Stratifying the Floodplain: A Remote Sensing Approach to Identifying Novel Methane Targets via Site Similarity and Suitability

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INTRODUCTION

The Driver: Riverine floodplains are significant methane sources driven by anoxic microsites — redox heterogeneities formed where moisture meets organic carbon.

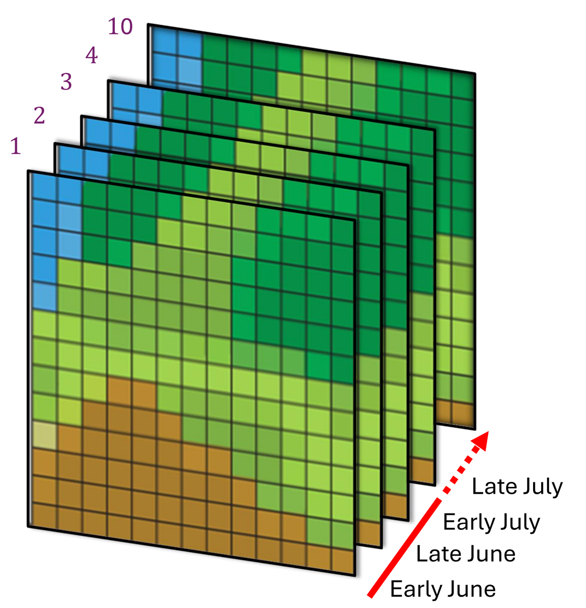
The Observation: Field sampling in the Slate River watershed confirmed that while microsites determine local variability, broad ecological conditions, like soil moisture, still correlate with overall methane flux magnitude.

The Hypothesis: Since we cannot map microsites directly, here we use remote sensing to model the Macroscopic Ecological Template for methane emissions - the combination of surface features (i.e., phenology, structure, topography) that sustain these invisible hotspots.

Methods: The Feature Space

A 5-dimensional Feature Space is used to resolve the ecosystem's structural signature: C:N Ratio, Canopy Height, DEM-derived Soil Moisture, Distance from Conifers, and the Moisture Retention Index.

