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

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Executive Summary

The FirEUrisk project aims at improving the methodologies devoted to fire danger assessment. The danger maps produced with the new methodology need to be validated using truth data. To this end, we could exploit thermal anomalies (hot spots) and burned areas detected by using satellites images. Nevertheless, even assuming a successful validation, the adoption of any product resulting from the use of new technologies by the end-users or practitioners would be eased and encouraged by an assessment of their economic/social/environmental value.

The deliverable D1.8 "Methodological handbook for collection of fire data and validation standards. Includes an assessment of the value of FirEUrisk geospatial information" is a deliverable of the WP1, "Fire risk assessment to improve prevention", of the FirEUrisk project. The document builds upon FirEUrisk deliverable D1.1, D1.4 and D1.6 and on the activity carried out in the framework of the Tasks 1.1 (Fire Danger Assessment), 1.2 (Exposure & Vulnerability) and 1.3 (Integrated Risk Assessment and Validation).

This document provides a preliminary validation of the fire danger index (FDI) particularly focused on their capacity to predict fire occurrence and fire radiative energy (FRE) release across Europe. An additional validation procedure based on the distribution of burnt areas (BA) could be made difficult by the known discrepancies on the BA distribution of different datasets curated by different agencies or projects (as shown more extensively, even if for a single European country, in Laneve et al. 2024). In this document we demonstrate that some efforts are still needed in order to make the comparison of different BA datasets possible and to improve their accuracy by means of a validation based on ground-truth data. Finally, the document provides some hints on the way to assess the socio-economic value of the geospatial information integrated, validated and delivered by FirEUrisk in order to: i) improve the decision making of practitioners and end-users, ii) encourage the acceptance and adoption of integrated FirEUrisk solutions.

Objectives not achieved:
The assessment of the Value of the Geospatial Information (VOI) probably requires conducting a survey through a series of specifically targeted questionnaires. This was not done to avoid burdening end users with additional surveys. Possibly a specific project should be devoted to this purpose.

Key take away messages:
Geography matter: Product validation is a complex task that could give different results in relation to the area considered. Local specificity should be considered every time.
One dataset in not enough: Burnt areas datasets made available from different agencies of projects are affected by method, spatial resolution and land cover maps. Even data collected on the ground by national/regional authorities are not free from errors.

Value of the information for users: End-users should be encouraged to adopt products based, in particular, on new technology. A way to achieve this is showing them, through examples, how some of the fire management related products could help in reducing economic, social and environmental costs.

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Copyright message

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List of Acronyms

Table 1: List of Acronyms

List of Acronyms	
AIC	Akaike Information Criterion
AUC	Area Under the Curve
BA	Burnt Area
BAER	Burn Area Emergency Response
BARC	Burn Area Reflectance Classification
CAMS	Copernicus Atmosphere Monitoring Service
CCI	Climate Change Initiative
CDS	Climate Data Store
CLC	CORINE Land Cover
CLMS	Copernicus Land Monitoring Service
C3S	Copernicus Climate Change Service
DDP	Data Decision Pathway
DOI	Department of Interior
DRMKC	Disaster Risk Management Knowledge Centre
EC	European Commission
EFFIS	European Forest Fire Information System
EMS	Emergency Management System
EO	Earth Observation
ESA	European Space Agency
EU	European Union
FC	Functional Classification

FDI	Fire Danger Index
FFI	Forest Fire Index
FI	Fireline Intensity
FIRMS	Fire Information for Resource Management System
FL	Flame Length
FRE	Fire Radiative Energy
FRP	Fire Radiative Power
GDP	Gross xxx Product
GPS	Global Position System
GWIS	Global Wildfire Information System
IBE-CNR	Istituto per la BioEconomia – Centro Nazionale delle Ricerche
IRI	Integrated Risk Index
JRC	Joint Research Council
LFMC	Live Fuel Moisture Content
MASIFF	Methodology for the Analysis of Socio-economic Impact of Forest Fires
MCC	Matthews correlation coefficient
MCD	MODIS Combined Dataset
MODAPS	MODIS Adaptive Processing System
MODIS	MODerate-resolution Imaging Spectroradiometer
MW	MegaWatt
NPBP	National Prescribed Burning Program
NPP	National Polar-orbiting Partnership
NWP	Numerical Weather Prediction
NWS	National Weather Service

OLCI	Ocean and Land Colour Instrument
PI	Probability of Ignition
PP	Probability of Propagation
PREFER	Prevention and REcovery of Forest Fires Emergency in the MediteRranean Area
PSD	Power Spectral Density
RESV	Relative Social Vulnerability
ROC	Receiver Operating Characteristic
SBS	Soil Burn Severity
SEBS	Sentinel Benefit Studies
VE	Value Exploration
VIF	Variance Inflation Factor
VIIRS	Visible Infrared Imaging Radiometer Suite
VOI	Value Of Information
WP	Work Package
WTP	Willingness To Pay
WUI	Wild Urban Interface

1 Introduction

1.1 Purpose of the document

The present document (Deliverable 1.8 "Methodological handbook for fire collection of data and validation standards. Includes an assessment of the value of FirEUrisk geospatial information") is part of the Task 1.3.2 "Demonstration and evaluation of risk assessment products" and showcases the general approach to collect, exchange and process data from different sensors at different spatial resolutions and an assessment of the socio-economic value of the geospatial information provided by the project.

This document contains a description of the procedure for collecting fire related data and performing products validation in order to facilitate the exchange, comparison, and integration of data coming from different sources and improve the fire-related data quality.

A second objective of the document is the assessment of the socio-economic value of the geo-spatial information provided by the FirEUrisk project by considering the impact of such information can have in improving decision making and encouraging the acceptance and adoption of integrated FirEUrisk solutions.

In order to properly assess the socio-economic value of the geo-spatial information, and particularly of the satellite based data, one should consider the way this new information will be employed in the fire management procedures. To this end specific questions have been addressed to practitioners during the demonstration events.

1.2 Structure of the Document

This document is organised in three main parts.

Part 1 is devoted to providing a methodology to validate the maps of fire danger computed using the methodology developed in the framework of the FirEUrisk project.

Part 2 is devoted at comparing burnt area datasets made available in the framework of different initiatives and based on different satellite sensors, aiming at assessing the uncertainty on quality of the fire related data and at providing few hints on how to improve the interpretation of the data.

Part 3 is devoted at illustrating some approaches to assess the socio-economic value of the geospatial information provided by the project.

2 FirEUrisk fire danger index validation

2.1 Key questions and objectives

This part of the document aims at describing the procedure adopted to validate the fire danger index implemented in the framework of the FirEUrisk project and the results obtained by analyzing the data provided for the fire season of the years 2023 and 2024. The goal is to provide a first assessment of the capability of such index to predict the areas more prone to be affected by large fires.

The FirEUrisk project has proposed a comprehensive scheme for assessing fire risk, as described by multiple metrics that quantify fire danger, exposure, and vulnerability [Chuvieco et al., 2023]. This report focuses on the "danger" aspect of the fire index, specifically examining the extent to which the index components correlate with actual fire activity across Europe. Since the fire index is reported daily on a 1 by 1 km grid, datasets that closely match this spatial and temporal resolution were selected for comparison. As we are unaware of prior analyses examining the spatial and temporal information content of this index, we proceed with the assumption that this scale is suitable, but will try to assess the effective spatial and temporal resolution of the dataset as well.

The existing fire danger literature documents numerous fire risk assessment systems [Laneve et al., 2020; Zacharakis and Tsihrintzis, 2023; Yu et al.,2023; Zacharakis and Tsihrintzis, 2023; Chronopoulos and Matsoukis, 2021; Pagnon Eriksson et al., 2023; Bisquert et al., 2012; Alonso-Betanzos et al.,2003]. While these methods vary, they commonly incorporate meteorological data to infer fuel moisture levels and land cover data to estimate fuel loads and ignition probabilities. As these inputs are proxies rather than direct measures of fire occurrence and spread, newer models often integrate additional datasets, frequently derived from remote sensing, to improve predictive power. These models may involve creating fuel types, estimating live fuel moisture content, and quantifying potential burnable biomass.

Earth Observation (EO) data is also valuable in fire activity assessment. Fires produce abrupt and persistent changes in surface reflectance, which burned area mapping algorithms can use to delineate affected areas. Additionally, thermal sensors on contemporary satellites can detect fire-related heat emissions, which enable fire detection and allow calculation of fire radiative power (FRP) — a measure of fire intensity and a proxy for the amount of biomass burned.

This report aims to integrate the FirEUrisk danger assessment dataset with EO-based fire observations to evaluate the predictive value of the Fire Danger Index (FDI) metrics in forecasting fire occurrence, size, and intensity. To accomplish this, we will analyse the predictive power of various FDI metrics through statistical modelling.

2.2 Data and Methods

2.2.1 The FirEUrisk Risk Assessment Dataset

The daily FirEUrisk grid, with a 1 km resolution covering the European continent, was used to collect data for the period between June and October 2023 and 2024. The dataset includes the following components:

- Danger-PP (Probability of Propagation)
- Danger-PI (Probability of Ignition)
- Danger-D
- IRI (Integrated Risk Index)
- Vulnerability-FFI (Forest Fire Index)
- Vulnerability-V
- Vulnerability-Human
- Vulnerability-Ecological
- Propagation-FI (Fireline Intensity)
- Propagation-FL (Flame Length)
- Vulnerability-RESV (Relative Social Vulnerability)

These metrics are divided between those primarily relevant to "danger" and those focused on "vulnerability." Our analysis emphasises the danger components, although certain variables calculated from danger data, such as Propagation-FI and Propagation-FL, contribute to the vulnerability assessment.

The key danger variables are the **Probability of Propagation** (PP) and the **Probability of Ignition** (PI). The probability of propagation (PP) reflects current conditions favorable to fire spread, responding to changes in fuel moisture and environmental conditions. In contrast, the probability of ignition (PI) is generally static, with minor dynamic input from lightning ignitions. As a metric, PI provides an indicator of historical fire occurrence, while PP indicates present conditions that may facilitate fire spread. Values for PP and PI fall between 0 and 1, although in this document we have sometimes scaled these values by 1000 to make them more readable in some of the plots/discussion.

These two variables are combined to form the overall danger index at a time *t* as follows:

$$D(t) = 2/3 \cdot PP(t) + 1/3 \cdot PI(t) \quad (1)$$

In Figure 1, we illustrate the total variation of the Danger-PP metric over summer 2023 across Europe. This metric shows significant spatial variability, with some regions experiencing substantial fluctuation while others remain stable. Figure 2 presents the median Danger-PI metric over the same period, showing higher values in the Mediterranean/Southern European region where fire occurrences are historically frequent.

It should be noted that these metrics are derived from a variety of inputs, including meteorological data, EO-based estimates of live fuel moisture content (LFMC), land cover data, and additional ancillary sources. While the detailed calculation process is beyond the scope of this report, future research may explore the specific impact of these components on the PP model. The *PI* metric is derived from a random forest classifier trained on historical data and various covariates.

2.2.2 The Fire Evidence Dataset

Thermal Remote Sensing Data: VIIRS Thermal Anomalies

To obtain consistent and comprehensive evidence of fire activity across Europe, we relied on thermal remote sensing data from the Visible Infrared Imaging Radiometer Suite (VIIRS) instruments on the Suomi NPP and NOAA-20 satellites. This dataset, available at a nominal 375 m resolution, identifies the location and timing of thermal anomalies along with the thermal power emission of each fire (measured as fire radiative power, FRP, in megawatts). FRP has been shown to correlate with instantaneous biomass combustion [Wooster et al., 2005]. Data corresponding to the FirEUrisk dataset period (June to October 2023, 2024) were acquired from the MODAPS web server, with no additional corrections applied to the VIIRS data.

To facilitate analysis, we constructed several intermediate datasets:

- **Gridded Fire Occurrence Dataset**: This dataset records the presence of a fire if multiple hotspots (at least two) are detected within a ±2-day period. This approach accounts for the approximate daily revisit rate of the VIIRS instrument, ensuring that fires detected on adjacent overpasses are not overlooked. We acknowledge that using only two hotspots may not be restrictive enough, but alternative thresholds have not yet been explored.

- **Gridded FRP Dataset**: For each 10 km grid cell, we aggregated FRP values over 5-day intervals. This aggregation serves as a proxy for individual fire events, using summed FRP values to estimate the fire radiative energy (FRE) of each event. While straightforward, this method leverages the entirety of the VIIRS dataset without introducing uncertainties or inconsistencies from additional data sources. The grid cell size and integration time were chosen to be consistent with the FirEUrisk dataset information content as examined by the effective resolution analysis.

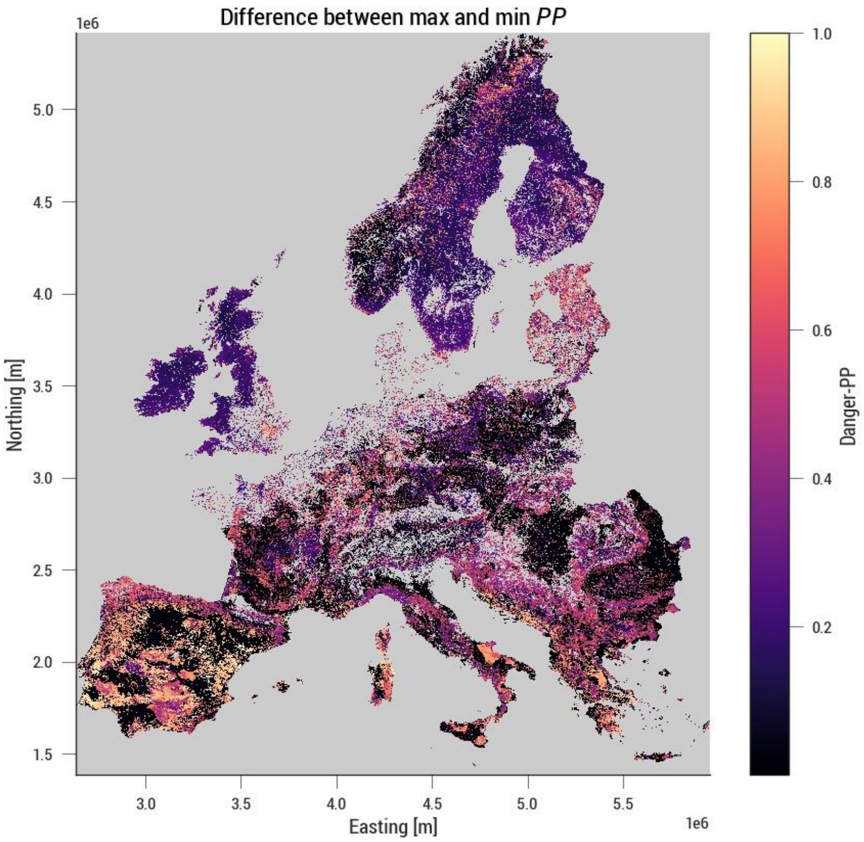


Figure 1. Total variation (difference between maximum and minimum) of Danger-PP over the summer of 2023 in Europe.

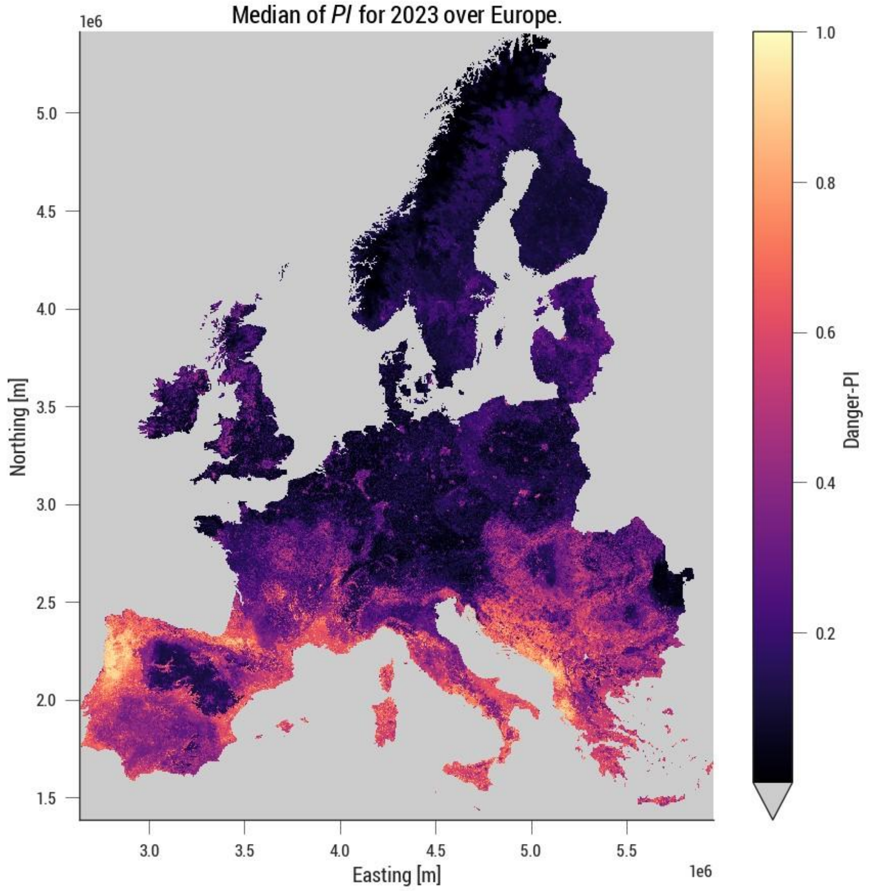


Figure 2. Median of Danger-PI over the summer of 2023 in Europe.

Optical Remote Sensing Data: EFFIS Database

We also incorporated data from the European Forest Fire Information System (EFFIS) (European Commission. Joint Research Centre. Institute for Environment and Sustainability, 2014), which provides manually delineated burn scars from summer 2023. The EFFIS database includes expert-verified boundaries of burn scars, offering insights into fire extent and dates. This dataset complements the FRP data by enabling exploration of fire events in terms of spatial extent. Although EFFIS is likely to miss smaller fires, it offers extensive coverage of larger events. Due to timing issues, we have not yet incorporated moderate resolution burned area products.

Figure 3 displays the centroids of EFFIS burn scars across Europe during summer 2023, with most fires concentrated in the Mediterranean region, and fewer in Northern and Central Europe.

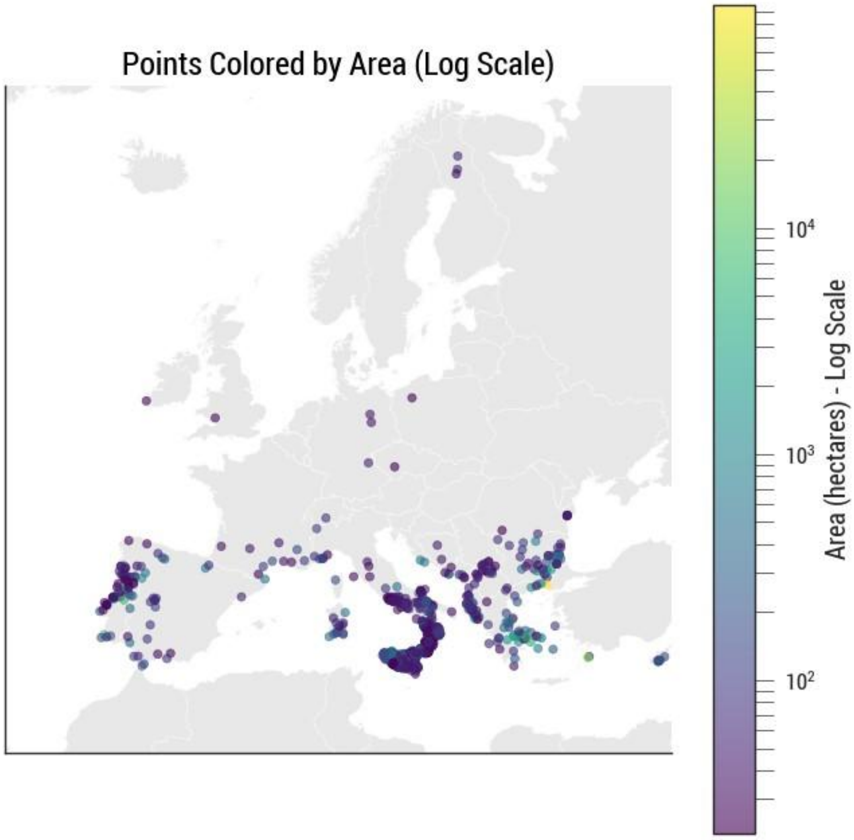


Figure 3. Centroids of EFFIS burn scars for June-September 2023 over Europe. The colour of the points represents the size of each fire.

2.2.3 Methods

Effective temporal and spatial resolution of the danger datasets

Although the FirEUrisk risk datasets are presented at a 1 km spatial resolution with daily updates, it is essential to examine their effective resolution. This can be assessed using power spectral density (PSD) analysis. In this approach, we compute the Fourier transform of the dataset in space and time, then square the amplitude of each frequency component to generate a power spectrum. For interpolated data, the spectrum tends to decline rapidly away from the zero-frequency component, suggesting limited spatial or temporal detail. We define a cutoff frequency ($f_{cutoff,t}$ for time and $f_{cutoff,s}$ for space) at a fraction of the maximum power, above which frequencies are neglected. The effective resolution can then be estimated by the Nyquist criterion as:

$$\Delta t_{eff} = 1/2f_{cutoff,t} \quad (2)$$

for time, and

$$\Delta s_{eff} = 1/2f_{cutoff,s} \quad (3)$$

for space. As the time dimension is short (≈120 days), we apply an oversampling with a factor of four via zero padding to increase the resolution of the resulting spectrum. To deal with the finite sample size, we use a Hanning window to limit the resulting spectral leakage and reduce sidelobes.

Individual FDI metrics as predictors of fire occurrence

To evaluate the predictive power of the daily Fire Danger Index (FDI) metrics for fire occurrence, we employed logistic regression models. Using the fire occurrence dataset as the dependent variable and the FDI metrics as independent variables, we tested each metric individually as a predictor. The model's predictive performance was quantified by the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) curve, where an AUC of 0.5 indicates no predictive power, and an AUC of 1.0 represents perfect predictive power. In addition, standard classification metrics (precision, recall, and F1 score) were calculated to further assess model performance. For multivariate models involving several predictors, we used Lasso regression for variable selection, standardising all variables to zero mean and unit variance, and determining the regularisation parameter through cross-validation.

FDI metrics as predictors of FRE and fire size

Linear regression models were applied to examine the capacity of FDI metrics to predict fire radiative energy (FRE) and fire size. Here, the dependent variable was either the gridded FRE dataset or the EFFIS fire sizes, both log-transformed, while FDI metrics served as independent variables. We evaluated the models' performance using the coefficient of determination ($R^2 \in [0,1]$), indicating the fraction of variation in the dependent variable explained by the model. For multivariate models, variables were added iteratively if they improved the model, with the Akaike Information Criterion (AIC) and R^2 used as criteria to evaluate model goodness-of-fit. The Variance Inflation Factor (VIF) was also calculated to detect multicollinearity, with models only considered acceptable if all VIF values were below 2.

Lagged FDI metrics

Preliminary analysis suggested that lagged values of the probability of propagation (PP) might be predictive of fire activity, potentially due to PP capturing short-term fuel drying effects. We calculated lagged medians of PP for periods of 3, 5, 10, and 15 days. For each fire event, the earliest fire date was taken as a reference, and median values of the lagged PP metrics were calculated for grid cells intersecting with the fire. The reported initial fire date from EFFIS burn scars or the central timestep from the gridded 5-day FRP dataset served as temporal reference points. We additionally calculated the slope of PP over the same time lags as the running medians.

Model fitting

To optimise predictive accuracy, the model selection process involved identifying an optimal set of covariates (e.g., variables from the FirEUrisk risk index, or their lagged versions) for predicting the transformed dependent variable (e.g., fire size or FRE). Each model subset was evaluated based on R^2 and AIC, with all covariates standardised and the target variable log-transformed for normality and consistency. Only models with VIF values under 2 were considered, ensuring minimal multicollinearity. The process prioritised models maximising R^2 while minimising AIC, iteratively updating the best-fit model configuration. This procedure is repeated for each threshold of the sum of FRP values (50, 150, and 200 MW) to assess the model's performance across different fire sizes.

