Wildfire Risk Indicator – Prioritizing the Protection of valuable European Forests from Wildfires

Amin Casutt, Javier Feller, Leon Brüniger, Maximilian Lengenfelder
GitHub: https://github.com/mlengenfelder/GEO888

1 Introduction

Wildfires play a crucial role in ecosystems and have both positive and negative impacts on biodiversity, biogeochemical cycles, or landscapes (Arrogante-Funes et. Al., 2024). Forest ecosystems are in general sensitive to abrupt external changes due to the long lifespan of trees. Moreover, it is expected that under a warming climate, forest disturbance regimes will intensify and thus, adaptation strategies including ones for forest fires will become increasingly important (Forzieri et. Al., 2021). Based on that, it seems important to develop environmental indicators which can point to vulnerable forests in Europe that might need special protection and attention to prevent severe wildfires.

We identified two main research gaps in our scoping literature review. First, methodologically, we found that most indicators regarding forest vulnerability to wildfires are descriptive. Only a few performance-based indicators exist, meaning that they are related to policy targets, although making research more relevant for implemented policies is key (Berchtold et. Al., 2025). Second, substantively, existing research has mainly focused on explaining vulnerability, risk, *or* ecological value with respect to wildfires (Mihajlovski & Zhyianski, 2025). Few studies focused on integrating ecosystem services, vulnerability, and policy dimensions in one index.

The aim of this analysis is to support the SDG goal 15 – *"protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, halt and reverse land degradation and halt biodiversity loss"* (United Nations - Department of Economic and Social Affairs, 2026). More specifically, our research question is the following:

"How can we measure wildfire risk in Europe and track change over time considering ecological value, vulnerability and policy goals to prioritize protection of important ecosystems?"

To answer this question, we developed a simplified environmental indicator for forests in Europe, which will be discussed in the following sections. Since this is not a full-scale research project, the indicator is based on literature and pre-existing data and comes with several limitations, which will be briefly discussed as well. For instance, the direct exposure and vulnerability of anthropogenic infrastructure and human life threatened by wildfires was left out. Instead, the forests as the asset to being protected and their value both to nature and society was the focus of this project.

2 Methods

2.1 Workflow

Our analysis was mainly conducted in a Python-/Jupyter Environment. For some parts of the vulnerability sub-index calculation, QGIS was used in addition. In line with research best practices, a reproducible workflow was implemented for all analyses, accessible together with the necessary input data under the GitHub link, mentioned in the title.

In the following sections, after the definition of forest area the general conceptualization of the indicator as well as the operationalization of each sub-index is introduced.

2.2 Definition of forest

Since the scope of this analysis is limited to forest areas, the definition of “forest” is crucial. According to the definition of forest information system for Europe, forest is “land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use.” (FISE 2025, https://forest.eea.europa.eu/resources/glossary/forest?)

Thus, following the EU definition and based on the nomenclature of the Corine dataset, we explicitly included broad-leaved forest (311), coniferous forest (312), and mixed forest (313), but not other types such as agro-forestry areas (European Environment Agency, 2019).

2.3 Conceptualization

To answer our research question, we conceptualize our index into two main dimensions: Ecological value and vulnerability (Figure 1). In a second step, this bivariate index is then related to policy targets, elevating it to a performance-based indicator. In the following section, the development and operationalization of the vulnerability, ecological value as well as policy dimension are described in detail.

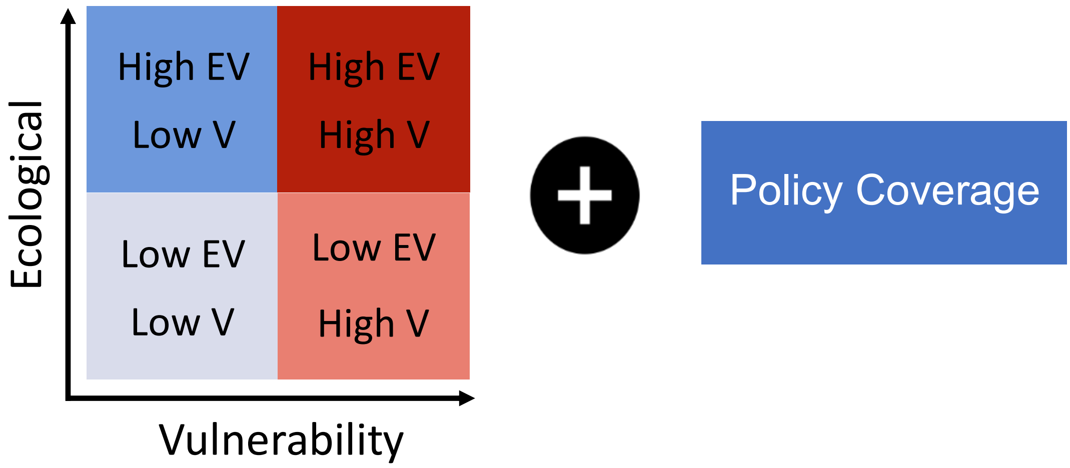

Figure 1. Conceptualization of our index with ecological value in the y-axis and vulnerability in the x-axis. In a second step, the policy dimension is added.

2.4 Vulnerability dimension

2.4.1 How do we define vulnerability of forests to wildfires?

When it comes to wildfire vulnerability of forests, there are several approaches to assess it based on different geographical and environmental parameters. As the aim of this project was to generate a bivariate indicator and the ecological value of forest ecosystems are considered in a separate sub-indicator, the focus was only set on parameters considered to be relevant regarding the outbreak, spread, and fighting of a wildfire in general. The vulnerability index here was based on an approach suggested by Oliveira et. al. (2018). There, it was intended to develop a stepwise framework for wildfire vulnerability for mediterranean forests, but it seemed feasible to apply its basic approach to all of Europe.

First, three main components of vulnerability were distinguished: exposure, sensitivity, and coping capacity (Oliveira *et al.*, 2018). Exposure refers to the “presence and extent to which a region, resource, or group experiences stressors, in terms of various changes occurring at different scales that cause stress” (Marshall *et al.*, 2010). We interpreted it to represent the exposure of an area to potential wildfires rather than the damage to anthropogenic infrastructure, as our project focused on the forests themselves to be protected from negative wildfire impacts. Thus, our exposure component includes the average of the daily values from 2020 to 2025 of the McArthur Mark 5 forest fire danger index (Copernicus Climate Change Service, 2026; Eidg. Forschungsanstalt für Wald, Schnee und Landschaft WSL, 2026) and the historical occurrence of wildfires in Europe and since 2007 for the whole year (EFFIS team, 2026). Secondly, the general sensitivity of European ecoregions to forest fires was considered to represent the basic sensitivity of certain ecosystem types (Dinerstein et al., 2017). Again, the anthropogenic component here was ignored as the forests were our main interest. To consider the coping capacity in a simplified manner, we finally took the availability of open water (European Environment Agency, 2018) and distance to fire stations (OpenStreetMap, 2026) into account. Table 1 briefly summarizes the parameters considered.

