

Review

From Ecological Monitoring to Prevention Decision Support: A Critical Review of Artificial Intelligence for Forest Fire Prevention

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Abstract

Forest fire prevention increasingly depends on translating ecological monitoring into earlier, more reliable decisions about ignition risk, fuel condition, spread potential, and management intervention. This critical review evaluates artificial intelligence (AI) for forest fire prevention through full-text extraction of core studies and contextual synthesis of foundational fire-science literature. The evidence base contains 179 unique references, including an AI-focused corpus, classical deterministic and probabilistic fire-danger and spread models, global ignition and lightning studies, remote-sensing and fuel-moisture foundations, decision-support tools, and governance literature. We define prevention-facing AI as systems that support pre-ignition or pre-escalation decisions and compare studies by data source, model design, validation protocol, forecast horizon, transferability, interpretability, and management action. The synthesis shows that AI is most mature for multimodal sensing, smoke/fire detection, susceptibility mapping, and short-horizon forecasting, but less mature for prospective decision-support validation, cross-ecosystem transfer, and operational accountability. AI is therefore most useful when it is hybrid, interpretable, and deployment-aware: it should complement established fire-weather and spread-model baselines while converting ecological observations into timely and actionable prevention judgments.

Keywords: forest fire prevention; ecological monitoring; early warning; ignition risk; lightning; spread-risk forecasting; decision support; explainable artificial intelligence



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1. Introduction: Why Prevention-Facing AI Needs a Critical Review Now

Forest fire prevention now operates under faster ecological change, stronger climatic stress, and more complex human pressure than the literature of a decade ago assumed. Drying trends, fuel instability, infrastructure expansion, and denser activity around forested landscapes all raise the cost of late or weak prevention decisions. In parallel, AI has spread rapidly across wildfire-related research, from sensing and ignition-risk mapping to spread forecasting and planning support. The problem is not that this technical growth is unreal. It is that claims of prevention relevance have expanded faster than critical synthesis of what actually improves pre-fire judgment in forest systems.

A prevention-facing synthesis requires a stricter premise than generic wildfire-AI overviews. Forest fire prevention is not a single prediction problem, but a linked decision chain that starts with ecological monitoring, moves through warning and anticipation, and ends in concrete intervention under institutional constraints. AI should therefore be evaluated not only by classifier accuracy or benchmark performance, but also by its ability to capture prevention-relevant state variables, clarify why risk is increasing, remain robust across place and season, and support decisions about where, when, and how to intervene. The key implication is that better model scores do not automatically imply better prevention decisions.

In forestry and ecological-monitoring contexts, this framing connects monitoring outputs to prevention decisions in real forest systems. Rather than offering a broad review of wildfire analytics, the synthesis focuses on prevention-facing AI, with explicit attention to ecological monitoring, monitoring-to-prevention linkage, management implications, and interdisciplinary integration. These criteria define the corpus boundaries.

1.1. Why the Literature Needs a Prevention-First Reframing

Earlier reviews were valuable because they established that machine learning could be applied to occurrence mapping, danger estimation, fuel analysis, and detection. That baseline is now insufficient. The recent literature is more multimodal, more data-intensive, and more ambitious in its claims of operational relevance. It includes fuel-moisture retrieval, explainable ignition-risk models, simulation-coupled spread forecasting, UAV- and satellite-based monitoring pipelines, and management-facing tools for treatment or exposure prioritization [1–3]. The relevant issue is therefore no longer whether AI can contribute to wildfire science, but whether the literature has become sufficiently prevention-oriented to justify strong operational claims.

The evidence is uneven. Some parts of the field have matured substantially, especially where ecological monitoring is connected to warning logic, treatment targeting, or planning support [4–7]. Other parts remain vulnerable to overstatement. Many studies are still region-bound, benchmark-centric, or dependent on curated data conditions while implying broader operational significance. Others concern suppression, post-fire analysis, or visually obvious detection, yet are still described as prevention relevant with limited evidence that they would alter preventive action. A critical review is warranted because the expanding literature can obscure the field's actual level of operational maturity.

That heterogeneity is visible in the range of studies often presented under the same umbrella: regional likelihood mapping in Algeria and the Sikkim Himalaya [8,9], socio-economic driver modeling in Spain and exploratory Google Earth Engine analyses for Australia [10,11], and neural-network scale prediction beside shorter-horizon warning frameworks such as RAFFIA [12,13]. Together, they confirm that AI has diffused across many task families. They also show the need to distinguish strategic framing from true warning and intervention support in prevention-oriented wildfire AI.

1.2. From Model Catalogs to Monitoring-to-Prevention Systems

The existing literature is often organized by algorithm, sensor, or target variable and then compared mainly through predictive metrics. That structure is understandable, but it is less suitable for a prevention-focused synthesis. Forest fire prevention unfolds through linked decisions. Ecological monitoring identifies latent conditions such as fuel stress, structural fuels, hydrological deficit, lightning activity, or human-pressure exposure. Warning translates those observations into interpretable risk signals. Scenario analysis asks how conditions may worsen. Decision support determines whether those signals can

guide patrols, restrictions, treatment priorities, firebreak design, or readiness measures. Governance and deployment determine whether the entire chain is credible enough to use.

Organizing the literature around the monitoring-to-prevention chain changes the basis of comparison from model families to prevention utility. A smoke-detection system can be technically impressive and still remain only loosely preventive if it enters the workflow after visible fire signatures emerge. A lower-profile fuel-moisture or structural-fuel model may matter more because it supports earlier intervention. A susceptibility map is not equivalent to an early-warning product, and a scenario model is not automatically valuable unless it changes what managers do before hazardous behavior develops. The review therefore reorganizes the field around prevention utility rather than technical novelty alone.

That monitoring-to-prevention framing also clarifies the scientific scope of the review. A prevention-centered synthesis should show how ecological monitoring becomes prevention intelligence in forest systems rather than adding another catalog grouped around CNNs, random forests, or generic AI techniques. Governance and deployment are treated as cross-cutting constraints because they determine whether model outputs can change pre-fire actions.

1.3. Why Ecological and Management Fit Must Stay Central

Wildfire AI is increasingly sophisticated technically while remaining uneven ecologically. Forest fire prevention is not reducible to abstract pattern recognition. It depends on vegetation condition, fuel moisture, canopy structure, topography, weather timing, access, ignition pathways, and the ability of institutions to intervene early enough to matter. AI systems therefore need to be judged not only by statistical fit but also by whether they represent the ecological variables and management horizons that actually matter for prevention. Studies that estimate fuel state, canopy fuels, or human-pressure effects often contribute more to prevention than papers that only optimize visual detection of already visible smoke or flame.

Management fit is equally important. Prevention is not just hazard recognition; it is intervention choice under ecological and institutional constraints. A model matters more when it helps clarify where to patrol, when to restrict access, which stands to treat, where to reinforce firebreak infrastructure, or how to prioritize exposed interfaces [3,7,14]. Accordingly, the review gives special weight to ecology-to-management translation.

The same logic defines the scope of the synthesis. Suppression-only studies, post-fire recovery papers, smoke-health research, and generic fire-detection studies with weak prevention linkage remain important, but they are peripheral to prevention-facing AI. Borderline studies, including deep-learning warning papers, conference-style spatiotemporal studies, severity-oriented mapping, smoke-recognition work, and partially relevant multi-hazard frameworks [15–24], illustrate how easily wildfire AI can drift away from monitoring-to-prevention linkage in forests.

1.4. The Field's Main Weakness Is Weak Translation, Not Lack of Models

The main conclusion emerging from the evidence base is that the field's biggest weakness is no longer a lack of methodological creativity. It is a weak translation from benchmark performance to prevention value. The corpus shows no shortage of models, sensing pipelines, and technically ambitious forecasting systems. What remains less mature is evidence that these systems are transferable across ecosystems, interpretable to managers, resilient under realistic latency and missingness, and embedded in accountable prevention workflows.

This translational gap recurs across major application areas. In early warning, susceptibility maps are often described as operational warning products without clear temporal logic. In sensing, additional modalities are sometimes assumed to improve prevention simply because they enrich inputs. In spread forecasting, scenario models may remain detached from intervention choices. In decision support, risk products are often presented without specifying who uses them and for what action. In governance, systems with planning consequences may be discussed as if they were neutral predictors. The synthesis therefore evaluates studies through ecological fit, prevention timing, management usefulness, interpretability, transferability, deployment realism, and governance readiness.

1.5. Contributions of the Review

This synthesis makes four contributions: it uses prevention utility as the organizing criterion; treats ecological monitoring as a data-to-decision system rather than a list of sensors; compares AI studies by translational credibility and management relevance rather than reported metrics alone; and traces interdisciplinary integration across forestry, ecology, wildfire science, remote sensing, geospatial analytics, machine learning, and governance.

