Drivers of Soil Moisture Dynamics over Continental United States

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Capturing Soil Moisture Dynamics over Continental United States (and beyond..)

Feature Space

Static & Dynamic Input Data

Stakeholder-Model Interface (RAG)

Soil Moisture Prediction Model

"The soil moisture in your corn field is predicted to be adequate next week, with levels around 25-30%."

LLM Interface (Ollama)

Farmer

"What's the soil moisture forecast for my corn field next week?"

Planned Future Research:

Land Characterization

+

Ecological Site Classification

Target Space

ISMN Soil Moisture Data

Feature Importance

Data Preprocessing

vector   matrix   tensor

Vision Transformers

(Captures Global Spatial & Temporal Dependencies)

Attention

Many repetitions

Adaptive Optimizer

Dataloader Pipeline

Output

Soil Moisture: A Crucial Driver of Aquifer Recharge

Infiltration and Percolation: Soil moisture facilitates the infiltration of precipitation into the ground

Soil Moisture Gradient: Higher soil moisture creates a downward hydraulic gradient, driving water movement from the soil surface to deeper aquifer layers, enhancing recharge rates and vice versa

Storage and Regulation: Soil moisture acts as a temporary storage reservoir, regulating the timing and volume of water reaching aquifers by buffering rainfall and reducing runoff, especially in unsaturated zones.
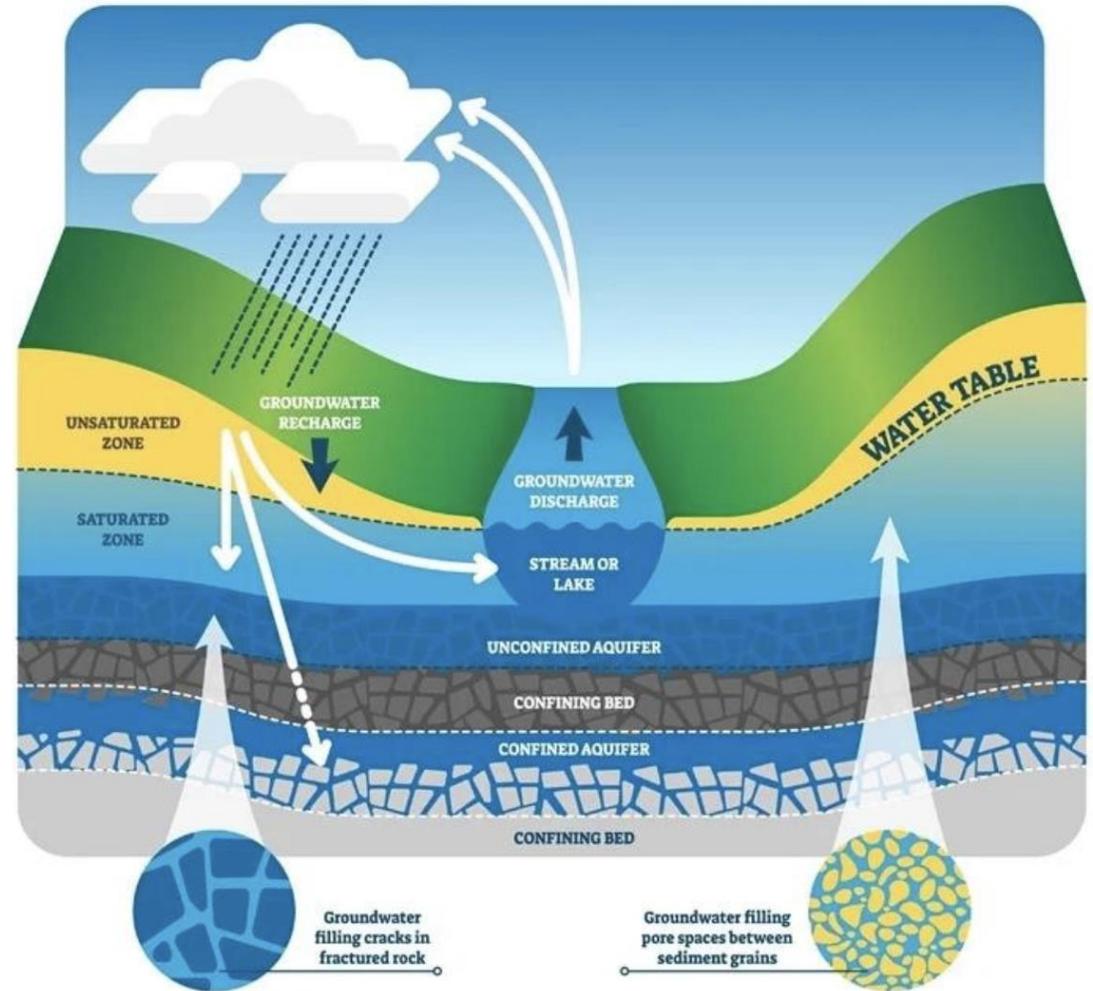
We have a diverse range of input attributes from 360 heterogeneously distributed ISMN stations over CONUS...

ISMN Stations Used in This Study
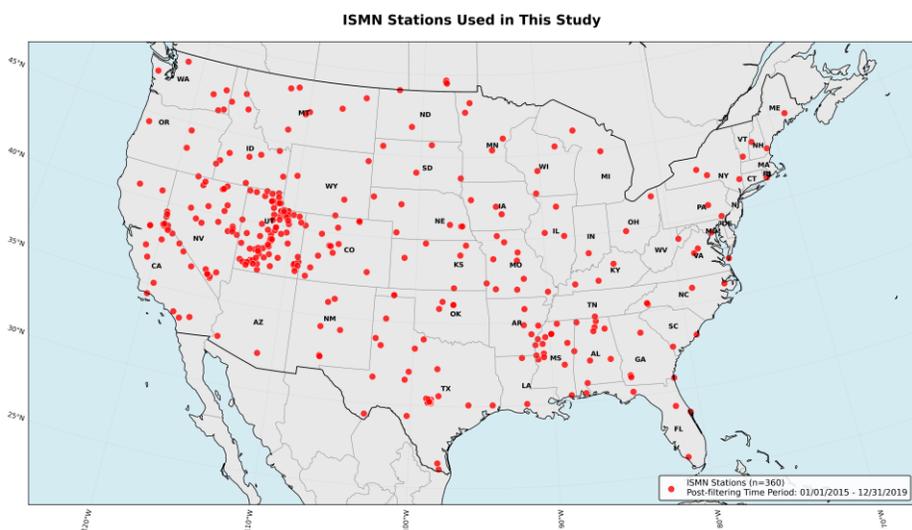
Table 1: Static and Dynamic Input Features Used in Soil Moisture Prediction

