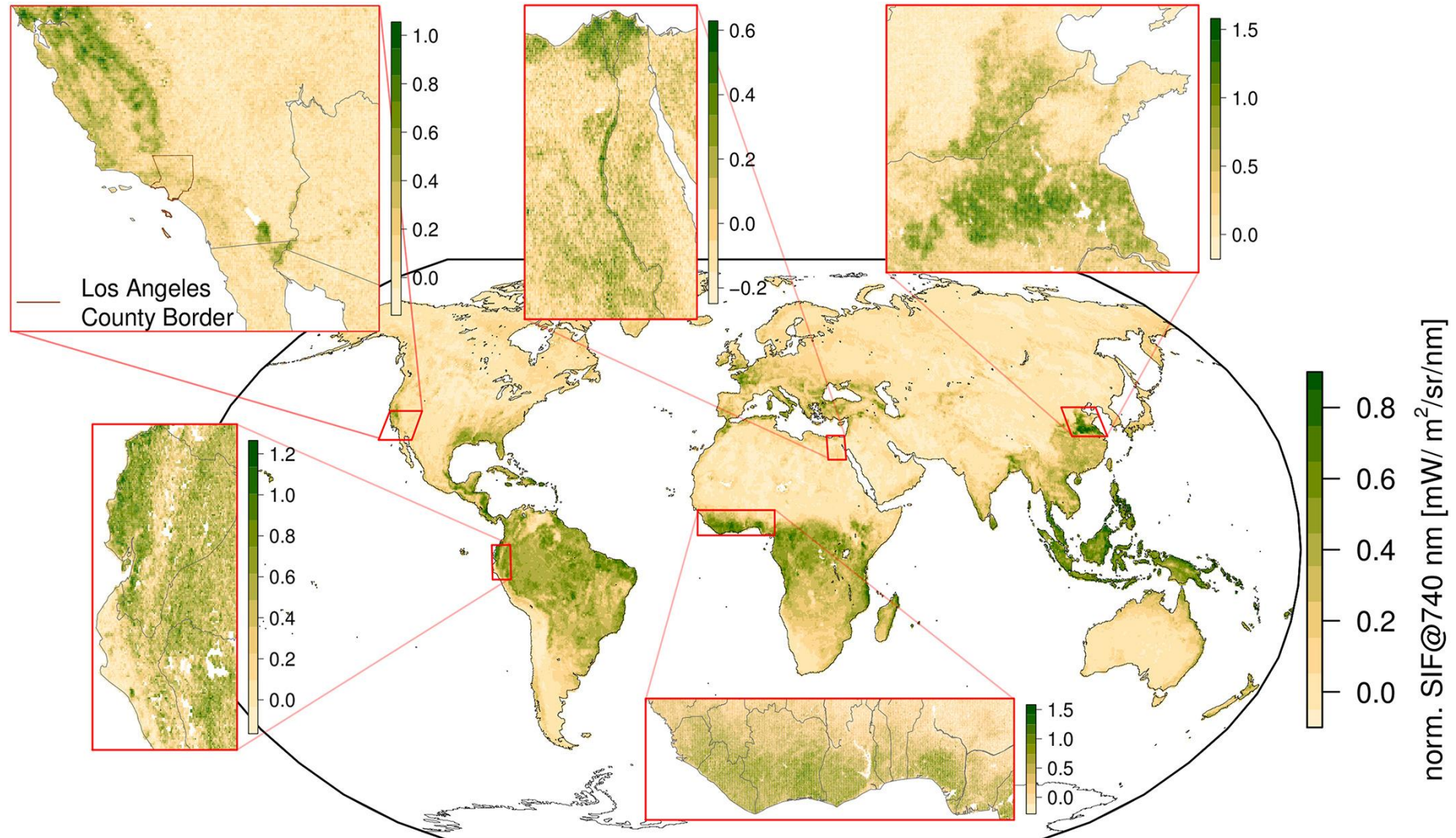


TROPOMI delivers daily global δD at 7×5.5 km
with boundary-layer sensitivity

[Schneider et al. 2020](#)

SRON

TROPOMI SIF: Vegetation Transpiration from Space

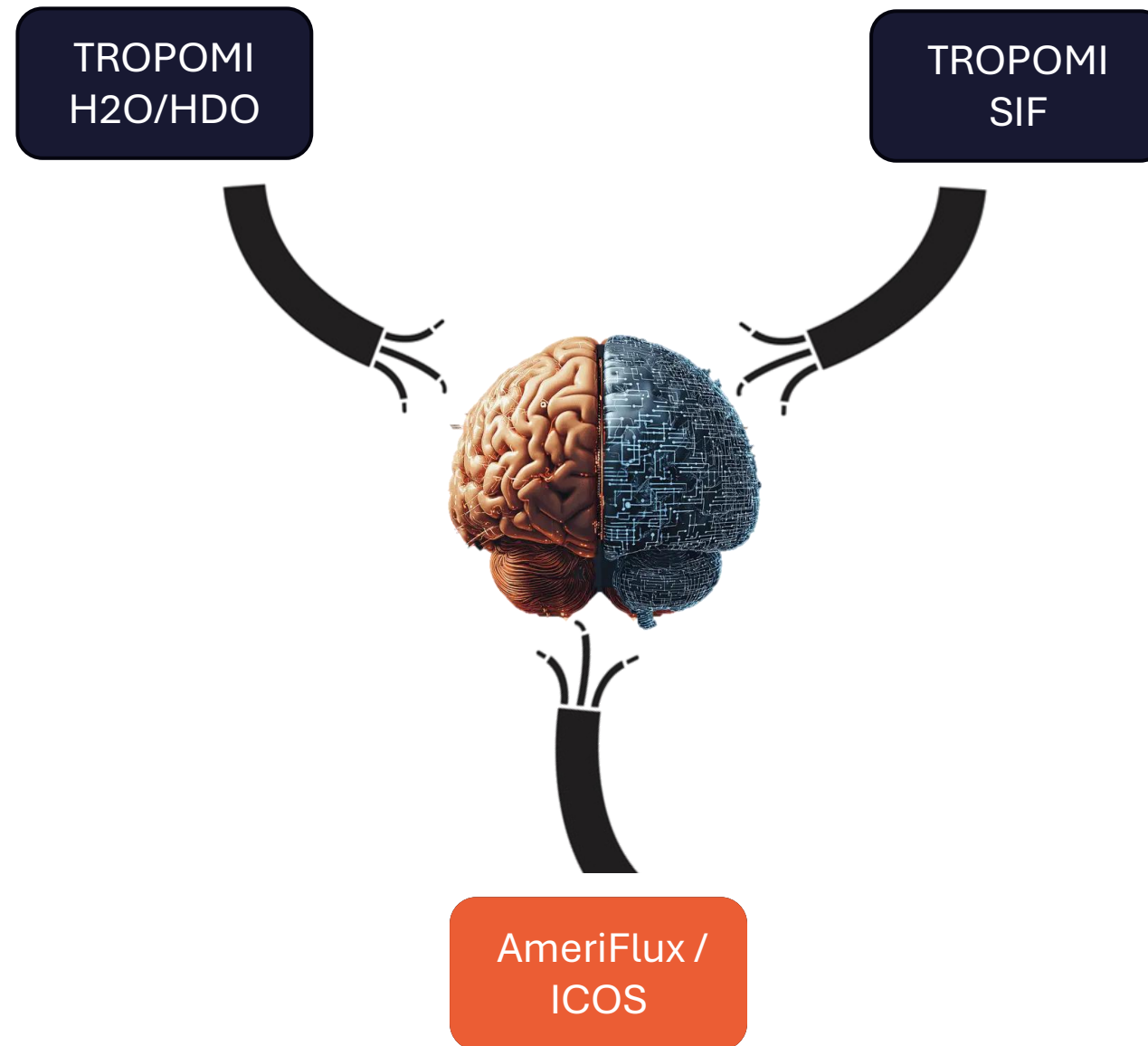


SIF directly constrains vegetation transpiration — the same TROPOMI footprint as HDO/H₂O enables natural data fusion

