Complementing Topographic Wetness with Sentinel-2 Phenological Indices to Map Soil Moisture Gradients in a Snowmelt-Driven Mountain Floodplain

Edward Turk[1] *(emturk@usfca.edu)*, Kenneth Celis[2], Kathryn Farber[3], Elizabeth Paulus[3], Vincent Noël[3], Kristin Boye[3], Ruth Tinnacher[4], Amrita Bhattacharyya[2], Amalia Kokkinaki[1]

[1] Department of Environmental Science, University of San Francisco (USF) · [2] Department of Chemistry, USF · [3] SLAC National Accelerator Laboratory, Stanford · [4] Department of Chemistry and Biochemistry, Cal State University East Bay

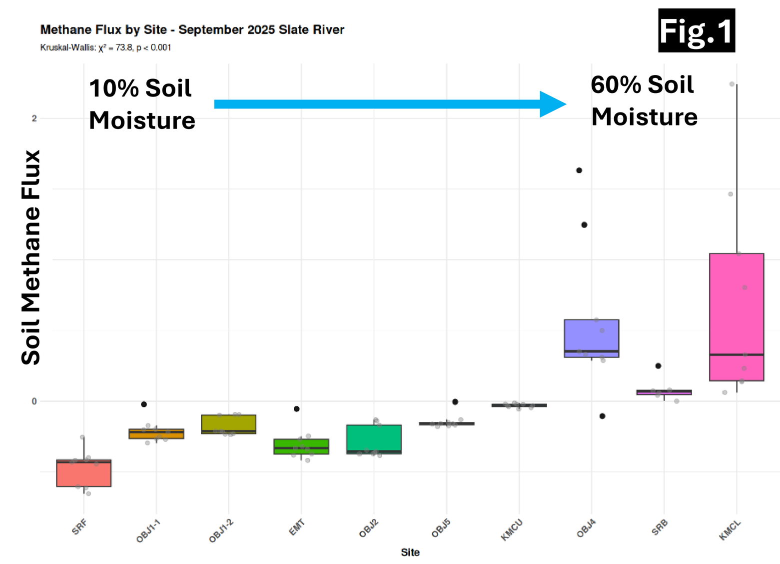
UNIVERSITY OF SAN FRANCISCO

Introduction

Floodplain ecosystems are notoriously heterogeneous, mosaics of moisture regimes, plant communities, and soil types that fuel strong **biogeochemical fluctuations** across short distances. They are also a **lesser-known hotspot for methane (CH_4) emissions**.

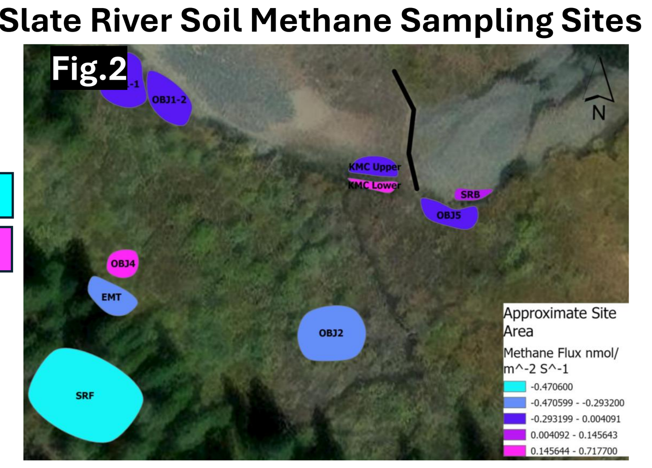
We measured CH_4 flux at sites along the Slate River floodplain (Crested Butte, CO). Sites cluster into sinks and sources, with **soil moisture controlling** observed CH_4 flux (Fig.1). To scale up predictive models of CH_4 emissions, we need to map soil moisture at large scales.

