An Integrated Multi-Sensor UAV System for Early Wildfire Detection and Risk Assessment

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Abstract
Wildfires are increasing in frequency and severity throughout California due to anthropogenic climate change (e.g., prolonged drought) and expanding development near wildland areas, creating an urgent need for improved methods of identifying wildfire risk before ignition. Existing satellite and ground-based monitoring systems provide valuable information but are often limited by low spatial resolution or delayed detection after combustion has begun. Specifically, from a satellite's perspective, high optical depth from wildfire smoke significantly disrupts hotspot and active wildfire detection. This project presents a conceptual design of an integrated unmanned aerial vehicle (UAV) platform that combines sensing approaches, including weather sensors, multispectral imaging, light detection and ranging (LiDAR), thermal imaging, and air-quality sensors, to monitor environmental conditions associated with wildfire ignition. Machine learning approaches are incorporated as a proposed component for analyzing the collected data, identifying patterns linked to wildfire risk, and supporting earlier detection of developing fires. The resulting research-supported UAV design demonstrates how multiple sensing technologies can be merged into a unified wildfire prediction and detection system. Such a platform could improve wildfire risk assessment, enable earlier mitigation strategies, and support more effective emergency response while reducing wildfire impacts on ecosystems and nearby communities. Additionally, the platform could be scaled through the coordinated deployment of multiple UAVs to increase aerial coverage and enable broader monitoring across wildfire-prone regions.

Keywords
Unmanned Aerial Vehicle (UAV), Wildfire Detection, Wildfire Risk Assessment, Remote Sensing, Thermal Imaging, Multispectral Imaging, LiDAR, Environmental Monitoring, Machine Learning, Sensor Fusion

1. Introduction
Wildfires have become one of the most significant environmental challenges facing California and many other regions around the world. Rising temperatures, prolonged drought, changing precipitation patterns, and expanding development near wildland areas have increased the frequency, size, and severity of wildfires over recent decades (1, 21). Across western U.S. forests, the annual area burned by large wildfires increased by approximately 1,200% between 1984 and 2015, with climate change identified as a major driver of this increase (8). In California specifically, the annual area burned by wildfires increased by approximately 405% between 1972 and 2018, while forested regions experienced increases exceeding 760% during the summer fire season (21). These long-term trends in California are illustrated in Figure 1, which shows the substantial increase in annual burned area across the state over recent decades.

The growing frequency and severity of wildfires have significant environmental, ecological, and societal consequences. Wildfires threaten ecosystems, reduce biodiversity, damage infrastructure, degrade air quality, endanger human health, and impose substantial economic costs while placing increasing demands on emergency response agencies (1, 21). Researchers

attribute much of this increase in wildfire activity to anthropogenic climate change, which has produced warmer temperatures, and reduced fuel moisture, creating conditions that favor wildfire ignition and rapid fire spread (21). As wildfire activity continues to increase, improving methods for assessing wildfire risk before ignition has become an increasingly important area of scientific research (14).

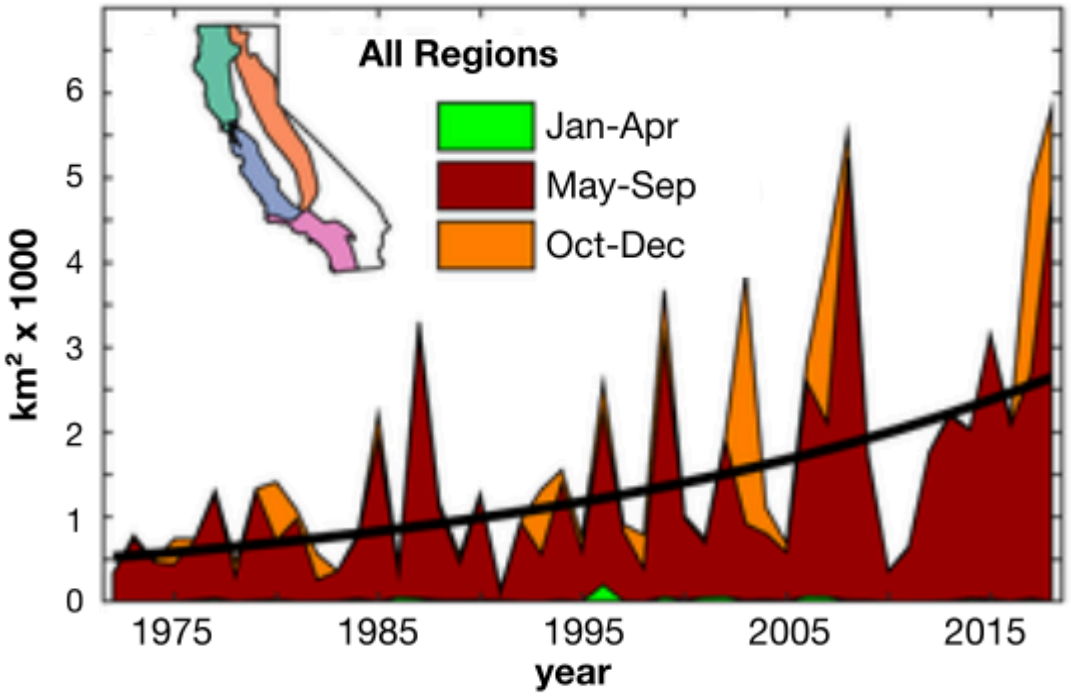


Figure 1. Annual burned area (x1,000 km^2) in California from 1972 to 2018 illustrating the long-term increase in wildfire extent. The burned area is categorized by January–April (green), May–September (red), and October–December (orange), while the bold black curve indicates the statistically significant long-term trend ($p < .05$). The figure shows a substantial increase in annual burned area over recent decades, particularly during the primary wildfire season. Adapted from "Observed impacts of anthropogenic climate change on wildfire in California", by A. P. Williams et al., 2019, *Earth's Future, 7*(8), 892–910. https://doi.org/10.1029/2019EF001210.

Increasing temperatures have significantly elevated wildfire risk by creating conditions that promote fire ignition and spread. California has warmed by approximately 1.8°F (1°C) since the early twentieth century, with the greatest warming occurring during summer months when wildfire conditions are most severe (21). In California's Sierra Nevada, each 1°C increase in average summer daily temperature was associated with a 19–22% increase in wildfire occurrence and a 22–25% increase in burned area (10). These increasing risks emphasize the need for improved methods to assess wildfire conditions and identify potential ignition events before fires become difficult to control.

Current wildfire monitoring relies primarily on satellite imagery, weather stations, and ground-based observations (14). Although these systems provide valuable information about

environmental conditions and active fires, they also have important limitations. Satellite observations often provide broad regional coverage but may be limited by revisit frequency, cloud cover, smoke interference, or insufficient spatial resolution for detecting localized hazardous conditions, while ground-based weather stations are restricted to fixed locations and cannot easily monitor remote or rapidly changing environments (14). Consequently, hazardous environmental conditions that contribute to wildfire ignition may not be identified until after combustion has already begun.

Recent advances in unmanned aerial vehicles (UAVs), remote sensing technologies, and machine learning provide new opportunities for wildfire monitoring. UAVs can collect high-resolution environmental data while carrying multiple sensors capable of measuring weather conditions, vegetation characteristics, terrain features, surface temperature, and combustion-related gases (2, 14, 17). Integrating these complementary measurements into a single platform may provide a more comprehensive assessment of wildfire risk by capturing interactions among atmospheric, vegetation, terrain, thermal, and combustion-related variables that influence wildfire development. Machine learning algorithms can further analyze multiple environmental variables simultaneously to identify patterns associated with wildfire susceptibility and support earlier identification of hazardous conditions (14).

Despite significant progress in UAV-based wildfire monitoring, much of the existing research focuses on individual sensing technologies rather than combining multiple environmental measurements into a unified prediction system (2, 14, 17). This project addresses that gap by investigating which environmental variables are most strongly associated with wildfire ignition, evaluating the sensing technologies capable of measuring those variables, and developing a conceptual integrated UAV platform for wildfire risk assessment. Specifically, this study asks: *How can an integrated multi-sensor UAV platform improve the prediction of wildfire ignition risk and enable earlier wildfire detection compared to current monitoring methods?*

2. Literature Review

Weather conditions are among the most influential environmental factors affecting wildfire ignition and behavior (11). Sadatrazavi et al. (2022) examine the relationship between meteorological variables and wildfire occurrence and identify relative humidity, air temperature, wind speed, precipitation, and atmospheric pressure as important predictors of wildfire susceptibility (18). The study demonstrates that high temperatures and low relative humidity reduce fuel moisture content (FMC), causing vegetation to become drier and more susceptible to ignition (8, 18). Climate-driven increases in atmospheric dryness and fuel aridity have also been identified as major contributors to increasing wildfire activity across the western United States (8). Additionally, strong winds contribute to wildfire development by increasing oxygen availability and transporting embers that accelerate fire spread (11). These findings demonstrate that weather variables are critical inputs for wildfire prediction models; however, no single meteorological measurement is sufficient to accurately predict wildfire occurrence. Although weather-based wildfire prediction has been extensively studied, fewer studies investigate the simultaneous collection of multiple atmospheric variables using UAV-based sensor systems for real-time wildfire risk assessment (18).