[Köhler et al. 2018](#)

SRON

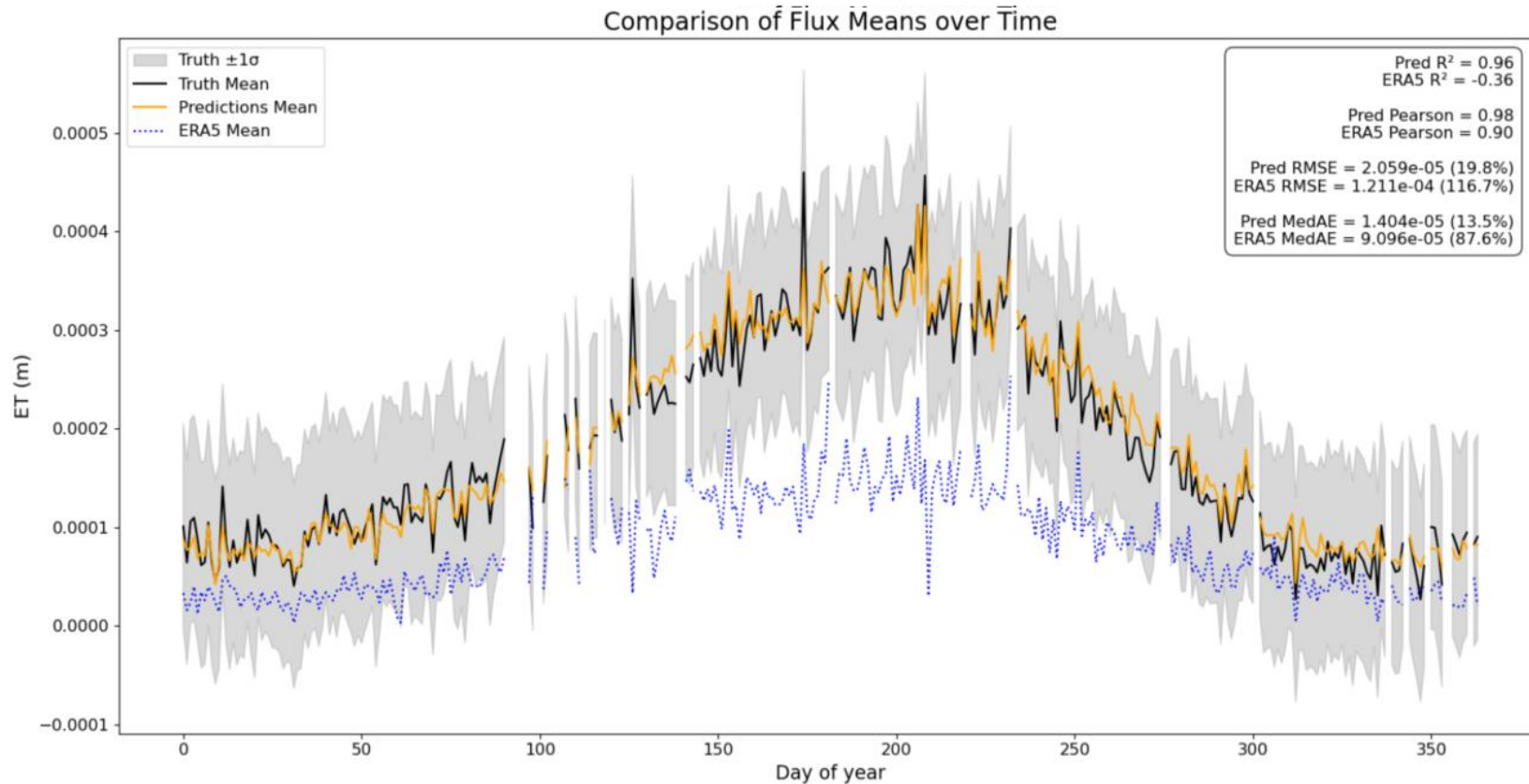
Synergistic AI approach



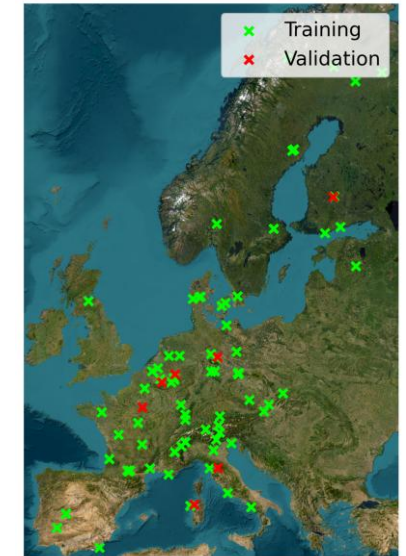
Validation against Flux Towers (North America)

