Deep Learning for Wildfire Danger Forecasting at Different Spatiotemporal Scales

Presenter - Ioannis Prapas

Motivation

Climate change will aggravate fire danger increasing the frequency and severity of wildfires

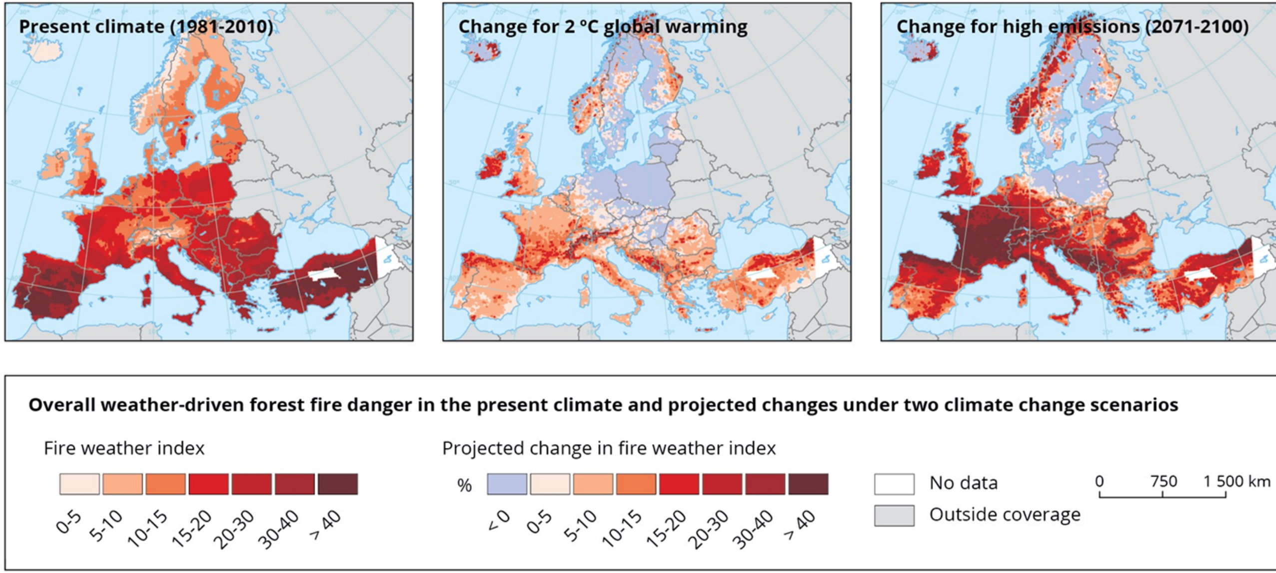
Anticipation of fire danger

- Days in advance (short term)

Manage resources, dispatch units, monitor forests

- Weeks, months (long-term)

