Understanding Drought through Spatial-Temporal Learning

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Neural Information Processing Systems

Introduction

- Drought is among the most disastrous and costly natural hazards. Frequent subseasonal-to-seasonal droughts affects water resources, agricultural yields, heat waves, and land carbon sink [1].
- Existing drought prediction models consider the interaction of biological drivers, while systematically leveraging datasets of relevant climate and vegetation features is needed [2,3].
- Thus, we integrate climate, physical, and vegetation conditions that are related to droughts from various remote sensing and reanalysis datasets to create the DroughtSet.
- To forecast drought, we propose SPDrought, a spatial-temporal drought prediction model that incorporates geographic neighbor features fusion. It jointly leverages both static and dynamic features to accurately predict three key drought indices.

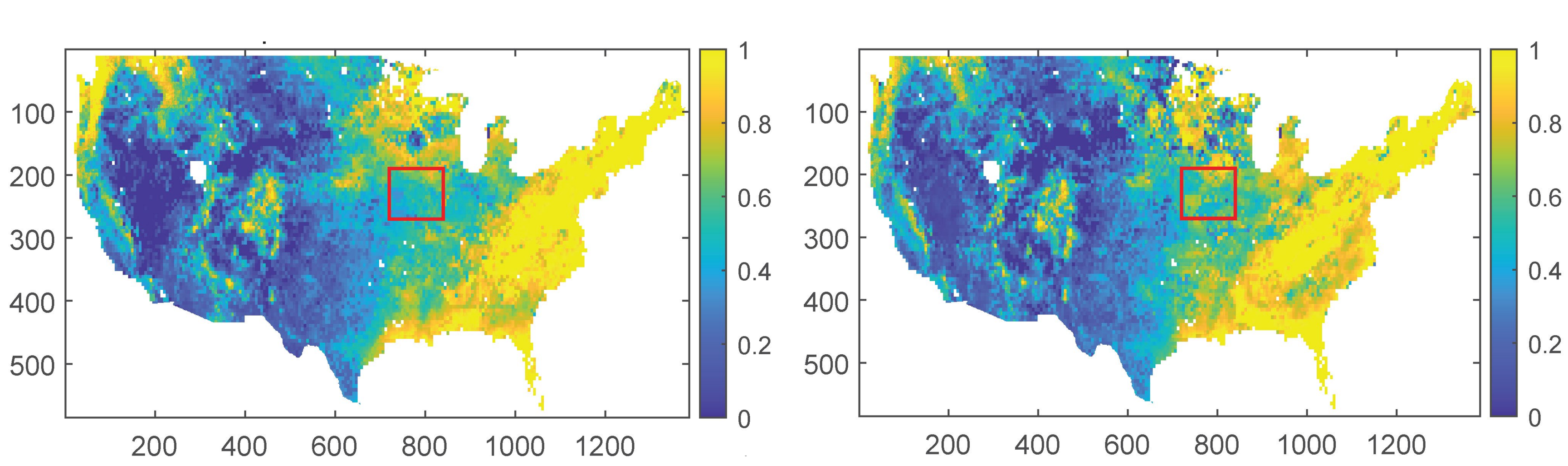
DroughtSet

- Includes nationwide weekly climate-related data from 2003 to 2013 across the contiguous United States. The area over 8,000,000 km^2 is represented as a grid of 585×1386.
- **Three types of droughts**: agricultural drought, ecohydrological drought, and ecological drought.
- **Physical and climate conditions**: Elevation, Air Temperature, Precipitation, Radiation, Vapor Pressure Deficit, Wind Speed, Potential Evapotranspiration, Palmer Drought Severity Index, Surface Pressure, soil moisture root.
- **Vegetation dynamics**: Biomass dynamics (Leaf Area Index), Vegetation Optical Depth, Canopy Height.

Variables to quantify three types of drought and predictive features

Drought/Feature Type	Variables	Dynamic or Static	Dataset & Resolution
Soil moisture drought	Soil moisture across depths (SM)	Dynamic	NLDAS [19], hourly, 1/8° SMAP [20], daily, 9 km NLDAS or SMAP blended with in situ data [21], daily, 4 km
Ecohydrological drought	Evaporative Stress Index (ESI)	Dynamic	ALEXI [22], weekly, 0.25°
Ecological drought	Solar Induced Fluorescence (SIF)	Dynamic	CSIF [23], 4-day, 0.05°
Physical & climate features	Temperature, Radiation, VPD, Precipitation, Wind Speed, PET, PDSI, SP	Dynamic	gridMET [24], daily, 4 km ERA5 [25], hourly, 9 km
	Elevation	Static	SRTM [26], 30 m
Vegetation features	Vegetation Optical Depth (VOD)	Dynamic	VODCA [27], daily, 0.25°
	Leaf area index (LAI)	Dynamic	MODIS [28], 8-day, 500 m
	Canopy Height	Static	GLAD [29], 30 m
	Land Cover	Static	NLCD [30, 31], 30 m

