

A Modular, Cloud-Based GIS Platform for Automated Wildfire Risk Index Mapping

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Abstract

Wildfires are a growing environmental and socio-economic threat driven by climate change and land abandonment. As fire frequency and intensity increase, suppression alone is no longer sufficient, making prevention and preparedness essential. Earth Observation and Geographic Information Systems (GIS) enable the integration of environmental and socio-economic factors into decision-support tools for wildfire risk assessment. This work presents a modular, web-based platform that computes a Wildfire Risk Index (WRI) through multi-criteria analysis and the Analytic Hierarchy Process (AHP). Two complementary risk formulations are developed for Galicia, northwestern Spain: a Static WRI, aimed at characterising baseline wildfire predisposition and supporting long-term prevention planning, and a Dynamic WRI, which incorporates short-term changes in vegetation and meteorological conditions to support operational preparedness. The Static WRI prioritises socio-economic factors (43.6%), while the Dynamic WRI gives greater weight to vegetation (45.6%) and meteorology (30.3%). The resulting maps show distinct spatial risk distributions, reflecting their different purposes. Validation of the dynamic model against MODIS active-fire detections yielded AUC-ROC values between 0.4935 and 0.8333, with six of eight validation periods exceeding 0.5. Both indices are integrated into a cloud-based Wildfire App, enabling automated risk calculation, visualisation, and updating through an interactive GIS dashboard. The results demonstrate the potential of combining static and dynamic WRI approaches to support complementary wildfire prevention and preparedness decisions.

1. Introduction

Wildfires affect ecosystems and communities by altering landscapes, degrading soils, reducing biodiversity, and harming living organisms. In recent years, larger fires have been recorded (El Mazi et al., 2024), affecting large areas and hindering suppression efforts.

Climate change is altering fire regimes by lengthening droughts and increasing aridity, while land-use change and rural depopulation also contribute (de Diego et al., 2023). The lack of activity in rural areas leads to the progressive accumulation of plant biomass, such as shrubland, pruning residues and dead trees, which act as fuel for wildfires. Traditionally, agricultural and livestock practices helped to reduce this fuel load through grazing, cultivation, and the maintenance of paths and woodland areas. Without these activities, the landscape becomes more continuous and dense, facilitating the rapid and uncontrolled spread of fire and increasing its intensity and danger. Moreover, most forest fires most forest fires are caused by human activity, whether intentional or accidental. Common causes include negligent fire use in agricultural, forestry, or recreational activities and deliberate ignition (Parvar et al., 2024).

These interacting factors make regions such as southern Europe particularly vulnerable to severe wildfire. In these areas, rising temperatures, prolonged periods of drought and the accumulation of vegetation fuel contribute to the occurrence of increasingly frequent, intense and difficult-to-control fires (Quishpe-Vásquez et al., 2024).

Investment in fire suppression resources, although necessary, remains insufficient (Tedim et al., 2018). Prevention strategies are therefore needed to reduce fuel loads and wildfire risk. Wildfire risk encompasses the likelihood of fire occurrence, its potential intensity, and its consequences in a given area (Vallejo-Villalta et al., 2019).

Digital tools can support wildfire prevention and risk management. Remote sensing techniques, supported by satellite imagery, remote sensors and Geographic Information Systems (GIS), enable continuous monitoring of critical variables such as fuel moisture, vegetation condition, surface temperature and changes in land use. GIS platforms also allow the integration of multiple factors influencing fire risk into the analysis, beyond fuel, such as climatic conditions, terrain topography and proximity to infrastructure and wildland–urban interfaces. Open services such as Copernicus, provide current land-monitoring and emergency data that can support risk mapping, prevention planning, and decisions by public agencies and local communities.

This work presents a wildfire prevention application co-designed with regional and local authorities, practitioners, and communities through a series of stakeholder workshops, whose feedback was incorporated into the platform's interface and functionalities. The web-based system integrates terrain, infrastructure, weather, vegetation, and high-resolution satellite data to automatically generate static and dynamic Wildfire Risk Indices (WRI) and predictive risk maps through an interactive dashboard. Its modular architecture supports the integration of additional data sources, including satellite, drone, and community-collected

observations.

2. Materials and Methods

2.1 Case Study

The study area comprises the autonomous community of Galicia, located in northwestern Spain, and is characterised by a humid temperate oceanic climate, although climate change is modifying this regime through warmer winters and springs, increasingly rainy autumns, and longer drought periods (Naranjo, 2006).

Galicia has a highly diverse and extensive forest landscape, with forests covering approximately 69% of its territory. Native species such as oaks and chestnuts coexist with extensive pine and eucalyptus plantations, the latter being particularly flammable under dry conditions (de Diego et al., 2023). At the same time, rural depopulation, population ageing, and the decline of agricultural and livestock activities have contributed to land abandonment and reduced landscape management. These conditions have favoured vegetation accumulation and landscape degradation, increasing wildfire hazard. Consequently, Galicia is among the regions most severely affected by wildfires in the Iberian Peninsula and southern Europe. Between 2001 and 2010, Galicia accounted for more than 42% of the total burned area in Spain (de Diego et al., 2023). This situation was further highlighted in summer 2025, when 393,278.99 ha were burned across 6,103 incidents in Spain, according to EFFIS and the Copernicus programme.

