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# Fire risk: an integrated modelling approach

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**Abstract.** Wildfires are key to landscape transformation and vegetation succession, but also to socio-ecological values loss. Fire risk mapping can help to manage the most vulnerable and relevant ecosystems impacted by fires. However, few studies provide accessible daily dynamic results at different spatio-temporal scales. We develop a fire risk model for Sicily (Italy), an iconic case of the Mediterranean basin, integrating a fire hazard model with an exposure and vulnerability analysis under present and future conditions. The integrated model is data-driven but can run dynamically at a daily time-step, providing spatially and temporally explicit fashion results through the k.LAB platform. K.LAB provides an environment for input data integration, employing modeling methods such as Geographic Information System, Remote Sensing and Bayesian Network algorithms. All data and models are semantically annotated, open and downloadable in agreement with the FAIR principles (Findable, Accessible, Interoperable and Reusable). The fire risk analysis reveals that 45% of vulnerable areas of Sicily are at high probability of danger in 2050. The risk model outputs also include qualitative risk indexes, which can make the results more understandable for non-technical stakeholders. We argue that this approach is well suited to aid in landscape management and preventing wildfires due to climate change.

## 1 Introduction

Fire, as a natural disturbance, has played an important role in shaping forest structure, increasing biodiversity and leading the species' evolution (Bond and Keeley, 2005; Pausas et al., 2004). However, the balance between the natural fire regime and the ecosystem is often disrupted when humans modify the environment to their needs. In recent years, the rural depopulation and simultaneous spread of urban areas as residential buildings into the countryside have increased the fire frequency and burned areas (Faivre et al., 2014; Robinne et al., 2016). Although this is a worldwide problem, the Mediterranean climatic area had a great impact (Kocher and Butsic, 2017; Leone et al., 2009; Pausas and Fernández-Muñoz, 2012).

Sicily (Italy), the largest island of the Mediterranean Sea with 25711 km², has been the cradle of several civilizations and its traditions with continuous and intense human exploitation of natural resources (forestry, grazing, agriculture) (Antrop, 2005; Sereni, 1961), encompassing multiple agricultural and agroforestry landscapes (Baiamonte et al., 2015; Di Maida, 2020). Due to its great variability of topography, lithology, pedology (Catalano et al., 1996) and climate (Bazan et al., 2015) (Bazan et al.,

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2015), Sicily is rich in biodiversity and ecosystems (Cullotta and Marchetti, 2007; Peruzzi et al., 2014). Therefore, the island can be viewed as representative of the Mediterranean basin as a whole.

Moreover, Sicily is the most populated island in the Mediterranean Sea with nearly 5 million inhabitants, similar to Denmark or Finland (Planistat Europe and Bradley Dunbar Association, 2003). As a consequence, year after year the environment has undergone degradation due to the increase of intensive farming practices, the urbanization growth in the most populated and tourist areas and the loss of traditional agricultural and forest management because of the rural population abandonment (Bazan et al., 2019; Falcucci et al., 2007; Prestia and Scavone, 2018). In the last 50 years, the increase of forest and scrub mass due to the abandonment of traditional land management (Bonanno, 2013; Ragusa and Rapicavoli, 2017) and the increase in the frequency of long droughts created optimal conditions for the occurrence of wildfires (Mouillot et al., 2005; Ruffault et al., 2020). The population living in the wildland-urban interface zone is particularly at risk due to exposure to fire and difficulty in evacuation.

Uncontrolled fires in Sicily have increased in recent years, making Sicily the Italian region with the highest number of fire events (Figure 1a) and the largest affected area (Figure 1b). Fire hazard is mainly linked to ignition source, forest fuels and environmental conditions (Ganteaume et al., 2013; Hantson et al., 2015; Ricotta and Di Vito, 2014). The ignition sources are usually divided into natural causes (mainly lightning but geological causes too) and human (accidentally or intentionally) (Aldersley et al., 2011; Ganteaume et al., 2013; Rodrigues and de la Riva, 2014). The main causes of wildfires in Sicily are human-driven (Corrao, 1992; Ferrara et al., 2019). Arson and accidental fires, set up to create new pasture resources or to burn stubble, are the first causes of wildfires, especially in areas where vegetation interfaces with urban structures.

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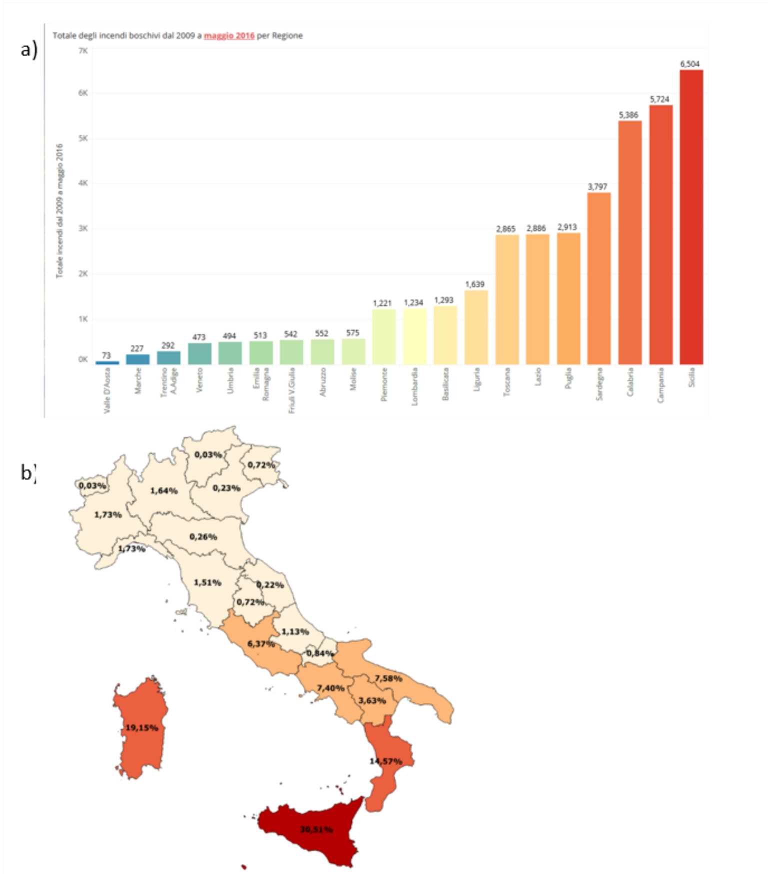


**Figure 1: a) Cumulative frequency of fire events between 2009 and 2016 in Italy by region. b) Total area affected by fire in Italy from 2009 to 2016. Source: Statistiche sull'attività antincendio, Servizi AntiIncendio Boschivo, Roma, www.corporeforestale.it**

The consequences of fires exceed the loss of forest cover, vary over time and can be long-lasting. Some ecosystem properties and functions that represent a benefit to humans, known as ecosystem services (Daily et al., 1997; Roces-Díaz et al., 2022), are lost when fires occur, such as biodiversity, carbon sequestration or outdoor recreation locations (Moreira and Russo, 2007). After the majority of wildfires in summer, with the arrival of the first heavy rains, there can be extensive erosion in burned areas, loss of organic matter or pollution of adjacent water bodies (Bisson et al., 2005; Certini, 2005).

The literature on fire modeling, at different spatio-temporal scales, is vast (Ganteaume et al., 2013; Jain et al., 2020; Tymstra et al., 2020). Due to its drought sensitivity, most studies focus on the Mediterranean climatic region (Oliveira et al., 2012; Satir et al., 2016; Wittenberg and Malkinson, 2009). Among the different methods applied, machine learning models are gaining traction due to increased computing power and data access. Many algorithms have been tested, including artificial neural networks, support vector machines, maximum entropy or random forest (Jain et al., 2020).

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Risk fire mapping has been one of the most widely studied approaches in the forest fire literature. Even so, many models have become obsolete and have not been renewed (Ager and Finney, 2010; Mohajane et al., 2021), the spatial-temporal resolution is too coarse (Lozano et al., 2017) or does not take into account the distribution of forest fuel types (Bacciu et al., 2021; Michael et al., 2021), which is essential for risk reduction (Castellnou et al., 2019). Moreover, risk conditions for society are induced by progressive changes in environmental conditions. For this reason, it is indispensable to create open models that can incorporate new transdisciplinary data and knowledge (Nikolakis and Roberts, 2022; Wunder et al., 2021) that have arisen since 2016 (Artés et al., 2019; Duane et al., 2021).

On the society side, knowledge plays a key role in risk reduction, decision-making, coordinated policy action, and re-learning on fire. Vulnerability is associated with a lack of risk communication, especially a lack of sufficient information that can lead to a misunderstanding of risk (Birkmann et al., 2010). This has important implications for motivation and perceptual capacity to act and adapt to climate change (Grothmann and Patt, 2005). Moreover, understanding the fire risk processes can help society to comprehend the landscape transformation needed for a lower-risk environment (Otero et al., 2018). Although efforts are being made, still few resources are allocated to the accessibility, sharing, and integration of knowledge at multiple scales across different stakeholders (Weichselgartner and Pigeon, 2015). Therefore, it is crucial to develop accessible tools and methods for fire risk assessment, where managers and stakeholders can consider social and environmental consequences.

Similarly, on the scientific side, lack of transparency has been one of the traditional characteristics of modeling (black box model), even the decision support systems leading to various scientific, management and ethical issues (Guidotti et al., 2018). Moreover, most of the models and resources developed by scientific research are not transferable or shared between different machines or languages. To connect the scientific knowledge generated, we applied the Integrated Modeling approach of ARtificial Intelligence for Environment & Sustainability (ARIES) implementing the FAIR principles (Wilkinson et al., 2016) through the k.LAB platform. These principles apply to the generated data and models, which must be:

- Findable: simple to identify by humans and computers;
- Accessible: easy access to metadata and resources stored;
- Interoperable: should be ready to be exchanged, interpreted and combined in a (semi)automated way with other datasets and;
- Reusable: sufficiently well-described to be reused in future research and integrated with other data sources.

This study analyses wildfire activity for the years 2007-2020, with the aim of modeling fire risk in Sicily. Due to the wide variety of definitions of fire risk, we have relied on the definition provided by (IPCC, 2012). Thus, in this article we focus on answering three questions:

1. Where is it likely to occur,

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2. What ecosystem services might it affect, and
3. How significant would it be for the environment and society?

To this end, we have developed a set of models in the k.LAB platform. These models are modular and interconnected under k.LAB, where we simulated the current wildfires and their interaction with key human and biophysical drivers, using a machine learning algorithm. Furthermore, as proof of the advantages of using FAIR data and resources, it has been possible to analyze future fire risk under climate change and see the consequences for different ecosystem services using models included in ARIES and developed by other experts.

## 2 Material and Methods

### 2.1 Study area

The case study was carried out on the island of Sicily, the largest and most populated island in the Mediterranean. Within its 2,571 ha, the altitudinal range reaches 3,357 m at the peak of one of the most active volcanoes in the world (Thomaidis et al., 2021). The island has a Mediterranean climate with mild and wet winters and dry and hot summers, highlighting the southwest coast, where the climate is affected by the African currents and summers. Rainfall is scarce leading to water deficits in some provinces. Moreover, the change in land use has gradually modified the climate, with less rainfall and drier rivers (Drago, 2005; Ragusa and Rapicavoli, 2017).

The land use change caused mainly by the intense deforestation throughout Sicily's history had favored intense agricultural practices nowadays, especially in the center and southwest Thus, agricultural areas cover 57% of the island, whose 35% are arable lands and 22% permanent crops and roughly a third of Sicily is forest, shrublands and open areas. Woodlands and semi-natural areas are sparse in the agricultural area and denser in areas with special protection, being the most important the Mount Etna surroundings, in the Nebrodi Mountains Regional Park and in the *Natural Reserve of Bosco della Ficuzza* (Sicilia Assessorato beni culturali ed ambientali e pubblica istruzione, 1996). Due to its long-lasting socio-ecological history, location in the Mediterranean Sea, its fragility to climate change, and increasing fire regime, Sicily represents an ideal study area representative of the Mediterranean socio-ecological context.

### 2.2 Fire risk analysis

The interaction of environmental and social processes drives the risk (Table 1), determined by the combination of a physical hazard and the vulnerability of the socio-ecological elements exposed (IPCC, 2012).

**Table 1. Fire risk is defined by vulnerability and hazard components (IPCC, 2012).**

| RISK |
|---|

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| **1. Hazard** | **2.Exposure** | **3.Vulnerability** |
|---|---|---|
| *Physical event (natural or human-induced) that may occur and damage the elements in the same time-space context.* | *Elements that are in a context where a hazardous event, such as fire, may happen.* | *The tendency of socio-ecological exposed elements to be adversely affected by a hazardous event. Predisposition, susceptibility, fragility, weakness, defect, or lack of ability drive adverse effects on the exposed elements.* |
| Fire Components<br>● Weather:<br>○ Temperature<br>○ Weekly Maximum temperature<br>○ Days without precipitation<br>○ Weekly precipitation<br>○ Solar radiation<br>● Biophysical drivers:<br>○ Forest fuel<br>○ Elevation<br>○ Slope<br>● Human drivers:<br>○ Distance to protected area<br>○ Distance to road<br>○ Distance to human settlement | Ecosystem services exposed<br>● Vegetation carbon mass<br>● Pollination<br>● Outdoor recreation<br>● Biodiversity<br>● Soil retention | Vulnerability<br>● Wildland-Urban Interface (WUI)<br>● Wildland-Agricultural Interface (WAI)<br>● Nationally designated areas (CDDA) |

Fire hazard captures the probability of fire occurrence, based on historical fires and drivers such as biophysical factors and human-modified areas. The fire hazard interacts with the elements exposed; we highlight exposed ecological values and ecosystem services such as biodiversity, pollination, carbon mass, soil retention and outdoor recreation that may be affected by fire occurrence.