Lease equipment, manage fuel



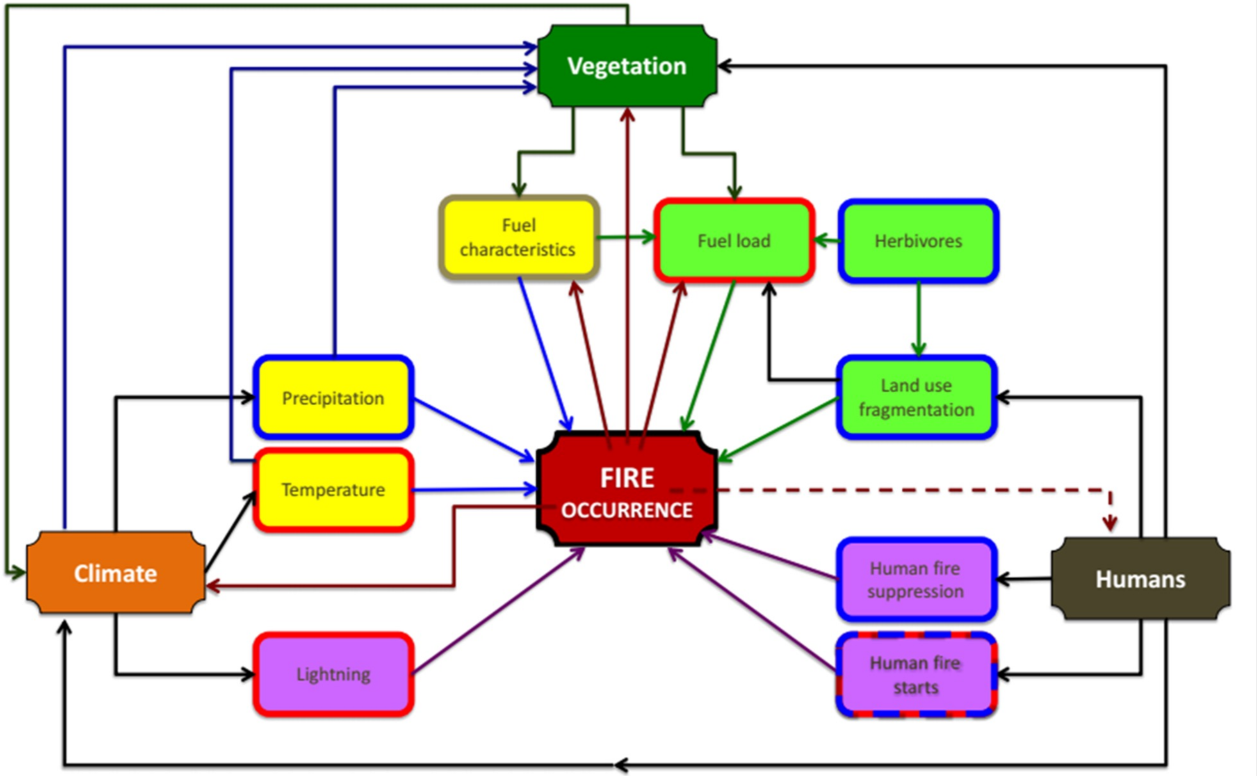
Challenges

Fires are the result of **complex interactions** between humans, climate, vegetation

Proposed solution

Use **Machine Learning** on historical Earth Observation data

Associate conditions of fire drivers to past **burned areas**



Fire Drivers. *Source: Hantson et al. "The status and challenge of global fire modelling" (2016)*

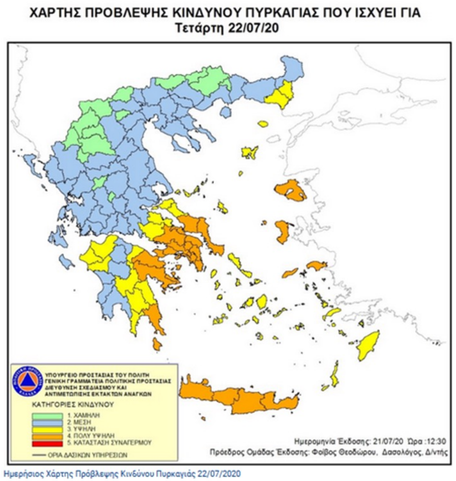
Short-term Wildfire Danger Forecasting

Current Status

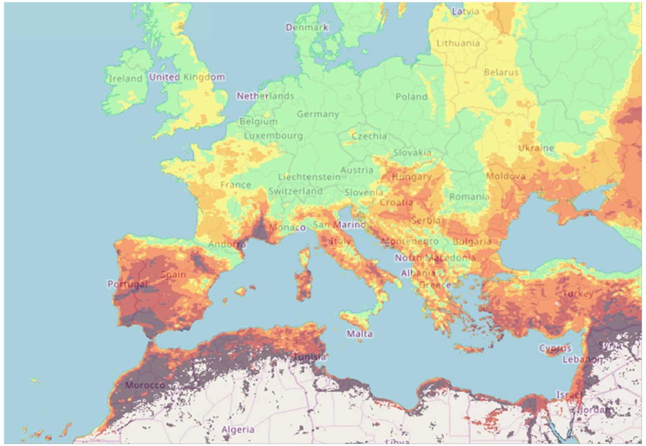
EFFIS (8kmx8km)
Fire Weather Index

National Danger maps

- Low or regional resolution,
- Based only on meteo or hand-crafted rules



Fire danger maps from Greek Civil Protection



Source: EFFIS fire danger forecast for July 16th 2020
https://effis.jrc.ec.europa.eu/about-effis/

Data-driven fire danger

What is fire danger?

“Fire danger assesses the conditions that allow a fire to ignite and spread.” from Pettinari, M. Lucrecia, and Emilio Chuvieco. "Fire danger observed from space." (2020)

Objective

“Associate conditions of fire drivers to large burned areas.”

FireCube - Data Collection and Harmonization

<u>Variables</u>

Meteo (ERA5-Land): Temperature, Wind speed & direction, Precipitation, Relative Humidity (9km)

Satellite (MODIS): Land Temperature, NDVI/EVI, LAI/FPAR, Evapotranspiration

Soil moisture (European Drought Observatory)

Topography (EU-DEM): Elevation, Slope, Aspect

Land Cover (Corine)

Population Density (WorldPop)

Roads Density (OpenStreetMap)

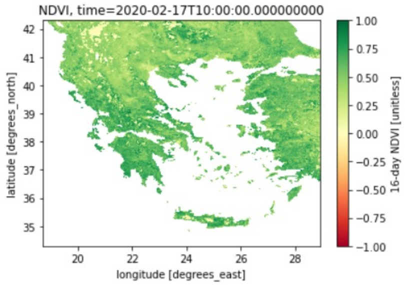
Burned areas (EFFIS)

