Deep Learning for Wildfire Danger Forecasting at Different Spatiotemporal Scales

Ioannis Prapas, *Spyros Kondylatos, Michele Ronco, Nikolaos-Ioannis Bountos, Ilektra Karasante, Zisoula Dasiou, Maria Piles, Lazaro Alonso, Dimitrios Michail, Nuno Carvalhais, Gustau Camps-Valls, Ioannis Papoutsis*

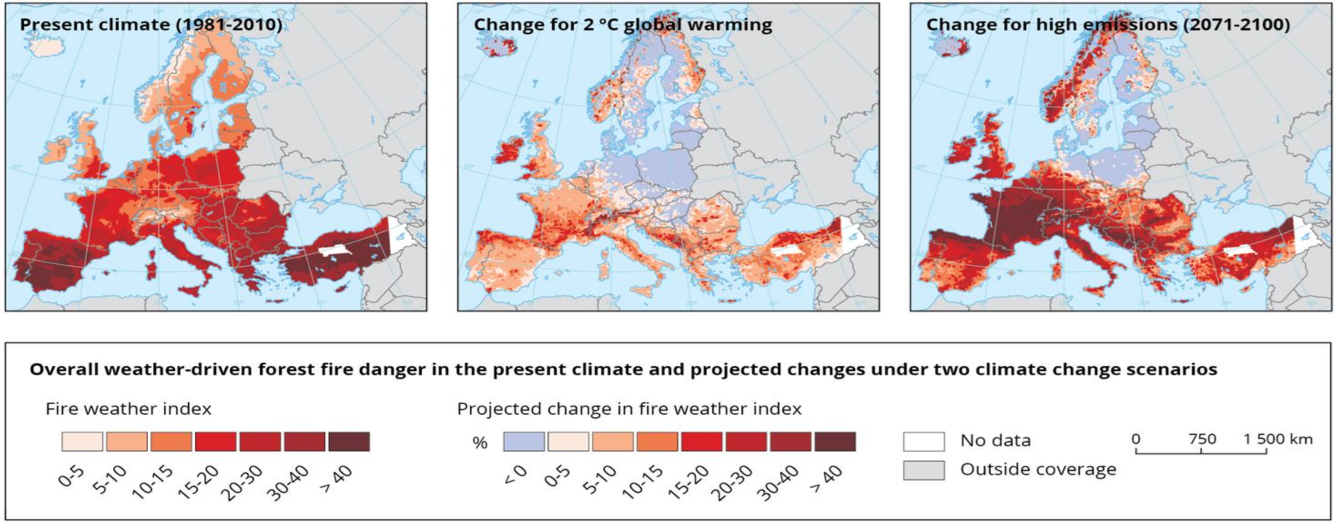
AI for Good Workshop, July 5th 2023, Geneva

Motivation

Climate change will aggravate fire danger by increasing wildfire frequency and severity

<u>Short-term forecasting</u> (hours, days)
Manage resources, squads, Plan evacuation

<u>Long-term forecasting</u> (weeks, months)
Lease equipment, Manage fuel



Fire danger in Europe under projected climate. Source: De Rigo, Daniele, et al. Forest fire danger extremes in Europe under climate change: variability and uncertainty. (2017)