Feature Group	Attribute	Description	Source
Dynamic Weather	Temperature	2m air temperature (°C)	ERA5
	Precipitation	Total precipitation (mm)	ERA5
	Solar Radiation	Surface solar radiation (W/m²)	ERA5
Static Physical	slope	Terrain slope	USGS 3DEP
	cfvo	Coarse fragments volume	
	bdod	Bulk density	
	clay_fraction_1	Clay content (top layer)	
	clay_fraction_2	Clay content (sub layer)	
	sand_fraction_1	Sand content (top layer)	
	sand_fraction_2	Sand content (sub layer)	SoilGrids
	silt_fraction_1	Silt content (top layer)	
	silt_fraction_2	Silt content (sub layer)	
	saturation_1	Saturation (top layer)	
	saturation_2	Saturation (sub layer)	
Static Chemical	ocs	Organic carbon stocks	
	cec	Cation exchange capacity	
	nitrogen	Total nitrogen content	
	ocd	Organic carbon density	
	phh2o	pH in HO	SoilGrids
	soc	Soil organic carbon	
	organic_carbon_1	Organic carbon (top layer)	
	organic_carbon_2	Organic carbon (sub layer)	
Static Hydraulic	wv0010	Water content at 10 kPa	
	wv0033	Water content at 33 kPa	SoilGrids
	wv1500	Water content at 1500 kPa	
Environmental	landcover_2020	MODIS land cover class	MODIS
	climate_1	Köppen-Geiger climate type (primary)	
	climate_2	Köppen-Geiger climate type (secondary)	ISMN Metadata

What is Computer Vision? How can we apply it to Ag Drought?
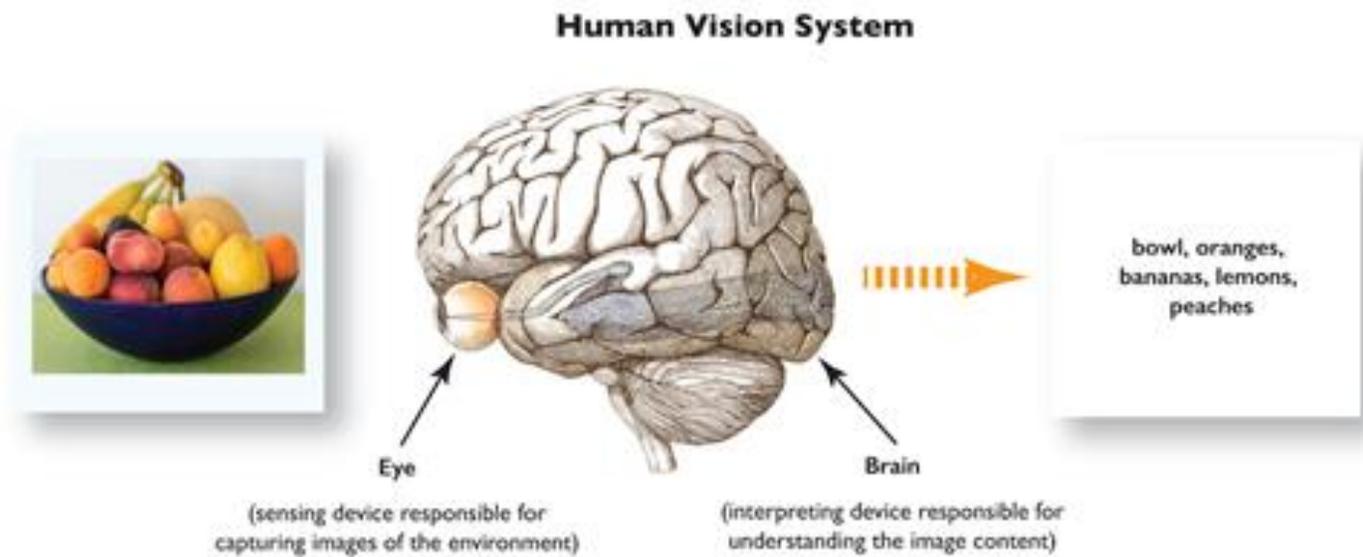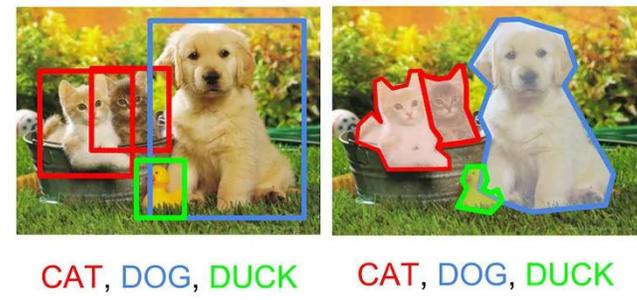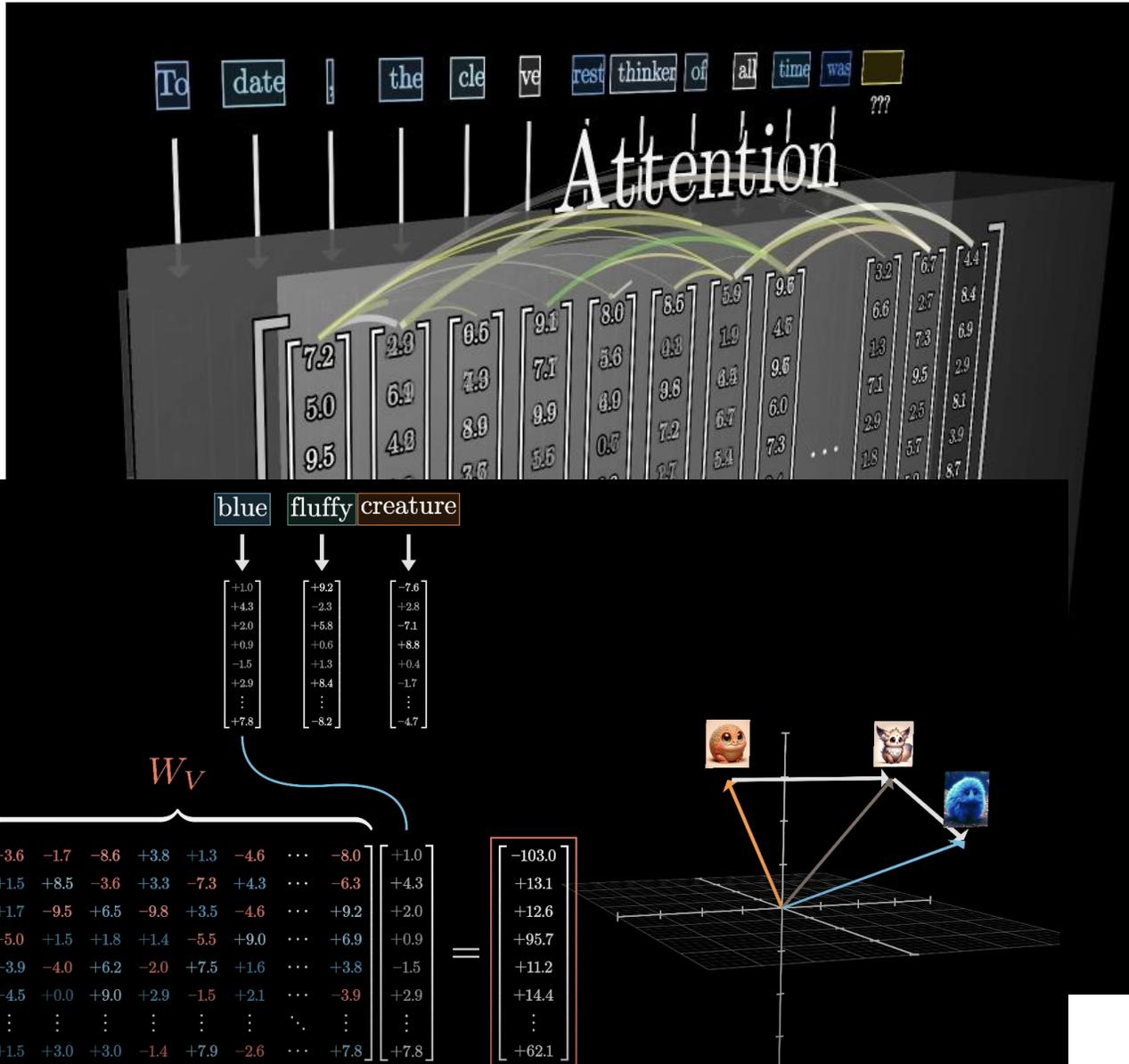
Attention is all you need....to contextually predict soil large-scale moisture dynamics!