These contributions are built on a curated evidence base of 100 retained English-language records assembled through a topic-specific core corpus and a targeted recent supplement. That corpus is broad enough to support a critical synthesis but selective enough to preserve topic coherence. It is also explicit about its limits: the evidence base reflects full-text extraction for core analytical studies, supplemented by contextual bibliographic screening. These constraints limit pooled numerical comparison but still allow qualitative synthesis of how different evidence classes support specific prevention decisions. All synthesis conclusions presented in this review are derived from comparative analysis of the retained full-text studies rather than conceptual interpretation alone. The following sections trace the monitoring-to-prevention chain. After defining the corpus and analytical boundaries, the synthesis examines sensing, warning, spread-risk forecasting, prevention planning, and cross-cutting issues of robustness and governance, before returning to the central criterion that AI is most valuable when it turns ecological monitoring into timely, interpretable, and actionable management judgment in real forest systems.

The monitoring-to-decision chain provides an evaluation framework that goes beyond the thematic organization of AI studies. Each AI application can be judged by three linked questions: what prevention decision it supports, what full-text evidence supports that claim, and what ecological or operational limits would affect deployment. This produces a synthesis that goes beyond classification: fuel-moisture and vegetation-stress models are most relevant to seasonal readiness and treatment timing; ignition-risk and lightning-aware models are most relevant to patrol, warning, and access-control decisions; smoke, thermal, UAV, camera, and IoT models are useful only when latency and verification workflows are specified; spread-forecasting and simulation-coupled models are relevant to scenario planning only when forecast horizon and uncertainty are explicit; and WUI, infrastructure, and decision-support models are most useful when the responsible actor and feasible preventive action are identified. The framework is introduced in Section 2 and operationalized in Tables 1–3 and Sections 4–7.

This framing also treats lightning as a primary ignition driver rather than a background variable. Lightning is especially important in boreal, montane, and remote forests, where access-related ignition is not the only or dominant trigger. Studies of North American boreal fires and Canadian fire records show that lightning can control the occurrence of large fire years, while human ignitions expand the seasonal and geographic fire niche in populated landscapes. Prevention-facing AI must therefore represent both ignition pathways and should not generalize from human-pressure proxies alone. Operational

lightning observations from Lightning Location Networks, particularly the World Wide Lightning Location Network (WWLLN), further strengthen this prevention framework by providing near-real-time information on lightning-caused ignitions and supporting AI-assisted early-warning systems [25–27].

Table 1. Review protocol, evidence extraction fields, and analytical boundaries.

Protocol Element	Analytical Implementation	Analytical Purpose
Prevention definition	Pre-ignition or pre-escalation decisions that reduce ignition probability, hazardous fuel/exposure, or warning delay.	Separates prevention from detection-only, suppression-only, and post-fire mapping studies.
Core evidence requirement	Full text or open full-text version available for methods, data, validation, findings, and limitations extraction.	Ensures that evaluative claims are based on extractable full-text evidence rather than abstract-level information alone.
Extraction fields	Region, ecosystem, inputs, method, comparator, validation, horizon, uncertainty, decision target, limitations.	Supports technical and operational synthesis rather than topic classification.
Evidence grading	Strong, moderate, limited, contextual, based on validation rigor, transfer testing, and decision linkage.	Prevents model accuracy from being treated as operational prevention value.
Reference expansion	Classical fire models, lightning, fire-weather indices, remote sensing, WUI, governance, and global AI case studies.	Internationalizes the evidence base and connects AI to established fire science.

AI methods should be interpreted against classical fire-science baselines. Rothermel-type spread equations, the Canadian Forest Fire Weather Index System, the National Fire-Danger Rating System, FARSITE, FlamMap, fuel-model libraries, and ensemble fire simulations define many of the variables and thresholds that operational users already understand [28–46]. AI is most persuasive when it improves, updates, or operationalizes those baselines rather than replacing them with opaque scores.

2. Review Methodology: Full-Text Evidence Extraction, Scope Rules, and Evidence Boundaries

Fire prevention is defined here as pre-ignition or pre-escalation decision support that can reduce ignition probability, reduce hazardous fuel or exposure conditions, increase warning lead time, or guide prevention-oriented allocation of patrols, inspections, treatments, firebreaks, access restrictions, and public preparedness. The search and screening logic retains a prevention-facing focus while expanding the evidence base beyond AI applications alone. The evidence base uses an AI-focused corpus as the starting point, supplemented by classical deterministic and probabilistic fire-science literature and international work on lightning ignition, human ignitions, fire-weather indices, fuel moisture, remote sensing, spread simulation, WUI exposure, and decision support. Contextual references are used to define baselines and mechanisms; evaluative claims about AI performance are limited to studies for which methods, data, validation, and limitations could be checked from full text or an open full-text source.

The reference base addresses two important evidence needs for this topic. First, AI studies are interpreted against non-AI fire-science baselines, including Rothermel-type spread modeling, the Canadian Forest Fire Weather Index System, the National Fire-Danger Rating System, Keetch-Byram drought logic, FARSITE, FlamMap, fuel-model libraries, fire-atlas products, and ensemble or probabilistic fire-spread simulation [28–46]. Second, the evidence base includes international studies and reference baselines on remote sensing,

fuel moisture, active-fire detection, and fire-product baselines [47–56]; global fire regimes, climate-change effects, pyrogeography, and burned-area dynamics [57–66]; human and lightning ignitions, WUI exposure, and ignition-distribution modeling [67–82]; lightning climatology, Lightning Location Networks (particularly the World Wide Lightning Location Network, WWLLN), and decision-support systems [25–27]; and fire-weather sensitivity, occurrence databases, global fire modeling, risk governance, and decision support [83–102]. Chinese studies remain where they provide relevant evidence, but broad claims about AI for forest fire prevention are supported by international evidence rather than by regionally concentrated examples alone.

For each core study, the extraction fields were as follows: region and ecosystem; prevention stage; ignition source or fire process addressed; input data; AI or hybrid method; deterministic, probabilistic, or operational comparator when available; validation design; reported performance metric; forecast horizon or update frequency; uncertainty or explainability treatment; management action enabled; and stated limitations. Evidence was graded qualitatively as strong, moderate, limited, or contextual according to validation rigor and decision linkage, not according to benchmark score alone.

The analysis is designed as a scientific synthesis rather than a classification exercise. References are not used only to populate thematic categories. They are used as evidence for specific judgments about data adequacy, model assumptions, validation design, operational horizon, transferability, uncertainty, explainability, and management relevance. Where a cited study does not provide enough information to support such judgments, it is treated as contextual rather than as core evidence. This boundary reduces the risk of overclaiming; evaluative language is tied to what the reviewed papers demonstrate, not to what AI systems might ideally provide. As illustrated in Figure 1, the overall methodological framework adopted in this review is presented below.

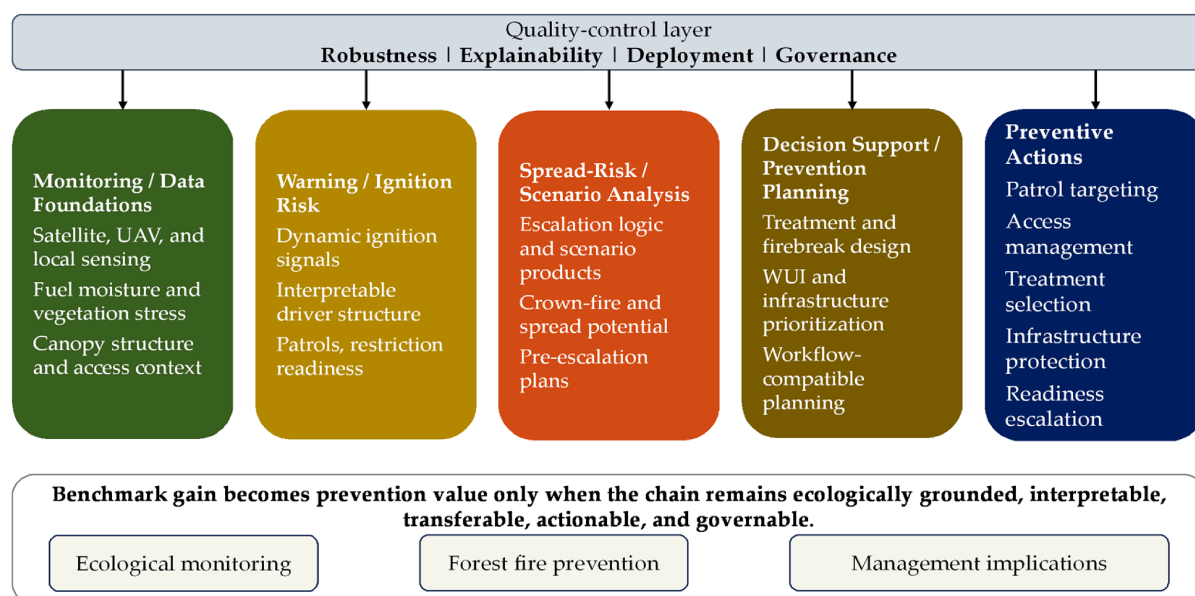


Figure 1. Monitoring-to-prevention analytical framework.