Vulnerability identifies exposed elements that are more susceptible to being highly or irreparably damaged due to their intrinsic or contextual characteristics. Wildland-Urban Interface (WUI) is particularly fire-prone because it is a forested area less than 200 meters from an urban area (Ganteaume et al., 2021; Intini et al., 2020), due to the relationship between the ignition points and populated areas (Chappaz and Ganteaume, 2022). It also represents a high weakness for human settlement, as they are extremely close to the forest, becoming a problem in fire management (Cohen, 2008). Wildland-Agricultural Interface (WAI) is a forest area in close proximity (less than 200 meters) to an agricultural area and highly predisposed to burning due to the fire used for clearing forest and pasture or crop establishment (Leone et al., 2009; Ortega et al., 2012). Moreover, fire impacts

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agricultural land, making food safety susceptible to hazards (Baas et al., 2018). Natural areas with special protection (UNEP-WCMC and IUCN, 2022) are particularly fragile with species with different endemism ranges and sensitive to social, climate and environmental changes (Baiamonte et al., 2015).

### 2.2.1 Fire hazard model

Accurate spatio-temporal detection is essential for modeling and analyzing the probability of fire risk. Through k.LAB, it is possible to know the data origin and its traceability by verifying that the information has been validated through reliable sources. The data collected from different sources can be classified into two categories: historical fires and explanatory variables, which include weather, human and biophysical drivers. The data collection and processing are discussed in the following paragraphs. All the data and resources are semantically annotated, openly accessible and interoperable within ARIES models.

Historical fire data from 2007 to 2020 were collected from two different sources: The Regional Agency of Fire Control in Sicily was used to identify the fire perimeter and the Fire Information for Resources Management System (FIRMS) satellite data to locate the ignition point (Table 2).

**Table 2. Information about historical fire data**

| | **Historical fire perimeter** | **Historical fire ignition** |
|---|---|---|
| **Source** | Regional Agency of Fire Control in Sicily | FIRMS |
| **Spatial resolution** | - | *MODIS*: 1km<br>VIIRS: 375m . |
| **Temporal resolution** | 1 January 2007 - 31 December 2019 | MODIS Collection 6: 11 November 2000 - present<br><br>VIIRS: 20 January 2012 - present |
| **CRS** | EPSG:102092 - Monte_Mario_Italy_2 - Projected for the years 2009 and 2017: EPSG:3004 - Monte Mario / Italy zone 2 - Projected | EPSG:4326 - WGS 84 - Geographic |
| **Feature Type** | Polygon | Point |

The regional agency collects the perimeter data of historical forest-fires and provides the fire start and finish dates collected by the Forestry Information System (SFI) and the forestry command corps of the Sicilian region (Comando Del Corpo Forestale Della Regione Siciliana). FIRMS was developed by the University of Maryland, to locate active fires at near real-time by data from MODIS (Moderate Resolution Imaging Spectroradiometer) and VIIRS (Visible Infrared Imaging Radiometer Suite)

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(Giglio et al., 2016; Schroeder et al., 2014). MODIS is an instrument aboard Terra and Aqua satellites that provides global coverage every 1-2 days and VIIRS sensor is on board the Suomi JPSS-1 satellites and provides full global coverage every 12 hours. When there was information from both satellites for the same fire perimeter, VIIRS was prioritized. Due to its spectral and spatial resolution, VIIRS sensor is more accurate in fire detection (omission and commission of errors) thanks to the detection of the radiative power of the fire, especially in low biomass areas (Fu et al., 2020).

Satellite data was used to locate the fire ignition point inside the perimeter provided by the regional agency. The centroid was considered the ignition point for the perimeters when it wasn't identifiable using satellite data. To prevent double-counting from the data sources, each fire perimeter was double-checked to verify that there was only one ignition point by fire perimeter. We obtained a total of 7,492 points linked with their ignition date (day, month and year).

In addition to the ignition data, we prepared an equal number of locations without fire events. This is needed in order to preserve a balanced dataset of observations that represent ignition and the absence of ignition. The points without ignition were randomly generated with seeds within the study area between the 01-01-2007 and 31-12-2020 periods. It was verified that none of these points overlap with historically burned perimeters in date and location. The "*ign*" attribute differentiates ignition points (1) from non-ignition points (0) (Figure 2, Table 3).

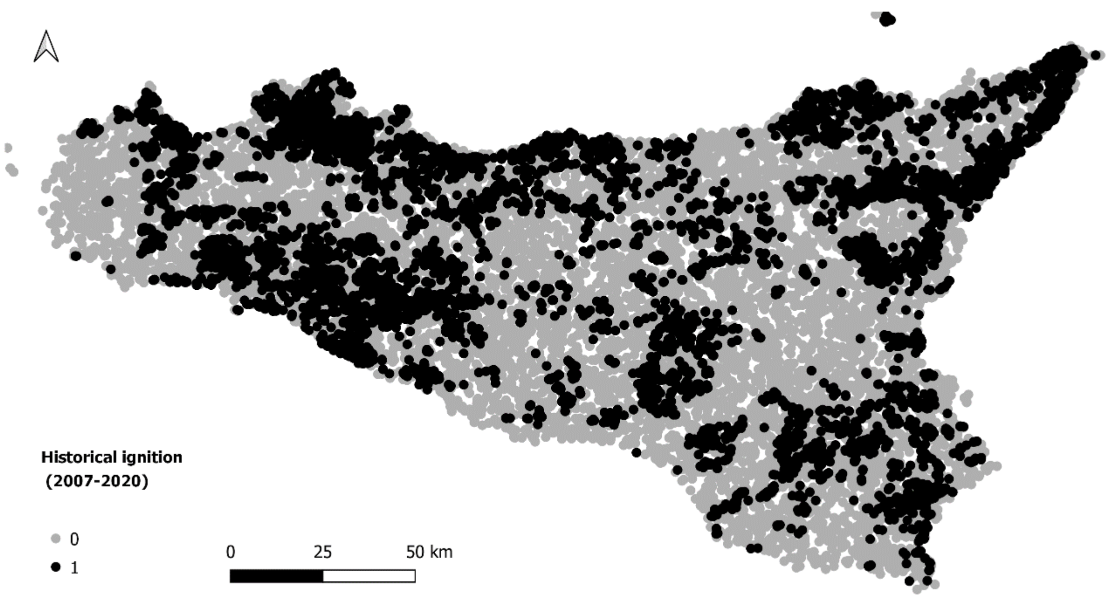


**Figure 2: Distribution of historical fires (category 1, black color) and no fires (category 0, grey color) in the Sicily region from 2007 to 2020.**

**Table 3. Historical fire data in k.LAB**

| Variable (k.IM language) | Description | Type | Unit | Source |
|---|---|---|---|---|

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| | | | | |
|---|---|---|---|---|
| occurrence of Fire within Site | Present and absent | Discrete | 1 (fire) - 0 (no fire) | ARIES and SFI/FIRMS |

The data feeding the machine learning model comes from open resources on the cloud provided by well-known and reliable institutions. Those input data are incorporated automatically, depending on the spatio-temporal needs of the model. In the Sicily model, the data comes from the Regional Government of Sicily, the University of Catania or E-OBS project, among others (Table 4).

In the case of Sicilian forest fires, the human factor is one of the main triggers that lead to the depopulation of country areas by land managers and the increasing number of tourists and visitors. The human drivers used as explanatory variables in the model are distance to protected areas, distance to road and distance to human settlement. Additionally to human drivers, the fire danger also depends on (I) weather (especially due to long dry seasons), (II) topography and (III) environment, characterized by the high flammability of the Mediterranean forests (Corrao, 1992). Those drivers influence fuel type, moisture levels and fire behavior.

**Table 4. Explanatory variables in the BN model**

| **Variable (semantic language)** | **Description** | **Type** | **Unit** | **Source** |
|---|---|---|---|---|
| Atmospheric Temperature | Mean temperature | Continuous | Celsius | E-OBS |
| Weekly Maximum Atmospheric Temperature | Mean of maximum temperature in the last week | Continuous | Celsius | ARIES (based on E-OBS data) |
| count of Day without Precipitation | Counting days since last precipitation | Continuous | mm | ARIES (based on E-OBS data) |
| Weekly Precipitation Volume | Accumulated precipitation during a week | Continuous | mm | ARIES (based on E-OBS data) |
| Solar Radiation | Total solar radiation | Continuous | J/m^2 | E-OBS |
| Biomass of Forest during Fire | Combustible biomass found in forests | Discrete | (S1) Fig. S1 | University of Catania |
| Elevation | Geographical elevation above sea | Continuous | m | University of Catania |

| | | | | |
|---|---|---|---|---|
| | level, as described by a digital elevation model | | | |
| Slope | Inclination of the above-water terrain in a geographical region | Continuous | grade | University of Catania |
| distance to ProtectedArea | Distance to protected area | Continuous | m | ARIES (based on OSM) |
| distance to Road | Distance to road | Continuous | m | ARIES (based on OSM) |
| distance to Human Settlement | Distance to human settlement | Continuous | m | ARIES (based on OSM) |

Meteorological data were obtained from the E-OBS Copernicus project (Cornes et al., 2018). We used the last version released in March 2021 to obtain data from 2017-01-01 to 2020-12-31. The data were processed with R software to obtain the meteorological data needed on each specific day as daily temperature and daily solar radiation (Table 4).

In addition, heatwaves and long periods of drought are great drivers for the majority of extreme forest fires (Narcizo et al., 2022; Nojarov and Nikolova, 2022; Parente et al., 2018). Moreover, with climate change, these episodes will increase in number, frequency and intensity, especially for the projections for RCP 8.5 (Molina et al., 2020). We have taken into account variables such as the mean of maximum temperatures, the number of days without rain and the precipitation accumulated during the previous week.

The topographic factors used (slope and elevation) are constant components of the fire risk model. They have a strong influence on other parameters such as fuel conditions and weather. Slope and elevation were generated from a Digital Elevation Model (DEM) at a 10 meters' resolution.

Fuel type and land cover composition have a significant effect on fire ignition. Deep knowledge of the fuel bed is key to fire management, as it is one of the main components of fire risk. Fuel bed has been reformulated into fuel models for easier use in models and systems. The fuel type used ranges between 1 to 7 (S1, Table S1) according to the Prometheus project (Lasaponara et al., 2006). The land cover map source is based on the Italian Nature Map (Angelini et al., 2009). Landcover is mainly composed of extensive crops and complex farming systems (46%) so, the main fuel type is ground fuels such as grass (50% of land in Sicily). 29% of the land cover on the island is non-combustible.

Among the models that were tested, one of them had the fire frequency as input, calculated with the historical fires from 2012-2020. This model had an accuracy above 95%. After several literature searches and discussions with experts, it was decided not to incorporate fire frequency into the model. Although the accuracy was much better than the model finally chosen (83.6%), the main disadvantage was the possibility of overfitting. In addition, it may lower the likelihood of detecting fires in unusual

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areas due to changes in land use or phenomena such as climate change. Finally, the difficulty of accessing new fires to incorporate into the frequency variable was another important reason.

Bayesian Networks (BN) (Pearl, 1988) have been widely used in recent years and have been highlighted as a powerful tool for modeling complex problems, representing uncertainty and assisting stakeholders when the data is highly interlinked (Henriksen et al., 2007; Kangas and Kangas, 2004; Penman et al., 2011). Thus, the BN model is especially useful in environmental modeling as wildfire risk because (i) involves a high level of uncertainty, (ii) has limited or incomplete data on key system variables, (iii) contains both qualitative and quantitative information or data in different forms, and (vi) integrates multidisciplinary systems (Chen and Pollino, 2012). In addition, the system is transparent in its process, as its nodes table shows the dependency's strength between nodes and their parents in terms of conditional probability distribution and the relationships between variables are made explicit.

A BN is a model that graphically represents causal assertions between variables as patterns of probabilistic dependencies. The Directed Acyclic Graph (DAG) of a BN is built with nodes (variables) and edges between the nodes (dependencies and mutual relationships between variables). Each successor node (children) is only determined by the values of its immediate predecessors (parents) known as parental Markov property (Pearl, 2009). Roots are the nodes without any parent and with marginal distribution (Borsuk, 2008).

The BN has been learned using the WEKA (Waikato Environment for Knowledge Analysis) library integrated in the k.LAB platform (Bouckaert, 2004; Frank et al., 2016; Willcock et al., 2018). WEKA is an open source JAVA library providing a collection of machine learning algorithms. The WEKA interface provides graphical and text components to inspect some BN's properties as basic algorithm information, the bayesian network structure, the probability distribution table or the accuracy by class.

