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FIREURISK - DEVELOPING A HOLISTIC, RISK-WISE STRATEGY FOR EUROPEAN WILDFIRE MANAGEMENT

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Executive summary

This deliverable presents the integration scheme developed within the FirEURisk project. Following well-established terms in natural hazards, the scheme includes three main components, related to the likelihood a fire may ignite or propagate (fire danger), the extent to which fire may spatially overlap with valued assets (exposure), and the potential losses and resilience to those losses (vulnerability). We detailed the variables that this integrated fire risk system includes, along with the approaches taken to combine those components into synthetic risk indices. The scheme is part of the FirEURisk risk assessment WP, but it also considers fire reduction efforts and envisages policies to better adapt to future fire regimes. To mitigate negative impacts of fire, those responsible for managing risk must leverage the information available through the risk assessment process, along with an improved understanding of how the various components of risk can be targeted to improve and optimise the many strategies for mitigation and adaptation to an increasing fire risk. This text is part of the effort carried out by FirEURisk researchers to review current approaches to fire risk assessment, which has been recently published as a conceptual paper (Chuvieco et al. 2023). Several sections of this text are taken from this review paper, but what is included in this deliverable is exclusive responsibility of authors who participate in the FirEURisk consortium.

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1 Introduction: the need of fire risk assessment, reduction and adaptation

Wildfires are one of the critical factors affecting global ecosystems and societies, impacting atmospheric composition (van der Werf et al. 2017), vegetation succession (Gleason et al. 2019), soil erosion and runoff, and societal values (resources and assets) (Bowman et al. 2020a). Recent studies estimate that every year more than 4 million km^2, which is approximately the size of India and Pakistan combined, are burned globally (Giglio et al. 2018; Lizundia-Loiola et al. 2020). Notably, those estimations are likely to be conservative, as they are based on coarse resolution satellite images, which tend to miss small fires that are quite frequent in Tropical regions (Chuvieco et al. 2022).

Fire is a natural process in several ecosystems (Kelly and Brotons 2017; Pausas and Keeley 2009), but in others it negatively affects biodiversity, particularly when natural fire regimes change abruptly (Lewis et al. 2015). Wildfires have also important socio-economic implications, and can affect lives, houses and other human values. Catastrophic seasons with many human casualties and/or large burned areas have occurred in the last decades, mainly associated with heat waves and droughts (Bowman et al. 2020b; Bowman et al. 2017). For this rea-son, most industrialized countries affected by wildland fires have fire management strategies in place (Fitch et al. 2018). Countries involved in managing fire do assess risk in at least an informal way, often supported by systems that evaluate certain components of risk (e.g. fire danger systems). However, formal risk assessment systems that consider an integrated strategy for wildfire risk are still not widespread. The growing concern of extreme fire seasons (Jain et al. ; Tedim et al. 2018), caused by intense weather anomalies (Duane et al. 2021), have heightened the interest in wildfire risk assessment systems. They are part of a general approach to evaluate threat conditions for a certain area and period of time, and feeds into making risk-informed decisions to reduce unwanted impacts (Calkin et al. 2011). Risk assessment can consider a wide range of variables that affect fire ignition, propagation, potential impacts and some valuation of the importance of those impacts (Thompson et al. 2016). Risk assessment, along with the communication of that risk, should be adapted to the end users of risk information, who may include first responders, landowners, land managers, civil society organisations, and the general public (Moore 2019).

This document reviews terminology from natural hazards and applies it to wildfire risk assessment. Then, it presents the FirEURisk integrated approach that covers risk assessment, reduction and adaptation to future conditions, although in this deliverable only the first aspect is covered. This integration section includes the description of methods to generate input variables and integrate them into synthetic risk components at different spatial scales, both for the European territory (ET) and selected pilot sites (PS).

2 Natural hazards terminology

Growing concern on the impacts that natural hazards may have on human lives and the built environment has motivated work on a variety of international programs focused on risk assessment and mitigation. For

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example, the United Nations Office for Disaster Risk Reduction (UNDRR) recently implemented the Sendai Framework (UNISDR 2017), which is a major international agreement advocating for effective risk management and disaster risk reduction. The Sendai Framework highlights the crucial importance of development and application of analytical frameworks to understand and quantify risk. According to the Sendai Framework's guiding principles and priorities for action (UNISDR 2017), Disaster Risk Reduction (DRR) must be accomplished through international, regional, subregional, transboundary, and bilateral cooperation and also shared between central governments, relevant national authorities, sectors, and stakeholders. It requires a multi-hazard and inclusive risk-informed decision-making approach. The priorities for action are: understanding disaster risk, strengthening disaster risk governance to manage it, investing in risk reduction to increase resilience, and enhancing disaster preparedness for effective response and recovery.

Following common terminology of natural hazards, risk can be defined as "the potential for adverse consequences or impacts due to the interaction between one or more natural or human-induced hazards, exposure of humans, infrastructure and ecosystems, and systems' vulnerabilities." (Tagarev and Papadopoulos 2020, p. 55). Therefore, assessing risk entails a comprehensive analysis of the various dimensions. The three most commonly identified are hazard, exposure, and vulnerability (Field et al. 2014; McGlade et al. 2019; Tagarev and Papadopoulos 2020), with risk being the combination of the three . A working definition of the three risk dimensions may be the following:

- "Hazard, i.e. the process, phenomenon or human activity that carries the potential to cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation. Hazards can be natural (e.g. wildfires, earth-quakes, droughts, floods) or anthropogenic (e.g. oil spills, terrorist attacks) in origin and can be characterised by their location, likelihood of occurrence, intensity or magnitude, duration, and extent." (Tagarev and Papadopoulos 2020, p. 56). Hazard therefore implies estimating the probability and intensity that a certain negative event occurs.
- "Exposure represents the people and assets at risk of potential loss or that may suffer damage to hazard impact. It covers several dimensions like the physical (e.g. building stock and infrastructure), the social (e.g. humans and communities) and the economic dimensions" (Poljanšek et al. 2017, p. 59). For other authors, it refers "the extent to which a value, resource, asset or geographic area may be subject to or come into contact with a potential source of harm" (Thompson et al. 2016). Therefore, exposure assessment implies the inventory of elements in an area in which hazard events may occur and during the time they may occur. Exposure analysis is the process of identifying the exposures to which various resources or assets could be subjected.
- "Vulnerability, i.e. the propensity or predisposition of an individual, a community, infrastructure, assets or systems (incl. ecosystems) to be adversely affected (UNDRR, 2016). Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt (Birkmann et al. 2013)." (Tagarev and Papadopoulos 2020, p. 57). In other words, vulnerability is "the characteristics and circumstances of a community, system or

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asset that make it susceptible to the damaging effects of a hazard." (UNISDR 2009). While most natural hazards are beyond human control, vulnerability can be modified by human actions, either increasing (vulnerable societies) or decreasing it (resilient societies).

Overall, Risk assessment is the process of integrating information about the three dimensions: hazard, exposure, and vulnerability. It should consider a wide range of factors, affecting both the physical phenomena (weather, geology, vegetation cover, topography, seismic activity, etc.) and the human dimensions that can potentially mitigate or increase the damaging effects of the event. Risk assessment entails understanding the nature, sources, and causes of risk; as well as the valuation of magnitude, extent, and duration. The magnitude of risk is sometimes conceived as the values at stake times the likelihood of occurrence. In this regard, risk management greatly benefits from analysing historical occurrence (Thompson et al. 2016).

3 Adaptation to wildfire risk assessment

Following general terminology of natural hazards, wildfire risk assessment should include all factors that affect both the likelihood of occurrence and the potential damages (including exposure and vulnerability) that the fire may cause on human lives and assets, as well as natural values. Historically, wildfire risk literature developed a particular set of concepts and terms, sometimes independent from general literature on natural or technological hazards (Bachmann and Allgöwer 2001). FAO terminology (FAO 1986), for instance, defined in 1986 Fire Danger as "the resultant, often expressed as an index, of both constant and variable factors affecting the inception, spread, and difficulty of control of fires and the damage they cause", while fire hazard was related to fuel conditions and fire risk was related to causative agents. Growing acceptance of the UN natural hazards terminology by the fire community implies that those terms are nowadays mostly discontinued, although reminiscences are still found in historical risk assessment systems. In any case, most fire managers now consider that integrated fire risk assessment should consider both the factors affecting fire ignition and propagation (e.g., fire causes, fuel properties, terrain and weather conditions), as well as the evaluations of assets at stake, those that may be affected by direct or indirect impacts of fires (human health and lives, houses, infrastructures, ecosystem services and ecological values).

Adapting the standard concepts used in natural hazards to fire risk is not a trivial issue. Terminology used in fire prevention planning has a long tradition, especially in the USA and Canada (San Miguel-Ayanz et al. 2017), but it has presented some controversy, as most fire risk assessment systems have focused just on the estimation of the likelihood that a fire ignites and propagates. These systems are commonly named fire danger (Chuvieco and Salas 1996; Costa et al. 2020; Flannigan and Wotton 1989; Vasilakos et al. 2007; Viegas et al. 1999; Wotton 2009; Zacharakis and Tsihrintzis 2023), which we will also use in this paper. The two other components of risk, exposure and vulnerability, have much less tradition in the wildfire community. In fact, there are not yet operational systems that incorporate a full consideration of those two components, although several authors have suggested new approaches to include in the assessment the potential damages of fire (Chuvieco et al. 2014a; Chuvieco et al. 2010; Thompson et al. 2011; Thompson et al. 2010). Recent

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analyses have extended these approaches to incorporate the exposure concept (Oliveira et al. 2020; Oliveira et al. 2021), which in fire events tend to be quite extended, as most territory with burnable vegetation may potentially be burned.

In summary, fire risk assessment entails an estimation of when, where, why and how fires are more likely to occur and propagate, which areas are potentially exposed and what potential damages these fires may imply. Therefore, a comprehensive risk characterization should always include these three dimensions of risk. Ideally, a risk assessment system should be comprehensive (all relevant risk variables considered), flexible (applicable to a wide range of spatial and temporal conditions), coherent (internally logical) and replicable (based on transparent methods).

The constituents of such a system can be grouped in two categories: on one hand, components, which identify the different dimensions of risk that the system is considering (for instance, natural ignition, propagation potential or landscape resilience), and, on the other hand, variables, which indicate specific parameters. These variables can be further divided into first-order quantities (those directly measurable, such as wind speed or population density) and second-order quantities (those estimated from a combination of first order variables, such as fire rate of spread). The aggregation of variables (either of first or second order) into different dimensions of risk will lead to generating risk components. For instance, human ignition is a component that requires different input variables related to how humans may generate fires, either intentionally or by carelessness. Propagation potential requires characterization of fuels, weather conditions, topography and extinction resources.

3.1 Danger

Wildfire danger indicates the likelihood that a fire ignites and propagates in a certain area and period. Even though most natural hazard terminologies name this component as Hazard, Danger is more commonly used in the fire management community (such as the American, Canadian, Australian or European systems) to indicate a similar concept. Danger assessment considers human and natural causes leading to a fire ignition, as well as those factors that must be present to start a fire or affect fire behaviour, including fuel state, slope and weather conditions (Fig. 1).

Ignition probability can be divided into the human and natural ignition, defined according to the main causes. Prestemon et al. (2005) differentiated between three broader categories of fire causes: natural (basically referring to lightning) and anthropogenic, the latter of which was further divided into accidental and intentional.

Propagation potential is closely related to fire spread, but these terms are not fully identical. They both refer to the likelihood or probability that fire will spread in a particular direction or over a specific area, along with information about the severity and speed of that spread. Fire spread depends on concrete weather, topography, and fuel conditions, where these conditions represent either current, historical, or possible future scenarios. Propagation potential should provide a more general understanding of the observed area

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and conditions prevailing there (Rothermel 1972, 1983). These conditions can be observed through shorter or longer time periods (ranging from 1 hour to even decades).

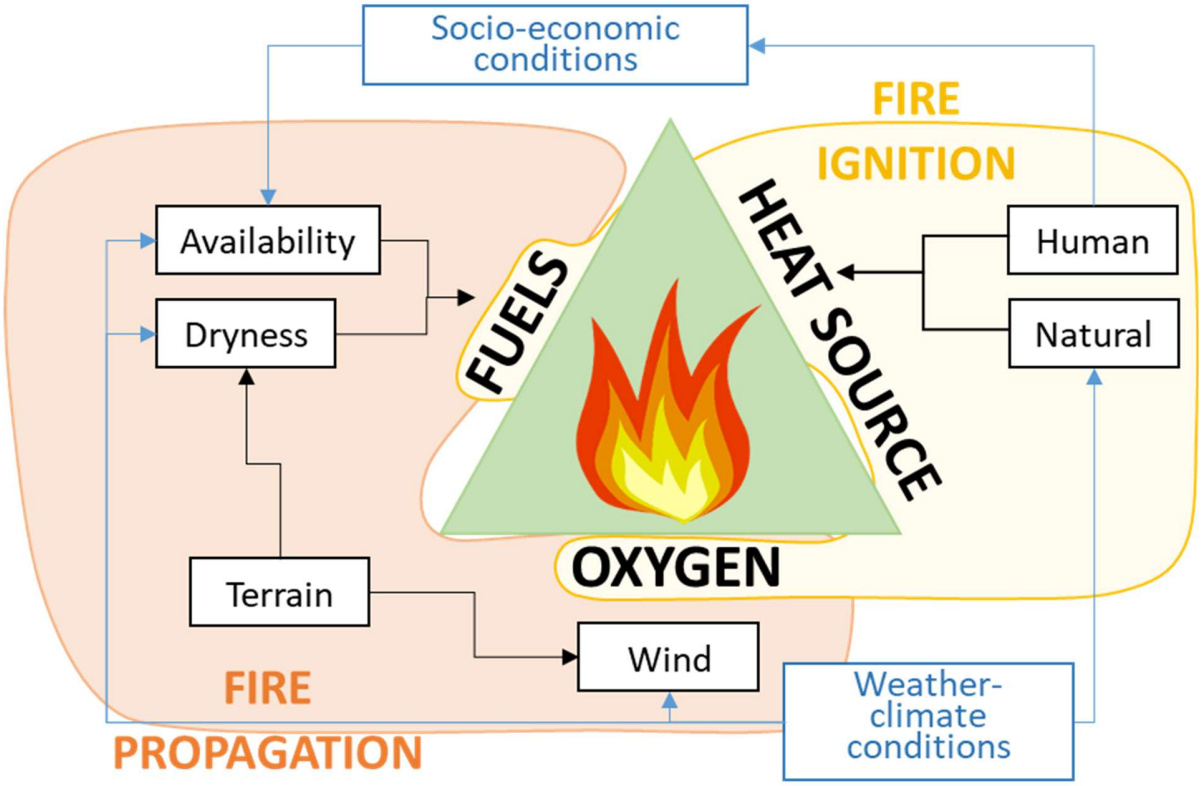


Figure 1: Fire danger components and variables

3.2 Exposure

Exposure indicates the extension to which people, infrastructure, and other tangible human assets, as well as natural values, could be adversely affected by fires. Areas may be exposed directly through the spreading of the fire or via flaming embers, or indirectly through dispersion of smoke, or by causing changes in the hydrological cycle or soil erosion. The actual exposure to fire may change even in short periods of time as a result of weather patterns (e.g., heatwaves, changes in wind conditions that transport smoke in different directions) or population movements (summer holidays).