Figure 2 illustrates the publication trend and thematic evolution of the reviewed studies.

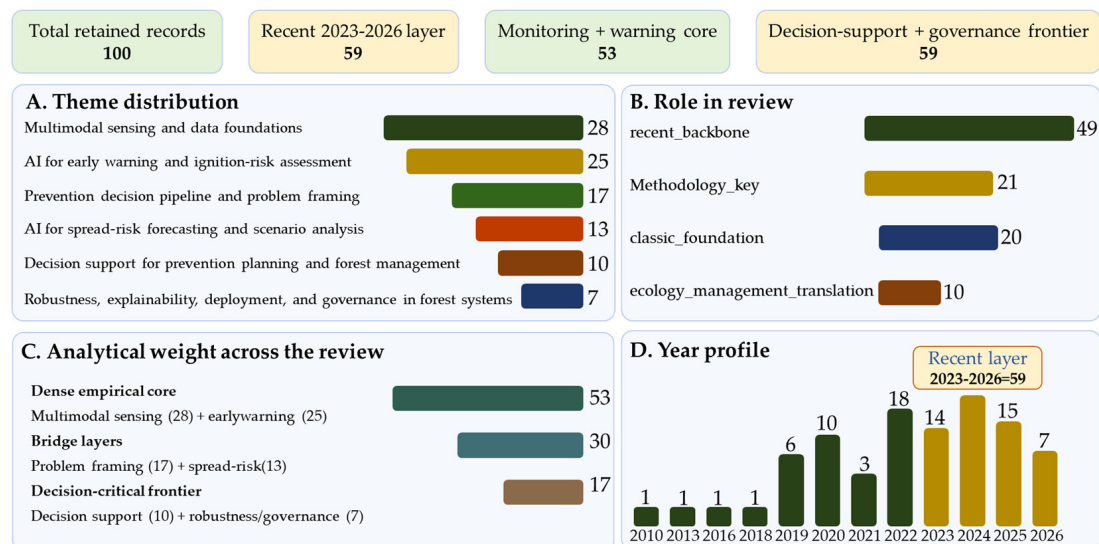


Figure 2. Evidence landscape of the retained and expanded corpus.

3. Multimodal Sensing and Data Foundations for Forest Fire Prevention

For prevention-oriented AI, the key issue is not only which model performs best, but what monitoring foundation such systems depend on. Forest fire prevention begins before any model outputs a warning score. It begins with what is sensed, how often it is updated, whether the variables are ecologically meaningful, and whether the observations can be translated into prevention-relevant information before conditions deteriorate [2,5]. Accordingly, sensing is treated as part of a monitoring-to-prevention pipeline rather than as a toolbox of interchangeable devices.

Based on a comparative analysis of the retained studies, the most consistently supported data foundations are not those that maximize the number of platforms in the abstract. They are those that capture variables with real prevention value, remain interpretable across ecosystems, and can be sustained at the temporal and institutional scales required by forest management [6]. That distinction matters because this theme is large and methodologically diverse. The evidence base includes satellites, UAVs, IoT and wireless sensing, benchmark datasets, fuel-moisture estimation, and canopy-fuel mapping, but these contributions are not equivalent. Some mainly improve incipient-event recognition; others more directly support prevention by characterizing fuel condition, vegetation structure, and environmental stress before ignition or rapid spread.

3.1. From Sensor Platforms to Prevention-Relevant Monitoring

One of the clearest lessons from the retained evidence is that sensing should be judged by the prevention question it can answer. Remote-sensing reviews and dataset papers are useful not because they show that many sensors are available, but because they clarify which observations contribute to prevention before severe fire behavior emerges [2,103]. It is therefore necessary to distinguish wildfire monitoring in the broad sense from prevention monitoring in the stronger sense. Systems designed for burned-area reconstruction, active-fire tracking, or post-event analysis may matter to wildfire science, but they are only indirectly preventive if they do not improve what managers can know and do before escalation.

Ecological monitoring should therefore remain central to prevention-oriented sensing. The most prevention-relevant variables are not always the most visually obvious ones. Smoke and flame recognition can shorten the interval between incipient combustion and detection, which is useful, but prevention also depends on monitoring latent conditions such as live and dead fuel moisture, vegetation stress, canopy fuels, hydrological deficit, and

access or exposure. These variables explain why a landscape is becoming more dangerous before visible fire signatures dominate the scene.

3.2. Satellites, UAVs, and Local Sensors Are Complementary

No single sensing platform is sufficient across prevention tasks. Satellite systems provide synoptic coverage and consistent monitoring of fuel condition, vegetation dynamics, and broad environmental stress. UAV systems provide flexible deployment and high spatial resolution for local surveillance, targeted verification, and stand- or corridor-scale monitoring. IoT and wireless sensor systems can provide persistence where fixed infrastructure is feasible [104–106]. The key implication is therefore not that one platform should dominate, but that different platforms occupy different positions in the monitoring-to-prevention chain.

This complementarity matters because the literature sometimes overstates platform-specific solutions. UAV papers are often framed as if better smoke detection or aerial perception solves the prevention problem by itself. In practice, UAV systems are strongest when they reduce latency or provide targeted local intelligence within a broader monitoring architecture. The same is true of IoT-oriented systems. They can be powerful around infrastructure, protected areas, or priority corridors, but they rarely suffice at landscape scale without broader environmental context. A prevention-oriented synthesis should therefore resist platform evangelism and ask how platforms can be combined into monitoring systems that remain useful across regional, local, and near-real-time horizons.

Recent platform work reinforces the need to avoid equating detection with prevention. Much of it remains centered on smoke or flame recognition from UAV, video, satellite, or drone imagery, including enhanced YOLO pipelines and learning-without-forgetting smoke detection [107–109], multiscale drone detection and machine-vision experiments [110–112], and staged YOLO ensembles with autonomous hyperspectral satellite detection [113–115]. These systems can reduce latency, but they usually enter the workflow only after visible signatures emerge. Their prevention value rises sharply when they are embedded within broader ecological monitoring rather than treated as standalone solutions. Figure 3 illustrates this cross-scale logic by showing how regional satellite products, landscape- and stand-scale UAV/LiDAR observations, and local IoT or ground-verification streams can be fused into ecological-state interpretation, warning/forecasting, and prevention planning.

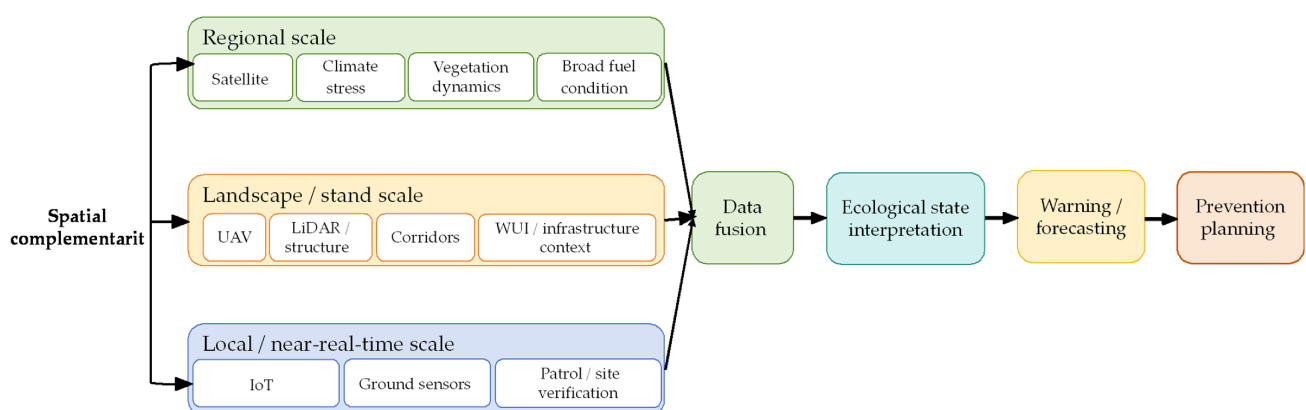


Figure 3. Cross-Scale Monitoring Architecture for Prevention Intelligence.

