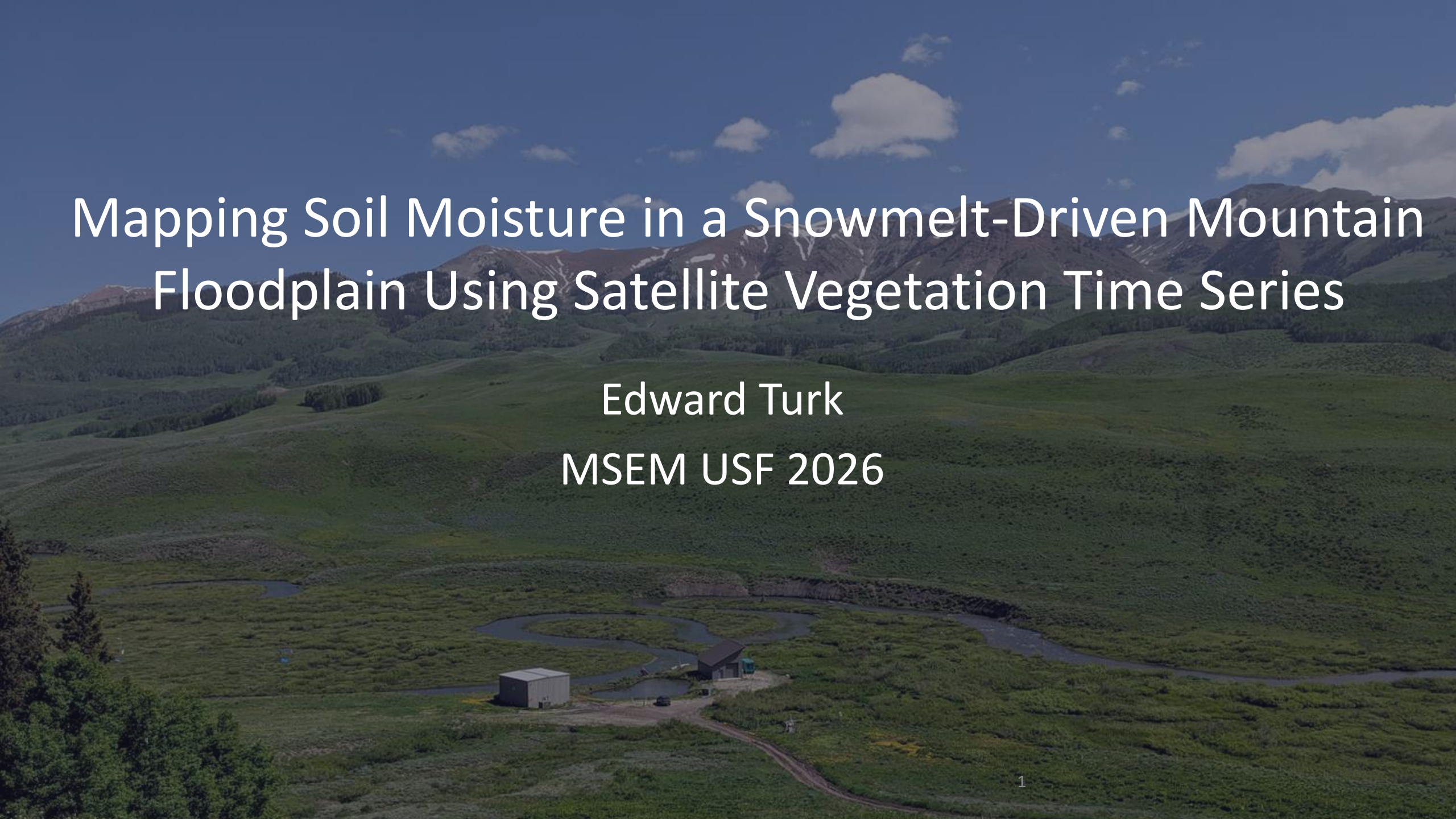




Mapping Soil Moisture in a Snowmelt-Driven Mountain Floodplain Using Satellite Vegetation Time Series

Edward Turk

MSEM USF 2026

Presentation Outline

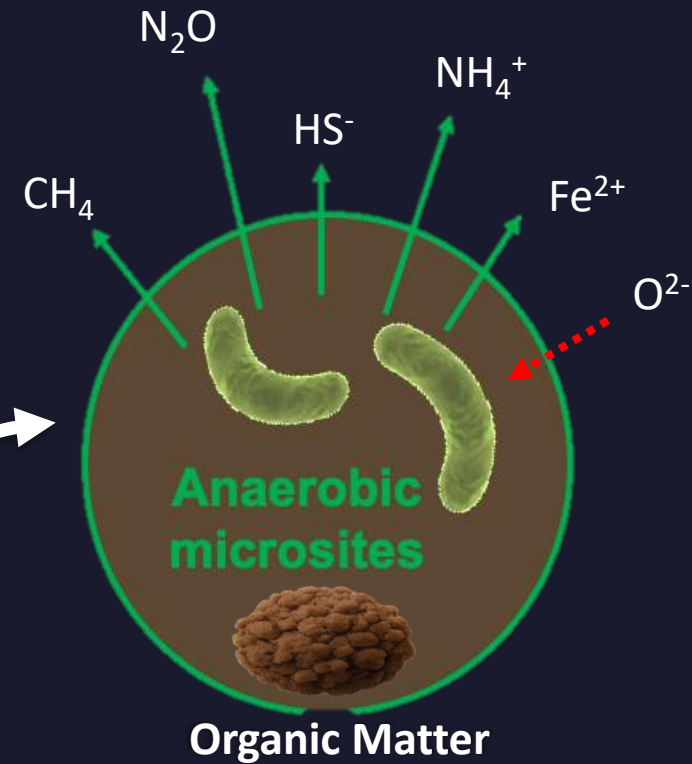
- Introduce the Larger Body of Methane Emission Research happening at USF
- How Participating in This Research Inspired My Thesis
- My Thesis
- Results
- Conclusions

Understanding Anoxic Microsites and Methane Emission



Water Table

Photo Credit: E. Turk, K. Farber, E. Paulus

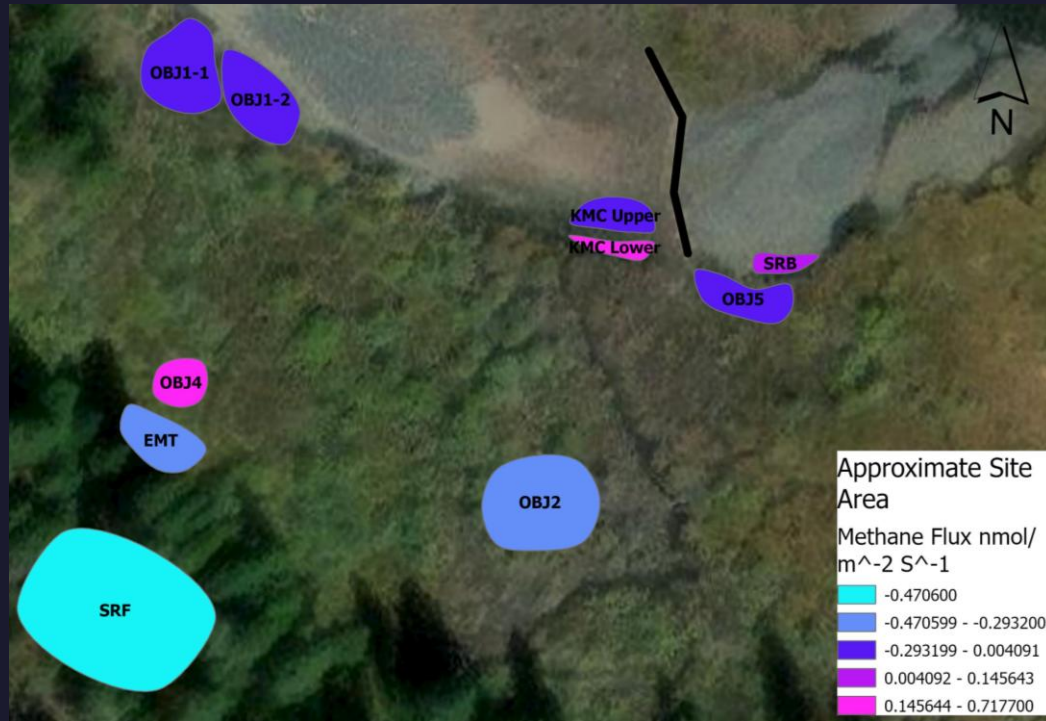


21% of global CH_4 production is attributed to anoxic microsites!