Table 1: Summarizing overview of considered variables in the applied vulnerability index.

Category	Vulnerability Component	Operationalization	Dataset	Source
Coping Capacity	Distance to nearest surface water	Euclidian distance to nearest water pixel	Corine land cover 2018	EEA, 2018
Sensitivity	Ecoregion sensitivity	Sensitivity scores 0-1	Ecoregions2017	Dinerstein et al., 2017
Coping Capacity	Distance to nearest fire station	Bivariate: 10 km buffer around fire stations (0 or 1)	OpenStreetMap	OSM, 2026
Exposure	Historical fire occurrences	Rasterization; Historic Fire yes / no (0 or 1)	European Forest Fire Information System	EFFIS team, 2026
Exposure	Climate favorability	Normalization (0-1) of mean daily value (2020-2025)	Fire danger index	Copernicus Climate Change Service, 2019

The general sensitivity of forest ecosystems to wildfires was represented through a European ecoregion dataset (Dinerstein et al., 2017). First, the Ecoregions2017 vector dataset was clipped to the study area. Since the dataset contains qualitative biome classifications rather than quantitative vulnerability information, sensitivity scores were assigned based on the relative wildfire vulnerability and recovery characteristics of major European forest biomes reported by Dinerstein et. Al. (2017). Mediterranean forests, woodlands, and scrub were assigned the lowest sensitivity score of 0.3 due to their comparatively high adaptation to recurring fire events. Temperate broadleaf and mixed forests as well as temperate conifer forests received intermediate scores of 0.5 and 0.6, respectively. Boreal forests and taiga were assigned the highest sensitivity score of 0.8 because of their generally slower regeneration and lower adaptation to frequent wildfires. The resulting vector layer was rasterized and normalized to a range between 0 and 1.

Surface water bodies were extracted from the CORINE Land Cover 2018 dataset (European Environment Agency, 2018). Specifically, the classes *Water Courses*, *Water Bodies*, *Coastal Lagoons* and *Sea and Ocean* were selected and converted into a binary raster, where water pixels received a value of 1 and all remaining land cover classes a value of 0. Using the GDAL proximity algorithm implemented in QGIS, the Euclidean distance from each raster cell to the nearest water pixel was calculated. The resulting raster represents the straight-line distance to the nearest available surface water body. Higher values therefore indicate lower availability of water resources for firefighting and consequently a higher vulnerability. To ensure comparability with the remaining variables, the distance raster was normalized to a value range between 0 and 1.

The raster layer regarding climate favorability was calculated with the mentioned Copernicus data on the McArthur Mark 5 forest fire danger index. First, these data were clipped to the extension of Europe.

Then, the daily values from 01.01.2020 to 31.12.2025 were averaged to one mean value. Since the spatial extension was too large, the data was gridded to 0.009° (WGS84). The resulting file “Europa_FDI_Mittelwert_1km.tif” was then used in the further process.

To generate a meaningful raster layer of historical fire occurrences, the previously cited data were transformed from a vector geometry to a raster grid with 0.009° cell size (WGS84). So first, an empty raster grid containing 0-values in each cell was created for the required spatial extension. Then, the polygons were overlayed. If a polygon, representing a historic wildfire area, touches a raster cell, it gets a value of 1. “Europa_Brandgebiete_1km_WGS84.tif” was the resulting file we continued with.

The distances to the nearest fire stations were calculated with the previously cited OSM-fire stations (point data). It was decided to work with a buffer distance of 10km around each fire station to distinguish areas that can be quickly accessed by firefighters, which corresponds to values in the literature (Rodrigues et. Al., 2019). The process was simplified to a linear buffer to not overcomplicate the process. Furthermore, it would have been necessary to distinguish between different road types, their current state etc. if the road network were to be considered properly. So first, the coordinates of each recorded fire station were opened in QGIS. After that, a linear buffer of 10km was applied to each fire station, and overlapping buffers were unified to one polygon. This vector polygon file was rasterized to 0.009° (WGS84) in QGIS. Raster cells outside a buffer zone were given the value of 1 and within a value of 0, resulting in the final file “firestations_buffer_raster_1km.tif”.

2.4.2 Creation of vulnerability sub-index

The final creation of the vulnerability index was based on the approach of Oliveira et. al. (2018), where the vulnerability was created as a product of exposure, sensitivity, and coping capacity, more specifically using the following formula:

$$Exposure \cdot 0.5 + Sensitivity \cdot 0.3 + Coping\ Capacity \cdot 0.2$$

We preserved the basic weights but gave individual weights to each of our considered sub-indices, resulting in the following formula:

$$(Climate\ Favorability \cdot 0.8 + Historical\ Fires \cdot 0.2) \cdot 0.5 + Ecoregion\ Sensitivity \cdot 0.3 \\ + (Distance\ to\ Surface\ Water \cdot 0.5 + Distance\ to\ Firestation \cdot 0.5) \cdot 0.2$$

It was difficult to find literature matching our specific application when it comes to the sub-weights. In the first parameter, the areas containing historical wildfires were weighed considerably less than the fire danger index, as a historic fire does not indicate future fires. Nevertheless, historic fires were considered since most of the forest fires are started due to anthropogenic causes (Genteaume et. Al., 2012). Thus, historic fire areas might indicate regions more prone to human activities triggering wildfires. The sensitivity component contains just one variable, so no weighting was necessary here, whereas our coping capacity contains two variables. Here, it was decided to weigh the distance (buffer) to fire stations and surface water equally. It seemed too difficult to justify a different weighting score over the wide set of geographies across Europe, as both fire stations with equipment and staff and open water spaces to supply firefighting helicopters or planes seem essential to stop a forest fire.

To finally create the overall vulnerability index and avoid biased or distorted results, the values in the previously discussed layers needed to be normalized, as indicated by some document names in the equation above. The original value range for each data set can be seen in table 2. These were normalized to a range of 0 to 1, meaning that 0 represents the lowest and 1 the highest occurring value. After this normalization, the layers were combined to the final layer “final_vulnerability_layer.tif” through the equation described previously.

Table 2: Summarized value-ranges for each variable before normalization.

Dataset	Value-range	High values = high vulnerability
Ecoregion Sensitivity	0.3 - 0.8	True
Dist. to Fire stations	0 - 1	True
Fire Occurrence	0 - 1	True
Climate Favorability	0 - 28	True

2.5 Ecological Value dimension

2.5.1 How do we define ecological value/ecosystem value of forests to wildfires?

First, we compute the whole area of forest as an extent of the analysis. Following the categorization of ecosystem services proposed by (Rodríguez-Loinaz et al., 2015), we included the following datasets for the ecosystem value subindex of forests (Table 3).

