Fuel-aware Forest Fire Danger Rating System RISICO: a Comparative Study for Italy

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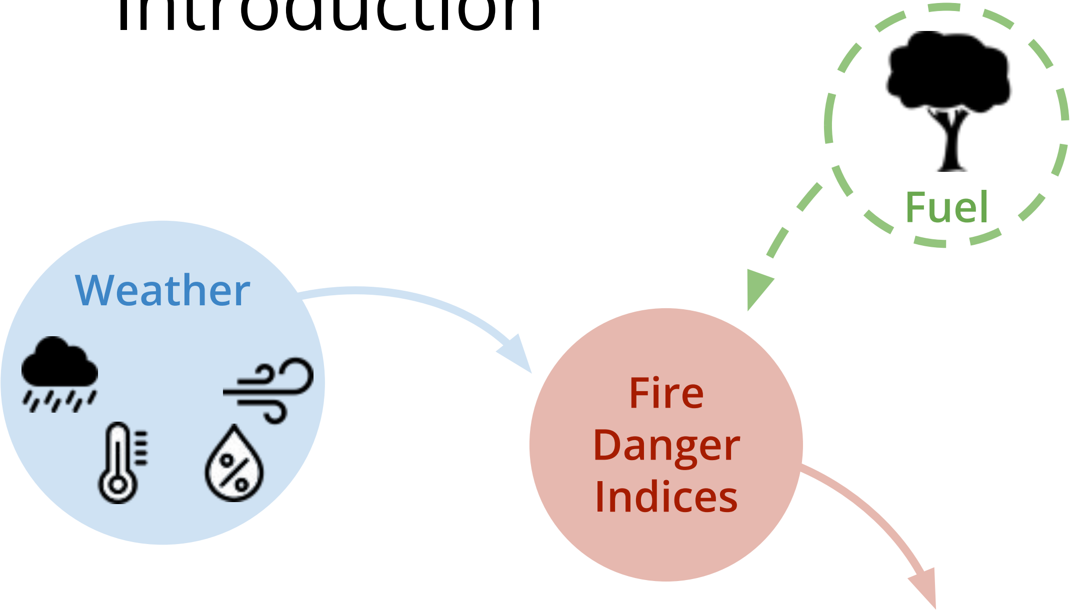
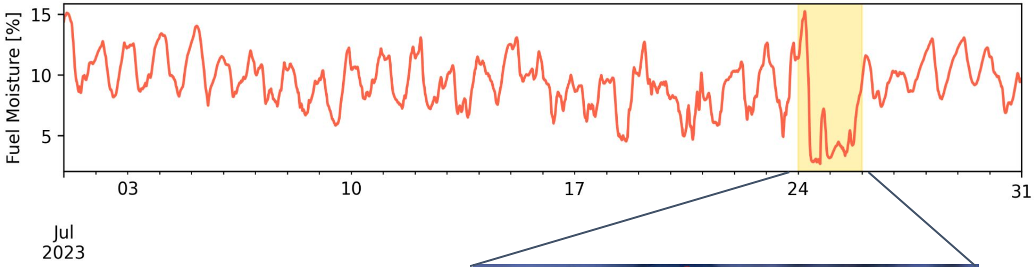
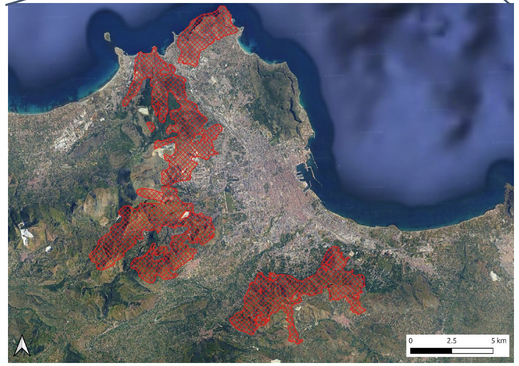
Introduction







Palermo Wildfires
~6000 ha burnt area

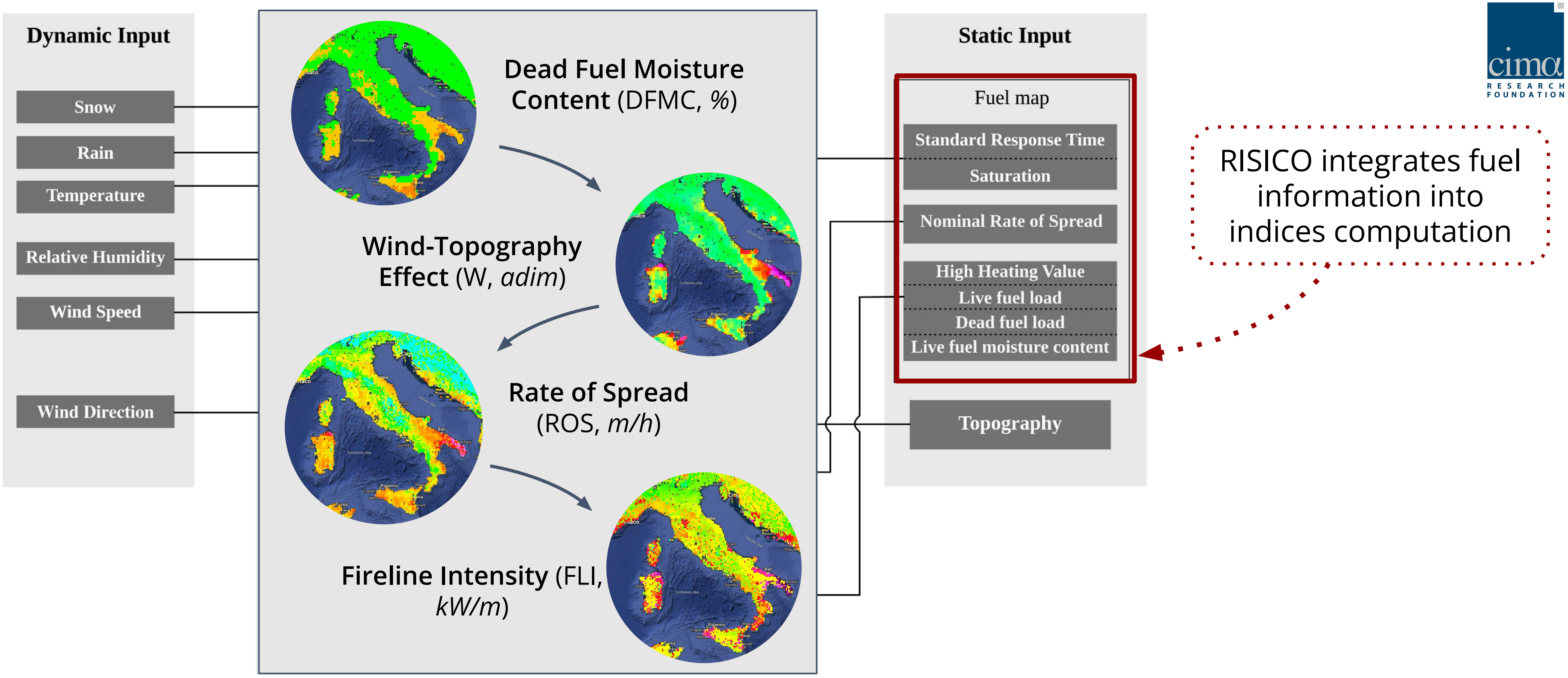
Fire danger indices play an essential role in the wildfire risk management cycle, supporting the various phases (mitigation, preparedness, response).

Most of these indices rely solely on weather conditions, **without taking into account fuel**, which instead plays an important role in defining potential wildfire behavior.

