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**Title of document:**

# **Evaluation methodology**

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## **Work package 3**

Evaluating the pilot actions

### **Activity 3.1**

Evaluation methodology elaboration

#### **Deliverable 3.1.1**

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# Table of Contents

<b>1</b>	<b>Introduction</b>	<b>7</b>
<b>2</b>	<b>Evaluation Scope and Use Cases</b>	<b>12</b>
2.1	Pilot site: Sežana, Slovenia	13
2.1.1	Pilot area description	13
2.1.2	Use Cases	14
2.1.2.1	UC1 – Preventive inspection of areas	15
2.1.2.2	UC2 – Monitoring of the fire scene after the intervention	15
2.1.2.3	UC3 – Informing the Public About Danger	16
2.1.2.4	UC4 – Monitoring of Wildfire Intervention	17
2.2	Pilot site: Rocca di Cerere UNESCO Global Geopark, Italy	17
2.2.1	Pilot area description	17
2.2.2	Use Cases	18
2.2.2.1	UC1 - UAS Monitoring in Rocca di Cerere Park	18
2.3	Pilot site: National Park Una, Bosnia and Herzegovina	19
2.3.1	Pilot area description	19
2.3.2	Use cases	20
2.3.2.1	UC1 – Preventive monitoring and early warning in the Una National Park of remote and inaccessible areas with a high fire risk index	20
2.3.2.2	UC2 – Aerial surveillance of floods caused by climate change in the Una National Park	21
2.4	Pilot site: Ulcinj, Montenegro	22
2.4.1	Pilot area description	22
2.4.2	Use Cases	22
2.4.2.1	UC1 – Preventive Monitoring of Remote Areas	22
2.4.2.2	UC2 – Enhanced Aerial Support for Active Wildfire Response	23
2.4.2.3	UC3 – Wildfire Aftermath Damage Assessment	24
2.5	Pilot site: Mali Lošinj, Croatia	24
2.5.1	Pilot area description	24
2.5.2	Use cases	25
2.5.2.1	UC1 – Preventive Monitoring of Remote Areas with High-Fire Danger Index	25
2.5.2.2	UC2 – Locating and Monitoring the Spread of Fire	26
2.5.2.3	UC3 – Preventive Monitoring of Remote Areas	26
2.5.2.4	UC4 – Inspection of Fire Protection Routes	27
2.5.2.5	UC5 – Response to Illegal Fire Ignitions	27

2.6	Pilot site: Baixo Alentejo, Portugal	27
2.6.1	Pilot area description	27
2.6.2	Use Cases	28
2.6.2.1	UC1 – Preventive monitoring due to high fire danger index (summer)	28
2.6.2.2	UC2 – Support of firefighting operations in case of fire.	29
2.6.2.3	UC3 – Post-incident documentation and analysis	29
<b>3</b>	<b>Key Performance Indicators (KPIs) Framework</b>	<b>31</b>
3.1	Pilot site: Sežana, Slovenia	34
3.1.1	UC1 – Preventive inspection of areas	34
3.1.1.1	Coverage of high-risk areas	34
3.1.1.2	Accuracy of Real-Time Data	34
3.1.2	UC2 – Monitoring of the fire scene after the intervention	35
3.1.2.1	Burned Area Mapping Accuracy	35
3.1.2.2	Post-fire Assessment Efficiency	36
3.1.3	UC3 – Informing the Public About Danger	37
3.1.3.1	Public Warning Reach	37
3.1.3.2	Public trust and acceptance	37
3.1.4	UC4 – Monitoring of Wildfire Intervention	38
3.1.4.1	Hotspot Detection Accuracy	38
3.1.4.2	Streaming Data Latency	39
3.1.5	Overview of KPIs	40
3.2	Pilot site: Rocca di Cerere UNESCO Global Geopark, Italy	42
3.2.1	UC1 - UAS Monitoring in Rocca di Cerere Park	42
3.2.1.1	Accuracy of fire/smoke detection	42
3.2.1.2	Streaming Data Latency	42
3.2.1.3	Coverage of sensitive areas	43
3.2.2	Overview of KPIs	44
3.3	Pilot site: National Park Una, Bosnia and Herzegovina	46
3.3.1	UC1 – Preventive monitoring and early warning in the Una National Park of remote and inaccessible areas with a high fire risk index	46
3.3.1.1	Coverage of inaccessible areas	46
3.3.1.2	Fire Detection Timeliness	47
3.3.2	UC2 - Aerial surveillance of floods caused by climate change in the Una National Park	48
3.3.2.1	Coverage of flood areas	48
3.3.2.2	Flood Response Effectiveness	49
3.3.3	Overview of KPIs	50

3.4	Pilot site: Ulcinj, Montenegro	51
3.4.1	UC1 – Preventive Monitoring of Remote Areas	51
3.4.1.1	Reduction of burnt area	51
3.4.1.2	Fire Hazard Responsiveness	52
3.4.2	UC2 – Enhanced Aerial Support for Active Wildfire Response	53
3.4.2.1	Hotspot Detection Accuracy	53
3.4.2.2	Operational Responsiveness	54
3.4.3	UC3 – Wildfire Aftermath Damage Assessment	55
3.4.3.1	Burned Area Mapping Accuracy	55
3.4.3.2	Post-Fire Cleanup Prioritization Efficiency	55
3.4.4	Overview of KPIs	57
3.5	Pilot site: Mali Lošinj, Croatia	58
3.5.1	UC1 – Preventive Monitoring of Remote Areas with High Fire Danger Index	58
3.5.1.1	Coverage of fire-prone areas	58
3.5.1.2	Streaming Data Quality	59
3.5.2	UC2 – Locating and Monitoring the Spread of Fire	60
3.5.2.1	Accuracy of fire/smoke detection	60
3.5.2.2	Tactical Responsiveness	60
3.5.3	UC3 – Preventive Monitoring of Remote Areas	61
3.5.3.1	Preventive Flight Regularity	61
3.5.3.2	Persistent Hotspot Frequency	62
3.5.4	UC4 – Inspection of Fire Protection Routes	63
3.5.4.1	Route Safety Assessment	63
3.5.4.2	Inspection Coverage Rate	64
3.5.5	UC5 – Response to Illegal Fire Ignitions	65
3.5.5.1	Fire Ignition Responsiveness	65
3.5.6	Overview of KPIs	66
3.6	Pilot site: Baixo Alentejo, Portugal	68
3.6.1	UC1 – Preventive monitoring due to high fire danger index (summer)	68
3.6.1.1	Accuracy of Fire/Smoke Detection	68
3.6.1.2	Coverage of high-risk areas	68
3.6.2	UC2 – Support of firefighting operations in case of fire.	69
3.6.2.1	Operational Responsiveness	69
3.6.3	UC3 – Post-incident documentation and analysis.	70
3.6.3.1	Burned Area Mapping Accuracy	70
3.6.4	Overview of KPIs	71

<b>4</b>	<b>Methodological Approach: MCA Supported by AHP</b>	<b>72</b>
4.1	Introduction	72
4.2	Multi-Criteria Analysis (MCA)	72
4.3	Role of the Analytic Hierarchy Process (AHP)	73
4.4	Pairwise comparisons and matrix construction	73
4.5	AHP application	74
4.6	Integration of AHP Weights into MCA	75
<b>5</b>	<b>Preliminary operations for the evaluation report</b>	<b>77</b>
<b>6</b>	<b>Conclusions</b>	<b>78</b>
	<b>References</b>	<b>81</b>

## List of abbreviations and terms

<b>Abbreviation</b>	<b>Definition</b>
<b>AHP</b>	Analytic Hierarchy Process
<b>CR</b>	Consistency Ratio
<b>DSS</b>	Decision Support System
<b>GNSS</b>	Global Navigation Satellite System
<b>KPI</b>	Key Performance Indicator
<b>LiDAR</b>	Light Detection and Ranging
<b>MCA</b>	Multi-Criteria Analysis
<b>NBR</b>	Normalised Burn Ratio
<b>NDVI</b>	Normalised Difference Vegetation Index
<b>SAR</b>	Search and Rescue
<b>UAS</b>	Unmanned Aerial Systems
<b>UAV</b>	Unmanned Aerial Vehicle
<b>UC</b>	Use case

## 1 Introduction

Wildfires constitute an important environmental factor with a presence that dates back to the time when any form of terrestrial vegetation existed on the planet. For the Mediterranean basin, in particular, forest fires, as a phenomenon with a periodic presence and an important ecological role, date back to the early stages of the establishment of the Mediterranean type climate (Trabaud 1987, 1994), approximately 3 million years ago (Suc 1984), as a result of the transition from a subtropical climate type to one with a characteristic seasonality in the distribution of rainfall and a prolonged dry period during the summer months. Since then, the role of fire in shaping the Mediterranean landscape has been so important that only species that either possessed or developed mechanisms to overcome the devastating consequences of a fire have managed to survive in this bioclimatic space. In fact, such is the adaptation of various plant species to the periodic presence of fires that some scientists, in the early seventies, formulated the view that Mediterranean plants are favored by fires to such an extent that they have developed mechanisms for promoting fire (Mutch 1970, Rundel 1981). This view, of course, despite any experimental or non-experimental efforts (Williamson and Black 1981, Buckley 1983, 1984), could never be based on serious scientific data and a logical scientific basis (Snyder 1984, Troumbis and Trabaud 1989, Bond and Midgley 1995, Schwilk and Kerr 2002).

For millions of years, fire was a natural environmental factor caused by natural causes, such as lightning strikes, volcanic eruptions, rock falls, etc. (Edwards 1984, Kruger and Bigalke 1984, Whelan 1995), which had a periodic presence (fire cycle) leading as a natural result to the periodic renewal of ecosystems. Later, however, and after man's transition to a phase of shaping the environment in which he lives, fire became for him an important tool for shaping better living conditions. He used it to create areas suitable for the development of agricultural activities, to improve pastures, and even as a weapon against animals that were causing him problems. Thus, fire gradually transformed from a natural factor into a destructive factor for the natural environment, with a much more frequent appearance in the same places (smaller fire cycle), without however being treated as such by man (Naveh and Dan 1973).

However, a lot has changed since then. Man continues to be a rather structural element of forest ecosystems, only his role within them and the services they offer him are completely different. Forest ecosystems are no longer an obstacle to his evolution and development, but a necessary condition for his sustainable presence. This has resulted in forest fires being

treated nowadays as perhaps one of the greatest threats to the natural environment and therefore to the well-being of man himself.

Subsequently, from the beginning, but mainly from the middle of the last century, various strategies for dealing with fires have begun to be implemented in all areas with frequent occurrence of fires, with varying levels of success. The treatment of forest fires essentially consists of three distinct but interrelated phases: prevention, suppression and restoration. For a wildfire management strategy to be effective, all three of the above phases must function effectively.

As far as prevention is concerned, it can be said with certainty that it is still at a premature level in almost all countries being unable to prevent ignitions and to prevent the evolution of an ignition into a wildfire. Perhaps the most indicative example of the failure to prevent forest fires is the lack of reliable data, both statistical and geographical, concerning the real causes of wildfires. On the contrary, the prevailing view has been that forests are burned almost exclusively by fires caused by deliberate and malicious arson. However, the failure to properly identify and analyze the real causes of wildfires inevitably leads to the problem not being solved since no problem can be solved if the causes that create it have not been previously analyzed.

The suppression system, in addition to its own endogenous problems, also has to deal with an increased load as a result of the limited performance of the previous stage of fire prevention. At an operational level, the suppression system rarely takes into account the specific conditions created by the specificities of the fuel at each time, while there is insufficient knowledge and information regarding fire behavior under specific conditions of flammability, topography and weather conditions. It continues to rely on fire protection measures, such as the interruption of the continuity of the fuel with firebreaks, which have for decades proven to be insufficient and ecologically destructive. On the contrary, other fuel management measures that have been applied in various fire prone areas and have been effective are not adequately considered. The result is that the suppression system is on the one hand costly, since aerial means are now used indiscriminately, and on the other hand its effectiveness has not reached a level that ensures the sustainable presence of natural ecosystems. New solutions that will provide accurate data of the fuel load and condition, which will be based on contemporary sensors, such as lidar, are necessary for improving the efficiency of the fire suppression system. Furthermore, contemporary fire behavior simulation tools that will take advantage of the accurate fuel data have to be employed to improve our understanding of wildfire behavior and increase the level of preparedness and alert.

It is easy to see that the current strategy for dealing with forest fires in Europe is often based on a misconception about the phenomenon of forest fires. It aims to completely eliminate the phenomenon without analyzing its role in both space and time. However, the complete elimination of wildfires is practically impossible and ecologically extremely controversial. After all, forest fires have imposed their presence through the historical role they have played in the current formation of the landscape in the Mediterranean and other fire prone regions. Even if the existing fire protection system operated with exceptional efficiency, eliminating the phenomenon for a long period of time, this would create an ecological imbalance, leading to an enormous and unnatural concentration of fuel, so that when at some point an ignition occurs it would lead to a real and possibly irreversible ecological disaster.

The forest fire must be treated as a living organism with a specific geographical distribution, determined by climatic conditions, with specific behavior in space and time and with specific weaknesses. The goal of an effective fire protection strategy should not be the utopia of eliminating the phenomenon of forest fires. The goal should be to transform it from a voracious organism that devours everything in its path into a vulnerable and manageable organism with a discreet presence and an ecological role that it will continue to play, without creating the problems that it currently creates in the natural environment and in the modern role that it is called upon to play.

However, in order to achieve the above goal, there must be in-depth knowledge of its possible behavior in a specific geographical area with its specific characteristics, both topographic and biological and climatic. This will make it possible to develop alternative solutions for dealing with it with measures and actions that will not disrupt the ecological balance and will ensure the sustainable presence of forest ecosystems and the modern role that they have to play.

As demonstrated in the Preliminary Data Collection and Processing Study (Deliverable D1.1.1), all six pilot areas of FRED project—from Croatia to Portugal, from Italy to Montenegro—display a convergence of ecological, climatic, and socio-economic conditions that make fire prevention and management a strategic priority for local and national authorities.

The FRED project responds to this urgent challenge by developing and deploying the FRED platform, an integrated, transnational ICT ecosystem designed to support all phases of wildfire management. FRED brings together UAS-based remote sensing, geospatial analytics, advanced fire-risk modelling, satellite-derived environmental indicators, and real-time

operational tools in a single harmonised environment. The platform serves as both a technological framework and a decision-support infrastructure, enabling the consistent processing, visualisation, and interpretation of multi-source data—from satellite imagery and meteorological forecasts to ground-truth measurements, pyric history indicators, and UAS-captured thermal or LiDAR datasets.

While Deliverable D1.1.2 defines the operational methodology for UAS deployment and data acquisition across the pilot sites, the present deliverable moves one step further: it establishes the methodology for evaluating the efficiency and operational value of the FRED platform itself. Assessing the platform’s performance is critical for three reasons:

- To demonstrate measurable added value for fire brigades, civil protection agencies, and decision-makers responsible for wildfire mitigation.
- To ensure technological harmonisation across diverse Mediterranean contexts, where terrain, vegetation, fire behaviour, and institutional capacities vary significantly—as shown in D1.1.1 through detailed geomorphological, ecological, climatic, and remote-sensing analyses of each pilot area.
- To validate the platform’s suitability for large-scale adoption and long-term operational integration, both within and beyond the Interreg Euro-MED geographical area.

Efficiency in wildfire management cannot be measured through a single metric. Rather, it emerges from a complex interplay of indicators across the entire fire-management cycle. For this reason, the introduction of this deliverable frames efficiency across four operational dimensions:

- Prevention, where FRED must demonstrate improved capacity to detect fuel accumulation, identify high-risk areas, and integrate dynamic indicators such as FDI, FWI, and pyric history (PHI), all of which were characterised in D1.1.1 for each pilot region.
- Preparedness, where the platform should enhance planning, scenario modelling, and training, providing fire services with accurate spatial data (DEM, CHM, land cover, access routes) and real-time updates.
- Response, where efficiency includes faster situational awareness, improved hotspot detection, enhanced coordination of UAS missions (as described in D1.1.2), and more effective allocation of suppression resources.

- Post-fire assessment, where multispectral and LiDAR outputs contribute to burn severity mapping, ecological impact assessment, and recovery planning.