As a component in fire risk assessment systems, exposure forms a link between fire danger and vulnerability. Hence the assessment of exposure is a crucial step in establishing the location and characteristics of landscape entities that may be adversely affected by wildfires. Exposure does not account for the properties of the given value at risk (as these are part of its vulnerability characteristics; see next section), but merely reflects the potential of a given place to be affected by wildfires. Therefore, studies on fire exposure are often based on the intersection of predictions of fire behaviour models, with available data on the presence of

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values at stake. For example, Bar-Massada et al. (2009) overlaid the locations of built structures on top of the gridded predictions of burn probability derived from the FARSITE model (Finney 1998) to estimate housing exposure to wildfires under both normal and extreme weather conditions in northern Wisconsin. Similarly, Alcasena et al. (2016) estimated the exposure of highly-valued resources and assets in Navarra, Spain, based on the intersection of their locations and predictions of burn probability from the Flammap model (Finney 2006). A simpler approach (without fire spread modelling) was used by Beverly et al. (2010) to estimate the exposure of four communities in Alberta, Canada, to wildfire based on the composition of hazardous fuels within multiple buffer distances around them, which reflect different mechanisms of fire spread (radiant heat, short-range and long-range spotting).

One of the most critical aspects of fire exposure entails the wildland urban interface (WUI) mapping (Argañaraz et al. 2017; Radeloff et al. 2005). WUI maps typically use a set of predefined rules and parameters to identify where human settlements adjoin or intermingle with flammable vegetation, to highlight locations of potential fire exposure across landscapes. To date, there are multiple WUI mapping approaches (Bar-Massada et al. 2013; Modugno et al. 2016; Radeloff et al. 2005), and these methods have been applied in many regions and at spatial scales ranging from local to global (Beverly et al. 2010; Carlson et al. 2022). Information derived from these maps allowed policy makers and land managers to direct management efforts to reduce potential exposure to wildfires via the prioritization of fuel treatments around exposed areas.

3.3 Vulnerability

The concept refers to the potential damages caused by wildfires on a particular ecological or socioeconomic value, including the losses directly caused by fires but also the ability (or lack of) to recover afterwards. Vulnerability is a term which encompasses several thematic elements (e.g., social, economic, physical, ecological, institutional vulnerability) describing a broad range of phenomena. Fire damages include both social values (human lives, houses, infrastructures and ecosystem services) and ecological values (soil erosion potential, loss of biodiversity, landscape visual quality, protected areas, biomass, etc.). These potential losses are related to how pre-fire values are reduced (or lost) as a result of fire behaviour characteristics (particularly fire intensity and residence time) and system resistance to the disturbance, as well as the social or ecological capacity to recover the pre-fire values after the event occurs. Both resistance and recovery properties are commonly grouped under the concept of resilience, although some authors consider resilience just to the second aspect, the capacity to return to near-prior conditions (Swanston et al. 2016). A longer-term perspective is to characterize the end-point impact and its deviation from the pre-disturbance stage so that the system is considered as vulnerable when not recovering, resilient when recovering at a similar state variable than before the disturbance or adaptive when recovering at an improved state variable than before the disturbance (White and Jentsch 2001).

The boundaries of the definition of vulnerability are unavoidably blurred, due to the various thematizations of the term produced, through time, by different research perspectives and academic fields. Societal vulnerability, for instance, refers to the inability of people, organisations, communities, and societies, to resist

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adverse impacts from stressors to which they are exposed (Birkmann et al. 2013). Societal vulnerability to wildfires may be understood as both the magnitude of societal impact deriving from wildfires, and the inability of local societies to cope with stressors to which they are exposed as a consequence of a wildfire (Oliveira et al. 2018; Oliveira et al. 2020). However, from an ecological point of view, vulnerability has been defined as the interaction among exposure, sensitivity and recovery (also called resilience or adaptive capacity) (Turner et al. 2003). Leaving aside exposure, commonly separated from vulnerability in most natural hazards, sensitivity is the degree to which a system is affected or harmed by the disturbance, as an intrinsic feature of the system but also driven by local environmental conditions (Turner et al. 2003). Sensitivity, also named resilience, includes the coping capacity, that indicates the resistance of the ecosystem to be negatively affected by the fire, and the ability to recovery. The final stage of evolution indicates whether the ecosystem is resilient (if arriving to a similar pre-fire state), vulnerable (lower) of adaptive (higher) (Lei et al. 2014).
In practical terms, the assessment of vulnerability required not only consideration of the spatial and temporal scales, but also hierarchical scales, from the individual organisms, plus the structural and functional relationships between them, and the abiotic environment (De Lange et al. 2010). All these reflect the inherent intricacy of ecological systems which make their vulnerability rather difficult to quantify and be reduced to a single or few metrics (Beroya-Eitner 2016).

3.4 Fire risk variables

Fire risk variables are the input variables required to generate a risk component. They can be measured with specific metrics. First order variables are generally estimated from original sources (census, field work, remote sensing, etc.), while second-order variables are modelled through empirical or physical models, from a set of first-order variables. The most commonly used variables in fire risk assessment are related to meteorological conditions (temperature, precipitation, wind, relative humidity), since they have a paramount importance in both fire ignition and propagation. Weather variables are a critical element and widely used into existing wildfire risk assessment systems, which generally address only the fire danger component. Weather plays a key role in the ignition and propagation of wildfires. Temperature, atmospheric humidity (relative humidity and vapour pressure deficit), wind speed and direction are the common meteorological inputs to danger rating systems (Zacharakis and Tsihrintzis 2023). Weather patterns also affect natural ignitions, both directly to the convergence of lightning and drought, as well as the characteristics of strikes and thunderstorms. Lightning strikes are one of the most common natural causes of wildfires, accounting for around 10-15% of all wildfires worldwide. Lightning-induced wildfires are particularly prevalent in regions with a high incidence of thunderstorms and dry vegetation (Nieto et al. 2012; Veraverbeke et al. 2017).
Topography, particularly shape and morphology, has a great importance both for fire ignition and behaviour. The former through wind regimes, solar exposure, rainfall and air temperature and humidity distribution, which all impact vegetation distribution (Tymstra et al. 2010) and moisture contents (Nyman et al. 2015). Impacts of terrain on fire behaviour include shape of the terrain and relations to prevailing winds. The

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presence of concave terrain like in canyons or gullies will induce a fire acceleration that is quite independent of the prevailing wind conditions (Viegas and Pita 2004).

Vegetation load, structure, composition and moisture status play a key role in wildfire ignition and spread: their characterization and mapping are therefore of paramount importance to fire risk assessment and reduction. Wildland fuels can be described in terms of chemical characteristics, flammability, and physical properties, which affect the combustion process and include quantity, size and shape, compactness and arrangement (Pyne et al. 1996; Riccardi et al. 2007). These characteristics are commonly described under the term fuel types, while the quantitative parameters that govern fire propagation are termed fuel models. In addition to geometric structures of fuels (biomass loads, particle size distribution, horizontal and vertical continuity), an important property of vegetation for risk characterization is the fuel moisture content (FMC). FMC is defined as the ratio of the water content to dry mass within the fuel and is usually expressed in percentage (Simard 1968). It is commonly divided into live (LFMC) and dead fuel moisture content (DFMC), which relate to the FMC of living (e.g., grass, foliage) and dead (e.g., litter, woody debris) vegetation components, respectively (Yebra et al. 2013). While dead fuel moisture responds to short-term weather conditions (Aguado et al. 2007), live fuel is more responsive to longer-term weather events, such as dry spells, and plant species-specific water use strategies (Jolly and Johnson 2018), although it has been also demonstrated to respond to short heatwaves events as well (Ruffault et al. 2018).

The human dimension of wildfire risk assessment includes two main components: one linked to the beginning or the suppression of the fire, as a causative or control agent, respectively, and the other one as an element of vulnerability, related to the people's lives and values potentially affected by fires. Humans may also play an indirect role in fire occurrence by changing land covers and landscape pattern, particularly through fragmentation (increase in land use intensity) or abandonment (reduction), which impact fire propagation. Human relations to fire are very diverse in different continents, ranging from the traditional use of managed fires by indigenous communities (Bilbao et al. 2019; Rodríguez et al. 2018), to the total fire exclusion policy (Cochrane and Bowman 2021).

In terms of exposure, the variables commonly used to characterise the potential connection of fire and human and ecological values are the population density and the demographic characteristics of the population of fire-prone areas, and the proximity of natural and man-made infrastructures to burnable areas. As regards vulnerability, it implies considering the different values that would be potentially affected by fire impacts. This includes societal values (houses, infrastructures), ecosystem services (ES) and ecological values. The ES may be defined as the human benefits provided by nature, such as forest, fauna, water, soil, or minerals, the latter being the stock of renewable and non-renewable resources that using an economic terminology can also be identified as natural capital (Bateman and Mace 2020). ES are drivers of social wellbeing emerging through their interaction with human and social capitals (Costanza et al. 2014). For instance, the contribution to human wellbeing derived from forestry and agriculture ecosystems require human labour energy, and capital (machinery) input to convert them in societal benefits (e.g., crops and timber) (Bateman and Mace 2020). In terms of fire vulnerability, the most commonly affected services are

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timber supply, carbon sequestration and storage, pastures, hunting, mushrooms collection and recreation (Martino et al. 2022).

Ecological values (EV) are defined by Cordell et al. (2005) as "the level of benefits that biotic or abiotic components provide for the maintenance of any living organisms", except humans. In turn, beside ecosystem services related to humans, Ratcliffe (1997) provided a list of criteria to assign EV to an entity, considering different aspects: its size (extent), diversity, naturalness, rarity, fragility, typicalness, recorded history, position within an ecological/geographical unit, and potential value. As these criteria remain loosely defined, EV actually used for vulnerability assessment to wildfires or to other disturbances are largely heterogeneous in the literature. The loss of ecological and ecosystem values is closely related to the resilience characteristics of the landscape and society. Resilience indicates the capacity of a certain resource to resist and absorb the impact of fires (or to avoid being affected by) and naturally recover the pre-fire value after it occurs (Ingrisch and Bahn 2018). Therefore, resilience is composed by two elements: coping capacity and recovery time. The former can be defined as the resistance of the system to the disturbance and its ability to reinitiate a recovery after the disturbance.

3.5 Integration approaches

Even though the different risk components can be valuable in themselves for the end user (IPBES 2022), an integrated evaluation of fire risk conditions frequently requires merging the risk components into synthetic ones, so the actual integration approach can be attained. For doing so, two conceptual steps need to be developed, on the one hand defining common integration scales of measurement, and on the other hand finding suitable methods to weigh the importance of each component.

3.5.1 Risk integration scales

To obtain synthetic risk indices from the risk components previously reviewed, they need to be converted to a common measurement scale, since each component is likely measured with a different metric. For instance, ignition probability is commonly measured in a 0-1 probability scale, while FMC is expressed in percentage of dry weight, and propagation potential is calculated as rate of spread (m/s) or fire line intensity (kW/m). Combining all these variables requires generating a common risk metric, where all inputs can be later on merged into synthetic indices.

Methods to obtain those common measurement scales are diverse, but the most used are normalisation, qualitative categorisation and probabilistic approaches. Normalization implies modifying the original measurement scale to a common range (0/1 or 0/100). This is generally done using the extremes of the distribution (min and max values), using a single algorithm:

$$Vout = \frac{Vin - Vmin}{Vmax - Vmin} * c \quad (1)$$

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where Vout is the resulting value, Vin, min and max are respectively the input, minimum and maximum one, and c is a constant for convenience scaling (100 or 1 are the most common). Instead of the minimum and maximum values, the user can select a certain percentile (5 and 95%, for instance). When the target variable has a skewed distribution, non-linear normalization approaches can be used instead.

Qualitative categorization implies converting the original measurement scale into classes, generally ordered into risk importance or priority of intervention. Risk categories are commonly identified by a set of experts dealing with fire suppression or fire prevention. They assign danger levels and weights according to their own perception of fire risk in the area (Yool et al. 1985). The main problem of this approach is its subjectivity and its excessive orientation to local characteristics, which reduces its generalization potential. Experts make the decisions based on their familiarity with fire events in the study area, but their judgement may not be applicable to other regions.

Alternatives for quantitative categorization entail the use of statistical or physical models. A good example of the former is the application of empirical models to estimate ignition probability, based on historical fire occurrence (Bistinas et al. 2014; Costafreda-Aumedes et al. 2017; Syphard et al. 2007). Physical models are based on the properties of risk variables related to any of the fire risk dimensions. For instance, FMC values can be converted to probability of ignition (PI) based on the concept of moisture of extinction (ME), which indicates the moisture threshold above which fire cannot be sustained (Rothermel 1972). Since the vegetation is unlikely to burn above that value, the ME can be used as a threshold of ignition probability, lowering the probability as FMC exceeds the ME of that fuel. The shape of that function may be exponential or linear depending on whether the assumption of abrupt changes above a threshold stands or not (Chuvieco et al. 2004).

Even though it is not related to fire risk, a good example of an integrated approach to measure a multifaceted problem is the Environmental Performance Index (EPI: https://epi.yale.edu/, last access April 2023), developed by different US institutions to quantify the countries' environmental operation. The index synthetizes a wide range of indicators (32 in the version of 2020) of environmental sustainability into a single number. All those indicators were converted to a common suitability 0–100 scale, from worst to best performance, respectively, utilizing normalization process. Some of the variables were log-transformed before normalization to avoid the impact of highly skewed distribution (Wendling et al. 2020). The normalization to the 0-100 score of each indicator was based on the distance-to-target technique, considering the best and the worst performance (similar to eq 1), being the best the value that would follow ideal performance (targeted by international treaties or expert judgement).

