

# SeasFire

## Earth System Deep Learning towards a Global Digital Twin of Wildfires

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Max Planck Institute  
for Biogeochemistry



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# Vision - A digital twin of wildfires

## Monitoring

- Detection, nowcasting

## Causality

- Effect of the human activities, climate change

## Anticipation

- Extreme Events
- Interannual variability

## Simulation (What-if scenarios)

- Assessing the impact of land use changes
- Assessment of wildfire practices, policies

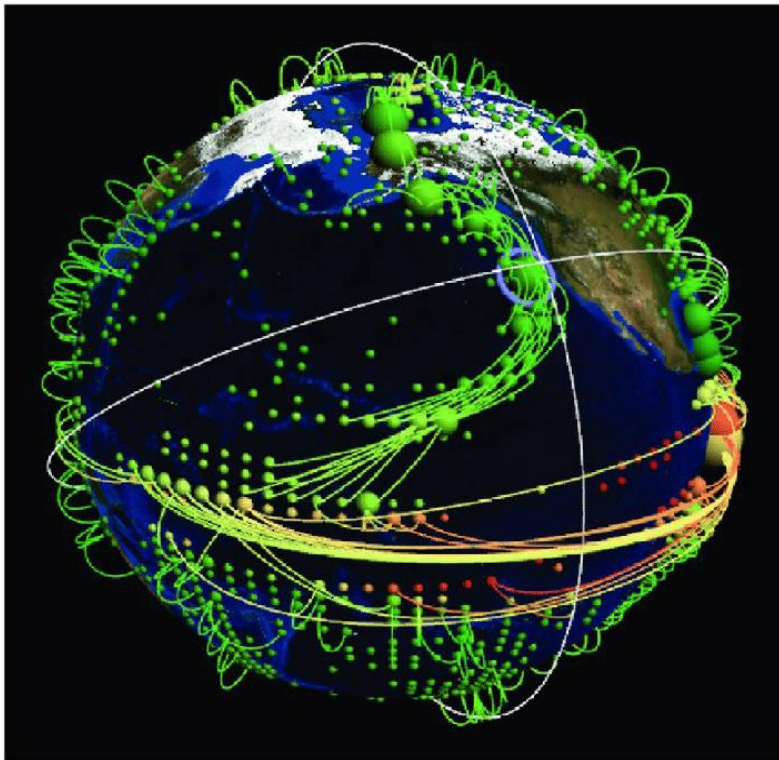
## Impact Quantification

- Interaction with other twins
- Ecosystem damage and recovery



A digital twin of wildfires imagined by Stable Diffusion

# Earth is a complex interconnected system



Fan, Jingfang, et al. "Statistical physics approaches to the complex Earth system." *Physics reports* 896 (2021): 1-84.

**Teleconnections** are long-range spatio-temporal 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. Vegetation drought response after previous year drought.

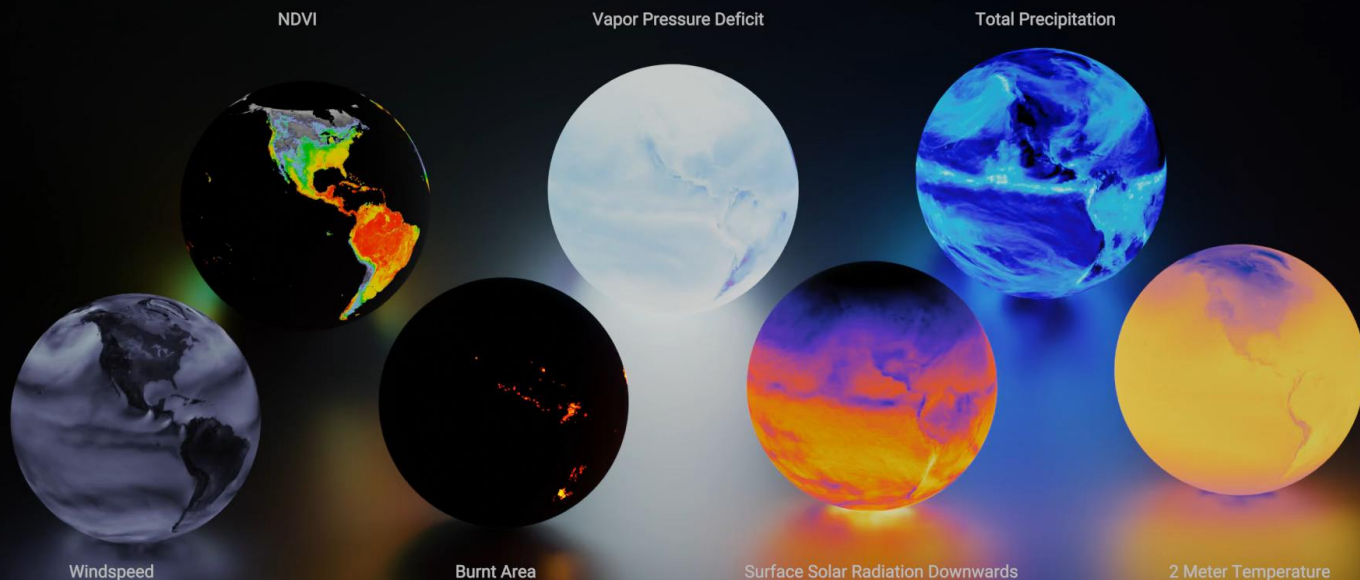
Why Deep Learning?