2.2 Materials

2.2.1 Wildfire Risk Index. The Wildfire Risk Index (WRI) integrates geospatial and meteorological datasets representing four main components of wildfire risk: topography, vegetation, socio-economic factors, and meteorology. The datasets include raster and vector formats and combine spatial information with temporally variable satellite and meteorological observations.

The topographic component is based on a Digital Terrain Model (DTM) from the Spanish National Geographic Institute (CNIG-IGN), provided as GeoTIFF raster data at 2 m spatial resolution for 2021.

The vegetation component comprises two complementary types of information. First, a forest fuel map from the Spanish Ministry for the Ecological Transition and the Demographic Challenge, provided as vector data at 2 m spatial resolution, was used to represent the spatial distribution of fuel types. Second, vegetation condition is characterised using multispectral Sentinel-2 imagery. The red, near-infrared (NIR), and short-wave infrared (SWIR) bands, provided as GeoTIFF rasters at 10–20 m spatial resolution with a revisit time of approximately 3–5 days, are used to obtain the Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1973) and Normalized Difference Moisture Index (NDMI) (Gao, 1996). A Sentinel-2 observation acquired on 11 August 2025 was used. Additionally, for validation purposes, eight wildfire risk maps were generated using Sentinel-2 imagery acquired during the periods from 15 April to 15 May and from 15 August to 15 September for each year between 2022 and 2025.

The socio-economic component includes infrastructure and Wildland–Urban Interface (WUI) information. Roads, railways, and power lines are obtained from OpenStreetMap as vector

geospatial data and are used to represent infrastructure-related ignition and accessibility factors. Land-cover information from the Copernicus Land Monitoring Service (CLC), provided as vector data at 100 m spatial resolution, is used to characterise WUI areas.

The meteorological component combines satellite-derived and meteorological information. Land Surface Temperature (LST) is obtained from Sentinel-3 SLSTR products at 1 km spatial resolution. In addition, daily meteorological data at 1 km resolution from the MeteoGalicia THREDDS server, covering the period from 12 July to 11 August 2025, include air temperature, precipitation, relative humidity, and wind speed and direction. These variables provide the meteorological inputs required to obtain the Fire Weather Index (FWI) (Van Wagner, 1987).

All spatial datasets are integrated into a common projected coordinate reference system (UTM Zone 29N, EPSG:32629) and raster framework. Data processing is implemented in Python using open-source libraries, including GDAL, Rasterio, GeoPandas, Shapely, NumPy, Pandas, PyProj, and SciPy.

2.2.2 Wildfire Application. The Wildfire Assessment Application (WFA) is a cloud-based web-GIS platform that provides browser-based access to spatial wildfire risk information without requiring local installation of specialised GIS software. The platform integrates geospatial data management, risk calculation, visualisation, and user management within a modular architecture.

The system comprises three main components: a web frontend, a backend, and a wildfire risk engine. The frontend provides the graphical user interface and interactive map environment, while the backend manages application data, users, assessment models, and communication with the risk engine. The risk engine performs the spatial risk calculations and generates the resulting raster layers.

The platform is supported by open-source services, including PostgreSQL/PostGIS for relational and geospatial data management, GeoServer for geospatial layer publication and visualisation, Keycloak for authentication and access control, and NGINX for web serving and reverse-proxy functionality. The components are deployed in a containerised environment and communicate through defined interfaces.

The platform also includes an API for interoperability with external applications and uses a single-page application (SPA) architecture, enabling interactive visualization through standard web browsers. The underlying data model manages assessment configurations, spatial geometries, simulation outputs, and associated metadata, while shared workspaces and access permissions support controlled access to assessment models and results.

2.3 Methodology

2.3.1 Wildfire Risk Index. The Wildfire Risk Index (WRI) was developed to integrate the main environmental and anthropogenic factors influencing wildfire occurrence and spread. The methodology combines geospatial analysis with a multi-criteria decision analysis based on the Analytic Hierarchy Process (AHP; Saaty, 1980). Two complementary formulations were developed: a Static WRI, representing the baseline predisposition of the territory to wildfire, and a Dynamic WRI, incorporating short-term variations in vegetation and meteorological conditions.

The WRI is structured into four thematic components: topography, vegetation, socio-economic factors, and meteorology (Figure 1)

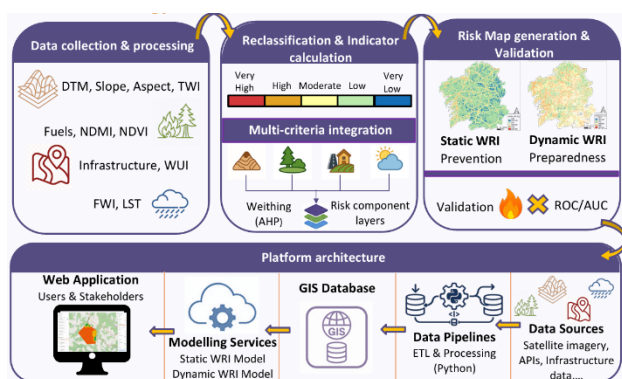


Figure 1. Modelling Workflow. Steps include data collection and preprocessing (topography, vegetation, infrastructure, meteorology), indicator reclassification and AHP-based multi-criteria integration, and generation of static and dynamic WRI maps, followed by validation using ROC/AUC metrics. The lower panel illustrates the system architecture supporting the process, from data sources and processing pipelines to GIS database to web application.