For fire occurrence, the model selection followed similar procedures but utilised a logistic regression model due to the binary nature of the target variable. Performance was assessed using the AUC of the ROC curve, with values above 0.7 indicating useful discrimination. This approach ensured robust, parsimonious models with optimal predictive capacity and controlled multicollinearity.

2.3 Results

2.3.1 Effective resolution of the FDI metrics

For Danger-PP, the temporal PSD results are shown in Figure 4 and the spatial PSD is presented in Figure 5. The effective temporal resolution is around 9 days, whereas the spatial effective resolution is around 12 km. For Danger-PI, the spatial PSD is shown in Figure 6, and the effective resolution is around 4.5 km. In both cases, the effective spatial resolution is much larger than the nominal resolution of the dataset, suggesting that the dataset is quite smooth. Similarly, the effective temporal resolution is much larger than the nominal resolution of the dataset, suggesting an important amount of interpolation.

This analysis informs how we phrase the rest of the comparisons. Comparisons with fire evidence in the same scale as the effective resolutions (e.g. 5 km, 5-10 days) are likely to be more informative than comparisons at the nominal resolution of the dataset, where to the comparison of the information contained in the FDI metrics would also be convolved with the interpolation process.

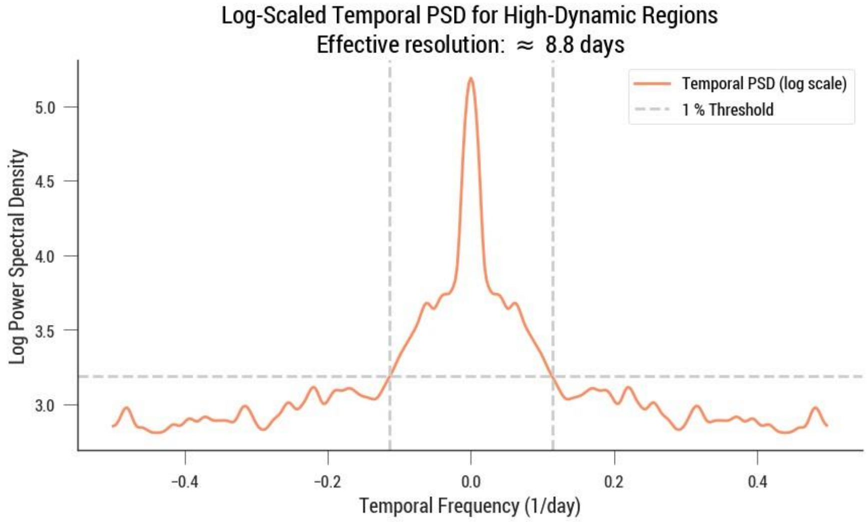


Figure 4. Power Spectral Density plot of Danger-PP over time for dynamic regions. Frequency cutoff points shown in grey.

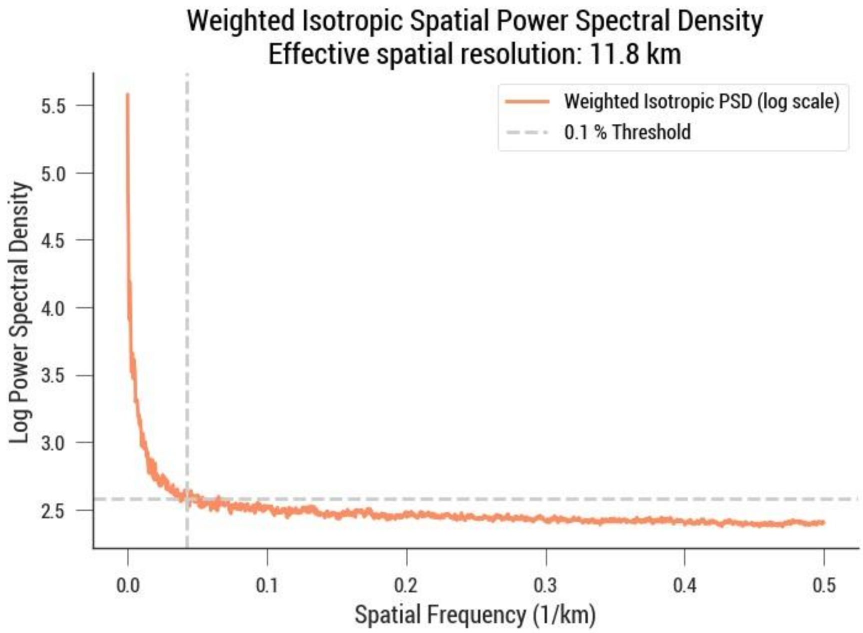


Figure 5. Power spectral isotropic density plot of Danger-PP. Frequency cutoff points shown in grey.

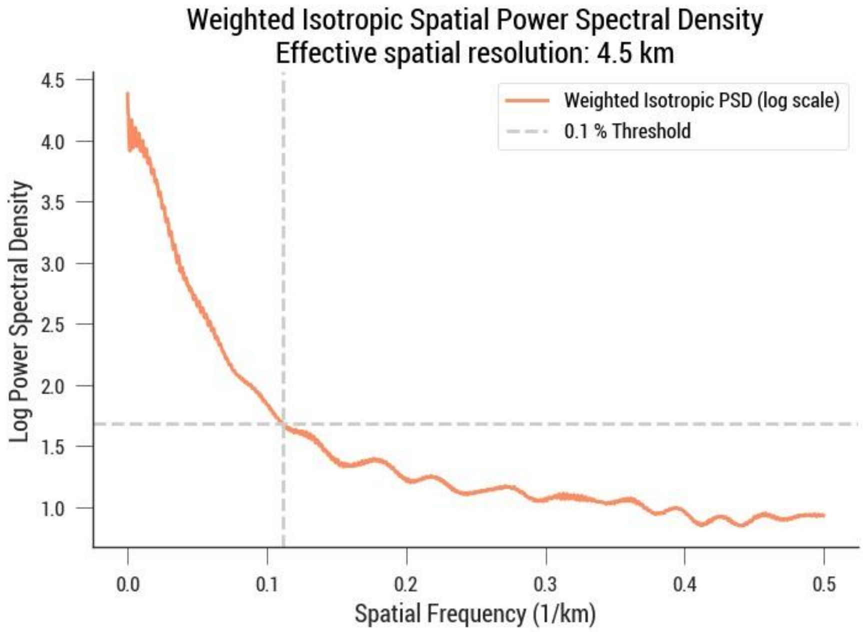


Figure 6. Power spectral isotropic density plot of Danger-PI. Frequency cutoff points shown in grey.

2.3.2 FDI metrics as predictors of fire occurrence

A first look at the data shows that some of the FDI metrics are strongly correlated among themselves. This is expected, as some variables are indeed used as inputs for other metrics. This observation suggests that it is probably not very sensible to try to test multi-variable models on their own, but rather guided by the decisions taken in selecting the variables themselves. The correlation matrix of the FDI values is shown in Figure 7. For example, there is little correlation between the Danger-PP and Danger-PI metrics, suggesting that they do indeed relate to independent aspects of the fire process.

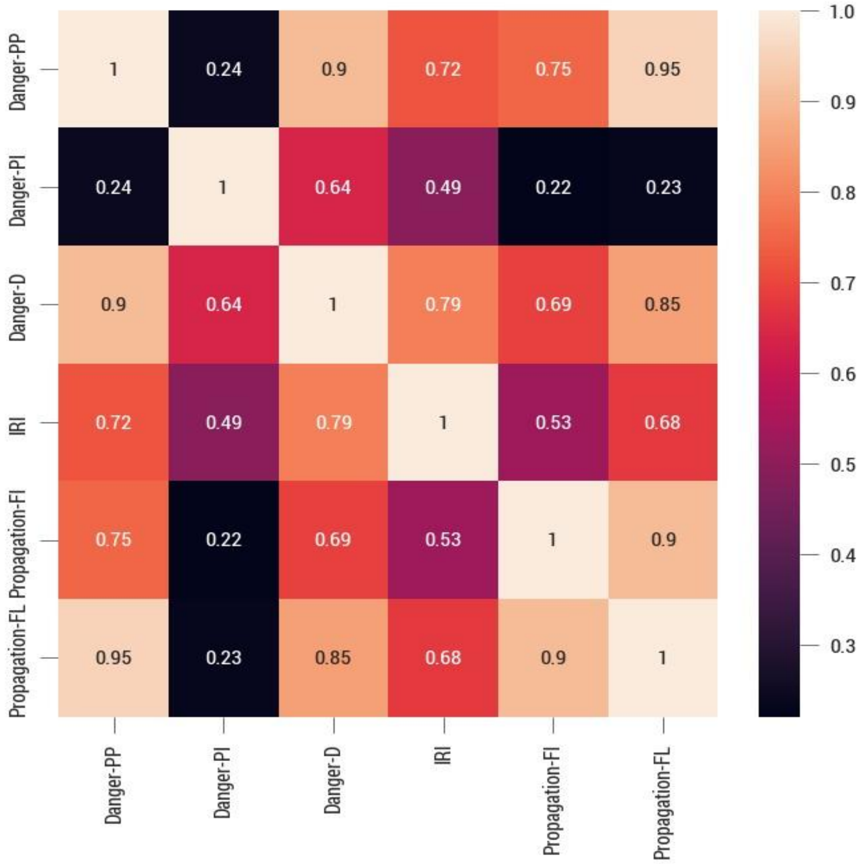


Figure 7. Correlation matrix of the different FDI metrics calculated for summer 2023 over Europe.

We have tested the predictive power of the different FDI metrics as predictors of fire occurrence using standard logistic regression. The results are shown in Table 2 and in Figure A1 (see Appendix A). The ROC curves are summarised in Figure 8. The results show that the Danger-PP and Danger-PI metrics are the most informative, with AUC values of 0.7 and 0.6, respectively. The other metrics have AUC values below 0.6, indicating that they are not very informative in terms of assessing fire occurrence.

All in all, we can say that the Danger-PP and Danger-PI metrics are the most useful, although this statement needs to be made with extreme care, as the omission and commission errors are very large, and the overall accuracy is only middling.

Table 2. Single variable logistic regression results for different FDI metrics as predictors of fire occurrence.

FDI	AUC	F1	Precision	OA	OE	CE
PI	0.66	0.67	0.65	0.66	0.37	0.31
D	0.62	0.66	0.59	0.62	0.5	0.26
FL	0.58	0.43	0.66	0.58	0.16	0.68
PP	0.55	0.34	0.62	0.55	0.14	0.77
IRI	0.52	0.53	0.52	0.52	0.5	0.47
FI	0.5	0.64	0.5	0.5	0.89	0.1

2.3.3 FDI metrics as predictors of burned areas

Using the FDI metrics PP and PI (as well as temporally-lagged versions of PP) as predictors of EFFIS burned area for 2023 showed very poor results. The R^2 values were very low ($R^2 \leq 0.06$), and the models were not informative. We will not report further on these.

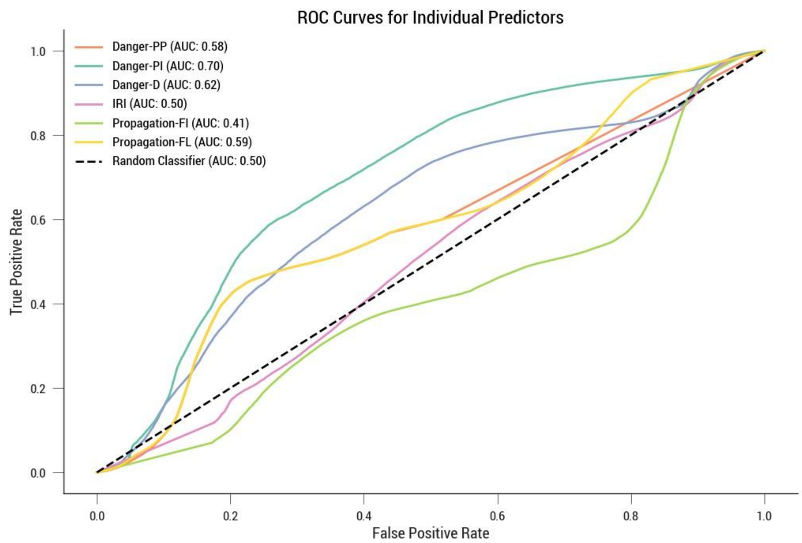


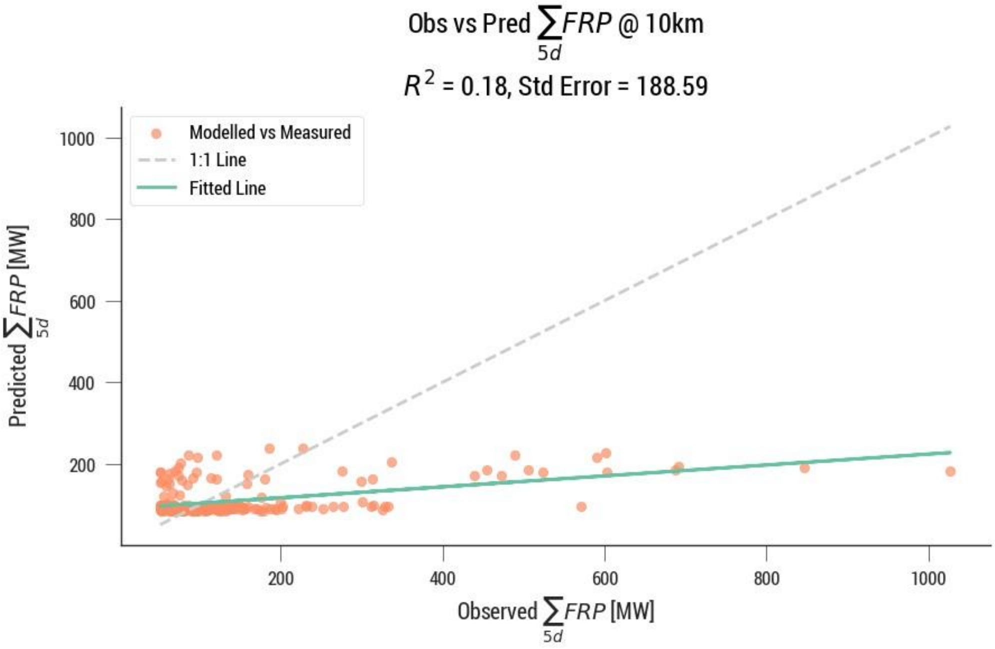
Figure 8. ROC curves for the different FDI metrics calculated for summer 2023 over Europe.

2.3.4 FDI metrics as predictors of aggregated FRP

We have tested the effectiveness of PP and PI in predicting the FRE (estimated over a 5-day interval over a 10km grid cell) using a linear regression model, and using a log-transformation for the target variable (we also tested a Box-Cox transformation, but the log transform yielded better results). The input variables were also standardised prior to fitting the model. We have also calculated the variance inflation factor (VIF) to assess multicollinearity in the model, and only selected parameter combinations that had VIF values lower than 2 (indicating low multicollinearity).

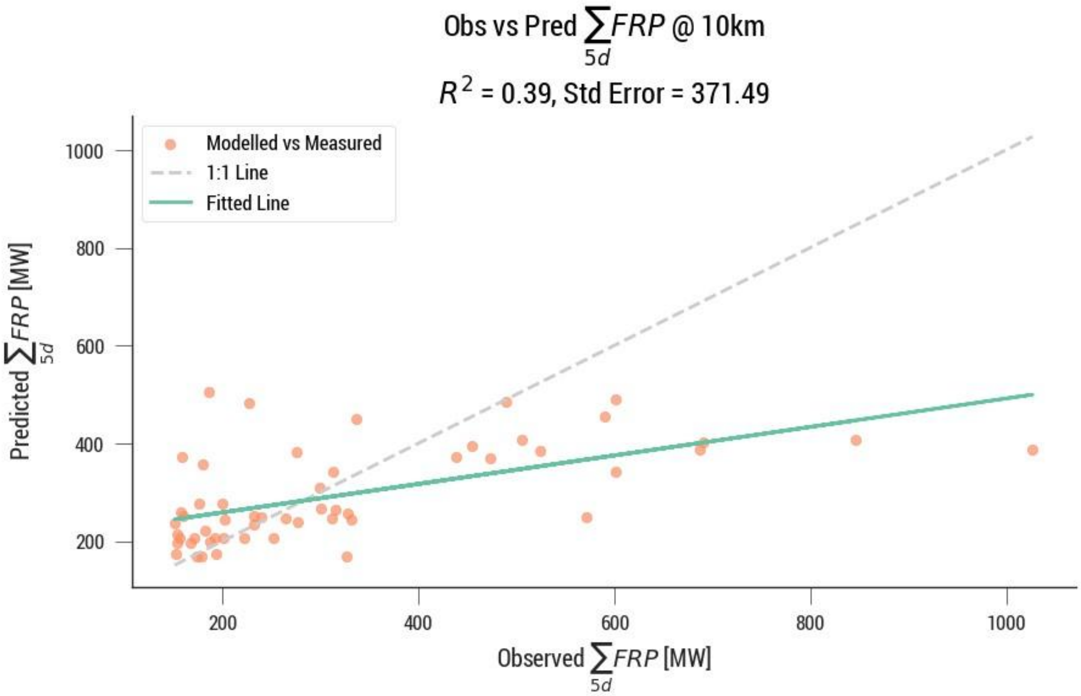
The proposed model (e.g. $FRE \sim \beta_0 \cdot PP + \beta_0 \cdot PI$) is shown in Figure 9, Figure 10 and Figure 11 for different thresholds of the sum of FRP values. The three thresholds were 50, 150 and 200 MW, which, respectively, correspond to 97.5th, 99.5th and 99.75th percentiles of the dataset. The results including all fires over 50MW show a poor model performance, with an $R^2 < 0.2$. Most of this disappointing figure is due to small fires that are overestimated by the model. The results for the 150 and 200 MW thresholds are better, with $R^2 \approx 0.4$, suggesting a limited predictive ability for larger fires. We can however see that the model underestimates the largest fires, possibly as the training data is dominated by smaller fires.

We then extended the model using the slope of PP and the median value of PP over a lagged period. The model performance increased slightly, with values of R^2 of 0.5 and 0.6 when using a model made up of the slope of PP with a lag of 5 and 15 days, the median value of PP over 15 days, and the value of PI. The results for our three thresholds are shown in Figure 12, Figure 13 and Figure 14. The results are better, but still limited. When small fires are included, the R^2 is marginally higher, going up to 0.24. The results for the 150 and 200 MW thresholds are better, with $R^2 = 0.5$ and $R^2 = 0.6$ for grid cells larger than 150 and 200 MW, respectively. Again, we notice that even these better and more complex models are also underestimating the largest FRE values. We note that extending the model selection to include an interaction term (e.g. $PP \times PI$) did not improve the model performance, and this additional term was not included in any of the selected models.



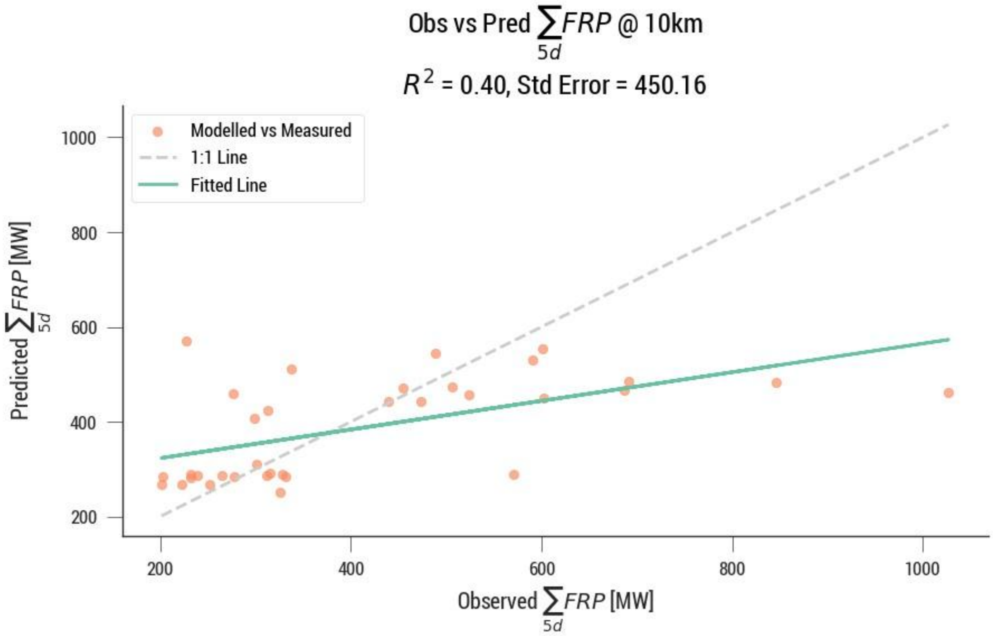
	coef	std err	t	P>|t|	[0.025	0.975]
const	4.644	0.037	126.544	0.0	4.572	4.717
pp	0.25	0.039	6.377	0.0	0.173	0.327
pi	0.043	0.039	1.095	0.275	-0.034	0.12

Figure 9. Plot of the observed and predicted FRE values for the linear regression model using PP and PI as predictors for grid cells where $\sum_{5d}$FRP > 50 MW. Table shows the model summary and selected variables. Rows are coloured in green if the variable is significant at the 0.05 level.



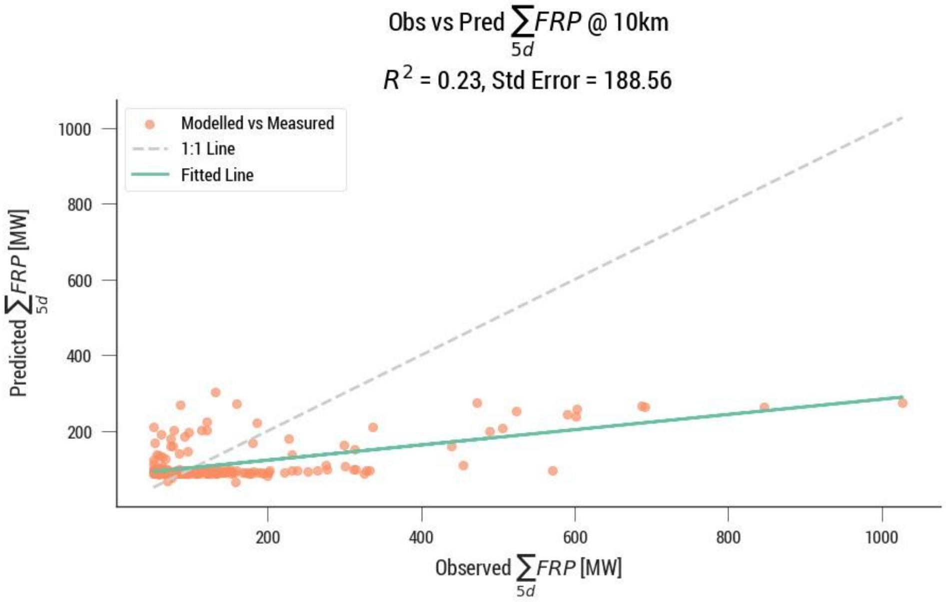
	coef	std err	t	P>|t|	[0.025	0.975]
const	5.633	0.056	100.974	0.0	5.521	5.745
pp	0.258	0.059	4.358	0.0	0.139	0.376
pi	0.124	0.059	2.101	0.041	0.006	0.243

Figure 10. Plot of the observed and predicted FRE values for the linear regression model using PP and PI as predictors for all grid cells where $\sum_{5d}$FRP > 150 MW. Table shows the model summary and selected variables. Rows are coloured in green if the variable is significant at the 0.05 level.



