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*Review*

# Artificial intelligence and remote sensing frameworks for wildfire monitoring and risk analysis across multiple ecosystems: a review

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**Abstract:** In this review, we synthesized advancements in remote sensing and machine learning (ML) for wildfire risk assessment, early detection, and spread prediction across forests, grasslands, shrublands, and WUI ecosystems. We examined the capabilities and limitations of key satellite, UAV, and multisensor datasets, alongside the performance and transferability of ML and deep learning models. Major research gaps were identified in cross-ecosystem generalization, real-time data integration, model optimization, and uncertainty quantification. In the review, we contribute an ecosystem-inclusive comparison of RS–AI frameworks and outline future directions for operational, next-generation wildfire monitoring.

**Keywords:** artificial intelligence; climate change; fire risk assessments; machine learning; NBR; remote sensing & GIS; wildfire prediction; real time fire detection

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## 1. Introduction

Wildfires have intensified in frequency and scale across global landscapes, creating urgent demands for improved prediction and management systems. literature remains fragmented in scope and limited in operational capability. Most researchers focus on single ecosystems, sensors, or modeling strategies, resulting in narrow, region-specific insights that do not generalize well. As a consequence, systematic cross-ecosystem benchmarking of RS datasets, indices, and machine learning (ML) model performance is largely absent, leaving unclear which approaches transfer effectively across forests, grasslands, shrublands, and wildland–urban interface (WUI) environments. [1–5].

Building on these concerns, advances in Earth observation have increased access to satellite constellations, UAV platforms, and continuous environmental monitoring. However, real-time data integration remains underdeveloped. Many ML models rely on historical or static datasets, limiting their value for time-critical tasks such as early detection, ignition likelihood estimation, or fast-evolving fire-spread scenarios [6,7]. Furthermore, model optimization is weakly addressed in research. Few studies systematically evaluate hyperparameter tuning, ensemble frameworks, computational efficiency, or deployment suitability for edge devices and operational platforms [8–10]]. Moreover, researchers are exploring how remote sensing data can contribute to the study of fire ecology [11].

A further limitation is the persistent lack of uncertainty quantification. Although AI- and RS-based wildfire models have advanced, the literature repeats fragmented themes without articulating a coherent, unified research gap. Three critical limitations consistently emerge: (i) Weak ecosystem transferability, models trained in one biome often fail when applied elsewhere; (ii) inadequate uncertainty quantification, most models produce deterministic outputs that limit operational reliability; and (iii) limited integration of explainable AI (XAI), despite its ability to support transparent fire-management decision-making. Researchers using SHAP-based interpretability highlight how XAI can reveal variable contributions and improve trust in model predictions, yet operational adoption remains sparse. Moreover, most prediction studies provide point estimates without probabilistic confidence, reducing practical usability in risk-informed planning. Approaches capable of expressing uncertainty, such as interval prediction trees, probabilistic ML models, or physics-informed hybrid systems, remain significantly underutilized. Moreover, remote sensing and ML-driven methods continue to advance, with algorithms demonstrating strong capacity to identify subtle relationships across geospatial, meteorological, and remote sensing datasets [3,11–16].

In response to these gaps, in this review, we provide a structured synthesis of RS–ML integration for wildfire risk assessment, detection, and behavioral prediction across multiple ecosystems. We (i) evaluate the comparative strengths and limitations of RS datasets and sensors, (ii) analyze ML and deep learning methods with respect to cross-ecosystem generalizability, (iii) examine emerging real-time data assimilation and optimization strategies, and (iv) highlight the limited but growing work on uncertainty modeling. By consolidating these dimensions, we outline a more robust, multi-ecosystem, and operationally relevant framework for next-generation wildfire prediction and management [17]. The refinement of hotspot-detection pipelines in wildfire monitoring parallels advancements in solar-module hotspot identification, where AI-enabled thermal and multispectral analytics similarly enhance anomaly detection, underscoring strong cross-domain methodological relevance [17,18]

The world map shown in Figure 1 illustrates global fire activity for May 2025 from NASA's Earth Observatory, showing the spatial distribution of active fires detected across regions. The color scale represents fire intensity in terms of fire pixels per 1,000 km$^2$ per day, highlighting major hotspots in Central and Southern Africa, South America, Southeast Asia, and Australia, along with smaller clusters in North America and Eastern Europe. This global perspective underscores the need for prediction systems that are adaptable across ecological and climatic settings. To contextualize the global scale and spatial heterogeneity of wildfire occurrence, Figure 1 presents a world map of active fire activity for May 2025 derived from NASA Earth Observatory data. The figure highlights pronounced fire hotspots in Central and Southern Africa, South America, Southeast Asia, and Australia, illustrating the strong geographic variability in fire intensity. This global distribution underscores the need for wildfire prediction frameworks that are transferable across ecosystems and climatic regimes rather than being region-specific.

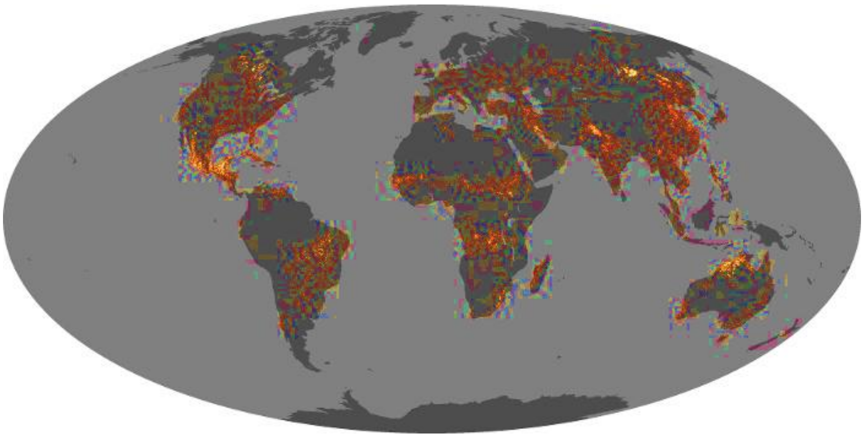

**Figure 1.** World map showing areas of which are most prone to wildfire as of May 2025 [10].

Research has demonstrated significant advancements in wildfire forecasting through the collaboration of remote sensing and ML [19,20]. Technologies such as satellites and drones facilitate real-time data collection over large areas using remote sensing. This data is processed through ML algorithms, which identify early warning signs of fire and analyzed complex variables such as weather and geography. Predictive analytics models can forecast fire spread paths and intensities, thereby aiding resource allocation and evacuation planning [20]. This integration enhances efforts to combat wildfires, assess risks, and develop adaptation strategies, addressing shifting fire patterns driven by climate change [21,22]. The combination of remote sensing and ML represents a paradigm shift in analysis of disaster, mitigating the adverse effects on ecosystems and communities [23,24]. Although many disasters occur naturally, their destructive potential is intensified by human activities and the looming threat of climate change [25]. Despite significant improvements in firefighting and management, the global incidence of wildfires remains high. The intense wildfire season of 2020 serves as a stark example of the unprecedented severity of these events [26,27].

The integration of remote sensing data, advanced computing, and ML offers transformative potential for wildfire prediction, despite challenges such as limited observations and methodological constraints. ML contributes through supervised, unsupervised, and agent-based approaches: Supervised learning supports classification and regression tasks using labeled datasets and algorithms such as Random Forest and Support Vector Machines for fire risk forecasting, land-use change analysis, and climate-related impacts [28,29].Unsupervised learning applies techniques, like k-means clustering and Principal Component Analysis, which are used to reduce data complexity and identify anomalies indicative of fire risk; and agent-based learning, using reinforcement strategies, such as Deep Q Networks and Genetic Algorithms, simulates fire behavior under varying environmental conditions to enhance response planning. Optimization methods further strengthen model accuracy, and decision-support frameworks improve the timeliness of operational responses. Integrating artificial intelligence (AI) with remote sensing deepens these capabilities, as multispectral satellite data and ML models detect fire, smoke, and vegetation changes with improved accuracy, enabling real-time situational awareness and supporting evacuation and firefighting decisions [30,31]. Advances in data processing accelerate the preparation of inputs for deep learning models, enabling algorithms to learn subtle patterns linked to emerging wildfire threats. Combined with visualization dashboards that consolidate multi-source data, these tools facilitate informed and rapid decision-making, promoting a more coordinated and effective approach to wildfire forecasting and suppression among scientists, experts, and local authorities. Figure 2 synthesizes the major ML methodologies applied in wildfire detection, including classical algorithms (e.g., Random Forest and SVM), deep learning architectures (CNNs, LSTMs), and hybrid approaches. The figure illustrates how these techniques contribute to enhanced detection accuracy by leveraging multispectral, thermal, and temporal remote sensing inputs. In this overview, we establish the methodological foundation for subsequent comparative analysis of model capabilities and limitations.

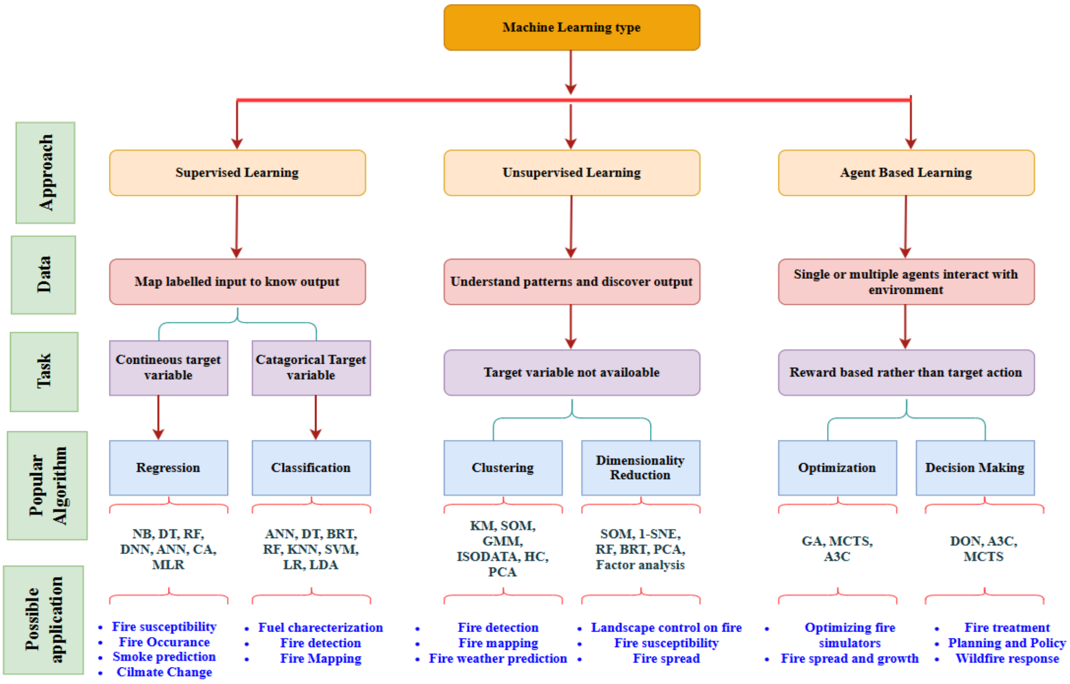

**Figure 2.** ML Approaches in fire detection. Key methodologies contributing to enhanced fire detection accuracy and effectiveness.

