Understanding Fire Danger with Explainable Artificial Intelligence

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Max Planck Institute
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Challenges

- Fires are the result of **complex interactions**
- Use **Machine Learning** on large historical data
- Associate fire drivers with past **burned areas**
- Rely on **Explainable AI** to interpret fire danger

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

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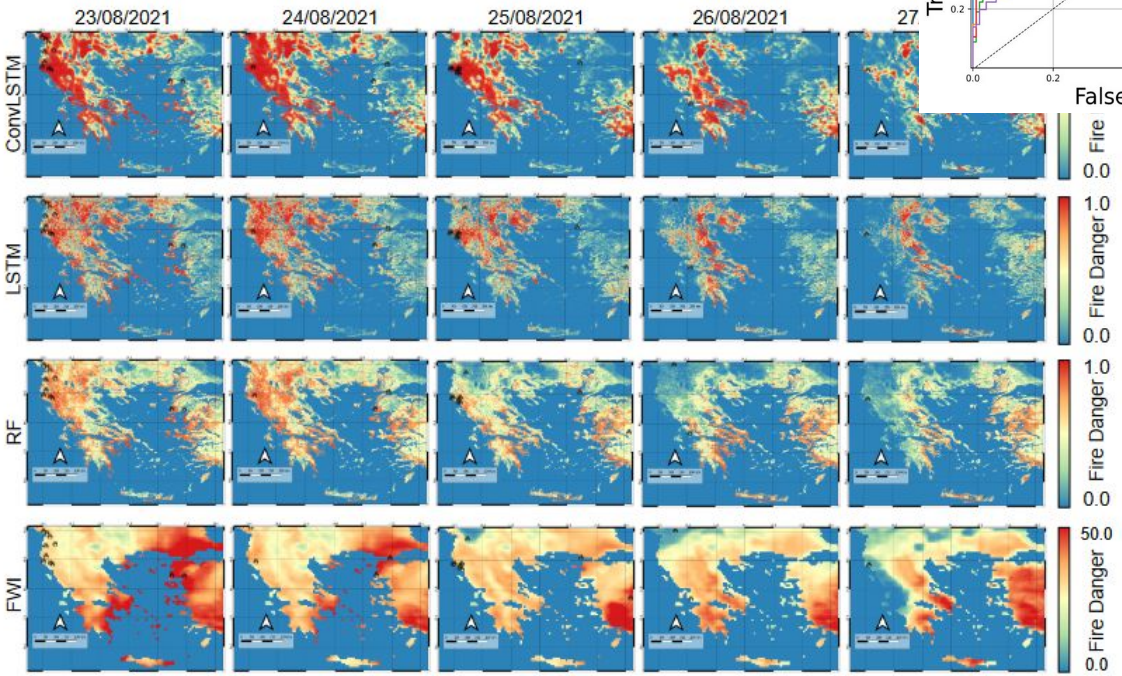
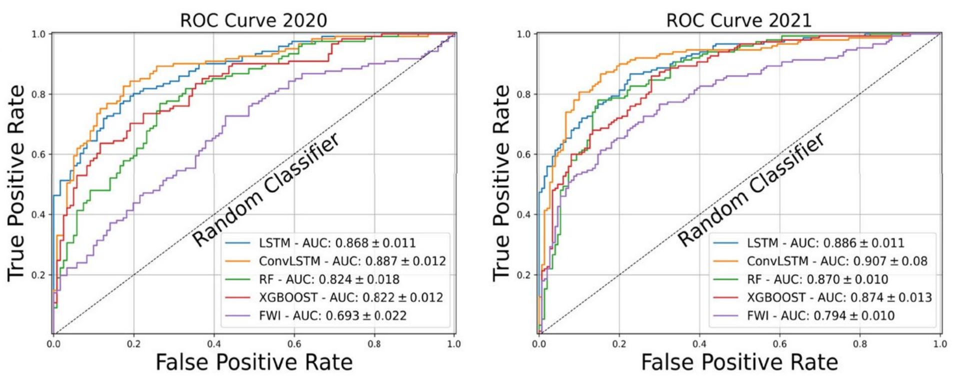
ML vs FWI Fire Danger Maps