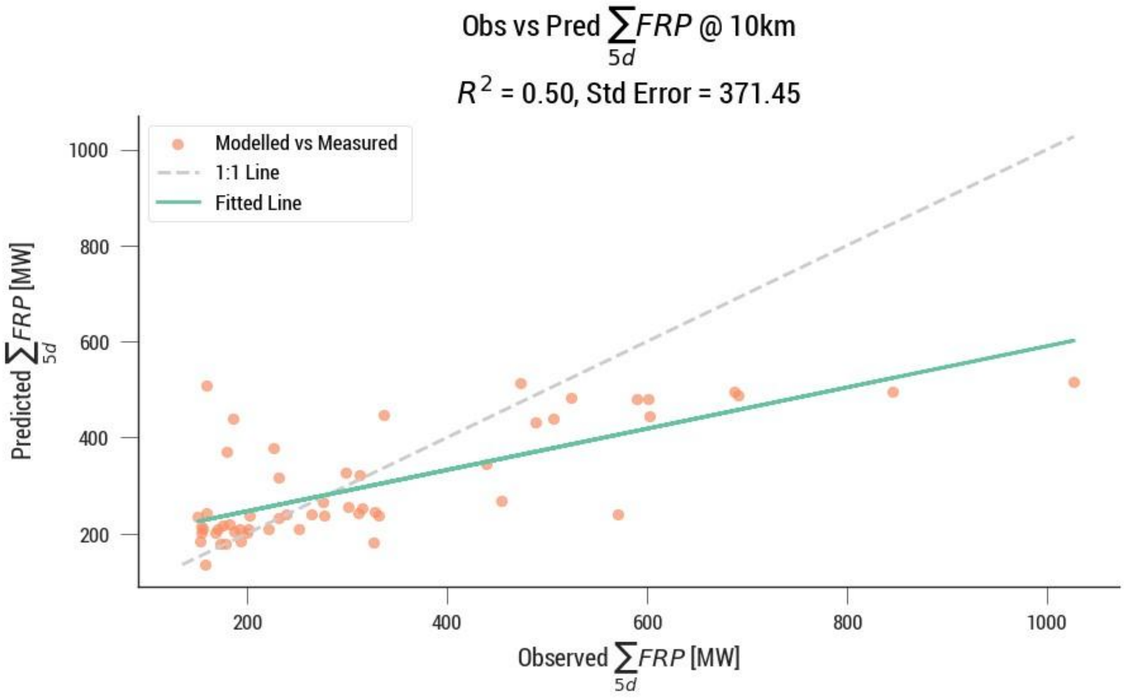
	coef	std err	t	P>|t|	[0.025	0.975]
const	5.922	0.06	98.598	0.0	5.799	6.044
pp	0.266	0.061	4.38	0.0	0.142	0.39
pi	0.031	0.061	0.505	0.617	-0.093	0.155

Figure 11. Plot of the observed and predicted FRE values for the linear regression model using PP and PI as predictors for all grid cells where $\sum_{5d}$FRP > 200 MW. Table shows the model summary and selected variables. Rows are coloured in green if the variable is significant at the 0.05 level.



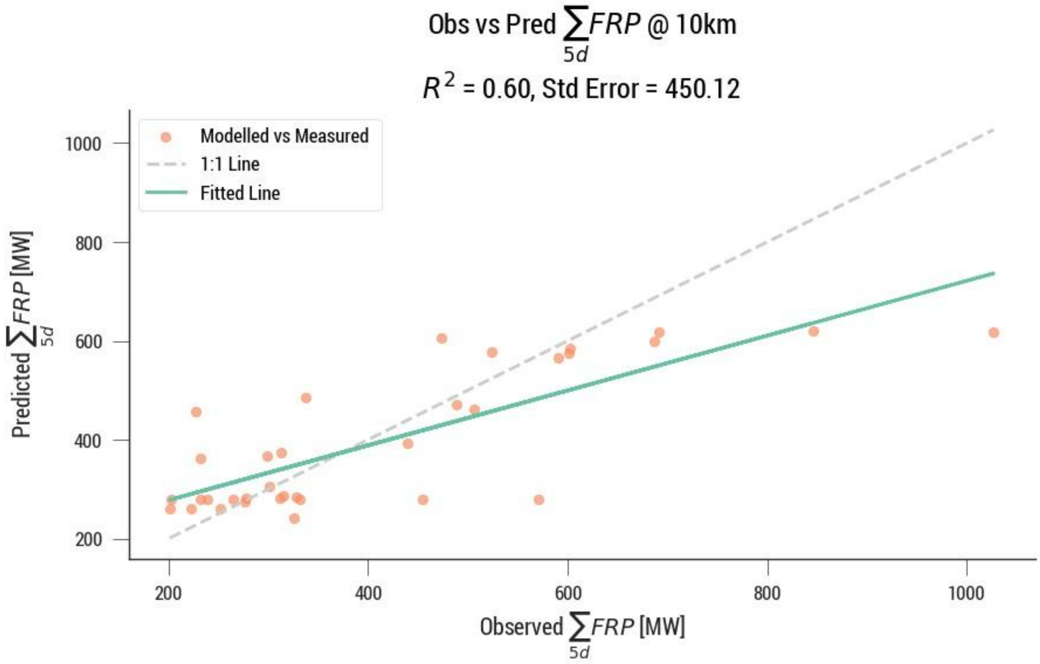
	coef	std err	t	P>|t|	[0.025	0.975]
const	4.644	0.036	129.825	0.0	4.574	4.715
slope_N5	-0.116	0.041	-2.85	0.005	-0.196	-0.036
slope_N15	0.092	0.041	2.215	0.028	0.01	0.173
pp_median_N15	0.217	0.041	5.262	0.0	0.136	0.299
pi	0.038	0.039	0.972	0.332	-0.039	0.115

Figure 12. Plot of the observed and predicted FRE values for the linear regression model using PI, the slope of PP at lags 5 and 15 days, and the median value of PP over the 15 days prior to the fire as predictors for all grid cells where $\sum_{5d}$FRP > 50 MW. Table shows the model summary and selected variables. Rows are coloured in green if the variable is significant at the 0.05 level.



	coef	std err	t	P>|t|	[0.025	0.975]
const	5.633	0.051	109.467	0.0	5.529	5.736
slope_N5	-0.127	0.055	-2.301	0.026	-0.238	-0.016
slope_N15	0.079	0.054	1.448	0.154	-0.031	0.188
pp_median_N15	0.233	0.06	3.865	0.0	0.112	0.354
pi	0.096	0.056	1.715	0.093	-0.016	0.207

Figure 13. Plot of the observed and predicted FRE values for the linear regression model using PI, the slope of PP at lags 5 and 15 days, and the median value of PP over the 15 days prior to the fire as predictors for all grid cells where $\sum_{5d}$FRP > 150 MW. Table shows the model summary and selected variables. Rows are coloured in green if the variable is significant at the 0.05 level.



	coef	std err	t	P>|t|	[0.025	0.975]
const	5.922	0.051	116.882	0.0	5.818	6.025
slope_N5	-0.07	0.067	-1.046	0.304	-0.207	0.067
slope_N15	0.134	0.069	1.96	0.06	-0.006	0.275
pp_median_N15	0.216	0.054	4.004	0.0	0.106	0.327
pi	0.038	0.051	0.731	0.471	-0.068	0.143

Figure 14. Plot of the observed and predicted FRE values for the linear regression model using PI, the slope of PP at lags 5 and 15 days, and the median value of PP over the 15 days prior to the fire as predictors for all grid cells where $\sum_{5d}$FRP > 200 MW. Table shows the model summary and selected variables. Rows are coloured in green if the variable is significant at the 0.05 level.

2.3.5 FDI metrics as predictors of fire (EFFIS burnt scars)

Under the working assumption that the EFFIS dataset contains most of the fire events that are of a sufficient magnitude to be concerning, we have used the EFFIS burnt scars dataset to assess the predictive power of the FDI metrics.

We have used both PP and PI to assess the presence of fire. Using only PP and PI on the starting day of the fire shows a moderate predictive power, with an AUC around 0.89 (more details in Figure 15). The estimated coefficients are 1.4 for PI and 0.2 for PP, suggesting that PI is a much stronger predictor of fire occurrence than PP.

Using the lagged indicators suggests that the addition of the slope of PP in the 15 days before the fire adds relevant information. The coefficient for PI is around 1.76, the slope in the 15 days prior to the start of the fire is 0.69, and the PP value on the starting day of the fire is 0.14. The AUC for this model is 0.89, suggesting that the model is moderately informative. The results are shown in Figure 16 for all EFFIS fires, and suggests that the model is informative, but that the information is mostly carried by PI, and that this is only helped by adding the slope of PP on the

15 days prior to the fire. The information carried by the PP value on the starting day of the fire appears to be marginal.

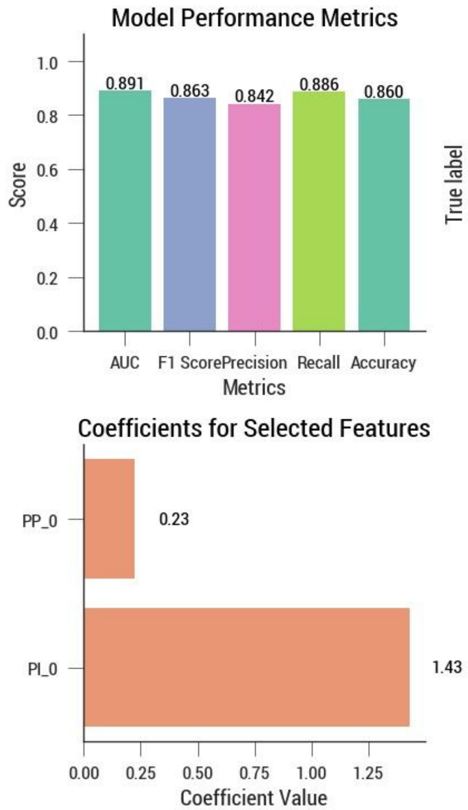


Figure 15. (Top left) Classification metrics of the fire occurrence model (EFFIS burnt scars) using only PP and PI on the starting day of the fire. (Top right) Confusion matrix. (Bottom left) Estimated model coefficients.

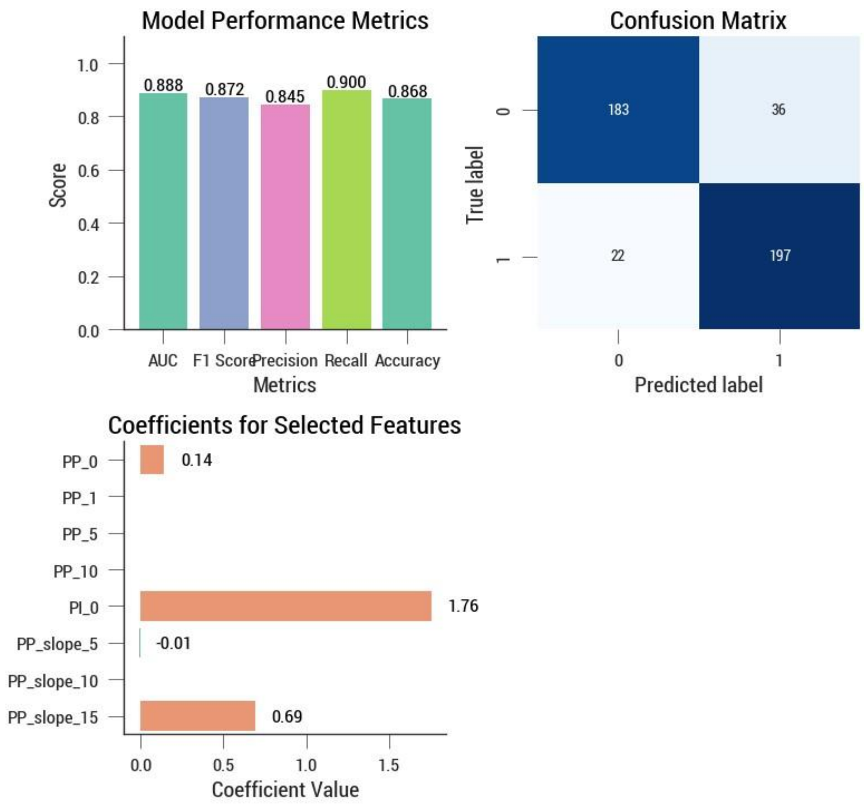


Figure 16. (Top left) Classification metrics of the fire occurrence (EFFIS burnt scars) model using all variables. (Top right) Confusion matrix. (Bottom left) Estimated model coefficients.

2.3.6 Extension to year 2024

While all of the analysis so far has focused on 2023, we have recently started analysing the 2024 data. An initial assessment over the whole continent (Figure 17) suggests that 2024 was a more fire prone year than 2023 in Europe. Given the issues with underestimation of FRE shown by the 2023 analysis, this could be problematic. Ultimately, since PP is a transformed version of predictions of fire intensity FI, it might be more realistic to use FI directly in any comparisons, or to define some local extreme FRP values and see how well the indices react to them.

We have also looked at two important fires in 2024: the Attica fire in Greece in August 2024, and the fires in northern Portugal in September 2024.

The outline of the Attica fire is shown in Figure 18, and we can see that the region covered by the burnt scar is characterised by a very high value of PP (PP ≥ 0.95), which was higher than the median summer values (around 0.82), as seen in Figure 19 and Figure 20, respectively. Figure 19 shows an increase of PP from the around the 2nd of August towards the start of the fire, although we note that a similar increase also happened some three weeks earlier and did not result in a fire.

It is worth noting that the value of PI was already quite large over the region (PI > 0.7), suggesting this is an area with frequent fire activity.

For the Portuguese fires around September 15th (Figure 22), we can see that again we are in a historical fire-prone area (median summer PI > 0.75), and with PP > 0.75 for the month prior to the fire. We also see a marked increase in PP about 10 days before the start of the fire, with PP increasing even as the fire had already started.

In both study cases, we notice how PP increases towards the start of the fire, suggesting a drying out of fuels, and that PP at this stage tends to be over the seasonal average in an area historically fire prone. However, Figure 23 shows that similar fire conditions were observed earlier in the same area that did not result on a large fire, which is consistent with the large omission/commission errors reported elsewhere in this report.

It is also worth pointing out that our effective resolution analysis is also borne out by e.g. Figure 20 or Figure 24, showing some clear spatial smoothness suggesting that most of the information is carried out in the lower frequencies.

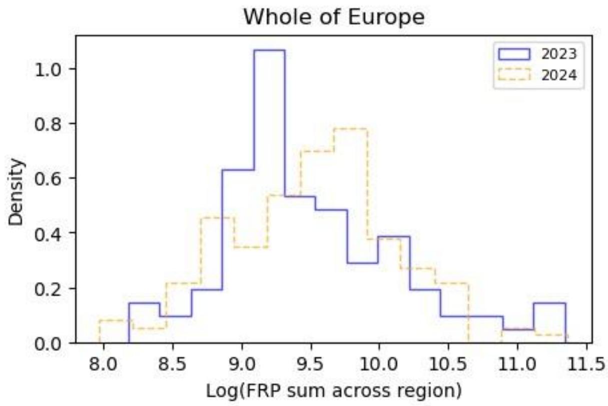
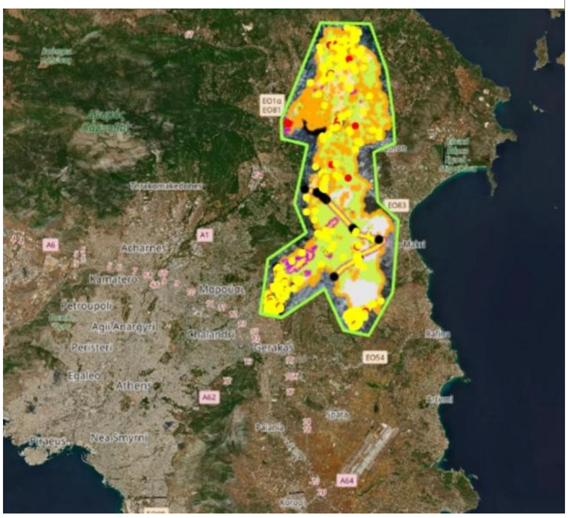


Figure 17. Distribution of FRP over the European territory for summer'23 and summer'24.

Figure 18. Spatial extent of the fires.



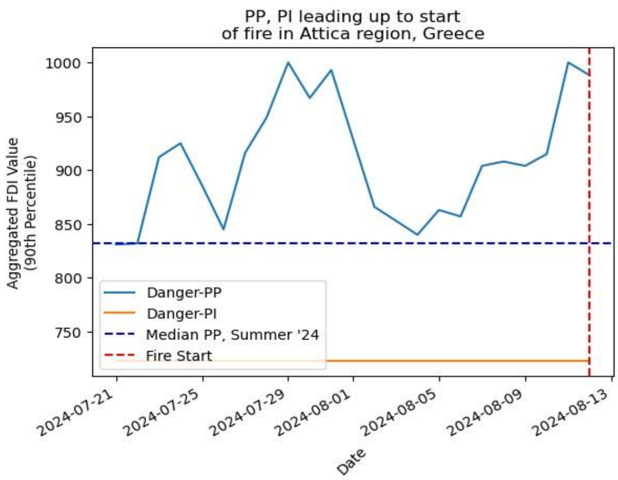


Figure 19. Evolution of FirEUrisk danger indices PP and PI prior to the start of the Attica fire.

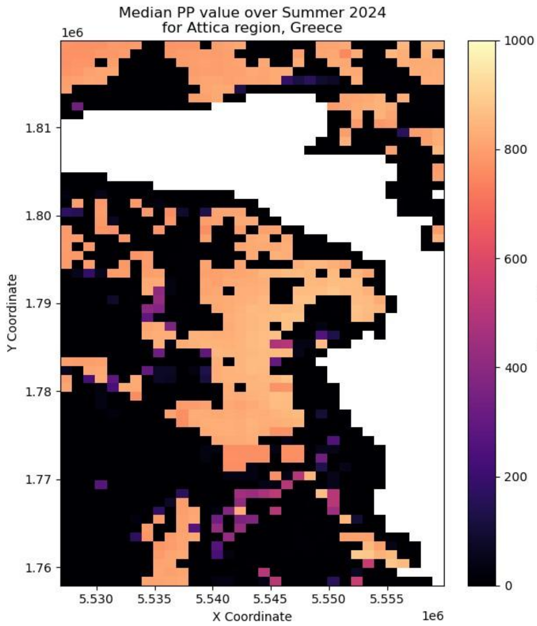


Figure 20. Median value of PP around the Attica fire region for summer 2024.

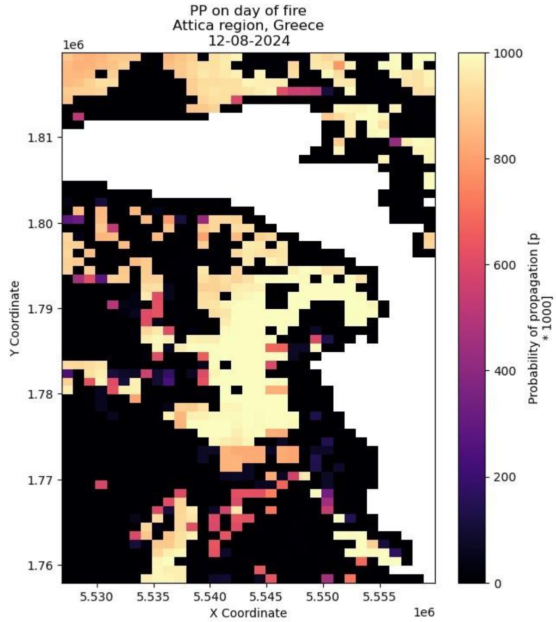


Figure 21. Spatial distribution of PP on the start of the Attica fires.

Figure 22. Spatial extent of the fires.

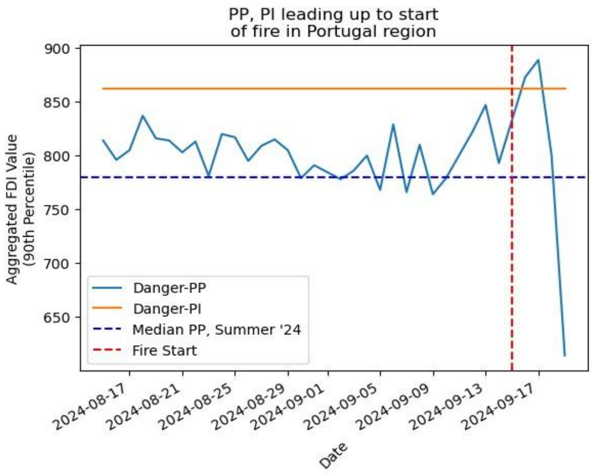
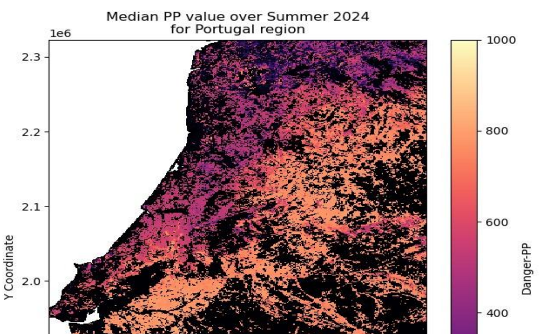


Figure 23. Evolution of FirEUrisk danger indices PP and PI prior to the start of the Portuguese fires.



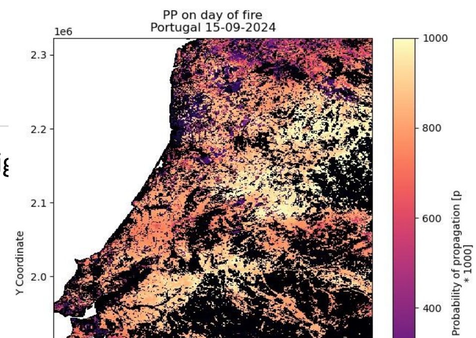


Figure 25. Spatial distribution of PP on the start of the Portuguese fires.

2.4 Discussion

The results shown above introduce a limited validation of the FirEUrisk fire danger rating system. We have used a limited dataset, and have focused on 2023, a year with a relatively low fire activity in Europe.

In terms of fire **occurrence**, the results suggest that the Danger-PP and Danger-PI metrics are individually the most informative, with AUC values of 0.7 and 0.6, respectively. The other metrics have AUC values below 0.6, indicating that they are not very informative in terms of assessing fire occurrence. This is perhaps unsurprising, as the PI metrics is derived from historical fire data, and with fires occurring often in similar locations over the course of the years, PI is able to include this information.

It is also worth noting that these results are a global (or at least European) average, biased towards the Mediterranean basin, where fires are more common and make up most of the fire evidence dataset. The results are likely to be different in other regions of Europe, where fires are less common, but this might be hard to assess with a dataset with a limited temporal coverage.

We found that the FDI metrics are not very informative in predicting the **burned area** as reported by the EFFIS dataset. This might be because burned area in a European context is not only controlled by fire danger, but also by dynamics of fuel accumulation and land use. Forrest et al. (2024) developed a model for burned area in Europe that found that burned area in non-crop vegetation and in croplands were controlled by different factors, with both fire weather and gross primary productivity being important variables. It may be interesting to assess the predictive power of the FirEUrisk metrics in the context of this model, although we note that the overall predictive ability of the proposed model was quite limited.

Using FRE as a proxy for fire intensity, we found that a linear combination of PP and PI did not provide a good model for predicting FRE unless the focus was restricted to the larger, more energetic fires. The results improved when using lagged values of PP, suggesting that the drying of fuels in the days prior to the fire is an important factor in determining the intensity of the fire. The results are still limited, and the model underestimates the largest fires. This might be due to the fact that the training data is dominated by smaller fires, and that the model is not able to capture the dynamics of the largest fires. Since 2023 was not a particularly fire-prone year (low fire weather) in Europe, it is an open question whether the underestimation of FRE would be even more pronounced in a year with increased fire activity. This is something that will need to be addressed using the 2024 data that shows some substantially higher distribution of FRE (Figure 17).

In this report, we have not assessed where the information on fire risk is coming from: the fire indices used in the validation are calculated from a set of different variables (fuel model estimates, landcover information, meteorological data, etc.), and we have not evaluated where the information content emanates from. To do this, we would need to consider the drivers of both PP and PI, and related them to e.g. FRE or fire occurrence. This would provide a more detailed understanding of the information content of the FDI metrics, and would allow us to assess the relative importance of the different components of the FDI metrics. This would be an important step in understanding the limitations of the FDI metrics, and also proposing new ways of combining the different components of the scheme.

We additionally suggest that a comparison with other widely used fire danger schemes within the European context (e.g., the use of an adapted version of the Canadian Fire Danger Rating System by EFFIS) would be beneficial. Comparisons with fire danger rating systems that only use meteorological inputs might help understand the role of additional non-meteorological inputs in fire danger rating in the European context.

The dataset that we have used has flaws: in a European context, fires are actively suppressed, and in many cases, fires will have been suppressed before they are detected by a satellite. In many cases, suppression efforts will be successful, and potentially large fires will have been averted, even though conditions for them to grow were adequate.

