

Wildfire Detection and Monitoring

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ABSTRACT

Wildfires are an increasing global threat, exacerbated by climate change. Traditional detection methods, such as ground patrols and satellites, often face delays, limited coverage, or high costs. This paper presents Evolonix, an autonomous drone-based wildfire detection system developed by Fraunhofer IISB, Fraunhofer IIS and Friedrich-Alexander University Erlangen-Nuremberg. The system integrates a fixed-wing VTOL UAV, computer vision-based smoke detection, a web-based alert platform, and an automated base station for continuous operations. A comparative analysis with existing detection technologies (sensor networks, cameras, and satellites) highlights the advantages of UAV-based monitoring in detection speed, flexibility, and real-time verification. Initial results confirm its potential for rapid wildfire detection and improved emergency response. While challenges remain, such as regulatory constraints and nighttime detection, this research demonstrates UAVs' role in enhancing wildfire monitoring and response, offering a scalable and adaptable solution to mitigate wildfire risks.

Keywords

Wildfire detection, UAV, computer vision, emergency response, autonomous drones

INTRODUCTION

In recent years, many forests and wilderness areas have been burned and devastated. Wildfire is viewed as a natural, uncontrolled disaster that poses a significant threat to a country's economy, annually destroying millions of acres of land and resulting in substantial losses of human life, vegetation, and forest resources. Wildfires are also responsible for enormous CO₂ emissions. Prompt detection and rapid response from fire departments are essential to ensure that forest fires are quickly extinguished, minimizing economic damage and loss of life (Bouguettaya et al., 2022; Jones et al., 2024; Simoes et al., 2020). While global burned area and average fire intensity have declined this century, largely due to fewer low-intensity fires in African grasslands, burn severity is increasing in more regions than it is decreasing (Cunningham et al., 2024). Additionally, as forests become drier, fires will spread more rapidly than before, leading to more severe damage. Therefore, rapid availability of information about the fire location becomes crucial in combating the flames (Schneider, 2021).

Until now, wildfire detection has relied heavily on human resources, such as foot patrols, aerial surveillance, or observation posts in towers. Currently, researchers and industry are working on developing products that enable not only early but also fully automated fire detection. These systems have only become feasible due to recent advancements in other technological fields (Schneider, 2021). For example, developments by companies like SpaceX have fundamentally changed the cost structure of the space sector, making the deployment of a larger number of satellites no longer an insurmountable financial hurdle (Reddy, 2018). Similarly, significant progress has been made in the field of long-range drones in recent years. Increasingly powerful and reliable systems now

enable the fully automated monitoring of vast areas (Telli et al., 2023). Progress is also evident on the ground. IoT sensor networks have become significantly more efficient, reliable, and cost-effective (Sarin et al., 2025). Combined with advanced artificial intelligence, large amounts of data can now be analysed in real time to detect wildfires more precisely (Lelis et al., 2024).

Wildfire detection is a complex challenge addressed by terrestrial, orbital, and aerial systems, with trade-offs in coverage, latency, and reliability. UAVs offer a promising middle ground, combining mobility with high-resolution sensing (Honary et al., 2025; Mohapatra & Trinh, 2022). However, much of the existing research remains theoretical or component-focused, lacking real-world integration and evaluation.

This work presents a complete UAV-based detection system developed and tested over two years. Unlike purely conceptual studies, our hands-on development enables a grounded analysis of where UAVs can add value within the broader wildfire detection landscape—and where limitations remain.

We first provide background on wildfire dynamics, detection methods, UAVs, and computer vision. Then we outline the system design and development conditions, followed by results from testing and expert interviews. A comparative analysis highlights the system's potential role within the broader wildfire detection landscape, and the paper concludes with a discussion of implications and future directions.