[Kondylatos, et al, GRL, 2022]

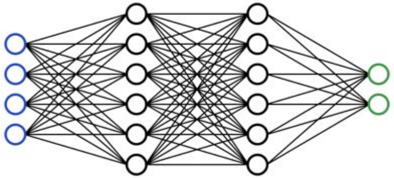


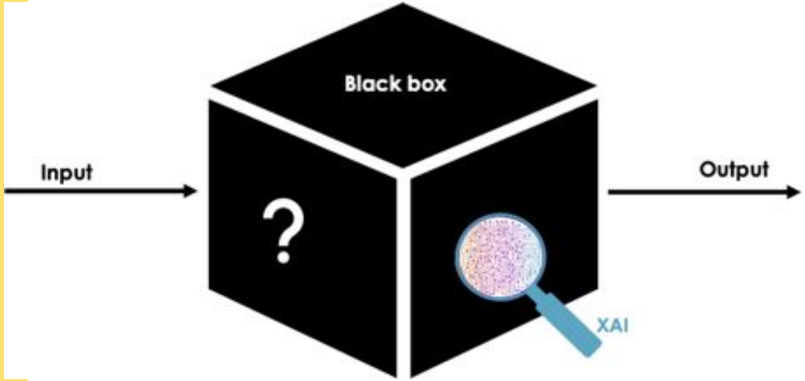


Model	TP(↑)	FP(↓)	TN(↑)	FN(↓)	Precision	Recall	F_1
(a) Results 2020							
RF	740	138	2,318	488	0.843	0.603	0.703
XGBoost	888	154	2,302	340	0.852	0.723	0.782
LSTM	**927**	150	2,306	**301**	0.861	**0.755**	0.804
ConvLSTM	879	**73**	**2,383**	349	**0.923**	0.716	**0.806**
(b) Results 2021							
RF	3,073	418	8,396	1,334	0.880	0.697	0.778
XGBoost	3,172	488	8,326	1,235	0.867	0.720	0.786
LSTM	**3,769**	402	8,412	**638**	0.904	**0.855**	**0.879**
ConvLSTM	3,543	**186**	**8,628**	864	**0.950**	0.804	0.871

DL models with **spatio-temporal context** are better than FWI

Explainable AI





- How can we **interpret** the predicted fire danger ?
- Why is the danger high on a given day or location?
- Which are the **main drivers** leading to wildfires?
- What is the **main mechanism** behind fire occurrence and spread?
-
- When can we **trust** model's predictions?