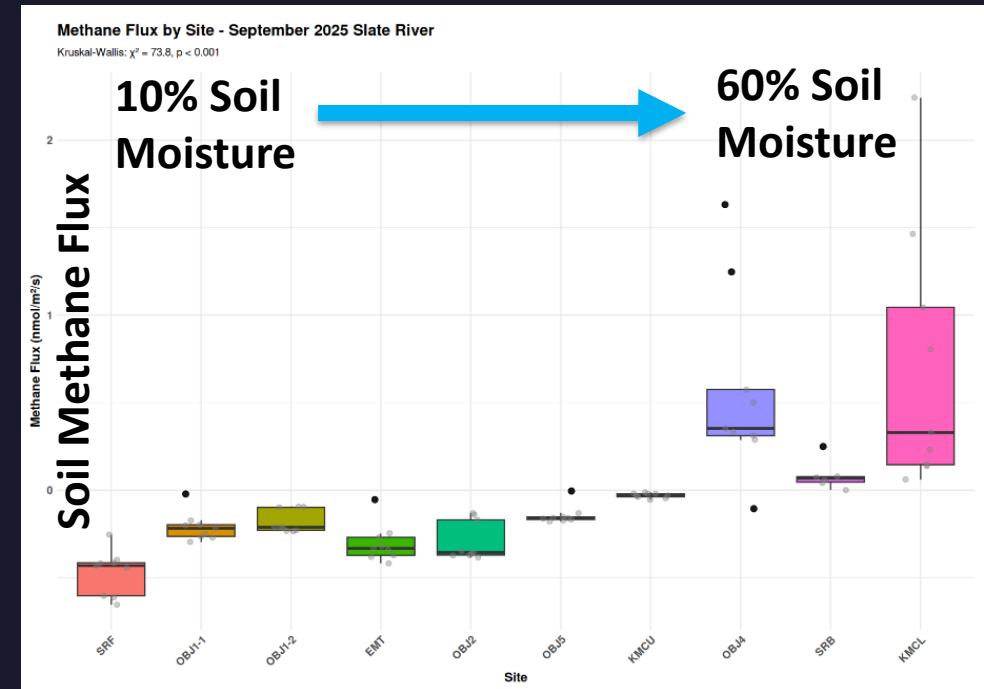
- Methane is associated with anaerobic, water-saturated soil conditions
- We detect methane even in soil that is partially wet
- Small pockets of organic matter cause microbes to deplete oxygen at a very local level causing methane to be emitted
- This methane can be detected escaping the soil surface as a gas flux

Research Motivation: Soil Methane Flux Response to Moisture

Slate River CO Sampling Sites



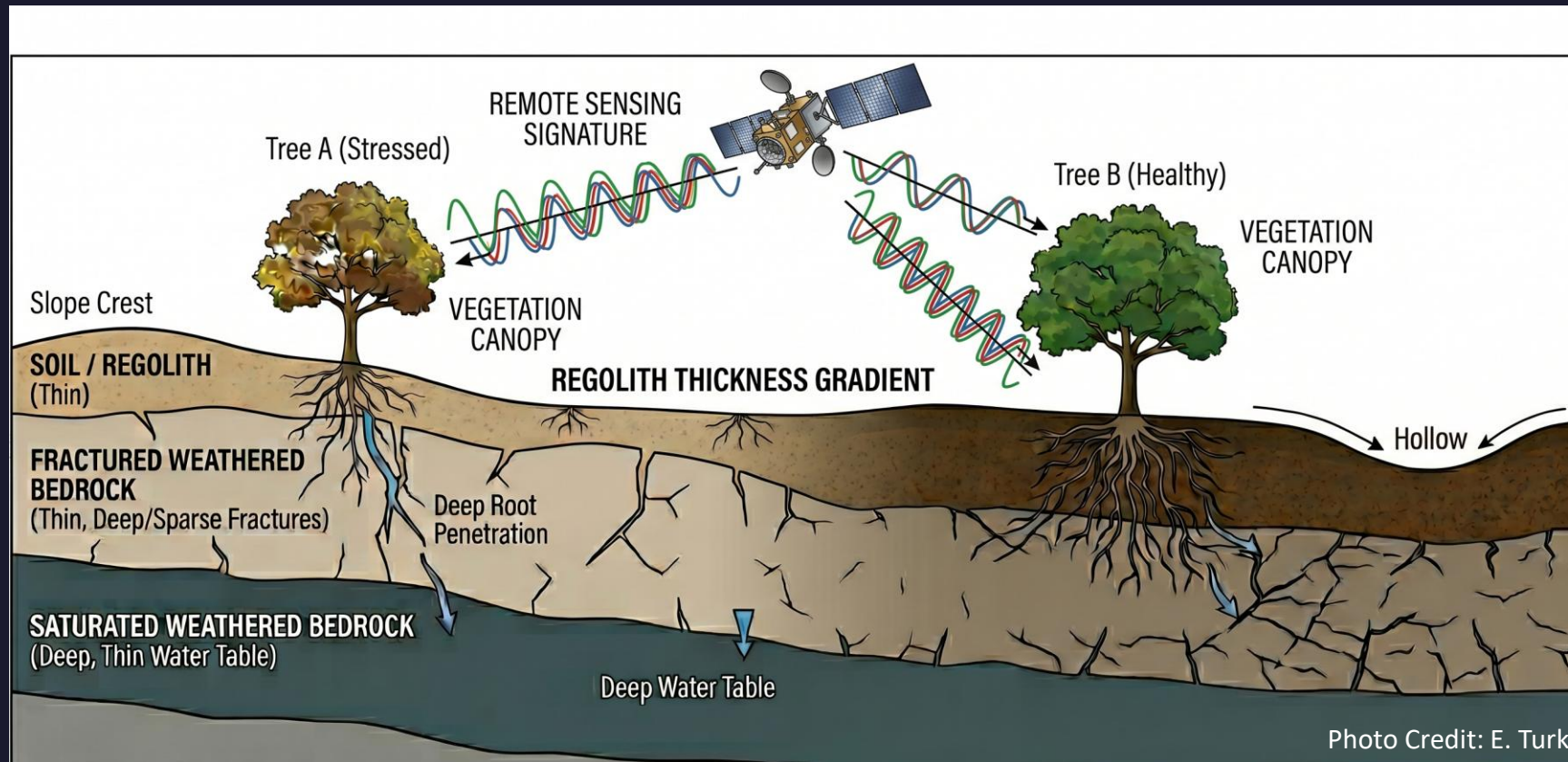
Soil Methane Flux across Soil Moisture Gradient



- We observed a strong relationship between methane and soil moisture in the field
- Moisture gradients partially control the **extent of microsite activity**
- Research goal: **how can we predict soil moisture gradients across an entire watershed?**

Research Hypothesis – Vegetation as a Sensor for Soil Moisture

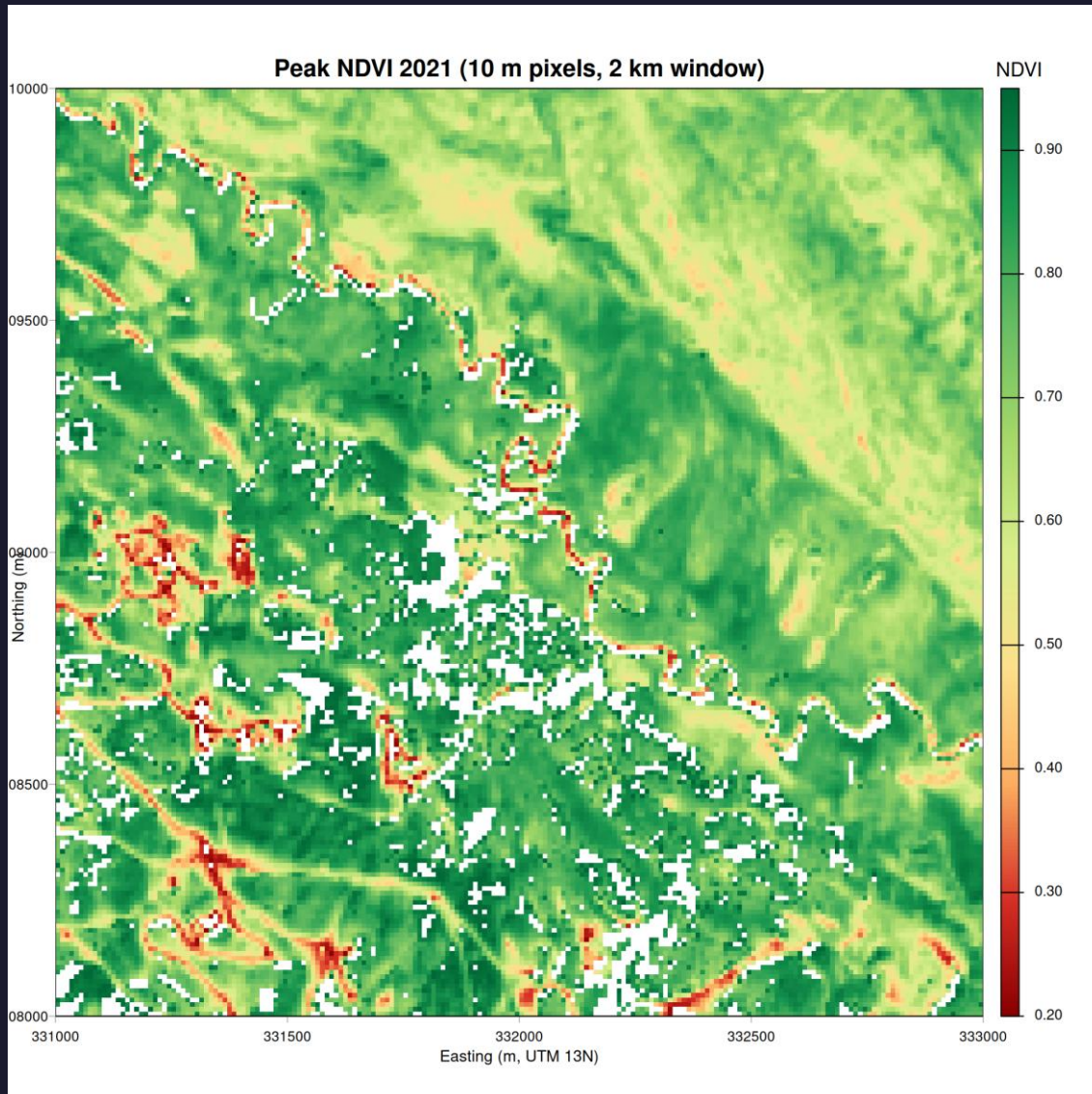
Satellite Imagery can detect stress in vegetation by measuring plants greenness



