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

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Executive Summary

The aim of this deliverable is to develop a conceptual framework for integrating wildfire risk assessment, mitigation and adaptation in a consistent approach that allows testing the impact of different scenarios. The framework is based on the integration scheme developed in WP1, which includes the main variables identified by the FirEURisk project as relevant for the assessment of wildfire danger, exposure and vulnerability. Based on this integration scheme, a software tool has been developed to combine the different input variables into synthetic indices. From this integration, hypotheses on the impacts of different mitigation and adaptation strategies can be assessed. Some examples of these potential scenarios are presented in this deliverable. As all variables are represented as geographical datasets in the integrated system, the outputs of the simulations are also geographically explicit, allowing the spatial impacts of these scenarios to be analysed. Therefore, the conceptual framework also becomes a practical tool to simulate the spatial impacts of potential policies in different target areas, leading to the reduction of the negative impacts of fire, including current and future conditions. This, of course, requires that both the input data and the simulation conditions are properly characterised. The system is scale-independent, as it can be used at regional scales (such as the ET area from which all examples in this document are taken), but also in the other pilot sites of the project, or even in the demo areas. Obviously, the smaller the regions, the finer the spatial resolution of the input data required and the more locally adapted the scenarios proposed for the simulations. The same applies to the temporal scales. This document includes static risk scenarios, assuming extreme conditions, but specific periods of time, or even daily use, can also be considered.

Main highlights:

- A conceptual integration of wildfire risk assessment, mitigation and adaptation is proposed, using the same variables within a consistent and scale-independent framework.
- The integration scheme incorporates key factors related to fire danger, exposure and vulnerability.
- The system allows the creation of different scenarios by modifying the risk input variables.
- Both the input and output layers are geographical datasets; therefore, the consequences of choosing a scenario can be analysed geographically. This feature is particularly important for the use of the system at different spatial scales, as the target scenarios can be adapted to local or regional characteristics.

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List of Acronyms

CC	Coping capacity
D	Danger
DGVM	Dynamic Global Vegetation Model
E	Exposure
ES	Ecosystem services
ET	European Territory, covering most European area
EV	Ecological Vulnerability
FL	Flame Length
FLI	Fireline Intensity
HV	Human Vulnerability
IP	Ignition potential
IRI	Integrated Risk Index
LFMC	Live fuel moisture content
NFDRS	National Fire Danger Rating System (USA)
PP	Propagation Potential
RESV	Reduction of Ecosystem Services Values
REV	Reduction of Ecological values
RSEV	Reduction of House Values
RT	Recovery time
V	Vulnerability
WUI	Wildland Urban Interface

1 Introduction

The negative impacts of fires on society have driven the establishment of fire management strategies in most industrialized countries, commonly leading to fire suppression (Chuvieco et al. 2023). The growing concern of extreme fire seasons — with extensive areas being burned, human casualties and destruction of houses (Jain et al. 2021; Tedim et al. 2018) — driven by previously-unobserved weather anomalies, has heightened the interest in wildfire risk assessment systems, moving beyond fire suppression to more holistic policies for fire risk management. Risk assessment should consider a wide range of variables that affect fire ignition, propagation, potential impacts, as well as some procedures to integrate them, according to their contribution to those impacts along with strategies to communicate risk information to a variety of end users, including first responders, landowners, land managers, civil society organizations and the general public (Chuvieco et al. 2023; Moore 2019).

Following the common terminology of natural hazards, wildfire risk can be defined as the integration of three components: hazard (on wildfire is more commonly termed 'danger'), exposure and vulnerability (Tagarev and Papadopoulos 2020; UNISDR 2009). This was the basis of the FirEURisk integration scheme, presented in D1.7 and in Chuvieco et al. (2023). Following these two documents, we defined fire danger as the probability that a fire starts or propagates in a certain area and point in time; fire exposure represents the people and assets that may suffer damage from wildfires, while fire vulnerability estimates the conditions that make an area susceptible to having higher or lower negative impacts from fires, either because it is highly valuable or because it has low resilience to fire, but most commonly because of a combination of the two.

Wildfire risk assessment entails an estimation of when, where, why and how wildfires are more likely to occur and propagate, which areas are potentially exposed and what potential damages those fires may imply. Ideally, any risk assessment system should be comprehensive (all relevant variables considered), flexible (applicable to a wide range of spatial and temporal conditions), coherent (internally logical) and replicable (based on transparent methods). Therefore, a comprehensive wildfire risk characterization should include the three dimensions of risk (danger, exposure and vulnerability), being properly combined, and adapted to different spatial and temporal scales.

Currently available operational fire risk assessment systems focus on the estimation of fire danger, particularly those variables related to weather conditions leading to extreme fires (e.g. long droughts, high temperatures, strong winds), but they regularly do not consider exposure or vulnerability (Chuvieco et al. 2023). They are also not very consistent when considering ignition causes, particularly those related to human activity, which are more difficult to predict than natural ones (Bowman et al. 2017; Parisien et al. 2016). While in most natural hazards, such as volcanic eruptions or earthquakes, danger is beyond human control, in the case of wildfires, danger conditions can be reduced by minimizing human-caused ignitions or managing those fuel characteristics

that minimise the occurrence or the intensity of fires.[1] It is also possible to reduce wildfire exposure, by improving land use zoning and including land management strategies that decrease the contact between houses and wildland fuel. Finally, fire risk management should consider ways to reduce vulnerability, creating more resilient landscapes, for instance by improving their coping capacity to fire (resistance) and/or enhancing its post-fire recovery (Chuvieco et al. 2014; Thompson et al. 2011).

Following this scope, the FirEUrisk project defined a framework to integrate the different factors of fire risk (Oom et al., 2022; Chuvieco et al. 2023). Figure 1 includes the summary of this framework which integrates the different components of wildfire risk, along with the main variables associated with each component.

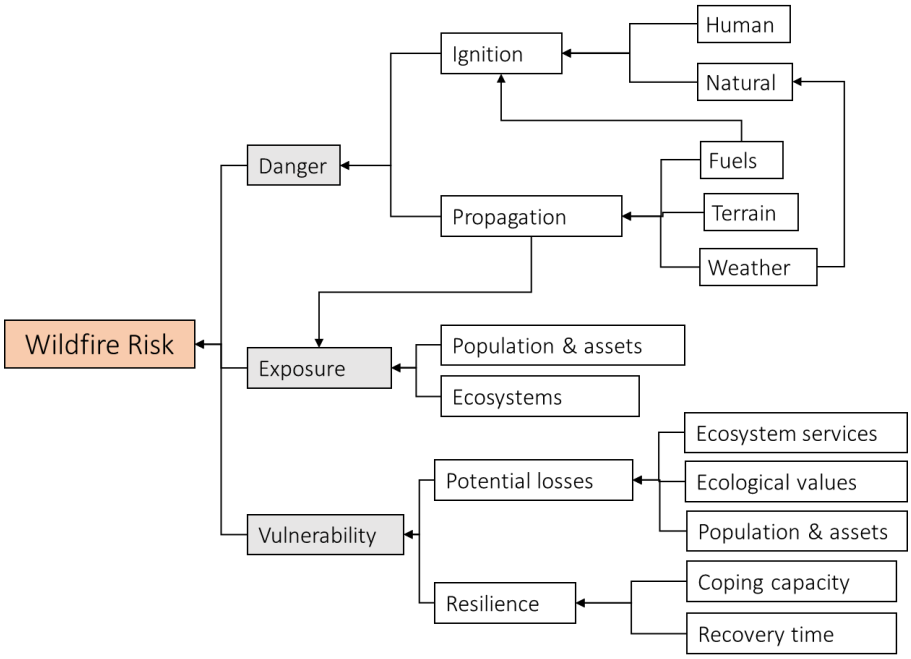


Figure 1: Conceptual integration of wildfire risk assessment components within the FirEUrisk project (after Chuvieco et al., 2023).

A previous FirEUrisk deliverable (D1.7) dealt with the risk integration approach developed for the project within the activities of WP1 (risk assessment). The present document aims to solve some of the issues found in the first version of the integration code, as a result of the experience in using it and the comments of the project's reviewers. In addition, we extend the integration approach to different phases of the project,

[1] As it is well known, fire propagation is conditioned by fuel, terrain and weather conditions, only the former being human controlled. When fires are active, fire suppression activities are also aimed to reduce fire propagation, with more or less efficiency depending on fire and weather conditions.

emphasizing the links between wildfire risk assessment (WP1) and mitigation (WP2), as well as to provide guidelines for adaptation to future fire conditions (WP3).

2 Linking Wildfire Risk Assessment, Reduction and Adaptation

Wildfire risk assessment is a critical part of reducing fire impacts. However, it should also be linked to different strategies to mitigate the negative impacts of fire, both on society and ecosystems, as well as to adapt better to future risk conditions (Swanston et al. 2016; Tedim et al. 2018; Thompson et al. 2012). Wildfire risk management involves assessments of the likelihood and magnitude of wildfire impacts, while developing appropriate responses to reduce ignitions or decrease exposure and vulnerability (Fairbrother and Turnley 2005; Finney 2005; Thompson and Calkin 2011). In addition, climate and societal changes require adaptation policies that may prevent the negative impacts of changing fire regimes (Kelly et al. 2020), potentially affecting areas that have much less contact with fire in the past, and therefore are naturally more vulnerable than other territories where fire has shaped vegetation and human communities for centuries. Adaptation is generally defined as the process of adjustment to expected climate and societal changes, to be better prepared to reduce their negative impacts and benefit from the positive ones.

Several authors have emphasized the impact of climate change on fire occurrence, particularly the increasing frequency of drought periods and heatwaves (Abatzoglou et al. 2019; Jones et al. 2022) leading to extreme events (Jones et al. 2024; Turco et al. 2019). These climatological changes interact with trends of agricultural abandonment, particularly in the South of Europe, as many areas experience a rural exodus (Sil et al. 2019). Therefore, these areas face new and heightened risks as landscapes shift from managed, mosaic types with ample variation in fuel density and distribution, to more pyrologically homogenous land covers of even-aged stands with dense, continuous understories (Fernandes et al. 2013; Moreira et al. 2011; Sil et al. 2019). The expansion of anthropic interfaces and values into fire-prone wildlands explains why WUI (Radeloff et al. 2018) is currently a major concern, both in terms of human lives and economic losses, especially when coupled with limited financial and labour resources, creating limitations in the application of land, fuel and wildfire management programs (Alcasena et al. 2019; Syphard et al. 2013; Wunder et al. 2021).

Paradigms that focus on complete fire suppression versus integrated fire management and prevention of unwanted fires are still prevalent in many regions, including Europe, as society prevalently considers fire a negative hazard, causing damages to people and properties. Given the expenses and labour resources involved, the ecological effects of fire exclusion on fire-adapted ecosystems, and the evidence that complete fire exclusion is likely to cause larger-more dangerous fires, both research and policy communities recognize the need to deal with the so-called ‘fire paradox’, implying the use of fire to reduce its negative impacts (Canadas et al. 2023; Moritz et al. 2014; North et al. 2015).

However, prescribed fires are not a gold solution, facing serious issues regarding their use in areas close to houses (WUI) or their negative impact on air quality. Therefore, mitigation and adaptation to wildfire risk should include a wide range of alternatives that consider both social and ecological conditions, as well as what is feasible from an economic and social point of view. To prioritize activities in the highest-risk areas and identify the best management strategies (Ager et al. 2010; Oliveira et al. 2020; Palaiologou et al. 2021; Salis

et al. 2016), options must be assessed based on wildfire risk and related components, clear management objectives, and the coherent identification of management priorities (Calkin et al. 2010; Thompson and Calkin 2011).

Risk reduction and adaptation strategies span an ample range of targets, strategies and spatial patterns, depending on the objectives, legal structures, socioeconomic considerations, and physical constraints in the local context (Hand et al. 2014; Reinhardt 2008; Salis et al. 2016). Implementing and adopting wildland fire prevention programs requires knowledge of what to do, an awareness of the risks involved, even after mitigation measures are implemented, and often the risks associated with taking no action (Hesseln 2018). A number of recent studies have explored some of the spatial and temporal considerations of fire risk mitigation and adaptation strategies, including constraints and performance evaluations (Parisien et al. 2020; Sample et al. 2022; Schoennagel et al. 2017). Several such studies apply probabilistic modelling approaches based on fire spread simulators, quantifying the spatial and temporal variations in wildfire transmission and losses using measurable variables or metrics (e.g., burn probability, flame length, fire size, source-sink ratios) (Ager et al. 2012; Metlen et al. 2021; Parisien et al. 2020). Outputs from these approaches can be used to characterize and quantify wildfire danger and exposure, as well as to estimate uncertainty associated with wildfire events in terms of timing, location, duration, spread and behaviour, and environmental conditions in terms of weather and fuel characteristics (Salis et al. 2021). Defining priorities is critical for preparing long-term adaptation measures, but conflicting interests or different perspectives make it difficult to establish them. Therefore, community practices are convenient for preparing strategies, which in turn should guide specific actions. In this framework, combining likelihood and confidence can help to establish priorities (Swanston et al. 2016). The perception of local residents to introduce these actions should also be considered, particularly in the case of the WUI (Olsen et al. 2017).

In this regard, scenario-based approaches for addressing fire risk have been proposed, aiming to include the drivers of risk, including climate, socioeconomic, and land-use changes, to build fire resilience at the landscape level (Campos et al. 2021; Pais et al. 2020). Some studies assess the opportunities to manage fire risk at landscape scales through land management strategies, such as prescribed burn, silvo-pastoralism, or mechanical removal of fuels (Neidermeier et al. 2023). However, the uncertainty and social factors surrounding many of the drivers of risk makes the selection and implementation of landscape-level risk management strategies difficult. In the case of prescribed burns, for example, it has been observed in the United States that the number and distribution of days that meet meteorological safety and ecological requirements have decreased in some areas due to climate change (Baijnath-Rodino et al. 2022; Kupfer et al. 2020), limiting the options for their use. In addition, most adaptation studies have been conducted at the local level, placing more emphasis on the ecological impacts of fire or the reduction of vulnerability in the WUI (Metlen et al. 2021; Schoennagel et al. 2017; Swanston et al. 2016). In this regard, the most common strategies are those that aim to sustain fundamental ecological functions, reduce the impact of biological stressors (plagues), maintain or create refugia and biological corridors, or promote landscape connectivity (Swanston et al. 2016).

Another topic is the dynamism of many of these processes, particularly land-use changes related to urbanization as well as practices of forest conversion or afforestation efforts (Schoennagel et al. 2017), creating tension

between fire risk planning and the provision of necessary ecosystem services, such as carbon sequestration and biodiversity (Hurteau et al. 2014; Moghli et al. 2021). Adaptation to future fire risks will need to integrate anticipated patterns of land cover and use, socioeconomic trends, and trade-offs for ecosystem services, including the diversity of stakeholder perspectives, to design more fire-resilient landscapes (Neidermeier et al. 2023; Syphard et al. 2013).

