Digital Twin-Enhanced Fire Response Through Unmanned Aerial Reconnaissance System

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Abstract. *This paper first examines the digital twin as a conceptual framework and then as an implementation method. Several existing definitions are reviewed, and a new one is proposed, emphasising the time dimension where the digital object represents a future state of the physical object. A key element is the inclusion of an observer or decision-maker (man in the loop). An AI-based automated decision-making system (AI agent) is also proposed and discussed within this framework. The concept is applied to a real-world case: the coastal reconnaissance segment of the Croatian fire-fighting system.*

Keywords. Digital twin, unmanned aerial vehicles, fire-fighting system, human in the loop, AI Agent.

1 Introduction

In recent years, particularly during the summer months, wildfires have become a frequent and severe threat in the Republic of Croatia and across other Mediterranean countries. Despite Croatia's long-standing firefighting tradition and a relatively well-developed fire protection system, wildfires still occur with potentially devastating consequences, including significant material damage and loss of human life. According to the Croatian Firefighting Association, in 2024, the ten largest fires affected a total of 13,378 hectares, which corresponds to 133.78 million square meters (Croatian Firefighting Association, 2025 (a)).

The primary causes of such large-scale fires include mild winters, more frequent and intense heatwaves compared to previous years, and human-related factors. To protect coastal and near-coastal areas, where the most destructive fires typically occur, Croatian firefighting forces carry out systematic observation and reconnaissance. This is done using cameras installed primarily on antenna towers operated by *Odašiljači i veze Ltd*. (OiV, the national provider of broadcasting and communication infrastructure in Croatia) as well as on infrastructure belonging to mobile network operators. In certain cases, manned aircraft and unmanned aerial vehicles (UAVs) are deployed. By 2024, 220 cameras had been installed at 110 locations, providing 360-degree visual coverage (Zaštita.info, 2025). In addition, systems such as the Pilatus PC-9 and the Orbiter 3 UAV are used for early fire detection, reconnaissance in hard-to-reach areas, and real-time fire monitoring (Croatian Firefighting Association, 2025 (b)).

These facts clearly show that technology plays a critical role in fire prevention and early warning, leaving room for further enhancements. One promising direction is the development of a digital twin of the early fire detection system. Such a model could include spatial mapping of camera coverage, detection of under-monitored areas, and the application of optimization algorithms to support UAV-based reconnaissance. In uncovered regions, UAV routes can be optimized using bio-inspired algorithms such as Max-Min Ant Colony Optimization (MMAS), which dynamically adapt to spatial and temporal variables, including the fire weather index.

In addition, the proposed framework incorporates an AI-based automated decision-making system (AI agent) within the digital twin. This agent enhances the model's ability to analyse incoming data, optimise UAV reconnaissance routes, and support timely decision-making in dynamic wildfire conditions. The aim of this research is to design a digital twin of the fire detection subsystem.

2 Theoretical background of digital twins

The digital twin is one of the key concepts emerging within the paradigm known as the Fourth Industrial Revolution (Industry 4.0). This revolution is based on the integration of digital technologies, such as the Internet of Things (IoT), artificial intelligence, automation, and simulation, into industrial processes. The concept of the digital twin was first applied during research space missions conducted by NASA in the 1960s (NASA, 2025) (Allen, 2021). During the Apollo 13 mission, an oxygen tank explosion endangered the crew, but thanks to NASA engineers testing real-time scenarios on physical and digital simulators, the astronauts returned safely, an experience now seen as a precursor to today's concept of the digital twin: a continuously updated simulation that mirrors a real system.

The idea of simulating a real-world system that receives data and responds dynamically, much like the physical system itself, was also proposed by computer scientist David Gelernter in his 1991 book Mirror Worlds (Gelernter, 1991). The term digital twin was first used in this context by Santiago Hernandez & Luis A. Hernandez-Ibanes (1997), authors of the paper Application of Digital 3D Models on Urban Planning and Highway Design. The paper highlights the advantages of creating three-dimensional digital models for construction projects and demonstrates how such models overcome the limitations of conventional design through three practical case studies.

The foundations for applying the digital twin concept in industry were laid by American scientist Michael Grieves in 2002, when he first comprehensively formulated the concept within the context of Product Lifecycle Management (PLM). In his work Origins of the Digital Twin Concept (Grieves, 2016), Grieves described the key elements of a digital twin as the physical space, the virtual space, and the connection between the two throughout the entire product lifecycle.