3.5.2 Generation of synthetic risk indices

Once the variables have a common risk scale, the integration of the different components and variables into integrated wildfire danger, exposure and vulnerability indices can be carried out. There are different alternatives to obtain those integrated indices, including qualitative and quantitative approaches.

If the variable was converted to a categorical risk scale, the obvious alternative is a cross-tabulation analysis (Alcasena et al. 2019; Chuvieco and Salas 1996), in which the different risk components are integrated by

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assigning qualitative ranks to the different combinations of the two-variable categories being compared. A previous conversion from the original scale to ordinal levels of risk (low, medium, high, and very high) facilitates this cross-tabulation process (Chuvieco et al. 2014b). The assignment of output risk values to those combinations is based on experts' judgement.

Multicriteria evaluation techniques may be a good alternative to reduce the subjectivity of this assigning process, since the opinion of experts may be quantitatively assessed (Gómez-Delgado and Tarantola 2006). Moreover, each expert's opinion may be weighed according to his/her degree of knowledge in the field or the study area (Alcázar et al. 1998; Andersen and Sugg 2019).

Quantitative integration methods can be based on simple conceptual formulas, for instance the estimation of risk as by multiplying danger and vulnerability (Bachmann and Allgöwer 1998) or the potential damages by the product between danger, economic value and ecosystem vulnerability (Parente and Pereira 2016). Probabilistic approaches may also be used, for instance by estimating the joint probability of two independent components using the Kolmogorov probabilistic rule (Tarantola 2005). This approach was followed by Chuvieco et al. (2014a), to integrate ignition probability derived from causative agents P(Ca) as a result of the human ignition probability P(H) and lightning probability P(L) following:

$$P(Ca) = P(H) + P(L) - P(H) \cdot P(L) \quad (2)$$

Statistical models based on regression analysis between fire historical occurrence and explanatory variables have also been widely used in fire risk assessment, including interval scale regression models (Martínez et al. 2009; Oliveira et al. 2012), logistic regression (Vasconcelos et al. 2001), geographically weighted regression (Koutsias et al. 2010; Rodrigues et al. 2014) and global additive models (Fernandez-Anez et al. 2021). More recently, machine learning methods have been extensively used for integrating different risk variables, based also on historical fire occurrence. The most common algorithms are Random Forest (Chuvieco et al. 2021; Leuenberger et al. 2018), Neural Networks (Vasconcelos et al. 2001; Vega-García et al. 1996), MaxEnt (Yang et al. 2021) and Support Vector Machines (Hong et al. 2018).

An alternative for the merging of the different risk components is the Pareto ranking aggregation (Ben-Tal 1980), which has been used with the pan-European risk assessment system to preserve the ranking of values even when the input components are modified (Oom et al. 2022).

Outside of the wildfire risk assessment field, it is worth quoting again the EPI approach (Wendling et al. 2020), as it integrates multiple indicators into single indices easily understandable and comparable. Once the different performance indicators are normalized to a common score, they are combined into integrated indices by weighed averages. For instance, the two main sub-indices, Ecosystem Vitality and Environmental Health, receive a weight of 60 and 40%, respectively, to compute the final index. Within each of these sub-indices, the indicators are weighed according to their relative importance and uncertainty of the input data (Wendling et al. 2020).

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3.5.3 Risk validation

Risk assessment aims to mitigate the negative impacts of fire on people, infrastructures and natural values, by improving how societies deal with fire risk conditions. This implies that fire risk assessment is considered an estimation of potential fire occurrence, both in time and space. Therefore, the evaluation of the quality of a particular fire risk assessment system seems logically related to how well it estimates fire ignition or behaviour, or to how much it reduces the exposure or vulnerability. The former is easier to verify, as statistics on fire ignitions and, to some extent, on fire propagation may be obtained after fire occurs. For this reason, most researchers developing wildfire risk assessment systems have compared their results with actual fire occurrence, either obtained from fire reports (Chuvieco et al. 2010; Viegas et al. 1999) or from satellite observations (Parente and Pereira 2016). The former approach is based on national statistics derived from fire suppression services and usually includes a high accuracy, even for small sizes, but may be not homogeneous for large territories (Moreno and Chuvieco 2013). The latter relies on global observation of active fires or burned areas, and provides a regional to global view of fire occurrence, very useful for those regions with few suppression resources. Active fires are detected by thermal sensors and provide a high accuracy for medium-size fires, particularly in terms of dating the ignitions (Chen et al. 2017; Chuvieco et al. 2020), while burned area products provide a more detailed assessment of the total area affected by fire, as well as fire persistency (Hawbaker et al. 2020; Jones et al. 2022; Zheng et al. 2023) and specific fire characteristics (Andela et al. 2019; Artés et al. 2019).

Regarding wildfire exposure and vulnerability, the validation is much more complex, as the estimation of affected resources is done assuming a certain fire scenario (intensity or persistency), which may or not be similar to the one actually occurring. In any case, the validation of the specific variables that are used for exposure or vulnerability estimation should be validated independently of their integration (Stehman and Foody 2019). For instance, smoke dispersion models can be validated with specific measurements performed in real or prescribed fires, and therefore those models can be considered accurate enough regardless whether the pre-fire modelled conditions are similar or not to the those occurring in actual fires.

However, we should emphasise that likelihood of occurrence is not the same as occurrence, particularly when dealing with specific components. For instance, meteorological danger indices, used in all operational fire danger systems, help estimating when and where a fire may ignite, but high meteorological danger does not necessarily correlate with high fire occurrence (Shah et al. 2023). Reasons for this apparent disparity of danger indicators and actual occurrences vary for different regions and in many cases remain speculative. Realization of high danger into a strong fire depends on both fire ignition and suppression. Depending on region, local habits, agriculture and forestry practices, the same level of fire danger may lead to very different fire patterns.

4 Description of the FirEURisk assessment system

This section presents the integrated wildfire risk strategy being developed within the FirEURisk project. The overall strategy includes three phases of wildfire risk: assessment, reduction and adaptation. Once the main

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factors of risk are defined and assessed, different approaches to reduce the negative impacts of fires on society and ecosystems need to be considered, including minimizing the causes of fire ignition, decreasing the propagation potential leading to extreme conditions, reducing exposure of people and assets and increasing resilience of societies, ecosystem services and ecological values to fire damages (Alcasena et al. 2019). In addition, the FirEURisk strategy includes modelling how the main risk components will evolve in the future, according to the expected climate and socio-economic changes, to propose adaptation measures that would reduce the negative impacts of wildfires in the foreseeable future (Sample et al. 2022). Within this document, the focus will be on the assessment phase. The approach was designed to cover a wide range of temporal and spatial scales, as well as users, including European, national and regional managers, decision makers, local communities and policy makers. The description of the system includes methods for retrieving the risk components and variables and integrating them into synthetic risk indices for comprehensive characterization of fire risk conditions.

4.1 Spatial and temporal resolution

An integrated risk system should be as scale-independent as possible. However, the availability and the quality of input datasets is highly dependent on the target scale. Generally speaking, global-continental scales tend to cover larger territories using coarse resolution data, while regional-local scales cover smaller territories at much higher spatial resolution data. For the FirEURisk project, two target scales have been developed: the European Territory (ET), with a total area of around 5 Mkm^2 of land covering 33 countries at a target resolution of 1 km^2, and selected pilot sites (PS), covering a few thousand square kilometres and a minimum resolution of 0.01 km^2 (1 hectare). The ET area covers European Union member states, with the exception of their Tropical islands and Cyprus, plus the United Kingdom, Switzerland, and Norway. The selection of PS aimed to take into account the variety of fire conditions in Europe, including regions in Portugal, Spain, Greece, Germany, and Sweden.

Two temporal scales have been considered for assessing risk conditions: near-real time and reference scenarios. The former involves evaluating current conditions, especially for those variables that can change rapidly such as fuel moisture, precipitation, wind speed and direction. For the FirEURisk project they will be updated daily (weather variables) or weekly (live fuel moisture content). This near-real time temporal scale should be useful for pre-emergency management and tactical decisions.

Historical reference scenarios, on the other hand, are useful for long-term planning, for instance to estimate how much area would be exposed in case those reference conditions would occur again. Since the FirEURisk project is mostly interested on extreme fires, two reference scenarios leading to very high or high-risk conditions were selected. The first one was defined by selecting the 95% highest percentile of weather parameters at 12 h for high-risk days, while the average high-risk conditions scenario was computed from the same set of high-risk days but taken instead the 50% percentile of the weather parameters. High-risk dates were obtained by selecting the ignition dates of any fire that burned more than 2,000 hectares in the ET area. The selection of ignition dates was based on the analysis of the 2001 to 2019 time-series of the FireCCI51

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burned area product. This dataset was produced within the European Space Agency Climate Change Initiative's programme (Plummer et al. 2017), based on satellite earth observation data (Lizundia-Loiola et al. 2020). The original product was available at 250 m, organized in global monthly files that extend from 2001-2019. To estimate ignition points, burned pixels of the FireCCI51 were grouped into burned patches using a contextual algorithm that accounted for the spatial proximity and the date of detection (Laurent et al. 2018). Ignition points (and respective dates) were obtained by computing the geographic centroid of the contiguous pixels that have no other neighbouring pixels with a previous fire date. A total of 403 high-risk days corresponding to those ignition points was obtained for the 19 years of the available FireCCI51 time series. Weather parameters for those 403 days were computed from ERA5-Land global reanalysis data (https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=overview last access March 2023). A topography-based transfer function (Tesfa et al. 2020) was applied to the 9 km-resolution time series of the hourly ERA5-Land reanalysis data (https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=overview, last access March 2023) for the following variables: Temperature, Dew Point Temperature, Relative Humidity, Wind and daily Precipitation. Particularly, for each climate variable simulated by the reanalysis, the statistical downscaling was based on three steps: 1) For all the variables and for each time step (with 0.073°×0.073° resolution), a purely geo-statistical approach was performed to a 1km×1km grid by using AIC-based stepwise regression (Murtaugh 1998) with topological and geographical parameters (latitude, longitude and distance to the Atlantic Ocean and Mediterranean Sea), and bilinear model for the residual errors. In addition, altitude was taken into consideration in the case of temperature. 2) Similarly, for each targeted time step, residual errors of the AIC-based stepwise regression were interpolated from the original grid (0.073°×0.073°) to the final 1km^2 grid by using a bilineal model. 3) Finally, the projected value for each time step was obtained by adding the result of Step (1) and Step (2), obtaining climate scenarios in a 1km^2 grid at an hourly timescale (daily in case of precipitation).

4.2 FirEURisk integration scheme

In line with the main risk dimensions described in section 3, the FirEURisk integrated wildfire risk assessment system includes the assessment of danger, exposure and vulnerability (fig. 2). It was built on previous integrated approaches that took into account those elements at different spatial scales (Chuvieco et al. 2014a; Chuvieco et al. 2010). The integration of the different components aimed to provide a comprehensive view of risk conditions, which may be later on integrated with other natural hazards while considering the potential cascading multi-risk effects. This section covers the three main components of wildfire risk, while the following one deals with the variables of those components.

4.2.1 FirEURisk Danger

Danger was estimated from ignition causes and propagation potential. The former includes human and natural fire ignitions, while the latter includes the estimation of fire behaviour considering fuel and terrain characteristics, as well as the weather scenarios indicated in section 4.1. Section 4.3 contains a detailed analysis of the variables generated for this component, including probability that lightning causes fires,

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human factors that lead to accidental or intentional ignitions, as well as fuel moisture content and propagation modelling.

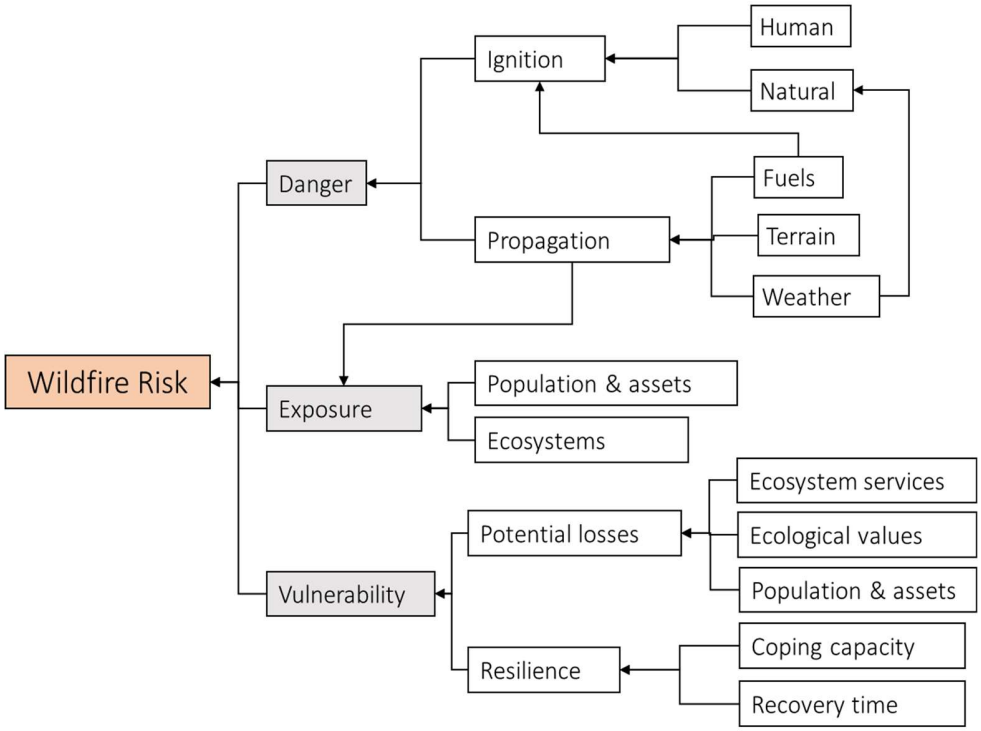


Figure 2: Conceptual integration of wildfire risk assessment components within the FirEURisk project. This scheme could also be eventually applied to risk reduction and adaptation

4.2.2 FirEURisk Exposure

Exposure potential was quantified based on the juxtaposition of fire exposed elements with the spatial distribution of fire metrics. The final output was the fire exposure potential (ranging from 0 to 1, for a combination of a given fire metric and element at risk), which was computed using the following equation:

$$Exposure\ potential\ = \frac{Fire\ metrics \times Values\ at\ risk}{Max\ (Fire\ metrics \times Values\ at\ risk)} \quad (3)$$

where the fire metrics include the main fire propagation characteristics (see 4.3.4), such as fire line intensity or rate of spread, but also atmospheric emissions (gases and particulate matter), while values at risk include both human assets and ecosystem services. As a first approach to estimate this variable, the exposure of population and assets was calculated taking as a case study one of the PS of the project (see details in 4.3.5).