This is one of the places where interdisciplinary integration becomes concrete rather than rhetorical. Effective prevention intelligence requires interaction among remote sensing, ecological understanding, communication infrastructure, geospatial analytics, and institu-

tional deployment capacity. A monitoring system that is technically rich but operationally fragile does not satisfy the goal of prevention.

A different subset is more structurally relevant because it addresses monitoring persistence, deployment architecture, or scale matching rather than only image classification. IoT-enabled networks and federated green-IoT detection [116–118], wireless-sensor/deep-learning systems and territorially specialized satellite models [119,120], and early dataset-building or deployment-oriented studies [121–123] all point to the operational question of how monitoring can be maintained across regional and local horizons. Even here, however, the main value lies in workflow integration, calibration, and scale complementarity rather than in the existence of another detector.

3.3. Fuel Moisture, Vegetation Structure, and Other Latent State Variables

The strongest qualitative shift in the sensing literature is movement away from exclusive focus on fire/no-fire imagery toward latent ecological state variables that matter before ignition or rapid spread. Monitoring smoke plumes or visible flames can support very early recognition, but it does little to explain why a forest is becoming flammable or where preventive action should be concentrated before ignition. By contrast, monitoring live and dead fuel moisture, canopy fuels, vegetation stress, and related state variables can directly support restriction timing, treatment planning, readiness posture, and broader prioritization [6,124,125].

Ecological monitoring should not be treated as a passive data supplier to AI. It is the first step in turning forest conditions into prevention intelligence. Smoke and flame detection remain relevant, especially when they reduce recognition delay and fit into early intervention workflows, but they should not dominate prevention-focused sensing.

3.4. Datasets, Benchmarks, and Domain Shift

Benchmark datasets and reusable training resources are an important methodological advance because they encourage clearer problem formulation and make comparisons less dependent on isolated regional case studies. Yet, benchmark growth does not resolve the central weakness of the sensing literature: domain shift. Many wildfire-monitoring datasets remain region-bound, sensor-bound, season-bound, or visually simplified relative to the diversity of real forest environments [103,126,127]. A model can therefore perform well within a benchmark and still generalize poorly across ecosystems, imaging geometries, seasonal regimes, or background conditions.

The problem is not only technical. It is ecological. Forest systems differ in canopy structure, moisture dynamics, reflectance conditions, access patterns, and ignition context. A benchmark may show that a task is learnable under curated conditions, but it does not prove that a monitoring pipeline is ready to support preventive action across real forest-management settings. Datasets and benchmarks are therefore necessary but insufficient. They improve methodological discipline, but they do not substitute for external validation or ecological realism.

3.5. What Counts as a Strong Data Foundation

Taken together, the retained evidence supports a demanding standard for multimodal sensing in forest fire prevention. A strong data foundation should monitor variables with real pre-fire decision value, integrate scales in ways that match prevention practice, remain explicit about latency and maintenance, and produce information that managers can interpret and act upon. By that standard, the literature is improving but still uneven. The best contributions are not necessarily those with the most complex architectures. They are the ones that make ecologically meaningful state variables visible, preserve monitoring continuity, and clarify how observations enter prevention workflows.

The synthesis indicates that multimodal sensing is only as valuable as the prevention relevance of the variables it captures and the stability of the monitoring-to-decision system it supports. This criterion prevents platform cataloging from displacing the central issues of ecological monitoring, forest fire prevention, management implications, and interdisciplinary integration.

The full-text synthesis separates monitoring studies by the decision they can support. Fuel-moisture and vegetation-stress products are relevant to seasonal readiness and treatment timing; smoke, thermal, and camera products are relevant to short-latency verification; and WUI, road, powerline, lightning, and human-activity layers are relevant to targeted prevention. This distinction matters because a technically accurate sensor product may still have low prevention value if its update frequency, spatial resolution, or uncertainty does not match the decision horizon [47–56,67–72].

A second distinction concerns data provenance. Studies based on curated image datasets can be valuable for algorithm comparison, but they often under-represent haze, complex terrain, partial canopy occlusion, seasonal background changes, night-time scenes, and communication failure. By contrast, satellite and operational fire archives provide broader spatiotemporal coverage but may be too coarse for stand-level prevention decisions. Sensing studies should therefore be evaluated by the match between data scale and prevention use: regional hazard zoning, daily patrol prioritization, local field verification, infrastructure inspection, or fuel-treatment planning. This prevents a camera detector, a MODIS/VIIIRS active-fire product, and a fuel-moisture model from being treated as interchangeable evidence. The main characteristics of the representative studies reviewed in this paper are summarized in Table 2.

Table 2. Comparative synthesis of prevention-facing AI task families with representative reference numbers.

Task Family	Typical Inputs and Scale	AI or Hybrid Methods	Evidence from Full-Text Synthesis	Prevention Decision Supported	Representative References
Fuel and ecological-condition monitoring	Fuel moisture, vegetation indices, canopy structure, LiDAR, satellite and UAV products	Random forest, CNNs, sequence models, physics-guided learning	Most convincing when remote estimates are checked against field, physical, or operational baselines.	Fuel-moisture alerts, treatment timing, seasonal readiness	[5–7,28–56,124,125]
Lightning, weather, and ignition-risk assessment	Lightning, FWI/NFDRS/KBDI, drought, topography, roads, settlements, historical ignitions	Logistic regression, random forest, boosting, XAI, spatial ML	Useful for patrol and warning when ignition causes and temporal validation are separated.	Patrol routing, access control, ignition-source mitigation	[28–32,57–86,128–151]
Smoke, flame, and active-fire detection with prevention relevance	UAV, camera, satellite thermal anomaly, IoT smoke and weather sensors	YOLO, CNNs, ensembles, federated or edge learning	Prevention value depends on lead time, false-alarm handling, latency, and verification workflow.	Early alert, field verification, local escalation avoidance	[15–24,28–52,103–123,152–157]
Spread-risk and scenario forecasting	Current perimeter, weather, fuels, topography, remote-sensing grids, simulation outputs	ConvLSTM, CNNs, surrogate models, hybrid simulation-ML, ensemble learning	Strongest when compared with deterministic spread models and when forecast horizon is explicit.	Pre-positioning, closure decisions, firebreak and fuel-treatment prioritization	[28–46,78–94,158–169]

Table 2. Cont.

Task Family	Typical Inputs and Scale	AI or Hybrid Methods	Evidence from Full-Text Synthesis	Prevention Decision Supported	Representative References
Decision support and prevention planning	Risk layers, WUI exposure, powerline corridors, fuel treatments, severity potential, social constraints	Optimization, neural networks, XAI, multicriteria GIS, decision-support systems	Smaller evidence base, but clearest link to prevention when outputs map to management actions.	Fuel treatment, firebreaks, powerline inspection, WUI prioritization	[3,7,95–102,166–174]

4. AI for Early Warning and Ignition-Risk Assessment

Early warning and ignition-risk assessment form the operational center of prevention-oriented AI for forest fire prevention. At this stage, ecological monitoring shifts from observation toward decision support. The density of evidence on early warning and ignition-risk assessment allows a more demanding evaluation than whether machine learning can predict wildfire-related outcomes. The relevant criteria are which warning products are useful for prevention, which ecological signals make them defensible, and where the literature still confuses predictive success with operational readiness.

For prevention-oriented forest management, practical value cannot be reduced to accuracy. Prevention agencies do not act on benchmark scores. They act on signals that help them target patrols, time restrictions, prioritize treatment zones, identify recurring ignition settings, or increase readiness when environmental conditions deteriorate rapidly. Lightning detection products derived from WWLLN can further support patrol prioritization and rapid verification of lightning-caused ignitions when integrated with AI-based early-warning systems [175]. The most useful studies in this literature are therefore not simply those with the highest metrics, but those that convert weather, vegetation, hydrology, topography, and human-pressure information into interpretable warning logic that can plausibly support decisions in real forest systems.

4.1. From Static Susceptibility to Prevention-Relevant Warning

The earlier literature established an important baseline: wildfire occurrence is shaped by nonlinear interactions among terrain, vegetation, climate, and human-access variables, and machine-learning methods often outperform simpler baselines when those interactions need to be represented [128–130]. These foundational susceptibility papers remain conceptually useful because they showed that ignition risk cannot be understood through any single variable family. Yet, most of them remained closer to strategic susceptibility mapping than to genuine early warning. Their outputs were often retrospective, region-specific, and weakly tied to short-horizon intervention.

