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WP03 setup of wildfire prevention systems for case study 1

D3.2: WRI Database

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Abstract

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Abstract of the deliverable

This deliverable introduces the conceptual, regulatory and methodological basis for delivering a **dataset** aimed at recalculating a **Wildfire Risk Index (WRI)** with a prevention and preparedness focus in Galicia (Spain), the first pilot of the STORCITO project.

A state-of-the-art review (2023–2025) confirms the recurrent use of topographic variables (DTM, slope, aspect), vegetation indicators (NDVI, NDMI, fuel types), meteorological factors (temperature, humidity, wind, precipitation, LST, FWI), socio-economic descriptors (WUI, Land-use) and infrastructure data (waterpoints, road, railway and power networks), alongside MCDA/AHP approaches. Based on these insights, the deliverable provides a fully integrated and documented dataset enabling two complementary products: a Static Map for prevention planning—weighted through AHP and based on slow-varying drivers—and a Dynamic Map for daily preparedness, incorporating high-revisit spectral indices, LST and FWI, together with baseline layers and TWI.

The technical design prioritises interoperability, standardisation, data availability and scalability to other contexts, while noting the developmental nature of the model and its forthcoming validation in *D3.4 Wildfire App 1*.

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1. Executive Summary

This deliverable outlines the initial results and methodology for Task 3.2: Review of Wildfire Risk Indices, developed under Work Package 3 (WP03) of the Horizon Europe project STORCITO. Task 3.2 is a core component of the project's technical activities and directly contributes to Objective O3.1: Update fire risk indices with open data and new inputs from case study work, as defined in the Grant Agreement.

The main purpose of this task is to review the state-of-the-art wildfire risk indices (WRIs) and re-calculate them by clustering existing but previously unconnected datasets together with newly collected data. The work focuses initially on Spain, particularly Atlantic climatic regions, and sets the foundation for future interoperability and adaptation to other European areas (Tasks 4.3 and 4.4). At this stage, the deliverable reports on:

- Context and motivation
- Policy and governance framing
- Literature review of recent Wildfire Risk methodologies
- Dataset for re-calculate WRI in Galicia, Spain

2. Introduction

Forests and rural landscapes are pivotal to Europe's sustainability ambitions. They underpin poverty mitigation, climate regulation, food security, biodiversity conservation, and the sustainable use of natural resources, making their protection a societal and economic priority (Abedi Gheshlaghi, 2019). Rural areas (home to one-third of the EU population and covering 83% of its territory) host critical ecosystems and natural resources but face diverse biogeographical and socio-economic conditions that demand tailored, innovative solutions (Eurostat, 2022). Despite this relevance, rural fires often receive less public and institutional attention than forest wildfires, masking their severe impacts on rural livelihoods, particularly where agriculture and livestock husbandry sustain local economies (Bowman, *et al.,* 2011).

Climate change and other natural and anthropogenic drivers are intensifying wildfire hazards across Europe. Over the past 15 years, fire events have increased in extent and severity, with significant consequences for nature, people and the economy: between 2019 and 2021, the associated costs reached USD 24 billion, and in 2023 approximately 460 thousand hectares burned, emitting 25 million tonnes of CO_2 (European Commission, Joint Research Centre, 2023). The EU recognises prevention as one of the most efficient ways to address this escalating threat.

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Impacts are especially concentrated in rural regions of Southern Europe—primarily Atlantic and Mediterranean climates in Portugal, Spain and Greece—where roughly 90% of wildfire damage occurs (Publications Office of the European Union, 2023). Following a wildfire event, several severe post-fire effects emerge that have a major impact to rural societies such as enhanced soil erosion ((Shakesby, 2011), (Karamesouti et al., 2016)), landslides (Deligiannakis et al. 2021), increase of surface run-off, leading to flooding events ((Moody & Martin, 2001), (Candela, Aronica, & Santoro, 2005)) and debris flows (Esposito et al., 2023). Indeed, Mayor et al., (2007) reported a three-order magnitude larger total runoff in a small (2.1 ha) burnt compared with a larger (22.9 ha) unburnt control catchment in the Xortà mountain range in Spain. Moreover, soil post-fire erosion monitoring in a Mediterranean catchment demonstrated that erosion increased by more than one order of magnitude during the first year following the fire (Alexiou et al., 2024). In addition, apart from vegetation removal, wildfires cause a severe topsoil organic matter depletion, affecting soil texture, permeability and nutrients and overall may cause loss of soil fertility (e.g. Shakesby, 2011).

To strengthen prevention, the European Commission launched the Wildfire Prevention Action Plan in autumn 2022, focusing on three topics—(a) improved capacity to prevent wildfires, (b) improved knowledge for increased prevention, and (c) increased financing of prevention actions—and highlighting four pillars: (i) governance, (ii) planning, (iii) forest management, and (iv) people (Casartelli & Mysiac, 2023). Operationally, Europe benefits from common danger assessment through the European Forest Fire Information System (EFFIS), which standardises monitoring using the Canadian Fire Weather Index (FWI) and supports cross-border civil protection. However, methodological heterogeneity persists across Europe: countries and research teams adopt varied wildfire risk methods that are not always comparable, despite the transboundary nature of fires (Jacome Felix Oom, y otros, 2023).