Advancements in wildfire research have highlighted the growing role of ML, remote sensing, and geospatial technologies for predicting and managing fire risks. A case of application of deep learning model leveraging deep neural networks and long short-term memory was applied for assessment of wildfire risk in the United States. However, their reliance on historical data limited the inclusion of real-time predictive factors [2]. Similarly, researchers provided an extensive review of ML methodologies applicable to forest fire research but overlooked the integration of GIS-based decision support systems [25]. Another study emphasized the importance of remote sensing in regional-scale fire disaster management but did not address real-time data analytics or predictive modeling [26]. ML applications have been reviewed in wildfire research, covering fuel characterization, fire detection, and weather forecasting; however, optimization methods for AI models and real-time data fusion were absent [27]. A systematic review of decision-support techniques in fire management highlighted case studies and model performance but neglected future research directions and real-time capabilities [32]. Advanced image processing and deep learning for real-time wildfire detection have focused narrowly on image-based solutions without addressing broader risk assessment models[33]. Moreover, researchers summarized sensor-based early warning systems for fire prevention but lacked exploration of AI-based predictive analytics [34]. ML models were reviewed in forest fire science but explicitly omitted comparisons across ecosystems and systematic evaluations of model optimization[35]. In this review, we address the gaps identified in prior studies by integrating ML algorithms with real-time data analytics, remote sensing, and GIS-based decision support systems. We emphasize multi-ecosystem evaluations, optimization techniques for AI models, and future research directions to provide a comprehensive framework for wildfire risk assessment and management. By synthesizing these elements, we aim to advance predictive capabilities and foster adaptive strategies for mitigating wildfire impacts in diverse environments. Table 1 provides a comparative assessment of prior review studies against key dimensions such as real-time data integration, multi-ecosystem evaluation, optimization strategies, and GIS-based decision support. The table demonstrates that most reviews address only isolated components of wildfire modeling, whereas in this review, we uniquely integrate real-time analytics, cross-ecosystem evaluation, and future-oriented optimization strategies.

**Table 1.** Comparison of key contributions.

| Feature | Hu et al. [33] | Küçükarslan [34] | Ferrelli [35] | Jain et al. [36] | Bot & Borges [37] | Özel et al. [38] | Carta et al. [39] | Alkhatib et al. [40] | This Review |
|---|---|---|---|---|---|---|---|---|---|
| Focus on ML Algorithms | ✓ | ✓ | ✗ | ✓ | ✓ | ✓ | ✗ | ✓ | ✓ |
| Use of Remote Sensing Data | ✗ | ✗ | ✓ | ✓ | ✓ | ✗ | ✓ | ✓ | ✓ |
| Real-Time Data Integration | ✗ | ✗ | ✗ | ✗ | ✗ | ✓ | ✓ | ✗ | ✓ |
| Multi-Ecosystem Evaluation | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✓ |
| Optimization Techniques for AI Models | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✓ |
| GIS-Based Decision Support Systems | ✗ | ✗ | ✗ | ✗ | ✓ | ✗ | ✗ | ✗ | ✓ |
| Future-Oriented Research Directions | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✓ |

Despite advancements in wildfire detection and management technologies, significant research gaps remain in the integration of multidisciplinary strategies that combine remote sensing data, ML algorithms, and user-friendly technology. Wildfire management remains a complex challenge, and there are several critical gaps in the research and methodologies. Few researchers have successfully integrated multidisciplinary strategies, such as remote sensing, ML, and user-friendly tools, to develop comprehensive solutions for wildfire prediction and management. Comparative analysis of ML methods across ecosystems is limited, leaving uncertainties about the most effective models for wildfire prediction. Additionally, models are often data-centric, with minimal incorporation of real-time analytics, which could significantly enhance early detection and adaptive response capabilities. Fuel type mapping using remote sensing remains problematic due to terrain variability and seasonal changes, while many predictive models lack optimization through techniques, like hyperparameter tuning and ensemble learning, which can improve accuracy. The inherent uncertainty in wildfire behavior necessitates probabilistic modeling and advanced uncertainty quantification to build reliable systems. Scalability and generalization of ML models remain a hurdle, as models often struggle to perform consistently across regions; transfer learning and domain adaptation could address this limitation. Finally, decision support systems are not sufficiently user-centric, lacking interactive dashboards and GIS-based platforms that could empower responders with actionable insights, improving wildfire preparedness and response. Addressing these gaps through innovative, integrative approaches is essential for advancing wildfire management globally.

In this review paper, we aim to identify and analyze the following:

- Provide a comprehensive synthesis of remote sensing and ML techniques for wildfire risk assessment, detection, and control.
- Bridge the research gap by integrating real-time data analytics, remote sensing, and GIS-based decision support systems into a unified wildfire management framework.
- Conduct a comparative evaluation of ML models across ecosystems to assess predictive performance and adaptability.
- Introduce optimization approaches (e.g., hyperparameter tuning and ensemble learning) to enhance the accuracy and robustness of AI models for wildfire prediction.
- Propose a future-oriented framework, emphasizing multidisciplinary integration and user-friendly, interactive platforms for improved wildfire preparedness and response.

## 2. Materials and methods

### *2.1. Fire risk assessment*

Wildfire risk assessment relies on combining remote sensing (RS) indicators with ML models to map ignition likelihood and fuel conditions. RS datasets such as Landsat, Sentinel-2, MODIS, LiDAR, and hyperspectral imagery provide spatial information on vegetation type, fuel moisture, canopy structure, terrain, and prior burn scars. Key RS-derived variables, NDVI, NDWI, NBR, land surface temperature, and fuel model classifications, form the basis for hazard mapping across forests, shrublands, grasslands, and WUI regions. These inputs support multi-ecosystem evaluation, overcoming the limitations of local field surveys that are often time-consuming and scale-restricted [39,41–43].

#### 2.1.1. Application of remote sensing data for fire risk assessment

Remote sensing data play a crucial role in AI-based wildfire monitoring, not because of the sensor mechanics, but because of the constraints they impose on model performance. Instead of describing each sensor in detail, we highlight the three limitations most relevant to AI models:

Noise and Spectral Uncertainty: Satellite imagery often contains radiometric noise from atmospheric interference, sensor instability, and varying illumination conditions. This noise directly affects indices, such as NDVI, NBR, and LST, reducing feature reliability and causing misclassification in CNN, U-Net, and transformer-based models. AI pipelines must therefore incorporate noise-robust preprocessing (e.g., smoothing and denoising autoencoders), uncertainty quantification, or ensemble predictions.

Cloud Cover and Occlusion: Clouds, haze, and smoke frequently obscure fire fronts and fuel conditions, resulting in missing or corrupted pixels. Since deep learning models are highly sensitive to incomplete spatial patterns, this limits their ability to generalize in real-time detection. Cloud-gap filling, multi-temporal compositing, and thermal-infrared fusion are typically required to maintain model continuity, but even these can introduce uncertainty.

Domain Shift and Transferability Across Regions & Sensors: AI models trained on one sensor (e.g., Sentinel-2) or one ecosystem (e.g., pine forests) often fail when transferred to another due to differences in spatial resolution, spectral response, seasonal conditions, and land-cover composition. This domain shift reduces cross-ecosystem generalization, a core challenge in wildfire AI. Transfer learning, domain adaptation, and multisensor harmonization (e.g., Sentinel–Landsat fusion) are, therefore, more important than the differences between the sensors.

Fire hazard evaluation has become more accurate and scalable with advancements in remote sensing. Satellite imagery and aerial photography provide detailed information on land cover [35], soil texture [36], dumping and refuse grounds [37], vegetation health [38], and moisture levels [39], all of which are essential for assessing wildfire vulnerability[40]. Multispectral and hyperspectral sensors further enable detection of subtle vegetation and environmental changes [44], helping identify areas prone to changes [45].

Accurate fuel-type mapping remains critical for understanding fire behavior and maintaining ecosystem resilience [46]. While field surveys were traditionally relied upon, modern remote-sensing technologies, including multispectral and hyperspectral imaging, VHR imagery, and LiDAR, substantially reduce the time and effort required to quantify fuel structure, such as height, density, and spatial distribution [42,43,47]. Systems like the Canadian Fire Behavior Prediction System and the U.S. NFDRS support this process, though challenges persist due to natural variability in fuel types [48–51].

To address these limitations, researchers integrate CNNs with multisensor remote-sensing data, improving fuel-mapping accuracy even in dense or obscured forest canopies. The resulting high-resolution fuel maps, derived from combined remote-sensing and ground-based modeling approaches, enhance wildfire management and mitigation efforts. Ongoing technological progress continues to strengthen fire-hazard assessment and supports more effective forest-management strategies.

### 2.1.2. ML for wildfire risk assessment

According to the study by Jodhani et al.[3], efficient processing of large volumes of remote sensing data is essential for precise fire risk assessment. To analyze intricate links between environmental conditions and past fire occurrences, researchers have employed sophisticated techniques, including random forests, support vector machines, and neural networks[53]. To produce accurate fire danger forecasts, these models consider several factors, such as terrain features, weather trends, and human activity. [34,53].

### 2.1.3. Integration and mapping in wildlife risk assessment

The development of comprehensive fire risk maps is made possible by the combination of ML and remote sensing data, as indicated in the introduction. These maps help with efficient resource allocation and land management by categorizing geographic areas according to different fire risk levels. The proposed method highlights how ML and remote sensing can be used to predict wildfires. Wildfire management teams can priorities important interventions like building firebreaks, managing controlled burns, and organizing evacuation preparations with the aid of these maps [46]. In conclusion, fire risk assessment and mapping have greatly improved thanks to the integration of ML algorithms with data from remote sensing. The practical advantages of remote sensing demonstratedby the results of numerous studies, which give stakeholders useful information to help them make well-informed decisions for various applications [36,52,53].

### 2.1.4. Advanced AI methods for wildfire risk assessment

The real-time wildfire tracking system integrates adaptive sensor inputs from UAVs, thermal cameras, and ground-based detectors, with Dempster–Shafer Theory (DST) employed as an evidential reasoning framework to manage uncertainty during data fusion. DST enables the combination of heterogeneous sensor observations by assigning belief and plausibility measures to fire-state hypotheses, rather than relying on single deterministic probabilities. This enables the system to explicitly represent epistemic uncertainty arising from sensor noise, data gaps, and conflicting observations. As new sensor data are assimilated, belief functions are dynamically updated, improving the robustness and reliability of fire spread tracking and situational awareness during rapidly evolving wildfire events].

