# A machine learning approach for wildfire susceptibility and hazard mapping at supranational level: The case study of Eastern Mediterranean

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# Hazard Mapping

The presented analysis deals with *Susceptibility, Intensity* and *Hazard* considered as **static** maps (resolution: 500m) to help with wildfire management and planning in a large area ( ~ 1,612,500 km2)

| Susceptibility | Intensity | Hazard |
| --- | --- | --- |
| Static probability of experiencing wildfires in a certain area, depending on the intrinsic characteristics of the terrain. | (proxy for the ) Rate of heat energy released by the fire, determined by fuel type | Spatial distribution of the areas where **severe** wildfires are **likely** to occur. |

# Study Area: an ongoing step-by-step journey

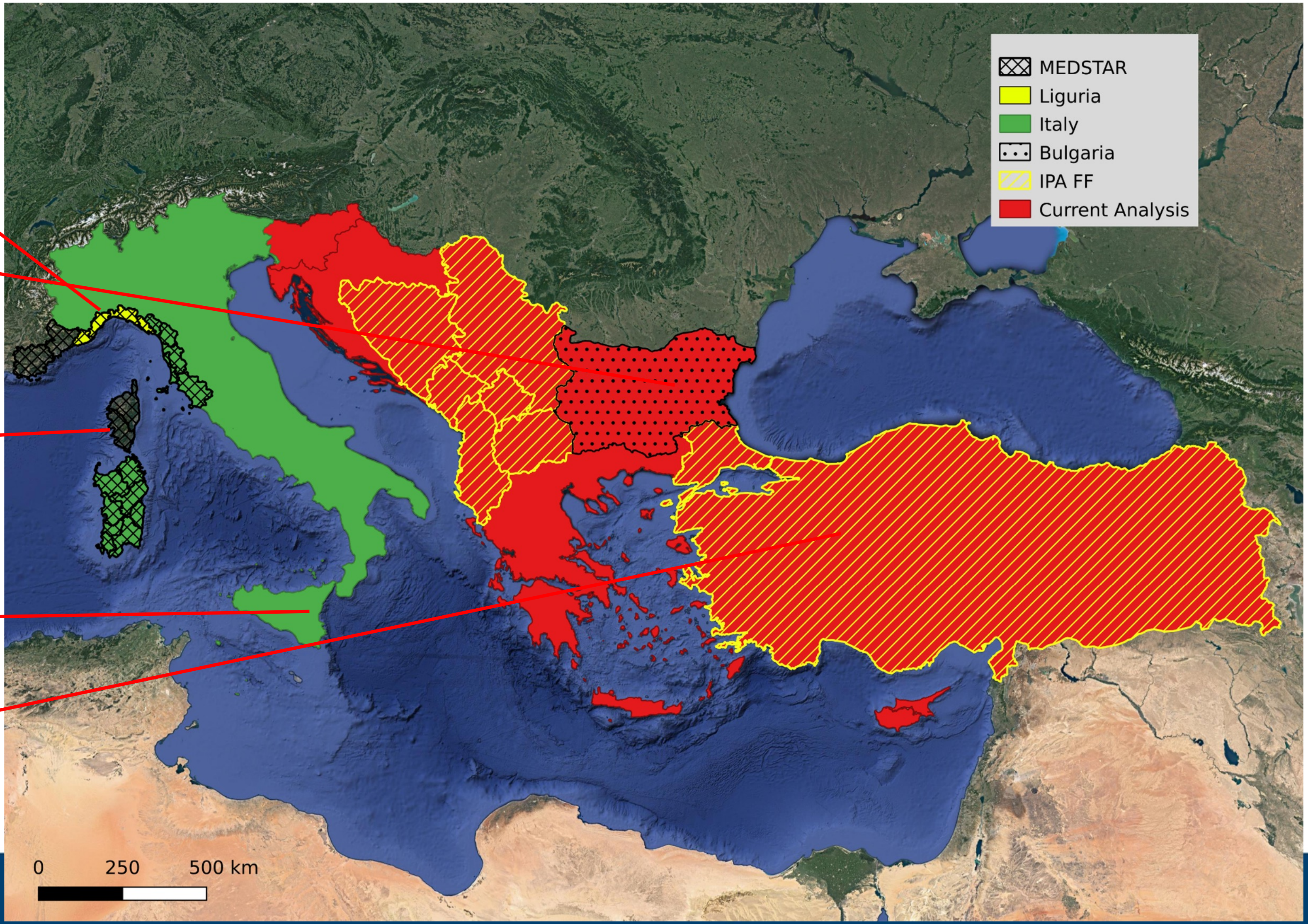
Liguria region *(Tonini et al 2020, Trucchia et al. 2022b)*

Bulgaria Risk assessment 2020/2021 (Technical Report WB)

Interreg Marittime MEDSTAR: susc. and hazard assessments (2021)