Establishing a robust methodology for evaluating FRED's efficiency also requires acknowledging several challenges. The six pilot areas differ substantially in climatic regimes, topography, vegetation composition, land-use patterns, and fire history—differences clearly presented through the detailed maps, datasets, and analyses in D1.1.1

Moreover, partners operate diverse UAS platforms, sensors, and pre-existing data infrastructures. Therefore, the assessment methodology must ensure:

- comparability across heterogeneous contexts,
- integration of qualitative and quantitative indicators,
- technical interoperability of datasets, and
- scalability for future adoption by additional stakeholders.

Against this backdrop, the goal of this deliverable is to provide a comprehensive, evidence-based methodology to assess how effectively FRED supports wildfire prevention, preparedness, response, and recovery. The methodology is designed to:

- Define consistent efficiency indicators—operational, technical, environmental, spatial, temporal, and user-centric.
- Provide measurement protocols based on the data flows captured in D1.1.1 and the operational SOPs defined in D1.1.2.
- Enable cross-pilot comparability using harmonised evaluation criteria.
- Establish procedures for field validation, stakeholder feedback, and iterative refinement of the platform.
- Support future capitalisation, replication, and integration into regional and national wildfire-management strategies.

Ultimately, this deliverable contributes to the overarching ambition of FRED: to create a resilient, technologically empowered, and collaboratively managed Mediterranean region capable of addressing the growing threat of wildfires. By rigorously assessing the performance of the FRED platform, the project ensures that its digital innovations translate into measurable environmental, operational, and societal benefits.

## 2 Evaluation Scope and Use Cases

The evaluation covers a wide range of operational scenarios (Table 1) that were defined by each pilot site based on their specific needs, environmental conditions, and organisational priorities, as reported in Deliverable 1.1.2 -Pilot case implementation methodology paper.

Table 1 – Field/Scopes of action and use cases for FRED pilot sites

PILOT SITE	USE CASE	FIELD/SCOPE
<b>Sežana, Slovenia</b>	1. Preventive inspection of areas	Prevention and mitigation
	2. Monitoring of the fire scene after the intervention	Post-fire status damage assessment
	3. Informing the public about the danger	Prevention and mitigation
	4. Monitoring of wildfire intervention	Active wildfire response
<b>Rocca di Cerere UNESCO Global Geopark, Italy</b>	1. UAS Monitoring in Rocca di Cerere Park	Prevention and mitigation
<b>National Park Una, Bosnia and Herzegovina</b>	1. Preventive monitoring and early warning in the Una National Park of remote and inaccessible areas with a high fire risk index.	Prevention and mitigation
	2. Aerial surveillance of floods caused by climate change in the Una National Park.	Prevention and mitigation
<b>Ulcinj, Montenegro</b>	1. Preventive monitoring of remote areas	Prevention and mitigation
	2. Enhanced aerial support for active wildfire response	Active wildfire response
	3. Wildfire Aftermath Damage Assessment	Post-fire status damage assessment
<b>Mali Lošinj, Croatia</b>	1. Preventive monitoring of remote areas with high danger fire index	Prevention and mitigation
	2. Locating and monitoring the spread of fire	Active emergency response /S&R
	3. Preventive monitoring of remote areas	Prevention and mitigation
	4. Inspection of fire protection routes	Inspection of fire and access roads
	5. Response to a report of illegal fire igniting	Active emergency response /S&R
<b>Baixo Alentejo, Portugal</b>	1. Preventive monitoring due to high fire danger index (summer)	Prevention and mitigation
	2. Support of firefighting operations in case of fire.	Active wildfire response
	3. Post-incident documentation and analysis	Post-fire status damage assessment
	4. Ancient paths inspection	Prevention and mitigation
	5. Rural access roads	Prevention and mitigation

These use cases illustrate the different ways in which drones and the FRED platform can support wildfire-related activities—from prevention to emergency response and post-event analysis.

In several pilot sites, the focus is on preventive monitoring of high-risk areas, where regular drone flights help identify early signs of fire hazards. Other sites concentrate on early detection, using aerial imagery and onboard sensors to identify smoke, hotspots, or ignition points at an early stage. Some pilots also explore the use of drones for public alerting and risk communication, delivering timely information to at-risk communities. Drones are also used to support inspection of fire protection routes, such as firebreaks and access corridors, ensuring that prevention infrastructures remain effective.

In addition, several sites extend the use of the system to monitor climate-related hazards, including floods or other environmental risks, demonstrating the versatility of the UAS beyond wildfire management. During active emergencies, drones play a crucial role by providing real-time situational awareness to firefighting teams, improving coordination and supporting tactical decisions.

Beyond emergency phases, the use of drones also contributes to post-fire damage assessment, providing detailed imagery and thermal data to evaluate the extent and severity of burned areas.

## **2.1 Pilot site: Sežana, Slovenia**

### 2.1.1 Pilot area description

The Sežana pilot site is located in the western part of Slovenia, within the Karst (Kras) region, an internationally recognised landscape known for its unique geomorphology, dry Mediterranean climate, and recurrent wildfire activity. The region is characterised by extensive karst plateaus, sinkholes, rocky outcrops, shallow soils and a mosaic of forest, shrubland and abandoned agricultural land. These features create a complex and highly flammable environment, where vegetation structure and microclimatic conditions strongly influence fire behaviour.

The Sežana area has experienced numerous large wildfires in recent decades, including some of the most severe ever recorded in Slovenia, largely due to its combination of dense pine forests, persistent summer droughts and strong regional winds such as the burja. Fuel accumulation is widespread, driven by depopulation, land abandonment and natural succession, resulting in continuous vegetation cover that is highly combustible during the summer months. The terrain itself—characterised

by uneven relief, rocky surfaces, and limited water availability—adds further complications to fire management, creating access challenges for firefighting units and restricting the deployment of heavy equipment.

The region also contains critical infrastructure—including highways, railways, energy lines and settlements—embedded within fire-prone landscapes. Protecting these assets requires a high level of coordination among fire brigades, civil protection authorities and municipal services. During major wildfire events, visibility is often reduced by smoke columns that rise above the karst plateau, making aerial situational awareness particularly valuable. Because suppression efforts are often hindered by steep terrain, limited road access and rapid fire spread driven by wind, UAS-based monitoring emerges as an essential support tool for early detection, tactical planning and real-time observation.

From a prevention standpoint, the area presents several challenges. Large sections of degraded or abandoned land accumulate biomass that cannot be easily managed with traditional means. Illegal burning or the improper use of fire near forest edges can quickly lead to ignition under summer conditions. Moreover, the region borders Italy and lies close to critical cross-border infrastructure, meaning that coordinated monitoring is necessary to address transboundary fire risk.

These characteristics make Sežana a strategically important pilot site for testing and evaluating the FRED platform and UAS-based methodologies. The region's combination of complex karst topography, high fuel loads, rapid fire spread potential and operational access limitations provides a realistic, demanding environment for validating new technologies. The pilot site allows the project to demonstrate how real-time aerial data, hotspot detection, preventive surveillance and post-fire assessment can enhance conventional fire management systems. Sežana is therefore positioned as a benchmark location within the Fire Free MED initiative, illustrating how digital tools and drone operations can significantly improve preparedness, prevention and tactical response in one of Europe's most fire-prone karst landscapes.

## 2.1.2 Use Cases

The Sežana pilot site's Use Cases are derived from operational needs identified by ZGRS Sežana and are designed to leverage FRED and UAS technologies to address both prevention and active response challenges. While the full table of Use Cases begins in D1.1.2 Section 4.1.2, the overall logic aligns with the fire environment described in D1.1.1. Below is an extended

synthesis of the Use Cases, integrating contextual factors from both deliverables.

### 2.1.2.1 UC1 – Preventive inspection of areas

The Sežana region, located in the southwestern Slovenian Karst, faces recurring wildfire threats due to its dry limestone terrain, strong winds, extensive shrublands, and human activity in remote agricultural or forested areas. During periods when fire danger is officially declared, preventive inspections play a decisive role in stopping wildfires at their earliest stage, often even before ignition occurs. This use case involves deploying unmanned aerial systems (UAS) across the most fire-prone areas to conduct systematic aerial surveillance.

The preventive inspection missions focus on identifying any early indications of danger, including unauthorized burning, smoldering organic material, improper disposal of cigarettes, or human presence in restricted zones. The drones use thermal imaging to detect hidden or emerging hotspots that may not yet be visible to ground teams. Real-time video streaming allows the command center to observe conditions live, evaluate threats remotely, and decide whether to dispatch ground units.

The value of this use case lies in its ability to rapidly cover large and fragmented terrain that would otherwise require considerable time and personnel to patrol. Because the Karst region contains steep slopes, forests with low visibility, and abandoned agricultural lands, drone-based preventive inspection offers a level of coverage and precision that manual patrols cannot provide. The FRED platform enhances this by storing flight data, logging observations, and ensuring the information is immediately available to fire services.

Preventive inspections function as the first barrier in the fire management cycle. By detecting anomalies early, they reduce the likelihood of fire outbreaks and help authorities maintain continuous situational awareness across vast, difficult-to-access terrain. This UAS–FRED combined workflow aims to transform preventive fire management into a faster, more precise, and more efficient process.

### 2.1.2.2 UC2 – Monitoring of the fire scene after the intervention

Once a wildfire event in the Sežana region has been contained, a thorough evaluation of the burned area is required to understand the fire's behavior, quantify damage, identify residual hazards, and support ecological restoration. This use case focuses on the deployment of drones equipped

with photogrammetry and LiDAR sensors to produce high-resolution spatial documentation of the affected terrain.

The Karst landscape—characterized by irregular surfaces, cavities, and mixed vegetation—requires precise mapping tools to capture burn severity, ground deformation, canopy loss, and the potential for reignition. Using UAS, the fire service can rapidly generate 2D orthomosaics and 3D terrain models with centimeter-level accuracy. These models help identify smoldering materials, burned root systems, or structural hazards that could pose risks after suppression.

The FRED platform integrates and stores these datasets, allowing analysts and field teams to access, measure, annotate, and compare burn patterns. The data also supports the evaluation of firefighting tactics by showing how the fire progressed, where it changed behavior, and which defensive lines were most effective. Over time, repeated post-fire assessments contribute to building a fire history archive that enhances long-term fire-risk modelling and recovery planning.

This use case provides critical information for environmental authorities, landowners, and municipal decision-makers. It supports rapid restoration planning, infrastructure protection, and identification of areas needing stabilization or remediation. In a region where fires spread across cross-border terrain and can exhibit complex underground burning, accurate post-fire assessment is essential for preventing re-ignition and supporting ecosystem resilience.

### *2.1.2.3 UC3 – Informing the Public About Danger*

The Sežana region includes dispersed rural settlements, isolated farms, and extensive forested terrain where public-warning systems face limitations. During emergencies such as rapidly spreading wildfires or hazardous conditions, drones equipped with loudspeakers and high-intensity lighting can be deployed to warn residents who may not be reachable through conventional channels.

This use case involves UAS flying over affected zones to deliver evacuation messages, instruct individuals to leave fire-prone areas, or warn hikers, tourists, and local residents about imminent danger. The drone becomes an aerial communication platform that enhances operational reach, especially in areas with limited mobile coverage, narrow roads, or high vegetation where ground units cannot quickly reach people.

FRED platform supports this workflow by tracking mission areas, logging communication events, and ensuring a record of when and where warnings

were issued. Authorities are thus able to analyze the effectiveness of their public-alert strategies and verify compliance. The mechanism also reduces the time required for authorities to deliver warnings manually, increases coverage, and minimizes risks to personnel by avoiding deployment into hazardous terrain during emergency conditions.

This use case is particularly important in preventing casualties and ensuring rapid movement of people away from fire fronts or dangerous zones during intervention. Drone-based public communication represents a modern extension of civil protection capability.

#### *2.1.2.4 UC4 – Monitoring of Wildfire Intervention*

Active wildfire incidents in the Sežana region often unfold under challenging conditions, including strong winds, steep karst slopes, and vegetation that can transition rapidly from surface to crown fire. To maintain situational awareness, drones are deployed to monitor fire behavior in real time, detect emerging hotspots, and observe the advance of the flame front.

This use case involves continuous aerial surveillance where drones stream high-resolution visual and thermal imagery directly into the command center. FRED processes and displays these feeds, allowing commanders to assess fire intensity, identify dangerous zones, anticipate spread directions, and decide on tactical maneuvers such as redeployment of units, selection of safe access routes, or prioritization of assets for protection.

The drone's ability to access hazardous or inaccessible terrain makes it a vital tool for real-time risk assessment. It can reveal hidden hotspots behind smoke, identify spot fires that may be forming beyond the main fireline, and monitor the effectiveness of firefighting actions on the ground. The real-time nature of this information significantly enhances decision-making under pressure and contributes to firefighter safety by reducing uncertainty during complex operations.

## **2.2 Pilot site: Rocca di Cerere UNESCO Global Geopark, Italy**

### **2.2.1 Pilot area description**

The Rocca di Cerere UNESCO Global Geopark is located in the central area of Sicily and spans a geomorphologically diverse landscape characterised by hills, limestone mesas, deep valleys and rocky outcrops formed through complex geological processes. As part of the UNESCO Global Geoparks network, Rocca di Cerere is a protected area of high naturalistic, cultural and archaeological importance. The region includes ancient land-use structures,

terraced agricultural plots, dry-stone walls, forest patches, and semi-natural shrubland ecosystems. The mosaic-like structure of the landscape makes it ecologically valuable but also highly sensitive to environmental stressors.

Wildfire risk in the Geopark is influenced by its Mediterranean climate, characterised by hot, dry summers and recurrent drought conditions that increase fuel accumulation and dryness across forests and shrublands. Steep slopes, rugged terrain, and remote interior areas hinder access for ground-based monitoring and intervention. Furthermore, human activities such as agricultural burning, maintenance fires, and unauthorized biomass removal can easily lead to ignition during the driest months. These challenges highlight the need for continuous monitoring and rapid systems of early detection, especially in ecologically sensitive zones where wildfire could cause irreversible damage.

The park hosts rich biodiversity, including species adapted to karstic and semi-arid environments, and features important cultural heritage resources that require protection. For these reasons, the Rocca di Cerere area is an ideal pilot site for demonstrating the capacity of the FRED platform and UAS operations to support preventive monitoring, environmental protection, and fire-risk mitigation.

The pilot site's characteristics—complex topography, ecological sensitivity, heterogeneous vegetation, remote areas and recurrent ignition drivers—make it a valuable testing ground to validate advanced UAV-based fire prevention strategies within the Fire Free MED project.

## 2.2.2 Use Cases

### 2.2.2.1 UCI - UAS Monitoring in Rocca di Cerere Park

The aim of this use case is to implement a continuous and technologically enhanced monitoring system across the Rocca di Cerere UNESCO Global Geopark to support fire prevention, early detection, environmental surveillance, and compliance with mitigation measures. The landscape of the Geopark includes both easily accessible areas close to settlements and highly inaccessible sectors composed of cliffs, stratified rock formations, deeply incised valleys, and dense shrublands. These conditions create blind spots for ground-based patrols and significantly delay traditional detection systems.

Unmanned Aerial Systems (UAS) provide a transformative approach to surveillance by offering immediate aerial access to remote zones, high-resolution imaging, and the ability to collect environmental indicators that would otherwise go unnoticed. Each drone mission is designed to detect

hotspots, monitor vegetation health, identify human activities that increase fire risk, and assess ongoing mitigation efforts imposed on landowners or required by the park's management plan.

Thermal cameras are used to detect subtle heat anomalies that may indicate smouldering remains, unauthorised burning, or pre-ignition conditions. These thermal signatures are especially important in forest edges, abandoned agricultural lots, and zones where organic material decomposes under high temperatures. Multispectral imaging enables the monitoring of vegetation status by detecting changes in canopy vigor, moisture stress and other factors that contribute to increased flammability. These data layers help the management authority recognise areas where fuel load is building up or where vegetation has become physiologically stressed, making it more susceptible to fire.

Real-time data transmission through the FRED platform allows information to be delivered instantly to park authorities. Any detected threat, illegal activity or fire precursor can be relayed to forest rangers, municipal agencies or landowners responsible for maintaining safety around their properties. This strengthens enforcement of mitigation obligations, especially those requiring vegetation management, fuel reduction or compliance with fire-risk regulations. The system helps ensure that prevention measures are not only planned but actively monitored.

The combination of multispectral sensing, thermal detection, real-time visual streaming and sound diffusion technologies allows the UAS to fulfil multiple roles: environmental monitoring, enforcement, risk detection, and public safety. By integrating these operations into FRED, the pilot site achieves a fully digitalised monitoring cycle where captured data is archived, visualised and available for risk modelling and future planning. This approach substantially enhances the Geopark's capacity to protect both natural ecosystems and cultural landscapes from wildfire events.