In this context, and within the STORCITO project's mission to empower rural communities towards climate neutrality—addressing (1) sustainable forest management and wildfire prevention, (2) energy transitions, and (3) inclusive climate-neutral mobility—this work advances an operational, prevention-focused solution. A new Wildfire Risk Index (WRI) is proposed. Thus, the deliverable is structure as follows: Section 3 describes different kind of rules and legislative frameworks at different scales (European, National and regional levels); Section 4 performs a literature review of the most recent research in Wildfire Risk methodologies; finally, section 5 briefly presents the methodology proposed by the STORCITO project together with the dataset for the case study 1 established in Galicia (Spain).

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3. Legislation

Fire risk management in Europe is based on a diverse regulatory framework, combining coordinated EU-level standards with national and regional implementation. In Europe, the assessment of wildfire risk is supported by a legal framework that encourages the use of common climate indices and prevention methods. The European Forest Fire Information System (EFFIS) is the European Commission's main platform for monitoring wildfires and assessing fire danger across Europe. Since its creation in 1998, EFFIS has supported several EU initiatives and regulations on forest fire prevention and civil protection. EFFIS uses the Canadian Forest Fire Weather Index (FWI) as the standard tool for measuring fire danger and helping with cross-border monitoring. Through its different modules, such as the Wildfire Risk Assessment module, EFFIS offers consistent, cross-border data that support EU actions to improve forest resilience, strengthen early-warning systems and ensure that Member States follow the requirements of European rules on wildfire prevention and risk management (European Commission, Joint Research Centre, s.f.).

At national level, as in Spain, The State Meteorological Agency (AEMET) is the entity responsible for providing the meteorological fire risk index (España. Jefatura del Estado, 2022). The metadata for this index, based on the FWI, is contained in a document issued by the agency at the start of each campaign to support the fight against forest fires. This document outlines the area covered by the system, the operational aspects of the campaign, the theoretical basis used to calculate the index and its calibration, as well as examples of the resulting maps. The FWI System relies on data obtained from meteorological stations and a numerical model, using measurements taken at 12:00 UTC on the day of calculation (Agencia Estatal de Meteorología, 2019). The input variables are dry-air temperature (°C), relative humidity (%), wind speed (km/h) and precipitation recorded over the previous 24 hours (mm). Both analysis and forecast data refer to 12:00 UTC, as this time reflects the period of maximum fire danger, and the resulting value remains valid for several hours before and after midday. The FWI is a cumulative index because it incorporates the values calculated on the previous day, meaning that each daily estimate considers information from both the current and preceding days. At AEMET, the data used to compute the index comes from its network of synoptic and automatic stations and from the HIRLAM 0.05 model, which has a spatial resolution of 0.05° and includes 47,367 grid points. Each grid point represents the centre of a 5 km × 5 km pixel, making each value representative of an area of 25 km^2 (2,500 ha). The resulting FWI maps offer high spatial resolution and continuous coverage, including provincial and regional boundaries.

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However, there are discrepancies when comparing this framework with other European countries. For example, in Greece, Under Greek Law (3013/2002 and 4662/2020), local authorities are assigned primary responsibility for civil protection across all phases of the disaster cycle, with particular emphasis on prevention, preparedness and post-event restoration. Their statutory duties include supporting hazard analysis and mapping activities, conducting public awareness and prevention campaigns, and preparing local emergency response plans. There is a general plan for local authorities dealing with emergencies due to Forest Fires named IOLAOS 2 that is a planning instrument for wildfire preparedness, coordinating procedures, setting roles and defining clear responsibilities for key actors. However, it does not incorporate any hazard mapping and risk analysis and does not include prevention measures even though the Greek legal framework refer that local authorities have such duties. It mainly serves to coordinate the actions of civil protection in order effectively respond to emergencies to support the Fire Brigade in the suppression of forest fires. Overall, wildfire governance in Greece remains heavily oriented towards emergency response and the imposition of restrictions on activities that may ignite fires during periods of high predicted hazard. According to WWF Greece (WWF Greece, 2022), there is a major imbalance in Greece's wildfire strategy since data for 2016–2020, demonstrate that approximately 83.95% of available funds were allocated to suppression measures, while only 16.05% were invested in prevention. The General Secretariat of Civil Protection publishes a national Fire Hazard Forecast Map every day at 12:30 p.m., forming the basis for the Fire Service's operational planning. It also guides the preventive and preparedness actions of local authorities, civil protection officers and volunteers. First introduced in 2003, the map is issued daily from 1 June to 31 October and is widely disseminated by national media. Despite its importance, the system has a major technical limitation: the map is produced through a "black box" process, with neither the input data nor the methodology publicly disclosed or subject to expert review. Although other institutions, such as NOA, generate similar hazard maps, these are not officially integrated into prevention or preparedness planning. In Greece, since 2020, during a hazard crisis the 112 (the European Civil Protection emergency communication number) is activated sending mass alerts to mobile phones in danger zones, informing residents about the approaching fire and the need to evacuate or not.