Fig.1



Slate River Soil Methane Sampling Sites

Fig.2

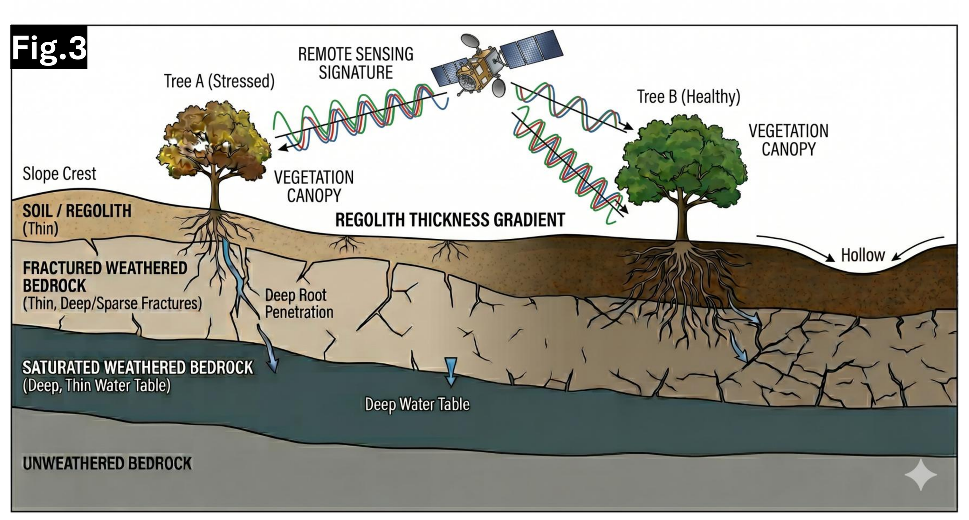


Research Question:
Can **Sentinel-2 phenology** complement **topographic wetness** to map soil-moisture gradients across the river floodplain.

Background & Methods

Vegetation acts as a sensor of subsurface conditions, particularly soil moisture. Spectral signatures coming from the vegetation are read by satellite.

Fig.3



Hydrological conditions and subsurface properties influence how vegetation changes over the season. To measure these changes, se utilize NDVI (Normalized Difference Vegetation Index), a spectral metric for a plant's greenness (Fig.3).

Phenology features. Per map pixel, we fitted a harmonic curve to the seasonal NDVI time series (May–Nov, 2018–2025) and extracted amplitude, June mean, **peak value,** peak day-of-year, and September mean (Fig.5).

Stack 17 NDVI Images/Season

Fig.4

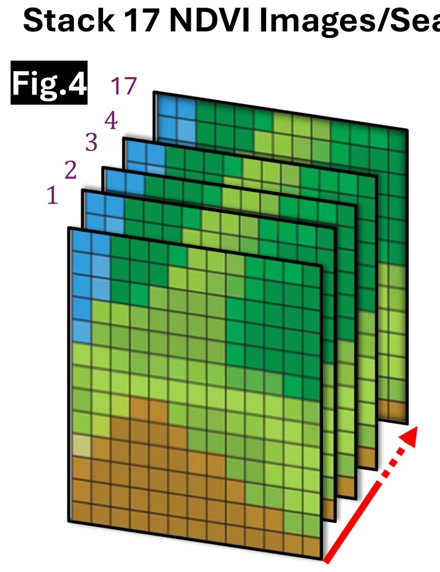
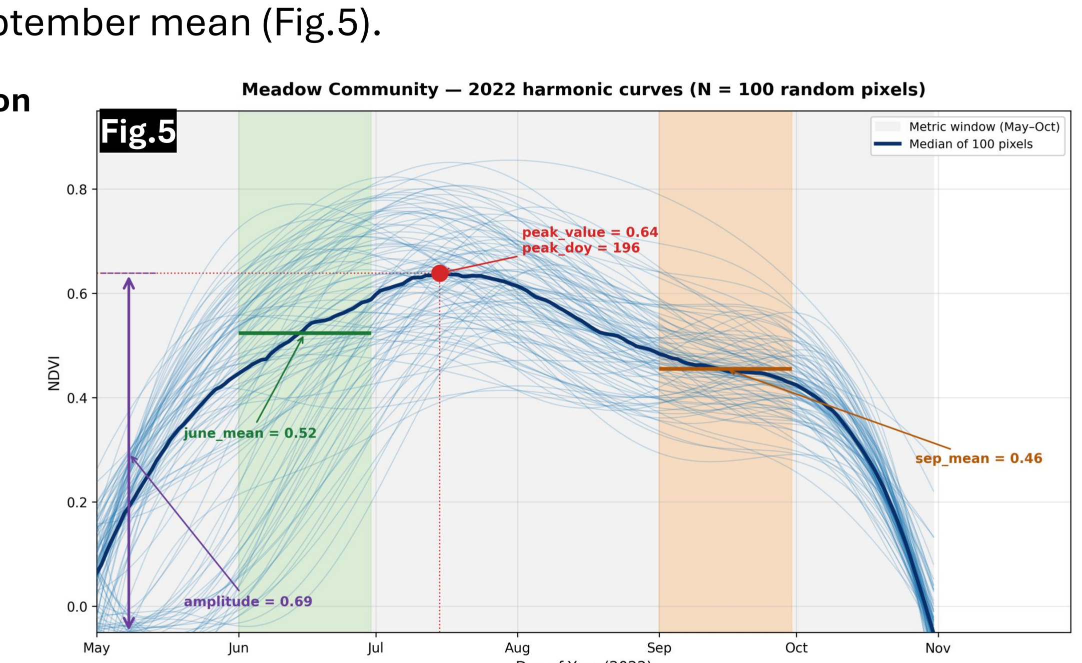