3 Integration of Assessment, Reduction and Adaptation

3.1 Strategies for wildfire risk assessment within FirEURisk

As indicated earlier, FirEURisk developed an integrated scheme in WP1 that considers the main variables affecting fire danger, exposure and vulnerability. The system inputs weather data, fuel types and models, topographic slope and aspect, human and natural ignition, exposure, the value of houses and ecosystem services, ecological values and resilience (defined by coping capacity and recovery time). The outputs include ignition and propagation potential, danger, expected reduction of the values from wildfire for both socio-economic assets and ecological values, total vulnerability and an integrated index.

This integration system has been implemented at two spatial scales: pilot sites, comprising areas between 2,000 and 8,000 km^2 defined by high-spatial resolution datasets (targeting 1 ha), and the ET region, covering most European countries, comprising more than 4,6 Mkm^2 at 1 km^2 of spatial resolution. The examples for this document are taken from the ET region, as it provides a more comprehensive view of European diversity in terms of fire regimes and impacts. The system can be run with different weather scenarios, as it was the case of D.1.7 in which extreme and high-risk conditions were considered, and in near-real-time operation, computing daily those components that were related to weather and fuel moisture conditions. The latter has been tested semi-operationally during the summer of 2024 and is currently in process of being validated (D1.8, in progress), by comparing the different indices with active fire information derived from satellite data.

We have developed a computer code to calculate operationally the different components of the FirEURisk integration scheme. This code has facilitated the operation of the integrated scheme in semi-operational conditions, linking the input variables that change daily (weather predictions, natural ignitions) or weekly (live fuel moisture content) with the static variables (slope, coping capacity, recovery time, etc.).

The implementation of the system is based on the first version (D1.7), with a few modifications based on end users and reviewer comments. The system has been recently presented at the ET Demo event that took place in Milan on September 16, 2024.[2] The comments of the attendants to the meeting (both in person and online)

[2] The questionnaire that was filled by the participants in the ET Demo event indicated that between 73 and 87% of respondents either mostly or totally agreed with the methods presented to compute the different danger variables.

have also been taken into account. A more detailed explanation of the new version of the integration scheme is presented in section 4.

3.2 Strategies for wildfire risk reduction within FirEURisk

In terms of risk reduction, different strategies are considered, including actions related to mitigate human ignitions and vulnerability. The general scope of the guidelines developed in this section is the entire ET area, with specific integration of certain measures at the PS or DA scale.

First, after a screening of policies developed throughout Europe, guidelines have been released to reduce the number and potential of citizen-driven (arson or negligent) and operations-based (e.g., electrical and communication networks) fire ignitions. This includes specifications for appropriate fuel management along power lines, roads, and railroads, which have been specifically integrated at the PS5-Attica region scale in Greece.

Controlled fires in agro-pastoral areas, in agreement with the needs of local communities, were developed in two DA: Sardinia (Italy) and the French Alps. The challenge here consists of integrating the most appropriate technical way to practice these controlled fires in accordance with the local context, communities' capabilities and resources, and regional and national regulations. This confirms that the integration of such polemic practices requires fine-tuning at a local level.

With regard to the application of fuel management strategies for risk reduction, three alternatives have been modelled: herbivory (grazing, browsing, domestication, and wild), prescribed burns (professional and pastoral), and mechanical removal (silviculture, pruning, and clearing). A literature review provided the set of rules needed to model the suitability of each of these strategies in the European territory based on existing spatial datasets (Neidermeier et al. 2023). This model is being used in conjunction with climate models to estimate future fire regimes for adaptation purposes.

To improve the response to fire, models have been developed and operationalized to predict and map smoke releases (and associated health adverse effects) and to describe extreme fire behaviour (e.g., eruptive fires, junction fires, and oscillatory effects). These models have been integrated on a set of past fires in different Pilot Sites: PS3 - Portugal, PS4 - Spain, PS 5 - Greece. The model has also been integrated in the specific case of the demonstration area of Chernobyl Region, to visualize the diffusion of smoke with radionuclide components.

These modelling tools for smoke and extreme fire behaviours have also been integrated in a general handbook with guidelines for responders to fires, with a European scope. This handbook suggests the most appropriate strategies and techniques to address extreme fires, fires in the WUI, and fires at high latitudes and high altitudes.

Regarding the specific case of fires in the WUI, Deliverable 2.8, which is under finalization, will deliver dedicated guidelines to reduce communities' vulnerability, based on feedback from a wide set of past extreme fires that have been analysed throughout Europe and beyond.

Finally, and transversally to several activities of this Work Package, participatory research methods (e.g., focus groups and questionnaires) were carried out to understand better the perceptions of the local population through fire. This participatory approach has been specifically tested in several DA and PS countries: Sardinia (Italy), Portugal, Spain, and Greece.

3.3 Strategies for wildfire adaptation within FirEUrisk

To understand how current policy, socioeconomic, and environmental dynamics may affect future fire risk, FirEUrisk has focused on further improving fire-enabled Dynamic Global Vegetation Models (DGVMs) that simulate vegetation and fire patterns under future climate and land use scenarios. Realistic future land use scenarios are an integral component of such fire-enabled DGVMs. FirEUrisk has developed land use scenarios which incorporate critical variables related to fuel distribution and thus fire hazard, such as afforestation, forest fragmentation, and land abandonment. The land use scenarios are based on two Shared Socioeconomic Pathways (SSPs) developed in the 6th Assessment Report by the IPCC (Masson-Delmotte et al. 2021) which are also bias-corrected for European climate conditions: SSP 1, "Sustainability", and SSP3 "Regional rivalry". The pathways lay out how changes in global mean temperature and greenhouse gas emissions may be affected by global economic and environmental drivers based on a set of storylines.

The resulting demands for goods and services (e.g., crops or livestock), local spatial characteristics, and climate change scenarios were allocated across the landscape using CLUMondo, a spatially explicit and dynamic land system change model (van Asselen and Verburg 2013). Using the land use results from CLUMondo, which cover the decades from 2020 to 2050, the DGVMs then simulate vegetation patterns, highlighting specific areas that may present greater fire risk as a result of increases in burned area and fire-induced impacts on vegetation as simulated by their embedded process-based fire model. The DGVMs, however, also require historic land use data that is consistent in terms of spatial characteristics with the future land-use scenarios. Thus, the CLUMondo results were linked to representations of historical land use extending back to the year 1960 provided via the HILDA+ dataset (Winkler et al. 2021), which combines several open data streams to estimate land use change. The resulting dataset is the first long term Europe-specific land use scenario set that is aligned with a historic reconstruction, improving the ability of the DGVMs to forecast future fire regimes (Forkel et al. 2019) at a fine spatial resolution. While the final time series is based on a 1 km^2 resolution, the results were converted to a 9 x 9 km resolution to match the resolution that is used natively in the DGVMs and harmonize the land cover class legend to the fuel map generated within the project (Aragoneses et al. 2023).

To harness these developments to study potential adaptation measures, FirEUrisk also created stylized fuel management scenarios that explore the potential to manage future fire risk using land management strategies that link land use scenarios from CLUMondo and associated vegetation patterns simulated in the DGVMs. Together, the findings are synthesized into a series of stylized fuel management scenarios representing low and high adoption of land management strategies to reduce future fire risk and minimize potential trade-offs between them and other desired outcomes, such as biodiversity and ecosystem services. The results will help to understand better how anticipated changes to forest structure and distribution may respond to policy initiatives such as the EU Green Deal and if they will still hold under climate change conditions. The results

will be a helpful tool in calibrating adaptation policy with diverse stakeholder goals (including fire risk, carbon storage, biodiversity, etc.), thus reducing the risk of policy failure and unintended consequences.

4 Proposals for integration of assessment, reduction and adaptation

4.1 Rationale

In line with recent studies that have proposed strategies for wildfire adaptation management to climate and socioeconomic changes based on scenarios of risk conditions (Canadas et al. 2023; Metlen et al. 2021; Sample et al. 2022; Schoennagel et al. 2017; Swanston et al. 2016), we propose the use of the same integration scheme that was developed for wildfire risk assessment (WP1: Figure 1). To connect the three phases of wildfire risk, that have been covered by FirEURisk, the system is able to deal with the three main phases of fire risk management: assessment, indicating the analysis of current risk conditions; mitigation, implying methods to reduce the negative impacts of fire; and adaptation, considering the foreseen scenarios of wildfire risk in the coming decades (target 2050) based on climate and DGVM models.

The integration of reduction and adaptation with assessment should consider both the effect of acting on different risk factors and the analysis of their impacts on the overall wildfire risk, including regional impacts. The implementation of the proposed actions is beyond the scope of this report, as it would require specific social, economic and ecological analyses that consider both national and regional conditions. The main goal of this deliverable is to demonstrate the possibilities of approaching the three phases of risk using a holistic, integrated and consistent framework.

As a starting point to demonstrate this conceptual framework for integration, we have developed a set of simulation scenarios. First, we present the updating of the integration formulas (originally presented in D1.7) that consider the different risk variables and derived indices, and then describe the different scenarios of mitigation and adaptation, showing some of the potentials of simulating different strategies to reduce the negative impacts of fire.

We have developed this approach on the ET pilot site, including examples of the potential application of our integration scheme and implementation code. The ET area is attractive in this respect as it provides a global view of the different fire regimes and impacts across the European territory, but it is worth noting that the same approach could be used with smaller areas (regional pilot sites or even demo areas). In this case, the integration system would be essentially the same, but it should be fed with finer spatial resolution data sets and more specific mitigation scenarios, taking into account the local characteristics of the target areas. The strength of our approach is that it is consistent, using the same variables, and suitable for providing relevant information to guide the three phases of wildfire risk management at different spatial and temporal scales. Following the designed FirEURisk reviewer's suggestions, we show with these examples 'the units used in each component and how they should be combined to quantify risk and to explore the dimensions of risk reduction and adaptation that are absent in the conceptual diagram'. We will try to demonstrate that the integration is

comprehensive, going beyond the components that current wildfire risk assessment systems use in their operational functioning (mostly weather conditions, with very little analysis of human ignition and almost none of vulnerability). In terms of consistency, the use of the same scheme for the three phases of wildfire management should be a good starting point for a coherent while flexible utilization of the system.

4.2 Description of the integrated fire risk index (IRI)

The IRI has been calculated semi-operationally for the ET area for the summers of 2023 and 2024, as well as with climate scenarios based on extreme and high-risk conditions. In all cases, the geographical framework of the areas was the same, covering most European territory, with the following cartographic standards:

- Projection: Lambert Azimutal Equal Area EPSG 3035;
- Datum ETRS 1989;
- Corner coordinates: UL 2635914.000, 5414917.000 and LR 5955914.000, 1384917.000;
- Resolution: 1000 m (X and Y).

Previous exercises to calculate the IRI were tested with two climate static scenarios, considering extreme and high-risk fire conditions, as well as with daily weather conditions, demonstrating that the system can be adapted to different temporal scales. We are currently in the process of extending the spatial scales of the system by implementing them into different PS. This regional-base implementation will have the same variables of the ET area, but they will be input at a much higher spatial resolution. Since this document is mostly methodological, aiming to show the potentials of our scheme for integrating different wildfire management actions, we focus on static climate scenarios, assuming extreme conditions, as they are more suitable for estimating the impact of different actions to assess, mitigate and adapt to risk.

With regards to the reviewer's comments on decomposing the integration scheme 'in different sub-models, each with significant units of value, space and time', we consider that this is included in the original proposal, which identified three main components: danger, exposure and vulnerability, with their own outputs and interactions. However, we also consider that the integration into synthetic indices is relevant for fire managers, as they will have access to a comprehensive tool that considers not only danger, but also exposure and vulnerability conditions, with a particular set of variables (sub-indices) and metrics.

The input variables and sources of information used to run the ET simulations including in this deliverable ar shown in Table 1, indicating in each case the units and the sources of information. Obviously, when applying the IRI to other regions, sources should be properly adapted to the adequate target resolution.

Since the FirEUrisk project is mostly interested in extreme fires, we have kept the two reference scenarios leading to very high or high-risk conditions that were selected for the integration of risk conditions (WP1 and D1.7). The first one was defined by selecting the 95% percentile of the worst weather parameters at 12 h for those days where large fires (>2000 ha) occurred anywhere in the ET area in the period 2001-2019, while the high-risk conditions scenario was computed from the same set of high-risk days but taken instead the 50% percentile of the worst weather parameters.

Table 1: Input parameters to run the simulations to compute the integrated risk index of FirEUrisk

Variable	Units	Sources
TP, Temperature	º C	ERA5-Land global reanalysis data
Cl, Cloud cover	%	ERA5-Land global reanalysis data
WS, Wind speed	m/s	ERA5-Land global reanalysis data
RH, Relative Humidity	%	ERA5-Land global reanalysis data
FT, Fuel types	Fuel classes	Satellite data and biophysical models (Aragoneses et al. 2023)
IP, Ignition Potential[3]	0/1000	Random Forest model (Ochoa et al. 2024)
LFMC, Live fuel moisture content	% Dry Weight	Satellite data
E, Exposure	0, 0.8, 1	WUI and fuel map
VH, Value of Houses	€/ha	European Statistics
ESV, Ecosystem service values.	€/ha/year	European Statistics
EVA, Ecological values	0/1000	Cartographic & vegetation databases
CC, Coping capacity	0/1000	Plant functional traits, forest maps
RT, Recovery time	years	Plant functional traits, forest maps

The selection of ignition dates was based on the analysis of the time-series of the FireCCI51 burned area product (Lizundia-Loiola et al. 2020), generated within the Climate Change Initiative Programme of the European Space Agency (https://climate.esa.int/en/projects/fire/about/, last access October 2024). 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), which were spatially interpolated to 1 km^2 resolution (see D1.7 for details) to compute the dead fuel moisture content, using the 10-h moisture code of the NFDRS. Because computing the live fuel moisture content (FMC) for the same 403 days would be quite complex (as Sentinel-3 data was only launched in 2017, and therefore LFMC estimations from this satellite prior to that date are not available), we estimated the worst conditions in terms of this variable by selecting for each pixel the 5 (extreme scenario) and 10 (high-risk scenario) percentiles of the lowest FMC values for each pixel in the ET area computed for the year 2023-24, from daily observations at 300 m resolution.

[3] For the use of the IRI in near-real time, this variable was split between natural and human ignition. This was not possible in the scenario simulations, because long-term information on natural lighting was not available.