## **2.3 Pilot site: National Park Una, Bosnia and Herzegovina**

### **2.3.1 Pilot area description**

Una National Park is located in the northwestern part of Bosnia and Herzegovina and represents one of the country's most ecologically valuable and diverse protected areas. The park encompasses vast forested landscapes, mountainous zones, river valleys, and a complex network of streams, cliffs, remote plateaus and riparian environments dominated by the Una, Unac and Ostrovica rivers. These natural features create a

spectacular mosaic of habitats but also present significant challenges for monitoring and emergency response.

The park's terrain is largely inaccessible in many areas, with dense forest cover, deep canyons and steep slopes that complicate both routine surveillance and rapid intervention. The extensive forest ecosystems are highly susceptible to wildfire during the dry summer months. These wildfire risks are intensified by rising temperatures, prolonged periods without rain and the growing impacts of climate change. Human presence is scattered across the park—often including tourists or local visitors who may be unaware of fire hazards—adding another layer of complexity to prevention efforts.

Moreover, Una National Park faces an additional hazard increasingly linked to climate change: seasonal flooding. Heavy or irregular rainfall can cause the Una and Unac rivers to overflow, leading to damage to trails, infrastructure, and ecological zones. Flooding also isolates certain areas, making situational awareness and rapid response difficult for ground teams.

These characteristics—vast remote areas, difficult terrain, dual hazards of wildfire and flooding, and ecological sensitivity—make Una National Park an ideal pilot site for demonstrating the operational value of UAS and the FRED platform. Through aerial monitoring, real-time data transfer, and enhanced situational awareness, the park authorities can significantly strengthen both wildfire prevention and crisis-response capacity.

## 2.3.2 Use cases

### 2.3.2.1 *UC1 – Preventive monitoring and early warning in the Una National Park of remote and inaccessible areas with a high fire risk index*

During the summer season, Una National Park experiences frequent fire outbreaks, especially in its remote forested zones where access is limited and visibility is restricted. Many ignition events occur in areas unreachable by vehicle, and in some cases even by foot, meaning that early detection is often delayed. This use case addresses this critical gap through systematic UAS monitoring and early warning in high fire-risk areas.

Drones are deployed to patrol forest corridors, steep mountain flanks, remote plateaus and river-adjacent forest zones where wildfire ignition is historically recurrent. The UAS provides real-time thermal and visual imagery that allows operators to immediately detect smoke plumes, hotspots and unusual temperature anomalies, even when the area is obscured by dense canopy cover.

The advantage of drone-based preventive monitoring in Una National Park is twofold. First, it provides access to areas that are otherwise impossible or too dangerous to monitor through traditional patrols, significantly reducing the time needed to identify emerging threats. Second, UAS contributes to situational diagnosis of any potential ignition: determining whether a disturbance represents a real fire event, a minor hazard, or harmless human activity. This enables park authorities to make informed decisions on whether to mobilize firefighting units or simply continue monitoring.

Integration with the FRED platform ensures that all detections, anomalies and mission recordings are stored, mapped and available for real-time decision-making. In a large and rugged national park, this use case establishes a highly efficient framework for wildfire prevention, reducing both detection time and unnecessary deployment of personnel.

### *2.3.2.2 UC2 – Aerial surveillance of floods caused by climate change in the Una National Park*

In addition to wildfire risk, Una National Park is increasingly affected by flood events caused by climate change. Intense seasonal rains create rapid fluctuations in water levels in the Una, Unac and Ostrovica rivers. These fluctuations can trigger sudden inundation of riverbanks, submergence of trails, damage to tourism infrastructure, and isolation of visitors or personnel in remote areas.

Ground-based monitoring of flood conditions is particularly challenging in the park's steep river valleys and forested riverbanks. This use case introduces aerial drones as a rapid and effective means of assessing flood extent, monitoring water-level progression, identifying dangerous currents, and mapping zones where infrastructure or ecosystems are at risk.

During flood events, drones provide real-time visual imagery that enables park authorities to track the movement of water across the landscape. Through the FRED platform, this information is rapidly shared with crisis-response teams, ensuring that evacuation routes are identified early and that decisions can be taken with a complete overview of the evolving situation. The aerial view is particularly crucial for identifying isolated hikers, trapped vehicles or damaged sections of trails.

UAS surveillance during floods thus becomes a vital operational tool for maintaining safety, managing visitor movement, evaluating environmental damage, and coordinating emergency response teams—especially in a national park where ground access is naturally restricted.

## 2.4 Pilot site: Ulcinj, Montenegro

### 2.4.1 Pilot area description

The Ulcinj municipality is situated in the southernmost coastal region of Montenegro, an area defined by Mediterranean climatic conditions, extensive olive groves, dense shrublands, semi-natural forests and mixed rural–urban interfaces. Ulcinj’s landscape includes a complex combination of coastal plains, cultivated agricultural zones, hilly hinterlands, and remote pockets of vegetation where landowners regularly conduct maintenance by burning branches or clearing dry biomass.

These characteristics make the region highly susceptible to wildfire ignition, especially during the summer months when temperatures are high, vegetation moisture is low, and human activity intensifies. The traditional practice of burning leftover vegetation in olive groves—common among local landowners—creates significant fire hazards when conducted without oversight. Many of these groves are located in isolated, hard-to-reach areas where ground patrols are infrequent and access is limited. The rugged terrain, narrow rural roads, and large distances between settlements further complicate early detection and rapid intervention.

Ulcinj’s topography also includes sections where standard fire trucks cannot reach, either due to steep pathways, dense vegetation or the absence of serviceable roads. This creates potentially dangerous blind spots for fire services, not only during ignition but also during active firefighting and post-fire assessment. For these reasons, Unmanned Aerial Systems (UAS) present a powerful operational advantage, enabling aerial access to remote olive groves, forest patches and marginal lands where ignition typically starts.

The pilot site’s selection is therefore strategic: Ulcinj offers a representative example of a Mediterranean rural–coastal region where human activity, climatic conditions and landscape characteristics converge to create complex, high-risk wildfire scenarios. The use of UAS integrated with the FRED platform provides the municipality with a modern technological toolkit to prevent, detect, monitor and assess wildfire-related dangers across its expansive territory.

### 2.4.2 Use Cases

#### 2.4.2.1 UCI – Preventive Monitoring of Remote Areas

In Ulcinj, a primary source of wildfire ignition stems from the seasonal maintenance of olive groves, where residents or landowners traditionally burn branches and other vegetation residues. These practices often occur in

remote or semi-remote areas without proper fire-safety measures, creating conditions where even a small lapse in control can result in wildfire ignition. This use case aims to monitor these remote zones proactively with UAS technology to prevent potentially dangerous situations before they escalate.

Drones patrol olive groves and forest-adjacent lands during peak-risk periods, identifying visible smoke plumes, unextinguished embers, or active burning that may be unauthorized or carried out without required safety precautions. Equipped with thermal imaging sensors, drones can detect early signs of uncontrolled heat even when flames are not visible. This is particularly valuable in dense olive groves where vegetation can obscure visual cues from the ground.

Real-time data transfer enables the Ulcinj fire service to review live video feeds, verify potential threats, and deploy resources efficiently. When dangerous or unauthorized burning is observed, authorities can immediately intervene, instruct landowners to extinguish fires or dispatch units to address the hazard before it becomes unmanageable.

This proactive surveillance approach significantly reduces the risk of fires starting due to human negligence. It also supports municipal efforts to enforce fire regulations, educate landowners, and reduce the burden on ground patrols. Within FRED, all detections and drone flight data are logged and archived, providing an evidence-based record of conditions in remote groves and improving future risk modelling.

#### *2.4.2.2 UC2 – Enhanced Aerial Support for Active Wildfire Response*

When wildfires occur in Ulcinj, response efforts often face significant operational challenges. The region's terrain includes remote hillsides, dense shrubs and forested pockets inaccessible to fire trucks or difficult for firefighters to reach quickly on foot. These obstacles delay response times and increase the risk to both emergency personnel and communities.

This use case introduces drone-based aerial support as a critical enhancement to firefighting operations. Drones equipped with thermal cameras, live streaming capabilities and geolocation tools provide a continuous overview of fire spread in areas that are otherwise difficult or dangerous to monitor. They help identify the active fire front, its direction of movement, the location of hotspots and any secondary ignitions caused by wind-driven embers.

By delivering this real-time intelligence to the command center through the FRED platform, drones enable firefighters to position teams strategically, identify safe evacuation routes, assess whether certain approaches are

viable, and anticipate shifts in fire behavior. The immediate visualization of the situation helps avoid sending personnel into hazardous zones while improving the precision of suppression efforts.

Beyond fire mapping, drones can assist in locating civilians, finding safe exit paths, and evaluating whether firefighting resources are deployed effectively. In Ulcinj's varied landscape, where access limitations can significantly hamper response, drone-based intelligence becomes essential for reducing risks and improving operational outcomes.

#### *2.4.2.3 UC3 – Wildfire Aftermath Damage Assessment*

Following a wildfire, Ulcinj authorities must assess the impact to land, infrastructure and vegetation. However, burnt areas often remain inaccessible due to damaged terrain, unstable ground or residual hot spots. This use case deploys drones to conduct detailed post-fire assessment safely and efficiently.

Drones capture high-resolution visual data and thermal readings to map the extent of the burned area and identify remaining hotspots that could reignite. This information is processed through FRED to produce accurate spatial outputs that support environmental assessment, restoration planning and reporting to municipal or national authorities.

Drone-based post-fire assessment helps determine the severity of vegetation loss, identify damaged power lines or buildings, evaluate impacts on olive groves and detect erosion risks on newly exposed soils. It greatly accelerates recovery planning and allows authorities to prioritize limited resources.

## **2.5 Pilot site: Mali Lošinj, Croatia**

### 2.5.1 Pilot area description

Mali Lošinj is located on Lošinj Island in the northern Adriatic Sea and is one of Croatia's most important island municipalities. The landscape is characterised by dense Mediterranean vegetation, extensive pine forests, shrublands, dry grasslands, maquis and karstic terrain. The region experiences hot, dry summers with strong winds such as the "bura" and "maestral," which increase the flammability of vegetation and accelerate the spread of wildfires during peak season.

A key challenge in Mali Lošinj is the combination of high fire danger and intense seasonal tourism. From June to September, the island's population increases dramatically as thousands of visitors arrive, many of whom engage

in outdoor recreational activities—camping, beach barbecuing, hiking in forested areas—that can inadvertently trigger ignition. Due to the island’s elongated shape and fragmented terrain, emergency services must cover a large and varied surface area, including remote coves, wooded slopes, and isolated beaches where access is limited and response times can be delayed.

Mali Lošinj also has a complex network of fire protection routes, many of which are unpaved, narrow or partially overgrown. Their accessibility and condition have a direct impact on firefighting effectiveness. Ensuring these routes remain passable requires frequent inspection—yet manual inspection is time-consuming, labour-intensive and sometimes dangerous due to dense vegetation or challenging topography.

The local fire service faces additional constraints: limited personnel, long distances between settlements, and restricted access to neighbouring islets where tourism activities occur. For these reasons, UAS deployment—integrated with the FRED platform—offers a transformative operational advantage, enabling fast aerial inspections, early detection of hazards, monitoring of human activities that elevate fire risk, and detailed post-fire assessment. Mali Lošinj’s characteristics make it an ideal Mediterranean island pilot site for testing the full spectrum of UAS-supported wildfire management operations.

## 2.5.2 Use cases

### 2.5.2.1 *UC1 – Preventive Monitoring of Remote Areas with High-Fire Danger Index*

During the summer months, Mali Lošinj experiences extremely high levels of fire danger, driven by low humidity, high temperatures and large volumes of tourists engaging in outdoor activities. This use case focuses on proactive, daily UAS deployment across fire-prone zones to identify potential ignition sources and detect early-stage hazards before they escalate into full-scale fires.

Drones are deployed to monitor remote beaches, forested slopes, recreational hotspots and dispersed areas where visitors often gather. Because many tourists are not aware of local restrictions, barbecues or open flames may be used in unsafe locations. Drones equipped with thermal imaging and live video streaming identify any heat anomalies, smoke columns or risky human behaviors. This real-time awareness allows authorities to intervene early, preventing fires at their origin point.

The UAS missions are supported by the FRED platform, which logs flight paths, archives detections and transmits live streams to the local fire

brigade. This ensures that potentially dangerous activities can be verified immediately, and ground teams can be dispatched with precise coordinates. The goal of this use case is to reduce ignition probability during the most dangerous months, when the island's ecosystems are most flammable and tourist activity is at its peak.

#### *2.5.2.2 UC2 – Locating and Monitoring the Spread of Fire*

In the event of a wildfire, Mali Lošinj's complex island topography makes rapid situational assessment challenging. Narrow roads, dense vegetation, and the presence of steep slopes can prevent fire crews from gaining a clear visual overview of a fire's direction and intensity. This use case deploys drones to provide real-time monitoring of fire evolution during an active incident.

Drones equipped with thermal sensors, geolocation tools and high-definition cameras allow operators to determine the precise location of the fire front, track its spread, and identify newly developing hotspots. Drones can fly above smoke plumes, over inaccessible terrain, and across large distances more quickly than ground vehicles, giving firefighters a full aerial perspective from the earliest stages of the incident.

Through FRED, the command center receives live imagery, allowing for immediate adjustments to response strategies. Fire crews can be redirected, safe approaches evaluated, and predicted spread paths confirmed with greater accuracy. This greatly enhances tactical decision-making and allows the fire service to operate faster and more safely.

#### *2.5.2.3 UC3 – Preventive Monitoring of Remote Areas*

This use case expands on the preventive concept by incorporating daily, routine seasonal surveillance from June through September. Because fire risk fluctuates daily based on weather conditions, tourism density and vegetation dryness, drones are deployed systematically to monitor remote areas, identify accumulations of dangerous activities, and support compliance with fire restrictions.

Daily drone flights allow authorities to identify patterns, such as areas where tourists repeatedly gather, informal campsites, or zones where barbecues are frequently used despite bans. This ongoing surveillance contributes to a highly dynamic prevention strategy that responds to day-to-day shifts in visitor behaviour and fire danger.

FRED organizes and archives the entire dataset, enabling authorities to compare daily risk levels, create risk trend maps and plan targeted ground

patrols. This greatly reduces unnecessary patrols and ensures that resources are allocated to areas where risk is highest.

#### 2.5.2.4 UC4 – Inspection of Fire Protection Routes

The island's fire protection routes are essential for ensuring safe and rapid emergency response. Many of these roads are dirt or gravel paths that degrade due to vegetation overgrowth, erosion or disuse. This use case employs drones to inspect these routes regularly, ensuring they remain passable for fire trucks and emergency vehicles.

UAS flights generate updated visual and orthomosaic maps that help authorities evaluate the condition of access routes, document potential obstacles, and identify areas needing maintenance. Drones can also fly routes that are partially blocked or unsafe for vehicles, allowing crews to plan interventions more effectively.

#### 2.5.2.5 UC5 – Response to Illegal Fire Ignitions

Illegal ignition—especially beach barbecues, open flames or campfires—is a recurring problem during Mali Lošinj's tourist season. In many cases, these incidents occur in remote coves or small islets inaccessible by car. UAS provide a rapid response tool for investigating reports of illegal fires, verifying their accuracy and locating the individuals involved.

Drones can quickly reach areas far from the main town, issue warnings via loudspeaker or lighting, and provide precise locations to ground teams. This decreases the need to mobilize large crews for every reported incident and increases the efficiency of enforcement actions.

## 2.6 Pilot site: Baixo Alentejo, Portugal

### 2.6.1 Pilot area description

Baixo Alentejo, located in southern Portugal, is a region characterised by expansive rural landscapes, undulating plains, isolated agricultural properties, mixed forest patches and a climate strongly influenced by Mediterranean conditions. It is one of the Portuguese regions most affected by recurrent wildfires due to a combination of high summer temperatures, prolonged droughts and the wide distribution of fuel across extensive open areas.

The territory is marked by low population density, with many rural homesteads, agricultural estates and farm buildings dispersed across large properties. Because properties are far apart and often located at the end of

long, unpaved access paths, emergency response teams face significant challenges in reaching both people and infrastructure during wildfire events. Many of these rural pathways are narrow, eroded or overgrown, making vehicle access difficult and often dangerous during fire operations.