A S2S drought in July 2012 represented by evaporative stress

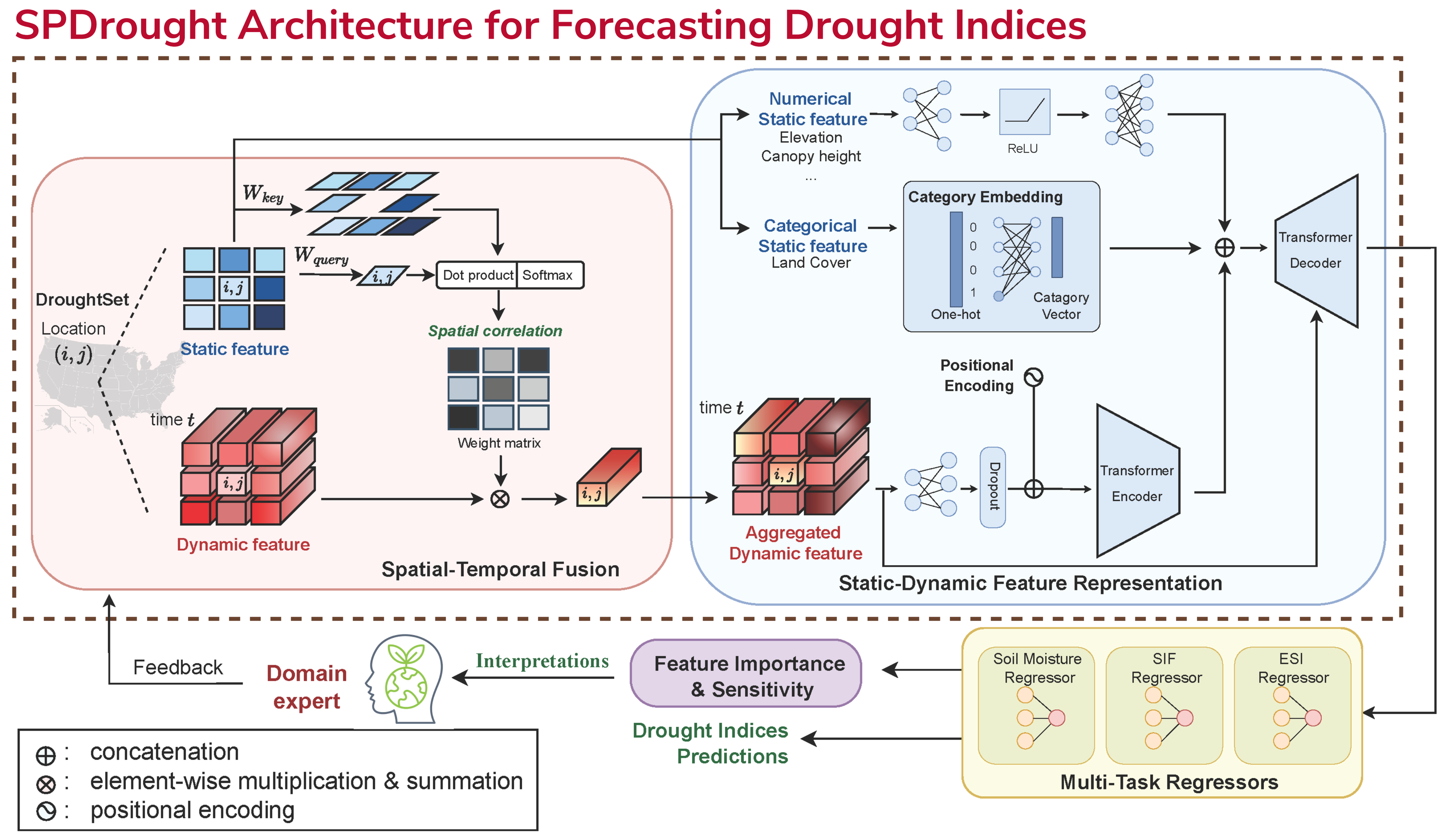


Conclusion and Future Work

- We introduces DroughtSet, a specialized time-series forecasting dataset designed for predicting drought indices. It integrates vegetation and climate predictors, incorporating static and dynamic features.
- We propose a framework, SPDrought, which leverages spatial-temporal interactions to accurately **predict drought indices**, and **interpret the prediction** results to advance our understanding of drought development and propagation.
- We will conduct a comprehensive analysis of the temporal interplay and dependencies related to flash droughts.