The model has been written in a semantically explicit way using the *knowledge-Integrated Modeling* language (k.IM) (Figure 3), which compiles in Web Ontology Language (OWL) (Bao et al., 2012) and allows to ontologically define and model natural language-like logical expressions. A model written in k.IM is able to interoperate with other models available in the k.LAB environment. When modeling in k.IM concepts that have been previously defined in a knowledge-base are invoked, examples are *earth:Site* and *chemistry:Fire* as depicted in Figure 3. Those concepts carry out meanings facilitating a semantic integration within the system (Villa et al., 2017).

```
@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 3: Bayesian network learning model written in the k.IM semantic language.**

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The BN is built with categorical values, so in case the data are continuous they have to be discretized. Discretization allows the establishment of non-linear values between variables and more complex distributions (Friedman and Goldszmidt, 1996). Discretizing the data helps to interpret the results more easily when it comes to decision-making processes by facilitating communication between modelers and end users. However, the interval selection interferes in the final results. We have been taking into account that the higher the number of intervals, the more data is needed to find significant dependencies (Aguilera et al., 2011); the nodes become weak when there are many intervals because there is less data for each distribution

Among the methods to discretize (Beuzen et al., 2018), in this study we use both the equal-width and equal-frequency binning unsupervised methods. In the first case, the algorithm divides the data into k intervals of equal size and in the case of equal frequency, the user specifies the sub-ranges to divide continuous data by the sorted values into k intervals (bins) with approximately the same number of values (Liu et al., 2002). The bins number is determined by arity k, in our case, we observe the data histogram (S1 Fig. S1) and try different intervals. After modeling with different discretization ranges and obtaining similar accuracy results (S2 Table S2), we have chosen for each of the variables the minimum number of intervals in order to keep ecological sense, statistical significance and lose less information. The discretization applied is shown in Table 5.

**Table 5. Discretization applied to the variables used on the fire occurrence modeling.**

| Semantic | Method | Bins |
|---|---|---|
| occurrence of Fire within Site | equal-weight | 2 |
| AtmosphericTemperature in Celsius | | 10 |
| Weekly Maximum AtmosphericTemperature in Celsius | | 10 |
| SolarRadiation in J/m^2 | | 5 |
| Weekly PrecipitationVolume in mm | | 10 |
| value of Forest during Firec | | 8 |
| ount of Day without Precipitation | equal-frequency | 5 |
| Slope in grade | | 5 |
| Elevation in m | | 5 |

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| | | |
|---|---|---|
| distance to ProtectedArea in m | | 5 |
| distance to Road in m | | 5 |
| distance to Human Settlement in m | | 5 |

In order to learn the BN, we selected the K2 algorithm (Cooper and Herskovits, 1992). This type of score-based algorithm searches for the most probable belief-network structure through a heuristically search. The K2 algorithm processes each node in turn and greedily considers adding edges from previously processed nodes to the current one, adding the edges that maximizes the network's score. It turns to the next node when (i) it has reached the maximum number of parents, (ii) there are no more parents to add, (iii) the score has not improved (Chen et al., 2008). The number of parents for each node can be restricted to a predefined maximum (e.g. maxparents = 1) to mitigate overfitting.

The BN predictors have been distributed in graph form (DAG) as shown in Figure 4, assigning probabilities to each variable's predictor; anthropogenic and biophysical factors such as meteorology, topography and environment. 80% of the dataset was used to learn and 20% to test the relationship between historical fires (observations) and explanatory variables.

Finally, in order to be more understandable for end-users and stakeholders, the results of the model were divided into 3 equal intervals, related to the level of occurrence (high:more than 66% of chance, medium: between 33 and 66%, low:probability of fire less than 33%).

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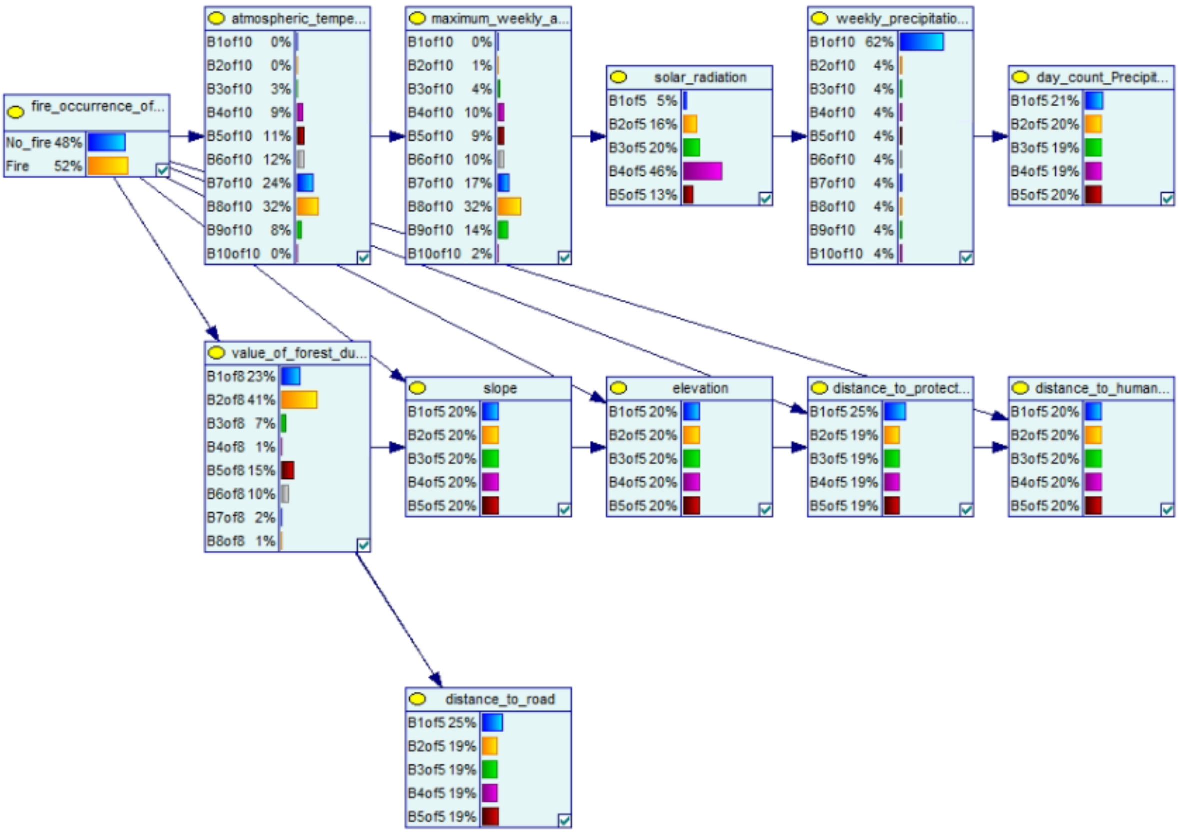


**Figure 4: DAG of fire occurrence BN model.**

### 2.2.2. Drivers of vulnerability

260 Social and environmental vulnerability have been assessed as the tendency of exposed elements to be potentially damaged by a fire hazard due to its intrinsic or contextual conditions (IPCC, 2012). First, we used models developed in previous projects in k.LAB in order to determine the socio-ecological exposed elements. The ecosystem services models considered are those included in the ARIES global model set (Martínez-López et al., 2019). Once the fire hazard model is in k.LAB, all the data and models can interoperate between them through the semantics (Villa et al., 2017). Thus, we can reuse previous ecosystem services models developed (Martínez-López et al., 2019; Willcock et al., 2018) applying them to a different context and creating new knowledge. In this case, due to the specificities of Sicily and its linked with ecosystem services affected by fires, we choose the ecosystem services models of (i) vegetation carbon mass, (ii) pollination, (iii) outdoor recreation, (iv) biodiversity and (v) soil retention. These models are published (Martínez-López et al., 2019; Willcock et al., 2018) thus we don't fully describe them in this article.

270 To create a comprehensive indicator of ecosystem services, we converted the ecosystem services related modeling output to a common scale, using quantitative and qualitative criteria. In order to calculate the potentially reduced social and ecological

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services, we used the normalization method, instead of others such as qualitative categorization and probabilistic approaches (normal, Poisson, binaria) (Chuvieco et al., 2003). We transformed each modelling output rescaling them from 0 to 1, using the minimum and maximum value within the Sicily context. The quantitative scale was classified into 3 categories (1-low, 2-medium, 3-high) using equidistant intervals; thus integrating all ecosystem services into a single value. In this quantitative cross-assessment, the most valuable component was prioritized. The final map was overlap with wildland ares

Once we had the exposure, we located the most vulnerable elements that were exposed to fire. Spatial data were generated for WUI, WAI and protected areas. In order to create the WUI area, we generated a 200m buffer map from the human settlements, then overlaid it with the forest areas. The WAI map followed the same procedure, but with the buffer map from the agricultural areas. Finally, we use the FAO map (UNEP-WCMC and IUCN, 2022) for the protected areas. Vulnerable areas were overlapped with the ecosystem services exposure map.

Finally, we use the fire occurrence model developed to predict how these ecosystem services may be affected in the future by fire risk under climate change conditions. The future climate data is Coupled Model Intercomparison Project 5 (CMIP5) for RCP 8.5 from COordinated Regional climate Downscaling EXperiment (CORDEX) (Giorgi et al., 2009). The data are bias-corrected and simulated by state-of-the-art global and regional climate model pairs. To generate the climatic variables, we use the same process as the current variables.

## 3. Results

### 3.1. Historical data analysis

During the analysis period (2007-2020) 28,8814.698 ha were burnt in 12,749 fire perimeters and the data shows significant interannual variability (Figure 5). The average area burnt is equivalent to 20,630 ha with 910 ignitions per year, being 2012 the worst year, with 1,274 ignitions and 55,699 ha burnt. However, the monthly distribution over this period is skewed toward July and August, due to the weather's favorable fire conditions. August is clearly the month with more fires in all the years analyzed, with 4,166 ignitions and 118,481 ha burnt in total (26% more area than July, the second worst month).

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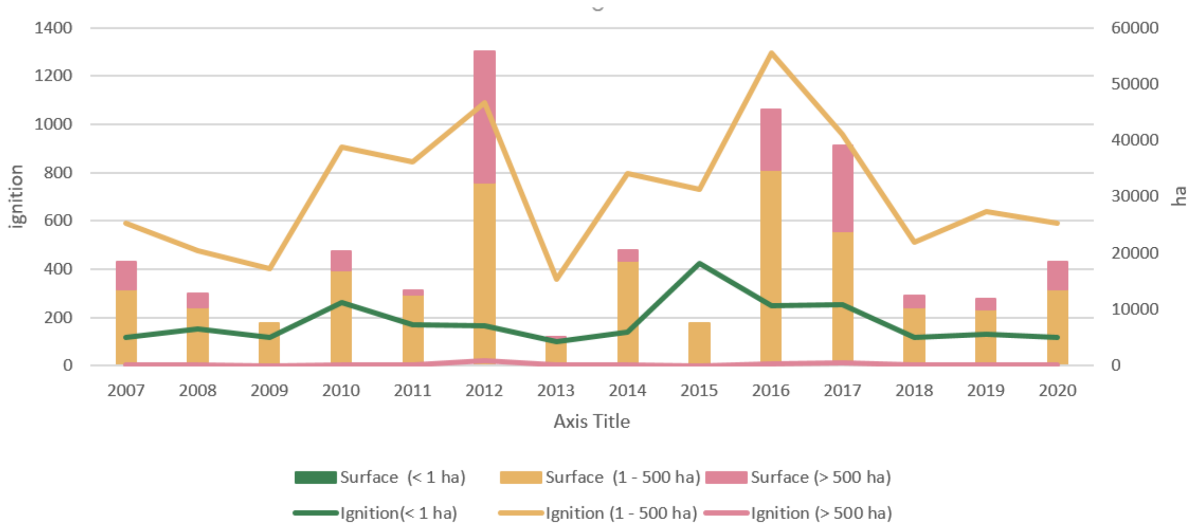
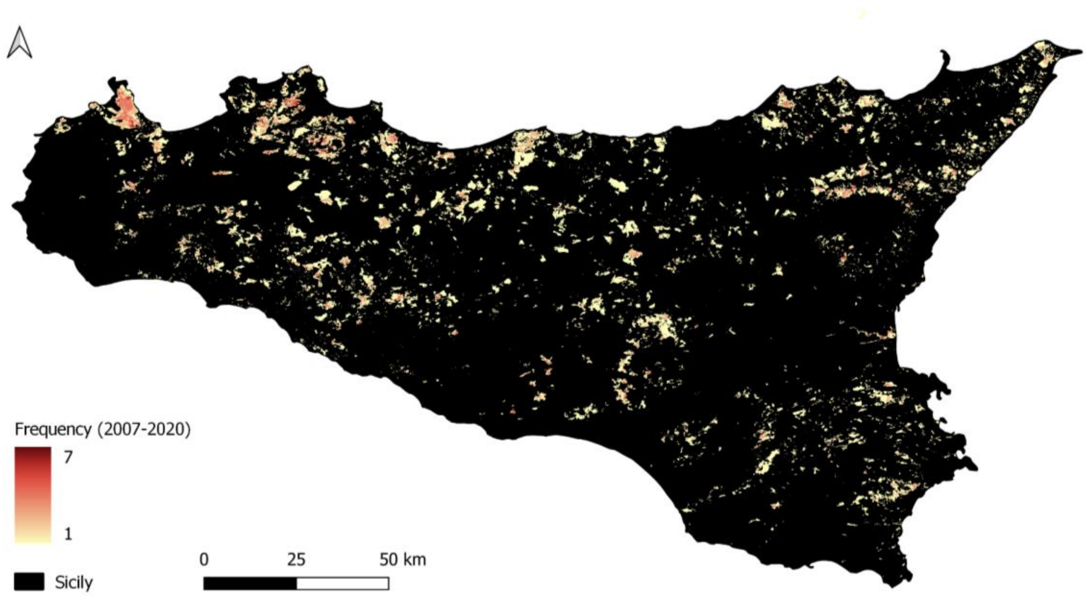



295 **Figure 5: Number of ignitions vs. burned area by year from 2007 to 2020.**

Fire frequency analysis (Figure 6) showed that a quarter of the area affected during 13 years (from 2007 to 2020) has burnt once and 34.8% twice. 23.1% have burnt three times or more, and nearly 6% have been burnt more than 5 times in 13 years. Burned area is spread throughout Sicily, however, areas close to cities, such as Palermo, have been burnt more than others.

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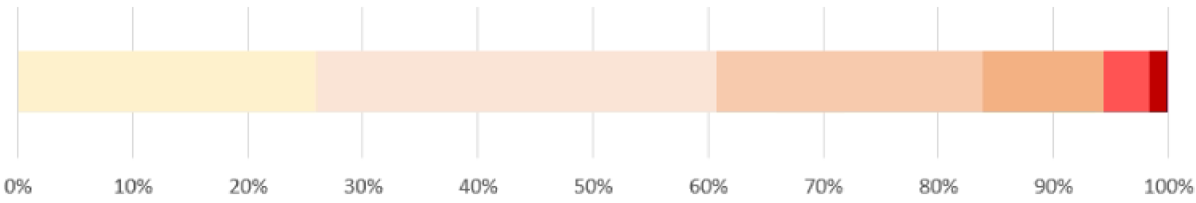
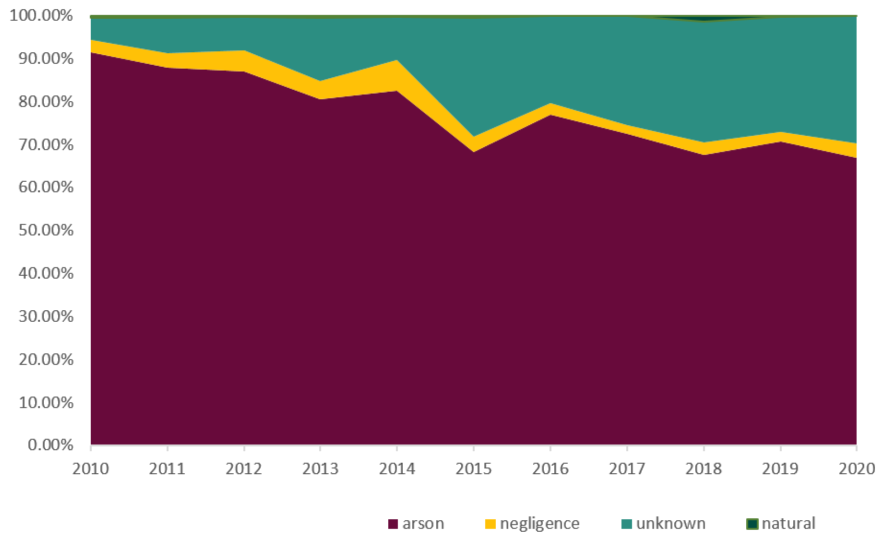



