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Tackling Climate Change with Machine Learning Workshop

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Predicting Concurrence of Heatwaves, Droughts, and Wildfires with Spatiotemporal Deep Learning

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1. Introduction

Climate extremes like heatwaves, droughts, and wildfires increasingly occur together. Their concurrence exacerbates ecological and societal impacts. Traditional models typically treat each hazard in isolation, missing cross-hazard interactions. We explore a multi-task learning approach that jointly predicts these events, aiming to:

- Capture spatiotemporal dependencies and shared risk factors.
- Enhance the accuracy of compound hazard forecasts.
- Inform proactive strategies for climate risk mitigation and resilience planning.

2. Approach

Objective: Develop a unified spatiotemporal deep learning model that predicts summer (June–August) aggregates of key climate hazards. By leveraging shared representation learning, we aim to enhance forecasting accuracy for policy-relevant planning and early warning systems (**Figure 1**).

Modeling Indicators:

- **Heatwaves:** Three consecutive days above the 90th percentile of daily maximum temperature (T_{90}), computed within Köppen–Geiger zones.
- **Droughts:** Standardized Precipitation–Evapotranspiration Index (SPEI), derived from an 8-day water balance transformed via a logistic CDF.
- **Wildfires:** Historical burned-area polygons indicating past fire-affected regions.

3. Baselines

We aim to benchmark multiple spatiotemporal architectures, each representing a distinct modeling paradigm:

- **ConvGRU** [6]: GRU with spatial convolution for dynamic feature extraction.
- **ConvLSTM** [5]: Recurrent LSTM with embedded spatial gates for sequence learning.
- **Earthformer** [1]: Transformer with cuboid attention for long-range dynamics.
- **Time-SSM** [3]: Compact State Space Model for efficient time series forecasting.

Each model employs a shared encoder with task-specific output heads, enabling cross-task knowledge transfer while preserving hazard-specific characteristics.

4. Benchmarking and Evaluation

Region: Greece — chosen for history of compound hazards [2].

Dataset: *FireCube* [4], a 1 km-resolution dataset spanning 2009–2020, integrating climate, vegetation, and human activity.

Training: Time-based split; train until 2018, test on 2018–2020.

Evaluation: Mean-squared error (MSE) normalized per task to balance scale disparities and ensure fair optimization.

Early Results: ConvGRU baseline shows consistent loss decrease across tasks; further work needed to better capture rare events like wildfires.

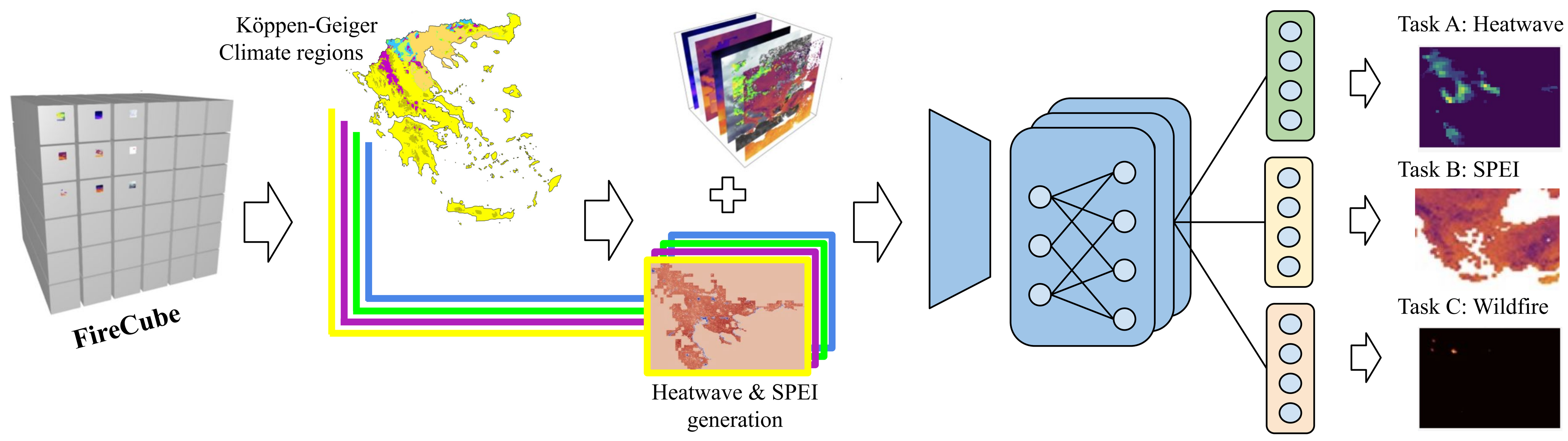

Figure 1: *Joint model learning shared spatiotemporal patterns while predicting heatwaves, droughts, and wildfires.*

5. Impact and Next Steps

Policy Relevance: Our unified forecasting framework should support:

- Strategic deployment of emergency resources for compounding climate hazards.
- Data-driven planning for wildfire prevention and climate-resilient agriculture.
- Health risk advisories during high-impact heatwave–drought–fire events.

Scientific Insight: Joint modeling of multiple hazards provides interpretable patterns to support climate disaster research and uncover shared drivers of compounding extremes.

Open Science: All datasets, indicators, and models will be openly released to foster transparency, reproducibility, and downstream applications.

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