Continuing at the regional level, and focusing specifically on the Autonomous Community of Galicia, where the first pilot case of the STORCITO project is based, in Spain, it is the responsibility of the Autonomous Communities to prepare reports, and prevention plans on forest fires. For the case study located in the Autonomous Community of Galicia, the Plan for the Prevention and Defence against Forest Fires in Galicia (PLADIGA) aims to establish the organization and operating procedures for the resources and services owned by the Autonomous Community of Galicia, those that may

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be assigned to it by the General State Administration, as well as those that may be provided by other public or private entities to tackle forest fires within Galician territory. Among the technological improvements that are being implemented within PLADIGA, the Daily Forest Fire Risk Index (IRDI) is established as the official daily fire-risk indicator at the municipal scale and is based on the Canadian Fire Weather Index system, which estimates the potential intensity of a wildfire (Xunta de Galicia, Conselleria do Medio Rural, 2025). The higher the index, the greater the expected fire intensity and thus, the more difficult suppression becomes. To determine the daily value, several factors that influence fire behaviour are assessed, including drought conditions over recent months, which affect shrub moisture; drought over recent weeks and days, which influences the state of grasses and medium to coarse dead fuels; current humidity and temperature, which determine the condition of fine dead fuels; and prevailing wind conditions, which directly affect fire spread. The meteorological variables required for its calculation are the same as for FWI. Temperature, humidity and wind speed are taken at 12:00 UTC from the WRF numerical model at 1 km resolution provided by MeteoGalicia, while accumulated rainfall is derived by combining data from MeteoGalicia's network of meteorological stations with observations from the radar located on Mount Xesteiras (Cuntis). These datasets are processed through spatial interpolation to produce maps at a resolution of 200 m, which also corresponds to the final resolution of the IRDI. To assign a risk level to each municipality, the 50th percentile of the index values within the boundaries of each of the 313 municipalities in Galicia is calculated, and then classified as low, moderate, high, very high or extreme (Xunta de Galicia, Consellería do Medio Rural, 2025).

4. State Of the Art

This section presents a literature review conducted using academic databases such as ScienceDirect and Elsevier. For this purpose, keywords including "GIS", "remote sensing", "wildfire", "risk", and "assessment" were used to search for recently published articles (2023, 2024, and 2025). As a result, 14 studies were identified that integrate thematic layers within GIS and apply various combination methods, such as the Analytic Hierarchy Process (AHP), Fuzzy Logic, MCDA, and machine learning techniques. The main objective of this review is to define the dataset upon which the model applied to the case study 1, named, "*Wildfire prevention actions and monitoring systems*" within the STORCITO project will be developed.

(Vallejo-Villalta, Rodríguez-Navas, & Márquez-Pérez, 2019) defines wildfire risk as the likelihood of a fire breaking out in a specific area, considering not only the frequency with which they can occur but also the intensity of the fires and the potential impact they can generate. (Ortega-Hita, *et al.,* 2025) consider that, this risk is not limited solely to

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climatic parameters, such as those commonly used by public administrations in Spain, but instead incorporates a multi-layer analysis through the Analytic Hierarchy Process (AHP). Within this approach, each layer is assigned a specific weight reflecting its relative influence with respect to the others. The layers considered include, in the topographic domain, the Digital Terrain Model (DTM), slope, and aspect; in the vegetation domain, fuel models and the NDVI index. Socio-economic factors encompass the Wildland–Urban Interfaces and Distance to Roads. Finally, two additional components are included: the Fire Weather Index (FWI) within the Meteorologic topic and the historical wildfire occurrence, that is, the number of times that a wildfire took place at a certain place.

(Vujović, *et al.*, 2025) provide a national-scale assessment of wildfire susceptibility in Montenegro by comparing two modelling frameworks: a Geographic Information System–based Multi-Criteria Decision Analysis (GIS-MCDA) using fuzzy standardization with the Analytic Hierarchy Process (AHP), and a machine-learning approach. In this study, vegetation parameters such as Fuels Type and NDVI are considered. Related to meteorology, Mean Annual Air Temperature, Annual Precipitation amount, Annual Range of Monthly Vapor Pressure Deficit, Mean Monthly Near-Surface Relative Humidity, Mean Monthly Near-Surface Wind Speed are included. Topology encompasses Elevation, Slope and Aspect and finally, related to human activity Distance from Agricultural Areas, Roads and Settlements are considered.

(Sabancı, 2025) conducted a multifactorial wildfire analysis combining climatic, geomorphological, vegetation and human-induced drivers using remote sensing and GIS techniques. For that, vegetation is examined using NDVI and NDMI to determine vegetation health and moisture content, while climatic conditions are characterised through temperature, humidity, wind, precipitation, and indices such as LST, De Martonne, and Thornthwaite. Topographic factors include slope, aspect, and elevation. To identify affected areas and post-fire changes, Landsat 8 and 9 imagery (LST and NDMI) and Sentinel-2 SWIR combinations are employed, with land surface temperature derived using the single-channel algorithm applied to Landsat 8 Thermal Infrared Sensor (TIRS) data.

(Chepasev, *et al.*, 2025) developed a static wildfire hazard map through machine learning, in addition to a *webGIS* platform for real-time data dissemination. The model integrates a wide range of variables, including wildfire occurrence, climatic conditions such as mean annual temperature, maximum temperature of the warmest month, annual and seasonal precipitation, precipitation of the driest month, wind exposure index, diurnal anisotropic heating, and Köppen climate classification. Topographic factors include elevation, slope, aspect, and the topographic wetness index (TWI). Land cover and vegetation are represented by the percentage of tree cover, the NDVI, and land cover

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proportions. Finally, distance to major roads is incorporated as anthropogenic factor to account for human influence on wildfire ignition.

(Masoudian, Mirzaei, & Bagheri, 2025) assessed and predicted wildfire susceptibility through machine learning techniques. They considered a great set of variables grouped in four topics: Topography, Vegetation, Climatic factors and Anthropogenic factors. The analysed parameters comprised topographic variables (digital elevation model, slope and aspect), vegetation variables (EVI and NDVI), climatic variables (precipitation, temperature, humidity, wind speed, evapotranspiration, land surface temperature, land cover type and soil moisture), and anthropogenic variables (Euclidean distance to primary and secondary roads, populated centres and power lines, and population density).