Attention mechanism allows each element of the input images to **attend to** every other element of the input images.

We can capture **Global Dependencies** between elements:
- within the same input image
- between multiple input images
- between input and target images

We can capture the **'Teleconnections'** between pixels (driving drought occurrences)!

How our model captures the complex interplay between attributes and soil moisture variability...
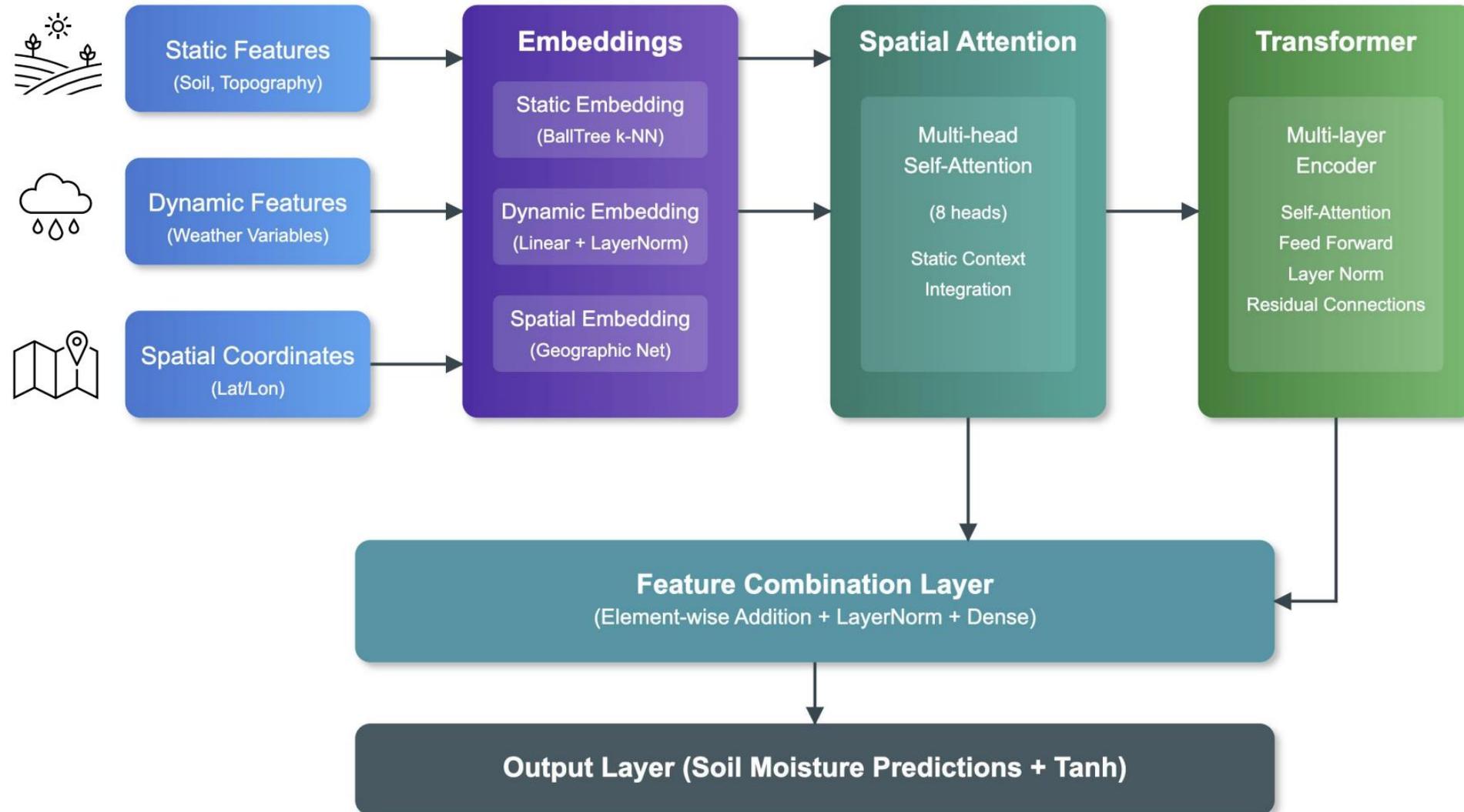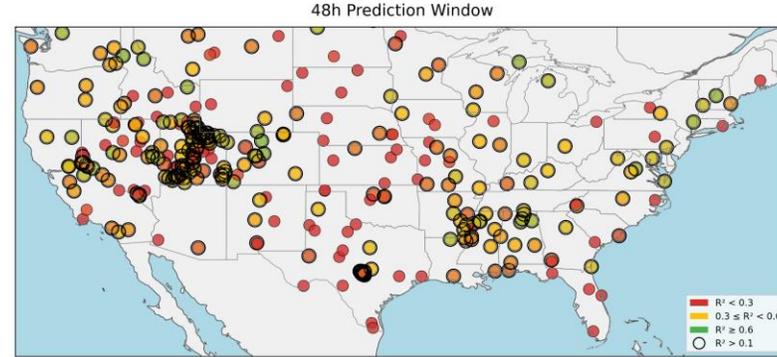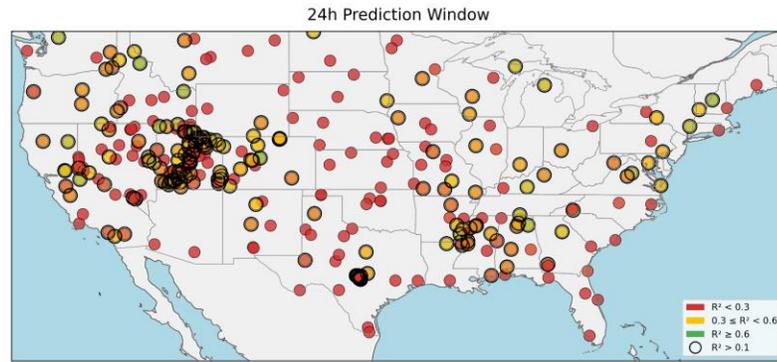
Our model captures the temporal dependencies...