## *2.2. Fire Mapping using deep learning and remote sensing*

Modern wildfire mapping integrates deep learning with high-resolution RS imagery to improve fuel, ignitability, and burn-severity characterization. CNN and U-Net architectures are widely applied for:

- Automated burnt-area delineation
- Severity assessment via NBR/NBR2 enhancement
- Pixel-level fire boundary detection

Fusion of LiDAR with multispectral imagery significantly improves fuel-model classification accuracy, especially in dense canopy ecosystems. Multimodal approaches also reduce omission/commission errors by capturing both horizontal and vertical fuel distributions [54]. The mapping procedure is much more accurate and efficient thanks to the use of deep learning. Additionally, the deliberate use of remote sensing data dataset, has revolutionized national environmental and land-use mapping initiatives [55,56].

### 2.2.1. Fire mapping and the integration of geospatial technologies

Advances in wildfire mapping increasingly rely on the integration of deep learning, remote sensing, GIS, and advanced imaging technologies to support rapid detection and monitoring. Deep learning models such as CNNs and U-Net outperform traditional methods by enabling accurate identification of fire occurrences, burnt-area mapping, severity assessment, and fire-behavior forecasting from satellite imagery, offering valuable insights for resource allocation and operational decision-making. However, these models face challenges related to complex data preparation and limited model validation systems. Operational innovations, such as Project WILDFIRE, which integrates aerial thermal imaging, GIS, and GPS tracking, demonstrate the potential for generating near-real-time fire-state maps within 15 minutes, though concerns remain regarding data transmission delays and accuracy. Similarly, fusing LiDAR with QuickBird multispectral imagery in East Texas significantly improved fuel-model classification accuracy from 76.52% to 90.10%, highlighting the advantages of combining structural and spectral information for predicting fire behavior.

### 2.2.2. Revolutionary future of fire mapping in wildfire prediction and management

Research further demonstrates the value of LiDAR, satellite imagery, and AI-driven modeling for wildfire prediction and management. In Northern Germany, surface and canopy fuels were modeled using LiDAR and Sentinel-1/2 combined with ML, identifying pine stands on slopes as high-risk under dry, windy conditions. In the Jambughoda Wildlife Sanctuary, India, integrating satellite-derived fire severity metrics (NBR) with GIS-based multi-criteria evaluation produced fire-probability maps that flagged bamboo forests and areas near human activity as particularly susceptible. In Greece, neural networks combined with the Vegetation-Enhanced Fire Weather Index reliably predicted wildfire risk, were validated using the 2018 Mati wildfire event. In the Mediterranean region, multispectral–LiDAR fusion generated detailed fuel maps by capturing fine-scale vegetation structure not detectable through conventional methods. Collectively, these studies highlight the importance of AI, remote sensing, and data-fusion approaches in delivering scalable, ecosystem-specific wildfire risk assessment solutions Remote sensing and AI also play a pivotal role in the rapid detection of active wildfires. Satellites and UAVs provide real-time imagery, enabling more proactive and accurate early-warning systems. ML enhances this capability by analyzing continuous data streams, distinguishing fire signatures from background noise, and reducing false alarms. A multi-sensor strategy is often required [49], combining thermal, infrared, and complementary sensors to detect temperature anomalies associated with wildfires. Moreover, advancements in fire-sensing technology have expanded capabilities for early warning and incident monitoring [57]. Thus, continued improvements in sensor technology, microelectronics, and data analytics are essential for increasing the speed and reliability of fire detection, ultimately safeguarding lives, infrastructure, and ecosystems. Active fire detection remains fundamental to wildfire monitoring [58]. Tables 2 and 3 summarize the principal sensor types and satellite-based active fire detection techniques, respectively. Together, these tables emphasize the trade-off between spatial resolution, temporal frequency, and detection accuracy across MODIS, VIIRS, GOES, Sentinel-3, Landsat, and ASTER platforms, reinforcing the importance of sensor selection for operational wildfire monitoring.

**Table 2.** Sensors and their applications.

| Type of sensors | Application | Reference |
|---|---|---|
| Gas and particulate sensors | These sensors discern gases and particles generated during combustion, effectively identifying fires indoors and outdoors, and contributing to early fire warning systems. | [59] |
| Cameras and imaging: | Visual cameras and imaging methods, encompassing infrared cameras, offer real-time visual insights into fire incidents. They find common use in fire monitoring and surveillance. | [60] |
| LiDAR (Light detection and ranging) | Leveraging laser light for distance measurement and 3D mapping, Lidar detects smoke plumes, fire fronts, and terrain changes resulting from fires. | [61] |
| Microphones | Acoustic sensors recognize distinct fire-related sounds like crackling flames or structural collapses. These sensors, when combined with other technologies, enhance fire detection precision. | [62] |
| Flame detectors | Tailored sensors designed to detect flames or fire specifically, responding to the unique spectral traits of flames. They are prevalent in industrial settings. | [63] |
| Integrated systems | Many fire detection systems amalgamate multiple sensors and technologies to enhance accuracy and redundancy. These systems offer comprehensive fire monitoring and early warning capabilities. | [64] |

Figure 3 illustrates the range of sensors currently employed in wildfire detection, including gas and particulate sensors, imaging systems, LiDAR, acoustic sensors, and integrated multi-sensor platforms. The figure highlights how sensor diversity enables complementary detection capabilities, forming the basis for multi-sensor data fusion in real-time wildfire monitoring systems.

**Table 3.** Active fire detection techniques.

| Satellites | Applications | Reference |
|---|---|---|
| MODIS (Moderate Resolution Imaging Spectroradiometer | Installed on NASA's Terra and Aqua satellites, MODIS furnishes high-resolution imagery to detect active fires based on their thermal emissions. It calculates the Fire Radiative Power (FRP) to gauge fire intensity. | [65] |
| VIIRS (Visible Infrared Imaging Radiometer Suite) | Found on satellites like Suomi NPP and NOAA-20, VIIRS offers high-resolution imagery in visible and infrared bands, enabling day and night fire detection. It calculates FRP and identifies burning areas similar to MODIS. | [66] |
| GOES (Geostationary Operational Environmental Satellite) | Geostationary satellites like GOES provide continuous real-time monitoring of large wildfires' development and movement, aided by the Advanced Baseline Imager (ABI) on GOES-R series satellites. | [67] |
| Sentinel-3 SLSTR (Sea and Land Surface Temperature Radiometer) | Aboard the Sentinel-3 satellite of the Copernicus program, SLSTR identifies fires by detecting elevated temperatures, crucial for monitoring fire-prone areas. | [68] |
| Landsat | Multispectral imagery from Landsat satellites aids in detecting fires by combining visible, near-infrared, and thermal bands to identify active fires and burned areas. | [69] |
| ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) | On NASA's Terra satellite, ASTER provides high-resolution thermal infrared data, facilitating accurate identification of active fire locations and intensities. | [70] |
| Himawari-8 and Himawari-9 | Japanese weather satellites with the Advanced Himawari Imager (AHI) capture high-resolution imagery, particularly beneficial for fire monitoring in the Asia-Pacific region. | [71] |
| Fire Weather Index (FWI) and Fire Danger Rating Systems | Utilizing weather data from various sources, these indices and systems assess fire potential based on factors like temperature, humidity, and wind speed. | [72] |
| Ground-Based Data | Complementing satellite observations, local weather stations and fire lookout towers provide vital weather and fire behavior data. | [73] |

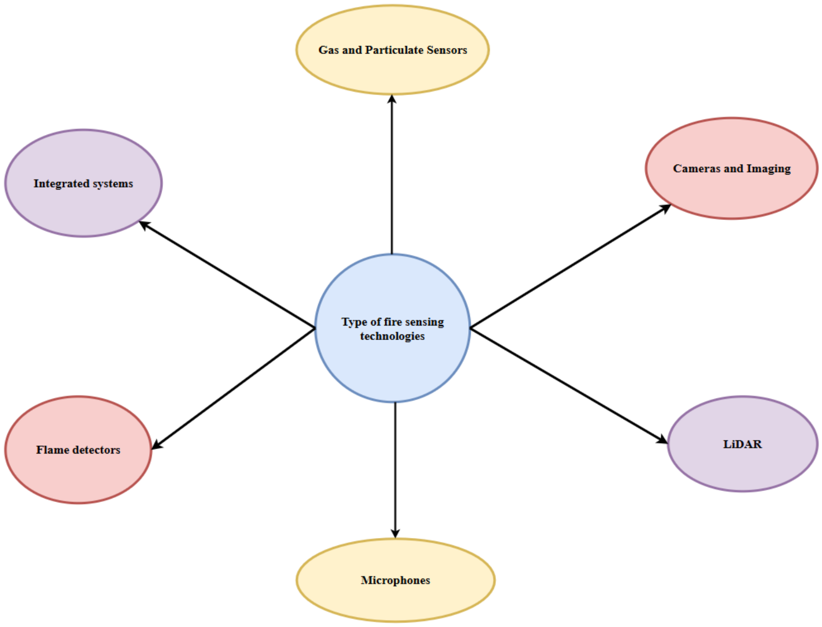

**Figure 3.** Types of fire sensors.

Researchers like Huot et al. have used MODIS for their work, while Grari et al. have used VIIRS sensor data for early wildfire detection [74,75]. Figure 4 depicts the timeline of fire sensor development from 1848 to the future, highlighting innovations like smoke detectors, thermocouples, optical fibers, AI-based detection, self-powered systems, and advanced fire extinguishing technologies.

### *2.3. Real time and edge AI for wildfire detection*

Advancements in wildfire detection increasingly emphasize how AI is deployed across cloud platforms, edge-computing devices, and UAV-based thermal and optical systems, each offering distinct operational capabilities and latency characteristics. Cloud-based infrastructures, such as Google Earth Engine, AWS, and Microsoft Azure, support computationally intensive deep learning models, including CNNs, LSTMs, for regional-scale fire detection, active fire monitoring, and risk forecasting. These systems typically operate with latencies ranging from several seconds to a few minutes, depending on satellite downlink frequency and server processing load. While unsuitable for immediate field deployment, cloud systems excel in high-resolution mapping, multi-temporal analysis, and integrating data from MODIS, VIIRS, Sentinel, and geostationary sensors.

In contrast, edge AI platforms (IoT nodes, Raspberry Pi, ARM Cortex processors, and embedded accelerators such as NVIDIA Jetson Nano) prioritize ultra-low-latency inference (50–200 ms) to support rapid, localized fire detection. These devices often use quantized or pruned neural networks optimized for limited power, memory, and field conditions. They enable on-site identification of temperature anomalies, smoke signatures, and gas/particulate indicators without relying on high-bandwidth connectivity. Edge systems are increasingly implemented in distributed sensor networks combining thermal imaging, acoustic signatures, infrared cameras, and gas sensors to provide fast and reliable early-warning capabilities.