**Figure 6: Fire frequency aggregated by year. The legend shows how many times the same area has been burnt during the period of 2007-2020.**

Fire ignition causes have been recorded since 2010. Figure 7 shows that, every year, more than 70% of fires are caused by arson, with 2010, 2011 and 2012 being particularly relevant. The percentage of fires caused by negligence or natural effects is of little relevance. In general, it seems that the trend of arson is decreasing significantly over the years, from 91.54% to 67.06%. A large part of the percentage that decreases due to arson is replaced by fires of unknown origin, so we cannot be confident that this trend is real.




310 **Figure 7: Percentage of ignition caused by year from 2010 to 2020.**

### 3.2. The Bayesian data-driven approach

The Bayesian network model shows the probability of each child node under the fire occurrence parent node. For this purpose, the state of the parent node based on historical fire is set to the state of fire occurrence, which means that the state of fire occurrence is “Fire = 100%”, indicating that wildfire is certain. The posterior probability of each node is then obtained as per each Conditional Probability Table (CPT) (Figure 8).

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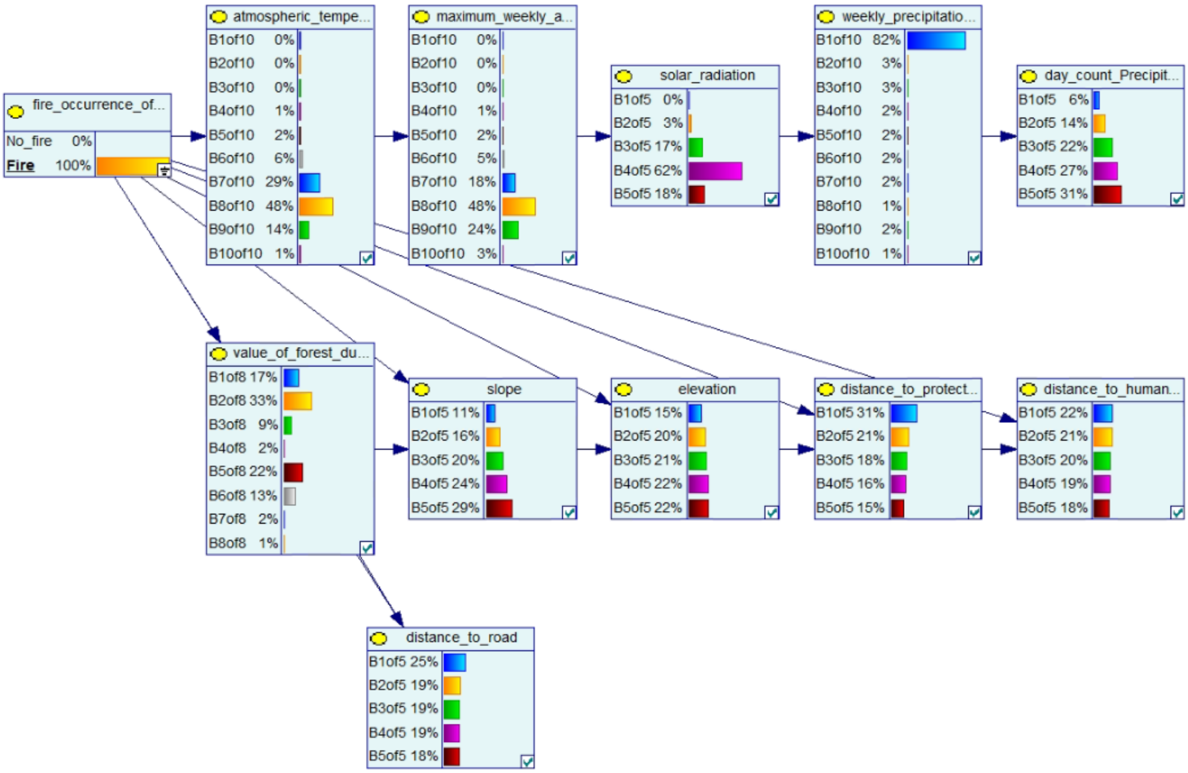


**Figure 8: Distribution of probability by BN node in the case of fire occurrence.**

Accordingly, the fire occurrence probability at "Atmospheric temperature" is highest between 18.75ºC and 25.55ºC and the weekly maximum temperature is around 27.92ºC. In over 80% of the cases, the weekly precipitation accumulated is below 0.03 mm for fire occurrence. Moreover, the more days without precipitation and higher solar radiation, the higher the probability of fire occurrence. As for the topographic variables, the most important is the slope, since the probability of fire is directly proportional to the slope. The same is observed in the case of elevation but in a less obvious pattern. The probability of fire is higher in locations that are closer to human activities such as roads or buildings. Finally, in the case of the environmental variables, the highest fire probability in fuel forest type (S1 Table S1) is in the shrubland vegetation (type 4), followed by broadleaf and coniferous forest and grasslands (Figure 9).

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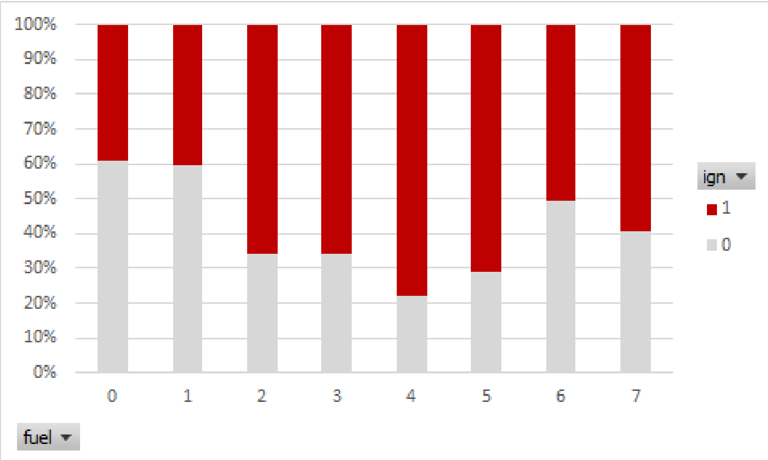


**Figure 9: Distribution of fire (red) and no-fire (grey) by fuel type from 2007 to 2020.**

The most influential variables according to our BN algorithm are atmospheric temperature and fuel type. While atmospheric temperature is expected to increase in variability and increase fire danger with limited options for human mitigation, fuel type can be managed with punctual landscape interventions reducing its combustibility level where it is more necessary.

The k-fold cross-validation algorithm has been used to estimate the model's accuracy. This algorithm uses the training/testing process "k" times and averages the results. The results for k=10 showed that 83.997% of the instances were correctly classified in two values: occurrence and non-occurrence of forest fires.

We use the confusion matrix in order to measure the performance of the classification (Table 6). The results show 12,172 correctly classified instances, but also 1,426 false positives and 893 false negatives. The type I error (false positive), i.e. detecting a fire where in reality is not, could lead to allocating efforts to unnecessary areas. Type II error (false negative), could not identify the probability of fire in risk situations and, therefore, would not be managed properly. A false negative rate (0.11) is calculated as the number of incorrect positive predictions divided by the total number of negatives; the best false positive rate is 0.0.

**Table 6: Confusion matrix of fire occurrence BN modeling.**

| | | **Real** | | |
|---|---|---|---|---|
| | | **No fire** | **Fire** | *Sum* |
| **Predicted** | **No fire** | 5573 | 893<br>(type II error) | *6466* |
| | **Fire** | 1426<br>(type I error) | 6599 | *8025* |

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| | | | | |
|---|---|---|---|---|
| | *Sum* | *6999* | *7492* | *14491* |

The Bayes theorem is key to interpreting the output of binary classification problems using the calculated confusion matrix. Precision is the confusion matrix probability P(Fire/TotalPredictedFire) = 6599/8025 = 0.822. It is the probability that the fire predicted as fire is true. Recall P(Fire/TotalActualFire) = 6599/7492 = 0.881 is the percentage of the actual fires that were correctly predicted by our classification algorithm. Table 7 also shows that the precision for the negative class (no fire) is 0.822. Moreover, the overall accuracy (weighted average between fire and no fire) is 0.841 and 0.840 for precision and recall respectively and gives an overall picture of our model. These weighted results are close to our precision and recall values for fire variables because our model is balanced (7492 fires (51.70%) vs. 6999 no fires (48,29%)). Hence, the overall accuracy (0.84) is a good metric in this situation.

**Table 7: Sensitivity analysis of fire danger model.**

| | **TP Rate** | **FP Rate** | **Precision** | **Recall** | **F-Measure** | **MCC** | **ROC** | **PRC** |
|---|---|---|---|---|---|---|---|---|
| **No fire** | 0.796 | 0.119 | 0.862 | 0.796 | 0.828 | 0.681 | 0.915 | 0.922 |
| **Fire** | 0.881 | 0.204 | 0.822 | 0.881 | 0.851 | 0.681 | 0.915 | 0.903 |
| Weighted Avg. | 0.84 | 0.163 | 0.841 | 0.84 | 0.84 | 0.681 | 0.915 | 0.912 |

The confusion matrix is also useful for measuring other significant metrics such as the ROC curve that summarizes the performance of the Bayesian classifier over all possible thresholds (Bradley, 1997; Fawcett, 2006). It measures accuracy in a weighted sort and is appropriate when the observations are balanced between each class, as in our case. In the fire occurrence model, the ROC curve (Figure 10) has a strong result of 0.915 for the fire occurrence model, because the result is close to 1. We want to highlight the significant F-Measure (a harmonic mean of the precision and recall) with 0.847.

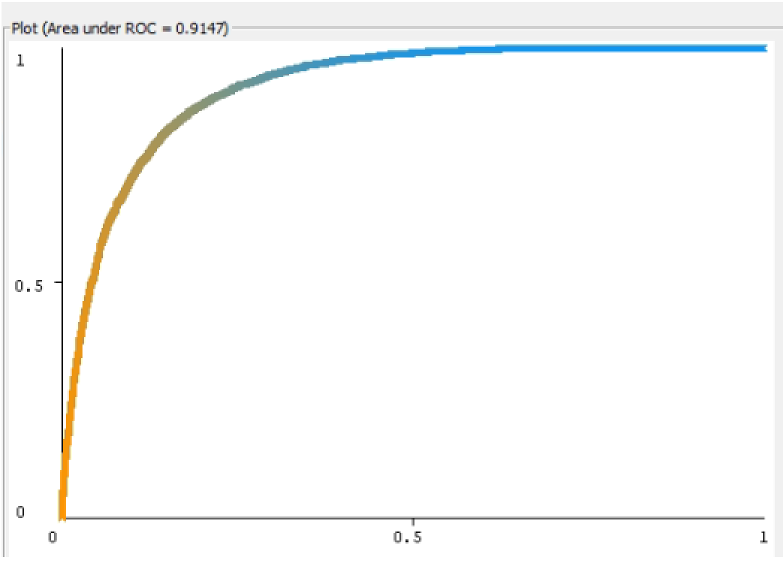


**Figure 10: ROC curve of fire occurrence model.**

As an example, we show the hazard fire model for August 2050 because this is the month with the most important historical fires in Sicily (Figure 11), assuming no changes in ecosystem management. Given the ease of access and reuse of models and data in k.LAB, the users can run the fire risk model at any time in the future until 2055, as the data are on the platform and are openly available.

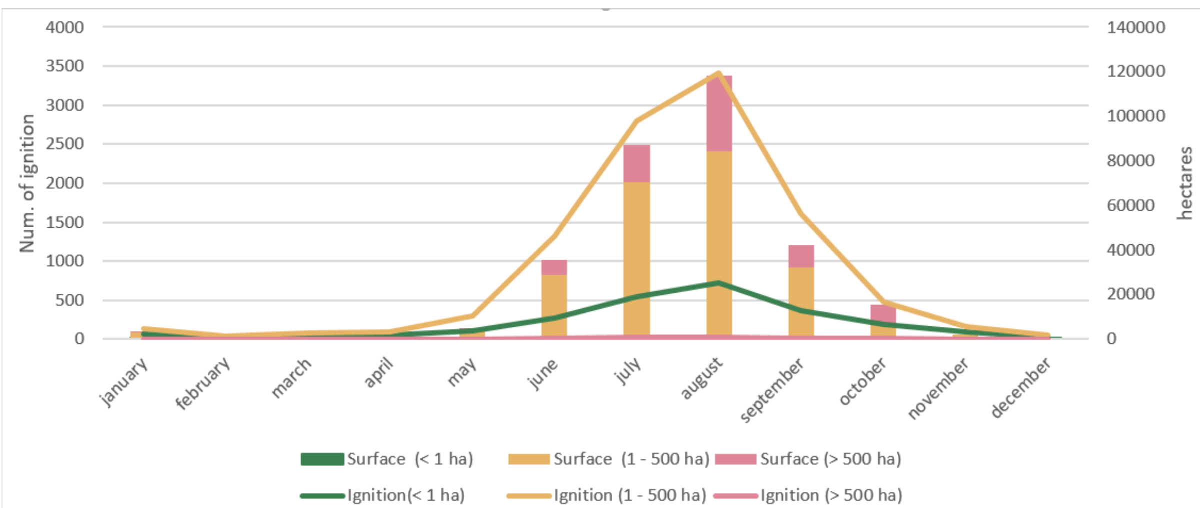


**Figure 11: Historical ignitions vs. burned area by month from 2007 to 2020.**

In order to be more easily understandable for end-users and stakeholders, the results of the model were divided into 3 equal intervals, related to the level of occurrence (low: probability of fire less than 33%, medium: between 33 and 66%, high: more than 66% of chance). Figure 12 shows the comparison between the average results for august in 2020 and 2050.

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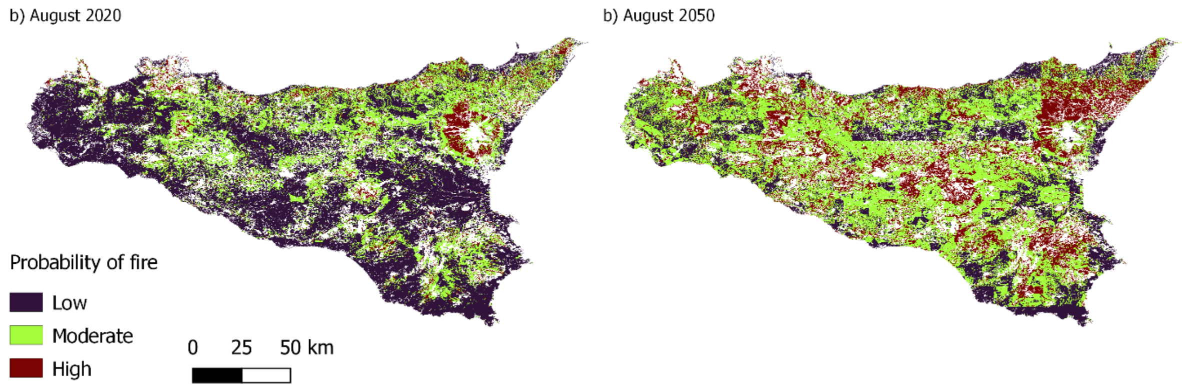


**Figure 12: Example of average fire occurrence in August 2020 (a) and 2050 (b).**

### 3.3. Wildfire risk levels and intermediate components

The wildfire risk map integrates a set of variables related to exposure and vulnerability. In this study, we analyze the areas with important ecological values and ecosystem services for both humans and nature, that would be potentially affected in case of fire due to its exposition.

Figure 13 compares the average spatial variability of the ecosystem services and ecological values exposed in August 2020 and August 2050. In the horizontal axes, the figures are distributed by levels of fire probability. (low, medium, and high), according to the fire hazard model. The 2020 vertical axis shows that the most exposed area corresponds to the low fire probability level. As the level of fire probability increases, the exposed area decreases. In contrast, the 2050 axis shows that the most exposed area corresponds to the medium danger level, followed by high and low probabilities.

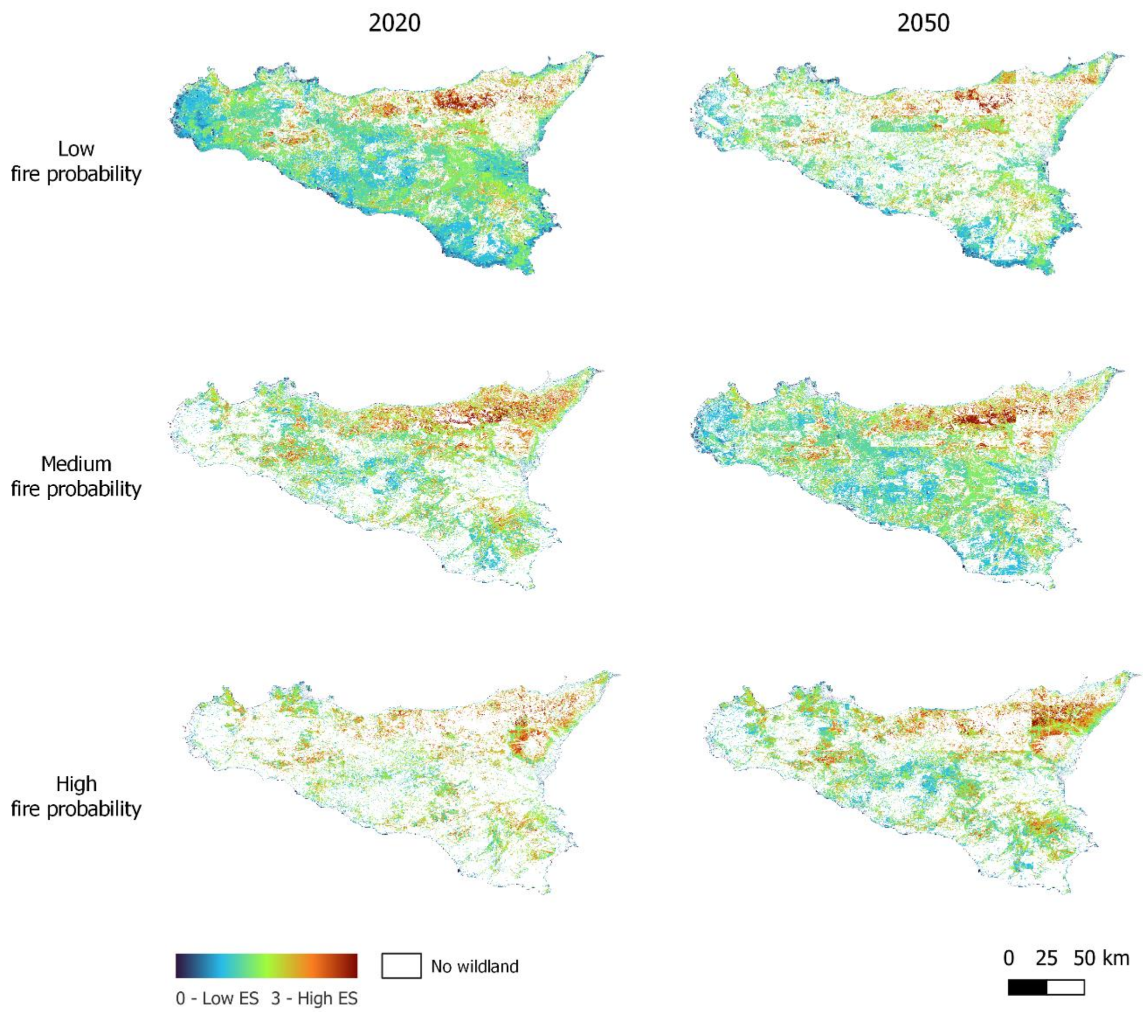


**Figure 13: Exposure map of ecological values and ecosystem services that may interact with fire in 2020 and 2050.**

Linked to Figure 13, Figure 14 shows the changes (in km²) broken-down by ES. As we observed in the exposure maps (Figure
380 13), the probability of danger increases in all ES. For example, the exposure to the Carbon Mass ecosystem service and Biodiversity will increase by more than 150% in the exposed areas with high fire probability (S3 Table S3). Outdoor recreation, Soil retention, and Pollination ecosystem services will increase by 117%, 100%, and 56%, respectively. In contrast, the exposure with low danger will decrease between 50% and 65% each.

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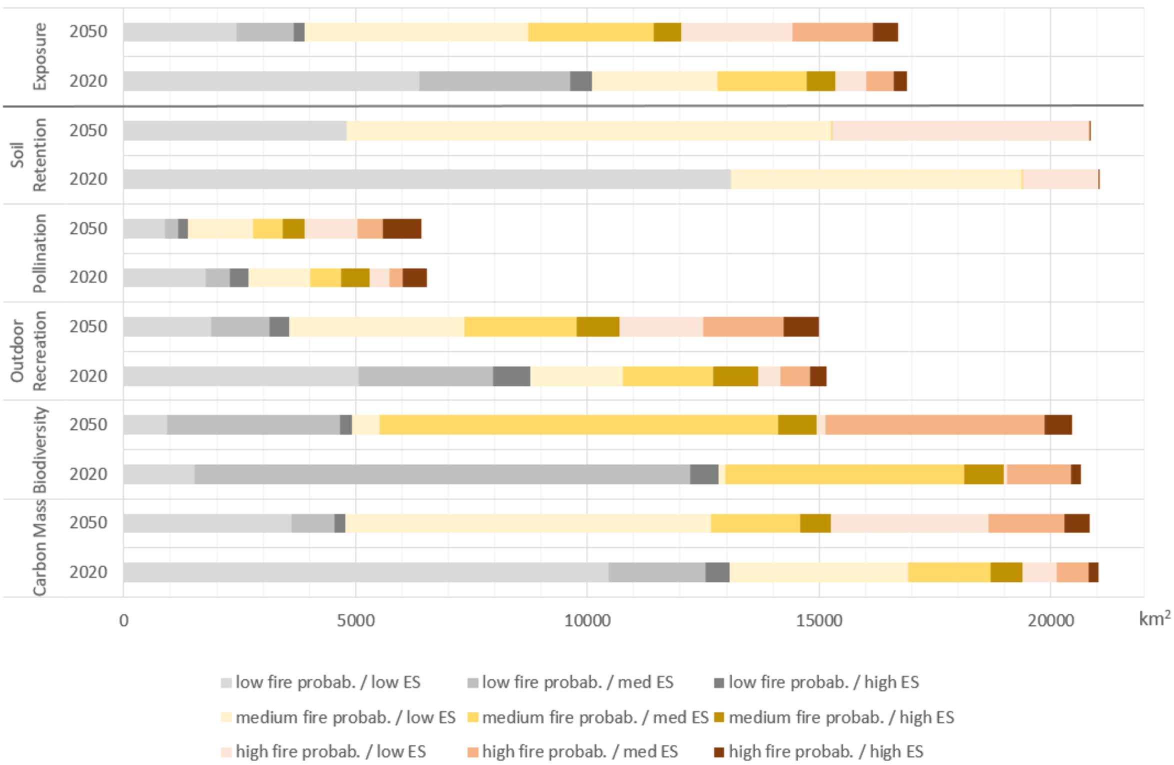
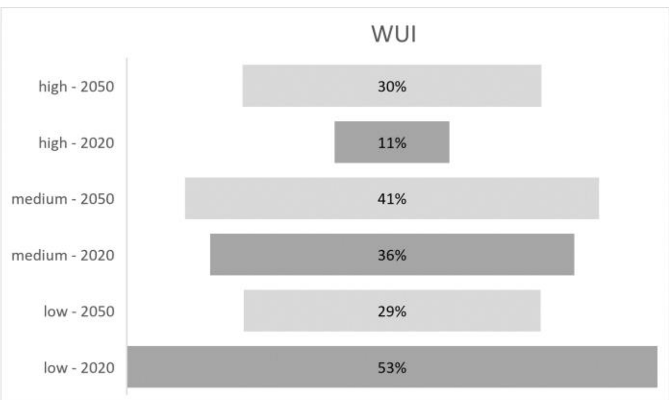



385 **Figure 14: Comparison of the fire hazard level -low (green), medium (yellow), high (red)- by the importance of the socio-ecological elements exposed in different color tones (low, medium or high). Values show the surface average (km²) in August 2018 and 2050.**

Figure 15 shows how the percentage of vulnerable areas is distributed in each of the variables analyzed as a function of the fire probability. Therefore, following the same trend as exposed areas, ecosystem services and ecological values increase fire risk with the influence of climate change. The WUI (WildLand-Urban Interface) case, increases by 19% for high fire