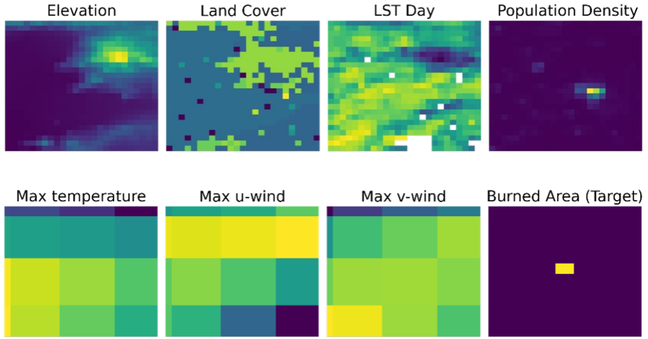
<u>Harmonization</u>

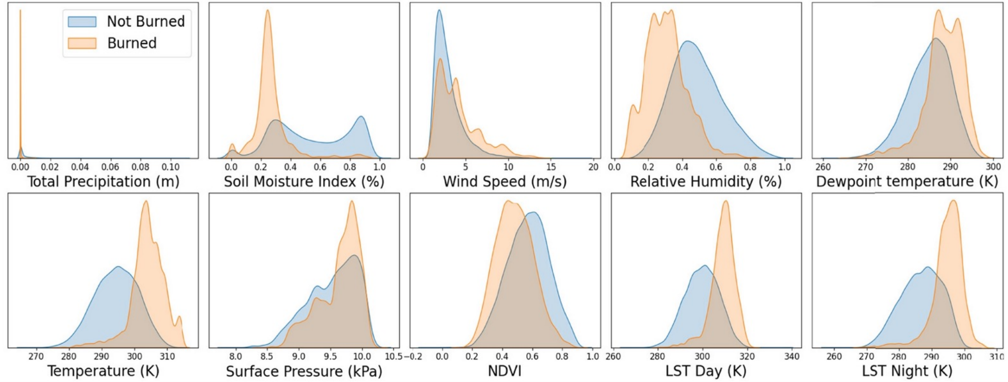
Resolution: 1km x 1km x 1day

Spatial Extent: Greece and eastern Mediterranean

Temporal Extent: 2009-2021



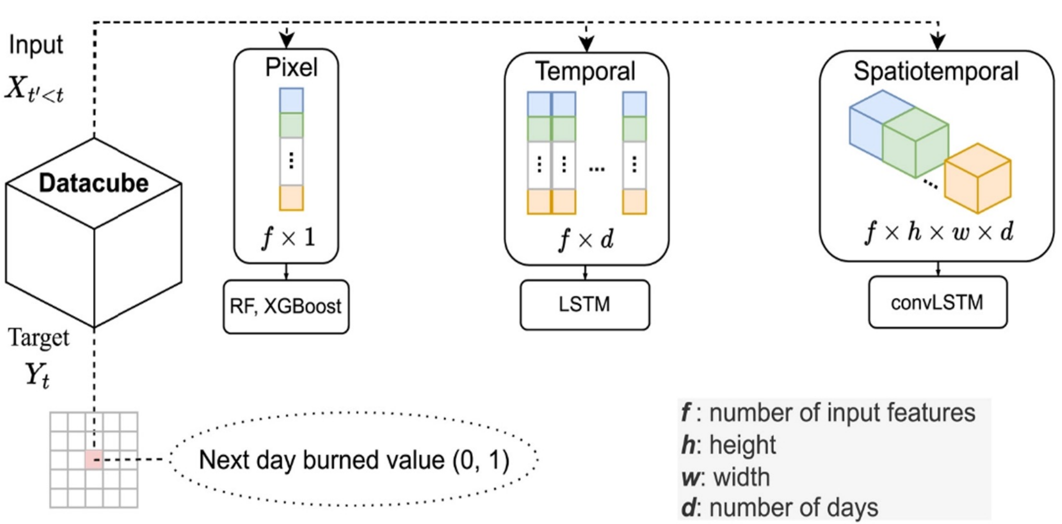




FireCube: A Daily Datacube for the Modeling and Analysis of Wildfires in Greece (1.0) [Data set]. Zenodo. [*https://doi.org/10.5281/zenodo.6475592*](https://doi.org/10.5281/zenodo.6475592)

Experimental Setup

- From the datacube we extract different types of datasets to feed to different models
  - Tabular dataset
  - Temporal Dataset
  - Spatio-temporal Dataset
- The target is always the same *If the cell with burn from a fire that starts the next day and becomes large*
- Negative samples are chosen from days with no fires in a large areas




Geophysical Research Letters

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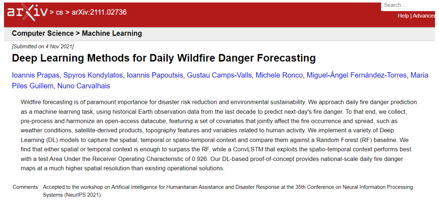
Wildfire Danger Prediction and Understanding With Deep Learning

Spyros Kondylatos, Ioannis Prapas, Michele Ronco, Ioannis Papoutsis, Gustau Camps-Valls, María Piles, Miguel-Ángel Fernández-Torres, Nuno Carvalhais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[Submitted on 4 Nov 2021]

Deep Learning Methods for Daily Wildfire Danger Forecasting

Ioannis Prapas, Spyros Kondylatos, Ioannis Papoutsis, Gustau Camps-Valls, Michele Ronco, Miguel-Ángel Fernández-Torres, Maria Piles Guillem, Nuno Carvalhais

