Earth System Deep Learning for Global Wildfire Forecasting

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Introduction

- In the context of climate change it is **crucial to understand fire in the Earth System.**
- **Earth is one interconnected system (Figure 1)**. Large-scale processes have an effect on the global climate and fire seasons [1, 2].
- **Deep Learning methods can help anticipate fire activity**, e.g. deep learning for short-term wildfire forecasting at national scale [3].

Contributions

- We gather a **global dataset with fire drivers and burnt areas (Figure 2) from 2001 to 2021 [4]**.
- Initial experiments, forecasting burned area as a segmentation task, **show high predictive skill of Deep Learning models [5]**.
- We propose the use of Deep Learning methods that treat the Earth as an interconnected system to forecast burned areas and quantify teleconnections that impact fire.

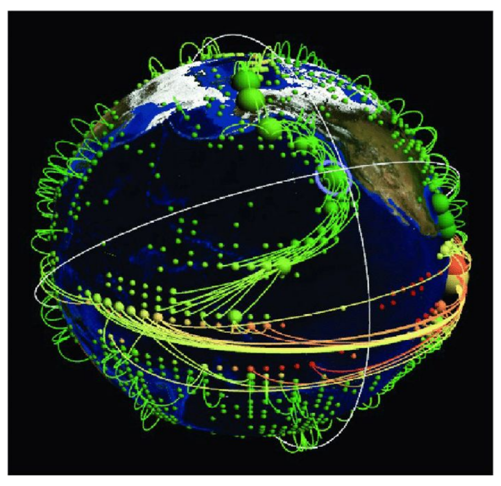
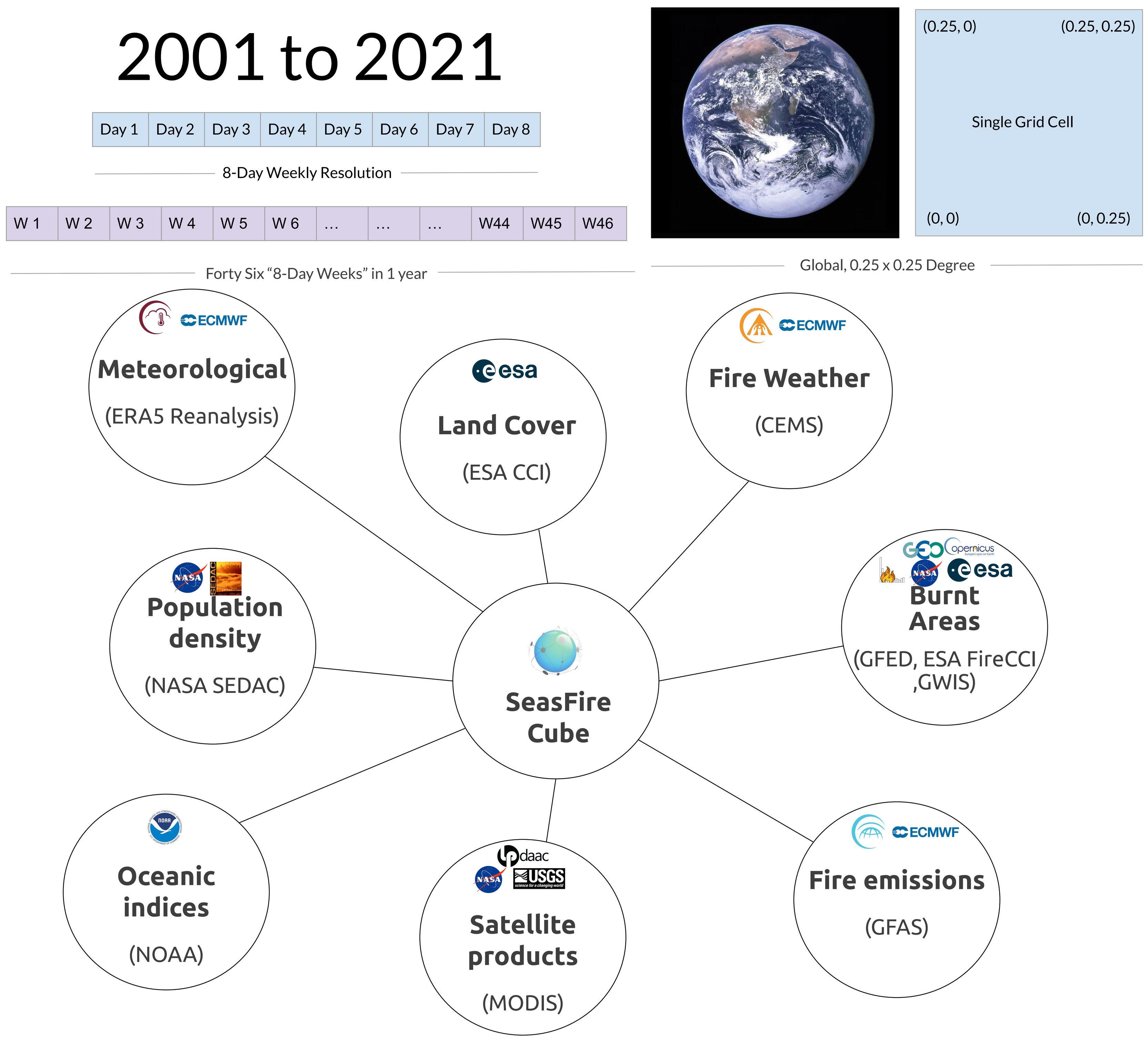