After selecting the weather parameters, the other parameters to run the fire propagation model developed within the project (see deliverable D1.1.5-2 – Propagation potential for Europe Territory (ET): Stipanicev et al., 2023) were the topographic and fuel models. The former was obtained from NASA Shuttle Radar Topography Mission data (https://lpdaac.usgs.gov/products/srtmgl1v003/, last access March 2023) and 90 m resolution and downscaled to 1 km^2, which was the target resolution for all variables. In terms of fuel characterization, the basis was the ET fuel map developed by Aragoneses et al. (2023) within FirEUrisk, from which fuel parameters were assigned for surface fuels based on the Scott and Burgan (2005) models, as indicated in the same paper. For forested areas, crown conditions were obtained from a new crown fuel dataset generated for the ET area by Aragoneses et al (2024) within the FirEUrisk project, based on satellite observations.

The fire propagation model was coded in Python to facilitate simulations for every cell in the ET area. It should be kept in mind that the final goal is not to simulate the propagation of a specific fire, but rather the potential propagation of any place in Europe in the case of having a fire considering the specific weather, fuel and topographic conditions of that area. The outputs of this code include the most common propagation parameters: Rate of Spread (RoS, m/s), Reaction intensity (RI, kW/m2), Fire line Intensity (FLI, kW/m) and Flame Length (FL, m). From them, we will focus on the simulations of this document in FLI and FL, since these two parameters are the most important in terms of estimating the potential damages of fire (see deliverable D1.4 "Report on methodological frameworks for Vulnerability assessment in the FirEUrisk-Wiki project": Bar-Massada et al., (2023). The simulations of propagation conditions with the previously mentioned weather scenarios (extreme and high-risk) were considered as the baseline scenario for comparison with all the simulations presented in this document.

From the FLI, Propagation Potential (PP) was standardized to a 0-1000 scale to facilitate integration with the other components of the FirEUrisk system, which are measured in very different units. The conversion from FLI to PP was based on a linear interpolation of three critical thresholds indicated by Rothermel (1983) in relation to the difficulty of fire suppression. The range from 0 to 346 kW/m (which Rothermel considers the limit for human attack of fire) was stretched to 0 to 500; from 346 to 1731 kW/m (considered the limit for machinery attack) was distributed linearly to the range of 500 to 750, and from 1731 to 17,000 kW/m (the maximum established for our simulations, beyond which it was saturated) was linearly interpolated from 750 to 1000.

The other branch of the Danger component of FirEUrisk integration scheme includes the human and natural ignition potential. Since no historical account of natural ignitions was available and the historical ignitions did not identify the causality of the fire, we decided to include all fires in a single model, regardless of their origin. Using the same FireCCI burned area dataset used for creating the weather scenario, but in this case also including smaller fires (larger than 100 ha), the ignition potential (IP) was estimated using a wide set of drivers of fire occurrence (Ochoa et al. 2024). The total number of fires larger than 100 ha during the study period was more than 33,000. The estimation was based on a Random Forest Model, providing both the range of probability and main explanatory factors (see details in Ochoa et al. 2024). The output was scaled to 0-1000 for the integration with other components of risk.

The combination of IP and PP followed a very simple compensation model, providing a higher weight to the propagation component:

$$D = 0.33*IP + 0.66* PP \qquad \text{(Eq 1)}$$

One can argue (as the reviewers did) that these terms can be multiplied, since without ignition or propagation, there will not be danger. However, we decided to use a more conservative compensatory approach, because the IP was based only on large fires, and propagation may occur even in areas with very low or no ignition potential of large events. In fact, we are not estimating the probability *strictu sensu*, but rather the potential of ignition and propagation based on historical conditions and on a certain size of fires. Despite this, and following the recommendations of the reviewers, we tested the option of integrating IP and PP using a multiplicative approach, and the outputs were not very realistic, with zero danger values in many areas of central and Northern Europe, therefore not providing a proper spatial view of danger variability.[4] This smoothing effect is particularly unreasonable when trying to simulate extreme risk conditions, as in fact large fires have also occurred outside of Mediterranean Europe.

For exposure three categories were considered: not burnable, burnable and areas with wildland urban interface (WUI), which were recoded as 0, 0.8, and 1, respectively. The non-burnable type corresponds to non-fuel classes (class 7 in the fuel map) and city centres (class 61, defined as continuous fabric), while the burnable types are forest, shrubs, croplands, wet peat, and semi-peat land. The WUI was identified within FirEUrisk by using different European datasets (Bar-Massada et al. 2013; Chuvieco et al. 2023).

Finally, both social and ecological aspects of vulnerability were considered. In each case, two components were taken into account: the fire values and, on the other, the capacity of the system to resist and recuperate after fire (resilience), therefore facilitating an estimation of potential damages derived from the fire.

The potential losses were computed separately for the socio-economic and ecological values. The former were calculated in monetary units (€/km^2), while the later in relative units using a standardized scale of 0/1000 (see deliverable D1.4 and Arrogante-Funes et al. 2024). For the final combination between the two, the socioeconomic values were also converted to a 0/1000 scale using linear normalization, since it was not feasible or desirable to express ecological values in economic terms.

Following the FirEUrisk framework, we computed the reduction in values that would occur as a result of fire, assuming the propagation conditions computed from the historical weather scenarios previously commented. For socioeconomic vulnerability, two aspects were considered: the value of houses and the value of ecosystem services. In both cases, the Reduction of values was estimated from the flame length (FL), based on the experience of FirEUrisk specialists in historical fire effects assessment (Molina-Martínez et al. 2019). FL

[4] Obviously, this formula can be easily modified, either to a different weighing or to include a multiplicative model whereas ignition points are more reliable and comprehensive, including all sizes, and therefore IP can be more realistically considered ignition probability. This is quite a challenge in many countries, which even have consistency issues among regions to properly identify ignition points, when they are surveyed by different institutions.

values estimated from the propagation conditions were converted into six categories to estimate the reduction of values caused by the fire, considering fire characteristics, in this case FL (Table 2).

From this table, the reduction of value of houses (RHV) was estimated assuming a certain conditions:

$$RHV = VH*LOSS1 \qquad \text{(Eq 2)},$$

where VH is the pre-fire value of houses and LOSS1 is the relative reduction of value as a result of a fire (unitless, from 0 to 1). LOSS1 is the inverse of the coping capacity (CC), as the value of houses would be reduced in inverse proportion to the resistance of building materials. More damages are expected for stronger fires and more flammable materials (wood houses would burn more easily than concrete-made houses). Since building materials was not available for the whole ET area, average values obtained from the analysis of Mediterranean fires were applied. LOSS1 values were estimated as 0.03, 0.12, 0.31, 0.48, 0.65 and 0.80 for FL categories I to VI, respectively (see also D1.4 for further details).

Table 2: Conversion of FL to expected impacts of fire in six categories

Average flame length (FL, m)	Foreseen Fire Impacts (FIP)
< 2	I
2 – 3	II
3 – 6	III
6 – 9	IV
9 – 12	V
> 12	VI

The same approach was applied to the reduction of ecosystem service values (ESV), considering greater losses for fires with greater intensity (higher FL). Values of nine ecosystem services were estimated from different European sources (see D1.4 and Martino et al., 2022) and aggregated in monetary units (€/km^2) for each cell of the ET area. Similarly to the VH, the reduction of values was computed as:

$$RESV_i = ESV_i*LOSS2_i \qquad \text{(Eq 3)},$$

where LOSS2 is the proportion of reduction, depending on the flame length (**Erro! A origem da referência não foi encontrada.**). Again, this should be considered as the inverse of the CC, assuming that some services are more resistant than others to loose value because of the fire. For example, timber is expected to have greater resistance than grasslands, as the latter will burn in higher proportions than the former for the same intensity of fire.

These losses were integrated throughout the period in which the service would not be available following a common discount rate (r) of 2%:

$$TESVi = RESVti \times \frac{1-(1+r)^{-loglog\,RT\,i}}{r} \qquad \text{(Eq 4)},$$

where RESV is the reduction in the value of ES i, r is the discount rate of 2%, and RT_i is the number of years to recover for ES i. This period was estimated from previous studies (Table 4). In the case of damages to houses, this parameter was not included, as it was assumed that houses are rebuilt in the minimum possible time.

Table 3: Estimated proportion of the losses of ecosystem services as a result of fire propagation

Ecosystem service	LOSS2					
	I	II	III	IV	V	VI
Timber	0.08	0.17	0.39	0.58	0.83	0.90
Olive_groves	0.08	0.17	0.39	0.58	0.83	0.90
Fruit_groves	0.08	0.17	0.39	0.58	0.83	0.90
Vineyard	0.08	0.17	0.39	0.58	0.83	0.90
Crop_pollination	0.08	0.17	0.39	0.58	0.83	0.90
Cattle	0.45	0.65	0.85	1.00	1.00	1.00
Sheep	0.45	0.65	0.85	1.00	1.00	1.00
Carbon_sequestration	0.16	0.40	0.60	0.85	0.98	1.00
Soil_retention	0.15	0.25	0.45	0.65	0.95	1.00

Table 4: Estimated recovery time for different ecosystem services

Timber	TIMB_YEARS (same as tree recovery rate)
Olive_groves	7 years
Fruit_groves	6 years
Vineyard	7 years
Crop_pollination	CROPPOL_YEARS (same as herbaceous crops)
Cattle	1 year
Sheep	1 year
Carbon_sequestration	CARBSEQ_YEARS
Soil_retention	SOILSEQ_YEARS

For timber, carbon sequestration and soil retention recovery times where computed for each forest species based on European forestry maps.

Socio-economic vulnerability (SEV) was finally computed by summing up the values of houses potentially damaged by the fire with ecosystem services potentially affected. Since both amounts are in different orders of magnitude (because of the high-value of houses), a logarithmic transformation of the total value was first applied.

$$SEV = LOG (RHV + \Sigma TESVi) \qquad (Eq\ 5),$$

Finally, the output values, measured in monetary units, were normalized to a 0/1000 scale using a linear procedure.

$$SEVn = (SEV - SEVmin)/ (SEVmax - SEVmin)*1000 \qquad (Eq\ 6),$$

Based on minimum and maximum values of historical conditions. In this way, the output could be later on combined with ecological vulnerability, which was not measured in monetary units.

Similarly to the socio-economic vulnerability, the Ecological vulnerability (EV) was computed by the expected Reduction of Ecological values (REV) which would be derived from extreme wildfires (we recall that weather scenarios considered extreme or high-risk conditions). First, the ecological values were computed for the ET area from a wide set of variables, including biological distinctiveness and conservation status, combined using a principal component analysis (Arrogante-Funes et al. 2024). The reduction of values in this case was based on estimating the resistance or coping capacity (CC) of the species potentially affected by fire.

$$REV = EVA*(1-CC) \qquad \text{(Eq 7)},$$

CC was computed from plant functional traits, considering the main forest species and average values for shrub and grasslands (see D.1.4 and (Arrogante-Funes et al. 2024). CC was assumed to be static in this case, independent of fire conditions, because consistent databases on the changes in CC with FL were not available.

Ecological losses were integrated over time using an estimation of recovery time (RT), which in this case was derived from the species distribution in the ET area, considering the reproductive strategies of the species and environmental conditions of each cell. The RT was used to integrate the losses throughout the period in which the ecological values would be lost after fire using a similar approach to Eq. 4:

$$TEV = REV \times \frac{1-(1+r)^{-loglog\ RT}}{r}, \qquad \text{(Eq 8)},$$

where r was also the discount rate at 2%. Similarly to SEV (Eq. 6), to combine the outputs of ecological and socio-economic vulnerability, the final estimation was converted to a 0-1000 scale using linear normalization using minimum and maximum historical values:

$$EVn = (TEV - TEVmin)/ (TEVmax - TEVmin)*1000 \qquad \text{(Eq 9)},$$

For the combination of social and ecological vulnerabilities, a simple weighed addition was used, with a higher weight on the socio-economic component:[5]

$$V = 0.6*SEVn+0.4*EVn \qquad \text{(Eq 10)},$$

Finally, the integration risk index (IRI), was computed by combining the Danger, Exposure and Vulnerability components, with the following formula:

$$IRI = (0.6*D + 0.4*V)*E \qquad \text{(Eq 11)},$$

As in the case of integration of Danger, we tested here a multiplicative approach of the three components, but the final integration was quite blurred, and we finally selected a compensatory approach, which better kept the

[5] In this point, the reviewers of D1.7 suggested to make a single addition of these components, but they did not notice that EV is not expressed in monetary units, but in a relative scale of 0-1000.

regional diversity of risk conditions. Obviously, the selected coefficients are a first approximation to merge the different variables, but more elaborated systems can also be considered, as well as changes in those values, using sensitivity analysis tools (Saltelli et al, 2008).

4.3 Uncertainties of the integrated wildfire risk components

As suggested by the reviewers, uncertainties of the integration scheme should be acknowledged, including those related to the input data and to the actual combination of those data into second-order indicators. Unfortunately, it was not possible to make a full uncertainty characterization, including all sources of potential error, because the sources were diverse and not always properly characterized. Validation was performed with those variables that were generated within the project (fuel types, fuel moisture content), while others rely on previous datasets that have their own validation or are based on field-work databases (CC or RT, for instance). Developing validation exercises for all datasets used as input to our integrated risk model would be a huge effort, exceeding the limits of the project, particularly for the ET area.

Meanwhile, we can recognize the main factors of potential error, which, in our opinion, do not affect the relevance of the overall integration approach, since we consider that the main contribution of the integration scheme is methodological rather than operational. We did not aim to develop wildfire risk strategic proposals here, but to propose an objective, comprehensive and consistent approach (and tool) to develop those strategies: whenever more accurate or more refined data are available the results will have more realistic implications, but the scheme will still hold. In other words, what matters in our opinion is the framework, rather than the specific outputs of the simulations. Needless to say, that we have tried to obtain the most accurate sources available, but undoubtedly when working at the ET scale, the sources of error and assumptions are more uncertain than when modelling smaller and less diverse areas.

As the main drivers of uncertainty, in terms of danger, the first challenge comes from fire statistics, which are derived from national sources, but have different shortcomings owing to a lack of European (or even national) standardization. The quality of statistics is diverse even within countries. For this reason, we decided to use satellite products, which also include errors (particularly in detecting small fires) but at least provide a spatially explicit and uniform assessment of fire occurrences. Our product is based on a coarse-resolution satellite (250 m); therefore, fires of less than 100 ha are expected to be poorly detected (Franquesa et al. 2022). The location of ignition points also includes uncertainties because it is based on an automatic algorithm that considers the burning dates of the pixels inside each burn patch (Laurent et al. 2018). National ignition points may have even greater inaccuracies and in addition they are not comparable among different European countries. Another limitation of national fire statistics is that most fire reports do not assign a specific cause; therefore, distinguishing between natural and human-caused fires is challenging. Therefore, we decided to include both causalities in the same model.