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

(b) ML works well with large-scale datasets

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

# SeasFire DataCube as a test-bed for wildfire twinning



**Resolution:** 8dx0.25°x0.25°

(Sub-seasonal to Seasonal)

**Extent:** Global, 2001 - 2020

## Fire drivers

Meteorology (ERA5)

Satellite Observations

(MODIS) - NDVI, LST

Oceanic Indices (NOAA)

Population Density

Land Cover (ESA CCI)

## Fire products

Burned Areas

(GFED, FireCCI, GWIS)

Fire Emissions (GFAS)

Source: MOD13C1, ECMWF/ERA5  
MPI-BGI DataVis Team

# Datacube Demonstration

Cloud-optimized zarr dataset

Rapid analytics without downloading the dataset

Can associate fire drivers to wildfires around the world



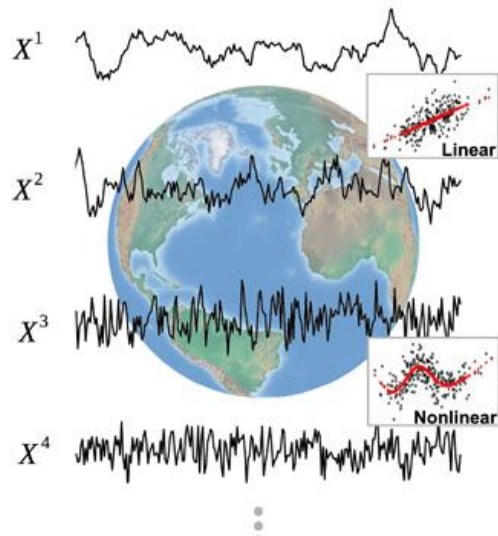
The screenshot shows a JupyterLab environment with the following content:

- File Explorer: Exploring\_the\_SeasFire\_Cube.ipynb
- Menu: File Edit View Insert Runtime Tools Help All changes saved
- Code Cell: `ds = xr.open_zarr('/content/drive/MyDrive/orionlab_datasets/seasfire.zarr')`
- Output: `xarray.Dataset` with dimensions (latitude: 720, longitude: 1440, time: 966), coordinates (3), data variables (54), indexes (3), and attributes including CRS (EPSG:4326) and a detailed description of the SeasFire Cube dataset.
- Next Step: Plot the NDVI of a particular 8-day period

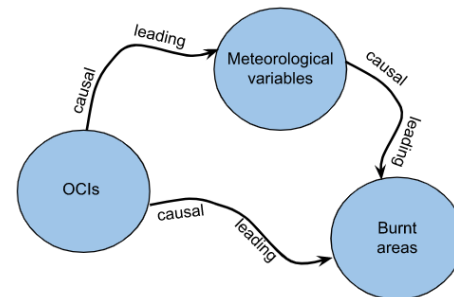
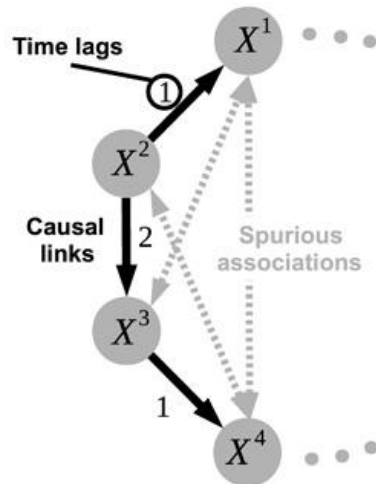