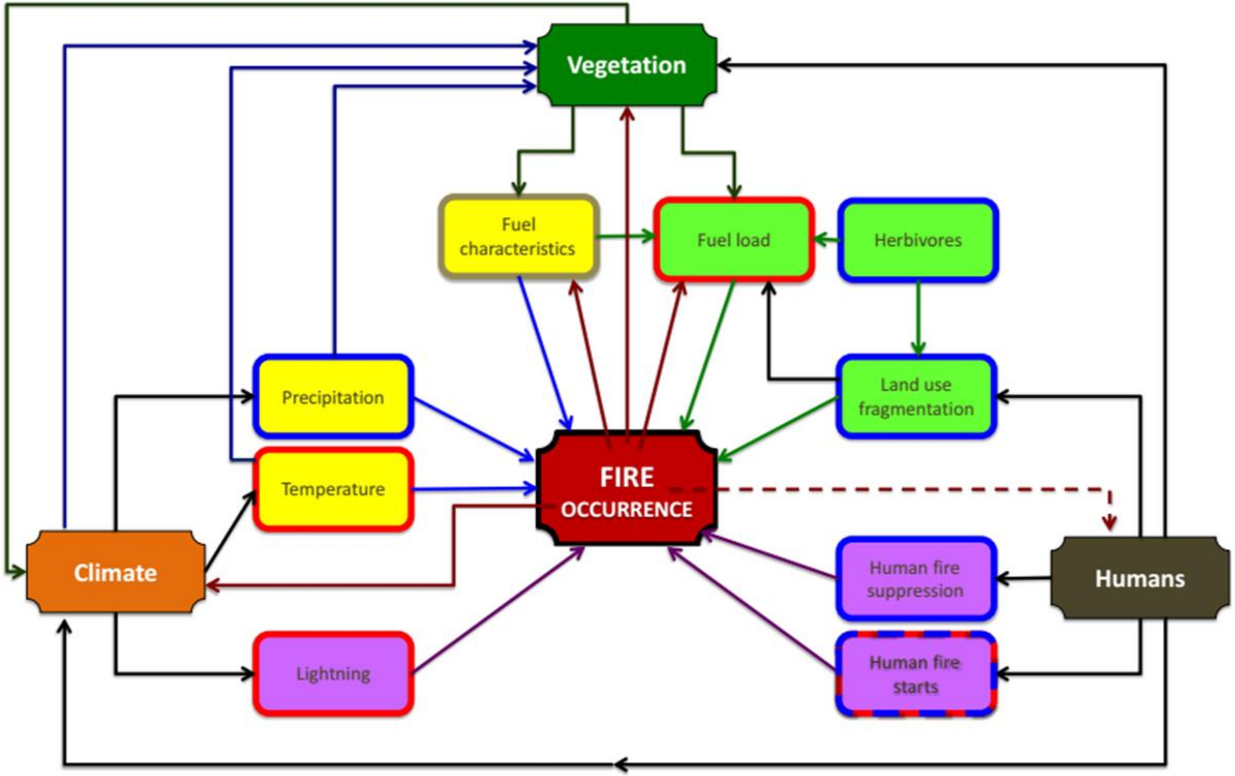
Challenges

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 with past **burned areas**



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

Short-term Wildfire Danger Forecasting

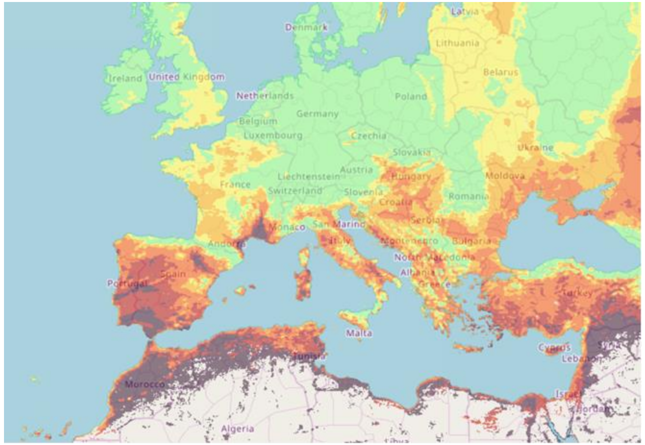
AI for Good Workshop, July 5th 2023, Geneva

Current Status

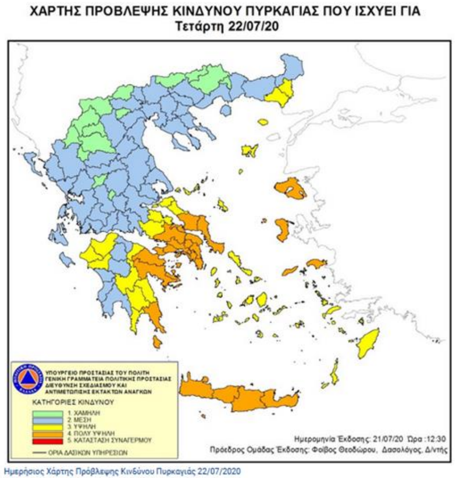
Fire Danger Forecasting in Europe

EFFIS (Fire Weather)
- Only meteo
- 8km x 8km
- Assumes pine fuel everywhere

National Danger maps
- regional level
- low resolution
- not explainable



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



Fire danger maps from Greek Civil Protection

Defining ML-based 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)

Data-driven fire danger

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

FireCube - Data Collection and Harmonization

Variables

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)

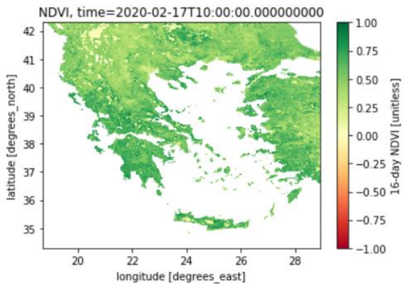
Burned areas (EFFIS)

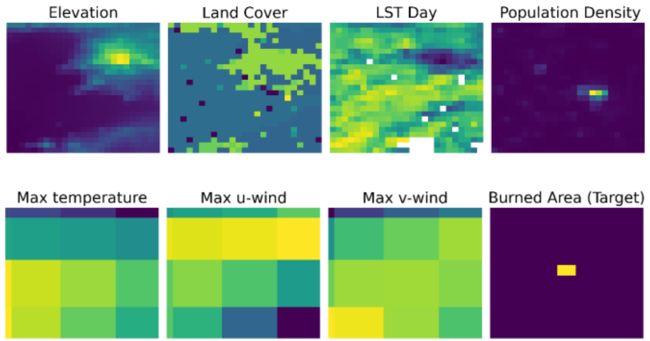
Harmonization

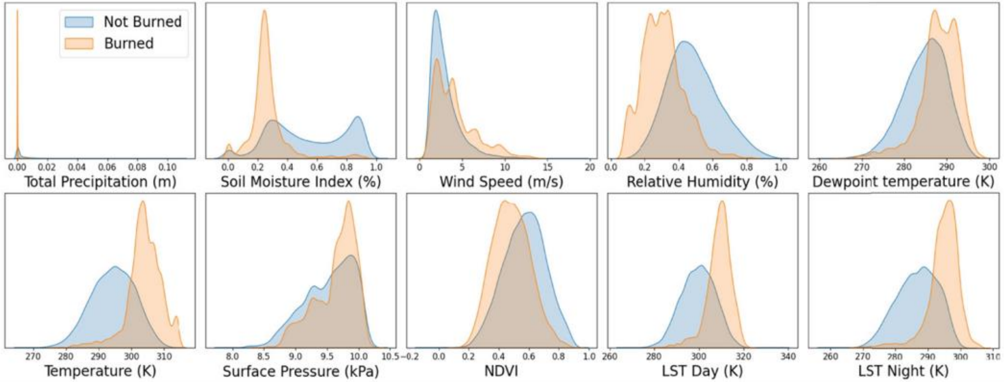
Resolution: 1km x 1km x 1day

Spatial Extent: Greece and eastern Mediterranean

Temporal Extent: 2009-2021





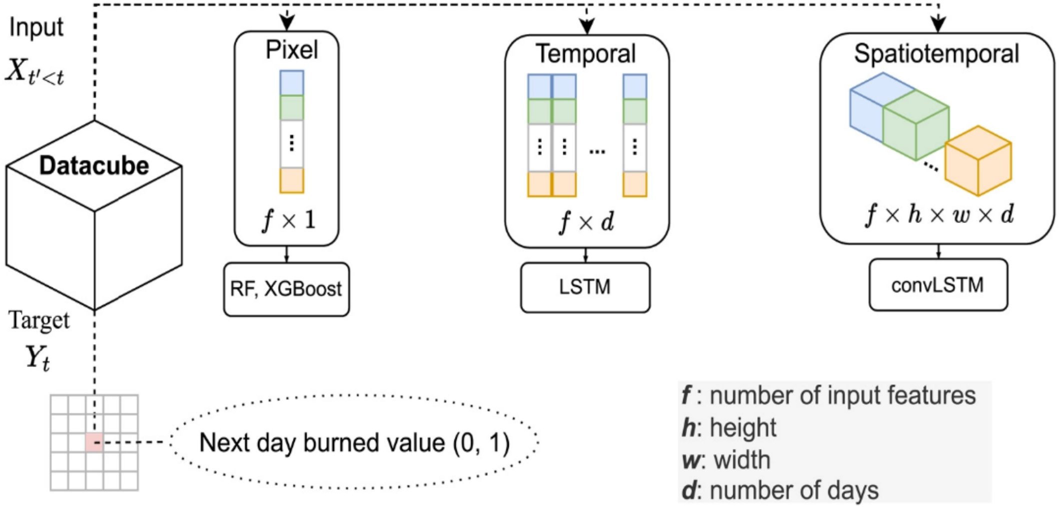


FireCube: A Daily Datacube for the Modeling and Analysis of Wildfires in Greece (1.0) [Data set]. Zenodo. [*https://doi.org/10.5281/zenodo.6475592*](https://doi.org/10.5281/zenodo.6475592)