Methodology Spotlight: Moisture Retention Index

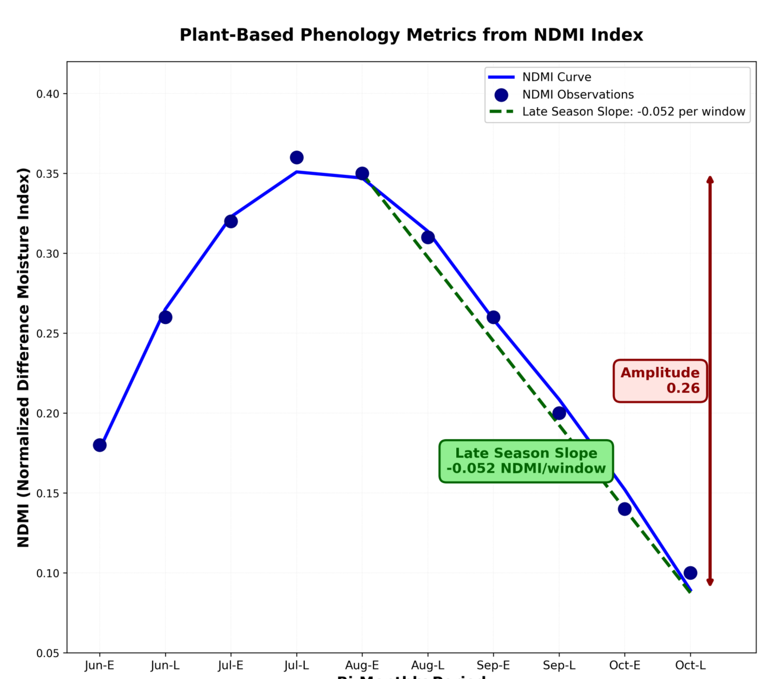


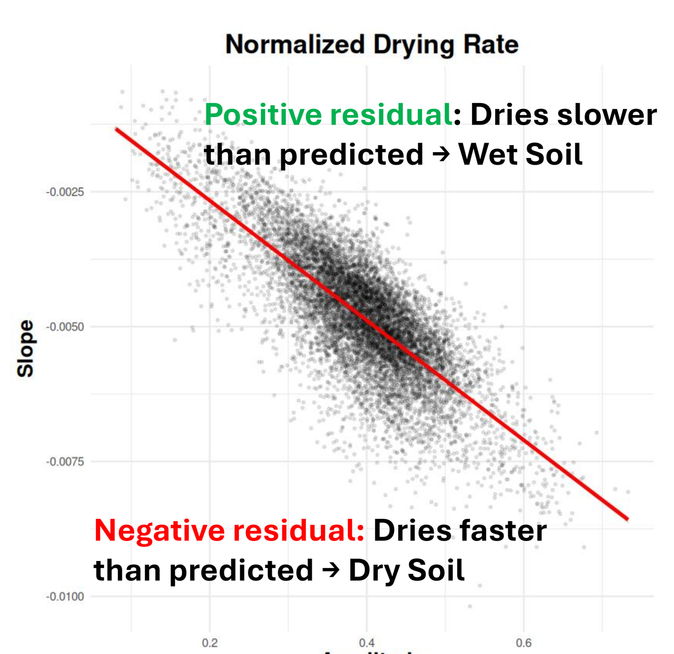
The Metric: We utilize Sentinel-2's Normalized Difference Moisture Index (**NDMI**) to proxy leaf liquid water content. Unlike simple greenness (NDVI), NDMI isolates physiological water stress. By modeling seasonal drying rates, we can use vegetation as a biological probe to infer the presence of otherwise unobservable subsurface moisture.

1 2 3 4 5 6 7 8 9 10

NDMI = ([0.35, 0.50, 0.62, 0.68, 0.65, 0.61, 0.58, 0.50, 0.42, 0.35])

The Process: By stacking 5 years of bi-monthly imagery (2019–2025), we fit Savitzky-Golay curves to characterize the full seasonal moisture trajectory of every pixel. From this time series, we extract the **Amplitude** (seasonal maximum drop in NDMI) and the **Senescence Rate** (rate of drying). These paired metrics allow us to normalize vegetation drying rates against NDMI levels.