BACKGROUND

Wildfire: Dynamics and Detection Methods

Forest fires are a significant and growing global threat with profound biological, ecological, and environmental consequences (Gajendiran et al., 2024). While they are a natural part of many ecosystems, occurring across various forest types—most frequently in arid deciduous forests and less often in evergreen, semi-evergreen, and montane temperate forests—their frequency and intensity have been exacerbated by human activities and climate change (Gajendiran et al., 2024; Mansoor et al., 2022). Wildfire susceptibility depends on three key factors: the availability of combustible materials, their moisture content, and the source of ignition, which can be natural (e.g., lightning) or human-induced (e.g., discarded cigarette butts, power line arcs, or deliberate sabotage) (Kharuk et al., 2021; Sari, 2023). The impacts of wildfires extend beyond the immediate loss of biodiversity and habitat, driving environmental transformation, deforestation, land use changes, and further accelerating climate change. Declining precipitation and rising seasonal temperatures, compounded by climate change, make wildfires an increasingly frequent and severe issue worldwide (Sari, 2023). Addressing these challenges requires proactive measures, particularly in mitigating human-caused fires, which are more predictable and preventable. Additionally, adapting ecosystem-based forest management strategies offers a sustainable approach to reducing wildfire risks and preserving forest ecosystems in the face of a changing climate (Ferster et al., 2016).

As highlighted in the literature (Alkhatib, 2014; Mohapatra & Trinh, 2022; Schneider, 2021), sensor-based wildfire detection techniques are commonly categorized into terrestrial (ground-based), aeronautical (airborne), and orbital (space-based) systems. Across these categories, four primary sensing approaches are discussed. Wireless Sensor Networks (WSNs) utilize low-power sensors—such as humidity, temperature, and gas detectors—to monitor specific areas and trigger fire alerts. These ground-level systems offer localized and early detection capabilities. UAVs provide real-time, high-precision data and access to remote or dangerous locations, enhancing situational awareness during fire progression. Camera networks, often mounted on watchtowers, enable wide-area surveillance through coordinated visual inputs. Lastly, satellite-based systems, deployed by organizations such as NASA, NOAA, and private companies like OroraTech, deliver broad-scale, high-altitude monitoring. Together, these technologies offer a multi-layered detection framework ranging from ground-level sensors to planetary observation.

UAVs: Technology and Applications

Unmanned Aerial Vehicles (UAVs), commonly known as drones, are aircraft that operate without a human pilot on board. They can be remotely controlled or fly autonomously using pre-programmed flight plans. UAVs are used in various applications, including object detection and tracking, security, surveillance, military operations, navigation, sensing, data sharing, emergency and crisis management, freight transportation, logistics and wildfire monitoring (Mohsan et al., 2022; van Blyenburgh & Peter, 1999; Yin et al., 2020). The UAV sector showcases AI applications, with control systems at its core. While automatic flight is achieved and intelligent autonomous controlled missions are possible, challenges remain. Future UAV advancements depend on AI progress (Yin et al., 2020).

Table 1: Number of Publications Related to 'Wildfire' and 'Drones' in Scopus Over the Past Five Years.

	2019	2020	2022	2023	2024
Number of Publications	15	22	37	61	90

The concept of utilizing drones in wildfire-related scenarios appears to have gained traction over the past five years, as suggested by the growing number of publications (see Table 1). Drones are being employed in a variety of innovative applications, ranging from environmental monitoring to active wildfire suppression. For instance, UAVs equipped with environmental sensors are being used to monitor critical parameters such as temperature, humidity, and vegetation, aiding forest fire prevention (Lelis et al., 2024). These capabilities are further enhanced by advances in sensor fusion, where optical, infrared, and synthetic aperture radar (SAR) data are combined to improve wildfire detection accuracy (Abdusalomov et al., 2024; Simoes et al., 2020). Additionally, drones equipped with acoustic sensors have enabled continuous localization of moving acoustic sources, providing a novel approach to tracking the spread of wildfires (Correia et al., 2022). Beyond detection and monitoring, drones can also serve in wildlife management during wildfires, monitoring large animals or small groups to ensure their safety (Ivanova et al., 2022). In active fire suppression efforts, drone swarms have been coordinated to carry fire suppressants, offering efficient solutions to combat wildfires (Blais & Akhloufi, 2024). Drone swarms can operate semi-autonomously, enhancing their utility in large-scale wildfire management (Harris & Li, 2023).

Computer Vision: Object Detection and Vision Language Models

Computer vision enables machines, including UAVs, to visually perceive their environment and respond to specific tasks. Inspired by the biological visual system, cameras act as eyes, while computer vision algorithms serve as the brain, extracting meaningful information from digital images and videos. In wildfire detection, object detection is the most applied computer vision task but comes with challenges such as scale variance, orientation differences, and cluttered backgrounds. To overcome these, architectures like YOLO (You Only Look Once), SSD (Single Shot MultiBox Detector), and Faster R-CNN are widely used, each with unique strengths and limitations (Bouguettaya et al., 2022; Ramos et al., 2024).