Experimental Setup

- From the datacube we extract different types of datasets to feed to different models
  - Tabular dataset
  - Temporal Dataset
  - Spatiotemporal 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

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




Geophysical Research Letters

Research Letter | Open Access

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


arXiv > cs > arXiv:2111.02736

Computer Science > Machine Learning

[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)

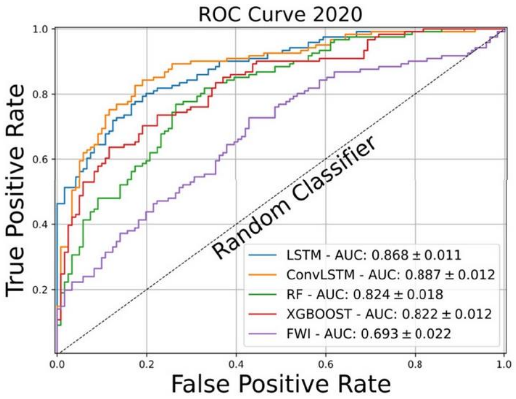
Evaluation

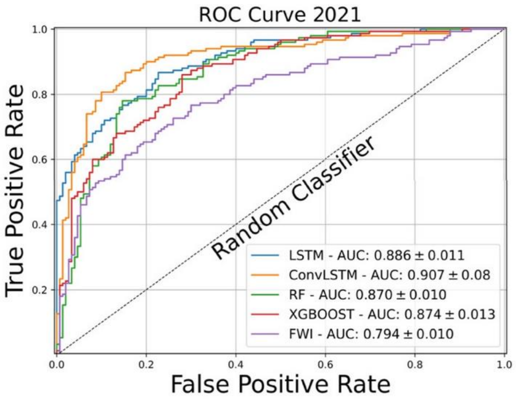
Models that leverage **temporal** and **spatiotemporal** data are best.

Comparison against the Fire Weather Index (FWI)

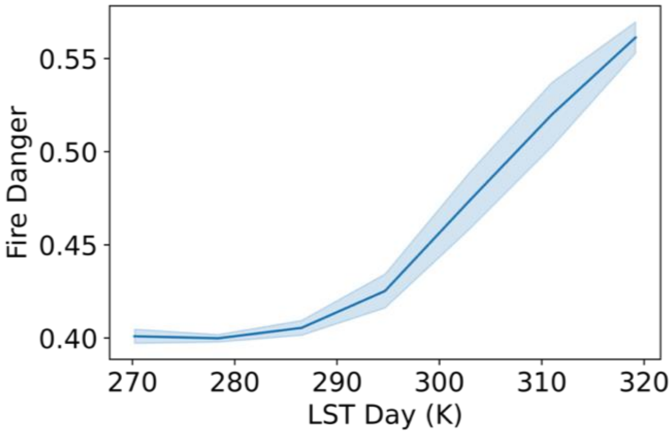
- For fires in the test set, we measure the predictive skill of each model and FWI
- Upscale all outputs to FWI's resolution

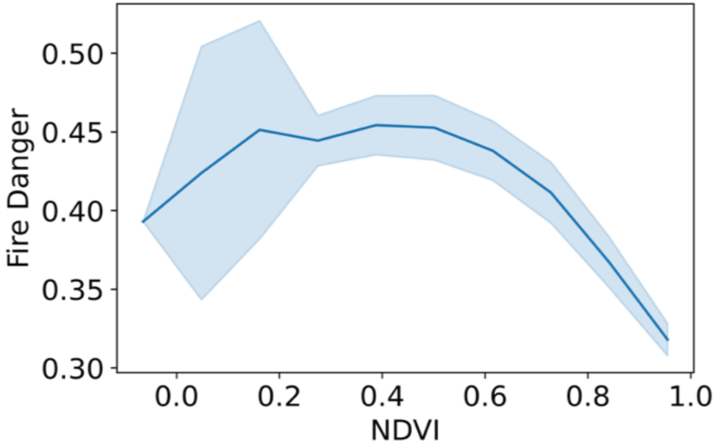
DL models are **better predictors** of large burned areas than the Fire Weather Index