Wildfire forecasting is of paramount importance for disaster risk reduction and environmental sustainability. We approach daily fire danger prediction as a machine learning task, using historical Earth observation data from the last decade to predict next-day's fire danger. To that end, we collect, pre-process and harmonize an open-access datacube, featuring a set of covariates that jointly affect the fire occurrence and spread, such as weather conditions, satellite-derived products, topography features and variables related to human activity. We implement a variety of Deep Learning (DL) models to capture the spatial, temporal or spatio-temporal context and compare them against a Random Forest (RF) baseline. We find that either spatial or temporal context is enough to surpass the RF, while a ConvLSTM that exploits the spatio-temporal context performs best with a test Area Under the Receiver Operating Characteristic of 0.926. Our DL-based proof-of-concept provides national-scale daily fire danger maps at a much higher spatial resolution than existing operational solutions.

Comments: Accepted to the workshop on Artificial Intelligence for Humanitarian Assistance and Disaster Response at the 35th Conference on Neural Information Processing Systems (NeurIPS 2021)

Code: https://github.com/Orion-AI-Lab/wildfire_forecasting

https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022GL099368

https://arxiv.org/abs/2111.02736

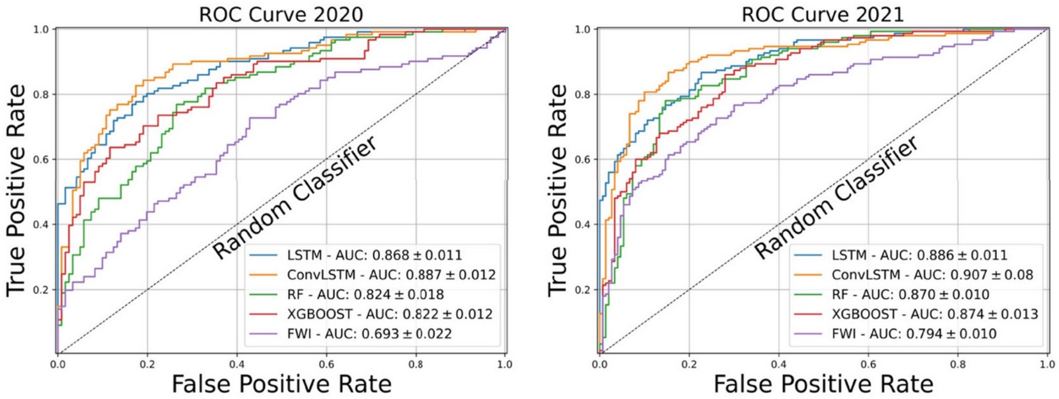
Evaluation

Models that leverage **temporal** and **spatio-temporal** data are best.

Comparison against the Fire Weather Index (FWI)

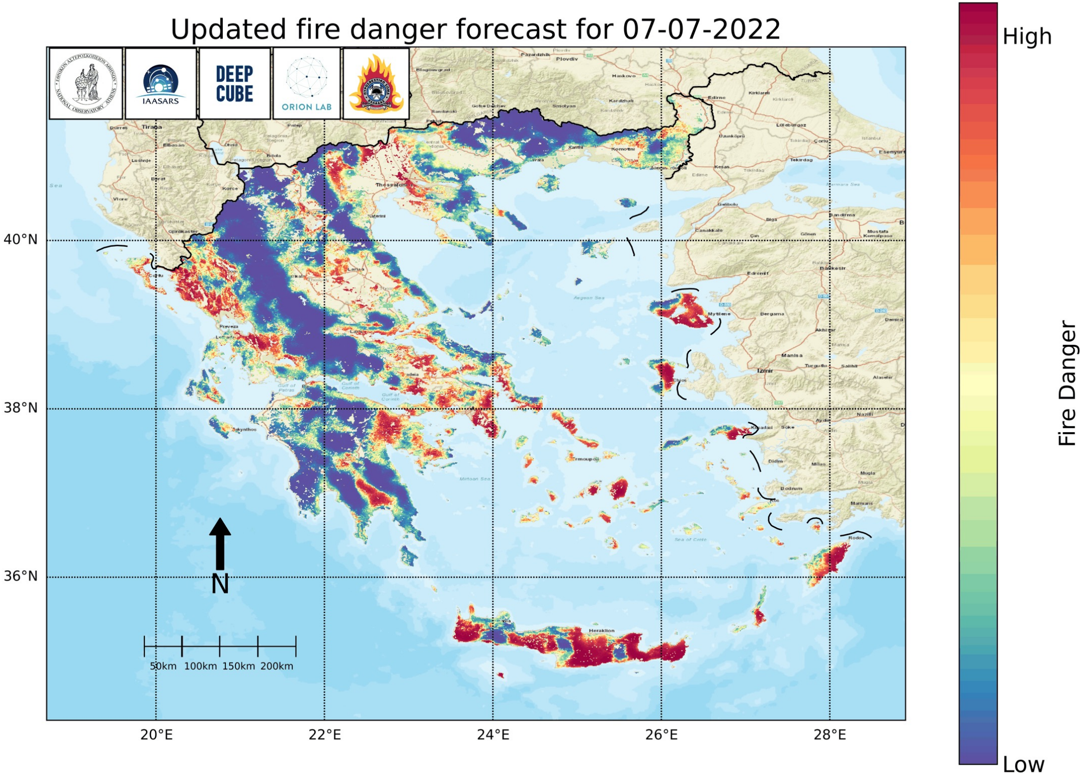
- For fires in the test set, we measure the predictive skill of each model and FWI
- Upscale all outputs to FWI's resolution