Recent advances in Natural Language Processing have led to the development of Vision Language Models (VLMs), a type of Large Language Model capable of processing visual inputs. These models can generate human-like descriptions of visual data, making them highly adaptable for interpreting images or videos. Trained in extensive datasets, VLMs offer remarkable generalization, enabling them to perform effectively without task-specific training (Wei & Kulkarni, 2024). This capability makes them well-suited for real-time wildfire monitoring, where immediate interpretation of visual information is crucial for practical applications.

METHODS

The UAV-based wildfire detection system was developed through a collaboration between Fraunhofer IISB, Fraunhofer IIS, and FAU Erlangen-Nuremberg, with the goal of creating a modular, field-deployable solution for real-time fire monitoring in high-risk, low-connectivity areas.

System Architecture

The UAV system consists of a fixed-wing vertical take-off and landing (VTOL) drone, a weatherproof base station for autonomous recharging, and a web-based control and alerting platform. The aircraft has a three-meter wingspan, and a lift-and-thrust configuration optimized for deployment from unprepared terrain. With a cruising speed of 65 kph and a flight time of approximately 90 minutes, the platform is capable of covering up to 100 km per mission.

An onboard NVIDIA Jetson Orin NX processes video in real time using a YOLOv8 instance segmentation model. The drone's payload includes a global shutter RGB camera with a large one-inch sensor. ROS2 manages flight control integration and supports low-latency inference via a TensorRT-optimized model running on a custom C++ node.

Data Collection and Model Training

The YOLOv8 model was trained on a custom dataset developed with support from German fire brigades, combining images from real wildfire incidents and controlled test burns. The dataset also included original drone footage captured during test missions as well as curated wildfire images and videos from publicly available online sources. All data were manually annotated and selected to reflect a range of smoke visibility conditions, scene complexity, and lighting environments.

Training was conducted using PyTorch in FP32 precision to preserve numerical stability, followed by TensorRT graph optimization and conversion to FP16 for efficient real-time edge deployment on the Jetson Orin NX. The final model was deployed as a TensorRT-optimized inference engine, integrated into a custom C++ ROS2 node for low-latency processing.

Stakeholder Interviews

To align system capabilities with operational needs, structured interviews were conducted with 15 experts from fire services, forestry, and disaster management agencies. Insights from these interviews informed both technical requirements (e.g., interface design, communication protocols) and the comparative framework used in evaluating UAVs alongside other detection systems.

Qualitative Analysis

For the last part of the discussion a qualitative analysis was conducted to evaluate the UAV-based wildfire detection system. Following Schneider's framework, functional (alerting, information, error susceptibility), non-functional (usability, readiness, integration), and administrative (environmental impact, parallel use, security) requirements were defined. Based on these, a questionnaire was developed, and 15 expert interviews were conducted across three key sectors: incident management (fire department control centres, wildfire response teams), disaster and fire protection authorities (state-level agencies overseeing wildfire suppression), and forestry experts (focusing on parallel use and prevention). The collected insights were analysed using a utility assessment, providing a structured evaluation of the system's applicability and effectiveness.

FINDINGS & DISCUSSION

Drone Platform and Components

For wildfire detection, a fixed-wing VTOL drone (see Figure 1 (a)) was selected due to its significant advantages over conventional aerial vehicles, including reduced landing space requirements, high agility, and superior cruising speed (Tielin et al., 2017). The VTOL configuration proved highly effective for wildfire scenarios due to its minimal launch space requirements and flexible deployment from remote or forested areas. The system's cruising performance enabled broad area coverage (up to 100 km per flight), supporting continuous monitoring missions without the need for dedicated infrastructure.

A key component of the system is the base station (see Figure 1 (a)), which primarily functions as an automated charging hub, allowing the drone to recharge between missions and facilitating continuous autonomous operation. Additionally, the base station serves as a communication relay, ensuring redundant and reliable data transmission between the drone and emergency services. Given the system's deployment in remote or unguarded locations, the base station also incorporates protective measures to safeguard against vandalism and external damage.

