



*Supplement of*

## **Fire risk modeling: an integrated and data-driven approach applied to Sicily**

**Alba Marquez Torres et al.**

*Correspondence to:* Alba Marquez Torres ([alba.marquez@bc3research.org](mailto:alba.marquez@bc3research.org))

The copyright of individual parts of the supplement might differ from the article licence.

# Supplement

S1

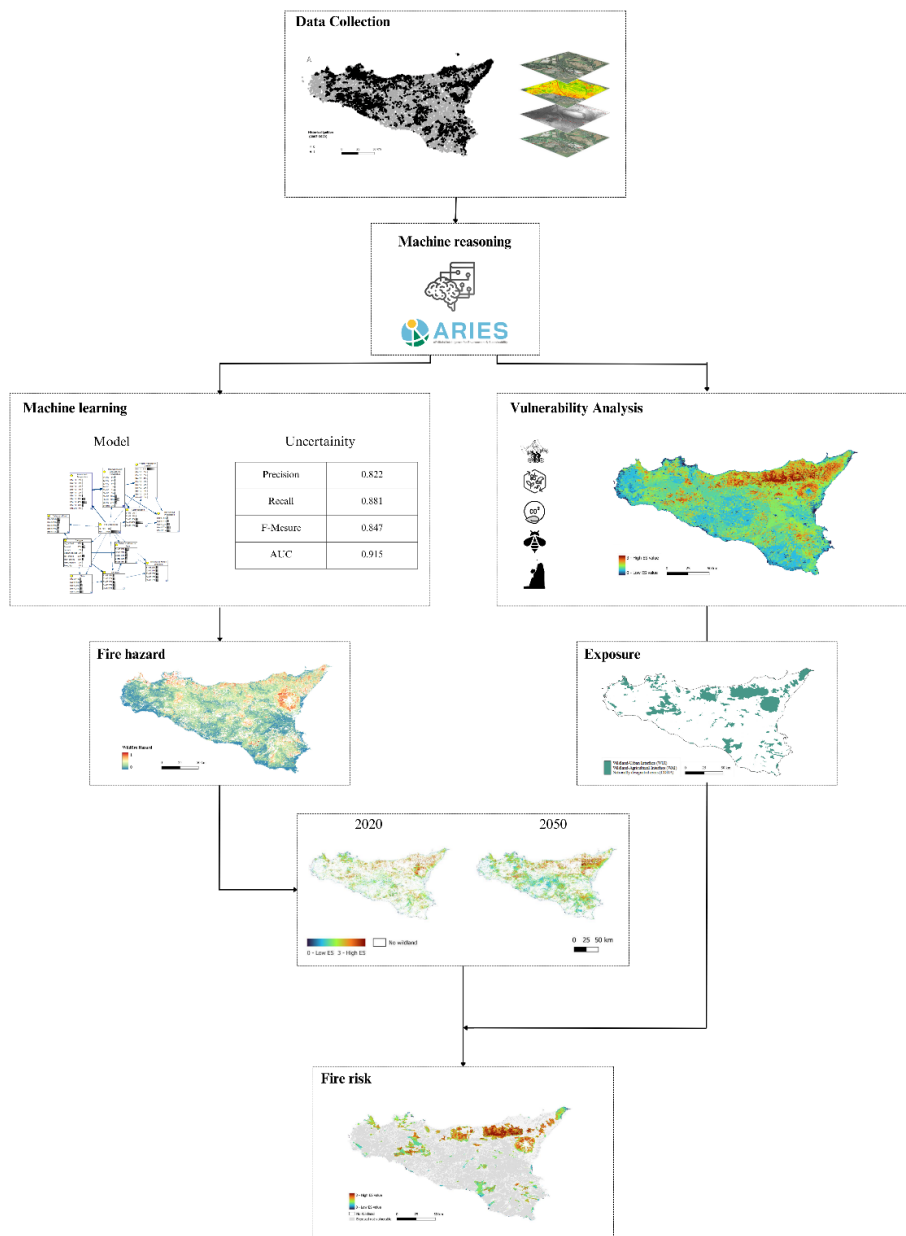


Figure S1. Global workflow of fire risk model.

```

@intensive(space)
learn occurrence of chemistry:Fire within earth:Site
observing
  @archetype earth:Site with occurrence of chemistry:Fire,

  @predictor (discretization = weka.discretizer.unsupervised(bins = 10)) earth:AtmosphericTemperature in Celsius named tg,
  @predictor (discretization = weka.discretizer.unsupervised(bins = 10)) im:Weekly im:Maximum earth:AtmosphericTemperature in Celsius named tx3,
  @predictor (discretization = weka.discretizer.unsupervised(bins = 5)) earth:SolarRadiation in J/m^2 named qq,
  @predictor (discretization = weka.discretizer.unsupervised(equalfrequency= true, bins = 10)) im:Weekly earth:PrecipitationVolume in mm named r7t,
  @predictor (discretization = weka.discretizer.unsupervised(equalfrequency= true, bins = 5)) count of im:Day without earth:Incubation:Precipitation named norain,
  @predictor (discretization = weka.discretizer.unsupervised(bins = 8)) value of ecology:Forest during chemistry:Fire named fuel,
  @predictor (discretization = weka.discretizer.unsupervised(equalfrequency= true, bins = 5)) geography:Slope in grade named slope,
  @predictor (discretization = weka.discretizer.unsupervised(equalfrequency= true, bins = 5)) geography:Elevation in m named elev,
  @predictor (discretization = weka.discretizer.unsupervised(equalfrequency= true, bins = 5)) distance to conservation:ProtectedArea in m named protect,