Method

SPDrought Architecture for Forecasting Drought Indices



- **Model Training** $$\min \sum_{k\in[K]} \sum_{t'\in\{T+1\ldots T+26\}} \sum_{i\in[I], j\in[J]} \mathcal{L}\left(\hat{d}^k_{i,j}(t'), d^k_{i,j}(t')\right)$$
- **Model Interpreting** $$(x) ::= (x_i - x'_i) \times \int_{\alpha=0}^{1} \frac{\partial F(x' + \alpha \times (x - x'))}{\partial x_i}\, d\alpha$$

Results

Prediction Performance Comparison

MAE ($\times 10^{-3}$)	SPDrought	Transformer	Informer	PatchTST	DLinear	iTransformer	TimesNet	LSTM
Soil Moisture	$21.39_{\pm 0.14}$	$34.56_{\pm 0.24}$	$38.08_{\pm 0.14}$	$36.32_{\pm 0.19}$	$47.61_{\pm 0.04}$	$32.34_{\pm 0.09}$	$25.96_{\pm 0.46}$	$31.36_{\pm 0.40}$
ESI	$4.40_{\pm 0.02}$	$5.99_{\pm 0.07}$	$6.37_{\pm 0.06}$	$6.37_{\pm 0.00}$	$6.82_{\pm 0.01}$	$6.06_{\pm 0.01}$	$5.11_{\pm 0.02}$	$5.83_{\pm 0.09}$
SIF	$12.21_{\pm 0.23}$	$16.00_{\pm 0.23}$	$17.71_{\pm 0.33}$	$21.36_{\pm 0.19}$	$20.99_{\pm 0.03}$	$15.47_{\pm 0.07}$	$14.11_{\pm 0.03}$	$15.35_{\pm 0.02}$
Total	$38.01_{\pm 0.35}$	$56.56_{\pm 0.05}$	$62.16_{\pm 0.43}$	$64.05_{\pm 0.34}$	$75.41_{\pm 0.05}$	$53.87_{\pm 0.16}$	$45.18_{\pm 0.44}$	$52.54_{\pm 0.40}$

Assessment of Drought Using Soil Moisture Percentiles

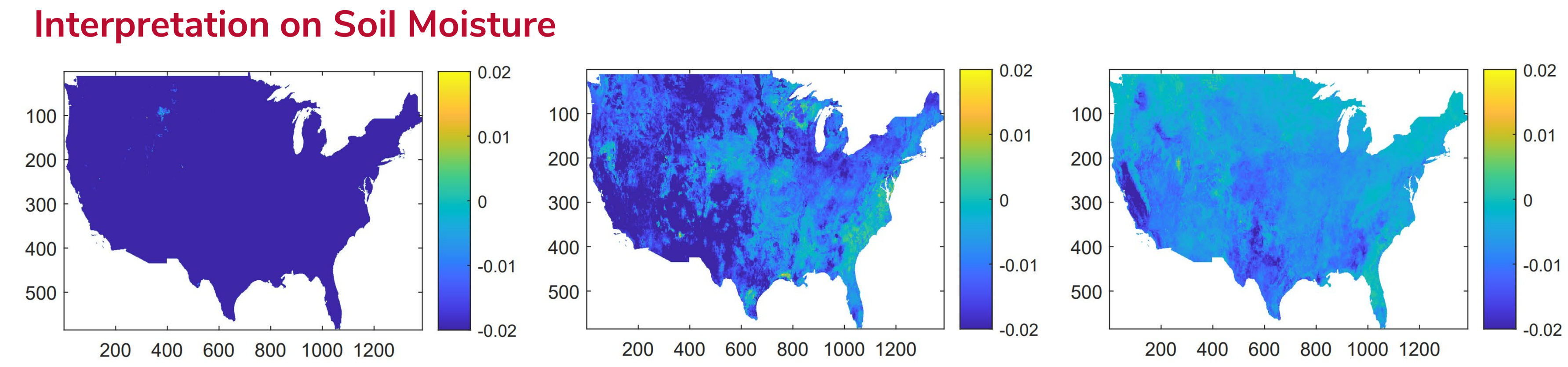
	SPDrought	Transformer	Informer	PatchTST	DLinear	iTransformer	TimesNet	LSTM
Accuracy	86.26	76.09	72.16	62.24	62.85	77.18	81.54	77.45
Precision	76.80	59.94	53.40	36.94	37.96	61.74	68.98	62.18

- Taking soil moisture as an example to assess flash drought. A flash drought can be identified when the soil moisture anomaly falls below the 30th percentile [4].