The web interface (see Figure 1 (b)) acts as the primary connection between the fire brigades and the drone system, offering real-time video stream and meteorological data such as wind speed, temperature, and humidity—critical parameters influencing both wildfire likelihood and propagation. The platform also provides precise, formatted coordinates for responders in standardized formats, streamlining emergency response workflows. Moreover, it integrates detailed maps, including a classification of the roads in regards to parameters such as load bearing capacity and road condition, ensuring an optimized approach strategy for emergency vehicles navigating forested terrain.

Field testing confirmed the system's ability to detect visible smoke within five minutes at distances exceeding 2 km, under moderately damp conditions. The global shutter camera and high-sensitivity sensor significantly improved image clarity, especially in complex outdoor environments. The YOLOv8 model, running in real time on the Jetson Orin NX, demonstrated reliable smoke detection performance. ROS2 integration ensured stable coordination between inference and flight control. Current development includes exploration of temporal

detection enhancements using LSTM and Transformer architectures, as well as the integration of Vision Language Models (e.g., LLaVA, Pixtral) to improve interpretability and contextual analysis during detection events.

(a) Drone and Basestation



(b) Web Interface

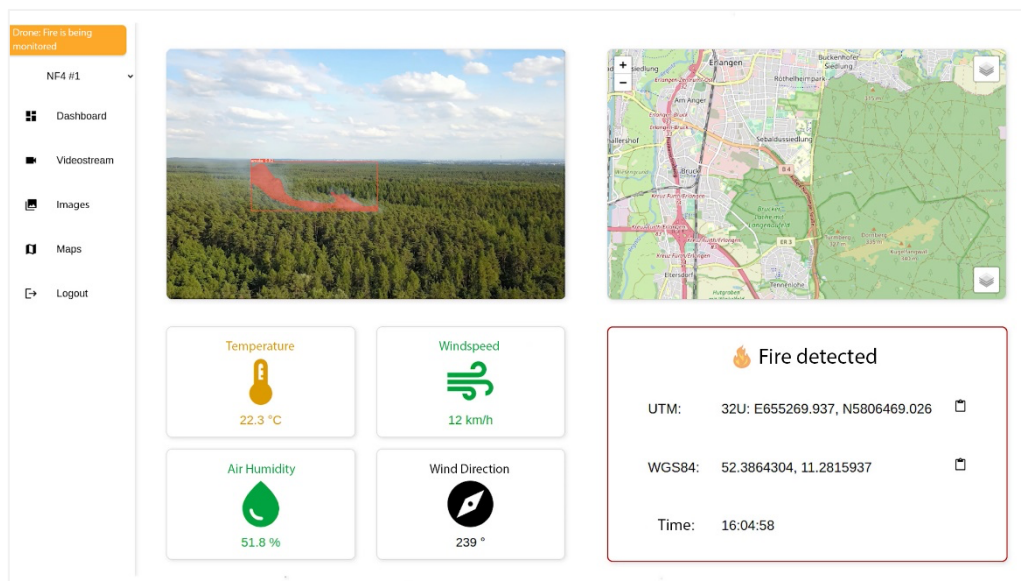


Figure 1: (a) Rendered image of the drone taking off from the base station to fly a mission and (b) screenshot of the web interface showing the video stream, map, meteorological data and coordinates.

Autonomous Operations

The wildfire detection system operates through the automated surveillance of predefined forest areas using previously described long-range UAVs. The operation begins with the drone taking off from its base station and following a pre-programmed flight route on autopilot. Throughout its flight, the drone continuously monitors the environment using an onboard camera system. The captured images are processed in real time by an integrated computing unit to detect signs of wildfire, such as smoke or flames.

If the drone identifies potential fire activity, it immediately generates an alert and transmits it to the responsible control centre via a dedicated online platform. Alongside the alert, the drone sends images of the detection and additional sensor data, allowing the control centre dispatcher to assess the situation remotely (see Figure 2 (a)). The transmitted information can include details on vegetation types, accessibility of the affected area, and nearby protection targets, providing crucial context for an informed decision-making process. Meanwhile the drone starts cruising to the fire source, to deliver further confirmation and data on the detection. The visualization of the fire situation supports the dispatcher in evaluating the severity of the event, determining the necessary deployment of firefighting resources, and minimizing false alarms by verifying detections before mobilizing emergency personnel. Unfortunately, forest fires are mostly caused by humans. Some fires have also been started deliberately by humans. Here, the system can also be used to preserve evidence at an early stage. This question will be investigated in further research.