Italian Scale susceptibility assessment *(Trucchia et al. 2022a)*

IPA FF (2021 - 2023) *Guidelines for FF Risk Mapping (in progress)*



# Wildfire Susceptibility

**What is it?**

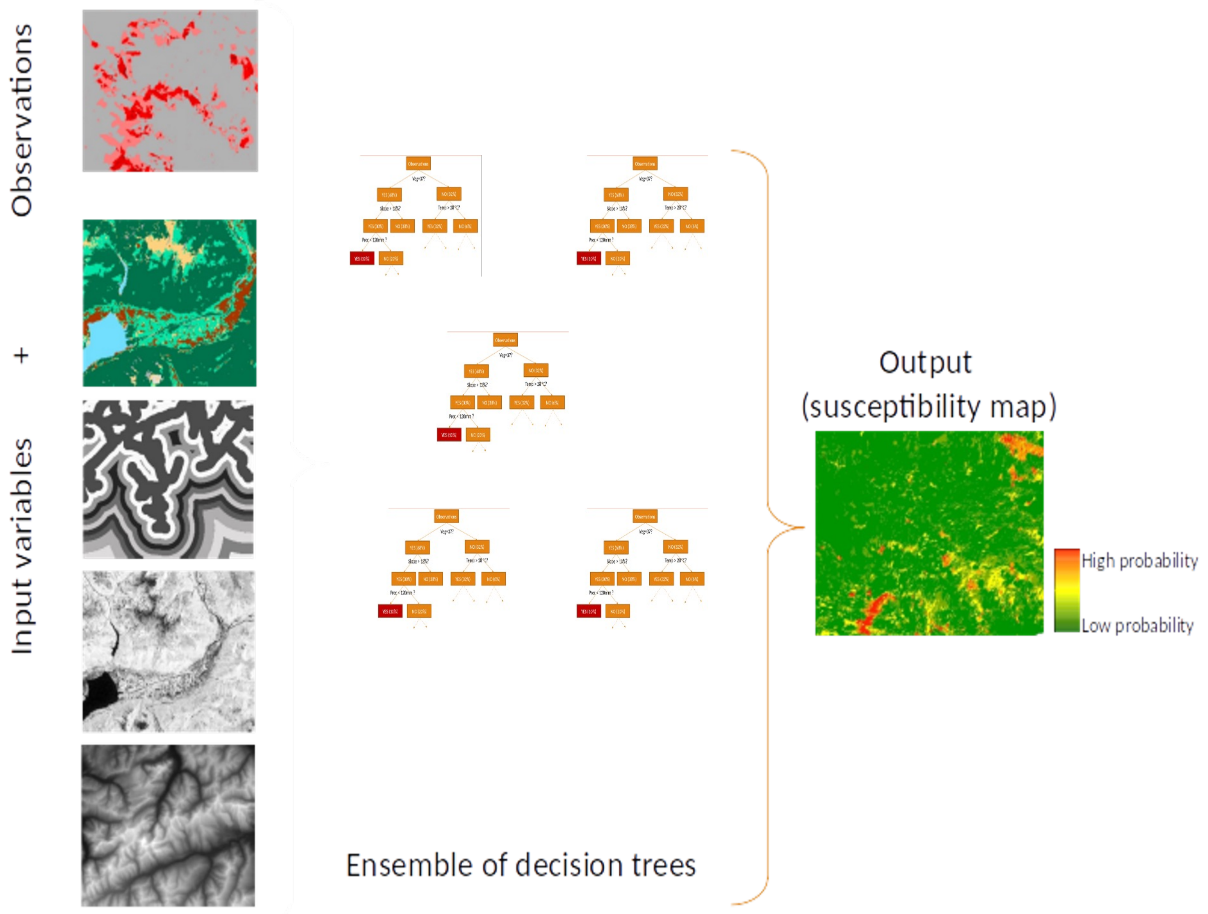
Static probability ("likelihood") for a place to be affected by a wildfire event. Spatially distributed static layer.

**How is it computed?**

Connecting the climatic, geographical and anthropic features (called *predisposing factors*) of each pixel to the history of past wildfire occurrences. **Algorithm used: Random Forest** (Machine Learning Model)

# Wildfire Susceptibility

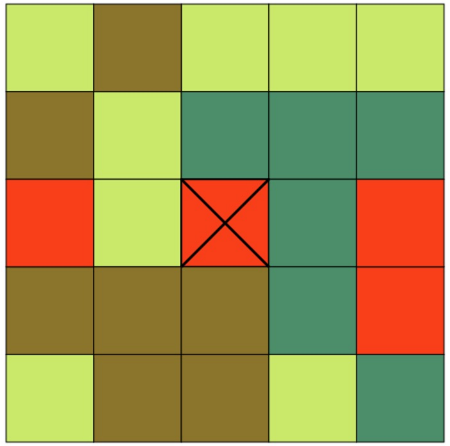
| | | |
|---|---|---|
| **Open Data!** | **Observations:** | **Wildfire polygons**<br>EFFIS 2008 - 2019 |
| | **Predisposing factors** | **Geophysical**<br>- Land use / vegetation cover<br>- Tree Cover Density<br>- DEM (elevation, slope, aspect) |
| | | **Climate factors** |
| | | **Anthropic**<br>- Population Density<br>- Distance from anthropic elements |

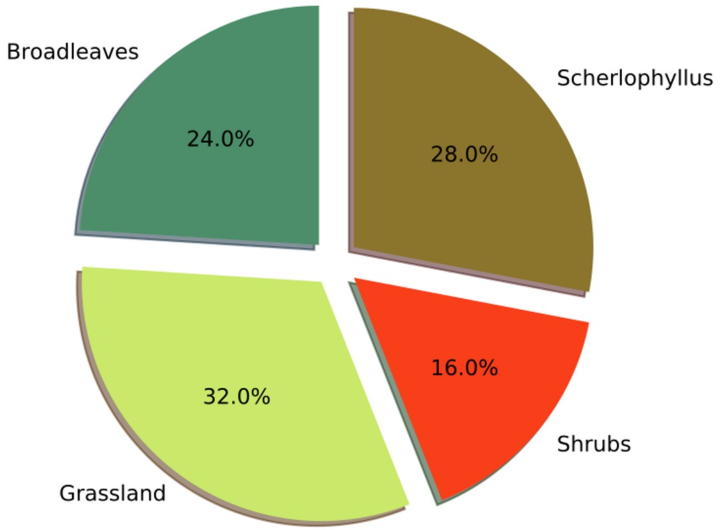


# Land cover factors

Every pixel bears information on:

- **CORINE Land Cover 2018** at 3rd level of detail
- Percentage of **neighboring** pixel of class “i”, for any class of vegetation.
- Copernicus **Tree Cover Density**

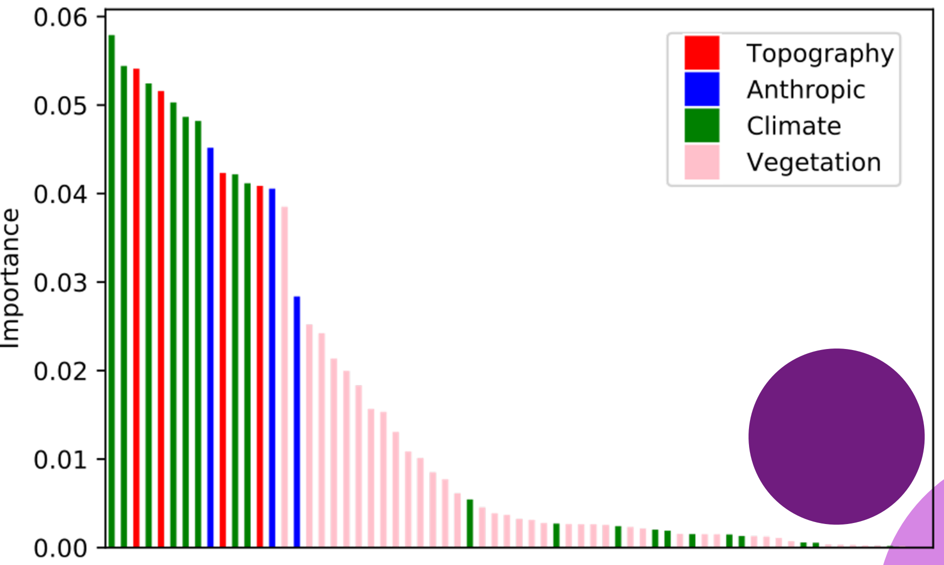




# Climate factors

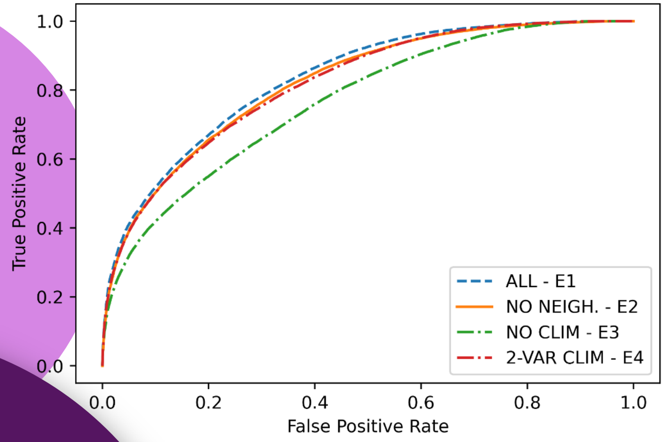
| Climatic Layer | Resolution | Description | Source |
|---|---|---|---|
| Mean precipitation | ~55 km | Average of yearly accumulated precipitation [mm] | WB Climate Change Knowledge Portal 1991-2020 |
| Maximum no. of consecutive dry Days | ~55 km | Number of days in the longest period without significant precipitation of at least 1mm. [Days] | |
| Max temperature | ~55 km | Average maximum temperatures [°C] | |
| Mean temperature | ~55 km | Average mean temperature [°C] | |
| Number of Summer Days | ~55 km | Average count of days where the daily maximum temperature surpassed 25°C.[Days] | |
| Number of Tropical Nights | ~55 km | Average count of days where the daily minimum temperature remained above 20°C [Days] | |
| Soil Moisture | ~25 km | Volumetric soil water (layer 1), 0-7 cm | ERA5 monthly averaged data on single levels from 1979 to present, from Copernicus Climate Data Store |
| Köppen-Geiger climate classification | ~7.4km | 8 climate classes of Köppen-Geiger [-] | Beck et al., 2018 |