Human activity is a major driver of ignition in Baixo Alentejo. Agricultural burning—often conducted without proper control—remains a key contributor to wildfire outbreaks. Residents and farm workers, especially during harvest or land-clearing operations, may unintentionally start fires that rapidly spread across dry vegetation. Local fire authorities also face challenges in preventing ignitions resulting from mechanical equipment, machinery failures, and negligence around fuel sources.

Due to the region’s geographic scale and the large distances between settlements, traditional ground patrols and inspection methods are insufficient to ensure effective prevention coverage. The combination of dispersed settlements, high fuel availability, difficult access and climate vulnerability makes Baixo Alentejo an ideal site for the deployment of UAS and the FRED platform. Drones provide a rapid and dynamic approach to inspecting properties, identifying risk conditions, supervising mitigation duties, guiding first response and supporting search and rescue when visibility is limited.

## 2.6.2 Use Cases

### 2.6.2.1 UCI – Preventive monitoring due to high fire danger index (summer)

This use case focuses on proactive wildfire prevention by deploying drones during periods when the fire danger index reaches critical levels, typically during the hottest and driest summer conditions. During these periods, environmental factors such as high temperatures, low humidity and dry vegetation significantly increase the probability of ignition, making early detection and monitoring essential.

Drone patrols allow authorities to systematically observe large rural areas and identify potential ignition sources before they evolve into major incidents. Through continuous aerial surveillance, drones can detect smoke, suspicious human activities, or environmental conditions that indicate a heightened fire risk.

The FRED system supports this preventive approach by organizing and processing the incoming aerial data in real time. By combining drone imagery, thermal monitoring and live video transmission, the system enables authorities to maintain an updated situational picture of the territory. This helps emergency services prioritize surveillance efforts in areas

where the fire danger index is highest and ensures that preventive actions are taken before fires can spread.

#### *2.6.2.2 UC2 – Support of firefighting operations in case of fire.*

This use case focuses on the operational use of drones during an active wildfire. In emergency situations, rapid access to accurate information about the fire behaviour and surrounding terrain is essential for effective decision-making. Drones are therefore deployed to assist firefighting teams by providing real-time aerial intelligence during fire suppression operations.

By capturing live aerial imagery and video streams, drones allow incident commanders to quickly assess the extent of the fire, identify critical hotspots and monitor the evolution of the fire front. The aerial perspective enables emergency teams to evaluate terrain conditions, locate risk areas and determine safe access routes for firefighting units.

Another important advantage of drone deployment is the ability to inspect hazardous or inaccessible areas without exposing firefighters to direct danger. In landscapes characterized by steep slopes, dense vegetation or difficult terrain, drones provide a safe and efficient method for reconnaissance and situational assessment.

Through the integration of drone data within the FRED system, the information collected during flights can be immediately shared with operational teams. This enhances coordination, improves the safety of firefighting personnel and enables more effective resource deployment during wildfire response.

#### *2.6.2.3 UC3 – Post-incident documentation and analysis*

This use case focuses on the post-fire phase, where drones are used to document the impacts of wildfire events and support the analysis of response operations. After a fire is extinguished, aerial surveys are conducted to assess the extent of the damage and evaluate how the incident was managed.

Through systematic drone mapping and aerial documentation, authorities can collect detailed information about the burned area, affected vegetation and infrastructure damage. Mapping techniques such as orthomosaic generation and structured flight patterns allow the creation of accurate spatial records of the incident area.

The collected data supports a comprehensive post-incident analysis, enabling authorities to review the effectiveness of firefighting operations and identify potential improvements in response strategies. This analysis

also contributes to training activities for fire brigades, helping them refine operational procedures and improve preparedness for future wildfire events. All information generated through these surveys is integrated into the FRED platform, where it can be archived and analyzed alongside operational data from the incident. By combining damage assessment with operational evaluation, authorities can strengthen future wildfire management strategies and reduce risks in subsequent emergencies.

### 3 Key Performance Indicators (KPIs) Framework

Key Performance Indicators (KPIs) are standardised, measurable variables that capture the performance, efficiency, usability, and impact of the implemented solutions. Within this evaluation framework, KPIs provide both quantitative and qualitative evidence of how drone-based operations and the FRED platform improve wildfire management processes.

The definition of KPIs was guided by an extensive review of scientific literature on UAV wildfire detection, drone-based suppression technologies, operational performance measurement, and advanced fire-recognition algorithms. This ensured that the selected indicators are aligned with state-of-the-art research and reflect the operational needs documented in previous studies.

Several key publications were examined to identify which technical and operational parameters are most relevant for assessing drone-supported wildfire management:

- *Li et al. (2024)* was considered because it highlights the importance of detection accuracy, precision, recall, false alarm rate, and real-time inference speed as essential KPIs for evaluating onboard fire-recognition algorithms.
- *Thompson et al. (2018)* informed the inclusion of indicators related to response effectiveness, resource use, firefighter exposure, and operational decision quality. This study provides a structured analysis of how KPIs should be used to understand performance in fire operations, and it emphasises indicators linked to safety, exposure reduction, and efficiency gains.
- *Jin et al. (2024)* contributed KPIs concerning hovering stability, payload deployment accuracy, and the effectiveness of drone-assisted suppression actions. These indicators reflect operational capabilities relevant to missions involving mapping, ignition support, and other proactive wildfire response tasks.
- *Wang et al. (2025)* was included because it introduces performance metrics such as small-flame detection capability, false-positive reduction, and edge-device inference speed, which are highly relevant for assessing the real-time fire detection functions integrated into UAV-mounted or platform-based analytics.

Drawing from this literature, KPIs were selected to cover the full spectrum of drone-enabled wildfire operations. Using a common, scientifically grounded KPI set across all pilot sites ensures methodological coherence, comparability of results, and robustness of the before–after evaluation.

All of the chosen indicators are shown in Table 2, where they are categorized into five macro-categories that represent the operational aspects of wildfire control, prior to a detailed discussion of each KPI:

1. **Technical Performance**, which measures how well the FRED platform and drones detect, process, and deliver data.
2. **Responsiveness & Timeliness**, whose focus is the speed of reaction across the system lifecycle.
3. **Coverage & Monitoring Capacity**, which includes the spatial reach and monitoring effectiveness of the FRED solution.
4. **Operational Effectiveness & Safety**, which demonstrates execution quality, safety, and operational processes.
5. **Impact & Outcomes**, which measures the real-world results and the general public perception of drone activities.

Table 2 – Selected KPIs per category

Category	KPI	Unit of Measurement
<b>Technical Performance</b>	Accuracy of fire/smoke detection	%
	Hotspot Detection Accuracy	%
	Accuracy of Real-Time Data	%
	Burned Area Mapping Accuracy	%
	Streaming Data Quality	survey score (1–10)
	Streaming Data Latency	minutes (min)
<b>Responsiveness &amp; Timeliness</b>	Fire Ignition Responsiveness	minutes (mins)
	Fire Detection Timeliness	minutes (mins)
	Fire Hazard Responsiveness	minutes (mins)
	Operational Responsiveness	minutes (mins)
	Tactical Responsiveness	minutes (mins)
<b>Coverage &amp; Monitoring Capacity</b>	Coverage of high-risk areas	%
	Coverage of sensitive areas	%
	Coverage of inaccessible areas	%
	Coverage of flood areas	%
	Coverage of fire-prone areas	%
	Inspection Coverage Rate	%
<b>Operational Effectiveness &amp; Safety</b>	Flood Response Effectiveness	survey score (1–10)
	Preventive Flight Regularity	%
	Route Safety Assessment	survey score (1–10)
	Public Warning Reach	%
<b>Impact &amp; Outcomes</b>	Reduction of burnt area	%
	Post-Fire Cleanup Prioritization Efficiency	survey score (1–10)
	Post-fire Assessment Efficiency	hours
	Public trust and acceptance	survey score (1–10)

To support consistent interpretation across pilot sites, each KPI is associated with four performance classes (Optimum, Acceptable, Critical, Not Acceptable); these classes define the expected performance range for the indicator and are used for normalization within the MCA process.

Some KPIs are applied across multiple pilot sites and operational scenarios within the project. In these cases, the same indicator definition and calculation method are intentionally reused to ensure methodological consistency and comparability of results between different use cases. While the operational context may vary (e.g., preventive monitoring, active fire intervention, or environmental surveillance), the underlying performance metric remains the same. This approach allows the evaluation framework to assess how similar monitoring capabilities perform under different operational conditions across the project pilots.

### 3.1 Pilot site: Sežana, Slovenia

#### 3.1.1 UCI – Preventive inspection of areas

##### 3.1.1.1 Coverage of high-risk areas

This indicator assesses whether drone monitoring is carried out with sufficient regularity and whether high-risk areas receive adequate coverage during danger periods. Operationally, this ensures that preventive patrols follow established schedules and that all vulnerable zones are observed frequently enough to detect early-stage threats.

**It is measured through the percentage ratio between the area inspected by drones and the total area classified as high risk within the monitoring period.**

$$\text{Coverage of high – risk areas (\%)} = \frac{\text{Area inspected by drones}}{\text{Total high\_risk area}} * 100$$

Coverage of high-risk areas (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>90%	75-90%	60-75%	<60%

In addition to spatial coverage, the effectiveness of preventive monitoring also depends on how frequently high-risk areas are revisited. Since ignition events may occur at any time during periods of elevated fire danger, a single inspection does not guarantee timely detection of hazards. For this reason, coverage results should be interpreted together with revisit frequency, defined as the number of times a high-risk area is monitored within a given time period (e.g., per day or week), as higher revisit frequencies increase the likelihood of early detection and improve overall surveillance effectiveness.

The baseline scenario represents the surveillance capacity achieved through conventional monitoring methods, including ground patrols and existing observation infrastructure. Coverage is estimated using patrol routes, visibility range and monitoring duration.

##### 3.1.1.2 Accuracy of Real-Time Data

This indicator measures the reliability of the visual and thermal data transmitted in real time from the drone to the FRED platform. Operationally, it evaluates whether the information provided to operators can be trusted to correctly identify potential threats, such as smoke, heat anomalies, or other indicators of hazardous situations during preventive monitoring missions.

**It is measured as the percentage of correctly identified threats detected through real-time drone observations compared to the total number of threats confirmed through field verification or subsequent inspection.**

$$\text{Accuracy of Real – Time Data (\%)} = \frac{\text{Correctly identified threats}}{\text{Total confirmed threats}} * 100$$

Accuracy of Real-Time Data (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>90%	75-90%	60-75%	<60%

Currently, threat identification relies on conventional monitoring methods such as ground patrols, ranger observations, or reports from local authorities. The same indicator can be calculated by comparing the number of threats correctly identified through these traditional monitoring activities with the total number of confirmed threats recorded during the monitoring period. This allows a direct comparison between the accuracy of conventional observations (baseline scenario) and the accuracy achieved through real-time drone monitoring within the FRED platform. Data on the number of threats correctly identified using traditional methods can come from previous years before the development of the FRED platform.

### 3.1.2 UC2 – Monitoring of the fire scene after the intervention

#### 3.1.2.1 Burned Area Mapping Accuracy

This indicator evaluates the accuracy of the spatial information produced during post-fire assessment using UAS-based photogrammetry or LiDAR data. Operationally, it determines whether the mapped burned area derived from drone imagery accurately represents the real extent of the burned perimeter and can therefore be reliably used for post-fire analysis, including burn-severity assessment, hazard identification, and restoration planning.

**It is measured as the percentage of the burned area correctly mapped through drone-derived spatial products compared to the burned area confirmed through reference observations (e.g., field surveys, GNSS perimeter mapping, or high-resolution satellite imagery).**

$$\text{Burned Area Mapping Accuracy(\%)} = \frac{\text{Correctly mapped burned areas}}{\text{Total confirmed burned area}} * 100$$

Burned Area Mapping Accuracy (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>90%	75-90%	60-75%	<60%

Currently, burned-area mapping is conducted using conventional approaches such as field perimeter mapping with GNSS, interpretation of aerial or satellite imagery, or manual reporting by fire services. The same indicator can be calculated by comparing the burned area mapped using these traditional methods with the confirmed burned perimeter. This allows a direct comparison between conventional post-fire assessment methods and the spatial accuracy achieved using UAS-derived datasets within the FRED platform. Another reference value that can be used to assess the performance of the platform is a comparison of the burned area identified using the proposed solution with the burned area mapping that is provided by the European Forest Fire Information System (EFFIS).

### 3.1.2.2 Post-fire Assessment Efficiency

This indicator measures the time required to produce usable post-fire assessment outputs from the moment data collection is completed. Operationally, it evaluates how quickly the acquired data can be processed into actionable information, such as burned-area maps, damage-assessment products, and spatial outputs that support restoration planning and post-fire decision-making.

**It is measured as the total elapsed time, expressed in hours, between the completion of data acquisition and the availability of the final processed outputs for operational use.**

$$\text{Post – fire Assessment Efficiency}(h) = T_p - T_a$$

Where  $T_p$  is the time of availability of the final processed outputs and  $T_a$  is the time of completion of data acquisition.

Post-fire Assessment Efficiency (Hours)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	<6h	6-12h	12-24h	>24h

In the baseline scenario, post-fire assessment is carried out using conventional methods such as field inspection, GNSS perimeter mapping, manual photo interpretation, or satellite-image analysis. The same indicator is measured as the time required from the completion of data collection to the production of final assessment outputs. Baseline values may be derived either from documented past operations, where available, or from expert estimation based on standard operational workflows routinely used by the responsible authority. This allows a direct comparison between the time efficiency of conventional post-fire assessment and the workflow enabled by UAS and the FRED platform.

### 3.1.3 UC3 – Informing the Public About Danger

#### 3.1.3.1 Public Warning Reach

This indicator evaluates the extent to which warning messages delivered through drone-based communication systems reach people located in potentially hazardous areas. Operationally, it measures the effectiveness of drone-supported public warning actions in informing individuals about imminent wildfire danger and enabling them to respond appropriately, such as evacuating or avoiding hazardous zones.

**It is measured as the percentage of the population located within the warning area that receives the warning message during a notification event.**

$$Public\ Warning\ Reach(\%) = \frac{\text{Estimated population reached by warning}}{\text{Estimated population at risk}} * 100$$

Public Warning Reach (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>90%	75-90%	60-75%	<60%

In the baseline scenario, public warnings are delivered through conventional methods such as ground patrol loudspeakers, emergency vehicles, fixed sirens, announcements by local authorities and text messages from Civil Protection Agencies. The same indicator can be estimated by calculating the proportion of the population located within the effective communication range of these traditional warning systems relative to the total population present in the risk area. This allows a comparison between the spatial communication reach of conventional warning methods and the reach achieved through drone-based warning systems integrated into the FRED platform. Text messages sent to all civilians present in a high-risk area most probably will reach a larger proportion of the population at risk. However, it has to be taken into account when estimating the efficiency of the proposed approach the way the people will respond to a text message and the way they will respond to an announcement made by the drone. It is highly likely that the civilians will be much more sensitive to such a way of communication.

#### 3.1.3.2 Public trust and acceptance

This indicator evaluates how individuals respond to drone-delivered public warnings and their level of trust in the use of drone-based communication during emergency situations. Operationally, it reflects whether drone-

supported communication contributes to safe behaviour, compliance with civil protection instructions, and public confidence in the warning system.

**It is measured through survey responses collected after warning events or simulation exercises, where individuals are asked to evaluate their level of trust and perceived effectiveness of the warning communication. Responses are aggregated to produce an average satisfaction score on a scale from 1 to 10.**

Public trust and acceptance (survey score 1-10)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>8	6 - 8	4 - 6	<4

In the baseline scenario, the same survey-based evaluation is conducted for conventional warning systems, such as announcements from emergency vehicles, fixed sirens, communication by local authorities, or text messages. Participants are asked to rate their level of trust and perceived effectiveness of these traditional warning methods using the same scoring scale. This allows a direct comparison between public perception of conventional warning systems and drone-based communication supported by the FRED platform.

### 3.1.4 UC4 – Monitoring of Wildfire Intervention

#### 3.1.4.1 Hotspot Detection Accuracy

This indicator evaluates how accurately drone-based thermal and visual observations identify active fire hotspots or residual heat sources during wildfire intervention. Operationally, it determines whether the information provided by the drone can reliably support incident commanders in identifying critical areas of fire activity and guiding tactical decisions during suppression operations.