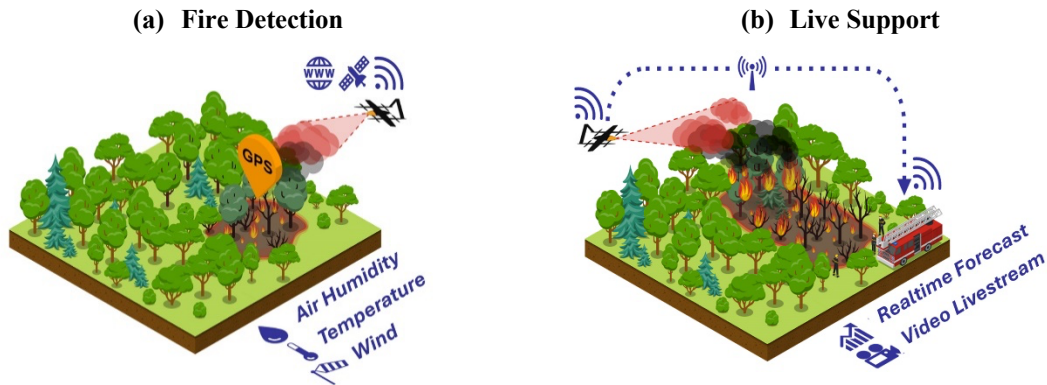


Figure 2: Isometric illustrations of (a) the drone detecting a wildfire and (b) the drone monitoring the situation and providing an overview of the situation for fire brigades.

Once the presence of a wildfire is confirmed, the control centre initiates the dispatch of firefighting forces to the scene. Throughout the entire operation, the drone remains in proximity, continuously transmitting updated images and situational data to both the control centre and the incident command (see Figure 2 (b)). This live data feed ensures that first responders receive up-to-date information even before arriving at the scene, enabling them to improve their approach to the scene of an emergency and better prepare for the specific challenges posed by the fire. In addition to visual data, the drone collects local meteorological information, including wind speed, humidity, and temperature, which aids in assessing fire dynamics, predicting fire spread, and planning containment strategies.

To further enhance operational effectiveness, the drone is designed to remain airborne over the affected area for its remaining flight time. During this critical initial phase of firefighting, it provides continuous aerial surveillance, delivering a comprehensive real-time overview of the situation as it evolves. This capability supports both tactical decision-making on the ground and strategic coordination from the control centre. Additionally, the drone can also search for people in the vicinity of the fires. As soon as these have been identified, optimal escape routes can be evaluated in combination with an analysis of the wind direction and information on the road network. Signals on the drone could be used to recommend the evacuation direction to people and guide them out of the danger zone.

At the conclusion of its mission or upon reaching the limits of its flight time, the drone autonomously returns to its base station, where it undergoes recharging in preparation for its next deployment. This automated cycle of surveillance, detection, and reporting ensures that the system maintains continuous wildfire monitoring with minimal human intervention, providing an efficient and reliable tool for early fire detection and response.

Testing

The testing phase was designed as a multi-stage process to systematically evaluate the stability and performance of the system. Since it was unrealistic to gather all relevant data in a single experiment, the tests were divided into distinct phases, each focusing on different aspects of the system's functionality.

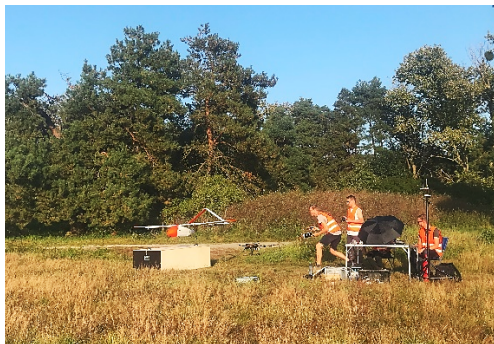
The first phase aimed to assess the long-term stability of the drone. Specifically, it was important to determine how individual components would perform under frequent and continuous operation. To investigate this, an endurance test was conducted in August and September 2023. Over a period of more than 30 days, the drone

completed approximately 50 flights in the Staatsforst Mark near the city of Möhrendorf, north of Erlangen. The primary focus was to identify potential fatigue effects on motors, sensors, and structural components. No significant material fatigue was observed, although one servo motor for a landing flap was damaged during transport due to improper handling. Additionally, the test evaluated communication reliability in rural areas with generally weaker network coverage. Interestingly, it was observed that the drone maintained a more stable connection in the air than on the ground. Due to delays in obtaining the necessary flight permits, all flights were conducted as visual line of sight flights. However, one anticipated aspect that could not be tested was the detection of actual wildfires, as the test period coincided with a relatively moist season. Given the inherent difficulty of encountering a wildfire even under drier conditions, a separate detection accuracy test was planned.