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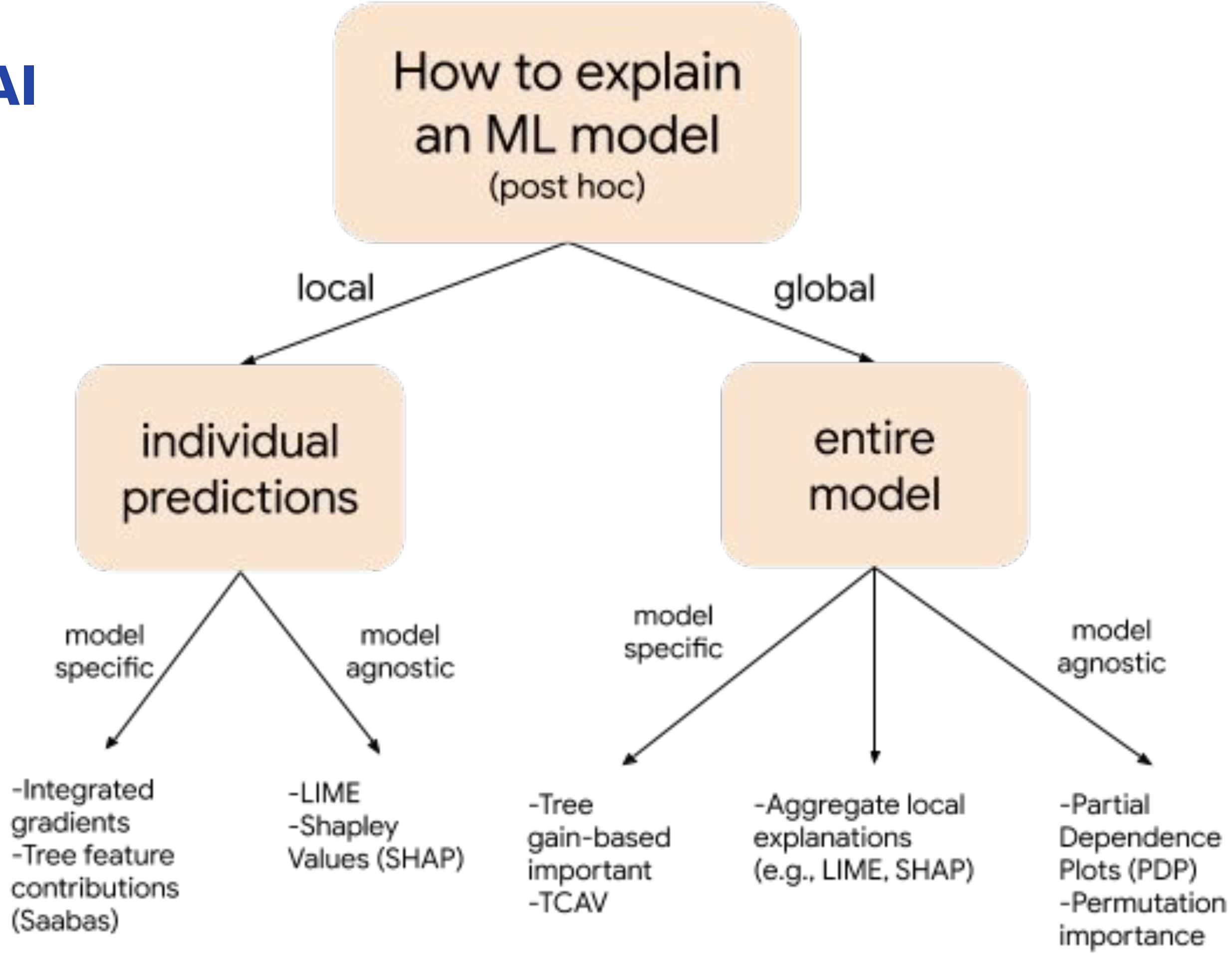
Bird's-eye view of xAI

- Global VS local
- Model-specific VS model-agnostic
- Gradient-based VS perturbation-based