DL models are **better predictors** of large burned areas than the Fire Weather Index



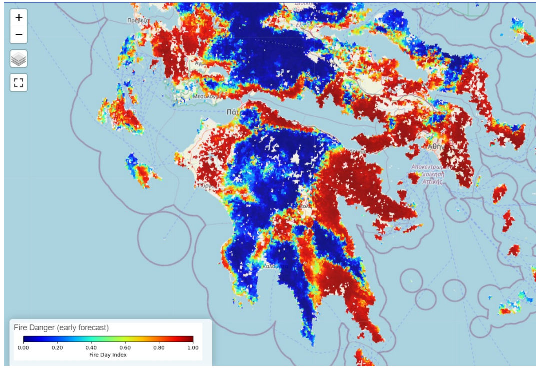
Fire Danger maps in summer 2022

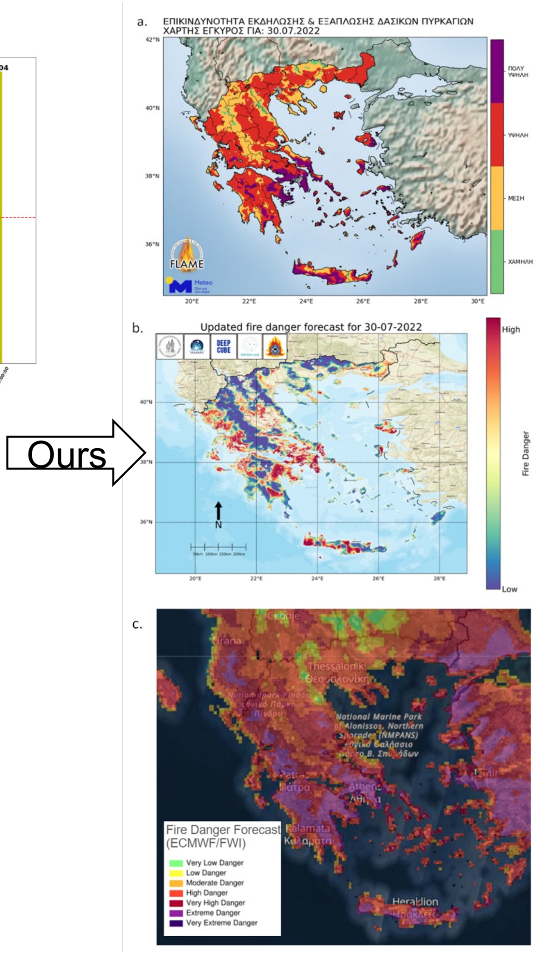
- We apply this setting with real-time data in the summer of 2022
- DL models are more biased to extreme values
- Generally higher resolution and precision than fire danger indices



Service

- **Email service for predictions** 2 times/day
- **Prototype web app** since this summer with predictions and all input variables
- In the summer 2022 high fire danger for most large fires (28/35) - **Greater precision** than existing solutions
- Very positive feedback from officials