In terms of propagation, uncertainties are related to both the input data (mainly fuel characterization and weather data) and fire propagation models. We validated the fuel map using independent datasets with an overall error of less than 20% (Aragoneses et al., 2023). In terms of weather, the performance of ERA

estimations and the upscaling of the original resolution to 1x1 km were not fully quantified, but in both cases, the calculations were based on state-of-the-art techniques. In terms of fire behaviour parameters, the formulas that we used are included in well-known models (Behave and Flammap), which provide reasonable estimations for the potential of propagation, with less uncertainty than when applied to the simulation of single fire growth.

In terms of exposure, we included a simple approach based on burnable and unburnable covers, with a higher weight for areas where houses intermix or interface with burnable vegetation. The sources in this case are quite reliable, based on 10 m land cover maps. Smoke dispersion was also considered, but it was finally not included as it greatly depends on specific fire and weather conditions, which are very difficult to replicate in weather scenarios. An alternative would have been to simulate multiple ignitions and propagation conditions, but it was quite complex from a computational point of view. Future updates may consider this aspect, which can be much more easily modelled for smaller areas: in fact, exposure maps for Pilot Sites were included in D1.4 and D1.5, including fire behaviour, smoke dispersion, urban and population datasets.

In terms of vulnerability, the analysis of the ET area complicates the generation of socioeconomic values. Both the values of houses and ecosystem services have been taken from the best available sources, but the existing databases are not always fully reliable, and a great diversity of conditions may exist within each country. There are gaps of the information in some of them, particularly for those not in the European Union (Norway and the UK). The Reduction in values for both houses and ecosystem services was taken from field campaigns performed in Spain. It is uncertain whether similar proportions are applicable to Northern and Central Europe. The same can be said of the estimations of recovery time for some ES, which are based on Mediterranean fires. Estimation of these potential losses provides a first simple approach to estimate CC, but further elaboration of this term should be done with socio-economic values (both houses and ES), adding other external factors, such as fire suppression resources or educational-training programs, which would make it possible to establish spatial variations of resilience to fire of different communities.

The estimation of CC for EV does not assume specific fire characteristics. This should again be amended when more experience of the impacts of functional traits has on fire effects. The same can be said of RT, although in this case, we should also take into account the fire history (areas previously burned in the region).

A final uncertainty source is the conversion of all secondary indicators to a common 0-1000 scale for combining with other indicators, as well as the weights assigned to the different components. Future studies should focus on sensitivity analysis that would provide at least a first approximation to the relevance of each variable and the weights assigned to their integration.

4.4 Simulation for mitigation actions

Different simulation scenarios were established to analyse the impact of different mitigation strategies. Using the IRI scheme, we can simulate what would be the effect of applying a certain strategy, providing a spatial assessment of the outputs because the entire system is spatially explicit. The target indicators were the reduction of the IRI, but also of the intermediate indices, including D and the different components of V. In each case, we aimed to analyse the changes in the reduction of values after a fire by reducing a certain risk variable.

The following variables were used for the simulation exercises: changing ignition potential, fuel load/depth, canopy bulk density, recovery time and coping capacity (Figure 2). They are examples of the range of strategies for risk reduction than could be developed. In the first four cases, we have tested the reduction of 10, 20 and 30% of the original variables, while in the last case, we tested an increase with the same magnitudes. The reduction of ignition, fuel load/depth or CBD should imply a reduction in ignition or propagation potential (and therefore also in Danger and Vulnerability), while the increase of CC or decrease in RT would only affect vulnerability (entailing also a reduction). CC and RT have only been tested with ecological vulnerability, because they can be more clearly linked to landscape management activities (change of species towards those more resilient to fire).

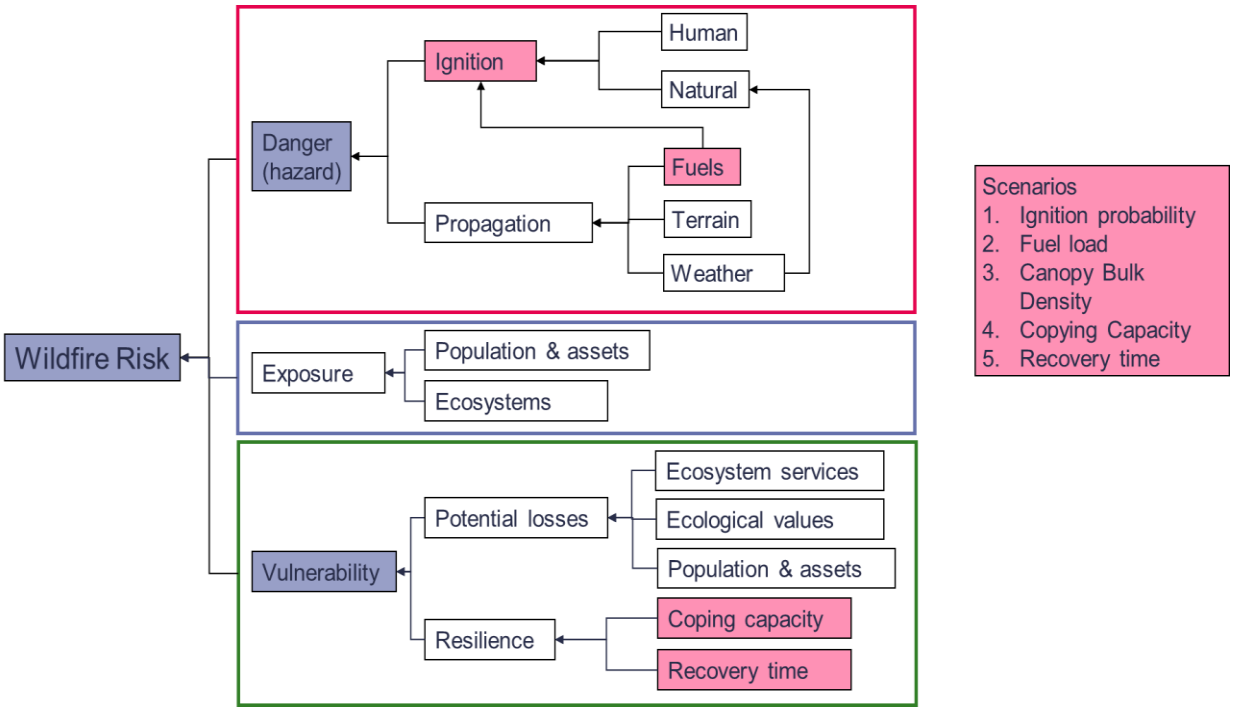


Figure 2: Simulation scenarios to assess different mitigation options. The simulations affect all intermediate components related to each factor

The outputs were compared with respect to the reference scenarios, defining by extreme and high-risk weather conditions. All these simulations were performed with the same two reference weather scenarios previously described: 95 and 50 percentile of weather parameters, and the impact of the different strategies in the ET area were analysed by comparison with these base conditions, including both the absolute (post-reference value) and the relative reduction: (post-ref value)/ref value. Because each mitigation scenario affects a wide set of intermediate outputs, we comment in this document only the outputs that compare the simulations with the base scenario of extreme conditions (derived from the 95 percentile of the worst weather conditions for the dates when a large fire occurred in the ET area), although all analysis have also been made for the high-risk scenario.

4.4.1 Reducing ignitions

In this case, we assumed that the ignition potential (IP) was reduced by 10, 20 and 30% over the current values generated from the analysis of recent historical trends (Ochoa et al. 2024). This variable impacts the values of Danger (D) and the final integration risk (IRI). Considering the weights assigned to IP, the reduction of this variable affects proportionally to D in relative terms depending on the importance of the propagation potential (PP). Table 5 presents the outputs of this simulations by fuel category and biome. To avoid excessive details, we have divided the continent in two biomes: Mediterranean, where most fires occur, and Non-Mediterranean, including Atlantic, Central and Northern European regions.

The main reductions of D values are observed in grasslands, both in the Mediterranean and Non-Mediterranean regions, although more significantly in the former. Danger in shrublands is reduced in a lower proportion than forest, again with lower values in the Non-Mediterranean region. IRI values were reduced in lower proportion to the reduction of IP, with higher values again for grassland. According to these statistics, the main area where the reduction of IP should be enforced should occur in areas dominated by grass fuels, particularly in Mediterranean areas.

Erro! A origem da referência não foi encontrada. provides a spatial view of the impacts of decreasing IP in D. Higher reduction of D values were observed in all areas where grassland or croplands dominate, particularly in Central Europe, Southern Scandinavia, Baltic states, and the Eastern United Kingdom. Reductions are less important in areas with high ignition occurrence, particularly in the Mediterranean countries and Eastern Romania and Bulgaria, as well as most of Scandinavia, Ireland, and the western regions of Great Britain.

Table 5: Average relative reduction in Danger and integrated risk as a result of reduction of IP

		Forest		Shrubland		Grassland	
		Mediterranean [%]	**Non-Mediterranean [%]**	**Mediterranean [%]**	**Non-Mediterranean [%]**	**Mediterranean [%]**	**Non-Mediterranean [%]**
Danger	10%	-4.12	-2.90	-2.23	-1.96	-9.62	-4.33
	20%	-8.24	-5.80	-4.46	-3.91	-19.26	-8.72
	30%	-12.36	-8.70	-6.69	-5.87	-28.90	-13.08
IRI	10%	-2.21	-1.18	-1.77	-1.60	-5.44	-2.85
	20%	-4.42	-2.36	-3.55	-3.20	-10.89	-5.76
	30%	-6.63	-3.54	-5.32	-4.80	-16.35	-8.64

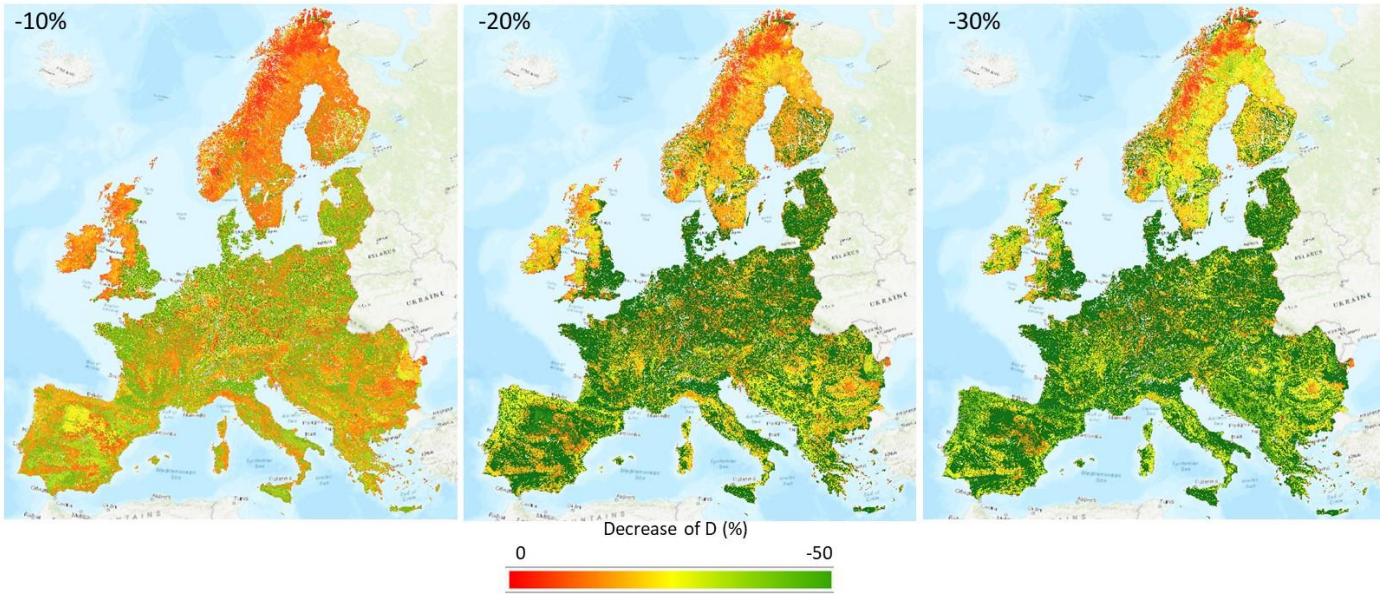


Figure 3: Relative reduction in Danger as a result of reduction in IP

4.4.2 Reducing fuel load/depth

In this case, the reduction of fuel load and fuel depth was applied to all types of surface fuels in proportion to its baseline fuel model. Since changing a single parameter may change the performance of the whole fuel model, we had two options to run this simulation: changing the fuel model assigned to a specific fuel type, selecting another one with lower loads while maintaining other parameters similar (for instance transition from tall grassland to short grasslands), or changing the two parameters that are more linked to load (fuel load and fuel depth). We decided to follow this second option, as this provides a more systematic analysis of the impact of reducing loads throughout the ET area and changing fuel models would involve complex decisions in some regions. We left simulation of fuel model changes for the PS, where these transitions of fuel models could be better controlled to produce realistic outputs. On the other hand, we have not considered here the possible mechanisms to reduce the loads, but the project has considered at ET scale three strategies, explained in deliverable D2.3 (Neidermeier et al., 2023): prescribed fire, herbivory or mechanical means.

The impact of reducing fuel load/depth in the ET area is very diverse, affecting almost all indices of the FirEUrisk integration scheme, both in the Danger (through the FLI), and Vulnerability components, mostly through the impact of FL change in the reduction in socio-economic values. The highest impact of reducing this parameter is observed in the propagation potential (PP), as a result of the influence of the FLI, with values that exceed the reduction rate in all categories (Table 6). Forest, shrubland and grasslands reduce their FLI in higher proportion than the reduction of load-depth, meaning that the relevance of this strategy on fire propagation is critical.