Topography was represented by four variables: digital terrain model (DTM), slope, aspect, and Topographic Wetness Index (TWI):

The **DTM** was obtained from the Spanish National Geographic Institute (CNIG-IGN) and reclassified into five risk classes, with lower elevations receiving higher risk scores: values below or equal to 200 m were assigned a risk score of 5, whereas elevations above 800 m were assigned a score of 1. Intermediate elevation ranges were classified into scores 2–4.

Slope was derived from the DTM and classified according to five intervals. Slopes within the range $0^\circ \leq \text{slope} \leq 5^\circ$ were assigned a risk score of 1. Slopes within the ranges $5^\circ < \text{slope} \leq 15^\circ$, $15^\circ < \text{slope} \leq 25^\circ$, and $25^\circ < \text{slope} \leq 35^\circ$ were assigned risk scores of 2, 3, and 4, respectively. Slopes greater than 35° received a risk score of 5.

Aspect was classified according to the orientation of the terrain. North-facing slopes were assigned the lowest risk score (1), whereas south and southwest orientations were assigned the highest score (5), reflecting their generally greater solar exposure and potential for reduced fuel moisture. East- and west-facing orientations were assigned intermediate scores.

The **Topographic Wetness Index (TWI)** was derived from the DTM following Beven and Kirkby (1979):

$$\text{TWI} = \ln(a / \tan(\beta)), \quad (1)$$

where a represents the upslope contributing area per unit contour length and β is the local slope in radians. TWI values were classified using spatial percentiles. The lowest 20% of TWI values ($\leq P_{20}$) were assigned the highest risk score (5), while the highest 20% ($>P_{80}$) were assigned a score of 1.

The **Vegetation** component was characterised using fuels type models (FTMs) and, in the dynamic model, the remotely sensed NDVI and NDMI:

The **FTM** layer classifies vegetation according to fuel models and dominant vegetation structures. The original fuel categories were converted to raster format and subsequently reclassified according to their relative structural flammability and corresponding fire behaviour. Dense and unmanaged shrublands and highly flammable forest structures received the highest risk scores, whereas deciduous formations, grasslands, and non-fuel areas received lower scores. Fuel classes associated with the highest Rothermel-based fire behaviour were assigned risk values of 5, while classes with lower flammability were assigned values between 1 and 4. Non-fuel areas were assigned a value of 0.

NDVI was calculated from the red (RED, B4) and near-infrared (NIR, B8) bands as:

$$(\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED}), \quad (2)$$

NDVI provides an indicator of vegetation density and physiological condition and was used to represent spatial variability in vegetation status. NDVI values were classified into six categories. Areas with NDVI values below 0.10 were assigned a score of 0, as they mainly correspond to non-vegetated surfaces, such as bare soil, urban areas, water bodies, or other land covers with insufficient biomass to sustain wildfire spread. The highest risk score (5) was assigned to the interval $0.10 \leq \text{NDVI} < 0.27$, representing sparse and potentially stressed vegetation with relatively low moisture content and higher flammability. Intermediate intervals of $0.27 \leq \text{NDVI} < 0.40$, $0.40 \leq \text{NDVI} < 0.54$, and $0.54 \leq \text{NDVI} < 0.67$ were assigned risk scores of 4, 3, and 2, respectively. Areas with NDVI values ≥ 0.67 received a score of 1, reflecting dense and healthy vegetation conditions associated with lower ignition susceptibility.

NDMI was calculated from Sentinel-2 bands B8 (NIR) and B11 (SWIR) as:

$$(\text{NIR} - \text{SWIR}) / (\text{NIR} + \text{SWIR}). \quad (3)$$

The B8 band has a spatial resolution of 10 m, whereas B11 is provided at 20 m; therefore, spatial resampling was applied to obtain a common grid. NDMI was used as an indicator of vegetation water content and moisture stress. Lower NDMI values were associated with greater wildfire risk. Values (≤ -0.20) were assigned a risk score of 5, whereas values (>0.40) received a score of 1.

Socio-economic factors represent the influence of human activity and the spatial relationship between infrastructure, settlements, and flammable vegetation. This component comprises distance to infrastructure (INFRA) and the Wildland–Urban Interface (WUI).

The **INFRA** layer was derived from vector data representing the transport network, including roads and railway lines. Relevant infrastructure segments (main roads and railways) were selected and converted into a series of distance buffers. At the regional scale, five 250-m intervals were used, producing a maximum considered influence distance of 1,250 m. Areas within 250 m of infrastructure received a risk score of 5, while areas between 1,000 and 1,250 m received a score of 1; areas beyond 1,250 m were assigned a value of 0.