4.2.3 FirEURisk Vulnerability

Vulnerability was determined by the initial values at risk and their resilience (in terms of coping capacity and recovery time) and comprised potential impacts of fires on both social (including here houses, infrastructures

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and ecosystem services) and ecological values. Figure 3 includes the general model that was used to estimate vulnerability, which is better adapted to ecological values (EV) but can also be applicable to social assets and ecosystem services (ES). Actual loss was obtained from how much of the pre-fire value would be lost as a result of fire. For EV, the number of losses depends on fire conditions, but also on landscape resistance to fire, while for ES depends on the characteristics of that specific service. For instance, with a mild fire the timber value may be reduced just in a small proportion, while pastures may be completely lost. The resistance of social assets would depend on the level of protection of houses and fuel density in the surroundings of the WUI.

The time length needed to recover up to the pre-fire conditions indicates the recovery time, which is related to the landscape resilience to regrowth after fire, in turn related to the plants reproductive strategies and the landscape abiotic conditions in the case of EV, while for ES and social assets would vary greatly depending on the ES considered (ie pastures would have a quick recovery, while timber would require a 20-40 years depending on the species and the biophysical conditions of the area).

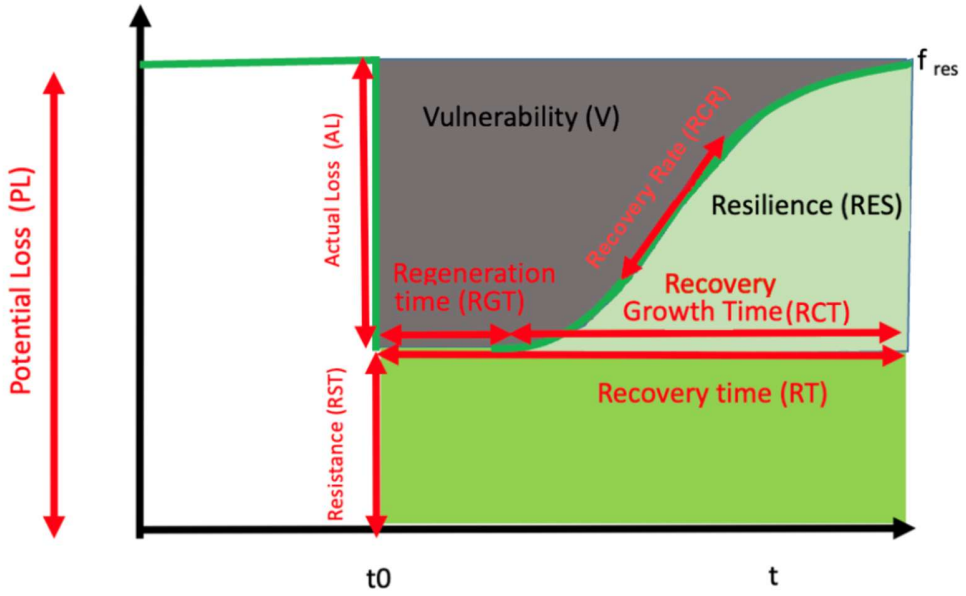


Figure 3: Conceptual model quantifying ecological vulnerability (V, grey area) as a function of potential loss (PL), coping capacity (resistance (RST), regeneration time (RGT)) and recovery time following the resilience curve f_{res}, parameterized with its recovery rate (RCR).

4.3 Methods to generate risk variables and components

4.3.1 Natural ignition

Natural ignition usually refers to lightning activity, which is the dominant natural cause of fires and can be the main ignition mechanism in remote areas with low population density and poor accessibility. The primary type of lightning that can ignite wildfires is lightning strikes with a long continuing current (LCC), which refers

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to a discharge that lasts for more than 40 ms in a return stroke. Compared to short-duration lightning, LCC lightning can heat wildland fuels for a more extended period and transfer more energy, making it more effective at igniting fuels. Therefore, lightning-caused wildfires can potentially be assessed based on the duration of lightning's discharge or the amount of energy it produces (Zhang et al. 2023). Another dimension is added to this by considering the polarity of the lightning strike: Latham and Williams (2001) theorized that positive Cloud-to-Ground (CG) strikes are more likely to ignite wildfires. Interestingly, regions with the highest number of lightning flashes do not necessarily produce the most flashes containing LCC (Bitzer 2017). In other words, less frequently occurring lightning is more likely to contain LCC. It is essential to take into account the change in the global occurrence rate and spatial pattern of total lightning due to climate change (Pérez-Invernón et al. 2023).

The first step of the natural ignition model was the prediction of the lightning flashes themselves. Despite the availability of global lightning observing systems, their quality and data availability may be problematic in many parts of the world. However, modern weather prediction models provide a sufficiently detailed description of convective clouds and thunderstorms, allowing for quite accurate lightning flash density prediction for up to a few days forward (Lopez 2016) (Fig. 4). The next step includes converting lightning flash density into fire ignitions. It involves numerous governing physical processes such as wind speed, precipitation occurrences and strength, lightning characteristics (e.g., presence of a long continuous stream of electrical current), and fuel readiness and availability to ignite. Therefore, statistical models seem more suitable for their description (Coughlan et al. 2021). The FirEURisk project utilizes the Fire Forecasting Model developed by the Finish Meteorological Institute, which employs a multi-step machine-learning procedure to construct a statistical model predicting the Fire radiative power (FRP). The model uses various meteorological parameters and Fire Danger Indices as predictors for training and predictions computing their corresponding contributions to total FRP. Then, Cloud-to-ground lightning flash density contribution to FRP serves as a proxy for natural ignition probability that is integrated with ignitions caused by humans.

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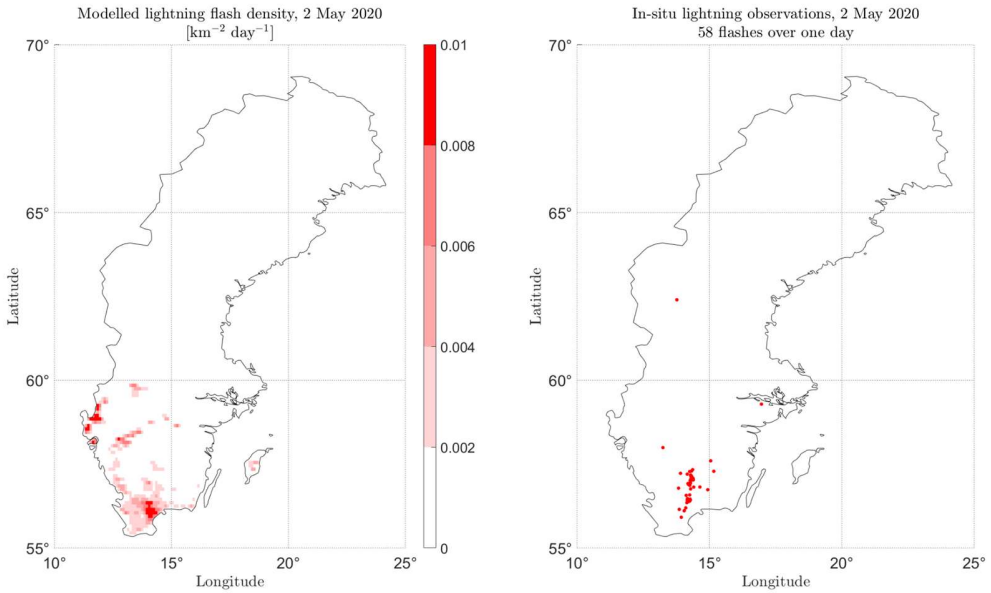


Figure 4: Daily total lightning flash density over Sweden forecasted for 2.05.2020 by weather prediction model of European Centre of Medium-Range Weather Forecast (ECMWF) (left panel) and in-situ observed lightning flashes during the same day (right panel) (data provided by Johan Sjöström).

4.3.2 Human ignition

Modelling of human ignition was approached from empirical models, based on historical fire occurrence. Unfortunately, there is not yet a centralized database in Europe where all fires are recorded, as temporal length and spatial accuracy of available fire reports varies throughout European countries. For this reason, the same method used to define the high-risk days (see section 4.1) was selected to define historical fire occurrence for human ignition modelling. However, in this case, ignition points from all sizes burned patches were considered, not just those from patches above 2000 has. Since those small patches included also agricultural fires, only those ignition points located in wildland areas were kept. Patches within wetlands or agricultural areas not interfacing with forested covers (>500 m) were removed. The final ignition point dataset included 55,214 fire observations (Fig. 5a).

The Ignition probability model was derived from a Random Forest algorithm (Breiman 2001), using a wide set of explanatory variables derived from different statistical and cartographic sources (Sueur-Ochoa and Chuvieco 2023): distance to roads, urban-forest, forest-grassland and forest-cropland interfaces, urbanization degree, livestock density, land cover and land cover change, gross domestic product, population density and senior population proportion (>65 years), and various bioclimatic indices. All were resampled at the target spatial resolution of 1 km^2. The RF model was run using a sample of 70% of ignition points for calibration and the remaining 30% for validation. Non-ignition points were selected randomly in the whole ET area, selecting 1.5 times the number of ignition points to avoid model unbalance. Several models were

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run, including all variables and only those that were human-related. Since fires in the Mediterranean have different characteristics to those in Central and Northern Europe, these two regions were modelled independently as well. Finally, two seasonal models were derived to account for variations between summer fires and late winter-early spring ones.

Results offered a high degree of accuracy, with omission and commission errors lower than 15% in most models. Spatial patterns of the model closely resemble the distribution of ignition points (Fig. 5b). The global model including all ignition points identified the livestock density, distance to roads and population aging as the most explanatory variables. When the biophysical variables were taken into account, average evapotranspiration and aridity index also had high importance. Partial dependency graphs showed non-linear relations in several variables, which indicate the complex patterns of fire-human relations (Sueur-Ochoa and Chuvieco 2023).

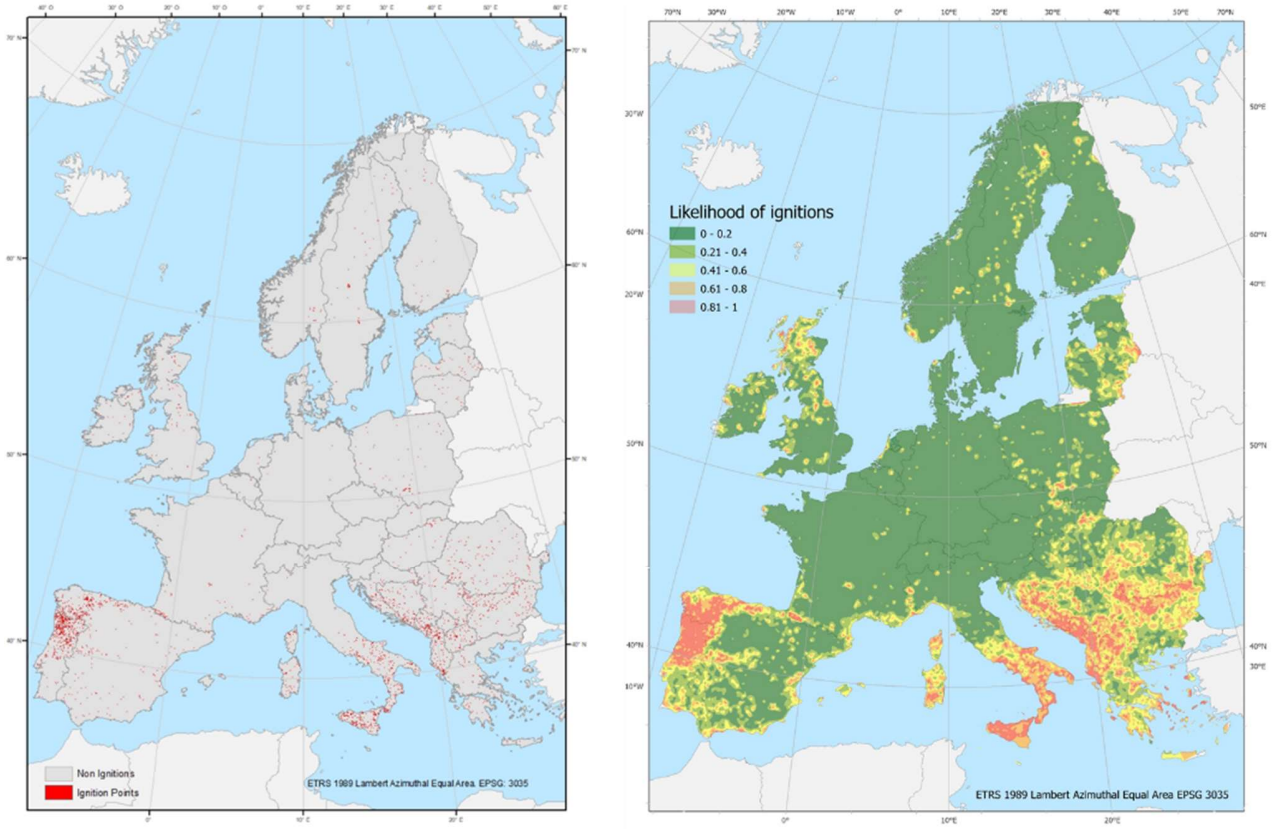


Figure 5: Ignition points selected for the human ignition model (left) and final output of the model (right). After (Sueur-Ochoa and Chuvieco 2023).