Fig.5

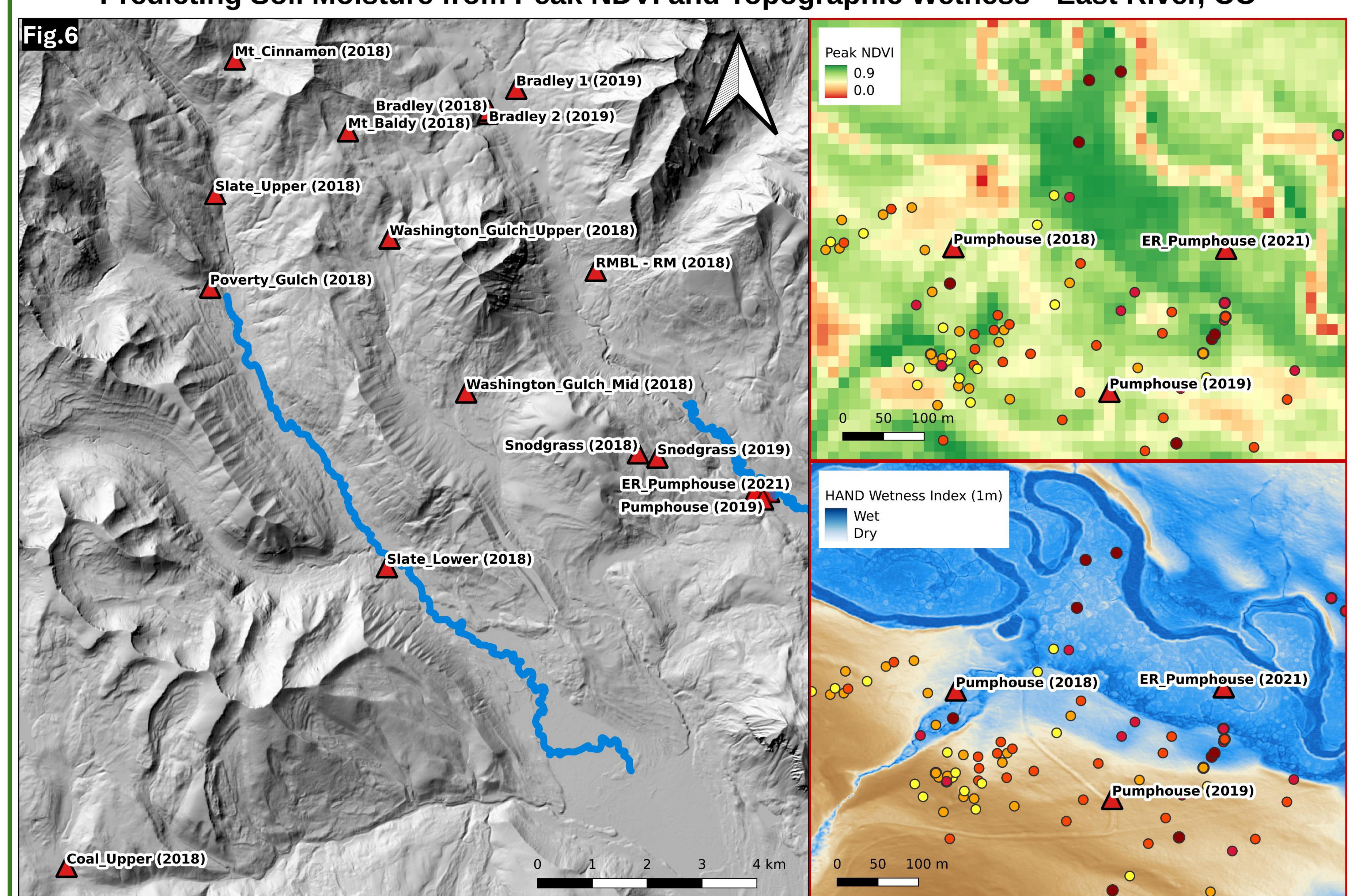


Predictors (per pixel). Peak NDVI from Sentinel-2 harmonic fit; topographic wetness derived using HAND from a 1 m DEM; vegetation community from NEON classification.
Response . In-situ volumetric water content at 17 sites (n = 335, 2018).
Model. Linear mixed model with site random intercept; out-of-site performance evaluated by leave-one-site-out (LOSO).