Subseasonal to Seasonal Wildfire Forecasting

Current Status

Weather anomalies

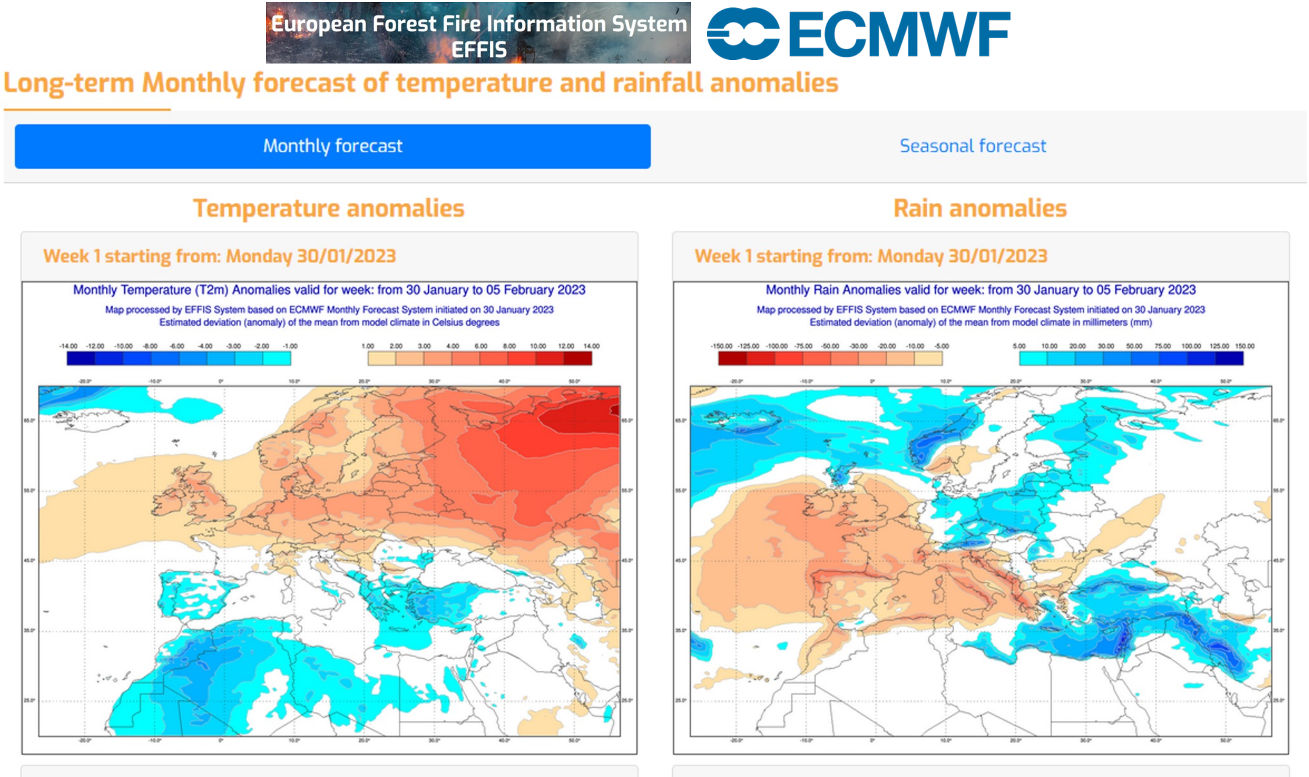
Sub-seasonal forecast

- Temperature, Rain Anomalies 1-6 weeks

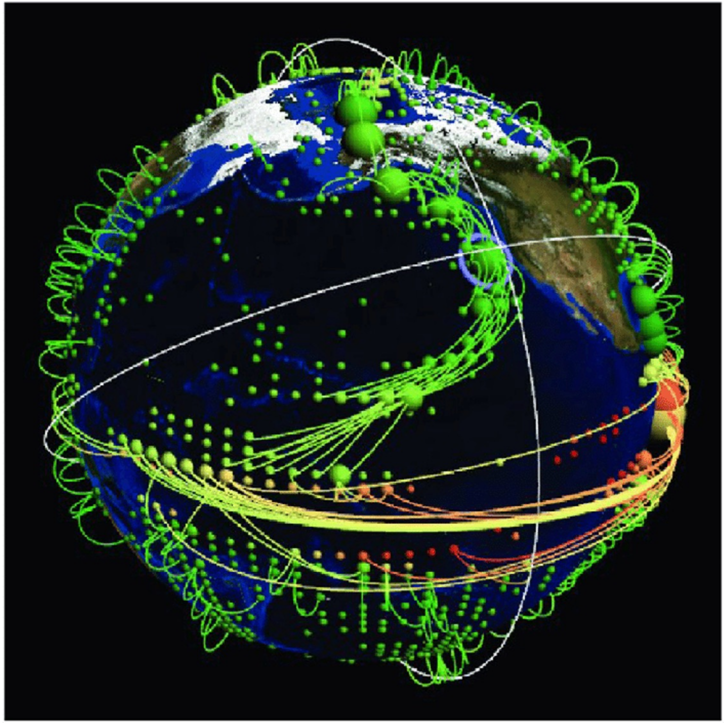
Seasonal Forecast

- Temperature, Rain Anomalies 1-6 months

For wildfire forecasting, other aspects are also important such as the vegetation, memory effects from previous seasons, human activity



Earth is a complex inter-connected system



Source: Statistical physics approaches to the complex Earth system

Teleconnections are long-range spatiotemporal connections in the earth system. *"Arctic oscillation anomalies linked to extreme wildfires in Siberia" Kim et al. (2020)*

Memory effects refer to the temporal dynamics of earth system variables. E.g. state of vegetation after previous year sustained drought.