To refine the parameters for fire detection, an additional test sequence was conducted in September 2023 (see Figure 3 (a)) near Calvörde, Saxony-Anhalt. Previous laboratory-based image analyses had confirmed that the AI was capable of detecting wildfires, but its detection accuracy, range, and response time under real conditions remained unknown. The objective of this field test was to determine the time required for fire detection, the maximum detection distance, the minimum detectable fire size, and the accuracy of fire localization. Since precise timing and location of fire ignition were crucial for these measurements, the test was conducted in collaboration with a research team within the TREEADS project, led by the German Federal Institute for Materials Research and Testing (BAM), the Otto von Guericke University Magdeburg, and OneSeven. Following a week of rainfall, the forest remained moderately damp on the test day, posing challenges in sustaining a fire larger than 2×2 meters. Despite these conditions, the system successfully detected the fire from a distance exceeding 2 km in under five minutes. However, due to the constraints of the test area, detection at greater distances (beyond three kilometres) was not assessed. The localization accuracy varied, with most detections falling within 500 meters of the actual fire location. Future tests are planned to refine these aspects, with a focus on greater detection distances and improved localization precision.

A further crucial step in the testing process involved the firefighter integration tests, particularly the development and validation of the base station (see Figure 3 (b)), which serves as the final link toward achieving fully autonomous operation. The base station was completed in July 2024 and has since undergone multiple test cycles. Initially, it was tested using manual drone control, with the station itself being remotely operated via an internet connection. The next phase involved training the automated landing system within a confined space, first a smaller test drone and later with full integration. By November 2024, the first fully autonomous landing of the drone on the base station was successfully completed. Looking ahead, long-term testing will be expanded.

(a) Detection Testing



(b) Basestation Testing



Figure 3: Images of (a) detection tests performed in September 2023 and (b) base station tests in July 2024.

Since December 2024, the research has obtained Beyond Visual Line of Sight (BVLOS) approval from the German Federal Aviation Authority (Luftfahrt-Bundesamt). This authorization will allow for autonomous flights beyond the pilot's line of sight, with the first BVLOS test flights scheduled for 2025. Further real-world wildfire detection tests will also be conducted to validate and refine the system under operational conditions.

Qualitative Comparison with Existing Systems

The qualitative comparison from Table 2 and following is based on expert interviews, technical documentation, and field experience gained during the system's development and testing. Criteria were defined collaboratively with practitioners to reflect operational priorities in wildfire detection. By comparing Evolonik to established detection approaches, this study highlights the specific operational contexts where UAVs can provide complementary benefits, particularly in regions with limited infrastructure or difficult terrain.

Table 2: Qualitative Comparison of Wildfire Detection Systems

	Detection Speed	Sampling Rate	Detection Accuracy	Coverage Area	False Alarm Mitigation	Night Ops	Multi-Purpose Use
Dryad (WSN)	max. 60 min (100 m radius)	continuous	medium to high (varies by terrain)	local (sensor radius 100–500m)	moderate	yes	environmental sensing
IQFirewatch (camera)	5–12 min	5 minutes	medium to high (varies by terrain)	wide (up to 20 km range)	operator filtering needed	yes	detection only
OroraTech (satellite)	max. 90 min	>25 times per day	low to medium (16 m ² –1 km ² fire size)	very wide (regional to global)	low (requires manual review)	yes	risk assessment & detection
Evolonic (UAV)	~5 min	60 minutes	high (camera + AI)	medium (500 km ²)	High (real-time visual confirmation)	no	search & rescue, mapping

Comparison of WSNs, UAVs, camera networks, and satellite detection as innovative tools for wildfire prevention is based on the reliability of reporting, the scope of information provided, and susceptibility to errors. Representative systems commonly used in Germany were analysed: Dryad (WSN), Evolonic (UAVs), IQFireWatch (camera networks), and OroraTech (satellite detection). The verification process included manufacturer datasheets, scientific studies, and expert interviews. To provide a qualitative comparative analysis, the following section combines expert opinion with information on each system gathered during the interviews.