The **WUI** layer was derived from the Copernicus Corine Land Cover (CLC) database by identifying built-up land-cover classes in contact with forested or potentially flammable vegetation. A 400-m influence zone was applied around these contact areas, following the approach proposed by Chas-Amil et al. (2013). The resulting layer was rasterised at 25 m and reclassified according to the surrounding vegetation type and distance to the WUI. Higher scores were assigned to areas associated with coniferous or eucalyptus forests, followed by mixed forests and shrublands, whereas agricultural and less densely vegetated areas received lower scores. Areas located more than 400 m from the WUI or without relevant vegetation were assigned a value of 0.

Meteorological conditions were represented by the Fire Weather Index (FWI) and the Land Surface Temperature (LST):

The **FWI** layer was calculated following the Canadian Forest Fire Weather Index System (Van Wagner, 1987), including the Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), Drought Code (DC), Initial Spread Index (ISI), Buildup Index (BUI), and final FWI. The calculation was performed sequentially using the time series of meteorological observations. Importantly, FWI contains moisture-related components with temporal memory; therefore, a sufficiently long meteorological antecedent period is required before the target date. Approximately one to two months of preceding data were incorporated to allow the DMC and DC to stabilise and preserve their temporal inertia. The meteorological variables required to calculate FWI—air temperature, precipitation, relative humidity, and wind speed and direction—were obtained from MeteoGalicía. At the regional scale, the data were retrieved as daily gridded datasets and processed to generate spatially continuous FWI layers. The resulting FWI was classified into five risk levels: values (≤ 3) were assigned a score of 1, [3–13] a score of 2, [13–23] a score of 3, [23–28] a score of 4, and values (> 28) a score of 5.

The **LST** layer derived from the Sentinel-3 SLSTR instrument. LST represents the thermal state of the land surface. LST values were classified using spatial percentiles: the lowest 20% of values ($\leq P_{20}$) received a risk score of 1, while the highest 20% ($> P_{80}$) received a score of 5. The intermediate percentile classes (P_{20} – P_{40}), (P_{40} – P_{60}), and (P_{60} – P_{80}) were assigned scores of 2, 3, and 4, respectively.

2.3.1.1 Static Wildfire Risk Index. The Static Wildfire Risk Map was developed as a prevention-oriented representation of the underlying spatial predisposition of the territory to wildfire ignition and spread. According to the [United Nations Office for Disaster Risk Reduction \(UNDRR\)](#), (2017b), prevention encompasses the activities and measures aimed at avoiding existing and new disaster risks and at reducing exposure and vulnerability before a hazardous event occurs. In the context of wildfire management, prevention therefore involves identifying areas where persistent environmental and anthropogenic conditions favour fire occurrence, so that long-term measures such as fuel management, infrastructure planning, surveillance, or territorial prioritization can be implemented.

The Static Wildfire Risk Map integrates variables that vary only slowly over time, namely the DTM, slope, aspect, fuel types, distance to infrastructure, wildland-urban interface (WUI), and the Fire Weather Index (FWI) corresponding to the most critical day of the previous year (11 August 2025, the most severe wildfire weather day recorded in Galicia). This conservative choice was adopted to support preventive planning under worst-case meteorological conditions. These variables are organised into

four thematic groups: topography, vegetation, socioeconomic factors, and meteorology. Their relative importance is established through a multi-criteria decision-making approach based on the Analytic Hierarchy Process (AHP) proposed by Saaty (1980). The pairwise comparison matrices used to assess the variables within each thematic group, together with the matrix defining the relative importance of the four groups, are provided in Tables 1 and 2.

TOPOGRAPHY	DTM	SLOPE	ASPECT	TWI
DTM	1	2	3	3
SLOPE	1/2	1	2	2
ASPECT	1/3	1/2	1	2
TWI	1/3	1/2	1/2	1
VEGETATION	FUELS			
FUELS	1	-	-	-
SOCIOECONOMICS	INFRA	WUI		
INFRA	1	2	-	-
WUI	1/2	1	-	-
METEOROLOGY	FWI			
FWI	1	-	-	-

Table 1. Pairwise comparison matrices used to weight the variables within each thematic component of the WRI model (Topography, Vegetation, Socio-economic factors, and Meteorology) according to the Saaty scale of relative importance, where 1 = equally important, 3 = moderately more important, 5 = strongly more important, 7 = very strongly more important, 9 = extremely more important, and the reciprocals (1/2, 1/3, etc.) indicate lesser importance of the compared variable.

TOPICS	TOPO-GRAPHY	SOCIO-ECONOMICS	VEGE-TATION	METEOROLOGY
TOPOGRAPHY	1	1/3	3	3
SOCIOECONOMICS	3	1	2	3
VEGETATION	1/3	1/2	1	2
METEOROLOGY	1/3	1/3	1/2	1

Table 2. Pairwise comparison matrix for topography, socioeconomics, vegetation, and meteorology, based on Saaty's scale.