(Bhattachayra, *et al.,* 2025) present a geospatial approach to forest fire risk delimitation using a combination of remote sensing techniques and GIS-based analysis. Climatic and biotic parameters, including land surface temperature (LST), normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and normalized difference moisture index (NDMI), were integrated with topographical variables such as slope, aspect, and elevation. Additionally, proximity to anthropogenic factors like roads and settlements were considered to enhance risk assessment accuracy.

(Phantanaikasem, Jamroen, & Surinkaew, 2025) propose in their study a new wildfire risk impact index (WRII) to assess wildfire risk severity on power distribution systems. The WRII is developed using the geographic information system (GIS) and analytical hierarchy process (AHP), integrating multiple spatial variables including air temperature, mean wind speed and relative humidity, topographic variables derived from a digital elevation model, and infrastructural and accessibility variables such as the distance of hotspots from power grids, fire stations and main roads, as well as the connectivity of power system points.

(Durlević, Čegar, & Ilić, 2025) develop an advanced wildfire susceptibility framework for the UNESCO Global Geopark Djerdap (Serbia) by integrating geographic information systems (GIS), multi-sensor satellite data, and state-of-the-art artificial intelligence (AI) algorithms. The study uses topographic variables including digital elevation model, slope and aspect; climatic variables such as average air temperature, annual precipitation, number of consecutive dry days, number of consecutive wet days and wind exposure; vegetation and moisture variables including NDMI, NDVI and dNBR; land use and land cover classes derived from Sentinel-2 data; and anthropogenic variables comprising the distance from settlements, roads and forest trails, and major rivers.

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(Nuthammachot, Jang, & Stratoulias, 2025) classify and map forest fire risk in a peat swamp forest in Khreng sub-district, Thailand. Geospatial, climatic, and topographic data (namely elevation, slope, rainfall, land use/land cover, normalized difference vegetation index, and proximity to rivers, settlements, and roads) are fed into the analytic hierarchy process (AHP) and Geographical Information System (GIS) methods to map the area into five fire risk categories.

(Yara EzAl, *et al.,* 2025) evaluate the fuel danger index (FDI) for Latakia forests, encompassing various vegetation types, including conifers, broadleaved trees, and their mixtures. The study integrates multiple indices – fuel danger index (FDI), human activity danger index (ADIr), weather danger index (WDI), topographic danger index (TDI), and differenced normalized burn ratio (dNBR) – to assess fire risk based on vegetation type, density, moisture, and human activities. Within this framework, FDI incorporates vegetation type, vegetation density derived from NDVI and moisture content derived from NDMI; ADIr is represented by the distance from roads; WDI includes temperature, relative humidity, wind direction and wind speed; and TDI comprises slope, aspect and elevation, allowing for a comprehensive assessment of fire risk driven by vegetation characteristics, meteorological conditions, topography and human activity.

(Horvat & Karleuša, 2024) describe a model designed to assess wildfire risk at the meso-scale by integrating the components of hazard, exposure and vulnerability. The approach focuses on environmental and anthropogenic descriptors derived from moderate- to high-resolution remote sensing data from Sentinel-2, Copernicus Land Monitoring Service datasets and other open sources. Risk indices were integrated using the multi-criteria decision analysis method, the analytic hierarchy process (AHP), in a GIS environment. Fire hazard is represented through indices related to fire ignition and propagation, including wildland–urban interface mapping, distance to roads, fuel type derived from land use and land cover data, live fuel moisture estimated using the Normalized Difference Infrared Index, terrain characteristics such as slope, aspect and concavity extracted from a digital elevation model, and meteorological conditions summarised by the Fire Weather Index, which incorporates temperature, relative humidity, wind speed and precipitation. Fire exposure is quantified by intersecting the fire hazard with the spatial distribution of population, built-up areas, transport networks and other assets derived from land use and infrastructure datasets. Fire vulnerability is assessed using indices based on population density within exposed wildland–urban interface areas, the density and type of built assets, the presence of protected areas such as Natura 2000 sites, and ecosystem vulnerability inferred from land use classes and ecosystem service supply.

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(Šiljeg, *et al.,* 2024) develop the first multi-hazard susceptibility model in Croatia for the settlement of Sali on the island of Dugi Otok, integrating geospatial technologies and local population perception. Specifically, the study aims to assess and combine susceptibility to wildfires, pluvial floods and soil erosion through multicriteria GIS analysis and the Analytic Hierarchy Process, comparing a model with equal weighting and another based on public perception, to identify areas most prone to multiple hazards and support risk management in vulnerable Mediterranean regions. The model includes slope, drainage density, the NDVI vegetation index, road distance and terrain aspect. It also considers the heat load index (HLI), distance to houses, insolation, terrain profile (PROF) and topographic depressions (sinks). Other relevant variables are elevation, distance to streams, the stream power index (SPI), the topographic ruggedness index (TRI) and the topographic wetness index (TWI). Finally, the specific catchment area (SCA), land surface factor (LSF) and plan curvature (PLAN) are included.