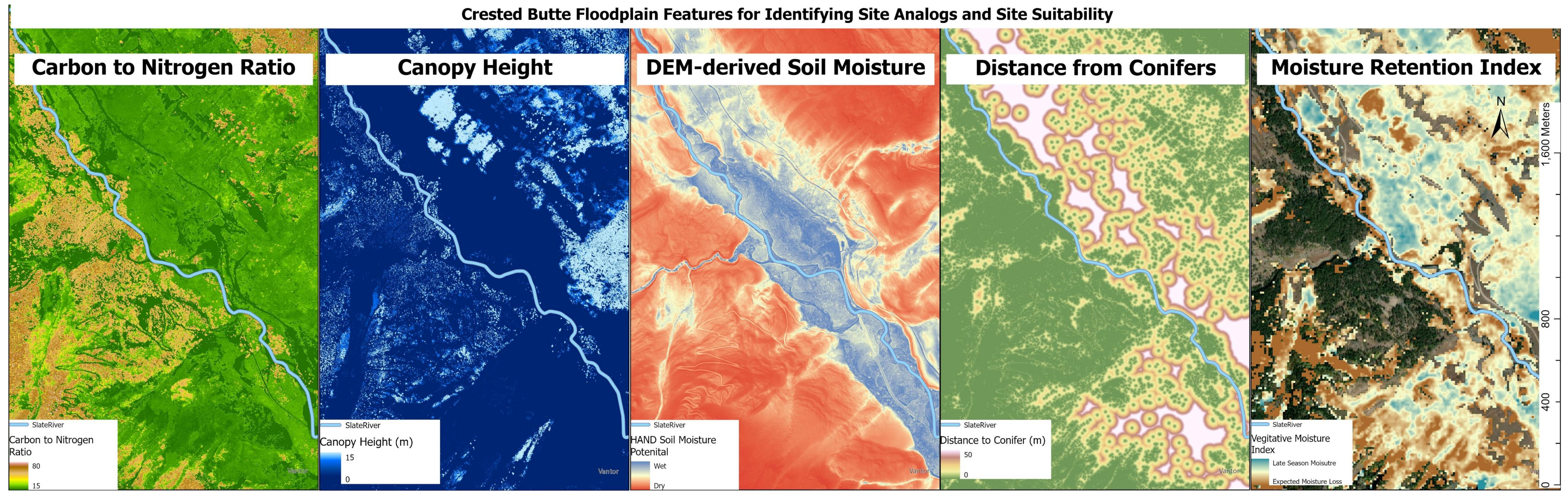




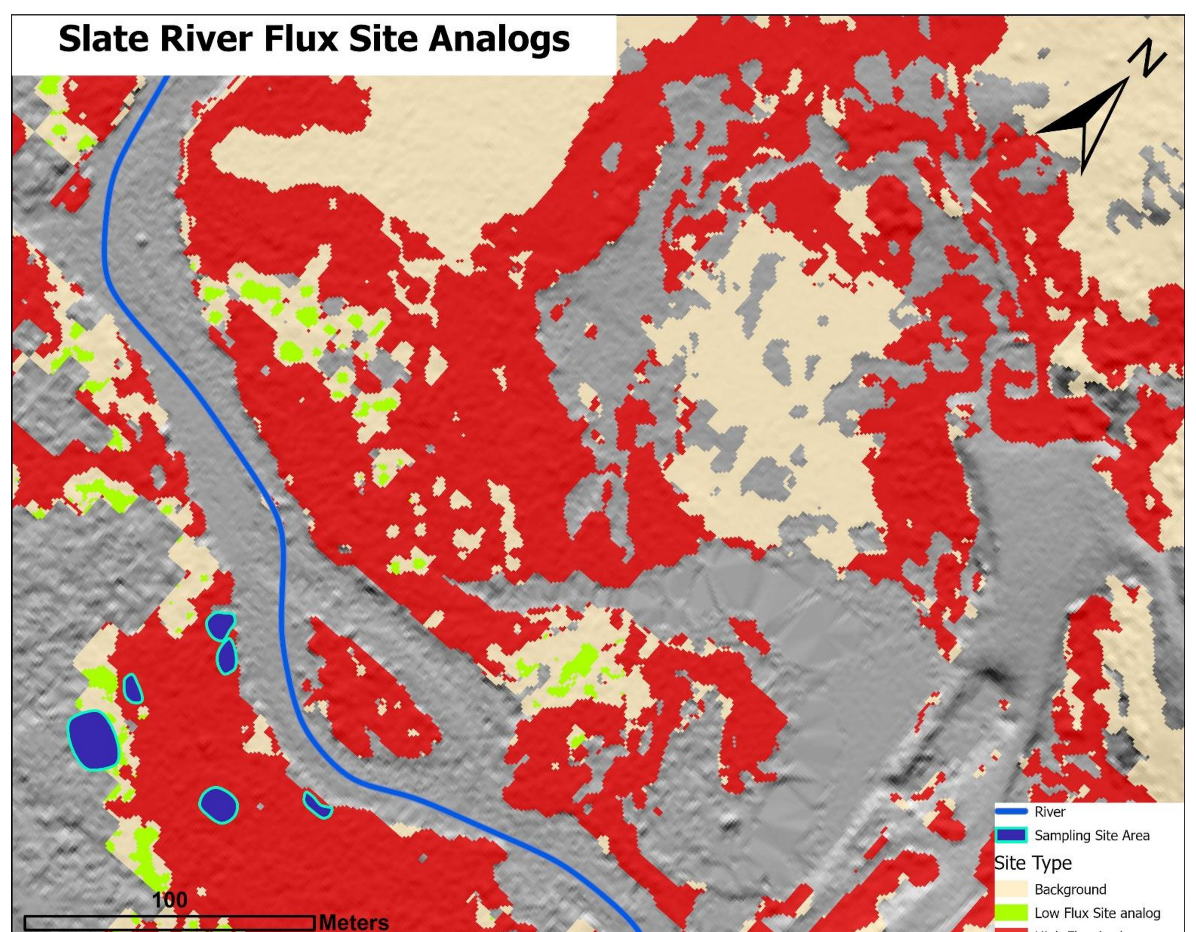
Normalizing the Drying Rate: We modeled the relationship (R^2=0.60) between slope and amplitude to identify the average biological drying response across species for each site.