Output. A continuous VWC raster of the Crested Butte watershed (2018–2025 mean), produced by applying the fitted model to every pixel.

Experimental Design

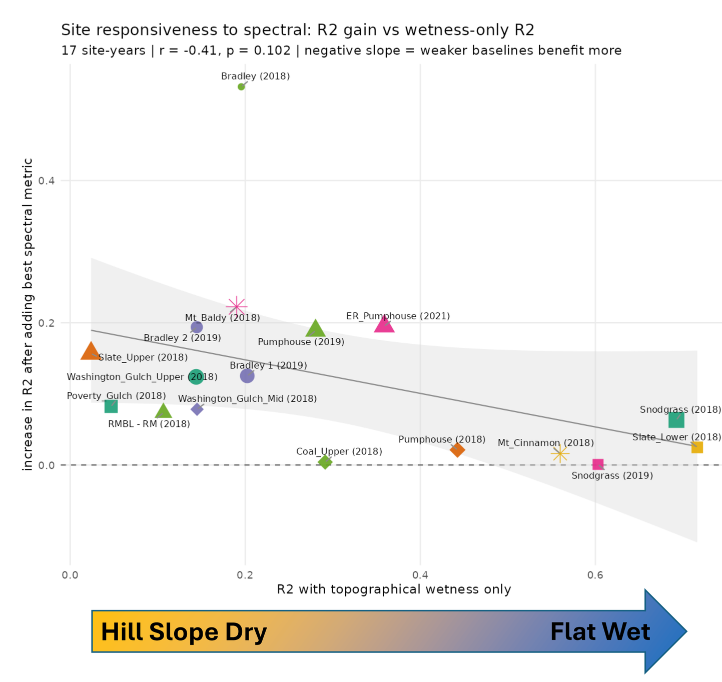
Predicting Soil Moisture from Peak NDVI and Topographic Wetness - East River, CO

Fig.6



In-situ volumetric water content used for model fitting.