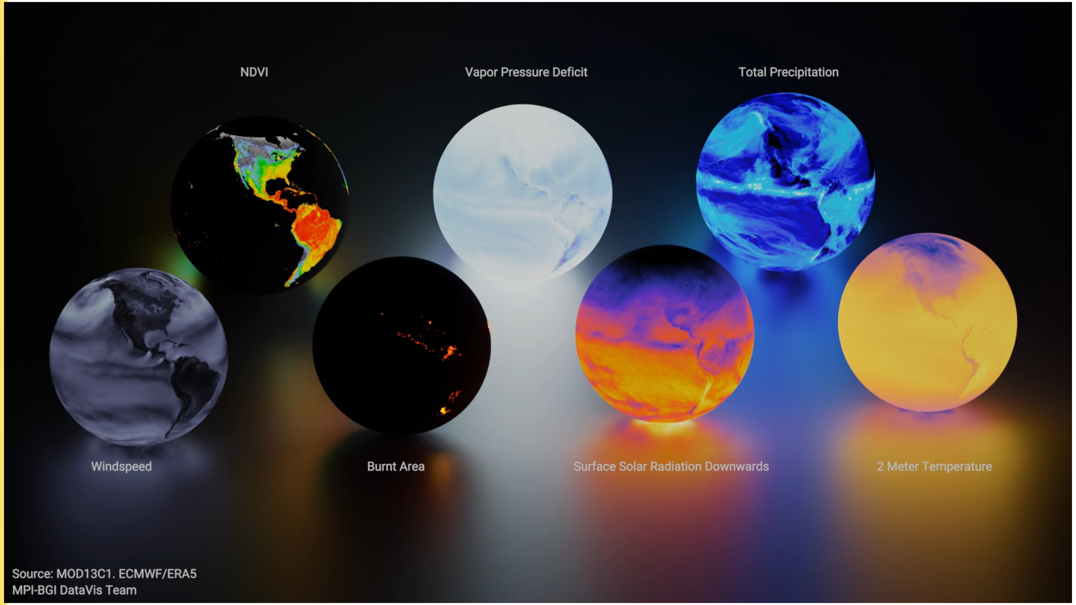
Why Machine Learning?

(a) Non-Linear Interactions: Hard to capture relationships on seasonal and sub-seasonal scales.

(b) Large Scale Datasets

(c) Modern ML methods like Transformers and Graph Neural Networks can leverage and learn from non-local variable interactions

SeasFire Datacube

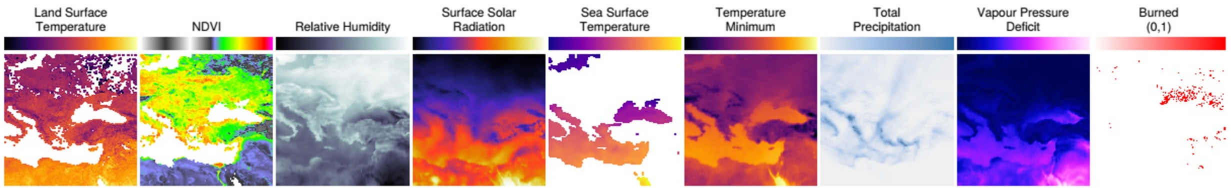


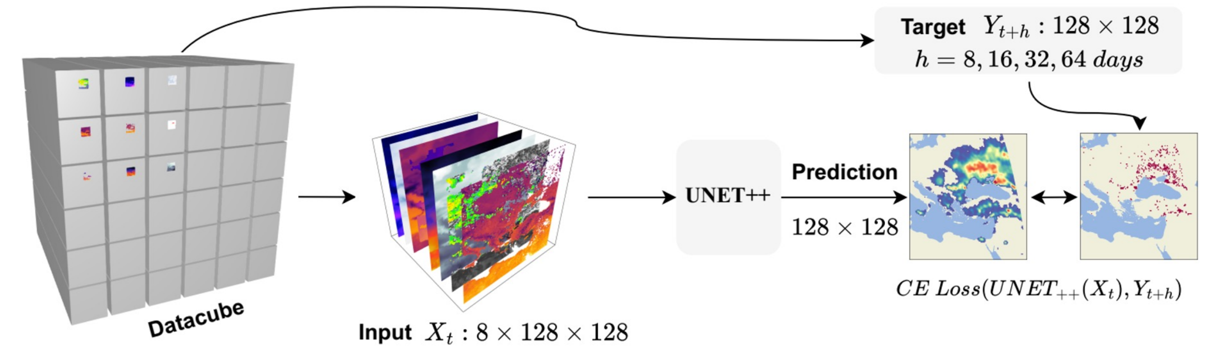
SeasFire Cube: A Global Dataset for Seasonal Fire Modeling in the Earth System [Data set]. Zenodo. [*https://doi.org/10.5281/zenodo.7108392*](https://doi.org/10.5281/zenodo.7108392)

- **Resolution**: 8days x 0.25° x 0.25°
- **Extent**: Global, 2001 - 2020
- **Wildfire drivers**
  - Meteorology (ERA5)
  - Satellite Observations (MODIS)
  - Vegetation, Surface Temperature
  - Oceanic Indices (NOAA)
  - Population Density (NASA SEDAC), Land Cover (ESA CCI)
- **Wildfire variables**
  - Burned Areas (GFED, FireCCI, GWIS)
  - Fire Emissions (GFAS)

Wildfire Forecasting as a Segmentation Task

- Input: 8 fire driver variables at time t.
  Stacked 128x128 patches
- Target: Presence of burned area at time t+h
  (h=8, 16, 32, 64 days)
- A separate UNET++ model is trained for each h
- Data split temporally:
  Training (2001 to 2017)
  Validation (2018)
  Testing (2019)