Rather than concentrating solely on fire behaviour or simulation models, (Riviére, *et al.,* 2023) adopt an integrated approach that considers ecological, physical and socio-economic factors to identify areas where assets such as populations, ecosystems and infrastructure are most exposed. The methodology applies to a spatial multi-criteria decision analysis (MCDA) based on the Analytical Hierarchy Process (AHP), combining quantitative data with expert judgement through a participatory approach. Spatial indicators are developed and aggregated to produce vulnerability maps, enabling the identification of primary and secondary hotspots and the underlying drivers. For population, indicators include population density, geographic isolation, age structure, housing type, household composition, unemployment, household wealth, risk experience, fiscal resources, access to healthcare, social isolation and education level. Ecosystem-related parameters encompass forest cover, intrinsic sensitivity, fuel load, surveillance coverage, defendability, firefighting access, adaptive capacity, fire return interval, risk experience, financial resources and property regime. Infrastructure indicators comprise building presence, wildland–urban interface, building use, firefighting access, building age, financial resources, risk experience, education level and geographic isolation. Finally, fire hazard is represented by the mean annual burned area derived from multiple fire model simulations.

In addition to the mentioned parameters of the literature review, there are other spectral indices that can be of interest in a wildfire risk assessment. These are the Global Vegetation Moisture Index (GVMI) of (Ceccato, *et al.,* 2002), designed for the rapid retrieval of vegetation water content; Green Coverage Index (GCI) or chlorophyll index (Wu, Niu, & Gao, 2012); and Drought metrics such as the Normalized Difference Drought Index (NDDI), which combines NDVI and NDWI and was proposed by (Gu, *et al.,* 2007) to capture drought severity in grasslands better. By overlaying (i) structural fuel metrics from

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Copernicus High Resolution Layers (HRL) and land-cover products with multi-temporal Sentinel-2 spectral indices and historical burned-area datasets, (ii) NDVI/NDWI/NDMI/GVMI/NDDI-based dryness indicators, and (iii) NBR-based burn severity and fire frequency, a spatially explicit wildfire hazard layer can be generated that reflects both current drought stress and the legacy of past wildfires.

Following the presentation of this literature review, the parameters most frequently considered across the analysed studies are identified. Table 1 presents the results of the literature analysis. Topographic parameters such as the digital terrain model, slope and aspect show the highest recurrence, while Topographic Wetness Index (TWI) is less frequently used but also appears in several studies. These are followed, within the vegetation category, by NDVI, land cover or fuel type, and NDMI. In terms of meteorological variables, temperature, relative humidity, wind speed and direction, and land surface temperature are the most used. Finally, among socio-economic factors, distance to roads and settlements and wildland–urban interfaces appear most frequently. To a lesser extent, dNBR is also included, reflecting the historical occurrence or recurrence of wildfires.

Domain	Parameter	Number of studies
Topography	Elevation/DEM/DTM	12
	Slope	11
	Aspect	10
	TWI (Topographic Wetness Index)	2
Vegetation	NDVI	10
	Fuels/Land cover	8
	NDMI (vegetation moisture)	4
Meteorology	Air Temperature	8
	Wind speed/direction	8
	Precipitation	7
	Relative humidity	6
	Land Surface Temperature (LST)	3
	FWI (Fire Weather Index)	2
Socioeconomic factors	Distance to roads	12
	Distance to settlements	4
	Wildland-Urban Interfaces	3
	Distance to rivers	3
Historic	dNBR (burn severity)	2

Table 1. Most Frequently Used Parameters in Wildfire Risk assessment studies. This table summarises the parameters most employed across 13 reviewed studies on wildfire risk assessment. Parameters are grouped by domain (topography, vegetation, meteorology, anthropogenic, historic) and ranked by frequency of occurrence.

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5. WRI Database

Building on the insights gained from the literature review (see Section 4) and the identification of the most recurrent variables influencing wildfire risk, this section provides a new dataset and clustering yet-not-connected but existing data obtaining a new framework for assessing Wildfire Risk Index in Galicia (Spain), by presenting a comprehensive methodology that combines advanced geospatial analysis and multi-criteria decision techniques.

The WRI model developed in this case study groups a set of parameters into four main thematic categories: topography, vegetation, socio-economic factors and meteorology. Each category is defined by a set of variables described below.

The topographic component comprises four variables. The digital terrain model (DTM) represents the elevation of the bare ground surface and provides the basis for deriving terrain-related parameters. Slope describes the rate of change in elevation and influences fire spread by controlling fuel preheating and flame propagation. Aspect indicates the orientation of the terrain surface and affects solar radiation exposure and fuel moisture conditions. The Topographic Wetness Index (TWI) (Beven & Kirkby, 1979) is a compound topographic indicator that reflects the spatial distribution of soil moisture as a function of local slope and upstream contributing area and can be obtained using

$$TWI = \ln \frac{a}{\tan b}, \qquad (1)$$

where a is the local upslope area draining through a certain point per unit contour length and b is the local slope in radians.

The vegetation component includes three variables. Fuel types represent the nature and distribution of combustible vegetation and determine fire behaviour and intensity. The Normalised Difference Vegetation Index (NDVI) (Rouse, Haas, Schell, & Deering, 1973) characterises vegetation density and greenness, serving as a proxy for biomass and fuel availability. NDVI read

$$NDVI = \frac{NIR - RED}{NIR + RED}, \qquad (2)$$

where NIR means Near InfraRed band and RED the visible colour red band.

The Normalised Difference Moisture Index (NDMI) (Lykhovyd & Sharii, 2024) indicates vegetation water content and fuel moisture conditions by means of

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$$NDMI = \frac{NIR - SWIR}{NIR + SWIR}, \quad (3)$$

where NIR means Near InfraRed band and SWIR means Short Wave InfraRed band.