UAV-based AI systems serve as an intermediate, highly adaptive layer for real-time surveillance. Drone-mounted thermal and multispectral cameras deliver near–real-time analytics with latency usually below 1–2 seconds, depending on onboard compute capacity and communication bandwidth. UAV thermal-vision models have incorporated SHAP-guided explainability methods, where pixel-level thermal contributions are highlighted to improve hotspot interpretation and operator confidence during aerial reconnaissance. This enhances the precision and transparency of fire-front identification, particularly in spatially heterogeneous or smoke-obscured environments.

Collectively, cloud, edge, and UAV-based AI systems form a complementary operational architecture. Cloud platforms provide large-scale prediction and multi-sensor data fusion; edge devices deliver rapid point-of-detection alerts necessary for ground response; and UAVs supply high-resolution, adaptive monitoring for hotspot confirmation and tactical support. This structured integration moves beyond catalogue-style listings and clarifies the practical deployment roles and latency constraints that govern real-time AI-enabled wildfire detection. Figure 4 presents a historical timeline of fire-sensor development, tracing progress from early smoke detectors to contemporary AI-enabled, self-powered, and intelligent sensing systems. This evolution reflects the increasing role of automation, real-time analytics, and AI integration in modern wildfire detection infrastructures.

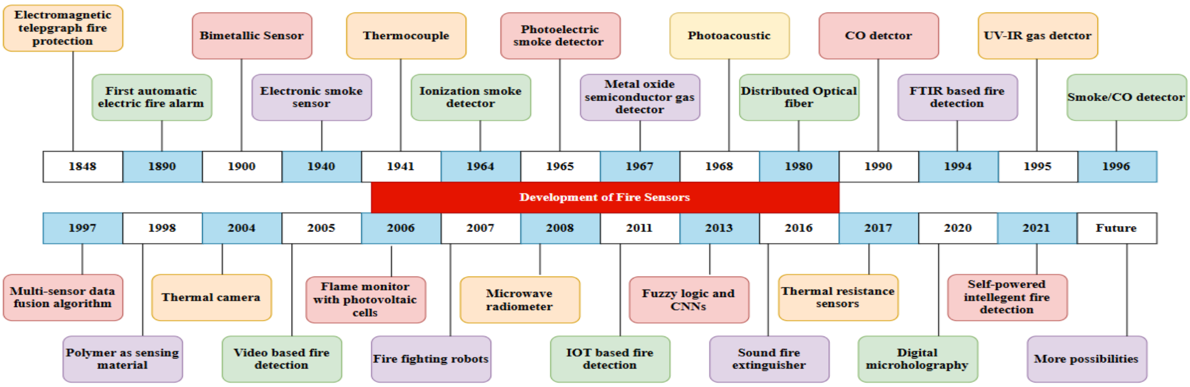

**Figure 4.** Sensors used over time.

## 3. Fire prediction methodology

### *3.1. Dynamic data-driven application systems (DDDAS)*

Advanced forecasting techniques are becoming increasingly important as wildfires become more common and fierce. The combination of AI/ML with remote sensing was examined in this review, with a focus on the Dynamic Data-Driven Application Systems (DDDAS) paradigm. Real-time data were included in this method to improve wildfire prediction. AI/ML examines these inputs to create prediction models for fire management, whereas remote sensing offers vital environmental insights. This procedure was enhanced by the DDDAS framework, which continually integrated real-time data and enabled dynamic model adaptation. Real-time data assimilation from sources such as satellites and weather reports is a fundamental component of DDDAS, and it enhances model accuracy by considering changing conditions into account. Furthermore, when conditions change, AI/ML algorithms continuously improve the model parameters to guarantee accurate wildfire forecasts. Such adaptability is particularly beneficial when predicting rapidly changing fire behavior. The benefits of employing DDDAS approaches are as follows:

- Improvements of Early Warning Systems: Early warning systems can provide more accurate and timely warnings to the public and fire-fighting organizations using the application of DDDAS. Resource planning and evacuation scheduling become more accurate with the inclusion of real-time remote sensing data in forecasting models.
- Enhanced Fire Spread Modeling: Dynamic data assimilation can be used to update fire spread models as the fire evolves. Real-time information on wind patterns, topography, and fire intensity is considered to produce more accurate projections of the fire spread trajectories, which benefits firefighting operations. Excellent case studies illustrate the effectiveness of DDDAS in wildfire predictions, which predicts the following:

1. Inclusion of current weather conditions: The DDDAS can accurately forecast the effects of altering weather conditions on fire behavior by incorporating real-time meteorological data into predictive models. Providing fire management crews with timely information improves decision-making.
2. Emergency evacuation planning: DDDAS-based models can generate dynamic evacuation plans that respond to changing fire dynamics based on real-time information on the spread of fire and environmental conditions, leading to safer and more effective evacuations.
3. Adaptive Resource Allocation: By incorporating real-time data on the severity of fires and their propagation patterns, DDDAS optimizes the resource allocation. This, in turn, enables firefighting institutions to strategically place resources where they are most needed.

Figure 5 illustrates the Dynamic Data-Driven Application Systems (DDDAS) framework, showing how real-time environmental data streams are continuously assimilated to update wildfire prediction models. The visualization clarifies the adaptive feedback mechanism that enables improved early warning, fire spread forecasting, and resource allocation.

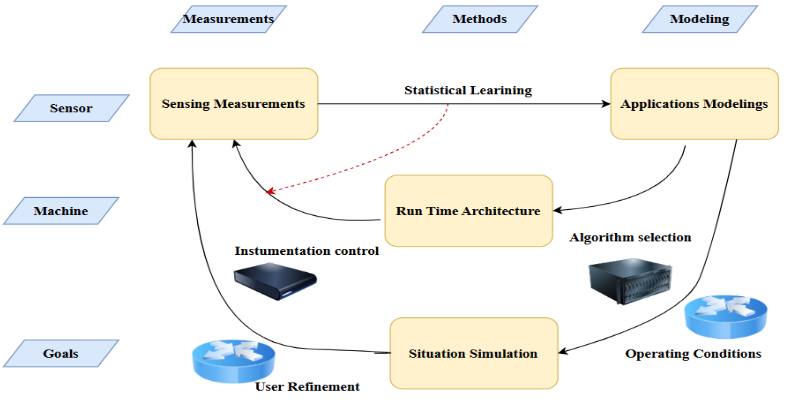

**Figure 5.** Dynamic data-driven application systems modeling visualization.

### *3.2. Boosted egression trees (BRT)*

A strong machine-learning method called BRT was used to predict the probability of fire incidents in a specific spatial and temporal unit called voxels. These three-dimensional voxels or samples combine previous fires in the area, current meteorology, and residual weather impact on fuel moisture. In BRT-based fire prediction, a complete framework with meteorology and fuel variables as explanatory variables and fire occurrence as the response variable was used. A central element of the BRT method is the building of a set of regression trees; decision trees for continuous outcome prediction. What distinguishes BRT from other methods is its iterative process, which builds trees incrementally to correct errors made in the previous step. Because it is an iterative method, BRT is most suitable for solving difficult phenomena where precise prediction and unambiguous interpretability are important.

Key Steps in the Process of Developing a BRT Model: Certain key procedures were followed to create accurate BRT models for predicting fire. First, the weather and fuel conditions were included in the inputs along with information on the presence (absent and present) of fire. Based on this dataset, predictive models can be created. Moreover, key factors such as learning rate, tree complexity, and the number of trees were tuned to enhance the efficiency of the model. The efficiency of the BRT approach is largely dependent on these factors. To measure the performance of BRT models, certain key metrics were used. The key metric used was the area under the receiver operating characteristic (ROC) curve (AUC). This is a measure used to evaluate the model's capability to discriminate fire occurrences and non-occurrences. To measure the accuracy of the model predictions, metrics like commission error (false positive rate) and omission error (false negative rate) were used. These measures of evaluation report information on the overall performance of the model. Figure 6 depicts the ensemble learning structure of the BRT model, demonstrating how multiple regression trees iteratively correct prediction errors. This figure supports the discussion on BRT’s ability to capture nonlinear interactions between meteorological conditions, fuel properties, and fire occurrence.

In terms of implementation, BRT models are created using R, a commonly used programming language for statistical modeling and graphical display, via the use of the 'gbm' package. This particular package enables the creation of a set of regression trees, thereby improving the iterative and boosting capabilities of the algorithm. A total of 25 BRT models were put together, and their outcomes were averaged to reduce the variability inherent in the model predictions. The ensemble approach improves the stability and consistency of the predictions.

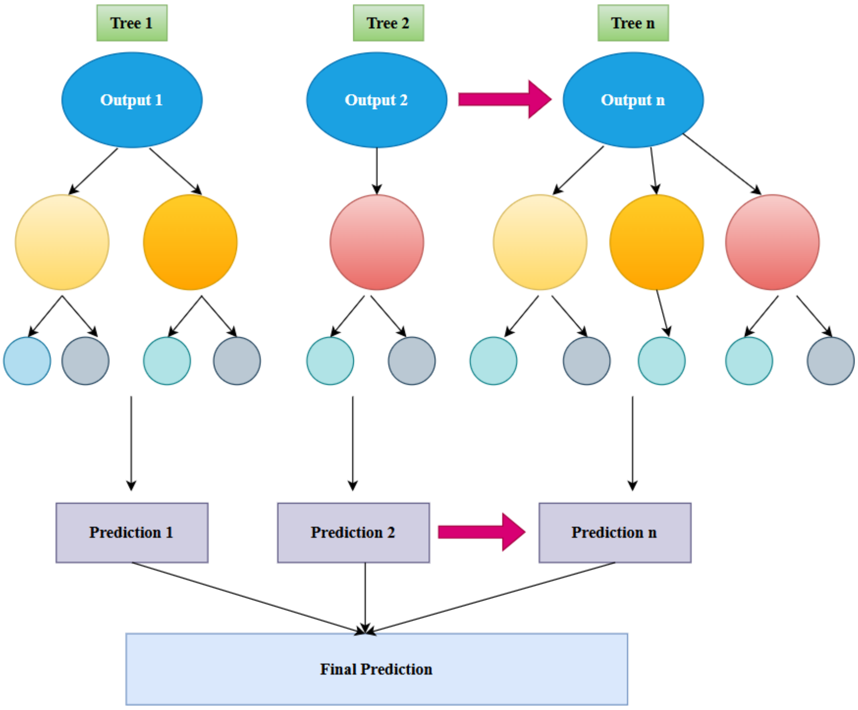

**Figure 6.** Boosted tree model interpretation.

### 3.2.1. Interpreting the results of the BRT model

BRT models provide useful information about the relative contributions of different factors to prediction precision. This was obtained through an examination of the relative importance of the aggregated squared improvements of each variable in the overall tree model. Through the similarity of relative importance of the input variables, practitioners can better understand the underlying factors responsible for driving predictions of the occurrence of fire in a more significant way.

By incorporating historical instances of fire occurrences, meteorological weather, and the nature of the fuel, BRT presents a comprehensive fire forecasting method. The recursive element of BRT, combined with its ability to correct errors in subsequent trees, makes it an ideal candidate for tackling the complexity of fire occurrence prediction. With their accuracy and reliability, BRT models are a resource that can prove useful in expanding our knowledge and predictive capability regarding wildfire outbreaks.