Multi-window Prediction Comparison for Top 25 Stations
Ranked by 24h Test R² (01/01/2019-12/31/2019)
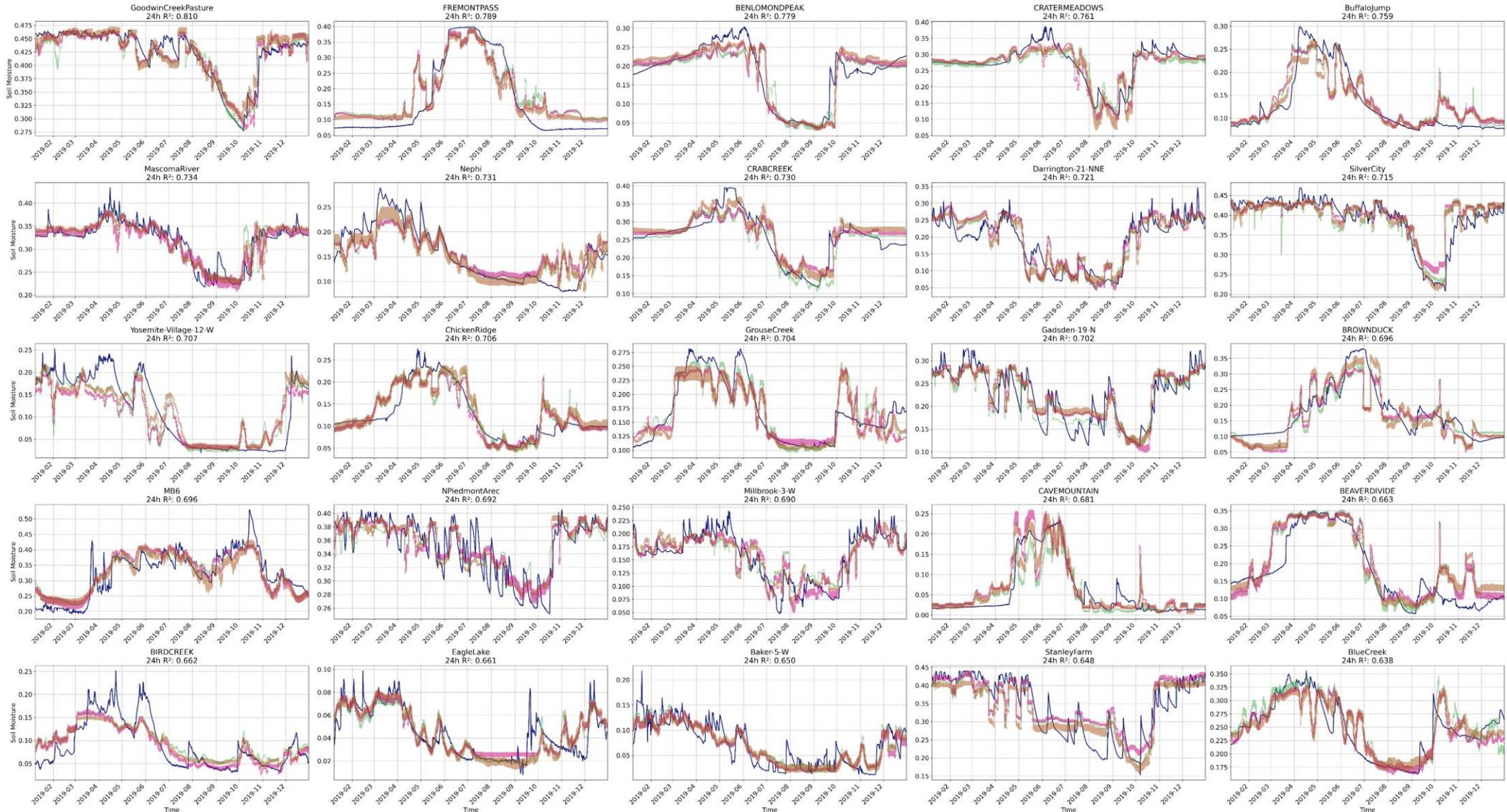
Our model captures the spatial dependencies...
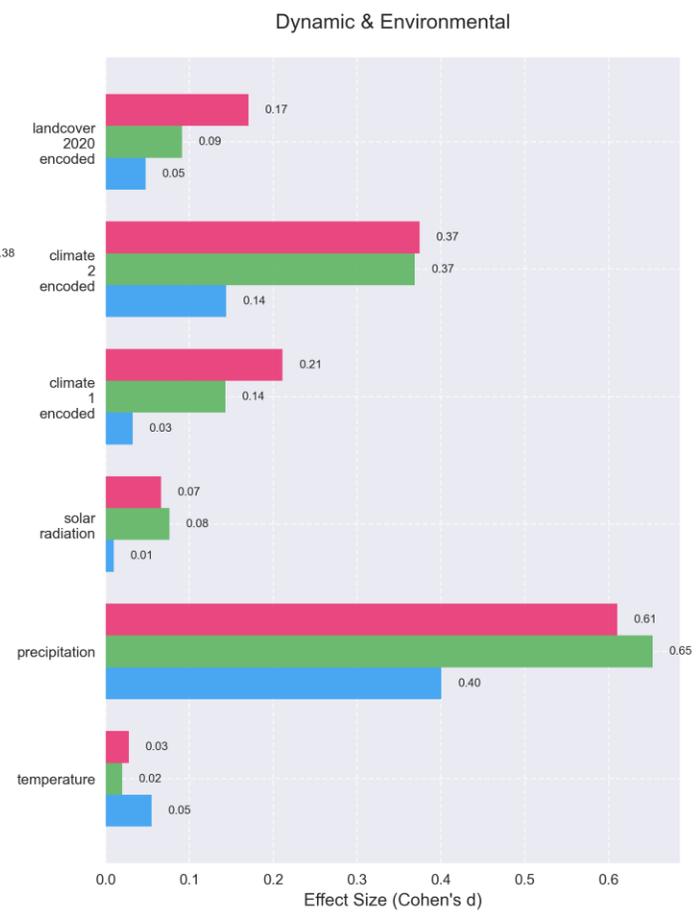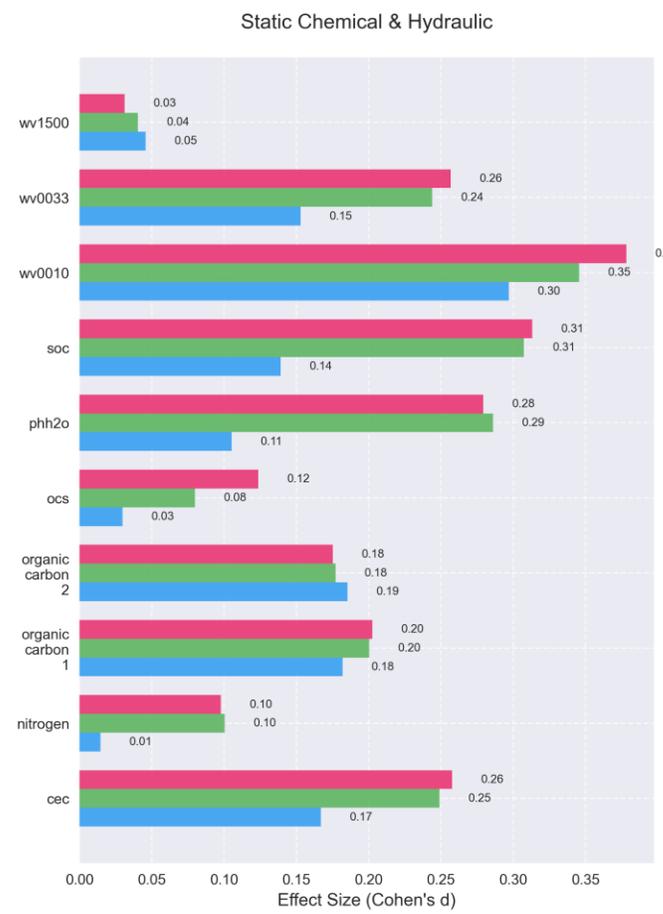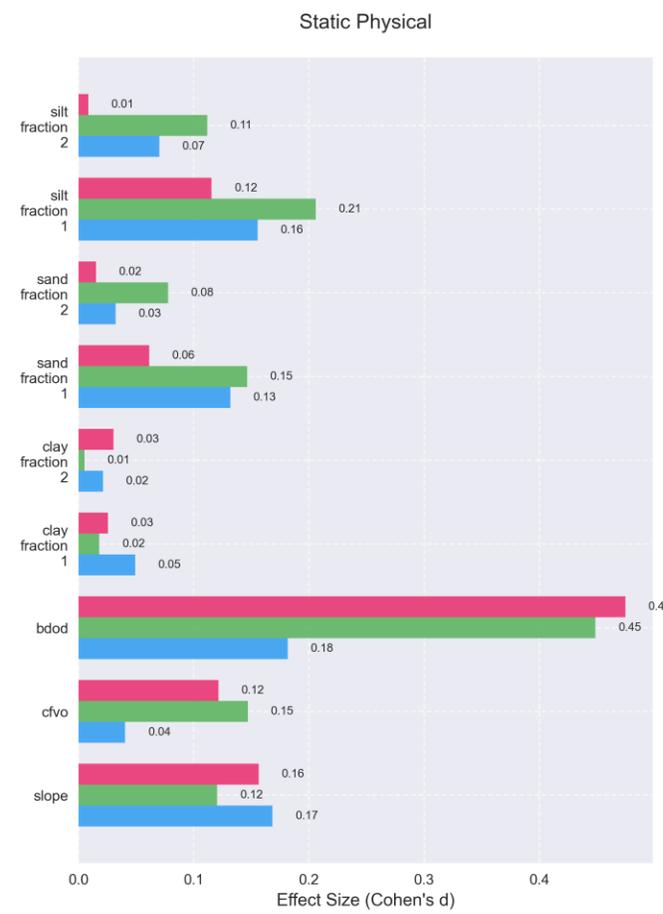# Systematic improvement of prediction skills over longer prediction windows...