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4.3.3 Fuel

To consider the great variety of European fuel conditions, first a hierarchical fuel classification system was developed, including surface and canopy fuels, which could be used for both target scales, ET and PS (Aragoneses et al. 2023). This FirEURisk classification system includes 80 fuel categories, structured into the following seven main fuel types: a) Forests (areas with canopy cover ≥ 15 % and canopy height ≥ 2 m); b) Shrublands (areas with shrubs, scrub, garrigue, and maquis); c) Grasslands (areas with herbaceous non-cultivated vegetation); d) Cropland: (areas with cultivated vegetation); e) Wet and peat/semi-peat land (which in turn comprises areas with a permanent mixture of vegetation and water, including marshes; moorland/heathland; peatlands and peat bog, and moss and lichens; f) Urban (areas with ≥ 15 % of built-up structures and/or buildings); g) Nonfuel: (areas with permanent water bodies, open sea, snow, ice, bare soil, sparse vegetation (< 10 % of terrain cover). Forest fuel types were subdivided as a function of both canopy characteristics: leaf type (broadleaf/needleleaf), phenology (evergreen/deciduous), and fractional cover (open/closed), as well as the understory characteristics, including type (grass/shrub/timber litter) and depth (three heights). Regarding the other main fuels, subcategories were based on fuelbed depth (grasslands and shrublands) and characteristics (herbaceous or woody, for croplands; tree, shrublands and grasslands for wet/semi peatlands). Urban fuels were split into continuous and discontinuous fabric.

This classification system was used to generate all fuel type datasets for the FirEURisk project, including the whole ET (Aragoneses et al. 2023) (Fig. 6a) and PS (Fig. 6b). The former were obtained from existing land cover and biophysical models, while the latter were generated from high resolution satellite image classification (Mohammadpour et al. 2022), with resolutions ranging from 100 to 20 m. Both ET and PS fuel type maps were associated to existing fuel models: a preliminary assignment for the ET area was done using the FBFM standard fuel models (Scott and Burgan 2005), where for the PS the fuel models were estimated from field data or biophysical regional estimations.

Fuel moisture content was computed for fire propagation potential. For dead fuels, the FMC was computed from weather variables using an adaptation of the Nelson model (Nelson, 2001) to estimate the 10h Dead FMC for high-risk and extreme-high conditions (see section 4.1). The weather inputs were obtained and rescaled from ERA-5 (https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5, last access March, 2023) and Worldclim (https://www.worldclim.org/data/worldclim21.htmland, last access March, 2023), and downscaled to 1 km^2. DFMC values were divided into four classes, according to the 10-h DFMC code: D1L1: Very low dead FMC, fully cured herb, D2L2: Low dead FMC, 2/3 cured herb, D3L3: Moderate dead FMC, 1/3 cured herb, D4L4: High dead FMC, fully green herb.

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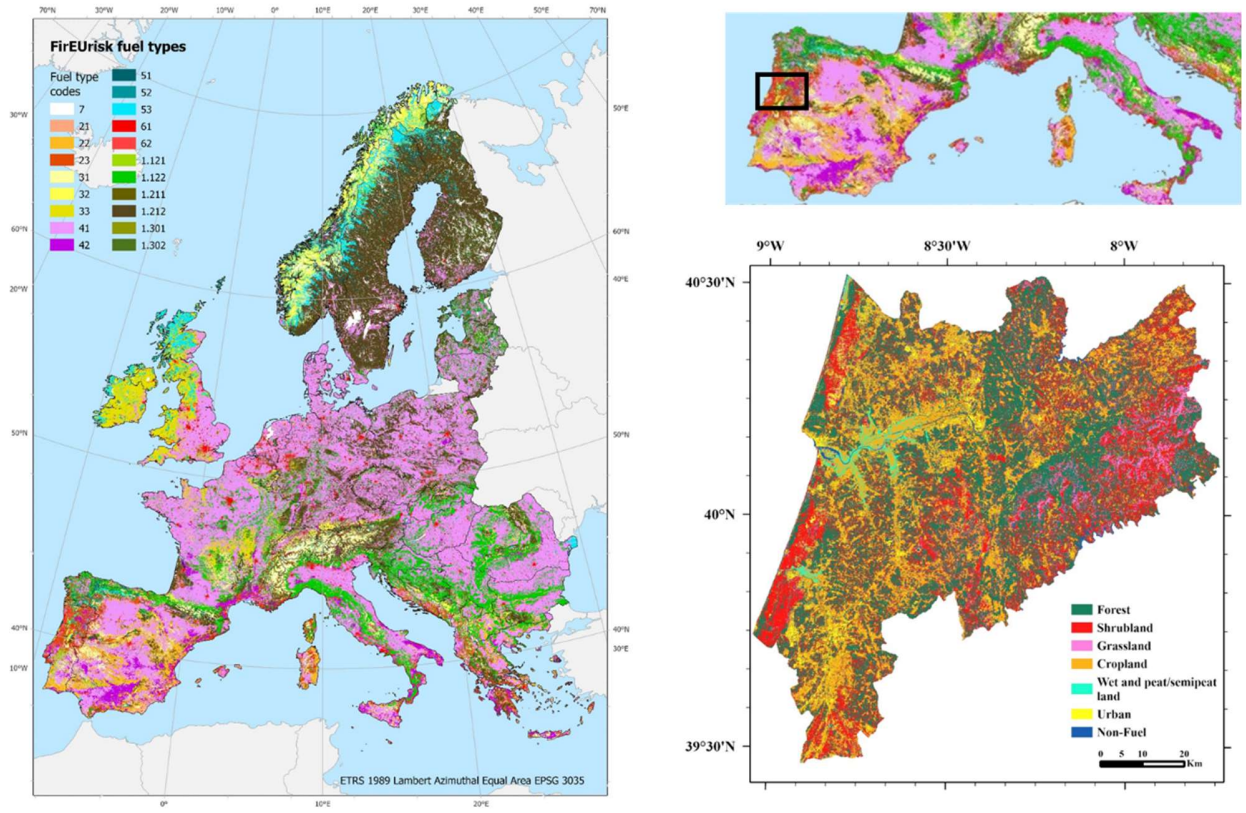


Figure 6: Fuel type classification of the ET area (right: (Aragoneses et al. 2023)) and the PS of Central Portugal (left, simplified version from (Mohammadpour et al. 2022)).

The procedure to estimate Live Fuel Moisture Content (LFMC) was based on retrieval from Sentinel-2 and Sentinel-3 satellite observations, following previous studies from Yebra and collaborators (Quan et al. 2021; Yebra et al. 2013; Yebra et al. 2018). The vegetation was described in terms of three basic vegetation types: grassland, shrubland and forest. The first two were represented using the combination of two Radiative Transfer Models (RTM): the PROSPECT-D leaf optical properties model (Féret et al. 2017) and the 4SAIL canopy bidirectional reflectance model (Verhoef et al. 2007). In addition, the forest vegetation type was described using the version of the Jasinski geometric model developed for GeoSail (Huemmrich 2001; Jasinski and Eagleson 1990), which allows the use of the 4SAIL output to represent discontinuous vegetation. In order to classify vegetated pixels into the three basic classes, the EU Worldcover 2021 (https://esa-worldcover.org/, last access March 2023) was used for the Sentinel-2's 10-20 meter resolution product, and Corine Land Cover 2018 (https://land.copernicus.eu/pan-european/corine-land-cover/clc2018, last access March 2023) for the Sentinel-3's 300 meter resolution product. These broad categories are used to differentiate the boundaries and distributions of the biochemical and geometric parameters that describe the leaf and canopy model.
To ensure the feasibility of the estimation of the parameters relevant to LFMC through an inversion procedures, Global Sensitivity Analyses of the different model combinations and parametrizations were

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performed in the Sentinel-2 MSI and Sentinel-3 OLCI and SLSTR channels (Pampanoni et al. 2022) using the spectral response functions published by ESA (https://sentinels.copernicus.eu/web/sentinel/user-guides/, last access March 2023).

The inversion strategy was based on Look-Up Tables (LUT), a methodology which is often favoured in the related literature for the sake of its performance and relative simplicity of implementation. In addition, using LUTs allows to leverage the parametrization studies performed in past years with the explicit objective of LFMC estimation (Yebra and Chuvieco 2009a; Yebra and Chuvieco 2009b). The 300-meter resolution product based on Sentinel-3 was developed for different PS areas of the FirEURisk project (fig. 7), while the 10-20 m product based on Sentinel-2 was computed only for certain demo areas.

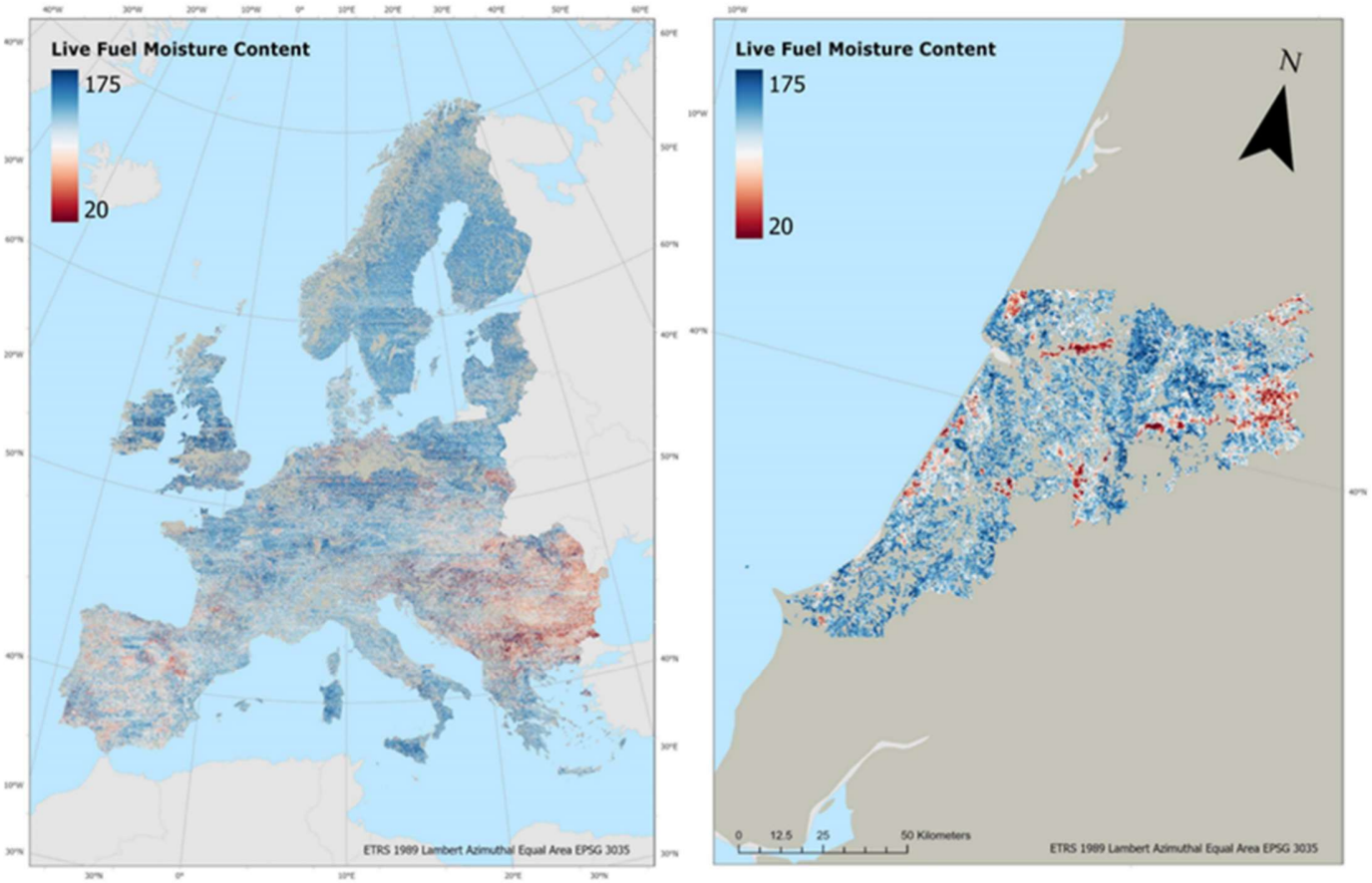


Figure 7: Sentinel-3 based LFMC in the ET (left) and in the PS of Central Portugal (right) on the 8th of March 2023

4.3.4 Propagation

Modelling of propagation variables was carried out with two different methodologies. For the ET area, custom implementation of Rothermel's equations for cell-based wildland landscape fire growth simulations was carried out. These equations take into account mid flame wind speed, fuel moisture, elevation, aspect and

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fuel model. Exact pixel values for slope and mid flame wind speed were used. Each weather scenario (see section 4.1) represented either the average or extreme weather conditions associated with a specified wind direction scenario (e.g., northeast wind). 95th percentile values were used to define extreme conditions, while 50 percentile values were used to define high-average ones. Outputs of Rothermel equations were: Rate of Spread (m/s), Reaction intensity (kW/m^2), Fire line Intensity (kW/m) (see fig. 8) and Flame Length (m). These variables were computed for the ET area using the two reference weather scenarios, with the DFMC modelled for those conditions and the fuel type dataset described in 4.3.3, using the adaptation to the Scott and Burgan fuel models (2005), done by Aragoneses et al. (2023). Elevation data was downloaded and rescaled from NASA Shuttle Radar Topography Mission data (https://lpdaac.usgs.gov/products/srtmgl1v003/, last access March 2023). Both aspect and slope data were extracted from this dataset.