### 3.2.2. Maximum entropy model (MaxEnt)

The growing frequency and intensity of wildfires have increased the demand for reliable spatial prediction tools capable of identifying high-risk locations before ignition. MaxEnt has become widely used in wildfire modelling because it can generate accurate probability surfaces even when fire-occurrence data are sparse. In wildfire applications, MaxEnt integrates remote sensing variables, such as vegetation indices, fuel type, topography, temperature, land-use patterns, and moisture indicators,with historical fire points to estimate the spatial likelihood of fire occurrence. The model operates by determining the probability distribution of wildfire presence that is closest to uniform while satisfying constraints imposed by the environmental predictors. This results in continuous probability maps that highlight areas most susceptible to ignition and spread.

A standard MaxEnt wildfire-prediction workflow includes the following steps:

1. Input Data Preparation:
- Collect presence-only fire-occurrence points from fire records or satellite hotspots (MODIS, VIIRS).
- Extract environmental predictors from remote sensing products (e.g., NDVI, NBR, land surface temperature, elevation, slope, and fuel models).
2. Variable Selection and Pre-Processing:
- Remove redundant predictors, normalize variables, and assess collinearity.
- Prepare predictor layers at a consistent spatial resolution.
3. Model Training:
- MaxEnt uses environmental variables as constraints to estimate a probability distribution of wildfire occurrence.
- Regularization parameters are tuned to avoid overfitting.
4. Model Evaluation:
- Performance is assessed using AUC, TSS, or cross-validation with withheld fire-occurrence points.
5. Prediction and Mapping:
- The model generates continuous susceptibility maps that identify high-probability ignition zones.
- These maps support mitigation planning, resource allocation, and risk-based management.

#### 3.2.3. MaxEnt-boosted predictive modeling

ML techniques enhance MaxEnt's predictive capability by enabling more robust parameter tuning and improved handling of nonlinear relationships. When combined with historical fire data and remote sensing variables, MaxEnt can effectively capture complex environmental interactions and dynamically update predictions under changing climatic or vegetation conditions. Yang et al. [56] emphasized the utility of MaxEnt in wildfire forecasting, demonstrating how remote sensing inputs and ML-supported parameterization substantially improve ignition-risk mapping. This makes MaxEnt particularly valuable for operational wildfire science, especially in regions with limited or incomplete fire-occurrence datasets.

### *3.3. Remote sensing's participatory function*

The work of Mohajane et al. [76] emphasizes the paramount significance of remote sensing in the field of fire ecology. Coupling important information on vegetation dynamics, fire behavior, and post-fire impacts can be derived from satellite data. Inclusion of such data into the MaxEnt model enables more precise predictions of fire spread, intensity, and potential ecological impacts. The utilization of real-time data streams is also referenced. Recent advances have underscored the significance of the inclusion of real-time data streams for predictive modelling of wildfires in an adaptive manner. Current information related to atmospheric conditions, fuel moisture content, and fire behavior can be derived from satellite imagery and ground sensors. The probabilistic nature of the MaxEnt model enables easy integration of real-time information, thereby increasing the responsiveness and the accuracy of the model. Overcoming Challenges and Future Directions: Despite of its benefits, the application of the MaxEnt model in wildfire prediction has several challenges. It is important to employ appropriate constraints and variables while carefully preventing overfitting. Furthermore, the inclusion of high-resolution remote sensing data can improve the spatial precision of predictions generated by the MaxEnt model. Figures 7 and 8 illustrate the IP3 framework and its uncertainty-aware prediction structure. These figures highlight how IP3 generates prediction intervals rather than deterministic outputs, providing explicit representation of uncertainty that is critical for risk-informed wildfire management.

### *3.4. Interval prediction trees*

The IP3 approach integrates the capabilities of ML and AI with comprehensive information derived from remote sensing, making it a promising tool in wildfire forecasting. Originating from the work of Chetehouna, Tabach, Bouazaoui, and others, IP3 has demonstrated strong potential in improving forecasting precision and enhancing strategic wildfire management [77].

#### 3.4.1. Principles and advances in interval prediction tree methods

The Interval Prediction Tree (IP3) method is an extension of regression tree models designed to better represent the variability and uncertainty present in wildfire-related data. This is especially relevant for aggregated temporal variables commonly encountered in wildfire analysis. Compared with simple regression trees, IP3 manages statistical measures such as mean and variance more effectively, improving the representation of fluctuating environmental conditions.

Important Qualities and Innovations: The IP3 technique includes several significant features and developments that increase its effectiveness:

1. Synchronized estimators, which improve the handling of statistical properties of numerical attributes [78,79].
2. The incorporation of Mahalanobis distance, which supports more informed node splits by jointly considering interactions between input features and target variables [80].

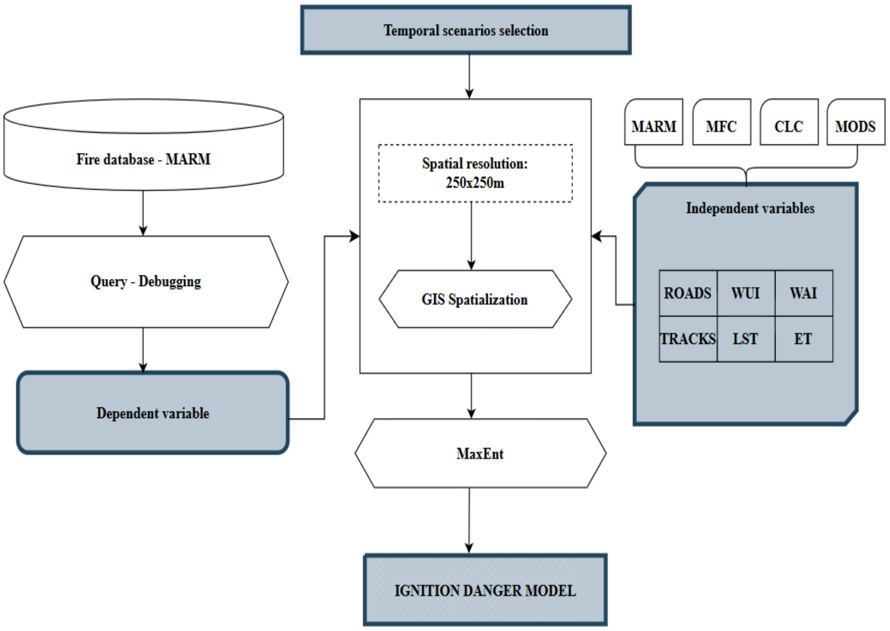

**Figure 7.** Fire risk modeling with data and spatial analysis.

### 3.4.2. Observations from prediction intervals

A defining feature of the IP3 method is its ability to generate **prediction intervals**, which reflect the uncertainty associated with each forecast. Rather than providing only a single deterministic output, IP3 communicates a range of plausible values, offering a clearer picture of confidence in the prediction. This information is crucial for planners and stakeholders who require transparent uncertainty estimates when assessing ignition risk or evaluating potential fire behavior [78].

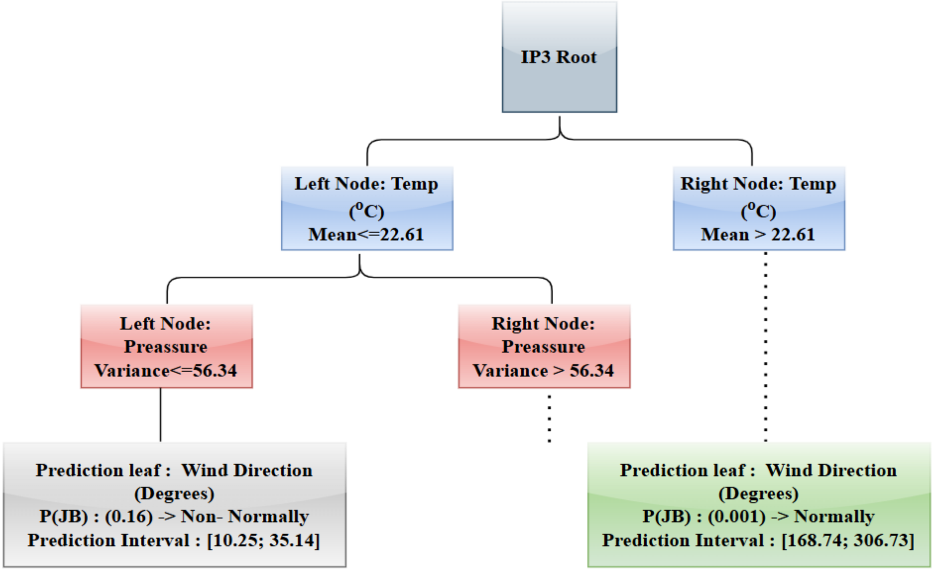

**Figure 8.** IP3 tree visualization.

### 3.4.3. Construction of the interval prediction tree

While the underlying construction of an IP3 model involves statistical estimators and distance-based measures, the central purpose of the approach is to integrate variability directly into the forecasting structure. By modeling both central tendencies and dispersion within the data, IP3 produces predictions that inherently account for dynamic environmental conditions. This embedded uncertainty representation distinguishes IP3 from more conventional tree-based models [78].

### 3.4.4. Integrating ML and remote sensing for prediction

The strength of the IP3 methodology lies in its ability to combine ML/AI techniques with remote sensing data. Remote sensing provides essential environmental indicators, such as vegetation cover, land surface temperature (LST), humidity gradients, and wind dynamics, that strongly influence ignition probability. IP3 leverages this information to model the complex relationships between environmental variability and wildfire risk, enhancing the interpretability and reliability of predictions. This integration positions IP3 as a robust framework for real-time monitoring and forecasting.

### 3.4.5. Practical applications and inherent advantages

The combined use of remote sensing, AI/ML, and the IP3 framework offers several practical advantages in wildfire risk modeling.

- Improved precision arises from the model's ability to incorporate diverse environmental inputs and represent their interactions.
- Uncertainty quantification, enabled by prediction intervals, provides decision-makers with detailed insights into the reliability of each forecast, supporting more cautious and informed management strategies.
- Real-time adaptability enables IP3 to update forecasts as new environmental data become available.
- Better resource allocation is achieved because interval-based predictions help identify areas of high risk and high uncertainty, guiding prioritized intervention efforts.

These strengths highlight the potential of IP3 in advancing environmental monitoring and enhancing disaster management efforts. Table 4 compares AI models in terms of computational requirements and deployment environments, ranging from cloud-based deep learning systems to edge-AI and embedded platforms. The table emphasizes the operational trade-offs between model complexity, latency, and scalability in real-time wildfire detection.