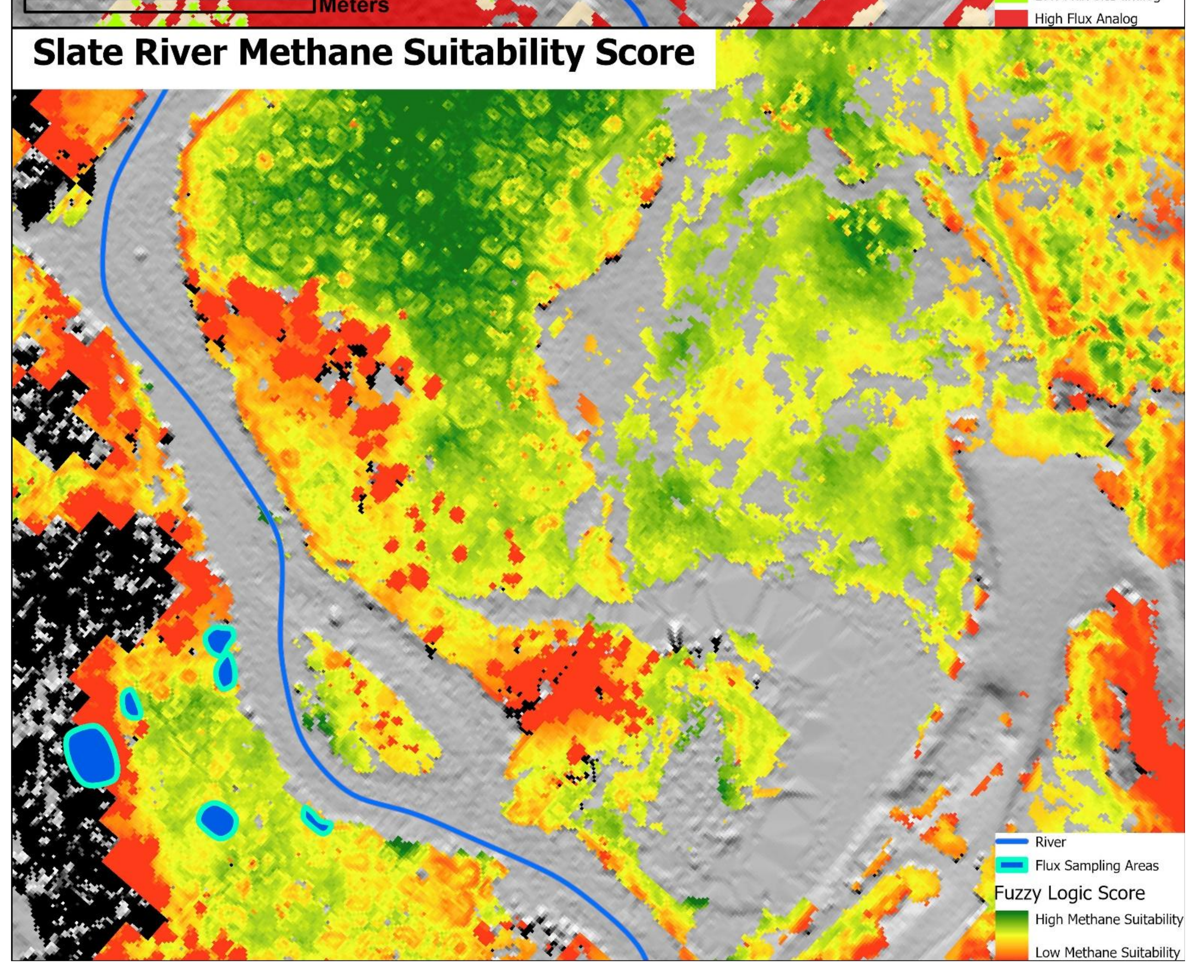
The residuals from this model isolate the hydrologic signal from the vegetation signal: pixels drying slower than the average normalized rate are hypothesized to have better access to groundwater.