Critical Zone Framing

- The vegetation is a sensor of subsurface conditions
- The roots connect the subsurface and the canopy
- Remotely sensed canopy properties may allow us to infer subsurface moisture

Remote Sensing Assets – NDVI Images from Sentinel-2 Satellite

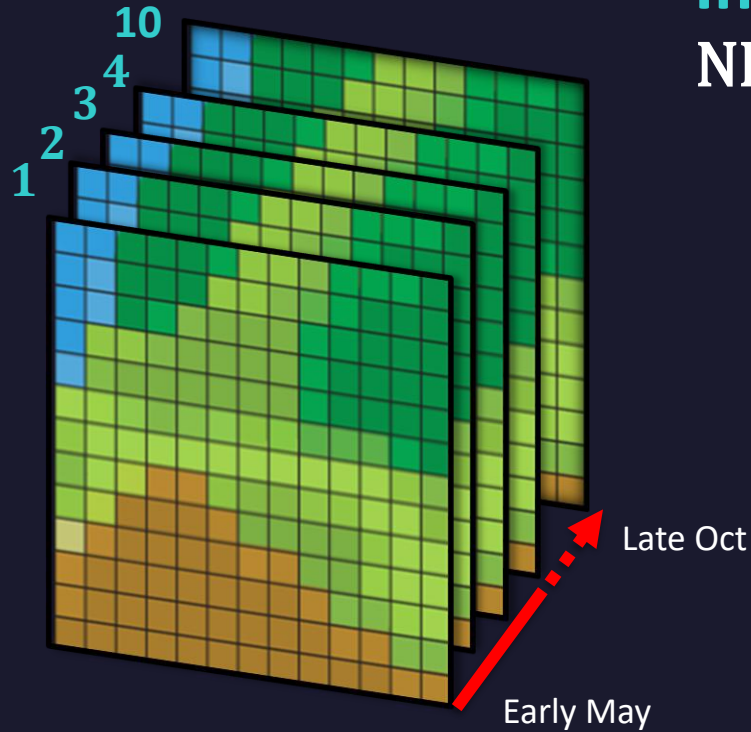


NDVI (Normalized Difference Vegetation Index)

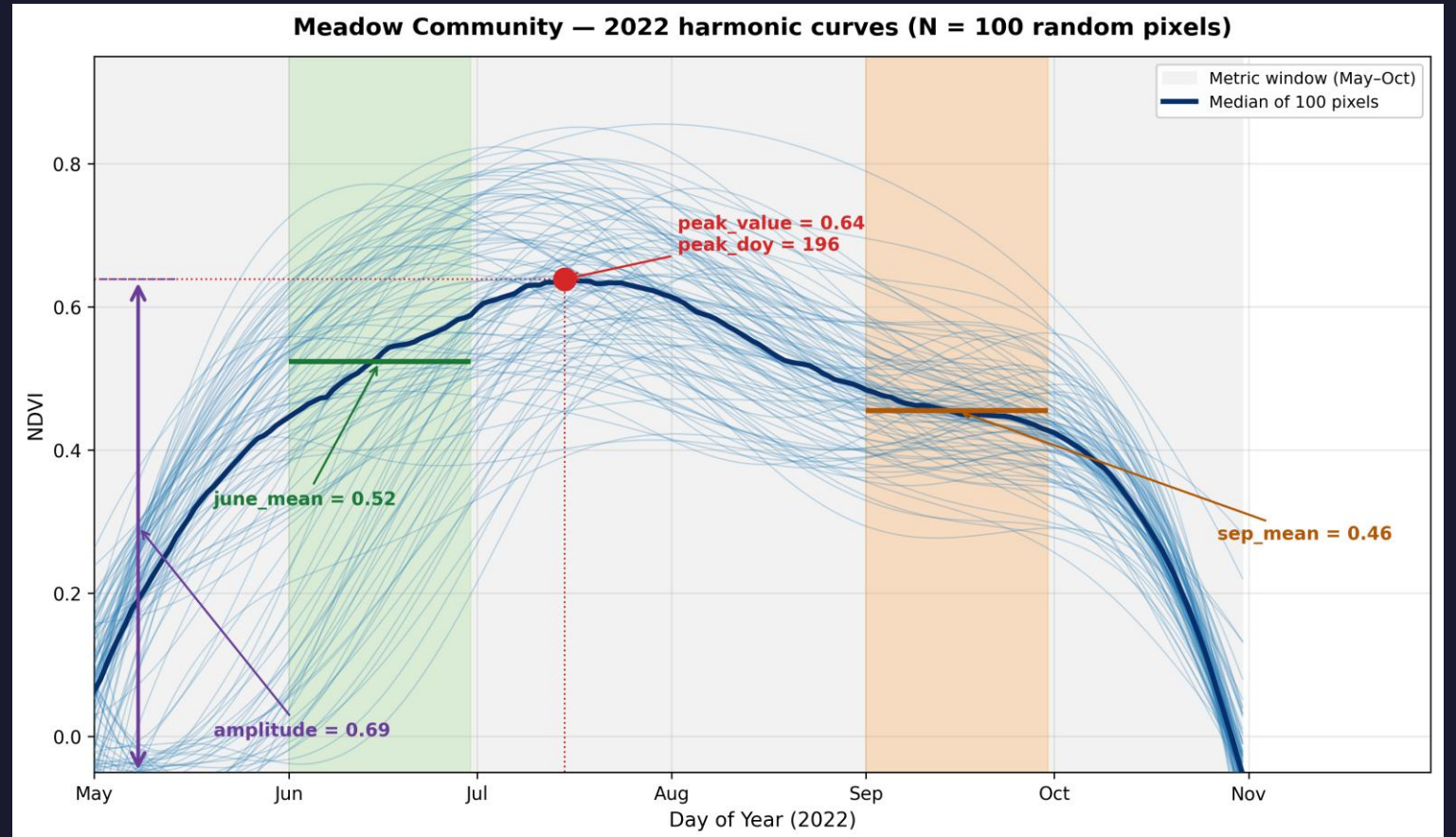
- The satellite measures light reflected from vegetation on Earth's surface
- From these spectral indices, we can quantify how green plants are
- Greenness is a measure of plant productivity, and soil moisture is one of the key drivers of vegetative productivity

Not Just One Image at a Single Date

Image 1 2 3 4 5 6 7 8 9 10
NDVI = ([0.35, 0.50, 0.62, 0.68, 0.65, 0.61, 0.58, 0.50, 0.42, 0.35])



