

# PREDICTING CONCURRENCE OF HEATWAVES, DROUGHTS, AND WILDFIRES WITH SPATIOTEMPORAL DEEP LEARNING

**Ana Trišović\*, Gabe Miller & Dimitris Bertsimas**  
Massachusetts Institute of Technology  
Cambridge, MA, USA

**Jie K. Hu**  
The Ohio State University  
Columbus, OH, USA

## ABSTRACT

Extreme climate events—heatwaves, droughts, and wildfires—pose critical challenges to sustainability. Their concurrence suggests shared risk factors, yet has not been explored in a deep learning predictive model. We aim to identify a state-of-the-art (SotA) multi-task spatiotemporal model to predict heatwaves, drought severity, and wildfire occurrences simultaneously. By unifying these hazards in a single framework, we aim to capture both their individual behaviors and common causes. Our goal is to advance climate extreme event modeling by (1) constructing a comprehensive dataset of these climate exposure indicators, (2) benchmarking models to identify the SotA approach, and (3) demonstrating that shared representation learning improves concurrent hazard modeling. Our findings will help inform climate preparedness, mitigate public health risks, and support risk-aware decision-making in a changing climate.

## 1 INTRODUCTION

Climate change has increased the frequency and intensity of extreme weather events such as heatwaves, droughts, and wildfires. These hazards increasingly manifest as compound events—multiple extremes occurring simultaneously or in close succession, where their interactions can amplify socio-ecological impacts (Zscheischler et al., 2018; Richardson et al., 2022). For instance, prolonged drought conditions can prime landscapes for more severe wildfires, and concurrent heatwaves can exacerbate both drought stress and fire spread. These cascading risks place significant burdens on water resources (Mishra et al., 2021), the atmospheric environment (Voulgarakis and Field, 2015), biodiversity (Archaux and Wolters, 2006), public health (Shaposhnikov et al., 2014), and the economy (Meier et al., 2023).

Traditional hazard prediction methods typically focus on single-event forecasts. For instance, wildfire risk models rely on vegetation indices, wind speed, and temperature to estimate fire probability or burned area (Gerard et al., 2023; Xu et al., 2024). Drought prediction methods use standardized indices based on precipitation and water balance (Vicente-Serrano et al., 2010), while heatwave alerts analyze temperature percentiles and consecutive-day exceedances (Khan et al., 2019). However, these models do not account for spatial and temporal interactions among hazards, limiting their ability to capture interconnected climate extremes. Recent Multi-Task Learning (MTL) research has integrated climate variables (Ling et al., 2022; Sadler et al., 2022) to better capture shared climate drivers and identify regions at risk of both single and compound events. MTL optimizes a shared representation to minimize error across related tasks, improving generalization and predictive performance. However, no studies have focused on heatwaves, droughts, and wildfires together. Understanding these interactions is crucial for timely interventions, such as prioritizing fire-prone areas during droughts or issuing heatwave health advisories.

Our hypothesis is that jointly predicting heatwaves, droughts, and wildfires within a single spatiotemporal MTL model will outperform separate models, particularly for compound-risk scenarios. Prior research has shown that deep MTL models outperform single-task models by leveraging shared representations across related tasks (Zhang and Yang, 2021). This advantage stems from

\*Corresponding author. Email: ana\_tris@mit.edu

MTL’s ability to utilize more data from diverse learning tasks, leading to improved generalization and robustness in climate prediction. We aim to evaluate a number of MTL baselines and identify the SotA model for predicting concurrent climate hazards.

## 2 APPROACH

Rather than focusing on daily fluctuations, we aim to identify the SotA model that predicts aggregated summer (i.e., June–August) climate variables, leveraging seasonal trends to align with policy-relevant decision-making timeframes. Our findings have the potential to enhance resource allocation and disaster response, serving as a pathway for informing mitigation policies aimed at safeguarding ecosystems, protecting public health, and promoting risk-aware decision-making in the face of climate change. In the following, we outline our approach to modeling climate exposure indicators, our multi-task baseline selection and our benchmarking approach to identify the SotA model for predicting concurrence of heatwaves, droughts, and wildfires while demonstrating the effectiveness of shared representation learning.