A final additional point is that the effectiveness of the proposed index in conjunction with forecasts of fire danger (coming from e.g. short- and medium-term weather forecasts) have not been explored. Given the relevance on fuel drying build up over time, this might be a useful extension to the index that might improve the temporal window on which remedial actions might be taken.

2.5 Conclusions

The FirEUrisk validation report provides an initial evaluation of the Fire Danger Index (FDI) metrics, particularly focused on their capacity to predict fire occurrence, fire radiative energy

(FRE) release, and burned area across Europe. The analysis, primarily centred on data from 2023, indicates that among the FDI components, the Probability of Propagation (PP) and Probability of Ignition (PI) metrics exhibit the most significant predictive capabilities for fire occurrence, albeit with moderate accuracy (AUC values of 0.7 and 0.6, respectively). This moderate level of predictability suggests that while these metrics can indicate elevated fire risk, they are limited by significant omission and commission errors, thus providing only a partial depiction of fire danger at the European scale.

In terms of fire intensity, represented through aggregated FRE values, the study reveals that PP and PI offer limited predictive power, particularly for smaller fire events. However, the predictive strength of the FDI metrics improves for larger fires and when lagged PP metrics are incorporated, implying that short-term fuel drying trends enhance the predictive utility of PP for intense fire events. However, even with these enhancements, the model tends to underestimate the highest FRE values, highlighting limitations when applied to large-scale fires, possibly due to a dataset dominated by smaller events in 2023, a year with relatively low fire activity.

The report also underscores the challenges in using FDI metrics to predict burned area. The metrics demonstrate poor predictive performance for this aspect, potentially due to the complex interactions in the European context, where fuel dynamics and continuity, land use practices, and fire suppression efforts significantly influence fire spread and area burned. This finding suggests that in Europe, fire danger assessments may benefit from integrating additional context specific variables, such as vegetation productivity, landscape connectivity/patchiness and local land management practices, which can impact fire spread independently of fuel amount and adequate meteorological conditions.

Finally, this validation highlights several avenues for future research, including the need to disentangle the specific contributions of individual components within the FDI metrics and its original drivers to refine predictive accuracy, and to provide an understanding of where the risk signal ultimately originates. Furthermore, expanding comparisons with other established fire danger rating systems used within Europe, such as the Canadian Fire Danger Rating System from EFFIS, may help underscore the advantages and limitations of FirEUrisk relative to traditional meteorology-based fire indices. The exploration of short- and medium-term weather forecasts in conjunction with FirEUrisk metrics is also recommended, as such integration may enhance the model’s capacity to anticipate fire-prone conditions over extended temporal windows, thus offering potential value for fire management and preventive action.

3 Burnt areas datasets comparison

3.1 Key questions and objectives

This part of the document aims at showing the results of the comparison between the burnt areas (BA) data reported in four datasets as retrieved by using medium/low resolution satellite images. The goal is to provide an overview of the difference existing between them and to provide a few hints on how to improve the interpretation of such data by end users.

3.2 Datasets characteristics

The analysis refers to four datasets corresponding to the initiatives:

- EFFIS. Since 1998, EFFIS (European Forest Fire Information System, https://effis.jrc.ec.europa.eu/ (accessed on 17 March 2023)) has supported the services in charge of the protection of forests against fires in the EU and neighbouring countries and provides the European Commission and the European Parliament with updated and reliable information on wildland fires in the territory of the Union.

- FIRMS. Since 2000, NASA's FIRMS (Fire Information for Resource Management System, "https://firms.modaps.eosdis.nasa.gov/download/ (accessed on 17 December 2023)") has provided active fire (and BA) data acquired from the moderate-resolution imaging spectroradiometer (MODIS) aboard the Aqua and Terra satellites and, more recently, from the visible infrared imaging radiometer suite (VIIRS) aboard S-NPP and NOAA 20 (formerly known as JPSS-1).
- CCI. The ESA CCI (Climate Change Initiative) project aims to improve the consistency of the BA, using better algorithms for both pre-processing and BA detection while incorporating error characterization in their product.
- C3S. The European Commission (EC) C3S project is one of the six thematic information services provided by the Copernicus Earth Observation Programme of the European Union (EU). C3S will provide past, present and future climate data and information on a range of themes, freely accessible through the Climate Data Store (CDS). The BA datasets developed in C3S are consistent with the existing European Space Agency Climate Change Initiative (CCI) products, with the same algorithm adapted to Sentinel-3 OLCI data.

The Copernicus Global Land Monitoring product has not been considered since the procedure to compute BA (originally based on PROBA-V images and now on Sentinel-3/OLCI) is being modified with respect to the one available online in the years immediately following 2020, which is the year taken into consideration in this brief analysis.
The characteristics of the datasets considered are given in Table 3.

Table 3. List of the datasets used to carry out the analysis.

Dataset	Source	Spatial Resolution	Timespan	Algorithm/Method Used
ESA CCI	MODIS	250 m	2001–present	NIR time series + active fires, ESA CCI land cover
EFFIS	MODIS	250 m	2000–present	Combination of bands, CORINE land cover
FIRMS/MCD64	MODIS	250 (500) m*	2000–present	NBR2 + active fire, MCD12Q1 land cover
C3S	OLCI	300 m	2017–present	NIR time series + active fires, C3S land cover

* Product based on MODIS 500 m spectral channels resampled to 250 m by using ENVI resampling tool, nearest neighbour algorithm.

The analysis covers the European countries most affected by fires: France, Greece, Italy, Portugal and Spain.

3.3 Results

The main objective of this analysis is to investigate the differences between some of the most consulted BA datasets using year 2020 as a reference.
Figure 26 shows, for each one of the five countries considered, the total extent of the burnt areas as extracted from the datasets listed in Table 3.

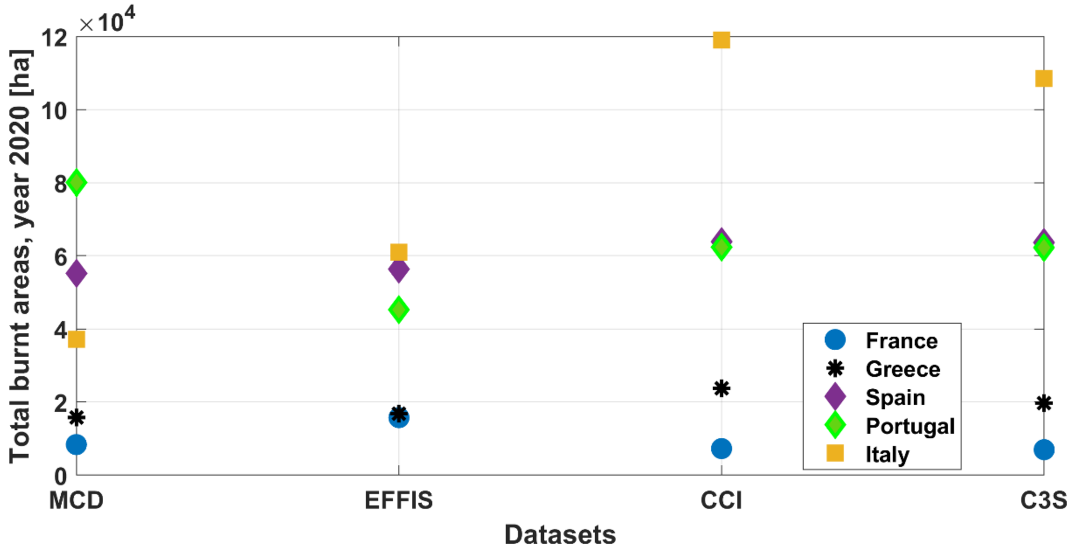


Figure 26. Total burnt areas [ha] in the five European countries considered, for year 2020, as extracted from the four datasets analysed.

As shown in Figure 26, the largest differences between burnt areas concern Italy and Portugal. In particular, in the Italian case, the greatest BA extent estimated by CCI (120000 ha) is three times the size of the smallest, estimated by MCD (39000 ha). In the case of Portugal, the greatest BA extent (80000 ha), given by MCD, is almost twice the size of the smallest (44000 ha), from EFFIS. In the case of France, Greece and Spain the differences are significantly smaller.

If we look at the cover type of the burned areas, by using the 2018 CORINE Land Cover (CLC) as reference, we obtain the results shown in Table 4. The CLC classes have been grouped in three classes: agricultural (classes: 211 - 242), forest (classes: 243 - 333), other.

It is interesting to observe that the amount of non-forested areas identified as burned is negligible in the case of EFFIS, apart for Greece and Italy. Specifically, in the case of Italy 28.7% of the burnt areas are labelled as agricultural areas by CORINE. In the case of Greece 15.8% of the BA are labelled as agricultural areas by CORINE.

Very different are the results for the other three datasets. In fact, in the MCD dataset the percentage of BA identified as agricultural areas ranges from the 5% of Portugal to the 58.3% of Italy. In case of CCI, the BA corresponding to agricultural areas goes from 7.4% of Portugal to the

72.5% of Italy. Finally, in case of C3S, the percentage goes from 7.7% of Portugal to the 71.2% of Italy. Therefore, two facts are common to all datasets:

- the relatively low values of agricultural areas identified as burnt in Portugal;

- relatively high incidence of the agricultural areas identified as burnt in Italy.

Table 4. Distribution of the cover types of the BA of the 4 datasets.

Distribution between land cover types based on CORINE LC				
Country	**MCD [%]**	**EFFIS [%]**	**CCI [%]**	**C3S [%]**
France	Agric: 32.6 Forest: 63.7 Other: 3.7	Agric: 3.3 Forest: 93.0 Other: 3.7	Agric: 19.1 Forest: 68.9 Other: 12.0	Agric: 11.0 Forest: 81.2 Other: 7.8
Greece	Agric: 42.3 Forest: 53.7 Other: 4.0	Agric: 15.8 Forest: 79.4 Other: 4.8	Agric: 38.5 Forest: 60.2 Other: 1.3	Agric: 45.8 Forest: 53.1 Other: 1.1
Italy	Agric: 58.3 Forest: 34.2 Other: 7.5	Agric: 28.7 Forest: 65.4 Other: 5.9	Agric: 72.5 Forest: 25.0 Other: 2.5	Agric: 71.9 Forest: 25.5 Other: 2.6
Portugal	Agric: 5.0 Forest: 60.5 Other: 34.5	Agric: 5.6 Forest: 91.7 Other: 2.7	Agric: 7.4 Forest: 90.8 Other: 1.8	Agric: 7.7 Forest: 90.3 Other: 2.0
Spain	Agric: 20.0 Forest: 77.9 Other: 2.1	Agric: 7.2 Forest: 91.7 Other: 1.1	Agric: 20.9 Forest: 76.8 Other: 2.3	Agric: 24.0 Forest: 73.9 Other: 2.1

This result has a series of implications, which we try to delineate hereinafter:

- The CLC map does not correctly describe the land cover classes of the territory, and this is particularly true for Italy;
- The BA datasets, to avoid or minimize false alarms, are using land cover maps other than CORINE;
- The algorithms adopted by the four datasets are not based on the same land cover map.

Figure 27 shows, for a single event, a comparison between the BAs in different datasets. The event refers to the Corsica Island. As it can be seen the areas identified as burned are significantly different. In the case of FIRMS, the impact of the lower resolution of the original

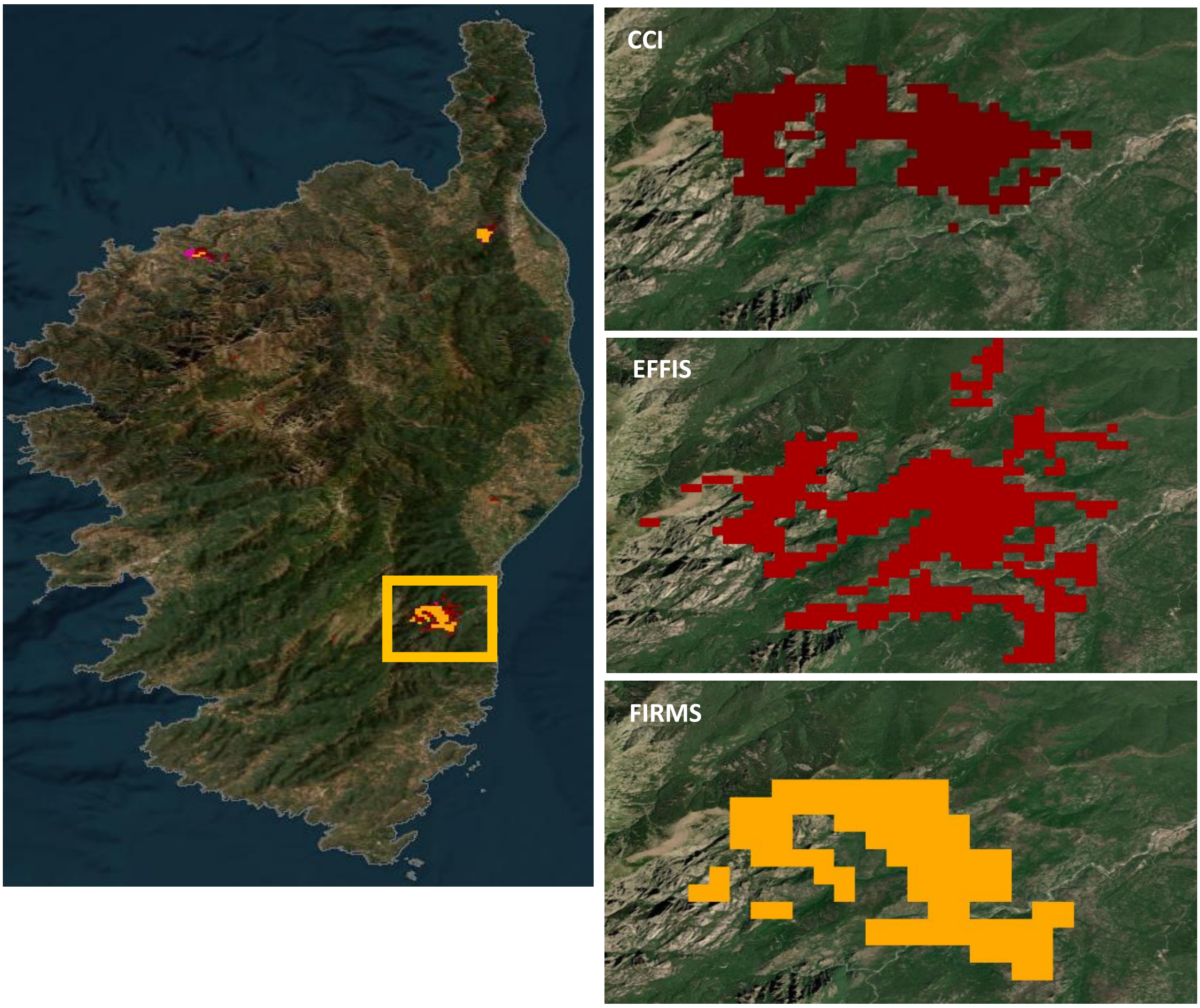


Figure 27. Comparison between burnt area maps of the same event provided by three datasets (CCI, EFFIS, FIRMS).

product is evident (500 m versus 250/300 m).

3.4 Comments

To assess which one of these datasets provides the best results we need to compare them with a ground truth. This was done just for Italy and the results are not reported here since they are limited to a single country. Results on the single country analysis are available in Laneve et al. 2024. However, even such a comparison is not enough to select the best approach, since omission and commission errors could be associated with, as said above, to land cover map used to distinguish burnable from not burnable areas or natural from agricultural areas. Therefore, the main suggestion to the data providers to enable a comparison between BA mapping methodologies not biased by the adopted land cover maps, consists in making available to download the aforementioned land cover maps in addition to the BA datasets themselves. This way the comparison on the accuracy of different approaches can be restricted to areas with common surface characteristics.

This suggestion extends to ground-based BA datasets too, since omission or commission errors could originate from the use of a more or less accurate land cover map than the ones used by remote sensing BA detection algorithms.

4 Value of satellite information (VOI) approach

4.1 Key questions and objectives

This document is part of the Work Package 1 "Fire risk assessment to improve prevention", whose main goal is to produce all risk-life-cycle variables, models, and methodological schemes required for state-of-the art risk assessment in current conditions, at different temporal (daily-D, seasonal-S) and spatial scales (from 1 km to sub-metric).

The goal of the specific task (A1.3.2 Demonstration and evaluation of risk assessment products) to which this deliverable refers is to develop overall capacity, methods and case studies to facilitate the way we understand, measure and promote the value of Earth observations, in the specific field of wildfire management, helping to justify the investments which are made. Case studies are being used to understand and measure the benefits, whilst storytelling is increasingly being used to promote the results. The goal is to provide clear benefits assessments of individual products or services and impact assessment of programmes. Whilst assessing the benefits and impacts is the primary goal, results lead also to a deeper understanding of the use of Earth observations which can help further market studies and promotional activities, (GEO-Value).
The utility of some applications of the information provided by satellite is well known. We are referring to the case of the Global Positioning System (GPS) or meteorological forecasts involving geostationary satellite data Jamilkowski et al., 2021, mention the case of Hurricane tracking and forecasting). Less analyzed is the role of satellite based information in enhancing the decisions support tools helping in reducing the impact of fires. For instance, Herr et al., (2020), using simulations carried out considering three scenarios characterized by different levels of information assessed the socioeconomic impact of using, to make tactical decision to tackle the fight, hot spot detected by satellite sensors. The study refers to a very rare case in which the fire lasted about one month. Another example [Bernknopt et al., 2021] considers the case of using satellite images (Landsat) to assess the post-fire damages and guide the BAER (Burn Area Emergency Response) activity, mainly devoted to identifying imminent post-wildfire threats to human life and safety, property, and critical natural or cultural resources (cascading effects in FirEUrisk). The SeBS (Sentinel Benefit Studies) initiative, funded by European Commission and ESA, aims to *gather quantitative evidence that the usage of Copernicus Sentinel data provides an effective and convenient support to various market application*. The studies are carried out in the frame of the initiative "Showcasing the benefits brought by the usage of Sentinels data to society, environment and economy". It is interesting to note as, among the 15 studies devoted to demonstrating the value of the satellite based information, no one is referring to the case of fires (https://earsc.org/sebs/). Actually, a case of use of Copernicus Sentinel data by regional authorities on the island of Crete is reported, but the potential advantage using 'various indices derived from Sentinel-2 data', is given as a possibility for easily quantify and analyze the extent of the damage.
Some studies analyze specifically the effectiveness of using Prescribed Burning (PB) to reduce the incidence of fires [Davim et al., 2022; Elia et al., 2016]. In one case a cost-effectiveness analysis to estimate how much fuel must be treated to determine fuel load removals with the lowest cost per hectare was conducted. In the other one, a quantification of the effect of PB on the reduction of wildfire extent was performed by using 35 years of fire mapping data in Portugal.
In both cases the use of satellite data as source of information to plan the PB activity has been considered.
Reports, studies devoted to proposing or implementing a common methodology to assess socio-economic damages caused by fires have been published in the past under EC-JRC contracts

(https://effis.jrc.ec.europa.eu/reports-and-publications/forest-focus-studies; MASIFF project, etc.). What is new here is the attempt to develop a methodology to assess the value of the geospatial information, provided by exploiting satellite images, from the point of view of the final users. That is, a procedure to estimate the economic advantages that the adoption of certain information, in the user fire management practices, can determine.
In the specific case mentioned above the assessment is made more complex by the fact that the PB practice is applied even in the absence of satellite information.

This activity led us to consider the following key questions:

- Which is the relevant information retrieved by using available satellite data to support authorities in the management of wildfires?
- Which impact added value information could have on the wildfire management: helping in preserving the environment, reduce the damages, save life, helping in the adaptation to the wildfire trend driven by the climate changes?
- How the value of such information can be assessed?

The objectives of this work were therefore the following:

- Identify the FirEUrisk information potentially useful to support an enhancement of the effectiveness and efficiency in the wildfire management;
- Define the way the FirEUrisk information will impact the present wildfire management procedures;
- Identify the elements entering in the estimation of the value (economic, ecological, etc.) of wild areas;
- Define the way to assess the impact of FirEUrisk information in wildfire management and then its value.

The following sections describe the way we met those objectives.

The application of EO data for societal benefit can be conceptualized as a value chain that is composed of *data*, *information*, *knowledge*, and *wisdom* [Ackoff, 1989; Sharma, 2008]. Information is packaged into "products" (e.g., solutions, tools, and services) that address specific purposes. Value is created when the decisions lead to improved outcomes for society [Virapongse et al., 2020].
Different types of actors work within the value chain to facilitate the contribution of data toward decision making for societal benefit. EO value chains include the following types of people:
a) Data providers that collect, manage, generate, analyze, integrate, aggregate, and transform Earth Science data into information;
b) Intermediaries that synthesize, translate, communicate, and help to disseminate information and decision-support products toward an end use;

c) End users that understand a particular set of information so that they can make decisions; and
d) Citizens that can be impacted by said decisions.

To increase the societal benefit of EO data, Virapongse et al. (2020) introduce three approaches:
1) Seeking out new users for existing data and data products;
2) Improving an existing value chain that already has data and users; and
3) Developing a new value chain to meet specific user needs.

Seeking new users. In this approach, data and data products exist, and data providers seek to identify new ways to apply and use data, as well as recruit new users. The main challenge with this approach is that the users may simply not exist, or the products are not usable by or useful for a targeted user group. Building capacity among potential users could be a strategy to add value to existing data, such as satellite observations [Hossain, 2015]. As one example, the Copernicus program generates data collected from satellites, air, ground, and seaborne stations, and sensors which are used mostly by large organizations. Current efforts focus on stimulating user uptake (Copernicus Academy, Copernicus User Forum, etc.) of such data through the development of new services and skills development in the space geo-information sector.
Value chain improvement. In this approach, an EO value chain exists, and specific actors in the chain seek to improve the value chain through increased efficiency or discovery of new opportunities, such as new products and services for
users.
Use-driven approach. Knowledge production in modern society has often occurred by small homogenous groups defining both the problem and solutions. In contrast, for the use-driven approach, users frame the solution seeking process, aligning different needs and expectations of those involved [Gibbons et al., 1994; Burns et al., 2006]. Releasing data, information and products that have not been specifically prepared for user consumption is increasingly considered inadequate for addressing societal problems [Patel et al., 2015].
Virapongse et al. (2020), provides 10 rules to guide data providers and intermediaries in implementing actions and best practices while planning and executing projects that seek to increase the societal value of EO data. In particular, the rules address the "value chain improvement" and "use-driven" approaches described previously. Such 10 rules are listed in Table 5, please refer to Virapongse et al. (2020) for a detailed description of each rule.

Table 5. List of rules for EO value chain improvement.

Rule	Short description
Identify the root causes of a problem	A well-defined problem helps direct problem-solving efforts toward addressing underlying issues rather than just its symptoms
Consider how data is really used	Understanding how different people need and want to use data and information can help identify the best solutions

Get the right people to the table	Building bridges between data and use is not easy, but identifying and accessing key intermediaries and users can help
Investigate all alternative solutions carefully	Comprehensive identification and analysis of potential solutions helps determine which (if any) solutions should be advanced
Evaluate, adapt, and iterate	Solutions must be strategically evaluated and refined to ensure their best possible fit within the context
Think globally	Data and data products should adhere to existing best practices, standards, and ethical considerations to increase their potential for interoperability and broad applicability
Trust is essential	Users must be able to easily determine that data and data products have been developed with transparency and scientific rigor
Lower barriers to entry	Adapting outcomes to user capabilities can help increase the uptake and success of data and information solutions
Document the process	Capturing lessons learned allows others to avoid repeating mistakes and to improve upon successes
Walk away when the solution has legs	Once the solution has been adopted, know when it's time to let users take over

The rules focus on problem-solving that cannot be done by a solitary individual, while aiming to enhance efficiency and effectiveness.