2.3.1.2 Dynamic Wildfire Risk Index. The Dynamic Wildfire Risk Map was developed as a preparedness-oriented assessment capable of representing short-term changes in wildfire danger. The United Nations Office for Disaster Risk Reduction (UNDRR), (2017a), defines preparedness as the knowledge and capacities developed by governments, response organisations, communities, and individuals to anticipate, respond to, and recover from the impacts of likely, imminent, or current disasters.

The dynamic map is designed to provide a short-term, daily assessment of the Wildfire Risk Index (WRI) by incorporating both rapidly changing environmental conditions and relatively stable baseline factors. Among the dynamic inputs are spectral indicators, such as NDVI and NDMI, which are updated according to the 3–5-day revisit period of the satellite data. The model also accounts for Land Surface Temperature (LST) and daily meteorological conditions, including air temperature, precipitation, relative humidity, and wind speed and direction, which are represented through the Fire Weather Index (FWI).

In addition to these time-varying parameters, the Dynamic Map incorporates the variables used to characterise baseline wildfire risk. These include DTM, slope, and aspect for the topographic component, complemented by the Topographic Wetness Index (TWI); fuel types for the vegetation component; and distance to infrastructure and wildland-urban interface (WUI) for the socioeconomic component.

The variables are integrated using the AHP approach. First, the parameters are organised according to their corresponding thematic categories, establishing a hierarchy of sub-criteria within each component. The resulting structure is presented in Table 3. Subsequently, the four main categories topography, vegetation, socio-economic factors, and meteorology are integrated to obtain the final Dynamic Wildfire Risk Map (Table 4).

TOPOGRAPHY	DTM	SLOPE	ASPECT	TWI
DTM	1	2	3	3
SLOPE	1/2	1	2	2
ASPECT	1/3	1/2	1	2
TWI	1/3	1/2	1/2	1
VEGETATION	FUELS	NDVI	NDMI	
FUELS	1	3	5	-
NDVI	1/3	1	2	-
NDMI	1/5	1/2	1	-
SOCIOECONOMICS	INFRA	WUI		
INFRA	1	2	-	-
WUI	1/2	1	-	-
METEOROLOGY	FWI	LST		
FWI	1	3	-	-
LST	1/3	1	-	-

Table 3. Pairwise comparison matrices used to weight the variables within each thematic component of the WRI model (Topography, Vegetation, Socio-economic factors, and Meteorology) according to the Saaty scale of relative importance.

TOPICS	TOPO-GRAPHY	VEGE-TATION	SOCIO-ECONOMICS	METEO-ROLOGY
TOPOGRAPHY	1	1/4	1/2	1/3
VEGETATION	4	1	3	2
SOCIOECONOMICS	2	1/3	1	1/3
METEOROLOGY	3	1/2	3	1

Table 4. Pairwise Comparison Matrix of Topography, Socioeconomics, Vegetation, and Meteorology, based on Saaty's scale.

2.3.1.3 Validation. The validation procedure was designed to determine whether the WRI maps discriminated between locations where fire activity was observed and locations where no fire activity was detected. The assessment compared the modelled risk values and independent fire observations obtained from MODIS.

First, the validation periods were defined as 15 April–15 May and 15 August–15 September for each year from 2022 to 2025. For each period, the corresponding WRI map was generated and used as the spatial reference for the validation.

Second, active-fire detections from NASA FIRMS were spatially overlaid with the corresponding dynamic WRI map for the Autonomous Community of Galicia. Each fire detection was assigned a binary value of 1 (fire presence), and the WRI class of the corresponding map cell was extracted.

Third, a set of randomly distributed control points was generated across the study area to represent locations without observed fire activity. These points were treated as pseudo-absences rather than verified absences. A fixed random seed was used to ensure reproducibility of the procedure. For each validation map, the number of control points was set to three times the number of observed fire occurrences, providing a consistent presence-to-absence ratio across all validation datasets. Sampling was repeated independently for each validation period, while the random spatial distribution of control points across Galicia minimized potential spatial clustering effects. Control points were

assigned a binary value of 0 (fire absence), and the WRI value of the corresponding map cell was extracted for each point.

The resulting validation dataset therefore contained, for each location, two variables: the observed fire status (0 = absence, 1 = presence) and the corresponding modelled WRI value. These two variables were used as the input for the ROC analysis.

The ROC curve (Hanley and McNeil, 1982) was then generated by progressively applying different thresholds to the five-class WRI scores (1-5) assigned to each validation point, rather than using a continuous risk variable. For each threshold, the True Positive Rate (TPR), corresponding to the proportion of observed fire locations correctly identified as higher risk, and the False Positive Rate (FPR), corresponding to the proportion of control locations incorrectly classified as higher risk, were calculated. The ROC curve represents the relationship between these two rates across all possible WRI thresholds.

