

Motivation

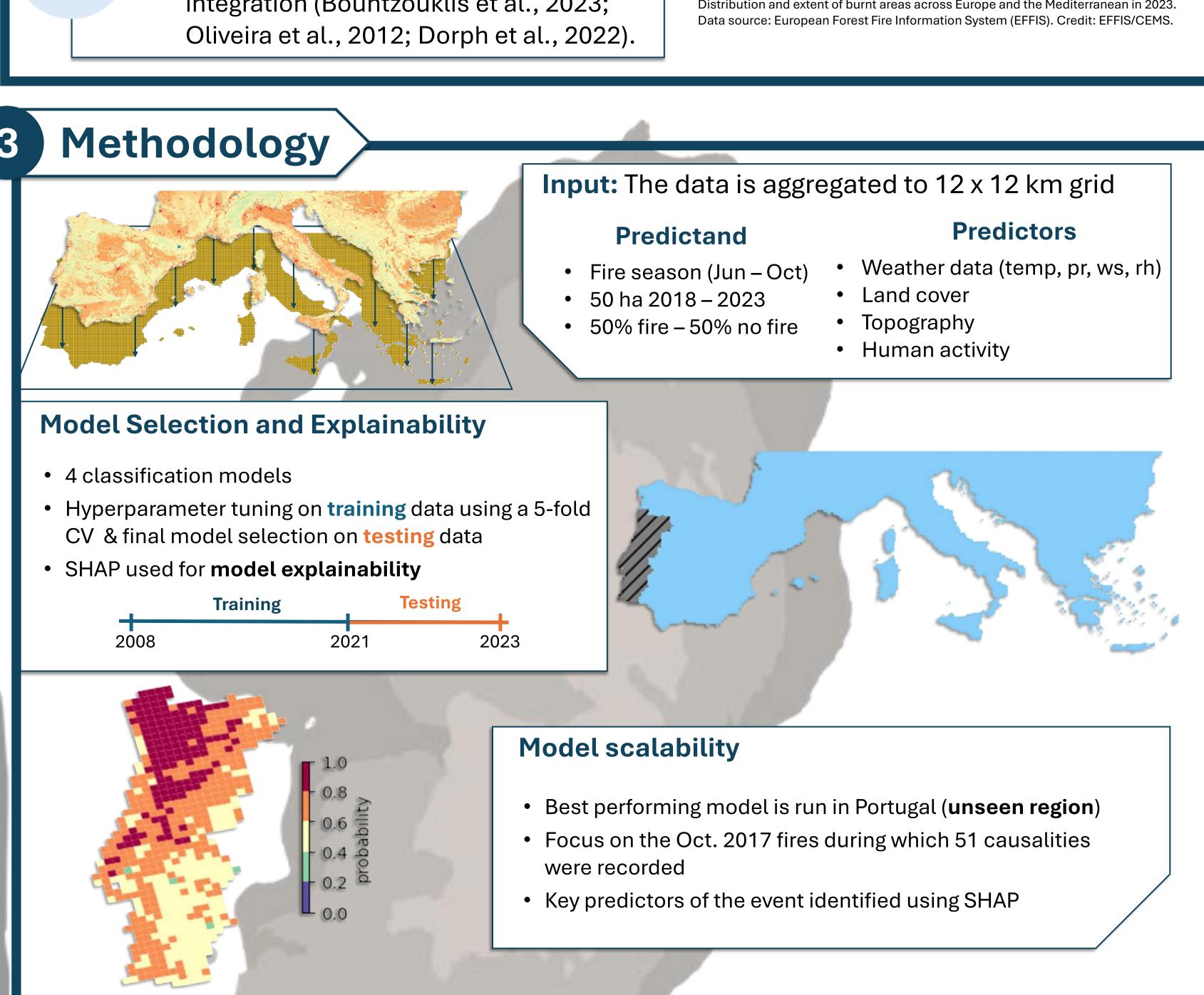
Scalable & explainable ML for wildfire risk modeling in Southern Europe: A case-study in Portugal