Križanić & Vrček (2025) used simulation experiment as a method for developing digital twin of a real production business process. The authors also proposed a new methodology for developing production digital twins, building upon existing business process management frameworks.

In 2012, NASA formalized its own definition of the digital twin, emphasizing it as the integration of multiple models, sensor data, and analytical tools into a cohesive virtual representation of a physical entity (Glaessgen & Stargel, 2012).

Various researchers have presented similar definitions of the digital twin. For example, the digital twin is a computer model of a physical device or system that represents all its functional features and is connected to its operational components (Chen, 2017). A digital twin is essentially a living model of a physical asset or system that continuously adapts to operational changes based on collected network data and information, and is capable of predicting the future state of the corresponding physical system (Liu, 2025). It is a set of virtual information that fully describes a potential or real physical product, ranging from the micro (atomic) level to the macro (geometric) level (Zheng et al., 2019). A digital twin is a digital representation of a physical item or assembly that uses integrated simulations and service data. This digital representation incorporates information from multiple sources throughout the entire product lifecycle (Vrabič, 2018). A digital twin is a virtual instance of a physical system that is continuously updated with data on its operation, maintenance, and condition throughout the system's entire lifecycle (Madni et al., 2019). It can represent both living and non-living entities, such as manufacturing processes, medical devices, or even people, by integrating sensor data, simulation, and analytics to provide insight into current and future operational states (Interagency Modeling and Analysis Group, 2025). Designed to accurately reflect its physical counterpart, a digital twin incorporates real-time data, simulation, machine learning, and reasoning to support decision-making across the lifecycle of the object or system (IBM, 2025).

According to IBM (2025), digital twins can be categorized based on their application domain and defined at various levels, from components to entire processes. Different types of digital twins may coexist within the same system or process. The main types include:

1. Component or part twins, which represent the smallest functional elements. While similar, part twins typically refer to less critical components.
2. Asset twins, which consist of two or more interacting components. They enable the analysis of component interactions and performance, generating valuable insights.
3. System or unit twins provide a broader view of how assets work together to form a complete, functional system. They help identify potential performance improvements.
4. Process twins operate at the highest (macro) level, representing how multiple systems collaborate across a production environment. They help determine whether systems are synchronized for maximum efficiency and identify delays that affect overall performance.

The concept of the digital twin has evolved from early space exploration applications to a foundational element of modern industrial systems, supported by advancements in data integration, simulation, and real-time analytics. Its layered structure, ranging from component-level twins to process-level representations, enables comprehensive modeling and optimization of complex systems throughout their entire lifecycle. This evolution and the diversity of interpretations were comprehensively reviewed by Dalibor et al. (2022), who analysed 1,471 publications, of which 356 were examined in detail, identifying conceptual properties, engineering practices, and evaluation methods. Building on the considerations presented above, this paper proposes the following definition of a digital twin: *A digital twin is an extension of a sociotechnical system composed of a physical element, integrated through automated information channels with its digital representation in both its current state and near future, and a human actor as a corrective factor within the system*.

3 Methodology

The methodology applied in this study follows a multi-layered approach to the development of a digital twin of a firefighting system, aimed at early wildfire detection and prevention. The digital twin architecture is structured into three core layers: the physical entity, the digital model, and the AI-supported decision-making layer.

The physical layer includes georeferenced surveillance infrastructure such as PTZ cameras distributed across coastal and near-coastal regions of Croatia, unmanned aerial vehicles (UAVs) equipped with high-resolution and thermal sensors, and a centralized data center. The digital model layer integrates multiple spatial and environmental data sources, including camera coverage zones, uncovered terrain points, UAV flyover coordinates, and fire risk indicators such as the Fire Weather Index (FWI), calculated using meteorological data. The UAVs' operational status, flight range, and current positioning are also modeled digitally.

The decision-making layer is supported by an AI agent capable of integrating heterogeneous inputs to autonomously generate UAV reconnaissance routes, dynamically prioritize zones based on FWI values and weather changes, and initiate missions in high-risk areas without human intervention. However, the system maintains a human-in-the-loop configuration, where the operator performs data verification, overrides automated decisions in critical scenarios, and provides feedback to improve system adaptability.