Recent work improves on that baseline by bringing susceptibility closer to an actionable warning. Newer retained studies are more likely to model risk as a dynamic interaction between ecological state and ignition pressure rather than as a static spatial property, and they more often combine environmental stress indicators with human-proximity or anthropogenic-pressure variables [4,131,132]. That is a substantive shift rather than simply a better classifier. A probability map becomes more useful when it helps answer why risk is elevated and what kind of prevention action becomes plausible as a result.

This distinction is central to monitoring-to-prevention logic. A susceptibility surface is informative, but it is not yet a prevention tool unless it clarifies what action it should influence and over what time horizon.

4.2. Ecological Monitoring Variables and the Expanding Predictor Ecology

One of the most important developments in the recent corpus is the expansion of the predictor ecology behind warning models. Older studies relied heavily on meteorology, topography, vegetation proxies, and, increasingly, lightning observations derived from operational lightning detection networks. Those inputs remain indispensable, but they are no longer sufficient if the goal is prevention-oriented warning rather than generic occurrence mapping. WWLLN provides near-real-time global lightning observations that can improve the identification of lightning-caused wildfire ignitions, particularly in remote forest ecosystems where natural ignition dominates [25–27]. The newer retained studies introduce cumulative dryness metrics, hydrological parameters, climate-linked forest condition indicators, and more explicit measures of human pressure or proximity [133–135]. This matters because prevention depends on ecological state, not only on historical fire occurrence.

The comparison that follows is sharper than many individual papers make explicit. Static susceptibility products remain useful for long-horizon zoning and persistent hotspot framing, whereas more dynamic warning systems become more useful when they integrate evolving dryness, hydrological stress, and human-pressure structure. The wider corpus reinforces that conclusion through regional susceptibility studies across Turkey, Serbia, China, Australia, and broader global products [136–139], as well as recent studies that further extend geographic and methodological range [140–145]. These studies remain valuable, but they also show a persistent problem: many products remain closer to strategic zoning than to temporally explicit early warning, even when framed as operational tools.

4.3. What Counts as Early Warning, and What Does Not

A recurring weakness in this literature is the loose use of the term early warning. Many papers describe early-warning systems when they are actually producing medium-term susceptibility maps or long-window occurrence probabilities. Those outputs can still be useful, but they are not equivalent. Strategic susceptibility mapping helps identify persistent hotspots and support zoning. True early warning should support short-horizon action such as increased surveillance, temporary restrictions, local readiness escalation, or targeted attention to high-risk corridors under rapidly changing conditions.

The retained recent literature is strongest when it keeps that distinction explicit. Studies that combine evolving weather conditions, fuel signals, and predictor-sensitivity analysis are closer to genuine warning because they are clearer about when their outputs are supposed to matter. Methodologically explicit studies are especially useful here. Studies in *Natural Hazards and Environmental Research Letters* sharpen the comparison between classical warning logic and newer machine-learning systems, while recent occurrence and ignition-probability papers strengthen the case for temporally explicit risk reasoning [131,132,146].

4.4. Explainability, Ignition Attribution, and Management Usefulness

The move toward explainability is one of the more constructive developments in this theme. Early-warning models are most valuable when they clarify driver structure rather than merely reporting elevated risk. Prevention is intervention-oriented, and different ignition regimes imply different actions. A model that indicates whether risk is driven mainly by fuel dryness, hydrological stress, access, or recurring human activity is therefore more useful than one that simply outputs a high score. Explainability matters here not as a generic transparency checkbox, but as part of the practical value of the warning system itself.

4.5. Transferability, Benchmarks, and Limits of Operational Claims

Transferability remains one of the largest unresolved problems in this evidence cluster. The retained studies span multiple regions and ecosystems, but geographic diversity is not the same as validation diversity. Most models are still trained and evaluated in local or regional settings with specific fuel structures, climatic regimes, land-use patterns, and sensing conditions. A warning model may therefore achieve strong local performance and still have limited prevention value if it fails under new fuel conditions, altered climatic stress, different access patterns, or degraded data inputs.

Benchmark design is part of the same problem. Many studies compare model families in curated settings without asking whether the benchmark reflects prevention practice. Recent studies from Hawai'i and Germany [147,148] and from India and Bangladesh [149–151] sharpen this point rather than overturn it. They extend the literature into more explainable, climate-linked, and geographically diverse settings, but they also confirm that transferability, temporal updating, and intervention closure remain harder than local model optimization.

4.6. Section Synthesis

For forest management, the practical implication of this literature is straightforward. Prevention agencies need warning products that are interpretable, updateable, and explicitly linked to intervention choices such as patrol targeting, restriction timing, identification of vulnerable ignition contexts, and local readiness escalation. A susceptibility model that cannot support any of these actions may still be scientifically interesting, but it has weak prevention value.

Across the reviewed studies, several recurring evidence patterns emerge. Most studies report strong benchmark performance under region-specific datasets, whereas comparatively fewer evaluate cross-region transferability, long-term operational deployment, or uncertainty. Dynamic ecological predictors and interpretable warning logic are increasingly incorporated, but independent validation remains relatively limited. These recurring patterns provide the basis for the following synthesis conclusions.

Taken together, the retained studies show a clear distribution of findings. Most studies focused on improving early warning performance using remote sensing and meteorological information, whereas comparatively fewer studies evaluated cross-region generalization, long-term operational deployment, or uncertainty. These observed patterns provide the basis for the following four evidence-based judgments. Early warning and ignition-risk assessment are among the most mature parts of prevention-oriented AI; the best recent progress comes from integrating ecological monitoring with interpretable warning logic rather than algorithmic novelty alone; management usefulness improves sharply when models clarify driver structure and temporal horizon; and the reviewed studies generally demonstrate promising experimental performance; however, evidence of operational deployment, independent validation, and uncertainty assessment remains comparatively limited. Therefore, operational-readiness claims should be interpreted with appropriate caution.

The evidence base includes concrete international examples. Susceptibility and occurrence studies from Algeria, India, Spain, Australia, Italy, Türkiye, Bangladesh, Germany, Hawaii, Korea, China, and global gridded analyses use different combinations of climate, topography, vegetation, proximity, ignition history, and human activity variables [8–14,128–151]. These studies are informative for prioritization, but the strength of evidence depends on whether validation is spatially and temporally independent, whether lightning and human ignition are separated, and whether outputs can guide patrols or access restrictions.

Detection studies using UAV imagery, fixed cameras, satellite thermal anomalies, and IoT networks often report high image-level performance [20–24,103–123]. They should not automatically be treated as prevention-ready. Their prevention value depends on false-alarm rates, communication latency, sensor maintenance, night and smoke conditions, and the existence of a field verification workflow. This distinction addresses the methodological risk of equating benchmark performance with prevention value.

The technical interpretation of ignition-risk models also depends on the validation design. Random train–test splits may inflate apparent skill when neighboring pixels share climate, vegetation, road access, or historical ignition patterns. More credible tests use spatial blocking, temporal holdout years, independent fire seasons, or explicit transfer across ecosystems. Metrics such as AUC, accuracy, F1-score, precision, recall, and Kappa are useful only when the positive class, spatial unit, temporal window, and decision threshold are clear. For prevention, calibration and false-positive burden matter as much as discrimination, because managers must decide whether a warning justifies patrol deployment, access restriction, public communication, or infrastructure inspection.

Lightning-focused evidence also changes how early warning should be interpreted. In human-dominated landscapes, roads, settlements, agricultural activity, and WUI expansion may dominate model explanations. In lightning-prone systems, fuel dryness, convective weather, holdover ignition, and remoteness may be more important. Globally useful prevention-oriented evaluation, therefore, should not rank variables as universally important, but should assess whether each model represents the ignition regime of the landscape in which it is intended to operate.

5. AI for Spread-Risk Forecasting and Scenario Analysis

Early warning estimates where pre-fire conditions are becoming dangerous, whereas spread-risk forecasting extends the assessment to what may happen if ignition occurs, how quickly conditions might escalate, and which stands, corridors, or exposed interfaces could experience hazardous behavior under plausible scenarios. This distinction is crucial for prevention-oriented synthesis. Although spread modeling is often associated with active-fire response, part of the recent literature is equally relevant to prevention because it supports anticipatory planning, fuel-treatment targeting, corridor design, readiness escalation, and ecological vulnerability assessment before catastrophic conditions are realized.

Although the spread-risk forecasting literature is smaller than the early-warning literature, it is analytically important because it connects ignition-focused warning to action under plausible future fire behavior. Prevention-relevant forecasting should be distinguished from response-only simulation, with AI approaches evaluated by whether they strengthen the monitoring-to-prevention chain.