Combine methods to get **complementary information**

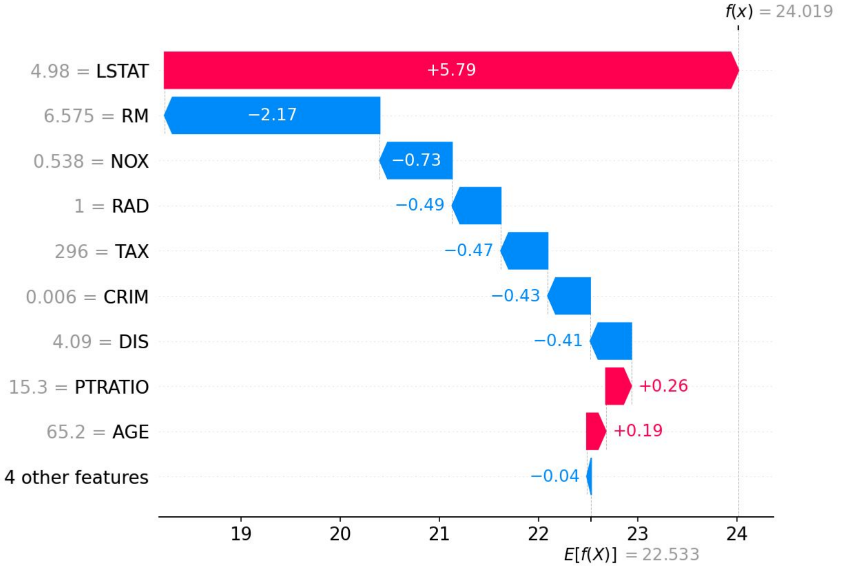


Shapley values

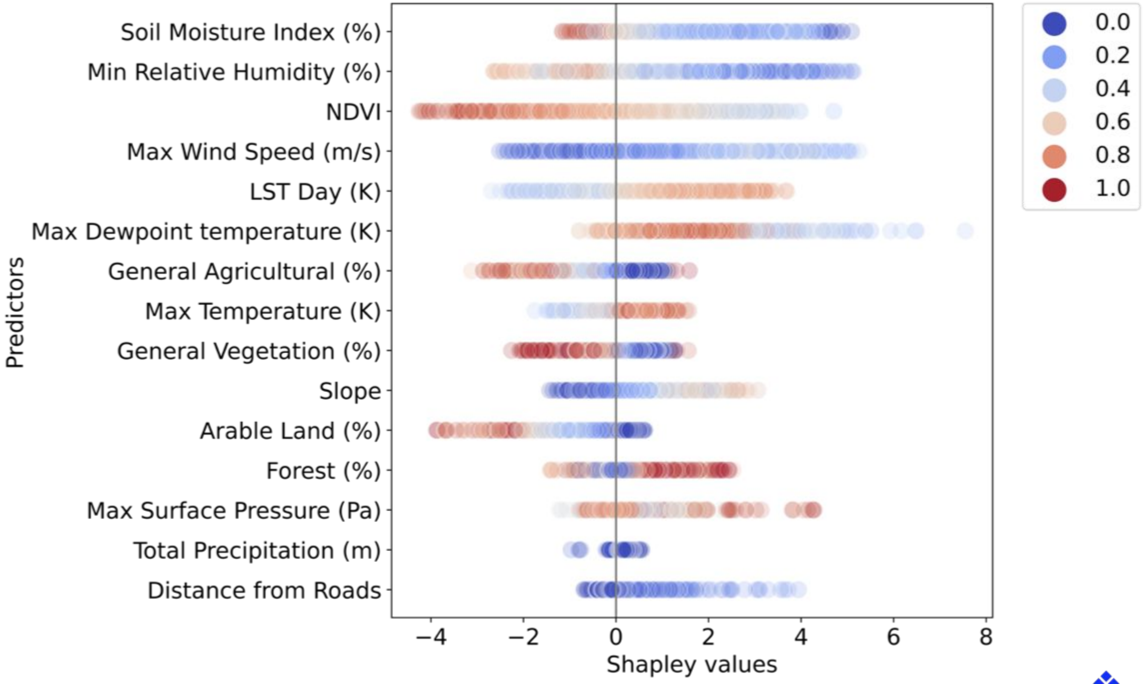
[Lundberg, Leee, A Unified Approach to Interpreting Model Predictions, NIPS 2017]
[Shapley, A value for n-person games, 1953]