### 2.1 MODELING CLIMATE EXPOSURE INDICATORS

To effectively capture key climate hazards, we define indicators for heatwaves, droughts, and wildfires while incorporating regional variations. Specifically, we integrate Köppen–Geiger climate zones, which classify the study area into distinct groups based on seasonal precipitation and temperature patterns, ensuring a more nuanced and regionally adaptive analysis (Kottek et al., 2006).

**Heatwave Indicator.** Heatwaves are identified using extreme temperature thresholds, which are the 90th percentile ( $T_{90}$ ) of daily maximum temperatures for each Köppen–Geiger zone, using data from a baseline period (Meehl and Tebaldi, 2004). If  $T_{\max} > T_{90}$ , a temporary indicator is assigned a value of 1. A three-day rolling sum of this indicator is then computed, and a heatwave event is identified when this sum reaches three, indicating three consecutive days above the threshold.

**Drought Indicator.** Drought severity is measured using the Standardized Precipitation–Evapotranspiration Index (SPEI), based on an 8-day water-balance metric. We first compute an 8-day water-balance metric, defined as the rolling difference between precipitation (P) and evapotranspiration (ET) over an 8-day window (Vicente-Serrano et al., 2010):  $WB_8(t) = \sum_{i=t-7}^t P_i - \sum_{i=t-7}^t ET_i$ . Next, we derive the SPEI by fitting a generalized logistic distribution to the 8-day water-balance series for each climate zone, using a chosen baseline period (e.g., July–August in 2009–2015). After estimating the distribution parameters, each water-balance value is transformed via the distribution’s Cumulative Distribution Function (CDF) into a standard normal deviate:  $SPEI(x) = \Phi^{-1}(F_{\text{genlog}}(x))$ , where  $F_{\text{genlog}}$  is the generalized logistic CDF, and  $\Phi^{-1}$  is the standard normal quantile function. Within each zone, this produces an index capturing local moisture surpluses and deficits.

**Wildfire Indicator.** The wildfire indicator is derived from existing burned-area polygons, which delineate regions previously affected by wildfires. This serves as a key indicator, as wildfires are more likely to recur in these areas due to factors such as proximity to built-up regions, vegetation type, human activity, and climatic conditions (Elia et al., 2020).

### 2.2 BASELINES FOR FORECASTING CLIMATE HAZARD CONCURRENCE

We aim to identify and implement a selection of multi-task spatiotemporal learning baselines for forecasting the concurrence of climate hazards, leveraging a shared encoder with task-specific output heads for distinct hazard indicators—namely, heatwaves, SPEI-based drought severity, and burned-area probability (Figure 1). This design captures cross-hazard correlations while preserving task-specific distinctions, enhancing accuracy and mitigating data sparsity (Gonçalves et al., 2016).

To select baselines with different modeling approaches, we plan to consider the following models: **ConvGRU** integrates convolutional layers for spatial encoding with gated recurrent units (GRUs) for temporal dependencies, effectively modeling dynamic environmental patterns (Siam et al., 2017). **ConvLSTM** extends recurrent modeling by embedding convolutional operations in LSTM gates, jointly capturing spatial and temporal structures (Shi et al., 2015). **Earthformer**, a space-time