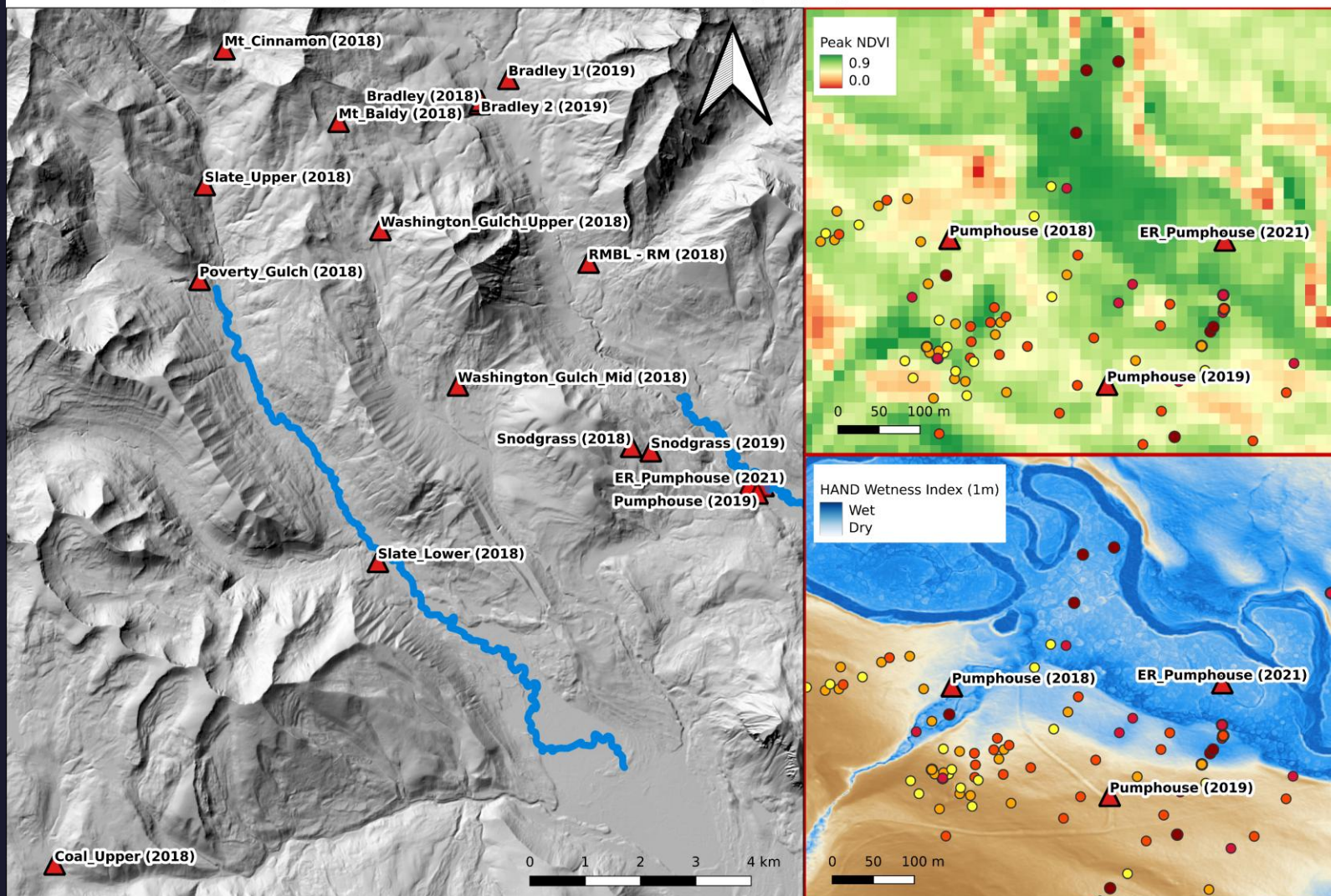
- Best fit line for NDVI readings each year (early May to late October)
- Metrics such as peak value are calculated based on best fit line



Amplitude, June Mean, Peak Value, September Mean

Predicting a Site's Soil Moisture with Topography and a Spectral Metric

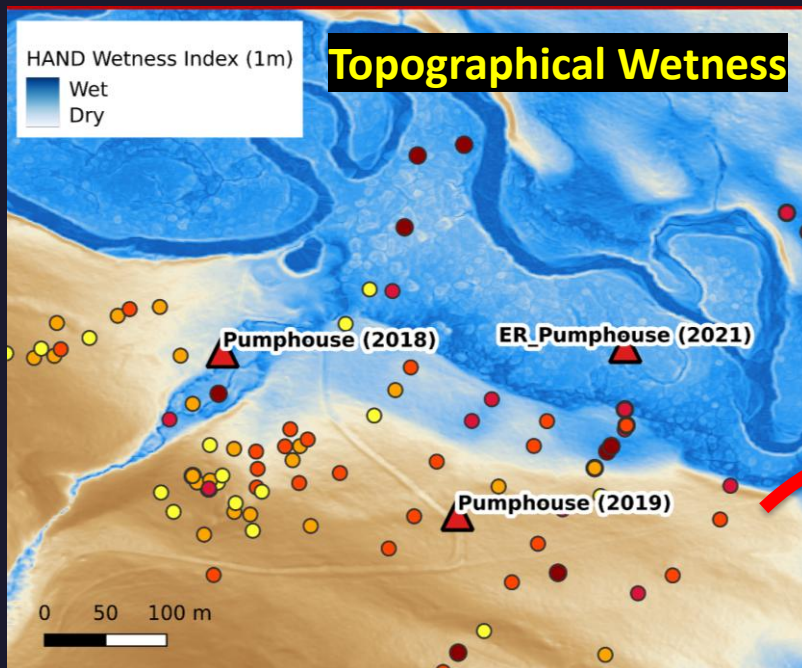
Predicting Soil Moisture from Peak NDVI and Topographic Wetness - East River, CO



- Data: **17 sites** across the watershed, **437 individual soil moisture point measurements** collected by other researchers
- Baseline Model: Topography derived moisture
- Proposed Model: Combine a spectral metric and topography to model moisture

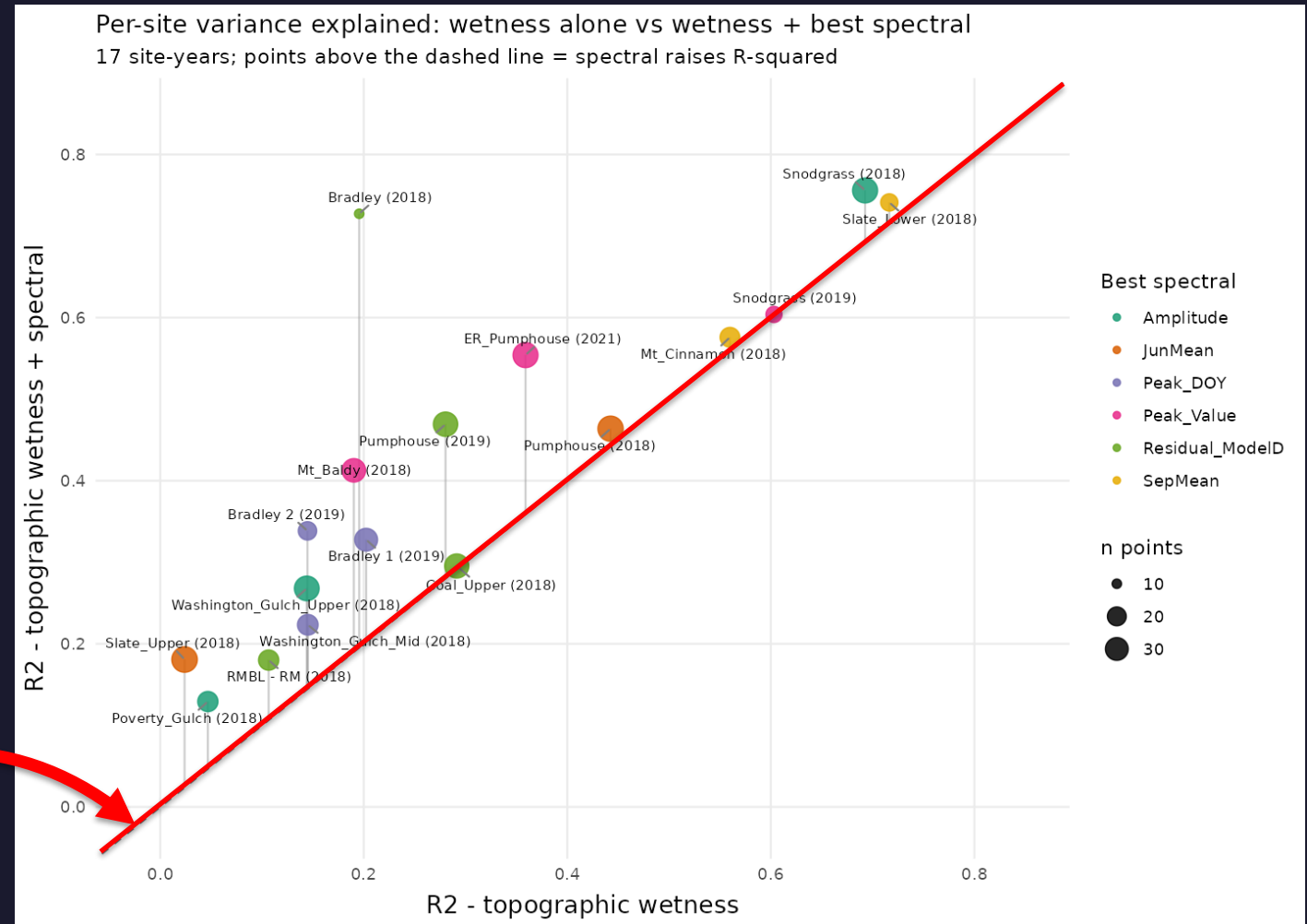
Site-by-Site Improvements in Moisture Prediction With the Addition of Spectral Metrics

- The red line shows how much predictive power the topographic wetness index has on its own for predicting moisture at a site