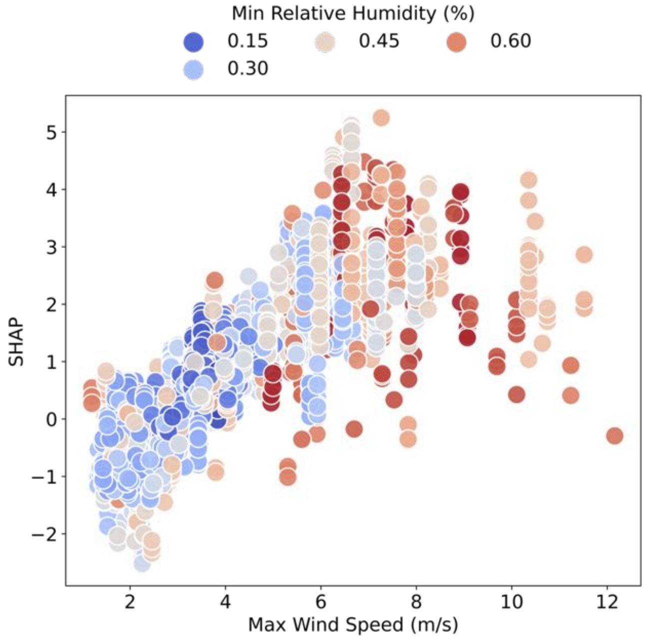
$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} [f_{S\cup\{i\}}(x_{S\cup\{i\}}) - f_S(x_S)]$$

$$f(\overline{x}) = g(\overline{x}) = \phi_0 + \sum_{i=1}^{D} \phi_i \overline{x}_i$$



Main drivers with SHAP





- ❖ **Type 1: driven by low Relative Humidity**
- ❖ **Type 2: driven by high Wind Speed**

Partial Dependency Plots

[Molnar, Interpretable Machine Learning]
[Zhao & Hastie, Causal Interpretation of Black Box models, 2021]

$$f : X \longrightarrow y$$

$$f(x_S) = E_{X_C}[f(x_S, X_C)] = \int f(x_S, x_C)dP(x_C)$$

Marginalization procedure

$$f(x_S, x_C) = h(x_S)g(x_C) \longrightarrow f(x_S) = h(x_S)\int g(x_C)dP(x_C) = const \times h(x_S)$$

PDP $\approx$ Causal effect of Xs on Y

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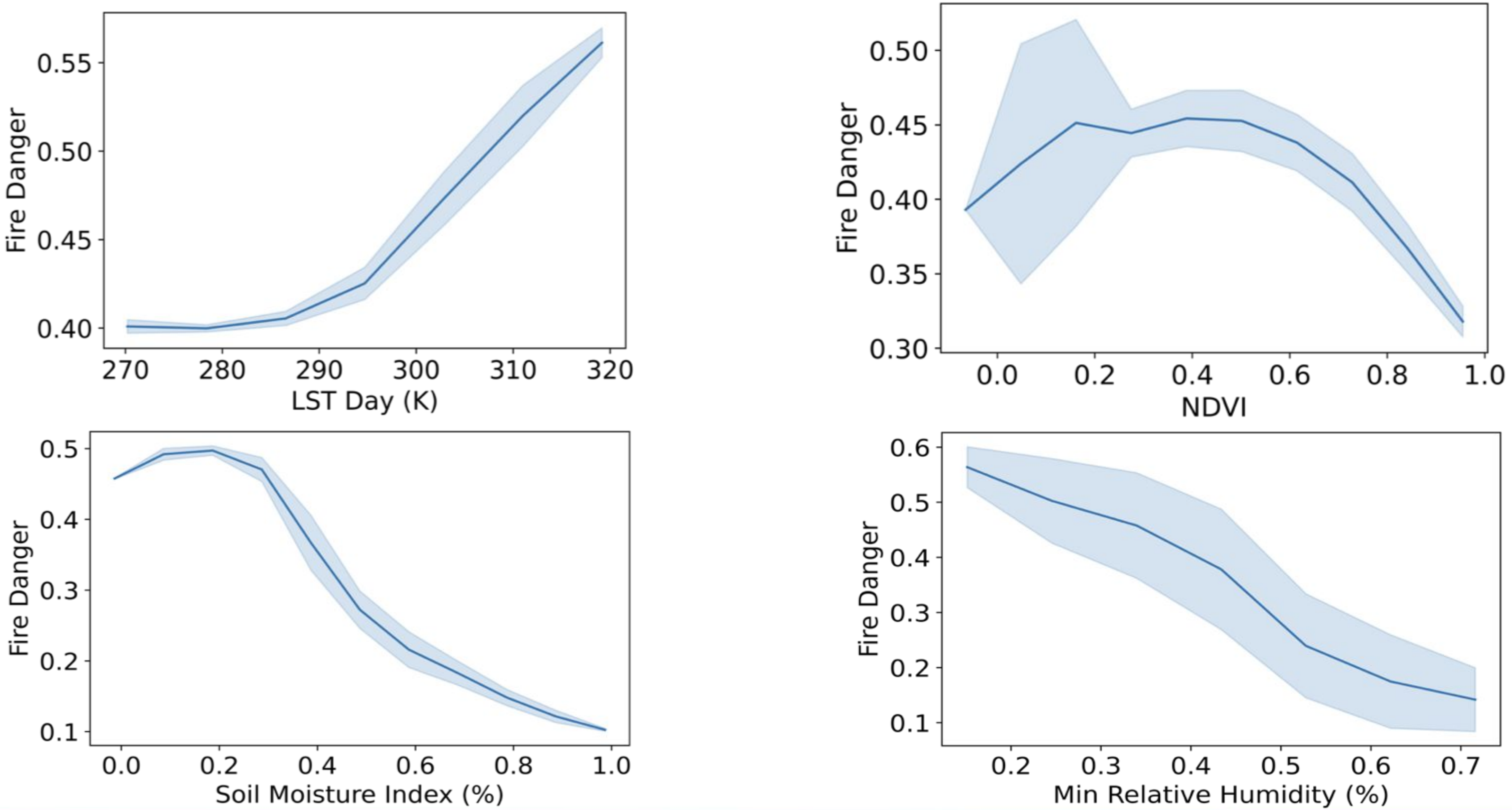
Univariate dependencies with PDP