Spatial Performance Analysis Across Prediction Windows
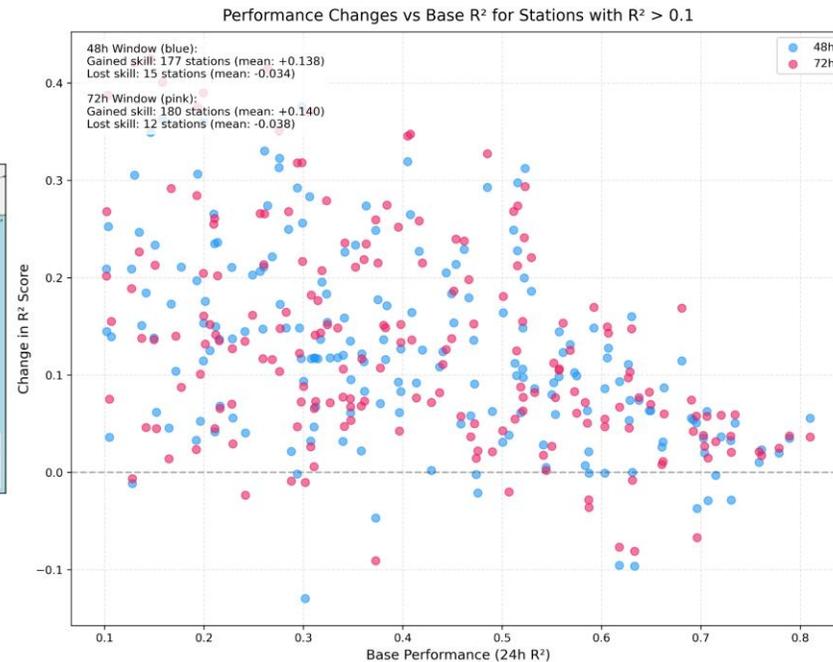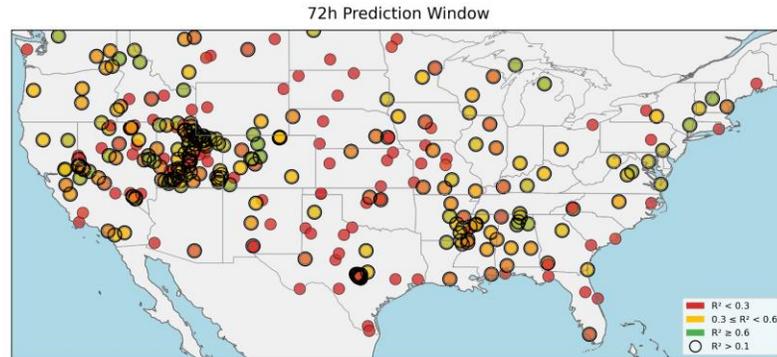
Effect size analysis reveals a hierarchical organization of soil moisture controls...
Soil physical structure and retention properties emerge as primary discriminators...
*Precipitation emerges as a global discriminator...*