Socioeconomic factors are represented by two variables. Distance to infrastructure captures human accessibility and potential ignition sources associated with roads, power lines and railways. Wildland–urban interfaces identify areas where built-up zones are in close contact with flammable vegetation, representing locations of increased ignition probability and potential impact.

Finally, the meteorological component integrates atmospheric conditions that directly affect fire behaviour. Air temperature, precipitation, wind speed, wind direction and relative humidity are combined within the Fire Weather Index (FWI), a composite indicator widely used to assess fire danger based on weather conditions (Van Wagner, 1987). In addition, land surface temperature (LST) is included as a separate variable to represent surface heating and its influence on fuel dryness.

¡Error! No se encuentra el origen de la referencia. presents the dataset used in the analysis, detailing the data sources, data types and spatial resolutions of the layers described above.

Dataset	Data Type/Index	Spatial Resolution	Temporal Resolution	Data Range Used	Application in Study (Layer)
CNIG – IGN Spain [Link]	Digital Terrain Model (DTM)	2 m	2 years	2021	DTM, Slope, Aspect, TWI
OpenStreetMaps [Link]	Roads, power lines, railways	Vector (m)	Continuous updates	Latest available	Distance to Infrastructure
Sentinel-2 (ESA) [Link]	SWIR, NIR, RED & GREEN bands	10 m – 20 m	3 - 5 days	01/01/2025-Nowadays	NDVI, NDMI
Sentinel-3 (ESA) [Link]	SLSTR Instrument, SL_2_SLT bands	1 km	3-5 days	2025 - Nowadays	LST
Copernicus Land Monitoring Service (CLC) [Link]	Land Cover	100 m	6 years	2018	Wildland-Urban Interfaces (WUI)
MeteoGalicia, THREDDS Server [Link]	Temperature, Precipitation, Wind speed/direction,	1 km	Daily	2024-Nowadays	Fire Weather Index (FWI)

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	Relative Humidity				
Most up-to-date forest map (Spain) - Ministry for the Ecological Transition and the Demographic Challenge [Link]	Fuels	2 m	6 years	2018	Fuels Map

Table 2. Overview of the datasets employed in the study, including data sources, data type or derived index, spatial and temporal resolution, period of data used, and their specific application as input layers for the wildfire risk assessment.

6. STORCITO's solution

Building on the dataset presented in the previous section, this section introduces the solution proposed by the STORCITO project, which is operationalised through the development of two complementary types of maps.; (i) the static one, containing information that does not vary in short-time periods and can be useful for prevention plans; and (ii) the dynamic map, which provides daily risk information and is designed for preparedness actions.

In addition to these two maps, additional qualitative features will be deployed to complete this WRI assessment, providing visual information regarding the location of important infrastructure such as , power lines, railway lines, landfills, fire hydrants, water tanks, paths or roads, as well as sites of high vulnerability settlements, camps, gas stations, nature reserves and protected areas etc. The idea of this qualitative part consists of fulfilling possible gaps in prevention plans or preparedness actions. As a result, a qualitative multiparameter map can be compiled (e.g. Papanikolaou et al. 2015) by overlapping different layers/thematic maps to highlight areas of high hazard (e.g. powerline crossing a pine forest) or infrastructure gaps (e.g. lack of water points or lack of access) or weak points (e.g. flammable/fire prone vegetation with no visibility and no water points nearby). The dynamic and static maps are generated using a series of codes developed during Task T3.2 and available in a GitHub repository. These codes will be further refined and optimized to be incorporated into the future Wildfire App, which is still under development. Further information will be provided in deliverable *D3.4 Wildfire app 1* in the 14th month of the project

This section is divided as follows: subsection 6.1 describes the concept of static map and the parameters used; subsection 6.2 provides the definition of dynamic map

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and also the parameters used; finally, subsection 6.3 contains the WRI obtained for case study 1 according to the two approaches considered.

6.1. Base (Static) Map

Prevention refers to activities and measures taken to avoid existing and new disaster risks, with the intention of eliminating the potential adverse impacts of hazardous events. While not all risks can be completely removed, prevention aims to reduce vulnerability and exposure such that the risk of disaster is reduced. Examples include structural measures like dams, land-use planning that restricts development in high-risk areas, and engineering designs that ensure resilience to hazards (United Nations Office for Disaster Risk Reduction, 2017). In this context, the Base or Static Map, can be defined as the WRI map that provides the base risk in a region obtained through parameters that don't change in short time periods. This aim of this map is to complete the wildfire risk assessment in a determined region and helps in the design of future prevention plans.

For obtaining this map, variables such as DTM, slope, aspect, fuels, distance to infrastructure, Wildland-Urban Interfaces, and FWI for the worst day of the previous year are considered and grouped in four topics (topography, vegetation, socioeconomics and meteorology) following multi-decision criteria as the Analytic Hierarchy Process (AHP) developed by (Saaty, 1980). Table 3 presents the comparison matrices proposed for the variables that compose each topic and the comparison matrix of the topics.