5.1. From Environmental Controls to Escalation Logic

One foundation of this literature lies in earlier efforts to explain how environmental variables shape burned area, fire potential, or rate of spread [158,176]. These studies matter because they shift attention from where fire may occur to how hazardous fire evolution may become, which is closer to the prevention question faced by managers deciding where to concentrate attention before severe behavior unfolds.

However, explanatory studies of burned area or spread proxies are not automatically prevention evidence. Their value increases only when the modeled outcome can inform a decision before, or at the earliest onset of, hazardous fire behavior. Spread-risk forecasting contributes to prevention when it supports anticipatory planning, ecological vulnerabil-

ity assessment, or scenario-based intervention design, not simply when it reconstructs outcomes after the fact.

5.2. *Learning-Based Forecasting and the Rise in Benchmarkable Tasks*

A major methodological advance in this space is the move toward explicit forecasting datasets and reusable learning tasks rather than isolated regional regressions [159–161]. Once spread prediction is framed as a benchmarkable machine-learning problem, the field can compare architectures, temporal horizons, and data regimes more systematically.

Recent retained work builds on that shift with spatiotemporal and multimodal forecasting systems. Daily spread prediction, multimodal deep learning, and near-real-time architectures all push the field beyond static hazard approximation. From a prevention perspective, that is promising because forecast products become more useful when they encode both spatial structure and time evolution. Even so, better architecture is not the same as better prevention value. The real gain lies in whether a model turns ecological observations into scenario products that can support preventive planning.

5.3. *Simulation Coupling, Process Constraints, and Ecological Plausibility*

One of the most promising developments in the retained evidence is the coupling of AI models with simulation or process-based reasoning [162–164]. This is an important improvement over purely black-box forecasting because fire spread is governed by physical, ecological, and atmospheric constraints that should not disappear simply because machine learning enters the workflow.

This direction is particularly important for forest fire prevention research because it preserves ecological plausibility while still allowing AI to improve speed, flexibility, or data integration. Simulation-coupled crown-fire potential estimation is a strong example: it connects ecological monitoring, stand structure, and simulation-informed hazard estimation to concrete forest-management questions. Process-aware integration similarly matters because it reduces the risk that predictive accuracy is being purchased at the cost of ecological coherence.

5.4. *Scenario Products, Forecast Horizons, and Prevention Relevance*

Not all prevention-relevant forecasting takes the form of explicit spread maps. Some retained papers model fire potential, crown-fire potential, or severity-related scenario products that can still inform prevention planning [164–166]. Such studies support prevention only when the output functions as a pre-fire planning tool rather than as a retrospective damage label. The crucial distinction is whether the scenario output changes what managers can do before conditions worsen.

The SEVERIA tool, the Upper Colorado severity study, and the Alaska process-based deep-learning model sharpen this distinction. They move forecasting toward planning or consequence anticipation, but they also show how easily spread-relevant analytics can drift toward severity description unless intervention logic stays explicit [167–169].

5.5. *Transferability, Operational Gaps, and Management Implications*

Spread-risk forecasting is constrained by the same transferability problem seen elsewhere in wildfire AI, but the consequences are potentially sharper. A susceptibility map that transfers poorly is a strategic problem. A spread forecast that transfers poorly may distort operational planning under rapidly changing conditions. Many studies remain methodologically sophisticated within one region or dataset, yet relatively few demonstrate that their logic remains stable across ecosystems, fuel complexes, and climate regimes.

Data cadence and integration burden deepen the problem. Spread-risk forecasting depends heavily on timely weather information, ecologically meaningful fuel descriptors,

remote-sensing updates, and, in some cases, simulation inputs. The most defensible systems are therefore not simply the most technically sophisticated. They are the ones whose forecast horizon, data dependencies, and uncertainty structure match the decisions they claim to support. Prevention-oriented spread-risk forecasting matters when it changes planning before escalation occurs, not when it merely improves after-the-fact explanation.

5.6. Section Synthesis

The reviewed studies consistently show three recurring patterns. First, recent work increasingly adopts spatiotemporal and multimodal forecasting frameworks. Second, process-aware or simulation-coupled approaches provide stronger ecological plausibility than purely data-driven models. Third, relatively few studies evaluate transferability, operational deployment, or uncertainty under real management conditions. These patterns support the following synthesis conclusions.

Taken together, the reviewed studies reveal several consistent trends. Most studies emphasized improving prediction accuracy through spatiotemporal or multimodal approaches, whereas comparatively fewer studies assessed robustness, transferability, or operational applicability under real management conditions. These recurring findings support the following three synthesis judgments. Spread-risk forecasting and scenario analysis are increasingly important but remain less mature and less standardized than early-warning mapping. Comparative analysis indicates that the most consistent methodological progress has been achieved through spatiotemporal learning, benchmarkable forecasting tasks, and process- or simulation-coupled frameworks that preserve ecological plausibility. The same criterion also frames the evaluation of decision support.

Spread-risk forecasting requires explicit comparison with deterministic and probabilistic fire-behavior knowledge. Classical models and operational simulators encode fuel, wind, slope, and moisture mechanisms that remain essential for interpreting AI output [28–46]. Machine learning contributes most when it assimilates remote-sensing observations, builds fast surrogate models, estimates uncertain inputs, or supports scenario ensembles at a forecast horizon that managers can use.

Recent AI spread studies include next-day spread datasets, ConvLSTM and multimodal deep models, and simulation-coupled approaches that connect remote sensing, weather, topography, vegetation, and active fire perimeter information [158–169]. The synthesis therefore distinguishes retrospective burned-area reconstruction from prospective forecasting. A model that predicts tomorrow's grid cell can support closure or pre-positioning decisions; a model trained only on retrospective perimeters may not have the same operational value.

The prevention value of spread forecasting also depends on how uncertainty is communicated. A single deterministic perimeter may be convenient for display, but managers usually need a range of plausible trajectories under wind shifts, fuel-moisture uncertainty, suppression assumptions, and alternative ignition locations. Hybrid AI-simulation systems are promising because they can accelerate scenario exploration, but they should report where the surrogate model is reliable and where it departs from physical fire-behavior expectations. Without this information, a visually precise spread map may encourage overconfidence rather than better prevention.

6. Decision Support for Prevention Planning and Forest Management

The practical value of prevention-oriented wildfire AI is realized only when monitoring and forecasting outputs are converted into decisions that change what managers, planners, utilities, and local authorities do before hazardous conditions escalate. Decision support should therefore be treated as a core theme rather than as an add-on application

area. Ecological monitoring may be timely and forecasting methodologically sophisticated, but neither becomes prevention in the strong sense unless it affects intervention choices such as where to patrol, which stands to treat, where to strengthen firebreak infrastructure, or which interfaces are most exposed. Table 3 captures this translation layer by mapping AI products to preventive actions, users, time horizons, and deployment constraints.

Table 3. Management translation matrix from AI products to preventive actions.

AI Product	Evidence Needed Before Operational Use	Preventive Action	Risk if Evidence Is Missing	Representative References
Ignition-risk map	Ignition-cause separation, temporal validation, lightning and human-pressure layers	Patrol planning, public-warning targeting, access restrictions	Static maps can be mistaken for daily prevention guidance.	[67–82,128–151]
Fuel-moisture or vegetation-stress estimate	Field/physical validation, update frequency, uncertainty range	Readiness level, treatment timing, seasonal staffing	Remote-sensing estimates may not transfer across canopy and ecosystem conditions.	[5–7,47–56,124,125]
Smoke or flame detector	False-alarm rate, latency, night/smoke/terrain tests, verification workflow	Early field verification and escalation control	High image accuracy may not produce useful warning under field constraints.	[20–24,28–52,103–123,152–157]
Spread forecast or scenario map	Comparison with fire-behavior model, horizon, wind/fuel sensitivity	Closure, pre-positioning, fuel-break prioritization	Retrospective fit can be mistaken for prospective decision support.	[28–46,83–94,158–169]
WUI or infrastructure exposure model	Asset data quality, feasibility, governance and equity constraints	Powerline inspection, defensible-space campaigns, community mitigation	Technically accurate risk layers may be institutionally unusable.	[14,68–72,95–102,170–174]

Decision-support evidence is smaller than the sensing and warning clusters, but it is conceptually central because it has explicit ecology-to-management translation value. It is the clearest test of whether AI-supported information can help forest managers choose better prevention actions under ecological and operational constraints rather than merely describe hazard patterns more precisely.

6.1. Decision Support as the Integrative Layer

Decision support should not be treated as a late-stage add-on to monitoring and forecasting. It is the integrative layer that determines whether earlier analytical outputs are useful in practice. A risk surface or forecast may be scientifically informative, but its prevention value remains limited if it is unclear who should use it, for what action, on what time horizon, and under what ecological constraints. This is a recurring weakness in the literature.