Presented in NeurIPS 2022 Workshop on Tackling Climate Change with AI

https://www.climatechange.ai/papers/neurips2022/52

Results – Quantitative

- Area Under the Precision Recall Curve and F1 more fit for imbalanced datasets
- Models' predictive skill is **better than mean seasonal cycle**
- Burned area patterns can be skillfully predicted **2 months** in advance

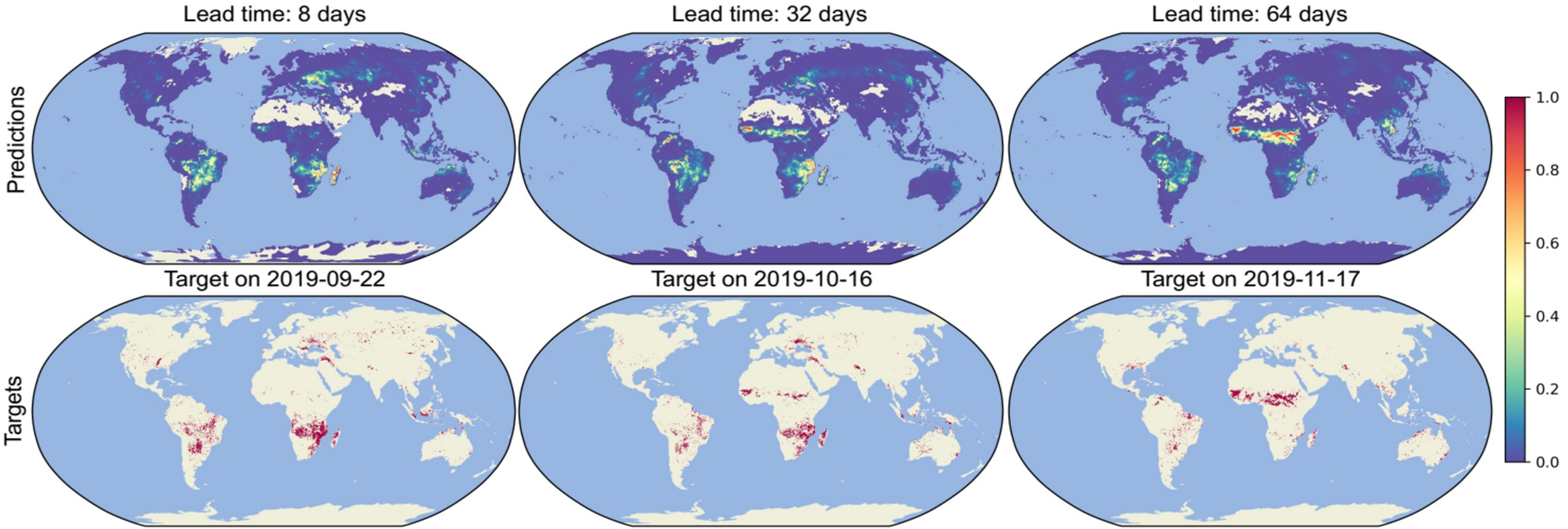
Table 1: AUPRC, F1-score for the UNET++ model forecasting with different lead times on the test dataset (year 2019). Baseline values for the weekly mean seasonal cycle also reported.

	Lead time (days)	AUPRC	F1-score	AUROC
UNET++	8	0.550	0.507	0.976
	16	0.547	0.489	0.975
	32	0.543	0.473	0.973
	64	0.526	0.424	0.971
Weekly Mean Seasonal Cycle	-	0.429	-	0.918

Results - Qualitative

Main patterns are captured

- Shift from the southern to the northern African savanna
- Reduction in fire activity in eastern Europe
- Increase in fire activity in Indochina



Main Takeaways

Machine Learning can increase the skill of wildfire danger maps

Short-term versus Long-term

- In the short-term (days), temporal context is mostly enough
- In the long-term (weeks, months), spatial context becomes important

Evaluation should be in fire danger terms

- Problem-specific metrics
- Normal versus extreme seasons
- Compare with existing tools

From research to operations

- Understand user's operations
- Data availability is an issue

Links

- Code
  - https://github.com/Orion-AI-Lab/wildfire_forecasting
  - https://github.com/SeasFire
- Data
  - FireCube: A Daily Datacube for the Modeling and Analysis of Wildfires in Greece (1.0) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.6475592
  - SeasFire Cube: A Global Dataset for Seasonal Fire Modeling in the Earth System (0.0.2) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.7108392
- Publications
  - Prapas, Ioannis, et al. "Deep learning methods for daily wildfire danger forecasting." arXiv preprint arXiv:2111.02736 (2021).
  - Kondylatos, Spyros, et al. "Wildfire danger prediction and understanding with Deep Learning." Geophysical Research Letters 49.17 (2022): e2022GL099368.
  - Prapas, Ioannis, et al. "Deep Learning for Global Wildfire Forecasting." arXiv preprint arXiv:2211.00534 (2022).

Thank you!