The reliability and accuracy of wildfire alerts are critical, especially in regions where fire departments predominantly depend on volunteer firefighters, such as Germany, where 96.5% of firefighters serve on a voluntary basis. False alarms strain resources and disrupt lives, making accuracy essential. The effectiveness of a system is determined by its ability to provide timely and precise alerts while minimizing false alarms. Furthermore, any added value must exceed the status quo, where wildfires are typically reported by the general public. IQFireWatch has demonstrated high reliability in wildfire detection, particularly in flat terrains. Scientific studies, including artificial smoke and real fire tests, to assess its performance. The system successfully detected 75% of artificial wildfires and 50% of natural wildfires within a 10 km range. Its localization accuracy ranges from 400 m within 10 km to 800 m at distances up to 20 km (Hsieh, 2023). In comparison to similar systems, the results were satisfactory but still derived from what experts were mentioning across interviews, which might be due to a small sample size during testing. Factors such as vegetation, wind conditions, camera tower height, and topography further influence the accuracy. False alarms, often caused by agricultural dust, can be filtered out by experienced operators who recognize differences in smoke behaviour leaving room for automated recognition systems. Dryad's WSN-based detection system provides precise local alerts as sensors are positioned every 100 meters (500 meters in remote areas), offering a detection accuracy comparable to camera networks in close proximity. It is particularly effective for detecting small and smouldering fires at the ground level, which aids in identifying reignition events. However, verification can be achieved when multiple sensors trigger alarms simultaneously causing detection times to fluctuate and thus a lack of real-time verification. Additionally, gas dispersion by wind may lead to multiple simultaneous sensor activations, complicating localization (DRYAD, 2025; Göttelein et al., 2023). OroraTech's satellite-based detection varies significantly based on the satellite's resolution, typically requiring fire sizes between 16 m² and 1 km² to be detected. The system is particularly beneficial for monitoring large wildfires in remote areas but is less effective for small fires. The resolution limitations affect precise localization, and false alarms can arise from heat sources such as newly paved roads or industrial zones. While many false alerts can be filtered based on geographical context, each detection requires manual verification, highlighting potential for further automation. However, verifying fire detections remains challenging due to the limited availability of more precise local data. Evolonic's UAV system provides highly precise alerts and can cover up to 500 km². Initial tests suggest effective fire detection within 5 minutes under ideal conditions. The onboard RGB camera allows accurate real-time localization and verification alerts,

significantly reducing false positives caused by agricultural dust or other heat sources.

Information Scope and Multi-Purpose Use refers to the availability of additional information enhances decision-making for emergency responders. Firefighting operations benefit from comprehensive situational awareness, including fire behaviour predictions and real-time imagery. Given the high cost of these technologies, their ability to serve additional purposes is also an advantage. IQFireWatch provides live imagery from fixed cameras, allowing a rough estimation of fire size. However, it does not support operational assistance or multi-purpose use. Dryad offers a similar estimation of fire extent based on sensor activity and plans to open their mesh network to third parties, by integrating additional and external environmental sensors in the future. OroraTech combines fire location data with topographical and meteorological information, aiding in fire spread predictions. It is particularly valuable for large-scale monitoring but has limited utility for small fires. Evolonic UAVs offer real-time imagery of the fire and surrounding areas, report detailed information using VLMs, and collect meteorological data such as wind speed, humidity, and temperature. This makes them highly versatile for various emergency applications beyond wildfire detection.