Recent advances in UAV remote sensing have improved the ability to evaluate vegetation characteristics and terrain features associated with wildfire susceptibility (9, 14). Mohapatra and Trinh (2022) review the use of UAV-mounted RGB, multispectral, hyperspectral, and LiDAR sensors for analyzing vegetation type, biomass availability, canopy structure, and fuel moisture content (14). Vegetation characteristics strongly influence wildfire behavior because different plant communities contain varying levels of combustible material, moisture retention, and fuel availability (12). Mohapatra and Trinh (2022) discuss vegetation indices, including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Red Edge Index (NDRE), and Normalized Difference Moisture Index (NDMI), which estimate vegetation health, biomass conditions, and fuel moisture through multispectral imagery (14). UAV-based remote sensing provides high-resolution measurements that can improve characterization of vegetation conditions compared with traditional satellite observations, particularly in areas with complex terrain or rapidly changing environmental conditions (9). However, much of the existing UAV research focuses primarily on vegetation mapping rather than integrating vegetation measurements with atmospheric and chemical sensing technologies into a unified wildfire prediction platform (14).

Thermal imaging and multispectral sensing provide additional methods for identifying wildfire risk conditions and detecting environmental changes associated with increased ignition potential (2, 13). Barber et al. (2021) investigate the use of UAV-mounted infrared and visible-light sensors to estimate fuel moisture conditions in vegetation (2). The study demonstrates that UAV-based thermal and optical measurements can assess vegetation moisture variability, which is an important factor influencing wildfire susceptibility because drier fuels ignite more easily. Thermal infrared imaging provides information about surface temperature conditions, while multispectral sensing evaluates vegetation characteristics associated with changing fuel conditions. Remote sensing approaches that combine spectral information with thermal measurements have been shown to improve the assessment of vegetation stress and moisture conditions related to wildfire risk (13). Combining thermal and multispectral measurements has the potential to provide a more complete assessment of wildfire risk than relying on either sensing method independently. However, many existing studies evaluate these technologies separately rather than integrating thermal measurements with atmospheric and chemical data collected from the same UAV platform (2).

Air-quality sensors provide another approach for improving early wildfire detection by identifying combustion-related indicators before flames become visible. Rjoub et al. (2023) evaluate UAV-compatible air-quality sensors capable of measuring particulate matter 2.5 (PM2.5), carbon monoxide (CO), carbon dioxide (CO_2), and other combustion products (17). The study demonstrates that increased concentrations of particulate matter and combustion gases can indicate active or smoldering combustion, allowing UAVs equipped with lightweight chemical sensors to monitor wildfire-prone areas rapidly. These sensors provide an advantage over traditional visual detection methods because they can identify atmospheric changes associated with combustion before large visible fire activity develops. However, chemical sensing alone does not provide a complete assessment of wildfire risk, and relatively little research combines air-quality measurements with thermal, vegetation, terrain, and weather data for comprehensive wildfire prediction (17).

Integrated analysis of biomass, terrain, and environmental conditions further demonstrates the importance of combining multiple wildfire risk variables. Wang et al. (2026) examine how biomass density, vegetation structure, and topographical characteristics influence wildfire intensity and spread (20). Using UAV-based multispectral imaging and LiDAR measurements, the study demonstrates that greater biomass availability provides additional fuel for wildfire development, while steep terrain accelerates fire movement through preheating and increased spread rates. These findings show that combining vegetation analysis, terrain mapping, and environmental monitoring produces a more accurate representation of wildfire risk than evaluating individual variables independently (14, 20). However, despite improvements in integrated environmental datasets, limited research explores UAV platforms capable of simultaneously collecting atmospheric, vegetation, terrain, thermal, and air-quality measurements while using machine learning algorithms for real-time wildfire prediction (20).

Collectively, these studies demonstrate that wildfire behavior is controlled by multiple interacting environmental factors, including atmospheric conditions, vegetation characteristics, terrain features, thermal conditions, and combustion indicators (2, 14, 17–18, 20). Existing research validates the effectiveness of individual sensing technologies for wildfire monitoring; however, a significant gap remains in developing an integrated UAV platform capable of combining these measurements into a unified wildfire prediction system.

3. Methods

3.1 Research design

This study uses a qualitative literature review and engineering design approach to investigate how an integrated unmanned aerial vehicle platform can improve wildfire prediction and early wildfire detection. The term UAV platform is used rather than simply drone because the proposed system integrates the aircraft with multiple sensing technologies and data-processing capabilities as a unified monitoring system. Compared with ground-based systems, a UAV platform also provides greater mobility and flexibility for collecting localized environmental data across wildfire-prone areas. Rather than collecting experimental field data, the study synthesizes findings from peer-reviewed scientific literature to identify environmental variables associated with wildfire behavior, evaluate UAV-compatible sensing technologies, and develop a research-supported conceptual UAV platform. The engineering design process integrates evidence from multiple scientific disciplines to propose a UAV system capable of simultaneously monitoring atmospheric, vegetation, terrain, thermal, and combustion-related conditions associated with wildfire risk.

3.2 Literature review and source collection

The literature review includes approximately 20 peer-reviewed research articles obtained through Google Scholar, scientific databases, academic journals, and credible scientific, engineering, and government research organizations. Sources were selected based on their relevance to wildfire prediction and detection, UAV-based remote sensing, environmental monitoring, and sensing technologies applicable to wildfire management. Preference is given to recent publications, highly cited studies, review articles, and research published in engineering, environmental science, wildfire science, and remote sensing journals.

Each source is evaluated by identifying the environmental variables investigated, the documented relationship between each variable and wildfire susceptibility, ignition, intensity, or spread, the sensing technologies used for measurement, the limitations identified by the authors, and the potential application of the findings within an integrated UAV wildfire monitoring platform. Information from all reviewed studies is organized into a Variables of Investigation document that links each environmental variable to supporting literature, identifies appropriate UAV-compatible measurement instruments, records commercially available integrated sensor systems, summarizes research limitations, and serves as the primary reference for selecting sensors incorporated into the proposed UAV design.

3.3 Identification of wildfire prediction variables

The reviewed literature is analyzed to identify physical variables that consistently influence wildfire susceptibility, ignition, intensity, location, and spread. Environmental variables are organized into four primary categories: atmospheric variables, vegetation and fuel variables, terrain variables, and combustion indicators. Atmospheric variables include relative humidity, air temperature, wind speed and direction, wind gusts, precipitation, and atmospheric pressure. Vegetation and fuel variables include vegetation type, biomass availability, fuel moisture content (FMC), and vegetation health estimated using the Normalized Difference Vegetation Index (NDVI), Normalized Difference Red Edge Index (NDRE), and Normalized Difference Moisture Index (NDMI). Terrain variables include topographical slope and landscape structure, while combustion indicators include particulate matter, carbon monoxide, carbon dioxide, and thermal anomalies.

Variables are included only if they appear consistently across multiple peer-reviewed studies, demonstrate a documented relationship with wildfire ignition or spread, and can be measured using commercially available UAV-compatible sensing technologies. Each variable is evaluated according to its predictive target, relationship to wildfire behavior, UAV compatibility, required measurement instrument, and ability to complement other environmental measurements. These findings are summarized in a Variables of Investigation comparison table that identifies the variable type, predictive target, relationship to wildfire risk, required sensing technology, integrated sensor package, and supporting literature.

Comparisons across the reviewed studies identify meteorological variables such as temperature, relative humidity, wind, precipitation, and atmospheric pressure as consistent predictors of wildfire behavior because they influence fuel moisture content, atmospheric stability, and fire development (15–16, 18, 22). Wind–terrain interactions and topographical slope are also evaluated because they influence wildfire propagation and rates of spread (4, 6, 19).

3.4 Evaluation of wildfire detection methods

Five UAV-compatible wildfire detection approaches are evaluated: thermal infrared imaging, smoke detection using particulate matter sensors, gas sensing using carbon monoxide and carbon dioxide measurements, RGB image-based smoke and flame recognition, and multispectral imaging. Each detection method is compared according to the type of data collected, detection capability, operational advantages, limitations, and compatibility with UAV implementation.

Thermal infrared imaging detects hotspots and elevated surface temperatures associated with active fires, while smoke detection identifies increased particulate matter associated with combustion. Gas sensing measures elevated concentrations of PM2.5, CO, and CO_2 that may indicate smoldering combustion before visible flames appear (17). RGB imaging supports computer vision and artificial intelligence algorithms for smoke and flame recognition, whereas multispectral imaging evaluates vegetation health, biomass, fuel moisture content, canopy characteristics, and thermal anomalies associated with increased wildfire susceptibility (2, 14, 20). The comparison of these sensing methods forms the basis for selecting complementary technologies capable of improving wildfire prediction and early detection.

3.5 Sensor selection criteria

Commercially available UAV-compatible sensors and integrated instrument packages are reviewed to identify sensing technologies suitable for inclusion in the proposed UAV platform. Sensor selection considers measurement accuracy, payload weight, power requirements, commercial availability, compatibility with UAV platforms, ability to collect real-time environmental data, and potential integration with onboard machine-learning systems. When multiple sensors measure the same environmental variable, their performance characteristics are compared to identify the most appropriate component for the proposed platform.