Outline:

- RISICO Model
- RISICO Fuel Map
- Comparative Analysis
- Conclusions

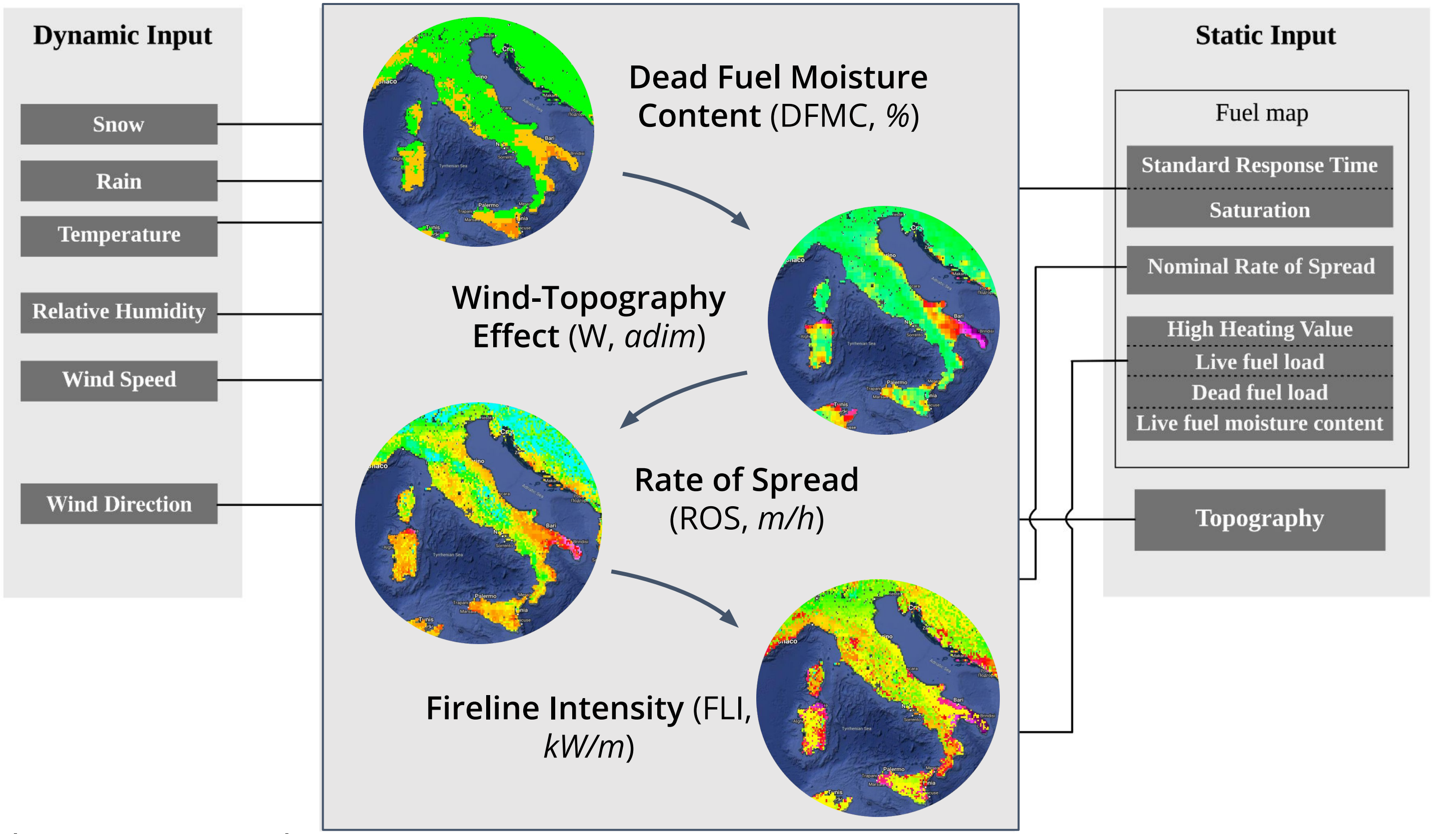
RISICO



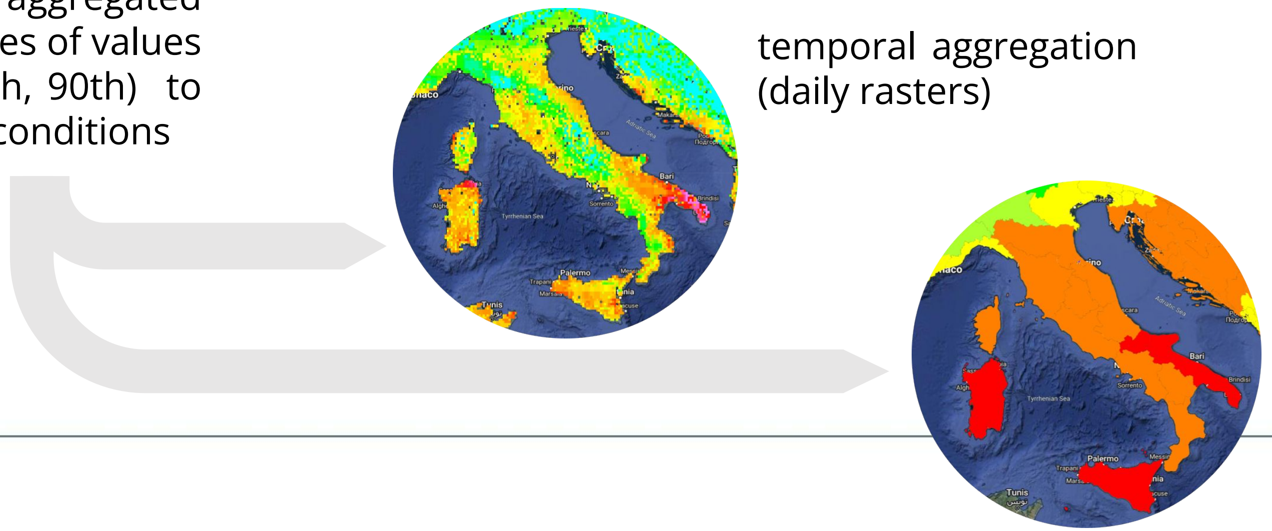
The RISICO indices are produced with **sub-daily resolution** following the temporal resolution of the weather inputs and spatial resolution of the static inputs

Italian implementation:
1 hour, 1 km

RISICO



The ourly RISICO indices are then aggregated into daily indices by adopting averages of values over different percentiles (50th, 75th, 90th) to highlight **persistence** of fire danger conditions



temporal aggregation (daily rasters)

spatio-temporal aggregation at different administrative levels (for fire danger bulletins)

RISICO Model

Dead Fuel Moisture Content

Rate of Spread

Wind-Topography Effect

Fireline Intensity

- rain [mm]
- relative humidity [%]
- temperature [°C]
- wind speed [m/s]

[*Perello et al. 2025*]

Rain > R_0

yes → **Rain phase**

The fuel moisture increases towards a **saturation value**, with rapidity depending on rain amount

saturation level [%]

no → **No-rain phase**

drying process

wetting process

The fuel moisture evolve towards the **Equilibrium Moisture Content**, with a **response time** that differentiates between drying and wetting processes

standard response time [h]