# After the Susceptibility Model is built…



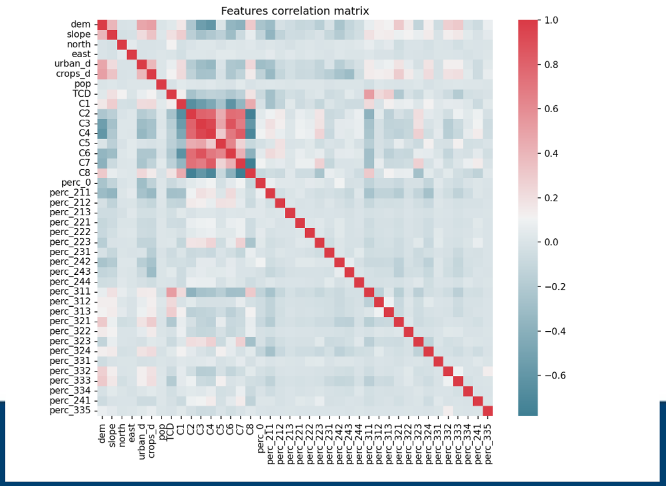

Variable ranking

ROC Curves



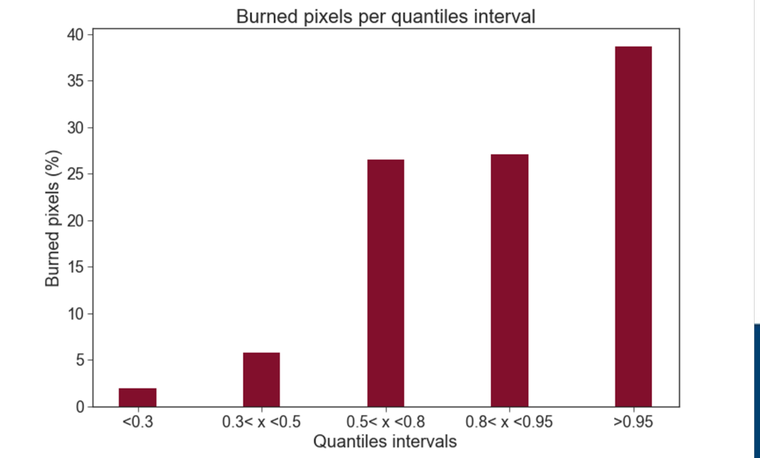

| | |
|---|---|
| *AUC E1* | *0.833* |
| *AUC E2* | *0.822* |
| *AUC E3* | *0.767* |
| *AUC E4* | *0.819* |

Correlation Analysis

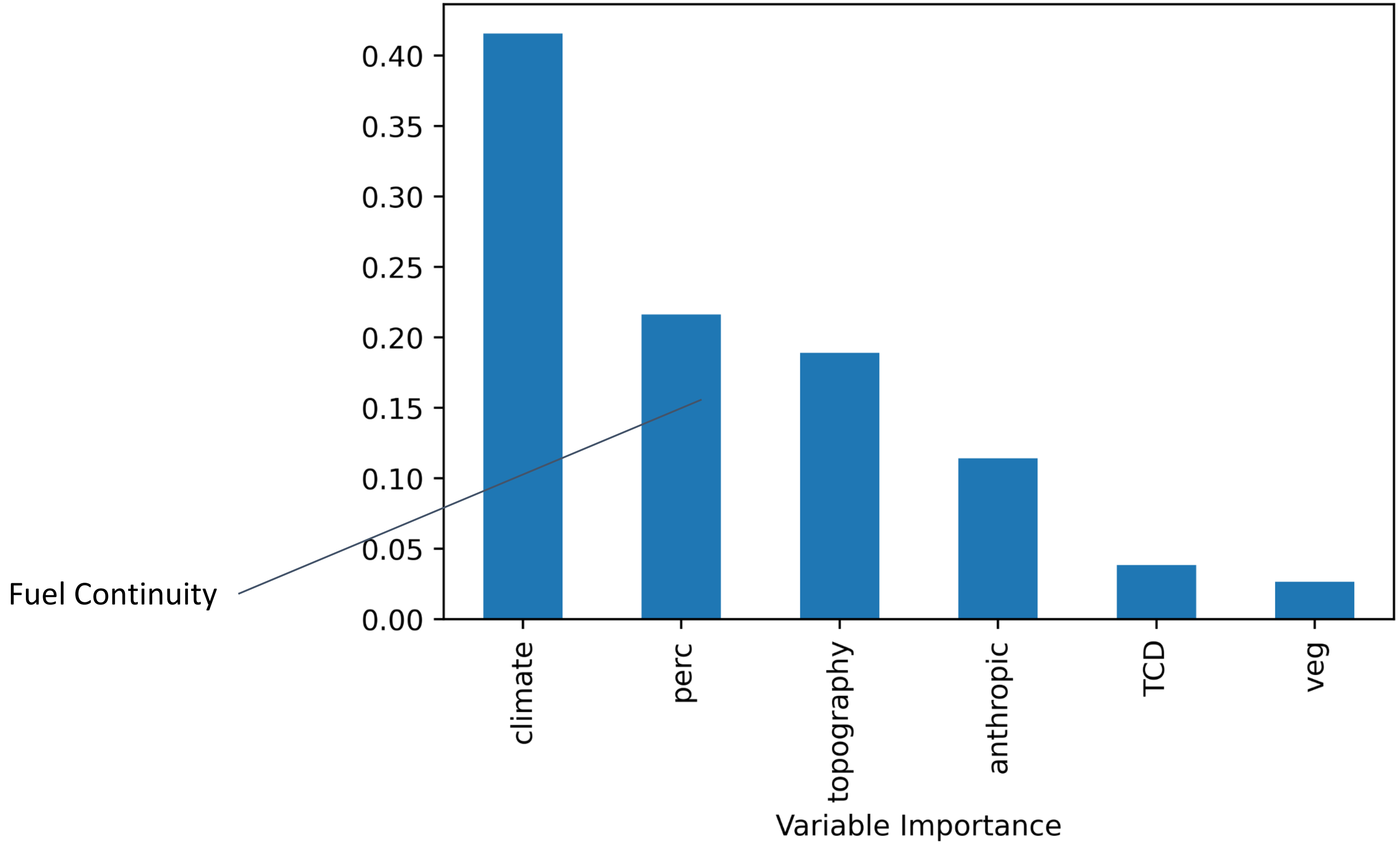



Indicators on OOB data

Quantile based analysis of testing burned area



# Aggregation of importance classes



# Results from trained model:

- Performances are not altered if a less redundant climate factor set is chosen (i.e., precipitation and temperature).
- Climate variables are more important than vegetation variables at this scale. However, removal of neighboring vegetation degrades the final result - importance of flammable fuel continuity
- The algorithm correctly classify most of the 2020-2021 test burned area into high susceptibility classes of the produced map
- Among the climatic variables,  mean precipitation,  max no. of consecutive dry days, and soil moisture emerged to be more important than temperature based layers.