Its impact of reduction in FL is also very significant. The absolute differences clearly favour the action on shrublands, in both Mediterranean and Non-Mediterranean biomes, with reductions of more than 1.5 m (

% of reduction in fuel load-depth	Forest		Shrubland		Grassland	
	Mediterranean [%]	Non-Mediterranean [%]	Mediterranean [%]	Non-Mediterranean [%]	Mediterranean [%]	Non-Mediterranean [%]
10%	-19.35	-19.48	-19.00	-19.00	-26.87	-20.95
20%	-36.92	-37.10	-36.00	-36.00	-48.10	-39.42
30%	-52.54	-20.26	-51.00	-51.00	-64.50	-55.43

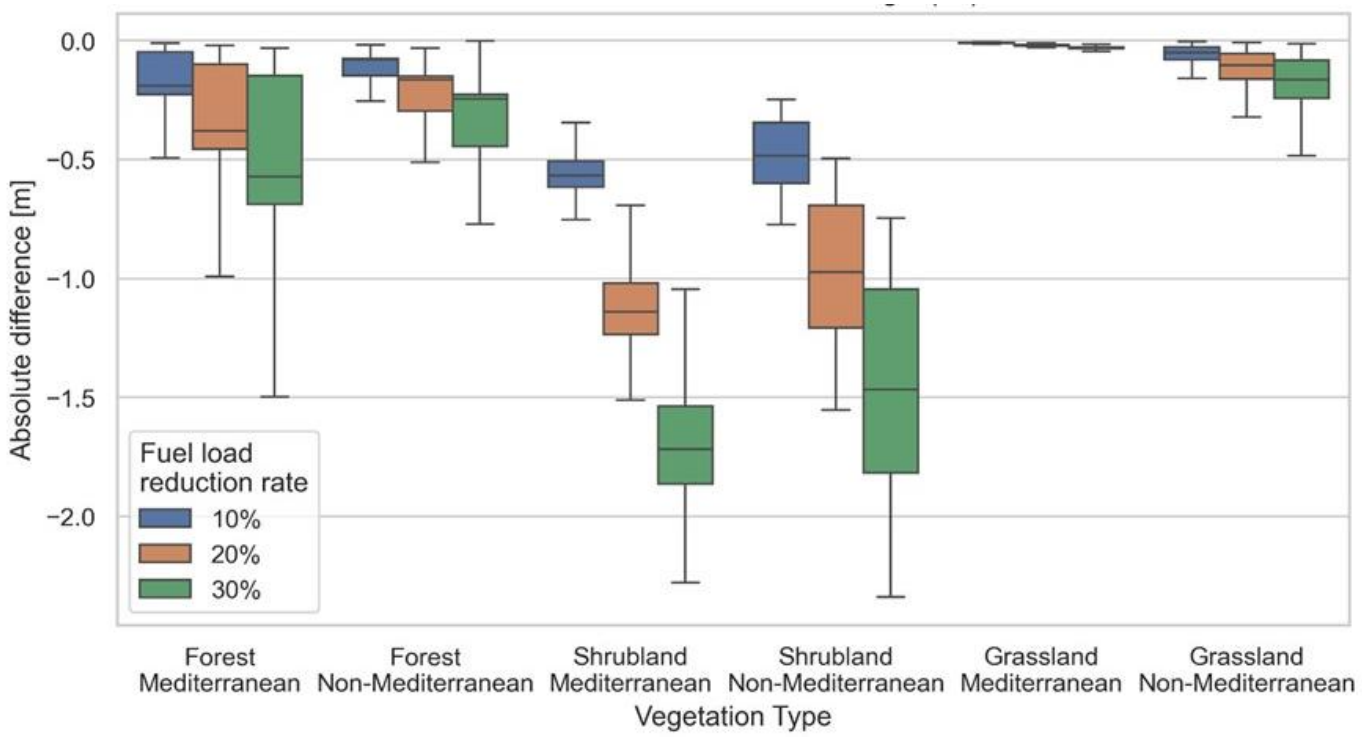


Figure 4). For forested areas, Mediterranean areas seem more sensitive to this parameter than Non-Mediterranean ones. Grasslands showed low reductions of FL in all simulations, although Non-Mediterranean areas are more sensitive to reduce FL than Mediterranean areas.

The impact of this scenario on Vulnerability is lower than in propagation in both relative and absolute terms (

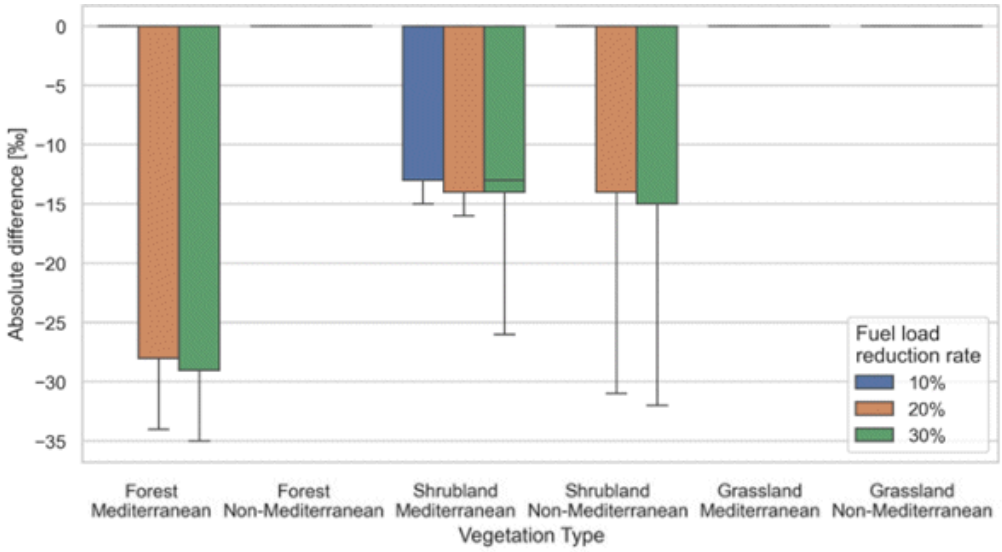


Figure 5). In forested areas, only the two highest reductions show significant impacts, while for shrubs, only the Mediterranean areas are sensitive to this mildest reduction scenario.

Table 6: Average relative reduction in Fireline Intensity for different fuel types as a result of reduction of Fuel load-depth

% of reduction in fuel load-depth	Forest		Shrubland		Grassland	
	Mediterranean [%]	Non-Mediterranean [%]	Mediterranean [%]	Non-Mediterranean [%]	Mediterranean [%]	Non-Mediterranean [%]
10%	-19.35	-19.48	-19.00	-19.00	-26.87	-20.95
20%	-36.92	-37.10	-36.00	-36.00	-48.10	-39.42
30%	-52.54	-20.26	-51.00	-51.00	-64.50	-55.43

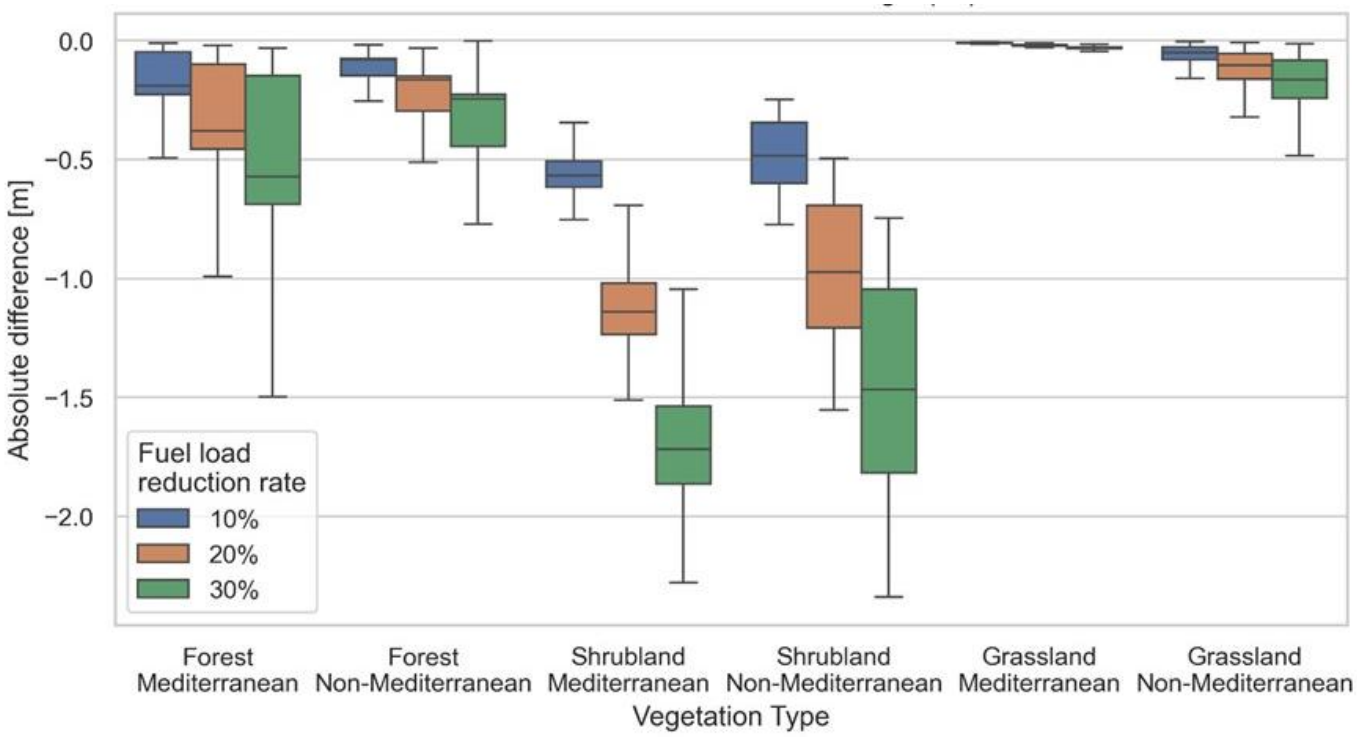


Figure 4: Boxplots indicating the impact of reducing fuel load-depth in FL for different fuel types: absolute differences.

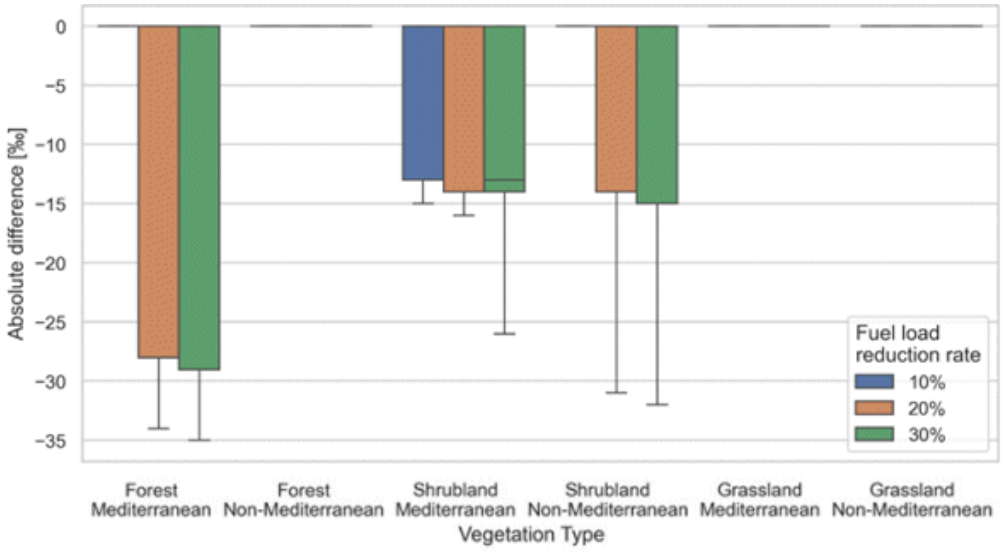


Figure 5: Boxplots indicating the impact of reducing fuel load-depth in vulnerability for different fuel types.

Regarding the analysis of regional patterns, Figure 6 shows the relative reduction in FL that would occur as a result of different proportions of load-depth reductions. Even though the absolute importance of FL reduction on surface fuels is low, its relative importance is higher in areas where those fuels are more important, driving fire propagation, as is the case in Central Spain, South Italy, and Easter Romania in areas occupied mostly by

crops and grasslands, this is also the cases of central and Northern Europe for the highest reduction scenario. The relative reduction in FL is lower in most Scandinavia, Ireland, and Scotland, as well as in forested areas of Mediterranean countries.

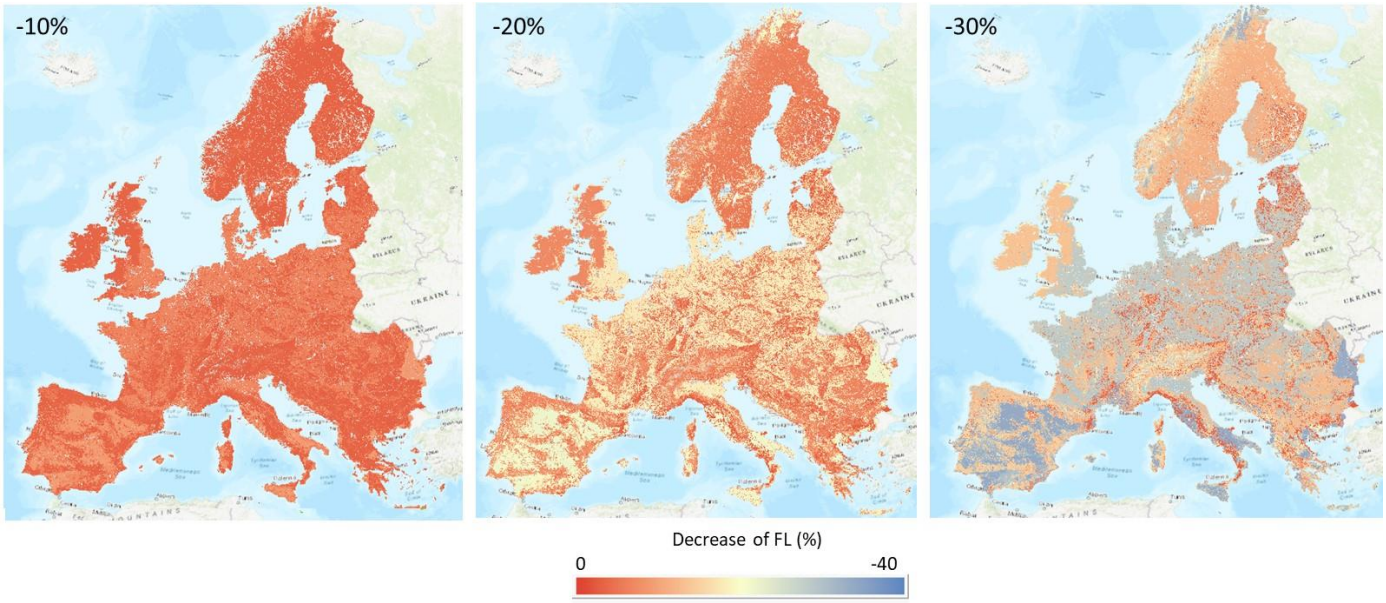


Figure 6: Relative Flame length reduction with different proportions of fuel load-depth reduction

Regarding the final integration index, the reduction in fuel load-depth implies a significant decrease in IRI values but more clearly in Non-Mediterranean fuel types (Figure 7). The strongest contrast in terms of IRI reduction value is observed in Non-Mediterranean grasslands. More humid forests offer also higher values of IRI reduction than the Mediterranean forest, whereas shrublands have a very similar behaviour in both climatic regions.