Finally, the Area Under the ROC Curve (AUC-ROC) was calculated to summarise the discriminatory performance of each risk map. The AUC measures the probability that a randomly selected location with observed fire activity receives a higher WRI value than a randomly selected control location. Values approaching 1 indicate strong discriminatory capacity, whereas values close to 0.5 indicate performance comparable to random classification. Consequently, higher AUC values indicate a stronger correspondence between the spatial distribution of observed fire activity and the risk levels predicted by the model. The resulting AUC values for each validation period are reported in Table 5.

Year	Period	Observed fires	AUC
2022	Spring	15	0.6230
	Summer	3	0.667
2023	Spring	4	0.7917
	Summer	1	0.8333
2024	Spring	19	0.4935
	Summer	70	0.5823
2025	Spring	13	0.5907
	Summer	64	0.6632

Table 5. Number of observed fire detections and AUC-ROC values obtained for each validation period (2022-2025).

2.3.2 Wildfire App. The Wildfire App (WFA) was developed as a browser-based, GIS-driven decision-support application designed to integrate wildfire risk modelling, spatial data management, and visualisation within a single environment. The application follows a modular client–server architecture composed of a web frontend, a backend, a risk engine, spatial data services, database management, and authentication services. This architecture separates the user interface from the computational and data-management processes, allowing risk assessments to be executed asynchronously while maintaining interactive access to the application.

The workflow begins with user authentication through Keycloak, which provides secure login, session management, and role-based access control. Once authenticated, the frontend communicates with the backend through authenticated requests. The backend manages the assessment configuration, user permissions, model status, and communication with the risk engine. Assessment information and geospatial data are stored in PostgreSQL/PostGIS, providing a relational database structure optimised for spatial queries. A separate PostgreSQL instance is used for authentication data. GeoServer is used to publish and serve

spatial layers, while NGINX provides the web-server layer for the frontend.

Risk assessments are configured through the web interface and submitted to the backend for execution. Each assessment is assigned an execution state and processed through an asynchronous workflow, with computational tasks dispatched to the isolated risk engine. Once the calculation is completed, the resulting raster datasets are automatically ingested by the backend and registered in GeoServer. The generated layers can then be retrieved and visualised through the integrated WebGIS interface.

The application also includes an analytics service to derive summary information from the resulting risk maps. These calculations include the overall risk score, the spatial extent of the assessed area, and the distribution of pixels among the predefined risk classes. The resulting metrics are stored and cached to facilitate rapid access through the application dashboard. The system also maintains the configuration, execution status, spatial information, and outputs associated with each assessment, enabling previously generated assessments to be stored, duplicated, versioned, shared, and compared.

Real-time communication is implemented using Server-Sent Events (SSE) to provide users with updates on the execution status of their assessments. The asynchronous task architecture allows calculations to continue independently of the active browser session, while completion or failure notifications can subsequently be delivered through the configured notification channels. This workflow enables the application to manage computationally demanding geospatial analyses while maintaining a responsive user interface.

The WFA is deployed using containerized architecture and automated continuous integration and continuous deployment (CI/CD) pipelines. Individual components can therefore be updated independently, supporting the progressive incorporation of new data sources, analytical functions, and visualization services. The resulting architecture provides a scalable framework in which wildfire risk calculations, spatial data management, and decision-support functionalities are integrated into a single web-based environment.

3. Results

3.1 Static Wildfire Risk Index.

AHP analysis was applied to determine the relative importance of the variables included in the Static Wildfire Risk Index. At the submodel level, the topographic component assigned the highest weight to DTM (45.1%; 0.451), followed by slope (26.1%; 0.261), aspect (16.9%; 0.169), and TWI (11.9%; 0.119). The resulting consistency ratio was $CR = 0.026$, which is below the 0.10 threshold, indicating a consistent pairwise comparison.

For the vegetation component, fuel models were the only criterion considered and therefore received a weight of 100% (1.000). As only one criterion is included, no pairwise inconsistency arises and the consistency ratio is $CR = 0$.

For the socio-economic component, infrastructure distance (INFRA) was assigned a weight of 66.7% (0.667), compared with 33.3% (0.333) for the WUI. The resulting weights reflect the 2:1 relative importance assigned to infrastructure in the pairwise comparison. Since the matrix contains only two criteria, it is inherently consistent ($CR = 0$).

For the meteorological component, FWI was the only criterion considered and consequently received a weight of 100% (1.000). The matrix is therefore inherently consistent ($CR = 0$).

At the highest level of the hierarchy, the four thematic components were combined through a global AHP matrix. The resulting weights assigned the greatest importance to socio-economic factors (43.64%; 0.4364), followed by topography (29.08%; 0.2908), vegetation (16.96%; 0.1696), and meteorology (10.33%; 0.1033). The global consistency ratio was $CR = 0.0968$, remaining below the 0.10 threshold and therefore indicating an acceptable level of consistency in the pairwise comparisons.