# Wildfire Intensity

**What is it?**

A wildfire intensity map aims at identify the areas in which a possible wildfire occurrence could be more disruptive

**How is it computed?**

*Empirical classification* on land cover map based on expert judgment aiming at discriminating different wildfire types on they expected severity. In this case, mapping made straight from CORINE Land Cover CLC18.

| Wildfire Intensity classes | Description |
| --- | --- |
| 1 | Low intensity surface fires (e.g. grassland fires) |
| 2 | Medium intensity surface fires (e.g. broadleaves litter) |
| 3 | High intensity surface fires (e.g. high dense bushfires) |
| 4 | Very high intensity crown fires (e.g conifers) |

# Hazard classification

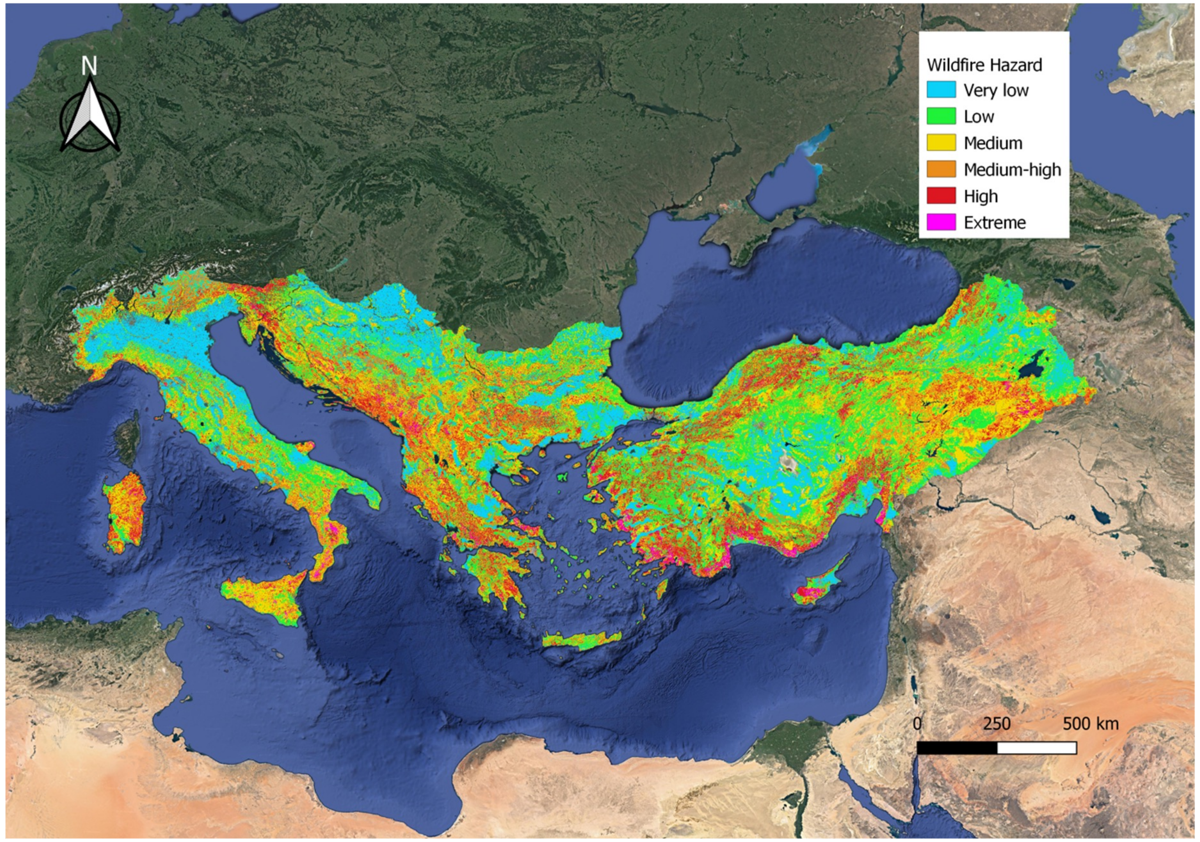
**H = f(S,I)**

A **contingency matrix** approach has been adopted:

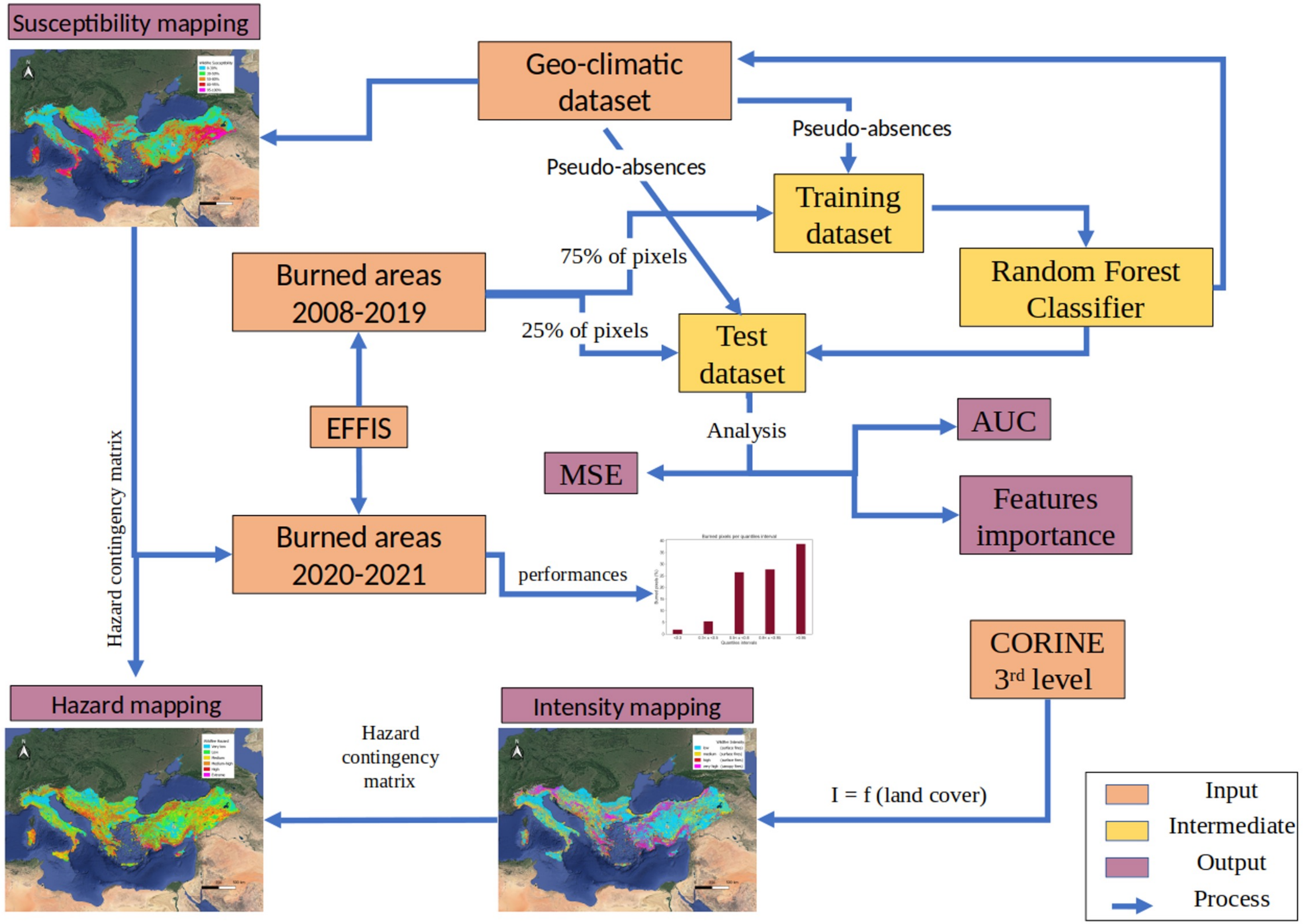
coupling the information of the **wildfire susceptibility** with the proposed **empirical intensity** map it is possible to associate an hazard class to a **different** range of possible **wildfire occurrence**, from low probability of having surface wildfires (class 1) to high probability of intense crown fires (class 6)

| Susceptibility / Intensity | Low Intensity | Medium intensity | High Intensity | Very high Intensity |
|---|---|---|---|---|
| Low Susceptibility | 1 | 2 | 3 | 4 |
| Medium Susceptibility | 2 | 3 | 4 | 5 |
| High susceptibility | 3 | 4 | 5 | 6 |

Spatial distribution of the areas where **severe** wildfires are **likely** to occur.