Adding Spectral Metric

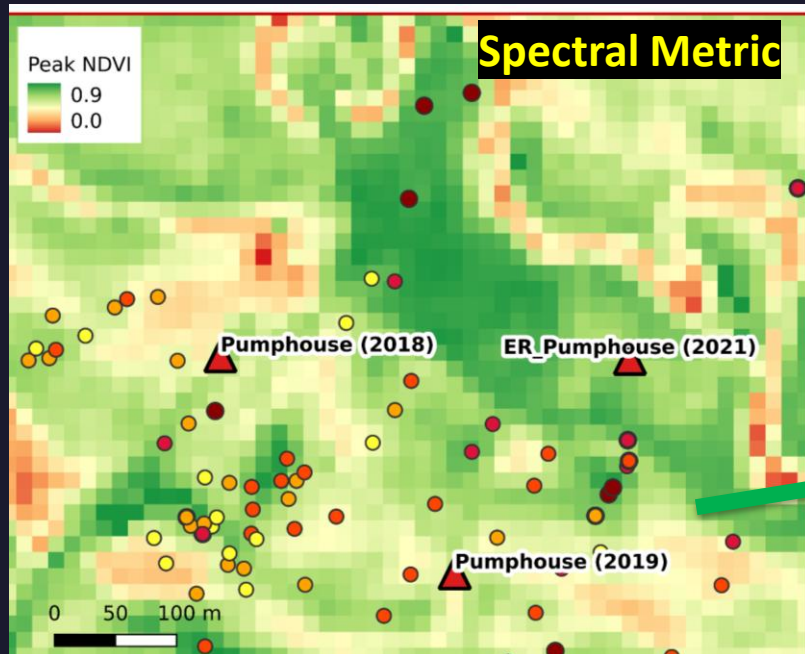
How Do the Two Predictors Complement Each Other?



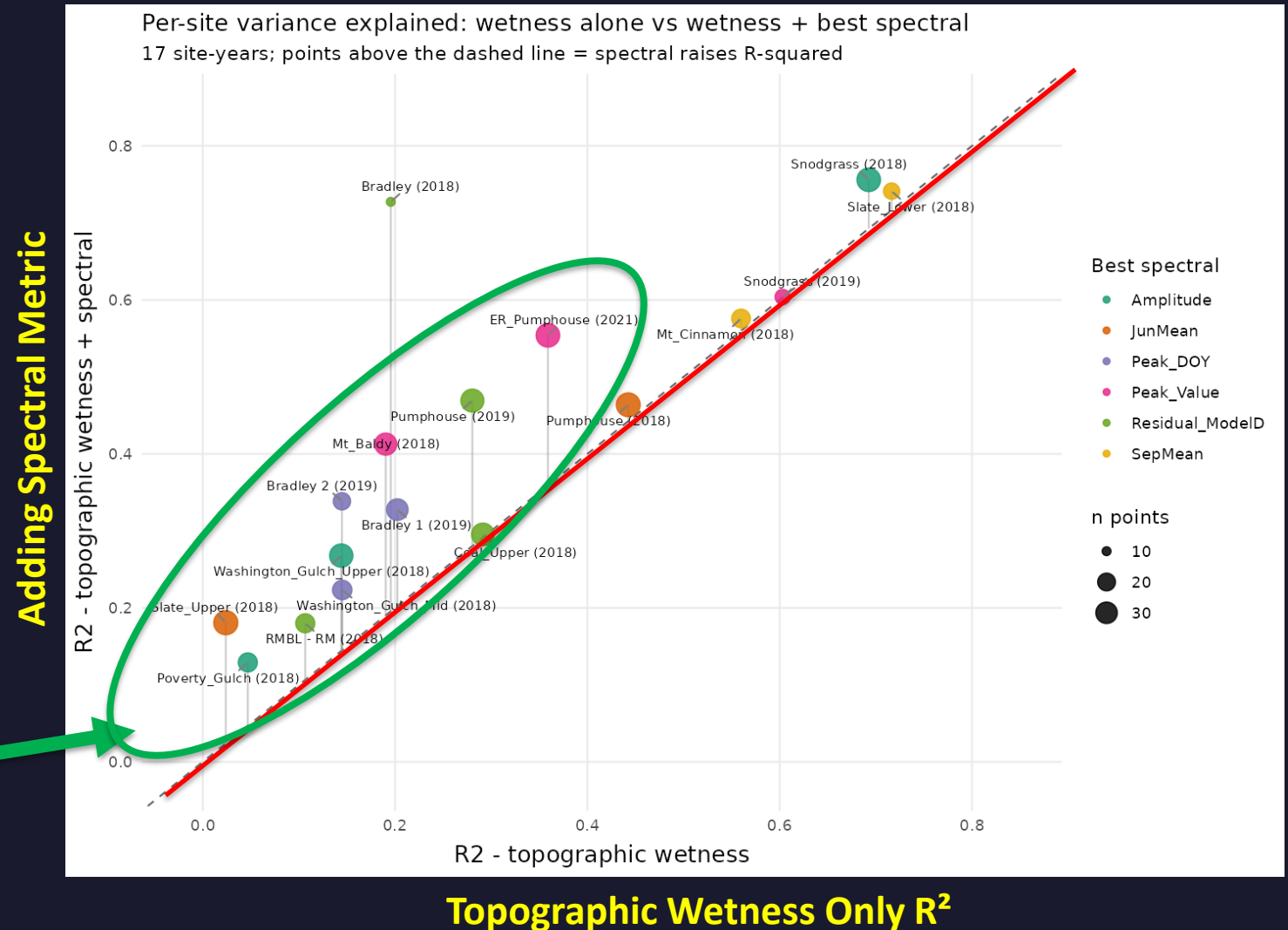
Topographic Wetness Only R^2

Site-by-Site Improvements in Moisture Prediction With the Addition of Spectral Metrics

- Where topographic wetness is a poor predictor, spectral metrics improve the R^2



How Do the Two Predictors Complement Each Other?

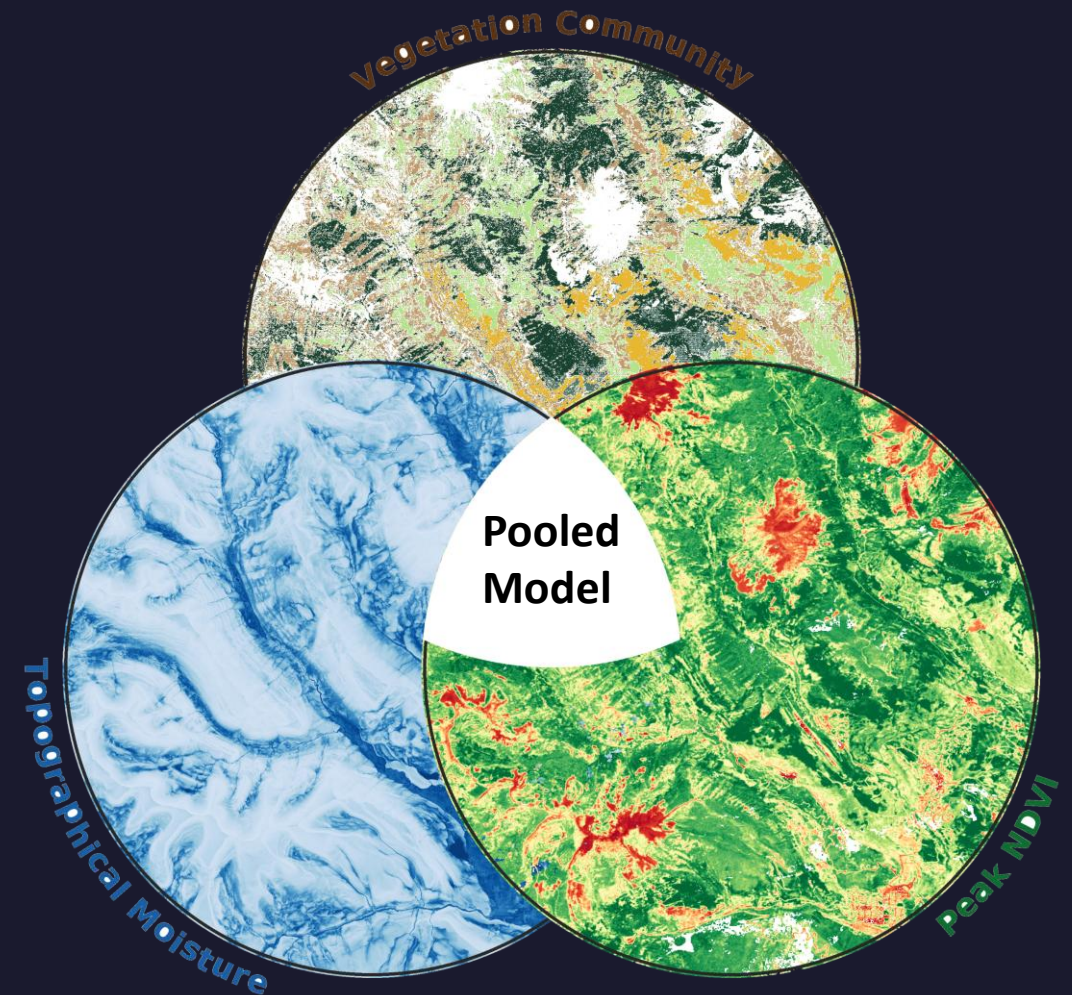


Combining All Sites to Fit One Large Model for the Entire Watershed

Soil Moisture $\sim$ Topographical Moisture + Peak NDVI + Vegetation Community

Fitting a Model across All Sites

- To make a watershed-scale soil moisture map, we need one big model that works across all sites and uses the best single spectral metric
- Soil moisture measurements pooled from 12 sites (N=335)
- **Peak NDVI was the best spectral metric for predicting soil moisture across all sites**