Figure 1: Visualization of a climate network with teleconnections [1].

SeasFire Cube

- An **open-access datacube [4]** for modeling global wildfires and their impacts.
- Global variables containing **burnt areas, wildfire-related emissions**, and fire drivers such as the **meteorology, vegetation, land cover, population density and oceanic indices**.
- At a common spatiotemporal grid **0.25° x 0.25 ° x 8-days,** covering years **2001 to 2021.** (will be made available at 1° x 1° spatial resolution as well)



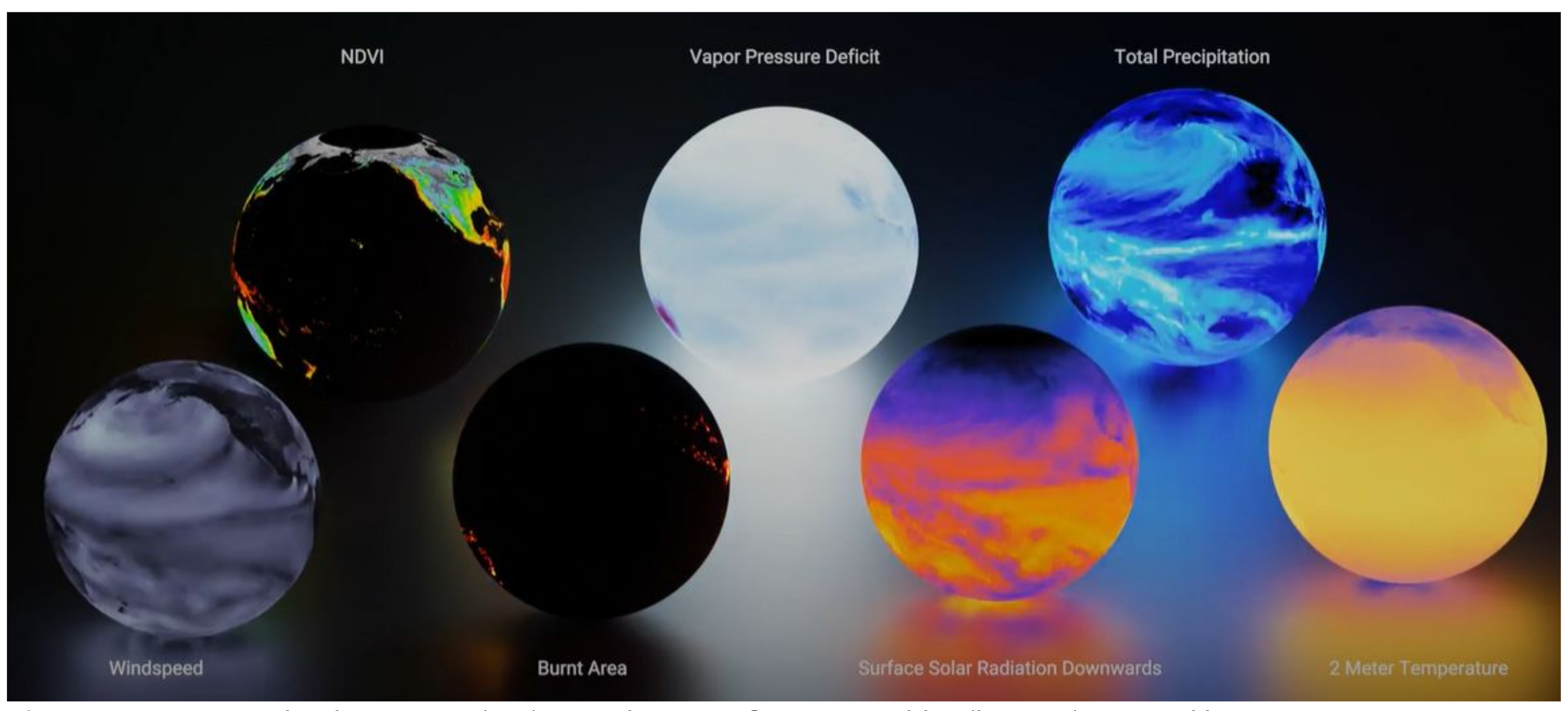


Figure 2: SeasFire Cube description (top). Visualization of some variables (bottom), created by MPI-BGI DataVis Team.