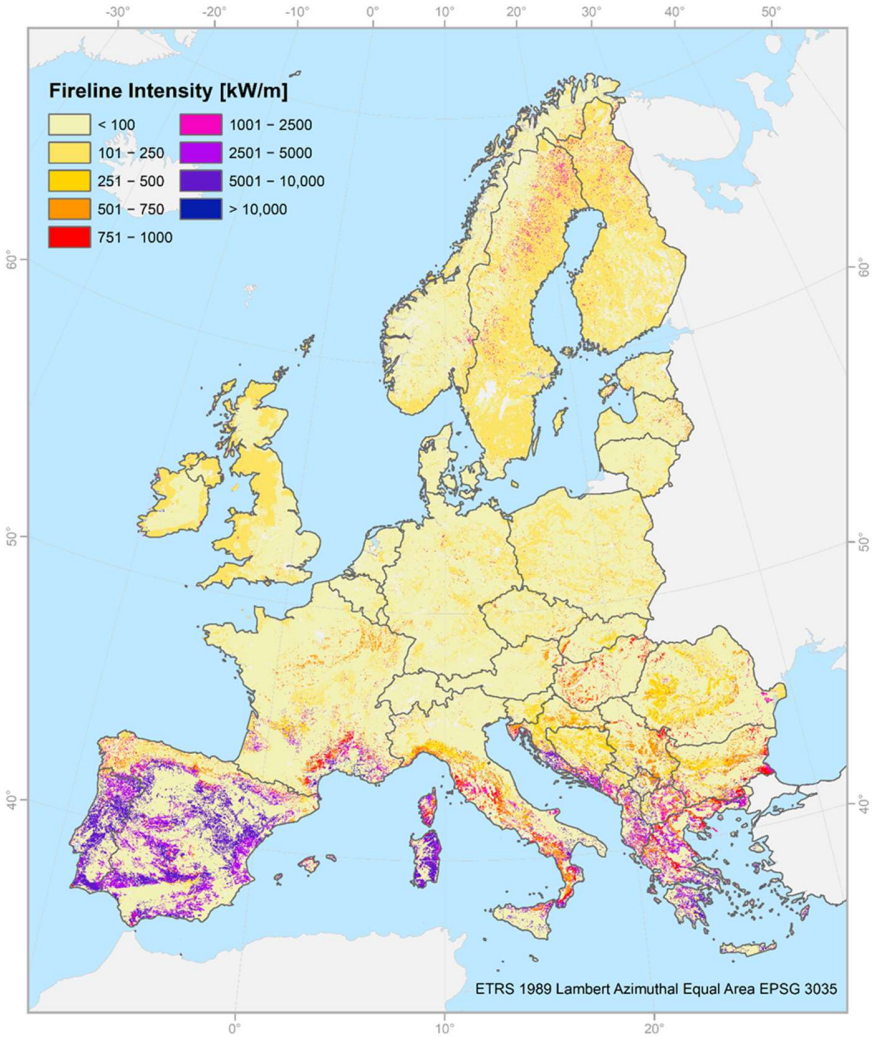


Figure 8: Estimation of Fireline Intensity (FI) (kW/m^2) for extreme 95th percentile wind speed and 5th percentile fuel moisture

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The method used to estimate propagation for the different PS of the project was based on a different approach to obtain a more detailed analysis of spatial variations within those sites, based on higher resolution spatial datasets. Propagation modelling was based on the MTT algorithm provided by FlamMap (Finney 2006), which estimates burn probability for every pixel based on certain weather conditions, fuel parameters and topography, using a stochastic method. To obtain the reference weather conditions, historical fire ignitions were obtained from national statistics, taken at least from the last 20 years. Only weather scenarios responsible for more than 10% of overall detected burned area were taken for further examination. Fuel types were obtained from high-resolution products (as indicated in 4.3.3). In this case, the propagation model included forest canopy characteristics. Tree Cover Density data was obtained from the Copernicus land service (https://land.copernicus.eu/pan-european/high-resolution-layers/forests/tree-cover-density, last access March 2023), while tree height was obtained from Simard et al. (2011). Canopy bulk density (CBD) and canopy base height (CBH) were spatialized using canopy height and canopy cover data intervals, using average CBD and CBH data extracted from the PREVINCAT project (https://previncat.ctfc.cat/en/index.html, last access March 2023).

4.3.5 Exposure to population and assets

As previously mentioned (section 4.2.2) the method to estimate the spatial distribution of exposure was based on the juxtaposition of the geographic location of fire exposed elements (e.g. population density, number of residential structures or the length of the main roads) with the spatial distribution of fire metrics (e.g. fireline intensity or emitted smoke). The selected test area was one of the Mediterranean PS of the project (the province of Barcelona). This area is in northeast Spain and encompasses 7.726 km². It includes the metropolitan area sprawling around the city of Barcelona, with high density of population and extensive WUI zones. More than 22% of this area includes some nature protection figures, experiencing high touristic pressure. Exposure was estimated for different exposed elements and fire metrics for the whole PS with a spatial resolution of 0.01 km^2.

National maps were used to generate a point file with residential house locations, in order to accurately identify all individual residential structures. The road network was obtained from the OpenStreetMap dataset (https://wiki.openstreetmap.org/wiki/Downloading_data, last access March 2023), and the Natura 2000 protected sites were downloaded from the European Environment Agency (https://www.eea.europa.eu/data-and-maps/data/natura-14, last access November, 2022). The GISCO database was used to obtain the spatial distribution of the population in the study region (https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/population-distribution-demography/geostat, last access November 2022). Its database contains core geographic data (e.g, administrative boundaries, and population grid data) covering the whole of Europe and is based on the official statistics from National Statistical Institutes.

A large set of modelled fire perimeters corresponding to more than 12,000 years or iterations using the FlamMap algorithm (Finney 2006), were used to generate rate of spread (m/s), reaction intensity (kW/m2), fire line Intensity (kW/m) and flame length (m), for each grid cell (see section 4.3.4). Moreover, atmospheric

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emissions were estimated by a bottom-up approach where the main required input data were the fuel type, fuel load, burned area (ha), fuel consumption (t/ha), fire intensity (kW/m), and emission factors (g kg^{-1}) by combustion phase (i.e., flaming and smouldering) (Fernandes et al. 2021). The fuel type and fuel load were obtained from the FirEURisk products (see 4.3.3). Fire line intensity was used to provide separate estimates of flaming and smouldering for each fuel type by assuming that flaming combustion cannot be sustained below an intensity of about 15 kW/m (Albini and Reinhardt 1997). The burned area per grid cell was estimated also using the fire progression provided by the outputs results from FlamMap. To estimate fuel consumption, an empirical model developed by Prichard et al. (2017) was used. A literature review was performed to obtain the most suitable emission factors for the European Region (Prichard et al. 2020; Vicente et al. 2019).
Figure 9 illustrates the results of these calculations showing the spatial distribution (at 0.01 km^2 resolution) of the building's potential exposure to fire line intensity (a) and the population's potential exposure to PM10 emissions (b), from wildfires in the Barcelona province. The average potential exposure of buildings to fire line intensity is low (98% of the values were lower than 0.2), with an average of 0.03 and a standard deviation of 0.05. The higher values were found in the surroundings of the village of El Mas d'en Gall, NW of Barcelona (red box indicated in Figure 9). Regarding exposure of population to smoke emissions, the average potential exposure was also low (99% of the values were lower than 0.2), with an average of 0.01 and a standard deviation of 0.03. The higher values were found in the surroundings of the city of Mataró, located in the NE of Barcelona (red box indicated in Figure 9). This method to calculate exposure potential produces inputs for the integrated risk calculation (section 4.4.2), by delivering exposure data in the context of human assets (roads and buildings) and population vs. fire behaviour characteristics (i.e., direct exposure to fires, as well as exposure to smoke).

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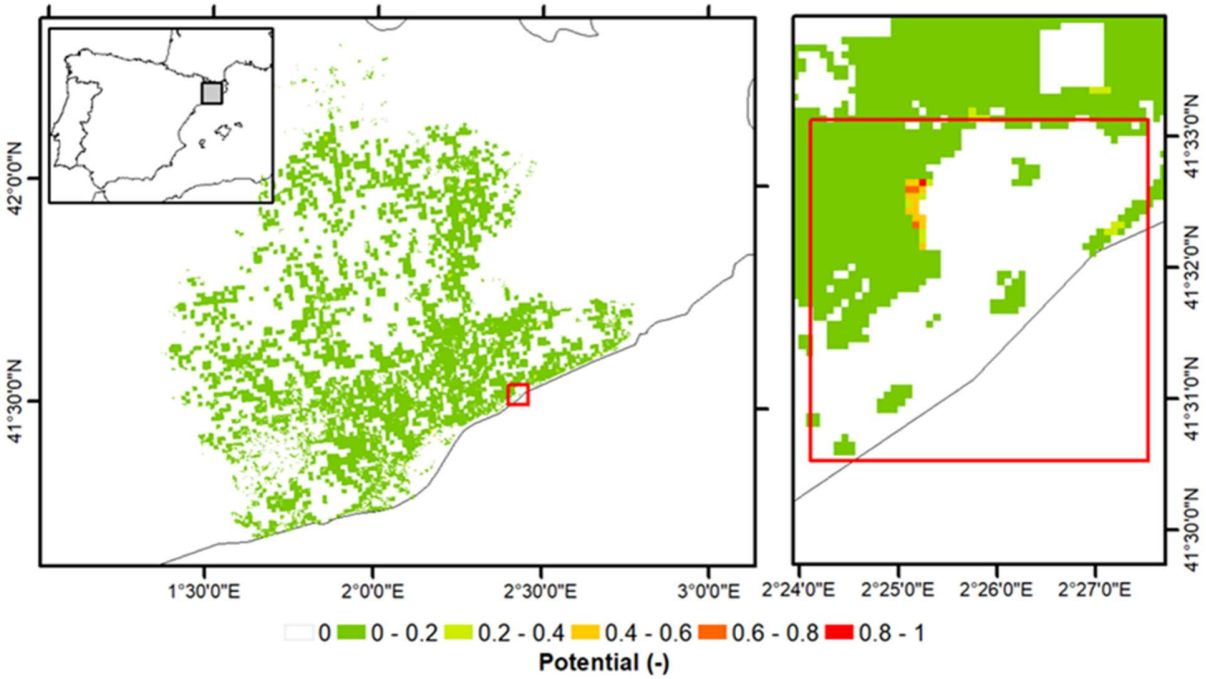


Figure 9: Spatial distribution (at 0.01 km2 resolution) of (top) the building's potential exposure to fire line intensity, and (bottom) the population's potential exposure to PM10 emissions from wildfires in the Barcelona province. The red box indicates the area with the maximum fire exposure potential values (i.e., 1).

4.3.6 Ecosystem services

Assessment of regulating ES for the FirEURisk project for the ET area was done using the standard methods of natural capital used previously in Europe: including the work of La Notte (2021) and outputs generated by the INCA project carried out by the JRC (https://ecosystem-accounts.jrc.ec.europa.eu/, last access March 2023) on crop pollination, flood control, carbon sequestration, water purification and soil erosion. Provisioning services provided by the agricultural and forestry sectors were estimated for the stock of perennial crops (fruit trees, olive trees and vineyards), timber and livestock. Manufactured capital like residential properties in the WUI was also considered. To estimate the value of the natural and manufactured capital (expressed in euros per hectare in 2021 constant price), our approach has integrated statistical information (biophysical indicators) provided by EUROSTAT at NUTS1 or NUTS2 scale with the Corine Land Cover maps (https://land.copernicus.eu/pan-european/corine-land-cover, last access March 2023), for each of the habitats and land use assessed, and prices of each asset provided by different sources (reports, peer reviewed papers and information from the websites)[1]. Figure 10 includes an example of the total value of the ES assessed expressed in monetary units (€/ha year), in 2021 constant prices.

[1] For a more detailed analysis of ES, please check the FirEURisk Deliverable 1.4 "Report on methodological frameworks for Vulnerability assessment (D, S) in the FirEURisk- Wiki available at the web repository.

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ES values at local scale for the different PS areas were generated using the SEVEIF model (Rodríguez y Silva et al. 2013; Rodríguez y Silva et al. 2014), which integrates a broad range of ecosystem services, such as timber, fruits and cork harvesting, pasture, hunting, carbon sequestration, soil protection, landscape and recreational resources. The objective of SEVEIF model is the monetary quantification (in terms of euros per hectare) of the impact that wildfires have on natural resources, based on the net value change of the resources (NVC). The model considers the pre-fire value of each resource and a depreciation ratio based on wildfire scenarios simulated by Visual SEVEIF software (www.labif.es, last access March 2023). Fire propagation was classified into seven categories of fire Intensity to predict expected damages. The depreciation ratio for each of these levels and each ES is expressed as a percentage of value to simplify the methodology and field inventories. Finally, the net value change of each resource (value loss or value gain) was calculated as the product between ES values and fire intensity level. SEVEIF model incorporates the net-value change based on field inventories performed for large wildfires, comparing burned areas with unburned control areas for each of the ES. The sum of all potential impacts on environmental services is presented as the potential fire impacts in each PS. In this sense, SEVEIF tool involves more than an economic assessment of natural resources, showing the potential losses to fire (fig. 11).

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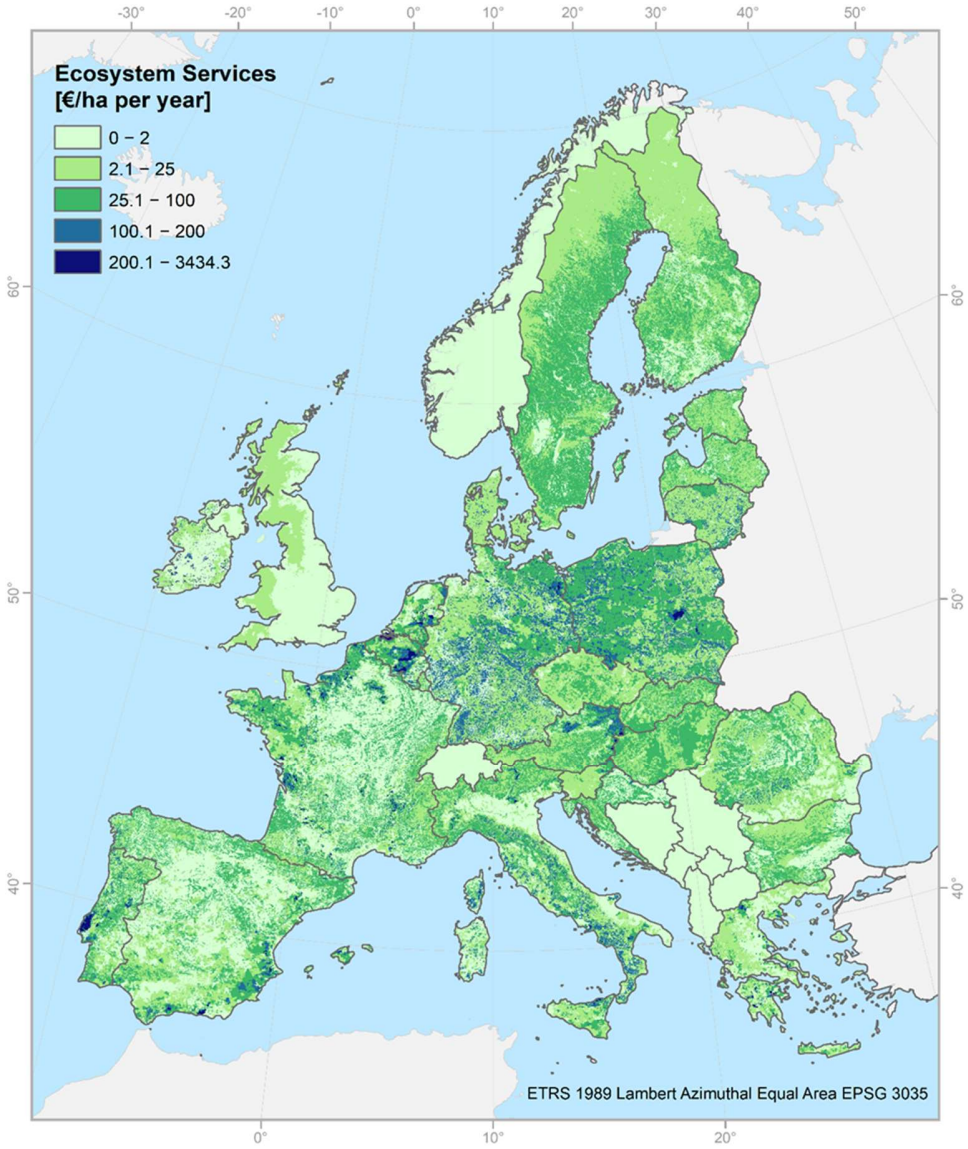


Figure 10: Value of ecosystem services for the ET area.