Feature Importance Analysis Across Prediction Windows

Prediction Window
- 24h
- 48h
- 72h

Static Physical

Feature	24h	48h	72h
silt fraction 2	0.07	0.11	0.01
silt fraction 1	0.16	0.21	0.12
sand fraction 2	0.03	0.08	0.02
sand fraction 1	0.13	0.15	0.06
clay fraction 2	0.02	0.01	0.03
clay fraction 1	0.05	0.02	0.03
bdod	0.18	0.45	0.47
cfvo	0.04	0.15	0.12
slope	0.17	0.12	0.16

Effect Size (Cohen's d)

Static Chemical & Hydraulic

Feature	24h	48h	72h
wv1500	0.05	0.04	0.03
wv0033	0.15	0.24	0.26
wv0010	0.30	0.35	0.38
soc	0.14	0.31	0.31
phh2o	0.11	0.29	0.28
ocs	0.03	0.08	0.12
organic carbon 2	0.19	0.18	0.18
organic carbon 1	0.18	0.20	0.20
nitrogen	0.01	0.10	0.10
cec	0.17	0.25	0.26

Effect Size (Cohen's d)

Dynamic & Environmental

Feature	24h	48h	72h
landcover 2020 encoded	0.05	0.09	0.17
climate 2 encoded	0.14	0.37	0.37
climate 1 encoded	0.03	0.14	0.21
solar radiation	0.01	0.08	0.07
precipitation	0.40	0.65	0.61
temperature	0.05	0.02	0.03

Effect Size (Cohen's d)

Feature Relationships Across Prediction Windows

*Clear transition from weather-dominated to soil-controlled dynamics as prediction windows extend...*

Strengthening correlations between soil chemical properties at longer horizons suggest their combined influence on extended forecasts...