Training and validation tower locations

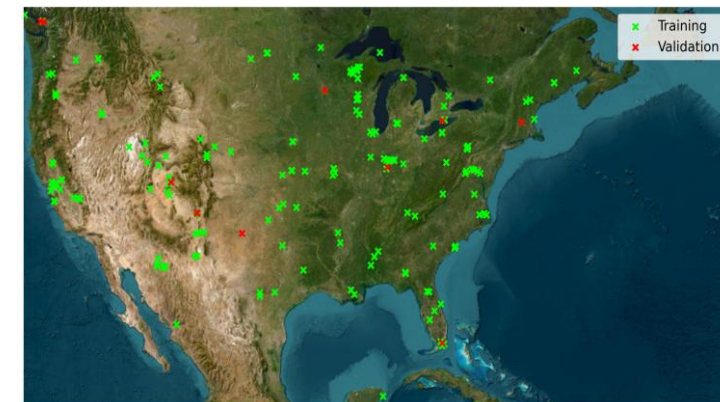
Trained with AmeriFlux / ICOS



European Station Map



American Station Map



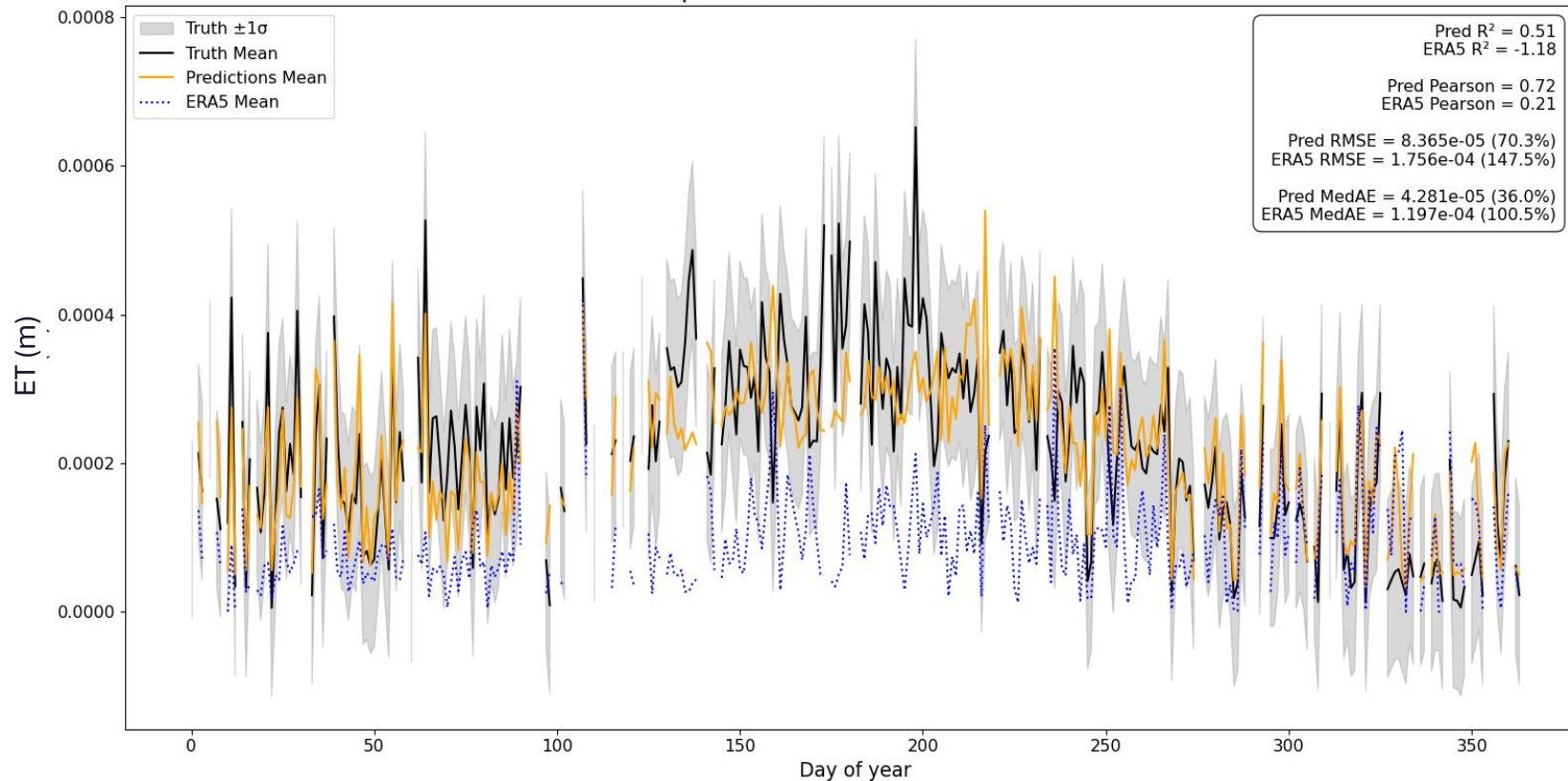
Evaluation on Flux Towers used during training but unseen in 2023
Our Model: $R^2 = 0.96$ vs. ERA5: $R^2 = -0.36$

Validation against Flux Towers (North America)