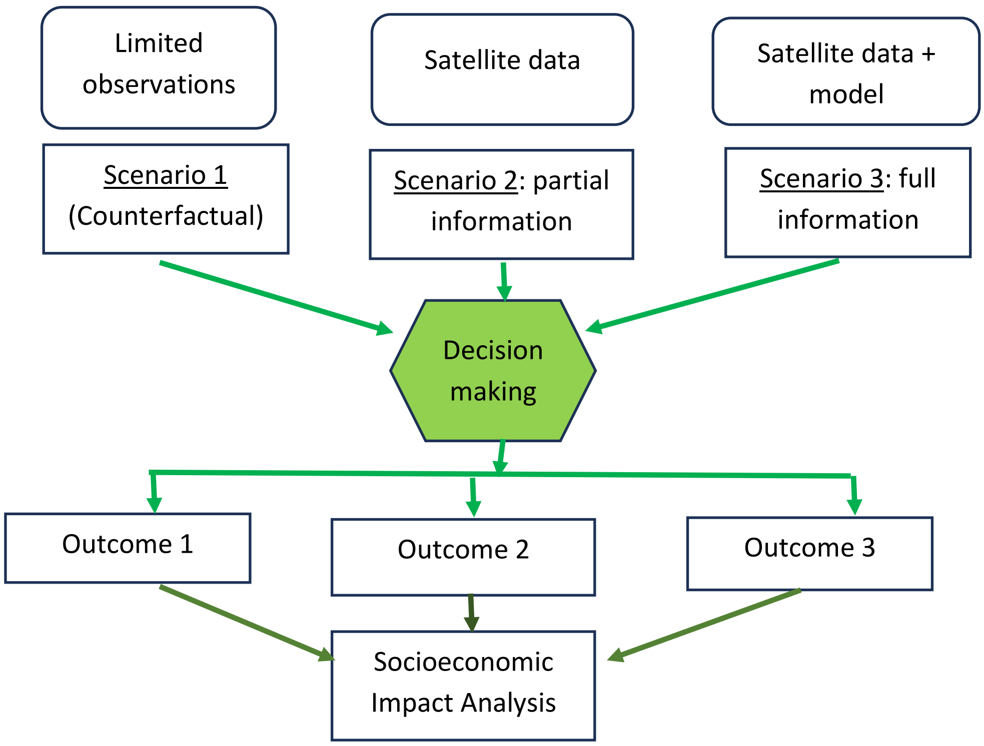


Figure 28. Scheme of the flows from different information scenarios to the decision and corresponding outcomes.

The VOI approach employs the concept of value chain [Kuwayama, 2017]. A value chain can be defined as the set of value-adding activities that one or more organizations perform in creating and distributing goods and services [Longhorn and Blakemore, 2007]. In the context of geospatial information, the value-chain concept can be applied to measure the socio-economic benefits of the data, considering the sources of geospatial data, the processing of the data into value added information to be incorporated into decision-support systems, leading to decision makers' actions [Harshadeep, 2018].
The value chain approach can be extended by incorporating a decision tree that can be applied to one or more use cases in order to assess the VOI for decision-making. The decision tree illustrates the marginal impact of the information in decision making compared to the counterfactual if the information was not available (Figure 28).
In principle the benefit of including satellite based information in the decision making process could be computed as shown in Figure 29. Of course, the main difficulty resides in the definition of the socioeconomic costs to include in order to estimate the socioeconomic benefits.

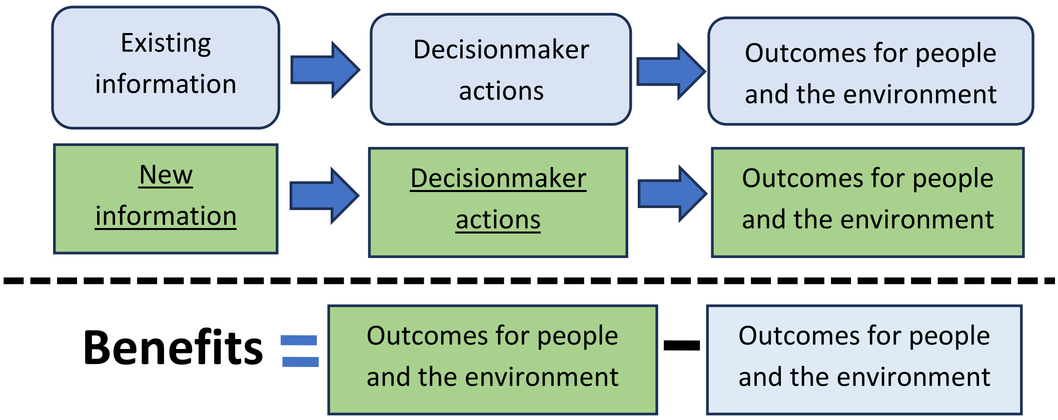


Figure 29. The basic idea for computing the value of the geospatial information. (Courtesy of Y. Kuwayama, Resources for the Future).

4.2 FirEUrisk information

FirEUrisk aims at combining the best wildfire management practices available in Europe to assess the vulnerability of communities and reduce fire risk by integrating societal factors and communication and support the adaptation to the future climate and socioeconomic conditions. The project is mainly focused on the development of products (services) capable to support the first one of the three phases in which the wildfire management strategy could be distinguished: prevention, fighting, recovery. Therefore, FirEUrisk products are intended for supporting the activity of prevention/reduction/adaptation. More specifically, FirEUrisk products can be distinguished in 5 categories (Figure 30, Conceptual integration of fire risk components within the FirEUrisk project):

- Danger (hazard) indices: the sum of the factors affecting the ignition, spread, and resistance to control in a given area.
- Exposure maps: i.e. the presence of people, infrastructure, housing, production capacities, species or ecosystems, and other tangible human assets in places and settings that could be adversely affected by one or multiple hazards. In other words, "exposure represents the people and assets at risk of potential loss or that may suffer damage to hazard impact.
- Vulnerability maps: the probability of fire damage; potential effects of fire on values.
- Risk reduction practices: the techniques which refer to systematic methods of reducing risks. The ideal method of reducing risk is by design procedures, preventive measures and training.
- Risk adaptation strategies: adaptation refers to actions taken at the individual, local, regional, and national levels to reduce risks from even today's changed climate conditions and to prepare for impacts from additional changes projected for the future.

Table 6 synthetically lists the main products provided in the framework of the FirEUrisk project with an indication of the intended use in the fire management practices. Identifying the fire management procedures which could benefit of the information produced by using satellite images is of paramount importance to assess their socio-economic value.

Table 6. List of products to be developed in the framework of the FirEUrisk project

Products for risk assessment	**Short description**	**Fire management phase involved**	**Intended use**
Human ignition probability map	Estimate of the probability that a human caused fire ignite	Risk assessment/prevention	Resources allocation
Geospatial integrated risk and vulnerability map	Map based on a multi-criteria analysis of data that take into account: meteorology, geomorphology, vegetation and sociological factors.	Prevention/preparedness/response	Resources allocation
Fire danger map	Spatial distribution of the fire danger (hazard).	Prevention	Resources allocation
Products for risk reduction			
Smoke modelling and health impact	Smoke dispersion modelling at local scale	Prevention/Preparedness	Alert to population
Land management	Best practices and guidelines to reduce fires risk. Identification of areas deserving fuel removal practices	Prevention/mitigation	Efficient fuel removal
Fire behaviour predictive models	Identification of the conditions that lead to extreme fire	Response	Population Alert, resources allocation

	behaviour (EFB) and definition of the methods to predict them in space and in time and provide an early warning to the authorities and population.		
Products for risk adaptation			
Database of global changes effects on vegetation resilience to disturbance	Information on how climate change factors affect plant post-fire regeneration mechanisms and resilience to disturbance, at the European scale	Preparedness	To be defined through interviews
Adaptation to future fire regime	A description of the impacts of changed future fire regimes on provision of ecosystem services	Prediction/Scenario evaluation/mitigation	To be defined through interviews

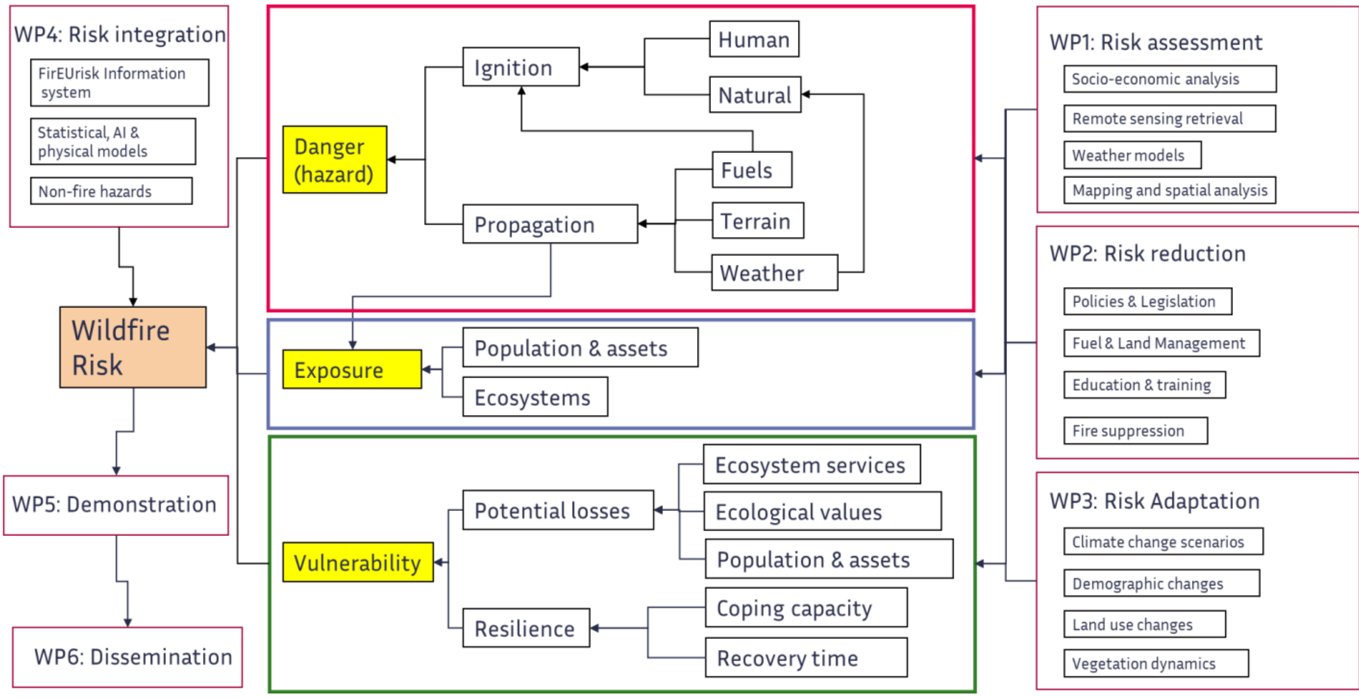


Figure 30. Conceptual integration of fire risk components within the FirEUrisk project.

4.3 Wildfire related potential losses definition

In order to assess the value of the geospatial information retrieved by satellite images when applied for supporting wildfire management practices it is necessary to identify the socio-economic-ecological value of the assets endangered by fire.

Sawyer et al. (2022) define six dimensions of benefit, to be considered to assess the value of the information (VOI), namely: economic, environmental, regulatory, innovation and entrepreneurship, science and technology, societal.
In the following, with specific reference to the contribution of satellite based data in the management of forest fires, we will consider only three of them [Sawyer et al,. 2022]:

- Economic, impacts related to the production of goods or services, or impacts on monetary flow or volume, such as revenue, profit, capital and (indirectly, through turnover generation) employment;
- Environmental, impacts related to the state and health of the environment, particularly as regards the ecosystem services on which human societies depend;
- Societal, impacts related to broader societal aspects, such as public health, citizen security and welfare.

Economic impact

Among the economic benefit of adopting satellite based services, we will here exclude that directly related to the EO service provider since we are interested in evaluating the VOI from the point of view of the user which will adopt the service in the own fire management procedures.
The economic impact of a fire includes the following elements:

1. Capital expenditure reduction or avoidance: reduction of capital expenditure which would or could otherwise have been incurred (e.g. cost of restoration);
2. Cost savings: reduction of operating expenditure which would or could otherwise have been incurred (e.g. cost for firefighting);
3. Increased revenues: Income through the commercial exploitation of environmental assets (e.g. tourism);
4. Reduction of risk: Reduction of risk and consequential costs;
5. Employment: Increased employment in the ecological service provider (e.g. touristic agencies);

Environmental impact

The environmental impact of a fire includes the following elements:

1. Reduced pollution: Reduction of unwanted material in the environment (air, water, soil, etc.)
2. Reduced impact on biodiversity: Denotes the impact (negative or positive) on the local ecosystems or on the biodiversity of its fauna/flora;
3. Natural resource depletion: destruction or consumption of natural resources.

Societal impact

The societal impact of a fire includes the following elements:

1. Public Health: deterioration to public health through exposure to pollutants, death, disease etc.;

2. Civil Security: reduction of citizens' sense of safety and protection;
3. Public Awareness: Provision of information to the general public with the aim of supporting public duties, raising awareness of hazards or danger, or improving transparency;
4. Public Utility: reduced access to public utility;
5. Community and Quality of Life: reduced sense of the quality of life through reduced perception of the country/region/town etc. as a place to live;
6. Improved Oversight: reduced propensity to stakeholder coordination and improved governance through a common operational picture.

Even if everything can be measured [Douglas, 2014], for some of the so called "intangibles" mentioned above it is hard to identify a way to provide quantitative measurements.
Therefore, in the following we will focus on tangible elements to give to them a value (Table 7). It should be also underlined that we are not considering here the impact of other effects that fire can bring (cascading effects, FirEUrisk deliverable D4.6 'Report on cascading effects') in combination with other natural hazards, which may potentially increase negative impacts of fire.
In estimating the VOI we assume that the use of satellite based information, or more in general, geospatial information derived by the fusion of data coming from different sources, will produce a decrease of the incidence of the phenomenon of interest here allowing to:

- Enhancing the efficacy of decisions;
- Reducing the incidence of the fire events;
- Enhancing the effectiveness of the intervention;
- Enhancing and limiting the prevention actions.

The improvement in the prevention activity and the reduction of the incidence of the events will contribute to reducing the extent of the area affected by fires or, better, the frequency of high-intensity fires. Therefore, the VOI can be computed by multiplying the area saved from fire for the values (€ per hectares) shown in Table 8. To this value of course we have to subtract the cost for producing the information we are referring to. To assess the decrease in the burnt area (or the benefits of the change due to the availability of information to a decision-maker) due to the adoption of the products provided by FirEUrisk we have to define the so called counterfactual, that is identify a case or cases representing the behaviour of the phenomenon of interest if provided information are not adopted. In case of forest fires identify a counterfactual is quite difficult since we cannot compare one year (no adoption of information) with the following one (information adopted) as fluctuations in the annual incidence of fire events are naturally due to inter-annual changing weather conditions. Therefore, the analysis should cover several years.

Table 7. List of elements to which a monetary cost could be assigned.

Element	Cost definition	Cost items
Capital expenditure reduction or avoidance	restoration	Plantation, tree losses
Cost savings	Fighting	Fire extinguishing costs

Increased revenues	visitors	Presence of tourists
Reduction of risk	patrol	Personnel cost
Employment	employees	GDP growth

Some details on different costs which should be considered in the estimation of damages caused by wildfires are given in the FirEUrisk deliverable D1.4 'Report on methodological frameworks for Vulnerability assessment'. This deliverable aims to report on the different approaches to fire exposure and vulnerability assessment developed and implemented within the framework of FirEUrisk project, Task 1.2 – Exposure and Vulnerability.

The report, based on an extended papers review provides an estimate of:

- the values of natural capital assets which includes the ecosystem services provided by forests (Table 8);
- the values of forests as recreational resources (Table 9);
- the values of natural areas with reference to the productive wealth embodied in labour (Table 10).

In the same document, some examples of economic values of assets are given (Figure 31,

Figure 32). In a case the value of timber land expressed in euros per hectare (€/ha) is reported at national scale in the European Union in 2021 currency (

Figure 32). It is calculated by taking the growth rate of timber expressed in m^3/ha in in each country provided by EUROSTAST. Value of properties, expressed in €/square meter in 2021 currency is shown in Figure 31. The information has been aggregated at national scale with detailed maps of local GDP assuming a linear relation between the value of a property and the income of the geographic zone where the asset is located.

Table 8. List of monetary values at stake for natural capital affected by wildfires.

Author	Value at stake	Valuation method	Geographic area	Monetary value	Unit
Huang et al., 2013	Carbon (effect of forest treatment on carbon stock balance and the carbon units to be issued in offsetting markets, through reserving carbon loss risk)	[marginal] Abatement (applied to estimated carbon credits for the treatment alternatives)	Oregon (US)	2.65- 404.65	US $/ha
Molina, Herrera & Rodríguez y Silva, 2019	Carbon (economic value of fire impacts on carbon storage)	Scenario analysis of fire impacts on carbon stock values per type of land use Single average prices (based on EU ETS)	Two sites (Vértice and Catena) affected by fires in Andalusia (Spain)	Vértice: 54.64-811.79 Catena: 1,375.94-12,398.68	€/ha
Molina, Zamora & Rodríguez y Silva., 2019b	Biodiversity (flagship species asset value applied to estimate biodiversity loses from dead individuals in a wildfire event, and decrease in population due to migration to other areas)	1) Recovery cost (based on public investment in recovery programs over the last 12 years) 2) Contingent valuation	Two protected areas (Doñaña and Segura) affected by fires in Andalusia (Spain)	Doñaña 1) 74.89-81.70 2) 105.7-115.3 Segura 1) 0.76-0.94 2) 3.75-3.92	€/ha total wildfir impact

Author	Value at stake	Valuation method	Geographic area	Monetary value	Unit
Sil et al., 2019	Provisioning services (cultivated biomass: timber, firewood and wild biomass: mushrooms)	Market valuation (prices reported in the study area) of income losses due to wildfires	Upper basin of the Sabor river (Portugal)	-1,021 -2,222 -3,038	€/ha
Varela et al., 2017	Multiple benefits from enhancing forest management practices (increasing carbon sequestration, biodiversity through diversification of forests, increasing the land available for recreation and reducing burnt areas)	Choice experiment (estimate social preferences (WTP) for environmental externalities, including a scenario that reduces the burned area)	Aleppo pine forest in Catalonia (Spain)	2,044.23	€/ha

Table 9. List of monetary values at stake for recreational values affected by wildfires.

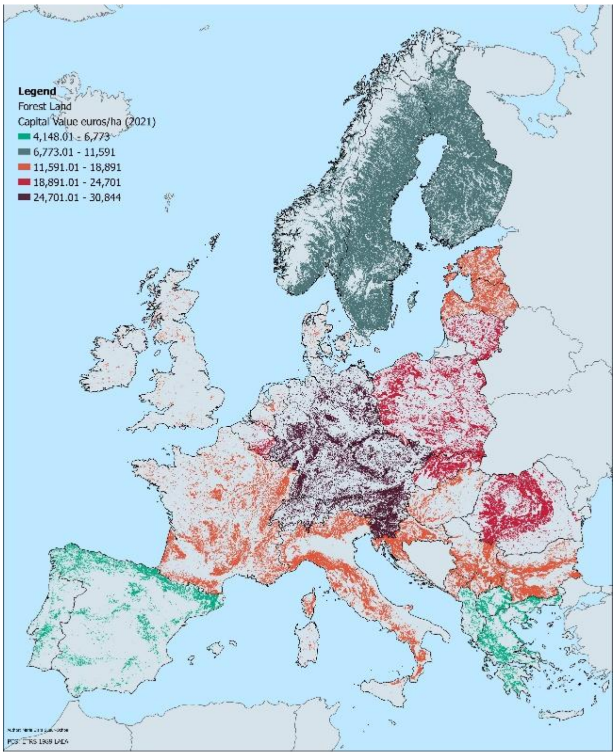
Author	Value at stake	Valuation method	Geographic area	Monetary value	Unit
Boxall and Englin 2008	Recreation (river sport)	Travel cost and contingent valuation	Nopiming Provincial Park, Canada	Increased value of route immediately following fire (1-year), declining at 10 years post burn, and then increasing again 35 years post burn	$/trip
Loomis et al 2001	Recreation (hiking and biking)	Travel cost and contingent valuation	Colorado national forests	Bikers – Trip increase from 1.29 to 3 between 0 to 40 years post crown fire. Value increase $62 - $138. No change for non-crown fire. Hikers – trip decrease from 3.03 to 2.78 0 to 40 years post crown fire, and value from $145 to $55. Non-crown fire trips increase 2.65-3.97, but value decrease $34-$24	Number of trips $/trip
Hesseln et al 2004	Recreation (hiking and biking)	Travel cost	Montana national forests	No change in trip frequency for hikers or bikers	Number of trips
Sanchez et al 2016	Recreation (hiking)	Travel cost and choice experiment	San Jacinto Wilderness	Welfare gain for hikers for 25% of	$/trip

			Area, California	trail burned mean of $106.35. Loss of sites access due to fire welfare loss of $23.92 to $164.05, with loss of all sites at $281.23	
Molina et al 2019	Recreation (hiking)	Travel cost	Sierra de Aracena y Picos de Aroches Natural Park, Spain	Potential loss to park based on recreation value and vegetation resilience estimated at between 31,210,807 and 89,460,204 Euro	Euro
Hesseln et al 2003	Recreation (hiking and biking)	Travel cost and contingent valuation	New Mexico national forests	Bikers – Trip decrease from 0.02 to 0 between 0 to 40 years post crown fire. Value decreases $9.66 - $7.19. For non-crown fire trips decrease from 6.91 to 0.73, and value from $150.53 to $25.80 Hikers – trip decrease from 1.24 to 0.95 0 to 40 years post crown fire, and value increase from $90.92 to $107.35. Non-crown fire trips decrease 1.93-0.06, and value decrease $130.24-$51.87	Number of trips $/trip

Table 10. Monetary values relating to health emerging from the papers reviewed in DEL1.4.

Author	Value at stake	Valuation method	Geographic area	Monetary value	Unit
Jones et al.	health	Benefit transfer method using BenMAP-CE,	Albuquerque, New Mexico	COI $74,000 – $111,000 WTP $338,000 – $429,000	Dollars (total value f entire community)

		defensive behaviour method, cost of illness, willingness to pay		for Albuquerque metropolitan area	
Richardson et al.	health	Defensive behaviour method, willingness to pay, cost of illness	California, USA	COI $9.50, WTP $84.42 per person per exposed day	$/person *exposed day
Tan-Soo et al.	health	Social-cost-benefit analysis	Indonesia	$392 lifetime income loss per person	$/person
Jones	health	Life satisfaction approach, willingness to pay	USA	WTP $129 per person per exposed day	$/person * exposed day
Richardson et al.	health	Cost of illness, defensive behaviour method, contingent valuation method, willingness to pay	California, USA	DMB WTP $86.87 CVM WTP $95.03 COI $3.02 – $16.87 per person per symptom day	$/person * symptom day



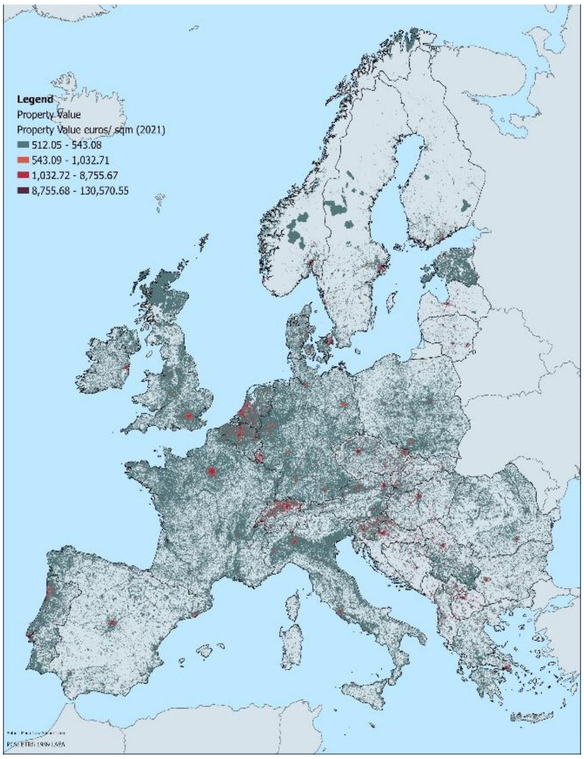


Figure 32. Representation of timber net revenue for 2021 in euros/ha, in FirEUrisk deliverable D1.4 'Report on methodological frameworks for Vulnerability assessment'.

Figure 31. Representation of value of property in Europe for 2021 in euros/sqm, in FirEUrisk deliverable D1.4 'Report on methodological frameworks for Vulnerability assessment'.