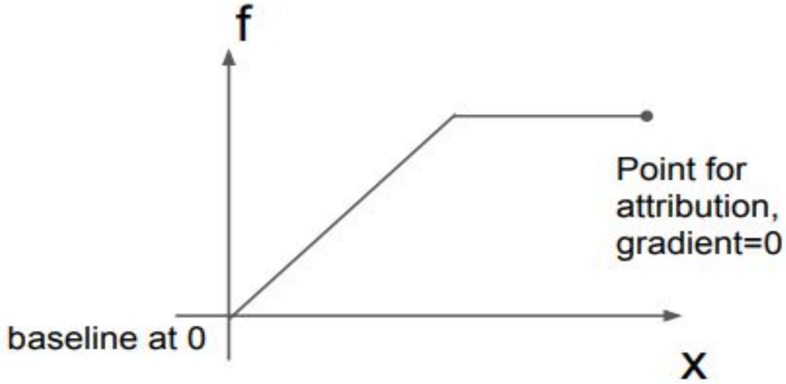


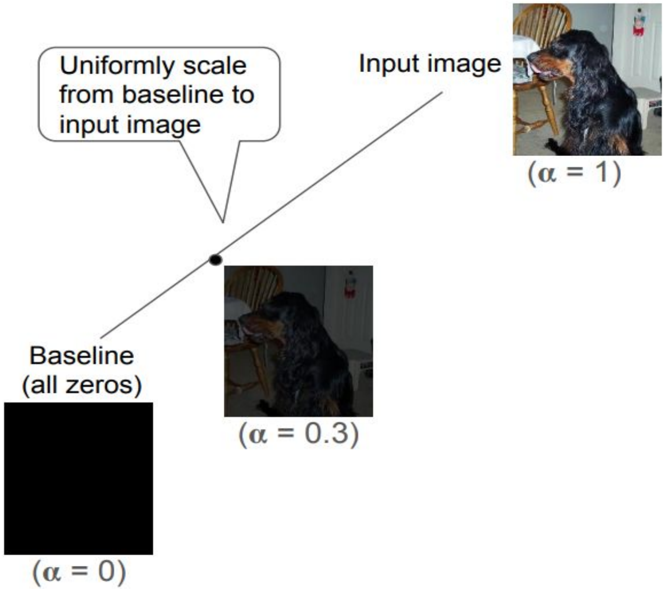
Integrated Gradients

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

$$(x_i - z_i) \times \int_0^1 \frac{\partial f_c(z + \alpha \times (x - z))}{\partial x_i} d\alpha$$