RISICO Model

Dead Fuel Moisture Content

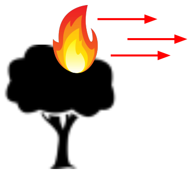
Rate of Spread

Wind-Topography Effect

Fireline Intensity

nominal rate of spread

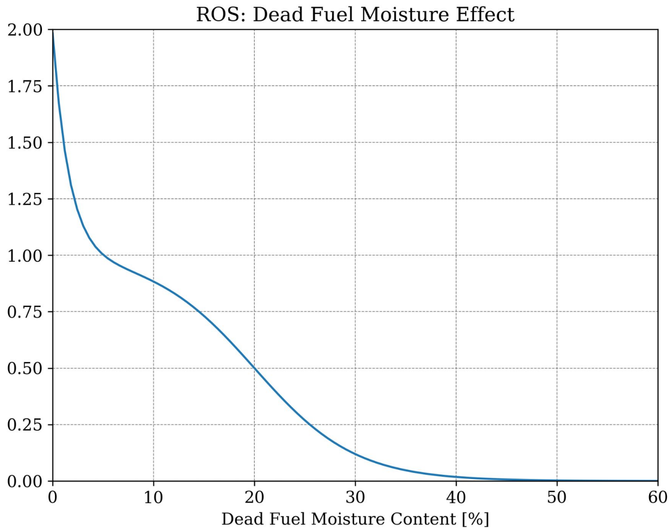
fuel-specific rate of spread in no-wind no-slope condition depending



$$ROS = v_0 \, M \, W$$

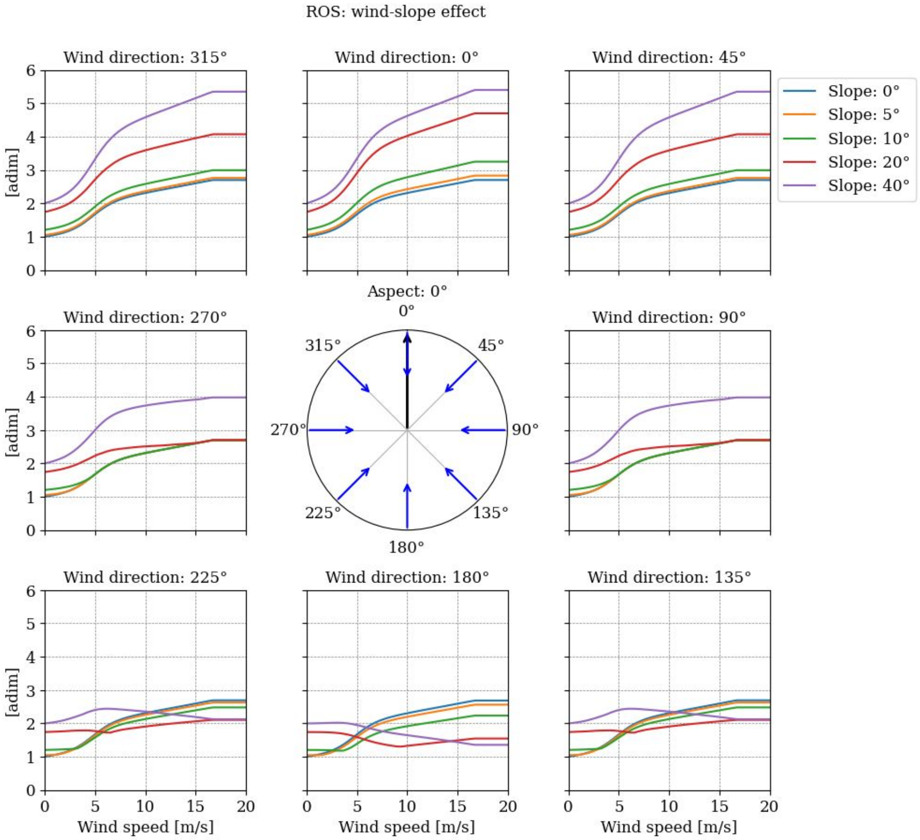
fuel moisture effect

ROS reduces toward zero for DFMC values greater than 40% and while increase v_0 for very dry conditions (i.e., less than 5%)



Wind-Topography Effect (W)

computed as the worst-case wind-topography combined effect in fire propagation from PROPAGATOR [*Trucchia et al. 2020*]



RISICO Model

Dead Fuel Moisture Content

Rate of Spread

Wind-Topography Effect

Fireline Intensity

FLI = (ROS/3600)(lhv_0 d_0 + lhv_1 d_1)

Fuel density of dead (i=0) and live components (i=1), depending on *fuel types*

Lower heating value computed based on higher heating value (hhv), depending on *fuel type*, and fuel moisture contents for dead (i=0) and live components (i=1)

$$lhv_i = hhv(1 - \frac{u_i}{100}) - 2442(\frac{u_i}{100})$$

The moisture content of dead fuel corresponds to the Dead Fuel Moisture Content index, while for live is considered fixed as *worst case scenario* and depending on fuel types

RISICO Fuel Map

Vegetation classes
potential fire behavior

grassland & croplands; broadlevaes; shrubs; conifers

Wildfire susceptibility
tendency to experience wildfires

susceptibility classes
(*low, medium, high*)

Fuel Map

	grassland (G)	broadleaves (B)	shrubs (S)	conifers (C)
low susc.	**G1**: low intensity surface fire, low likelihood	**B1**: medium intensity forest fire, low likelihood	**S1**: high intensity bushfire, low likelihood	**C1**: high intensity forest fire, low likelihood
medium susc.	**G2**: low intensity surface fires, medium likelihood	**B2**: medium intensity forest fire, medium likelihood	**S2**:high intensity bushfire, medium likelihood	**C2**: high intensity forest fire, medium likelihood
high susc.	**G3**: low intensity surface fire, high likelihood	**B3**: medium intensity forest fire, high likelihood	**S3**: high intensity bushfire, high likelihood	**C3**: high intensity forest fire, high likelihood

RISICO Fuel Map

Vegetation classes
potential fire behavior

grassland & croplands; broadlevaes; shrubs; conifers

Wildfire susceptibility
tendency to experience wildfires

susceptibility classes
(*low, medium, high*)

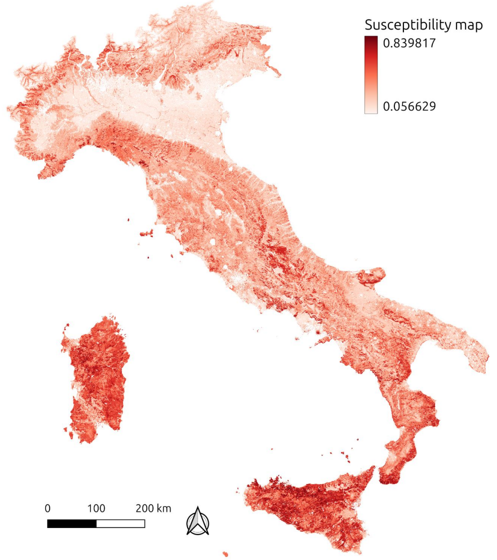
+ → **Fuel Map**

Susceptibility Model

	Predisposing factors
Geo-env.l inputs	Elevation
	Slope
	North and South direction (aspect)
	Vegetation type
	Tree cover density
	Neighbor vegetation
Climatic inputs	Annual average temperature (43-years mean)
	Annual average max daily temperature (43-years mean)
	Annual cumulative precipitation (43-years mean)
	Annual average wind speed (43-years mean)
	Annual maximum consecutive dry days (43-years mean)
	Annual maximum consecutive wet days
	Annual relative humidity (43-years mean)