390 probabilities in 2050 and almost half of the fires will be at medium risk. In both WAI (Wildland-Agriculture Interface) and protected areas, half of their area could face a high fire risk in the future, doubling the 2020 data.



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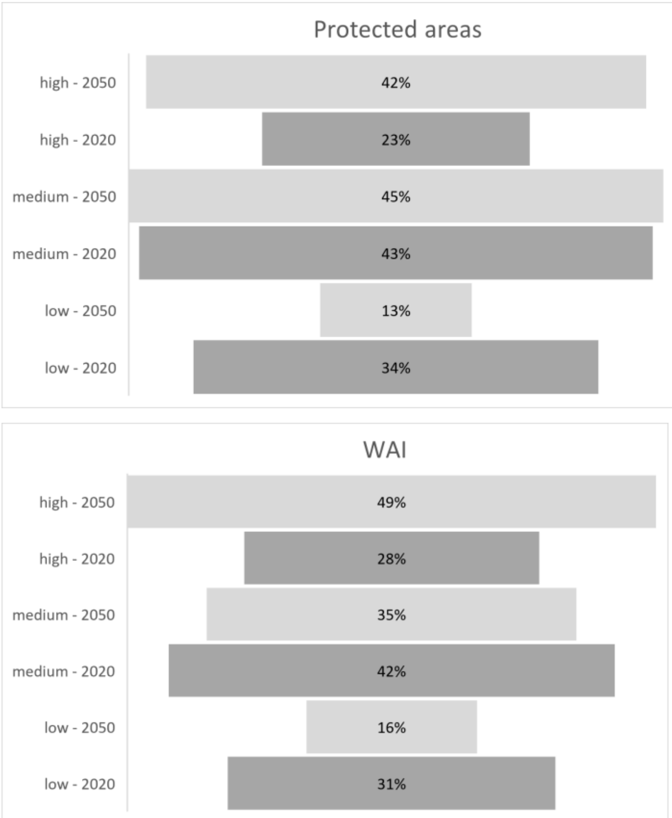


**Figure 15: Percentage of the vulnerable areas distributed in each of the variables analyzed (WUI, WAI, Protected Areas) as a function of the fire probability.**

Most of the vulnerable locations close to agricultural areas have a high probability of fire. However, one of the areas with high vulnerability in the protected area overlaps with sites that are difficult to access for the population, such as the Nebrodi Regional Park or the Madonie Regional Natural Park (Figure 16).

Overall, the area with the highest socio-ecological value is in the northeastern quadrant of the island, coinciding with the areas of highest fire risk. In contrast, low-protected regions are primarily agricultural areas, urban surroundings, or areas that have been affected by fire in the recent past. These non-vulnerability areas dominate most of the Sicilian territory.

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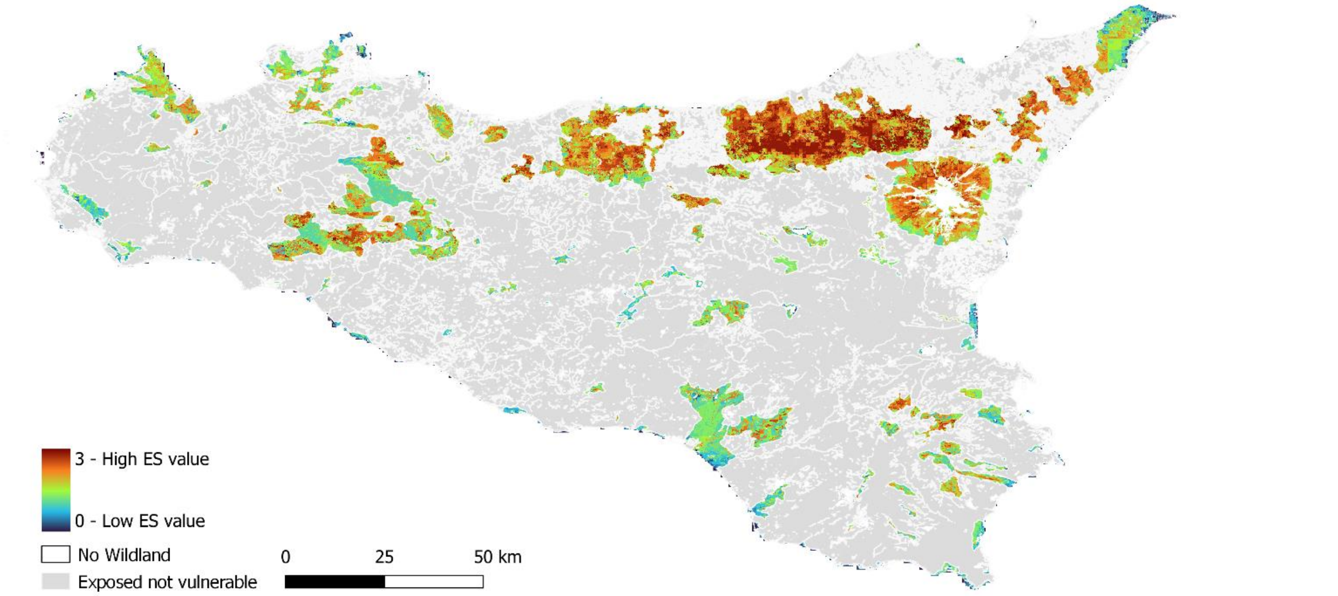


405 **Figure 16: Risk map of socio-ecological values exposed in protected areas, Wildland Urban Interface and Wildland Agricultural Interface in August 2020. Colored from red with a value of 0 (low socio-environmental value) to blue with a value of 3 (high socio-environmental value). Exposed but not vulnerable areas are shaded in grey. No wildland areas and no exposed are in white.**

## 4. Discussion

Concerning data sources, although historical fire data is becoming more accessible and findable, there is still much to be done for enhancing their full fruition. The most reliable data are those collected in the field, usually by local administration, while the satellite data can help to verify the in situ information, but in many cases, it is extremely difficult to access and download field data. Moreover, it has to be taken into account that fire sometimes cannot be properly detected by satellites: it needs a minimum fire size or intensity (linked to the resolution), there can be false alarms (commission errors), the information can be obscured by clouds or overstory vegetation, or the time of satellite overpass may not coincide with the fire. (Hantson et al., 2013, p.201; Schroeder et al., 2008).

Satellite and field data common problems are the scarce harmonization among data formats and the lack or bad quality of metadata. In this study, the main difficulties were the differences in parameters such as coordinate reference system, lack of metadata information and fire attributes between the yearly perimeters of fire. These problems were solved by integrating the data in k.LAB, where the reliable resources were harmonized, properly classified, and uploaded to a Geoserver to be accessible and with complete metadata.

Concerning the model quality, model errors are related to data location, spatio-temporal resolution or logical consistency (Guptill and Morrison, 2013; Kraak and Ormeling, 2020). Utilizing multiple data sources adds strength to the model and has been especially useful for detecting small fires related to land management: the vast majority of fires in Sicily. These kinds of

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fires may be too short-lived for the administration technicians or not intense enough to be captured by satellites. Moreover we consider that this strategy avoided a bias in the estimation of predictors' probabilities (Roy et al., 2005).

The historical fire set was analyzed, filtered, cleaned and processed prior to fire danger modeling. The frequency of fires from 2007 to 2020 was analyzed; some areas have burned more than once in the same year or more than 5 years during the 13-year period. We suggest that future studies would have to study why this phenomenon can happen and how it could be avoided, as such a high frequency of fires disrupts the cycle of natural processes of plants and animals, the loss of vegetation structure and composition and the associated ecosystem services.

Once the perimeters of each of the fires were identified, the associated information from the administration's fires was combined with the active fire points from the satellites to find the fire ignition area. Some differences were observed in the satellite and the government data. This may be due to reasons mentioned above: fires not detectable by satellites, or agricultural burnings detected as fires when the administration does not consider them as such. A great deal of effort was spent on data collection, cleaning, validation, pre-processing, and storage that complies with FAIR principles obtaining a reliable and open dataset: the basis of the occurrence of the fire model.

The model strength has been improved by extracting information from the predictors' data with dynamic and static variables such as meteorological or topographic data, respectively. Thus, the predictors have informed the model with values specific to each fire event. In addition, the predictors come from reliable and tested sources such as Copernicus or the Italian government as well as expert researchers and technicians. Some of the resources already existed within k.LAB such as protected areas or human settlement distribution and others were added, as fuel types or high resolution digital elevation model. The new information has been annotated in the semantic language k.IM and, like the historical fire data, now is open to any user and can interact with other k.LAB models in line with the FAIR principles.

It should be noted that this model has taken into account some of the explanatory variables at the time of ignition, but also some variables describing the ex-ante situation. Variables such as the average maximum temperature of the previous week, the accumulated precipitation or the number of days without rain were prior to the fire. The influence of climatic factors can help to predict the occurrence of fires related to climate change and the stress to which the forest was exposed (Halofsky et al., 2020; Trumbore et al., 2015).

The machine learning algorithm used, BN (Bayesian Network), provides a flexible and adaptable approach to structure the peculiarities of fire occurrence modeling: different data sources, changes in spatio-temporal resolution and dynamic versus static input data. In addition, the evaluation of BNs presents much lower costs and efforts than other options, even when the dataset is partly incomplete, which is quite common for environment-related data (Bielza and Larrañaga, 2014). Most of the remaining issues are related to meteorological conditions and environmental data, either due to the punctual failure of nearby stations or problems in post-processing. However, these problems can be solved by integrating more complete data, which, once semantically annotated, will automatically substitute lower-quality resources.

Another advantage of BNs is that they are not a black box models: the direct interpretation of the results, based on the probabilities of the predicting variables, is given in each node probability distributions. traditional modeling it is often difficult to access the details of the model accuracy for the end user, leading to a lack of reliability. Thanks to k.LAB and its web browser k.Explorer, the accuracy of the model is accessible and interpretable for non-expert end-users as stakeholders or land managers as we showed in the results. In line with FAIR principles, the final output and all the variables needed to compute the fire occurrence are supported by a narrative report produced at runtime to facilitate its interpretation. All these outputs are open and downloadable.

The algorithm used has provided significant values to detect areas with a high probability of fire occurrence. Thus, BNs provide a fast, reliable and accessible tool for land managers through k.LAB and semantics. The metrics related to type I and II errors can have great implications in practice, their acceptable values give credibility to the application and use of the model in real situations.

The integrated model has been able to simplify a problem as complex as the occurrence of forest fires by combining very disparate datasets. Given the results, we successfully identified the different degrees of fire occurrence probability. The model results change according to the most influential variables that can change over time and space, such as meteorological, biophysical data and human pressure on the landscape.

By using k.LAB, a modeller can reutilize the model at any point in time, including calculating the probability of fire occurrence in real-time or in future scenarios. For example, we have run the model with future data for 2050 assuming forest management does not change. It has been analyzed how, due to extreme temperatures and the stress that they will place on vegetation, the probability of fires will be higher in a large part of Sicily and, therefore, new areas will be affected. The easy adaptation of the BN models together with k.Explorer visualization facilities by the stakeholders simplifies the incorporation of new data in the future to test different land management alternatives.