5 VOI estimation methodology

5.1 Review of values estimation

5.1.1 Scope of the review

This section is devoted to providing a review of existing formulas and techniques used to estimate the values of the elements potentially affected by forest fires (Table 11).

In the framework of the FirEUrisk project the SEVEIF model [Rodríguez y Silva et al., 2007] was adopted. This model incorporates calculations on the losses of valuable economic and natural resources affected. The process of economic losses assessment integrates two concepts, the value of the resource (pre-fire) and the fire behavior (flame length). The integration of the two concepts is accomplished using a matrix of depreciation rates based on flame length, called a "depreciation matrix" [Molina et al., 2011; Rodríguez y Silva et al., 2012].

The valuation of damages caused by forest fires requires individualized study of the value (pre-fire) of each of the resources (tangible and intangible) and their change in net value in relation to fire intensity and ecosystem resilience [Rodríguez y Silva et al., 2012].

The algorithms for assessing the value of the resources (pre-fire) (€/ha) are shown in Table 11 [Rodríguez y Silva et al., 2012]. The methodological approach for valuation of the impact on the timber resource (E) is based on an algorithm that integrates the valuation tools, which include trees of both natural and artificial origin.

The valuation of non-timber resources is based on expressions used in the Manual for the Valuation of Losses and Estimation of Environmental Impact by Wildfires [Martínez Ruíz, 2000]. The evaluation of the impact on the hunting resource is carried out through the adjustment proposed in [Zamora et al., 2010]. The valuation of environmental services includes three resources: carbon fixation, erosion control and faunal biodiversity. The valuation of carbon fixation includes both the amount fixed at the time of the fire's occurrence and the amount unfixed from that time on, with prior knowledge of bark, aerial biomass and annual increment volumes being necessary.

Table 11: Algorithms for assessing the value of the resources before the fire event included in the VISUAL-SEVEIF software, for each different resource considered.

Resource	Algorithm[1]	Source
Timber	V_{tim} = (1.7*E*B)/(E+0.85*B) *Immature stands* $E = C_0 * p\,[r^e + g*(r^e - 1)] + 0.5*C_0/z*(r^e - 1)$ $B = [(P*V*1.025^n)/1.04^n] * [1-(1.025/1.04)^e] * [1 + X*h*p]$ *Mature stands* $E = [P*V - P_1*V_1] + P*V\,[(r^{(T-e)} - 1)/(r^{(T-e)})]$ $B = V*h*t[R*P + (1 - R)*P_1]$	Rodriguez y Silva et al., 2012

Firewood use	$V_{firewood} = P_x*R_x*[((1+r)^n - 1)/(r*(1+r)^n]$	Molina et al., 2011
Hunting	$V_{hun} = P_x*R_x*[((1 +r)^n - 1)/(r*(1+r)^n] + S$	Zamora et al., 2010
Carbon fixation	$V_{carb} = CF*PM+IF*PM*RC*[((1+i)^{T-e} - 1)/(i*(1+i)^{T-e}]$	Molina et al., 2008
Erosion control	$V_{eros} = R_1*P_1+R_2*P_2*[((1+r)^n - 1)/(r*(1+r)^n]$	Molina et al., 2009
Biodiversity, landscape, recreation, unused	$V_{bio} = R_x*[((1+r)^n - 1)/(r*(1+r)^n]$	Molina, 2008

1. where E is the timber valuation (€/ha), B is the timber valuation adapted from the American Model (€/ha), C_0 is the cost of replanting one hectare of land (€/ha), p is the percentage burned stand based on fire behavior, r is the compound annual interest rate and depends on species growth rate: fast growth (1.06), medium growth (1.04), slow growth (1.025) and very slow growth (1.015); e is the estimated stand age at the time of the fire, V is the timber volume (m3/ha), P is the price of the timber (€/m³), n is the time or years remaining until the hypothetical harvesting rotation or senescence age, M is the tree mortality coefficient depending on fire intensity, h is the percentage of the species in the canopy, z is the reduction in replanting cost due to the self-regenerative phenomenon based on the rotation, P_1 is the price of damaged wood with commercial use (€/m3), V_1 is the volume of damaged wood with use (m3/ha), P_x is the price per unit of measurement of the resource (€), Rx is the annual income per unit area, S is the reproductive stock per unit area (€), CF is the amount of CO_2 retained at the time of the fire (t/ha), PM is the price per fixed ton (€/t) , IF is the annual increase in CO_2 retained (t/ha), RC is the income generated by fixing a ton of carbon in a year (€), R_1 is the average amount of soil lost the first year (t/ha), R_2 is the average amount of soil lost until recovery of the original cover (t/ha). "i" is the annual silvicultural cost factor and depends on species growth rate: fast growth (1.27), medium growth (1.1) slow growth (1.1) and very slow growth (0.93).

A study funded by EC-JRC in 2007 named 'Proposal for a harmonized methodology to assess socio-economic damages from forest fires in Europe' [Pettenella et al., 2010] describes different approaches (equations) to estimate the economic values of the elements potentially impacted by a forest fire (Table 12).

Table 12: Algorithms for assessing the value of the resources before the fire event [Pettenella et al., 2010].

Goods	Value (formula)
Timber	$ED_w = area*Vol*(P_{ro}-C_{fl})/(1+r)^m$, where ED = environmental damage due to wood-producing loss (€); area = area burned by the fire (hectares); Vol = volume of wood lost after the fire (m³/ha); P_{ro} = mean roundwood price at roadside (€/m³); C_{fl} = felling and logging costs (€/m3); r = discount rate; m = years needed to reach the mean rotation age.
Land use	$K_0 = B*(P^n-1)/P^n$, where K_0 = is the return from the soil for year of non-use; B = Soil value; n = years of missed productivity; P = rate of interest. Missed income = K_0*area.

Loss of biodiversity	$ED_{bio} = 0.5*area*DL*PC*(1+r)^n$, where ED_{bio} = environmental damage (€); area = area burned by the fire (ha); DL = damage level of the fire; PC = planting costs (€/ha); r = discount rate; n = number of years needed for reconstruction.
Tourism	$ED_{rec} = V_{rec}*N_{rec}*[(1+r)^g-1]/[g*(1+r)^g]$, where ED_{rec} = environmental damage from loss of tourism-recreational activities (€); V_{rec} = mean value of one visit (€); N_{rec} = mean number of visitors per year; r = discount rate; g = years of lost tourism-recreational business following the fire.
Restoring	$CR = \sum_t^T \sum_{j=1}^n \sum_{t=1}^m p_i \cdot q_{tji} \cdot (1+r)^{-1}$, where CR = restoration costs; p_i = price; q_{ij} = quantity of productive factors adopted for restoration (units of input); r = discount rate (%); t = time (years); T = time to recover; y= quantity of the necessary inputs by natural resources; m = productive factors adopted for restoration of I; n = natural resources. CR = RC*BA*DL, where CR = restoration cost (€); RC = reconstruction cost (€/ha); BA = burnt area (ha); DL = level of damage caused by the fire. $RC = PC*(1+r)^n$, where RC = reconstruction cost (€/ha); PC = planting cost (€/ha); r = discount rate; n = number of years needed for reconstruction.
Firefighting costs	$C_{spc} = C_m + (2*N_{tot}-N_{un})*D*C_{mh}$, where C_{spc} = cost of extinguishing the fire (€); C_m = cost of air vehicles; N_{tot} = the total number of persons who participated in fire suppression; N_{un} = total number of unpaid persons; D = duration of the operation, including the time needed to get to the operations zone (hours); C_{mh} = mean hourly cost of paid personnel (€/hour).

Defined the way to evaluate the economic values of the elements entering in the socio-economic fire losses assessment we can proceed in identifying the procedure to assess the impact of the change in the decisions taken based on the information provide by projects like FirEUrisk.

It should be underlined that the value of certain information could be assessed in two ways [Graham-Tomasi, 1988; Gardner et al., 1993; Hashemi et al., 2019]:

- through an *ex-ante* VOI study, which seeks to estimate the potential benefits or VOI prior to any decisions made with the information;
- through an *ex-post* VOI study, which examines the benefits and costs of decisions or policies after they have been implemented.

In order to estimate the VOI, we have to know how the FirEUrisk (or, in general, satellite based information to support fire management decisions) information are adopted into the decision-making flow of stakeholders and how they guide the change in the decisions.

Anyway, we can make some hypothesis to proceed, referring, as example, to some of the information provided by FirEUrisk.

Hypothesis I

Using prescribed burning (PB) to reduce the incidence of wildfire. In this case the cost of the application of such a practice should be compensated by a reduction of the fire events and then burnt areas.

Hypothesis II
Using danger maps to display resources on the territory. In this case the daily updated maps of the distribution of the fire danger in the area of interest could guide the distribution on the territory of the personnel with prevention functions.

Figure , taken from an IBE-CNR presentation [Cabiddu et al., 2023], shows the impact of the application of the prescribed burning, in a certain area of Sardinia, in reducing the number of fire events. The practice has been applied since 2012.

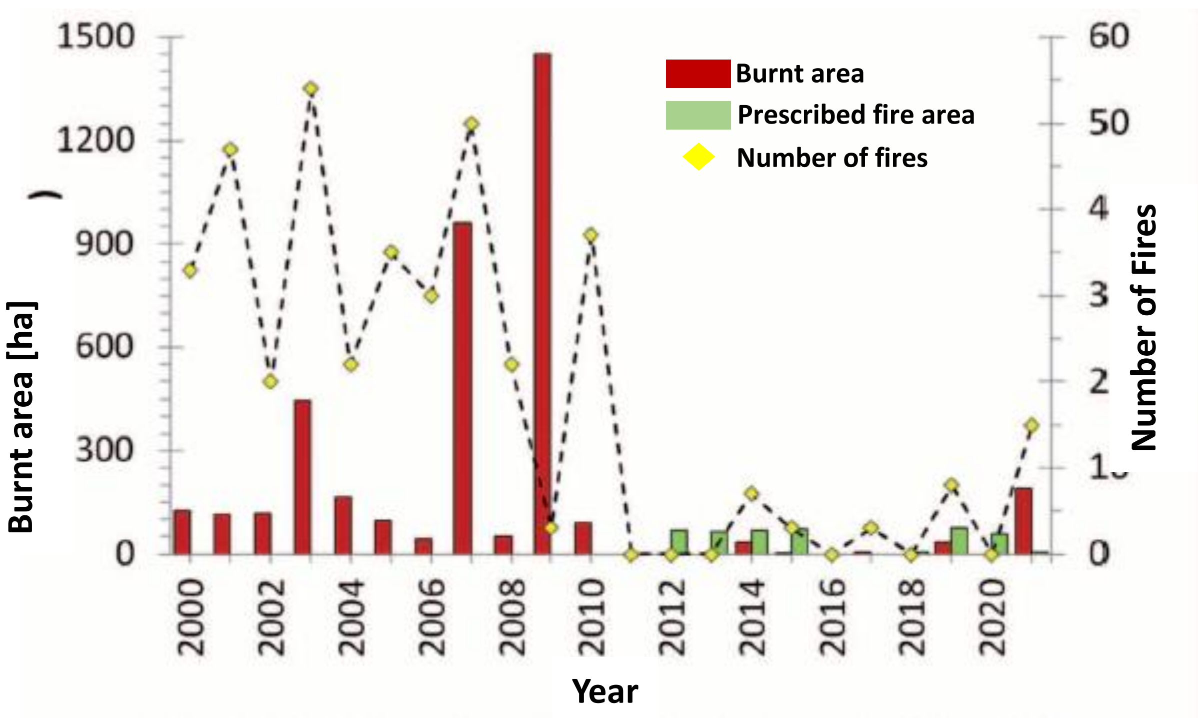


Figure 33. Annual distribution of wildfires in the municipality of Suni (Sardinia) (years 2000 – 2020). Green bars represent the extent of the areas where prescribed fires were applied [Cabiddu et al., 2023]. A decrease of the number of events, after the application of the technique, started in 2012, can be observed.

On average, in the 11 years preceding the application of the PB, 35 fires per year occurred, whereas in the years following the 2012 this number is reduced, in average, to 5.
In order to estimate, roughly, the losses reduction due to the decrease in the number of events we compute the average size of a fire in the area of interest just considering three recent years (2019, 2020, 2021). We found an average size of 11.7 ha/fire. Therefore, the reduction corresponds to 351 ha/year. The computation of the VOI, in this case could be estimate as follows:

$$VOI = VA - CPB - CPI \ [€/year]$$

Where VA = value of the assets not burned, CPB = cost of the application of the PB practice; CPI = cost for producing the information.
Example (Table 13):

Table 13. Simplified example of ex-post VOI estimate.

VA	CPB	CPI
Wood production = 1000 €/ha Touristic function = 50 CO_2 sequestration function = 100 €/ha Planting cost = 3000 €/ha Extinguishing cost = 20.000,00	Fuel removal cost = 1000 €/ha Based on Fig. 2, the prescribed burning is applied, in average, to an area of 50 ha.	Map production cost = 100 €
VA = 4150,00*351 + 20.000,00 * (35-5) = 2.056.650,00 [€/year]	CPB = 50 * 1000 = 50.000,00 €/year	CPI = 3500 €/year

Anyway, currently the practice of PB is applied even without using satellite images. This makes it more complex to identify the counterfactual compared to which the VOI could be assessed. Assuming that the maps produced by using satellite data could be used to double the extent of the treated surface (typical of 50 ha) and that for each PB hectare burned, 5 hectares of surface are saved, the VOI could be computed as:

$$VOI = VA_{sat\_inf} - VA_{no\_sat} - CPB - CPI \ [€/year]$$

where VA_{sat_inf} = value of the assets not burned when satellite information is applied; VA_{no_sat} = value of the assets not burned when no additional information is used (counterfactual); CPB = cost of the application of the PB practice; CPI = cost for producing the information.
Applying the same example of Table 13, we obtain the results shown in Table 14.

Table 14. Simplified example of ex-post VOI estimate when the EO data concur in driving the decision.

VA	CPB	CPI
VA_{sat_inf} = 500*4150,00	CPB_{sat_inf} = 100*1000,00	Map production cost = 100 €

VA_{no_sat} = 250*4150,00	CPB_{no_sat} = 250*4150,00	
VOI = 4150,00*(500 – 250)	CPB = 50 * 1000 = 50.000,00 €/year	CPI = 3500 €/year
VOI[1] = 4150,00*(500 – 250) – (100 – 50) * 1000,00 – 3500,00 = 984.000,00 €/year		

As a second example, Figure 34, taken from the PREFER FP7 project results, shows the variation of the area (in pixels) classified at high or very high fire danger during the 2015 summer season in three of the PREFER test areas. Now, we can hypothesize that the fire danger map would be used for selecting the areas to be subjected to patrolling for fire prevention.
Therefore, any information capable of better defining the areas at high or very high risk (or danger) can allow saving money by reducing the area to patrol.

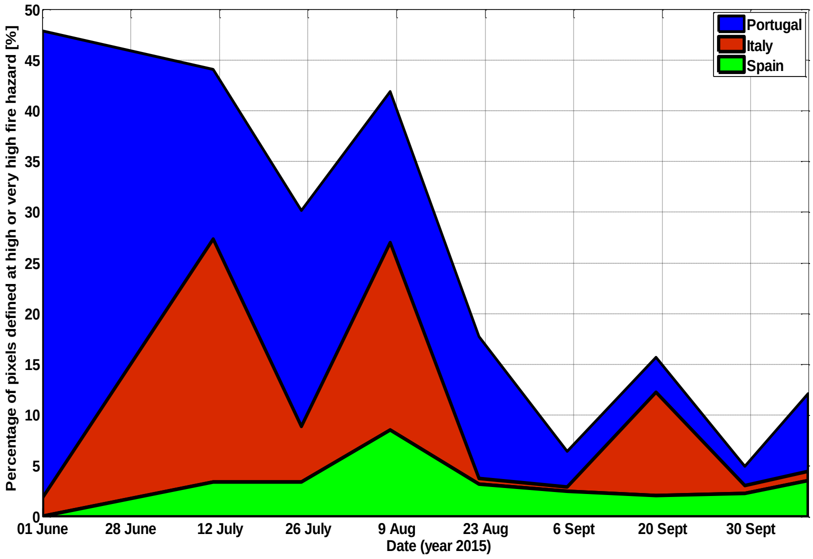


Figure 34. Percentage of the total number of pixels covering the area of interest, identified as at high and very high risk of fire.

In order to show how to estimate in this case the potential value of the spatial information coming from the exploitation of satellite data we have to find a way to define the cost of patrolling the areas at risk of fire. In 2022, Sardinia region allocated two million of euro to perform the surveillance of areas at risk for two months. Now, to identify the extent of such areas we can use the map of areas in available by Sardinia region in 2017 danger (Aree di Pericolo 2017, http://webgis2.regione.sardegna.it/download/). The map distinguishes 4 level of danger: 1 = very low, 2 = low, 3 = medium, 4 = high. Figure 35 shows the distribution of the danger in the island. Based on such a map it results that the area at medium or high risk covers the 43.6% of the total area of the region (24100 km^2). Therefore, from that we can infer that the surveillance

[1] In the evaluation of the VOI we neglected the money saved by reducing the number extinguishing interventions.

costs 2,000,000.00/(0.436*24100) = 190.0 €/km^2. Now, if we look at Figure 34, we see that in case of Sardinia, the danger index, in average, in the two months of July and August, labels at high or very high risk the 15% of the whole regional territory. Then, if the patrolling is restricted to this area, the money saved reducing the area covered is: 190.0*(0.436 – 0.15)*24100 = 1,309,000.00 €.

An *ex-ante* VOI estimate could be obtained by exploiting the continuous advancement of fire modelling approaches (FARSITE, FLAMmap, etc.), which could offer the possibility to evaluate the impact of fuels treatment in limiting fire spread, fire severity and potential losses change with varying levels of fuel treatment, suppression, and post-fire rehabilitation (Huffman et al., 2020; Young et al., 2020). An example is given here, in the case of the application of the PB practice.

We consider the case of a fire occurred in Sardinia on July 3rd, 2014, which burned about 485 ha. The FARSITE simulation, opportunely parameterized (we know the burned area and, approximately, the fire time duration), is capable to reproduce the real event, providing a time duration of 4 hours and 30 minutes.

Table 15 lists, in the first column, the types of vegetation interested by the fire. The second column provides the actual extend of the burned area divided by vegetation type. The burned area mostly consists of garrigue and maquis shrubland. The other three columns report the extent of the burned area obtained by simulating a fire in the same areas after the application of a low, moderate and complete fuel reduction practice.

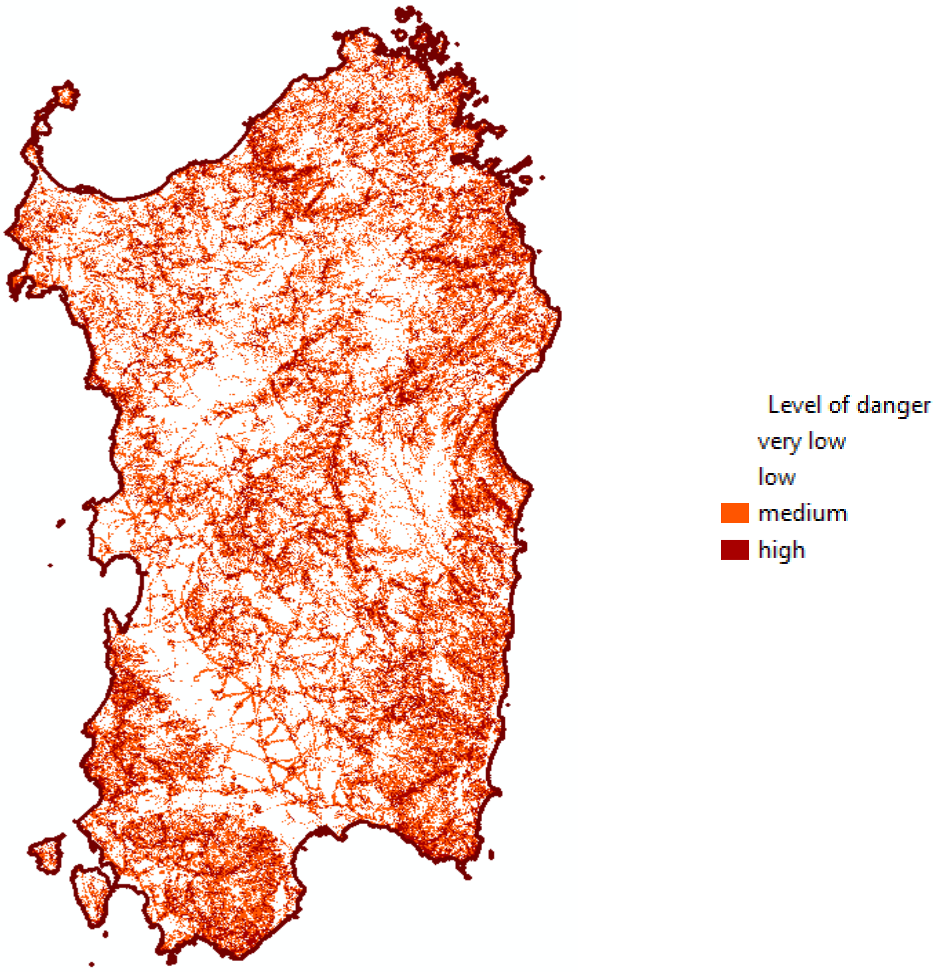
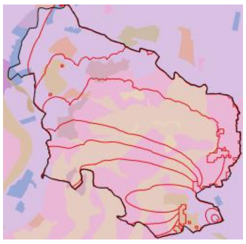
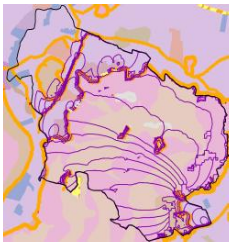
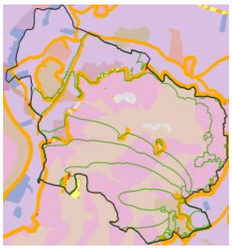


Figure 35. Distribution of the areas at medium and high fire danger, based on the map available on Sardinia region geoportal.

It is interesting to observe as applying a complete reduction of the fuel, that is, the fuel is completely removed in the areas of high/moderate ignition probability, the burned area would reduce to only 13 ha, composed by agricultural land. Therefore, all the natural area (garrigue and maquis) could be saved by the fire. However, applying a moderate level of fuel reduction, that is, the 50% of the fuel is removed, would reduce the burned area from 485 ha to 353 ha. The area deserving a fuel removal was identified by using a fuel reduction map.

Table 15. Example of a simulated estimate of the PB impact on fire spread.

Land cover	Effective burnt surface No fuel load reduction	Simulated burnt surface (ha)		
		Low fuel reduction	Moderate fuel reduction	Full reduction of the fuel load
Garrigue	165	136	136	0

Maquis shrubland	143	143	143	0
Agricultural land	114	59	24	13
Transitional woodland-shrub	20	10	10	0
Agro-forestry areas	20	19	9	0
Non-irrigated arable land	9	3	3	0
Natural grasslands	9	0	0	0
Vineyards	5	0	0	0
Total	**485**	**370**	**353**	**13**
				
Starting point	The orange and red bands indicate the buffer zones for the application of the fuel load reduction. The time duration of the simulation corresponds to 4^h 30’. The coloured lines (red, violet, green, cyan) indicate the fire propagation for each simulation, the time step is 30’.			

We applied the method on a real event to check the capability of FIRSITE to simulate the fire, but, of course, it can be applied everywhere to assess, in advance, the potential impact of the fuel management. For this reason, we present this case as an example of ex-ante estimate of the VOI.