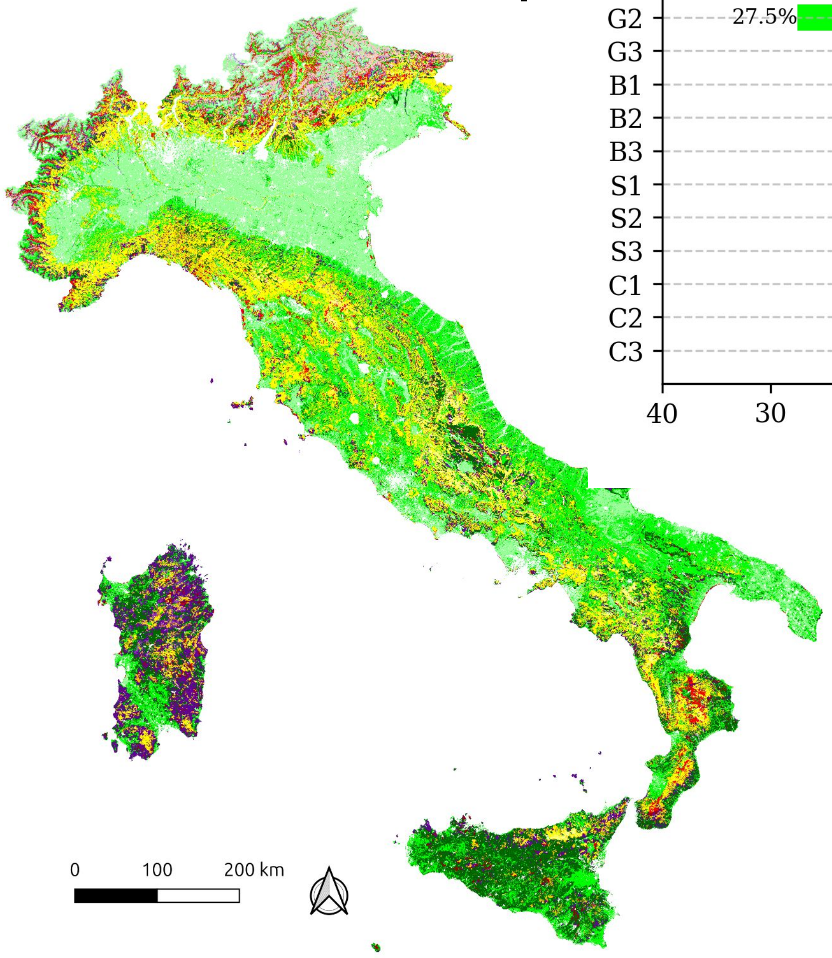
→ **Random Forest Classifier** → Pan-European Wildfire Susceptibility model →

EFFIS burned areas database (2008-2022) at Pan-European level

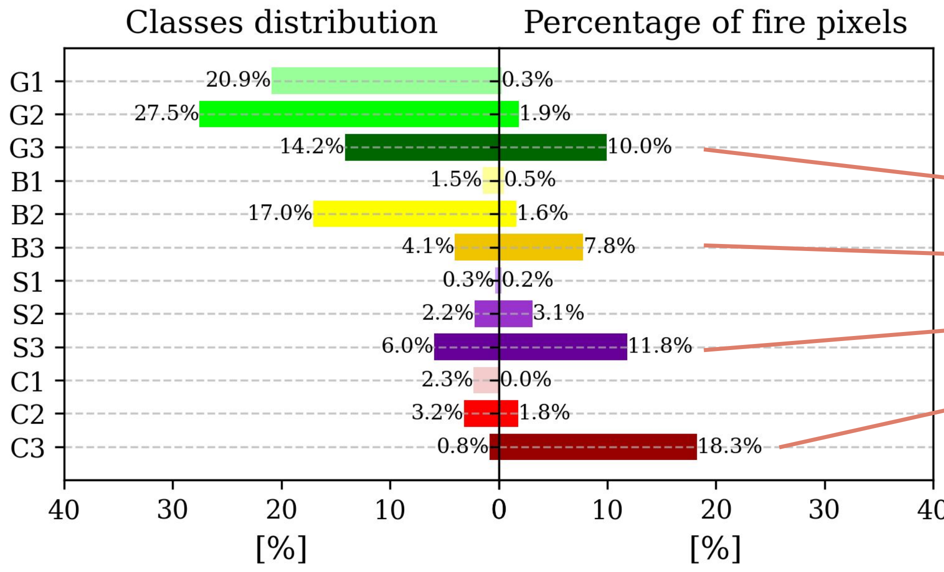


susceptibility classes based on national percentiles (25th, 75th)

RISICO Fuel Map



100 m Italian fuel map



Analysis on Italian wildfires 2007-2022

The classes with high susceptibility are limited in extension (~25% of the territory) but are heavily affected by wildfires.
They represent the areas where **attention is needed**

RISICO fuel models	SUSCEPTIBILITY			DFMC		FLI			
	low	*medium*	*high*						
	ROS								
	v_0 [m h^{-1}]			T_0 [h]	sat [%]	d_0 [kg m^{-2}]	d_1 [kg m^{-2}]	hhv [kJ kg^{-1}]	umb [%]
grasslands & croplands (G)	**G1**	**G2**	**G3**	12	40	0.5	-	17 000	-
	84	96	120						
broadleaves (B)	**B1**	**B2**	**B3**	60	60	1.5	3	20 000	60
	77	88	110						
shrubs (S)	**S1**	**S2**	**S3**	24	40	1	3	21 000	45
	98	112	140						
conifers (C)	**C1**	**C2**	**C3**	48	50	1	4	21 000	55
	84	96	120						

Comparative Analysis

Use of reanalysis dataset to test the **potential predictability** of the model [*Di Giuseppe et al. 2016*]

FFDR Index	With memory	Dynamic inputs				
		T	*RH*	*Ws*	*Wd*	*Rain*
RISICO (4)	yes					
FWI (6)	yes					
Mark 5	yes					
Nesterov	yes					
Orieux	yes					
Angstrom	no					
Fosberg	no					
HDW	no					
Sharples (2)	no					

CHAPTER Dataset [*Tartaglione et al. 2024*]
Downscaling of the ERA5 dataset with WRF
- Spatial resolution: ~2km
- Time resolution: 1 hour
- Time span: 1981-2022

- Output resolution: 1 km
- The hourly indices have been reported to daily resolution following the *75th-percentile average* (RISICO method)

Comparative Analysis

FFDR Index	With memory	Dynamic inputs				
		T	*RH*	*Ws*	*Wd*	*Rain*
RISICO (4)	yes					
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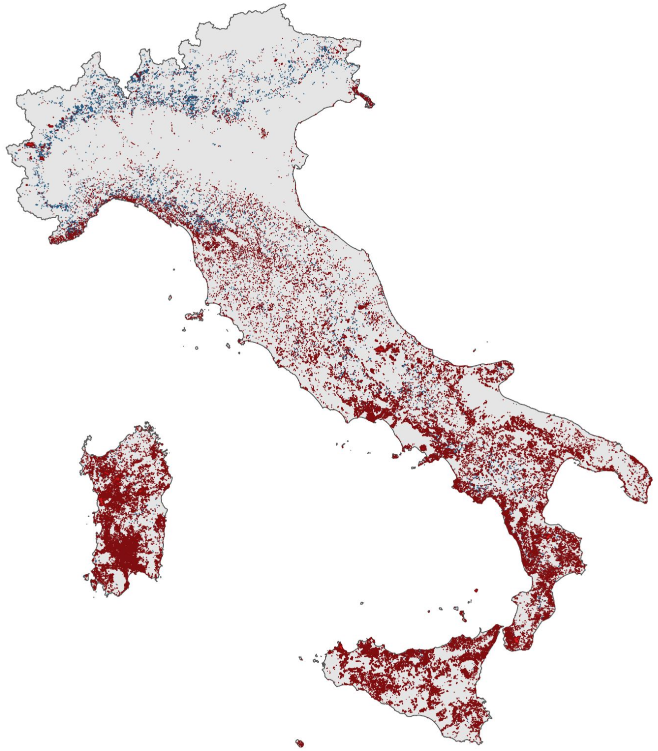
HDW	no					
Sharples (2)	no					

The models outputs have been analyzed against past wildfire events in Italy from **2007** to **2022.** The dataset comes from ground-retrieved burned areas***,** containing **geometries** and **ignition dates**.