- Implementation invariance
- Completeness





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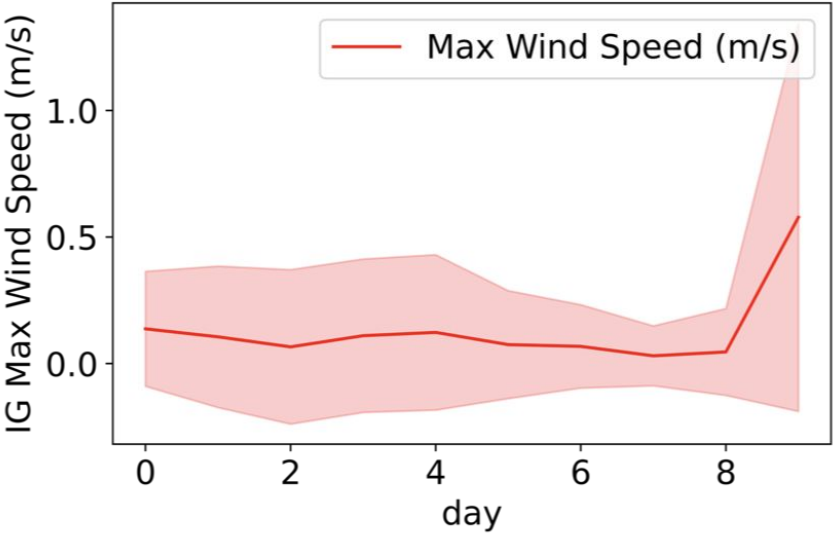
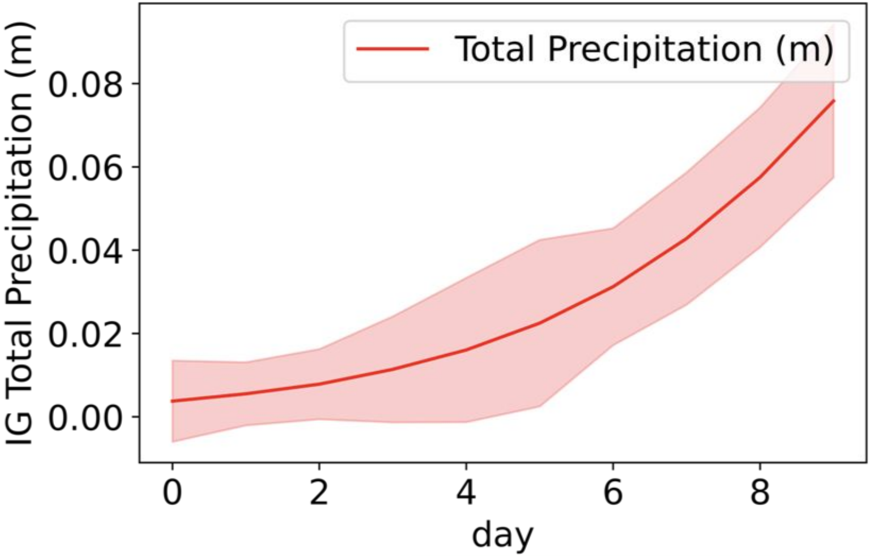
Explainability: short-term temporal behaviour from IntGrad