3.6 UAV system design development

A preliminary conceptual UAV platform is developed by matching the environmental variables identified in the literature with commercially available sensing technologies. The proposed design considers payload capacity, sensor compatibility, flight endurance, navigation accuracy, communication capability, and real-time processing requirements. A hexacopter configuration is selected because it provides greater payload capacity, improved flight stability, and redundancy in the event of a single motor failure.

The proposed payload integrates a thermal imaging camera for hotspot detection and surface temperature measurement, a multispectral camera for assessing vegetation health, biomass, and fuel moisture content, a LiDAR sensor for measuring vegetation structure and topographical slope, a weather sensor package for monitoring temperature, relative humidity, wind speed, wind direction, and atmospheric pressure, and air-quality sensors for measuring PM2.5, CO, and CO_2. Additional system components include RTK GPS for high-precision hotspot mapping, a PX4 autopilot for autonomous navigation and sensor integration, radio telemetry and LTE communication for UAV control and long-distance data transmission, and an NVIDIA Jetson Orin NX computer for onboard machine-learning processing and real-time environmental analysis.

3.7 Sensor integration and system analysis

The proposed UAV platform integrates multiple sensing technologies into a single environmental monitoring system rather than relying on individual sensors independently. Integrated sensor configurations are compared according to measurement accuracy, sensor compatibility, payload requirements, and the ability to collect complementary environmental measurements simultaneously.

The conceptual UAV platform is also compared with existing wildfire monitoring approaches, including satellite observations, ground-based weather stations, and previously developed UAV monitoring systems. Comparisons focus on spatial resolution, localized environmental measurements, simultaneous collection of atmospheric, vegetation, terrain, thermal, and combustion-related data, and the potential for earlier wildfire prediction and detection through integrated sensing.

3.8 Data organization and analysis

Research findings are organized using the Variables of Investigation document, wildfire variable comparison tables, wildfire detection method comparison tables, and UAV system design comparison tables. Each reviewed study is linked to the environmental variable investigated, the sensing technology used, the corresponding UAV-compatible measurement instrument, and its proposed application within the conceptual UAV platform.

Comparisons across studies identify the environmental variables most consistently associated with wildfire susceptibility, ignition, intensity, and spread. Variables that appear consistently across multiple peer-reviewed investigations receive greater emphasis during sensor selection and system design. The analysis also identifies sensing technologies with the greatest predictive value, evaluates combinations of complementary sensors, and determines which environmental variables are most suitable as machine-learning input features for future wildfire prediction models. These findings are synthesized to develop a research-supported conceptual UAV platform capable of improving wildfire risk assessment and early wildfire detection through integrated environmental sensing.

4. Results

4.1 Environmental variables associated with wildfire risk

Eight primary environmental variable groups were identified as relevant to wildfire susceptibility, ignition, intensity, spread, and detection. Six variables—relative humidity, air temperature, wind speed, vegetation health, biomass availability, and terrain slope—primarily characterize environmental conditions associated with wildfire risk, including atmospheric conditions, fuel characteristics, and landscape features (12, 16, 18–20, 22). In contrast, thermal anomalies and combustion gases primarily serve as indicators of active or developing fires and support early fire detection (14, 17). Together, these variables provide complementary information spanning pre-ignition wildfire risk assessment and active-fire detection.

To compare these variables systematically, the Variables of Investigation tables summarize atmospheric and environmental variables (Table 1) and fuel, terrain, vegetation, and combustion variables (Table 2) according to their predictive targets, relationships to wildfire behavior, required measurement instruments, and integrated sensor packages. The comparison demonstrates that no individual variable provides a complete assessment of wildfire risk. Instead, atmospheric measurements, vegetation characteristics, terrain information, thermal observations, and air-quality indicators provide complementary information that supports more comprehensive wildfire prediction when integrated within a single UAV platform.

Table 1. Atmospheric and meteorological variables associated with wildfire susceptibility, intensity, spread, and timing, including their predictive targets, wildfire relevance, and UAV-compatible measurement instruments. FMC = fuel moisture content; IMU = inertial measurement unit. The table summarizes the primary atmospheric and meteorological variables considered in the proposed UAV-based wildfire monitoring system. Each variable is linked to a specific wildfire prediction target and describes its relationship to wildfire susceptibility, intensity, spread, or timing. The listed instruments represent UAV-compatible approaches for measuring these conditions, with measurements intended to characterize fuel-drying conditions, atmospheric behavior, and environmental changes that may influence wildfire development and propagation

Variable Type	Predictive Target	Wildfire Risk Connection	Instruments for Measurement
Relative humidity	Susceptibility, intensity	Low relative humidity → drier fuel, lower FMC, greater ignition and spread	Thermohygrometer
Wind speed/direction	Location, intensity	Strong winds → faster spread and greater fire intensity	Ultrasonic anemometer
Wind gusts/direction changes	Location, intensity	Gusts → increased intensity and changing fire direction	3-axis ultrasonic anemometer/IMU
Temperature	Susceptibility, timing, location	Higher temperature → greater evaporation, lower FMC, easier ignition	Thermometer/thermohygrometer; radiometric microbolometer; multispectral/hyperspectral sensors
Precipitation	Timing, intensity	More precipitation → higher moisture and lower burn potential	Disdrometer/rainfall estimation sensors
Barometric pressure/atmospheric stability	Intensity, location	Instability/low pressure → stronger winds and vertical air movement	Barometer

Table 2. Fuel, terrain, vegetation, and combustion variables associated with wildfire susceptibility, intensity, spread, and detection, including their predictive targets, wildfire relevance, and UAV-compatible measurement instruments. NDIR = non-dispersive infrared; NDVI = normalized difference vegetation index; NDRE = normalized difference red edge index; NDMI = normalized difference moisture index. The table condenses the fuel, terrain, vegetation, and combustion-related variables incorporated into the proposed UAV-based wildfire monitoring system. These variables provide information about fuel availability and condition, terrain effects on fire behavior, vegetation characteristics, and atmospheric indicators of combustion. The listed sensing approaches are intended to provide complementary measurements that support both pre-fire wildfire risk assessment and the detection and characterization of active or recent fire conditions

Variable Type	Predictive Target	Wildfire Risk Connection	Instruments for Measurement
Available biofuel (biomass)	Intensity, duration	Greater biomass → more fuel, intensity, and burn duration	LiDAR/ multispectral camera
Topographical slope (steepness)	Location, speed of spread	Steeper slopes → faster uphill spread through preheating	LiDAR; multispectral camera
Chemical indicators ($PM_{2.5}$, CO, CO_2)	Intensity, location	Elevated levels → indicate active or recent combustion	Gas sensors; electrochemical CO; NDIR CO_2; optical $PM_{2.5}$
Vegetation type (fuel characterization)	Susceptibility, intensity	Vegetation type → affects flammability, fuel load, and moisture retention	RGB; multispectral; hyperspectral camera + machine learning
Vegetation health (FMC, NDVI/NDRE/NDMI)	Susceptibility, timing	Lower moisture/health → greater burn potential; indices indicate biomass and moisture	Multispectral camera; thermal camera; LiDAR

4.2 Comparison of UAV-based wildfire detection methods

Five UAV-compatible wildfire detection methods are evaluated to determine their suitability for early wildfire detection and environmental monitoring. These methods include thermal infrared imaging, smoke detection using particulate matter sensors, gas sensing using carbon monoxide

and carbon dioxide measurements, RGB image-based smoke and flame recognition, and multispectral imaging.

A comparison of the data collected and primary advantages of each detection method is provided in Table 3. Thermal infrared imaging provides rapid hotspot detection through surface temperature measurements, while particulate matter and gas sensors identify atmospheric indicators associated with combustion. RGB imaging supports computer vision and artificial intelligence algorithms for smoke and flame recognition, and multispectral imaging evaluates vegetation health, fuel moisture content, biomass availability, and vegetation stress associated with elevated wildfire susceptibility. Collectively, the comparison demonstrates that these sensing approaches complement one another by providing different types of environmental information that improve situational awareness and increase the potential for earlier wildfire detection than any individual sensing technology alone.

Table 3. Comparison of UAV-compatible wildfire detection methods, including the data collected and their primary advantages for early wildfire detection and environmental monitoring. The methods provide complementary information from thermal, atmospheric, optical, and multispectral sensing approaches. The methods are intended to provide complementary measurements, with thermal and atmospheric sensors supporting detection of combustion-related indicators and optical sensors supporting hotspot, smoke, flame, vegetation, and fuel-condition assessment

Detection Method	Data Collected	Advantage Provided
Thermal infrared imaging	Surface temperature/hotspots	Detect active/recent hotspots
Smoke detection ($PM_{2.5}$)	PM concentration	Detect combustion before visible flames
Gas sensing (CO, CO_2)	Combustion gases	Detect smoldering combustion
Visible/RGB vision	Smoke/flame recognition	AI image detection/recognition
UAV multispectral imaging	Vegetation reflectance, vegetation health, fuel moisture, biomass, and vegetation stress	Assess wildfire susceptibility and fuel conditions

4.3 Proposed integrated UAV platform

A conceptual integrated UAV platform is developed by combining the environmental variables identified throughout the literature review with commercially available sensing technologies. The proposed system uses a hexacopter configuration to provide sufficient payload capacity, improved flight stability, and redundancy in the event of a single motor failure.