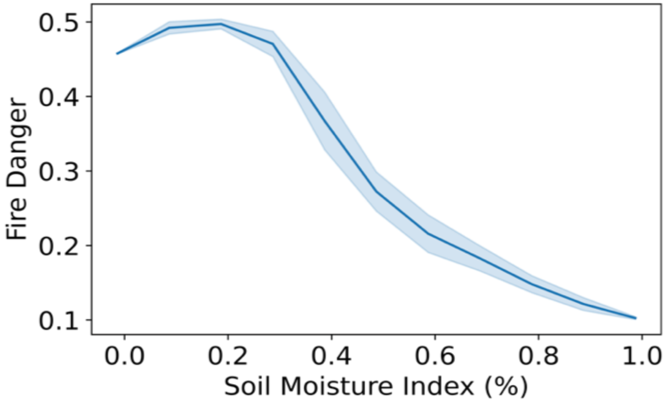


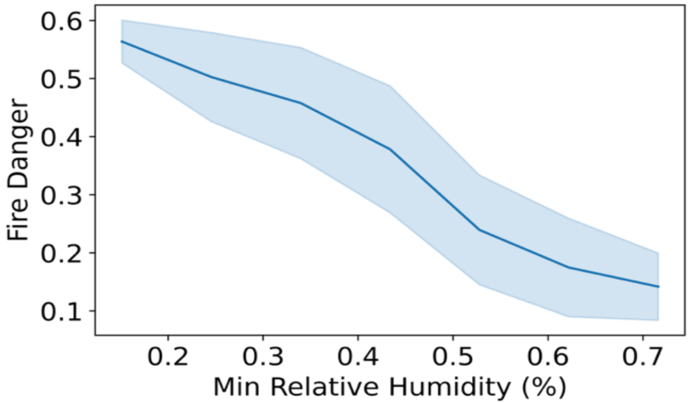


Explainability: partial dependencies



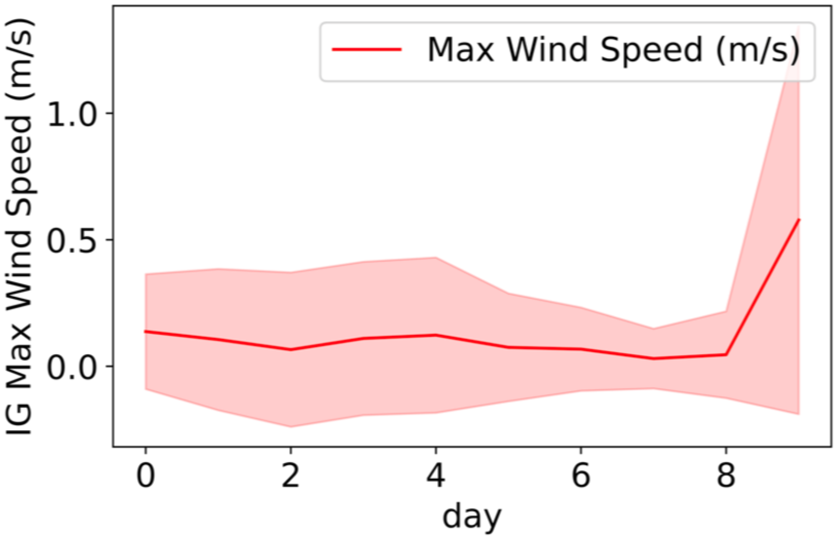






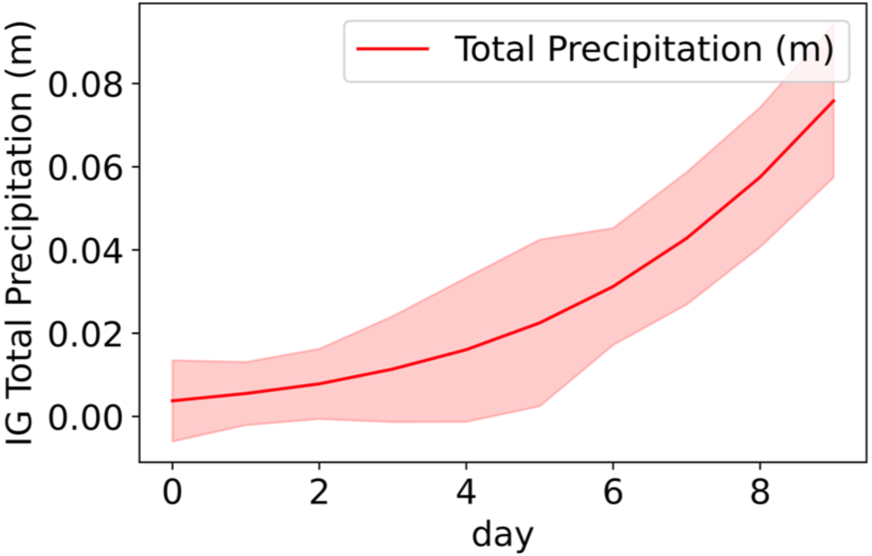
Explainability: temporal contribution

[Sundararajan, et al., Axiomatic Attribution for Deep Networks, ICML 2017]



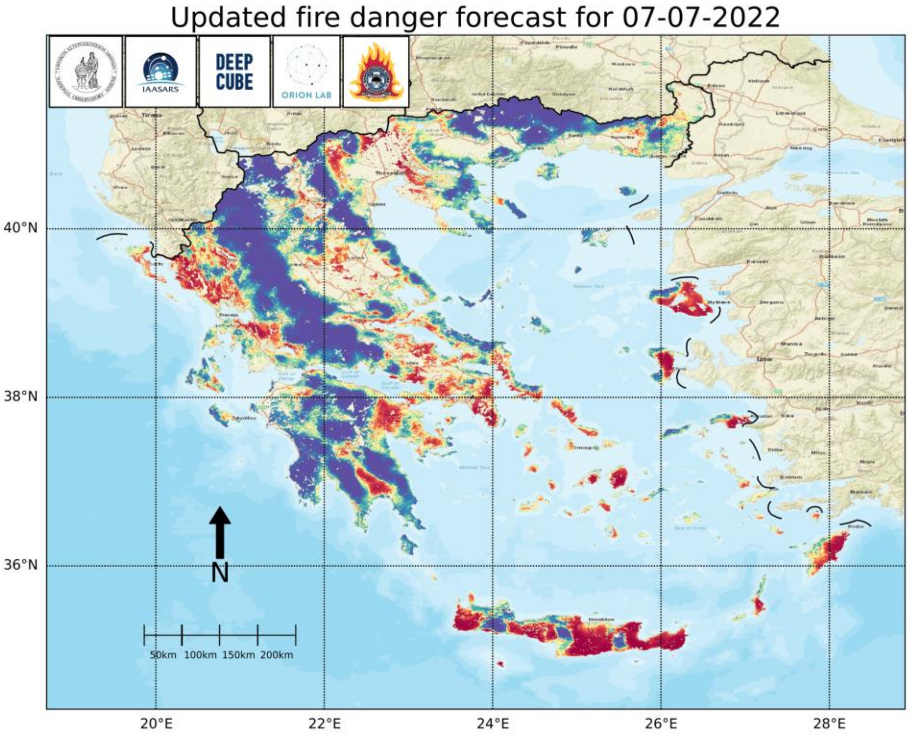
Sudden-onset activation: instantaneous effects

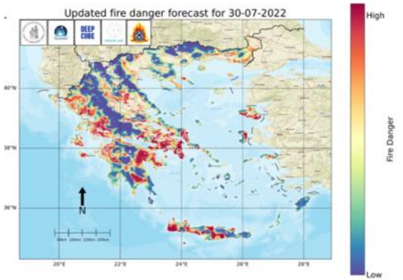
Slow-onset activation: accumulation effects

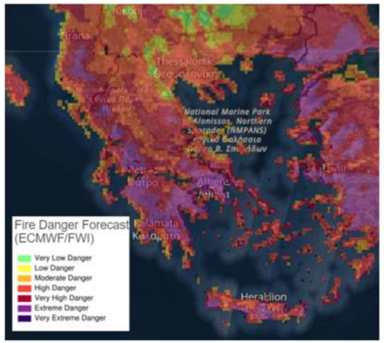


Fire Danger maps in summer 2022

- We apply this setting with real-time data in the summer of 2022
- Generally higher resolution and precision than fire danger indices
- Evaluation from officials