Initial Experiments

- We define **burnt area pattern forecasting as a segmentation task**, using 8 input variables (Figures 3, 4) in time t to forecast the spatial pattern of burned areas on time t+h [5].
- The models demonstrate **higher predictive skill than the mean seasonal cycle** (Table 1).
- In Figure 5, we see that the models' predictions closely match the target burnt area, and **capture major fire activity patterns.**

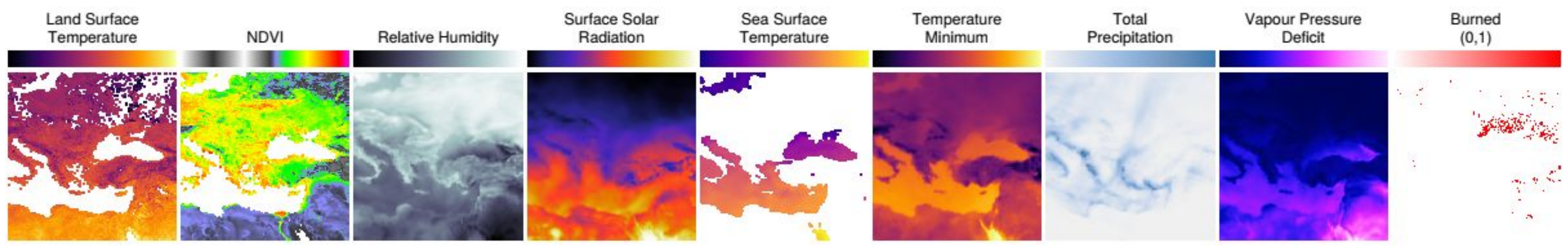


Figure 3: Visualization of the input and target variables chosen for the experiments.

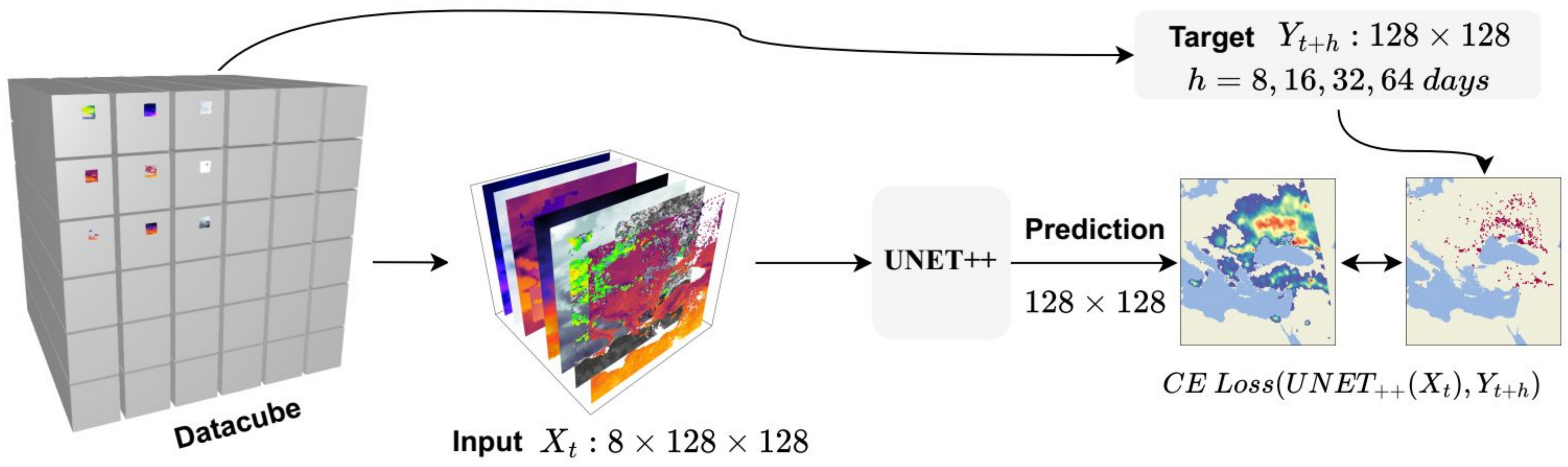


Figure 4: ML pipeline. The dataset is extracted from the datacube and fed to a UNET++ model that is trained with the Cross Entropy loss with inputs valid at time t to predict the target on time t + h.