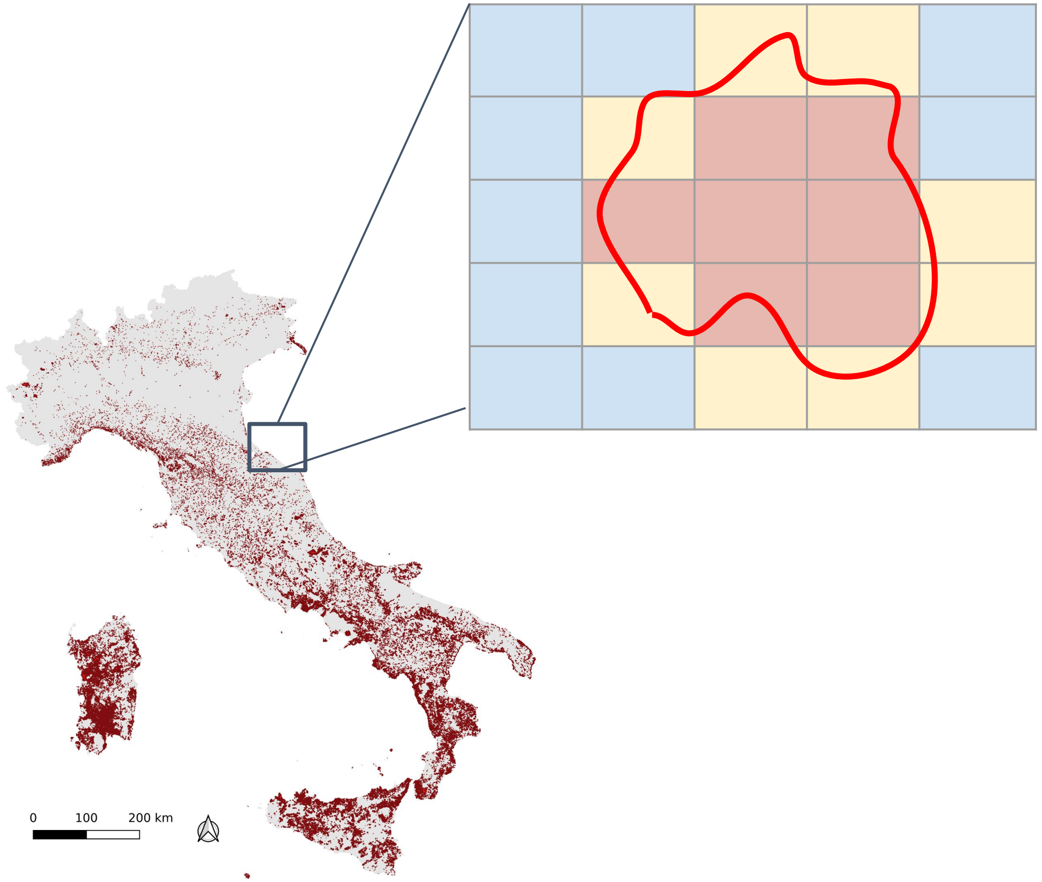


The analysis has been also conducted separately for the Summer Fire Season (May-October) and the Winter Fire Season (November-April)

*Burned areas are collected by Forestry Corps "Corpo Forestale dello Stato" until 2016 and by "Carabinieri forestali" since 2017. The wildfire data for the regions with special statute and autonomous provinces were collected by the competent regional and provincial authorities.

Comparative Analysis

What is a "fire pixel" (true positive) ?



Fire pixel

a pixel burned for at least 20% (wildfire greater than 20 ha)

Fire day

a day in which at least a fire pixel is selected

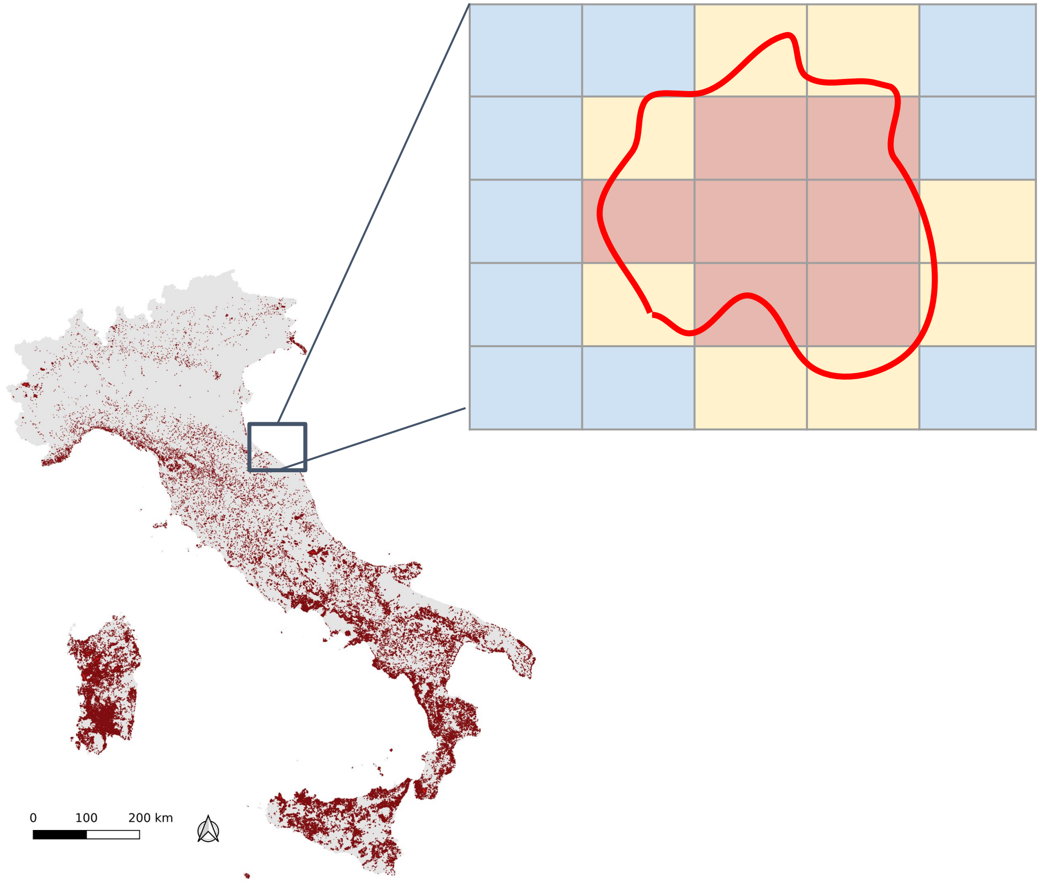
Pixel removed

a pixel partially burned and/or associated with small wildfires

No-fire pixel (*true negative*)

a pixel not burned in a fire day

Comparative Analysis



Cautionary Note: all the comparative methods adopted have to consider that the different distributions and ranges of the indices, requiring **distribution-independent** measures for comparison [*Eastaugh et al. 2012]*

Discrimination skills → Fire pixels ranking with respect to total distribution
Rank-Percentile Method [*Eastaugh et al. 2012]*

Detection skills → Fire pixels against false alarms
ROC curves [*Richardson et al. 2024]*