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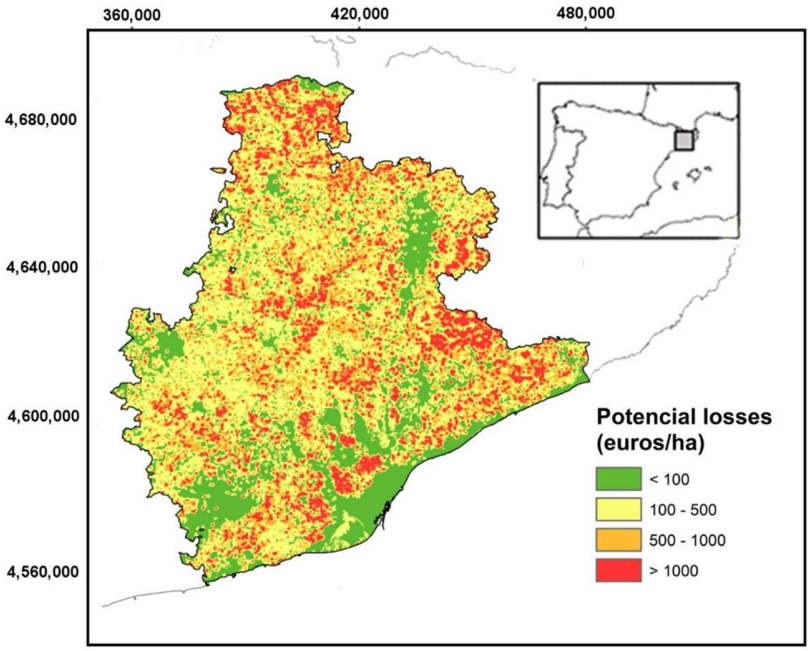


Figure 11: Values of ES potentially lost by wildfires for the Barcelona PS

4.3.7 Ecological values

The EV included in the first version of the FirEURisk integrated scheme took into account four components: soils, vegetation, fauna and the conservation value through natural protected areas. The ecological values of soils were first assessed as the main resource for vegetation growth, regeneration and survival. Soils provide the water storage and nutrient supply for plant growth. The subsoil and topsoil Available Water Content (AWC) based on soil texture, soil depth and rock fragment content provided by the JRC (https://esdac.jrc.ec.europa.eu/content/european-soil-database-derived-data, accessed on 10 March 2023) was used. Soil N and P content was also available from the JRC referring to top soil N and P concentration in soils and it was used as the standard fertility status without disturbance (https://esdac.jrc.ec.europa.eu/themes/npk-european-soils, accessed on 10 March 2023).

Ecological values related to vegetation were assessed through forest biomass (Santoro et al. 2021), maximum tree height as a proxy of forest diversity (Chen and Niu 2020) taken from (Potapov et al. 2021) (https://glad.umd.edu/dataset/gedi, accessed on 10 March 2023), landscape habitat diversity based on tree cover from Hansen et al. (2013) (https://data.globalforestwatch.org/documents/tree-cover-loss/explore, accessed on 15 March 2023), and tree height coefficient of variation within a 1km grid cell from the 30m resolution raw data.

Animal species diversity was obtained from the potential habitat data for each species of mammals, birds, reptiles, and amphibians available in the IUCN repository (https://www.iucnredlist.org/resources/spatial-data-download, accessed on 20 January 2023). Bird biodiversity analysis was taken from Fusco et al. (2021)

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(http://datazone.birdlife.org/home, accessed on 10 March 2023). For reptiles and amphibians, the data were produced by Sillero et al. (2014) (https://www.seh-herpetology.org/distribution-atlas, accessed on 15 March 2023) and for mammals the input data came from the European atlas for mammals (https://discovermammals.org/projects/the-2nd-european-mammal-atlas/, accessed on 15 March 2023). From these databases, the presence of each species was resampled at 1 km^2, following the target resolution of the FirEURisk project. The same source was used to estimate the potential habitat data for each species belonging to the category of "critically endangered", "endangered" and "vulnerable" of mammals, birds, reptiles, amphibians and vascular plants.

Finally, places of special conservation were used to weigh each ecological value according to human perception and strategies of conservation priorities. Data were downloaded from the World Database on Protected Areas (WDPA) (https://www.protectedplanet.net/en/thematic-areas/wdpa?tab=WDPA, accessed on 15 March 2023). Only the terrestrial protected areas classified under the International Union for Conservation of Nature's categories I–IV were considered, since they have reliable data, verified on the ground, and they are managed in a similar way, thus enabling us to assume that they all have the same biodiversity conservation values. The vector data layer was converted to raster binary data by assigning the value 1 where a WDPA was located and 0 where it was not.

Objective valuations for conservation areas were estimated from the Key Biodiversity Areas (KBA) maps (Potapov et al. 2017). KBAs have outstanding biodiversity value due to their extraordinary ecological integrity, globally significant ecosystems, or significant populations of animals, fungi, and plants. The Intact Forest Landscapes (IFL) dataset (Potapov et al. 2017) was used to obtain the extent of the forests and terrestrial ecosystems that remain unaltered by humans, with a minimum mapping unit of 500 km^2. Human pressure was also used as a surrogate of landscape fragmentation produced by human infrastructures, road and railways, with the highest percentages corresponding to highly degraded or heterogeneous landscapes and the lowest to areas that are unfragmented or homogeneous. The database was collected from the United Nations Environment Program (www.unep.org%2Fdata-resources&usg=AOvVaw3tEdJJmd7wlzixU-1TIMNN, accessed on 25 January 2023). Old growth undisturbed forests were derived from forest cover change dataset of Hansen et al. (2013).

All the variables were normalized between 0 and 1 through a linear function for an equal weight assemblage in a Principal Components Analysis (PCA) (Bro and Smilde 2014). This technique reduces the complexity of a multivariate dataset by extracting the most explicative axis that summarizes the input variables by minimizing the correlation among the new components. PCA has been previously used for spatial assessment of ecosystem multifunctionality (Salata and Grillenzoni 2021). In the context of ecological values, PCA can be used to identify the most important factors that contribute to biodiversity, ecosystem health, or other ecological measures. For example, a PCA analysis of ecological data might identify factors such as habitat diversity, soil quality, water quality, and nutrient availability as the primary drivers of ecosystem health in a particular area (Figure 12).

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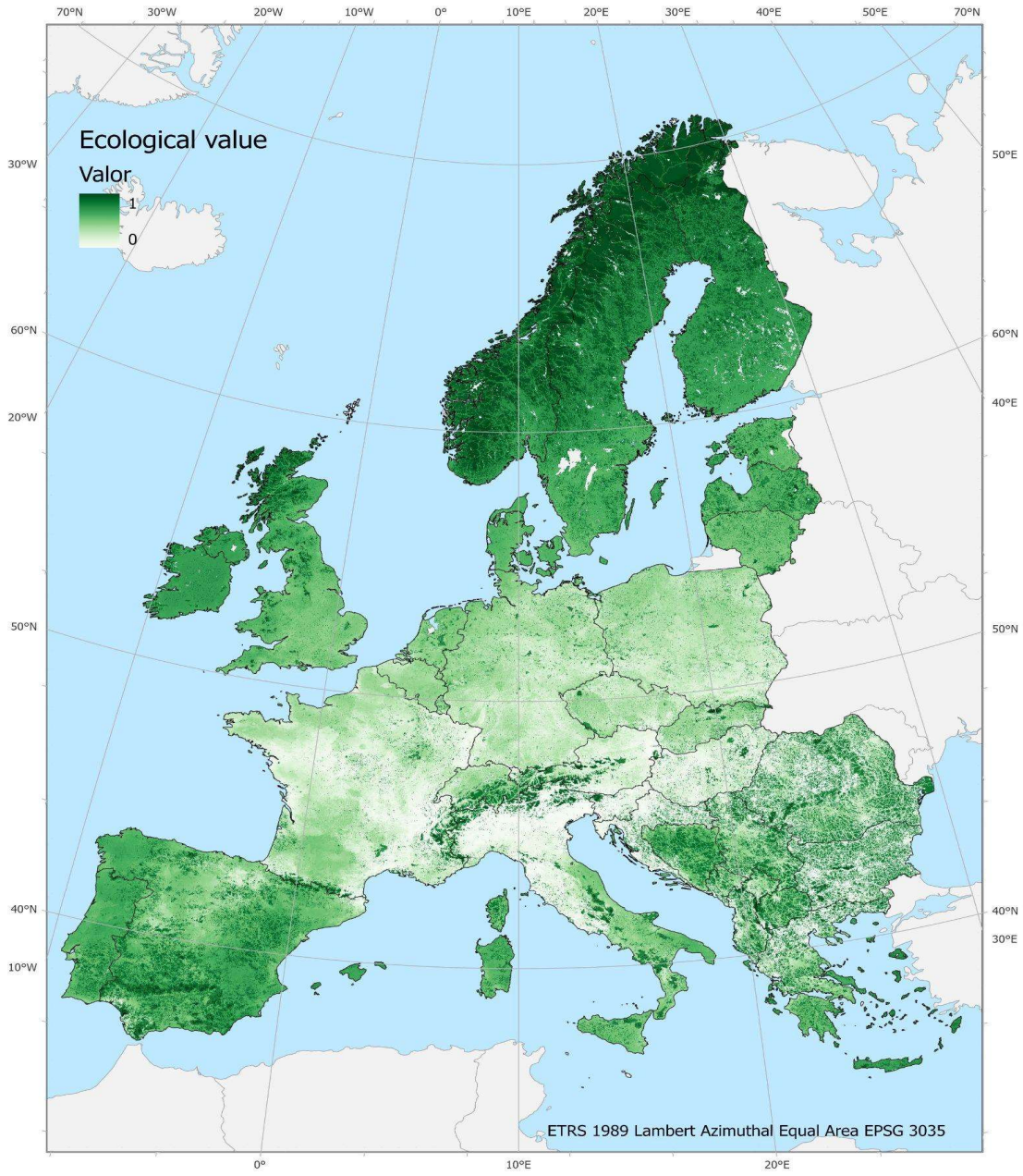


Figure 12: Normalised scale for ecological values of the ET area. The highest ecological values are shown in dark green, while those with the lowest value are shown in light green

4.3.8 Resilience

Following the general integration scheme and the resilience theory (see 2.3.7) a conceptual mechanistic approach using plant species strategies of resistance and coping capacities to generate an ET resilience map based on plant species distribution was used as a more consistent approach to identify and assemble

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keystone variables related to ecological resilience. As a first step, the actual loss (AL) caused by a fire occurring at time t0 can be calculated as follows:

$$AL = PL - RST \quad (4)$$

where PL is the potential loss and RST the species resistance to the disturbance.
The second step integrates the post fire regeneration delay, which is the period after the fire when the vegetation remains at state RST during the regeneration time (RGT) until viable regeneration material is available on site. As a third step, the recovery time can be estimated from a generic logistic function, which was used by several authors for post disturbance dynamics (Amani et al. 2022) and applied for multiple ecosystem functions as follows

$$f_{res}(t\text{-}RGT) = AL / (1+e^{(-RCR*(t\text{-}RGT-RCT/2))}) \quad (5)$$

Where f_{res} is a function of time after fire t, with parameters related to recovery concepts of Recovery growth time (RGT), as the time need to fully recover to pre-fire ecosystem state) and recovery rate (RCR) as the slope the maximum recovery at the inflexion point occurring at time ti=RCT/2. The main parameters of equation 4 and 5 were deduced from species functional traits and forest growth models. Resilience (RES) was finally evaluated as the area under the curve while the regeneration process takes place.
Based on the dominant tree species map from the European Atlas (https://forest.jrc.ec.europa.eu/en/european-atlas/atlas-data-and-metadata/, last access March 2023), the information on resistance and recovery of vegetation to fire for each of these species was obtained from the BROT 2 and TRY databases. The BROT 2.0 (Tavşanoğlu and Pausas 2018) is a database of functional traits for vascular plant species of the Mediterranean Basin (https://www.uv.es/jgpausas/brot.htm, last access March 2023). The database includes 25,764 individual records of 44 traits from 2,457 plant taxa distributed in 119 taxonomic families. Trait data were obtained from a comprehensive literature review, plus some field and experimental observations. All records are fully referenced and, in many cases, include geographic coordinates. The TRY (TRY Plant Trait Database) data is a global database of plant traits (Kattge et al. 2011) that provides standardised information on the characteristics of plant species from around the world (https://www.try-db.org/TryWeb/Home.php, last access March 2023). The TRY database contains information on a wide range of plant traits, including morphological, physiological, biochemical, and ecological traits. The data were completed for temperate and boreal from collaborative expert knowledge.
Resistance was assessed through species traits on bark thickness, wood density, and specific wood composition as cork (as in the *Quercus suber* species). The ecosystem resistance at 1 km^2 resolution was calculated as the weighted mean of traits according to species cover.
Vegetation regeneration time (RGT) was assessed through species regeneration strategies (seeders or resprouters). Recovery rate (RCR) was assessed through shade and drought tolerance, and growth rate

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obtained from forestry models (Mahnken et al. 2022; Schelhaas et al. 2018). The ecosystem recovery at 1 km^2 resolution was calculated as the weighted mean of RGT and RCR traits according to species cover.