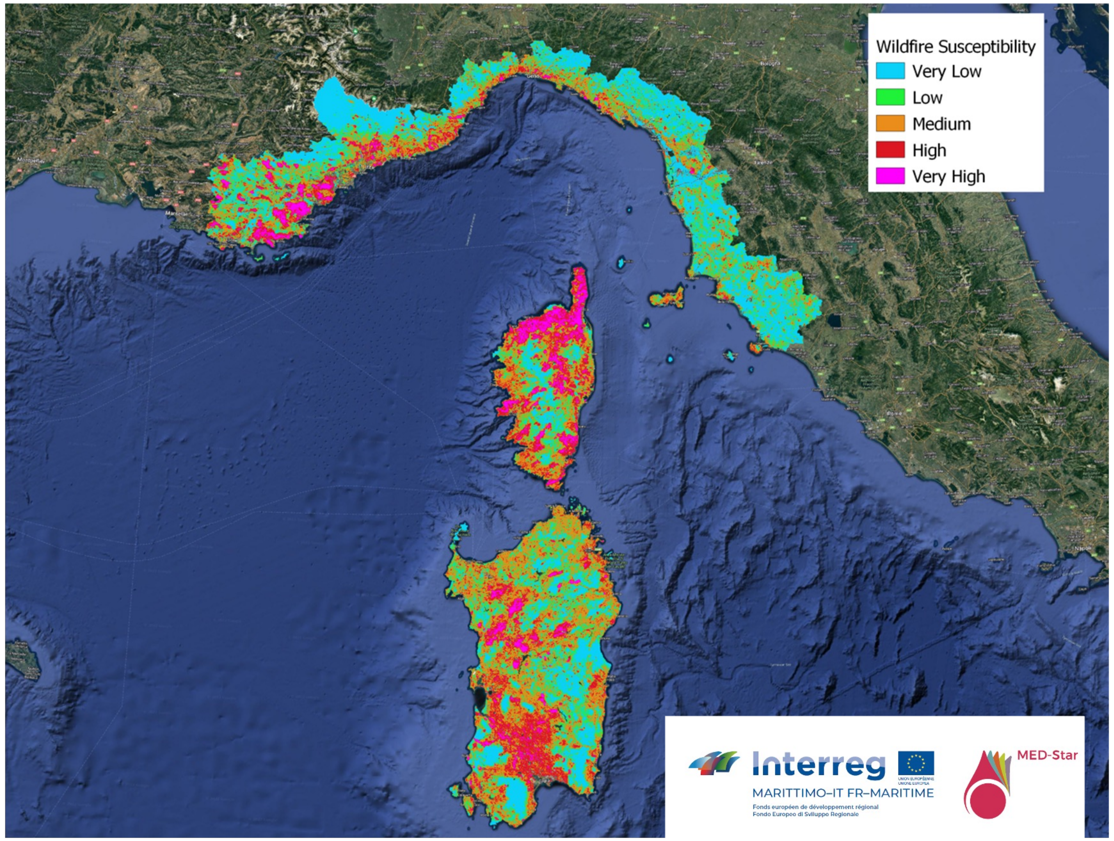
# Adopted framework - resume



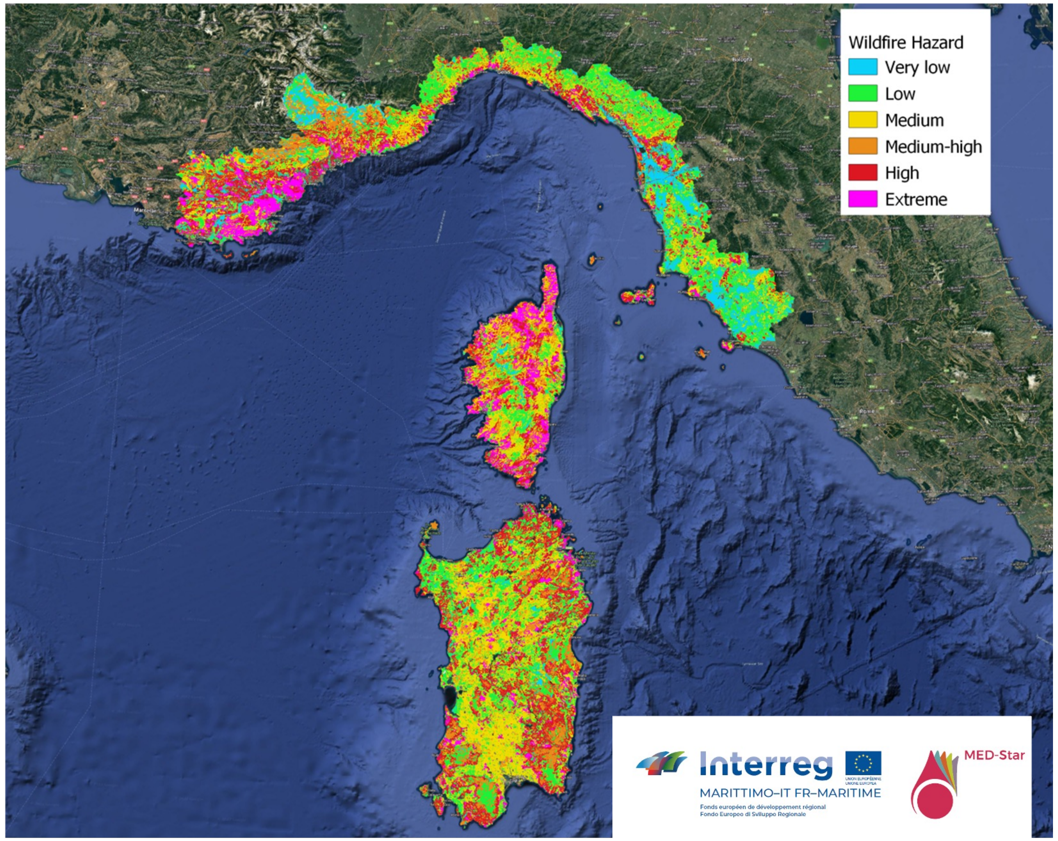
# Other implementations - MEDSTAR Project

The proposed framework and methodology are applied to MEDSTAR project for inter-regional wildfire hazard and susceptibility maps.

**Susceptibility**




**Hazard**




Official local fire perimeters over long time series of wildfire data are used (1973-2020 for French fires, 1997 - 2020 for Ligurian fires); Strategic project funded under the Italy-France Maritime Cross-border Cooperation Programme INTERREG 2014-2020.