Danger classification → Alerted area vs. fire classification
Frequency matrices

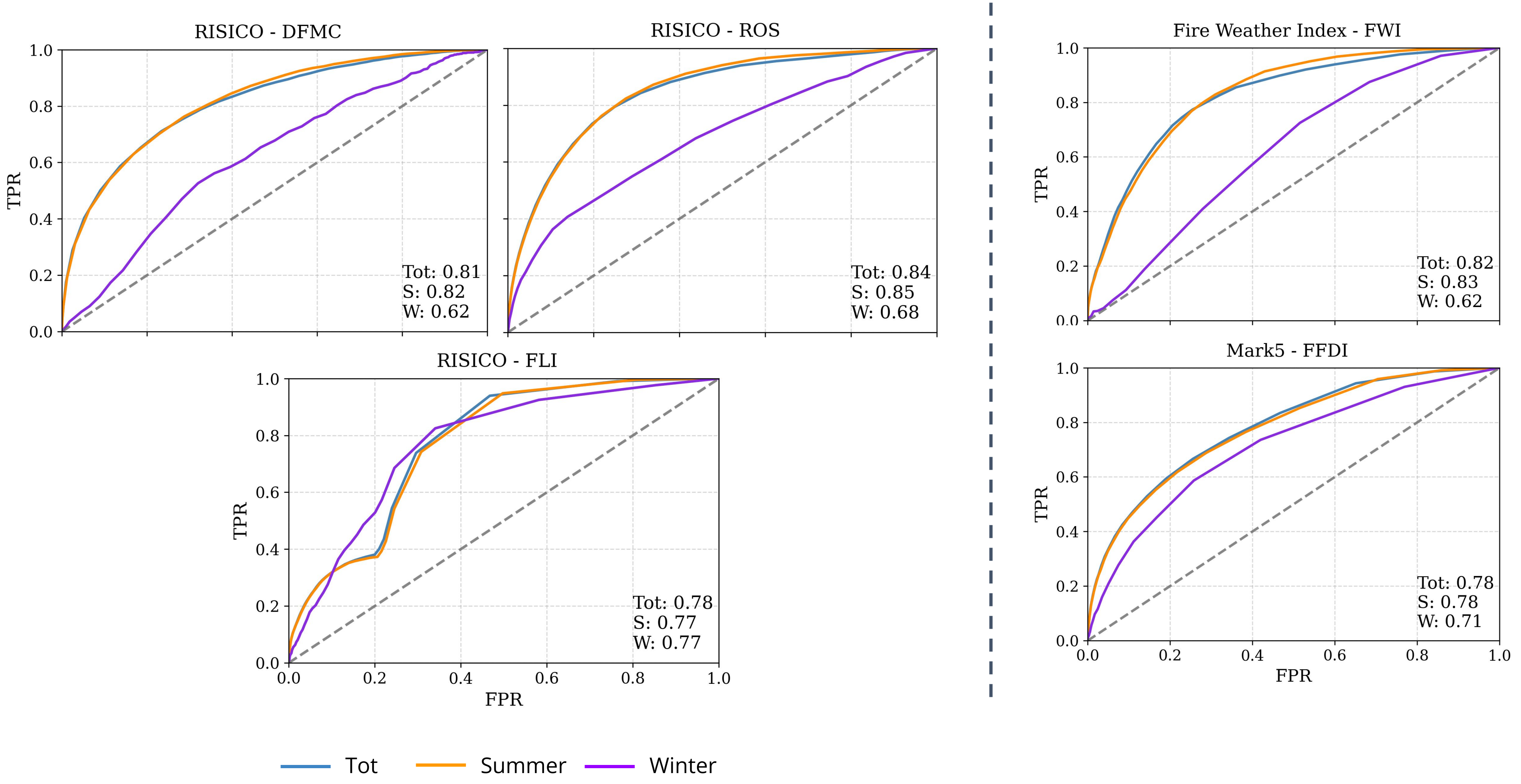
Comparative Analysis

Detection Skills

	AUC		
Index	Tot	S	W
RISICO - DFMC	0.81	0.82	0.62
RISICO - ROS	0.84	0.85	0.68
RISICO - FLI	0.78	0.77	0.77
RISICO - W	0.64	0.65	0.60
FWI - FFMC	0.83	0.83	0.68
FWI - DMC	0.79	0.79	0.56
FWI - DC	0.76	0.77	0.38
FWI - BUI	0.79	0.80	0.56
FWI - ISI	0.84	0.84	0.66
FWI - FWI	0.82	0.83	0.62
Mark5 - FFDI	0.78	0.78	0.71
FFWI	0.78	0.79	0.67
Sharples - FMI	0.80	0.80	0.65
Sharples - F	0.81	0.82	0.63
HDW	0.83	0.84	0.61
Angstrom	0.80	0.80	0.69
Orieux - WR	0.80	0.81	0.58
Nesterov	0.79	0.79	0.60

RISICO indices

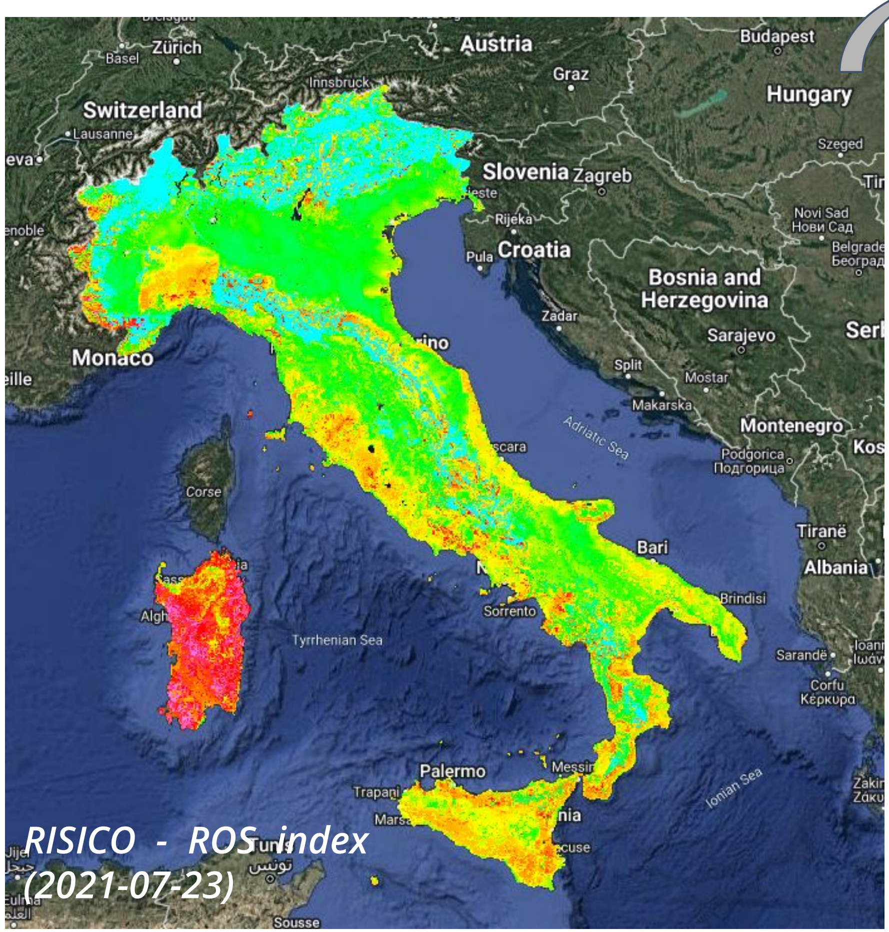
Benchmarks



Comparative Analysis

Danger classification

In order for an index to be used operationally, it should be able to **limit the alerted area** discriminating within the territory