The selected platform characteristics are designed to balance flight endurance, positioning accuracy, navigation, communication, and onboard processing. The proposed 30–45 minute flight time provides adequate duration for localized wildfire surveys while accounting for the increased power requirements of a heavier, sensor-equipped UAV. RTK GPS provides high-precision positioning for accurate mapping and georeferencing of collected data. PX4 Autopilot enables customizable waypoint-based flight paths and supports autonomous navigation, while radio telemetry provides reliable short-range control and LTE enables longer-range communication and data transmission. The NVIDIA Jetson Orin NX provides onboard processing capabilities for real-time machine-learning analysis during flight, reducing reliance on continuous communication with a ground station.

A system comparison table summarizes the selected UAV platform, onboard sensors, navigation components, communication systems, autopilot, flight characteristics, and artificial intelligence hardware (Table 4). Together, these components demonstrate how an integrated UAV system can simultaneously collect multiple environmental measurements required for wildfire prediction and early wildfire detection.

Table 4. Proposed integrated hexacopter UAV platform, onboard sensing systems, navigation and communication components, flight characteristics, and AI processing hardware. The hexacopter configuration is selected to provide payload capacity, flight stability, and redundancy in the event of a single motor failure. The listed flight time is an estimated operational range based on the expected payload and is subject to variation with battery capacity, UAV mass, environmental conditions, flight profile, and sensor power requirements. RTK GPS, PX4 Autopilot, radio telemetry, LTE communication, and NVIDIA Jetson Orin NX processing are proposed to support precise positioning, autonomous navigation, real-time communication, and onboard machine-learning analysis, respectively

Component	Proposed System Configuration
UAV Platform	Hexacopter (higher payload capacity, increased stability, and redundancy if one motor fails)
Flight Time	30-45 min (heavy UAV with high payload will have lower flight time than a lightweight one, but should be enough time for a thorough survey)
Payload	Multispectral camera + thermal camera + LiDAR + all-in-one weather sensor package + air-quality sensors
GPS/Navigation	RTK GPS (provides high-precision positioning for accurate mapping and hotspot location)

Autopilot/Flight path	PX4 Autopilot (autonomous navigation and waypoint-based flight control)
Comms	Radio telemetry + LTE (short-range UAV control with long-range data transmission capabilities)
AI Processing	NVIDIA Jetson Orin NX (16 GB, compatible with variety of sensors, lightweight, real-time detection)

4.4 Integrated system architecture

The proposed integrated UAV system architecture combines atmospheric, vegetation, terrain, thermal, and combustion-related sensing technologies within a single hexacopter platform. The general orientation of the primary sensors is illustrated in the front-view sensor orientation diagram (Figure 2). The diagram shows the spatial arrangement and sensing coverage of the weather sensors, LiDAR scanner, multispectral camera, thermal camera, and air-quality sampling inlet, providing an overview of how the individual sensing systems contribute to environmental monitoring from a common UAV platform.

The weather sensors are positioned to provide approximately omnidirectional measurements of atmospheric conditions surrounding the UAV, including air temperature, relative humidity, wind speed, and wind direction. The air-quality sampling inlet is similarly oriented to allow sampling of surrounding air for particulate matter and combustion-related gases, including PM2.5, CO, and CO_2. These measurements provide atmospheric and chemical indicators that can be used to characterize conditions associated with wildfire susceptibility and identify evidence of active or recent combustion.

The downward- and forward-oriented remote-sensing instruments provide complementary spatial information. The LiDAR scanner provides broad coverage for measuring terrain and vegetation structure, allowing the system to characterize topography, vegetation height, canopy structure, and fuel distribution while minimizing side and rear blind spots through its near-360° horizontal monitoring capability, enabling detection across a full 360-degree circle around the UAV from left to right. The multispectral camera provides a 62° horizontal field of view (HFOV) for assessing vegetation characteristics and spectral indicators such as NDVI, NDRE, and NDMI. These measurements can be used to estimate vegetation health, moisture conditions, biomass characteristics, and potential fuel stress over the surveyed area. The thermal camera provides a 60° HFOV for detecting surface-temperature anomalies and potential hotspots that may indicate active or recently initiated combustion.

The orientation of these sensors is intended to maximize complementary coverage rather than rely on a single detection method. Atmospheric and air-quality sensors characterize the conditions surrounding the UAV, LiDAR provides three-dimensional information about terrain and vegetation structure, multispectral imaging characterizes vegetation and fuel conditions, and thermal imaging identifies temperature anomalies. Together, these measurements create a multidimensional representation of the wildfire environment.

The integrated architecture is therefore designed around sensor complementarity. Measurements from the individual sensing systems can be georeferenced using the RTK GPS system and combined by the onboard computing system. The NVIDIA Jetson Orin NX can process sensor data and support machine-learning algorithms that identify relationships among environmental conditions, vegetation characteristics, terrain, thermal anomalies, and combustion indicators. This sensor-fusion approach allows the UAV to move beyond identifying individual wildfire indicators and instead evaluate multiple indicators simultaneously.

The overall design is intended to support two related functions: wildfire risk assessment before or during the early stages of combustion and rapid detection of potential wildfire activity. Environmental measurements such as temperature, humidity, vegetation condition, biomass, and terrain can contribute to identifying areas with elevated susceptibility, while thermal, particulate, and gas measurements can provide evidence of active or recent combustion. By integrating these measurements on a single UAV platform, the proposed system provides a unified approach to environmental monitoring, early wildfire detection, and situational awareness.

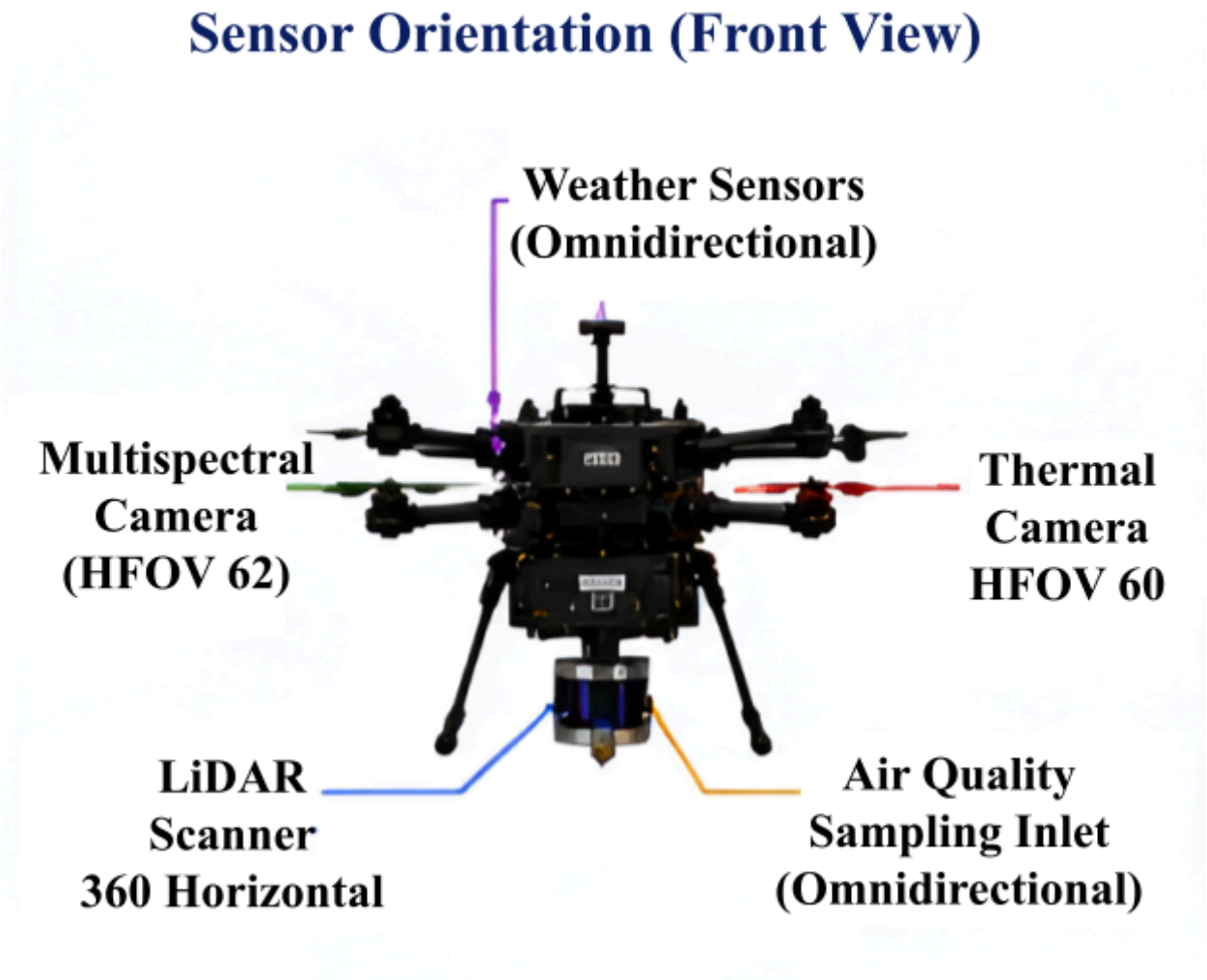


Figure 2. Sensor orientation and field of view of the proposed integrated UAV platform (front view)
Preliminary conceptual illustration generated using ChatGPT Images (OpenAI) to visualize the proposed UAV sensor field-of-view and coverage relationships. Errors may still be present. AI system/agent: ChatGPT Images (OpenAI). Generated: August 6, 2026, 3:15 PM PT. Post-processing: None.