Based on these AHP-derived weights, the Static WRI was calculated through a weighted linear combination of the four thematic components and their respective subcriteria:

$$\begin{aligned} \text{Static}_{\text{WRI}} = & 0.436 \cdot (0.667 \cdot \text{INFRA} + 0.333 \cdot \text{WUI}) \\ & + 0.291 \cdot (0.451 \cdot \text{DTM} + 0.261 \cdot \text{SLOPE} \\ & + 0.169 \cdot \text{ASPECT} + 0.119 \cdot \text{TWI}) \quad (4) \\ & + 0.170 \cdot \text{FUELS} + 0.103 \cdot \text{FWI}, \end{aligned}$$

The resulting Static Wildfire Risk Map (Figure 2) was obtained by applying the weighted linear combination defined in Equation (4). The resulting WRI values were subsequently classified into five risk categories, ranging from very low to very high risk. The map shows that 70.15% of the study area was classified as low risk, 13.02% as moderate risk, 10.95% as very low risk, 5.87% as high risk, and 0.01% as very high risk.

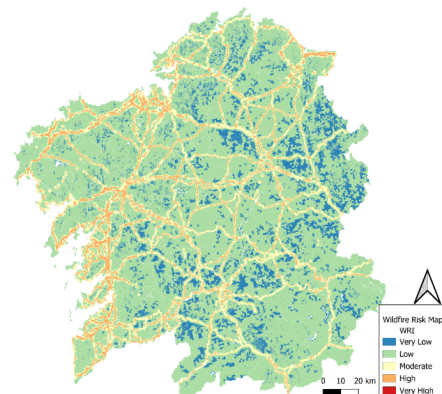


Figure 2. Wildfire risk map (Wildfire Risk Index, WRI) for Galicia, based on permanent factors such as topography, vegetation and socio-economic variables, combined with the worst day of the year according to the Fire Weather Index (FWI). Risk levels are classified into five categories: very low (blue), low (green), moderate (yellow), high (orange) and very high (red).

3.2 Dynamic Wildfire Risk Index.

The AHP analysis was applied to determine the relative importance of the variables included in the Dynamic Wildfire Risk Index. At the submodel level, the vegetation component assigned the highest weight to fuel models (64.8%; 0.648), followed by NDVI (23.0%; 0.230) and NDMI (12.2%; 0.122). The consistency ratio was $CR=0.01$.

For the meteorological component, FWI received a weight of 75.0% (0.750), while LST accounted for the remaining 25.0%

(0.250). Since the comparison involves only two criteria, the matrix is inherently consistent.

The topographic component retained the same weighting structure as the baseline assessment. DTM was assigned the highest weight (46.7%; 0.467), followed by slope (27.8%; 0.278), aspect (16.0%; 0.160), and TWI (9.5%; 0.095). The resulting consistency ratio was CR=0.06.

For the socio-economic component, infrastructure distance (INFRA) was assigned a weight of 75.0% (0.750), compared with 25.0% (0.250) for the WUI.

At the highest level of the hierarchy, the four thematic components were combined through a global AHP matrix. The results show that vegetation was the most influential component (45.6%; 0.456), followed by meteorology (30.3%; 0.303), socio-economic factors (14.6%; 0.146), and topography (9.4%; 0.094). The global consistency ratio was CR=0.030.

The resulting Dynamic WRI was calculated through a weighted linear combination of the four thematic components and their respective subcriteria:

$$\begin{aligned} \text{Dyna}_{\text{WRI}} = & 0.456 \cdot (0.648 \cdot \text{NDMI} + 0.230 \cdot \text{NDVI} \\ & + 0.122 \cdot \text{FUELS}) \\ & + 0.303 \cdot (0.75 \cdot \text{FWI} + 0.25 \cdot \text{LST}) \\ & + 0.146 \cdot (0.75 \cdot \text{INFRA} + 0.25 \cdot \text{WUI}) \\ & + 0.094 \cdot (0.467 \cdot \text{DTM} + 0.278 \cdot \text{SLOPE} \\ & + 0.160 \cdot \text{ASPECT} + 0.095 \cdot \text{TWI}), \end{aligned} \quad (5)$$

The resulting Dynamic Wildfire Risk Map (Figure 3) was obtained by applying the weighted linear combination defined in Equation (5). The resulting continuous WRI values were subsequently classified into five risk categories, ranging from very low to high risk. The map shows that 46.78% of the study area was classified as moderate risk, 27.35% as low risk, 25.47% as high risk, 0.36% as very low risk, and 0.02% as very high risk.

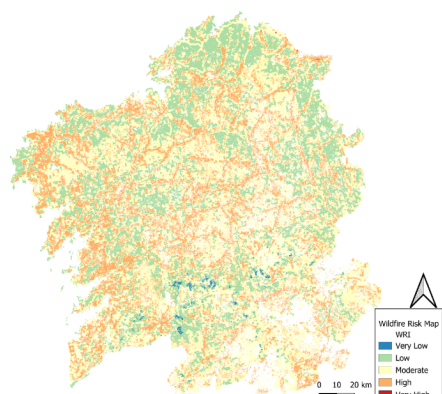


Figure 3. Dynamic wildfire risk map (Wildfire Risk Index, WRI) for the autonomous community of Galicia, where short-term factors such as meteorology and vegetation exert the greatest influence, while socioeconomic and topographic components have less impact. Risk levels are classified into five categories: very low (blue), low (green), moderate (yellow), high (orange), and very high (red).