For geospatial processing and visualization, all maps used in the study were created using QGIS, an open-source geographic information system. The maps were generated in the EPSG:3765 projection (HTRS96/TM), the official coordinate reference system for the Republic of Croatia. QGIS was used to define camera coverage zones, visualize UAV flight paths, and overlay FWI values to identify critical surveillance gaps.

To communicate system structure and component interactions, a UML component diagram was employed in Visual Paradigm, capturing the high-level architecture and illustrating interfaces between modules such as the data center, AI agent, digital model, and physical subsystems.

4 Digital twin of the fire-fighting system for fire prevention and early detection

This section describes a digital twin of a firefighting system designed for fire prevention and early detection. The digital twin belongs to the category known as system or unit twins. In the following, the architecture of the digital twin, its key functional components, and the way it supports the optimization of unmanned aerial vehicle (UAV) routing within the firefighting system are presented.

4.1 Physical object

In this digital twin, the physical object is the firefighting system, more precisely, its subsystem that is, in this context, considered an independent system focused on fire prevention and early detection. The physical object includes the following elements: the monitored terrain, surveillance panoramic cameras, unmanned aerial vehicles (UAVs), a data center.

The monitored terrain represents a system element which, although not a device like cameras, data centers, or UAVs, is nevertheless a key part of the physical reality that must be captured for the digital representation to be meaningful. Since the terrain is observed, measured, modeled, and used for decision-making, it constitutes the central physical entity. Without its digital representation, fire simulations and predictions would lack practical value.

Surveillance panoramic cameras are deployed across the coastal and near-coastal areas of the Republic of Croatia. A total of 230 cameras have been installed at 115 locations, with each location equipped with two PTZ (Pan-Tilt-Zoom) cameras. This type of camera enables horizontal rotation up to 360°, vertical tilt up to 90°, and optical and/or digital zoom, allowing for detailed monitoring of objects at long distances. Figure 1 shows the locations of the panoramic cameras in Croatia. Each dot on the figure represents a single location, and since each location contains two cameras, it is assumed that the system is designed with redundancy to ensure operational reliability.

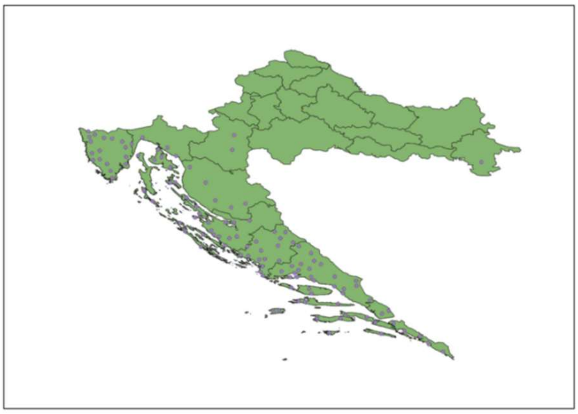

Figure 1. The spatial distribution of PTZ cameras for fire detection in the EPSG:3765 projection

Unmanned aerial vehicles (UAVs) serve as mobile sensor platforms used for reconnaissance of remote or hard-to-reach areas that are either not covered by cameras or where existing cameras are non-operational for various reasons. These UAVs are equipped with high-resolution cameras, thermal sensors, and/or air quality sensors, enabling rapid data collection over large terrain areas. The UAVs are connected to a communication system and transmit the collected data in real time to a central server, where it is further processed and integrated into the digital twin representation. Their use enables early detection of fire indicators such as elevated temperatures, smoke, or changes in vegetation.

The data center represents the physical component of the system where data collected from the field are stored, processed, and distributed. This includes images and videos from surveillance cameras, data from unmanned aerial vehicles (UAVs), as well as information on topography, vegetation, and microclimatic conditions. Depending on the system architecture, the data center may be located locally (i.e., edge computing) or in the cloud. In either case, it plays a crucial role in creating and maintaining an up-to-date digital representation of the real world. Its computational power enables real-time processing of large volumes of data, which is essential for timely detection and response to potential threats such as wildfires. In addition, the data center hosts algorithms for optimizing terrain reconnaissance, including one that calculates the optimal UAV flight route based on uncovered areas, weather conditions, and available resources.