  @predictor (discretization = weka.discretizer.unsupervised(equalfrequency= true, bins = 5)) distance to infrastructure:Road in m named road,
  @predictor (discretization = weka.discretizer.unsupervised(equalfrequency= true, bins = 5)) distance to infrastructure:HumanSettlement in m named human

using im.weka.bayesnet(
  discretization = weka.discretizer.unsupervised (bins = 2),
  resource = fire.ml.ignition.bayes.fireml, search = weka.bayes.k2(bins=2)
);

```

Figure S2: Bayesian network learning model written in the k.IM semantic language.

S2

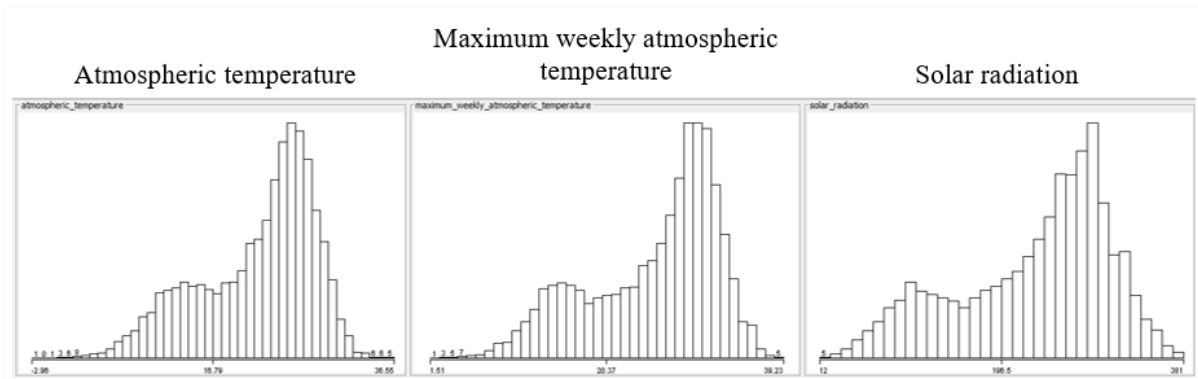
Table S1. Fuel type classifications developed for Mediterranean ecosystems (Lasaponara et al., 2006).

id	Fuel type	Description
0	No natural vegetation	
1	Ground fuels (cover >50%)	Grass
2	Surface fuels (shrub cover >60%; tree cover <50%)	Grassland, shrubland (smaller than 0.3-0.6m and with a high percentage of grassland), and clear-cuts, where slash was not removed.
3	Medium-height shrubs (shrub cover >60%; tree cover <50%)	Shrubs between 0.6 and 2.0 m.
4	Tall shrubs (shrub cover >60%; tree cover <50%)	High shrubs (between 2.0 and 4.0 m) and young trees resulting from natural regeneration or forestation
5	Tree stands (>4m) with a clean ground surface (shrub cover <30%)	The ground fuel was removed either by prescribed burning or by mechanical means. This situation may also occur in closed canopies in which the lack of sunlight inhibits the growth of surface vegetation
6	Tree stands (>4m) with medium surface fuels (shrubs cover >30%)	The base of the canopies is well above the surface fuel layer (>0.5). The fuel consists essentially of small shrubs, grass, litter, and duff.
7	Tree stand (>4m) with heavy surface fuels (shrub cover >30%)	Stands with a very dense surface fuel layer and with a very small vertical gap to the canopy base (<0.5m)