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 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, 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	TOPOGRAPHY	SOCIOECONOMICS	VEGETATION	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

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Table 4. Pairwise Comparison Matrix of Topography, Socioeconomics, Vegetation, and Meteorology, based on Saaty's scale (1 = equally important, 3 = moderately more important, 5 = strongly more important, 7 = very strongly more important, 9 = extremely more important; reciprocals indicate the inverse preference)

This AHP-based model is currently under development and should be interpreted with caution. The base map primarily reflects inherent risk factors that change little over time, such as topography and infrastructure. Dynamic factors, including vegetation and the Fire Weather Index (FWI), are incorporated to represent conditions on the worst fire day of the previous year. However, it is important to note that this "worst day" does not necessarily occur on the same date across different years, and inter-annual variability may affect the model's outputs. The methodology and its refinement will be developed in greater detail in deliverable *D3.4 Wildfire App 1*.

6.2. Dynamic Map

Preparedness is the knowledge and capacities developed by governments, response and recovery organisations, communities and individuals to anticipate, respond to and recover from the impacts of likely, imminent or current disasters. It involves actions taken in advance, such as contingency planning, stockpiling supplies, establishing coordination arrangements, evacuation planning, public information systems, training and field exercises, supported by appropriate institutional, legal and budgetary capacities (United Nations Office for Disaster Risk Reduction (UNDRR), 2017). In this regard, Dynamic Map emerges as a tool to advise and support the most immediate decisions and actions, for example, in forest management, resource deployment, and related operations. The Dynamic Map assesses the Wildfire Risk Index (WRI) for a short period, such as daily. To achieve this, it incorporates spectral indices with a revisit frequency of 3–5 days, including NDVI, NDMI. It also contains information on land surface temperature (LST) and meteorological variables such as temperature, precipitation, relative humidity, wind speed and direction, through the Fire Weather Index (FWI), which can be obtained daily. In addition to these factors, the map integrates those considered in the baseline risk, such as DTM, slope and aspect, adding as an extra the TWI for topography; fuel types for vegetation; and distance to infrastructure and wildland–urban interfaces for socio-economic factors. To combine these variables, a hierarchical analysis process is followed. First, the variables are grouped into categories. Table 5 presents the hierarchy of sub-criteria (parameters) within each topic. Next, the four categories are combined.

Table 6 displays the comparison matrix of these categories.

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	-

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FUELS	1	3	5	-
NDVI	1/2	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 5. 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	TOPOGRAPHY	VEGETATION	SOCIOECONOMICS	METEOROLOGY
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 6. Pairwise Comparison Matrix of Topography, Socioeconomics, Vegetation, and Meteorology, based on Saaty's scale

This AHP-based model is currently under development and should be interpreted with caution. The resulting map represents dynamic wildfire risk, analysed from the perspective of variables that vary over short time scales. The assessment focuses on dynamic factors such as NDVI, NDMI and the Fire Weather Index (FWI), which can change over periods ranging from days to weeks and are therefore suitable for capturing rapidly evolving wildfire risk conditions. The methodology and its further refinement will be developed in greater detail in Deliverable *D3.4 Wildfire App 1*.

6.3. Study Case 1: Wildfire Risk Index (WRI) in Galicia. Preliminary Risk, Static Map

Figure 1 shows the base wildfire risk map for the autonomous community of Galicia, which represents the preliminary wildfire risk in the case study area. To calculate this risk, the Analytic Hierarchy Process is applied, considering topography and infrastructure together with Wildland-Urban Interfaces (WUIs), grouped under socio-economic factors, as the most influential components since they change least in the short term. Regarding vegetation, fuel types are taken into account, and finally, the Fire Weather Index (FWI) for the worst day of the year is included, which in this case is 11 August 2025, when temperatures reached up to 43°C in some populated areas (Gil Pazos, 2025).

The risk level is classified into five categories according to the following scale: from 0 to 0.5 is considered no risk, from 0.5 to 1.5 very low risk (blue), from 1.5 to 2.5 low risk (green), from 2.5 to 3.5 moderate risk (yellow), from 3.5 to 4.5 high risk (orange), and

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finally, from 4.5 to 5 very high risk (red). The figure also shows that moderate and high-risk areas tend to appear near settlements and infrastructure, while green and blue tones are distributed across the rest of the territory, coinciding with forested or mountainous zones. This risk distribution aligns with the definition provided by (Vallejo-Villalta, Rodríguez-Navas, & Márquez-Pérez, 2019) in Section 4 of this document, that is, the likelihood of a fire to start.