As the model of fire occurrence was incorporated into the k.LAB modelling environment,, this new model was able to interact and connect with existing models (Villa et al., 2017). Thus, we overlapped the future probability of fire occurrence with ecosystem services that were already developed and published by scientific researchers. We choose the ecosystems that are directly affected by fire such as pollination, soil retention, outdoor recreation, biodiversity and carbon mass.

## 5. Conclusions

Models informing environmental decisions are usually developed in isolation, self-contained and with results mostly accessible to code owners and their collaborators. However, in a globalized world with increasingly complex and intertwined problems, it is key to connect knowledge and develop methods that can identify integrated solutions (Balbi et al., 2022). The application of appropriate and reliable risk assessment techniques is key to understanding and potentially preventing future damage, but so is making this knowledge accessible to stakeholders. This study combines the power of Artificial Intelligence and, in particular, machine learning and machine reasoning to model the risk of fire to ecosystem services in Siciliy, the largest island in the Mediterranean Sea. We used the K.LAB technology, which provides a common platform to make data and models interoperable and accessible to non-technical users (Balbi et al., 2022).

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In this study, we integrated historical fire data from 2012 to 2019 and other explanatory variables to identify the areas at the highest risk in present and future scenarios. We developed a data-driven model using a Bayesian Network (BN) classifier. Model analysis demonstrates that the BN algorithm applied to the historical fires data and their real-time variables achieves a high range of predictive accuracy. Despite the identified limitations as the resolution of meteorological data or detect small fires, the findings reveal the usefulness of the method, including the possibility to rerun the model at different time steps, and spatial scales in a static or dynamic fashion.

The fire risk spatial results are easily accessible through a web browser that can be used freely by land managers and stakeholders. This can help to create new prevention guidelines or focus on the risky areas. Moreover, the model gives scientists and land managers indications about the variables that mostly affect fire probability and how they can mitigate this environmental risk.

*Code availability.* Code used in this research is open and available at (Marquez Torres, 2023)

*Data availability.* Data used in this research is open and available at (Marquez Torres, 2023)

*Supplement.* The supplement related to this article is available on- line at: https://doi.org/10.5281/zenodo.7618466

*Author contributions*. AMT, FV, SB conceptualized the project. AMT, GS provided the data. AMT developed and calibrated the model and ran the simulations. AMT analysed the data and carried out the investigation. AMT visualized the data. AMT drafted the paper. GS, SB, SK, GA reviewed and edited the paper.

*Competing interests*. The contact author has declared that none of the authors has any competing interests.

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https://doi.org/10.5194/egusphere-2023-138
Preprint. Discussion started: 20 February 2023


## References


Ager, A. and Finney, M. A.: Climate change impact on fire probability and severity in Mediterranean areas, In: Viegas, D. X., ed. Proceedings of the VI International Conference on Forest Fire Research; 15-18 November 2010; Coimbra, Portugal. Coimbra, Portugal: University of Coimbra. 9 p., 2010.

Aguilera, P. A., Fernández, A., Fernández, R., Rumí, R., and Salmerón, A.: Bayesian networks in environmental modelling, Environmental Modelling & Software, 26, 1376–1388, https://doi.org/10.1016/j.envsoft.2011.06.004, 2011.

Aldersley, A., Murray, S. J., and Cornell, S. E.: Global and regional analysis of climate and human drivers of wildfire, Science of The Total Environment, 409, 3472–3481, https://doi.org/10.1016/j.scitotenv.2011.05.032, 2011.

Angelini, P., Bianco, P., Cardillo, A., Francescato, C., and Oriolo, G.: Gli habitat in Carta della Natura - schede descrittive degli habitat per la cartografia alla scala 1:50.000, Istituto Superiore per la Protezione e la Ricerca Ambientale (ISPRA), 2009.

Antrop, M.: Why landscapes of the past are important for the future, Landscape and Urban Planning, 70, 21–34, https://doi.org/10.1016/j.landurbplan.2003.10.002, 2005.

Artés, T., Oom, D., de Rigo, D., Durrant, T. H., Maianti, P., Libertà, G., and San-Miguel-Ayanz, J.: A global wildfire dataset for the analysis of fire regimes and fire behaviour, Sci Data, 6, 296, https://doi.org/10.1038/s41597-019-0312-2, 2019.

Baas, S., Conforti, P., Ahmed, S., and Markova, G.: The impact of disasters and crises on agriculture and food security, FAO, 2018.

Bacciu, V., Hatzaki, M., Karali, A., Cauchy, A., Giannakopoulos, C., Spano, D., and Briche, E.: Investigating the Climate-Related Risk of Forest Fires for Mediterranean Islands' Blue Economy, Sustainability, 13, 10004, https://doi.org/10.3390/su131810004, 2021.

Baiamonte, G., Domina, G., Raimondo, F. M., and Bazan, G.: Agricultural landscapes and biodiversity conservation: a case study in Sicily (Italy), Biodivers Conserv, 24, 3201–3216, https://doi.org/10.1007/s10531-015-0950-4, 2015.

Balbi, S., Bagstad, K. J., Magrach, A., Sanz, M. J., Aguilar-Amuchastegui, N., Giupponi, C., and Villa, F.: The global environmental agenda urgently needs a semantic web of knowledge, Environmental Evidence, 11, 5, https://doi.org/10.1186/s13750-022-00258-y, 2022.

Bao, J., Kendall, E. F., McGuinness, D. L., and Patel-Schneider, P. F.: OWL 2 Web Ontology Language Quick Reference Guide (Second Edition), 2012.

Bazan, G., Marino, P., Guarino, R., Domina, G., and Schicchi, R.: Bioclimatology and Vegetation Series in Sicily: A Geostatistical Approach, anbf, 52, 1–18, https://doi.org/10.5735/085.052.0202, 2015.

Bazan, G., Castrorao Barba, A., Rotolo, A., and Marino, P.: Geobotanical approach to detect land-use change of a Mediterranean landscape: a case study in Central-Western Sicily, GeoJournal, 84, 795–811, https://doi.org/10.1007/s10708-018-9892-1, 2019.

Beuzen, T., Marshall, L., and Splinter, K. D.: A comparison of methods for discretizing continuous variables in Bayesian Networks, Environmental Modelling & Software, 108, 61–66, https://doi.org/10.1016/j.envsoft.2018.07.007, 2018.

Bielza, C. and Larrañaga, P.: Discrete Bayesian Network Classifiers: A Survey, ACM Comput. Surv., 47, 5:1-5:43, https://doi.org/10.1145/2576868, 2014.

Birkmann, J., Buckle, P., Jaeger, J., Pelling, M., Setiadi, N., Garschagen, M., Fernando, N., and Kropp, J.: Extreme events and disasters: a window of opportunity for change? Analysis of organizational, institutional and political changes, formal and informal responses after mega-disasters, Nat Hazards, 55, 637–655, https://doi.org/10.1007/s11069-008-9319-2, 2010.

Bisson, M., Favalli, M., Fornaciai, A., Mazzarini, F., Isola, I., Zanchetta, G., and Pareschi, M. T.: A rapid method to assess fire-related debris flow hazard in the Mediterranean region: An example from Sicily (southern Italy), International Journal of Applied Earth Observation and Geoinformation, 7, 217–231, https://doi.org/10.1016/j.jag.2005.04.003, 2005.

Bonanno, G.: Adaptive management as a tool to improve the conservation of endemic floras: the case of Sicily, Malta and their satellite islands, Biodivers. Conserv., 22, 1317–1354, https://doi.org/10.1007/s10531-013-0473-9, 2013.

Bond, W. J. and Keeley, J. E.: Fire as a global 'herbivore': the ecology and evolution of flammable ecosystems, Trends in Ecology & Evolution, 20, 387–394, https://doi.org/10.1016/j.tree.2005.04.025, 2005.

Borsuk, M. E.: Bayesian Networks, in: Encyclopedia of Ecology, edited by: Jørgensen, S. E. and Fath, B. D., Academic Press, Oxford, 307–317, https://doi.org/10.1016/B978-008045405-4.00144-0, 2008.

Bouckaert, R. R.: Bayesian network classifiers in Weka, Department of Computer Science, Waikato University, Hamilton, 2004.

Castellnou, M., Prat-Guitart, N., Arilla, E., Larrañaga, A., Nebot, E., Castellarnau, X., Vendrell, J., Pallàs, J., Herrera, J., Monturiol, M., Cespedes, J., Pagès, J., Gallardo, C., and Miralles, M.: Empowering strategic decision-making for wildfire management: avoiding the fear trap and creating a resilient landscape, fire ecol, 15, 31, https://doi.org/10.1186/s42408-019-0048-6, 2019.

Catalano, R., Di Stefano, P., Sulli, A., and Vitale, F. P.: Paleogeography and structure of the central Mediterranean: Sicily and its offshore area, Tectonophysics, 260, 291–323, https://doi.org/10.1016/0040-1951(95)00196-4, 1996.

Certini, G.: Effects of fire on properties of forest soils: a review, Oecologia, 143, 1–10, https://doi.org/10.1007/s00442-004-1788-8, 2005.

Chappaz, F. and Ganteaume, A.: Role of land-cover and WUI types on spatio-temporal dynamics of fires in the French Mediterranean area, Risk Analysis, https://doi.org/10.1111/risa.13979, 2022.

Chen, S. H. and Pollino, C. A.: Good practice in Bayesian network modelling, Environmental Modelling & Software, 37, 134–145, https://doi.org/10.1016/j.envsoft.2012.03.012, 2012.