Crested Butte Floodplain Features for Identifying Site Analogs and Site Suitability



Layer	Source	Metric	Ecological Interpretation
CN Ratio	NEON AOP hyperspectral + tissue samples	Leaf carbon:nitrogen	Nutrient availability, litter quality
Canopy Height (CHM)	NEON AOP LiDAR	Maximum vegetation height (m)	Structural complexity, rooting depth potential
Soil Moisture Index	DEM-derived (HAND)	Topographic wetness (0-1)	Water table proximity, drainage potential
Distance from Conifers	Derived from CHM	Distance (m)	Ecotone proximity, elevation proxy
Vegetation Moisture Retention Index	Phenology residuals (Methods Spotlight)	Anomalous late-season plant moisture	Subsurface hydrology, groundwater access





Defining Site Analogs

To identify areas statistically identical to our observed high methane flux sites, we calculated the **Euclidean distance** between every floodplain pixel (p) and the centroid of our high-flux sites (q) within the 5-dimensional feature space:

$$d(p, q) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2}$$

Multivariate, Not Geographic: Crucially, d(p,q) measures similarity in environmental conditions, rather than physical proximity on the map.

The Threshold: Pixels with a distance less than the internal variance of the measured high-flux sites were classified as Site Analogs.

Defining Suitability

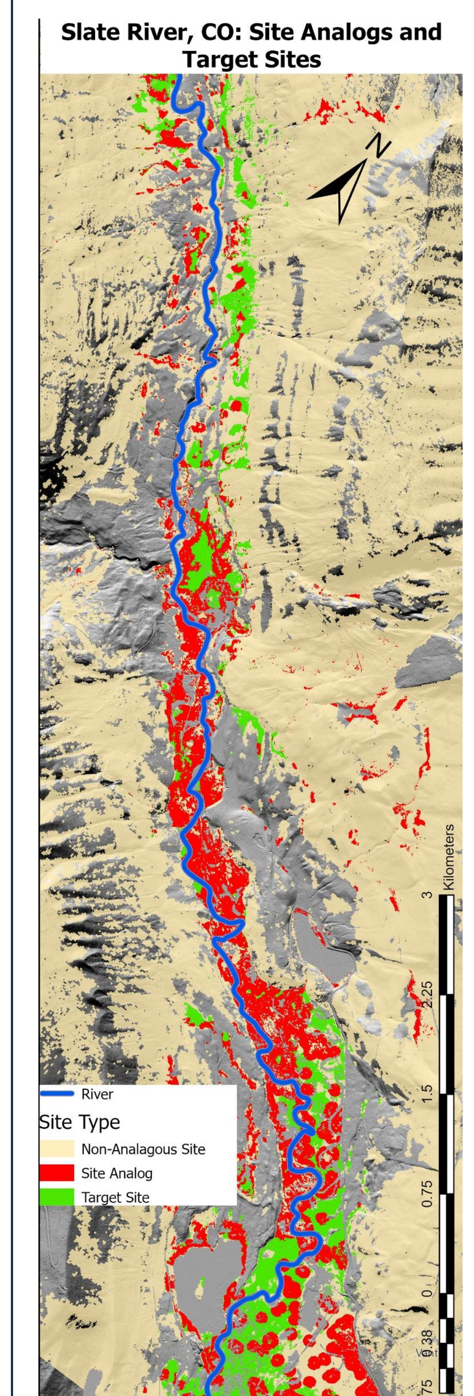
To identify areas that should theoretically result in positive methane fluxes, we converted the feature space layers into Fuzzy Membership rasters (0–1 scale), a method that quantifies the continuous degree of suitability rather than imposing artificial binary boundaries.