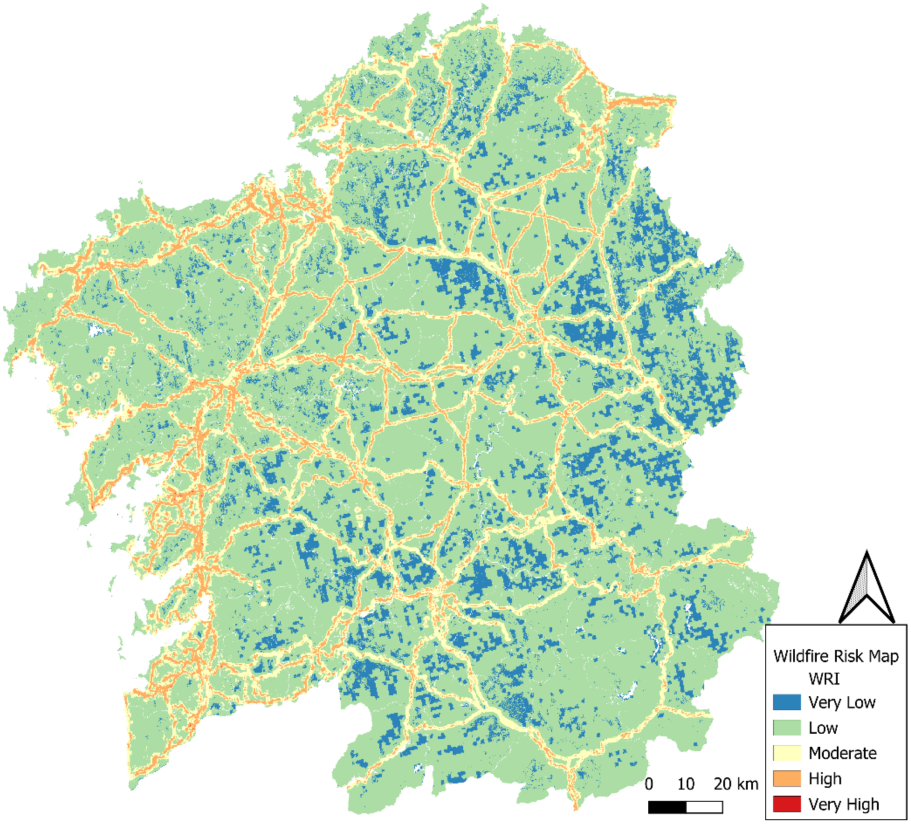

Figure 1 Wildfire risk map (Wildfire Risk Index, WRI) for Galicia, based on permanent factors such as topography, vegetation and socio-economic variables, combined with the worst day of the year according to the Fire Weather Index (FWI). Risk levels are classified into five categories: very low (blue), low (green), moderate (yellow), high (orange) and very high (red).

6.4. Study Case 1: Wildfire Risk Index (WRI) in Galicia. Dynamic Map

Figure 2 shows the wildfire risk map from a dynamic perspective, ensuring that the most influential factors are those that change over short periods, such as the spectral indices NDVI and NDMI together with fuel types grouped under the vegetation topic, land surface temperature, and the Fire Weather Index (FWI), grouped under meteorology, followed by socio-economic factors and topography in the last position. As in the previous subsection, the colour scale remains the same: blue for very low risk, green for low risk, yellow for moderate risk, orange for high risk, and red for very high risk.

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In this figure, the risk distribution changes significantly. It can be observed that moderate risk increases in areas where the base risk is low, and high-risk zones expand into areas previously classified as low or moderate risk, driven by the variable parameters that become more influential. There are hardly any areas with very low risk. However, populated areas and infrastructure continue to accumulate the highest risk levels, due to its likelihood to ignite due to human activities, which is consistent with the wildfire risk definition provided by (Vallejo-Villalta, Rodríguez-Navas, & Márquez-Pérez, 2019) and presented in Section 4.

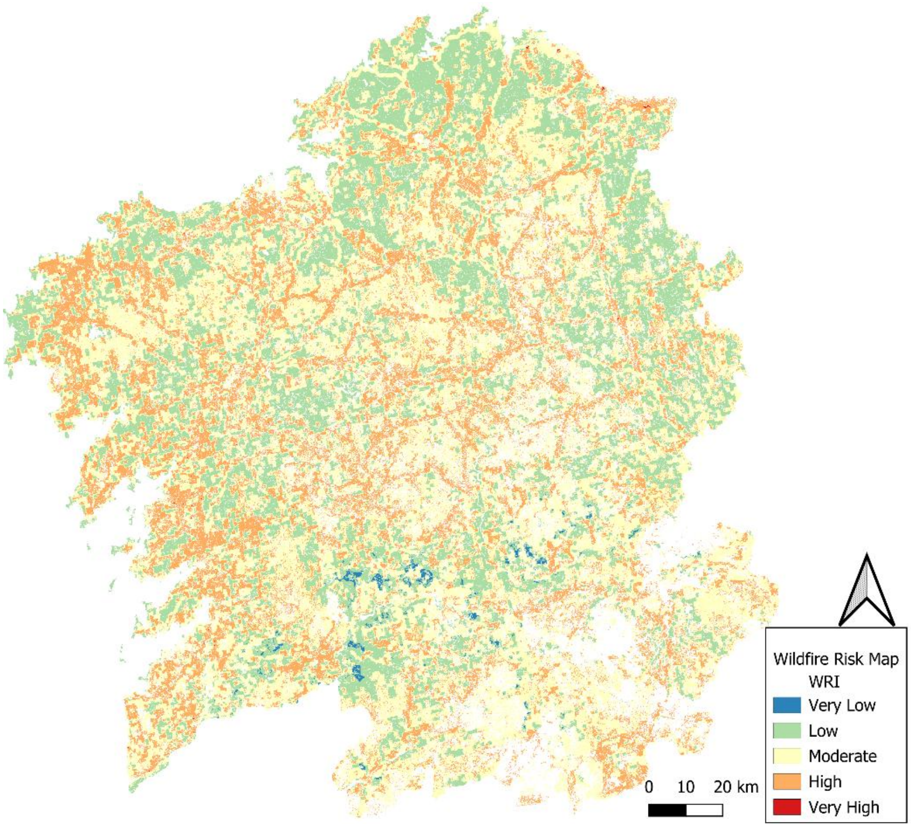

Figure 2 Dynamic wildfire risk map (Wildfire Risk Index, WRI) for the autonomous community of Galicia, where short-term factors such as meteorology and vegetation exert the greatest influence, while socioeconomic and topographic components have less impact. Risk levels are classified into five categories: very low (blue), low (green), moderate (yellow), high (orange), and very high (red).

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