Fig.7



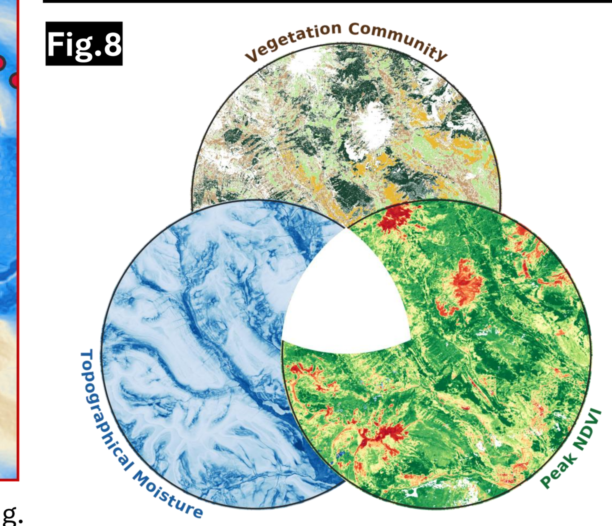
Single Site Evaluations

- Model fitting: 335 moisture data points distributed across 17 sites (Fig.7) were used.
- We first evaluate each site independently to understand which spectral metric best predicts soil moisture.
- We found that spectral metrics added real value in predicting soil moisture in sites that are on hillslopes, rather than valley floors.

All Sites Pooled: Global Model (Eq. 1):

Soil Moisture ~ Topographical Moisture + Peak NDVI + Vegetation Community + (1 | Site)

Fig.8

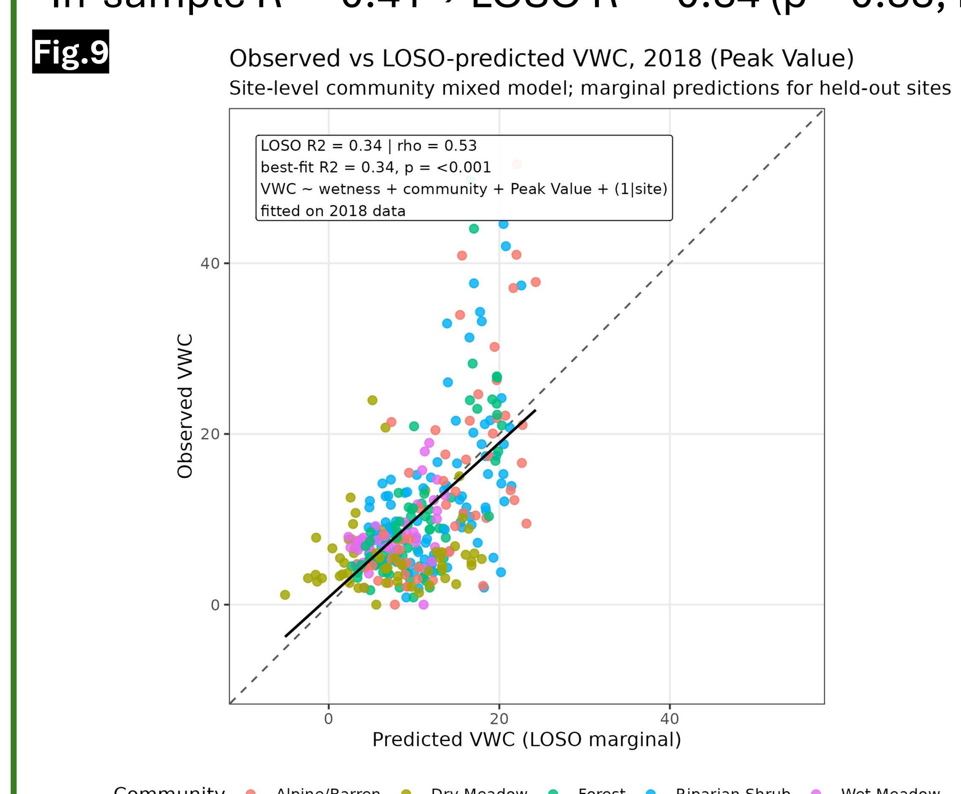


Question: What spectral metric is best at mapping moisture gradients globally (i.e., across sites)?
Data: All 335 in-situ VWC (Volumetric Water Content) point measurements pooled across sites for fitting a model over the entire watershed.
Model. We fitted a mixed-effects regression (Eq.1) on all the soil moisture measurements across all sites using 3 predictors: **vegetation community, Peak NDVI**, and **Topographical Moisture (Fig.8).**

Results

Peak NDVI is the best spectral complement to Topographical Moisture and Vegetation Community.
In-sample $R^2 = 0.41 \rightarrow$ LOSO $R^2 = 0.34$ (ρ = 0.53, n = 335, p < 0.001).