Table 3: Summarizing overview of considered variables in the applied ecological value index.

Category	Ecosystem/ Ecological value	Operationalization	Dataset	Sources
Forest area	Extent of analysis (where wildfires are possible)	km2	CORINE Land Cover 2018 (vector/raster 100 m), Europe, 6-yearly	Copernicus EU agency
Biodiversity	Species richness/endangered species (red list)	Natura2000 habitat yes/no	Natura2000	European Environment Agency (EEA)
Biodiversity	Value of forest	Share of old-growth forests/primary	Corinne land	Lozano et al., 2025
Provisioning	Timber production	Ton per ha of timber production	BAWS Map 2020 (Forest Biomass Available for Wood Supply)	Avitabile, V. (2023) via Figshare
Cultural	Recreation	Continuous 0-1 metric (proportion of landscape modified)	Global Human Modification (HM)	Kennedy, C. et al. (2018) via Figshare
Regulating	Climate local regulation function -> Biomass	Ton per ha of dry aboveground forest biomass density	Biomass map 2020	Avitabile, V. (2023) via Figshare Collection
Regulating	Improved air quality	Areas near cities	European air quality data for 2019	European Environment Agency (EEA) via EEA SDI Portal

Besides the forest area defining the extent of the analysis (Copernicus EU agency), for assessing ecological value we use species richness (Natura2000 European Environment Agency (EEA)) the value of forest meaning the share of old-growth forest (Lozano et al., 2025), timber production per area (Avitabile, V. (2023), recreation value (Kennedy, C. et al. 2018), climate local regulation function (Avitabile, V. (2023) and improved air quality (European Environment Agency (EEA). The selection of these ecosystem values is also based mainly on (Rodríguez-Loinaz et al., 2015) but was adapted by the authors for assessing forests in particular (Orsi et al., 2020). In this specific CORINE raster these forest classes are stored as internal raster values 23, 24, and 25.

All available input raster layers were then transformed to a shared grid, ensuring a common projection (EPSG:3035) and spatial resolution (1000m). For the integration of the different inputs, an equal weighting at category level was used. In a final step, the category-weighted MESLI was normalized to the full observed min to max range (MESLI_ecological_value_1000m_epsg3035.tif). It serves as the y-axis of the bivariate indicator together with the vulnerability dimension. Outside CORINE forest classes 311, 312, and 313, all final score layers and MESLI are set to NoData.

2.6 Bivariate Index

We combine the ecosystem value dimension (y-axis) and vulnerability dimension (x-axis) to a bivariate index. For this, we ensured again full alignment of shared grid regarding projection (EPSG:3035), resolution (1000 m) and extent (forest mask). Then we classified each pixel into one of four quadrants using Fisher-Jenks breaks (k=2), applied independently to the ecosystem value and vulnerability dimension. As low ecosystem values were classified all pixels with values below 0.4332, all others have "high ecosystem value". For vulnerability, all pixels below 0.5123 were classified as "low vulnerability", above as "high vulnerability". These thresholds were obtained through the Fisher-Jenks breaks.

2.7 NLP Retrieval

To elevate the bivariate index to a potentially performance-based indicator, data about how European countries address wildfire in their national policies is required. Since no dataset is available for wildfire policy in Europe, we screened the EU Wildfire report 2024 using natural language processing (NLP) to retrieve wildfire policy coverage and automatically classify countries regarding their policy coverage. First, the report was separated into text files for each country based on page number. Second, for each text file following keywords indicating more wildfire policies were searched for:

"Prevention", "Adaptation", "Strategy", "Research activities", "Wildfire management", "Awareness campaigns", "Information campaigns"

This keyword search is based on the assumption that countries reporting more about their wildfire measures and strategies, are also more advanced regarding wildfire policy. The underlying hypothesis is that member states are required to report wildfire occurrences and damage, but it remains voluntary to state prevention measures and strategies. Thus, countries with more advanced policies and higher resources dedicated to this area are hypothesized to be more likely to voluntarily report on these measures. Limitations of this approach are discussed in section 4.

The resulting classification is exported as a tabular excel file and as a spatial layer that is consumed as an optional overlay in notebook 2's interactive map. Each country is classified as the absolute number of matching keywords. The scope of this retrieval are not only EU member states, but all members of the Fire management system including Switzerland and the United Kingdom. The results were validated by reading manually through four countries' sections. All steps were automated to ensure full reproducibility.

3 Results

3.1 Ecological Value & Vulnerability

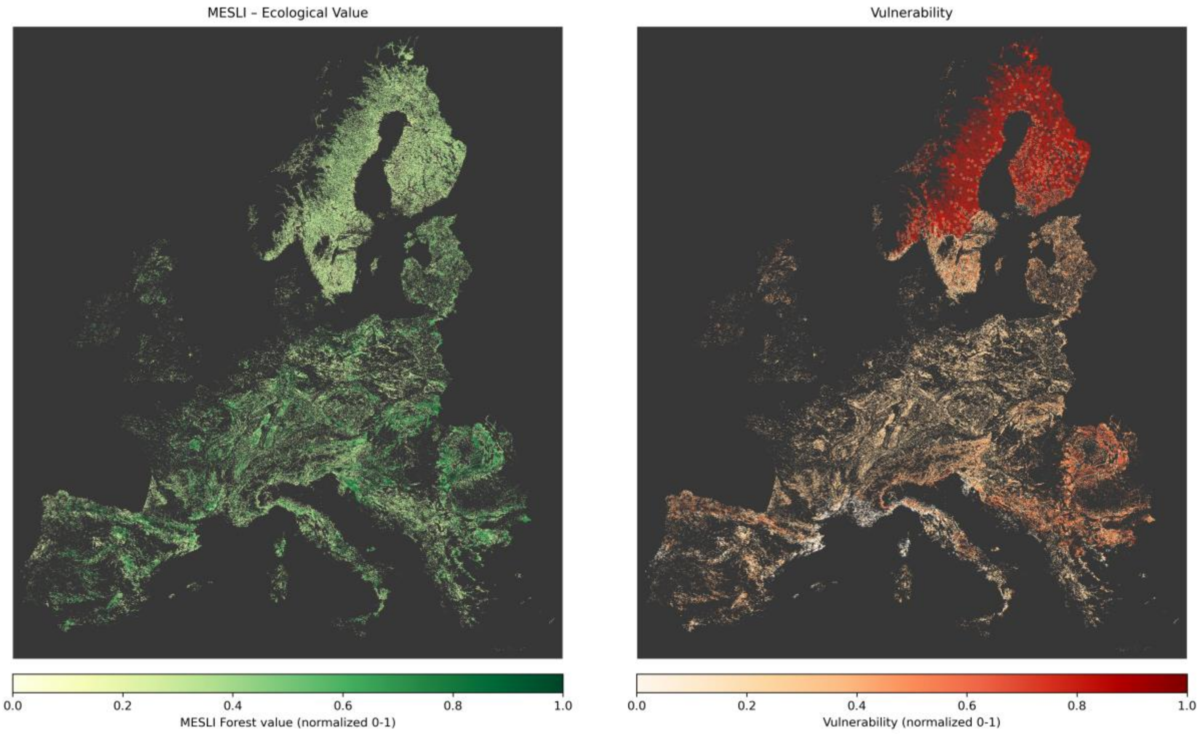

Figure 2: Result of the calculated MESLI index for the ecological value and wildfire vulnerability index for Europe, respectively, considering our forest mask based on the Corinne data set.