S3

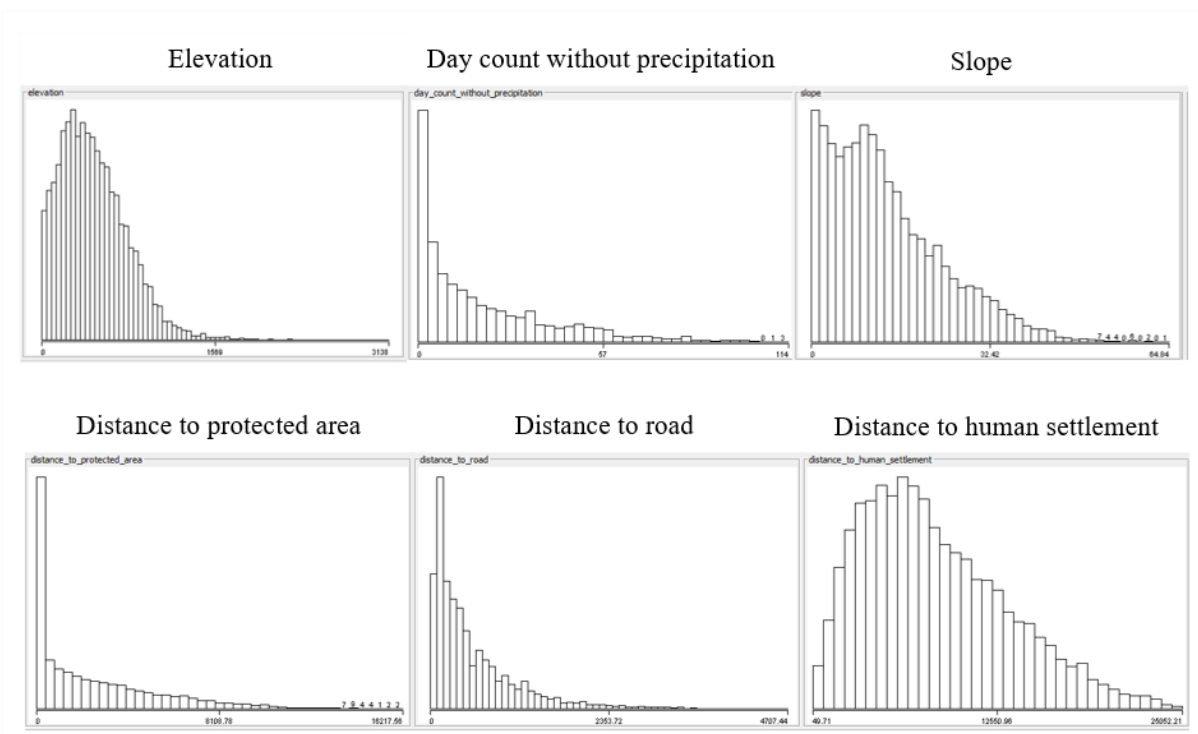
We used the most appropriate discretization method, mostly according to the data distribution of each variable and by trial and error. However, factors to be considered include the shape and spread of the data, the purpose, and level of detail of the analysis, as well as the number and size of bins. The optimal number and size of bins depends on a trade-off between information loss and information gain.

In general, equal-width binning was applied to more uniformly distributed input data as for atmospheric temperature, maximum weekly atmospheric temperature, and solar radiation.



**Figure S3. Data distribution of atmospheric temperature, maximum weekly atmospheric temperature and solar radiation variables.**

For skewed distributions as for elevation, number of days without precipitation, slope, distance to protected area, distance to road, and distance to human settlement, we used Equal-frequency binning.



**Figure S4. Data distribution of elevation, day count without precipitation, slope, distance protected area, distance to road and distance to human settlement variables.**

The disadvantage of equal-frequency is that it can distort the distribution of the data and create irregular bin widths. That was the case with the “weekly precipitation” variable. After several tests, we realized that the equal-frequency produced a wrong data binning, this is the reason why we apply equal frequency in spite of its skewed distribution.

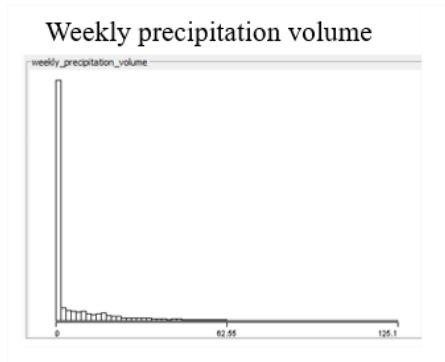


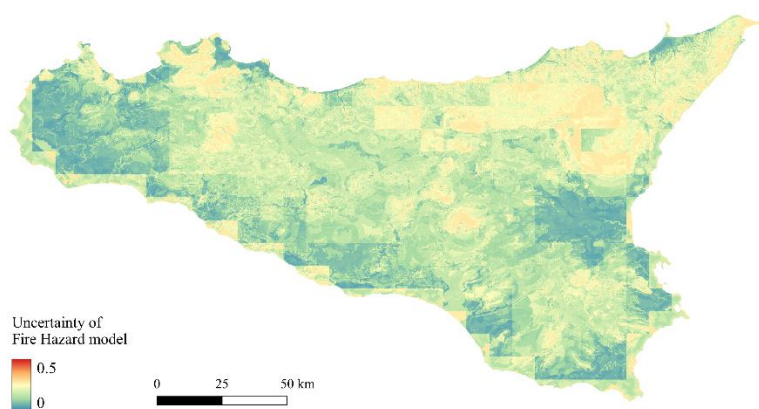
Figure S5. Data distribution of weekly precipitation volume variables.