Chen, X.-W., Anantha, G., and Lin, X.: Improving Bayesian Network Structure Learning with Mutual Information-Based Node Ordering in the K2 Algorithm, IEEE Transactions on Knowledge and Data Engineering, 20, 628–640, https://doi.org/10.1109/TKDE.2007.190732, 2008.

Chuvieco, E., Allgöwer, B., and Salas, J.: Integration of Physical and Human Factors in Fire Danger Assessment, in: Wildland Fire Danger Estimation and Mapping, vol. Volume 4, WORLD SCIENTIFIC, 197–218, https://doi.org/10.1142/9789812791177_0007, 2003.

Cohen, J.: The wildland-urban interface fire problem: A consequence of the fire exclusion paradigm, Forest History Today. Fall: 20-26., 20–26, 2008.

Cooper, G. F. and Herskovits, E.: A Bayesian method for the induction of probabilistic networks from data, Machine learning, 9, 309–347, 1992.

https://doi.org/10.5194/egusphere-2023-138
Preprint. Discussion started: 20 February 2023


Cornes, R. C., Schrier, G. van der, Besselaar, E. J. M. van den, and Jones, P. D.: An Ensemble Version of the E-OBS Temperature and Precipitation Data Sets, Journal of Geophysical Research: Atmospheres, 123, 9391–9409, https://doi.org/10.1029/2017JD028200, 2018.

Corrao, C.: Forest fires in Sicily, in: The Management of Mass Burn Casualties and Fire Disasters: Proceedings of the First International Conference on Burns and Fire Disasters, edited by: Masellis, M. and Gunn, S. W. A., Springer Netherlands, Dordrecht, 60–63, https://doi.org/10.1007/978-0-585-33973-3_9, 1992.

Cullotta, S. and Marchetti, M.: Forest types for biodiversity assessment at regional level: the case study of Sicily (Italy), Eur J Forest Res, 126, 431–447, https://doi.org/10.1007/s10342-006-0166-y, 2007.

Daily, G., Postel, S., Bawa, K., and Kaufman, L.: Nature's Services: Societal Dependence On Natural Ecosystems, Bibliovault OAI Repository, the University of Chicago Press, 1997.

Di Maida, G.: The earliest human occupation of Sicily: A review, The Journal of Island and Coastal Archaeology, 0, 1–18, https://doi.org/10.1080/15564894.2020.1803460, 2020.

Drago, A.: Desertification processes and possible mitigation actions [Sicily], Tecnica Agricola (Italy), 2005.

Duane, A., Castellnou, M., and Brotons, L.: Towards a comprehensive look at global drivers of novel extreme wildfire events, Climatic Change, 165, 43, https://doi.org/10.1007/s10584-021-03066-4, 2021.

Faivre, N., Jin, Y., Goulden, M. L., Randerson, J. T., Faivre, N., Jin, Y., Goulden, M. L., and Randerson, J. T.: Controls on the spatial pattern of wildfire ignitions in Southern California, Int. J. Wildland Fire, 23, 799–811, https://doi.org/10.1071/WF13136, 2014.

Falcucci, A., Maiorano, L., and Boitani, L.: Changes in land-use/land-cover patterns in Italy and their implications for biodiversity conservation, Landscape Ecol, 22, 617–631, https://doi.org/10.1007/s10980-006-9056-4, 2007.

Ferrara, C., Salvati, L., Corona, P., Romano, R., and Marchi, M.: The background context matters: Local-scale socioeconomic conditions and the spatial distribution of wildfires in Italy, Science of The Total Environment, 654, 43–52, https://doi.org/10.1016/j.scitotenv.2018.11.049, 2019.

Frank, E., Hall, M. A., and Witten, I. H.: The WEKA Workbench. Online Appendix for "Data Mining: Practical Machine Learning Tools and Techniques," 4th ed., Morgan Kaufmann, 2016.

Friedman, N. and Goldszmidt, M.: Discretizing Continuous Attributes While Learning Bayesian Networks, Proceedings of the 13th International Conference on Machine Learning, 157–165, 1996.

Fu, Y., Li, R., Wang, X., Bergeron, Y., Valeria, O., Chavardès, R. D., Wang, Y., and Hu, J.: Fire Detection and Fire Radiative Power in Forests and Low-Biomass Lands in Northeast Asia: MODIS versus VIIRS Fire Products, Remote Sensing, 12, 2870, https://doi.org/10.3390/rs12182870, 2020.

Ganteaume, A., Camia, A., Jappiot, M., San-Miguel-Ayanz, J., Long-Fournel, M., and Lampin, C.: A review of the main driving factors of forest fire ignition over Europe, Environ Manage, 51, 651–662, https://doi.org/10.1007/s00267-012-9961-z, 2013.

Ganteaume, A., Barbero, R., Jappiot, M., and Maillé, E.: Understanding future changes to fires in southern Europe and their impacts on the wildland-urban interface, Journal of Safety Science and Resilience, 2, 20–29, https://doi.org/10.1016/j.jnlssr.2021.01.001, 2021.

https://doi.org/10.5194/egusphere-2023-138
Preprint. Discussion started: 20 February 2023


Giglio, L., Schroeder, W., and Justice, C. O.: The collection 6 MODIS active fire detection algorithm and fire products, Remote Sensing of Environment, 178, 31–41, https://doi.org/10.1016/j.rse.2016.02.054, 2016.

Giorgi, F., Jones, C., and Asrar, G.: Addressing Climate Information Needs at the Regional Level: the CORDEX Framework, 175–183 pp., 2009.

Grothmann, T. and Patt, A.: Adaptive capacity and human cognition: The process of individual adaptation to climate change, Global Environmental Change, 15, 199–213, https://doi.org/10.1016/j.gloenvcha.2005.01.002, 2005.

Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Giannotti, F., and Pedreschi, D.: A Survey of Methods for Explaining Black Box Models, ACM Comput. Surv., 51, 93:1-93:42, https://doi.org/10.1145/3236009, 2018.

Guptill, S. C. and Morrison, J. L.: Elements of Spatial Data Quality, Elsevier, 219 pp., 2013.

Halofsky, J. E., Peterson, D. L., and Harvey, B. J.: Changing wildfire, changing forests: the effects of climate change on fire regimes and vegetation in the Pacific Northwest, USA, fire ecol, 16, 4, https://doi.org/10.1186/s42408-019-0062-8, 2020.

Hantson, S., Padilla, M., Corti, D., and Chuvieco, E.: Strengths and weaknesses of MODIS hotspots to characterize global fire occurrence, Remote Sensing of Environment, 131, 152–159, https://doi.org/10.1016/j.rse.2012.12.004, 2013.

Hantson, S., Pueyo, S., and Chuvieco, E.: Global fire size distribution is driven by human impact and climate, Global Ecology and Biogeography, 24, 77–86, https://doi.org/10.1111/geb.12246, 2015.

Henriksen, H. J., Rasmussen, P., Brandt, G., von Bülow, D., and Jensen, F. V.: Public participation modelling using Bayesian networks in management of groundwater contamination, Environmental Modelling & Software, 22, 1101–1113, https://doi.org/10.1016/j.envsoft.2006.01.008, 2007.

Intini, P., Ronchi, E., Gwynne, S., and Bénichou, N.: Guidance on Design and Construction of the Built Environment Against Wildland Urban Interface Fire Hazard: A Review, Fire Technol, 56, 1853–1883, https://doi.org/10.1007/s10694-019-00902-z, 2020.

IPCC: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation — IPCC, IPCC, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2012.

Jain, P., Coogan, S. C. P., Subramanian, S. G., Crowley, M., Taylor, S., and Flannigan, M. D.: A review of machine learning applications in wildfire science and management, Environ. Rev., 28, 478–505, https://doi.org/10.1139/er-2020-0019, 2020.

Kangas, A. S. and Kangas, J.: Probability, possibility and evidence: approaches to consider risk and uncertainty in forestry decision analysis, Forest Policy and Economics, 6, 169–188, https://doi.org/10.1016/S1389-9341(02)00083-7, 2004.

Kocher, S. D. and Butsic, V.: Governance of Land Use Planning to Reduce Fire Risk to Homes Mediterranean France and California, Land, 6, 24, https://doi.org/10.3390/land6020024, 2017.

Kraak, M.-J. and Ormeling, F.: Cartography: Visualization of Geospatial Data, 4th ed., CRC Press, Boca Raton, 261 pp., https://doi.org/10.1201/9780429464195, 2020.

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.

https://doi.org/10.5194/egusphere-2023-138
Preprint. Discussion started: 20 February 2023


Leone, V., Lovreglio, R., Martín, M. P., Martínez, J., and Vilar, L.: Human Factors of Fire Occurrence in the Mediterranean, Earth Observation of Wildland Fires in Mediterranean Ecosystems, 149–170, https://doi.org/10.1007/978-3-642-01754-4_11, 2009.

Liu, H., Hussain, F., Tan, C. L., and Dash, M.: Discretization: An Enabling Technique, Data Mining and Knowledge Discovery, 6, 393–423, https://doi.org/10.1023/A:1016304305535, 2002.

Lozano, O. M., Salis, M., Ager, A. A., Arca, B., Alcasena, F. J., Monteiro, A. T., Finney, M. A., Del Giudice, L., Scoccimarro, E., and Spano, D.: Assessing Climate Change Impacts on Wildfire Exposure in Mediterranean Areas, Risk Analysis, 37, 1898–1916, https://doi.org/10.1111/risa.12739, 2017.

Marquez Torres, A.: amarqueztorres/fire_risk_sicily: Fire Sicily, , https://doi.org/10.5281/zenodo.7616451, 2023.

Martínez-López, J., Bagstad, K. J., Balbi, S., Magrach, A., Voigt, B., Athanasiadis, I., Pascual, M., Willcock, S., and Villa, F.: Towards globally customizable ecosystem service models, Science of The Total Environment, 650, 2325–2336, https://doi.org/10.1016/j.scitotenv.2018.09.371, 2019.

Michael, Y., Helman, D., Glickman, O., Gabay, D., Brenner, S., and Lensky, I. M.: Forecasting fire risk with machine learning and dynamic information derived from satellite vegetation index time-series, Science of The Total Environment, 764, 142844, https://doi.org/10.1016/j.scitotenv.2020.142844, 2021.

Mohajane, M., Costache, R., Karimi, F., Bao Pham, Q., Essahlaoui, A., Nguyen, H., Laneve, G., and Oudija, F.: Application of remote sensing and machine learning algorithms for forest fire mapping in a Mediterranean area, Ecological Indicators, 129, 107869, https://doi.org/10.1016/j.ecolind.2021.107869, 2021.