As visible in figure 2, the overall result for our wildfire vulnerability index shows some interesting characteristics. First, it is clearly visible that in tendence the vulnerability in Scandinavia seems to be notably higher than in central and parts of southern Europe. Mountain regions like the Alps, the Scottish Highlands or the Carpathian Mountains visually seem to come with higher vulnerability scores as well. It is visible that there are larger areas of relatively consistent vulnerability values, and the boundary to bordering areas is often very sharp. On the other hand, it seems that in Scandinavia, the ecological value of forests is generally lower compared to the central and parts of southern Europe. There are no large areas with very homogenous values, and the transition between ecosystems seems to be more gradual than in the vulnerability index.

3.2 Bivariate Index

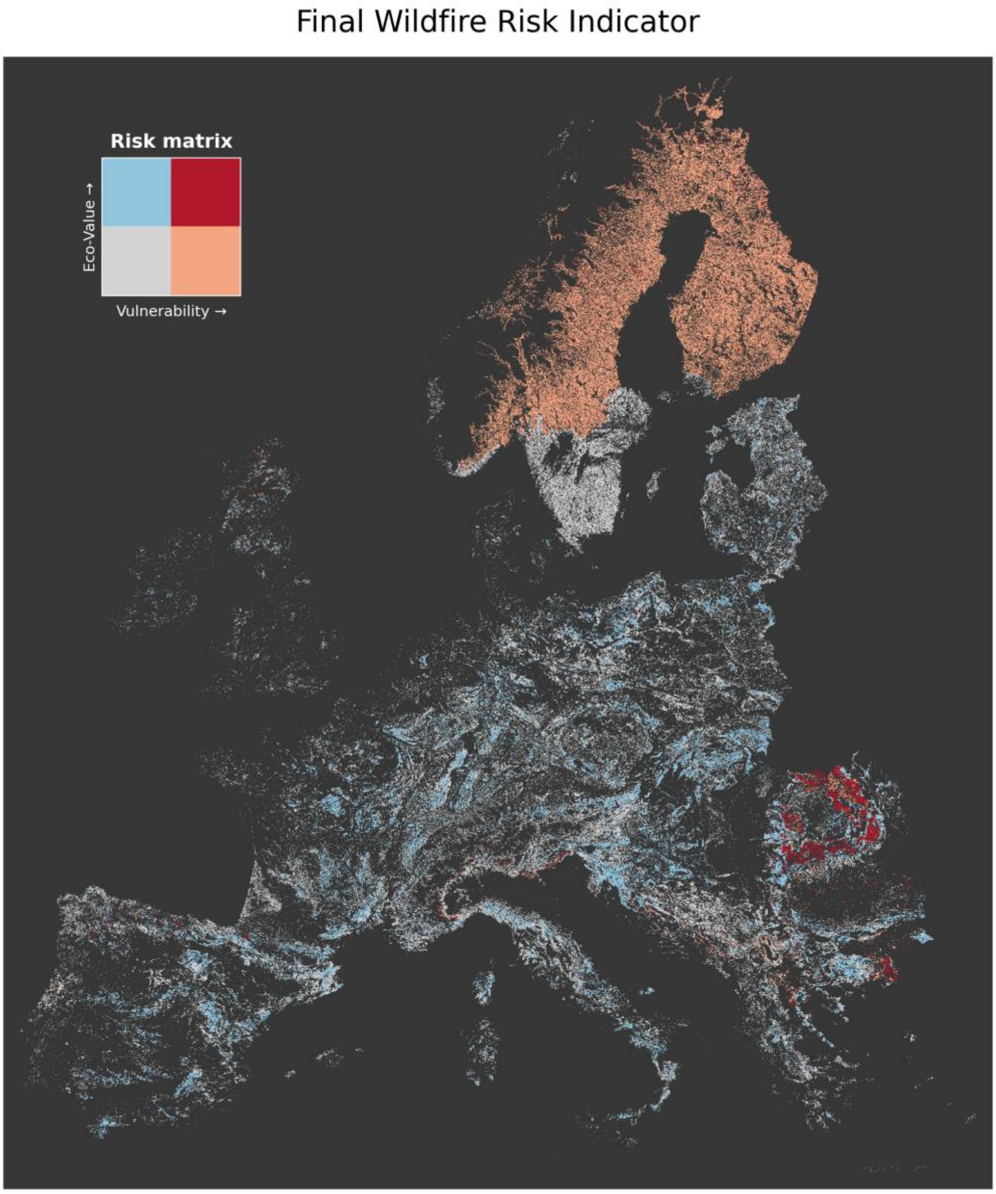

Figure 3. Result of the final wildfire risk indicator visualized as a bivariate matrix and with the vulnerability and ecological value combined to one final index value. Interactive map: https://mlengenfelder.github.io/GEO888/

In figure 3, the result of our combined wildfire risk indicator can be seen for all considered forest areas in Europe. It stands out that some of the sharp boundaries, especially in Scandinavia, from previously discussed vulnerability results, are clearly visible here in the final index as well. The areas with both high ecological value and vulnerability seem to be mainly located in the Carpathian Mountains, Bulgaria, and the Southern Alps. The low mountain ranges of central Europe, such as the Schwarzwald or Massif Central, show in general a high ecological value, but low vulnerability. Especially in large parts of Scandinavia, the opposite seems to be the case.