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Burnt areas across Europe and the Mediterranean in 2023 Wildfires in Europe Wildfires are among Europe's most destructive natural hazards, affecting ecosystems, economies, and communities (EEA, 2024). Wildfires in Europe Traditional fire indices rely mainly on weather, missing key human and landscape drivers Wildfires in Europe Data: European Forest Fire Information System (EFFIS) • Credit: EFFIS/CEMS Remote sensing data enable ML-based PROGRAMME OF THE EUROPEAN UNION OPERAICUS Lunges tytes on Larth wildfire risk assessment through data integration (Bountzouklis et al., 2023; Distribution and extent of burnt areas across Europe and the Mediterranean in 2023. Oliveira et al., 2012; Dorph et al., 2022). Methodology



Objectives Use explainable Al Develop a data-Assess model driven model to to quantify the scalability and estimate daily impact of key robustness in an wildfire probability unseen region predictors

Model Selection & Performance

Models trained

0.8

 Support Vector Machine (SVM), Random Forest (RF), K-nearest neighbors (kNN) and Logistic Regression (LR)

Model performance

Model	F1 score	Log loss
SVM	0.91	0.38
RF	0.91	0.38
kNN	0.90	0.72
LR	0.88	0.44

RF model selected for scalability and computational cost

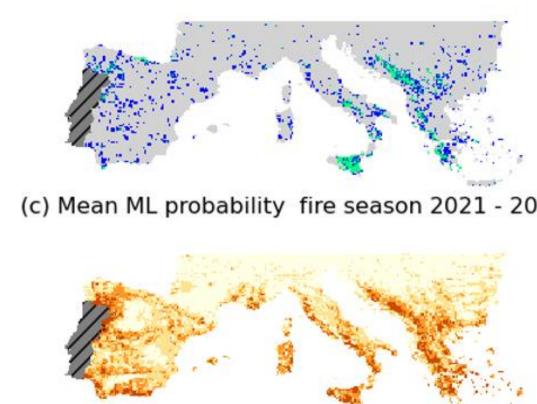
(a) ROC curves

RF model evaluation over 2021 - 2023

- Model run daily with the classification probability used to assess wildfire risk.
- Good agreement between historical record of fires and mean wildfire probability.

RF model can successfully represent high wildfire risk areas

(b) Recorded fires fire season 2021 - 2023



(c) Mean ML probability fire season 2021 - 2023 € 0.4 - 0.8 .≥ - 0.6 🚡 SVM (AUC = 0.91) - 0.4 g ₾ 0.2 — RF (AUC = 0.91) - 0.2 kNN (AUC = 0.90)False Positive Rate (Positive label: 1)

High model output Monthly precipitation Temperature Relative Humidity Precipitation Shrub fraction Relative humidity Slope fraction < 15° Weekly precipitation Slope < 15° 3 monthly precipitation Crop fraction Evergreen forest fraction Precipitation Temperature Population density Shrub fraction Wind -0.3 -0.2 -0.1 0.0 0.1 0.02 0.04 Mean(|SHAP value|) (average impact on SHAP value (impact on model model output magnitude) output magnitude)

(a) Recorded fires 2017-10-15 (b) ML fire risk 2017-10-15 (c) FWI 2017-10-15 - Extreme Very high - Moderate : No Fire - Very low Fire (d) Time series at grid cell with most fires recorded Fire recorded ₹ 0.6 --- Shrub fraction --- Slope fraction < 15°</p> Days in October 2017

Spatial assessment:

- Close alignment between the RF model high probability (Fig a.) and the **recorded fires** on the same day (Fig b.)
- The FWI (Fig c.) is not able to capture the areas where wildfires where recorded.

Temporal assessment (Fig d.):

- ML fire risk high when fires were recorded and drops in the second half of the month
- Drop in fire risk associated with drop in the SHAP values of the weather variables but

Conclusion & next steps

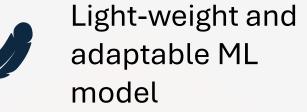


Results

Explainability of ML model used to identify influential predictors for wildfire risk

Scalability of model demonstrated by running model in unseen region

Pathways to Impact





Identification of key wildfires drivers



Support for policy & land management decisions

Next steps

- Extend analysis to other regions
- Future projections of wildfire risk

References

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