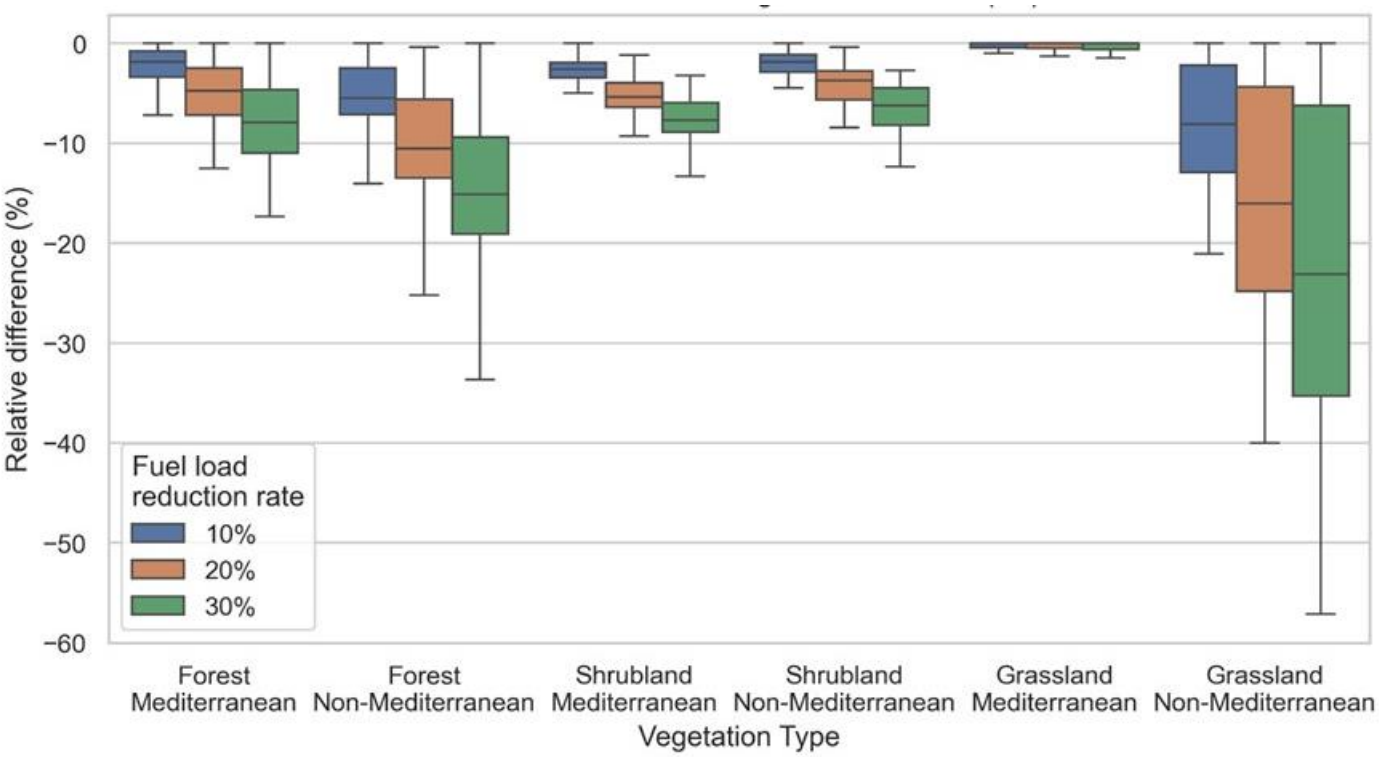


Figure 7: Relative difference in IRI values as result of changing the fuel load-depth

4.4.3 Reducing canopy bulk density

In this case, the reduction of fuel load is focused on crown fuels, and therefore the implementation should mainly focus on mechanical thinning or pruning, or in very specific places crown prescribed fires. However, because it is very unlikely to have only crown fires, we have combined this scenario with the reduction in the surface fuel load as well. Therefore, it is similar to the previous scenario, but with the addition of a reduction in crown fuel.

As expected, the impact of this mitigation scenario is mostly evident in the propagation parameters, in s similar proportion to the reduction scenarios. The relative reductions of FL are higher for Closed Deciduous forest, while the lowest impacts were observed for closed mixed fuels (

Table 7). The proportion of FL reduction is similar to the actual reduction of loads-depth, again with higher proportions for deciduous and lower for mixed fuels.

Table 7: Average relative proportion of FL reduction (in %) for different levels of CBD reduction.

	10%	**20%**	**30%**
Open Deciduous	-9.29	-18.64	-28.06

Closed Deciduous	-15.08	-26.33	-35.57
Open Evergreen	-9.31	-18.65	-28.07
Closed Evergreen	-9.17	-18.43	-27.81
Open Mixed	-9.51	-18.90	-28.29
Closed Mixed	-5.27	-11.20	-17.92

Other indices are also affected by this reduction of fuel in the canopy layer, particularly those related to D, but also V, because of the impact of FL reduction of losses (RSEV and RESV). In fact, reducing CBD by 10, 20 and 30% implies reducing the final wildfire risk between 2 and 15 % for Mediterranean forest and between 5 and 18 % for Non-Mediterranean forest (Figure 8), with a proportional reduction of IRI following the reduction of load-depth.

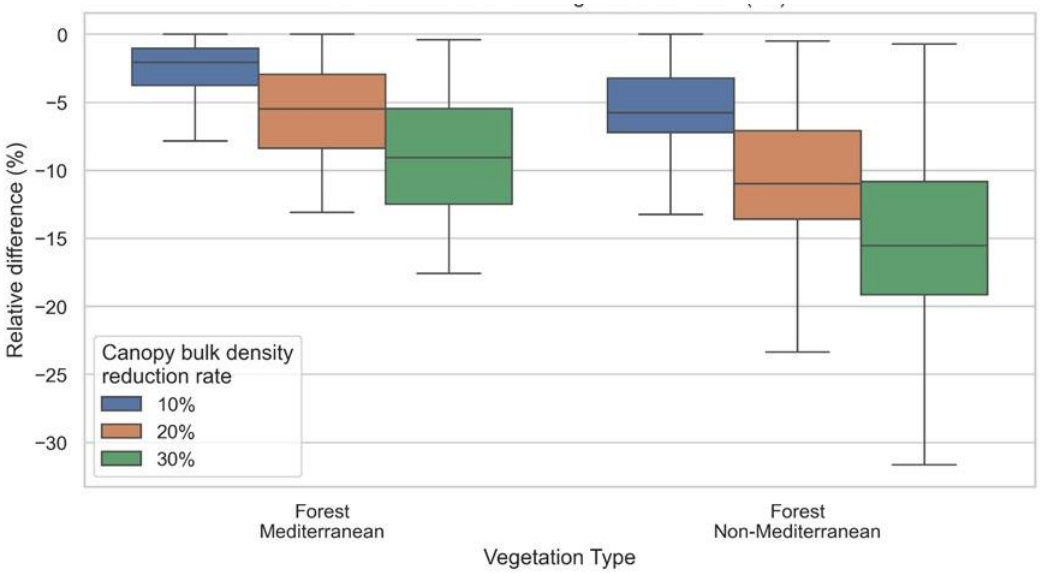


Figure 8: Relative reduction in IRI values as a result of reducing CBD

4.4.4 Reducing ecological vulnerability by increasing coping capacity.

In addition to acting on the factors of ignition or propagation, a wildfire risk strategy should also deal with decreasing exposure or vulnerability, thereby making societies or landscapes more resilient to the negative effects of fire. For this exercise, we considered two variables related to vulnerability: increase in coping capacity and decrease in recovery time.

The coping capacity indicates the resistance of the system to the negative effects of fire. This can refer to ecological or socioeconomic aspects. The former relates to plant functionalities related to fire, and the latter is linked to the level of social preparedness and resources to resist fires and recover after them. For the ET area

we have focused on the former, as it was not possible to find suitable procedures to calculate the vulnerability of social assets (protection of houses and ecosystem services) for the whole ET region, so it was not modelled here, but it could be included for simulation exercises at the PS scale.

As indicated in D1.4 and Arrogante-Funes et al. (2024), the CC was calculated from species' resistance to fire, based on a database of plant functional traits. Therefore, the increase in CC should come from changing the species composition of a certain area towards favouring more resistant species, or, at landscape level, reducing densities and therefore horizontal continuity through selective logging. In the case of societal vulnerability, improving CC would entail strengthening the societal preparedness for fire, either by improving citizen training or suppression and evacuation resources, as well as by favouring the higher resistance of certain ecosystem services (for example, carbon sequestration provided by more resistant species to fire).

As it was expected, increasing the CC reduces ecological vulnerability, although by a much smaller amount than expected, probably because of the combined effect of recovery time and the relative importance of ecological values. Since in this exercise only ecological CC was considered, the impact of increasing this variable is only relevant for EV (Figure 10), with low impacts for overall V and the IRI. The average relative values of this variable generally decrease below 2% for a 10% increase in CC, below 4% for 20% increase in CC and below 6 % for 30% increase in CC. The impacts in this case are more evident for forest species, because trees are more resistant to fire than shrubs or grasslands. Non-Mediterranean forest was found more sensitive than Mediterranean to reducing vulnerability, but with a minor difference between them.

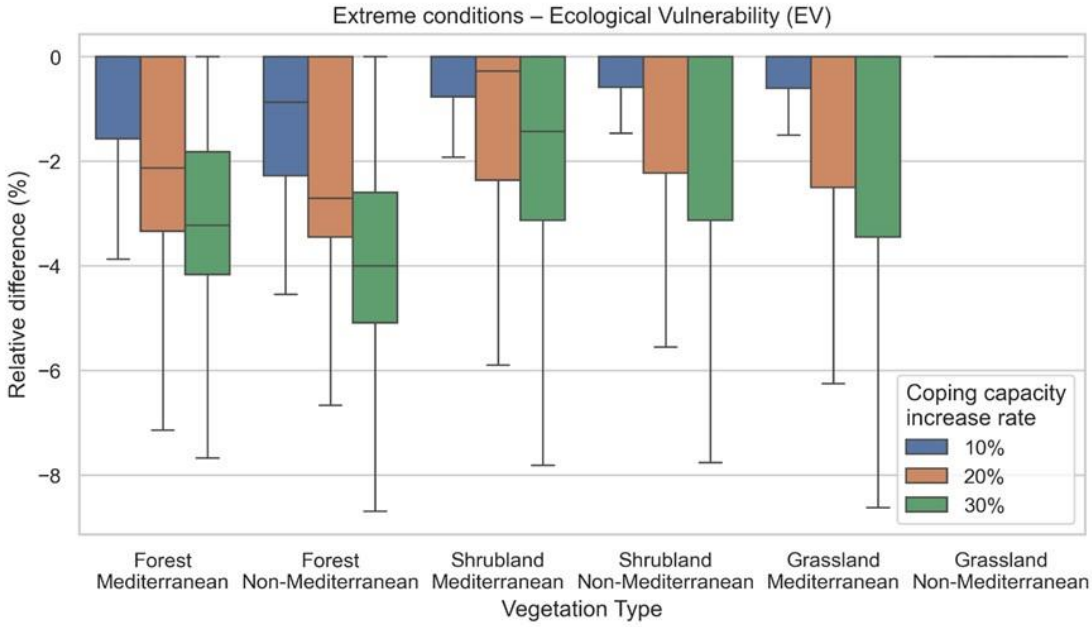


Figure 9: Relative decreases in ecological vulnerability as a result of decreasing CC.

4.4.5 Reducing vulnerability by decreasing recovery time.

This is a similar approach to reduce vulnerability, but in this case favouring those species that are better adapted to fire and therefore can more easily recuperate after the event. It should be noted that we do not favour here

to fast-growing species, because they may be more flammable and create additional problems in terms of increasing ignition potential, but rather to those that are better adapted to fire effects, and therefore recover quicker the pre-fire conditions.

The implications of decreasing recovery time (RT) affect both human and ecological vulnerability, although the two RT were computed from a different perspective: the former using data from Table 4, and the latter from plant functional traits applied to vegetation species distribution.

The impacts of decreasing RT by 10, 20 and 30% are more evident in ecological than in human vulnerability (Table 8). Average reduction in HV was below 4% for all fuel types and biomes, with lower values for forests. Most areas reduced human vulnerability by less than 2% in areas dominated by forest species, less than 3% in shrublands, and less than 6% in grasslands. EV is more clearly affected by reducing RT, with average values ranging from -3.5 to 52%, which is much higher for grasslands than for forests and shrublands. However, both absolute and relative differences have a high variability (Figure 10).

Table 8: Average relative reduction in vulnerability as a result of decreasing RT

		Forest		Shrubland		Grassland	
	RT reduction rate	**Mediterranean [%]**	**Non-Mediterranean [%]**	**Mediterranean [%]**	**Non-Mediterranean [%]**	**Mediterranean [%]**	**Non-Mediterranean [%]**
Human Vulnerability	10%	-0.28	-0.27	-0.39	-0.33	-0.59	-0.91
	20%	-0.60	-0.58	-0.85	-0.71	-1.27	-1.96
	30%	-0.98	-0.95	-1.39	-1.15	-2.07	-3.22
Ecological Vulnerability	10%	-3.54	-4.02	-6.49	-6.18	-12.45	-17.72
	20%	-7.67	-8.62	-14.05	-13.49	-26.62	-36.54
	30%	-12.01	-13.27	-21.63	-19.74	-39.98	-51.70

The spatial distribution of the impacts of reducing RT on ecological vulnerability provides interesting insights into the effectiveness of this potential action (Figure 11). As indicated earlier, we do not consider the practical implications of carrying out these measurements but only the methodological approach to offer guidance for prioritizing different mitigation possibilities.