4.5 System vision and spatial sensing strategy

Following the physical sensor arrangement, the proposed system is envisioned as a multi-sensor UAV capable of observing the wildfire environment across multiple spatial scales. The relationship between the individual sensor fields of view and their projected ground coverage is illustrated in the nadir-view footprint diagram (Figure 3). The diagram provides a simplified representation of how the LiDAR, multispectral, thermal, and air-quality sensing systems contribute complementary spatial observations beneath and around the UAV.

The LiDAR system provides the broadest conceptual spatial coverage, with a 360° horizontal scanning capability represented by the blue dashed circle in Figure 3. This broad coverage supports the collection of terrain and vegetation-structure information surrounding the UAV. LiDAR measurements can contribute information regarding elevation, terrain slope, vegetation height, canopy structure, and biomass distribution. These measurements provide spatial context for interpreting the other sensor observations and can help characterize areas where terrain and fuel conditions may influence wildfire behavior.

The multispectral and thermal cameras provide more focused ground observations. The multispectral camera is represented by a 62° horizontal field of view, while the thermal camera is represented by a 60° horizontal field of view. Their similar but distinct footprints allow the same general ground region to be evaluated using different sensing modalities. Multispectral observations can characterize vegetation conditions and spectral indicators such as NDVI, NDRE, and NDMI, while thermal observations can identify surface-temperature anomalies and potential hotspots. The substantial overlap between these footprints provides an opportunity to associate vegetation and fuel conditions with thermal observations within the same area.

The air-quality sensing system provides an additional measurement domain that differs from the optical and spatial sensors. Its omnidirectional sampling region is represented conceptually by the orange dashed circle in Figure 3. Rather than producing an optical image of the ground, the air-quality system samples atmospheric conditions surrounding the UAV and can provide measurements of particulate matter and combustion-related gases such as $PM_{2.5}$, CO, and CO_2. These measurements can therefore provide atmospheric evidence that complements the spatial information collected by the imaging and LiDAR systems.

The overlap among the illustrated footprints represents an important aspect of the proposed system vision. A single area of interest may be observed simultaneously through multiple sensing modalities, allowing thermal anomalies to be evaluated alongside vegetation condition, terrain structure, and atmospheric indicators. This spatial overlap provides the conceptual basis for sensor fusion, in which measurements from different sensors can be associated with the same geographic region rather than being interpreted independently.

The proposed system is therefore envisioned not simply as a UAV carrying multiple sensors, but as an integrated environmental observation platform. During a survey, the UAV could progressively build a spatial representation of the surrounding environment by combining terrain, vegetation, thermal, atmospheric, and combustion-related measurements. This approach could support both pre-fire risk assessment and early identification of developing wildfire conditions by allowing multiple environmental indicators to be considered together.

The ground footprints shown in Figure 3 are conceptual representations rather than fixed physical dimensions. Actual ground coverage would vary according to UAV altitude, sensor mounting angle, camera geometry, and operating conditions. The figure is therefore intended primarily to demonstrate the spatial relationship and overlap among the proposed sensing modalities.

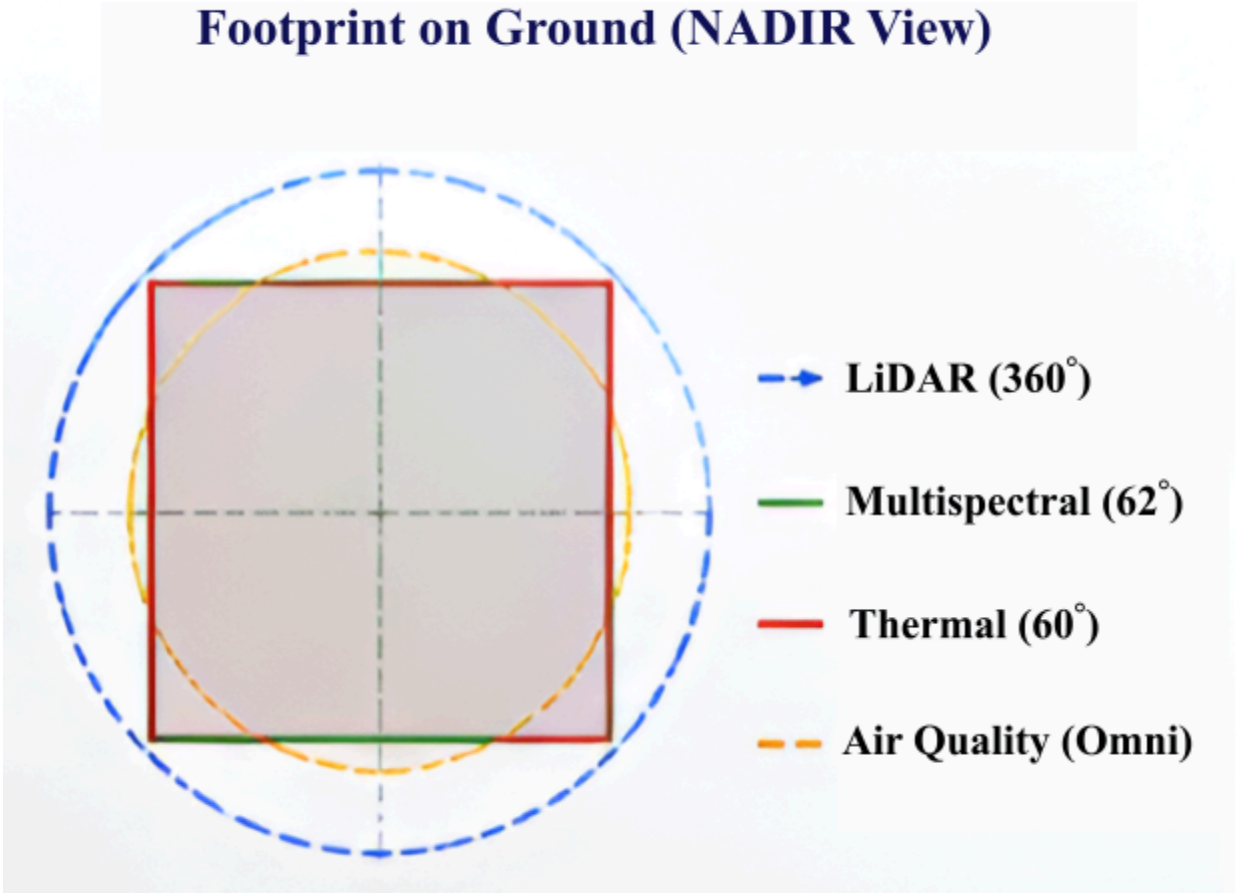


Figure 3. Ground footprint and sensor coverage of the integrated UAV platform (Nadir view)
Preliminary conceptual illustration generated using ChatGPT Images (OpenAI) to visualize the proposed UAV sensor field-of-view and coverage relationships. Errors may still be present. AI system/agent: ChatGPT Images (OpenAI). Generated: August 6, 2026, 3:15 PM PT. Post-processing: None.

4.6 Data acquisition, processing, and decision-support stream

The spatial sensing strategy described in Section 4.5 establishes how the proposed UAV observes the environment; the next stage is the organization and processing of the resulting measurements. The proposed data stream connects sensor acquisition, geographic referencing, sensor fusion, onboard processing, and analytical outputs into a continuous workflow, as illustrated in Figure 4. This architecture is intended to transform raw measurements from individual sensors into spatially coordinated information that can support wildfire risk assessment and early detection.

The data stream begins with simultaneous or near-simultaneous collection from the onboard sensing systems. Atmospheric sensors provide measurements such as temperature, relative humidity, wind speed, and wind direction, while the air-quality system measures combustion-related indicators including particulate matter, CO, and CO_2. The LiDAR system collects spatial information regarding terrain and vegetation structure, while the multispectral and thermal cameras collect imagery representing vegetation characteristics and surface-temperature conditions. Each sensing modality therefore contributes a different component of the overall environmental dataset.

RTK GPS provides the geographic reference required to associate these measurements with specific locations. Precise positioning allows sensor observations to be mapped to their corresponding areas on the ground and supports the spatial alignment of measurements collected by different sensors. When combined with the overlapping sensor footprints described in Figure 3, georeferencing enables observations from different sensing systems to be compared within a common spatial framework.

The next stage of the data stream is sensor fusion. Measurements from the individual sensors can be combined to create a more comprehensive representation of environmental conditions than any single sensor could provide independently. For example, a thermal anomaly could be evaluated together with multispectral information about vegetation condition, LiDAR measurements of vegetation and terrain structure, and air-quality measurements indicating particulate or combustion-related activity. This integration allows potentially significant observations to be evaluated in the context of other environmental variables.

The fused data can then be processed by the onboard NVIDIA Jetson Orin NX. Onboard processing provides the proposed system with the capability to perform machine-learning analysis while the UAV is operating rather than requiring all raw data to be transmitted to an external computer before analysis. The processing system can evaluate sensor measurements and identify combinations of environmental conditions associated with elevated wildfire susceptibility or potential active combustion. The resulting analytical outputs can support several levels of wildfire monitoring. Environmental variables such as temperature, relative humidity, vegetation condition, biomass characteristics, and terrain can contribute to an assessment of wildfire susceptibility. Thermal anomalies, particulate concentrations, and combustion-related gases can provide additional evidence of active or recent combustion. Combining these outputs can allow the system to distinguish between individual environmental indicators and patterns in which multiple indicators occur simultaneously.