Molina, M. O., Sánchez, E., and Gutiérrez, C.: Future heat waves over the Mediterranean from an Euro-CORDEX regional climate model ensemble, Sci Rep, 10, 8801, https://doi.org/10.1038/s41598-020-65663-0, 2020.

Moreira, F. and Russo, D.: Modelling the impact of agricultural abandonment and wildfires on vertebrate diversity in Mediterranean Europe, Landscape Ecol, 22, 1461–1476, https://doi.org/10.1007/s10980-007-9125-3, 2007.

Mouillot, F., Ratte, J.-P., Joffre, R., Mouillot, D., and Serge Rambal, and: Long-term forest dynamic after land abandonment in a fire prone Mediterranean landscape (central Corsica, France), Landscape Ecol, 20, 101–112, https://doi.org/10.1007/s10980-004-1297-5, 2005.

Narcizo, L., Santos, F. L., Peres, L. F., Trigo, R., and Libonati, R.: The impact of heat waves in forest fires over the Amazon rainforest, Copernicus Meetings, https://doi.org/10.5194/egusphere-egu22-10772, 2022.

Nikolakis, W. and Roberts, E.: Wildfire governance in a changing world: Insights for policy learning and policy transfer, Risk, Hazards & Crisis in Public Policy, 13, 144–164, https://doi.org/10.1002/rhc3.12235, 2022.

Nojarov, P. and Nikolova, M.: Heat waves and forest fires in Bulgaria, Nat Hazards, https://doi.org/10.1007/s11069-022-05451-3, 2022.

Oliveira, S., Oehler, F., San-Miguel-Ayanz, J., Camia, A., and Pereira, J. M. C.: Modeling spatial patterns of fire occurrence in Mediterranean Europe using Multiple Regression and Random Forest, Forest Ecology and Management, 275, 117–129, https://doi.org/10.1016/j.foreco.2012.03.003, 2012.

Ortega, M., Saura, S., González-Avila, S., Gómez-Sanz, V., and Elena-Rosselló, R.: Landscape vulnerability to wildfires at the forest-agriculture interface: half-century patterns in Spain assessed through the SISPARES monitoring framework, Agroforest Syst, 85, 331–349, https://doi.org/10.1007/s10457-011-9423-2, 2012.

Parente, J., Pereira, M. G., Amraoui, M., and Fischer, E. M.: Heat waves in Portugal: Current regime, changes in future climate and impacts on extreme wildfires, Science of The Total Environment, 631–632, 534–549, https://doi.org/10.1016/j.scitotenv.2018.03.044, 2018.

Pausas, J. G. and Fernández-Muñoz, S.: Fire regime changes in the Western Mediterranean Basin: from fuel-limited to drought-driven fire regime, Climatic Change, 110, 215–226, https://doi.org/10.1007/s10584-011-0060-6, 2012.

Pausas, J. G., Bradstock, R. A., Keith, D. A., and Keeley, J. E.: Plant Functional Traits in Relation to Fire in Crown-Fire Ecosystems, Ecology, 85, 1085–1100, https://doi.org/10.1890/02-4094, 2004.

Pearl, J.: Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference, Morgan Kaufmann, 576 pp., 1988.

Pearl, J.: Causality, Cambridge University Press, 486 pp., 2009.

Penman, T. D., Price, O., Bradstock, R. A., Penman, T. D., Price, O., and Bradstock, R. A.: Bayes Nets as a method for analysing the influence of management actions in fire planning, Int. J. Wildland Fire, 20, 909–920, https://doi.org/10.1071/WF10076, 2011.

Peruzzi, L., Conti, F., and Bartolucci, F.: An inventory of vascular plants endemic to Italy, Phytotaxa, 168, 1–75, 2014.

Planistat Europe and Bradley Dunbar Association: Analysis of the island regions and outermost regions of the European Union: Part I The island regions and territories, European Commission, 2003.

Prestia, G. and Scavone, V.: Enhancing the Endogenous Potential of Agricultural Landscapes: Strategies and Projects for a Inland Rural Region of Sicily, in: Smart and Sustainable Planning for Cities and Regions, Sspcr 2017, New York, 635–648, https://doi.org/10.1007/978-3-319-75774-2_43, 2018.

Ragusa, M. A. and Rapicavoli, V.: Levels of desertification risk in the Sicilian forests according to MEDALUS-ESPI protocol, AIP Conference Proceedings, 1863, 530004, https://doi.org/10.1063/1.4992674, 2017.

Ricotta, C. and Di Vito, S.: Modeling the Landscape Drivers of Fire Recurrence in Sardinia (Italy), Environmental Management, 53, 1077–1084, https://doi.org/10.1007/s00267-014-0269-z, 2014.

Robinne, F.-N., Parisien, M.-A., Flannigan, M., Robinne, F.-N., Parisien, M.-A., and Flannigan, M.: Anthropogenic influence on wildfire activity in Alberta, Canada, Int. J. Wildland Fire, 25, 1131–1143, https://doi.org/10.1071/WF16058, 2016.

Roces-Díaz, J. V., Santín, C., Martínez-Vilalta, J., and Doerr, S. H.: A global synthesis of fire effects on ecosystem services of forests and woodlands, Frontiers in Ecology and the Environment, 20, 170–178, https://doi.org/10.1002/fee.2349, 2022.

Rodrigues, M. and de la Riva, J.: An insight into machine-learning algorithms to model human-caused wildfire occurrence, Environmental Modelling & Software, 57, 192–201, https://doi.org/10.1016/j.envsoft.2014.03.003, 2014.

Roy, D. P., Jin, Y., Lewis, P. E., and Justice, C. O.: Prototyping a global algorithm for systematic fire-affected area mapping using MODIS time series data, Remote Sensing of Environment, 97, 137–162, https://doi.org/10.1016/j.rse.2005.04.007, 2005.

Ruffault, J., Curt, T., Moron, V., Trigo, R. M., Mouillot, F., Koutsias, N., Pimont, F., Martin-StPaul, N., Barbero, R., Dupuy, J.-L., Russo, A., and Belhadj-Khedher, C.: Increased likelihood of heat-induced large wildfires in the Mediterranean Basin, Sci Rep, 10, 13790, https://doi.org/10.1038/s41598-020-70069-z, 2020.

Satir, O., Berberoglu, S., and Donmez, C.: Mapping regional forest fire probability using artificial neural network model in a Mediterranean forest ecosystem, Geomatics, Natural Hazards and Risk, 7, 1645–1658, https://doi.org/10.1080/19475705.2015.1084541, 2016.

Schroeder, W., Csiszar, I., and Morisette, J.: Quantifying the impact of cloud obscuration on remote sensing of active fires in the Brazilian Amazon, Remote Sensing of Environment, 112, 456–470, https://doi.org/10.1016/j.rse.2007.05.004, 2008.

Schroeder, W., Oliva, P., Giglio, L., and Csiszar, I. A.: The New VIIRS 375m active fire detection data product: Algorithm description and initial assessment, Remote Sensing of Environment, 143, 85–96, https://doi.org/10.1016/j.rse.2013.12.008, 2014.

Sereni, E.: Storia del paesaggio agrario italiano, 1961.

Sicilia Assessorato beni culturali ed ambientali e pubblica istruzione: Linee guida del piano territoriale paesistico regionale / Regione siciliana, Assessorato dei beni culturali ambientali e della pubblica istruzione, Regione siciliana, Assessorato regionale dei beni culturali ed ambientali e della pubblica istruzione, \Palermo!, vii+472 pp., 1996.

Thomaidis, K., Troll, V. R., Deegan, F. M., Freda, C., Corsaro, R. A., Behncke, B., and Rafailidis, S.: A message from the 'underground forge of the gods': history and current eruptions at Mt Etna, Geology Today, 37, 141–149, https://doi.org/10.1111/gto.12362, 2021.

Trumbore, S., Brando, P., and Hartmann, H.: Forest health and global change, Science, 349, 814–818, https://doi.org/10.1126/science.aac6759, 2015.

Tymstra, C., Stocks, B. J., Cai, X., and Flannigan, M. D.: Wildfire management in Canada: Review, challenges and opportunities, Progress in Disaster Science, 5, 100045, https://doi.org/10.1016/j.pdisas.2019.100045, 2020.

UNEP-WCMC and IUCN: Protected Planet: The World Database on Protected Areas (WDPA) [Online], Cambridge, UK: UNEP-WCMC and IUCN., 2022.

Villa, F., Balbi, S., Athanasiadis, I. N., and Caracciolo, C.: Semantics for interoperability of distributed data and models: Foundations for better-connected information, F1000Res, 6, 686, https://doi.org/10.12688/f1000research.11638.1, 2017.

Weichselgartner, J. and Pigeon, P.: The Role of Knowledge in Disaster Risk Reduction, Int J Disaster Risk Sci, 6, 107–116, https://doi.org/10.1007/s13753-015-0052-7, 2015.

Wilkinson, M. D., Dumontier, M., Aalbersberg, Ij. J., Appleton, G., Axton, M., Baak, A., Blomberg, N., Boiten, J.-W., Santos, L. B. da S., Bourne, P. E., Bouwman, J., Brookes, A. J., Clark, T., Crosas, M., Dillo, I., Dumon, O., Edmunds, S., Evelo, C. T., Finkers, R., Gonzalez-Beltran, A., Gray, A. J. G., Groth, P., Goble, C., Grethe, J. S., Heringa, J., Hoen, P. A. C. 't, Hooft, R., Kuhn, T., Kok, R., Kok, J., Lusher, S. J., Martone, M. E., Mons, A., Packer, A. L., Persson, B., Rocca-Serra, P., Roos, M., Schaik, R. van, Sansone, S.-A., Schultes, E., Sengstag, T., Slater, T., Strawn, G., Swertz, M. A., Thompson, M., Lei, J. van der, Mulligen, E. van, Velterop, J., Waagmeester, A., Wittenburg, P., Wolstencroft, K., Zhao, J., and Mons, B.: The FAIR Guiding Principles for scientific data management and stewardship, Sci Data, 3, 1–9, https://doi.org/10.1038/sdata.2016.18, 2016.

https://doi.org/10.5194/egusphere-2023-138
Preprint. Discussion started: 20 February 2023


Willcock, S., Martínez-López, J., Hooftman, D. A. P., Bagstad, K. J., Balbi, S., Marzo, A., Prato, C., Sciandrello, S., Signorello, G., Voigt, B., Villa, F., Bullock, J. M., and Athanasiadis, I. N.: Machine learning for ecosystem services, Ecosystem Services, 33, 165–174, https://doi.org/10.1016/j.ecoser.2018.04.004, 2018.

Wittenberg, L. and Malkinson, D.: Spatio-temporal perspectives of forest fires regimes in a maturing Mediterranean mixed pine landscape, Eur J Forest Res, 128, 297, https://doi.org/10.1007/s10342-009-0265-7, 2009.

Wunder, S., Calkin, D. E., Charlton, V., Feder, S., Martínez de Arano, I., Moore, P., Rodríguez y Silva, F., Tacconi, L., and Vega-García, C.: Resilient landscapes to prevent catastrophic forest fires: Socioeconomic insights towards a new paradigm, Forest Policy and Economics, 128, 102458, https://doi.org/10.1016/j.forpol.2021.102458, 2021.