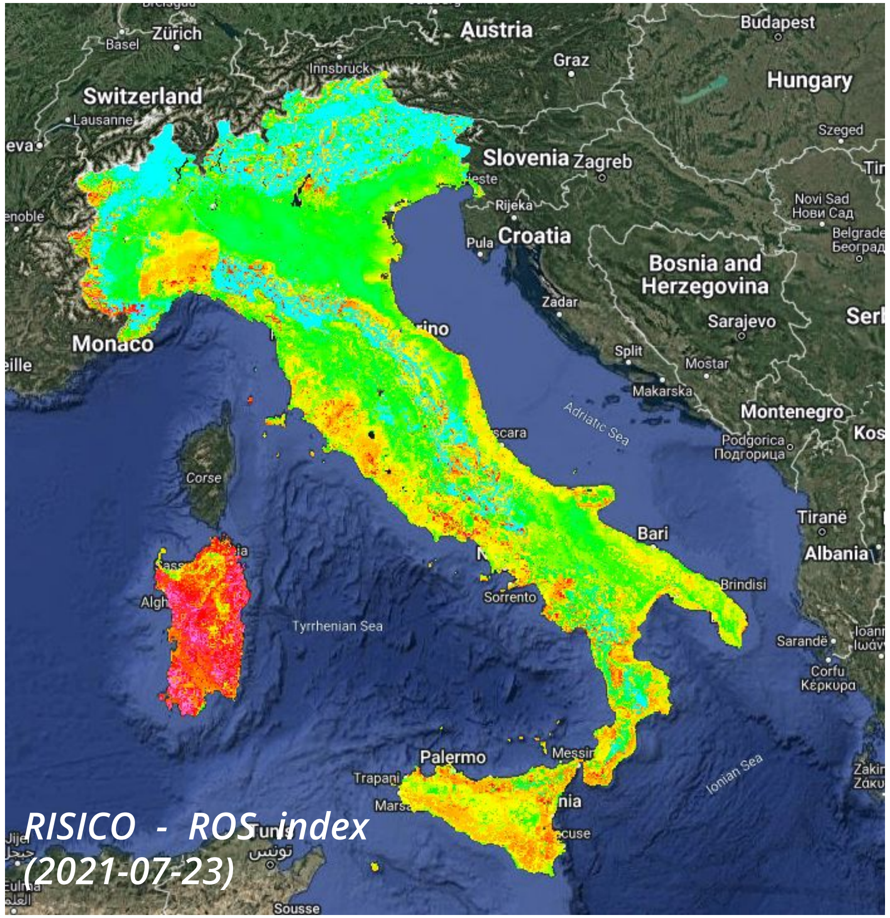


RISICO - ROS index
(2021-07-23)

Wildfire events
(2021-07-23)

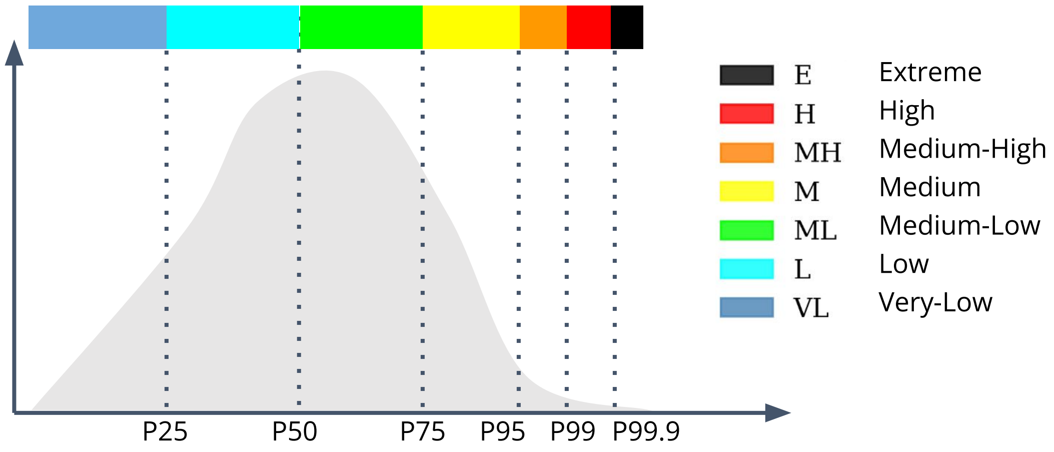
Comparative Analysis

Danger classification



RISICO - ROS index (2021-07-23)

The danger classes were defined based on the **percentiles of the distribution**



The percentile values were established by the operational version of RISICO

Comparative Analysis

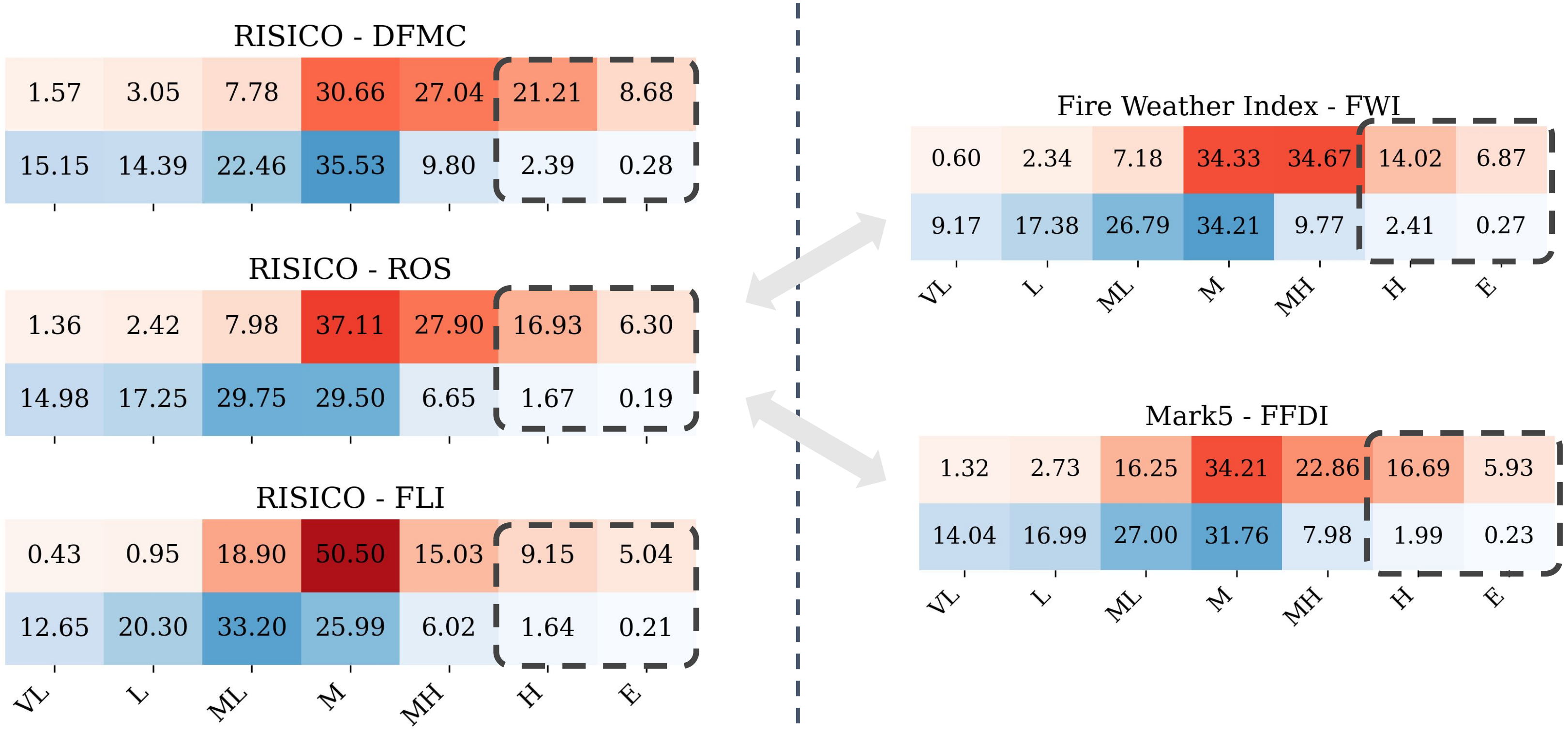
Danger classification

Percentage of fire pixels classification
vs
Classification of territory during *fire days*