3.3 Validation.

The AUC-ROC values obtained for the eight dynamic risk maps ranged from 0.4935 to 0.8333, showing considerable variability across years and seasons. The highest discriminatory performance was observed in summer 2023 (AUC = 0.8333), followed by spring 2023 (AUC = 0.7917). In contrast, the lowest value was obtained in spring 2024 (AUC = 0.4935), which was approximately equivalent to random classification.

Overall, six of the eight validation periods achieved AUC values above 0.5, indicating better-than-random discrimination between fire and control locations. The mean AUC across all periods was approximately 0.656. The observed variability may be partly related to differences in the number of recorded fire events and to the temporal nature of the dynamic model, as meteorological and vegetation conditions can change rapidly. In addition, the spatial resolution of MODIS hotspots may introduce uncertainty because detected thermal anomalies do not necessarily correspond to the exact ignition location. Taken together, these results indicate variable rather than consistently strong discrimination across validation periods.

3.4 Wildfire App

The implemented WFA prototype integrates the wildfire risk assessment workflow into a single web-based environment, enabling users to configure, execute, visualise, and manage spatial risk assessments (Figure 4). The assessment process follows a guided workflow in which users define the temporal parameters, select the area of interest (AOI), configure the risk components, review the settings, and submit the assessment for processing. Both static assessments for specific historical dates and dynamic assessments over user-defined multi-day periods are supported. The AOI can be delineated directly on the interactive map or provided through geospatial files, with a buffer tool allowing the selected area to be expanded in 100-m increments up to 2 km.

Assessments are processed asynchronously, and the platform generates a continuous wildfire risk surface and a classified map ranging from 1 (very low) to 5 (very high), together with the corresponding factor layers and metadata. Results are presented through an interactive WebGIS interface together with key indicators, including the overall weighted risk score, assessment area, risk-class distribution, and the area classified as high or very high risk. A temporal indicator compares the current assessment with the previous result for the same model using the percentage change in the overall weighted risk score. A $\pm 5\%$ stability band is used to classify trends as stable, improving, or worsening, avoiding changes caused by minor fluctuations.

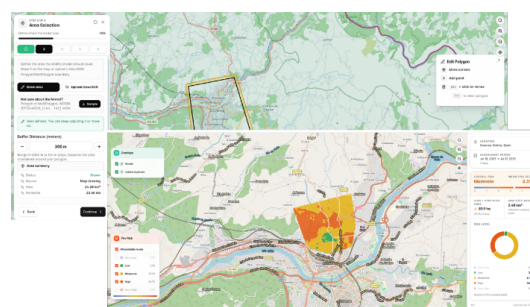


Figure 4. Wildfires Risk Assessment App interface showing the simulation setup used to obtain the WRI for a given area, and the results and information available for the calculated WRI.

The prototype also includes tools for assessment management and comparison. Users can monitor execution status and access, duplicate, share, compare, or delete assessments, while synchronised maps and comparative statistics facilitate the evaluation of different dates or scenarios. Real-time notifications, user management, feedback, and configuration functions further support operational use. Overall, the prototype provides an integrated environment for generating, visualising, analysing, and sharing spatial wildfire risk information to support decision-making.

4. Discussion and Conclusions

This work presents a WRI integrating geospatial analysis and the Analytic Hierarchy Process (AHP) to support both prevention (Static WRI) and preparedness (Dynamic WRI). The Static WRI identified a predominantly low-risk landscape (70.15%), with moderate- and high-risk areas representing 13.02% and 5.87% of the territory, respectively. Higher-risk concentrations near infrastructure and wildland-urban interfaces are consistent with the model's high weighting of anthropogenic factors.

In contrast, the Dynamic WRI showed a substantially different distribution, with 46.78% of the study area classified as moderate risk and 25.47% as high risk. These differences are mainly explained by the inclusion of dynamic indicators such as NDVI, NDMI, and LST, together with a greater weighting of vegetation and meteorological factors. Consequently, the Dynamic WRI captures short-term environmental variability and reveals that areas with low baseline risk may experience elevated risk under unfavourable conditions.

Validation results showed variable discriminatory performance, with AUC-ROC values ranging from 0.4935 to 0.8333 and an average AUC of approximately 0.656. Six of the eight validation AUC values above 0.5, indicating better-than-random discrimination in most periods, although performance varied across seasons and years and may have been influenced by uncertainties in MODIS active-fire detections

Overall, the results indicate that Static and Dynamic WRI should be considered complementary. The Static formulation supports the identification of persistent prevention priorities, whereas the dynamic formulation provides information on current wildfire conditions for preparedness and operational decision-making. Furthermore, the current framework combines factors related to both ignition and fire propagation; future work should investigate their explicit separation to improve the interpretation and predictive capacity of the model.

The cloud-based GIS platform operationalises the method as a decision-support tool. Its modular structure allows heterogeneous geospatial, satellite, and meteorological data to be integrated and updated as new sources become available.

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