4.2 Digital representation

The digital model represents a computer-based representation of the system for fire prevention and early detection. It is based on georeferenced data regarding the locations of surveillance cameras and the coordinates of areas not covered by the cameras, which need to be monitored by unmanned aerial vehicles (UAVs). The model also includes indicators of fire risk, such as the Fire Weather Index (FWI), which is used to assess the likelihood of fire ignition and spread based on meteorological data, as well as a digital model of the UAV itself, which in its basic version indicates the current position and flight path of the UAV in space. Thus, the model consists of multiple interconnected layers.

The first layer, as previously mentioned, contains spatial data on the positions of the surveillance cameras and points that are not within their fields of view. Around each camera, a zone with a radius of 10 kilometres is defined, and the points outside these zones represent areas that require additional UAV reconnaissance. Figure 2 shows the zones covered by the surveillance cameras. However, camera visibility is limited by terrain relief Geographic areas not covered by cameras are indicated by red points, which also represent UAV flyover points. These points are either manually entered by an operator or automatically generated by an artificial intelligence-based algorithm.

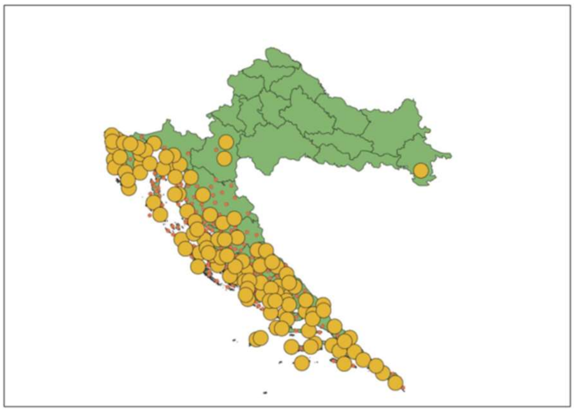

Figure 2. Map showing UAV flyover points (EPSG:3765 projection)

The second layer of the model is the temporal-dynamic component, which includes values of the Fire Weather Index (FWI). The Fire Weather Index is a meteorological indicator widely used around the world to assess wildfire danger. It consists of various components that take into account the effects of fuel moisture and wind on fire behavior and spread. The higher the FWI value, the more favorable the meteorological conditions are for fire ignition and propagation (Copernicus, 2025). Although FWI is typically calculated once per day, within this digital model it can be updated more frequently, depending on the availability of high temporal resolution meteorological data.

Based on the FWI values, reconnaissance priority is assigned to specific areas. In cases where the FWI is low, the UAV may omit such locations from its route and instead focus on zones with increased risk. In this way, the flight path is optimized, and the efficiency of territory surveillance across the Republic of Croatia is improved.

Figure 3 shows a map of the Republic of Croatia with calculated FWI values over an extended time period, while Table 1 presents the classification values used to interpret wildfire risk levels. If the FWI values for a specific area fall between 0 and 21 (see Table 1), the UAV will not pass-through points within that area, as the fire risk is considered low to moderate.

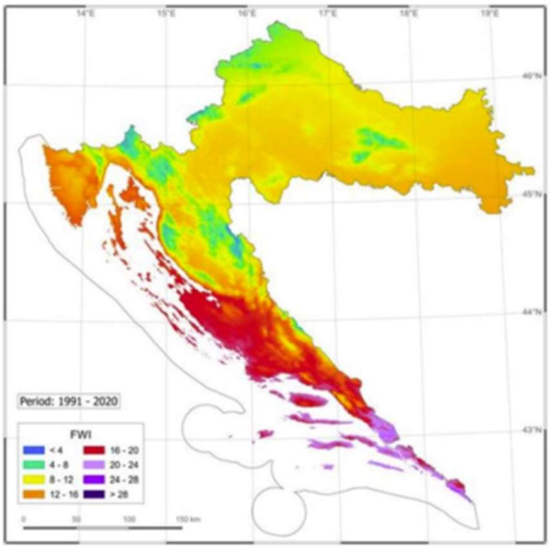

Figure 3. Fire Weather Index over an extended time period (Source: https://www.sumins.hr/en/projekti/modflux/)

Table 1. Interpretation of FWI values

FWI Range	Fire Danger Rating	Comment
0 – 5	Very Low	Moist conditions, low chances of fire ignition or spread.
5 – 12	Low	Moderately dry conditions, fire may ignite but spread is limited.
12 – 21	Moderate	Conditions allow ignition and limited fire spread.
21 – 30	High	Dry and windy conditions, rapid fire spread is possible.
30 – 50	Very High	Very favorable conditions for uncontrolled fire spread.
> 50	Extreme	Extremely hazardous conditions; fire spreads quickly and is hard to control.