Coming Next: Scaling up to the Mediterranean

AI for Good

Mediterranean Datacube (Mesogeos)

Specifications

- Resolution: 1km x 1km x 1-day
- Temporal extent: 2006 - 2022
- Shape: {time: 7488, x: 4714, y: 1752}
- 28 variables related to wildfires
- In-memory size 5.5 TB

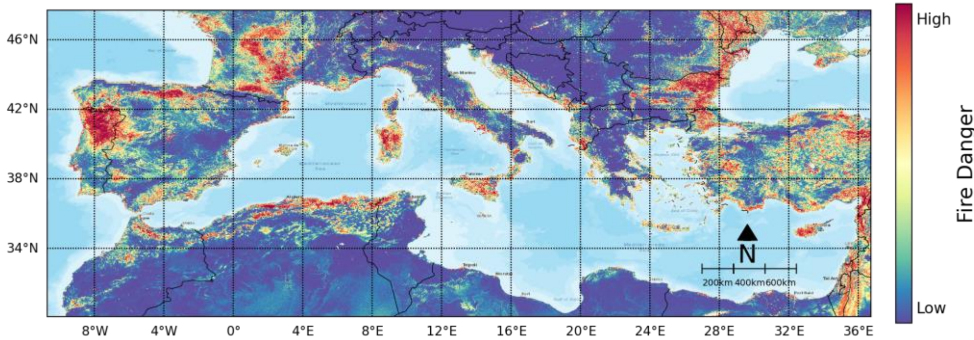
Uses: Modeling Wildfire Danger, Susceptibility, Spread, Extreme wildfires

orion-ai-lab.github.io/mesogeos/

Mesogeos: A multi-purpose dataset for data-driven wildfire modeling in the Mediterranean

Spyros Kondylatos (1, 2), Ioannis Prapas (1, 2), Gustau Camps-Valls (2), Ioannis Papoutsis (1)
(1) Orion Lab, IAASARS, National Observatory of Athens
(2) Image & Signal Processing Group, Universitat de València

Paper | Dataset | Code | arXiv



Mediterranean-scale fire danger prediction

Subseasonal to Seasonal Wildfire Forecasting

AI for Good Workshop, July 5th 2023, Geneva

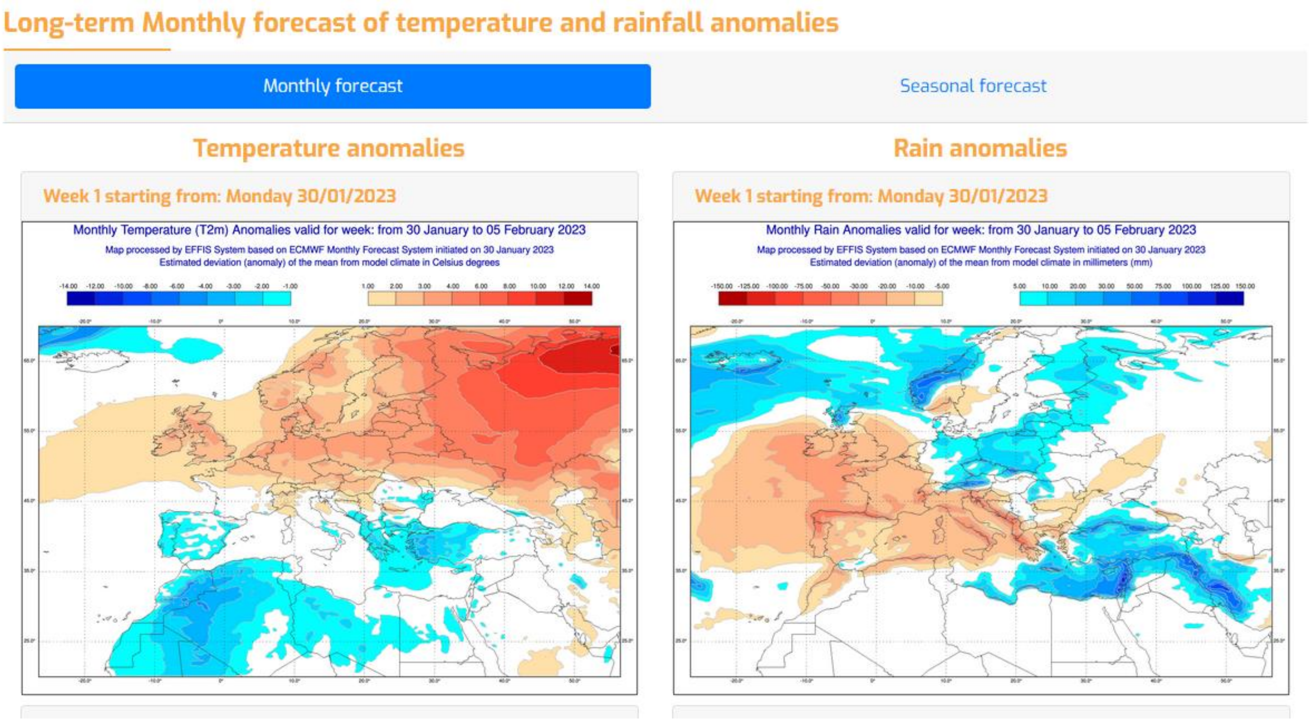
Current Status - Long-term weather anomalies