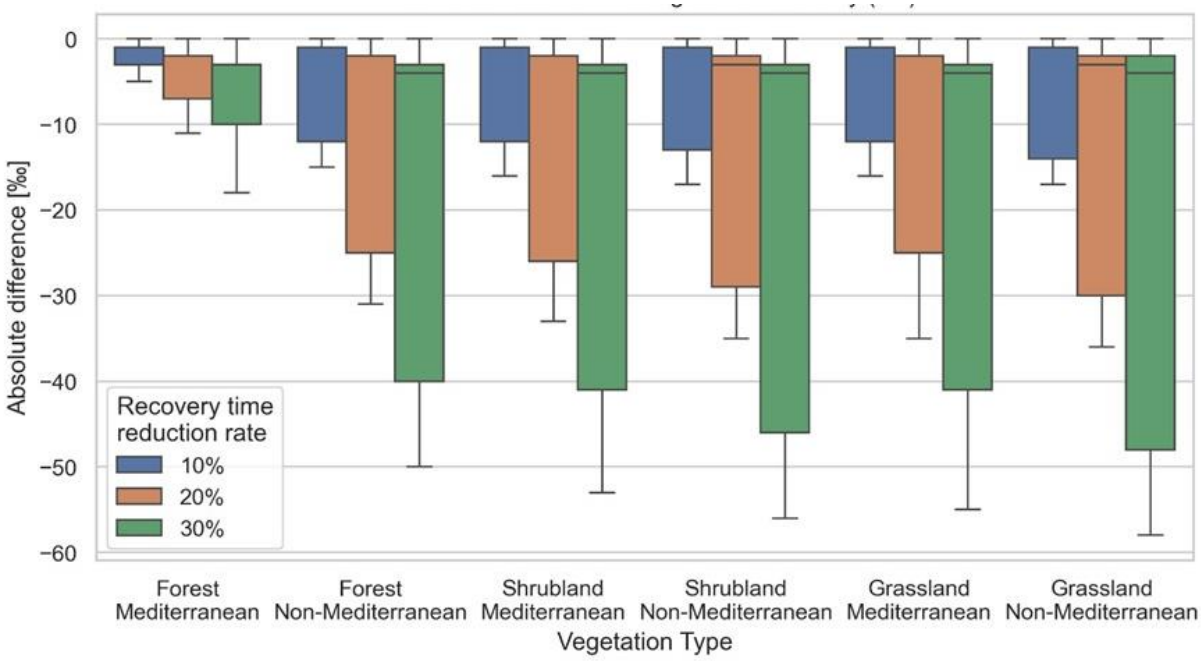


Figure 10: Absolute differences in ecological vulnerability for different fuel types by reducing RT.

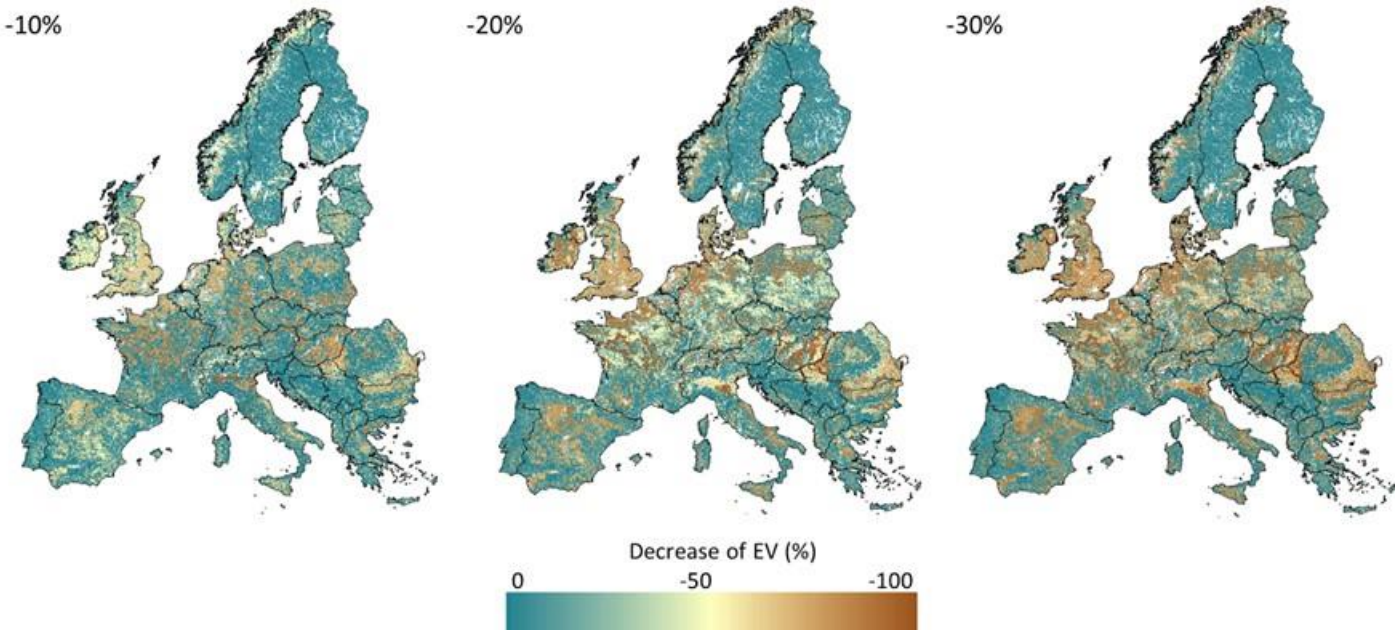


Figure 11: Relative change in ecological vulnerability for different decrements of recovery time

As expected, the higher the reduction scenarios (10, 20 and 30%), the proportionally higher the reduction in EV. The main reductions in vulnerability come from areas with dominance of croplands and grasslands, clearly

observable in the British Islands, the border between Romania, Hungary, and Serbia, the Po Valley, central Germany, and Poland. The reduction in vulnerability in these regions ranged from 30 to 90%. Mediterranean grasslands and croplands also presented higher decrements but lower decrements than in more humid climates. Forested areas offer much lower relative decreases in vulnerability for the same reductions in RT, with values between 4 and 12%, with small differences in biomes and between evergreen and deciduous species. In any case, it is clear that decreasing RT by favouring species which are more resilience to fires is relevant in terms of reducing vulnerability.[6]

4.4.6 Summary of the impact of different mitigation actions

As indicated earlier this chapter has presented some examples of using the integrated wildfire risk framework developed within FirEUrisk to assess the impact of different mitigation strategies. Each of simulation scenarios affects more clearly a certain component of the FirEUrisk integration scheme, which is obviously related to the relevance of the target variable in the overall scheme and in a particular risk component. For instance, changing CC affects V (and in turn the final IRI values), because CC is one of the direct inputs to this component, while changing fuel load-depth on the contrary affects not only fire behaviour variables (PP, FL, FLI), but also D and V, since estimation of reduction of values after fire is related to fire propagation potential (particularly impacts FL).

As a summary of the importance of each of each of the mitigation actions, we have built several tables with the average reduction of risk for the main components of the FirEUrisk integration scheme: D, V and IRI. In the three cases we have selected the strictest reduction scenario (30%) to simplify the comments. We include in the following tables the average impact of the different simulation strategies used in this document in the fuel types (as derived from our fuel typology: Aragoneses et al., 2023). We are not considering here fuels that occupy less than 1% of the ET region.

The first table relates to the impact of simulations on relative reductions of Danger. D was affected by three simulations: reducing IP, fuel load-depth and CBD. Within the most important fuel types, which are presented in Table 9, the herbaceous croplands (almost 40% of total ET area) are clearly more affected by reducing IP (scenario 1) than by any other strategy, as fuel loads are low in this category and CBD does not affect it (there are no crown fuels in this fuel type). The relative reduction of D values caused by IP reductions ranges in a similar proportion to the effort required (30%). Woody and low croplands show a similar behaviour, although they are much less abundant in Europe. For shrublands, the fuel load-depth reduction scenario had the greatest impact although much lower than for croplands and close to the impact of reducing IP, particularly in high shrubland. Medium and high grasslands have much higher impact on reducing Danger from the fuel load-depth

[6] However, it is important to remark that this aspect should be combined with other considerations, as we do not intend to value fast-growing species that my affect soil fertility and biodiversity or may reduce coping capacity or increase fuel load. In this exercise we are aiming to simulate single variables, to simplify the analysis of the outputs, but more sophisticated simulations, considering the impacts of various factors simultaneously should be run for operational conditions.

reduction scenario than IP reduction. The same can be said of grass on peatlands, clearly more influenced by fuel load reduction than by other factors. It is worth mentioning that discontinuous fabric (mostly related to wildland urban interface or intermixed) finds a similar reduction in D by reducing fuel load-depth. For forest species, both fuel load-depth and CBD reduction (scenario 3) offer the highest reductions of D, particularly for closed evergreen fuel, which are the most abundant in the ET area (almost 20% of all fuels and 53% of all forested areas). For deciduous trees, the CBD reduction provides higher reductions than load reduction. In the closed mixed category, low values of reduction were observed from scenarios 2 and 3, and only IP reduction have significant impacts of reducing Danger.

Table 9: Relative reductions of Danger for different mitigation strategies (in %)

	Area		Reducing 30% IP		Reducing 30% load-depth		Reducing 30% CBD*	
Fuel class	**(km2)**	**%**	**Mean**	**STD**	**Mean**	**STD**	**Mean**	**STD**
Medium Shrubland	136980	3.00	-5.62	2.44	**-9.12**	2.92	**-9.12**	2.92
High Shrubland	117282	2.57	-7.58	2.21	**-8.21**	2.88	**-8.21**	2.88
Low Grassland	195399	4.28	**-27.15**	7.21	-4.43	11.84	-4.43	11.84
Medium Grassland	165242	3.62	-11.81	8.62	**-34.59**	18.19	**-34.59**	18.19
High Grassland	177073	3.87	-6.58	3.78	**-39.21**	8.03	**-39.21**	8.03
Herbaceous cropland	1762378	38.56	**-26.25**	7.24	-6.25	11.16	-6.25	11.16
Woody cropland	113827	2.49	**-28.41**	5.67	-2.68	12.14	-2.68	12.14
Tree peatlands	47321	1.04	-3.90	3.11	**-7.51**	6.14	**-7.51**	6.14
Grass peatlands	181187	3.96	-4.57	4.53	**-37.55**	13.87	**-37.55**	13.87
Discontinuous fabric	79780	1.75	-12.02	5.30	**-26.10**	10.66	**-26.10**	10.66
Closed Deciduous	449566	9.84	-6.45	2.67	**-15.70**	6.02	**-18.01**	5.05
Closed Evergreen	848740	18.57	-7.02	5.11	**-38.89**	9.80	**-39.01**	8.88
Closed Mixed	230516	5.04	**-23.51**	5.41	-1.66	29.02	-9.08	10.10

(*) In all cases reduction of CBD only affects crown fuels. The highest value for each fuel type is emphasized in bold

Regarding the average reduction of Vulnerability, the four mitigation strategies that affect this component had much lower impact that those related to Danger in all fuel categories (Table 10). Only the reduction of RT (scenario 5) showed a remarkable impact in reducing vulnerability. It should be taken into account that in our simulations CC only affected the EV, which reduced the practical interest of this strategy, as our integration scheme conceded more importance (higher weights in Eq. 10) to the human vulnerability. The higher reductions of V were observed in herbaceous fuels, particularly in grasslands of different heights and croplands, with higher values for taller grasses. Since the initial conditions of RT for this category were one year, the reduction of 30% implies that recovery would occur in about 8 months, which may be not very realistic in semi-arid climates, but this would greatly depend on the date of the fire during the growing season and the patterns of precipitation.

Table 10: Relative reductions in Vulnerability for different mitigation strategies (in %)

	Reducing 30% fuel load		Reducing 30% CBD		Reducing 30% CC		Reducing 30% RT	
Fuel class	**Mean**	**STD**	**Mean**	**STD**	**Mean**	**STD**	**Mean**	**STD**
Medium Shrubland	-2.76	3.41	-2.76	3.41	-0.43	1.21	**-5.42**	11.95
High Shrubland	-2.06	3.46	-2.06	3.46	-0.41	1.36	**-7.44**	16.92
Low Grassland	-0.01	0.41	-0.01	0.41	-0.41	1.33	**-18.96**	27.38
Medium Grassland	-0.02	0.46	-0.02	0.46	-0.31	1.25	**-27.06**	24.89
High Grassland	-0.05	1.35	-0.05	1.35	-0.17	0.97	**-44.76**	41.17
Herbaceous cropland	-0.13	1.28	-0.13	1.28	-0.16	0.83	**-9.64**	23.42
Woody cropland	-0.01	0.36	-0.01	0.36	-0.26	0.56	**-2.47**	1.93
Tree peatlands	-3.38	6.34	-3.38	6.34	-0.39	1.27	**-6.10**	8.51
Grass peatlands	-0.09	1.30	-0.09	1.30	-0.16	0.84	**-10.50**	10.29
Discontinuous fabric	-0.63	2.99	-0.63	2.99	-0.25	1.85	**-5.22**	17.73
Closed Deciduous	-3.42	4.13	**-4.07**	4.68	-0.38	0.76	-2.12	3.70
Closed Evergreen	0.01	0.51	0.00	0.18	-0.56	1.00	**-2.37**	3.41
Closed Mixed	0.92	4.39	-0.17	1.61	-0.35	0.76	**-2.03**	4.24

*The highest value for each fuel type is emphasized in bold

For shrublands and forest fuel types the scenario of reducing RT is also the one facilitating higher decreases of vulnerability. although reductions are significantly lower than for grasslands, in the range of 2 to 2.5%. Only in the closed deciduous category, the reduction of CBD provides higher decrements of V than those provided by decreasing RT, although still with low values. The impact of reducing fuel load-depth is only visible in tree-covered fuel types, particularly for tree peatlands and closed deciduous, but also in shrublands, medium and high. In any case the impact is quite low in comparison with the intensity of the reduction proposed by this simulation scenario.

Finally, we computed the relative reductions of the final index, the IRI, considering only the most important reductions of the different strategies. The importance of the first scenario (reducing IP) is higher for areas with short surface fuels (low grasslands and croplands). Medium and high grasslands, grass peatlands, shrublands and WUI areas benefit more from scenarios 2 and 3 (reducing load-depth and CBD), as well as all forest fuel types with the exception of closed mixed forest (Table 11). Within the simulation scenarios proposed in this exercise, the reduction of IP shows a higher impact in those fuel types with lower biomass load, including grasslands and croplands. The reduction of fuel load and CBD is more important for fuels with higher loads, such as medium or high grassland, shrublands, peatlands and forests, with the exception of closed mixed forest, which may be affected by including two contrasting fuel models in the Scott and Burgan classification system. The reduction of IRI values for urban intermix areas is also higher for fuel load-depth and CBD reduction.