The more mature studies in this theme move beyond that weakness by making their decision structure explicit. They clarify the likely decision-maker, the preventive target, and the ecological context of the action. These papers show that prevention-oriented AI

should be judged not by whether it generates a map, but by whether it helps organize intervention logic under real forest-management constraints.

6.2. Fuel Treatments, Firebreaks, and Infrastructure-Oriented Prevention

The clearest decision-support contributions concern intervention targeting. Fuel-treatment selection is a particularly strong example because it is one of the most tangible prevention decisions in forest management [7]. Models that help identify which treatment types are most appropriate under heterogeneous terrain, fuels, and operational constraints speak directly to planning rather than abstract hazard description.

The same logic applies to firebreak-oriented studies. Structural detection and LiDAR-informed analysis are prevention-relevant because they can feed a specific intervention: firebreak design and maintenance [170]. Infrastructure-oriented prevention around power-line corridors and similar assets is equally important because many prevention failures arise from concrete ignition pathways, infrastructural vulnerabilities, and maintenance gaps. AI systems that address those pathways may deliver more immediate prevention value than broad regional risk models, provided they are embedded in real asset-management workflows [171].

6.3. Human Activity, WUI Exposure, and Spatial Prevention Planning

Another important trend is the incorporation of human activity and exposure into prevention planning. Many forest fire prevention problems are inseparable from how people use and occupy landscapes. Human access, structural features of activity, and proximity to interfaces can all reshape where prevention attention is most needed. Work on human-activity-aware wildfire risk and human-proximity-integrated occurrence prediction shows that decision support becomes more realistic when anthropogenic pressure is treated as a structural part of the prevention problem rather than as residual noise around biophysical hazard [172,173].

This logic becomes even clearer in wildland–urban interface and exposure-oriented studies. WUI-focused deep-learning assessment broadens the meaning of management implications because prevention is not limited to stand-level treatment decisions. It also includes spatial exposure prioritization, interface planning, and preventive measures where ecological vulnerability overlaps with settlement or infrastructure risk [174].

6.4. Decision-Support Systems and Workflow Compatibility

The literature also contains a smaller but important systems-level discussion of decision-support tools. One of the strongest lessons from that subset is that decision support is rarely a single-model problem. It is a workflow problem involving data-update cycles, uncertainty communication, institutional interpretation, and compatibility with how managers actually make decisions [3]. A model can produce a high-quality signal and still fail as decision support if it does not fit the cadence, vocabulary, or accountability structure of the organization using it.

Some retained studies also show that ecological interpretation itself can function as decision support. When explainable models clarify which drivers dominate in a given month, landscape, or forest type, they can help managers time surveillance, treatment preparation, or seasonal prevention measures more effectively. Monthly XAI analysis of European summer wildfires and hybrid Sentinel-2 risk mapping in Similipal both make that point from different angles [177,178].

6.5. *Why Decision Support Is Still Less Mature than It Appears*

Despite these advances, decision support remains underdeveloped relative to model generation. Many papers stop at hazard characterization and then imply management relevance in discussion language rather than in system design. They identify risky areas, influential drivers, or vulnerable interfaces without specifying which intervention they are meant to change, how often the output can be updated, or what decision trade-offs it is supposed to organize.

Transferability is a particularly important concern here. Management decisions are embedded in ecological and institutional context, so the relevance of a decision-support model depends not only on predictive quality but also on whether its assumptions travel across ownership patterns, treatment regimes, forest types, and local governance settings. Another limitation is the lack of closed-loop intervention design. Very few papers compare preventive alternatives explicitly, quantify uncertainty in a manager-interpretable way, or separate strategic from seasonal and near-real-time uses with enough clarity.

6.6. *Section Synthesis*

The reviewed decision-support studies reveal several recurring evidence patterns. Most studies successfully identify management-relevant risk information; however, comparatively fewer explicitly connect AI outputs with intervention workflows, quantify uncertainty, or evaluate practical deployment under operational forestry conditions. These recurring findings form the basis of the following synthesis conclusions.

Taken together, the reviewed decision-support studies demonstrate an uneven distribution of evidence. Most studies focused on identifying management-relevant risk information and supporting planning decisions, whereas comparatively fewer studies evaluated uncertainty, independent field validation, or sustained operational deployment. These recurring findings support the following three synthesis conclusions. Decision support for prevention planning and forest management is where wildfire AI becomes most relevant to forestry practice; the strongest studies are those that connect AI products to specific management targets such as fuel-treatment selection, firebreak planning, infrastructure maintenance, WUI exposure assessment, or human-pressure-aware prioritization; and the field still tends to overstate management relevance. Many studies remain one step short of true decision support because they produce informative risk products without specifying the decision architecture they are meant to support.

7. **Robustness, Explainability, Deployment, and Governance**

AI for forest fire prevention has advanced across ecological monitoring, warning, forecasting, and management-facing decision support, but these advances do not automatically translate into credible operational systems. The critical issue is whether such systems remain reliable, interpretable, governable, and deployable when exposed to the ecological and institutional complexity of real forest environments, not simply whether machine learning can produce useful wildfire-related predictions under curated study conditions. Figure 4 formalizes the evaluative chain from benchmark-centric reporting to credible prevention value through ecological fit, transferability, latency, explainability, management usefulness, and governance readiness.

The small number of studies focused on robustness, explainability, deployment constraints, and governance should not be misread as low importance. It reflects a structural imbalance in the literature. Model construction and performance reporting are far more mature than explicit work on robustness, explainability, deployment constraints, and governance readiness. For prevention-oriented AI, these issues cannot be secondary.

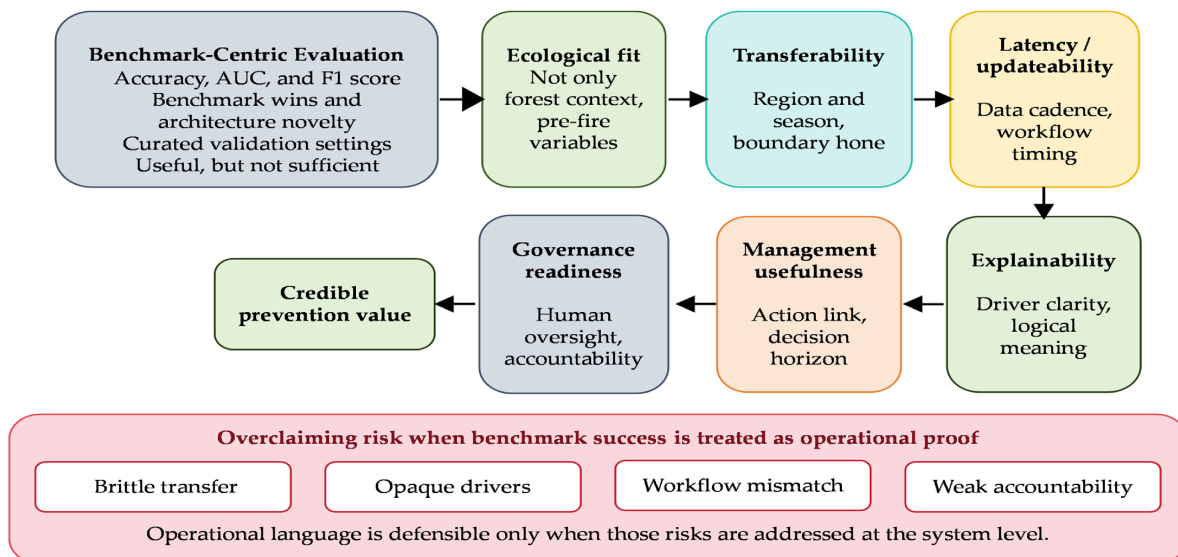


Figure 4. From benchmark performance to operational prevention value.

7.1. Robustness Is the Real Test of Prevention-Oriented AI

Wildfire AI is usually developed under conditions narrower than the decisions it is expected to support. Many models are trained in one region, on one sensing configuration, or over one limited period. That is understandable from a data-availability perspective, but it creates a structural mismatch between benchmark performance and practical reliability. Forest fire prevention operates across variable fuel structures, climatic regimes, land-use pressures, institutional capacities, and sensing conditions. A model that performs well in one setting may degrade sharply when these conditions shift.

Therefore, robustness should be regarded as an essential requirement for prevention-oriented AI rather than a secondary technical consideration. A model that is brittle under environmental change, sensor variation, or altered human-pressure conditions has limited prevention value regardless of local validation scores. The evidence synthesized from the reviewed studies suggests that reported algorithmic improvements are more frequently accompanied by benchmark validation than by evidence of cross-region transferability, long-term deployment, or robustness under varying data-quality conditions [152,179]. Even older remote-sensing comparisons remain instructive because they show that algorithm substitution alone does not answer questions of transferability, interpretability, or workflow fit [153].