**Table 4.** Comparison of AI models by computational requirements and deployment platforms.

| AI model type | Computational requirements | Deployment platform | Reference paper |
|---|---|---|---|
| Deep learning models (CNNs, RNNs, Transformers) | High-performance GPUs (e.g., NVIDIA A100, TPU v4) | Cloud-based (Google Earth Engine, AWS, Microsoft Azure) | [81] |
| Traditional ML Models (Random Forests, Decision Trees, SVMs) | Low-power processors | Edge devices (IoT sensors, Raspberry Pi) | [76] |
| Quantized Neural Networks (QNNs) | Optimized for low-power hardware | Embedded systems (NVIDIA Jetson Nano, ARM Cortex) | [82] |

### *3.5. Artificial nural network (ANN)*

Artificial Neural Networks (ANNs) contribute significantly to wildfire prediction by improving the management of uncertainty inherent in remote sensing data and environmental variability. Wildfire occurrence depends on nonlinear and interacting factors (i.e., fuel conditions, vegetation stress, land surface temperature, and rapidly changing meteorological variables), each carrying substantial measurement and temporal uncertainty. ANNs are particularly effective in this context because they learn complex, nonlinear relationships directly from multi-source remote sensing inputs, enabling them to accommodate noisy datasets, missing values, and imperfect observations more robustly than traditional statistical models.

A key advantage of ANNs is their ability to reduce uncertainty through automatic feature extraction. By identifying salient patterns in high-dimensional remote sensing inputs, ANNs minimize the influence of redundant or unstable variables and amplify features with strong predictive value. Their capacity to model spatiotemporal dependencies further enhances reliability: By incorporating historical fire patterns, seasonal cycles, and time-lagged environmental indicators, ANNs smooth short-term fluctuations and reduce error introduced by rapidly changing conditions.

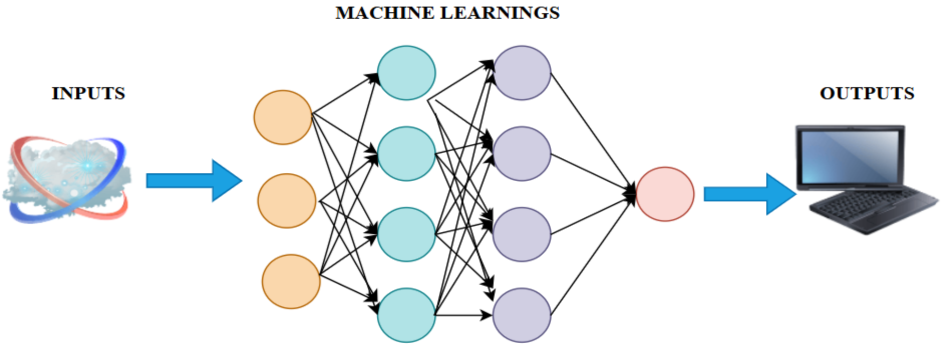

**Figure 9.** Machine learning approach.

Transfer learning also aids uncertainty reduction by enabling models trained on related tasks, such as vegetation classification or drought assessment, to be adapted to wildfire prediction, thereby stabilizing performance in regions with limited fire-history data. Additionally, ANN architectures can incorporate probabilistic outputs or ensemble approaches, producing confidence estimates that help fire managers interpret prediction reliability across heterogeneous landscapes. Figure 9 presents a generalized machine-learning workflow for wildfire prediction, illustrating the progression from remote sensing data acquisition to feature extraction, model training, and prediction. This schematic clarifies how AI models are embedded within end-to-end wildfire forecasting pipelines.

Overall, ANNs strengthen wildfire prediction frameworks by absorbing data noise, capturing nonlinear interactions, and generating more reliable probability estimates under uncertain and dynamic environmental conditions. Their integration with remote sensing data supports more informed decision-making, especially where uncertainty is highest and results into faster decision-making process [77].

### *3.6. Fuzzy logic modeling*

Fuzzy logic modeling contributes to wildfire prediction by improving how uncertainty, ambiguity, and incomplete information are handled in remote sensing–based assessments. Environmental variables such as temperature, humidity, wind speed, fuel moisture, and vegetation stress fluctuate rapidly and are often measured imprecisely. Fuzzy logic accommodates this uncertainty through membership functions and linguistic descriptors (e.g., low, moderate, and high), enabling wildfire likelihood to be expressed as graded levels of risk rather than rigid thresholds. This reduces sensitivity to noise in satellite observations and enhances the stability of predictions [83].

Building on foundational studies by Jain et al.[36], Szpakowski and Jensen [84], and Yang et al. [56], developments emphasize integrating fuzzy reasoning with remote sensing and AI/ML techniques to strengthen system adaptability. A key element of this hybrid approach is adaptive rule tuning, where AI/ML algorithms optimize membership functions, refine rule bases, and adjust inference behavior under evolving environmental conditions [85–87]. These adaptive mechanisms address the limitations of expert-defined fuzzy systems, improving scalability and reducing subjectivity, while capturing dynamic wildfire patterns from historical and satellite-derived data.

Overall, fuzzy logic enhances wildfire forecasting by explicitly modeling uncertainty, improving interpretability, and providing robust risk estimates when input data are noisy or incomplete. Its adaptive learning capabilities make it particularly valuable for early-warning systems, and its uncertainty-aware reasoning aligns naturally with multi-agent decision frameworks that coordinate responses under variable and uncertain wildfire conditions. Table 5 contrasts fuzzy logic and deep learning approaches with respect to interpretability, uncertainty handling, computational efficiency, and data requirements. The comparison highlights why hybrid models that combine deep learning accuracy with fuzzy-logic interpretability are increasingly favored for operational wildfire applications.

**Table 5.** Fuzzy logic vs deep learning: strengths and limitations.

| Factor | Fuzzy logic strength | Deep learning limitation | Reference |
|---|---|---|---|
| Interpretability & Transparency | Provides clear, rule-based outputs that are easily understood by experts and decision-makers, enhancing trust and facilitating informed actions. | Functions as a "black-box," making it challenging for users to interpret the rationale behind certain predictions, which can hinder trust and the ability to make informed decisions. | [88]. |
| Handling Uncertainty in Data | Excels in managing imprecise, incomplete, or uncertain data, which is common in environmental monitoring scenarios like wildfire prediction. | Requires large, well-structured datasets for accurate performance and may struggle with missing or noisy data, leading to potential inaccuracies in predictions. | [89] |
| Computational Efficiency | Lightweight and requires less processing power, making it suitable for deployment on low-power devices and facilitating real-time decision-making in resource-constrained environments. | Computationally intensive, necessitating high-performance hardware such as GPUs and substantial memory, which can limit real-time applicability, especially in field conditions. | [90] |
| Integration of Expert Knowledge | Allows for the incorporation of expert knowledge through manual rule adjustments, enabling quick adaptation to new environments or changing conditions without the need for extensive retraining. | Lacks straightforward mechanisms for integrating expert knowledge, making adaptation to new conditions slower and more cumbersome due to the need for retraining with new datasets. | [91] |
| Performance with Limited Data | Capable of functioning effectively with limited or small datasets by utilizing linguistic variables to generalize risk, making it robust in data-scarce scenarios. | Typically requires large, well-labeled datasets to achieve reliable performance; in data-scarce situations, the model's accuracy and generalization capabilities may be compromised. | [92] |
| Real-Time Decision Support | Offers immediate risk assessments, supporting real-time decision-making crucial for effective wildfire management and rapid response strategies. | May experience delays due to complex processing requirements, which can hinder timely decision-making in fast-evolving wildfire situations. | [93]. |

### *3.7. Analysis of methodologies and comparisons*

In this section, we critically synthesize the wildfire prediction methodologies reviewed in Sections 3.1–3.6, moving beyond descriptive comparison to evaluate how each modeling paradigm addresses the key research challenges identified in the Introduction: (i) Cross-ecosystem transferability, (ii) real-time data integration, and (iii) uncertainty quantification. Table 6 is therefore interpreted as a consolidation tool rather than an endpoint, with emphasis placed on methodological complementarities and operational trade-offs.

Transferability remains one of the most persistent limitations in wildfire modeling. Statistical and semi-empirical approaches such as BRTs and MaxEnt demonstrate strong performance within the ecosystems on which they are trained, particularly due to their robustness to limited data and ability to identify dominant environmental drivers. However, their reliance on ecosystem-specific feature distributions restricts generalization across heterogeneous landscapes such as forests, grasslands, shrublands, and WUI regions. Models trained in fuel-homogeneous environments often exhibit degraded performance when applied to regions with distinct vegetation structure, fire regimes, or sensor characteristics. Table 6 synthesizes the predictive methodologies reviewed in this study, comparing their objectives, data dependencies, and modeling strategies. The table demonstrates that no single method addresses all operational challenges, thereby motivating the proposed Hybrid Predictive Framework that integrates real-time adaptability, uncertainty quantification, and cross-ecosystem generalization.

**Table 6.** Comparative synthesis of wildfire prediction methodologies against key operational challenges.

| Methodology Used | Authors | Objective | Cross-Ecosystem Transferability | Real-Time / Dynamic Integration | Uncertainty Quantification | Key Strengths | Key Limitations & Gaps |
|---|---|---|---|---|---|---|---|
| Fuzzy Logic Models | Vakalis et al. [94] | Rule-based fire risk assessment | Low–Moderate – rules often ecosystem-specific | Moderate – can accept streaming inputs but requires rule updates | Implicit – via membership functions | High interpretability; robust to noisy RS data | Poor scalability; limited adaptability across heterogeneous biomes |
| ANN (Shallow / Classical) | Zhang et al. [95]; Chetehouna et al. (2015) [77] | Nonlinear fire occurrence prediction | Moderate – improves with diverse training data | Moderate – retraining required for updates | Limited – typically deterministic outputs | Captures nonlinear interactions; flexible | Black-box behaviour; weak uncertainty expression |
| Boosted Regression Trees (BRT) | Parks et al. [96] | Fire susceptibility & severity modelling | Low – sensitive to local feature distributions | Low – relies on static historical datasets | None | Strong performance with limited data; interpretable drivers | Poor real-time suitability; weak generalisation |
| MaxEnt | Yago et al. [97] | Spatial ignition probability mapping | Low–Moderate – presence-only bias across ecosystems | Low – static probability surfaces | Limited – probabilistic output without confidence bounds | Effective with sparse fire data | No dynamic updating; weak operational use |
| Deep Learning (CNN, FCN, LSTNet) | Huot et al. [98]; Ghali et al. [99]; Lin et al. [100] | Fire detection, spread & severity | High (conditional) – requires multi-regional training | High – supports satellite/UAV streaming data | Low – typically deterministic | High accuracy; strong spatiotemporal learning | Computationally intensive; low interpretability |
| Hybrid ML Models | Mohajane et al. [17]; Pham et al. [101] | Fire susceptibility & risk optimisation | Moderate–High – depends on fusion strategy | Moderate – partial dynamic updating | Partial – ensemble variability | Improved robustness via model fusion | Still limited uncertainty formalisation |
| Interval Prediction Trees (IP3) | Dima Alberg [78]; Chetehouna et al. [77] | Uncertainty-aware fire prediction | Moderate – transferable with recalibration | Moderate – interval updates possible | Explicit – prediction intervals | Transparent uncertainty representation | Scalability issues in high-dimensional RS data |
| Reinforcement Learning / DDDAS-Based Frameworks | Yoon et al. [102]; Gandikota et al. [103] | Adaptive, real-time fire prediction | High – policy learning across domains | Very High – continuous data assimilation | Partial – policy uncertainty not always explicit | Dynamic adaptation; operational relevance | High system complexity; limited field deployment |

In contrast, Artificial Neural Networks (ANNs) and deep learning architectures offer improved transferability when trained on multi-regional or multisensor datasets, as they learn higher-order, nonlinear feature representations that are less dependent on local thresholds. Nevertheless, this advantage is contingent on the availability of large, diverse training datasets and careful mitigation of domain shift. Interval Prediction Trees (IP3) and fuzzy logic models, while more interpretable, show limited scalability across ecosystems due to their reliance on predefined rules or statistical assumptions that do not readily adapt to changing biome characteristics. These observations reinforce that no single model achieves universal transferability, highlighting the need for hybrid and adaptive frameworks.