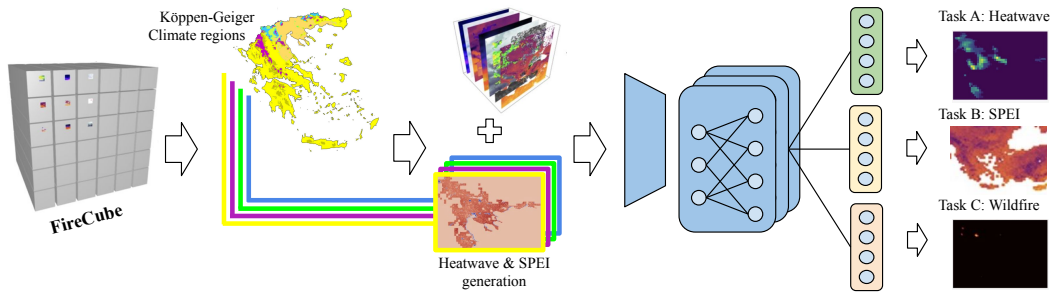


Figure 1: Training a concurrence forecasting baseline. The input features include generated heatwave and SPEI indicators, along with wildfire data and other ecological and infrastructure variables.

Transformer, employs cuboid self-attention to efficiently model long-range dependencies in spatiotemporal data (Gao et al., 2022). **Time-SSM**, a novel State Space Model (SSM)-based foundation model tailored for time series forecasting, captures long-range dependencies with a compact architecture and strong predictive performance (Hu et al., 2024).

### 2.3 BENCHMARKING AND IDENTIFYING THE SOTA MODEL

Our goal is to benchmark the selected baselines and assess their effectiveness in concurring climate hazard forecasting, evaluating trade-offs in spatiotemporal modeling, cross-hazard interactions, and generalization. Due to its history of heatwaves and wildfires events (Lagouvardos et al., 2019; Giannaros et al., 2022; Santos et al., 2024) and the availability of detailed data for the region, Greece serves as an ideal setting for our SotA model identification.

**Data Source.** For baseline model benchmarking, we aim to use the FireCube dataset (Prapas et al., 2022; 2021), which provides comprehensive coverage of Greece and surrounding areas from 2009 to 2020. It integrates climate, vegetation, and human activity variables relevant to wildfire dynamics, harmonized into a high-resolution  $1 \text{ km} \times 1 \text{ km} \times 1 \text{ day}$  spatiotemporal datacube spanning  $700 \text{ km} \times 562 \text{ km}$ . In total, this publicly available dataset includes 19 dynamic and static features.

**Benchmarking.** Each baseline will be trained with a  $n$ -day sequence of climate variables (e.g., 30 days), ensuring consecutive observations are processed together. A time-based train/test split ensures chronological separation, training on data up to September 2018 and validating on data through September 2020. In addition to benchmarking and comparing baselines, further tests include using sample weighting to improve learning of extreme events, experimenting with loss functions (e.g., focal loss) and incorporating additional weather, climate, fire or vegetation features.

**Evaluation Metric.** The evaluation goal is to minimize the mean-squared error (MSE) across the three outcomes. To balance task disparities (e.g., sparse wildfires vs. continuous drought indicators), each MSE term is normalized by baseline variance before summing, preventing any single task from dominating gradient updates. An optimization loop jointly updates all parameters, with per-task validation metrics and visualized predictions assessing performance across hazards.

**Current Progress.** The ConvGRU baseline shows promise in preliminary results, with training and validation losses steadily decreasing across all three tasks. However, varying error magnitudes suggest challenges in predicting rare events (e.g., wildfires) and variable phenomena (e.g., heatwaves).

## 3 PATHWAY TO IMPACT

By integrating multiple climate hazards, agencies can identify compound stress hotspots, optimize emergency responses, and improve adaptive strategies in water management, agriculture, and public health. A unified hazard model would enhance early warning and mitigation by predicting fire risks for emergency services, informing irrigation and crop protection strategies, and guiding land management through wildfire forecasting. Joint modeling of multiple hazards reveals interpretable patterns that support climate disaster research and uncover shared drivers of compounding extremes, strengthening the scientific basis for coordinated action. Our approach extends to other regions and

concurrent hazards, such as air pollution episodes or crop yield failures, via MTL, broadening its applicability in climate hazard forecasting.

Last, our methodology carries uncertainties, limitations, and assumptions. While these are common across frameworks, transparent communication is crucial for proper interpretation. For this reason, our plan is to publicly release the dataset containing concurrence indicators, along with the accompanying code and results as one of the outputs of this project.

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