7.2. Explainability as Ecological and Management Interpretation

Explainability has become one of the most visible responses to the robustness problem, but in wildfire AI, its value should not be reduced to generic transparency. Explainability matters because it can connect model behavior to ecological understanding and management judgment. If AI systems are to support prevention, they must do more than output a score. They must clarify which environmental, climatic, structural, or human-pressure variables are driving risk in ways that managers can inspect and act upon [154,155].

At the same time, the section remains critical. Not every variable-importance output produces a meaningful ecological interpretation. Explainability can remain shallow when it only redescribes statistical association without clarifying causal plausibility or management action. Interpretability is strongest when it bridges ecological monitoring and management reasoning rather than simply improving model acceptability in the abstract.

7.3. Deployment Readiness and the Gap Between Benchmarks and Operations

Deployment readiness is where robustness and explainability become practical constraints. Across the reviewed studies, operational deployment is commonly discussed, whereas comparatively fewer studies provide evidence of sustained real-world implementation or long-term operational validation. Genuine deployment requires more: stable inputs, acceptable latency, tolerance to missing or noisy data, maintainable update cycles, calibration across seasons and sensor regimes, interpretability for users, and compatibility with institutional workflows.

This gap is especially important for monitoring-to-prevention linkage. In practice, the opposite can occur if the workflow becomes too complex, too fragile, or too opaque for field use. A model is not operational simply because it can run. It becomes operational when the surrounding organization can sustain its use.

7.4. Governance, Accountability, and Appropriate Use

Governance is the least standardized but arguably most consequential dimension of prevention-oriented AI deployment. Once AI outputs begin to influence planning or prioritization across landscapes, questions of fairness, transparency, accountability, uncertainty communication, and institutional interpretation become central rather than optional. A model that reallocates preventive attention is not merely a technical predictor; it participates in governance [156,157].

Based on the comparative evidence synthesized in this review, current studies support AI as a decision-support tool rather than a replacement for professional forest management. It supports a narrower and more defensible claim: AI can strengthen prevention when used as an interpretive and prioritization aid within accountable decision processes. This boundary is essential because forest fire prevention remains an ecological, managerial, and governance problem rather than a purely predictive task.

7.5. Requirements for a More Mature Field

Taken together, the evidence suggests that the next phase of progress should not be defined primarily by larger models or marginal benchmark gains. A more mature field would be distinguished by stronger robustness testing, ecologically grounded interpretability, clearer deployment reporting, and better governance framing. The dominant pattern remains asymmetrical: model construction is more mature than documentation of robustness, deployment, and governance.

7.6. Section Synthesis

Robustness, interpretability, deployability, and governance readiness are essential criteria for judging whether AI can support credible forest fire prevention. Comparative evidence from the retained studies does not justify a simple conclusion that AI is transforming prevention in a straightforward way. A more defensible interpretation is that AI is most promising when it is treated as part of an ecological-monitoring-to-prevention system whose value depends on technical reliability, managerial interpretability, operational deployment conditions, and accountable governance.

Robustness is a central criterion for prevention-oriented AI. Prevention models must remain credible when fuel conditions, climate regimes, ignition sources, sensor platforms, and management practices change. Studies should therefore be evaluated by whether they test spatial transfer, temporal transfer, calibration, uncertainty, class imbalance, and sensor shift, rather than by accepting a single random holdout accuracy or AUC value as sufficient evidence.

Explainability is useful only when it improves ecological and managerial interpretation. XAI studies that identify fuel aridity, precipitation deficits, human proximity, lightning-related variables, and topographic controls can help managers judge whether warnings are plausible [67–82,128–151]. Post hoc feature rankings alone are insufficient if they do not check ecological coherence, data leakage, or action thresholds.

Deployment readiness requires latency, maintainability, governance, and accountability. Edge-AI and IoT systems must tolerate power and communication constraints; satellite products must handle cloud, revisit time, and sensor-change issues; and decision dashboards must define who receives an alert, who verifies it, what action is permitted, and how false positives are recorded. These requirements explain why model performance must be distinguished from workflow compatibility and governance accountability [95–102].

The governance discussion also recognizes that prevention decisions are not purely technical. Fuel treatment, firebreak placement, powerline inspection, public warning, and WUI mitigation involve budgets, property rights, agency authority, liability, and community acceptance. An interpretable AI model may identify a high-risk corridor, but implementation still depends on whether land managers can act, whether the intervention is socially acceptable, and whether responsibility for missed or false warnings is defined. For this reason, operational prevention value is treated as a socio-technical property rather than a model metric alone.

8. Discussion and Future Directions for Prevention-Oriented AI in Forest Fire Prevention

The comparative synthesis of the retained studies supports a restrained but evidence-grounded conclusion. AI has clear value in forest fire prevention when it improves a defined part of the monitoring-to-decision chain. It is less convincing when studies relabel detection, susceptibility, or retrospective mapping as prevention without showing how the output changes pre-fire action. The most credible studies connect ecological variables, validation design, forecast horizon, uncertainty, and management use.

Five directions follow from the evidence. First, benchmark design should include deterministic and probabilistic baselines rather than only comparing AI models with one another. Second, ignition-risk studies should separate lightning, human, infrastructure, and land-use ignition processes when data allow. Third, spread-forecasting studies should state the forecast horizon, uncertainty, and decision use. Fourth, decision-support studies should test whether managers can act on outputs under staffing, cost, legal, and governance constraints. Fifth, international transfer tests should become routine because a model useful in one forest type, climate regime, or data infrastructure may be unreliable elsewhere.

The practical implication is that AI should be evaluated as part of a prevention system. In data-rich regions, AI can support high-resolution fuel monitoring, daily warning, powerline inspection, WUI prioritization, and scenario forecasting. In data-sparse regions, simpler fire-weather baselines, satellite products, and interpretable statistical models may be more robust than complex deep systems. The global value of AI therefore depends less on algorithmic novelty than on ecological calibration, data continuity, uncertainty communication, and institutional authority.

The synthesis has clear limits. Although the evidence base is broader in international coverage and more strongly anchored in classical fire science, the literature remains heterogeneous. Studies use different spatial units, definitions of fire occurrence or susceptibility, validation splits, and reporting practices. Accordingly, algorithms are not ranked by pooled accuracy. Instead, each class of study is evaluated according to whether it provides enough evidence for a defined prevention decision. This conservative approach is

appropriate because the literature is too heterogeneous to support a single pooled ranking of AI methods.

Practical maturity can be judged by whether a study specifies the decision actor, the time available for action, the spatial unit of intervention, the acceptable false-alarm burden, and the uncertainty that should accompany the output. A study remains preliminary when it reports only image accuracy, susceptibility ranking, or retrospective fit without these operational details. This distinction helps reconcile the rapid growth of AI wildfire studies with the slower development of deployable prevention systems.

Negative findings and limited-transfer results are as important as high-scoring models because they show where AI systems fail under new fuels, sensors, regions, or decision constraints and help prevent premature claims of readiness. Such limits are especially important for agencies that must choose robust tools rather than merely novel algorithms, because public safety, limited budgets, legal accountability, field staffing, cross-agency coordination, and public trust shape prevention choices in real forest landscapes.

A prevention-oriented research agenda should therefore reward transparent reporting, reusable datasets, independent validation, and clear links between model output and feasible action. These requirements may appear less novel than new architectures, but they are the conditions under which AI can move from promising demonstrations to accountable forest fire prevention practice.

9. Conclusions

1. AI is most useful when it supports actionable prevention decisions before ignition or escalation, rather than focusing solely on detection accuracy or susceptibility mapping.
2. Prevention value depends on selecting monitoring variables that are appropriate for specific management decisions and ecological conditions.
3. Classical deterministic and probabilistic models remain necessary, and AI should be compared with, coupled to, or used to update fire-danger and spread baselines such as FWI, NFDRS, KBDI, Rothermel-type spread models, FARSITE, FlamMap, and ensemble simulation.
4. Overall, the reviewed literature demonstrates substantial progress in AI-based prevention, while evidence for operational validation, cross-region transfer, and governance remains comparatively limited.
5. Lightning activity should be included alongside human pressure where it is ecologically relevant, especially in boreal, montane, and remote forest systems.
6. The most applicable near-term AI systems are hybrid, interpretable, and deployment-aware, combining remote sensing, meteorology, ignition-source data, fire-science baselines, uncertainty reporting, and clear management action after local validation against ecosystem conditions, sensor availability, agency workflows, and governance constraints.

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