The integration of real-time or near-real-time data is essential for operational wildfire management. Conventional models such as BRT and MaxEnt rely primarily on static historical datasets, limiting their effectiveness under rapidly changing fire conditions; frequent retraining is computationally intensive and unsuitable for time-critical applications. In contrast, dynamic learning-based approaches, including ANNs, deep learning models, and DDDAS, can assimilate continuous data streams from satellites, UAVs, IoT sensors, and meteorological sources, enabling adaptive and timely updates of fire risk and spread predictions. This capability, however, increases computational demands and reduces model transparency, particularly in cloud-based deployments, while edge and UAV-based implementations mitigate latency at the expense of simplified model complexity and potential accuracy loss.

IP3 and fuzzy logic systems offer advantages for uncertainty-aware wildfire prediction. IP3 explicitly provides prediction intervals, capturing epistemic and aleatory uncertainty arising from environmental variability and data aggregation, while fuzzy logic models handle imprecision by expressing fire risk through graded membership functions rather than rigid thresholds, improving robustness under noisy or incomplete remote sensing inputs. However, both methods face limitations in scaling to high-dimensional datasets and large spatial domains. Thus, studies highlight hybrid approaches that integrate probabilistic reasoning (IP3 or Bayesian inference), fuzzy rule-based uncertainty handling, and data-driven adaptability from ANNs or deep learning models as the most effective strategy, enabling high predictive accuracy alongside transparent and interpretable risk communication.

The comparative analysis in Table 6 demonstrates that wildfire prediction performance is inherently context-dependent, influenced by data availability, ecosystem variability, temporal dynamics, and computational constraints. Rather than a single optimal model, the findings support a hybrid predictive paradigm that leverages complementary strengths: BRT and MaxEnt for identifying key drivers and baseline susceptibility, ANN and deep learning models for capturing spatiotemporal dynamics and enabling real-time forecasting, and IP3 and fuzzy logic approaches for embedding uncertainty awareness critical to operational trust. Accordingly, we propose a Hybrid Predictive Framework (HPF) that integrates real-time remote sensing with adaptive ML, probabilistic uncertainty modelling, and explainable decision layers, directly addressing the challenges of transferability, real-time integration, and uncertainty quantification.

## 4. Burned area and severity assessment

Landscapes are significantly altered by wildfires; thus, efficient assessment and control are crucial. Estimating the magnitude of the burned area is a crucial undertaking that offers important information on the effects of wildfires. This discipline has changed dramatically with advances in AI/ML and remote sensing. A deep learning model that uses Sentinel-2 data from Google Earth Engine to improve coarse burned area maps and create a high-resolution (10m) burned area map is shown in Figure 10. Professionals are better equipped to handle wildfire issues, develop recovery plans, and improve wildfire management due to this combination of innovation and technology. Figure 10 illustrates a deep-learning-based burned area mapping approach using high-resolution Sentinel-2 imagery, while Table 7 summarizes key parameters influencing burned area estimation. Together, they demonstrate how AI-enhanced remote sensing improves spatial precision and supports post-fire damage assessment and recovery planning.

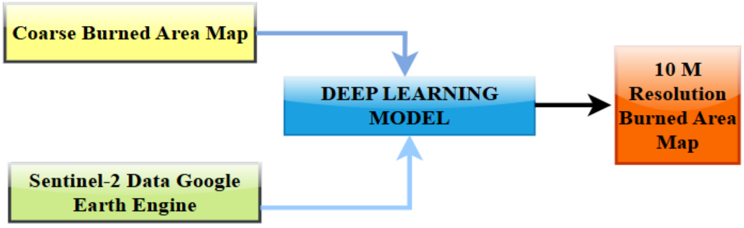

**Figure 10.** Area mapping using a deep learning model.

**Table 7.** Different parameters of burned area estimates.

| Area | Description | Reference |
|---|---|---|
| Burned areas assist | The estimate of burned areas helps manage wildfires. It assists with assessing damage, directs firefighting efforts and informs recovery plans. Without accurate estimates, rehabilitation strategies cannot be put in place; we cannot allocate resources effectively. In doing so, burned area estimation generates straightforward information to aid in effective decision-making and improve the efficiency and focus of broad-scale efforts in reducing the impacts of wildfire. | [83] |
| Using Remote Sensing and AI-ML for data estimation | Combining remote sensing with AI/ML was a game changer for wildfire. By integrating satellite and aerial data with the ability of AI to analyze complex patterns, it produces accurate estimates of burned areas. This enables decision-makers to gain actionable insights for concise resource allocation, immediate responses, and enhanced recovery strategies, improving the overall approach to wildfire management. | [104,105] |
| Research insights and method improvements | Advances in burned area estimation have taken place over the years, beginning with Siljander's 2009 predictive fire modeling, which enabled proactive wildfire management. This change has improved resource allocation and prevention. Kurbanov et al.'s 2022 focus on predictive modelling has further enhanced our ability to forecast fire spread, estimate burned areas, and optimize response strategies. | [104,106] |
| New techniques and comparison | OBIA (Object-Based Image Analysis) is an innovative technique changing the way fire management is done, giving a more precise view of the post-fire landscape. In contrast to the traditional pixel-based methods, OBIA evaluates features and their interactions to find burned areas with much more precision. | [107,108] |
| Execution and future steps | New remote sensing technologies, including drones and satellites, are changing the management of wildfires. Real-time data provides fire teams with critical insights into fire dynamics, enabling effective resource and large data sets to inform fire containment policy, enhance evacuation planning, and target recovery interventions in the most affected areas. Apply full-range data analysis to maximize fire management, enhance evacuation procedures, and target recovery in the most affected areas by fire. | [109,110] |

### *4.1. Burned severity assessment*

An essential part of post-wildfire investigations is the assessment of burn severity, which provides vital information about the ecological effects of flames. Burned severity evaluation has become a highly accurate and effective method using developments in remote sensing technology and the incorporation of AI and ML techniques.

Burn severity assessment is a critical component of post-wildfire analysis, providing valuable insights into the ecological impact of fires. Advances in remote sensing technology, coupled with AI and ML techniques, have significantly enhanced the accuracy and efficiency of burn severity evaluation. High-resolution satellite imagery and aerial photography enable researchers to capture detailed burn patterns, while spectral signature analysis enables the identification of landscape changes caused by fire. AI-driven classification algorithms, such as Random Forest, Support Vector Machines (SVM), and Convolutional Neural Networks (CNN), further refine severity assessments by leveraging spectral indices like the NBR and textural properties. ML models trained on pre- and post-fire datasets can predict burn severity levels in previously unobserved areas, ensuring timely and precise evaluations. Remote sensing-based assessments offer a comprehensive and objective approach, facilitating large-scale analysis, rapid data acquisition, and standardized severity classification, which are essential for effective wildfire recovery and mitigation planning.

The evaluation of burn severity has been transformed by merging remote sensing, AI, and ML methods. Researchers can precisely identify and measure burned regions by examining spectral shifts and using sophisticated algorithms, providing important insights for wildfire management and ecological restoration efforts.

## 5. Challenges and future directions

### *5.1. Data skewness and batch training issues*

One of the most challenging issues in ML applications for hotspot prediction in wildfires is the highly imbalanced class distribution. Non-hotspot occurrences occur many more times than hotspot occurrences, which enables models to be very accurate by predicting no hotspots most of the time. To handle this, resampling strategies are employed to balance the training set, and an even balance of hotspot and non-hotspot examples is generated. This balancing enhances model performance by enabling it to more easily separate the two classes. An additional challenge results from the Landsat 7 satellite's uneven orbit, which generates missing data in the satellite image time series. This interferes with neural network training by inducing dimensional mismatches, which typically requires a batch size of 1. While padding schemes provide a solution, their usage in satellite image time series data represents an area that requires further exploration.

### *5.2 Model specification and implementation challenges*

Building a machine model requires careful consideration of feature choice and spatial autocorrelation beyond mere data issues. More variables do not always lead to better accuracy or model interpretability. The selection of the right features depends on the degree of expertise required to guarantee precision, control computational cost, and avoid overfitting. Techniques such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GAs) facilitate efficient best feature subset selection, thereby enhancing model performance. Geographical autocorrelation is a further issue in that it breaches the independence assumption in parametric models and has the potential to reduce performance. Subsampling methods are employed to counteract this by eliminating geographical bias and enhancing model robustness.

### *5.3 Use of CNNs for spatial autocorrelation*

Convolutional Neural Networks (CNNs) efficiently handle spatial autocorrelation by learning spatial features from data. Compared to conventional parametric models, CNNs efficiently take advantage of the spatial dependencies present in wildfire data and can learn complex patterns and relationships. CNNs are thus a highly effective tool for dealing with the issue of spatial autocorrelation, greatly enhancing the accuracy of wildfire hotspot forecasts.

The accurate prediction of wildfire hotspots requires an integrated strategy that combines domain knowledge with advanced technologies. The major methods involve resampling for balancing data distribution, missing time step management using new batch training methods, and information feature selection with spatial autocorrelation management. CNNs provide an effective solution by realizing and exploiting spatial correlations, thereby providing enhanced predictive accuracy. Wildfire prediction can be improved by incorporating expertise, interdisciplinary research, and the implementation of advanced technology. The technology will improve the management and mitigation of wildfires and result in improved disaster response and prevention initiatives.

### *5.4. Future prospects for wildfire forecasting*

The discipline of fire forecasting is moving toward substantial progress with the intersection of several varied inputs, i.e., enhanced modeling techniques, remote sensing imagery, and ML algorithms. Ongoing research advancement within these domains will enhance precision in forecasts and enable the formulation of more effective wildfire management planning.

In the future, promising developments may improve the effectiveness, precision, and overall quality of techniques for wildfire control techniques. Tables 8 and 9 consolidate numerical performance benchmarks and future research priorities for wildfire prediction and assessment. These tables translate methodological advances into quantifiable improvements, reinforcing the practical relevance of AI- and RS-based wildfire monitoring systems.