Sub-seasonal forecast

- Temperature, Rain Anomalies 1-6 weeks

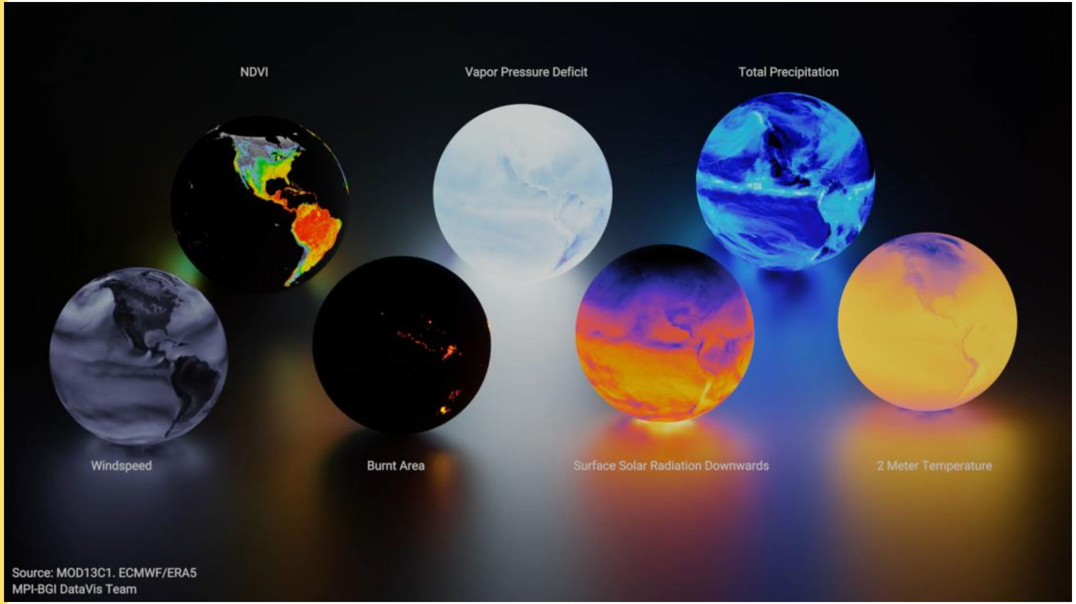
Seasonal Forecast

- Temperature, Rain Anomalies 1-6 months



EFFIS long-term forecasts *https://effis.jrc.ec.europa.eu/apps/effis.longterm.forecasts/*

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*

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

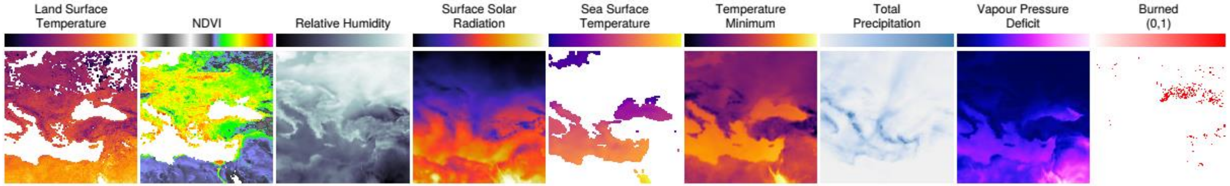
- Input: 8 fire driver variables at time t.
  Stacked 128x128 patches
- Target: Presence of burned area at time t+h
  (h=8, 16, 32, 64 days)
- A separate U-Net++ model is trained for each h
- Data split temporally:
  Training (2001 to 2017)
  Validation (2018)
  Testing (2019)

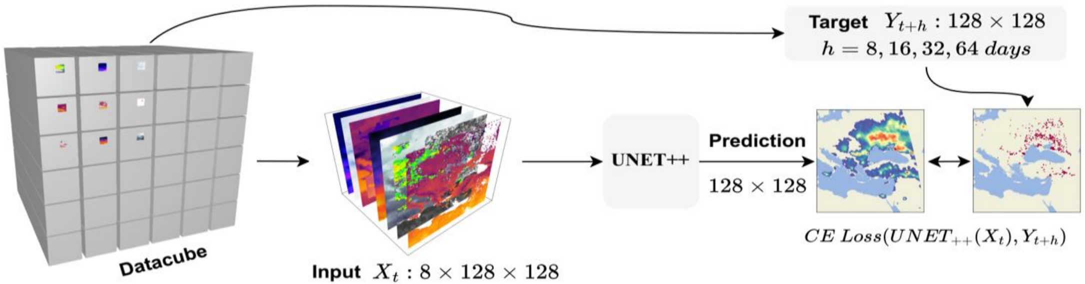
Presented in NeurIPS 2022 Workshop on Tackling Climate Change with AI

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

Deep Learning for Global Wildfire Forecasting

Ioannis Prapas[1,2], Akanksha Ahuja[1], Spyros Kondylatos[1,2], Ilektra Karasante[1], Eleanna Panagiotou[3], Lazaro Alonso[4], Charalampos Davalas[3], Dimitrios Michail[3], Nuno Carvalhais[4], and Ioannis Papoutsis[1]





Results – Quantitative

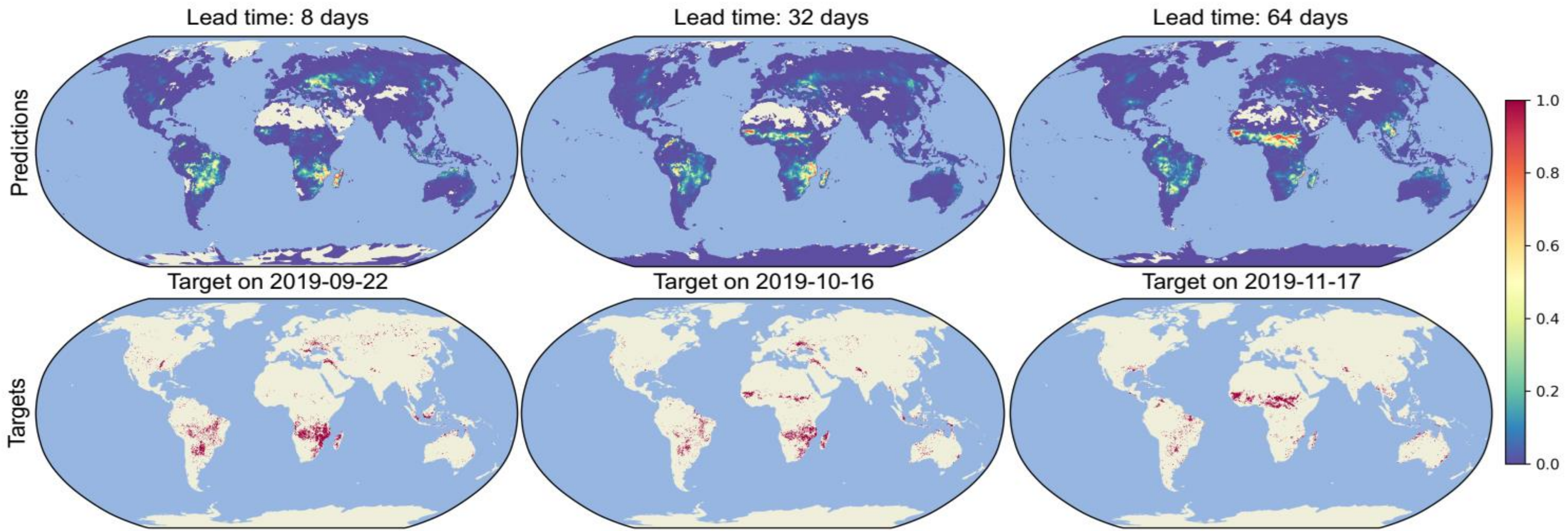
- Performance decreases as the forecasting window increases
- Models' predictive skill is **better than mean seasonal cycle**
- Burned area patterns can be skillfully predicted **2 months** in advance