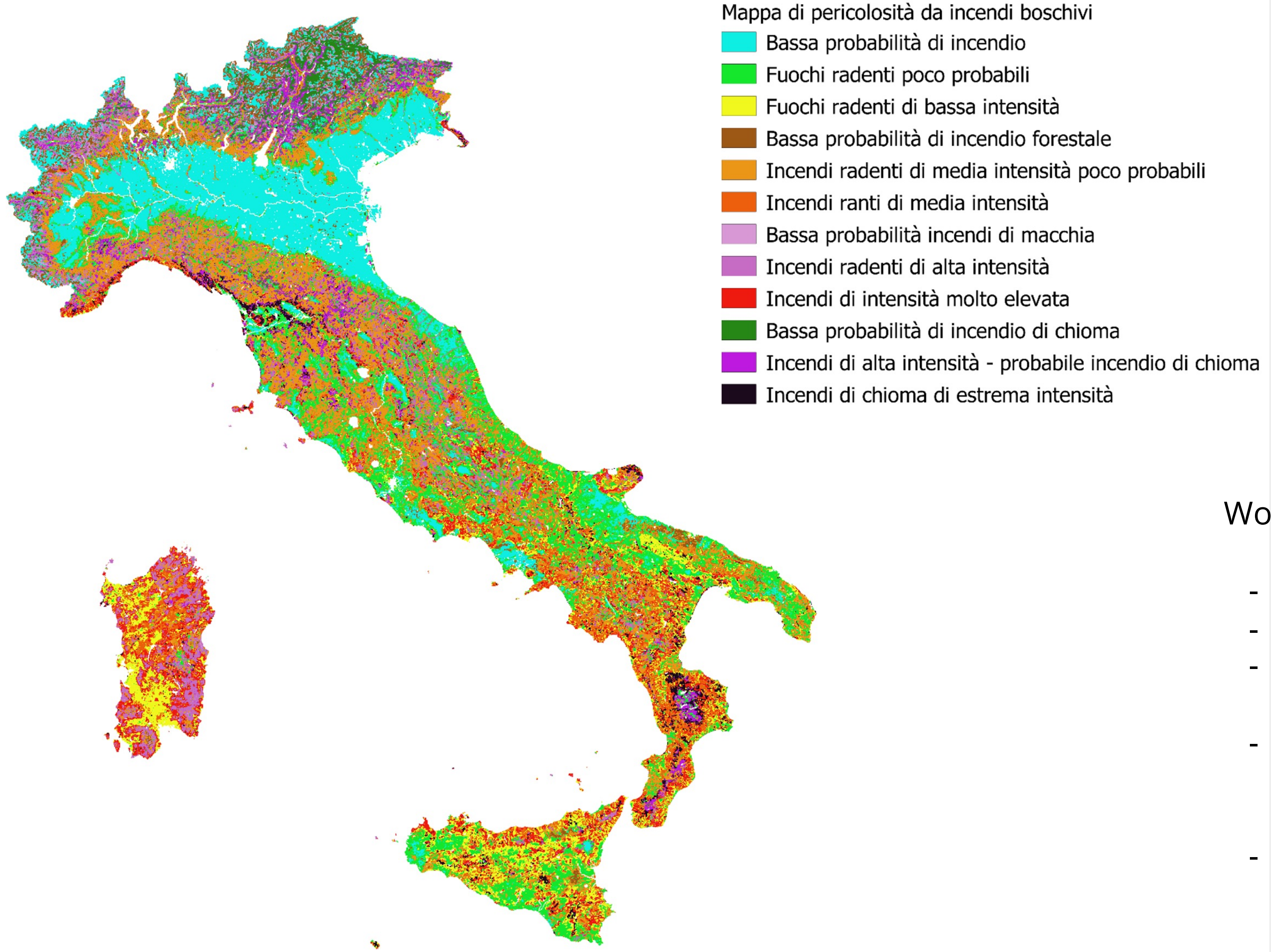
# Lesson Learnt and Future Perspectives

- Among the four categories of drivers considered here, vegetation and antropic features are the only manageable by planners and managers through specific interventions such as fuel treatment in highly populated areas
- Wildfire risk scenarios by including  exposed elements, their vulnerability and value, discriminating between priorities.
- **Wildfire risk mapping guideline** under development through the current European program IPA Floods and Fires (IPAFF)
- Further study can see the effect of high-fidelity burned area polygons comparing local and supernational analyses

# Aims of a technical guideline for Forest Fire Risk Mapping

In the context of IPAFF program, a technical guideline - is being developed with the aims of:

- Proposing a **methodology** for fire risk mapping at all governmental levels, from local to national
- Facilitating the **harmonization** of terminology, data, and processes
- Helping to consider **transboundary** fire events
- Empower **capacities** on Forest Fire Risk Mapping




Work which is now underway:

- Physical-based susceptibility
- Intensity -> Plant Functional Type
- Hazard is in this case a proxy for fuel classes.
- How to re-introduce anthropic factor? A ML layer of ignition probability? Coping capacity?
- If the susceptibility is trained mostly on climate, can it be shifted to future CC scenarios?

RESEARCH FOUNDATION

# Thank you for your attention!


- *(Tonini et al., 2020)* Tonini, M.; D'Andrea, M.; Biondi, G.; Degli Esposti, S.; Trucchia, A.; Fiorucci, P. A Machine Learning-Based Approach for Wildfire Susceptibility Mapping. The Case Study of the Liguria Region in Italy. *Geosciences* **2020**, *10*, 105. https://doi.org/10.3390/geosciences10030105
- *(Trucchia et al. 2022a)* Trucchia, A.; Meschi, G.; Fiorucci, P.; Gollini, A.; Negro, D. Defining Wildfire Susceptibility Maps in Italy for Understanding Seasonal Wildfire Regimes at the National Level. *Fire* **2022**, *5*, 30. https://doi.org/10.3390/fire5010030
- *(Trucchia et al. 2022b)* Trucchia, A.; Izadgoshasb, H.; Isnardi, S.; Fiorucci, P.; Tonini, M. Machine-Learning Applications in Geosciences: Comparison of Different Algorithms and Vegetation Classes' Importance Ranking in Wildfire Susceptibility. *Geosciences* **2022**, *in press.*
- Trucchia, A.; Meschi, G.; Fiorucci, P.; Provenzale, A.; Tonini, M.; Pernice, U. Wildfire hazard mapping in the Eastern Mediterranean landscape. International Journal of Wildland Fire, **2023**
- Republic of Bulgaria/Ministry of Interior. Reimbursable Advisory Services on Accelerating Resilience to Disaster Risks (P170629) Component 3: National Disaster Risk Profile Assessment of Wildfire Risk in Bulgaria TECHNICAL ANNEX – 5, **2021**



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