**It is measured as the percentage of hotspots correctly detected through drone observations compared to the total number of hotspots confirmed through ground verification or post-intervention inspection.**

$$\text{Hotspot Detection Accuracy}(\%) = \frac{\text{Correctly detected hotspots}}{\text{Total confirmed hotspots}} * 100$$

Hotspot Detection Accuracy (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>85%	70-85%	50-70%	<50%

In operational wildfire conditions, the usefulness of hotspot detection does not depend solely on accuracy but also on how quickly hotspots can be identified and communicated to incident commanders. Drone-based monitoring can provide a rapid aerial overview of the fire scene and enable faster detection of emerging hotspots, particularly in areas that are difficult to access or where visibility is limited. For this reason, the interpretation of this indicator should consider the time required to identify and report hotspots during intervention operations.

In the baseline scenario, hotspot identification is carried out through conventional observation methods during firefighting operations, such as visual inspection by ground crews, lookout observations, or reports from field personnel. The same indicator can be calculated by comparing the number of hotspots identified through these conventional observation methods with the total number of hotspots confirmed during ground verification or post-event analysis. In addition, the time required for detection and communication of hotspots to the command unit can be recorded to allow comparison with the faster situational awareness typically provided by drone-based monitoring integrated into the FRED platform.

3.1.4.2 Streaming Data Latency

This indicator measures the delay between the acquisition of visual or thermal data by the drone and its availability on the FRED platform for operational use. During wildfire intervention, rapid access to updated situational information is essential for incident commanders to assess fire behaviour, identify emerging hazards, and coordinate firefighting resources effectively.

**Streaming Data Latency represents the time required for data captured by the drone sensors to be transmitted, processed, and displayed within the FRED system.**

$$\text{Streaming Data Latency (mins)} = T_d - T_a$$

where  $T_a$  is the time of data acquisition by the drone sensors and  $T_d$  is the time at which the data becomes available for visualization on the FRED platform.

Streaming Data Latency (min)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	<1	1-10	10-30	>30

Low latency enables near-real-time situational awareness and allows incident commanders to react more quickly to changes in fire behaviour or the emergence of new hotspots.

In the baseline scenario, situational information during wildfire intervention is communicated through conventional observation methods such as visual reports from ground crews, lookout personnel, or aerial observers. Information about fire behaviour or hotspot locations is transmitted to the command unit through radio communication or verbal reporting. The equivalent baseline indicator can therefore be expressed as the information transmission delay, defined as the time elapsed between the moment an observation is made in the field and the moment the information is received by the command unit, acknowledged, and recorded in the database system and/or in visualization library in case that exists. This allows comparison between the near-real-time information flow enabled by drone streaming and the communication delays associated with conventional reporting methods

### 3.1.5 Overview of KPIs

#### Pilot site: Sežana, Slovenia

Class	Optimum	Acceptable	Critical	Not acceptable
<b>Coverage of high-risk areas (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Piloting</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Accuracy of Real-Time Data (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Piloting</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Burned Area Mapping Accuracy (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Piloting</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Post-fire Assessment Efficiency (h)</b>				
<b>Baseline</b>	<input type="checkbox"/> <6h	<input type="checkbox"/> 6-12h	<input type="checkbox"/> 12-24h	<input type="checkbox"/> >24h

<b>Piloting</b>	<input type="checkbox"/> <6h	<input type="checkbox"/> 6-12h	<input type="checkbox"/> 12-24h	<input type="checkbox"/> >24h
<b>Public Warning Reach (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Piloting</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Public trust and acceptance (survey score 1-10)</b>				
<b>Baseline</b>	<input type="checkbox"/> >8	<input type="checkbox"/> 6 - 8	<input type="checkbox"/> 4 - 6	<input type="checkbox"/> <4
<b>Piloting</b>	<input type="checkbox"/> >8	<input type="checkbox"/> 6 - 8	<input type="checkbox"/> 4 - 6	<input type="checkbox"/> <4
<b>Hotspot Detection Accuracy (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >85%	<input type="checkbox"/> 70-85%	<input type="checkbox"/> 50-70%	<input type="checkbox"/> <50%
<b>Piloting</b>	<input type="checkbox"/> >85%	<input type="checkbox"/> 70-85%	<input type="checkbox"/> 50-70%	<input type="checkbox"/> <50%
<b>Streaming Data Latency (mins)</b>				
<b>Baseline</b>	<input type="checkbox"/> <1	<input type="checkbox"/> 1-10	<input type="checkbox"/> 10-30	<input type="checkbox"/> >30
<b>Piloting</b>	<input type="checkbox"/> <1	<input type="checkbox"/> 1-10	<input type="checkbox"/> 10-30	<input type="checkbox"/> >30

## 3.2 Pilot site: Rocca di Cerere UNESCO Global Geopark, Italy

### 3.2.1 UCI - UAS Monitoring in Rocca di Cerere Park

The following indicators evaluate how effectively FRED platform and UAS operations support monitoring, early detection and environmental protection throughout the Rocca di Cerere Geopark. These indicators are operational, measurable and implementable by park authorities and partners.

#### 3.2.1.1 Accuracy of fire/smoke detection

This indicator evaluates how accurately drone-based sensors identify early signs of wildfire ignition, such as smoke plumes or thermal anomalies, during preventive monitoring operations. Operationally, it assesses the reliability of the UAS monitoring system in detecting potential fire events at an early stage, enabling rapid response and reducing the risk of fire spread.

**It is measured as the percentage of fire or smoke events correctly detected through drone observations compared to the total number of confirmed events verified through field inspection, incident reports, or other reliable observations.**

$$\text{Accuracy of Fire/Smoke Detection}(\%) = \frac{\text{Correctly detected events}}{\text{Total confirmed events}} * 100$$

Accuracy of fire/smoke detection (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>90%	75-90%	60-75%	<60%

In the baseline scenario, early fire detection relies on conventional monitoring approaches such as lookout towers, ranger patrols, reports from local authorities or citizens, and satellite-based detection systems where available. The same indicator can be estimated by comparing the number of fire or smoke events identified through these traditional observation methods with the total number of confirmed events during the monitoring period. This allows comparison between the detection capability of conventional monitoring systems and the accuracy achieved through drone-based monitoring integrated into the FRED platform.

#### 3.2.1.2 Streaming Data Latency

This indicator measures the delay between the acquisition of visual or thermal data by the drone and its availability on the FRED platform for operational use. During wildfire intervention, rapid access to updated

situational information is essential for incident commanders to assess fire behaviour, identify emerging hazards, and coordinate firefighting resources effectively.

**Streaming Data Latency represents the time required for data captured by the drone sensors to be transmitted, processed, and displayed within the FRED system.**

$$\text{Streaming Data Latency (mins)} = T_d - T_a$$

where  $T_a$  is the time of data acquisition by the drone sensors and  $T_d$  is the time at which the data becomes available for visualization on the FRED platform.

Streaming Data Latency (mins)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	<1	1-10	10-30	>30

Low latency enables near-real-time situational awareness and allows incident commanders to react more quickly to changes in fire behaviour or the emergence of new hotspots.

In the baseline scenario, situational information during wildfire intervention is communicated through conventional observation methods such as visual reports from ground crews, lookout personnel, or aerial observers. Information about fire behaviour or hotspot locations is transmitted to the command unit through radio communication or verbal reporting. The equivalent baseline indicator can therefore be expressed as the information transmission delay, defined as the time elapsed between the moment an observation is made in the field and the moment the information is received by the command unit, acknowledged, and recorded in the database system and/or in visualization library in case that exists. This allows comparison between the near-real-time information flow enabled by drone streaming and the communication delays associated with conventional reporting methods

### 3.2.1.3 Coverage of sensitive areas

This indicator evaluates the extent to which drone monitoring activities cover environmentally sensitive areas within the Rocca di Cerere Geopark. These areas may include protected habitats, zones of high ecological value, or locations where environmental degradation or wildfire risk may have significant impacts. Operationally, the indicator measures how effectively drone monitoring missions inspect priority areas requiring regular surveillance.

**The indicator is calculated as the proportion of sensitive areas that are monitored during drone missions within a defined monitoring period.**

$$Coverage\ of\ Sensitive\ areas\ (\%) = \frac{Sensitive\ area\ monitored}{Total\ sensitive\ area} * 100$$

Coverage of sensitive areas (%)				
Class	Optimum	Acceptable	Critical	Not acceptable
Interval	>90%	75-90%	60-75%	<60%

In addition to spatial coverage, the effectiveness of monitoring also depends on how frequently sensitive areas are revisited. Environmental conditions and potential disturbances may change rapidly; therefore, periodic inspections are required to ensure timely detection of emerging risks. For this reason, coverage results should be interpreted together with revisit frequency, defined as the number of monitoring passes over the same sensitive area within a given time period (e.g., per day or per week), as higher revisit frequencies increase the likelihood of early detection of environmental changes or hazards.

In the baseline scenario, monitoring of sensitive areas is performed through conventional environmental monitoring approaches such as ranger patrols, periodic field inspections, or observations reported by park personnel. The same indicator can be estimated by calculating the proportion of sensitive areas visited or inspected during routine monitoring activities relative to the total extent of sensitive zones within the park. This enables comparison between the spatial monitoring coverage achieved through traditional surveillance methods and the coverage provided by drone-based monitoring integrated into the FRED platform.

### 3.2.2 Overview of KPIs

#### Pilot site: Rocca di Cerere UNESCO Global Geopark, Italy

Class	Optimum	Acceptable	Critical	Not acceptable
<b>Accuracy of fire/smoke detection (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Piloting</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Streaming Data Latency (min)</b>				
<b>Baseline</b>	<input type="checkbox"/> <1	<input type="checkbox"/> 1-10	<input type="checkbox"/> 10-30	<input type="checkbox"/> >30

<b>Piloting</b>	<input type="checkbox"/> <1	<input type="checkbox"/> 1-10	<input type="checkbox"/> 10-30	<input type="checkbox"/> >30
<b>Coverage of sensitive areas (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Piloting</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%

### 3.3 Pilot site: National Park Una, Bosnia and Herzegovina

#### 3.3.1 UCI – Preventive monitoring and early warning in the Una National Park of remote and inaccessible areas with a high fire risk index

##### 3.3.1.1 Coverage of inaccessible areas

This indicator evaluates the extent to which drone monitoring activities cover areas that are difficult or impossible to access through conventional ground-based monitoring. Such areas may include steep terrain, remote forested zones, cliffs, river canyons, or other locations where field inspections are limited by accessibility or safety constraints. Operationally, the indicator measures how effectively drone missions enable surveillance of priority areas that would otherwise remain unmonitored or only partially monitored.

**The indicator is calculated as the proportion of inaccessible areas monitored during drone missions within a defined monitoring period.**

$$\text{Coverage of inaccessible areas (\%)} = \frac{\text{Inaccessible area monitored}}{\text{Total inaccessible area}} * 100$$

Coverage of inaccessible areas (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>90%	75-90%	60-75%	<60%

Monitoring coverage can be estimated using the spatial footprint of drone flight paths combined with geographic information identifying areas that are difficult or unsafe to access through conventional field monitoring.

In addition to spatial coverage, the effectiveness of monitoring also depends on how frequently inaccessible areas are revisited. Environmental conditions and potential hazards may change rapidly; therefore, periodic inspections are required to ensure timely detection of emerging risks. For this reason, coverage results should be interpreted together with revisit frequency, defined as the number of monitoring passes over the same area within a given time period (e.g., per day or per week), as higher revisit frequencies increase the likelihood of early detection of environmental changes or hazards.

In the baseline scenario, monitoring of inaccessible areas relies on conventional methods such as ranger patrols, occasional field inspections, or observations from accessible vantage points. Due to terrain constraints, many of these areas may be visited infrequently or remain unmonitored. The same indicator can therefore be estimated by calculating the proportion of inaccessible areas that are inspected through routine monitoring activities

relative to the total mapped inaccessible zones. This allows comparison between the spatial monitoring coverage achieved through traditional monitoring methods and the coverage enabled by drone-based monitoring integrated into the FRED platform.

### 3.3.1.2 Fire Detection Timeliness

This indicator evaluates how quickly a fire event is detected during monitoring operations. In remote or difficult-to-access areas, early fire detection is particularly important because delays in identifying ignition events can allow fires to grow rapidly before response teams are able to intervene. Operationally, the indicator measures the time required for the monitoring system to identify and report a fire after ignition occurs.

**Fire Detection Timeliness represents the elapsed time between the ignition of a fire and the moment the event is detected and communicated to the monitoring or command unit.**

$$\text{Fire detection timeliness (mins)} = T_d - T_i$$

where  $T_i$  is the time of fire ignition and  $T_d$  is the time at which the fire is detected and reported by the monitoring system.

Fire Detection Timeliness (mins)				
Class	Optimum	Acceptable	Critical	Not acceptable
Interval	<1	1-10	10-30	>30

Shorter detection times increase the likelihood that response teams can intervene rapidly, limiting fire spread and reducing potential damage to natural ecosystems and infrastructure.

In the baseline scenario, fire detection relies on conventional monitoring methods such as ranger patrols, lookout towers, or reports from visitors and local communities. In remote or inaccessible areas, fires may only be detected after they become visible from accessible locations or after being reported by observers. The same indicator can therefore be measured as the time elapsed between the ignition of a fire and the moment it is detected through these traditional observation methods. This allows comparison between the detection speed achieved through conventional monitoring approaches and the improved detection timeliness enabled by drone-based monitoring integrated into the FRED platform.

### 3.3.2 UC2 - Aerial surveillance of floods caused by climate change in the Una National Park

#### 3.3.2.1 Coverage of flood areas

This indicator evaluates the extent to which drone monitoring activities cover areas affected by flooding within the monitored region. Flood-prone areas may include riverbanks, floodplains, and other zones where high water levels can cause environmental damage or threaten infrastructure and public safety. Operationally, the indicator measures how effectively drone missions provide situational awareness and monitoring of areas impacted by flooding.

**The indicator is calculated as the proportion of flood-affected areas monitored during drone missions within a defined monitoring period.**

$$\text{Coverage of Flood areas (\%)} = \frac{\text{Flood area monitored}}{\text{Total Flood area}} * 100$$

Coverage of flood areas (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>90%	75-90%	60-75%	<60%

In addition to spatial coverage, the effectiveness of monitoring also depends on how frequently flood-prone areas are revisited during monitoring operations. Flood conditions may change rapidly due to rainfall or river level fluctuations; therefore, periodic inspections are necessary to ensure timely detection of changes in flood extent or emerging hazards. For this reason, coverage results should be interpreted together with revisit frequency, defined as the number of monitoring passes over the same area within a given time period (e.g., per day or per week), as higher revisit frequencies increase the likelihood of timely situational awareness.

In the baseline scenario, flood monitoring relies on conventional observation methods such as field inspections, reports from local authorities or park personnel, or monitoring from accessible vantage points along rivers and floodplains. Due to safety and accessibility constraints, these observations may be limited in spatial coverage or frequency. The same indicator can therefore be estimated by calculating the proportion of flood-affected areas inspected through routine monitoring activities relative to the total mapped flood extent. This enables comparison between the spatial monitoring coverage achieved through conventional monitoring approaches and the

coverage enabled by drone-based monitoring integrated into the FRED platform.

3.3.2.2 *Flood Response Effectiveness*

This indicator evaluates how effectively drone-based monitoring supports emergency response operations during flood events. Drone observations can provide rapid situational awareness of flooded areas, enabling responders to assess flood extent, identify affected zones, and coordinate response actions more efficiently. Operationally, the indicator measures the perceived usefulness of drone-generated information in supporting decision-making and response coordination during flood management operations.

**The indicator is measured through feedback collected from emergency responders and operational personnel involved in flood response activities. After monitoring operations or simulation exercises, participants evaluate the usefulness of drone-provided information in supporting response activities.**

Flood Response Effectiveness (survey score 1-10)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>8	6-8	4-6	<4

The final indicator value corresponds to the average score obtained from all survey responses, reflecting the overall perceived effectiveness of the drone-supported monitoring system during flood response operations.

In the baseline scenario, flood response operations rely on conventional situational awareness methods such as field observations, reports from emergency personnel, ground inspections, or monitoring from accessible vantage points. Responders participating in these operations evaluate the effectiveness of these traditional information sources using the same scoring scale. This enables comparison between the perceived effectiveness of conventional response coordination methods and the enhanced situational awareness provided by drone-based monitoring integrated into the FRED platform.