	Lead time (days)	AUPRC
UNET++	8	0.550
	16	0.547
	32	0.543
	64	0.526
Weekly Mean Seasonal Cycle	-	0.429

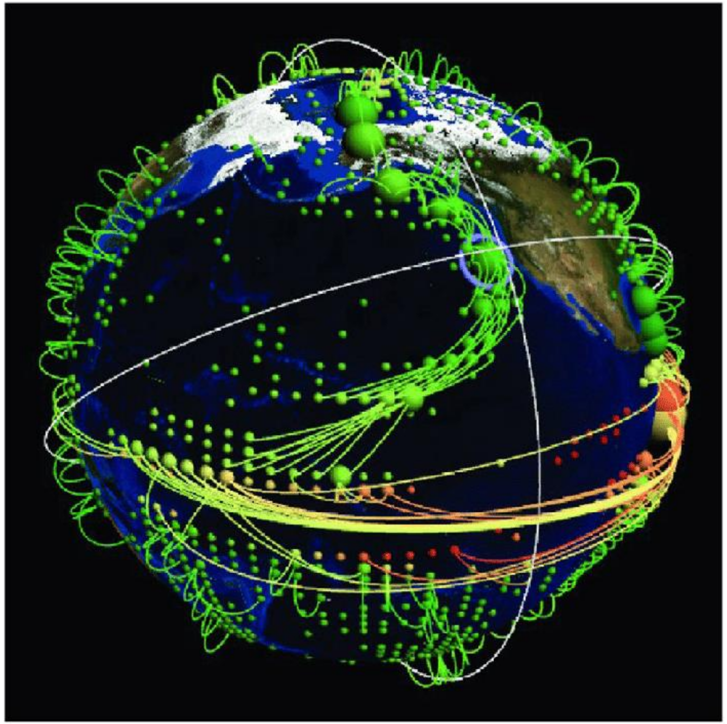
Results – Qualitative

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



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.

We need models that are able to capture large-scale spatiotemporal interactions that are omnipresent in the Earth System

Teleconnections modulate global wildfires

npj climate and atmospheric science
www.nature.com/npjclimatsci

ARTICLE OPEN
Check for updates

Arctic Oscillation and Pacific-North American pattern dominated-modulation of fire danger and wildfire occurrence

Flavio Justino[1], David H. Bromwich[2], Vanucia Schumacher[3], Alex daSilva[4] and Sheng-Hung Wang[2]

RESEARCH ARTICLE | CLIMATOLOGY

Extensive fires in southeastern Siberian permafrost linked to preceding Arctic Oscillation

Jin-Soo Kim[1,2], Jong-Seong Kug[3,*], Su-Jong Jeong[4,5], Hotaek Park[6] and Gabriela Schaepman-Strub[7]
+ See all authors and affiliations

Science Advances 08 Jan 2020:
Vol. 6, no. 2, eaax3308
DOI: 10.1126/sciadv.aax3308

nature communications

Article
https://doi.org/10.1038/s41467-023-3605

Climate teleconnections modulate global burned area

Received: 31 March 2022
Accepted: 12 January 2023

Adrián Cardil[1,2,3], Marcos Rodrigues[4,5], Mario Tapia[2], Renaud Barbero[6], Joaquin Ramírez[2], Cathelijne R. Stoof[7], Carlos Alberto Silva[8], Midhun Mohan[9] & Sergio de-Miguel[1,3]

Environmental Research Letters

PAPER

How much global burned area can be forecast on seasonal time scales using sea surface temperatures?

Yang Chen[1], Douglas C Morton[2], Niels Andela[2], Louis Giglio[3] and James T Randerson[1]
[1] Department of Earth System Science, University of California, Irvine, CA 92697, USA
[2] Biospheric Sciences Branch, NASA Goddard Space Flight Center, Greenbelt, MD 20771, USA
[3] Department of Geographical Sciences, University of Maryland, College Park, MD 20742, USA
E-mail: yang.chen@uci.edu

TeleViT: Teleconnection-driven Vision Transformer

- TeleViT combines fine grained local input with
  - Coarsened global input
  - Climatic indices
- Different inputs are independently tokenised
- Tokens are fed to a transformer network

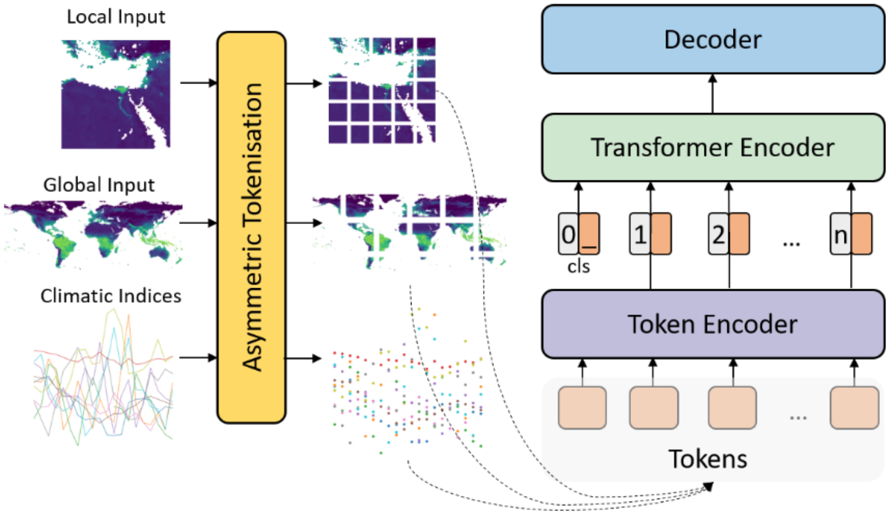


Figure 1. Full pipeline of the TeleViT architecture. The different multi-scale inputs *i.e.* local, global and teleconnection indices, are tokenized at different resolutions and fed to a Transformer encoder along with a prepended classification token. The linear decoder is based on the output of the classification token.