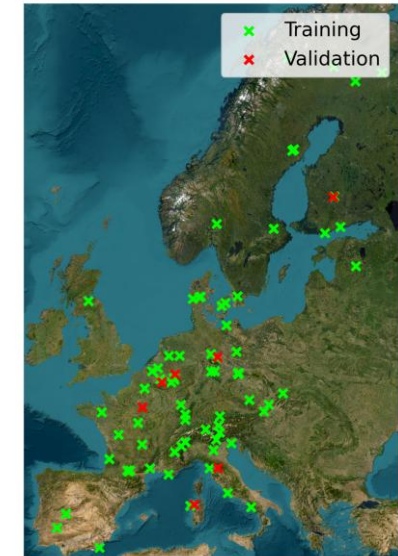
Training and validation tower locations

Trained with AmeriFlux / ICOS

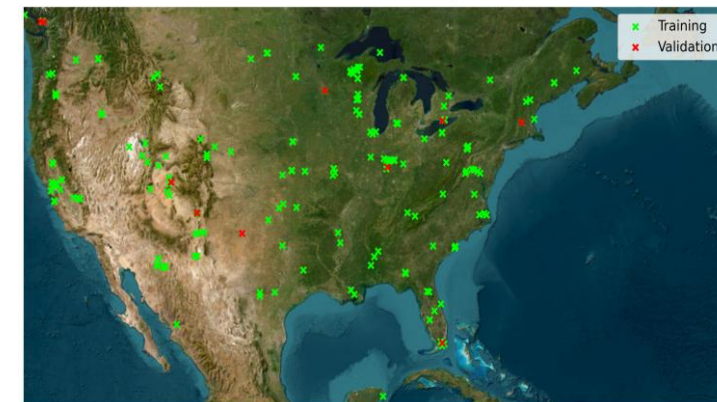
Comparison of Flux Means over Time



European Station Map



American Station Map

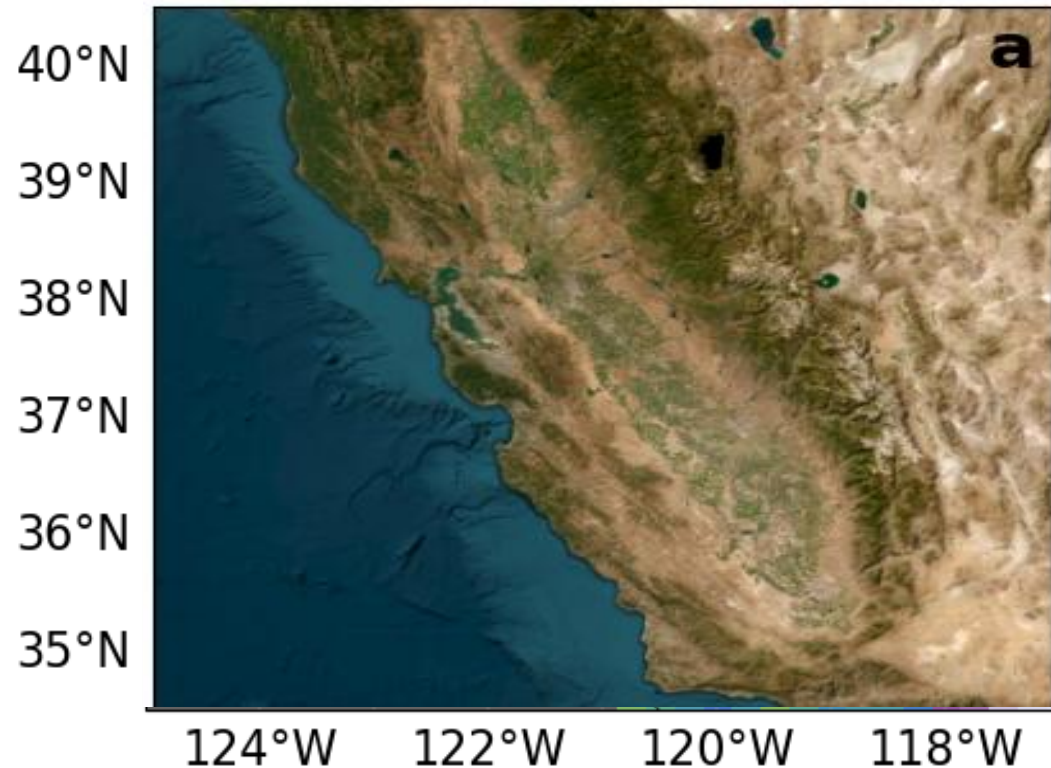


Evaluation on Flux Towers not used during training and unseen year 2023

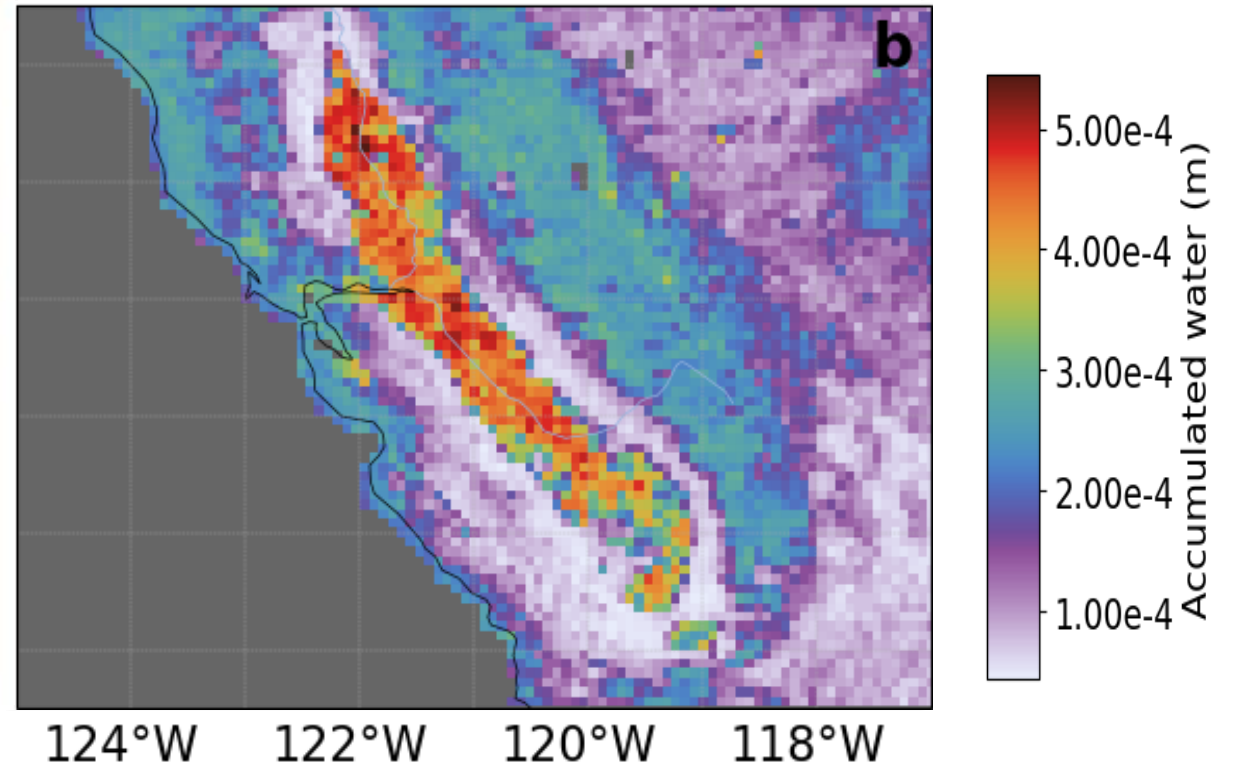
Our Model: $R^2 = 0.51$ vs. ERA5: $R^2 = -1.18$

California: Irrigation Patterns at 7 km

Satellite imagery — California Central Valley



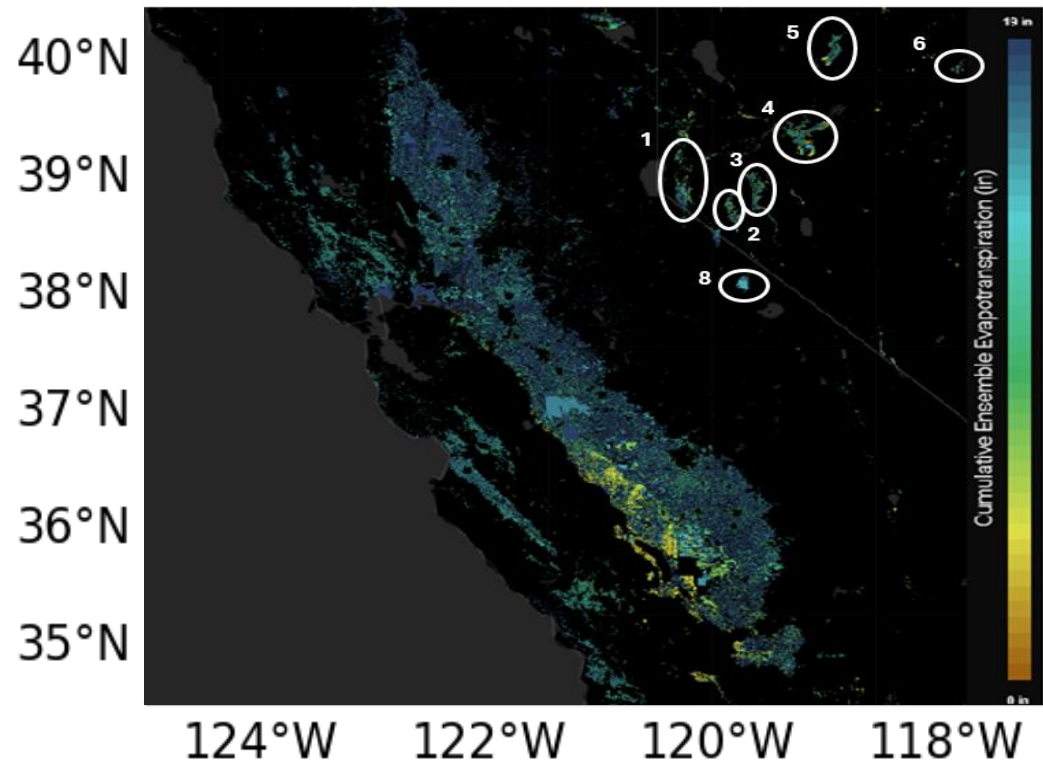
Model prediction — accumulated ET, summer (DOY 132–230, 2023)



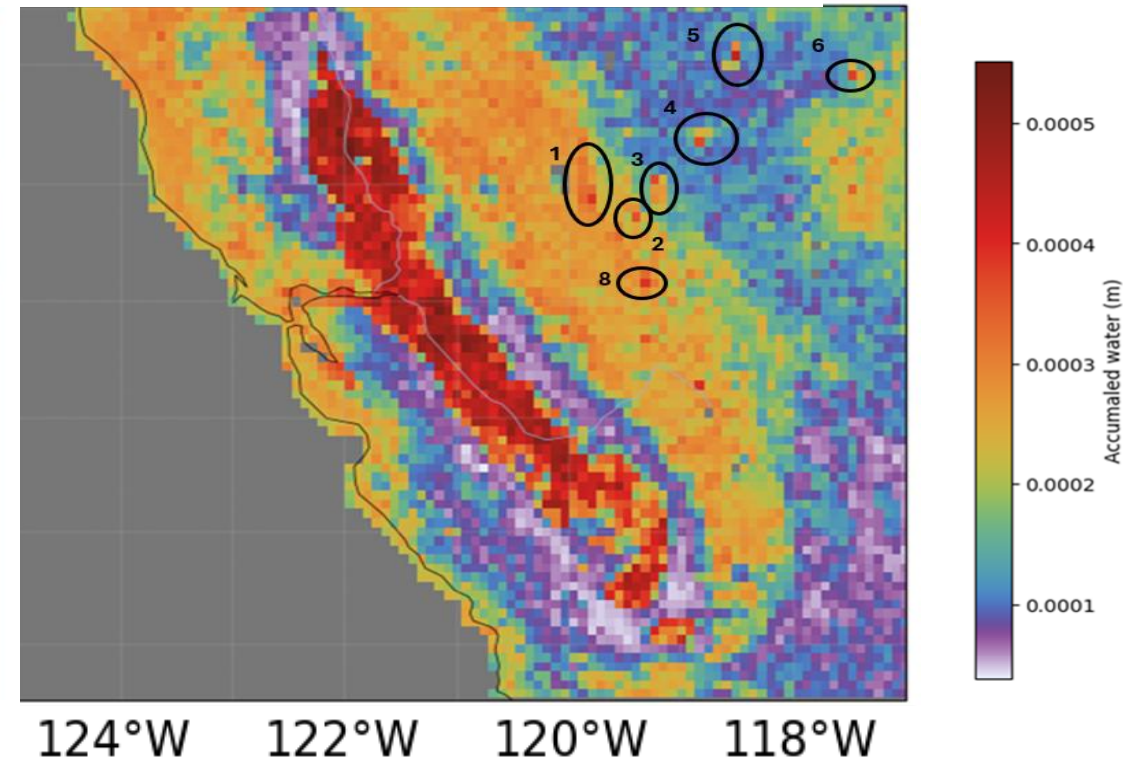
Model resolves the irrigated valley floor at $4\text{--}5 \times 10^{-4}$ m; ERA5 underestimates by 5–7×