**Table 8.** Numerical benchmarks for burned area mapping, severity assessment, and AI-Based wildfire prediction.

| Aspect | Metric / Parameter | Reported Numerical Range | Key References |
|---|---|---|---|
| Burned Area Mapping | Spatial resolution | 10 m (Sentinel-2 DL-based) vs. 250–500 m (MODIS) | [61,62,103,111] |
| | Overall accuracy | 88–94% | [99, 103,112] |
| | F1-score | 0.86–0.92 | [100,103] |
| | Commission error reduction | 15–25% | [99,100,103] |
| | Burned area correlation ($R^2$) | 0.72–0.89 | [112] |
| OBIA & Spectral Methods | Accuracy improvement over pixel-based methods | +5–12% | [99,100] |
| Burn Severity Assessment | Overall classification accuracy | 85–93% | [100,103] |
| | Kappa coefficient | 0.78–0.88 | [112] |
| | Improvement in high-severity class detection (DL-based) | +10–18% | [100,103] |
| | RMSE (severity prediction) | ≤0.15 (AI-based) vs. 0.22–0.30 (index-only) | [100,112] |
| | dNBR severity thresholds | <0.27 (Low), 0.27–0.44 (Moderate), >0.44 (High) | [100] |
| Data Skewness | Non-fire class proportion | 90–98% of samples | [71,113,114] |
| | Fire-class recall (imbalanced datasets) | <0.40 | [114,91] |
| | Fire-class recall after resampling (SMOTE/ADASYN) | 0.70–0.85 | [91,114] |
| | False-positive increase after resampling | 5–8% | [91,114] |
| Temporal Data Gaps | Cloud-induced missing data | 30–40% per scene | [61,62,111] |
| | Satellite revisit interval | 16 days (Landsat), daily (MODIS/VIIRS) | [61,62,111] |
| | Added uncertainty from padding/interpolation | 5–10% | [103,105] |
| Model Specification | Optimal number of predictors | ~20–25 variables | [98,101,114] |
| | Overfitting risk beyond optimal features | +10–15% | [98,114] |
| | AUC inflation due to spatial autocorrelation | 0.08–0.15 | [101,114] |
| CNN-based Hotspot Prediction | Accuracy improvement over traditional ML | 12–20% | [99,103] |
| | Precision | 0.80–0.88 | [99,103] |
| | Recall | 0.75–0.85 | [99,103] |
| Future Performance Targets | Early-warning latency | <60 s (edge/UAV AI) | [58,72,117] |
| | Operational spatial resolution | ≤10 m | [104,112] |
| | Ignition probability uncertainty bounds | ±10–15% | [73,75,109] |
| | Cross-ecosystem performance loss (target) | <10% | [18,94,102] |

**Table 9.** Key factors for fire risk assessment using AI and ML techniques.

| Aspect | Future Focus | Reference |
|---|---|---|
| Improved Data Inclusion | The integration of different sources of data, such as meteorological data, satellite images, past fire records, and real-time sensor readings. The use of advanced methods, such as data assimilation and spatiotemporal data mining, helps enhance the accuracy of forecasts. | [115] |
| Deep Learning and Neural Networks | Investigation of newer models such as RNN and Transformer-based models to identify temporal relations and complex patterns in wildfire data, improving the accuracy of prediction. | [116] |
| Quantification of Uncertainty | Technique development, such as Bayesian methods, ensemble learning, and probabilistic modeling, is used to estimate and minimize uncertainty when it comes to predicting wildfires. These methods enhance reliability through more accurate measures of risk and confidence. | [117] |
| Integrating Social and Behavioral Factors | The integration of behavior and social data with forecasting models is targeted at improving wildfire management with a particular focus on understanding how populations respond to evacuation orders, awareness messages, and risk messages. | [118] |
| Interpretable and Explainable AI | Creation of techniques to provide insights into variables affecting predictions, fostering stakeholder confidence and informed decision-making in wildfire control. | [119] |
| Real-time Adaptive Models | Development of models capable of adapting to real-time data streams (e.g., weather updates, sensor readings) for highly responsive and precise wildfire predictions. | [120] |
| Early Warning Systems | Integration of predictive models into early warning systems to improve catastrophe preparedness, providing timely notifications and risk assessments. | [121] |
| Collaboration and Open Data Sharing | Promotion of collaboration among researchers, agencies, and communities through centralized platforms for sharing data, methods, and models to advance wildfire prediction and management. | [122] |
| Ethical Considerations and Bias Mitigation | Addressing ethical issues and biases in wildfire prediction models to ensure fair, equitable, and effective wildfire management, considering socioeconomic differences and vulnerable populations. | [123] |
| Research-Practical Implementation Integration | Emphasizing the need for collaboration among scientists, policymakers, and practitioners to take advanced predictive models and use them to design effective prevention and management strategies for wildfires. | [124] |

Overall, the discipline of wildland fire prediction is a rich source of opportunity for innovation and development. By tapping into the wisdom of a wide variety of sources, including cutting-edge modeling techniques, remote sensing information, and ML, and by encouraging multidisciplinary collaborations, researchers and practitioners can collaborate to strive for a safer and more resilient future in the face of the increasingly formidable challenges of wildfires.

## 6. Discussion

Wildfire prediction models continue to face substantial challenges arising from ecosystem variability, data limitations, and operational deployment constraints. A central barrier is cross-ecosystem generalization, as model performance often deteriorates when approaches trained in one biome, such as temperate forests, are applied to shrublands, grasslands, or WUI regions. Differences in fuel structure, fire behavior, and remote sensing signal characteristics necessitate model architectures capable of systematic domain adaptation. Researchers employing ensemble learning, adaptive sampling strategies (SMOTE, ADASYN), and gradient-boosting methods such as XGBoost, CatBoost, and LightGBM demonstrate improved robustness across heterogeneous wildfire environments by capturing nonlinear fuel–climate interactions and mitigating class imbalance without sacrificing predictive sensitivity. Table 10 presents the real-world applications of AI-Based wildfire prediction systems.

**Table 10.** Real-world applications of AI-based wildfire prediction systems.

| Application | Technology Used | Impact | Reference Paper |
|---|---|---|---|
| Early Warning Systems for Forest Management Agencies | Remote sensing, ML models, IoT weather stations | Enables proactive wildfire prevention through predictive analytics and alerts. | [125] |
| AI-Driven Firefighting Drones | AI-powered suppression planning | Reduces human risk by guiding aerial fire suppression with precision. | [76] |
| Smart Cities and Infrastructure Protection | AI-driven surveillance cameras | Minimizes urban fire spread and enhances disaster response time. | [126] |

Equally critical is the issue of operational uncertainty, which arises due to atmospheric interference, inconsistent ground-truth data, hyperparameter instability, and mismatches in spatial–temporal resolutions across sensors. Uncertainty-aware approaches, such as probabilistic modeling, Bayesian ensembles, interval-based prediction (e.g., IP3), and dynamic data assimilation frameworks like DDDAS, remain essential for quantifying epistemic and aleatory uncertainty in real-time forecasting. These methods enhance practitioner confidence by supplying confidence intervals, probabilistic ignition likelihood, and uncertainty-aware spread projections that adapt to rapidly changing fire conditions. Addressing data scarcity through semi-supervised learning, transfer learning, and synthetic data generation further reduces uncertainty tied to limited fire-occurrence datasets, while multi-sensor fusion (thermal, LiDAR, SAR) helps overcome the constraints of optical imagery affected by smoke and cloud cover.

A third priority is practical explainable AI (XAI), which is indispensable for operational adoption. Fire managers require interpretable outputs rather than opaque model decisions, especially when predictions guide evacuation, suppression planning, and resource distribution. Moreover, SHAP-based interpretability frameworks [127] have shown strong promise in revealing feature contributions, such as fuel moisture, land surface temperature, or topographic exposure, thereby enabling transparent and defensible decision support. Incorporating XAI directly into real-time prediction workflows also assists in detecting model drift and identifying ecosystem-specific vulnerabilities that hinder generalization.

Finally, it is important to recognize that these methodological enhancements must consider computational cost, as high-resolution deep learning models and multimodal data fusion often require GPU-intensive cloud environments for training and deployment. Lightweight architectures, quantized neural networks, and edge-AI implementations offer a viable pathway to reduce resource demand while maintaining operational responsiveness in remote, connectivity-limited regions.

## 7. Conclusion

For this review, we were motivated by three persistent challenges in wildfire research: Limited cross-ecosystem transferability of predictive models, insufficient integration of real-time data streams, and inadequate representation of uncertainty and interpretability in operational systems. Through a systematic synthesis of remote sensing datasets, ML and deep learning methodologies, and uncertainty-aware modeling approaches, we consolidate fragmented literature into a coherent analytical framework applicable across forests, grasslands, shrublands, and WUI environments.

The comparative analysis demonstrates that no single modeling paradigm can independently satisfy the competing demands of predictive accuracy, scalability, real-time adaptability, and transparent decision support. Statistical and tree-based models such as BRT and MaxEnt remain effective for baseline susceptibility mapping but exhibit limited generalization across heterogeneous ecosystems. In contrast, ANN and deep learning models improve spatiotemporal prediction and real-time responsiveness but often operate as black boxes with high computational demands. Interval Prediction Trees and fuzzy logic approach explicitly address uncertainty and interpretability, yet face scalability constraints when applied to high-dimensional, multi-sensor data. These complementary strengths and limitations directly motivate the proposed Hybrid Predictive Framework (HPF).

The HPF represents the primary contribution of this review, integrating real-time remote sensing inputs with adaptive ML, probabilistic uncertainty modeling, and explainable decision layers. By combining data-driven learning with uncertainty-aware and interpretable components, the HPF directly addresses the research gaps identified at the outset of the review, enhancing cross-ecosystem transferability, enabling near-real-time prediction, and supporting risk-informed wildfire management rather than deterministic forecasting alone. Importantly, the framework provides a structured pathway for operational deployment across cloud, edge, and UAV-based platforms.

This synthesis enables several key research and application directions, including uncertainty-aware early warning systems, transfer-learning strategies for heterogeneous landscapes, lightweight edge-AI implementations for time-critical detection, and user-centric GIS dashboards that translate complex predictions into actionable guidance. By explicitly aligning methodological advances with operational requirements, the proposed HPF bridges the gap between wildfire research and real-world decision-making, offering a robust roadmap for next-generation wildfire prediction, monitoring, and adaptive response under increasing climate-driven fire risk.

More resilience and readiness are promised by ongoing advancements in sensor technology and AI algorithms, even though problems such as data resolution and overfitting exist. Future developments will enhance citizen science-based community participation, real-time monitoring, and predictive capabilities. In the end, the combination of AI/ML with remote sensing enables communities and scientists to adapt to a changing natural environment, reduce the effects of wildfires, and support ecological recovery.

## Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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## Conflict of interest

There is no conflict of interest in the present work

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