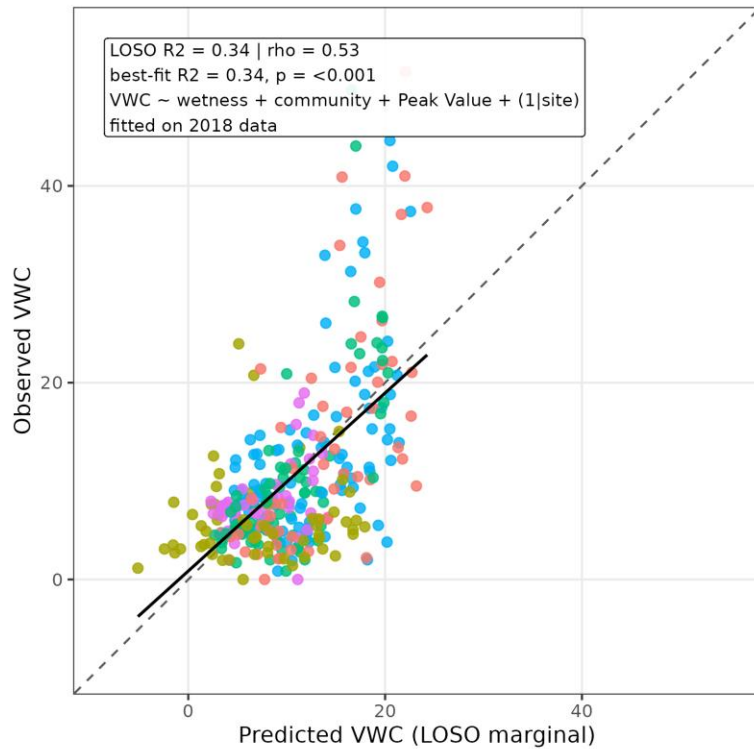


One Pooled Mixed Model Results

Inside Site: $R^2 = 0.416, \rho = 0.6, p < 0.001$

Outside Site: $R^2 = 0.34, \rho = 0.53, p < 0.001$

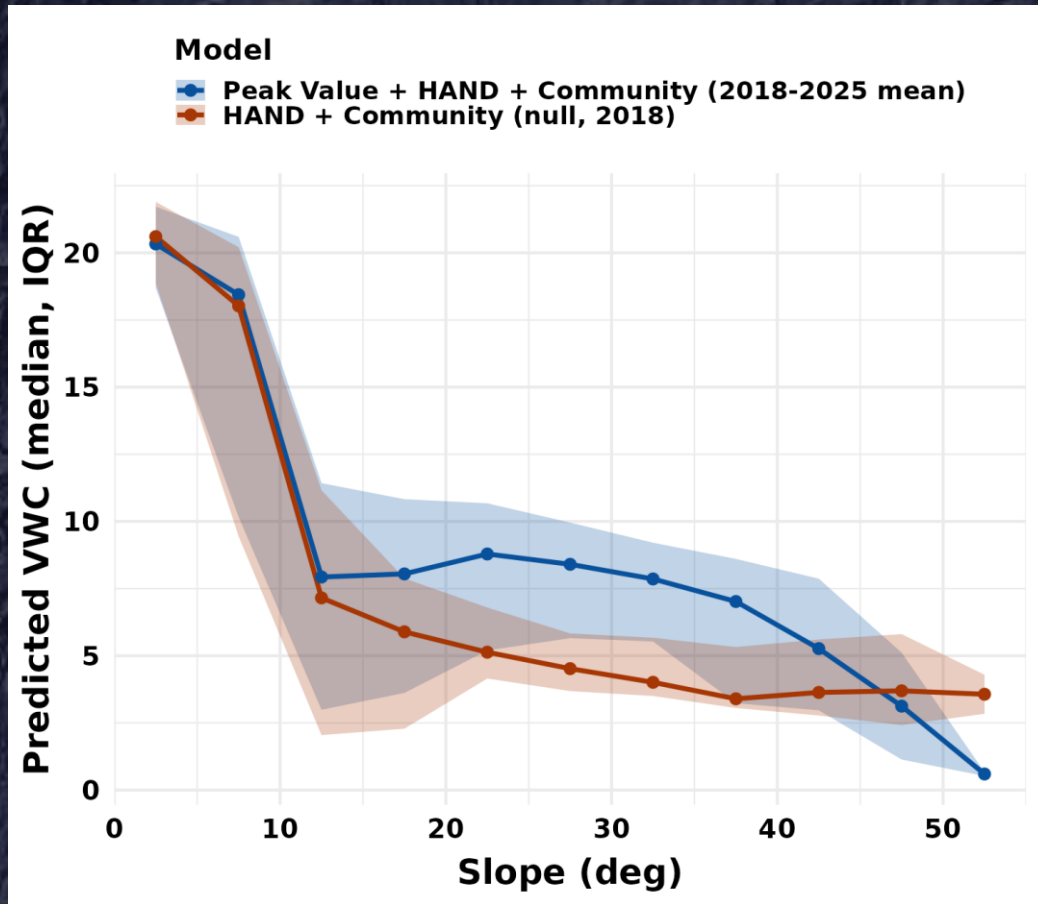
Observed vs LOSO-predicted VWC, 2018 (Peak Value)
Site-level community mixed model; marginal predictions for held-out sites



Community ● Alpine/Barren ● Dry Meadow ● Forest ● Riparian Shrub ● Wet Meadow

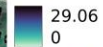
- A transferable moisture map needs to be good not just at explaining the fitted data (**Inside Site**) but outside of our sites as well (**Outside Site**)
- The model degrades by less than 20% when applied to a site it has never seen
- The **peak NDVI spectral metric is the most important variable** that allows the model to predict soil moisture in locations it's never “seen”
- The model appears to struggle at predicting moisture above ~24% VWC

Where on the Landscape Does Peak NDVI Add the Most Value?