California: Irrigation Patterns at 7 km

OpenET — cumulative evapotranspiration
(independent reference)



Model prediction — accumulated ET,
summer (DOY 132–230, 2023)

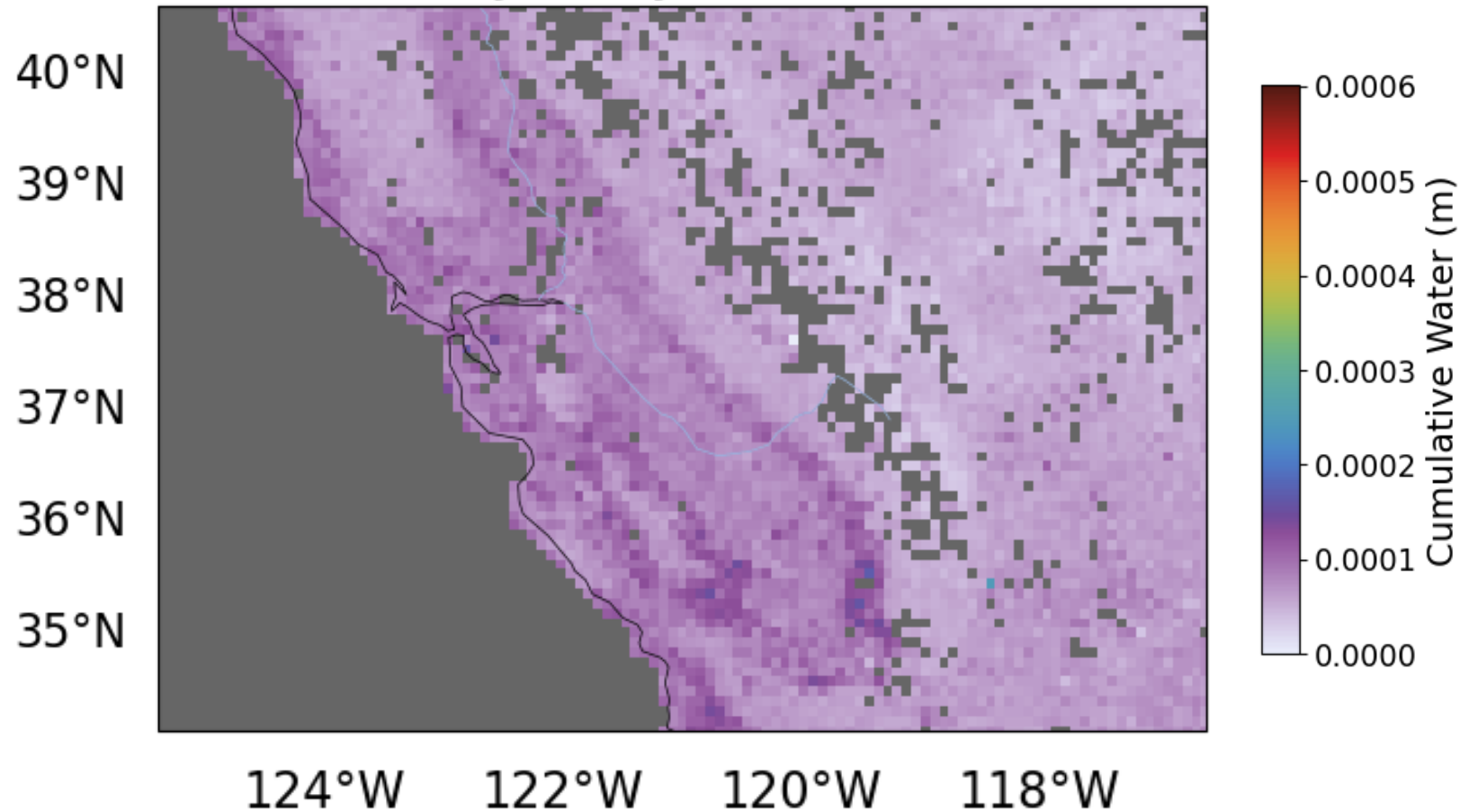


Irrigation field patterns and spatial boundaries confirmed by
independent OpenET product

California: The Agricultural Seasonal Cycle

TROPOMI ET prediction — monthly average, 2023

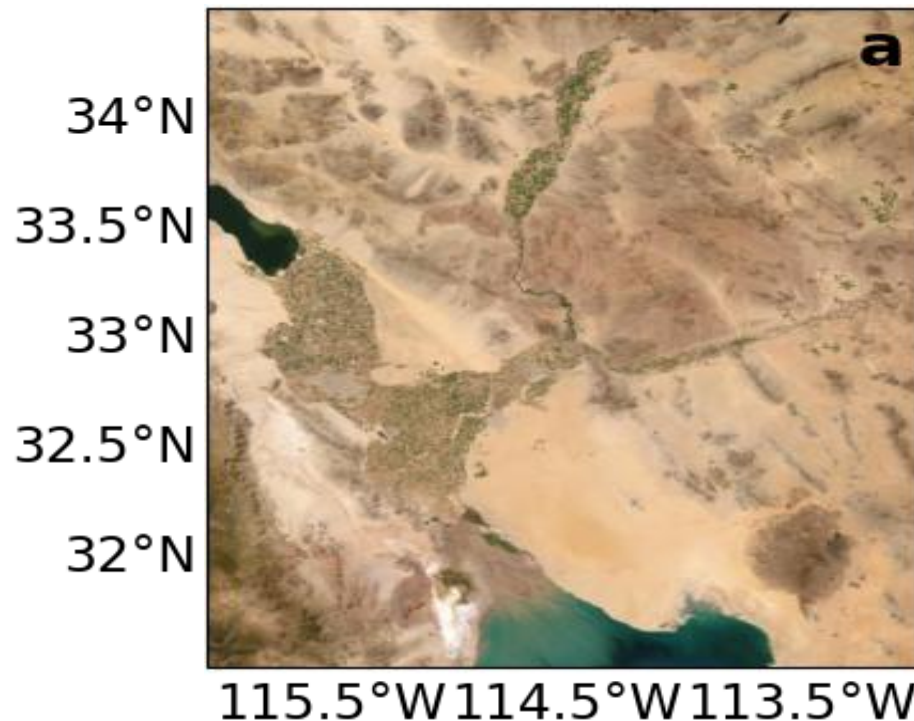
January — Pred



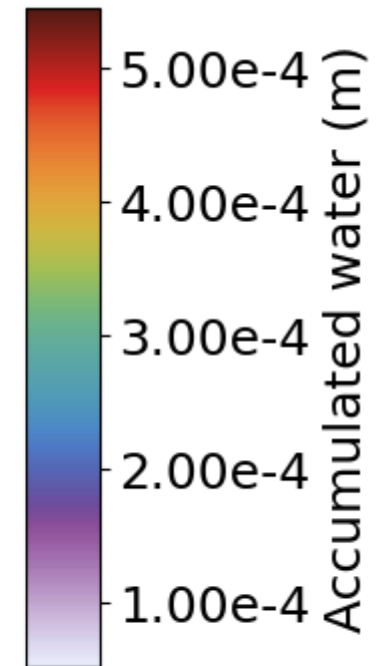
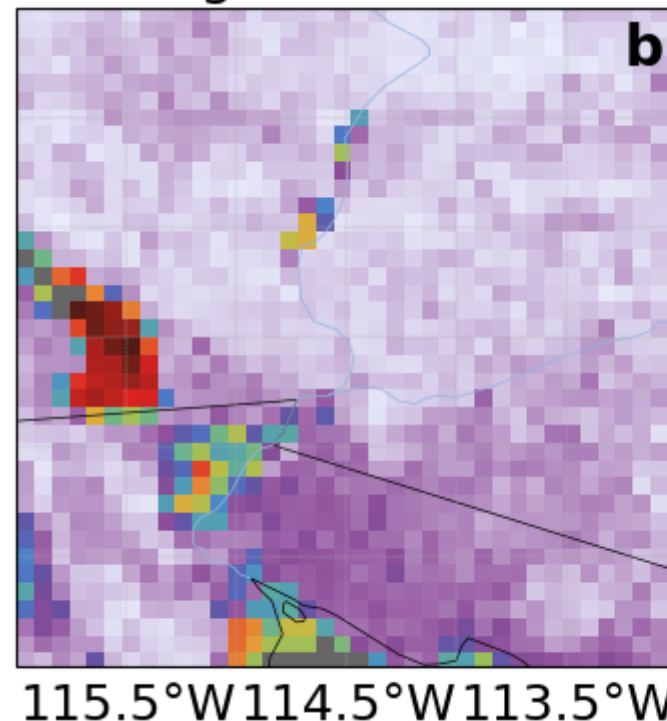
ET follows the agricultural calendar — absent in ERA5