The overall data stream therefore progresses from environmental measurement to geographic referencing, sensor fusion, onboard analysis, and decision support. This workflow represents the proposed pathway through which the UAV could convert heterogeneous sensor measurements into actionable environmental information. The four principal capabilities of this data-processing strategy are summarized in Figure 4.

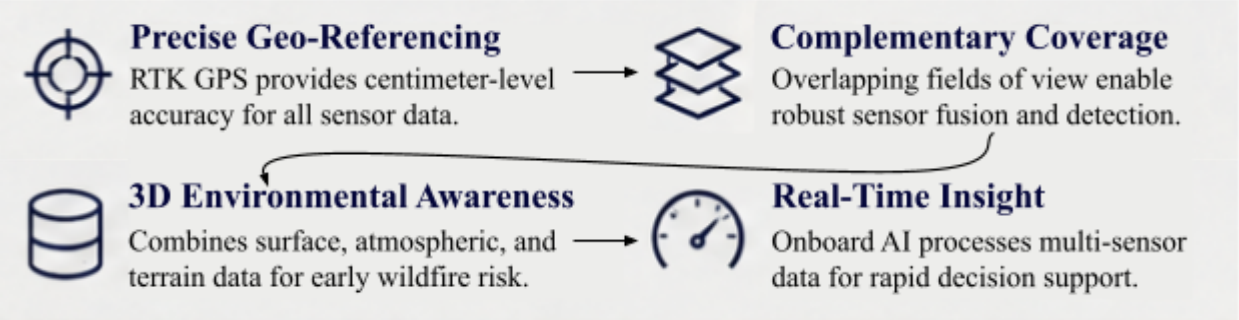


Figure 4. Core analytical capabilities and data objective stream of the integrated multi-sensor UAV platform
Preliminary conceptual illustration generated using ChatGPT Images (OpenAI) to visualize the proposed UAV sensor field-of-view and coverage relationships. Errors may still be present. AI system/agent: ChatGPT Images (OpenAI). Generated: August 6, 2026, 3:15 PM PT. Post-processing: None.

5. Analysis and Discussion

5.1 Interpretation of Findings

Wildfire susceptibility, ignition, intensity, and spread are interconnected processes influenced by interactions among atmospheric conditions, vegetation, fuel characteristics, and terrain. Temperature, relative humidity, wind speed, and wind direction influence fuel dryness and fire behavior, while vegetation condition and fuel characteristics determine the availability and continuity of combustible material (12, 16). Previous wildfire prediction studies have demonstrated the importance of meteorological variables in estimating wildfire occurrence and behavior, but these approaches primarily emphasize atmospheric conditions rather than simultaneously considering vegetation, fuel, terrain, and combustion indicators (18, 22). The proposed system extends this approach by integrating these environmental variables within a single UAV-based monitoring platform. Wind and terrain can further interact to influence fire propagation, particularly in rugged landscapes where topographic features can channel and accelerate fire spread (19). Meteorological variables have also been identified as important predictors of wildfire occurrence and longer-range fire behavior (18, 22). Once combustion begins, thermal anomalies and air-quality changes provide additional indicators that can help identify active fire conditions. Rjoub et al. (2023) demonstrated that air-quality sensors mounted on an unmanned aircraft system can contribute to early wildfire detection (17). The proposed system builds on this approach by combining air-quality measurements with thermal, multispectral, LiDAR, and meteorological observations, allowing combustion-related atmospheric changes to be evaluated alongside vegetation, terrain, and environmental conditions. Therefore, wildfire conditions are better characterized through the interaction of multiple environmental variables rather than through a single measurement.

The multi-sensor UAV system developed in this study addresses this limitation by combining thermal infrared, multispectral, LiDAR, meteorological, air-quality, and positioning and communication technologies within a single airborne platform. Thermal sensing provides localized measurements of abnormal heat associated with active or developing fires, while multispectral sensing can characterize vegetation condition and fuel-related properties. Previous UAV studies have demonstrated the use of infrared and visible-spectrum measurements to estimate fuel moisture (2), while recent research has investigated UAV multispectral imagery for estimating dead fuel moisture under varying vegetation conditions (20). These findings support the inclusion of multispectral sensing in the proposed platform because fuel moisture is an important component of pre-fire wildfire risk assessment. LiDAR contributes three-dimensional information about terrain, vegetation height, canopy structure, and fuel distribution, while meteorological and air-quality sensors provide measurements of environmental conditions and combustion-related atmospheric changes. The primary advantage of this configuration is therefore not simply the number of sensors, but the complementary information obtained from them. By collecting multiple environmental measurements from the same mobile platform, the proposed UAV provides a more comprehensive representation of wildfire-prone conditions.

Effective wildfire monitoring requires both pre-fire risk assessment and early-fire detection. Pre-fire measurements establish an environmental baseline against which subsequent changes can be evaluated. For example, elevated temperature combined with declining humidity, dry vegetation, favorable wind conditions, and fuel characteristics associated with increased flammability can indicate elevated wildfire susceptibility (16, 18). Once ignition occurs, deviations from this baseline—particularly localized thermal anomalies accompanied by changes in air-quality measurements—can provide stronger evidence of active combustion than any individual measurement alone (17). A thermal anomaly in isolation may have a non-fire explanation, whereas a spatially and temporally coincident anomaly across multiple sensing modalities provides stronger contextual evidence. The proposed UAV therefore connects pre-fire environmental risk assessment with early-fire detection, allowing the same platform to characterize conditions before ignition and identify changes associated with fire development.

5.2 Comparison with Existing Monitoring Systems

Existing wildfire monitoring approaches differ in their spatial coverage, mobility, and measurement resolution. Satellite systems provide broad regional observations, while fixed ground stations provide continuous measurements at specific locations (14). UAV-based monitoring provides a complementary approach by allowing localized measurements to be collected at specific locations and elevations. The proposed system therefore addresses a gap between broad-area satellite observations and spatially limited ground measurements by providing mobile, high-resolution environmental observations. Satellite systems provide broad-area observations that are valuable for monitoring large regions and identifying environmental changes, but their spatial and temporal resolution can limit the detection and characterization of small or rapidly developing events. UAVs can instead provide localized, high-resolution measurements and can be deployed to specific areas of interest. Reviews of early wildfire detection technologies identify UAVs as an increasingly useful platform because of their mobility, high spatial resolution, and ability to carry multiple sensing technologies (14).

Fixed ground stations provide continuous measurements at specific locations and are valuable for establishing persistent meteorological and environmental records. However, their fixed locations limit their ability to characterize spatial variability across large or topographically complex areas. The proposed UAV addresses this limitation by providing mobile measurements that can be collected at different locations and elevations as environmental conditions change. This capability is particularly useful where temperature, humidity, wind, vegetation condition, fuel characteristics, and terrain vary substantially over short distances. UAV-based sensing can also provide detailed measurements across large and heterogeneous environments, although coverage, flight endurance, and operational constraints remain important considerations (9).

The strongest application is therefore not to replace satellites or ground networks, but to establish a complementary space-air-ground monitoring system. This approach is supported by the broader use of UAVs for collecting detailed observations across large and heterogeneous environments, where mobility allows measurements to be targeted toward areas of interest (9). The proposed UAV would provide the localized airborne component of this network, while satellite and ground-based systems would continue providing regional and continuous observations, respectively. Satellites can provide broad-area screening, ground stations can provide continuous local observations, and UAVs can investigate areas where satellite or ground observations indicate elevated risk or uncertainty. This layered approach can improve situational awareness by connecting regional environmental information with localized, high-resolution observations. The proposed UAV is particularly valuable as the mobile component of this system because it can be redirected toward areas where additional measurements are needed.

5.3 Sensor Fusion and Machine Learning

The principal analytical advantage of the proposed platform is its ability to evaluate environmental variables collectively rather than independently. A single abnormal measurement does not necessarily indicate wildfire activity. For example, an elevated surface temperature could result from a non-fire heat source, while reduced humidity or elevated particulate concentrations may occur without active combustion. However, when several measurements change simultaneously in a spatially and temporally consistent manner, the combined pattern provides stronger evidence. A localized thermal anomaly occurring within dry vegetation, accompanied by an unusual air-quality measurement and supported by meteorological conditions favorable to combustion and fire spread, represents a stronger fire indicator than the thermal anomaly alone. This approach is consistent with the use of multiple environmental indicators for wildfire prediction and early detection (14, 17).

This interpretation is consistent with previous wildfire-monitoring research, which has increasingly moved from individual sensing approaches toward UAV-based systems that combine remote sensing, environmental measurements, and machine-learning methods for pre-fire assessment and active-fire detection (3, 14). Instead of applying independent thresholds to each sensor, a trained model can evaluate relationships among temperature, humidity, wind, vegetation characteristics, thermal signatures, air-quality measurements, terrain, and changes over time. The model could distinguish normal environmental variability from combinations of measurements that are more consistent with ignition or active combustion. This is particularly important when individual signals are weak or ambiguous because multiple variables can

provide additional contextual evidence. Machine-learning approaches have increasingly been investigated for wildfire prediction and detection using combinations of meteorological and remotely sensed information (14, 18).