## 3.3.3 Overview of KPIs

**Pilot site: National Park Una, Bosnia and Herzegovina**

<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Coverage of inaccessible areas (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Piloting</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Fire Detection Timeliness (min)</b>				
<b>Baseline</b>	<input type="checkbox"/> <1	<input type="checkbox"/> 1-10	<input type="checkbox"/> 10-30	<input type="checkbox"/> >30
<b>Piloting</b>	<input type="checkbox"/> <1	<input type="checkbox"/> 1-10	<input type="checkbox"/> 10-30	<input type="checkbox"/> >30
<b>Coverage of flood areas (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Piloting</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Flood Response Effectiveness (survey score 1-10)</b>				
<b>Baseline</b>	<input type="checkbox"/> >8	<input type="checkbox"/> 6-8	<input type="checkbox"/> 4-6	<input type="checkbox"/> <4
<b>Piloting</b>	<input type="checkbox"/> >8	<input type="checkbox"/> 6-8	<input type="checkbox"/> 4-6	<input type="checkbox"/> <4

### 3.4 Pilot site: Ulcinj, Montenegro

#### 3.4.1 UCI – Preventive Monitoring of Remote Areas

##### 3.4.1.1 Reduction of burnt area

This indicator evaluates the extent to which drone-supported monitoring contributes to reducing the total area affected by fires originating from agricultural residue burning. In the monitored region, fires are frequently caused by the burning of agricultural residues such as pruned branches and other vegetation waste. Drone-based monitoring enables authorities to supervise agricultural areas more effectively, discouraging unauthorized burning practices and allowing early intervention when such activities occur.

Operationally, the indicator measures the reduction in the total burned area associated with these activities during the monitoring period when drone surveillance is implemented.

**The indicator is calculated by comparing the burned area recorded during drone-supported monitoring operations with the burned area observed under conventional monitoring conditions.**

$$\text{Reduction of Burned Area (\%)} = \frac{BA_{baseline} - BA_{drone}}{BA_{baseline}} * 100$$

where  $BA_{baseline}$  represents the total burned area associated with agricultural residue burning under conventional monitoring conditions and  $BA_{drone}$  represents the burned area recorded during the monitoring period with drone-supported surveillance.

Reduction of burnt area (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>30%	15-30%	5-15%	<5%

A reduction in burned area indicates that monitoring activities are effective in discouraging unauthorized burning practices and enabling timely intervention by responsible authorities.

In the baseline scenario, monitoring of agricultural burning relies on conventional observation methods such as field inspections, reports from local authorities, or notifications from citizens. These approaches may allow illegal burning activities to occur without immediate detection. Baseline burned-area values can therefore be derived from historical records of fires associated with agricultural residue burning during previous years when drone monitoring was not implemented. This enables comparison between the burned areas observed under traditional monitoring conditions and

those recorded during the period when drone-based monitoring is used to supervise agricultural activities.

### 3.4.1.2 Fire Hazard Responsiveness

This indicator assesses how effectively drones provide immediate, actionable information that enables rapid response to developing fire hazards. In the monitored region, fires often originate from the burning of agricultural residues such as pruned branches and vegetation waste. Ulcinj's terrain often limits ground access, making fast aerial verification essential. A reliable response chain reduces the likelihood that unsafe burning will escalate into a wildfire.

**Operationally, the indicator measures the time required between the reporting of a potentially hazardous burning activity and the initiation of an intervention by responsible authorities.**

$$\text{Fire Hazard Responsiveness (mins)} = Tr - Td$$

where  $Td$  represents the time at which a hazardous activity (e.g., agricultural residue burning) is reported and  $Tr$  represents the time at which response actions are initiated by the responsible authority.

Fire Hazard Responsiveness (mins)				
Class	Optimum	Acceptable	Critical	Not acceptable
Interval	<10	10 - 20	20 - 30	>30

Shorter response times indicate that monitoring activities effectively support rapid intervention, reducing the likelihood that agricultural burning activities develop into uncontrolled fires.

In the baseline scenario, hazardous burning activities are detected through conventional observation methods such as field patrols, reports from local authorities, or notifications from citizens. Due to the absence of continuous aerial monitoring, detection and reporting may take longer, which can delay the initiation of preventive actions. The same indicator can therefore be measured as the time elapsed between the observation of a hazardous burning activity and the initiation of response actions under conventional monitoring conditions. This enables comparison between the responsiveness achieved through traditional monitoring methods and the improved response capability supported by drone-based monitoring integrated into the FRED platform.

### 3.4.2 UC2 – Enhanced Aerial Support for Active Wildfire Response

#### 3.4.2.1 Hotspot Detection Accuracy

This indicator evaluates how accurately drone-based thermal and visual observations identify active fire hotspots or residual heat sources during wildfire intervention. Operationally, it determines whether the information provided by the drone can reliably support incident commanders in identifying critical areas of fire activity and guiding tactical decisions during suppression operations.

**It is measured as the percentage of hotspots correctly detected through drone observations compared to the total number of hotspots confirmed through ground verification or post-intervention inspection.**

$$\text{Hotspot Detection Accuracy}(\%) = \frac{\text{Correctly detected hotspots}}{\text{Total confirmed hotspots}} * 100$$

Hotspot Detection Accuracy (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>85%	70-85%	50-70%	<50%

In operational wildfire conditions, the usefulness of hotspot detection does not depend solely on accuracy but also on how quickly hotspots can be identified and communicated to incident commanders. Drone-based monitoring can provide a rapid aerial overview of the fire scene and enable faster detection of emerging hotspots, particularly in areas that are difficult to access or where visibility is limited. For this reason, the interpretation of this indicator should consider the time required to identify and report hotspots during intervention operations.

In the baseline scenario, hotspot identification is carried out through conventional observation methods during firefighting operations, such as visual inspection by ground crews, lookout observations, or reports from field personnel. The same indicator can be calculated by comparing the number of hotspots identified through these conventional observation methods with the total number of hotspots confirmed during ground verification or post-event analysis. In addition, the time required for detection and communication of hotspots to the command unit can be recorded to allow comparison with the faster situational awareness typically provided by drone-based monitoring integrated into the FRED platform.

### 3.4.2.2 Operational Responsiveness

This indicator evaluates how quickly operational teams are able to respond to critical information provided during wildfire intervention operations. During active fire events, drone-based monitoring can provide real-time situational awareness of fire behaviour, hotspot locations, and potential risks to firefighting teams. Operationally, the indicator measures how rapidly response actions are initiated after relevant operational information becomes available.

**Operational Responsiveness represents the time elapsed between the moment when critical operational information is received and the initiation of response actions by firefighting personnel.**

$$\text{Operational Responsiveness (mins)} = T_r - T_i$$

where  $T_i$  represents the time when relevant operational information (e.g., hotspot location, fire spread direction, or emerging hazard) is received by the command unit, and  $T_r$  represents the time when response actions are initiated by operational teams.

Operational Responsiveness (min)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	<5	5-15	15-30	>30

Shorter response times indicate that monitoring activities effectively support operational decision-making and enable firefighting teams to react more quickly to changing fire conditions.

In the baseline scenario, operational decisions rely on conventional sources of situational information such as visual observations from ground crews, reports from field personnel, or observations from lookout points. Without drone-based aerial monitoring, the availability of real-time information may be limited by terrain, visibility conditions, and communication delays. The same indicator can therefore be measured as the time elapsed between the reception of operational information through these conventional observation methods and the initiation of response actions. This allows comparison between the responsiveness achieved through traditional operational monitoring and the improved response capability supported by drone-based monitoring integrated into the FRED platform.

### 3.4.3 UC3 – Wildfire Aftermath Damage Assessment

#### 3.4.3.1 Burned Area Mapping Accuracy

This indicator evaluates the accuracy of the spatial information produced during post-fire assessment using UAS-based photogrammetry and optical data. Operationally, it determines whether the mapped burned area derived from drone imagery accurately represents the real extent of the burned perimeter and can therefore be reliably used for post-fire analysis, including burn-severity assessment, hazard identification, and restoration planning.

**It is measured as the percentage of the burned area correctly mapped through drone-derived spatial products compared to the burned area confirmed through reference observations (e.g., field surveys, GNSS perimeter mapping, or high-resolution satellite imagery).**

$$\text{Burned Area Mapping Accuracy}(\%) = \frac{\text{Correctly mapped burned areas}}{\text{Total confirmed burned area}} * 100$$

Burned Area Mapping Accuracy (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>90%	75-90%	60-75%	<60%

Currently, burned-area mapping is conducted using conventional approaches such as field perimeter mapping with GNSS, interpretation of aerial or satellite imagery, or manual reporting by fire services. The same indicator can be calculated by comparing the burned area mapped using these traditional methods with the confirmed burned perimeter. This allows a direct comparison between conventional post-fire assessment methods and the spatial accuracy achieved using UAS-derived datasets within the FRED platform. Another reference value that can be used to assess the performance of the platform is a comparison of the burned area identified using the proposed solution with the burned area mapping that is provided by the European Forest Fire Information System (EFFIS).

#### 3.4.3.2 Post-Fire Cleanup Prioritization Efficiency

This indicator evaluates how effectively drone-based monitoring supports the prioritization of post-fire cleanup and restoration activities. After wildfire events, authorities must identify the most affected areas and allocate resources efficiently to support recovery actions such as debris removal, environmental rehabilitation, and infrastructure repair. Drone-derived imagery and spatial information can provide detailed and timely insights

into fire damage, allowing decision-makers to better identify priority areas for intervention.

Operationally, the indicator measures the perceived usefulness of drone-generated information in supporting decision-making and prioritization of post-fire cleanup and restoration actions.

**The indicator is assessed through feedback collected from relevant stakeholders involved in post-fire assessment and recovery planning. After monitoring activities or demonstration exercises, participants evaluate the effectiveness of drone-derived information in supporting prioritization decisions.**

Post-Fire Cleanup Prioritization Efficiency (survey score 1-10)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>8	6-8	5-6	<5

The final indicator value corresponds to the average score obtained from all survey responses, reflecting the overall perceived efficiency of the drone-supported monitoring system in guiding post-fire recovery actions.

In the baseline scenario, prioritization of post-fire cleanup and restoration activities relies on conventional assessment methods such as field inspections, manual surveys, and reports from local authorities or response teams. These approaches may require more time to obtain a comprehensive overview of fire impacts and may provide less detailed spatial information. Stakeholders participating in these assessments evaluate the usefulness of these traditional information sources using the same scoring scale. This enables comparison between the effectiveness of conventional post-fire assessment approaches and the improved situational awareness provided by drone-based monitoring integrated into the FRED platform.

## 3.4.4 Overview of KPIs

**Pilot site: Ulcinj, Montenegro**

Class	Optimum	Acceptable	Critical	Not acceptable
<b>Reduction of burnt area (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >30%	<input type="checkbox"/> 15-30%	<input type="checkbox"/> 5-15%	<input type="checkbox"/> <5%
<b>Piloting</b>	<input type="checkbox"/> >30%	<input type="checkbox"/> 15-30%	<input type="checkbox"/> 5-15%	<input type="checkbox"/> <5%
<b>Fire Hazard Responsiveness (mins)</b>				
<b>Baseline</b>	<input type="checkbox"/> <10	<input type="checkbox"/> 10-20	<input type="checkbox"/> 20-30	<input type="checkbox"/> >30
<b>Piloting</b>	<input type="checkbox"/> <10	<input type="checkbox"/> 10-20	<input type="checkbox"/> 20-30	<input type="checkbox"/> >30
<b>Hotspot Detection Accuracy (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >85%	<input type="checkbox"/> 70-85%	<input type="checkbox"/> 50-70%	<input type="checkbox"/> <50%
<b>Piloting</b>	<input type="checkbox"/> >85%	<input type="checkbox"/> 70-85%	<input type="checkbox"/> 50-70%	<input type="checkbox"/> <50%
<b>Operational Responsiveness (min)</b>				
<b>Baseline</b>	<input type="checkbox"/> <5	<input type="checkbox"/> 5-15	<input type="checkbox"/> 15-30	<input type="checkbox"/> >30
<b>Piloting</b>	<input type="checkbox"/> <5	<input type="checkbox"/> 5-15	<input type="checkbox"/> 15-30	<input type="checkbox"/> >30
<b>Burned Area Mapping Accuracy (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Piloting</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Post-Fire Cleanup Prioritization Efficiency (survey score 1-10)</b>				
<b>Baseline</b>	<input type="checkbox"/> >8	<input type="checkbox"/> 6-8	<input type="checkbox"/> 5-6	<input type="checkbox"/> <5
<b>Piloting</b>	<input type="checkbox"/> >8	<input type="checkbox"/> 6-8	<input type="checkbox"/> 5-6	<input type="checkbox"/> <5

### 3.5 Pilot site: Mali Lošinj, Croatia

#### 3.5.1 UCI – Preventive Monitoring of Remote Areas with High Fire Danger Index

##### 3.5.1.1 Coverage of fire-prone areas

This indicator evaluates the extent to which drone monitoring activities cover areas identified as having a high susceptibility to wildfire ignition. Fire-prone areas may include locations characterized by dry vegetation, accumulated combustible material, or environmental conditions that increase wildfire risk. Operationally, the indicator measures how effectively monitoring missions inspect priority areas where fire ignition is more likely to occur.

**The indicator is calculated as the cumulative proportion of fire-prone areas monitored during drone missions within a defined monitoring period.**

$$\text{Coverage of fire-prone areas (\%)} = \frac{\text{Fire-prone inspected by drones}}{\text{Total fire – prone area}} * 100$$

Coverage of fire-prone areas (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>90%	75-90%	60-75%	<60%

Monitoring coverage can be estimated using the spatial footprint of drone flight paths combined with geographic information describing the distribution of fire-prone areas within the monitored region.

In addition to spatial coverage, the effectiveness of monitoring also depends on how frequently fire-prone areas are revisited. Environmental conditions may change rapidly, particularly during periods of high fire risk; therefore, periodic inspections are necessary to ensure timely detection of hazardous activities or ignition events. For this reason, coverage results should be interpreted together with revisit frequency, defined as the number of monitoring passes over the same area within a given time period (e.g., per day or per week), as higher revisit frequencies increase the likelihood of early detection of potential fire hazards.

In the baseline scenario, monitoring of fire-prone areas relies on conventional observation methods such as ranger patrols, field inspections, or reports from local authorities and residents. These approaches may

provide limited spatial coverage and may not allow frequent monitoring of all high-risk areas. The same indicator can therefore be estimated by calculating the proportion of fire-prone areas inspected through routine monitoring activities relative to the total extent of identified fire-risk zones. This enables comparison between the spatial monitoring coverage achieved through traditional monitoring approaches and the coverage provided by drone-based monitoring integrated into the FRED platform.

### 3.5.1.2 Streaming Data Quality

This indicator evaluates the reliability and clarity of the real-time data stream transmitted from the drone system during monitoring operations. High-quality streaming data is essential for effective situational awareness, as it allows operators and decision-makers to clearly interpret visual or thermal information and identify potential fire hazards in monitored areas. Operationally, the indicator measures how effectively the drone system provides stable and usable real-time information during monitoring missions.

**The indicator is assessed through feedback collected from operators involved in monitoring operations. After flight missions or demonstration exercises, operators evaluate the clarity, stability, and overall usability of the streamed data in supporting monitoring and hazard detection tasks.**

Streaming Data Quality (survey score 1-10)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>8	6-8	5-6	<5

Higher scores indicate that the streaming data provides clear and reliable visual information, enabling operators to effectively monitor fire-prone areas and identify potential hazards.

In the baseline scenario, monitoring of fire-prone areas relies on conventional observation methods such as field inspections, patrols, or reports from local authorities and residents. These approaches may provide limited real-time situational awareness and may not allow continuous observation of monitored areas. The same evaluation scale can therefore be applied by asking operators or stakeholders to assess the clarity and usefulness of information obtained through these traditional monitoring methods. This allows comparison between the quality of situational awareness provided by conventional monitoring approaches and the

improved information quality supported by drone-based streaming integrated into the FRED platform.

### 3.5.2 UC2 – Locating and Monitoring the Spread of Fire

#### 3.5.2.1 Accuracy of fire/smoke detection

This indicator evaluates how accurately drone-based sensors identify early signs of wildfire ignition, such as smoke plumes or thermal anomalies, during preventive monitoring operations. Operationally, it assesses the reliability of the UAS monitoring system in detecting potential fire events at an early stage, enabling rapid response and reducing the risk of fire spread.