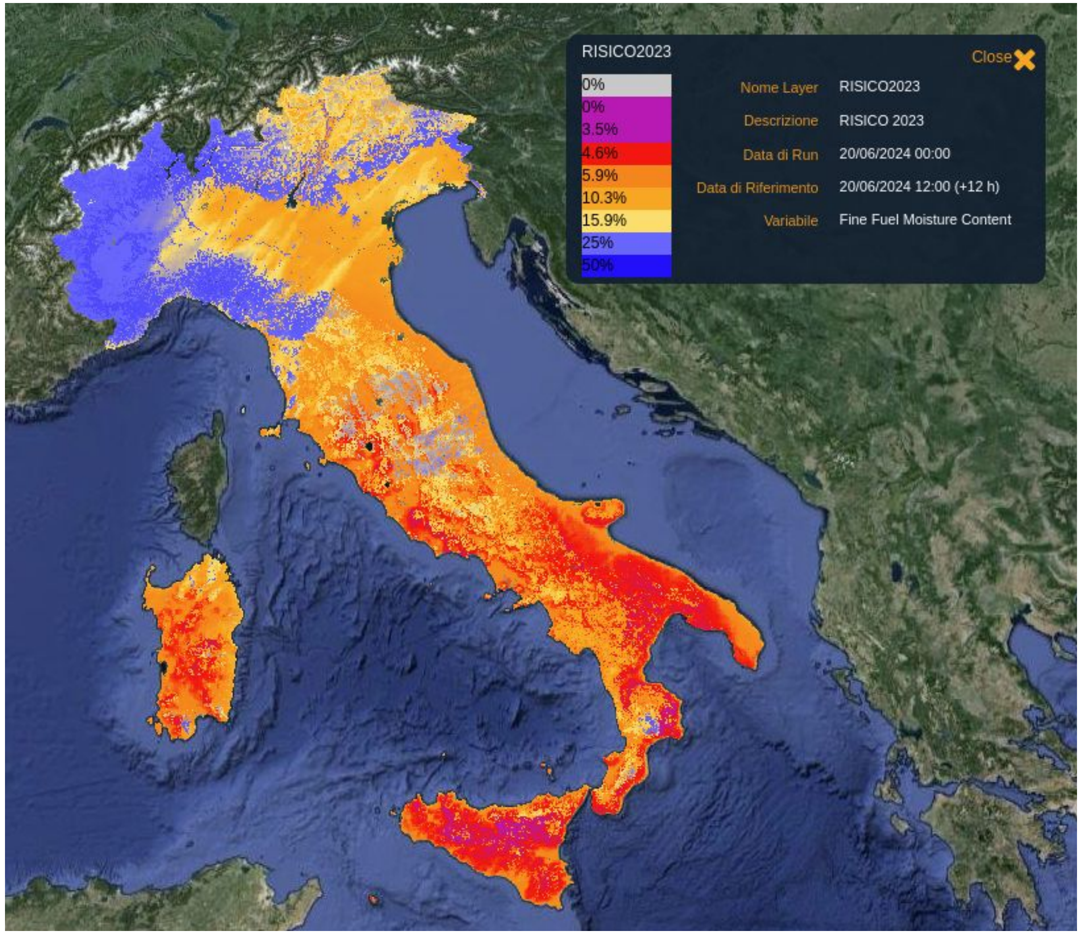
	Area vs. Fire Pixels Classification (H+E)	
Index	Area [%]	Fire [%]
RISICO - DFMC	2.67	29.89
RISICO - ROS	1.86	23.23
RISICO - FLI	1.85	14.19
RISICO - W	0.97	0.67
FWI - FFMC	2.62	25.61
FWI - DMC	2.69	13.15
FWI - DC	2.13	3.96
FWI - BUI	2.66	12.90
FWI - ISI	1.90	25.69
FWI - FWI	2.68	20.89
Mark5 - FFDI	2.22	22.62
FFWI	1.12	14.86
Sharples - FMI	2.64	25.42
Sharples - F	1.81	25.58
HDW	2.60	32.18
Angstrom	2.63	30.25
Orieux - WR	2.61	8.29
Nesterov	2.36	10.35

RISICO indices

Benchmarks



Conclusions



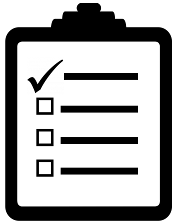
The RISICO model shows a **good detection** capability with respect to other fire danger indices in literature

RISICO effectively identifies fire danger conditions, enhancing the ability to **discriminate areas** across the territory with respect to other indices

Future RISICO developments:

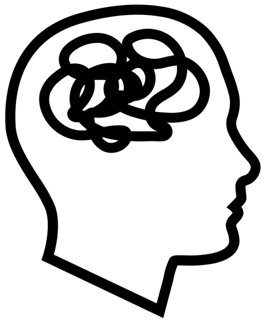
- transitioning from a static fuel map to seasonal fuel maps, taking into account possible different fire regimes;
- incorporating satellite-based vegetation indices that can provide insights into vegetation conditions.

Conclusions



Definition of accepted standards, procedures and datasets, especially for the analysis of spatialized fire danger indices, with particular attention of *operational usability*

We are working for making CHAPTER dataset and analysis results open as *datacubes*



Challenges in fire danger indices assessment

Ambiguity in defining "true positives"

- fire-prone conditions do not always lead to actual fires due to the absence of ignition
- not all the wildfires are the same! considering their *magnitude* rather than a simple binary classification (fire/no fire) would be more meaningful in assessing fire indices performances from an operational standpoint

What should we consider in assessing a fire danger index with respect to wildfire activity?

References

Di Giuseppe, F., Pappenberger, F., Wetterhall, F., Krzeminski, B., Camia, A., Libertá, A., & San Miguel, J. (2016). The potential predictability of fire danger provided by numerical weather prediction. *Journal of Applied Meteorology and Climatology, 55*, 2469–2491. https://doi.org/10.1175/JAMC-D-15-0297.1

Eastaugh, C. S., Arpaci, A., & Vacik, H. (2012). A cautionary note regarding comparisons of fire danger indices. *Natural Hazards and Earth System Sciences, 12*, 927–934. https://doi.org/10.5194/nhess-12-927-2012

Perello, N., Trucchia, A., D'Andrea, M., Degli Esposti, S., Fiorucci, P., Gollini, A., & Negro, D. (2025). An adaptable dead fuel moisture model for various fuel types and temporal scales tailored for wildfire danger assessment. *Environmental Modelling & Software, 183*, 106254.

Richardson, E., Trevizani, R., Greenbaum, J. A., Carter, H., Nielsen, M., & Peters, B. (2024). The receiver operating characteristic curve accurately assesses imbalanced datasets. *Patterns, 5*(6), 100994. https://doi.org/10.1016/j.patter.2024.100994

Tartaglione, N., Parodi, A., Bernini, L., Hachinger, S., & Kranzlmüller, D. (2024). CHAPTER: 3x3 km meteorological data 1981–2022 for Europe: 2D extracted fields [Data set]. *Leibniz Supercomputing Centre (LRZ), Garching b.M., Germany.* https://doi.org/10.25927/0ppk7-znk14

Trucchia, A., D'Andrea, M., Baghino, F., Fiorucci, P., Ferraris, L., Negro, D., Gollini, A., & Severino, M. (2020). PROPAGATOR: An operational cellular-automata based wildfire simulator. *Fire, 3*(3), 26. https://doi.org/10.3390/fire3030026

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Thank you!

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