3.3 Performance based (NLP Retrieval)

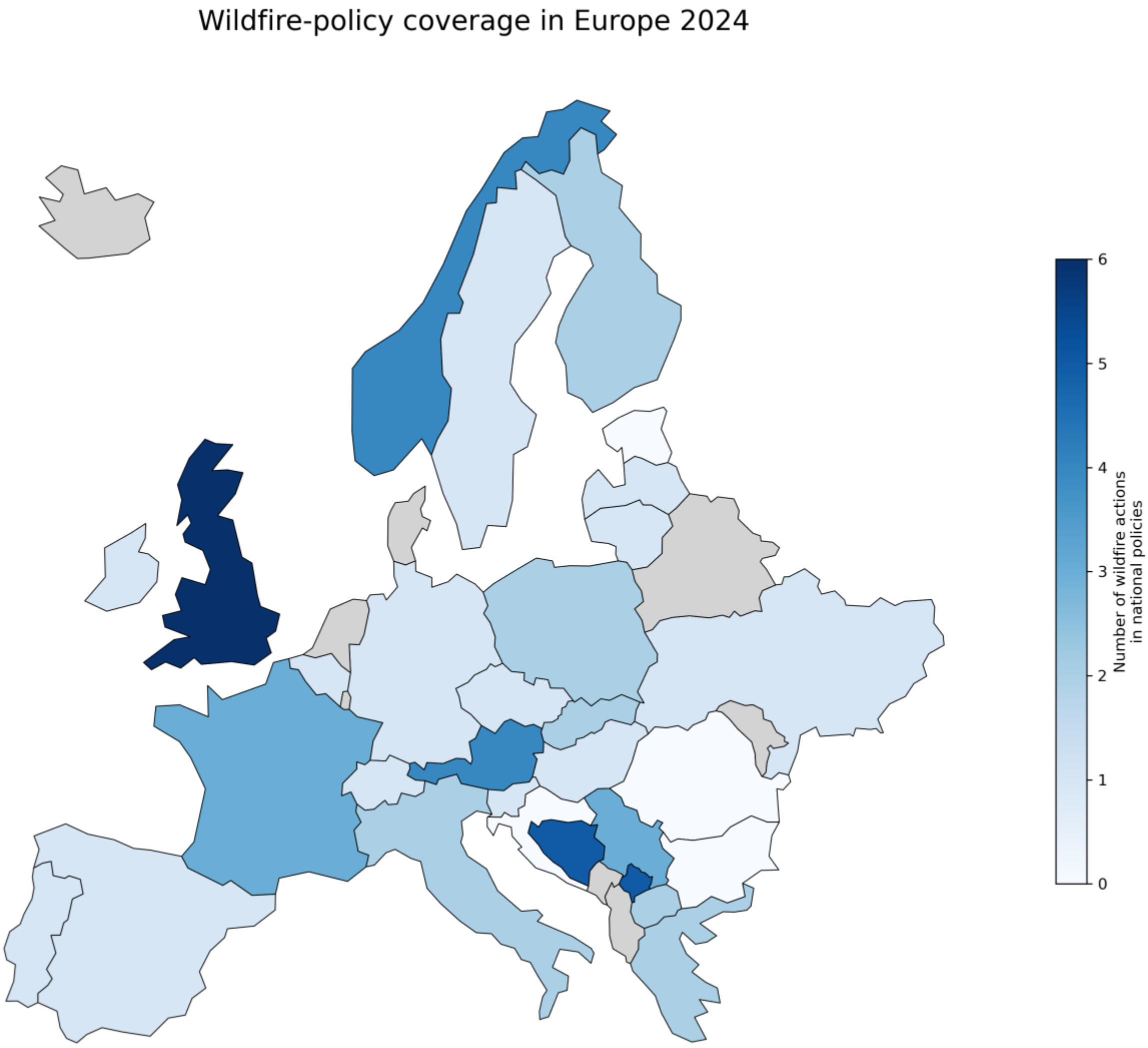

Figure 4: Result of NLP-Retrieval to visualize national wildfire policy coverage in Europe.

Figure 4 gives an overview of the wildfire policy coverage in Europe, generated through our conducted NLP-retrieval. According to the map, UK has with six matching keywords the highest number of wildfire actions in national policy under the performed analytical procedure. Other countries with a high wildfire policy coverage include France, Austria or Norway amongst others. On the other hand, Romania and Bulgaria, both containing noteworthy forest areas of both high vulnerability and ecological value, seem to have no policies in place. Some countries also have missing data as it is the case for Luxembourg or Island.

4 Discussion

4.1 Vulnerability

The resulting vulnerability map reveals several spatial patterns across Europe. Most notably, forest ecosystems in Scandinavia show comparatively high vulnerability values, while large parts of lowland Central Europe show lower and more consistent vulnerability scores. Elevated vulnerability can also be observed in several mountain ranges such as the Alps, the Carpathian Mountains and the Scottish Highlands. The map further displays relatively sharp transitions between vulnerability classes, which can largely be attributed to the ecoregion-based sensitivity component. Since broad biome categories were assigned common sensitivity values, neighboring regions belonging to different ecoregions often show abrupt changes in vulnerability.

At the same time, the indicator demonstrates that wildfire vulnerability cannot be explained by climate alone. The inclusion of ecosystem sensitivity and coping capacity introduces additional spatial variability. Areas located far from surface water bodies or firefighting infrastructure receive higher vulnerability scores, even if the climatic favorability for wildfires is comparatively low. This highlights the importance of considering both environmental and management-related factors when assessing wildfire risk.

Nevertheless, several limitations of the approach should be acknowledged. First, the sensitivity component was derived from expert-based scores assigned to four broad ecoregion classes. While these scores were obtained from literature, they represent a simplification of complex ecological processes and do not fully capture local differences in fire resistance and post-fire recovery. Furthermore, the coping capacity component was also strongly simplified. For example, accessibility to fire stations was represented by a fixed buffer distance rather than actual travel times along the road network. It seemed too complex for this project to assess accessibility through the road network, as there are for instance different types of roads which need to be distinguished and treated differently. Similarly, the distance-to-water variable assumes that all surface water bodies are equally suitable for firefighting operations, which may not always be the case.

Further limitations concern the weighting of the individual variables. Although we followed Oliveira et al. (2018), the sub-weights assigned within each component were based on literature review and expert judgement rather than statistical calibration. Different weighting schemes could therefore lead to somewhat different spatial patterns.

Finally, some results differ from some findings reported in the literature. For example, Arrogante-Funes et al. (2024) identify Mediterranean ecosystems as particularly vulnerable due to their ecological sensitivity and slow recovery. In contrast, we assigned lower sensitivity values to Mediterranean forest biomes because of their long-term adaptation to recurring fire events. This illustrates how methodological choices and indicator definitions can influence the resulting vulnerability assessment.

Despite these limitations, the vulnerability index provides a useful overview of forest areas that may be particularly affected by wildfires. By combining climatic conditions, ecosystem characteristics and factors related to firefighting capacity, it considers several different aspects of wildfire vulnerability rather than focusing on a single variable. The resulting map can therefore serve as a starting point for identifying areas that may require increased attention in wildfire management and forest protection. To get more robust results, it would be necessary to conduct a comprehensive analysis and more systematically assess the weighting scores, conduct a detailed sensitivity analysis, and validate the index with reliable ground truth data, for instance with disaster reports or remote sensing data.