5.1.2 Value chain approach

A value chain can be defined as the set of value-adding activities that one or more organizations perform in creating and distributing goods and services [Longhorn and Blakemore, 2007]. The concept was initially introduced by Porter (1985) and is widely used in evaluating business management and profitability. By understanding the ultimate “value” of a product and the components along the value chain, businesses can consider how to optimize processes. In terms of EO, the value-chain approach can be applied to consider societal benefits of the data and assess the value of data and data features. The EO value chain considers the geospatial data sources and the processing of the data into value added information to be incorporated into decision-support systems, leading to decision makers’ actions [Pearlman et al., 2019].
As done elsewhere the value chain has considered as having 4 “tiers”. Tier 1 is the “supplier” of the EO service, tier 2 is the “primary user”. Tier 3 are the “secondary users” i.e. all the specific users of the service provided by the primary user and tier 4 is the wider “citizens and society” (Figure 36). The tier 3 users are those directly linked to the function which the primary user is providing. For instance, in wildfire case, it may be institutions in charge of firefighting. There may be tertiary beneficiaries which sit alongside the main value chain, which may be government bodies or other institutions with a direct responsibility or interest in the sector. For

example, the Civil Protection and the Ministry of Interior would be relevant for a wildfire case. More specifically:

- In **tier 1**, the service provider is using the satellite data along with any other data and transforming it into maps or other information for the use of the primary user.
- In **tier 2**, the primary user is transforming the value through their process. Hence the business process needs to be understood to be able to estimate the values associated with its use.
- In **tier 3**, the tier 3 stakeholders are benefiting from the process within the activities of the primary user and hence are largely unaware that satellite data is being used. For example, a farmer may be using data concerning his fields to manage his crops, but his customers are only interested in the quantity and quality of the crops. Again, the business process must be evaluated to determine the benefit which is being generated.
- In **tier 4**, the benefits of the satellite data have become very diffuse and the general population, citizens and society, will even be unaware of that there are any links with satellites! They may suffer from an invitation to evacuate but have no idea of the process going on to achieve this or that satellite data has been used to determine the evacuation order.

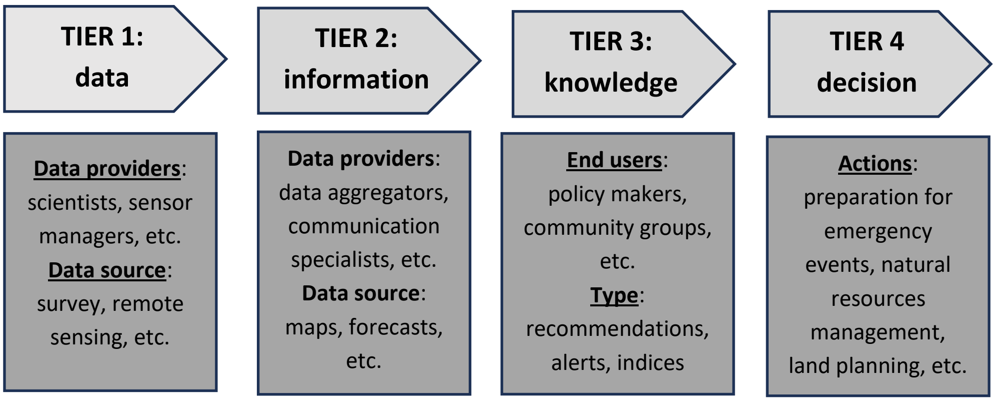


Figure 36. Value chain representation.

To perform the analysis, it is essential to understand how a specific EO-derived service is being used by an organisation which is in turn, benefiting others and ultimately society and citizens at large. The approach is bottom-up based on the evaluation of a value chain. Then, two information are requested:

1. Who will benefit from the services produced by FirEUrisk;
2. How such services will be used by the end-users.

Concerning the potential beneficiaries of the FirEUrisk products, we could refer to the work done in the WP6, Task 6.4, and, in particular, to the deliverable D6.14 ‘Policies review’.

Concerning the use of the provided services/information in decision chain of the end users, this point, to be answered, requires a questionnaire containing specific questions. However, preliminary information on the potential use of the project services/information in the fire management could be extracted from the user requirements reported in the deliverable D5.1 'User Requirements Data Base and Report'.
Table 16 reports the most popular requirements as expressed by end users compared with what is actually needed to reach the objective of assessing the VOI based on EO satellite for wildfire management.

Table 16. List of questions submitted to collect user requirements and most popular answers.

Question	Answer	Needed questions for VOI
What components do you need to improve wildfire risk assessments in your region of interest?	1. Data to monitor and assess fire propagation and/or smoke 2. Data to characterize vegetation 3. Data of elements exposed to wildfire	How data on fire propagation will l used? How data on vegetation characteristics will be used? How exposure data will be used?
What do you need to reduce wildfire risk in your region of interest?	1. Raise public awareness of wildfire risk 2. Strengthen resilience of the wildland-urban interface areas 3. Identify successful Land Management Strategies	How the public awareness will be raised? Developing an App for fire weather forecast, like meteo weather forecast? To which scale successful LMS will be adopted?
What do you need to improve adaptation to future fire regimes in your region of interest?	1. Fire adaptation strategies 2. The estimation of future changes in fire regimes 3. The impact assessment of future fire regimes	N/A
What do you need to improve integrated wildfire risk approaches in your region of interest?	1. Coordinated plans among policy makers, first responders, local communities 2. Communication strategies 3. Frameworks for assessing, reducing ad adapting to fire risk	N/A

5.1.2.1 VOI assessment in case of data fusion

The availability of fire danger indices allows, in principle, the implementation of a fire weather forecast App that, similarly to the case of meteorological forecast can be used by citizens to plan excursions, visits, tours in natural areas.
In this case two aspects should be considered:

- satellites are providing only some of the data needed to develop such a service;
- the WTP (willingness to pay) should be considered.

To pathfinder a procedure to assess the satellite based VOI in this case we can look at what was done in Jamilkoski et al. (2021), to assess the socioeconomic benefits of using GOES-R satellite imagery.
The economic concept used were:

1. the Weather Information Value Chain (IVC): as said above, the IVC is a conceptual model of the creation, communication, use, and value of information used in the analysis to articulate the process from observations through to end-user benefits.
2. Willingness-to-pay (WTP): is the maximum amount an individual is willing to pay to ensure that a welfare-increasing activity takes place. WTP is not a measure for advocating charging for weather information. Rather, it is the theoretically correct economic valuation measure for a non-market commodity such as weather information.
3. The expert elicitation interview protocol to determine what percent of the improvements in hurricane forecasts could be attributed to GOES-R information.

End-users may (or may not) use this information to make decisions about uncertain future fire (hydrometeorological in the example adopted here) events. It is within the context of information improving or changing the decisions of end-users, that economists would argue there is actual or potential economic value to this information.
The economic **impacts** of weather are “outcomes” that occur with the actualization of weather events and the decisions made by end-users. The **value of weather information** is in informing end-user decisions to change outcomes potentially for the better (e.g., improve benefits or reduce damages or costs). Weather information has *ex ante* value, and the economic impacts of weather are *ex post* measures of weather occurrences – not of information.
Information thus has value to assist in decision making before the event occurs. Economic impacts of weather are a result of the weather event that actually occurs and are thus after, or ex post, event measures.
Individuals have perceptions of the possible future states of the world (e.g., probability that a hurricane makes landfall near them) and make decisions based on these probability perceptions. Information can change those perceptions (hopefully making them more “accurate” or “correct”) and thus influence (or “improve”) decision-making. Following Letson et al. (2007) and Jamilkoski et al. (2021), we provide here a simplified decision model to illustrate the central concepts of the economic theory of VOI. We further define the concept of “willingness-to-pay”

or WTP as the correct valuation measure for a non-market commodity such as weather information. To assess the VOI, in this case, we have to estimate the contribution of satellite images in producing the weather (fire danger) information. Table 17 shows the estimate of the contribution attributed to GOES-R in the delivery of weather related information.

Table 17. Contribution attributed to GOES-R for some Weather products.

Mission Service Area	GOES-R program	Note (NOAA Tech. Rep.)
Aviation weather	20.47%	The contribution has been computed ranking the impact of different sources of data, apart GOES, as: radar, METOP, Rawinsonde, SNPP, DART, GPS Met, etc.
Winter Weather	11.19%	
Routine Weather	6.38%	
Hydrology and Water Resources	10.24%	
Severe Weather National Service Program	19.96%	
Fire Weather	14.02%	

Now, the assessment of the WTP was done [Lazo et al., 2009] by suggesting to respondents that a certain amount that they are currently paying in taxes is devoted to fund all NWS (National Weather Service) activities and asking if the services they are receiving are worth more than, worth exactly, or worth less than the amount indicated. Each individual was randomly presented 11 amounts ranging from 2$ a year to 240$ a year. By varying the amount that different respondents are told they are paying, the authors were able to derive a profile of the percentage of people willing to pay different dollar amounts for weather information. Different amounts correspond to different characteristics or accuracy of the information. Figure 37 reproduces the result obtained as explained above, using the responses of the 1,465 individuals who do use weather forecasts.

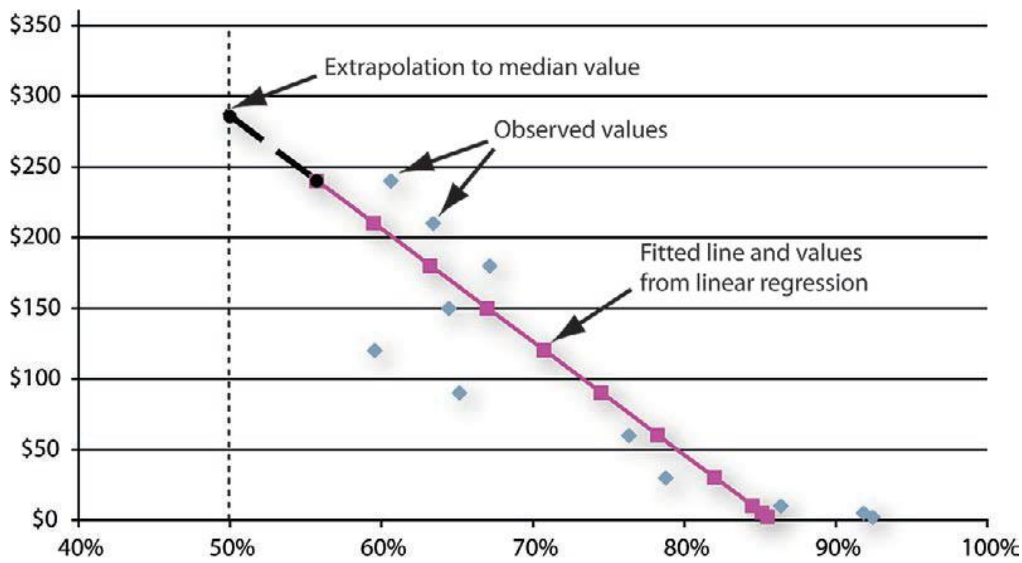


Figure 37. Assessment of value of all weather forecasting and information services to households (n = 1,465). For each of the 11 "offer" prices (vertical axis) the percent (horizontal axis) indicating worth "more than" or "exactly" that amount is plotted. Grey diamonds (◊) show actual

responses; solid pink line shows fitted line from linear regression; dashed black line shows extrapolation to median value of 286$ per household per year. On the x axis is depicted the quantity, in this case the percentage of people willing to pay. The survey question asked, "Do you feel that the services you receive from the activities of the NWS are worth more than, exactly, or less than $N a year to your household?" (Lazo et al. 2009).

In the specific case of our interest, we can assume that the improvement to a baseline fire danger index could consist in a better spatial resolution and more accurate information. Then, multiplied $286 by the number of households and the percentage of people willing to pay we obtain the total value of forecasts.

But this is not responding to our original question: which is the advantage from the user (a regional or national institution) point of view of adopting EO based information? Can we quantify the economic advantage for the user in terms of reduced impact of the fire (weather) events?

How the availability of improved fire weather information enters the end-users operative practices?

1. Enhancing the resources distribution on the territory to patrol more hazardous areas. In this case the use of EO based information helps in save money in terms of fuel and personnel.
2. Making citizens more aware of hazardous places and/or actions soliciting them to avoid certain places. In this case the advantage of using EO based information in supporting citizens' behaviour cannot be economically quantified or can be quantified as suggested above, inviting the citizens to quantify the VOI through their willingness to pay;
3. The use of new technologies (satellite data) makes citizens more certain of the information released by the relevant authorities and more satisfied with them. In this case the advantage of using EO based information does not necessarily translate into economic savings as citizens could request further investments to further improve the service.

5.1.3 Simulated scenario

In 2017 a report titled '*Copernicus ex-ante benefits assessment*', aiming at assessing the impact of the Copernicus Programme, in support of the European Commission, was published. We move from this document to try to further develop its findings. In such document the methodological approach to value to socio-environmental benefits of reduced forest fire areas is addressed by looking at the areas saved from burning thanks to EFFIS and the Copernicus EMS (Emergency Management System) mapping service and to analyse the environmental value that was prevented from being lost. The steps are:

1. Determine the size of the areas that could theoretically be saved from fire burning thanks to fire prevention strategies and preparedness.
2. Consider the 10-year recovery rate of burnt areas.
3. Apply a valuation coefficient to each type of areas that was not burnt and that has not recovered yet, which corresponds to the value that each type of land provides to the ecosystem.
4. Apply the contribution of Copernicus EMS mapping service and of EFFIS.

Their evaluation approach, quite simplified, is given in Figure 38.

Impact EUR]	=	Area of forest saved from fire due to improved prevention and responses	X	Attribution to Copernicus of part of this saved area through its services	X	Value of a hectare of forest on the ecosystem

Figure 38. Valuation approach for the social and environmental benefits due to reduced forest fire areas.

The authors of the report refer to the Khabarov et al. predictions [Khabarov et al., 2016], according to which, without any adaptation such as fire prevention methods and techniques, the burnt areas in Portugal, Spain, Italy, Greece and France are expected to increase by about 6.38% between the yearly average of 2017-2025 and the yearly average of 2026-2035. After an extrapolation to the whole of Europe, based on the fact that burnt areas in these countries account for 85% of the European burnt areas, it appears that the yearly average of saved areas is 229,412 ha in 2017-2025 and 282,353 ha in 2026-2035. Once the benefits of saving areas from fires thanks to adaptation has been calculated, the contribution of Copernicus to this adaptation is extracted. Two services play a role in this adaptation: EFFIS and the Copernicus EMS mapping service. As for EFFIS, it contributes to prevention and mitigation of forest fires and is assumed to be responsible of **between 10% and 15%** of the saved areas over the 2017-2035 period. EFFIS also contributes to preparedness and response through mapping of large forest fires (above 30 ha), which represent 80% of the burned areas. Its contribution ranges between **0.5% and 0.75%** in 2017-2025 to between **1% and 1.5%** in 2026-2035 of the areas saved from large fires. This contribution is calculated by considering the fact that by increasing the probability of fighting down a fire in just one day by 10%, it would lead to saving 30% of the burnt areas in 2090. As for the Copernicus EMS mapping service, which also contributes to preparedness through mapping of large fires, its contribution is of **0.31% in 2017-2025**, increasing to **1% in 2026-2035** of the areas saved from large fires. This contribution is also based on the boosting of the probability of putting out a fire within a day and on the solicitation of the mapping service by users. The activations of the on-demand rapid mappings covered 24% of the total burnt area from large fires in the five European countries mentioned above in 2015, and these activations are expected to reach 100% in the next ten years.

Is the information provided in the mentioned report of help in our case?

Unfortunately, the statement that EFFIS will contribute up to the 10% and 15% of saved areas over the 2017-2035 period, is not, at present, justified in any way. Mainly because it is not explained as EFFIS information are used by end users. Also, the hypothesis that adaptation could help in saving an area of 229,412 ha in 2017-2025 and 282,353 ha in 2026-2035 has not an explanation.

Furthermore, the hypothesis that the burned areas would increase of the 6.38%, in the period 2017 -2025, is not confirmed by the facts (Figure 39).

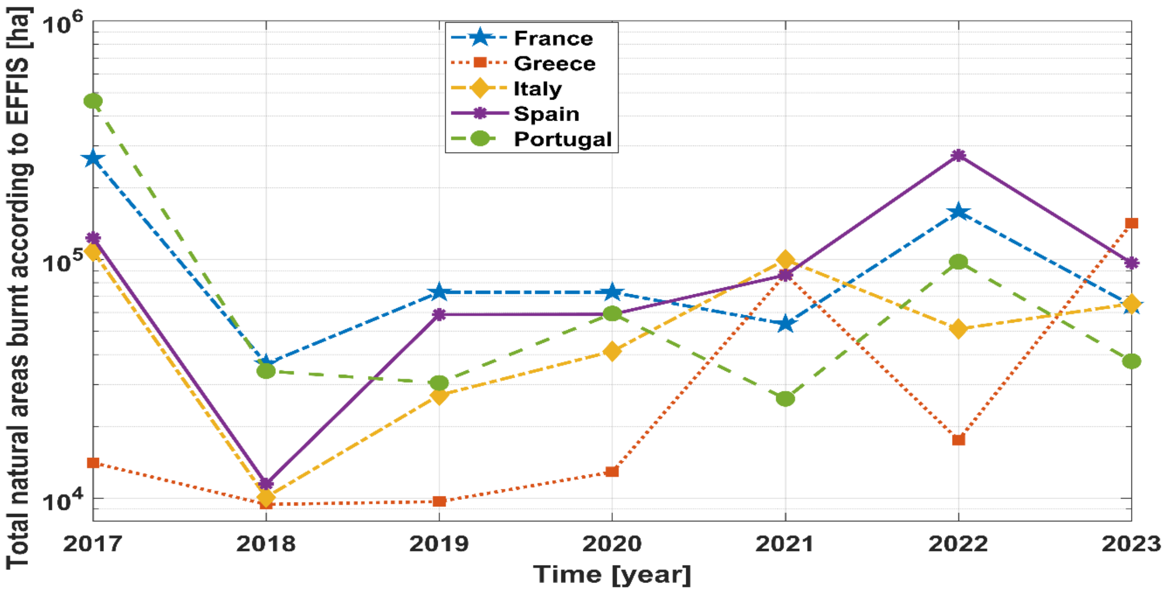


Figure 39. The annual distribution of natural burnt areas, in the five more affected European countries, according to EFFIS.

Finally, the assumption that the activation of the rapid mappings through EMS will cover 100% of the total burnt area from large fires is not supported by facts. In fact, as an example, in 2023, we do not find any activation, in Italy, in face of 61 fires exceeding 200 ha (https://activations.emergency.copernicus.eu/).

5.1.4 Different approach to the assessment of VOI

5.1.4.1 Assessment of Prescribed Burning cost effectiveness

As mentioned in deliverable D2.3 (Guidelines for Land Management Strategies: Applicability, socioeconomics and environmental concerns) the fuel removal can be carried out in different ways.

Herein we are considering the case of the prescribed burning practice for which a product has been made available in the framework of the project suitable to support this type of methodology.

The difficulty in estimating the value of the geospatial information delivered thanks to EO satellites comes from the fact that the PB practice does not necessarily need the support of satellite images. Therefore, as shown before in the case of the contribution of geostationary satellites in weather forecasting, the impact of EO images in planning and executing PB activity should be estimated.

Since, as shown in the previous paragraphs, PB application costs money, it will be interesting to have a look at the results provided by Pacheco et al. (2021) and Elia et al. (2016).

In one case [Elia et al., 2016], a cost-effectiveness analysis was carried out in three stages: (1) simulation of fire behavior, in terms of fireline intensity (FLI), in different fuel load reduction and wind direction scenarios across the study landscape; (2) estimation of WUIs (Wild Urban Interfaces) affected by wildfires within the study landscape; and (3) application of a cost-effectiveness ratio to determine fuel load removals with the lowest cost per hectare of unaffected WUI. The study refers to the Italian region of Apulia. The authors estimated a cost of 210,00 €/ton to remove fuel by using PB. Then, they reached the conclusion that, at best, for each hectare of WUI area saved it is necessary to spend 18.329,00 €.

Instead, Pacheco et al., evaluated the possibility of using carbon taxation to fund fire management measures in Mediterranean countries. The analysis was performed by converting prescribed burning savings in carbon emissions into their economic value. The study was performed for France, Greece, Italy, Spain, and Portugal, which was studied in more detail, since the country has a National Prescribed Burning Program (NPBP).

Under optimal conditions, assuming the 2% of the annually burned area treated by prescribed fire, and 3 ha decrease in the area burned by wildfire for each treated ha, in terms of CO_2 emissions tax they estimate an annual monetary saving of 2412 €/ha. However, other studies [Volkova et al. 2021] suggest limited potential for reducing net GHG (Greenhouse Gas) emissions through applying prescribed fire, with higher emissions from prescribed fire approximately offset by lower emissions and avoided carbon losses from the subsequent reduction in wildfire frequency.

5.1.4.2 Assessment of EO impact to inform post-event response

A full analysis of the cost effectiveness of using satellite imagery has been done by Bernknopt et al. (2021). Unfortunately, the analysis is part of the Burn Area Emergency Response (BAER), and the post-event fire management is not covered by the FirEUrisk project. Anyway, the procedure adopted by the authors could be of interest in our study. The approach of the authors involves comparing the costs associated with the production of a Burn Area Reflectance Classification (BARC) map, and with the implementation of a BAER when imagery from satellites (either

Landsat or a commercial satellite) is available, to the costs of BARC map production and BAER response when the BAER team relies on information collected solely by aerial reconnaissance. The study includes two evaluations with and without BARC products: (a) costs and cost savings for a specific wildfire incident request and (b) costs and cost savings of a multi-incident BARC map production program. In both cases, satellite imagery, and in particular, Landsat is the most cost-effective way to input burn severity information into the BAER program, with cost savings of up to $35 million over a five-year period. BAER is a component of post-fire emergency response activities that involves repairing or mitigating damages caused by fire suppression, post-fire rehabilitation, and long-term fire restoration. USFS (US Forest Service) and DOI (Department of the Interior) authority are specifically required to use the BAER protocol to do the following:

- Conduct assessments promptly on burned areas following wildfires larger than 200 ha to determine if a burned-area emergency exists;
- Undertake response actions or emergency stabilization when analysis shows that planned actions are likely to reduce risks within the first year following containment of the fire;
- Employ measures that provide sufficient protection at the least cost while meeting risk management objectives and emergency stabilization measures one year after fire containment; and
- Monitor emergency stabilization measures for up to three years from containment of the fire.

In this VOI impact assessment, the cost-effectiveness of using Landsat satellite imagery as the basis for BARC map production and BAER protocol implementation has been estimated. VOI approach is used to determine what information is worth by assessing the difference in how people decide with the information (using Landsat imagery as the reference case) and without it (using commercial satellite imagery or no satellite input as the counterfactual cases). The VOI approach relies on the premise that information can influence decision making; information is only meaningful in the presence of uncertainty and valuable when there is something at stake in a decision. To quantify the value of additional information, its application must be considered in a specific decision context. Satellite imagery is potentially valuable because it may reduce the incident operational costs of producing a BARC map and implementing the BAER assessment protocol relative to the case in which the Landsat imagery is not available. This analysis focuses on quantifying how using Landsat imagery to generate a BARC map reduces the cost of producing the SBS (Soil Burn Severity) classification. SBS is a classification that indicates the ecological impact of a fire on the burned region. A low rating means that the soil will require little to no maintenance; a high rating means that the soil exhibits unfavorable properties and will require extra maintenance or costly alterations. To assess the VOI retrieved from satellite images, the costs of producing a BARC map was evaluated for the reference and counterfactual cases in this analysis. The reference case comprises the use of Landsat and helicopter images.

The counterfactual case includes the use of helicopter images only. Ultimately, the use of satellite images allows to achieve a decision on the areas that require an intervention by drastically reducing the flight hours of the helicopter. Considering 50 large events (> 200 ha) per year (Italy case), according to Bernknopt et al. (2021) approach, the operating cost savings would be of the order of 500.000,00 €/year.

6 Roadmap for the VOI assessment of the EO information

6.1 Collection of information from users

To understand the value of EO, it is necessary to recognize how EO benefits users. In other words, the assessment of the value of the satellite based geospatial information relies on the premise that information has no value if it is not used in at least one decision [Pearlman et al., 2019]. Therefore, a decision tree allows to consider the types of decisions made using information and compare scenarios with and without information. One should identify the potential alternative decision pathways, the outcomes of those pathways, the probability of a decision maker choosing any pathway given the next best information, and the monetized value of each decision pathway. Each of the decision points in Figure 40 illustrate the simplified derivation of the value of information. To quantify the value of information under these assumptions the following formula could be used [Pearlman et al., 2019]:

$$VOI = [P^{*}xM^{*}] - ([P_1xM_1] + [P_2xM_2] + [P_3xM_3])$$

where P is the probability of a given decision pathway, M is the monetized value of a given decision pathway.