The Rules: We performed a Fuzzy Product Overlay to identify the intersection of optimal conditions: High Soil Moisture, High Vegetative Moisture (VMI), Low Canopy Height, Low C:N Ratio, and greater Distance from Conifers.

Identifying Novel Targets

We overlaid the two models to perform a gap analysis. **Novel Targets** are defined as non-analog areas where the theoretical suitability score exceeds the mean suitability of our site analogs. These represent potentially high methane location that are environmentally distinct from our current sampling areas.

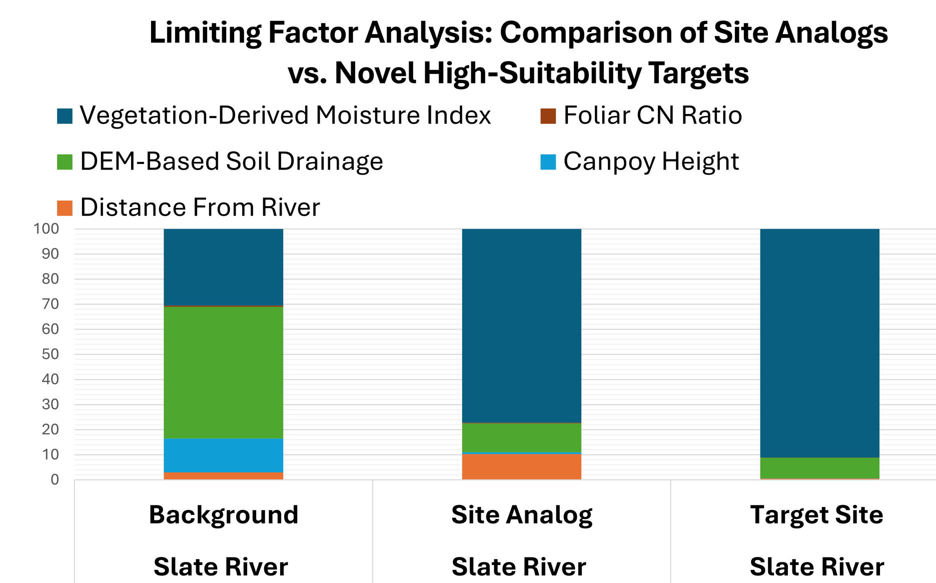
Watershed Scale Analysis



By synthesizing the Euclidean and Fuzzy models, we categorized the floodplain into two distinct priority zones:

High-Flux Analogs (Red): Areas statistically similar to known hot spots based on Euclidean distance. These are the site analogs or areas theoretically represented by our sample sites.

Novel Targets (Green): Non-analog areas where the Fuzzy Suitability score exceeds the mean of the High-Flux Analogs ($\mu > 0.192$). These sites represent areas of the floodplain that could be producing more methane than the sites where we sampled.



Discussion

Limiting Factor Analysis reveals which variables drive predicted methane flux suitability across different scales:

Landscape Scale: The broader Background Landscape is constrained by coarse geomorphology (Topographic Drainage, Canopy Height).

Target Scale: Within the High-Flux Analogs and Novel Targets, suitability is constrained by the Vegetation-Derived Moisture Index (VMI) > 90% of the time.

Conclusion

Mapping the Context: While remote sensing cannot resolve micron-scale anoxia, this workflow successfully delineates the macroscopic ecological template that allows it to exist.

A New Framework: This approach moves beyond opportunistic sampling, providing a stratified map to target "Novel Green Zones" (high-potential non-analogs) for future validation.

Isolating Cryptic Drivers: By controlling for obvious landscape variables, this model allows researchers to attribute remaining flux variance to soil microsite processes rather than confounding environmental factors.

The Phenology Advantage: Land surface phenology acted as a critical **Moisture Retention Index**, possibly resolving fine-scale hydrologic heterogeneity that remains invisible to standard topographic mapping.

Citations

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