4.2 Ecological value

The ecological value sub-index is a comprehensive metric encompassing all four ecosystem value categories showing the ecological value of different forest areas. By integrating six different datasets ranging from species richness to climate regulative function or cultural services, we were able to give an overview of many ecological information on one map. It shows forest areas which are more ecologically valuable, and are thus more important to protect than others, highlighting areas where wildfire mitigation measures should be prioritized. Thus, this analysis serves as crucial decision support of wildfire management and forest conservation. With a spatial resolution of 1km, the ecological value sub-index not only serves at supranational and national level but also allows for regional and local analysis. Comparing our results with existing literature proved to be challenging, since the exact combination of datasets was not used in other studies. Thus, different studies each focusing on one aspect were combined.

Central Europe with countries such as France and Germany but also the Adria region near Croatia, Italy or Bulgaria and Rumania show high ecological values of forest. Lower values are only detectable in Scandinavian countries. These findings are in line with previous findings in the literature (Avitabile *et al.*, 2024), which show that for example the mean Biomass of forest per area or the percent of forest area available for wood supply are low in Scandinavian countries. This can be explained by colder temperatures, reduced solar radiation and generally shorter growing season. It also points to the limitation of the operationalization of the ecological value index with these datasets, where rather than real ecological differences the mere geographical, positional differences explain part of the variability in the ecological value of forests. It remains difficult to quantify how much of the pattern can be explained by geographic region and how much by other factors.

However, at the same time, a global forest management study of (Lesiv *et al.*, 2022) showed, that primary forests in Europe were almost only present in the Scandinavian countries. Also, naturally regenerating forests occur more often than in other European countries. While our ecological value sub-index does not allow a direct comparison to it, the mapped low ecological value of forests for Scandinavian countries may suggest too low ecological value. In our opinion, a “biogeographic normalization” should be applied in these cases, where a supranational indicator is currently not considering the geographic and related climatic differences. In our map, often if there is forest, also its ecological value is high. This can be explained by the vital ecosystem functions of forests (Kirby, K.J; Watkins, C. (eds.), 2000). There are no large areas with very homogenous values, and the transition between ecosystems seems to be more gradual than in the vulnerability index.

This sub-index has also limitations. First, we didn’t consider that the ecosystem values can be strongly correlated such as the forest type and species richness. It is likely that in old-grown natural forests species richness is also significantly higher than in relatively new forests. By adding up these correlated values, some aspects may be overrepresented in comparison with the intended balance.

Second, although our weighting procedure and categorization was based on literature (Rodríguez-Loinaz, Alday and Onaindia, 2015), perhaps also a combination with expert-based weighting could have been used. For instance, since for the provisioning category only timber production was selected, it might have too much weight if we compare it to other categories such as biodiversity, which seem intuitionally more important.

Third, it is important to note that non-EU members such as Switzerland or Norway are likely to have forest with higher ecological value than depicted in the map. This is due to the fact, that for example for the species richness the dataset “Natura2000 habitat” was selected, which only covers EU-countries, although in reality these countries have also forest areas with high biodiversity. In addition to this, there are many more habitats with high biodiversity than only the protected Natura2000 habitats.

Finally, the selection of values was also strongly related to dataset availability. For example, for the category “cultural” we would have liked to include more datasets, but only limited data was available, since cultural factors are more difficult to measure quantitatively. Ultimately, our project is also prone to the general bias of data collection. Patterns, where no data was collected, were also simply not present in our analysis. The choice of what to measure predetermines to a certain extent not only the scope, but also the results of the study (Rubin and Little, 2019).

4.3 Bivariate index

The bivariate index shows two dimensions simultaneously, without the need to sum up both axes. Limitations include the abrupt classification of high to low vulnerability resp. ecosystem values with only two groups. However, we opted for this simplified classification, since the map and legend would be easier to interpret for our target non-academic audience such as policymakers. All other limitations were already previously discussed in each section of the sub-indexes.

4.4 NLP Retrieval

By using Natural language processing (NLP) retrieval, we were able to enrich our indicator by a policy dimension, making it a performance-based indicator instead of descriptive. Combined with the vulnerability and ecological value layer, the overview of wildfire policy coverage in Europe gives actionable insights into *where* wildfire policies need to be prioritized, answering our initial research question.

More specifically, our indicator shows that there are countries such as Romania and Bulgaria with forests of high ecological value and vulnerability, which at the same time have very few or no wildfire policies in place. Also, in Spain and Portugal, implementing wildfire policies seems to be highly beneficial, since its vulnerability and ecological value of forest are rather high, while the number of wildfires policies remains low. This highlights a high potential of wildfire policy implementation in these countries compared to other countries such as the United Kingdom, where wildfire policy coverage is high, but vulnerability and ecological value of forests are rather low. In general, it shows that wildfire policy is not always a mere response to actual wildfire risk, but rather a general product of national policy processes. Ultimately, the map shows where prioritizing measures is required, ensuring a more efficient allocation of resources.

However, mapping wildfire policy coverage using NLP has also limitations. When validating manually, countries with important wildfire policies in place such as Switzerland, were falsely not shown to have high policy coverage on the map. This is likely due to the fact, that in the EU wildfire report Switzerland declared very little on their existing wildfire measures. Thus, while the NLP itself worked correctly with the specified keywords, it is based on an assumption that is not entirely robust. Some countries with actual large wildfire policy efforts remain undetected, indicating a rather high number of “false negatives” (countries predicted as low policy coverage, although actually policy coverage is high).

However, countries mapped with high policy coverage, do also have in reality many measures in place (few “false positives”). According to the map, countries with high policy coverage are the United Kingdom, France, Austria or Norway. When validating manually, countries such as France do have advanced national strategies in place for wildfires such as the 3rd National Climate Change Adaptation Plan (PNACC-3) in France, where wildfires are specifically addressed with a “national strategy for the defense of forests and non-wooded areas against fires” in Art. 1 of the mentioned law (Sedano *et al.*, 2025). For the case of Austria, besides climate adaption policies in relation to wildfires, also funded research activities are reported, such as FIREDATA or the Austria Fire Futures (AFF) (Sedano *et al.*, 2025). These examples illustrate that the countries mapped as having a high number of wildfire policy coverage are correctly depicted, but more caution needs to be taken in countries mapped as low wildfire policy coverage, since they could still have advanced policies in place such as Switzerland but remain undetected. Thus, this map remains a conservative approach for giving a first overview of wildfire policy coverage.

Our approach could be improved by enlarging the corpus for the NLP retrieval with other wildfire documents, including national documents of all member states, although it would be out of scope for this project. However, methodologically, we showed that using NLP for mapping policy coverage can be a useful tool to develop a performance-based indicator.