**It is measured as the percentage of fire or smoke events correctly detected through drone observations compared to the total number of confirmed events verified through field inspection, incident reports, or other reliable observations.**

$$\text{Accuracy of Fire/Smoke Detection}(\%) = \frac{\text{Correctly detected events}}{\text{Total confirmed events}} * 100$$

Accuracy of fire/smoke detection (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>90%	75-90%	60-75%	<60%

In the baseline scenario, early fire detection relies on conventional monitoring approaches such as lookout towers, ranger patrols, reports from local authorities or citizens, and satellite-based detection systems where available. The same indicator can be estimated by comparing the number of fire or smoke events identified through these traditional observation methods with the total number of confirmed events during the monitoring period. This allows comparison between the detection capability of conventional monitoring systems and the accuracy achieved through drone-based monitoring integrated into the FRED platform

#### 3.5.2.2 Tactical Responsiveness

This indicator evaluates how quickly operational teams are able to respond to information regarding fire location and spread during wildfire intervention operations. During active fire events, drone-based monitoring can provide real-time situational awareness of fire behaviour, including the position of fire fronts and the emergence of new hotspots. Operationally, the indicator measures how rapidly response actions are initiated after relevant tactical information becomes available to the command unit.

**Tactical Responsiveness represents the time elapsed between the moment when operational information about fire location or spread is received and the initiation of response actions by firefighting personnel.**

$$\text{Tactical Responsiveness (mins)} = Tr - Ti$$

where  $T_i$  represents the time when relevant operational information (e.g., hotspot location, fire spread direction, or emerging hazard) is received by the command unit, and  $T_r$  represents the time when response actions are initiated by operational teams.

Tactical Responsiveness (min)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	<5	5-15	15-30	>30

Shorter response times indicate that monitoring activities effectively support tactical decision-making and enable firefighting teams to react more quickly to changes in fire behaviour.

In the baseline scenario, operational decisions rely on conventional sources of situational information such as visual observations from ground crews, reports from field personnel, or observations from lookout points. Without drone-based aerial monitoring, the availability of real-time information about fire spread may be limited by terrain, visibility conditions, and communication delays. The same indicator can therefore be measured as the time elapsed between the reception of tactical information through these conventional observation methods and the initiation of response actions. This allows comparison between the responsiveness achieved through traditional operational monitoring and the improved response capability supported by drone-based monitoring integrated into the FRED platform.

### 3.5.3 UC3 – Preventive Monitoring of Remote Areas

#### 3.5.3.1 Preventive Flight Regularity

This indicator evaluates the extent to which preventive drone monitoring flights are carried out consistently and according to the planned monitoring schedule during high-risk periods. Regular drone patrols over fire-prone areas can increase the likelihood of early detection of hazardous activities or ignition sources and improve overall situational awareness in areas vulnerable to wildfire. Operationally, the indicator measures how

consistently preventive monitoring missions are conducted during the defined monitoring period.

**The indicator is calculated as the proportion of preventive monitoring flights conducted relative to the total number of flights planned within the monitoring schedule**

$$\text{Preventive Flight Regularity (\%)} = \frac{\text{Number of preventive flights conducted}}{\text{Number of planned preventive flights}} * 100$$

Preventive Flight Regularity (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>90%	75-90%	60-75%	<60%

Higher values indicate that monitoring activities are implemented consistently and that preventive surveillance of fire-prone areas is conducted as planned.

In the baseline scenario, monitoring of fire-prone areas relies on conventional observation methods such as ranger patrols, periodic field inspections, or reports from local authorities and residents. These activities may occur irregularly and are often dependent on available personnel and resources. The same indicator can therefore be estimated by comparing the number of patrols or inspections conducted during the monitoring period with the number of patrols planned in routine monitoring schedules. This enables comparison between the regularity of traditional monitoring activities and the consistency of preventive surveillance achieved through drone-based monitoring integrated into the FRED platform.

### 3.5.3.2 Persistent Hotspot Frequency

This indicator evaluates how frequently recurring fire-risk locations or persistent hotspots are detected during preventive monitoring operations. Persistent hotspots may correspond to locations where hazardous activities or environmental conditions repeatedly create a risk of fire ignition. Regular identification of such locations allows authorities to better understand spatial patterns of fire risk and to implement targeted preventive measures. Operationally, the indicator measures the frequency with which hotspot detections occur repeatedly at the same locations within a defined monitoring period.

**The indicator is calculated as the number of repeated hotspot detections observed at identified locations during the monitoring period.**

Persistent Hotspot Frequency (hotspots)				
Class	Optimum	Acceptable	Critical	Not acceptable
Interval	<1	1-3	3-5	>5

Lower values indicate that preventive monitoring and mitigation measures are effective in reducing the recurrence of hazardous conditions that may lead to fire ignition.

In the baseline scenario, identification of recurring fire-risk locations relies on conventional monitoring approaches such as field inspections, reports from local authorities, or historical records of fire incidents. These approaches may provide limited information about spatial patterns of recurring fire hazards due to irregular monitoring frequency and incomplete reporting. The same indicator can therefore be estimated by analysing historical records of repeated fire or smoke incidents occurring at the same locations within the monitoring area. This enables comparison between the recurrence of hotspot detections observed under conventional monitoring conditions and the patterns identified through systematic drone-based monitoring integrated into the FRED platform.

### 3.5.4 UC4 – Inspection of Fire Protection Routes

#### 3.5.4.1 Route Safety Assessment

This indicator evaluates how effectively drone-based monitoring supports the inspection and assessment of fire protection routes. Fire protection routes, such as forest access roads and firebreaks, play a critical role in enabling firefighting units to access fire-prone areas and carry out intervention activities safely and efficiently. Drone-derived imagery and spatial information can provide rapid and detailed insights into the condition of these routes, helping authorities identify obstacles, vegetation overgrowth, or other factors that may limit accessibility.

Operationally, the indicator measures the perceived usefulness of drone-generated information in supporting the inspection and safety assessment of fire protection routes.

**The indicator is assessed through feedback collected from operational personnel responsible for monitoring and maintaining fire protection routes. After monitoring activities or demonstration exercises, participants evaluate the effectiveness of drone-derived information in supporting route inspection and identifying potential accessibility issues.**

3.5.4.1 Route Safety Assessment (survey score 1-10)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>8	6-8	5-6	<5

The final indicator value corresponds to the average score obtained from all survey responses, reflecting the overall perceived effectiveness of the drone-supported monitoring system in assessing the condition and accessibility of fire protection routes.

In the baseline scenario, inspection of fire protection routes relies on conventional monitoring methods such as field inspections, vehicle patrols, or reports from local authorities and maintenance personnel. These approaches may require significant time and effort to inspect large areas and may not always provide a comprehensive overview of route conditions. Stakeholders participating in these inspections evaluate the usefulness of these traditional methods using the same scoring scale. This enables comparison between the effectiveness of conventional inspection approaches and the improved situational awareness provided by drone-based monitoring integrated into the FRED platform.

#### 3.5.4.2 Inspection Coverage Rate

This indicator evaluates the extent to which fire protection routes are inspected during drone monitoring operations. Fire protection routes, such as forest access roads and firebreaks, play a critical role in enabling firefighting units to reach fire-prone areas quickly and safely. Regular inspection of these routes is necessary to identify obstacles, vegetation overgrowth, erosion, or other conditions that may affect accessibility. Operationally, the indicator measures how effectively monitoring missions inspect the network of fire protection routes within the monitored area.

**The indicator is calculated as the proportion of the length of fire protection routes inspected during drone missions within a defined monitoring period in relation to the total length of fire protection routes.**

$$\text{Inspection Coverage Rate (\%)} = \frac{\text{Length of inspected routes}}{\text{Total length of routes}} * 100$$

Inspection Coverage Rate (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>90%	75-90%	60-75%	<60%

In the baseline scenario, inspection of fire protection routes relies on conventional monitoring approaches such as field inspections, vehicle patrols, or reports from local authorities and maintenance personnel. These

methods may require significant time and resources to cover the entire network of routes and may result in incomplete or infrequent inspections. The same indicator can therefore be estimated by calculating the proportion of fire protection routes inspected through routine monitoring activities relative to the total length of routes requiring inspection. This enables comparison between the inspection coverage achieved through traditional monitoring approaches and the coverage provided by drone-based monitoring integrated into the FRED platform within a given time frame.

### 3.5.5 UC5 – Response to Illegal Fire Ignitions

#### 3.5.5.1 Fire Ignition Responsiveness

This indicator evaluates how quickly operational teams are able to respond after a fire ignition event is detected during monitoring operations. Early identification of ignition events allows responsible authorities to initiate intervention actions before the fire spreads, thereby reducing potential damage to ecosystems, infrastructure, and surrounding communities. Operationally, the indicator measures how rapidly response actions are initiated once information about a fire ignition becomes available to the command unit.

Fire Ignition Responsiveness represents the time elapsed between the moment when a fire ignition event is detected and the initiation of response actions by operational teams..

$$\text{Fire Ignition Responsiveness (mins)} = T_r - T_{di}$$

Where  $T_d$  represents the time when the fire ignition event is detected by the monitoring system, and  $T_r$  represents the time when response actions are initiated by the responsible authorities.

Fire Ignition Responsiveness (min)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	<5	5 - 15	15 - 30	>30

Shorter response times indicate that monitoring activities effectively support rapid intervention and enable authorities to respond quickly to emerging fire incidents.

In the baseline scenario, detection of fire ignition events relies on conventional observation methods such as visual reports from field patrols, lookout points, or notifications from local authorities and residents. Without drone-based aerial monitoring, detection and reporting of ignition events may be delayed due to limited spatial coverage and restricted visibility conditions. The same indicator can therefore be measured as the time

elapsed between the observation of a fire ignition event through these traditional methods and the initiation of response actions. This allows comparison between the responsiveness achieved through conventional monitoring approaches and the improved response capability supported by drone-based monitoring integrated into the FRED platform.

### 3.5.6 Overview of KPIs

#### Pilot site: Mali Lošinj, Croatia

Class	Optimum	Acceptable	Critical	Not acceptable
<b>Coverage of fire-prone areas (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Piloting</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Streaming Data Quality (survey score 1-10)</b>				
<b>Baseline</b>	<input type="checkbox"/> >8	<input type="checkbox"/> 6-8	<input type="checkbox"/> 5-6	<input type="checkbox"/> <5
<b>Piloting</b>	<input type="checkbox"/> >8	<input type="checkbox"/> 6-8	<input type="checkbox"/> 5-6	<input type="checkbox"/> <5
<b>Accuracy of fire/smoke detection (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >85%	<input type="checkbox"/> 70-85%	<input type="checkbox"/> 50-70%	<input type="checkbox"/> <50%
<b>Piloting</b>	<input type="checkbox"/> >85%	<input type="checkbox"/> 70-85%	<input type="checkbox"/> 50-70%	<input type="checkbox"/> <50%
<b>Tactical Responsiveness (min)</b>				
<b>Baseline</b>	<input type="checkbox"/> <1	<input type="checkbox"/> 1-10	<input type="checkbox"/> 10-30	<input type="checkbox"/> >30
<b>Piloting</b>	<input type="checkbox"/> <1	<input type="checkbox"/> 1-10	<input type="checkbox"/> 10-30	<input type="checkbox"/> >30
<b>Preventive Flight Regularity (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Piloting</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Persistent Hotspot Frequency (hotspots)</b>				
<b>Baseline</b>	<input type="checkbox"/> >5	<input type="checkbox"/> 3-5	<input type="checkbox"/> 1-3	<input type="checkbox"/> <1

<b>Piloting</b>	<input type="checkbox"/> >5	<input type="checkbox"/> 3-5	<input type="checkbox"/> 1-3	<input type="checkbox"/> <1
<b>Route Safety Assessment (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >8	<input type="checkbox"/> 6-8	<input type="checkbox"/> 5-6	<input type="checkbox"/> <6
<b>Piloting</b>	<input type="checkbox"/> >8	<input type="checkbox"/> 6-8	<input type="checkbox"/> 5-6	<input type="checkbox"/> <6
<b>Inspection Coverage Rate (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Piloting</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Fire Ignition Responsiveness (min)</b>				
<b>Baseline</b>	<input type="checkbox"/> <5	<input type="checkbox"/> 5-15	<input type="checkbox"/> 15-30	<input type="checkbox"/> >30
<b>Piloting</b>	<input type="checkbox"/> <5	<input type="checkbox"/> 5-15	<input type="checkbox"/> 15-30	<input type="checkbox"/> >30

### 3.6 Pilot site: Baixo Alentejo, Portugal

#### 3.6.1 UCI – Preventive monitoring due to high fire danger index (summer)

##### 3.6.1.1 Accuracy of Fire/Smoke Detection

This indicator evaluates how accurately drone-based sensors identify early signs of wildfire ignition, such as smoke plumes or thermal anomalies, during preventive monitoring operations. Operationally, it assesses the reliability of the UAS monitoring system in detecting potential fire events at an early stage, enabling rapid response and reducing the risk of fire spread.

**It is measured as the percentage of fire or smoke events correctly detected through drone observations compared to the total number of confirmed events verified through field inspection, incident reports, or other reliable observations.**

$$\text{Accuracy of Fire/Smoke Detection}(\%) = \frac{\text{Correctly detected events}}{\text{Total confirmed events}} * 100$$

Accuracy of fire/smoke detection (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>90%	75-90%	60-75%	<60%

Higher accuracy values indicate that the monitoring system reliably detects fire or smoke events, supporting early intervention and reducing the likelihood of uncontrolled wildfire development.

In the baseline scenario, early fire detection relies on conventional monitoring approaches such as lookout towers, ranger patrols, reports from local authorities or citizens, and satellite-based detection systems where available. The same indicator can be estimated by comparing the number of fire or smoke events identified through these traditional observation methods with the total number of confirmed events during the monitoring period. This allows comparison between the detection capability of conventional monitoring systems and the accuracy achieved through drone-based monitoring integrated into the FRED platform.

##### 3.6.1.2 Coverage of high-risk areas

This indicator assesses whether drone monitoring is carried out with sufficient regularity and whether high-risk areas receive adequate coverage during danger periods. Operationally, this ensures that preventive patrols follow established schedules and that all vulnerable zones are observed frequently enough to detect early-stage threats.

**It is measured through the percentage ratio between the area inspected by drones and the total area classified as high risk within the monitoring period.**

$$\text{Coverage of high – risk areas (\%)} = \frac{\text{Area inspected by drones}}{\text{Total high – risk area}} * 100$$

Coverage of high-risk areas (%)				
<b>Class</b>	Optimum	Acceptable	Critical	Not acceptable
<b>Interval</b>	>90%	75-90%	60-75%	<60%

In addition to spatial coverage, the effectiveness of preventive monitoring also depends on how frequently high-risk areas are revisited. Since ignition events may occur at any time during periods of elevated fire danger, a single inspection does not guarantee timely detection of hazards. For this reason, coverage results should be interpreted together with revisit frequency, defined as the number of times a high-risk area is monitored within a given time period (e.g., per day or week), as higher revisit frequencies increase the likelihood of early detection and improve overall surveillance effectiveness.

The baseline scenario represents the surveillance capacity achieved through conventional monitoring methods, including ground patrols and existing observation infrastructure. Coverage is estimated using patrol routes, visibility range and monitoring duration.

### 3.6.2 UC2 – Support of firefighting operations in case of fire.

#### 3.6.2.1 Operational Responsiveness

This indicator evaluates how quickly operational teams are able to respond to critical information provided during wildfire intervention operations. During active fire events, drone-based monitoring can provide real-time situational awareness of fire behaviour, hotspot locations, and potential risks to firefighting teams. Operationally, the indicator measures how rapidly response actions are initiated after relevant operational information becomes available.

**Operational Responsiveness represents the time elapsed between the moment when critical operational information is received and the initiation of response actions by firefighting personnel.**

$$\text{Operational Responsiveness (mins)} = T_r - T_i$$

where  $T_i$  represents the time when relevant operational information (e.g., hotspot location, fire spread direction, or emerging hazard) is received by the command unit, and  $T_r$  represents the time when response actions are initiated by operational teams.

Operational Responsiveness (min)				
Class	Optimum	Acceptable	Critical	Not acceptable
Interval	<5	5-15	15-30	>30

Shorter response times indicate that monitoring activities effectively support operational decision-making and enable firefighting teams to react more quickly to changing fire conditions.

In the baseline scenario, operational decisions rely on conventional sources of situational information such as visual observations from ground crews, reports from field personnel, or observations from lookout points. Without drone-based aerial monitoring, the availability of real-time information may be limited by terrain, visibility conditions, and communication delays. The same indicator can therefore be measured as the time elapsed between the reception of operational information through these conventional observation methods and the initiation of response actions. This allows comparison between the responsiveness achieved through traditional operational monitoring and the improved response capability supported by drone-based monitoring integrated into the FRED platform.