Detection Speed and Operational Availability offers the ability to detect fires quickly is critical in minimizing damage. Ultimately, effective systems should operate continuously and provide alerts with minimal delay. IQFireWatch conducts scans every five minutes, achieving fire detection times of 5–12 minutes based on studies in Canada. It functions effectively at night using near-infrared sensors (Schneider, 2021). Dryad's sensor network also provides continuous monitoring, though there is limited data on its exact response time. OroraTech scans up to 25 times per day, making it one of the most frequently updated satellite-based systems. However, cloud cover can obscure observations, and signal processing introduces latency of 30–90 minutes. Additionally, in Europe, reduced satellite coverage occurs during afternoon hours—coinciding with peak wildfire risk hours—limiting its early detection capabilities. In March 2025, OroraTech launched eight further dedicated wildfire satellites, providing real-time thermal data during critical periods—such as afternoon and night—when public satellite systems typically lack coverage, increasing their constellation to 25+ satellites (OroraTech, 2025). While Evolonic's UAV system depends on the drone fleet size in use, an hourly flight schedule can be expected to provide reliable fire detection. However, its reliance on optical cameras restricts nighttime operation, reducing its early detection capability compared to permanently deployed ground-based systems or satellites.

In summary, each system presents distinct strengths and weaknesses. Camera networks and WSNs offer high accuracy and rapid detection for localized monitoring, making them particularly valuable in populated regions where the risk of economic damages and casualties is high and where fire brigades have quick access. However, WSNs involve higher costs due to the large number of sensors required for deployment. Meanwhile, satellites provide extensive coverage but with delayed reporting, making them more suitable for remote areas that are less accessible and where potential damages are generally more manageable. UAVs bridge the gap by offering flexible, real-time verification and detailed situational awareness, allowing for faster response times and more targeted firefighting efforts. Their ability to quickly assess evolving fire conditions and relay critical data to emergency services, while still being able to cover vast surfaces enhances overall wildfire management, reducing the risk of uncontrolled spread. But, the limited practical application and experience with UAV-based systems currently hinder a reliable comparison with established wildfire detection methods.

CONCLUSION

The research demonstrates the potential of UAV-based autonomous wildfire detection, combining long range drone technology, real-time computer vision, and an integrated emergency response web interface. By developing a VTOL drone system capable of detecting and monitoring wildfires with high precision and transmitting critical data to emergency responders, the study addresses key challenges in early wildfire detection. The collaboration between academia, research institutions, and emergency services has enabled the creation of a functional proof-of-concept system, highlighting the feasibility of UAV-based solutions for wildfire monitoring.

Based on two years of hands-on development and field testing, this study offers a grounded comparative perspective on the role of UAVs alongside existing detection methods, such as sensor networks, satellite systems, and camera towers. UAVs offer unique advantages in mobility, responsiveness, and real-time verification, particularly in regions with limited infrastructure or difficult terrain. While this analysis is qualitative in nature, it reflects operational insights gathered through system deployment and expert interviews. This study is limited by the scope of field testing and the absence of quantitative benchmarking; however, the findings provide a starting point for integrating UAVs into broader wildfire management frameworks.

Despite promising capabilities, several limitations remain. The system's performance in large-scale wildfire scenarios is not yet fully validated, and environmental conditions such as heavy rain, strong wind, or dense smoke may affect detection accuracy. Furthermore, regulatory barriers—especially restrictions on beyond-visual-line-of-sight (BVLOS) flights—currently constrain fully autonomous deployment. Continued development of the base

station, including improvements in landing precision and energy efficiency, is also necessary to ensure long-term sustainability.

Looking ahead, future work will focus on expanding detection robustness, automating operations further, and exploring the use of UAV fleets and swarm coordination to increase coverage. Ongoing collaboration with emergency services and regulatory bodies will be essential for operational integration. As more long-term field tests are conducted, UAV-based detection can evolve into a reliable complement to existing wildfire monitoring systems.

While challenges remain, the research represents a meaningful step forward in applying autonomous UAV technology to wildfire detection. With targeted technical refinements and interdisciplinary cooperation, UAV systems have the potential to become a vital part of future wildfire response strategies.

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The technical foundation of the system builds on work conducted under “Project Silver,” which began in 2017 with the development of a fixed-wing VTOL drone for the New Flying Competition. The team’s early platform, based on a tailsitter configuration, evolved into a double-decker box-wing design and later a separate lift-and-thrust architecture, ultimately securing first place in both the 2020 and 2022 competition editions. These milestones played a critical role in shaping the current system architecture.

Following the competitions, the team refocused the project toward real-world applications such as gas pipeline inspection, agricultural monitoring, and ultimately wildfire detection. This shift led to the rebranding of the project as Evolonic and the development of a modular UAV platform integrating onboard computer vision, an automated charging base station, and a web-based alerting interface. The entire system remains at the prototype stage but demonstrates fully functional operational capabilities.

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