Generalisation ET Beyond the Training Area: Mexicali Valley (>500 km from nearest training flux tower)

Satellite imagery — Mexicali Valley,
US–Mexico border



Model prediction — accumulated ET,
summer (DOY 132–230, 2023)

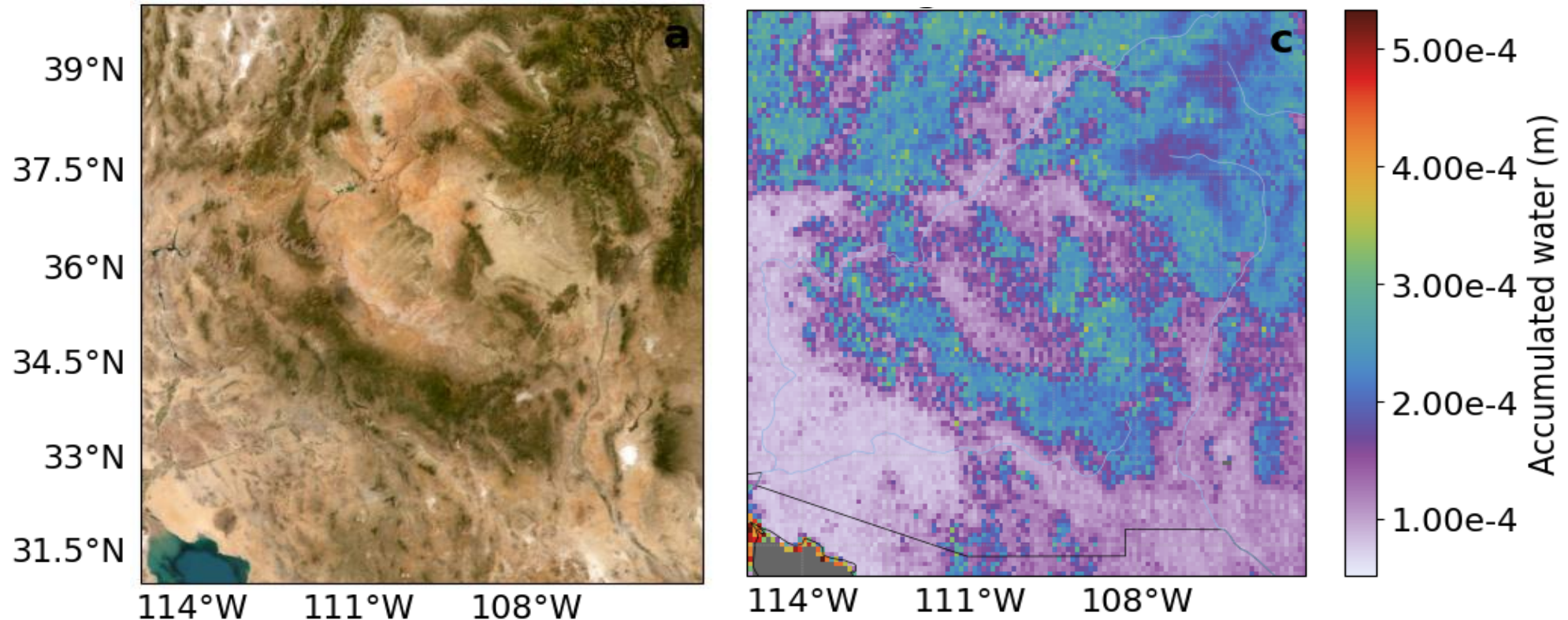


Model detects irrigation signals ($2\text{--}4 \times 10^{-4}$ m) against a desert background
— ERA5 shows no spatial structure

Complementary Information: HDO vs. SIF

Satellite imagery — southwestern
US desert/mountain transition

ERA5



HDO alone resolves spatial ET structure — SIF adds peak accuracy.
Both signals contribute independently.

Manuscript under preparation...

Full methodology and results are detailed in our manuscript, to be submitted to Atmospheric Measurement Techniques (AMT).



Mapping evapotranspiration at high spatial resolution: Synergistic use of TROPOMI HDO/H₂O and SIF satellite observations using deep learning

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Abstract.

Evapotranspiration (ET) is a key component of the terrestrial water cycle, linking the land surface and atmosphere alongside precipitation (P), yet remains difficult to quantify accurately at high spatial and temporal resolution. While precipitation can be measured reliably using in-situ and remote sensing techniques, ET estimates rely largely on indirect approaches and are

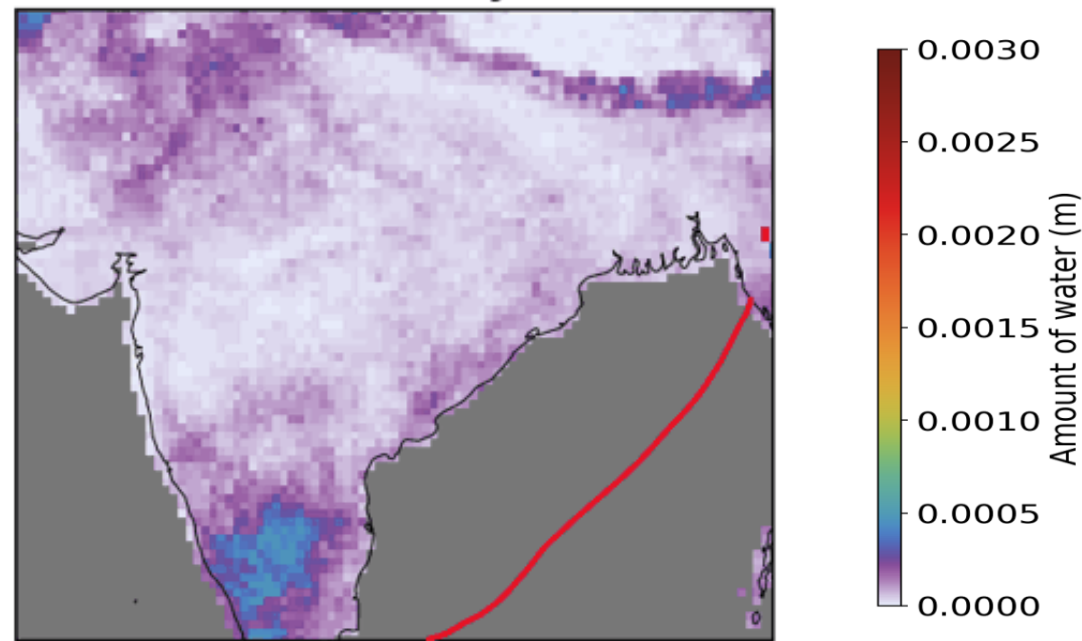
5 subject to substantial uncertainties.