S4

Table S2. Range of values of the explanatory variables and range in each discretized interval.

Variables	Range (min max)	Intervals									
		B1 (min max)	B2 (min max)	B3 (min max)	B4 (min max)	B5 (min max)	B6 (min max)	B7 (min max)	B8 (min max)	B9 (min max)	B10 (min max)
slope (m)	0.00 64.84	0.00 4.39	4.4 9.26	9.27 14.07	14.08 22.14	22.15 64.84					
elevation (m)	0.00 3,138.00	0.00 202.05	202.06 350.50	350.51 510.50	510.51 713.51	713.52 3,138.00					
distance to road (m)	0.00 4,707.44	0.00 120.71	120.72 291.42	291.43 504.95	504.96 932.67	932.68 4,707.44					
maximum weekly temperature (Celsius)	1.51 39.23	1.51 5.29	5.30 9.06	9.07 12.83	12.84 16.60	16.61 20.37	20.38 24.15	24.16 27.92	27.93 31.69	31.70 35.46	35.47 39.23
weekly precipitation (mm)	0.00 125.10	0.00 0.05	0.06 2.45	2.46 4.75	4.76 7.75	7.76 10.85	10.86 14.95	14.96 18.75	18.76 25.55	25.56 38.45	38.46 125.10
day without precipitation (#)	0.00 114.0	0.00 2.5	2.5 8.5	8.5 35.5	35.5 114.0						
distance to protected area (m)	0.00 16,217.56	0.00 0.00	0.01 1,014.50	1,014.51 2,582.48	2,582.49 4,859.73	4,859.74 16,217.56					

<b>distance to human (m)</b>	46.90 25,052.21	46.90 3,891.14	3,891.15 6,287.73	6,287.74 8,862.06	8,862.07 12,549.17	12,549.18 25,052.21					
<b>atmospheric temperature (Celsius)</b>	-2.96 36.55	-2.96 0.99	1.00 4.94	4.95 8.89	8.90 12.84	12.85 16.79	16.80 20.75	20.76 24.70	24.71 28.65	28.66 32.60	32.61 36.55
<b>solar radiation (J/m<sup>2</sup>)</b>	12.00 381.00	12.00 85.80	85.81 159.60	159.61 233.40	233.41 307.20	307.21 381.00					



**Figure S6. Uncertainty map of fire hazard model: standard deviation of the probability distributions simulated by the model ranges from 0 (blue) to 0.5 (red).**

## S5

**Table S3. Area (km<sup>2</sup>) of low, medium, or high ES (Ecosystem Services) value potentially exposed to fire and the percentage of change in area.**

		low fire probability			medium fire probability			high fire probability		
		low ES	med ES	high ES	low ES	med ES	high ES	low ES	med ES	high ES
Carbon Mass	2020	10,461	2,091	522	3,837	1,789	690	738	691	210
	2050	3,618	930	227	7,897	1,914	674	3,389	1,634	543
		-65%	-56%	-57%	106%	7%	-2%	359%	137%	159%
Biodiversity	2020	1,513	10,691	617	143	5,157	857	70	1,376	233
	2050	938	3,732	262	594	8,585	846	167	4,729	593
		-38%	-65%	-58%	317%	66%	-1%	138%	244%	155%
Outdoor Recreation	2020	5,073	2,878	820	1,983	1,953	979	472	650	354
	2050	1,888	1,257	414	3,780	2,439	924	1,805	1,717	769

		-63%	-56%	-50%	91%	25%	-6%	282%	164%	117%
Pollination	2020	1,773	509	409	1,316	687	603	428	289	531
	2050	880	284	221	1,400	646	473	1,126	552	829
		-50%	-44%	-46%	6%	-6%	-22%	163%	91%	56%
Soil Retention	2020	13,085	7	0	6,265	36	2	1,628	9	1
	2050	4,795	9	0	10,460	14	1	5,526	28	2
		-63%	29%	0%	67%	-61%	-50%	239%	211%	100%
Exposure	2020	6,381	3,235	474	2,709	1,924	626	667	603	266
	2050	2,424	1,242	225	4,826	2,719	584	2,403	1,732	547
		-62%	-62%	-53%	78%	41%	-7%	260%	187%	106%

## References

Lasaponara, R., Lanorte, A., and Pignatti, S.: Characterization and Mapping of Fuel Types for the Mediterranean Ecosystems of Pollino National Park in Southern Italy by Using Hyperspectral MIVIS Data, *Earth Interactions*, 10, 1–11, <https://doi.org/10.1175/EI165.1>, 2006.