The sensor-fusion process must also account for the spatial and temporal relationships among observations. Measurements collected at different altitudes, locations, and times cannot simply be combined without first being synchronized and georeferenced. The proposed UAV system can associate each observation with a geographic coordinate, timestamp, altitude, and sensor measurement. These data can then be aligned with satellite observations and ground-based measurements to create a more cohesive representation of environmental conditions. Differences in sensor resolution, sampling frequency, and measurement uncertainty must also be considered when combining datasets.

Integration with satellite and ground-based networks would further strengthen the system. Satellite observations could provide broad regional screening and identify areas requiring closer investigation, while ground stations could provide continuous meteorological measurements against which UAV observations could be compared. The UAV could then provide high-resolution observations to investigate localized anomalies and return updated information to the broader monitoring network. In this architecture, AI/ML could integrate observations collected at different times, altitudes, and spatial scales to determine whether multiple observations represent the same developing fire. This could provide a mechanism for connecting individual observations into a cohesive detection network rather than treating each sensor or monitoring platform independently.

A future machine-learning implementation could use a supervised tree-based model, such as Extreme Gradient Boosting (XGBoost), as an initial approach for analyzing the structured environmental data generated by the proposed UAV platform (5). A tree-based model could combine heterogeneous inputs, including temperature, relative humidity, wind speed and direction, precipitation, atmospheric pressure, vegetation indices such as NDVI, NDRE, and NDMI, fuel moisture content, biomass characteristics, terrain slope, thermal anomalies, PM2.5, CO, and CO_2. These variables are supported by previous wildfire prediction and UAV-based monitoring studies examining meteorological conditions, fuel moisture, and air-quality measurements (2, 17–18, 20, 22). Temporal features, such as changes in temperature, humidity, particulate concentration, and thermal measurements over successive observations, could also be incorporated to help distinguish normal environmental variability from developing fire conditions.

Training data for a future model could be constructed from historical California wildfire records combined with spatially and temporally matched environmental observations. CAL FIRE's historical fire-perimeter database could provide wildfire occurrence labels, while established vegetation and fuel datasets such as LANDFIRE could provide additional spatial predictors. Historical meteorological, remotely sensed, and air-quality observations could then be spatially aligned with these records to create labeled observations representing pre-fire conditions, active-fire conditions, and non-fire environmental conditions. Because historical fire records may contain incomplete or uncertain information, the resulting labels would require quality control before model training.

The model could be validated using both temporal and spatial holdout strategies rather than relying only on a random train-test split. For example, earlier California fire seasons could be used for training and later fire seasons reserved for testing, while geographically separated regions could provide an additional independent evaluation. This approach could reduce the risk of overfitting to particular fires, locations, vegetation types, or weather conditions. Model performance could be evaluated using precision, recall, specificity, F1-score, receiver operating characteristic area under the curve (ROC-AUC), false-positive rate, false-negative rate, detection latency, and localization error. Precision-recall analysis could provide additional information when fire observations are less common than non-fire observations (7). Different decision thresholds could also be evaluated to characterize the relationship between false alarms and missed fire events.

5.4 Engineering Trade-offs and Limitations

The integration of multiple sensors introduces significant engineering trade-offs. Increasing the payload increases aircraft mass, which increases power consumption and can reduce flight endurance. This trade-off is consistent with limitations identified in previous UAV research, where payload requirements, flight endurance, and the ability to collect measurements across large and heterogeneous areas can constrain operational performance (9). The proposed system therefore prioritizes complementary sensors that provide distinct environmental information rather than maximizing the number of instruments carried by the aircraft. Additional sensors also require mounting structures, wiring, data interfaces, onboard processing capacity, and electrical and thermal management. Consequently, sensor selection should be based on the information gained relative to payload mass and power requirements rather than simply maximizing the number of instruments. The proposed hexacopter configuration provides the payload capacity and redundancy necessary for the integrated sensor suite, but the system must still balance sensing capability with endurance, maneuverability, battery capacity, and operational range.

Measurement error represents another important limitation. Each sensor has its own uncertainty, resolution, response time, calibration requirements, and environmental sensitivity. When measurements are combined, errors from individual sensors can propagate through the sensor-fusion process and influence the resulting classification. This makes calibration and quality control particularly important. Previous UAV-based fuel-moisture studies have likewise relied on calibrated infrared and multispectral measurements, demonstrating the importance of accounting for sensor and environmental conditions when interpreting remotely sensed fuel characteristics (2, 20). The proposed system should therefore use laboratory calibration, reference measurements, repeated measurements, uncertainty characterization, and sensor cross-validation to identify and reduce systematic errors. Sensor-specific limitations should also be incorporated into the data-processing and machine-learning framework rather than treating every measurement as equally reliable.

Environmental conditions can further affect sensor performance. High temperatures can influence sensor electronics, detector response, battery performance, and calibration stability. Strong or changing winds can affect UAV stability, sensor orientation, and atmospheric measurements. Smoke and varying optical depth can also affect optical and thermal

measurements by altering the transmission of electromagnetic radiation. This limitation is particularly relevant to optical and thermal measurements because smoke and varying optical depth can alter the quality and interpretation of remotely sensed observations. These limitations can be addressed through temperature compensation, appropriate sensor protection, calibration across representative environmental conditions, monitoring of sensor health, and cross-validation between complementary sensing modalities. Multispectral and infrared measurements, for example, require careful calibration and interpretation when used to estimate vegetation or fuel characteristics (2, 20).

Flight operations introduce an additional limitation because environmental conditions directly influence endurance and data quality. Strong winds can increase power requirements and reduce flight time, while extreme temperatures can increase thermal stress on batteries and onboard electronics. The platform should therefore incorporate conservative operating limits, real-time battery and environmental monitoring, and mission planning that preserves sufficient energy reserves. These constraints make controlled experimental testing important before operational deployment. The system should be evaluated not only for detection performance but also for flight endurance, payload power consumption, sensor stability, measurement uncertainty, and data quality under representative operating conditions.

5.5 Scalability, Deployment, and Regulatory Considerations

The proposed UAV system can be scaled from a single monitoring platform to a distributed network of aircraft operating across larger wildfire-prone areas. Previous UAV research has demonstrated the usefulness of individual platforms for localized environmental monitoring, while broader research has identified UAVs and artificial intelligence as components of increasingly integrated wildfire-management systems (3, 9). Building on these approaches, the proposed system considers scalability from an individual UAV toward a coordinated network capable of sharing observations across a larger monitoring region. A multi-UAV system could divide a monitoring region into smaller sectors, allowing individual platforms to collect localized environmental measurements while a centralized system combines observations across the monitored area. Such an approach could increase spatial coverage and reduce dependence on a single aircraft. However, scaling the system would also introduce additional requirements for communication, data management, flight coordination, sensor calibration, maintenance, and operator oversight. These considerations are consistent with challenges identified in UAV-based wildfire monitoring, where limited endurance, sensor constraints, and coordination requirements can affect large-scale deployment (9, 14).

Regulatory compliance is another important consideration for future deployment. The proposed platform would need to be evaluated against applicable requirements governing UAV aircraft, pilot operations, airspace use, flight location, and mission conditions before being used operationally. These requirements should be incorporated into the system's design and mission-planning process rather than addressed only after development. Regulatory considerations would become increasingly important as the system expands from a single research platform to a distributed network because multiple aircraft would require coordinated operations while maintaining compliance with applicable aviation requirements.

Practical scalability would also depend on integration with existing wildfire-monitoring and emergency-response organizations. Partnerships with agencies such as CAL FIRE, local fire departments, fire protection districts, emergency-management organizations, and relevant land-management agencies could provide access to representative testing environments, operational expertise, historical fire data, and established response procedures. Integration with existing monitoring systems would allow UAV observations to complement satellite, ground-based, and other remote-sensing resources rather than functioning as an isolated detection system. The broader use of UAVs and AI across pre-fire, active-fire, and post-fire wildfire management further supports the value of integrating UAV platforms into established monitoring and response networks (3).

For large-scale implementation, the system should therefore be developed through a phased approach. Initial deployment should focus on validating one UAV and its integrated sensor suite, followed by limited multi-UAV testing and eventual expansion to larger monitoring regions. At each stage, system performance, communication reliability, sensor consistency, operational requirements, and regulatory compliance should be evaluated. This approach would allow technical and operational limitations to be identified before the system is expanded, supporting a more reliable transition from a conceptual platform to a scalable wildfire-monitoring network.

5.6 Future Research

Future research should first focus on experimental validation of the proposed hardware system before field deployment. This initial stage is necessary because previous studies have demonstrated the capabilities of individual UAV sensing approaches, such as fuel-moisture estimation and air-quality-based wildfire detection, but the performance of an integrated multisensor platform must be established experimentally before operational deployment (2, 17). A physical prototype should be constructed and tested under controlled conditions to determine actual power consumption, flight endurance, payload capacity, thermal behavior, sensor accuracy, data-transfer requirements, and stability of the integrated platform. Each sensor should undergo calibration and characterization across representative operating temperatures, wind conditions, and optical environments. Particular attention should be given to thermal-camera accuracy, multispectral calibration, LiDAR performance, meteorological sensor response to UAV-induced airflow, and air-quality sensor response to changing concentrations. These experiments could establish measurement uncertainty and identify sources of error before the system is evaluated in wildfire environments.