Here, we present a data-driven approach that exploits complementary physical information from two different TROPOMI satellite data products: water isotopologue ratios (HDO/H₂O), which reflect moisture recycling and evaporative processes, and solar-induced fluorescence (SIF), which constrains vegetation-driven transpiration. These data products are combined with meteorological variables in a deep learning framework to derive daily ET estimates at TROPOMI's native spatial resolution

Future work: Adding Precipitation to Close the Water Balance

TROPOMI precipitation prediction — India, week 22 (28 May, 2023)

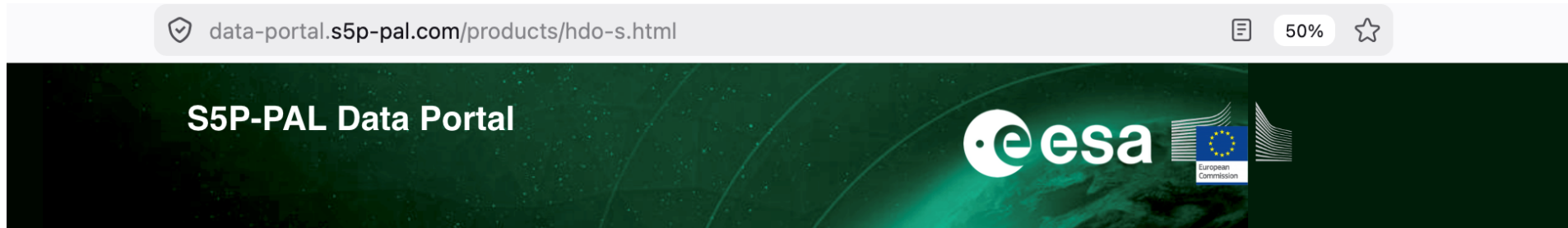
Week 22 (28 May) — Pred



Monsoon front (IMD, red line)

HDO/H₂O tracks the monsoon onset - first step toward global ET-P monitoring

S5P-PAL HDO/H₂O: Available for Download



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API info

HDO (SRON)

The HDO/H₂O retrieval algorithm is adapted from the algorithm of the operation CO product. It has been updated to account for an extended scientific HDO/H₂O total column data product from short-wave infrared (SWIR) measurements by TROPOMI, including both clear-sky and cloudy scenes. The retrieval is implemented using the existing SICOR algorithm. In contrast to the earlier version, which focused on clear-sky observations using strict cloud filters from the SWIR pre-processor, the updated algorithm uses a scattering-aware retrieval approach to fit total columns of isotopes (H₂O, HDO, H₂¹⁸O, CH₄, CO), surface albedo, spectral offsets, and wavelength-dependent reflectance. The retrieval window is optimized to capture strong HDO absorption lines, distinct from H₂O lines.

The hydrological cycle is a critical component in understanding climate change. Water vapor, as the strongest natural greenhouse gas, plays a key role in atmospheric feedback mechanisms and processes such as cloud formation. Accurate measurements of atmospheric humidity and its isotopic composition are essential for improving the projections of atmospheric general circulation models (GCMs), which are used to simulate climate-related processes.

Information about HDO (SRON)

The SRON HDO processor is developed and maintained by [SRON](#).

Available resources:

[Algorithm Theoretical Basis Document \(ATBD\)](#)

[Product User Manual \(PUM\)](#)

[Validation Report \(DOI 10.5194/amt-13-85-2020\)](#)

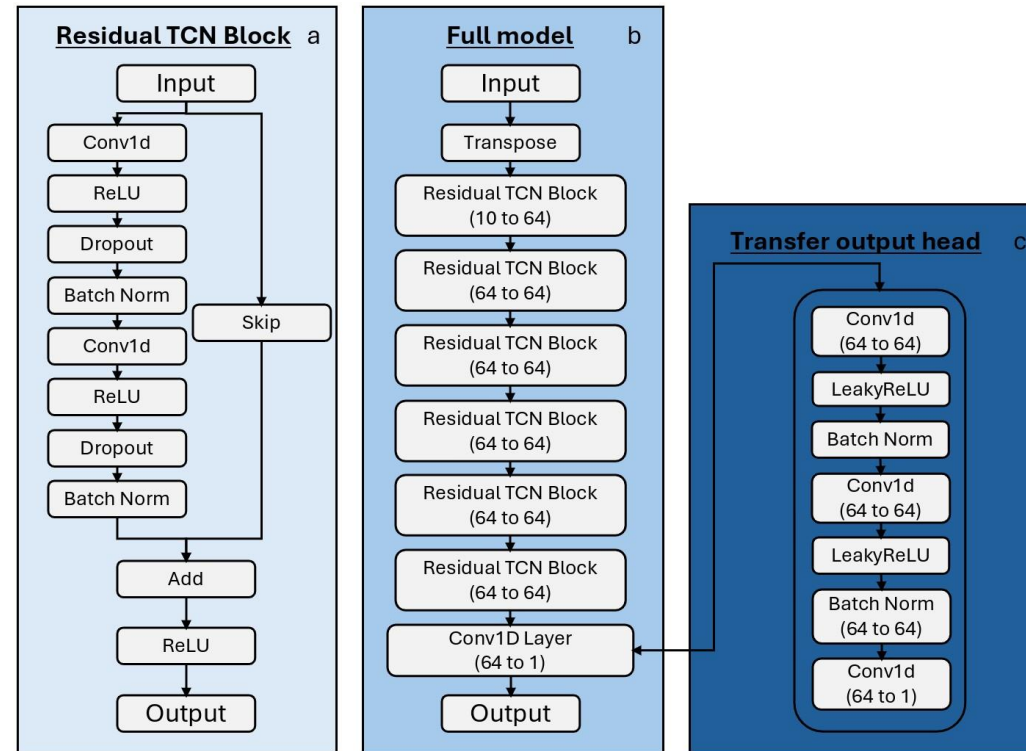
[Validation Report \(DOI 10.5194/amt-15-2251-2022\)](#)

Conclusions and Outlook

- Two-stage deep learning – ERA5 pre-training + flux tower transfer learning – produces daily TROPOMI ET at 7×5.5 km
- TROPOMI HDO/H₂O and SIF provide complementary, independent constraints on ET – evaporative flux and vegetation transpiration
- Working toward a global TROPOMI ET dataset beyond North America and Europe
- Adding precipitation estimation to close the water balance (ET – P)
- Denser flux tower networks and Sentinel-5 continuity needed for global scaling

The Neural Network: Temporal Convolutional Network (TCN)

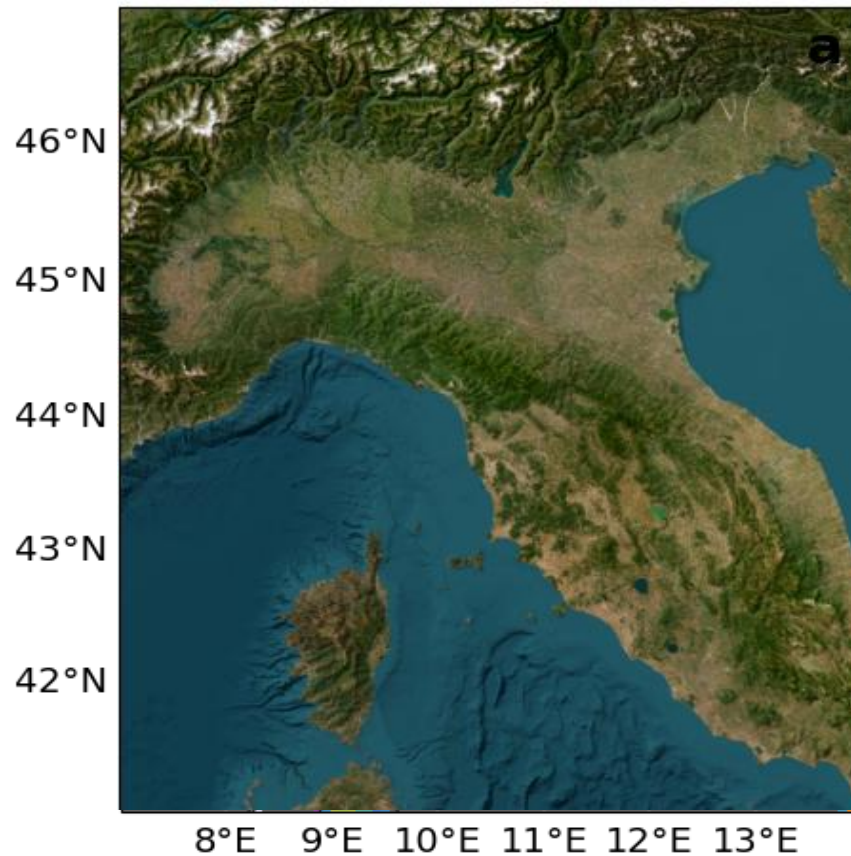
279,425 parameters · trained in ~1 hour on a 4 GB GPU ·
handles 50–90% missing data due to cloud cover