4.5 Quality of data and validation

This indicator is related to uncertainty. Uncertainty stems from the data itself, but also from the selected methods, definitions (Schulp *et al.*, 2014) and other present limitations, which were already discussed previously in section 4. Regarding the ecological value sub-index, one study conducted a systematic review of ecosystem services maps and their uncertainty on European scale. Maps regarding climate regulation an23d recreation were related to low uncertainty, while ecosystem services such as erosion protection or flood regulation were associated with large differences between studies, indicating high uncertainty (Schulp *et al.*, 2014). Since we didn't include these last ecosystem services, uncertainty of the ecological value sub-index remains comparably low.

To validate the results, several options are available such as sensitivity analysis, internal validity or visualization (Rykiel, 1996). We opted for visualization with existing literature as a goodness of fit check for both main dimensions ecological value and vulnerability and internal validity for the policy dimension.

For ecological dimension, our results are in good agreement with previous findings (Orsi et al., 2020). As can be derived from figure 5, also in Orsi et al the Scandinavian countries show rather low ecological values and central Europe has high values. It diverges to some extent regarding Bulgaria and Rumania, where our results indicate high ecological value, but on the validation map they are moderate.

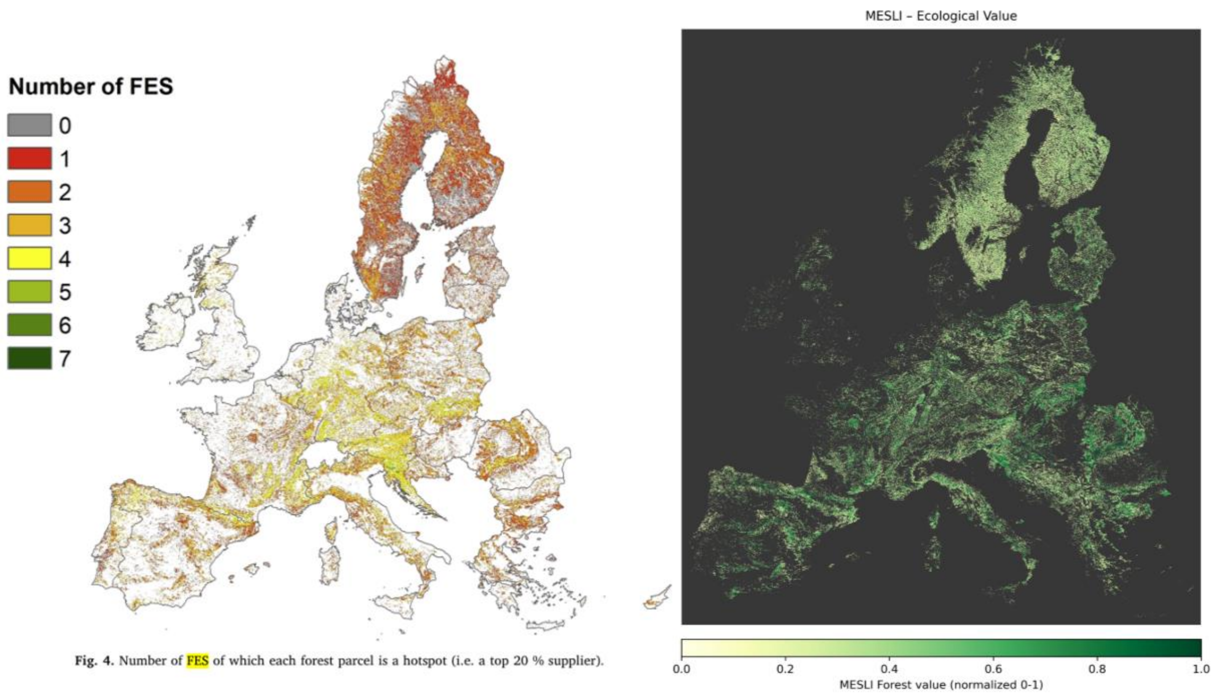

Figure 5: Number of forest ecosystem services as validation (left), and our ecological value sub-index result (right)

Regarding the vulnerability dimension additional uncertainty originates from the ecoregion sensitivity layer. Since no Europe-wide dataset describing wildfire sensitivity of forest ecosystems was available, relative sensitivity scores were assigned based on literature and expert judgement. Furthermore, the coping capacity component was simplified by using a fixed buffer distance around fire stations and Euclidean distance to surface water, which may not fully represent actual firefighting conditions.

5. Conclusion

This spatial analysis combines ecological value, vulnerability and policy dimensions to create a bivariate performance-based indicator of wildfire risk for Europe. It highlights areas where the protection of important ecosystems should be prioritized. The ecological value sub-index integrates six datasets covering biodiversity, climate regulation, cultural services, and other ecosystem functions to identify forests with high ecological importance. The vulnerability index assesses wildfire risk by combining climatic conditions, ecosystem characteristics, and firefighting capacity. The results highlight forest areas that are both, highly valuable ecologically and highly vulnerable to wildfires, making them priority targets for protection. Furthermore, using Natural Language Processing (NLP), we were able to map wildfire policy coverage for each country. Combined with the ecological value and vulnerability dimension, we show where the potential and impact of wildfire policies is highest, supporting the prioritization of measures. Our methodological contribution consists in demonstrating that using NLP for mapping policy coverage can be a useful tool to develop a performance-based indicator. Overall, this analysis serves as crucial decision support of wildfire management and forest conservation.

AI Statement

LLMs were used to improve grammar as well as creating and debugging code in this project, especially for content and challenges that go beyond the scope of the course. All content, analysis, and arguments remain the author's own, and any information derived from external sources is properly cited.

References

Arrogante-Funes, F., Mouillot, F., Moreira, B., Aguado, I., & Chuvieco, E. (2024). Mapping and assessment of ecological vulnerability to wildfires in Europe. *Fire Ecology*, *20*(1), 98. https://doi.org/10.1186/s42408-024-00321-8

Avitabile, V., Pilli, R., Migliavacca, M., Duveiller, G., Camia, A., Blujdea, V., Adolt, R., Alberdi, I., Barreiro, S., Bender, S., Borota, D., Bosela, M., Bouriaud, O., Breidenbach, J., Cañellas, I., Čavlović, J., Colin, A., Di Cosmo, L., Donis, J., … Mubareka, S. (2024). Harmonised statistics and maps of forest biomass and increment in Europe. *Scientific Data*, *11*(1), 274. https://doi.org/10.1038/s41597-023-02868-8

Berchtold, C., Petersen, K., Kaskara, M., Pettinari, M. L., Vinders, J., Schlierkamp, J., Kalapodis, N., Sakkas, G., Brunet, P., Soldatos, J., Lazarou, A., Casciano, D., Chandramouli, K., Deubelli, T., Scolobig, A., Silva, H., Plana, E., & Garofalo, M. (2025). Towards wildfire risk reduction goals and targets for Europe – Opportunities and challenges. *Climate Risk Management*, *50*, 100744. https://doi.org/10.1016/j.crm.2025.100744