# Causal Analysis

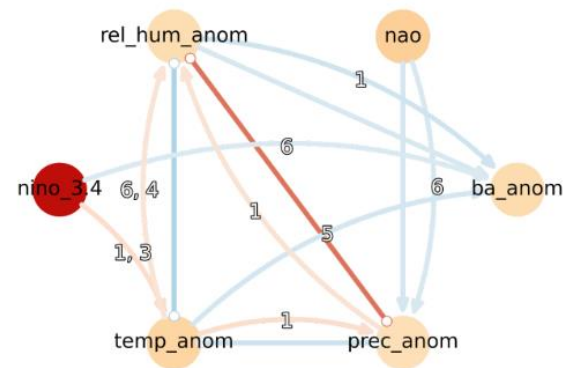
## A Large-scale time series dataset



## B Causal discovery



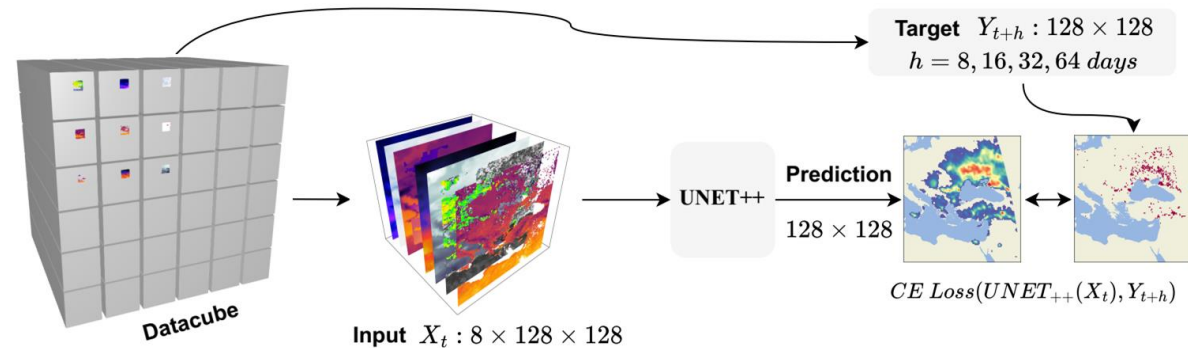
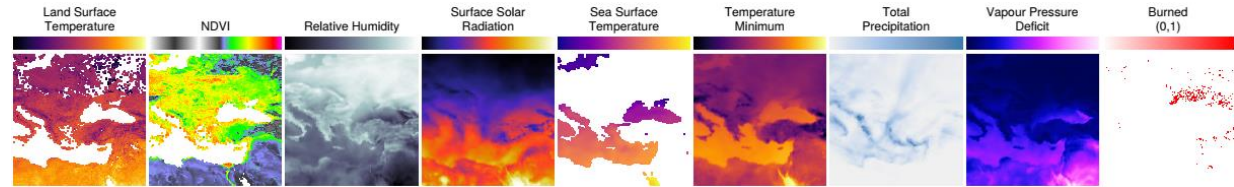
Mediterranean Forests, Woodlands & Scrub of Europe



Runge, Jakob, et al. "Detecting and quantifying causal associations in large nonlinear time series datasets." *Science advances* 5.11 (2019): eaau4996.

# Burned Area Forecasting

- **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>

# Global Prediction Maps

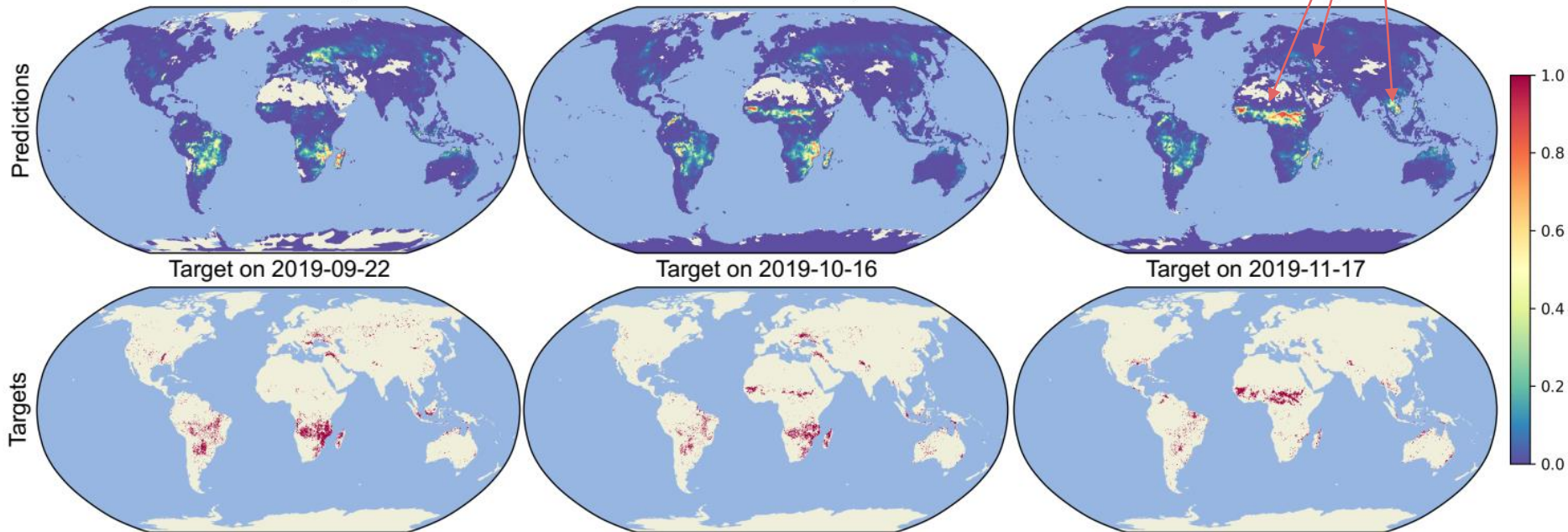
Captured change of fire activity in eastern Europe and south-east Asia, shift from the southern to the northern African savanna.