The third layer of the model refers to the operational elements of the system, specifically the digital representation of unmanned aerial vehicles (UAVs), their sensor capabilities, limitations in range and flight duration, and their current status (position, battery level, activity). UAVs in the model can be deployed based on predefined rules or route optimization algorithms, and their movement is simulated in real time.

The digital model also includes a logical component that connects input data with decision-making algorithms. Based on defined rules and thresholds, the model can automatically recommend changes in reconnaissance schedules, issue alerts to operators, or generate reports on uncovered high-risk zones.

This integrated approach enables not only real-time monitoring and planning but also short-term forecasting and the execution of simulations for training purposes, system efficiency assessment, and strategic decision-making in the context of fire prevention.

4.3 Human in the Loop

In the context of the firefighting system digital twin for early fire detection, the human (operator or analyst) remains a key element in the decision-making loop, especially in situations where the automated system is unable to make an optimal decision or when system verification is required. This human role, known as Human in the Loop (HITL), serves as a corrective and supervisory-decisional factor within an otherwise highly automated system.

In the implemented digital twin, the human fulfils multiple roles:

1. Data verification: Validates the accuracy of data automatically collected and processed by system components (e.g., cameras, sensors on UAVs).
2. Decision-making: Based on the current and projected system state (e.g., fire prediction using the FWI index), the human decides on activating UAV reconnaissance.
3. Intervention: In cases of unexpected system behavior (e.g., UAV malfunction, sudden weather changes), the human can modify algorithm-generated flight plans.
4. System learning and adaptation: Feedback provided by the human can be used to train and improve the performance of predictive models within the digital twin.

The role of the human is not only reactive but also proactive, as it involves interpreting complex scenarios and making decisions that go beyond the current capabilities of automated systems. Therefore, the digital twin does not replace the human in the system, but rather provides tools to support better situational assessment and more effective responses aimed at fire prevention and environmental protection.

5 Concept of developing an automated decision-making system (AI agent)

The role of the human as a corrective factor within the fire surveillance and reconnaissance system remains indisputable, particularly in decision-making under complex and unpredictable conditions. However, with the advancement of technological infrastructure and the increasing availability of real-time data, there is a growing need for a higher degree of automation. In this context, the concept of an automated decision-making system based on artificial intelligence becomes particularly prominent.

Such an AI agent, implemented within the digital twin of the firefighting system, is responsible not only for analyzing and interpreting data but also for making decisions within predefined boundaries of autonomy.

The level of autonomy of the AI agent may vary depending on the context and complexity of the situation. At the lowest level, the agent functions as a recommendation system, providing suggestions to the operator, while the human still retains final decision-making authority. In more functionally advanced scenarios, the agent autonomously handles routine tasks, such as identifying reconnaissance areas based on fire danger index values, while seeking human confirmation for more complex decisions. At the highest level of autonomy, the agent is capable of making and executing decisions in real time, relying on previously learned patterns, safety rules, and system operational constraints.

Within the digital twin, the AI agent integrates various input data, such as geospatial information on terrain coverage by surveillance cameras, Fire Weather Index values, real-time weather forecasts, operational status and availability of unmanned aerial vehicles (UAVs), historical wildfire data, and records of surveillance equipment failures. Based on this information, the agent is capable of autonomously generating optimal reconnaissance routes, dynamically adjusting priorities in response to changing weather conditions and assessed risks, estimating the required number of UAVs for a given operation, and, in emergency situations, initiating reconnaissance without the need for human intervention.

The goal of implementing such a system is not to eliminate the human from the decision-making process, but rather to increase efficiency and reduce system response time in situations that require urgent action. This creates the foundation for advanced early warning systems, in which the digital twin functions not merely as a passive reflection of reality, but as an active, predictive, and adaptive entity capable of acting in real time.

6 UML component diagram

The system architecture is modelled using a UML component diagram to illustrate the main modules and their interactions within the proposed framework. The digital twin is central to this architecture, integrating real-time surveillance data, predictive simulation models, and AI-based decision-making to support early wildfire detection and reconnaissance.

Figure 4 shows the main components, including the unmanned aerial vehicle (UAV) fleet, data centre, digital twin model, AI agent, optimisation algorithms (such as MMAS), and camera network, as well as the interfaces and dependencies between them. The diagram highlights how data flows from surveillance cameras and UAVs to the data centre, where it is processed and fed into the digital twin. The AI agent analyses this data, optimises UAV reconnaissance routes, and can initiate missions in urgent situations.