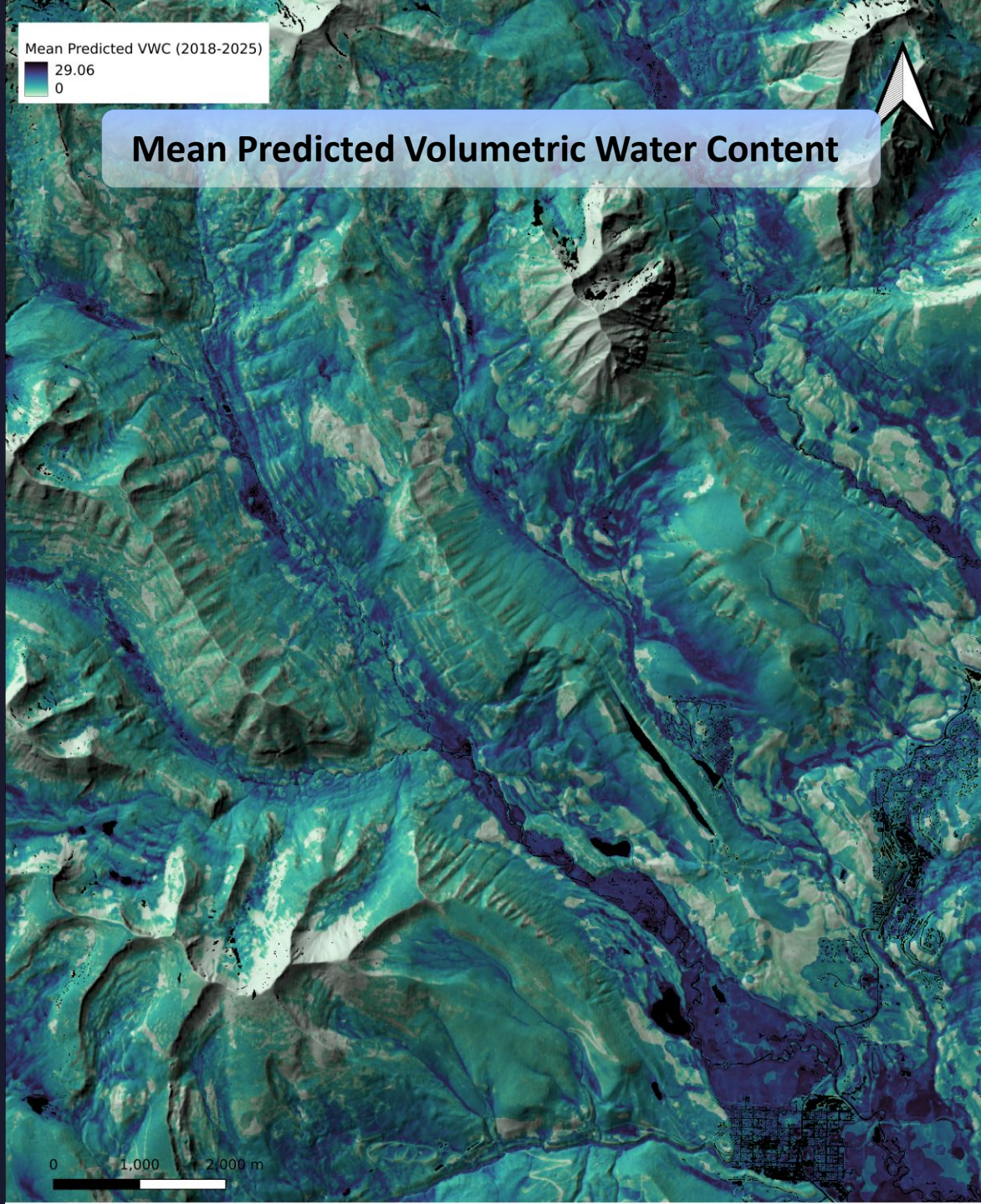


- A model with **just topographic moisture and community as variables (red)** underestimates soil moisture on hillslopes
- Adding Peak NDVI helps predict soil moisture on hillslopes **(blue)**
- These areas of moisture can be substantial contributors to increased microsite activity and thus methane emission

Mean Predicted VWC (2018-2025)



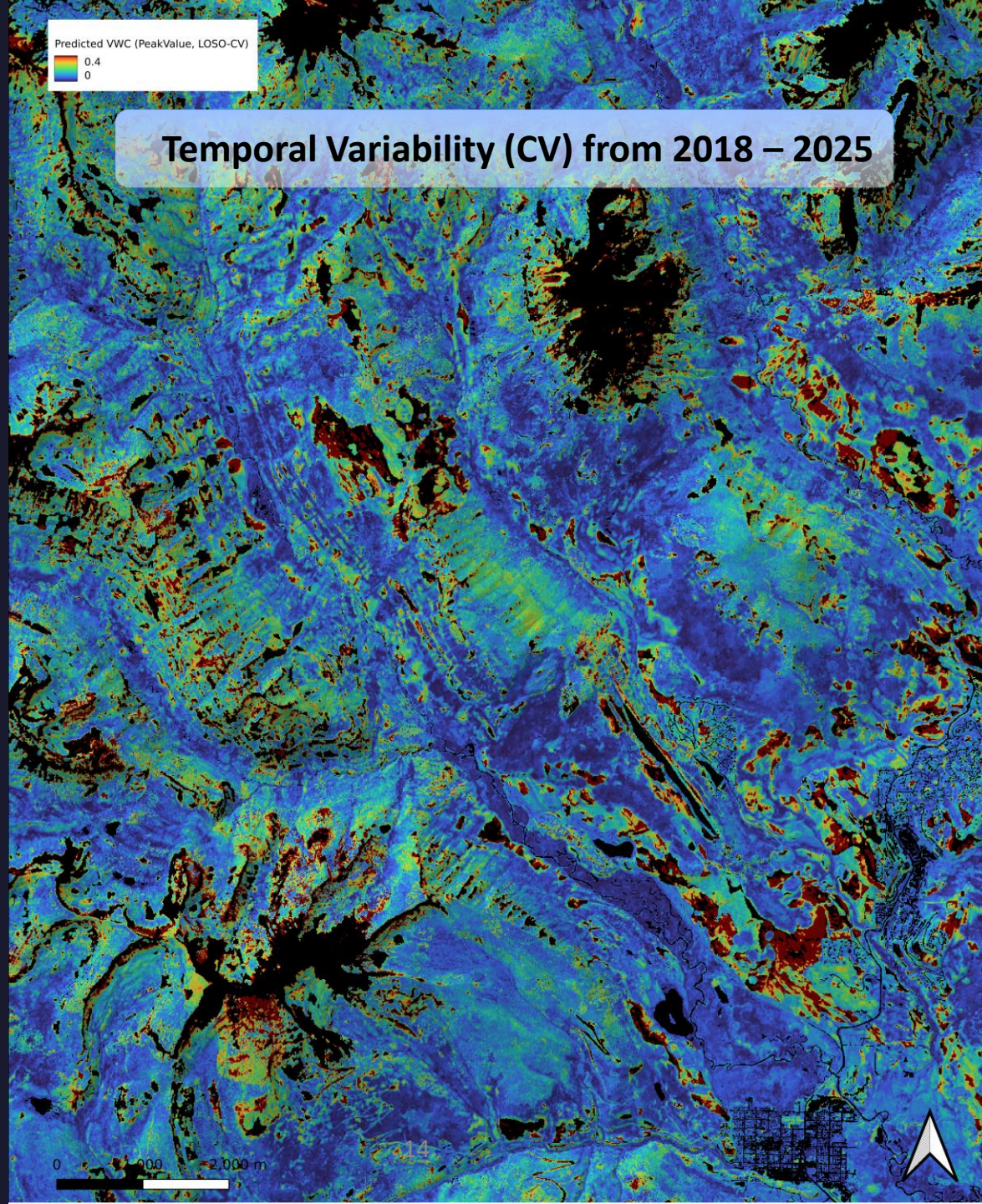
Mean Predicted Volumetric Water Content



Predicted VWC (PeakValue, LOSO-CV)



Temporal Variability (CV) from 2018 – 2025



Major Findings and Impact

Results

- **The peak NDVI spectral metric is a significant predictor of soil moisture**

Building on the Work of Others

- This research **supports the findings of a similar study** conducted by Dafflon et al. (2024)

Implications for environmental management

- **Free public inputs** (Sentinel-2 + LiDAR) → reproducible anywhere
- **Continuous VWC raster** → helps researchers map landscape heterogeneity for placing instrumentation and predicting methane flux
- **Multiyear mapping** → flags which vegetation communities are most sensitive to environmental change

Citations and Acknowledgments

Terrain & Wetness - RMBL Spatial Data Platform (CC BY 4.0)

Breckheimer, I. 1 m Multiscale Height-above-stream Wetness Index, Upper Gunnison Domain. RMBL SDP cat. 102. Method after Nobre et al. (2011).

Breckheimer, I. 1 m DEM, Upper Gunnison Domain (2015 + 2019 LiDAR). RMBL SDP cat. 83.

Vegetation Classification - DOE ESS-DIVE (CC BY 4.0)

Falco, N. et al. (2018, upd. 2024). Vegetation classification map, NEON AOP East River, CO. <https://doi.org/10.15485/1602034>

Methods: Falco et al. (2019), JGR Biogeosciences 124(6): 1618–1636. <https://doi.org/10.1029/2018JG004394>

Satellite Reflectance

Contains modified Copernicus Sentinel-2 L2A data (2016–2025), processed via Google Earth Engine (COPERNICUS/S2_SR_HARMONIZED). © ESA / European Commission.

Ground Soil Moisture - DOE ESS-DIVE / Watershed Function SFA (CC BY 4.0)

Falco, N., Lamb, J., Chen, J., et al. (2026). Geophysical survey, NEON AOP East River, CO 2018. <https://doi.org/10.15485/3013006>

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Wu, Y., Versteeg, R., et al. WFSFA EHG Sensor Towers, East River & Snodgrass, CO. ESS-DIVE.