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

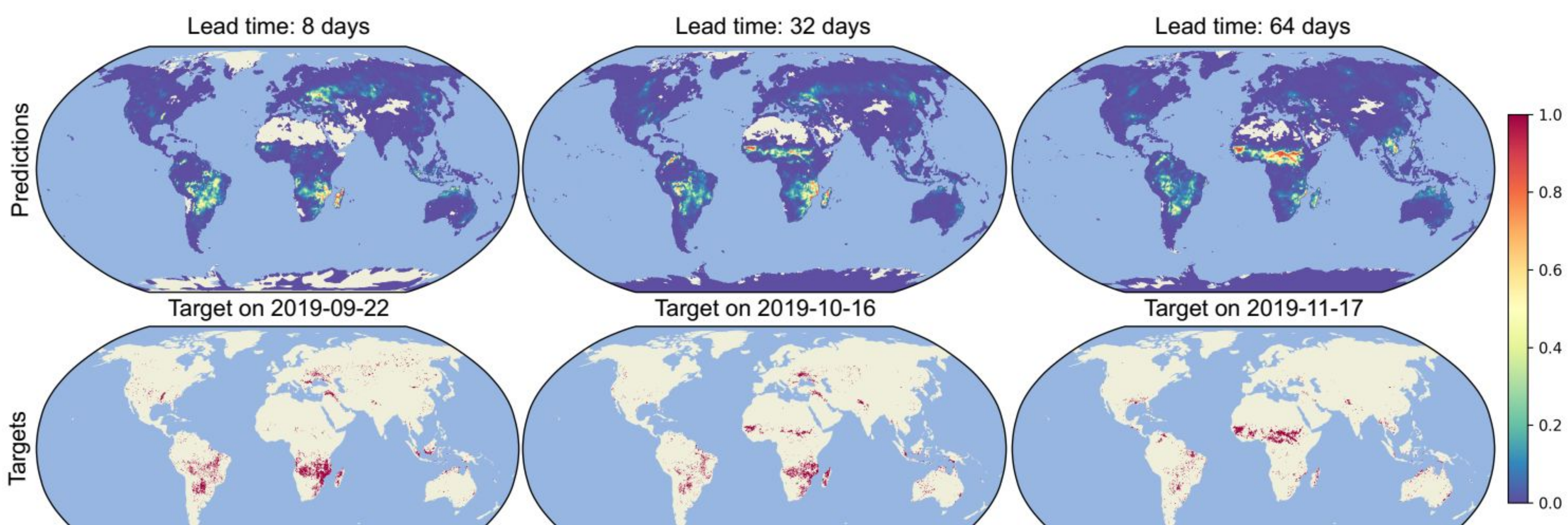


Figure 5: Prediction (top row) and target (bottom row) maps for lead forecasting times of 8 (left), 32 (middle) and 64 (right) days. Predictions lower than 0.0001 are visualized as missing values. Input the same for all models, from 2019-09-14.

Future Work

- **Earth System Deep Learning**: Move towards methods that can model the Earth as a system. Transformers and Graph Neural networks are promising to capture spatiotemporal interactions.
- **Temporal dynamics of the fire drivers**: Use time-series of the fire drivers instead of plain snapshots and borrow ideas from video forecasting.
- **Explainability to identify the focus** of the model and hint into known/unknown teleconnections.

References

[1] Fan, Jingfang, et al. "Statistical physics approaches to the complex Earth system." Physics reports 896 (2021): 1-84.
[2] Kim, Jin-Soo, et al. "Extensive fires in southeastern Siberian permafrost linked to preceding Arctic Oscillation." Science advances 6.2 (2020): eaax3308.
[3] Kondylatos, Spyros et al. "Wildfire Danger Prediction and Understanding with Deep Learning." Geophysical Research Letters", 2022. doi: 10.1029/2022GL099368
[4] Alonso, Lazaro, et al. SeasFire Cube: A Global Dataset for Seasonal Fire Modeling in the Earth System. 0.0.2, Zenodo, 30 Sept. 2022, p., doi:10.5281/zenodo.6834584.
[5] Prapas, Ioannis, et al. Deep Learning for Global Wildfire Forecasting. arXiv:2211.00534, arXiv, 1 Nov. 2022. arXiv.org, https://doi.org/10.48550/arXiv.2211.00534.

SeasFire
EARTH SYSTEM DEEP LEARNING FOR SEASONAL FIRE FORECASTING IN EUROPE

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