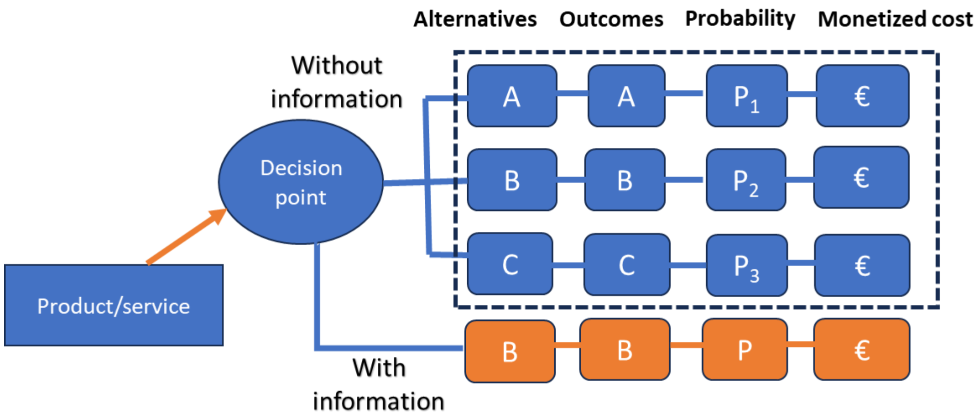


Figure 40. Earth Observation decision tree (inspired by Pearlman et al. 2019)

By connecting the value chain and the decision tree, a framework is created that allows for conceptualizing the value of EO in its many uses. One can then apply economic techniques to monetize the marginal benefit of an outcome with information versus one without [Pearlman et al., 2019].

6.2 Approach for VOI assessment

6.2.1 Value chain – information tree

At this point we can identify three general levels of relevance of satellite based information:

- Satellite products provide information otherwise missing at all, e.g. burnt areas in rural regions;
- Satellite products concur in enhancing the accuracy of the available information, e.g. weather forecast or, in our case, fire hazard maps;
- Satellite products concur in enhancing the citizen awareness about potential risk, e.g. hazardous areas and time.

To these three cases, different ways of monetizing the impact of EO information apply.

6.2.2 Monetization of the socioeconomic and environmental impact of EO

If a real advantage is identified in introducing satellite data into the operators' decision tree in terms of reduction of the damages caused by fires it would be relatively easy to recognize and monetize the socioeconomic and environmental impact of the geospatial information based on EO satellites.

In this case, once the size of the area saved from the fire has been estimated we can compute the VOI by computing the value of the unburnt area considering all the monetizable elements as shown in Table 11 and Table 12 and more extensively described in DEL1.4 (Report on methodological frameworks for Vulnerability assessment (D, S) in the FirEUrisk- Wiki).

In general, it would be difficult to assess the impact of some decisions based on the availability of additional information to reduce fire incidence, due to the annual variability of the frequency and entity of the phenomenon as consequence of changing weather conditions, human tendency, accidental events, etc. Fire modelling approaches (FARSITE, FLAMmap, etc.), which continue to advance, could offer the possibility to evaluate the impact of fuels treatment in limiting fire spread, fire severity and potential losses change with varying levels of fuel treatment, suppression, and post-fire rehabilitation [Huffman et al., 2020; Young et al., 2020], as shown in par. 5.1.1 (Table 15).

If EO data concur in enhancing the quality of the information provided to the operator (e.g. improving the spatial and/or temporal resolution of a fire danger map) the amount of such contribution should be determined based on expert evaluations.

If the satellite provides information useful to enhance the awareness regarding the impact of a certain phenomenon without causing the decision makers to take immediate actions, the way to monetize the VOI should follow a different approach. Possibly in this case the willingness-to-pay approach should be followed, as mentioned in par. 5.1.2.1. An assessment of the willingness to pay for services specifically related to wildfire management has been presented in few papers [Shrestha et al., 2021; Sánchez et al., 2022; Simon et al., 2022].

The VOI is defined as the expected gains from making more optimal decisions, as a result of acquiring additional information in the presence of uncertainty. The VOI is given by the difference in the values between (1) the “without
information” or “low information” and (2) “full information” (or at least “improved information”) cases. In our case, the difference is the change in total costs with and without additional information [Simon et al., 2022]. Therefore, in this case, the VOI could be evaluated by analyzing the willingness-to-pay of institutions or citizens to obtain more reliable information. To evaluate the willingness-to-pay it is necessary to develop a questionnaire and carry out a survey probably tailored focusing on two groups of responders: professionals and citizens. To eliciting the WTP from citizens, as mentioned above, it can be stated that public authority is considering using some state revenue as matching funds to help counties finance fire prevention programs. If the majority of residents vote to pay the county share of this program, for instance, the Prescribed Burning program would be implemented in that county on federal, state, and private forest and rangelands. Funding the Program would require that all users of forest and rangelands pay the additional costs of this program. If the Program is undertaken, it is expected to reduce the number of hectares burned by wildfires from the current value of XXX ha each year to a lower value of YYY ha [Loomis et al., 2009].
Figure 41 helps understanding how the benefits of having information (i.e., the value of information, VOI), impact decision makers or citizens and the corresponding monetary and non-monetary costs (e.g., competition for attention).
Glynn et al. (2022) provide a way to assess the VOI through data to decision pathways (DDPs).

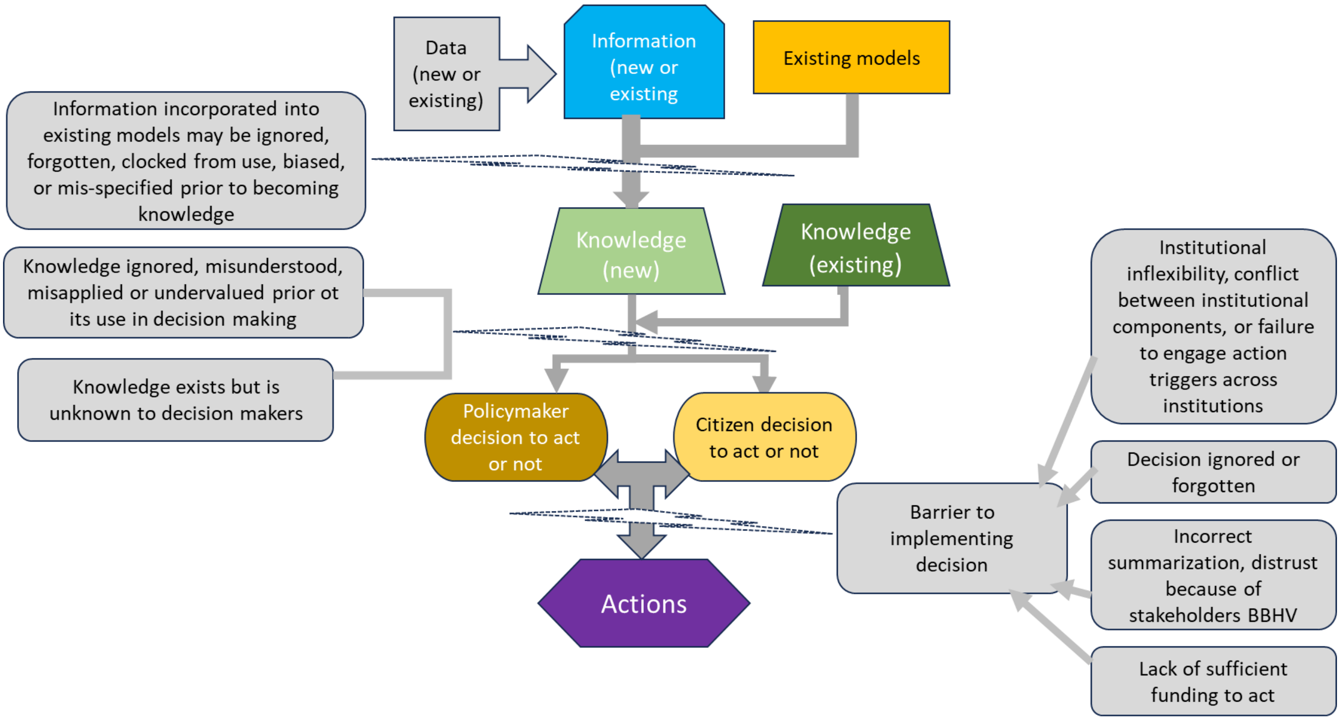


Figure 41. Potential barriers and challenges affecting Data Decision Pathway (DDP) progressions. Knowledge sources and actors involved also affect progressions, including resulting decisions and actions (inspired by Glynn et al., 2022).

A DDP involves progressing from data and observations to decision making and action (Figure 41). Data can have uncertainties and assumptions associated with their characterization or representation; and data that have been transformed or structured may be associated with additional uncertainties, assumptions, simplifications, or models of all types (conceptual, mental, scientific). Information is produced when data of many different types, are picked, organized, structured, appropriately documented, and something is produced that we sense or realize can be useful. We use the word "decisions" generally to imply that an actor (an individual, institution, or community) or a group of actors decides to act (or not to act) based on acquired and/or newly generated knowledge. We use "action" only when the nature or consequence of a specific action is relevant.

Efforts to understand the value that certain information adds to a DDP can take two forms [Graham-Tomasi, 1988; Gardner et al., 1993; Hashemi et al., 2019]. One form, an *ex-ante* VOI study, seeks to estimate the potential benefits or VOI prior to any decisions made with the information. *Ex-ante* studies, more generally, may consider and seek to predict 1) which information should be produced through data-gathering, study, or experimentation, 2) where to devote extra resources for dissemination of the data or information, and 3) the potential value of specific types of information to improve decision making. *Ex-ante* studies can also evaluate hypothetical outcomes from the use of information to determine to what degree it will change decisions and actions. The second form, an *ex-post* VOI study, examines the benefits and costs of decisions or policies after they have been implemented. For example, researchers may investigate what information and associated knowledge proved to be most useful within the initial set of decisions, or as part of a continuing effort to interactively assess and manage a given issue. *Ex-post* analyses are rarely undertaken because 1) clear points of comparison or reference are often not available and 2) incentives to conduct such studies are limited, especially if they might highlight failures, rather than positive benefits [Tomlinson and Atkinson, 1987; Dipper et al., 1998].

Figure 41 shows the structure of a data to decisions pathway, showing the role of models and some feedback and interactions in a progression to decisions (and possible actions). Filters and barriers can arise in the transition from decision to action. For example, a legislature might pass a law telling an administration to do something but does not designate or provide the funding needed. Figure 41 illustrates these challenges and alludes to differences between decisions made by different types of actors (e.g., a policymaker and a citizen). Value of information and pathways to decisions are actor-dependent.

Glynn et al. (2022), explored how social and behavioural factors affect the selection, communication, and reception of information and of associated processing and use models. The authors identified fifteen value explorations (VEs) (Table 18).

Table 18. Estimation of value in VOI methodologies

	Value derivation or method (VM); and/or valuation obstacle (VO)	**Benefits and opportunities**
Information for model refinement	VOI obtained from a stated purpose. Model context is presumably explicit—and not drastically changed by the additional information	Reduce existing model uncertainty
VOI determination by comparison with the counterfactual	VOI derived by comparison with and without information. Model context is present but is often not explicitly stated or sufficiently described.	The reference state or baseline provided by the “counterfactual” (model + information) may be very useful in properly assessing VOI
Information that challenges or disproves a model or hypothesis	VOI obtained from the “destruction” of a prior existing model (with associated purpose(s), scope, condition(s) and actors)	New information provides a major correction to an existing model, and/c allows a new model to be established thereby enabling improved understanding, predictions, and decision making
Information with clearly perceived direct impacts on individuals and communities	VOI evidenced through the individual or community decisions or actions that are taken in response to the presentation of information	The VOI is well defined *ex post* throug the reactions and response of a community or individuals. There is a possibility to use the VOI *ex ante* to anticipate (rather than react to) and proactively prevent or mitigate similar situations with direct impacts elsewhe
Information with poorly perceived indirect impacts	VOI of this type of information can only be assessed through explicit calculations and definition of an associated “context and response model.”	Assessing VOI for this type of situatior depends on explicitly defining a “context and response” model associated with the information.

Information with no perceived or actual relevance (from the perspective of given users)	Such information may offer a useful VOI reference state. The value will be negative because of the opportunity cost of its distraction effect (positive cost with zero benefit)	Recognizing that certain information i irrelevant, despite the cost of doing sc allows us to better focus on informati that matters, and in so doing, to move forward using only relevant data and information to make decisions
The sharing of information by communities	VOI derived through a diversity of shared but independent perspectives may be more realistic than the VOI assessed from a narrower or single perspective	As the sharing of various types of information has proceeded in association with a diversity of perspectives and motivations from different contributors, various structures have risen to organize the information sources more efficiently and to facilitate access. Altogether, th has resulted in an explosion of new us of the information being shared
The wise and discerned use of information by communities and communities—or lack thereof	Information without a model for context and use of the information is nearly useless. Shared information strands often come without associated models for context and use; and even when they do, there remains a multiplicity of models	Nonetheless, useful, and important information may be found and critical assessed by discerning individuals
Prioritization, discounting, and responsibility feedbacks	Problems with how our minds temporally discount information, and with how we inadequately understand and perceive risks associated with natural processes and environments	Our abilities as political and social animals living in the here and now are amazing. We are generally extremely well adapted at navigating complex social situations and properly assessin and valuing information in the contex of the here, the now, and the social.
Value ascribed through stated preferences or revealed preferences	Both Value method (VM) and valuation obstacle (VO) are commonly used for assessing VOI. Both are dependent on human perceptions. “Stated preferences” also brings in more explicitly an additional catering to norms and how we want to be perceived by others	Obtaining VOI and other measures of perceived value through stated and revealed preferences are commonly accepted practices in economics.
VOI assessed through an expenditure investment for information production	An estimate of the minimum worth of an information production capability as assessed by the size of the financial investment required to make it operational.	Large investments may get consideration and input from multiple parties and perspectives. In turn, this may help improve the assessments of the worth of the investment in producing the information
Exchange values determined by commercial or other proprietary societal ventures	VOI can sometimes be estimated from market-based exchange values, or from nonmarket valuations, or from capital investments in information acquisition made to acquire “protected information” by commercial entities or other proprietary ventures	Exchange values for information, as w as the investment costs incurred for th production and commercial trading of information, can provide a relatively simple method to estimate minimum VOI’s for given purposes and uses.

Mis-/Dis-information and other information communication pathologies	Misinformation or disinformation can have value to certain actors. Other pathologies affecting the valuation of information include behavioural reactions and effects relating to (a) credibility of information sources that are occasionally found to be wrong, (b) information that is deliberately skewed by its providers to compensate for biased public reactions, and (c) competition between narratives that point to competing information strands.	Mis-/dis-information and communication problems and pathologies occur, wilfully or not, because there is some value inherent their presence. Assessing those values whether they be the commercial valu of providing disinformation, or the tim value of a lack of communication, or t expected value of information receive and acted on, or some other type of inherent value, can provide informatic on behavioural drivers for individuals and groups. It also informs perception of "what matters"
Value ascribed through statistical analyses or other community or population assessments	Community and population analyses and associated measures of value (or risks) are highly informative and useful. Nonetheless, translation to individual or small group situations remains a barrier.	Statistical assessments, when done we provide one of the most objective sources of information and therefore have potentially high value to help address situations and risks affecting a broad community. Connecting and communicating these general assessments to individual situations takes great skill and attention and is somewhat analogous to doctor patien communications. This may not always be possible to do in decision pathway
Attention and resource needs, and equity issues impacting valuation and actionability of information	Community and population analyses and associated measures of value and potential risks are available; however, they may not be accessible to sub-collectives/ groups within the larger community in the forms in which they are available.	Engagement with communities or subsets of communities with a variety resource levels assists in developing V estimates that accurately reflect the characteristics. of the larger population being addressed. Leverage data presentatio and decision support tools to match resources available across community subgroups to facilitate equitable provision of data.
The issue of dependent information, and of "future-found" values	The value of a given type or strand of information to given purposes or utilities is often not discovered until the information is combined with other information. Information that is more general in nature and applicability, like geospatial information, has a greater chance of finding future utility than information that is too "narrow" in its concept or representation.	Highly general information, for examp geospatial information that describes the multiple characteristics of a syster or issue, is likely to have many more uses than may initially be conceived o imagined. The additional uses and valu streams for the information will likely come through the combination of the initial general information with other types or strands of information. Technology developments and shifting or new societal interests may also play role in establishing new utilities for th

		information or combinations of information.

Illustrative examples and supporting references for the 15 VE listed in Table 18 are given in Glynn et al. (2022).

Further help in characterizing and grouping case studies of the benefits of geospatial information is given by the introduction of the "functional classification (FC)" [Glynn et al., 2022]. Table 19Table 1 uses the VOI explorations and DDP examples to indicate possible social and behavioral factors that may also impact valuation of information and DDPs for the different functional classifications in the GEOValue case studies.

Table 19. Potential VOI and DDP issues related to 10 functional classifications of geospatial information created for the GEOValue Societal Benefits Repository [Glynn et al., 2022].

GEOValue repository functional classifications (FC):	Examples and association with potential VOI and DDP
FC1: Local spatial application (urban or rural)	Damage assessments. Hazard mitigation. Management of a local natural resource.
FC2: Regional spatial application	Health of a forest resource, wildfire mitigation, disease, pollution, loss of species
FC3: National spatial application	National industrial economic output through measurement of atmospheric pollution. Mineral or Energy resources assessment at a national scale
FC4: International to global spatial application	Estimation of global economic health or other "instantaneous" measure of planet health.
FC5: Long-term temporal observation of a local issue	Recovery of a local area affected by a disaster (natural or anthropogenic).
FC6: Long-term temporal observation of a regional issue	Drought
FC7: Long-term temporal observation of a national issue	Nutrient controls and algal blooms (estuarine or coastal). Observation and management of persistent, air-borne, or water-borne contaminants. Observation of trends in use of national transport infrastructure, with consequences for infrastructure controls or investments; or for assessing potential environmental and ecological impacts.
FC8: Long-term temporal observation of an international or global issue	Observation of trends in temperature, atmospheric CO2, or other biophysical or socio-economic characteristics.
FC9: Highly dynamic spatially migrating systems (local scale)	Observation and response to a fast-moving well-perceived hazard (e.g., wildfire).
F10: Highly dynamic spatially migrating systems (regional to national scale)	Hurricane tracking and prediction. Earthquake detection and tsunami observation/prediction. Transnational forest fires response involves international efforts and governance issues.

7 Conclusions

The Deliverable 1.8 – *Methodological handbook for fire collection of data and validation standards including an assessment of the value of FirEUrisk geospatial information*, divided in three parts presents:

in **part 1**

- a procedure to validate fire danger indices developed in the framework of the FirEUrisk project and its results based on the use of the satellite identification of active fires, the estimate of FRP/FRE and it comparison with fire danger prediction. The validation report provides an initial evaluation of the Fire Danger Index metrics, particularly focused on their capacity to predict fire occurrence, Fire Radiative Energy release, and burned area across Europe. The analysis, centred on data from 2023, indicates that the Probability of Propagation and Probability of Ignition metrics exhibit the most significant predictive capabilities for fire occurrence, albeit with moderate accuracy. However, the predictive strength of the FDI metrics improves for larger fires and when lagged PP metrics are incorporated, implying that short-term fuel drying trends enhance the predictive utility of PP for intense fire events. Finally, the validation highlights several avenues for future research, including the need to disentangle the specific contributions of individual components within the FDI metrics and its original drivers to refine predictive accuracy, and to provide an understanding of where the risk signal ultimately originates.

in **part 2**:

- a comparison of burnt areas datasets provided by different agencies or in the framework of different initiatives like EFFIS, FIRMS, CLMS, etc. The main conclusion consists in a suggestion of providing, together with the burnt areas, a description of the land cover map adopted in the burnt area detection algorithm. In this way the comparison on the accuracy of different approaches can be restricted to areas with common surface characteristics. This suggestion involves ground data too, since omission or commission errors could originate from the use of a more or less accurate land cover map than the ones used by remote sensing BA detection algorithms.

and in **part 3**:

- some insights on the problem of assessing the value of the geospatial information based on EO satellite imagery trying to quantify as such information, when translated in decisions, impact the socioeconomic and environmental losses of forest fires. Some examples of the procedures to follow to assess the value of the EO based geospatial information, in the management of forest fires, have been given. However, since the estimate of the VOI depends on how EO based information impact the end-users decision an extended analysis of how the information provided by FirEUrisk are operationally used by end users is requested.

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APPENDIX A

Additional material from Chapter 2.

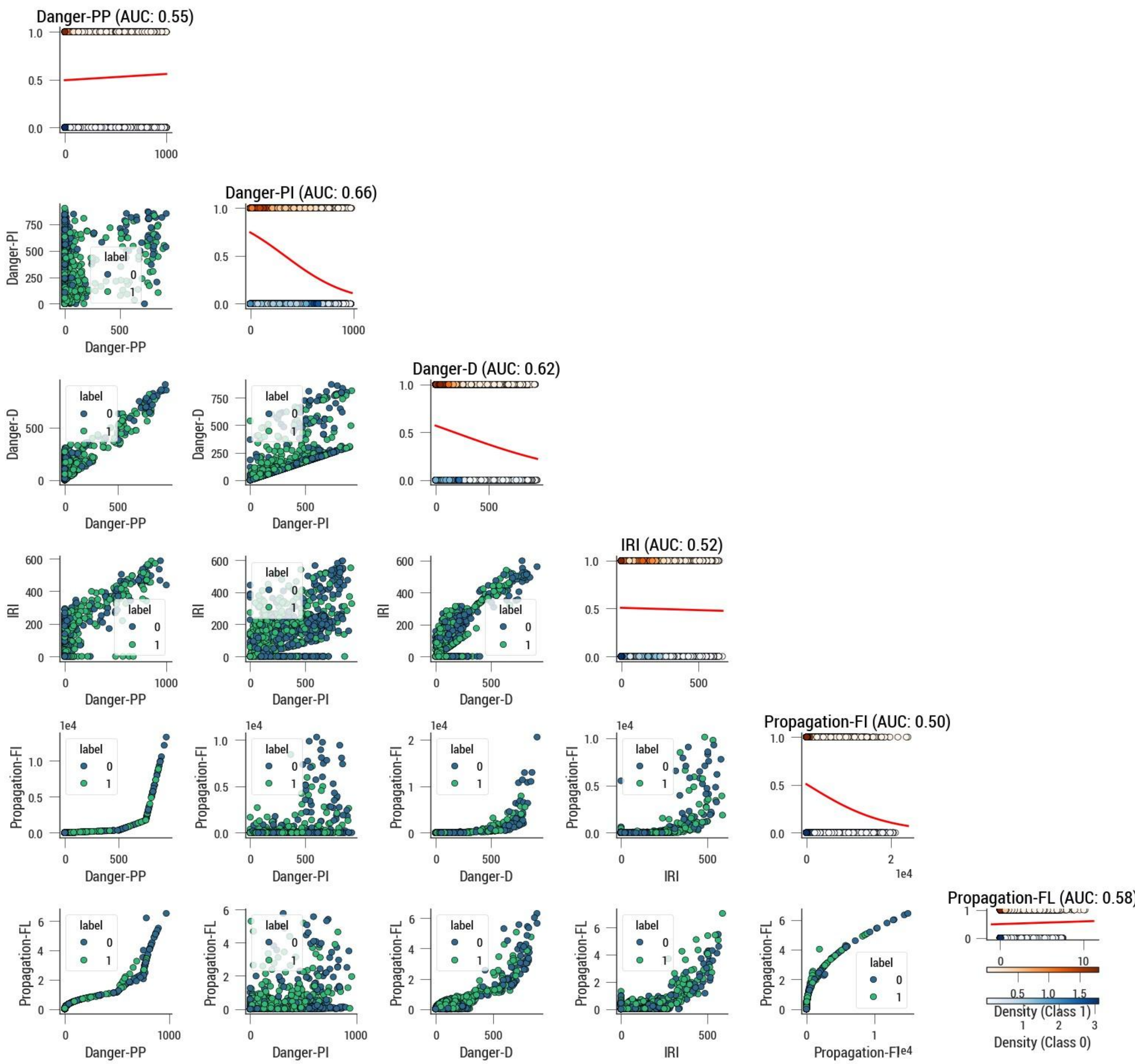

Figure A1. Correlation matrix of the different FDI metrics calculated for summer 2023 over Europe.