Drought Interpretation

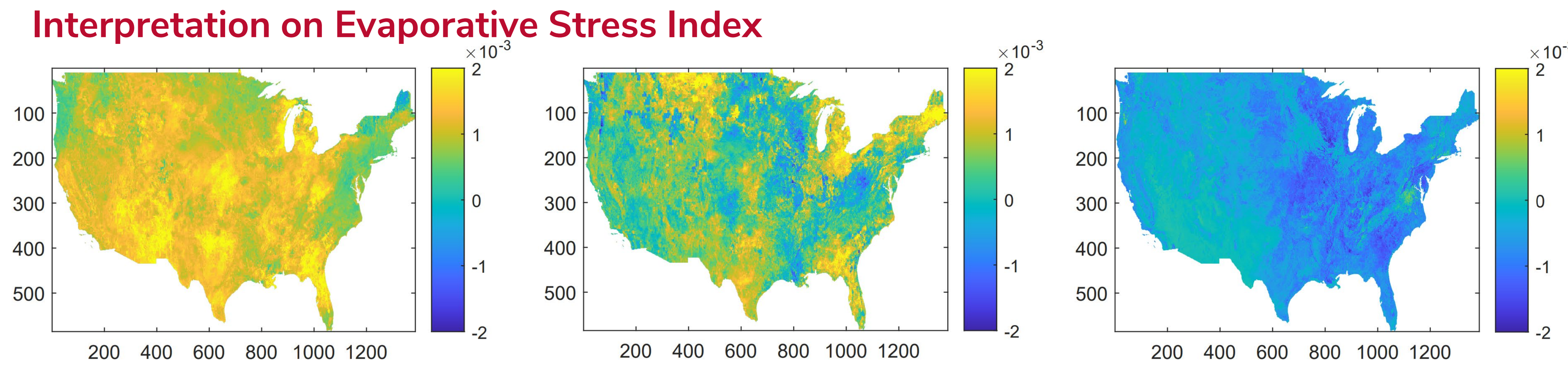
- We evaluate the influence of each variable on drought indices prediction in July 2012 by integrated gradient value. We select and present the top 3 significant influence variables.

Interpretation on Soil Moisture



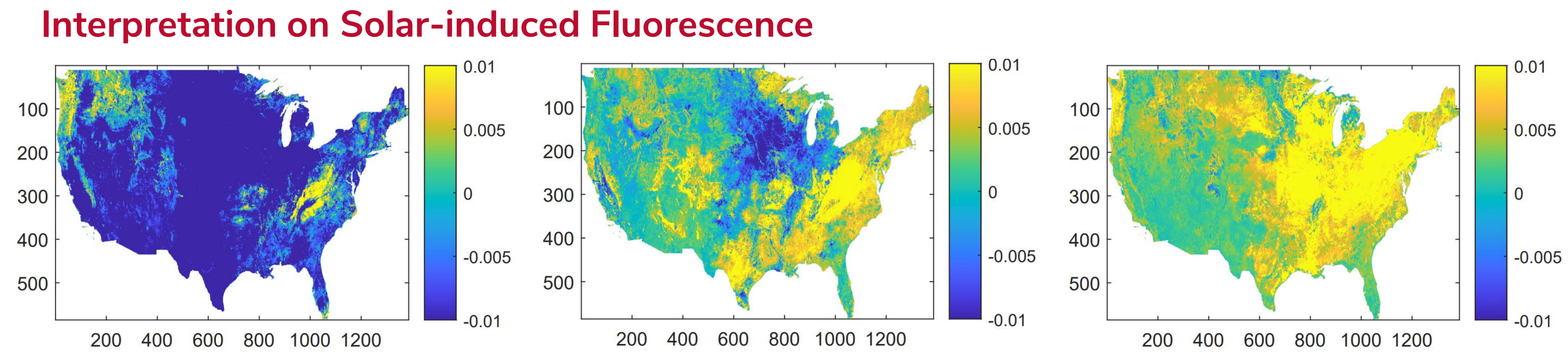
(a) Influence of Surface Pressure (b) Influence of Radiation (c) Influence of PET

Interpretation on Evaporative Stress Index



(a) Influence of Radiation (b) Influence of Pressure (c) Influence of SIF

Interpretation on Solar-induced Fluorescence



(a) Influence of Pressure (b) Influence of Radiation (c) Influence of SM root

Reference

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