Following controlled experimental testing, field trials should evaluate the complete system under realistic environmental conditions. Testing should occur across different vegetation types, terrain conditions, weather conditions, and levels of thermal and atmospheric activity. The performance of individual sensors and the integrated system should be evaluated using detection accuracy, false-positive and false-negative rates, localization accuracy, response time, flight endurance, and data quality. Repeated observations could also determine whether the system maintains reliable performance as environmental conditions change.

A subsequent research phase should develop and validate the machine-learning and sensor-fusion framework using appropriately labeled datasets collected from the UAV, satellites, and ground networks. An initial supervised model, such as XGBoost, could be trained using the

environmental and temporal inputs described in Section 5.3 (5). Historical California wildfire records could provide wildfire occurrence labels, while spatially and temporally matched meteorological, vegetation, thermal, and air-quality observations could provide model inputs. Models should be evaluated on their ability to distinguish normal environmental variability from pre-fire conditions and active-fire signatures while avoiding overfitting to a particular location, vegetation type, or weather regime. Validation should use temporally and spatially independent test data, such as later fire seasons and geographically separated regions, rather than relying only on a random train-test split. Performance could be assessed using precision, recall, specificity, F1-score, ROC-AUC, false-positive rate, false-negative rate, detection latency, and localization accuracy. Precision-recall analysis could provide additional information when fire observations are less common than non-fire observations (7). The resulting system should then be compared with existing satellite-based and ground-based monitoring methods. Research should also investigate how information collected at different spatial resolutions, altitudes, and time intervals can be synchronized to identify individual fire events and track their development.

Finally, future research should investigate operational scalability and regulatory readiness. Additional UAVs could be introduced to determine how a distributed fleet affects coverage, response time, communications, and data-processing requirements. Research should also examine automated mission planning, fleet coordination, onboard processing, and communication with emergency-response organizations. Partnerships with CAL FIRE, local fire departments, fire protection districts, and other relevant agencies could provide a pathway for evaluating the system within established wildfire-monitoring and emergency-response workflows. Together, these efforts could move the proposed platform from a conceptual research design toward a validated and scalable wildfire early-detection system.

6. Conclusion

This study presents a conceptual framework for an integrated multi-sensor UAV platform designed to improve wildfire risk assessment and early detection. The literature reviewed indicates that wildfire behavior is influenced by interconnected environmental factors, requiring monitoring approaches capable of capturing multiple conditions simultaneously. By integrating these measurements into a unified UAV system, the proposed approach provides a foundation for more comprehensive and adaptive wildfire monitoring.

The proposed UAV architecture demonstrates the potential of combining advanced sensing technologies with autonomous aerial platforms to support future wildfire management strategies. While additional development and field validation are required before operational deployment, the system provides a scalable framework that can be refined as UAV hardware, sensing technologies, and artificial intelligence methods continue to advance.

Future efforts should focus on transitioning the conceptual design into a validated prototype and evaluating its performance under realistic wildfire conditions. Continued development of integrated UAV monitoring systems may contribute to improved wildfire preparedness, more efficient environmental assessment, and enhanced decision-making for wildfire prevention and response.

References

1. Abatzoglou, J. T., & Williams, A. P. (2016). Climate change has added to western US forest wildfire. Proceedings of the National Academy of Sciences, 113(42), 11770–11775. https://doi.org/10.1073/pnas.1607171113
2. Barber, N., Alvarado, E., Kane, V. R., Mell, W. E., & Moskal, L. M. (2021). Estimating fuel moisture in grasslands using UAV-mounted infrared and visible light sensors. Sensors, 21(19), Article 6350. https://doi.org/10.3390/s21196350
3. Boroujeni, S. P. H., Razi, A., Khoshdel, S., Afghah, F., Coen, J. L., O'Neill, L., Fule, P. Z., Watts, A., Kokolakis, N.-M. T., & Vamvoudakis, K. G. (2024). A comprehensive survey of research towards AI-enabled unmanned aerial systems in pre-, active-, and post-wildfire management. Information Fusion, 108, Article 102369. https://doi.org/10.1016/j.inffus.2024.102369
4. Butler, B. W., Quarles, S., Standohar-Alfano, C., Morrison, M., Jimenez, D., Sopko, P. A., Wold, C., Bradshaw, L. S., Atwood, L., Landon, J., O'Brien, J., Hornsby, B., Wagenbrenner, N. S., & Page, W. (2020). Exploring fire response to high wind speeds: Fire rate of spread, energy release and flame residence time from fires burned in pine needle beds under winds up to 27 m s^{-1}. International Journal of Wildland Fire, 29(1), 81–92. https://doi.org/10.1071/WF18216
5. Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 785–794). Association for Computing Machinery. https://doi.org/10.1145/2939672.2939785
6. Coskuner, K. A., Papavasileiou, G., Giannaros, T. M., Benali, A., & Bilgili, E. (2026). Fire behavior and propagation of twin wildfires in a Mediterranean landscape: A case study from İzmir, Türkiye. Fire, 9(2), Article 86. https://doi.org/10.3390/fire9020086
7. Davis, J., & Goadrich, M. (2006). The relationship between precision-recall and ROC curves. In Proceedings of the 23rd International Conference on Machine Learning (pp. 233–240). Association for Computing Machinery. https://doi.org/10.1145/1143844.1143874
8. Dennison, P. E., Brewer, S. C., Arnold, J. D., & Moritz, M. A. (2014). Large wildfire trends in the western United States, 1984–2011. Geophysical Research Letters, 41(8), 2928–2933. https://doi.org/10.1002/2014GL059576
9. Fernández-Guisuraga, J. M., Sanz-Ablanedo, E., Suárez-Seoane, S., & Calvo, L. (2018). Using unmanned aerial vehicles in postfire vegetation survey campaigns through large and heterogeneous areas: Opportunities and challenges. Sensors, 18(2), Article 586. https://doi.org/10.3390/s18020586
10. Gutierrez, A. A., Hantson, S., Langenbrunner, B., Chen, B., Jin, Y., Goulden, M. L., & Randerson, J. T. (2021). Wildfire response to changing daily temperature extremes in California's Sierra Nevada. Science Advances, 7(47), Article eabe6417. https://doi.org/10.1126/sciadv.abe6417
11. Jolly, W. M., Cochrane, M. A., Freeborn, P. H., Holden, Z. A., Brown, T. J., Williamson, G. J., & Bowman, D. M. J. S. (2015). Climate-induced variations in global wildfire danger from 1979 to 2013. Nature Communications, 6, Article 7537. https://doi.org/10.1038/ncomms8537
12. Keane, R. E. (2013). Describing wildland surface fuel loading for fire management: A review

of approaches, methods and systems. International Journal of Wildland Fire, 22(1), 51–62. https://doi.org/10.1071/WF11139
13. Keeley, J. E., & Syphard, A. D. (2016). Climate change and future fire regimes: Examples from California. Geosciences, 6(3), Article 37. https://doi.org/10.3390/geosciences6030037
14. Mohapatra, A., & Trinh, T. (2022). Early wildfire detection technologies in practice—A review. Sustainability, 14(19), Article 12270. https://doi.org/10.3390/su141912270
15. Potter, B. E. (2012). Atmospheric interactions with wildland fire behaviour—I. Basic surface interactions, vertical profiles and synoptic structures. International Journal of Wildland Fire, 21(7), 779–801. https://doi.org/10.1071/WF11128
16. Reid, A. M., Fuhlendorf, S. D., & Weir, J. R. (2010). Weather variables affecting Oklahoma wildfires. Rangeland Ecology & Management, 63(5), 599–603. https://doi.org/10.2111/REM-D-09-00132.1
17. Rjoub, D., Alsharoa, A., & Masadeh, A. (2023). Unmanned-aircraft-system-assisted early wildfire detection with air quality sensors. Electronics, 12(5), Article 1239. https://doi.org/10.3390/electronics12051239
18. Sadatrazavi, A., Shafie-Pour-Motlagh, M., Noorpoor, A., & Ehsani, A. H. (2022). Predicting wildfires occurrences using meteorological parameters. International Journal of Environmental Research, 16(6), Article 106. https://doi.org/10.1007/s41742-022-00460-3
19. Sharples, J. J., McRae, R. H. D., & Wilkes, S. R. (2012). Wind–terrain effects on the propagation of wildfires in rugged terrain: Fire channelling. International Journal of Wildland Fire, 21(3), 282–296. https://doi.org/10.1071/WF10055
20. Wang, Y., Wang, X., & Xing, J. (2026). Inversion of the forest dead fuel moisture content by UAV multisepectral image under the new leaves shade. Frontiers in Physics, 14, Article 1795521. https://doi.org/10.3389/fphy.2026.1795521
21. Williams, A. P., Abatzoglou, J. T., Gershunov, A., Guzman-Morales, J., Bishop, D. A., Balch, J. K., & Lettenmaier, D. P. (2019). Observed impacts of anthropogenic climate change on wildfire in California. Earth's Future, 7(8), 892–910. https://doi.org/10.1029/2019EF001210
22. Zhao, F., & Liu, Y. (2021). Important meteorological predictors for long-range wildfires in China. Forest Ecology and Management, 499, Article 119638. https://doi.org/10.1016/j.foreco.2021.119638