Dynamic features show evolving relationships with static properties with increasing prediction horizons, reflecting complex interactions between weather and soil characteristics
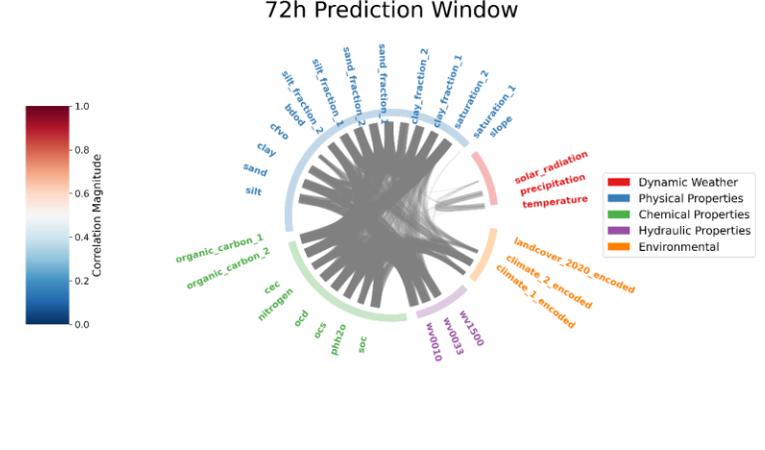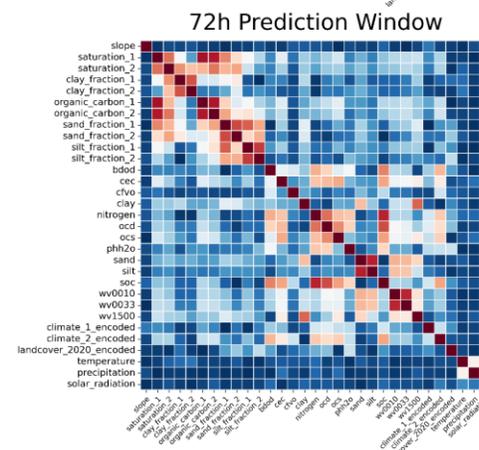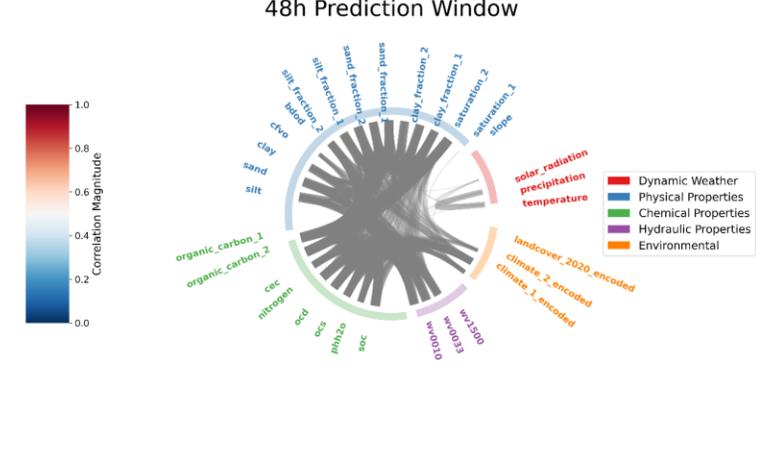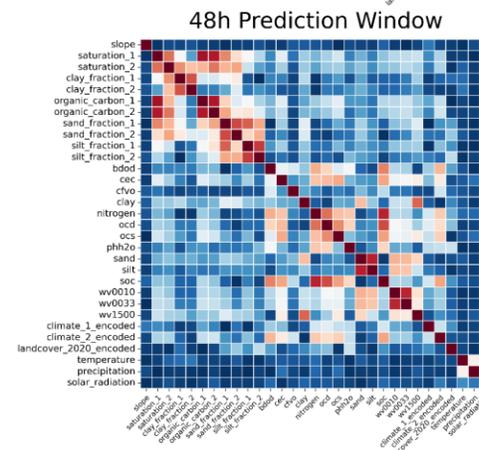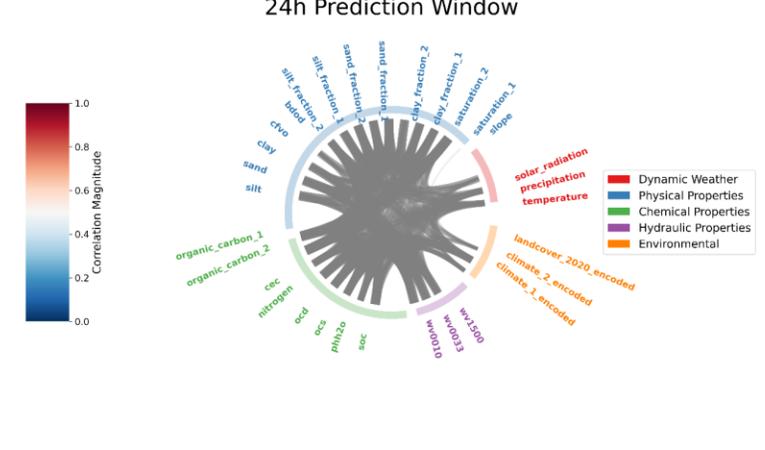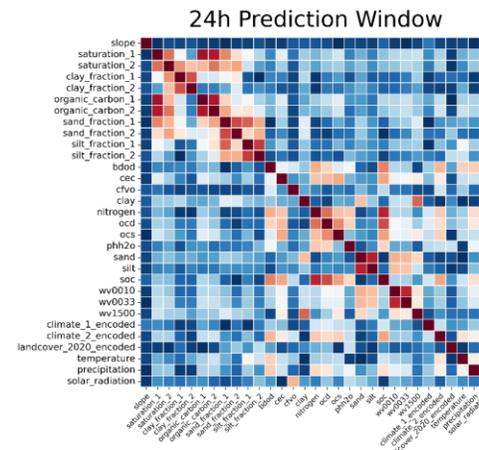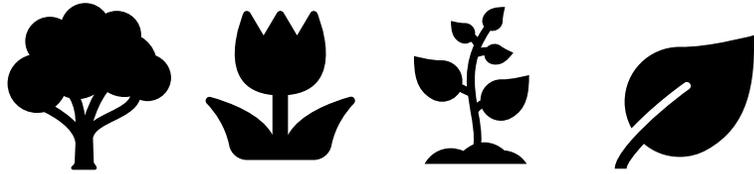
- *Solar radiation shows consistent predictive importance (local control) despite low (global) discriminative power*
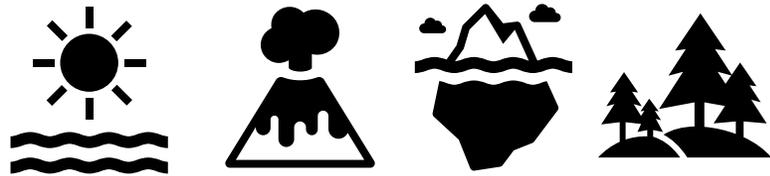
- *Clay content (+256%), organic carbon density (+107%), and cation exchange capacity (+59%) demonstrates increasing importance at longer prediction horizons*