Copernicus Climate Change Service. (2026). *Fire danger indices historical data from the Copernicus Emergency Management Service* [NetCDF]. https://doi.org/10.24381/cds.0e89c522

Copernicus Climate Change Service, Climate Data Store. (2019). *Fire danger indices historical data from the Copernicus Emergency Management Service. Copernicus Climate Change Service (C3S) Climate Data Store (CDS)*. Fire Danger Indices Historical Data from the Copernicus Emergency Management Service. https://doi.org/10.24381/cds.0e89c522

Dinerstein, E., Olson, D., Joshi, A., Vynne, C., Burgess, N. D., Wikramanayake, E., Hahn, N., Palminteri, S., Hedao, P., Noss, R., Hansen, M., Locke, H., Ellis, E. C., Jones, B., Barber, C. V., Hayes, R., Kormos, C., Martin, V., Crist, E., … Saleem, M. (2017). An Ecoregion-Based Approach to Protecting Half the Terrestrial Realm. *BioScience*, *67*(6), 534–545. https://doi.org/10.1093/biosci/bix014

EFFIS team. (2026). *Fire events in the European Forest Fire Information System (version 2-3-1).* [Dataset]. https://doi.org/10.2905/JRC.AJKEPV8

Eidg. Forschungsanstalt für Wald, Schnee und Landschaft WSL. (2026, May 20). *McArthur Mark 5 forest fire danger index*. https://wikifire.wsl.ch/tikiindex27fc.html?page=McArthur+Mark+5+forest+fire+danger+index

European Environment Agency. (2018). *CORINE Land Cover 2018 (raster 100 m), Europe, 6-yearly—Version 2020_20u1, May 2020* [Dataset]. https://doi.org/10.2909/960998c1-1870-4e82-8051-6485205ebbac

Forzieri, G., Girardello, M., Ceccherini, G., Spinoni, J., Feyen, L., Hartmann, H., Beck, P. S. A., Camps-Valls, G., Chirici, G., Mauri, A., & Cescatti, A. (2021). Emergent vulnerability to climate-driven disturbances in European forests. *Nature Communications*, *12*(1), 1081. https://doi.org/10.1038/s41467-021-21399-7

Ganteaume, A., Camia, A., Jappiot, M., San-Miguel-Ayanz, J., Long-Fournel, M., & Lampin, C. (2012). A Review of the Main Driving Factors of Forest Fire Ignition Over Europe. Environmental Management, 51(3), 651–662. https://doi.org/10.1007/s00267-012-9961-z

KIRBY, K.J.; WATKINS, C. (eds.). (2000). *Ecological History of European Forests*. CAB International. https://www.cabidigitallibrary.org/doi/book/10.1079/9780851992563.0000

Lesiv, M., Schepaschenko, D., Buchhorn, M., See, L., Dürauer, M., Georgieva, I., Jung, M., Hofhansl, F., Schulze, K., Bilous, A., Blyshchyk, V., Mukhortova, L., Brenes, C. L. M., Krivobokov, L., Ntie, S., Tsogt, K., Pietsch, S. A., Tikhonova, E., Kim, M., … Fritz, S. (2022). Global forest management data for 2015 at a 100 m resolution. *Scientific Data*, *9*(1), 199. https://doi.org/10.1038/s41597-022-01332-3

Marshall, N. A., Marshall, P. A., Tamelander, J., Obura, D., Malleret-King, D., & Cinner, J. E. (2010). *A framework for social adaptation to climate change: Sustaining tropical coastal communitites and industrie*s. https://www.cabidigitallibrary.org/doi/full/10.5555/20113007412

Mihajlovski, B., & Zhiyanski, M. (2025). Global Forest Fire Assessment Methods: A Comparative Analysis of Hazard, Susceptibility, and Vulnerability Approaches in Different Landscapes. *Fire*, *8*(10), 380. https://doi.org/10.3390/fire8100380

Oliveira, S., Félix, F., Nunes, A., Lourenço, L., Laneve, G., & Sebastián-López, A. (2018). Mapping wildfire vulnerability in Mediterranean Europe. Testing a stepwise approach for operational purposes. *Journal of Environmental Management*, *206*, 158–169. https://doi.org/10.1016/j.jenvman.2017.10.003

OpenStreetMap. (2026). *Fire_station* (No. 2002) [Dataset]. https://overpass-turbo.eu/

Orsi, F., Ciolli, M., Primmer, E., Varumo, L., & Geneletti, D. (2020). Mapping hotspots and bundles of forest ecosystem services across the European Union. *Land Use Policy*, *99*, 104840. https://doi.org/10.1016/j.landusepol.2020.104840

Rodrigues, M., Alcasena, F., & Vega-García, C. (2019a). Modeling initial attack success of wildfire suppression in Catalonia, Spain. *Science of The Total Environment*, *666*, 915–927. https://doi.org/10.1016/j.scitotenv.2019.02.323

Rodríguez-Loinaz, G., Alday, J. G., & Onaindia, M. (2015). Multiple ecosystem services landscape index: A tool for multifunctional landscapes conservation. *Journal of Environmental Management*, *147*, 152–163. https://doi.org/10.1016/j.jenvman.2014.09.001

Rubin, R. J. A. L., Donald B. (n.d.-a). *Statistical Analysis with Missing Data., 3rd Edition*. Retrieved June 5, 2026, from https://www.oreilly.com/library/view/statistical-analysis-with/9780470526798/

Rykiel, E. J. (1996). Testing ecological models: The meaning of validation. *Ecological Modelling*, *90*(3), 229–244. https://doi.org/10.1016/0304-3800(95)00152-2

Schulp, C. J. E., Burkhard, B., Maes, J., Vliet, J. V., & Verburg, P. H. (2014). Uncertainties in Ecosystem Service Maps: A Comparison on the European Scale. *PLOS ONE*, *9*(10), e109643. https://doi.org/10.1371/journal.pone.0109643

Sedano, F., San-Miguel-Ayanz, J., Broglia, M., Durrant, T., Boca, R., Maianti, P., Jacome, F. O. D., Branco, A., De, R. D., Suarez-Moreno, M., Ferrari, D., Roglia, E., Scionti, N., Liberta', G., & Tistan, A. (2025). *Forest Fires in Europe, Middle East and North Africa 2024*. JRC Publications Repository. https://doi.org/10.2760/0649290

United Nations - Department of Economic and Social Affairs. (2026, June 4). *Goal 15 | Department of Economic and Social Affair*s. https://sdgs.un.org/goals/goal15