- Main patterns shifts are captured
- Predictive skill better than the mean seasonal cycle
- Sub-second global inference

Lead time: 8 days

Lead time: 32 days

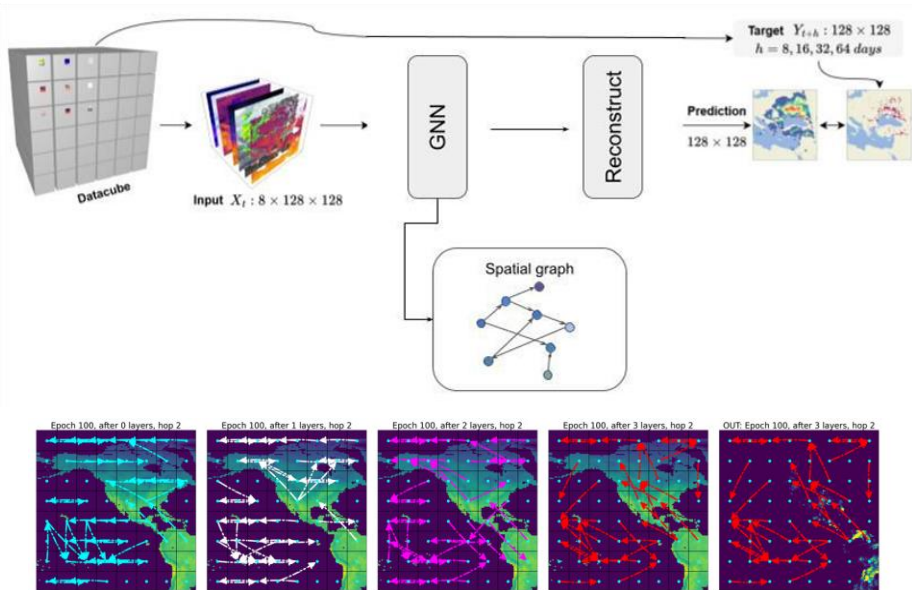
Lead time: 64 days





# Earth System DL: Leveraging non-local interactions

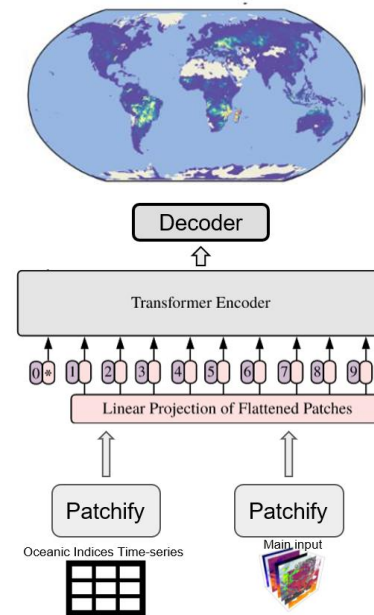
## Graph Neural Networks



### Learned edges of GNN hints into model's inner workings

Y. Wang, Y. Sun, Z. Liu, S. E. Sarma, M. M. Bronstein, and J. M. Solomon, 'Dynamic Graph CNN for Learning on Point Clouds'. (2019).

## Transformer models



### Better performance when adding info from oceanic indices.

Dosovitskiy, Alexey, et al. "An image is worth 16x16 words: Transformers for image recognition at scale." (2020).

# Main Takeaways

- SeasFire cube can serve as a test bed for digital twin models of wildfires (for sub-seasonal to seasonal scales)
- Deep Learning can increase our ability to forecast and simulate wildfires
- Modeling the earth as a system can enhance our understanding of large-scale processes

## Links

SeasFire Project: <https://seasfire.hua.gr>

Preprint: <https://arxiv.org/abs/2211.00534>

SeasFire Cube: <https://zenodo.org/record/7108392>

Tutorials: <https://github.com/SeasFire/seasfire-datacube>