A) Top Static Feature Impacts

B) Dynamic Feature Impact

C) Relative Change in Importance (24h to 72h)
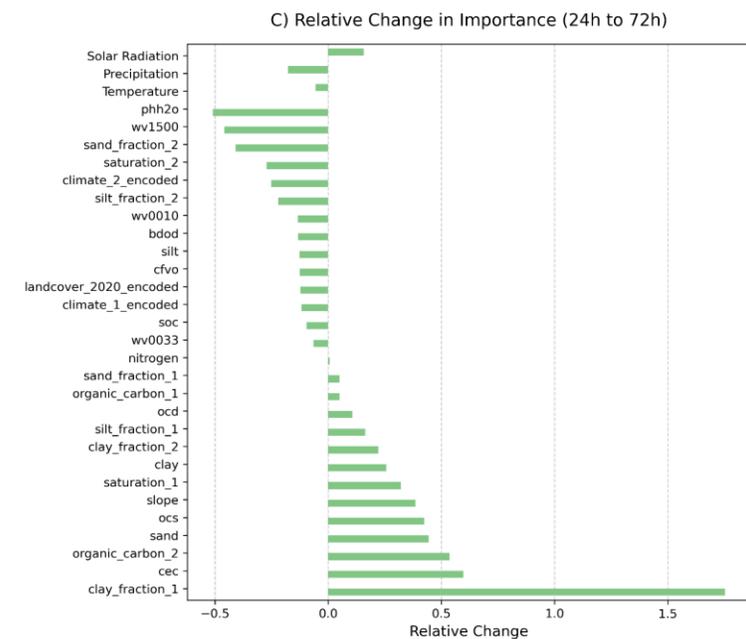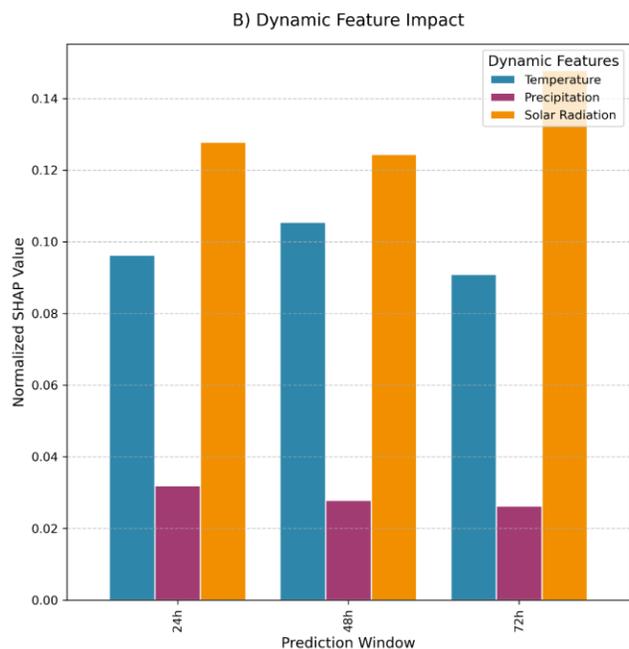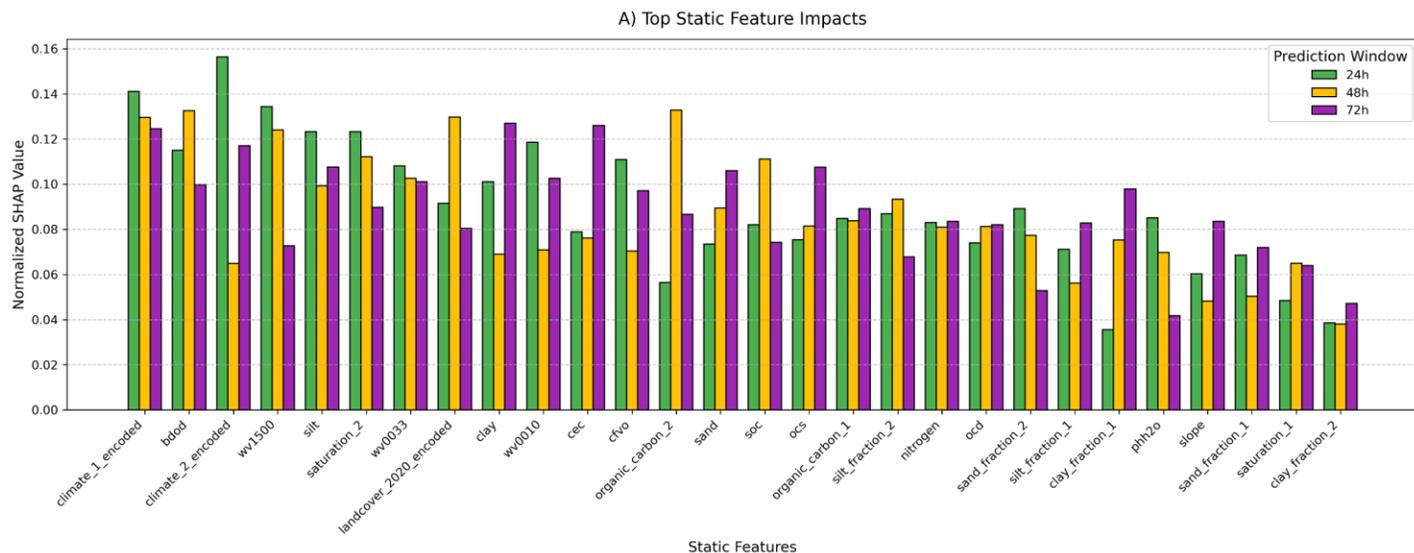
What's Next: Play with more diverse Input & Target features at different scales

Vegetation Dynamics (NDVI, LAI)

Additional Topographic Variables

Different Scales

Continued Work: Custom RAG Pipeline for Ecological Site Classification/Description

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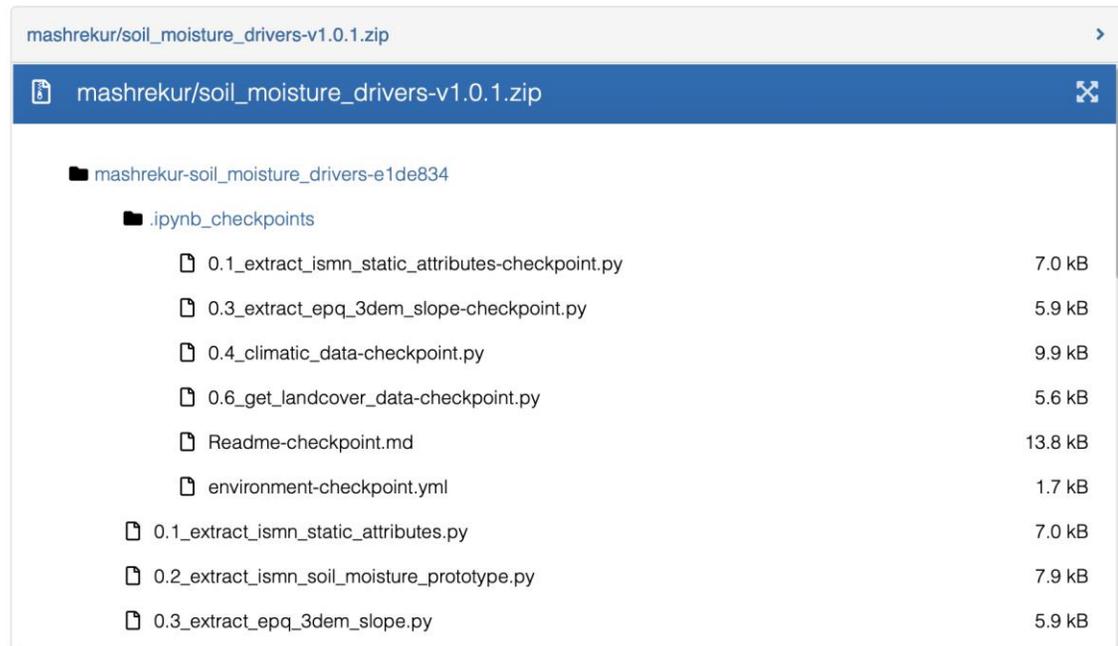(mashman@ucdavis.edu, mashrekur.rahman@usda.gov)

February 2025

mashrekur/soil_moisture_drivers: v1.0.1

mashrekur

Updated Release

Files

mashrekur/soil_moisture_drivers-v1.0.1.zip

mashrekur/soil_moisture_drivers-v1.0.1.zip

mashrekur-soil_moisture_drivers-e1de834

.ipynb_checkpoints

0.1_extract_ismn_static_attributes-checkpoint.py	7.0 kB
0.3_extract_epq_3dem_slope-checkpoint.py	5.9 kB
0.4_climatic_data-checkpoint.py	9.9 kB
0.6_get_landcover_data-checkpoint.py	5.6 kB
Readme-checkpoint.md	13.8 kB
environment-checkpoint.yml	1.7 kB
0.1_extract_ismn_static_attributes.py	7.0 kB
0.2_extract_ismn_soil_moisture_prototype.py	7.9 kB
0.3_extract_epq_3dem_slope.py	5.9 kB

Thank You!