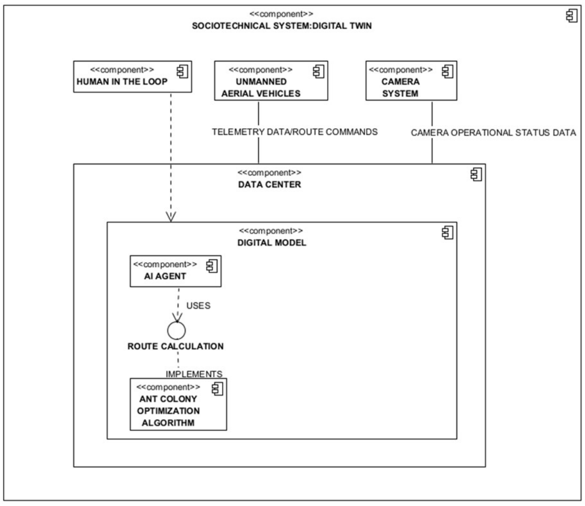

Figure 4. UML component diagram

In addition to the component diagram, other UML diagrams could also have been used to represent the system from different perspectives, such as use case diagrams, activity diagrams, sequence diagrams, class diagrams, and state diagrams. The component diagram was selected because it provides a clear and structured representation of the high-level architecture of the digital twin system. It effectively illustrates the key components, along with their interactions and dependencies. This makes it particularly suitable for communicating the modular structure and functional relationships within a complex socio-technical system.

System components:

- **Sociotechnical system** – The integrated framework combining human operators, technical infrastructure, and organisational processes for wildfire detection and reconnaissance.
- **Digital twin** – A virtual representation of the physical reconnaissance system that continuously integrates real-time data, enabling simulation, prediction, and decision-support.
- **Unmanned aerial vehicles (UAVs)** – Remotely piloted aircraft equipped with sensors and cameras for aerial reconnaissance of under-monitored or high-risk areas.
- **Camera system** – A network of fixed surveillance cameras providing continuous visual monitoring of wildfire-prone zones.
- **Telemetry data / route commands** – Data sent from UAVs to the data centre, including location, status, and sensor readings, and route instructions sent back from the control system.

- **Camera operational status data** – Information on the functional state of each camera, used for fault detection and maintenance planning.
- **Data centre** – The central hub for data collection, processing, and storage, hosting the digital twin and AI modules.
- **Digital model** – The core simulation environment within the digital twin that integrates real-time and historical data to predict system behaviour.
- **AI agent** – An AI-based automated decision-making module that analyses data, optimises UAV routes, and can autonomously initiate actions.
- **Route computation** – The process of calculating optimal UAV reconnaissance paths based on fire weather index, camera coverage, and UAV availability.
- **Algorithm** – Computational methods for optimisation, such as Max-Min Ant Colony Optimisation (MMAS), which dynamically adapts to changing conditions.

The component diagram was chosen because it provides a clear, high-level view of the architecture of the digital twin system and effectively conveys the modular structure and functional relationships within a complex socio-technical system.

7 Conclusion and future work

This paper presented a conceptual and architectural framework for the development of a digital twin of a firefighting system designed for early fire detection and prevention. By integrating physical components such as surveillance cameras, unmanned aerial vehicles (UAVs), and data centers with a multilayered digital model and an AI-based decision-making agent, the system enables real-time monitoring, adaptive response, and strategic planning. Special emphasis was placed on the interoperability between human operators and automated processes, highlighting the role of the human-in-the-loop in ensuring system reliability and informed decision-making.

The proposed approach demonstrates the potential of digital twins not only as passive representations of physical systems but as active, predictive, and autonomous tools capable of supporting complex operations in dynamic environments. The incorporation of real-time data streams, AI-driven route optimization, and scenario-based simulations lays the foundation for advanced early warning systems in wildfire management.

Future research will focus on enhancing the system's adaptability and autonomy by incorporating additional environmental and operational data into the optimization process. In particular, UAV routes in uncovered regions can be optimized using bio-inspired algorithms such as Max-Min Ant Colony Optimization (MMAS), which dynamically adapt to spatial and temporal variables, including the fire weather index.

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