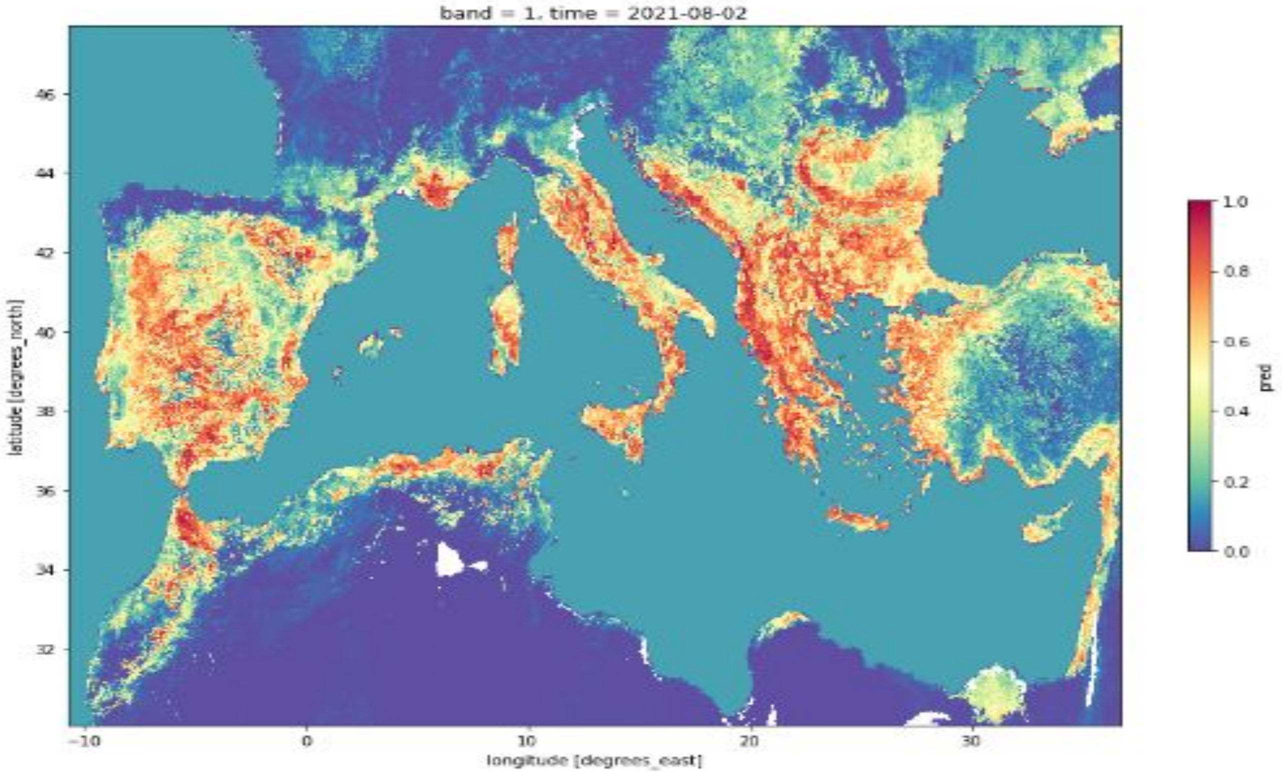
Sudden-onset activation: instantaneous effects

Slow-onset activation: accumulation effects

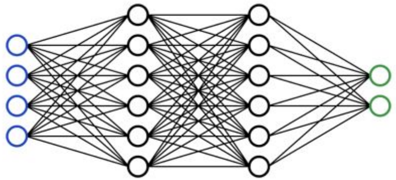


Scaling to the whole Mediterranean basin..

[Prapas, et al, in-preparation, 2023]



Next steps



- **Scale to the whole Mediterranean**
  - Bigger datacube
  - Models with more data
  - Study regional variability

- **Couple with terrestrial ecosystem** modelling (TEM) for carbon cycle, and add more info on vegetation (e.g. plant traits)

- **Extend validation** and compare against other solutions and models

- **Improve transparency** by evaluating xAI results with experts (e.g. fire risk managers), comparing explanations for different regions and time/space scales, combining multiple xAI methods

- **Hybrid modelling** to take into account physical propagation mechanisms

- Estimate **uncertainty with Bayesian networks**

Thank you!

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