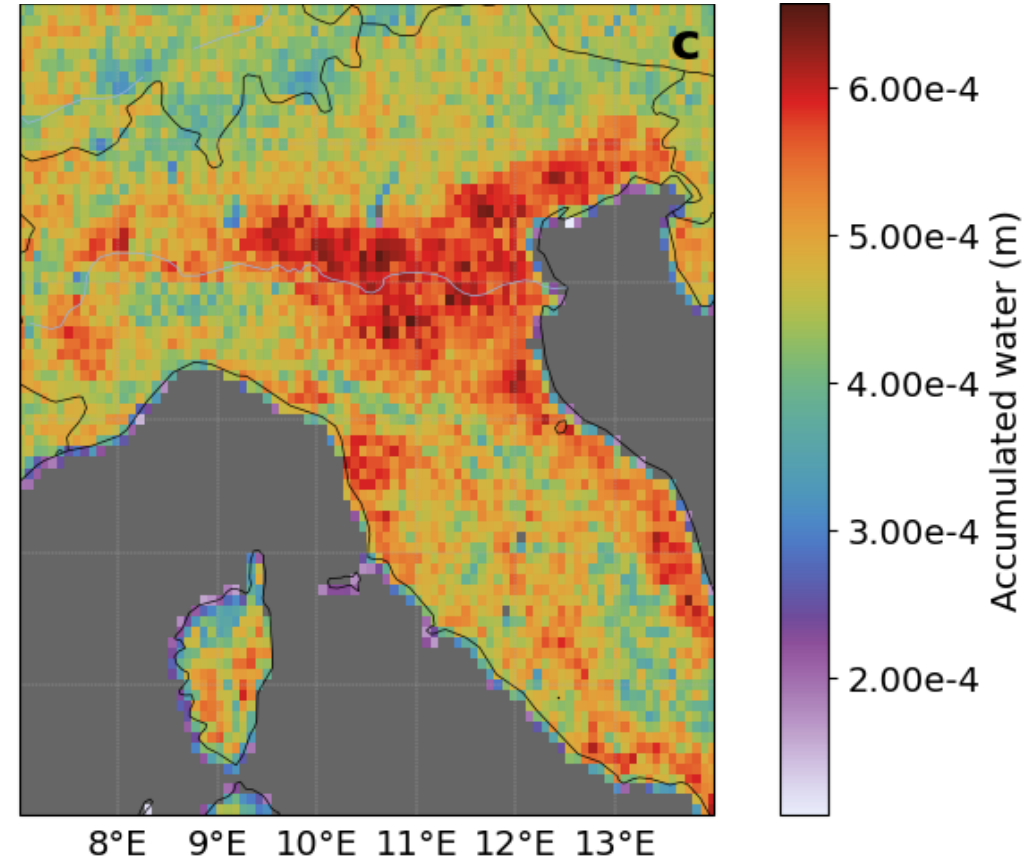
A backbone of stacked convolutional blocks learns the physical relationship between satellite signals and ET. A replaceable output head allows the same network to be first trained on ERA5 and then fine-tuned on flux tower data without retraining from scratch.

Italy Po Basin

Satellite imagery - Po River Basin,
northern Italy

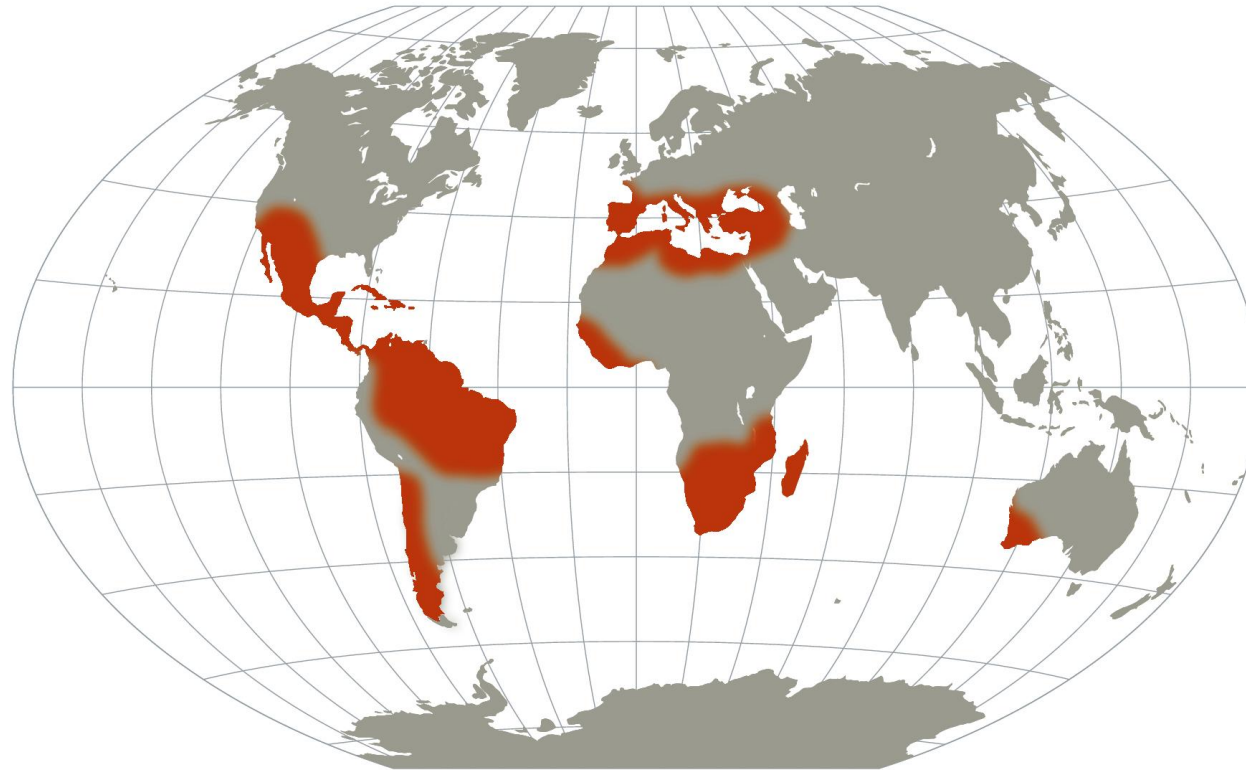


ERA5— accumulated ET, summer
(DOY 132–230, 2023)



Model distinguishes irrigated cropland ($6-7 \times 10^{-4}$ m) from surrounding forest ET — ERA5 cannot

The Water Cycle Under Pressure: Droughts and Climate Change



Regions where droughts are expected to worsen — IPCC AR6

IPCC Sixth Assessment Report, FAQ 8.3, Figure 1 | Schematic map highlighting in brown the regions where droughts are expected to become worse as a result of climate change. This pattern is similar regardless of the emissions scenario; however, the magnitude of change increases under higher emissions.

Accurate ET monitoring is critical for anticipating and managing drought impacts