From this standard potential resilience, local modifiers that alter regeneration and recovery were identified and assembled. The regeneration time RGT of species, according to their regeneration strategies, is affected by time since the last fire, as short fire intervals might prevent tree maturity and subsequent seed production allowing for regeneration (RGT). This information was built from the FireCCI51 burned area product (Lizundia-Loiola et al. 2020) for fire events larger than 250 ha. The daily burned date information at the pixel level was used to deduce the time since the last fire (in days), which was combined with fire size as a modifier for regeneration time, since non-resprouter species take longer time to colonize a large fire than a small fire. The pixel aggregation from Laurent et al. (2018) was used for the fire patch event database.

The recovery rate RCR locally depends on climate and edaphic conditions. ERA5-land mean annual temperature, solar radiation and precipitation were assembled at 5 km resolution, locally modified by slope, aspect and altitude derived from Aster-gDEM at 30m and resampled at 1 km^2 resolution. Post fire recovery rate (RCR) was also modified by soil AWC, soil fertility based on the standard soil N/P content (see sec. 4.3.7), affected by fires from volatilization and wind/water post fire erosion potentials.

Post-fire soil loss and recovery was assessed by estimating nutrient depletion as the amount of leaf N and P volatilized during combustion, as the product of Leaf Area Index (LAI), specific leaf area (SLA) (mm2 mg−1), leaf nitrogen content (LNC) (mg g−1) and leaf phosphorus content (LPC) (mg g−1). These datasets were obtained from Moreno-Martínez et al. (2018). Post fire N/P stock recovery was based on N Atmospheric deposition map (https://www.syke.fi/en-US/Current/Sciencepolicy_cooperation_has_improved_a%2859833%29, last access March 2023). Since water and wind erosion can affect soil AWC and N/P deposition from ashes through erosion processes, both factors were considered taken the information from Borrelli et al. (2016). To estimate post-fire soil erosion potential, the Soil Erosion map for Europe (https://data.jrc.ec.europa.eu/dataset, last access December 2022) was used as an input to the Revised Universal Soil Loss Equation (RUSLE). The values were then transformed into a categorical variable, 1 for lowest values and 5 to highest values according to the criterion for soil erosion due to water, proposed by the FAO (FAO/UNEP/UNESCO, 1979): 1 for values between 0-20, 2 for values between 20-50, 3 for values between 50-200 and 4 for values over to 200, which is also applicable to fire erosion processes (Chuvieco et al. 2014b).

Finally, humans might play a significant role in post-fire forest recovery by stimulating planting. For this variable we used different management maps (Hengeveld et al. 2012; Nabuurs et al. 2019) which affects the regeneration time (RGT) as a local modifier of regeneration.

From this mechanistic framework, all identified resilience variables were combined using again PCA to generate the final ecological resilience map.

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4.4 Integration approaches

4.4.1 Conversion to risk values

The original measurement scales of the different input values were converted to common risk scales using different approaches, adapted to the particularities of each variable. For the Ignition components, the original probability scale (0-1) was maintained. The FMC of live and dead fuels was kept as a percentage of dry weight to be included in the propagation potential model, along with slope, and wind conditions for the two reference wildfire scenarios described in section 4.1. Based on the propagation outputs, propagation probability (PP) was computed from the fire line intensity, which is considered as a synthetic measure of fire suppression difficulty. Based on previous studies (Chuvieco et al. 2014a), this conversion used the threshold values for fire suppression proposed by Rothermel (1983, Table IV-1). The PP values increased linearly from 0 for FI=0 kW/m to 0.5 for FI up to 1134 kW/m^2 (100 BTU/feet^2), implying fires that can be attacked by fire brigades, from 0.5 to 0.75 for FI between 1134 and 4539 kW/m2 (400 BTU/feet^2), where machine and aircrafts can be used, and from 0.75 to 1 for values ranging from that threshold to the maximum FI. Above 11,000 kW/m^2 control efforts ahead of the fire can be ineffective.

Potential losses were computed as an addition of the ecosystem services, population and assets and the ecological values. The socio-economic aspects were quantified in monetary units, while the ecological vulnerability was quantified by normalizing the results of principal component analysis, leading to a common risk score (0-1). To facilitate the integration between these two components, the monetary values were converted to a 0-1 score using a normalization process after logarithmic transformation, since the distribution of values was skewed by the high values of houses and infrastructures. Table 1 includes the methods used to generate common risk scales among the input variables generated within FirEURisk.

Table 1: Proposal to obtain a common risk scale for the different FirEURisk risk variables

Fire risk variables	ET and PS
Human ignition	Probabilistic
Natural ignition	Probabilistic
Weather scenarios + wind in real time	Probabilistic
Dead FMC	Physical ME
Live FMC	Physical ME
Propagation	Physical FLI
Exposure / WUI	Proportional
Ecological values	PCA
Ecosystem services	Normalisation
Population-Assets	Normalisation
Resilience	Normalisation

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4.4.2 Integrated risk indices

The original measurement scales of the different input values were converted to common risk scales using different approaches, adapted to the particularities of each variable. For the Ignition components, the original probability scale (0–1) was maintained. The FMC of live and dead fuels was kept as a percentage of dry weight to be included in the propagation potential model, along with slope, and wind conditions for the two reference wildfire scenarios described in Section 4.1.

Based on the propagation outputs, propagation probability (PP) was computed from the fireline intensity (FI), which is considered as a synthetic measure of fire suppression difficulty. Based on previous studies (Chuvieco et al. 2014a), this conversion used the threshold values for fire suppression proposed by Rothermel (1983, Table IV-1). The PP values increased linearly from 0 for FI = 0 kW/m to 0.5 for FI up to 346 kW/m (100 BTU/feet/s), implying fires that can be attacked by fire brigades with manual tools, from 0.5 to 0.75 for FI between 346 and 1731 kW/m (500 BTU/feet/s), where machines and aircrafts can be used, and from 0.75 to 1 for values ranging from that threshold to the maximum FI.

Vulnerability was estimated from potential losses in ecosystem services, population and infrastructures, and ecological values. The socio-economic aspects were quantified in monetary units, while the ecological vulnerability was quantified using principal component analysis, leading to a common risk score (0–1). To facilitate the integration between these two components, the monetary values were converted to a 0–1 score using a normalization process after logarithmic transformation, since the distribution of values was skewed by the high values of houses and infrastructures.

4.4.2. Integrated Risk Indices

To obtain the synthetic fire danger component, ignition and propagation probability were combined using the Kolmogorov probabilistic rule (following Equation (3)).

For the integration of the Danger component of the FirEURisk scheme, a simple weighed average of ignition potential (IP) related to causative agents and propagation probability (PP) was performed, following experiences from previous projects (Chuvieco et al. 2010). As a first approximation to Danger (D), PP was given twice the importance of the IP component:

$$D = 0.33 \times IP + 0.66 \times PP \quad (6)$$

The integrated vulnerability was obtained by merging the socio-economic and ecological vulnerability using a weighted average: the former was weighed by a factor of 0.6 and the latter by 0.4, assuming that human values are more important in wildfire risk assessment.

Finally, the FirEURisk integrated risk index (IRI) was obtained by combining the Danger, Vulnerability and Exposure. From the first two, higher weight was given to the danger component, which is more dynamic, than to the vulnerability component (0.6 and 0.4 respectively). The Exposure was divided into three classes: unburnable (0), burnable (0.8) and areas with a wildland urban interface or intermix (1), which are the most

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exposed in terms of human lives and houses. Exposure was included as a multiplicative factor, to avoid considering at risk unburnable covers. The final formula of the IRI was:

$$IRI = (0.6 \times D + 0.4 \times V) \times E \quad (7)$$

Figure 13 includes an example of the final index, considering the weather scenario related to historical occurrence of extreme fires, as indicated in Section 4.1. As expected, higher values are found in the Mediterranean countries, particularly in Western Portugal, Northwest and Central Spain, Southern Italy, the Balkans, Greece, Central Bulgaria and Romania. Lower values are found in Central and Northern Europe, with intermediate in Western British Islands and scattered regions in Central and Northern Europe, including the Baltic countries.

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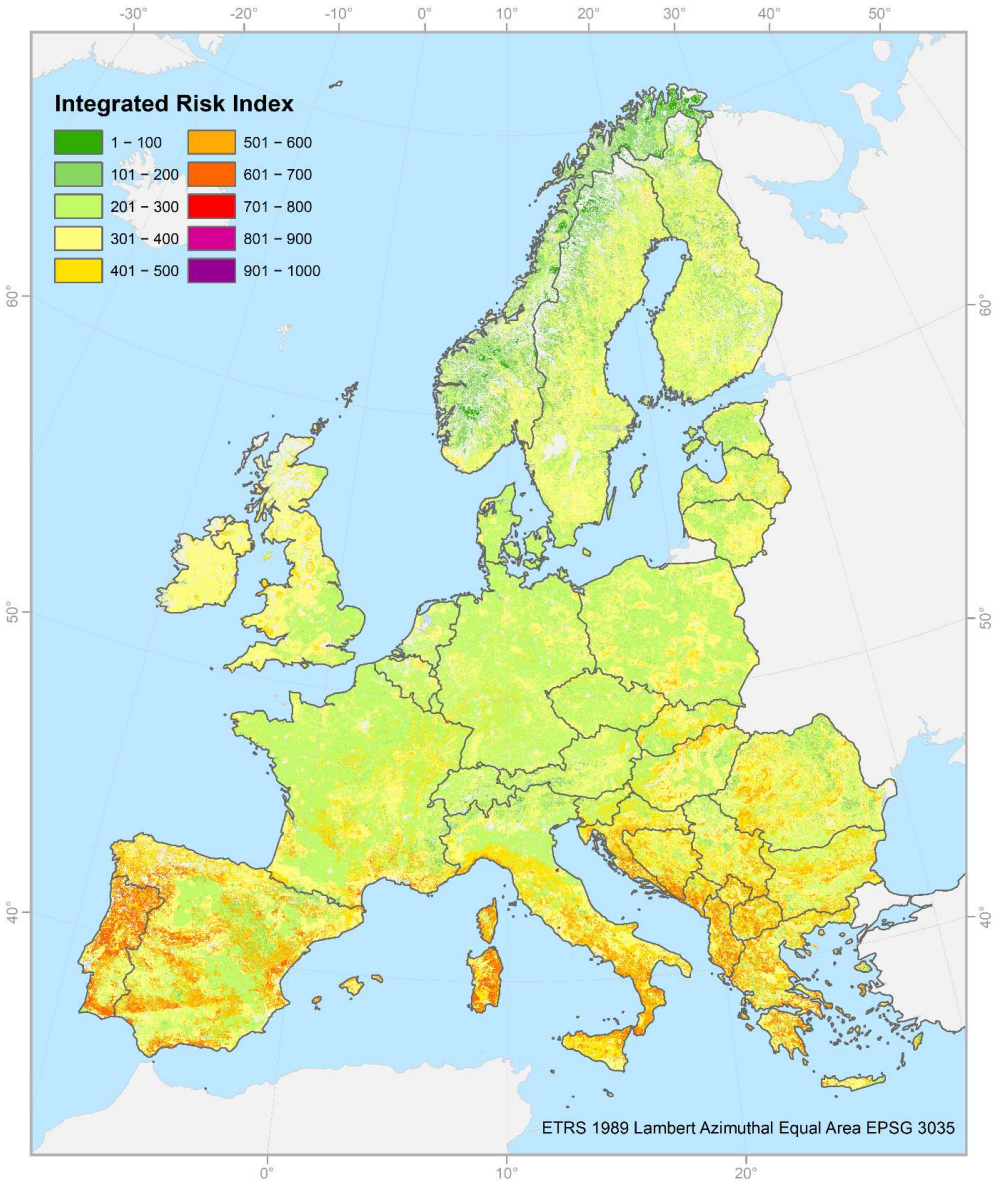


Figure 13: Example of the IRI for historical conditions leading to large wildfires. IRI values have been multiplied by 1000.

It should be considered that the integration of the different risk variables implies simplifying the different dimensions of risk, and therefore the FirEURisk risk assessment system will provide all intermediate risk products to the end-users, along with a flexible tool to combine them in different ways. In addition, the most experienced users may create their own combinations of variables, by assigning different weights to the risk components. In this way, the various end-users can access the information they are most interested on, as well as combine the different risk variables and components following his-her own priorities, while the

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general public and policymakers at least a first approximation to the integration of the different wildfire risk components.

4.5 FirEURisk information system

The FirEURisk project has built a dedicated platform to store all spatial data sets generated and geodatabases developed in the context of FirEURisk by the consortium partners for the ET and PS areas, which will be the primary target for integration. In addition, the system hosts all the risk components and variables considered in FirEURisk for the ET and PSs. Access to this information is available through a dedicated web mapping service. Some layers are also accessible through a dedicated mobile app, developed as a citizen-science application that allows ordinary citizens to report and gather fire risk information, such as fuel information or fire alerts.

Wildfire risk communication and citizen science applications can work hand-in-hand to improve the understanding and management of wildfires. In particular, citizen science applications can play an important role in wildfire risk communication by engaging the public in research and monitoring efforts, providing valuable data for fire management agencies, and increasing public awareness and understanding of wildfire impacts.

End users of wildfire risk information will test the relevant FirEURisk component in six Demonstration Events. In these events, the consortium will engage with stakeholders to show them preliminary results of the project. Representatives of the target audiences addressed in the different PS and ET areas will use web tools to provide relevant feedback via validation forms. The contributions collected from members of the scientific community, first responders, landowners/managers, policy and regulation makers, industrial stakeholders, civil society organisations, risk prevention communities, and the general public will help improve the FirEURisk information system in the following two years. The system was developed during the project's first half and will be demonstrated during the fire seasons of 2023 and 2024.

5 Conclusions

This deliverable presents the integrated approach to wildfire risk assessment that has been developed within the FirEURisk European project. It includes the general framework for the integration, a brief description of the variables that have been generated for the project (mostly at ET scale), and the integration of input variables into the different components of the risk index. Further details on the generation of the different datasets can be found in the different specific deliverables dealing with tasks assigned to WP1.

This document should be considered as a first version of an assessment scheme that will be improved during the second half of the project, after testing in the ET and PS, with the help of end users. A further integration should also consider how risk assessment is related to reduction and adaptation, as well as the cascading effects that wildfire brings along with other natural hazards.

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