Fig.9



Model performance

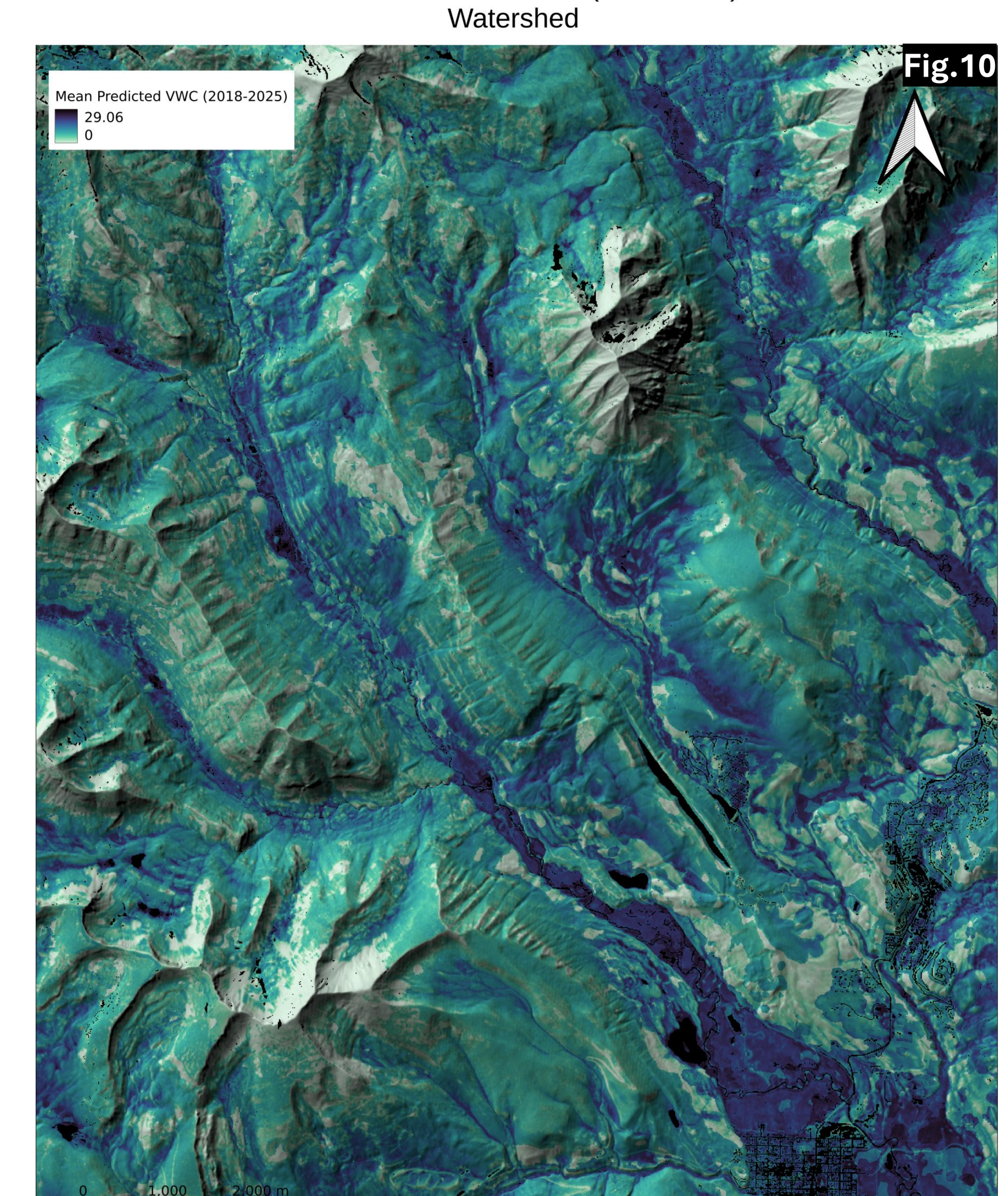
- The model's final fit is strong across ecosystems for moisture values below 22%, with the chosen variables explaining 34% of the variation in soil moisture.
- Model limitation: The model does not predict soil moisture values over about 22% VWC well (Fig. 9)

Peak value's role changes inside vs. outside a site.