Results

- Vanilla ViT* is mostly better than the U-Net++ baseline
- Teleconnection-driven transformers better performance, especially for longer temporal horizons
- Best performance from TeleViT with oceanic indices and global input

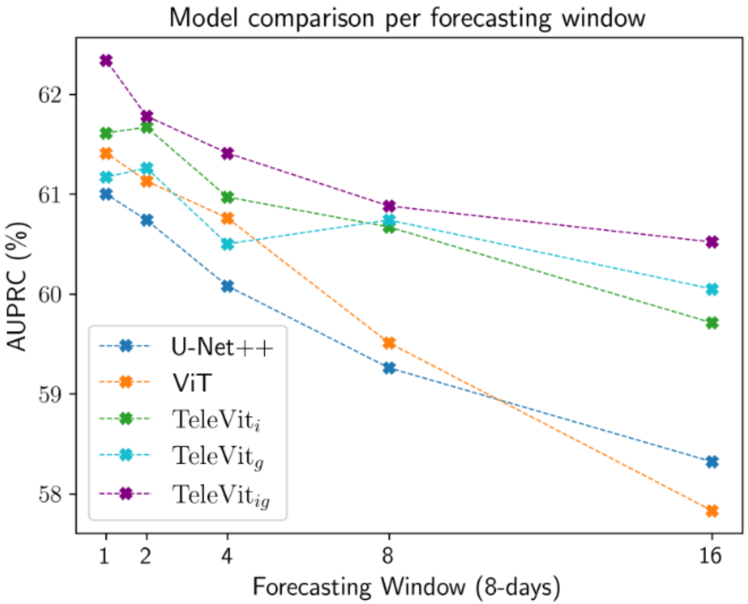
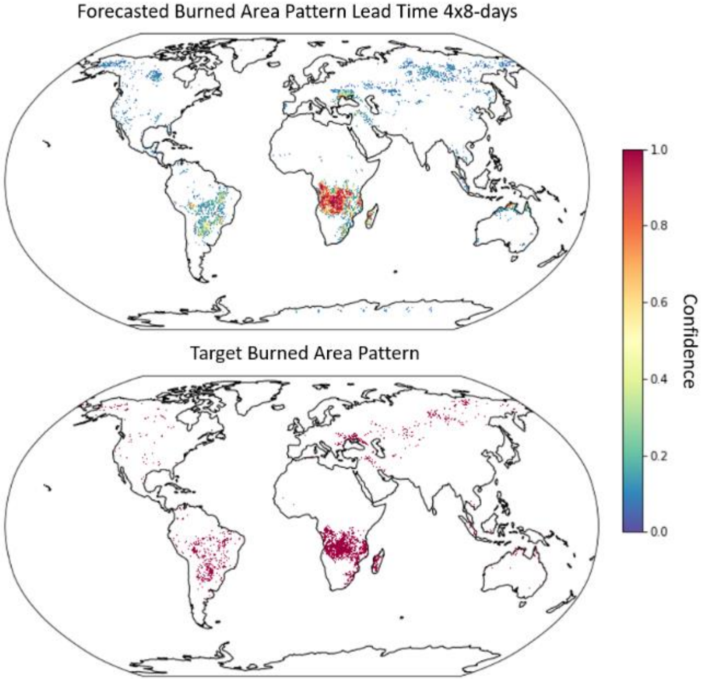


Figure 2. AUPRC performance of the different models for forecasting windows of 1, 2, 4, 8 and 16×8-days in advance.

*Dosovitskiy, Alexey, et al. "An image is worth 16x16 words: Transformers for image recognition at scale."

Results



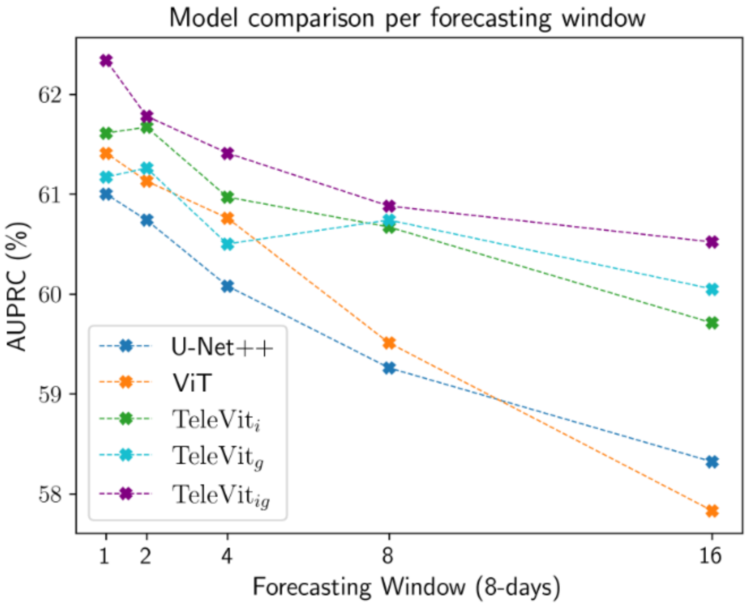


Figure 2. AUPRC performance of the different models for forecasting windows of 1, 2, 4, 8 and 16×8-days in advance.

Discussion and Next Steps (Long-term Forecasting)

- Deep Learning models are promising for global burned area forecasting
- Teleconnection-informed models can improve long-term forecasting capabilities
- Future work
  - Improve evaluation, use more baselines
  - Relative importance of the indices and the global input
  - Examine attribution, e.g. attentions maps
  - Time-series for local and global input
  - Beyond burned area pattern forecasting

Main Takeaways

Machine Learning can increase the skill of wildfire danger predictions

Short-term versus Long-term forecasting

- 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 against existing tools

Open Science

Code

- https://github.com/Orion-AI-Lab
- 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 (0.3.0) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.7108392

Papers

- 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).
- Kondylatos, Spyros, et al. "Mesogeos: A multi-purpose dataset for data-driven wildfire modeling in the Mediterranean." *arXiv preprint arXiv:2306.05144* (2023).
- Prapas, Ioannis, et al. "TeleViT: Teleconnection-driven Transformers Improve Subseasonal to Seasonal Wildfire Forecasting." *arXiv preprint arXiv:2306.10940* (2023).

Thank you!