Table 11: Relative reductions in IRI for different mitigation strategies (in %)

	Reducing 30% IP		Reducing 30% load-depth		Reducing 30% CBD		Reducing 30% CC		Reducing 30% RT	
Fuel class	**Mean**	**STD**	**Mean**	**STD**	**Mean**	**STD**	**Mean**	**STD**	**Mean**	**STD**
Medium Shrubland	-4.38	2.02	**-7.65**	2.45	**-7.65**	2.45	-0.09	0.19	-0.73	0.55
High Shrubland	-6.22	2.00	**-7.07**	2.46	**-7.07**	2.46	-0.05	0.13	-0.52	0.47
Low Grassland	**-16.03**	8.43	-2.89	7.87	-2.89	7.87	-0.16	0.58	-3.77	6.07
Medium Grassland	-7.48	6.97	**-19.90**	14.09	**-19.90**	14.09	-0.10	0.44	-8.10	8.52
High Grassland	-5.76	3.40	**-34.39**	9.52	**-34.39**	9.52	-0.02	0.13	-0.99	1.33
Herbaceous cropland	**-10.64**	8.10	-3.15	6.29	-3.15	6.29	-0.06	0.34	-1.93	3.34
Woody cropland	**-10.63**	3.91	-0.62	2.37	-0.62	2.37	-0.17	0.38	-1.53	0.94
Tree peatlands	-3.05	2.64	**-6.46**	4.51	**-6.46**	4.51	-0.07	0.21	-0.99	0.70
Grass peatlands	-3.20	3.55	**-25.00**	11.41	**-25.00**	11.41	-0.05	0.26	-2.47	1.70
Discontinuous fabric	-9.00	4.59	**-19.71**	10.27	**-19.71**	10.27	-0.03	0.14	-0.34	0.52
Closed Deciduous	-4.39	1.97	-11.61	4.25	**-13.39**	3.82	-0.12	0.20	-0.62	0.48
Closed Evergreen	-3.28	2.61	-18.17	7.67	**-18.27**	6.88	-0.30	0.48	-1.17	0.89
Closed Mixed	**-5.79**	4.29	5.09	26.50	-1.80	7.97	-0.24	0.50	-1.32	1.08

*The highest value for each fuel type is emphasized in bold

In summary, for the IRI the most influential variables are reduction of IP and fuel load-depth, including CBD for the forest fuels. With our current simulations, the reduction of CC and RT does not have a relevant role in any fuel type in comparison with other strategies. Figure 12 shows the spatial distribution of how IRI is reduced throughout the ET area following the two main mitigation strategies. As indicated above, the forested areas are more sensitive to reducing fuel loads and CBD, while the croplands and grasslands are more affected by reducing IP. The spatial distribution of reduction impacts show that the fuel load-depth and CBD reduction strategies would have higher relative impacts in areas that are now less affected by fires, particularly the British Islands and the Scandinavian peninsula, while Mediterranean areas seem more affected by a potential reduction of IP.

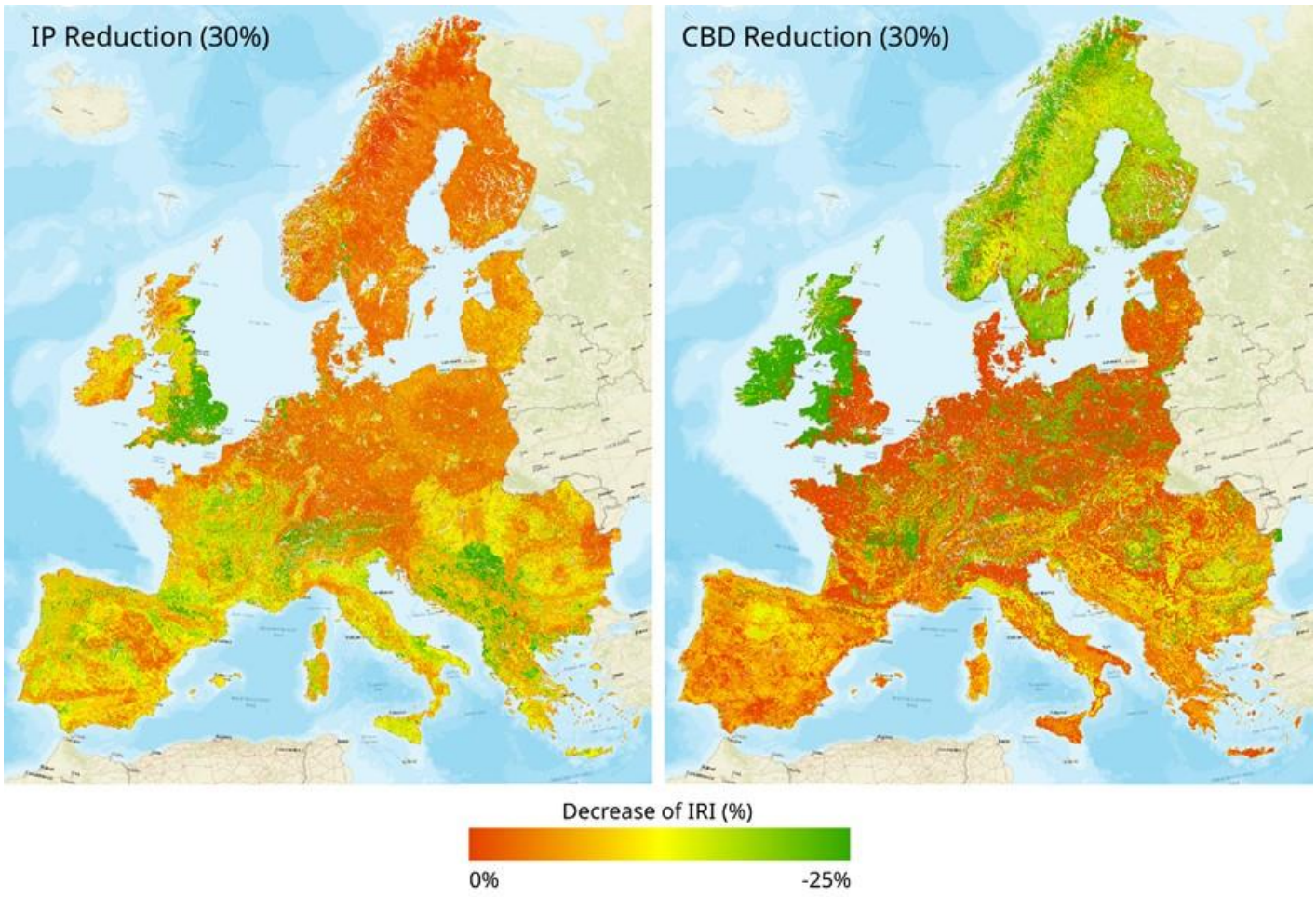


Figure 12: Spatial analysis of IRI relative reductions as a result of applying two reduction strategies.

4.5 Simulation for adaptation actions

This approach implies considering the estimation of future conditions for the main variables of risk. Obviously, estimating all fire risk components is quite challenging, as we do not have robust models to estimate how the fuels will behave in the future, or even more difficult how human factors will develop. A general estimation of how vegetation cover changes in the future is available through the integration of land cover and DGVM modelling with their embedded process-based fire models. But one has to note that they simulate average fire conditions under differing seasonal conditions, rarely are likely to simulate individual events. They cover fuel load, moisture and post-fire mortality of natural vegetation. Optionally, it is possible to assess fire spread on pastures. Because standard climate scenarios underrepresent possible future increased climate variability, incl. extreme weather conditions, respective simulations might miss out on future extreme fire conditions.

For this reason, we have only focused on weather conditions, which are a critical component of propagation in our fire risk model, affecting both D and V. Following our approach to emphasize the occurrence of extreme conditions, we selected the highest values of meteorological weather indices, as modelled by two IPCC

scenarios and the ensemble of three climate models used for climate projections within FirEURisk. Within the SSP126 scenario, a fairly optimistic emission scenario, the following climate models were used:

- Lower: MPI-ESM1-2-HR_ssp126
- Mid: EC-EARTH3_ssp126
- Upper: CNRM-ESM2-1_ssp126

For the more pessimistic emission scenario SSP370 (RCP7.0 and SSP3), the models were:

- Lower: MPI-ESM1-2-HR_ssp370
- Medium: CNRM-ESM2-1_ssp370
- Upper: CanESM5_ssp370

The simulation aimed to represent fire weather conditions for extreme events around the middle of the century (2050). To estimate these extreme conditions, we extracted the 95 percentile of the highest value of the FWI (a well-known meteorological danger index) computed from daily estimations between 2045 and 2055 to consider a sufficient number of years to avoid prediction artifacts. From the dates obtained for each cell in the ET area (in this case, 9 × 9 km because the high demand of climate models and their associated uncertainties did not allow the entire ET area to be run at 1 km2 simulation), the following parameters were extracted: Temperature, Relative Humidity, and Wind speed, which were input into the same fire propagation modeler that was used with the current weather conditions.

We assumed that the fuel properties are the same as in the present, which is obviously a very rough approximation to reality but useful considering that we are developing a methodological exercise in which the integration scheme could be used for mitigation and adaptation. An alternative would have been to model fuel characteristics using DGVMs, but this would have implied the simplification of the parameters required for running the same fire behaviour programs that have been used for estimating present conditions. We consider our approach reasonable in the framework of the exercise that is being shown in this document, since we do not intend to propose specific actions for adaptation to future fire regimes, but only to show the tools that could be used to establish consistent fire risk management across different target periods, present and future. Obviously, the uncertainties when applying these simulation scenarios to future conditions are much higher than those used for present characteristics, as many of the variables are unlikely to be stable (human ignition patterns, vegetation species distribution, fuel loads, fuel size distribution, etc).

Considering the limitations of this approach, we include here a single example of the potentials of using the integration scheme for future conditions. As indicated earlier, only the weather conditions have been simulated for future scenarios, not the fuel properties, which have been kept constant from current conditions. Therefore, the estimated changes only take into account what would be expected from new weather scenarios, assuming all other factors are constant.

With those limitations, and again considering that this simulation is only an example of possibilities of using an integrated tool for helping the development of adaptation strategies, Figure 13 shows the comparison of current and future FL, and the difference between them. In this case, we have included the variable and the

temporal difference in their original units (m). The exercise shows that expected FL will tend to be quite similar to current, with a tendency towards negative values. This is caused by an underestimation of wind speed conditions in the ensemble of the models used, which tended to smooth high speed values, providing lower values than present. This in turn affected the estimation of the moisture code and, in turn, the FL. However, the comparison of future and current conditions still showed higher positive values (that is expected higher FL) for croplands or grasslands of Mediterranean regions, particularly in Central Spain, Southern Italy and Greece, but in those regions, negative values (meaning lower FL than current conditions) were also observed in forested areas and dense shrublands. The comparisons can be done with all other components of the integration scheme, but uncertainties in other parameters increase, as they are more dependent on vegetation state, land-use or demographic conditions that were not included in the simulations.[7]

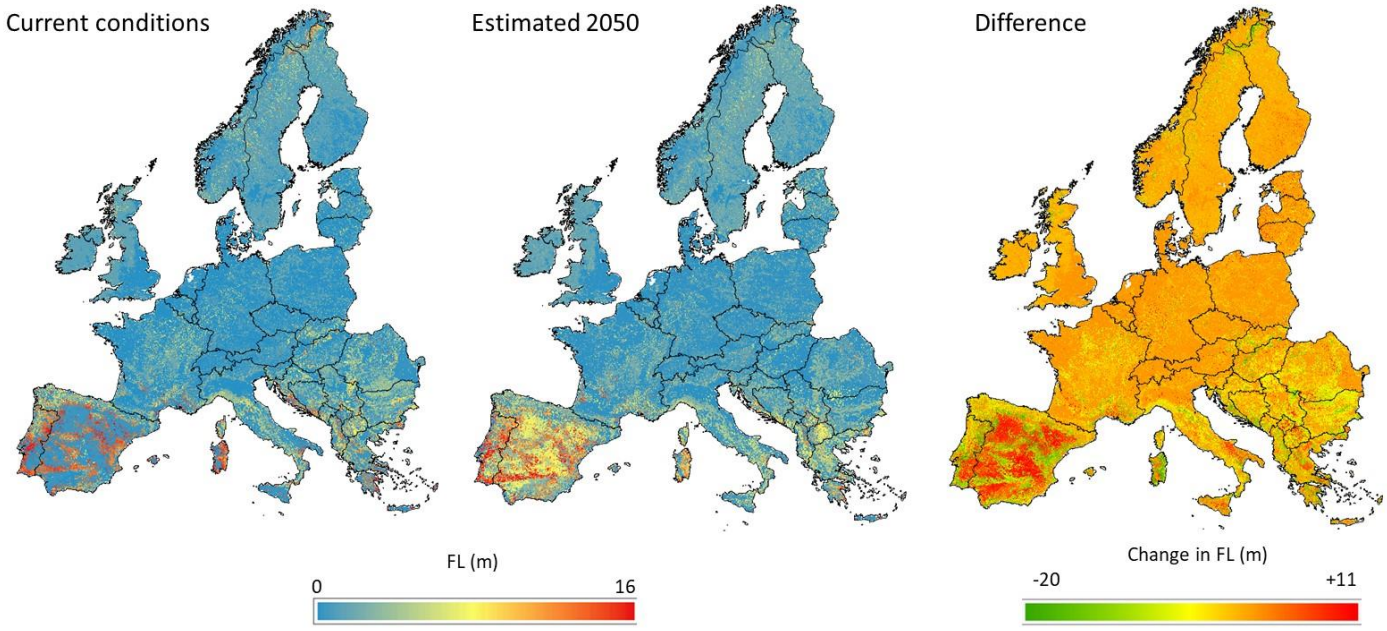


Figure 13: Comparison of FL for current and future conditions, assuming climate scenarios of 2050, but current fuel conditions

5 Conclusions

We have presented the application of the FirEURisk wildfire risk integration system to cover the three phases of risk management: assessment, reduction and adaptation. The main contribution of the system is to develop a comprehensive analysis of the main factors influencing fire danger, exposure and vulnerability in a holistic way, so that they can be used for simulating different scenarios at various spatial and temporal scales. We have

[7] Within the current tasks of WP3, some of these parameters are expected to be modelled during the remaining life of the project.

developed a computer tool to facilitate the integration of the different components of the FirEUrisk risk scheme. This computer code has been run for near-operational estimations considering daily changes in weather and fuel moisture (during the summer of 2024), as well as for historical analysis of extreme weather conditions. We have focused in this deliverable on how the integration scheme can be used for wildfire risk mitigation, with a simple exercise on its potential for estimating future fire risk conditions. The paper provides examples of how the computer tool can be used to test the impact of different risk reduction strategies. We have considered five scenarios (reduction of IP, fuel load-depth, CBD, CC and RT), but others could be proposed with different levels of reduction. Of course, these scenarios could also be combined to produce more complex risk reduction strategies (e.g. combining different levels of fuel load-depth reduction and RT). For the sake of simplicity, we have only covered single strategies here, but the tool can be used in many more sophisticated ways. We have shown a single example of the assessment of future conditions using the same integration scheme, although the results should be interpreted with caution given the limitations of this exercise. Future developments of this integration scheme may allow greater integration between mitigation and adaptation by better simulating future fire conditions, including fuel and land use expected changes. Within these future scenarios, exercises similar to those presented here for mitigation can guide adaptation planning.

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