- When the test site is in the training set, peak value is the *least* important predictor (~16% of model R^2).
- Held out under LOSO, its contribution **rises from ~16% to ~40%** - a 2.5× jump, equal to wetness and community.

Mean Predicted Volumetric Water Content (2018-2025) Crested Butte CO Watershed

Fig.10

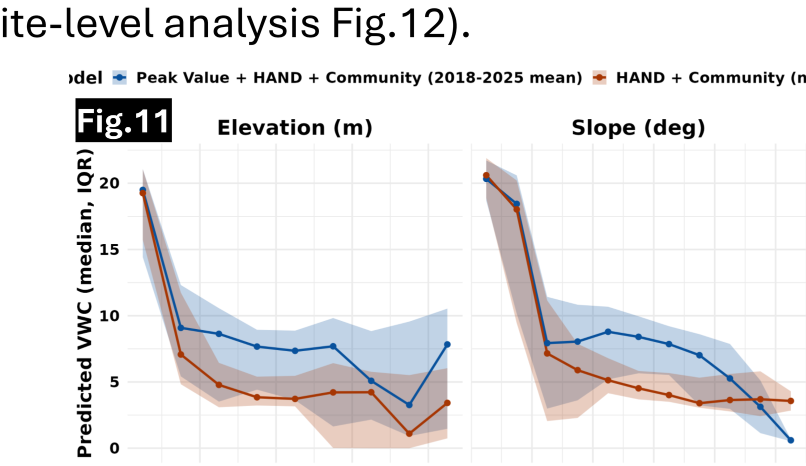


Mean predicted soil water content (% VWC), 2018–2025. Pixel-wise mean of eight annual 10 m predictions from a 2018-trained linear mixed model (*VWC ~ Wetness + Community + Peak_NDVI + (1|site)*; n=335, 12 sites, 5 communities). LOSO CV: R^2=0.34, RMSE=7.17 % VWC. Read as a relative moisture index calibrated to % VWC, not an absolute field measurement. Masked to soil-valid pixels, 0 ≤ NDVI ≤ 1.10. EPSG:32613.
Credits: Sentinel-2 (Copernicus/ESA) via Google Earth Engine; wetness = 5×5-smoothed TWI (Beven & Kirkby 1979) on Breckheimer (2019) 1 m DEM, Falco-group pipeline (ESS-DIVE 10.15485/1602034); community: Falco et al. 2024; calibration: NEON DP1.00094.001 + DOE WFSFA. Map: E. Turk, USF, 2026.

Discussion/Conclusions

Where peak NDVI adds value: Across elevation, slope, and aspect, the full model and a wetness-only null **agree on the valley floor and diverge on hill slopes,** the same pattern seen at the site-level analysis Fig.12).

Fig.11



Slope 20–40%: the wetness-only null model breaks down; peak value raises predicted VWC and tracks the data more closely.

Peak NDVI really improves the model's ability to predict moisture when you evaluate the model on a site it has not been trained on; **this is critical for creating a useful map.**

Our findings are consistent with and extending prior work from Dafflon et al. (2023), who showed that peak greenness predicted soil properties on a single hill slope at this study site. This work carries that result from one slope to a 6,000 km^2 watershed.

Broader implication. Peak NDVI is a remote, repeatable proxy for moisture where terrain alone fails. The model runs on free, public inputs: Sentinel-2 imagery and lidar-derived DEMs. The resulting maps can guide where field researchers place sampling plots and flux chambers and extend methane hotspot mapping from walked transects to full watershed scale.

References

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