Companion methods: Dafflon et al. (2023), Frontiers in Earth Science 11: 976227. <https://doi.org/10.3389/feart.2023.976227>

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Soil Methane Flux Gas Sampling

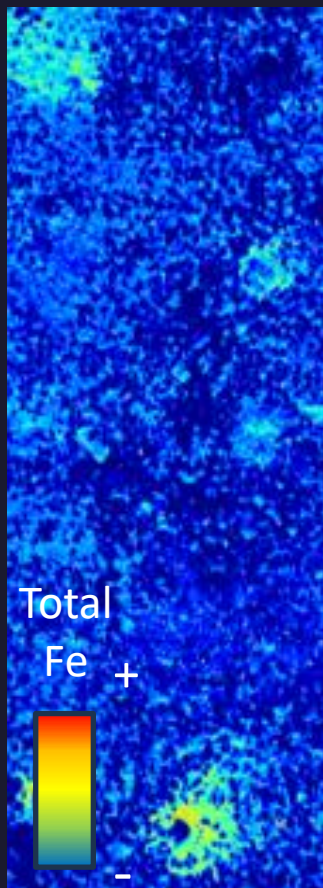


Soil Core Sampling



Imaging Anoxic Microsites

Total Fe mapping



Redox Fe mapping



- It's possible to take images of these anoxic microsites
- Multi-energy synchrotron μ -X-ray can be used to identify iron and its redox state in soil cores
- Reduced iron acts as a visual proxy for a microsite
- With this data we can begin to correlate microsites to soil methane flux

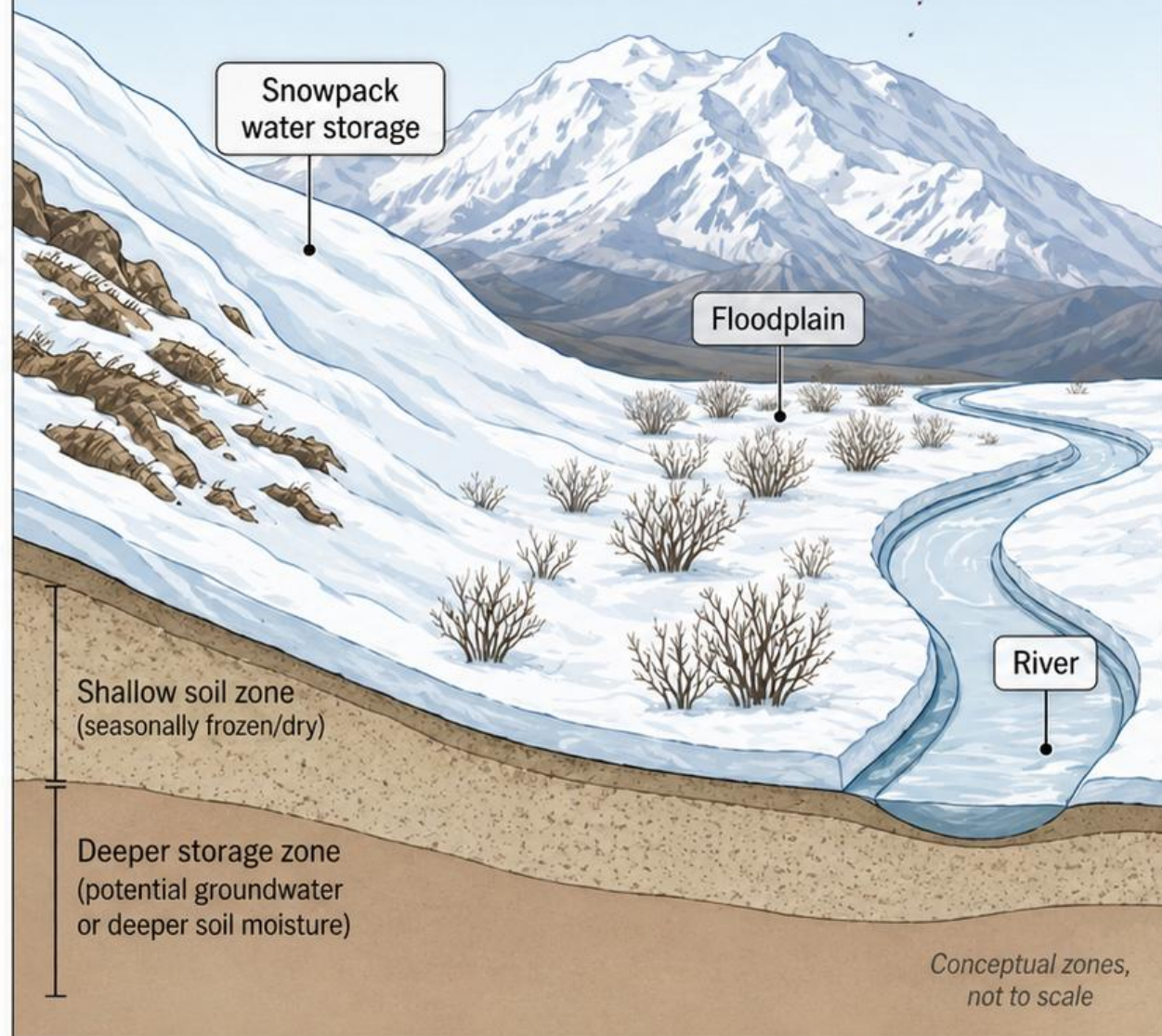
Photo Credit: V. Noel, E. Paulus



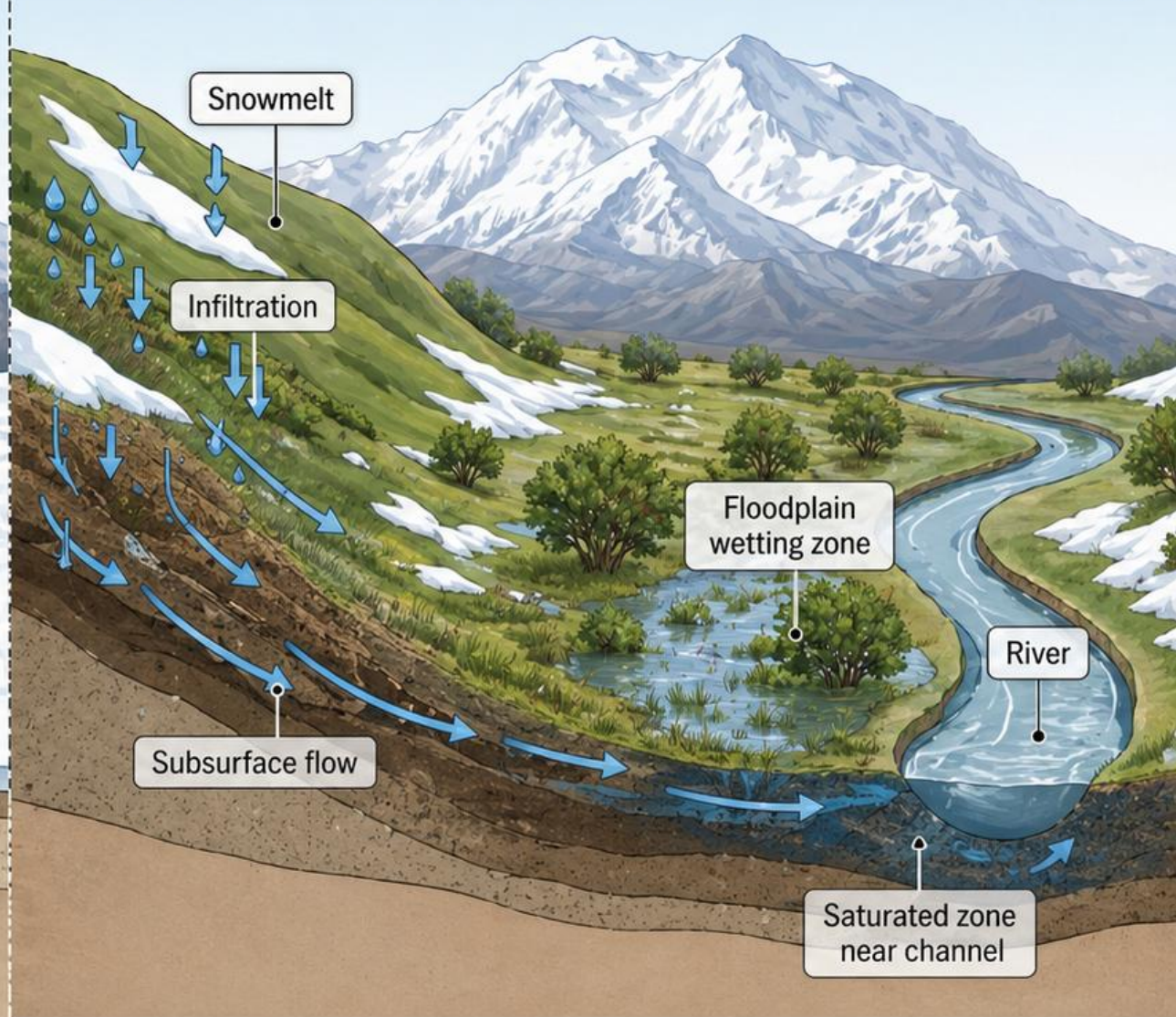
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ENERGY

Office of
Science

PRE-MELT: Snowpack Water Storage



POST-MELT: Snowmelt Infiltration & Floodplain Wetting



Frozen or dry soil



Moist to saturated soil



Snowmelt infiltration



Subsurface flow direction

Conceptual model showing how seasonal snowpack stores water before melt and later releases water through infiltration and subsurface flow, increasing floodplain soil moisture and river connectivity.

Research Timeline

June 2025

After snowmelt, when everything is wet, we take methane flux measurements and collect soil cores



Dec 2025

While preparing my thesis for the AGU conference, I was exploring ways to use remote sensing to predict methane



Next Steps 2026

Imaged the soil cores using SLAC's particle accelerator; mapped microsites and correlated them to methane levels from the incubation

Sept 2025

We return in September, when conditions have dried, and repeat the same sampling campaign



April 2026

Took the soil cores we collected in the field and set up a lab incubation to measure methane in a controlled setting

Redox Fe mapping