### 3.6.3 UC3 – Post-incident documentation and analysis.

#### 3.6.3.1 Burned Area Mapping Accuracy

This indicator evaluates the accuracy of the spatial information produced during post-fire assessment using UAS-based photogrammetry or LiDAR data. Operationally, it determines whether the mapped burned area derived from drone imagery accurately represents the real extent of the burned perimeter and can therefore be reliably used for post-fire analysis, including burn-severity assessment, hazard identification, and restoration planning.

**It is measured as the percentage of the burned area correctly mapped through drone-derived spatial products compared to the burned area confirmed through reference observations (e.g., field surveys, GNSS perimeter mapping, or high-resolution satellite imagery).**

$$\text{Burned Area Mapping Accuracy}(\%) = \frac{\text{Correctly mapped burned areas}}{\text{Total confirmed burned area}} * 100$$

Burned Area Mapping Accuracy (%)				
Class	Optimum	Acceptable	Critical	Not acceptable
Interval	>90%	75-90%	60-75%	<60%

Currently, burned-area mapping is conducted using conventional approaches such as field perimeter mapping with GNSS, interpretation of aerial or satellite imagery, or manual reporting by fire services. The same indicator can be calculated by comparing the burned area mapped using these traditional methods with the confirmed burned perimeter. This allows a direct comparison between conventional post-fire assessment methods and the spatial accuracy achieved using UAS-derived datasets within the FRED platform. Another reference value that can be used to assess the performance of the platform is a comparison of the burned area identified using the proposed solution with the burned area mapping that is provided by the European Forest Fire Information System (EFFIS).

### 3.6.4 Overview of KPIs

#### Pilot site: Baixo Alentejo, Portugal

Class	Optimum	Acceptable	Critical	Not acceptable
<b>Accuracy Fire/Smoke Detection (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Piloting</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Coverage of high-risk areas (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Piloting</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Operational Responsiveness (mins)</b>				
<b>Baseline</b>	<input type="checkbox"/> <5	<input type="checkbox"/> 5-15	<input type="checkbox"/> 15-30	<input type="checkbox"/> >30
<b>Piloting</b>	<input type="checkbox"/> <5	<input type="checkbox"/> 5-15	<input type="checkbox"/> 15-30	<input type="checkbox"/> >30
<b>Burned Area Mapping Accuracy (%)</b>				
<b>Baseline</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%
<b>Piloting</b>	<input type="checkbox"/> >90%	<input type="checkbox"/> 75-90%	<input type="checkbox"/> 60-75%	<input type="checkbox"/> <60%

## 4 Methodological Approach: MCA Supported by AHP

### 4.1 Introduction

Multi-Criteria Analysis (MCA) is a decision-support methodology used to systematically compare and aggregate indicators that differ in units, scales, or meaning - something common in environmental and technological assessments. As highlighted in the *Multi-criteria Analysis: A Manual (DCLG, 2009)*, MCA is designed to handle problems where “options need to be assessed against multiple criteria which are not easily reduced to a single common measure”.

This is exactly the context of the FRED evaluation, where KPIs range from technical performance metrics (e.g., detection accuracy) to operational measures (e.g., mission duration), usability assessments, and broader impact indicators.

MCA is also widely recognized in environmental decision-making. The review by *Huang et al. (2011)* shows a strong growth of MCA applications in the last decade, especially in areas dealing with uncertainty, multiple stakeholders, and heterogeneous data.

For these reasons, MCA represents a robust and transparent method to compare baseline and piloting scenarios across all FRED pilot sites.

### 4.2 Multi-Criteria Analysis (MCA)

MCA is used here to integrate all KPIs, regardless of their unit or nature, into a single evaluation score. The process follows a structured sequence, aligned with standard MCA practice:

- a. **Normalization:** Since KPIs express very different quantities (minutes, percentages, Likert-scale scores, etc.), they first need to be standardized. Normalisation converts each KPI into a value between 0 and 1 so that indicators are fully comparable. This step responds to the basic need of MCA to create a “common performance scale” when dealing with heterogeneous criteria (*DCLG, 2009*). In this evaluation, normalization follows a Fuzzy Logic-based approach, which allows each KPI to be mapped onto the [0–1] interval according to its performance class. Fuzzy Logic, originally introduced by *Zadeh (1965)*, extends classical Boolean logic by allowing elements to belong to a set with partial degrees of membership, rather than only “true” or “false.” In this context, each KPI value is associated with a *membership function* that expresses how well the observed performance fits within the “Optimum,” “Acceptable,” “Critical,” or “Not Acceptable” classes.

- b. **Weighting:** Not all criteria contribute equally to the project objectives. For this reason, each KPI is assigned a weight that reflects its relative importance. Weights are not chosen arbitrarily but they are derived using the Analytic Hierarchy Process (AHP), a rigorous pairwise-comparison method developed by *Saaty (1990)*. AHP transforms subjective preferences into mathematically consistent ratio-scale weights, enabling a transparent and systematic evaluation process.
- c. **Aggregation:** Normalised and weighted KPIs are combined to generate category scores, an overall evaluation score (Baseline and Piloting) and the Improvement Index, which quantifies the contribution of drones and the FRED platform.

This structured approach provides transparency, internal consistency, and comparability across pilot sites.

### 4.3 Role of the Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is used in this evaluation framework to determine the relative importance (weights) of both the macro-categories and the individual KPIs. AHP is particularly suitable in this context because it provides a structured and transparent way to turn stakeholder judgements into numerical weights through a pairwise comparison procedure. As explained by *Saaty (2001)*, comparing two elements at a time allows decision-makers to express preferences in a way that is intuitive and cognitively easier than assigning numerical weights directly.

### 4.4 Pairwise comparisons and matrix construction

In AHP, stakeholders are asked to compare criteria two at a time, answering the question:

*“Considering the evaluation goal, which of the two criteria is more important, and by how much?”*

Their answers are recorded in a pairwise comparison matrix, which is a square matrix where:

- each row and column represent a criterion,
- the cell  $a_{ij}$  expresses how much more important criterion  $i$  is compared to criterion  $j$ ,
- the matrix is always reciprocal, meaning that if  $a_{ij} = x$ , then  $a_{ji} = 1/x$  (*Saaty, 1990; Vargas, 1990*).

To express the strength of preference, stakeholders use the fundamental 1–9 scale developed by Saaty:

- 1 = equal importance,
- 3 = moderate importance,

- 5 = strong importance,
- 7 = very strong importance,
- 9 = extreme importance

For example, if “Technical Performance” is judged to be strongly more important than “Responsiveness & Timeliness”, the corresponding cell receives a 5, while the symmetric cell receives 1/5 (Table 3). This approach transforms qualitative judgements into ratio-scale numerical values, which is one of the fundamental properties of AHP highlighted in Saaty’s work.

Table 3 - Example of the AHP pairwise comparison matrix

Category/Criteria	T	R	C	E	I
Technical (T)	1	5	1/3	1/7	3
Responsiveness (R)	1/5	1	2	5	1/2
Coverage (C)	3	1/2	1	3	1/4
Effectiveness (E)	7	1/5	1/3	1	5
Impact (I)	1/3	2	4	1/5	1

Once the pairwise matrix is complete, AHP uses the principal right eigenvector of the matrix to derive the weights of the criteria. This method mathematically identifies the set of weights that best represents the judgements expressed in the matrix.

A key strength of AHP is that it also assesses the internal consistency of the judgements. Human comparisons are rarely perfectly consistent, but the AHP provides a Consistency Ratio (CR) to verify whether the level of inconsistency is acceptable. A CR value below 0.10 is considered acceptable according to Saaty’s criteria. If the ratio is higher, stakeholders are encouraged to review their comparisons.

#### 4.5 AHP application

AHP is applied in two steps within the MCA structure:

- Macro-category level:** stakeholders compare the importance of the five categories (Technical Performance, Responsiveness & Timeliness, Coverage & Monitoring Capacity, Operational Effectiveness & Safety, Impact & Outcomes). The pairwise comparison matrix produces a set of normalised weights for each category and a Consistency Ratio (CR < 0.1) to validate the reliability of the comparison.
- KPI level:** Within each macro-category, the relevant KPIs are compared using the same pairwise approach. This allows the evaluation framework to capture differences in importance even within a single operational dimension.

AHP is performed once, independently of the baseline and piloting measurements. This is consistent with the axioms of independence and completeness described by *Vargas (1990)*, which state that criteria weights reflect stakeholder priorities, not the performance values of the system.

#### 4.6 Integration of AHP Weights into MCA

Once the AHP process has produced the weights for each macro-category and KPI, these values are integrated into the MCA framework. For every KPI, the **weighted contribution to the final score** is calculated as:

$$\text{Weighted Score} = \text{Normalised KPI Value} \times \text{AHP Weight}$$

This ensures that each KPI influences the final evaluation in proportion to the importance assigned by stakeholders during the AHP process. As recommended in MCA guidelines (*DCLG, 2009*), weighting and scoring are performed before aggregation so that all indicators contribute consistently and transparently.

The **evaluation score** of all KPI categories is defined as:

$$\text{Score} = \sum_{j=1}^M \sum_{i=1}^N ws_i \cdot w_j$$

where  $ws_i$  is the weighted score of the  $i$ -th KPI belonging to the  $j$ -th category,  $w_j$  is the weight of the  $j$ -th category,  $N$  is the number of KPIs for the  $j$ -th category and  $M$  is the number of KPI categories.

The evaluation score is then defined in two phases:

- the baseline phase,
- the piloting phase.

The **baseline phase** evaluates wildfire management performance without drones and the FRED platform, relying solely on traditional monitoring and response techniques. In contrast, the **piloting phase** assesses performance through drone-assisted operations and FRED-enabled analytics. Identical KPIs are gathered in both scenarios to guarantee comparability, with their values normalised and weighted using AHP weights established at the outset of the evaluation and maintained consistently throughout the process. This approach ensures a fair and reliable before-and-after comparison, measuring improvements against stable, stakeholder-validated priorities.

Finally, the Baseline Evaluation Score ( $Score_{before}$ ) and the Piloting Evaluation Score ( $Score_{after}$ ) are aggregated to produce the **Overall Improvement Index**:

$$Overall\ Improvement\ Index = Score_{after} - Score_{before}$$

This index quantifies the **added value generated by drone operations and the FRED platform for each use case and pilot site**. It also provides a robust basis for comparing results across different environments and operational contexts.

## 5 Preliminary operations for the evaluation report

In order to apply the proposed methodological approach described in the previous chapter, stakeholders must be given a questionnaire to establish the relative order of importance of the indicators.

To this end, a spreadsheet will be implemented, asking stakeholders for their expert opinion on the relative importance of the KPI categories and KPIs through a pairwise comparison.

The forms will be administered during the implementation of the pilot actions so that the AHP pairwise comparison matrix can be assembled before their conclusion in order to draw up the evaluation report.

In parallel, FRED piloting partners (Fire and Rescue Service Sežana, Rocca di Cerere UNESCO Global Geopark, National Park Una, Municipality of Ulcinj, Public Fire Brigade of the Town of Mali Lošinj and Intermunicipal Community of Baixo Alentejo) will evaluate the values of the site-specific KPIs in baseline and piloting conditions.

## 6 Conclusions

The evaluation methodology presented in this deliverable establishes a rigorous, operationally grounded and scientifically informed framework for assessing the effectiveness of the FRED platform across six heterogeneous Mediterranean pilot sites. Through a combination of harmonised performance indicators, detailed use case definitions, and cross-pilot comparability criteria, the methodology ensures that the diverse technical, environmental and organisational characteristics of each region are addressed in a structured and coherent manner.

Drawing from the multi-disciplinary analyses presented in earlier project deliverables—including the geomorphological, climatic, ecological and remote-sensing baselines compiled in D1.1.1 and the operational UAS acquisition methodology of D1.1.2—this methodology positions FRED as a comprehensive digital ecosystem capable of supporting all phases of wildfire management. The six pilot areas—Sežana (Slovenia), Rocca di Cerere Geopark (Italy), Una National Park (Bosnia and Herzegovina), Ulcinj (Montenegro), Mali Lošinj (Croatia), and Baixo Alentejo (Portugal)—represent geographically and operationally distinct environments. Their diversity ensures that the evaluation framework is tested under a wide range of ecological conditions, risk drivers, terrain constraints and institutional capacities.

Across all pilot regions, several common insights emerge. Wildfires in the Mediterranean are no longer sporadic natural phenomena but rather complex socio-ecological events shaped by climatic change, human activity, altered fuel dynamics and expanding wildland–urban interfaces. Prevention remains the weakest link in existing fire-management systems, as evidenced by insufficient ground patrol coverage, limited fuel monitoring capacity, and the prevalence of human-driven ignitions. Suppression, although technologically advanced in many regions, is increasingly challenged by extreme fire behavior, resource constraints and the growing need for real-time situational awareness. Post-fire assessment, in turn, remains inconsistent across regions, often lacking reliable, high-resolution data to support ecological restoration or civil protection planning.

The FRED platform directly targets these systemic weaknesses by integrating UAS-based high-resolution data capture, thermal and multispectral sensing, fire-risk modelling, and real-time decision-support tools. The methodology developed in this deliverable ensures that the operational value of these innovations is measured in a systematic and quantifiable manner. The performance indicators defined for each pilot site

address the specific operational challenges of that region—ranging from the karst topography of Sežana to the ancient pathways of Baixo Alentejo—and transform them into measurable, comparable metrics. These indicators cover key dimensions of effectiveness: prevention efficiency, real-time situational awareness, accuracy of spatial assessments, influence on operational decision-making, and contribution to post-fire recovery workflows.

A central conclusion of this evaluation methodology is that technological efficiency cannot be assessed in isolation. Instead, it must be contextualised within broader operational workflows, institutional responsibilities, and environmental realities. For instance, the same UAS surveillance flight may have different operational impacts in Mali Lošinj—where tourist-driven ignition patterns dominate—compared to Ulcinj, where agricultural burning is the primary ignition source. Similarly, data accuracy requirements differ between post-fire assessment in dense karst forests and flood surveillance in riverine landscapes such as Una National Park. The methodology therefore adopts a flexible but harmonised structure, allowing each pilot site to tailor indicators to its specific needs while still contributing to a unified evaluation model.

Another important conclusion concerns the role of FRED as a long-term data-integration environment. By centralising thermal imagery, multispectral data, flight logs, risk layers, and post-event mapping outputs, FRED establishes a durable and scalable knowledge base. Over time, this accumulation of multi-source datasets can significantly enhance fire-risk prediction models, support adaptive management strategies, and allow authorities to evaluate long-term environmental changes—including vegetation recovery, shifting fuel loads, and evolving hotspot patterns. This contributes directly to broader Interreg Euro-MED objectives of climate adaptation, natural heritage protection and ecosystem resilience.

From an operational perspective, the methodology demonstrates that UAS integrated with FRED can substantially reduce uncertainty at every stage of the fire-management cycle. In prevention, drones fill critical gaps in patrol coverage, detect early anomalies, and provide objective evidence for enforcing regulations. During suppression, they create a continuous real-time operational picture, increasing the safety and efficiency of firefighting crews. In post-fire assessment, they produce rapid, accurate, and comprehensive documentation of impacts, supporting restoration planning and reducing the cost and time of field surveys.

Furthermore, the methodology highlights the importance of user-centric evaluation. Firefighters, park rangers, municipal authorities, and civil

protection agencies must be able to access, interpret and operationalise data generated by the FRED platform. For this reason, many performance indicators intentionally include simple, field-friendly measurement methods—such as detection times, coverage percentages, accuracy rates or time savings—that can be recorded during routine operations without requiring specialised technical expertise. This allows the evaluation framework to be applied consistently by all partners and integrated seamlessly into existing workflows.

Finally, this deliverable establishes a basis for future scaling and replication of the FRED solution. The methodology ensures that the platform’s efficiency can be assessed not only within the six pilot areas but also in other Mediterranean territories facing similar challenges. By defining common indicators, harmonised workflows and reference measurement protocols, the project creates the foundations for a Mediterranean-wide evaluation model that can be adopted by additional regions, institutions and civil protection authorities. This is crucial for capitalisation, policy integration and long-term implementation under the Interreg Euro-MED mission “Protecting, restoring and valorising natural heritage.”

In summary, the evaluation methodology presented here provides a rigorous, adaptable and field-validated framework for assessing the operational efficiency of the FRED platform. It ensures that technological innovation translates into measurable improvements in wildfire prevention, preparedness, response and recovery. By aligning scientific precision with operational practicality, the methodology supports the overarching goal of Fire Free MED: to build a more resilient, better prepared and technologically empowered Mediterranean capable of addressing the increasing threat of wildfires.

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